Universidade de Aveiro Departamento de Electrónica, Telecomunicações e Informática,
2020

Maria Margarida Carreira Pires Urbano

Contribuições para adaptação de cadeiras de rodas elétricas a pessoas com capacidades de manipulação reduzidas

Universidade de Aveiro Departamento de Electrónica, Telecomunicações e Informática,
2020

Maria Margarida Carreira Pires Urbano

Contribuições para adaptação de cadeiras de rodas elétricas a pessoas com capacidades de manipulação reduzidas

Contributions for adapting electric wheelchairs to people with reduced handling capabilities

Dissertação apresentada à Universidade de Aveiro para cumprimento dos requisitos necessários à obtenção do grau de Doutor em Engenharia Electrotécnica, realizada sob a orientação científica do Doutor José Alberto Gouveia Fonseca, Professor Associado do Departamento de Eletrónica, Telecomunicações e Informática da Universidade de Aveiro e do Doutor Francisco Alexandre Biscaia Godinho, Professor Auxiliar da Escola de Ciências e Tecnologia da Universidade de Trás-os-Montes e Alto Douro.

Dissertation submitted to the University of Aveiro in the fulfillment of the requirements for the degree of Doctor in Engenharia Electrotécnica, under the supervision of José Alberto Gouveia Fonseca, Professor Associado at the Departamento de Eletrónica, Telecomunicações e Informática of the University of Aveiro and co-supervision of Francisco Alexandre Biscaia Godinho, Professor Auxiliar at Escola de Ciências e Tecnologia da Universidade de Trás-os-Montes e Alto Douro.

o júri / the jury

Presidente /Chairman

Doutor Armando Jorge Domingues Silvestre

Professor Catedrático da Universidade de Aveiro

Vogais /Others members

Doutor José Boaventura Ribeiro da Cunha

Professor Associado com Agregação da Universidade de Trás-Os-Montes e Alto Douro

Doutor Carlos Baptista Cardeira

Professor Auxiliar da Universidade de Lisboa

Doutor Manuel Bernardo Salvador Cunha

Professor Auxiliar da Universidade de Aveiro

Doutor António Manuel Rodrigues Carvalho dos Santos

Professor Adjunto do Instituto Politécnico de Coimbra

Doutor José Alberto Gouveia Fonseca

Professor Associado da Universidade de Aveiro (Orientador/Supervisor)

agradecimentos / acknowledgements

É com muito gosto que aproveito esta oportunidade para agradecer a todos os que me ajudaram neste longo percurso. Demorou, mas como a esperança é a última a morrer, acabou por chegar ao fim.

Começo por agradecer ao meu orientador científico, Professor José Alberto Fonseca, que não hesitou em aceitar-me como sua orientanda, apesar de eu nunca ter sido sua aluna, nem aluna da Universidade de Aveiro. Além das suas preciosas orientações perspicazes, ajudas técnicas, científicas e linguísticas, tenho também de lhe agradecer o ambiente franco das nossas reuniões de trabalho. "Tens de dar corda aos sapatos" foi uma expressão que ouvi bastante, mas sempre com uma atitude de compreensão pela minha falta de disponibilidade para uma total dedicação a este trabalho.

Ao meu coorientador, Professor Francisco Godinho, que aceitou sem hesitação, ser coorientador já numa fase avançada do trabalho. O seu contributo foi fundamental dado que, o seu vasto conhecimento na área da reabilitação, permitiu-me aprofundar conhecimentos na área acessibilidade e tecnologias de apoio a pessoas com deficiência.

Claro está que muito tenho que agradecer a toda a minha família, nomeadamente, Pai e Mãe, irmãos e filho. Além de me incentivarem a acabar este trabalho, principalmente nos momentos menos bons, alguns até foram sujeitos ao teste experimental de condução de automóvel. Uma referencia especial ao Francisco pela paciência nas discussões sobre algoritmos de classificação e pelas dicas.

À ESTGA, claro está, por me ter possibilitado e apoiado ao longo de todo este percurso. A todos os meus colegas, pelas partilhas de bons e menos bons momentos, e principalmente pelas várias discussões multitemáticas, sempre saudáveis.

Ao Centro de Medicina e de Reabilitação da Região Centro-Rovisco Pais, por terem acedido ao meu pedido para a concretização dos testes com pacientes residentes e, em particular, ao Enfermeiro Pedro Miguel Gordo por todo o seu apoio, desde a verificação da disponibilidade de pacientes para a realização dos testes, assim como, do seu acompanhamento durante a sua execução.

A todos os meus amigos e amigas que me proporcionaram momentos de desabafo e de descontração, ajudando assim de forma indireta, ao término desta tarefa. Um especial agradecimento aos meus colegas de natação da AAC, pelo intenso convívio salutar.

palavras-chave Cadeiras de rodas elétricas, *joystick*,manipulação, *stress*, resposta galvânica, batimento cardíaco, perfil emocional, algoritmos de classificação.

Resumo

O uso de uma cadeira de rodas elétrica durante as atividades do quotidiano por pessoas com limitações motoras proporciona autonomia, aumentando qualidade de vida. No caso de pessoas com limitações mais severas, nomeadamente com manipulação reduzida, a utilização da cadeira de rodas elétricas pode estar comprometida, pois não conseguem controlar o joystick com a destreza necessária. Este trabalho pretende proporcionar a essas pessoas a possibilidade de conduzir a sua cadeira de rodas elétrica de uma forma confortável e segura.

Esta proposta de adaptação de uma cadeira de rodas elétrica tem essencialmente dois grandes objetivos. O primeiro é permitir a pessoas que não conseguem conduzir uma cadeira de rodas elétrica convencional por sofrerem de fraqueza muscular nos membros superiores, o comecem a fazer. Assim, para facilitar a condução da cadeira, propõem-se três modos de operacão. Além disso, o controlador da cadeira adptada vai ter que ter a capacidade de interpretar os novos impulsos dados no joystick, que dependem das capacidades de manipulação de cada utilizador, em comandos de direção

A condução da cadeira de forma consecutiva pode-se tornar rapidamente um fator de stress. Assim, o segundo objetivo é garantir que, enquanto a pessoa conduz a cadeira se mantenha sempre num estado calmo, evitando prejudicar o seu bem-estar e consecutivamente, a sua saúde.

É assim proposto a integração de um sistema de monitorização do seu estado emocional durante a condução da cadeira. Este sistema tem como principal objetivo alertar o utilizador que este atingiu níveis emocionais críticos que inviabilizam a continuação da condução em segurança. Nesta situação, quem passa a ficar responsável pelo comando da cadeira é o próprio controlador da cadeira.

A implementação do sistema baseou-se no uso de sensores de resposta galvânica e de batimento cardíaco. Com a informação adquirida por estes sensores, definiu-se o conceito de perfil emocional do utilizador e foram avaliados algoritmos de classificação de stress capazes de prever diferentes estados emocionais.

Este sistema foi testado por dois grupos de utilizadores. O primeiro grupo foi composto por condutores a conduzirem automóveis e o segundo grupo foi composto por pessoas tetraplégicas, a conduzirem as cadeiras de rodas elétrica pessoais.

Para pessoas sem deficiência confirmou-se, através dos sinais biométricos, que cada pessoa reage de forma diferente perante as mesmas situações. Esta diferença é mais flagrante na resposta da condutividade da pele. No que diz às pessoas tetraplégicas, confirmou-se que a resposta do sistema nervoso simpático não pode ser medida através da resposta galvânica da pele. Para a implementação da deteção de stress em tempo real foram usados diversos algoritmos de classificação. Para cada utilizador, foi encontrado o melhor modelo de classificação. Conclui-se que os melhores modelos variam de pessoa para pessoa e que também dependem do número e tipo de preditores utilizados.

Este trabalho resulta da colaboração entre a Universidade de Aveiro e o Centro de Medicina de Reabilitação da Região Centro - Rovisco Pais.

keywords Powered wheelchairs, joystick,handling, stress, galvanic skin response, heart rate, emotional profile, classification algorithms.

Abstract

The use of a commercial powered wheelchair during daily activities by people with motor limitations provides autonomy, increasing quality of life. For people with more severe restrictions, specifically reduced handling, the use of the powered wheelchair may be compromised as they cannot control the joystick with the required ability. This work is intended to give these people the ability to drive comfortably and safely their electric wheelchair.

This proposal for adapting a commercial powered wheelchair has essentially two main objectives. The first one is to allow people who cannot drive a conventional powered wheelchair because they have muscle weakness in their upper limbs to do so. So, and to facilitate the wheelchair navigation, three modes of operation are proposed. Therefore, the adapted wheelchair controller must able translate the new impulses provided by the joystick, depending of the user abilities, in direction commands.
Driving the powered wheelchair continuously can quickly become a stressor. Thus, the second goal is to ensure that during the powered wheelchair driving, its user always remains in a calm state, avoiding harming their well-being and their health.

It is thus proposed to insert a system for monitoring the emotional state of the wheelchair user. The primary purpose of this system is to alert its user when he reached critical emotional levels, which makes it impossible to continue driving safely. In this situation the wheelchair controller becomes responsible for the wheelchair command.

The implementation of the stress detection system was based in the galvanic skin response and heart rate sensors. With the acquired information, it was defined the user's emotional profile and evaluated several algorithms classification to predict new emotional states.

This system was tested by two users groups. The first group consisted of drivers driving cars and the second group consisted of tetraplegic people driving their powered wheelchair.

For people without disabilities, it was confirmed through biometric signals that each person reacts differently to the same situations. This difference is most striking in the response of skin conductivity. For tetraplegic people, we concluded and confirmed, that the sympathetic nervous system response cannot be measured by galvanic skin response.

Several classification algorithms were trained for stress detection in real-time. For each user, the best classifying model was found. We conclude that the best models vary from person to person and also depend on the number and type of predictors used.

This work results from the collaboration of the University of Aveiro and the Centro de Reabilitação e Medicina da Região Centro - Rovisco Pais.

Contents

Contents i

List of Figures v

List of Tables ix

1 Introduction 1

1.1 The Problem 1

1.2 The Thesis 4

1.3 Contributions 4

1.3.1 A proposal to adapt a commercial powered wheelchair to patients with reduced mobility in the upper limbs 5

1.3.2 An implementation of the novel legacy adapted mode operation 5

1.3.3 A simulation implementation of the semi-autonomous transfer mode operation 5

1.3.4 A proposal of a novel system to integrate homeostatic sensors in the commercial powered wheelchair control unit 6

1.3.5 An implementation of a stress detection system 6

1.3.6 Emotional user profile concept validation 6

1.4 Organization of the dissertation 7

2 An overview of basic concepts about mobility and stress 9

2.1 Introduction 9

2.2 Muscle weakness and mobility 9

Stroke and Mobility 13

Multi Sclerosis and mobility 13

Parkinson's Disease and Mobility 14

2.2.1 Spinal cord injury and Mobility . . . 14
Locomotion and tetraplegia . . . 16
2.3 Stress and body response to stress . . . 17
2.4 Conclusions . . . 21

3 Smart wheelchair and Stress Detection: a survey 23
3.1 Introduction . . . 23
3.2 Smart wheelchairs . . . 24
3.2.1 Introduction . . . 24
3.2.2 Smart wheelchair definition . . . 25
3.2.3 Smart wheelchairs form factor . . . 27
Modified powered wheelchairs . . . 28
Add on units . . . 31
Adapted Manual Wheelchairs . . . 36
3.2.4 Human Machine Interface . . . 36
3.2.5 Smart wheelchairs navigation methods and operating modes . . . 41
3.2.6 Obstacle detection sensors . . . 43
3.2.7 Commercial Smart Wheelchairs . . . 44
3.3 Stress Detection . . . 46
3.3.1 Introduction . . . 46
3.3.2 How to measure stress and stress scales . . . 46
3.3.3 Overall biosignals processing . . . 48
Features extraction and selection . . . 48
Stress classification techniques . . . 49
3.3.4 Types of stress detection systems . . . 50
Biofeedback stress detection system . . . 51
Open stress detection systems . . . 52
3.3.5 GSR and ECG analysis . . . 53
Galvanic Skin Response typical waveform . . . 53
ECG typical waveform . . . 55
Effects of acute stress on GSR and ECG . . . 57
Spinal cord injury and stress response . . . 59
3.4 Conclusions . . . 60

4 A proposal for an APW navigation system **63**

4.1 Introduction . . . 63

4.2 The overall APW model . . . 63

4.2.1 The overall APW architecture and operation . . . 65

4.3 The APW assistive mode . . . 69

4.3.1 The legacy adapted mode (LAM) . . . 72

4.3.2 A novel adaptation of LAM . . . 74

4.3.3 The Semi autonomous Transfer Mode (SaTM) . . . 81

The sensorial system . . . 82

Wheelchair representation and the referential . . . 82

The acceptance area . . . 83

The wheelchair angle . . . 84

4.4 The overall stress detection system model . . . 87

4.4.1 Stress detection system (SDS) operation requirements . . . 87

4.4.2 The stress detection system architecture and operation . . . 87

4.4.3 Integration of the user emotional state into APW . . . 90

4.5 Conclusions . . . 92

5 Support Tools **93**

5.1 Introduction . . . 93

5.2 Using simulation for the validation of LAM . . . 93

5.2.1 Introduction to the Stage Software . . . 93

5.2.2 Implementation of the LAM mode . . . 96

5.2.3 Implementation of the SaT mode on STAGE . . . 97

The trajectory planning . . . 99

5.2.4 Implementation of the LAM mode in a CPW . . . 101

5.3 Stress detection system implementation . . . 103

5.3.1 Acquisition and Register Module . . . 104

5.3.2 Analyzing and classification subsystem . . . 106

GSR and ECG offline analysis . . . 106

Creation of the user emotional profile . . . 109

Choosing the best stress classification algorithm . . . 113

5.4 Conclusions . . . 118

6 Experimental Results **119**

6.1 Introduction . . . 119

6.2 Results from using Stage to validate LAM and SaTM . . . 120

6.3 Acquisition and Register Module validation . . . 122

6.4 Vehicular navigation results . . . 122

6.4.1 Experimental Procedure . . . 122

6.4.2 Drivers matrix tables and their emotional profile . . . 123

6.4.3 Drivers emotional classification . . . 124

6.5 Powered Wheelchair Navigation Results . . . 130

6.5.1 Target Group . . . 130

6.5.2 Experimental Procedures . . . 131

6.5.3 Tests Results . . . 133

Results of the first test . . . 133

Results of the subsequent tests . . . 134

Comparison between values drawn by the Shimmer sensor and by the Biofeedback 2000 x-pert system . . . 135

Results of the tests with patients with type T injury . . . 135

6.5.4 Powered wheelchairs drivers emotional classification . . . 136

6.6 Conclusions . . . 141

7 Conclusions and Future Work **143**

Bibliography **147**

List of Figures

2.1 Schematic diagram of the Nervous System [1] 11
2.2 Dermatome Map of Upper Limb (Shoulder, Arm, and Hand)[2] 12
2.3 Map of the spinal cord and the affected area body [3] 15
2.4 Signalling pathway for the thermoregulatory centre [4] 20
2.5 Scheme of autonomic innervation of the heart [5] 20

3.1 Traditional Smart Wheelchair Block Diagram 26
3.2 General Smart Wheelchair Block Diagram [6] 27
3.3 Seat mobile robots SW examples [7, 8] 28
3.4 The SENA Robotic Wheelchair [9] 29
3.5 Researches and industry SW projects [10, 11] 31
3.6 Modular Smart Wheelchair Component System (SWCS) [12] 33
3.7 Drive-Safe System 34
3.8 IntellWheels prototype 34
3.9 The prototype TDS system [13] 39
3.10 The Emotiv EPOC and the electrodes location [14, 15] 40
3.11 The EMG headband and the respective data acquisition box [16] 40
3.12 Example of a commercial powered smart wheelchair 45
3.13 Block diagram of biosignals processing 48
3.14 GSR typical waveform states 54
3.15 GSR typical waveform 55
3.16 Einthoven's triangle [17] 56
3.17 Records of a normal ECG, lead II [18] 56
3.18 SCR waveform 57

4.1 Modeling the psychoanalytical processing sequence [19] 64

4.2 The adaptation of the ARS model to be used in the APW operation 65
4.3 Overall architecture of the proposal APW 67
4.4 The overall operation of the proposal APW 68
4.5 APW operation Finite State Machine 69
4.6 Commercial adapted joystick 70
4.7 Wheelchair autonomy / user skills 71
4.8 LAM operation FSM 74
4.9 LAM moving state 74
4.10 Novel LAM operation FSM 77
4.11 Novel LAM moving and stopped states 78
4.12 Example of a gradual increase in velocity considering k=5 80
4.13 Velocity stair shaped function used to stop the wheelchair 81
4.14 Example of a gradual decrease in velocity considering k=5 81
4.15 Door and referential 83
4.16 The wheelchair and the door 83
4.17 Wheelchair orientation angle 84
4.18 SaTM stopped and moving states 86
4.19 SaTM transition conditions 86
4.20 The Stress Detection System overview 89
4.21 Alert mode operation FSM 90
4.22 Alert mode temporal diagram 91
4.23 Alert APW navigation 91
4.24 Alert mode transition conditions 92

5.1 The architectural plant of the training house at the CMRRC-RP Center . . . 95
5.2 The Stage APW mode operation implementation 95
5.3 User parameters on STAGE 96
5.4 The LA mode operation implemented on STAGE 97
5.5 SaTM navigation flowchart 98
5.6 p_{ilc} positions 99
5.7 The trajectory planning 100
5.8 CPW architecture 101
5.9 Two possible ways of implementing the LA mode 102
5.10 sensors US CPW layout 103

5.11 Acquisition and register platform overview 105
5.12 Shimmer ECG and GSR sensors applications 105
5.13 Application Stress measurement principal view 106
5.14 MATLAB interface principal screen 108
5.15 List of occurrences 109
5.16 ECG and GSR features 109
5.17 marked events in GSR signal 109
5.18 Classification procedure 114
5.19 Comparison of classification algorithms 115
5.20 Classification Learner App principal screen 116
5.21 Confusion matrix 117

6.1 Confusion matrices for Driver 1 125
6.2 Confusion matrices for Driver 2 126
6.3 Confusion matrices for Driver 3 126
6.4 Confusion matrices for Driver 4 127
6.5 Confusion matrices for Driver 5 127
6.6 Confusion matrices for Driver 6 128
6.7 First experimental test GSR waveform 133
6.8 GSR signals with the electrodes in forehead 134
6.9 GSR Biofeedback results 135
6.10 T4 and T11 GSR signal 136
6.11 Confusion matrix - Patient 1 137
6.12 Confusion matrix - Patient 4 138
6.13 Confusion matrix - Patient 5 138
6.14 Confusion matrix - Patient 6 139
6.15 Confusion matrix - Patient 8 139
6.16 Confusion matrix - global dataset 140

List of Tables

2.1 Mobility Outcomes versus injury level [20] 17

3.1 Smart wheelchair based in commercial powered wheelchair reported in literature 30
3.2 Add on units Smart Wheelchair reported in literature 35
3.3 Input interface used in smart wheelchairs reported in literature 41
3.4 Smart wheelchairs operating modes 43
3.5 Obstacle detection sensors 44
3.6 Stress detection sensors 47
3.7 Stress algorithms review 50
3.8 GSR Selection Features 58

4.1 APW transition conditions 69
4.2 LAM mode transition conditions 75
4.3 Novel LAM transition Conditions 78

5.1 trajectory planning transition conditions 100
5.2 GSR and ECG features 108
5.3 Example of a matrix table 112
5.4 Example of a user emotional profile 112

6.1 LAM simulation results 121
6.2 Drivers emotional profiles (GSR and HR) 123
6.3 Performance metrics for driver 1 125
6.4 Performance metrics for driver 2 125
6.5 Performance metrics for driver 3 126
6.6 Performance metrics for driver 4 127
6.7 Performance metrics for driver 5 128

6.8 Performance metrics for driver 6 128
6.9 GSR and HR Metrics Models Comparison 129
6.10 GSR Metric Models Comparison 129
6.11 HR Metrics Models Comparison 129
6.12 Global dataset classifications resume 130
6.13 Chronological experimental tests 133
6.14 GSR features with 0,01 threshold 134
6.15 T4 and T11 GSR features (0,05 Threshold) 136
6.16 Powered wheelchair drivers emotional profiles (HR) 137
6.17 Performance metrics for patient 1 137
6.18 Models metrics for patient 4 138
6.19 Models metrics for patient 5 138
6.20 Models metrics for patient 6 139
6.21 Models metrics for patient 8 140
6.22 Models metrics for global dataset 140

Chapter 1

Introduction

1.1 The Problem

The problem of care taking of persons with physical disabilities will become more serious in the near future when a significant part of the global population will be in the 65 or over age group and the existing welfare model will not be able to meet the overall needs. According to the European Health and Social Integration Survey (EHSIS), in 2012 there were 70.0 million people with disabilities aged 15 and over in the European Union, equivalent to 17.6 % of the population that was aged 15 and over [21].

Based on the concepts used in the EHSIS, people with disabilities are those who face barriers to participate in any of 10 specific life areas due to a long-standing health problem and/or a difficulty in basic activities.

Mobility is one of these specific areas and it is defined as the ability to leave one's own home. According to [22] around three in five (60.9%) people with disabilities in the EU said that their participation in leisure activities is restricted, with this share reaching just above one in two (52.9%) for mobility.

Mobility impairments can have different causes, such as conditions present at birth, illness, physical injury and accidents [23].

Powered wheelchairs are the most common devices used in assisting people with mobility impairments into their daily life activities.

While the needs of many disabled people can be satisfied with a standard manual or powered wheelchair, a segment of this community finds extremely difficult or even impossible to use a commercial powered wheelchair (CPW) for activities of daily living [24].

Severe physical limitations can pose series difficulties to powered wheelchair navigation,

specially if space is restricted. One of the most stringent situations is at home, where space is limited and populated with obstacles.

In the last few decades, scientists and engineers have developed smart wheelchairs for helping handicapped people to live more independently and to achieve a higher degree of mobility than they had before.

The main purpose of an assistive technology (AT) such as a smart wheelchair, is to provide the necessary help for people with disabilities in performing their daily life activities, and to guarantee at the same time, that they have the same opportunities as people without disabilities.

The use of a smart wheelchair in the daily life activities allows the user to go from one location to another without outside assistance and to provide the capability of decision making in path planning and navigation, so that the mobility occurs in a safe and normal manner.

Therefore, the design of such a system needs to take into consideration the specific deficiency of the wheelchair user in order to maximize the physical and decision making capabilities. The goal is to adjust the interface to the impairment, to have a navigation system with different levels of autonomy and to trigger the autonomous mode only when necessary.

Even if the operational mode of the system is adapted to the user, there are psychological and emotional factors that can influence the normal and desired safe navigation.

Safe navigation is a challenge for all types of vehicle navigation systems. Driver assistance is one of the technologies that incorporate vehicular safety systems and car manufactures, for example, are constantly updating these systems. The information concerning the driver stress level is become increasingly considered in driver assistance system development.

The work described in this dissertation is an exploration of a solution that enables the incorporation of the emotional state of the patient in the control unit of the wheelchair, using emotional sensors to detect the stressing factors and their influence in the navigation.

An ideal wheelchair control system must gather sensory data, extract relevant information from the data and reach a decision considering the environmental situation as well as the user's psychic condition. The control system must have the capacity of processing sensors' data, in real-time, of reacting to unknown environmental situations, as well as reacting to the eventual changes of the wheelchair user's welfare. According to these attributes, an ideal smart wheelchair can be seen as an embodied autonomous agent.

Assistive technology innovation has to be interdisciplinary and collaborative. Physicians,

psychologists, and care takers guide the technology developers in finding solutions that meet the specific needs of the patients, since they are the ones capable of evaluating their physical and mental conditions.

This collaborative interdisciplinary sharing information constitutes the basis of work for the development of this proposal. Therefore, the architecture and operation of the Assisted Powered Wheelchair (APW) proposal were developed in collaboration with the "Centro de Medicina e Reabilitação da Região Centro - Rovisco Pais" (CMRRC-RP , therefore referenced as Rehabilitation Center) in Portugal and the collaboration with the University of Aveiro and the Institute of Computer Technology of the Vienna University (ICT-TU Wien).

From our work with the Rehabilitation Center clinicians, a problem was identified related to the manipulation of the legacy joystick by patients with reduced mobility in upper limbs, namely, insufficient strength in the arms and hands. This deficiency makes it impossible to conduct the wheelchair on an ongoing basis, and even if they can do it for a while, they get tired very quickly.

So, they agree and suggested that the ideal solution for the problem of these people would be to navigate the wheelchair without the need of continuous driving force. This was the base to develop the APW Human Machine Interface (HMI).

Concerning the navigation modes of the APW, they agree that it would be far more beneficial for the patients that the APW will be developed in a semi-autonomous navigation mode, rather than a completely autonomous mode, with the ability to self-adapt to the patient's disease state.

These clinicians know all about the evolution of patient's diseases and know how the APW navigating can become, very quickly, stressful. So, they have considered interesting and useful the application of a system that allows the emotional evaluation of the APW user during his or her driving. The goal of this system is to monitor the user's emotional state to avoid situations that can damage their health.

Therefore, this APW proposal was based in these three rehabilitation clinicians advice, namely, to the development of the HMI, to development of the modes of operation of the APW and the development of patients health monitoring system.

With these specific features, the assistive device APW can be considered as an embodiment autonomous agent and, as a result of our work with ICT-TU Wien, its control unit system was designed based on the bionic approach underlying the Artificial Recognition System (ARS) project.

The ARS project, renamed Simulation of the Mental Apparatus & Applications (SiMA in 2015, is a functional model of the human mind. The functional model itself was developed together with psychoanalysts and inspired from the Psychoanalytic Model of the human mind. SiMA follows a bionic approach and uses the model of the metapsychology as a framework for building a functional model of the human mind.

So, this concept of bionic approach was adapted in the APW control unit by incorporating the ARS project body perception layer through the integration of the internal user state and external APW environment.

Therefore, the proposal APW presented is based on an adaptive shared control system among the decision of the user, their emotional state and the environment that surrounds the APW.

This dissertation proposes an architecture and components for an APW to allow people with reduced mobility in upper limbs to achieve safe and healthy efficient indoor powered wheelchair navigation.

1.2 The Thesis

The thesis supported by the present dissertation argues that:

Adapting a commercial powered wheelchair joystick operation to the user disability and to enable the wheelchair navigation shared control between user decision and emotional user state, can improve autonomy and quality of life of their users.

1.3 Contributions

The main contributions of this dissertation are:

- A proposal to adapt a commercial powered wheelchair to patients with reduced mobility in the upper limbs;
- An implementation of a novel operation mode called legacy adapted mode;
- A simulation implementation of the semi-autonomous transfer mode operation;
- A proposal of a novel system to integrate homeostatic sensors in the commercial powered wheelchair control unit;
- An implementation of the emotional stress detection system;

- Emotional user profile concept validation.

The contributions are summarized below:

1.3.1 A proposal to adapt a commercial powered wheelchair to patients with reduced mobility in the upper limbs

An adaptation of a commercial powered wheelchair in order to facilitate its driving by people with reduced strength is proposed and evaluated.

Several models of operation are proposed and the adapted powered hardware architecture is based on a legacy joystick adapted wheelchair, on add-on units and in a shared control between the APW control and its user.

The proposal takes advantage of the add on units to guarantee, not only the physical safety of the APW but also, their emotional safety. That way, whenever a user's emotional security is at stake, the APW controller will take control of the APW navigation.

The user emotional state is obtained by the stress detection add on unit and, in this proposal, the majority of their functionalities are implemented.

1.3.2 An implementation of the novel legacy adapted mode operation

The novel legacy mode of operation is implemented with the robot simulator Stage. These simulations allow to evaluate the navigation algorithms and to evaluate the operational modes performance.

Some experimental real tests were made with tetraplegic patients with reduced strength in the arms and hands which were, at that time, in the center of Rehabilitation Center.

1.3.3 A simulation implementation of the semi-autonomous transfer mode operation

To simulate the semi-autonomous transfer mode, an implementation on the Stage software was made. The goal of this implementation was only to support the Legacy adapted mode operation, to evaluate if it was easy to the tetraplegic patients to switch between modes of operation.

This mode of operation was also tested with patients who were in the center of Rehabilitation Center.

1.3.4 A proposal of a novel system to integrate homeostatic sensors in the commercial powered wheelchair control unit

The proposal is based on the ARS project renamed SiMA (Simulation of the Mental Apparatus & Applications) [25]. The ARS project deals with the modelling of human mind functionalities by making use of multimodal sensory inputs to create perception and consistent representation of the surrounding environment [26]. This is accomplished on the base of a novel bionic approach introducing neuropsychoanalytic concepts to the field of computer science.

In this work, the integration of the homeostatic sensors in the commercial powered wheelchair control unit is made by biometric sensors fusion.

This proposal takes advantage of the model operation and depends on the user's decision and also of the user's emotional state. The commercial powered wheelchair navigation control unit will decide if received commands from the user or not. And, this decision, depends on the user's emotional state.

1.3.5 An implementation of a stress detection system

The technical solution to implement the stress detection system presents a wireless and non-invasive platform that acquires electrocardiogram (ECG) and galvanic skin response (GSR) biosignals and allows to register all occurrences. For each recorded occurrence it is possible to visualize the respective values of the biosignals. In addition, it is possible to view and analyze the biosignals time evolution.

All data is saved for posterior analysis in order to classify stress according to the circumstances the subject was dealing with.

1.3.6 Emotional user profile concept validation

This work supports the idea that each person has different emotional features from each one. And, to validate this idea, the user emotional profile is created by using the data obtained during different experimental tests.

Also, supports the idea that for each user's emotional profile there is a unique best classification model. So, several classification algorithms were trained to find the best classification model for each user's emotional profile. This classification model will be used to classify, in real-time, new biometric sensor's values.

1.4 Organization of the dissertation

Chapter 2 This chapter intends to identify the target people that can take advantage of the use of the APW proposed.

A resume of the causes of the impairment of the upper limbs will be presented, namely, the different situations that cause muscle weakness in the upper limbs.

Also, some consideration about stress and how the body reacts to stress will be made. The goal is to analyze how the different situations that can cause muscle weakness in upper limbs can affect the body stress reaction.

Chapter 3 This chapter presents a survey of smart wheelchairs and stress detection systems. Special attention is given to the person functional impairment mobility after a spinal cord injury, namely, the ability to manoeuvre a commercial powered wheelchair.

Concerning the smart wheelchairs, the form factor, the human machine interface, navigation methods and modes of operation and environmental sensors that are being used in this research area are presented.

Brief reference is also made to the commercial smart wheelchairs available on the market.

Concerning the stress detection, the types of sensors most used to measure stress are analyzed as also the extraction features techniques and stress classification algorithms. This chapter also presents the types of stress detection systems found in the literature.

Chapter 4 This chapter explains the proposed assistive powered wheelchair (APW) navigation system. The overall APW architecture and operation are presented. The different modes of operation are explained as, also, the adaptive shared control system between the decision of the user, his / her emotional state and the environment that surrounds the APW. This chapter also describes the adaptation of the ARS model to create a stress detection system and respective its implementation.

Chapter 5 This chapter describes how was implemented the legacy adapted mode and semi-autonomous transfer mode of operations on the Stage simulator. Also, some references for how to implement the legacy adapted mode in a real commercial powered wheelchair is made.

Concerning the stress detection system, it is explained how it is composed and what is the function of each of the components.

It is described how to build the user's emotional profile from the data acquired by the developed platform. Also, how to use the Matlab software to trained classifications models

and to decide which one is the best model for each user's emotional profile.

Chapter 6 This chapter presents the results of the simulation and real experimental tests of the proposed APW system. Results for tetraplegic patients using the Stage simulator are presented as also the results for car and powered wheelchair driving using the stress detection system.

From the experimental car driving tests, results to find which one of the biometric sensors has the best performance as a predictor are presented. From the experimental commercial powered wheelchair tests, the use of the GSR sensor as a stress detector in tetraplegic patients is evaluated.

Also, results on the use of a single stress classifier model for all car drivers and a single stress classifier model for commercial powered wheelchair drivers, are presented.

Chapter 7 This chapter presents the conclusions of the use and implementation of the proposed assistive powered wheelchair and the future research directions of this work.

Chapter 2

An overview of basic concepts about mobility and stress

2.1 Introduction

The solution proposed in this work is intended, to help people with reduced strength in arms and hands to manipulate his / her powered wheelchair. So, it is important to identify what are the target groups which can benefit from the use of this human machine interface. Also, and to support other parts of this work, it is important to analyze how the human body reacts to stress as well as if this body reaction can be affected by the different mobility impairment causes.

So, in this chapter, some medical issues are presented, like what are the possible causes that can lead to a reduced strength in arms and hands. Also, the consequences of these causes in what concerns the body stress response are discussed. A greater focus is given to the consequences of a spinal cord injury (SCI) due to the fact that all persons who were at the Rehabilitation Center, during the experimental tests phase, had suffered an SCI.

It is important to emphasize that these medical issues are presented not as a medical text but in a way that can contribute to understand the engineering solutions proposed and discussed in this work.

2.2 Muscle weakness and mobility

Muscles are the tissues responsible for movement. The contraction and distension properties of the muscles are what allows the movement performance.

Skeletal muscles are responsible for all kinds of movements of daily functions that people consciously perform, such as walking, swimming, writing and even talking. So, the muscular system gives body mobility.

Muscle weakness refers to loss of muscle strength. Weakness means the loss of strength or power, manifesting in the inability to generate normal force [27].

Weakness may occur in one muscle or may be selective, affecting more muscle groups than others and may even lead to a total loss of muscle function. So, if some of the skeletal muscle is affected, body mobility can be compromised.

The muscular system is controlled through the nervous system (NS). The nervous system can be thought of as the body's communication network, with three main functions: sensory input, integration of data and motor output. It is through the nervous system that the body communicates with the outside world and, at the same time, many mechanisms inside the body are controlled. The nervous system takes in information through sensors, processes the information and triggers reactions, such as making muscles move or causing to feel pain. Muscles provide motion in response to nerve impulses [28].

The nervous system has two parts, called the central nervous system (CNS) and the peripheral nervous system (PeNS) due to their location in the body (see figure 2.1).

The CNS includes the nerves in the brain and spinal cord. The brain is the body's "control center" and, is conceived as a system devoted to information processing, where an appropriate motor output is computed as a response to sensory input.

All of the other nerves in the body are part of the peripheral nervous system. It connects the CNS to the other body organ with efferent nerves that transmitting information from the sensory organs to the brain and afferent nerves that transmit impulses from the brain to limbs and organs. That means that the peripheral nervous system is divided into two parts, the sensory division and the motor division. On the other hand, motor division is divided in the somatic nervous system (SoNS) and in the autonomous nervous system (ANS) and the big difference between them is that the first one is a voluntary system and the second is an involuntary system:

- The somatic nervous system controls all the things that we are aware of and can consciously influence, such as moving our arms, legs and other parts of the body.

- The autonomous nervous system regulates the processes in the body that we cannot consciously influence. It is constantly active, regulating things such as breathing, heart

beat and metabolic processes.

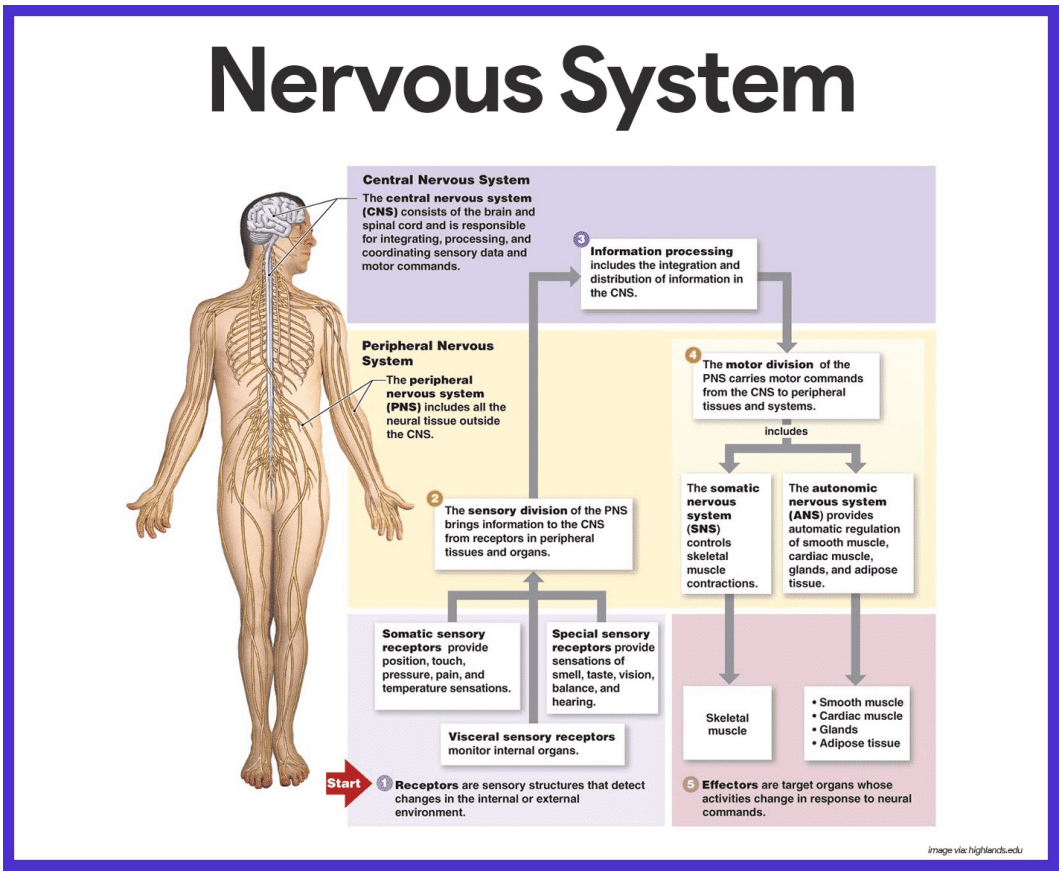


Figure 2.1: Schematic diagram of the Nervous System [1]

Spinal nerves are part of the peripheral nervous system and are responsible for voluntary movement and sensation. There are 31 pairs of spinal nerves and they are located at each vertebral level of the spinal cord and linked to specific muscles. The nerve supply to the upper limb is almost entirely provided by the brachial plexus; a complex intercommunicating network of nerves formed in the neck by spinal nerve roots C5, C6, C7, C8 and T1 as depicted in the figure 2.2:

So, for a person to intentionally move a muscle (called a voluntary muscle contraction), the brain must generate a signal that travels a pathway from [29]:

- The brain
- Through nerve cells in the brain stem and spinal cord
- Through nerves from the spinal cord to the muscles (called peripheral nerves)
- Across the connection between nerve and muscle (called a neuromuscular junction)

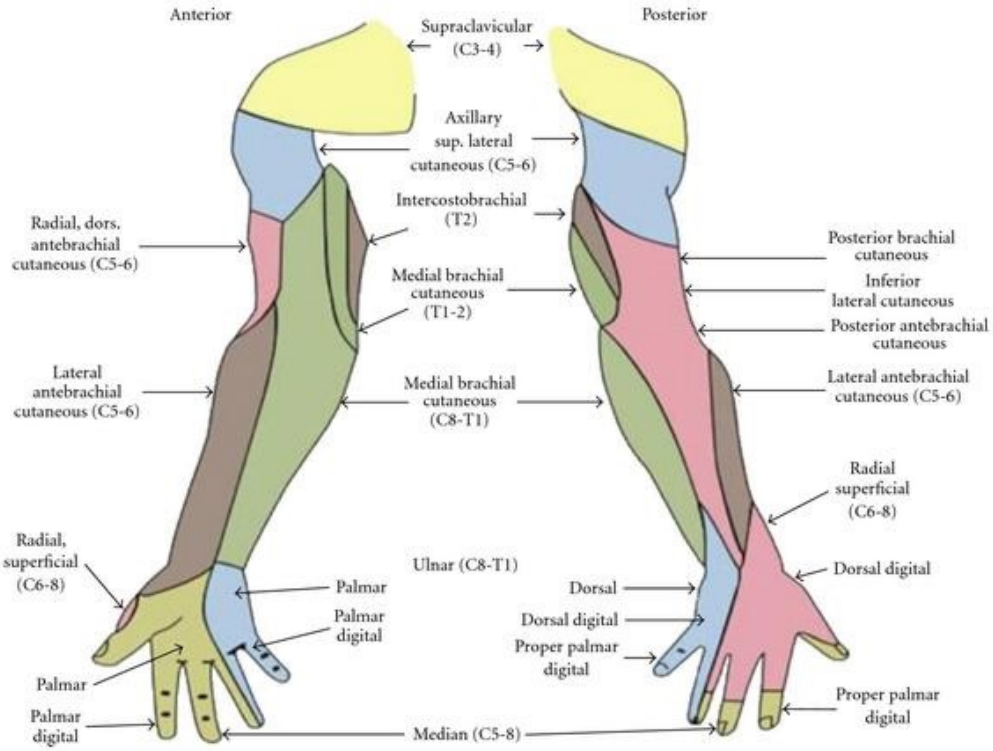


Figure 2.2: Dermatome Map of Upper Limb (Shoulder, Arm, and Hand)[2]

- The tissue must be able to contract in response to the signal from the nerves

A chain of processes in the nervous system and the muscle precedes voluntary muscle contraction and changes at any level of this pathway could impair force or power generation [30]. Therefore, muscle weakness results when one part of the pathway brain, spinal cord, nerves, muscles, or the connections between them — is damaged or diseased.

Regarding the upper limb muscle weakness, this can be caused by brain disorders like multiple sclerosis, Parkinson's and stroke or spinal cord disorder like SCI, among other causes.

People who are affected by these symptoms face constant challenges to have mobility and need constant attention from an assistant to move. Manual wheelchair has been widely adopted by persons unable to walk but they must have sufficient upper-limb strength to propel it [31]. The same question arises in the use of commercial powered wheelchair with joystick: they are limited only to people who can use the joystick.

Below, a resume of how the mentioned diseases could affect the ability to drive a commercial powered wheelchair, conventional joystick based, is presented.

Stroke and Mobility

Weakness or paralysis is the predominant impairment that contributes to dysfunction after stroke: it is a direct consequence of the lack of signal transmission from the motor cortex, which generates the movement impulse, to the spinal cord, which executes the movement via signals to muscles [32]. The common manifestations of upper extremity motor impairment, after a stroke, include muscle weakness, changes in muscle tone, joint laxity, and impaired motor control. These impairments induce disabilities in common activities such as reaching, picking up objects and holding onto objects [33].

In [34] the authors made a study to determine the effectiveness of joystick-controlled video console games in enhancing subjects' ability to control power wheelchairs and they concluded that the muscle activity during the power wheelchairs driving test showed that the elbow extensors and the flexors of the wrist and hand contributed more to joystick control.

So, the ability to drive a commercial powered wheelchair based on a conventional joystick could be compromised after a stroke because damage from a stroke often leaves arm muscles and nerves incapable of receiving integral messages to command the movement and objects being manipulated.

Multi Sclerosis and mobility

Multi Sclerosis is an abnormal immune system response that produces inflammation in the central nervous system damaging or destroying myelin. Myelin insulates and protects the axon and helps speed nerve transmission, allows signals to be transmitted rapidly from the nervous system to the rest of the body. When myelin is destroyed nerve signals are slowed or stopped.

Depending on the progression and type of multiple sclerosis, mobility needs can include manual wheelchairs or powered wheelchair. Power mobility devices benefit people with MS by enabling them to conserve energy, decrease fatigue, and participate in activities of daily living [35].

It is often advised to start by using with a proportional control (joystick) because this provides the most direct control for driving a power base.

As the disease progresses and the individual experiences more frequent fatigue, muscle weakness or other conditions affecting the ability to function, specialty powered wheelchair controls may be required for the individual to continue performing [36].

The types of electronics and drive control chosen for power wheelchairs are important

considerations for people with MS [35]. The control interface can have a major effect on the success or failure of a power wheelchair as a mobility device. The controller used has major implications for people with MS, since ataxia of the upper extremities is a concern in the later stages of the disease [36]. An ideal controller interface should follow the evolution of the disease.

Parkinson's Disease and Mobility

Parkinson disease is a progressive disorder of the nervous system. The disorder affects several regions of the brain, especially an area called the substantia nigra that controls balance and movement. The substantia nigra ordinarily secretes the neurotransmitter dopamine, which is involved in many of the brain's functions, including the control of motor activity.

Often the first symptom of Parkinson disease is trembling or shaking (tremor) of a limb, especially when the body is at rest. Typically, the tremor begins on one side of the body, usually in one hand. Tremors can also affect the arms, legs, feet, and face. These symptoms worsen slowly over time.

Similar to other progressive diseases, Parkinson's disease is categorized into five stages with regard the motor symptoms. In stage four, they are no longer able to walk and need help to have mobility.

Hand tremor can make it difficult to operate a conventional joystick. In [37], the authors made a study of a joystick control for the minimization of this tremor, their goal is to cancel the interference caused by tremors in the joystick controller, to develop better controls for people with tremor hand.

Other nearly universal symptoms are Bradykinesia (or movement slowing), Hypokinesia (or reduced movement amplitude) and Akinesia (or delayed movement initiation) and generally refer to a paucity and generalized slowing of movements in the absence of weakness. Movements take more time, and there is reduced frequency of spontaneous movements [38].

2.2.1 Spinal cord injury and Mobility

According to the Shepherd Center [39], which is a private, non-profit hospital specialized in medical treatment, research and rehabilitation for people with spinal cord injury and brain injury, a spinal cord injury (SCI) occurs when there is any damage to the spinal cord that blocks communication between the brain and the body. After a SCI, the person's sensory, motor and reflex messages are affected and may not be able to get past the damage in the

spinal cord.

The location of the SCI dictates the parts of the body that are affected and higher is the injury on the spinal cord, the more dysfunction can occur. As we can see in the next figure 2.3, the location of the SCI affects different body regions.

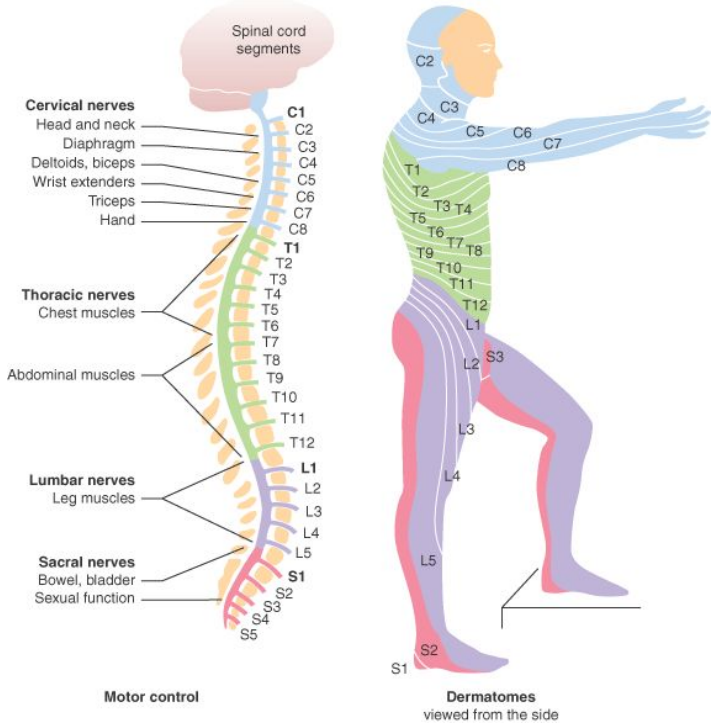


Figure 2.3: Map of the spinal cord and the affected area body [3]

The symptoms of spinal cord lesion depend on the extent of the injury or non-traumatic cause, but they can include loss of sensory or motor control of the lower limbs, trunk and the upper limbs, as well as loss of autonomic (involuntary) regulation of the body. This can affect breathing, heart rate, blood pressure, temperature control, bowel and bladder control, and sexual function [international perspectives]. The functionality of a person's body, like mobility and respiration system, will be different depending of the level of the injury. For example, someone with C3 or higher will be dependent on a ventilator to breathe [40] and someone with T1 can breathe normal, although respiration capacity and endurance may be compromised.

Tetraplegia is when a person has a spinal cord injury above the first thoracic vertebra or cervical SCI; this usually affects the cervical spinal nerves resulting in sensory and motor loss (paralysis) in the arms, body and legs.

The extent and severity of sensory, motor and autonomic loss from SCI depends not

only on the level of injury to the spinal cord, but also on whether the lesion is "complete" or "incomplete". According to [41] "complete" spinal cord injuries refer to any injury that results in the complete loss of function below the point of injury. An "incomplete" injury, on the other hand, refers to a spinal cord injury in which some feeling or movement is still evident below the point of injury. Many of the clinicians of the hospital rehabilitation centers use the American Spinal Injury Association Impairment Scale that is used to define and describe the extend and severity of a person's spinal cord injury [42].

A common scale for the measurement of functional ability is the Functional Independence Measure (FIM), based on the level of assistance s person requires. In [43] the authors presented a table with the FIM tasks and associated categories. The seven tasks are:

- Self-care
- Sphincter control
- Transfers
- Locomotion
- Communication
- Cognition

Locomotion and tetraplegia

Locomotion is one task of the motor category motor and is related with the functional ability to walk, to use stairs or CPW, that is, mobility skills.

Tetraplegic / paraplegic patients need a wheelchair to obtain mobility and, depending of the functional outcomes, they are able to use a manual wheelchair or they need a powered wheelchair. But, for someone to be able to drive a commercial powered wheelchair, he/she must have the motor skills to operate the joystick since this device is the primary interface between a person with a disability and a CPW.

Users with severe motor impairment may find it difficult to operate a wheelchair when they are in tight space (e.g., passing doorway) or when avoiding obstacles since they cannot command the wheelchair by means of a conventional joystick [44]. This is the case, for example, of some patients with tetraplegia. The next table 2.1 resumes the functional outcomes concerning the ability to use a wheelchair, according to the spinal cord injury classification.

Table 2.1: Mobility Outcomes versus injury level [20]

Injury level	Expected mobility outcomes
C1-C2-C3-C4	Can operate an electric wheelchair by using a head control, mouth stick, or chin control.
C5	May have strength to push a manual wheelchair for short distances over smooth surfaces. A power wheelchair with hand controls is typically used for daily activities.
C6	Can use a manual wheelchair for daily activities but may use power wheelchair for greater ease of independence.
C7-C8	Daily use of manual wheelchair.
T1-T12	A manual wheelchair may be used for everyday living, with the ability to go over uneven ground.

According to the table 2.1, the ability of using a manual or powered wheelchair depends of the types of muscles that have been affected. For example, a C1-C2-C3-C4 patient has full head and neck movement (depending on muscle strength) and no finger, wrist or elbow flexion or extension. So, in these cases, head and chin movement or "sip and puff" can be used to control a powered wheelchair. A C5 patient has no finger or wrist movement, no elbow extension but has good elbow flexion. Usually, they can learn to drive a power wheelchair with their arm and hand. They may need a support for the wrist and hand or a special joystick to be able to steer the chair. Also, they need special buttons to be able to use functions of the wheelchair, like velocity [45].

Smart or intelligent wheelchairs [46] can potentially improve the quality of life for people with disabilities, namely, people with SCI. As most of these patients always need someone to push their commercial powered wheelchair, they provide independence as they can get indoor or outdoor mobility without human help.

The adaptability to the individual and the fulfillment of safety requirements must be considered always when designing a smart wheelchair which means, the type of injury will define the human machine interface, the electronics and algorithms that must be used to guarantee a calm and safe wheelchair navigation. Also, indoor or outdoor environments will pose different requirements.

2.3 Stress and body response to stress

The term stress was borrowed from the field of physics by one of the fathers of stress research Hans Selye [47]. The term "stress", as it is currently used, was coined by Hans Selye in 1936, who defined it as "the non-specific response of the body to any demand for change"

[48].

According to the Global Organization for Stress [49], the definition of stress can be difficult even for those who are considered experts in the field of stress, stress management, and stress relief. In consequence, at least ten different definitions of stress were presented by those earlier researchers. And one of them is "Maintaining equilibrium" where stress can be considered as any factor, acting internally or externally that makes it difficult to adapt and that induces increased effort on the part of the person to maintain a state of equilibrium both internally and with the external environment".

This ability of all organisms to detect deviations and to maintain a constant internal equilibrium is called homeostasis. To survive, an organism must have ways to keep its internal conditions from changing as its external environment changes.

According to [50], stress occurs when the homeostasis is threatened or perceived to be so; homeostasis is constantly challenged by internal or external adverse forces termed stressors and homeostasis is re-established by various physiological and behavioral adaptive responses.

A stressor is any kind of situation or event that cause stress, like a trouble at work, illness, public speaking or vehicle driving, all of them situations, challenges, difficulties and expectations we are confronted with on a daily basis.

Stress is very personal, that is, everyone reacts in very different ways to the same situation, what makes the study of stress even more challenging. For example, an event well known to all is the celebration of Christmas. For some, it is a time of joy and they can deal with the typical stress of this occasion in a positive way but for others it can be synonymous of great anxiety and even sadness. Also, when a stressful situation first occurs, the person's reaction will be different when the same situation occurs at later times. The first response is a response to an unknown situation where the person reacts in an unprepared manner but then, given the human being's learning ability, the following responses are less stressful, that is, less harmful to health.

Stress can affect all the systems of the human body including the nervous, respiratory, cardiovascular, endocrine, gastrointestinal, musculoskeletal and reproductive systems [51], [52]. The American Institute for Stress lists 50 common signs and symptoms of stress ranging from headaches to heart palpitations [53].

According to the literature [54, 55], there are at least two types of stress: acute stress or chronic stress.

Acute stress is the most common form of stress and it can be good because the stress

hormones released help the mind and body in dealing with the stressor situation. A fast heartbeat and sweaty palms are two of the most common physical symptoms [55].

Chronic stress is a result of long-term stressful situations [51]. High blood pressure and high cholesterol are some of the symptoms of chronic stress. Many scientists think our stress response system is not designed to be constantly activated [50].

The specific situation for someone with reduced muscle strength try to drive a CPW, can cause him / her symptoms of acute stress. We can say that, for these patients and due to their inadequate physical abilities to manoeuver a CPW, driving a CPW can be stressful.

As mentioned earlier, the Autonomous Nervous System is the division of the nervous system that controls involuntary actions. It is divided into the Sympathetic Nervous System (SNS), and the Parasympathetic Nervous System (PNS)[52]. The SNS is responsible for the fight or flight reaction mechanism or acute stress response. It is responsible for increased heart rate, faster breathing, sweating and increased blood pressure and for activating the general metabolism of the body [56, 57].

The sympathetic division of the autonomic nervous system influences the various organ systems of the body through connections emerging from the thoracic and upper lumbar spinal cord [58].

Concerning sweating, nerve fibres that send signals to sweat glands [59], arise in the autonomic nervous system. Nerves in different vertebrae of the thoracic (T) and lumbar (L) portions supply sweat glands at different body sites [60] as depicted in figure 2.4:

- Upper limbs are supplied by nerves arising in vertebrae T2-8;
- Lower limbs are supplied by nerves arising in vertebrae T10-L2;
- Face and eyelids are supplied by nerves arising in vertebrae T1-4;
- Trunk is supplied by nerves arising in vertebrae T4-12

Concerning the increasing of heartbeat, the sympathetic part of the network of nerves that supply the heart is composed of fibres from the sympathetic trunk, largely derived from major autonomic ganglia along the cervical and thoracic spinal cord [5], see figure 2.5.

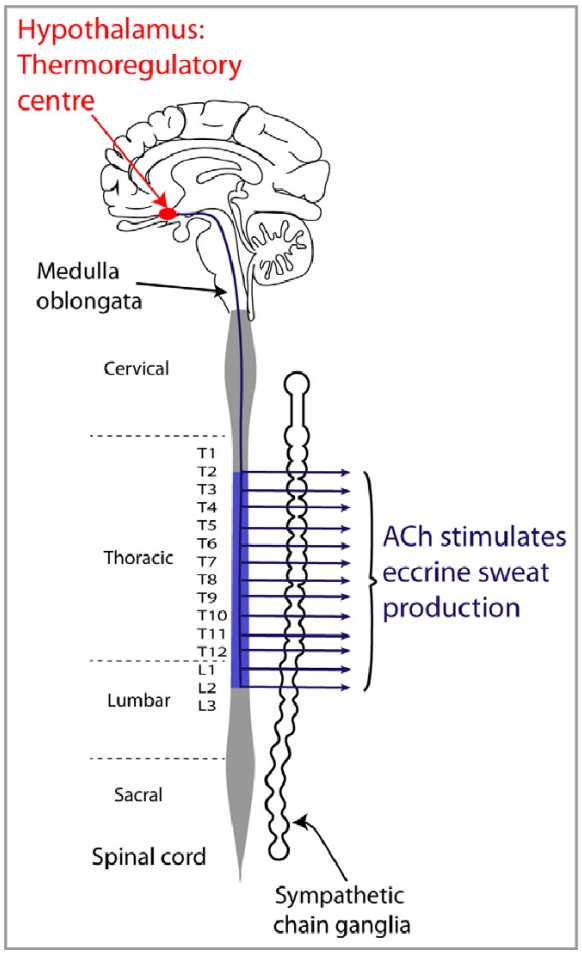


Figure 2.4: Signalling pathway for the thermoregulatory centre [4]

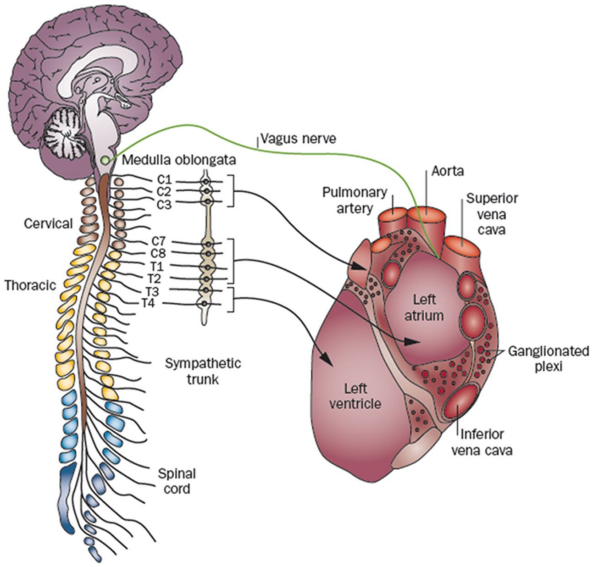


Figure 2.5: Scheme of autonomic innervation of the heart [5]

2.4 Conclusions

In this chapter, medical issues related to causes that can lead to reduced strength in the arms and hands have been presented. They are associated with the nervous system, and the functionalities of the central nervous and peripheral systems. Also, it is discussed how some of the nervous system diseases can cause reduced strength. In this topic, the greater focus has been given to the consequences of the spinal cord injury, in particular how this disease can disable a person to navigate a commercial powered wheelchair.

After, definitions concerning stress and body stress response were presented in this chapter. A brief study was conducted on how the sympathetic nervous system is responsible for the body reaction to stressful situations.

From the literature review it was found that the sympathetic nervous system is responsible for involuntary actions, like increased heartbeat and sweating that maybe will allow us to measure the reaction to stressful situations. However, if the path of these actions through the nervous system is interrupted, as it occurs in a spinal cord injury, it could impair measuring biometric signals commonly used to detect stressful situations, such as the galvanic skin response and the hearth rate.

In the next chapter, a review of the research on smart wheelchairs is presented. In addition, a review of the types of research and commercial stress detection systems, the most usual sensors to detect stress and the stress detection algorithms are also discussed.

Chapter 3

Smart wheelchair and Stress Detection: a survey

3.1 Introduction

This chapter presents a survey of the state of the art concerning smart wheelchairs technology and stress detection. The chapter is divided in two main sections: introduction to smart wheelchairs (section 3.2) and introduction to measuring and detecting stress technology (section3.3).

The first section presents the evolution and the state of art concerning smart wheelchairs. Some properties like form factor, human machine interfaces, operating modes and environmental sensors for detection obstacles are reviewed.

The second section presents state of the art concerning the sensors used in stress detection systems as also, stress classification techniques. Also, a review of the type of stress detection systems is made.

When considering the homeostatic sensors analyzed in this chapter, available to integrate a stress detection system (SDS), it was decided to devote a special attention to the galvanic skin response (GSR) and to electrocardiogram (ECG) sensors. This was necessary because these sensors were the two selected sensors to integrate the stress detection system developed. Also, it is discussed how a spinal cord injury can affect the sympathetic nervous system and, consequently, the impact on the heart rate and skin conductivity.

3.2 Smart wheelchairs

3.2.1 Introduction

When addressing the issue of smart wheelchairs, it is necessary to find out who can benefit from the use of an intelligent wheelchair, its corresponding definition, how to classify an intelligent wheelchair and what its components are.

This chapter aims to present a state of the art about intelligent wheelchairs concerning issues related to the navigation of the powered wheelchair and not with questions of comfort or stability of the user.

The initial purpose of the first smart wheelchairs was to ensure safe driving for their users, but, in the meantime, research has also been developed in which the aim was to provide the best possible comfort for the user. As example, in [61] the authors developed a wheelchair to maintain equilibrium of a seat in conjunction with a smart mobile device, the goal being to prevent the bedsores. Besides the analysis of technical aspects, in section 3.2.7 some comments about the commercialization and price estimation of smart wheelchairs are made.

Leaman at al. [62] presented a list of of institutions around the world that have produced a SW prototype since 2005. This list illustrates that the interest in the topic of SW has grown in recent years. As an example of collaboration on this field, sixteen organizations from the UK and France are coming together to launch the project called ADAPT (Assistive Devices for Empowering Disabled People Through Robotic Technologies). This project will help tackle mobility problems faced by elderly and disabled people, by developing a new smart electronic powered wheelchair and a virtual reality wheelchair simulator and it is expected that will end in 2021 [63].

According to [64] traditional manual wheelchairs provide mobility to individuals with physical impairments but are poorly suited for individuals with a combination of physical and cognitive or perceptual impairments. Manual wheelchairs are more physically demanding than commercial powered wheelchair; they require cognitive and physical skills that not all individuals possess. Also, in [64], the authors said that physical impairments that reduce the strength or coordination of individual's arms are often the factors in determining whether an individual needs a manual or a powered wheelchair. Upper-body physical impairments can also interfere with operation of a powered wheelchair.

In consequence, while the needs of many people with disabilities can be satisfied with standard manual or powered wheelchairs, a segment of the disabled community finds ex-

tremely difficult or impossible to use a CPW for activities of daily living [24]. This is the case of people with cognitive/motor/sensory impairment [62]. These individuals often lack independent mobility and rely on a caregiver to push them in a manual wheelchair [65].

In what concerns the diseases, in [64] the authors have identified a lot of them and the corresponding symptoms that might interfere with the wheelchair navigation. Fatigue or weakness or spasticity caused by several diseases like amyotrophic lateral sclerosis and spinal cord injury (SCI) are symptoms that may interfere with the wheelchair navigation and compromise the security of the user. Also, they made a survey of how many wheelchair users might benefit from autonomous navigation, from obstacle avoidance, from smart manual wheelchairs and smart powered wheelchairs. They concluded that 61 to 91 percent of the individuals observed would benefit from a smart wheelchair, *at least some of the time* of the day life.

So, smart wheelchairs researches developed were begin with the purpose to provide navigation help in a number of different ways like ensuring collision-free travel, allow navigation command or navigate between locations in an autonomous or semi autonomous way.

The purpose of the smart wheelchairs, in the beginning, was to eliminate the user's responsibility when driving the wheelchair. This was influenced by mobile robotics. But, over time, the purpose changed to assist the user navigation: the user began to have an important role in most of the navigation responsibilities as autonomous navigation would lead to provoke anxiety due to a sense of impotence in deciding navigation control.

3.2.2 Smart wheelchair definition

In [65], Simpson defines a smart wheelchair in this way: a smart wheelchair typically consists of either a standard power wheelchair to which a computer and a collection of sensors have been added or a mobile robot base to which a seat has been attached. In a literature review, the majority of research groups have developed smart wheelchairs which are CPW with a computer that receives the information coming from a collection of environmental sensors and from an adaptable human-machine interface and that implement algorithms that provide navigation assistance. The traditional overall design architecture of a smart wheelchair can be represented as in figure 3.1.

During normal operations, the user gives one direction and one velocity using a joystick. Meanwhile, the sensor system detects the range and position of the obstacles and the movement of the wheelchair and the map system translates this sensor information into a model

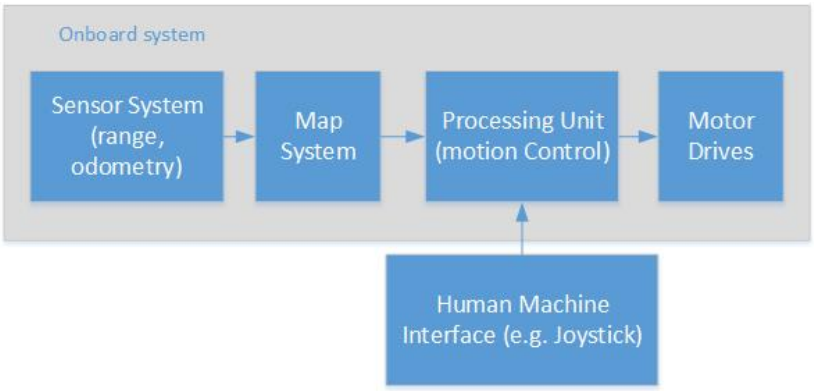


Figure 3.1: Traditional Smart Wheelchair Block Diagram

of the environment. This model serves to determine the areas into which it is safe for the wheelchair to move and to determine how it should go to reach the goal. Then, the processing unit processes all this information to plan a collision free travel in the direction specified by the user with the joystick. Control algorithms like obstacle avoidance or velocity tracking may have to be executed.

The variety of approaches to implementing control software for smart wheelchairs are based on the functions supported by the smart wheelchair and the sensors it uses and these functions define the level of autonomy of the wheelchair. Different levels of autonomy have been defined in order to adapt to the various disability levels of the user leading to different algorithms and technological solutions.

Depending on the disability of the wheelchair user it is required to initially select an appropriate interface as well as to decide which are the modes of operation implemented, e.g., if it is necessary for the wheelchair to be autonomous or semi-autonomous, which algorithms that implement the support functions are needed. Then is necessary to choose the sensors that derive better information of the environment according to the specifications of the respective algorithms.

So, the general architecture of a smart wheelchair control system must not only integrate a specific user disability interface but also a navigation module and environmental sensors module, like depicted in figure 3.2.

In general terms, the smart wheelchairs are composed of a physical structure and a set of navigation algorithms which, together, carry its user from one side to the other, always guaranteeing safety. So, the smart wheelchairs can be classified according to hardware and software features developed, like the type of the form factor, the type of human machine interface, the type of navigating system and also according to the type and function of the

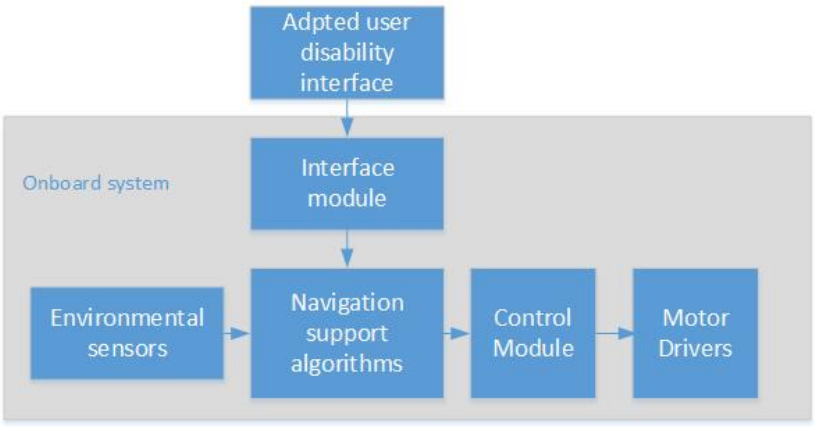


Figure 3.2: General Smart Wheelchair Block Diagram [6]

environmental sensors used. In what concerns the smart wheelchair architecture, the interface between the wheelchair controller and its user is an issue that will be presented in this section. Likewise, the environmental sensors and modes of operation usually used in smart wheelchairs will be briefly discussed to.

Madarasz et al in 1986 described the first steps in the design and construction of an autonomous vehicle for the physically and sensory disabled people: "the vehicle is basically a self-navigating wheelchair, which is designed to transport a person to a desired room within an office building given only the destination room number" [66]. The wheelchair has been equipped with an on-board microcomputer, a digital camera, and a scanning ultrasonic rangefinder.

3.2.3 Smart wheelchairs form factor

The classification of an intelligent wheelchair can be made according to their physical construction, e.g., the form factor.

According to the literature, e.g. [67, 6], the different smart wheelchairs can be grouped into 3 groups: seat on mobile robots, modified powered wheelchairs and add on units.

When this research area started, several researchers have used technologies originally developed for mobile robots to create smart wheelchairs. So, the first smart wheelchair prototypes that were developed were actually mobile robots to which seats were added [65].

The VAHM-1 prototype smart wheelchair was developed in the 80's (Véhicule Autonome pour Handicapé Moteur) and was conceived on a mobile base Robuter on which a wheelchair seat was fixed. It is a robotized wheelchair where the aim is to achieve an intelligent assistance to the electric wheelchair piloting, using techniques coming from mobile robotics [68, 69].

The mobile Robot "Mister Ed" has a seat for a passenger: to steer the vehicle the driver can directly interact with the navigation sensors, make suggestions through the joystick, or authorize various activities using a bank of toggle switches [7].

The OMNI(1998) prototype is built using an omnidirectional mobile base on which a seat of CPW wheelchair was adapted [8].

In all these projects, the major goal is to apply the models of autonomous navigation and sensor systems to a powered wheelchair, similar to what was done with mobile robots. To perform some tasks autonomously, like for example, steering around obstacles or turning at doors. As examples of these type of smart wheelchairs, Mister Ed and OMNI are presented in the figure 3.3.

(a) Mister Ed prototype (b) OMNI prototype

Figure 3.3: Seat mobile robots SW examples [7, 8]

Modified powered wheelchairs

After the initial solutions, the majority of research groups developed smart wheelchairs based on modified power wheelchairs [65, 6]. Examples of modified powered wheelchairs are the RobChair [70] and Wheelesley [71]. Both were designed and tested using as a basis commercial powered wheelchair to which integrate prototypes used for research projects from KISS Institute for Practical Robotics (KIPR).

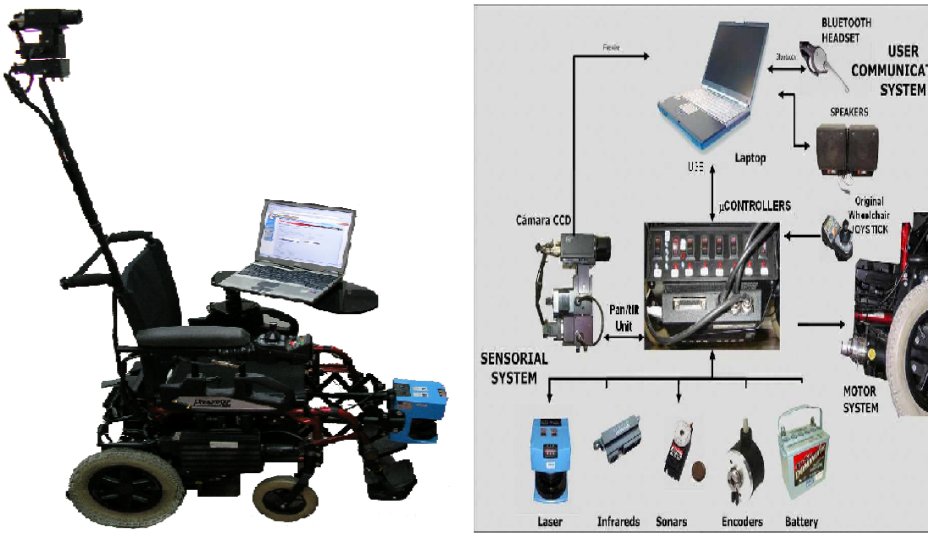
Another example of a modified power wheelchair is the intelligent wheelchair Luoson III. It was developed by the laboratory of National Chung Cheng University and used for assisting disabled people as convenient mobile tools for their daily activities [72]. With its equipped ultrasonic sensors and force feed-back control joystick, it can provide remote feedback control between the objects and the robot in the complex environment.

The Smart Chair project from the University of Pennsylvania led to an autonomous wheelchair controlled by an onboard computer, and including a projector, a camera, motors, and sensors. By using several types of input devices, the Smart Chair user interacts with the computer to move around, to communicate and access the Internet [73].

Other solutions relating to the development of smart wheelchairs have been emerging over time like COACH [74](1993), Rolland (1998)[75], NavChair (1999) [76], VHAM 2 (2001) [77], MAid [78], Sharioto [79], WAD project [80], SENA [81], SmartWheeler [82], Anti-collision skirt [83], LIASD-WheelChair [84] and Robotic Wheelchair Skills Test (RWST) [85].

As an example of a modified powered wheelchair it is shown in figure 3.4 the SENA Robotic Wheelchair: SENA is based on a commercial powered wheelchair (Sunrise Powertec F40) which has been equipped with several sensors to reliably perform high-level tasks in indoor environments [9].

In this figure, the various blocks added are identified: sensorial system, user communication system, camera vision, controllers and a laptop to process all information besides the legacy powered wheelchair.



(a) robotic wheelchair SENA (b) The SENA architecture layout

Figure 3.4: The SENA Robotic Wheelchair [9]

The table 3.1 lists the last mentioned works where reference is made to the trade mark of the CPW. Most of these projects lasted during several years, so the indicated date is just used to give an idea of the time scale.

Table 3.1: Smart wheelchair based in commercial powered wheelchair reported in literature

Designation	Date	Description
COACH	1993	"A computer assisted wheelchair for handicapped people, designed to assist its user to move in an every day environment and using a regular POIRIER electric wheelchair" [74]
Rolland	1998	"Bremen Autonomous Wheelchair "Rolland". It is based on the commercial power wheelchair Genius 1.522 manufactured by the German company Meyra, and it has been extended by a PC and several proximity sensor [75].
NavChair	1999	"The NavChair prototype, based on a Lancer power commercial wheelchair [76].
VHAM 2	2001	The second prototype developed from an electric wheelchair Power Push [77]
MAid	2001	"The system MAid is based on a commercial electrical wheelchair type SPRINT manufactured by MEYRA GmbH in Germany" [78].
Sharioto	2005	A standard electric wheelchair differentially driven [79].
WAD project	2005	WAD Project architecture, installed on a powered wheelchair model CRUISER from INVACARE [80].
SENA	2006	"The SENA robotic wheelchair, based on a commercial powered wheelchair Sunrise Powertec F40 [81].
Smart Chair	2006	The Smart Chair, a motorized wheelchair equipped with onboard processing and multiple sensors [86].
Smart Wheeler	2007	"SmartWheeler, built on top of a commercially available Sunrise Quickie Freestyle" [82].
Anti-collision skirt	2011	The Nimble Rocket power wheelchair anti-collision [83].
LIASD-WheelChair	2012	The LIASD-Wheelchair prototype, an adjustable adults' powered wheelchair with the same mechanical structure as Invacare Storm3 and monitored according to two operating modes [84].
RWST	2013	A navigation based upon a modified commercial wheelchair (Sunrise Medical, Model Quickie S646) [85].

Some other SW projects are result of collaboration between universities and wheelchair manufactures, like was the case when researchers from leading Japanese Wheelchair Industries and associated Japanese Universities have joined hands with researchers at RISE Research Center to introduce active wheelchair technology in Pakistan [10]. Another example was the intelligent wheelchair project where intelligent assistance-system was developed estimating the user's intention according to the given situation and the operator's reduced input. This project was an interdisciplinary co-operation between Chair II of the Department of Psychology and the Automation Laboratory of the Institute of Computer Engineering and was supported by the company Otto Bock HealthCare [11]. These two SW are shown in figure

3.5.

(a) Wheelchair from RISE and SAKURA Wheelchairs

(b) Wheelchair from Automation Laboratory and Otto bock

Figure 3.5: Researches and industry SW projects [10, 11]

Add on units

Another approach to design a smart wheelchair has been used to design an SW through "add-on" units that can be attached to and removed from the underlying power wheelchair. The idea was to add these "add-on" units to a variety of commercial power wheelchairs with minimal modification. The smart wheelchairs developed with the "add-on" units approach can offer flexibility in the configuration of sensors, in the interface and can enable a choice of input devices based on each individual user needs [87].

In the case of a disabled person, it is important to emphasize that the ability to drive a wheelchair can, progress with time. Because these people are subject treatments / rehabilitation exercises during their lifetime they acquire some skills that they did not initially have when they start to use the wheelchair.

Another critical issue is the final cost of a smart wheelchair. Maybe, one path to cost reduction is the modularization of the system to use the possibility of re-use of the smart wheelchair modules. In [88] it is highlighted that projects aiming at developing new concepts of Intelligent Wheelchairs are needed, mainly using multimodal interfaces and wheelchair interfaces adapted to the user characteristics to enable that possibility.

In this line of work, we made a literature review and we found add on units with different

goals and consequently with different degrees of complexity.

In 1997, the authors in [89] proposed the SENARIO (SENsor Aided intelligent wheelchaiR NavigatIOn project): developing a sensor-aided intelligent navigation system that provides high-level navigational aid to users of powered wheelchairs. The authors discuss new and improved technologies developed within SENARIO concerning path planning, sensing and positioning for indoor mobile robots as well as user interface issues.

The team from the Applied Autonomous Intelligent Systems R&D (Canada) [90], developed an the intelligent wheelchair project, called the TAO Project, intends to establish a methodology to design, implement, and test an effective add-on autonomy management system for use in conjunction with most common commercially available power wheelchairs. The add-on unit is integrated in the FORTRESS Model 760V commercial powered wheelchair so that, mechanical and electrical structure, the electronics, and the control circuitry of the original power wheelchair were used without modification. It aims to implement different wheelchair planned functions.

TetraNauta project developed a controller for standard electric-powered wheelchairs. One of the requirements that were defined for TetraNauta project was that no modifications of the wheelchair internal parts should be required (the resulting device should be externally adaptable to several commercial wheelchairs) [91].

In [92], the authors Fioreti et al. presents the design of a navigation system and its integration with a commercial powered wheelchair, equipped with a user interface and sensor devices. They developed two autonomy levels and also implemented a simple collision avoidance to stop the mobile base when an obstacle is detected.

Another project, based on modular architecture to develop a powered wheelchair to assist the mobility of disabled persons, was developed by the project SIAMO (Integral System for Assisted Mobility) [93]. Its modular architecture makes it easy to configure the wheelchair to meet the needs of different users with different types of disabilities. This modular architecture also makes it easy to adapt new functionality to the wheelchair, because e.g. the human-machine interface (HMI) can be changed, and new HMI can be made, without other changes to the wheelchair system [94].

For example, the Hephatestus Smart Wheelchair[95] is envisioned as a series of components that clinicians and wheelchair manufacturers will be able to attach to standard power wheelchairs to convert them into smart wheelchairs. A prototype of the system has been developed and mounted on an Everest and Jennings Lancer2000 wheelchair.The prototype

bases its navigation assistance behavior on the behavior developed for the NavChair Assistive Wheelchair Navigation System, but the underlying hardware and software are being designed to facilitate commercialization.

The Smart Wheelchair Component System, (SWCS) [12] from the University of Pittsburgh is being designed to accommodate all traditional input methods (analog joystick, touch-activated switches, pneumatic "Sip n' Puff" switches, etc.) and to be compatible with multiple brands of wheelchairs. The total SWCS consists of sensors, control electronics, computational hardware, and navigation assistance software. The modular Smart Wheelchair Component System (SWCS), shown in figure 3.6 can be added to a variety of commercial power wheelchairs with minimal modification.

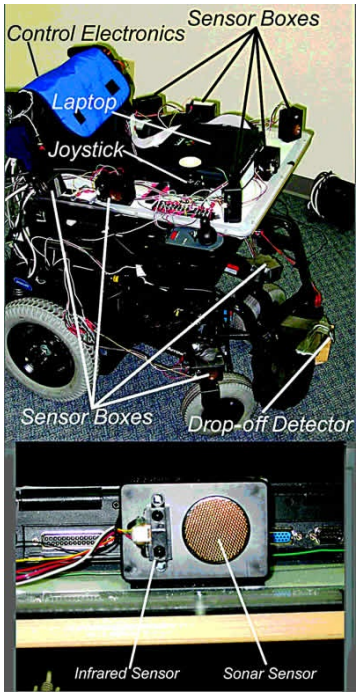


Figure 3.6: Modular Smart Wheelchair Component System (SWCS) [12]

The Drive-Safe System (DSS) is an add-on, distributed, shared control navigation assistance system for powered wheelchairs intended to provide safe and independent mobility [96]. It is designed to act as a specialty user interface, allowing it to connect with the control electronics of a variety of wheelchairs. The current DSS prototype has been tested on wheelchairs from Pride Mobility and Sunrise Medical and past prototypes were tested on wheelchairs by Invacare, Permobil and Everest and Jennings. clinical evaluation of the DSS was performed in a controlled laboratory setting with individuals who have a visual impairment but no mobility impairment [97], see figure 3.7

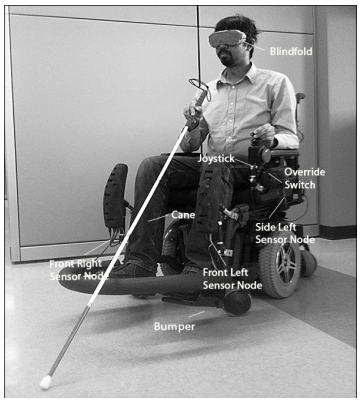


Figure 3.7: Drive-Safe System [97]

Another example is the LURCH [98](Let Unleashed wheelchairs Crawl the House) project where the goal was to developed an autonomous wheelchair able to avoid obstacles, self-localize and safely explore indoor environments. The LURCH system was designed to be easily adaptable to different kinds of electric wheelchairs, the control system is independent from the wheelchair.

In [48], Chang et al. developed and active safety system that includes automatic braking and steering. A mass-production electric wheelchair is remodeled to implement the control functions.

The IntellWheels platform was developed according to the multiagent paradigm and a modular concept to increase the flexibility of the system (a generic framework that can be implemented with almost any commercial wheelchair and assist people with different impairments) and facilitate the development of new IWs [99]. Figure 3.8 shows the prototype based on a commercial wheelchair (model Evolution Electronics, Vassilli) with an integrated IntellWheels hardware module.

Figure 3.8: IntellWheels prototype[99]

The SYSIASS project, started in December 2010 and ended on June 2014, was supported

by the European Regional Development Fund and the goals were to design and implement new devices for a powered wheelchair like guidance assistive device and a hands-free HMI and they must have the ability to interface with any commercially available powered wheelchair" [100].

The table 3.2 lists the last-mentioned works where reference is made to the add on units. Most of these projects lasted for several years, so the indicated date is just used to give an idea of the time scale.

Table 3.2: Add on units Smart Wheelchair reported in literature

Designation	Date	Description
Tin Man(I and II)	1995	A supplementary wheelchair controller installed between the joystick and standard wheelchair controller [101].
SENARIO	1997	A sensor aided intelligent navigation system for powered wheelchairs [89]
TAO(I and II)	1998	Add-on autonomy management system for use with the most commercially available PW [90].
A navigation system	2000	A navigation modular solution for adaptation of the module to different PW [92].
SIAMO	2001	A modular electronic guidance system based on environment and degree of handicap [93]
Hephatestus Smart Wheelchair	2002	An assistive wheelchair navigation system with hardware and software adaptations that facilitates commercialization [102].
Tetranauta	2002	A traffic management subsystem module and wheelchair motion control subsystem module [103].
SWCS	2004	A collection of components that can be attached to standard power wheelchairs from several different manufacturers to convert them into smart wheelchairs [104].
DSS	2011	A modular architecture drive-safe system [96].
LURCH	2012	Designed to be easily adaptable to different kinds of electric wheelchairs and it is completely separated from the wheelchair [98].
SYSIASS project	2013	Guidance assistive device and a hands-free HMI to interface with any commercially available powered wheelchair" [100].
Worcester Polytechnic Institute wheelchair	2014	Wheelchair add-on modules (WAMs) were developed as platform-independent sensor banks that can be mounted on any powered wheelchair[105].
Active Safety System	2015	An active safety system that includes automatic braking system and automatic steering system [48].
Intelligent Wheelchair	2016	The proposed Intelligent Wheelchair is made up of four modules: sensor-based obstacle avoidance, vision-based obstacle avoidance, situation recognition, and converter [106].

Adapted Manual Wheelchairs

At present, some groups of researchers design and implement every SW command system. They do not take advantage of the existing electrical structure of the PW but, they select, design and implement all the electrical/electronic components systems. For example, in [107] Kallam et al. propose a SW project by integrating different modules (Permanent Magnet DC Motor, Motor driver, Controller unit, Bluetooth interfacing module, Joystick, Sensors (Ultrasonic distance meter, IR range finder, Power supply) in a platform designed by Callidai Motor works (Model-Ganda 2K4 Rear Wheel drive Wheelchair).

Another example is presented in [108] where they aim designing a simple cost effective automatic wheelchair by using Micro-Electro-Mechanical Systems (MEMS) technology for quadriplegics with head and neck mobility. The automation intelligent wheelchair consists of hardware and software units like the ARDUINO UNO, MEMS devices, a GSM, driver circuit, DC motor, and Power Supply.

3.2.4 Human Machine Interface

It can be traced, the commercial electric wheelchair origin, to 1950. The necessary wheelchair has a joystick to control the wheelchair, two motors for the back wheels, their electronic controller and a battery and they aren't specific for each kind of user.

As already mentioned, legacy powered wheelchairs are based in a joystick to interface with the user. This conventional proportional joystick, a movement sensing joystick (MSJ), is usually built with potentiometers and outputs, periodically, two values representing its X and Y position. The interpretation of the X, Y values is the wheelchair desired speed and direction [1].

This joystick requires some ability to control it and, people who suffer from tremors or spasms or weakness have a short range of motion and cannot manipulate it to drive their powered wheelchair. So, to deal with this lack of ability of these people to manage the conventional joystick, several approaches have been proposed:

- To replace the joystick by another, completely different, HMI [6].
- To introduce a different joystick that has the same look but works differently [7].
- To adapt the output signals of the legacy joystick, giving different interpretation of its output signals and adapting them [8].

Some of the older research works have kept the conventional joystick but have made it shape changes to make it easier to use.

The type of physical disability limits or prevents the motor performance of the affected person. Some movements of hands, arms, torso, and head can be changed. The alternative HMI will depend and, must be developed, through bodily movements that each person is capable of performing. Thus, the researcher's groups were created over the years different alternatives to traditional joystick wheelchair. They took into account that it is necessary to have some guidelines: the HMI must be user-specific and noninvasive, which means, must be human-friendly designed. Also, it must be not expensive, and it must be easy to work with.

According to a literature review, the majority of the HMI's developed can be grouped into two major groups: based on verbal inputs and based on nonverbal signals. An HMI based on verbal data means that the smart wheelchair is controlled by speech recognition.

An HMI based on nonverbal signals can be developed by using sensors like vision camera to detect head movement or an HMI based in biosignals like electroencephalogram (EEG) to detect intention movements or Electromyograph (EMG) to detect shoulder movement.

Another form to classify HMI, according to [109], is to identify if they used intrusive or non-intrusive interfaces. For example, voice-based and vision-based are both non-intrusive interfaces and head, neck, or gaze-based interfaces are classified as intrusive HMI. The verbal communication, compared with others like head movement, remains the most natural.

The NavChair system [76] is being built to provide navigation assistance in the form of a hierarchy of operating levels, each of which requires varying degrees of control from the wheelchair user. In some of these operating levels, the voice controls the wheelchair, and the voice commands are elementary like stop, go forward, back forward. But low-level voice commands are discrete and give rough direction information. In domestic / office environments, usually with narrow spaces and dynamic obstacles, it is very difficult, or even impossible, to drive a wheelchair with low-level voice commands.

So, to make wheelchair voice-steering practicable, in RobChair[66], an assisted navigation module was developed. The navigation module follows hybrid architecture and one part of the proposed architecture, is a supported reactive controller, which turns feasible voice-steering. Three goals achieved: the risk of collisions substantially decreased; the obstacles are safely and smoothly avoided taking into consideration the user's intention, given by setting a rough direction; and a contour following task performed autonomously.

In SENARIO [89], the system's speech interface learns to understand user commands and

to translate them into actions.

In which concerns the non-verbal signals, the goal is to develop an HMI that takes advantage of any motion that could be done by the smart wheelchair user.

Like they said in [110], eye-gaze or head movement detection has been an active research in the past years. Both technologies are considered the most natural alternative interface methods. They serve a wide range of severely disabled people who has minimal motor abilities. The systems developed to detect eye gaze or head movement track the direction in which a person turned the head.

For example, in [71], the graphic user interface of the Robotic Wheelchair System Wheelesley has two access methods. The first is an eye-tracking device called EagleEyes, and the second is a single switch scanning device. The EaglesEyes system allows a person to control a computer through five electrodes placed on the head. These electrodes The electrodes measure the EOG (electrooculographic potential), which corresponds to the angle of the eyes in the head.

In [111], they have developed a robotic wheelchair system that detects the gaze direction of the user using a real-time stereo vision. This system can recognize the wheelchair position within the surrounding environment using a range sensor and a map. The head movement detection and tracking were studied and applied in [112, 113]. Head gestures were used in [114], where they have developed an electric wheelchair that is operated using a stereo camera that recognizes head gestures.

Hand gestures have been the subject of study of different research groups to assess your application to control wheelchair navigation. Examples are [115, 116] where a MEMS accelerometer detects the accelerations of a hand in motion.

Other researchers work, has an alternative input to the smart wheelchair control, proposed: head/chin controlled system [117, 118], sip and puff [102], shoulder and neck movement [119]. In [104], they used the EMG technique to detect neck movements.

The authors, in [120, 121] proposed systems that uses the movements of the patient's tongue to operate the power wheelchair. Also, in [13], the authors proposed a Tongue Drive System (TDS) (see figure 3.9) wireless and wearable assisted technology, designed to allow individuals with severe motor impairments such as tetraplegia to access their environment using voluntary tongue motion.

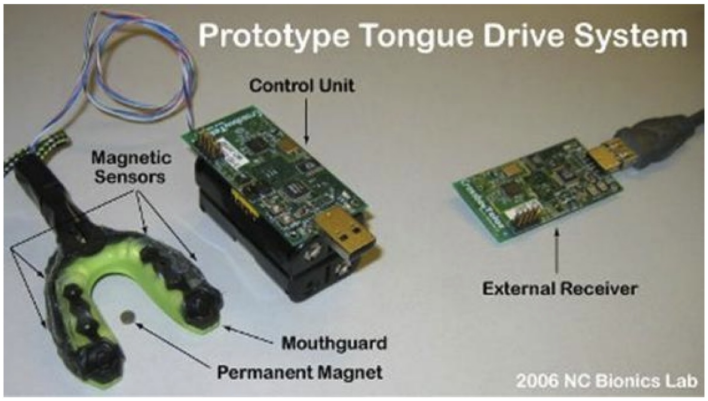


Figure 3.9: The prototype TDS system [13]

A vision-based human-robot interface is developed in [122] allow the user to interact with the wheelchair and the main components of the system are two cameras, a video projector, and a laptop tray.

In [123], they implement a multi-control system to control the movement of the wheelchair by integrating a finger movement tracking system and a small vocabulary speaker-dependent based word recognition system.

Head movements and the facial expressions are detected using the gyroscope and the cognitive suite of the Emotiv EPOC sensor, [14, 15].

Trivedi *et all*, in [124], they have the focus to design and develop a smart wheelchair where the user can control the wheelchair by using three interfaces, namely, keyboard, a webcam and a microphone. The webcam is used to detect head-tilt, which can turn the wheelchair and the microphone for controlling the wheelchair through discrete voice commands.

More recently, bio-potential signals or human physiological signals such are also deployed to control such kind of smart service robot smart/intelligent wheelchairs [125]. Some bio signals examples are electrooculographic (EOG), electromyographic (EMG) and electroencephalographic (EEG).

In [126] the authours used a eye-control method, based on electrooculography (EOG), for guiding and controlling a wheelchair for disabled people is proposed.

A nonverbal interface that used biopotential signals, such as electrooculargraphic (EOG) and electromyographic (EMG), captured by a simple brain-computer interface is presented in [127]. Based on the biopotential signals, the nonverbal interface to hands-free control of an electric wheelchair, recognizes the operator's gestures, such as closing the jaw, wrinkling the forehead, and looking towards left and right.

Figure 3.10: The Emotiv EPOC and the electrodes location [14, 15]

Brain Computer Interface (BCI) is also been used as an input method to control a SW. As they said in [128] a BCI system analyzes specific patterns in the user's brain activity and translates them into commands to control soft-or hardware devices. In [129, 130] an emotional BCI control system is proposed to drive a SW. The next figure 3.10 shows the Emotiv EPOC and the electrodes location for BCI.

Some researchers groups developed sensor fusion multi-modal interfaces, with bio and not biosignals sensors. For example, [131], propose an intelligent robotic wheelchair with various user-friendly human-computer interface based on electromyogram (EMG), face directional gaze and voice.

The next figure 3.11 shows the Cyberlink Brainfingers ^{TM} data acquisition box and the headband [16]. Lai Wei *et. al.* proposed a human machine interface derived from both facial EMG and face image information to control an intelligent wheelchair.

Figure 3.11: The EMG headband and the respective data acquisition box [16]

The recent development in research areas such as smartphones and the Internet of things contribute to increase the range of possibilities of the input interfaces for smart wheelchairs. These devices are being used to developed powerful controlling tools like, for example, face

recognition. In [132], the authors present an enhanced face recognition method tested on two different platforms using Windows and Android operating systems. In [133], they proposed enabling patients to move their wheelchairs by just tilting their Smartphone.

The Internet of Things (IoT) is a technological revolution in computing and communications. An overview of the Internet of Things for people with disabilities is made in [134], where the authors analyze how people with visual, hearing and physical impairments can interact with and benefit from the IoT.

The table 3.3 summarizes some others example references used in the field of input interface smart wheelchair research works [135].

Table 3.3: Input interface used in smart wheelchairs reported in literature

Input interface	References
Voice	[136, 137, 138, 139, 140]
Haptic feedback	[141, 142, 143]
Upper limb or head movements	[144, 145, 146, 147, 109]
Biometrics	[148, 129, 149, 150]
Muitimodal	[44, 151, 152, 153]

3.2.5 Smart wheelchairs navigation methods and operating modes

The goal of a smart wheelchair is transport a person from one location to another, indoor or outdoor environments. The "intelligence" of the wheelchair is its capacity to perceive its surroundings and, with the appropriates computer algorithms, generate the different operating modes. These operating modes must always be executed safety and can be like obstacle avoidance, wall falling, door passage, among others.

Smart wheelchairs can carry on their tasks, but they have to rely on the human operator ability, even if reduced, desire and experience.

The navigation control methods for a smart wheelchair can be categorized in autonomous control, semi-autonomous control and shared control [44].

In autonomous navigation mode, the user gives one location to go, and the wheelchair has the complete autonomy to navigate to the desired location. The intelligent wheelchair makes all the navigation decisions. For one wheelchair to be completely autonomous, it must have a lot of capacities to perform maneuvres like avoiding and contouring obstacles, wall following, door passages, at least.

An example of an autonomous wheelchair is explained in [154]. Mohammeda Alshraideh et all. developed a robotic intelligent wheelchair system (RIWS) where the patients do not

need to interact with the system in order to accomplish the desired task:"when autonomously controlling our IW, the subject must simply select the destination (clinic name/path) and the chair will automatically drive to the goal while avoiding collisions".

The general idea is to develop smart wheelchairs to help people in their mobility and not to develop wheelchairs to be autonomous. The vital point is the autonomy of the disabled person, not the autonomy of the wheelchair. So, the majority of the research groups have developed assistive smart wheelchairs where the user has a vital role in the decisions of most of the navigation responsibilities. It must have a shared SW control between the user and the wheelchair controller.

Two main approaches can be discriminated to do shared control. One is to delegate the responsibility of the controlling system to the user, and the second is the adaptive shared control. In the last one, the system is capable of changing nature, and the degree of the control shared between the user and the SW controller, during task execution. The goal of the adaptive shared control systems does adapt the skills and desire of the SW user to the SW assistance. The higher the driver's ability to drive, the less the need for the wheelchair controller assistance and vice-versa.

In [6] they made a list of some selective smart wheelchair prototypes, and they concluded that future research challenges in this field are recognized. With the analyses of this list and with a review of the literature, the first studies of smart wheelchairs prototypes provided various operating modes for wheelchair navigation. These operating modes reduce or eliminate the user's responsibility to drive a wheelchair. In most recent studies research, the user is more responsible for motion planning.

The table 3.4 listed some references of research works where different implemented modes of operation are presented and how each one makes the selection between them.

Table 3.4: Smart wheelchairs operating modes

Designation	Operating Modes	Operation mode selection
Navchair	general obstacle avoidance, door passage, automatic wall following.	For automatically selecting the most appropriate operating is based on a combination of the wheelchair's immediate situation and its global location [76]
Wheelesley	indoor and outdoor navigation	The system switches automatically between navigation modes through the use of a novel indoor/outdoor detector [71]
RobChair	autonomous mode and semi-autonomous	Resulting from a goal driven behavior and reactive sensor information from environment stimulus. [70]
Tetranauta	automatic, semiautomatic and manual	The user can switch among the three operation modes. In semi-autonomous mode the system applies a shared control: users can modify movements generated by the automatic navigation with the joystick citeR96
Worcester Polytechnic Institute wheelchair	Assisted control and semi-autonomous	Includes both assistive control behaviours such as wall following and obstacle avoidance and semi-autonomous navigation that relies on an adaptive motion control and user-input for specified destination goals[105].
Smart Chair	autonomous, semi-autonomous and manual modes	User lets the begin behaving autonomously, but can interrupt or change the system's behavior at any time the task is executing.[86]

3.2.6 Obstacle detection sensors

Smart wheelchairs must use sensors to perceive their surroundings. The environmental sensors usually used in smart wheelchairs are ultrasound, infrared, encoders, laser scanner, camera vision [65, 6] and the choice among them is based mostly on what are their tasks, i.e. if they will be used to detect obstacles (static or dynamic), or to the identification or recognition of an object or a landmark, or to construct a map of the environment and a trajectory planning, or even to perform self localization.

Obstacle detection is one of the challenging problems in the navigation systems, and every sensor has its weakness and strengths in terms of robustness and accuracy of detecting obstacles. For example, in [155] they show cases of the performance analysis of the ultrasound (US) and infrared (IR) sensors for the obstacles made of different type of materials such as cardboard, paper, sponge, wood, plastic, rubber and tile. They concluded that the choice of sensor types depends on the kind of obstacle materials.

In [156] the authors made a review of obstacle detection sensors and they say that US

and IR are amongst popular sensors used in Obstacle Detection System (ODS) because of their low cost.

The table 3.5 refers some papers where the authors had studied and tested the use of different types of sensors for obstacle detection / avoidance.

Note that the majority of research groups use more than one type of sensor. The goal of sensor fusion is to bridge the weakness of one sensor in one environmental state with the strengths of another in the same state.

Table 3.5: Obstacle detection sensors

Authors	Sensors technology
Deepesh K Rathore et all [157]	ultrasonic sensors
B. Mustapha [156]	ultrasonic and infrared
Tom Carlson and José del R. Millán[130]	sonar sensors and two web-cams
EF Lopresti et all [97]	ultrasonic rangefinders (sonars), IR rangefinders

3.2.7 Commercial Smart Wheelchairs

The area of the mart wheelchairs has been subject of considerable study by several research projects over, at least, the last 20 years. As already mentioned, the researchers call these products smart since they are developed to have the capacity of decision like environment navigation adaptability or/and user disability adaptability. But, for the wheelchairs to have this decision-making ability, to make them smart, they need to be equipped with various technologies and information processing.

Searching for the term smart wheelchair in websites yields several powered wheelchair companies where they use the word smart, due to easy folding, stair climbing or the basics functions like full power stand up. The figure 3.12 presents one example of a commercial smart wheelchair.

Figure 3.12: Example of a commercial powered smart wheelchair

In the field of SW research, the SW always have more provided modes of operation than commercial SW. One explanation, for this reason, is that the technology is still expensive and, mainly, because the precision and robustness of the existing technology still does not guarantee 100% the necessary security in this delicate area as smart wheelchairs in many research projects.

In [87, 62], the authors have the same opinion: Smile Smart System Wheelchairs (SSS) [158] is the only SW available to the consumer. This SW offers a collection of wheelchair controls and wheelchair switches that allow the replacement of the traditional joystick to one more appropriate. Also, it includes a line following capacity and anti-collision sensors to create an innovative control system offering freedom and independence.

Apart from the actual technical issues, a critical non-technical reason for the commercialization difficulties is the amount of experimental tests that must be made to guarantee user safety navigation. And, for doing these preliminary tests, real patients, i.e., available real human with deficiency must be found for the trials.

From our experience, first of all, it is necessary to obtain the Rehabilitation Center agreement. Then, it is needed to confirm with the personal staff if there are interested patients and in good health to make the experimental tests. And the probability of doing the same test multiple times with the same patient is very low. Several factors contribute to this such as, the patients either stay in the centre for a short time; the patients may be in a fragile health state and do not have the nurses' permission to do experimental test, or even if they are willing to take the test, they tire easily. Also, they have daily centre routines like

rehabilitation or visitors that make them not very available to the trials.

So, this whole process takes a long time. Companies will only be available to market SW if they are assured that SWs are 100% secure. But for this, many more real experimental tests will have to be done.

3.3 Stress Detection

3.3.1 Introduction

During the activities of daily living, several adverse or demanding circumstances can lead to a stressful situation.

A stress detection system allows evaluating, in real time, the human emotional / stress state. This system as the advantage to alert its user when there is a change in his / her emotional state.

This section pretends to identify the most usual sensors used to detect stress, stress classification methods and types of stress detection systems.

3.3.2 How to measure stress and stress scales

The areas of health care and medicine are two areas of application of sensors and have been benefiting from the evolution of electronic sensors. Several types of non-invasive stress sensors have been developed and widely used. It is now easier to access and read the psychological signs of stress through stress sensors.

Physical and physiological signals [159] can do the measurement of stress. Relevant physiological or biosignals like Galvanic Skin Response (GSR), heart rate (HR), blood pressure, electromyogram (EMG), electroencephalogram (EEG), skin temperature [159, 160] are very used to identify and classify stress levels. For example, it is known that under specific stress situations, the GSR, electromyogram, heart rate and blood pressure increase, the skin temperature decreases and the pupil dilates as well as the eye moves faster.

As examples of physical signals used to measure stress are pupil dilation [161], oxygen saturation [162] and voice analysis [163]. Hormonal changes [159] can be also be used to identify stress but measures stress hormones are obtained via invasive methods and must be performed by professional health staff.

Table 3.6 summarizes some works, from more recent investigations, where the stress level is detected with different data types given by different sensors.

Table 3.6: Stress detection sensors

Data sensors	Authors
electromyogram, ECG, GSR and respiration	Healey, J. et all [164]
galvanic skin response (GSR) and heart rate (HR)	de Santos Sierra, Alberto et all [165]
ECG, respiration, skin conductance, and EMG of the trapezius muscles	Wijsman, Jacqueline et all [166]
heart rate, skin conductivity, electromuscular activity, and respiration	Simon, Ollander et all [167]
EEG and GSR	Sharma, Nandita and Gedeon, Tom [168]

According to the literature, it can be noted that most sensor systems developed are sensory fusion systems and the GSR and the electrocardiogram stand out as the most used sensors.[169]. It is also interesting to note that in [159] they presented an empirical ranking of measures for measuring stress and the GSR and ECG are in first and second place in the table.

There are different ways to rate stress. Some researchers use the self-questionnaires analyses method, others the psychological sensors data collection analyses and others make a merge of the two methods.

An example of a self- questionnaire is the Perceived Stress Scale (PSS) which is a psychological instrument for measuring the perception of stress. In [170], they used the PSS-10 to measure the global stress that car drivers perceive in their everyday life. The PSS score is derived by summing the scores for the ten items, which are scored on a Likert scale with 0=never, 1=almost never, 2=sometimes, 3=fairly often and 4=very often.

According to [171], the questionnaire method provides only a momentary snapshot of the individual's stress level, as most individuals cannot accurately recall the history of the ebb and flow of their stress symptoms. Also, in [172], the author discusses the dangers of self-report, and he refers to two of their problems: honesty or the subjective ability of their participants.

In [164], they merge the two methods: they collected four sensors physiological data during real-world driving and immediately after each drive, they asked subjects to fill out the subjective ratings questionnaires. The questionnaire analysis was used to validate a perception of low, medium, and high stress during the rest, highway, and city driving periods.

Self-reports are cheaper and faster and easy to implement but are more subjective than psychological sensors data collection: they tend to be more expensive and spend more re-

sources, but they are more objective. An important point to keep in mind is that you always have to make sure to relate the results, from questionnaires or sensors, with the possible stress events.

3.3.3 Overall biosignals processing

The information coming from the biosignals must be treated thought to four step process [173, 174]like is depicted in fig. 3.13

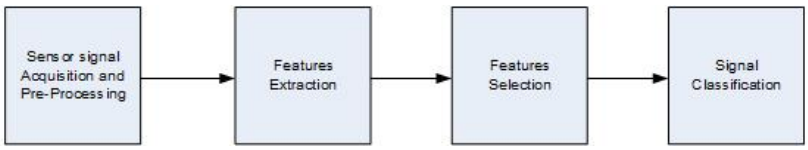


Figure 3.13: Block diagram of biosignals processing

In the block sensors signal acquisition, the sensors to use must be chosen and preprocessing the signal. In electrical biosignals sensors which use electrodes, preprocessing involves amplification, filtering and analogue-digital conversion [175]. After that, it is created a database with the software that reads the different types of sensor's signals.

Since the dimension of this database is too large, which increases computational complexity, the block "Feature extraction" extract the different features of each type of sensor.

Features extraction and selection

After the selection of stress sensors, is made the features extraction of each type of sensor signals.

Pattern recognition or feature extraction is the process from which parameters are obtained, which can be, for example, used in a classification process. The features extraction allows to reduces the amount of raw data into data segments, maintaining the vital information for pattern recognition.

Biosignals are usually analogical time signals, and they can be analyzed in the frequency domain or in the time domain. Also, there are statistical and signal-specific specific features which can be obtained from different ways of processing the signals.

Statistical features can be calculated for any biosignal, and they are, for example: mean, standard deviation, median, and standard deviation, range, ratio, minimum, and maximum. The signal specific features or syntactic features are specific for each type of signal. For

example, as the GSR waveform signal is different from a waveform ECG signal, the specific features are derived from the geometry of the waveform signal [176].

Features selection is the process that selects a subset of them. If the appropriate set of features is selected, a good classification accuracy can be achieved. One of the challenges for the development of a system for detecting stress is to choose the smallest possible number of features that can provide the form for proper stress level. In [177] propose a feature selection approach and prove that with appropriate selection of fusion method, less number of features can result in less time consumption and better correct rates.

According to [178] and [179] feature selection selects a subset of features from the original feature set without any transformation, and maintains the physical meanings of the original features. They also report that, for supervised classification algorithms, feature selection techniques can be organized into three categories, depending on how they combine the feature selection search with the construction of the classification model: filter methods, wrapper methods and embedded methods.

Stress classification techniques

According to [180] classification is one of the data mining techniques.

The classification is one of the supervised machine learning technique that is used to classify each selected feature into one of a predefined set of classes or groups. It is made in two steps: the first is to build the model on training data set, and the second is tested the classifier model with a predefined dataset [181]. The model will assign a class label to this last dataset. It is calculated the accuracy classifier is and if it is considered acceptable, applied to other data sets. In [180], they surveyed classification techniques in data mining. These classification algorithms can be implemented on different types of data sets like share market data, data of patients, financial data, among others. For instance, in [182] they made a comparative study of classification techniques like decision tree induction, Rule-based, Memory-based learning, Neural networks, Bayesian network and Support Vector Machines (SVM), evaluating the accuracy of each technique for voting data.

Also, in [181] they made a comparative study of classification algorithms and they concluded that each technique has its own feature and limitations.

Concerning stress models, several computational techniques have been developed. The goal is to classify emotional state to discriminate stressors conditions from others. In the literature, one founds that physiological emotion classification has been performed by var-

ious computational modelling techniques, like Fisher Projection (FP), k-Nearest Neighbor algorithm (kNN), Linear Discriminant Analyses (LDA), fuzzy logic, Bayesian classifier and Support Vector Machine (SVM) or Artificial Neural Network (ANN). In [182] and [159], they made a survey review of the various stress analysis methods that can be used to classify stress. These classify algorithms, recently, has been used in several works. The next table presents some of these works. It should be noted that in some cases, they used hybrid or extended classification techniques. And for example, in [183] they made a comparison study of five machine learning algorithms, including LDA, Naïve Bayes and SVM for classifying negative emotions. The next table 3.7 presents some researcher works based on different stress classification techniques.

Table 3.7: Stress algorithms review

Stress classification technique	Authors
SVM	Dayalin et al [184]; Sierra et al.,2011 [161]; Sun et al. [185]; Jang et al.[183, 186]; Vanitha et al. [187]; Sandulesco et al. [188]
Fisher's Analysis	Healey and Picard [164]
k-NN	Bong et al. [189, 190]; Tatiur Rahman et al. [184]
Fuzzy Logic	de Santos Sierra, Alberto [165]; Kumar M. G et al. [191]
Bayesian classifier	Selvaraj et al. [192]; Frank et al. [193]
LDA	Jang et al. [183]; Anusha et al. [194]

Although there are no many comparisons studies to evaluate stress models, the SVM modelling technique is the first one in the empirical ranking techniques review made in [159].

3.3.4 Types of stress detection systems

Currently, and according to a literature review, there are two main groups of developed stress detection systems: those to be used in autonomous and closed mode and those to be used in open mode.

In the first case, they use the biofeedback technique: the user reads the biosignals and reacts, adapting their behaviour to the temporal evolution of these signals. These systems are developed/marketed for use as personal use or as of assistance systems to professional health technicians.

Open systems are designed to integrate with other systems. That means, biosignals or the result of their processing, is sent to a receiver system. The information received shall be processed in a way that depends on the application. For example, information obtained can

be integrated with home/hospital care systems or with driver supports systems.

Biofeedback stress detection system

According to [195], biofeedback is a treatment technique in which people are trained to improve their health by using signals from their bodies. These systems are developed to provide the user with the reading of a physiological signal, aiming to make the person aware of his emotional state.

Once aware of the stressful circumstances, the individual may use some method of intervention to eliminate or reduce his or her state of stress when faced with new and known situations. The goal is, while the biosensors are monitoring the user, the biosignals are being acquired and analyzed in real-time. They can be presented in graph form and the analysis, in real-time, is usually a comparison analysis with predefined values. There may be warning beeps to notify the user that these preset values had been reached.

These systems can be used in different types of environments, such as the workplace. The primary purpose of its use is that the user himself can anticipate and avoid possible stressful situations that can occur daily. The application of biofeedback technique can be used in stress prevention and stress management.

Some of these systems have the option to save the received data for posterior analysis. In this case, software such as Excel or Matlab can read these data files. These files, usually, contains a large amount of information, and therefore the interpretation of these data can be a time-consuming task and not expeditious.

There are several types of applications, for mobile phone or for computer operating systems, that allow to analyze a psychological signal, such as temperature or GSR and its user visualizes the alert levels.

For example, the commercial system emWave PC Stress Relief System [196] from the manufacturer HeartMath Institute is used in [197] to evaluate the Psychophysiologic coherence assessed through monitoring the heart rhythms.

Another commercial biofeedback system is the Biofeedback Xpert. They announced it is the all-in-one package that provides everything that biofeedback trainers and therapists need in their everyday work. All relevant physiological parameters can be measured and displayed, including respiration, skin conductance, temperature, heart rate variability, pulse, muscle tension and motility" [198]. This manufacturer provides a set of tests in which the user interacts with the test platform. For example, it has the DT Determination Test, that

can be used to investigate behaviour under different levels of psychophysical stress, like for instance, in traffic situations [199].

BioZen or ShimmerCapture are two examples of Android application to measure body sensors like GSR, ECG, EEG or EMG.

BioZen, from the Defense Department's National Center for Telehealth and Technology, is a smartphone mobile application to help service members use the therapeutic benefits of biofeedback. This application shows, in real-time, data from multiple body sensors including electroencephalogram (EEG), electromyography (EMG), galvanic skin response (GSR), electrocardiogram (ECG or EKG), respiratory rate, and skin temperature [200].

ShimmerCapture is an Android application, developed by Shimmer [201] that can connect a Shimmer device, plot the data received by the sensors and save it in a CSV (Character Separated Values) file.

Open stress detection systems

In [164], the authors presented methods to assemble and analyze four biosignals during real-world driving tasks to determine a driver's stress level. Four types of physiological sensors were used during the experiment: electrocardiogram (ECG); electromyogram (EMG); skin conductivity (also known as galvanic skin response, GSR) and respiration. The sensors were connected to a FlexComp unit, and the collected data were subject to two types of analysis which includes the recognition of level stress. In [202], a Nonin pulse oximeter, a GSR, respiration and a Lead-II ECG sensory device were mounted in the driver body. These sensors communicated with a Mind Media BV's Nexus device and through it to an HP Compaq Tablet via IEEE 802.15.1 (Bluetooth). The collected data is then processed offline in MATLAB.

In [203], a real-time method to detect stress while driving, was presented. The Bayesian theory, and ECG, GSR and respiration signals and driving behaviours were used to identify stress. The use of Biopac MP100 system measured the sensors signals, and the Bayesian Network model incorporates the data information for stress event detection.

Recently, researchers develop wearable sensor systems [204, 205]. For example, autoSense is wearable sensor systems that collects and processes cardiovascular, respiratory, and thermoregulation measurements that can inform about the general stress state of test subjects in their natural environment and the wireless transmission to a mobile phone in real-time makes it possible monitoring of physiological responses to real-life stressors [206].

Currently, the car manufacturers are developing technologies to incorporate biometrics sensors in their car systems. For example, Ford is developing technology that limits driver's access to the cell phone, but only when the system senses that traffic is heavy and the driver is experiencing stress. For this purpose, heart rate and body temperature sensors are integrated into the steering wheel, while the driver's breathing rate sensor is integrated into the seat belt [207].

Also, a research team at the Technical University of Munich, in collaboration with researchers at the BMW Group, managed to develop a sensor system, also integrated into the steering wheel, that can monitor the health driver state. The proposed system monitors vital signs such as heart rate, skin conductance and oxygen saturation in the blood via sensors integrated in the steering wheel. The goal of the project is to get the vehicle to detect when the driver is no longer feeling well and to the initiate appropriate measures and, when a stress situation is detected by means of skin conductance values, phone calls can be blocked, for instance, or the volume of the radio turned down automatically [208].

3.3.5 GSR and ECG analysis

As the GSR and ECG are the most used biosignals to detect stress, this sub-chapter presents their typical waveforms as their most commonly used signal features. Also, the influence of acute stress in the GSR and ECG pattern is discussed.

Another critical issue is to analyze how the diseases responsible for the upper limb weakness muscles could affect the body stress response in terms of ECG and GSR variations.

Galvanic Skin Response typical waveform

Concerning the GSR, if the sympathetic nervous system is highly aroused, then the body activates sweat glands, which in turn increases skin conductance [209].

A GSR sensor measures the electrical conductance between two points on the body, typically measures hands (fingers) and feet, where the density of sweat glands is highest [185]. These sweat glands respond to psychological stimulation rather than merely to temperature changes in the body.

There are two primary components for GSR analysis, namely, the tonic and phasic phenomena. The main differences between these phenomena are related to their time scale and their relationship to the evoking stimuli [210, 211].

Skin conductance level (SCL) or the tonic component is the baseline level of skin con-

ductance. Corresponds to slowly changing part of the GSR signal when there is no stimulus. This measure describes the overall conductivity of the skin over longer time intervals, typically ranging from tens of seconds to tens of minutes. It can be computed as the mean value of skin conductance over a window of data. The rising and declining SCL is continuously changing within an individual respondent. It depends on their hydration, skin dryness, or autonomic regulation which led some researchers to conclude that, the actual tonic level on its own is not that informative.

A fast-changing part of the GSR signal or the phasic component is called skin conductance response (SCR), which occurs with a single stimulus. According with [211], an SCR is a discrete and short fluctuation in skin conductance that lasts several seconds and usually follows a characteristic pattern of an initial, relatively steep rise, a quick peak, and then a relatively slower return to baseline. The GSR typical waveform can be depicted by four states as is shown in figure 3.14 [20]: normal, arousing, stressed and relaxing.

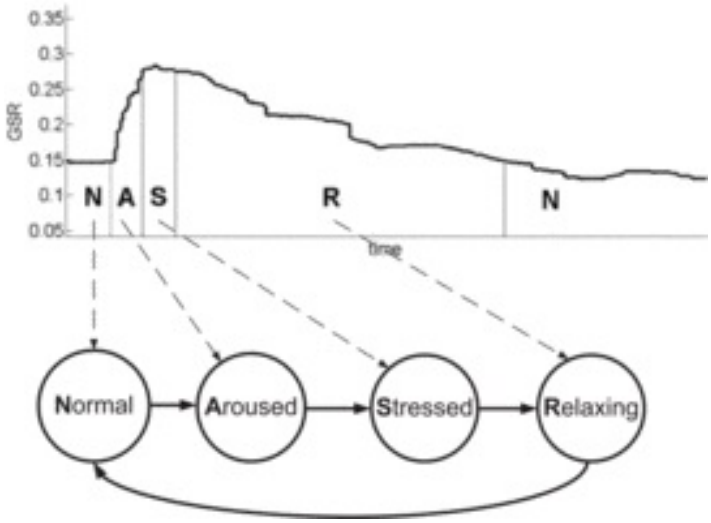


Figure 3.14: GSR typical waveform states[20]

Figure 3.15 show a GSR typical waveform with the identification of the most used signal features.

- latency time: is the time between the onset of the stimulus and the start of an SCR (lat.)
- rise time: is the time between the onset of the SCR and its peak amplitude (ris.t)
- peak amplitude: is the difference between the conductivity at the onset (the baseline) and the peak (amp)

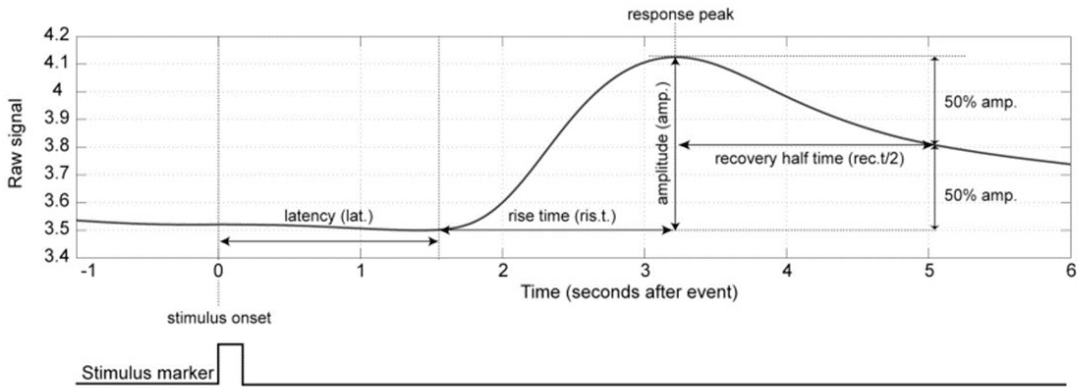


Figure 3.15: GSR typical waveform [211]

- recovery half time (rec.t/2) is highly correlated with rise time.

ECG typical waveform

Concerning the electrocardiogram (ECG) and, according to the literature, an ECG records electrical activity in the heart. An ECG sensor measures the flow of the electrical activity of the heart changes over time. According to [212], the ECG is measured from the surface of the skin, which can be done by placing two electrodes directly on the skin and reading the potential difference between them. The placement of these electrodes gives us the leads we use in recording an ECG. A lead consists of one positive and one negative pole [213]. Between the two poles lies an imaginary line representing the lead's axis, a term that refers to the direction of the current moving through the heart. Because each lead measures the heart's electrical potential from different directions, each generates its characteristic tracing [214].

The standard ECG has 3 standard limb leads: 2 leads situated on the right and left wrist (or shoulders), RA and LA respectively, and the lead situated on the left ankle (or left lower abdomen) LL, make up a triangle that surrounds the heart. Is known as "Einthoven's Triangle" and is showing in figure 3.16.

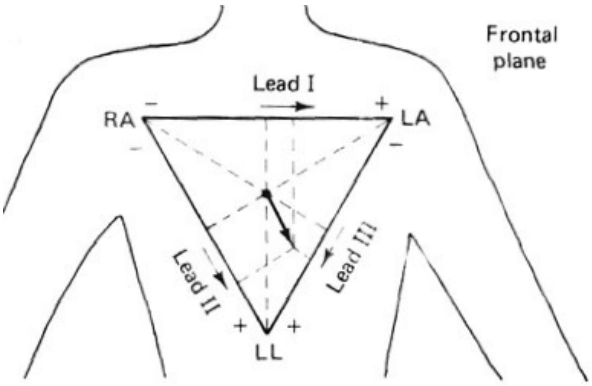


Figure 3.16: Einthoven's triangle [17]

Information between RA and LA is known as lead I; information between RA and LL is known as lead II, and information between LA and LL is known as lead III. This three limb frontal leads gives different views of the heart functioning. The lead II is almost parallel to the main axes of the heart and is the prefered recording of the ECG. A typical lead II record as 5 waveforms [215], arbitrarily designated P, Q, R, S and T is depicted in the figure 3.17.

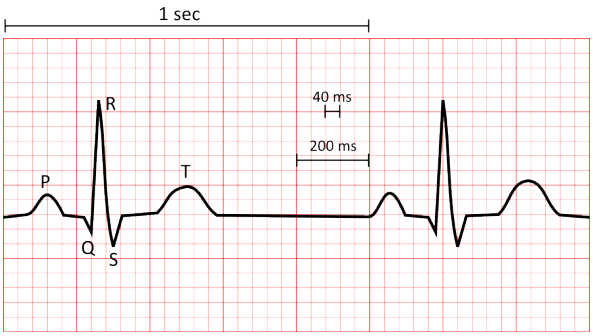


Figure 3.17: Records of a normal ECG, lead II [18]

Each wave represents the different phases of a cardiac cycle, for example, the QRS wave represents ventricular depolarization.

ECG features extraction scheme determines the amplitudes and intervals in the ECG signal for subsequent analysis. The amplitudes and intervals value of P-QRS-T segment determines the functioning of heart of every human. The amplitudes and intervals value of P-QRS-T segment determines the functioning of heart of every human [216].

So, ECG features extraction plays a important role in diagnosing heart diseases, helping in discover ECG abnormalities. According with the literature, the ECG features extraction has been the subject of study in the last few years and the precision in the identification of various parameters in ECG is of great importance. Features extraction techniques have been

developed like Fuzzy Logic Methods, Artificial Neural Networks, Genetic Algorithm, Support Vector Machines (SVM) or Wavelet based methods. In these works like [217, 216, 218, 219], the authors made a review of the most used algorithms used to analyze the electrocardiogram.

Effects of acute stress on GSR and ECG

When a person is stressed, the nervous system responds quickly by releasing sweat, and the variations in the phasic component are manifest as GSR bursts or GSR peaks. As already mentioned, in section 3.3.5, phasic response is also labelled skin conductance response as it is sensitive to specific emotionally arousing stimulus events as as is figured out in 3.18.

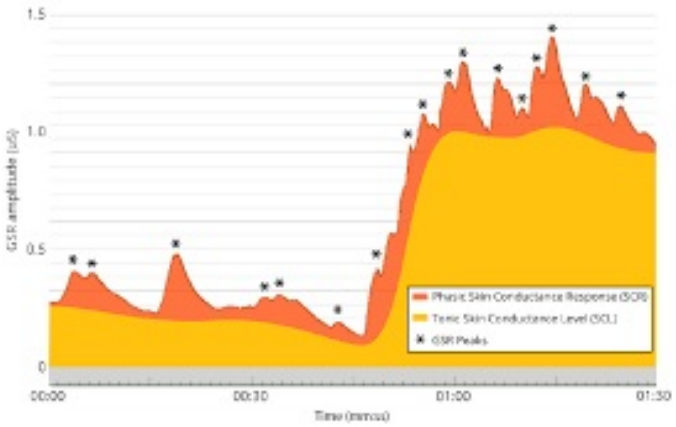


Figure 3.18: Emotional situations SCR waveform [211]

So, analyzing SCR data can be used to measure the human stress level.

One of the metrics used to define the stress level is the number of peaks after a stress event as, after that, the number of peaks will increase. Also, the SCR baseline will increase, and then the time necessary to return to this baseline will depend on the number of stress events. The peak amplitude is also used and reflects the intensity of the stressor. Statical metrics like mean, maximum and minimum of SCR amplitude, number of peaks, rising time as being used to detect stress.

The next table 3.8 summarizes some works where different GSR features selection was made.

Table 3.8: GSR Selection Features

Authors	GSR features
Healey, J.A.; Picard, R.W [164]	Mean, variance, total number of the onset, sum of startle magnitude, response duration and estimated areas.
H. Kurniawan and A. V. Maslov and M. Pechenizkiy [220]	Mean, minimum, maximum, standard deviation, peak height; the total number and the cumulative amplitude, rising time and energy of startle responses in segment.
Feng-Tso Sun et all [221]	Mean and standard deviation, total number of startle responses in the segment, sum of response magnitude and response duration.
Jing Zhai, Armando B. Barreto, Craig Chin, Chao Li[222]	Number of responses, mean value, amplitude, rising time, energy.
Rajiv Ranjan Singhi, Rahul Baetee [223]	Mean, variance,standard deviation, median,etc.

As said in [224], electrocardiogram (ECG) signal significantly reflects autonomic nervous system (ANS) activities during emotional stress changes. The QRS complex, an activity of the ANS that is derived from ECG provides information of the myocardial conduction system and can be used to understand the emotions experienced by a person [225]. Separate rhythmic contributions from sympathetic and parasympathetic autonomic activity modulate the HR intervals of the QRS complex in the electrocardiogram (ECG) at distinct frequencies.

HR variability has been considered as a stress marker in human body [226, 227]. Heart Rate Variability is a measure which indicates the variation in your heartbeats within a specific time frame: if the intervals between your heartbeats are rather constant, your HRV is low and if their length variate, your HRV is high. A little reading supports the dominance of the sympathetic – or 'fight or flight' - and is a state of high stress, whereas a high HRV reading suggests the supremacy of the parasympathetic branch. This 'rest and digest' state is one of low stress.

In [228], they made a review of studies providing a rationale for selecting HRV as a psychological stress indicator and they concluded that HRV is impacted by stress and supports its use for the objective assessment of psychological health and stress.

According with the authors of [229], time-domain and frequency-domain indices and geometric measures are standard clinical parameters.Time domain analysis measures variation in HR over tome between successive normal cardiac cycles.

Heart Rate (HR) is one of the simple time domain HRV measures. The R–R interval indicates the duration of a heartbeat (see figure 3.17) and the heart rate is the inverse of the

heart period.

When a person is in a stressful situation, the adrenaline hormone is released, which will speed up the heart rate, which will affect the ECG waveform pattern. So, during acute stress situations, it is expected that a healthy person as an increase of the heart rate.

All mentioned before was concerned about the possible effects of acute stress for non-disabled people.

People with disabilities are the focus of this work, people with various types of pathologies that affect upper limb mobility and manipulation. So, next, a brief discussion on how spinal cord response can change the stress response, namely the effects of GSR and HR responses. The justification based on the fact that all people we worked with, at CMRRP, suffered an SCI.

Spinal cord injury and stress response

Concerning the heart rate, according to [230], SCI affects conduction of sensory and motor signals across the site(s) of the lesion(s), as well as the autonomic nervous system. The autonomic cardiac control is altered depending on the level of the SCI lesion.

In [231], the authors said that, because heart sympathetic impulses arise from T1–T4 spinal cord segments, complete cervical and high thoracic SCI interferes with superior centers control over spinal sympathetic activity to the heart. In [232], the authors said that T6 is the lowest level of injury necessary for the development of altered autonomic cardiac control.

Cardiac arrhythmias are correlated with the level and severity of SCI. During an ECG, these arrhythmias can be detected. For example, the acute loss of sympathetic stimulation results in bradycardia [233], which is slower than usual heart rate. The typical heart rate, in rest, is between 60 a 100 times a minute and less than 60 times a minute reveals bradycardia.

The effect of mental stress was studied in [234], with ten patients suffering from complete chronic cervical spinal cord lesion. The authors compared the cardiac rate under mental stress in tetraplegic, paraplegic and healthy control group. They concluded that the cardiac rate of tetraplegics, in rest, was not significantly different than in the other groups but, during stress, values were substantially lower than those of paraplegics and controls.

Regarding the use of GSR for detection of the sympathetic nervous system response, for patients with lesions/diseases affecting the thoracic spine zone above T3, this signal cannot be used because there is no conducting pathway of sympathetic skin response [235, 236].

In [234], the sympathetic skin response (SSR) due to electrical stimulation of median

nerve and transcranial magnetic stimulation was examined in 70 patients with complete and incomplete spinal cord injury. They concluded that in patients with complete tetraplegia and paraplegics with high thoracical lesions (up to level T3) SSRs of the hands and feet were absent. In patients with complete paraplegia and thoracic lesions from level T4 up to T8 the SSRs could be evoked in the hands but not in the feet. However, in paraplegics with lumbal and thoracic lesions below level T8, SSRs of the hands and feet could be recorded.

In [236], sympathetic skin response was recorded in 17 healthy volunteers and 14 patients with spinal cord injury. Their results are that patients with a thoracic cord injury, some responded at the upper limbs but none at the lower limbs; some responded at neither upper nor the lower limbs; and some responded at both upper and lower limbs. The conducting pathway of sympathetic skin response in the spinal cord for the upper limbs descends to the upper thoracic cord (T4-6), and the conducting pathway for the lower limbs departs from the spinal cord at the lower thoracic cord (T9-10). They concluded that it appears that sympathetic skin response should be used for the evaluation of the functional abnormalities of the sympathetic nervous system in patients with spinal cord injuries.

3.4 Conclusions

In this chapter, the results of a literature review of the smart wheelchairs area has been presented. This research area was born as an application of the technology used in mobile robotics. In the beginning, it was the focus of many research teams all over the world. As these groups launched very ambitious projects, they resulted in rather complex solutions, which did not penetrate in the market. As an alternative, researchers began to focus on easy to implement add-on units for commercial wheelchairs with specific functions. This new perspective has made this area of research start to grow again. In the most recent works, the form factor that predominates is the one that meets the needs/deficiencies of the user such as semi-autonomous navigation based on add-on units.

Regarding the stress detection process, a summary of how stress detection signals are processed is given. Feature extraction and stress classification techniques have been reviewed. Additionally, in this chapter, a review of open biofeedback and open stress detection systems has been presented.

Concerning sensor stress detection, galvanic skin and electrocardiogram response sensors are the most commonly used. Therefore, their typical outputs have been discussed in more

detail. It is also discussed how a spinal cord injury can affect the sympathetic nervous system and, consequently, the impact on the heart rate and skin conductivity.

In the next chapter, a proposal to adapt a commercial powered wheelchair to empower safe navigation to people with reduced strength in arms and hands is described.

Chapter 4

A proposal for an APW navigation system

4.1 Introduction

This chapter presents a novel concept of adaptation of a commercial powered wheelchair (CPW) to develop an assistive powered wheelchair (APW) specifically target for people with a reduced strength in arms unable to manipulate a legacy joystick.

The majority of the patients who attend the Rehabilitation Center have suffered a spinal cord injury at the cervical vertebra level, and they need rehabilitation shortly after the accident. They all need a commercial powered wheelchair to obtain mobility. But their functional outcomes concerning the ability to use a commercial powered wheelchair are compromised because they don't have the skills to manoeuvre a legacy commercial joystick. So, they need an alternative to the conventional joystick functioning to be able to navigate their CPW.

But, conducting CPW during their daily activities can be stressful and consequently, exhausting challenge. This can negatively influence the CPW driver's ability. So, it can be a possible solution to take advantage from the use of an emotional monitoring system, in daily life activities, to guarantee their well-being. It comes then, in consequence, a proposed system intended to enable people with reduced handling, to navigate his/her APW safely.

4.2 The overall APW model

An ideal wheelchair control systems must gather sensory data, extract relevant information from the data and reach a decision considering the environmental situation as well as

the user's psychic condition.

The proposed APW control system should have the capability to process different types of sensor data, in real-time, so that it can have the ability to react to possible environmental changes around the CPW as well as any changes in the CPW user's welfare. A system which can fulfil all these requirements, like no other, can be represented by the human being itself.

Several bionic models of Artificial Intelligence have been proposed and developed to be applied to technical, economic, pedagogical, sociological and other applications. One of them is the one developed by the Artificial Recognition System (ARS) project. The ARS project was launched at the Institute of Computer Technology of the Vienna University of Technology in 1999.

As already said, the ARS project has been renamed to SiMA. The goal of this project was to model and simulate human thinking by methods of natural science and engineering via the scientific findings of psychoanalysis, and to eventually integrate the result into devices which require such intelligence (e.g. decision units for surveillance systems, robots, risk assessors, etc.) [25].

The ARS control architecture is based upon Sigmund Freud's 2nd topographical model where a number of psychic functions are identified. According to a top-down design approach basic functionalities are further divided into sub-functionalities. Figure 4.1 shows a simplified sketch of the ARS control unit which covers tasks like perception, scenario recognition or decision making. In [19] the model is explained in detail.

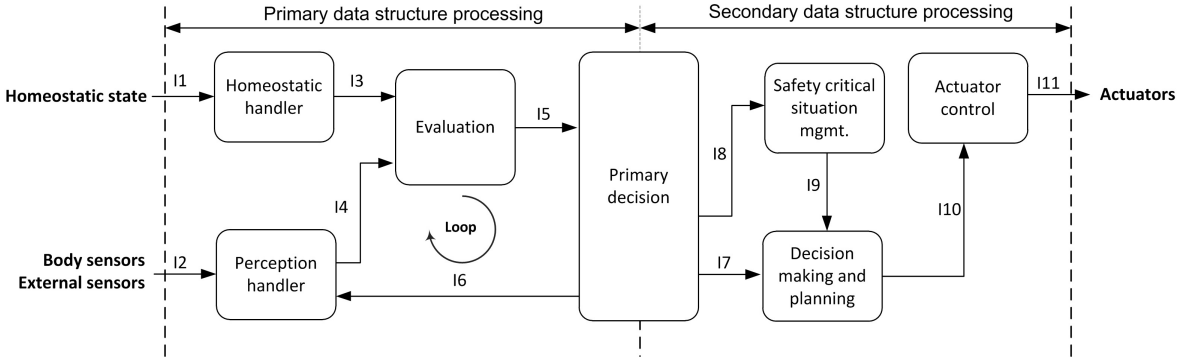


Figure 4.1: Modeling the psychoanalytical processing sequence [19]

The ARS / SiMA model incorporates not only environmental information but also homeostatic states into its calculations. This concept served as the basis for the proposal of adaptation of the SiMA model in the APW controller: considering as homeostatic state the

user emotional state.

The plan is to incorporate the user emotions into the concept of the system's homeostasis, which means that the user's physiological state is taken into consideration by the APW control unit as depicted in fig. 4.2. The user emotional state will interfere with the APW operating mode.

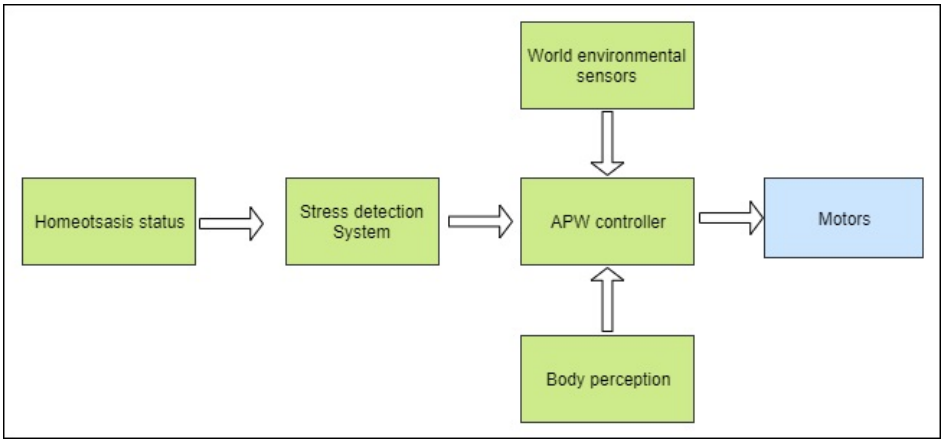


Figure 4.2: The adaptation of the ARS model to be used in the APW operation

In this work, the focus of the user emotional state will be the user stress state. The goal is to evaluate the user stress state during daily life activities and intervene in the APW normal operation when the user reach a high-stress level.

As known, all individuals react differently to stress. Different people respond differently to the same problem or stressor. For example, in our daily life, some individuals get stressed quickly, while others need several various stressful events before beginning to feel physical or psychological effects.

That is why it is crucial to evaluate, emotionally, each person. This is the goal of the user emotional profile: just as an ID card identifies each person in terms of her/his physical features, the emotional profile intends to identify each person in terms of emotional features. In this work, the emotional profile wants to identify each person in terms of oh his/her stress features.

The user stress state will be calculated through the use of the user stress profile and throughout homeostasis stress status in real-time.

4.2.1 The overall APW architecture and operation

Two main goals are proposed: helping people with reduced strength in the hands and arms in the navigation of their commercial powered wheelchair and guarantee that the psychic

conditions doesn't affect and isn't affected by the way that the user interacts with the APW.

To achieve the first goal, our proposal consists in maintaining the legacy CPW joystick and in modifying its mode of operation (section 4.3).

To achieve the second goal, our proposal consists in integrating the user stress state into the APW navigation using, for this, a stress detection system (section 4.4).

The APW architecture is based on add-on units, and the APW navigation control is shared between the APW user decision, and a control system that takes into consideration the user emotional state and the environment that surrounds the CPW.

The user decision is reflected in the selection of the mode operation of the APW. To do this, it is proposed to change the operating mode of the joystick and consequently, two different operation modes for the APW are proposed:

- Legacy mode: the joystick commands the wheelchair according to default settings.
- Assistive mode: the joystick commands the wheelchair according to new settings.

The emotional state of the user ensures that the APW user is in a emotional condition to continue to drive the APW. For this, the information about the emotional state of the user is fed into the control unit of the APW through a stress detection system.

The environment guarantees the physical safety of the user. An obstacle detection and contouring system is proposed, which supports two of the proposed modes of operation.

The proposed architecture is depicted in figure 4.3:

- AM_ON (Assistive Mode_ON) is the switch that chooses which of the controllers will be responsible for the navigation of the wheelchair.
- The CPW controller is the legacy CPW controller.
- The APW controller is the new add on unit controller.
- The Stress Detection Module (SDS) is a new add on module that will detect the user emotional state.
- The Sensors Module is the new add on unit that detects obstacles.

The figure 4.4 depicts the whole operation of the proposed wheelchair navigation system.

First, the APW user must choose whether to navigate the APW in the legacy mode or the assistive mode by using the switch MA_ON.

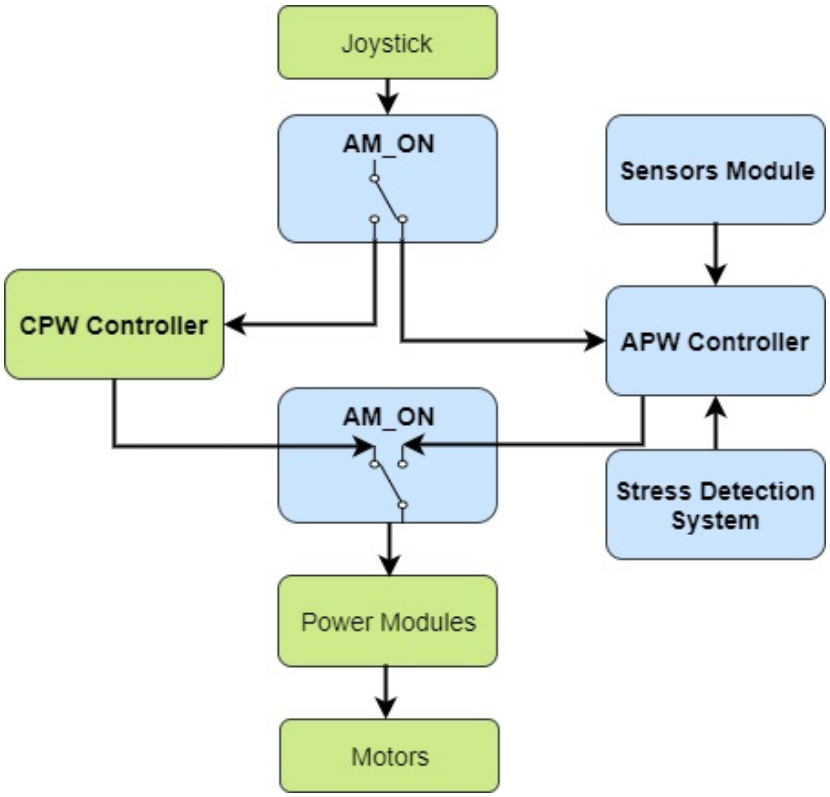


Figure 4.3: Overall architecture of the proposal APW

In the legacy mode, the APW works as it comes from the factory.

For the APW to operate in the assistive mode, the stress detection system must be activated. Only with these two conditions, SDS ON and MA ON, the user can profit of the three operation modes proposed, which are explained in sub chapter 4.3. The SDS aims to supervise the user APW emotional state when the assistive mode is selected.

When the SDS is ON the stress detection system is acquiring and is classifying, in real-time, the homeostatic sensors signals placed in the APW user.

From the moment that the SDS detects that the APW user has reached an emotional stress state, that puts in risk the navigation, all commands given by the joystick will not be considered to navigate the APW. In this situation, the APW user is alerted, and APW controller will be responsible for the APW navigation making, for example, the adjustment of the APW velocity until it stops. This situation is one example that corresponds to an one navigation alert mode and is described in section 4.4.3.

The on-line stress detection system provides, in real-time, a measure of the emotional driver state to the vehicle control system. Only when the emotional state of the APW user returns to a level that is considered as of no stress, the user can return to command the APW

navigation through the joystick. This step corresponded to the Impulses APW navigation of the proposed APW operation and described in sections 4.3.2 and 4.3.3.

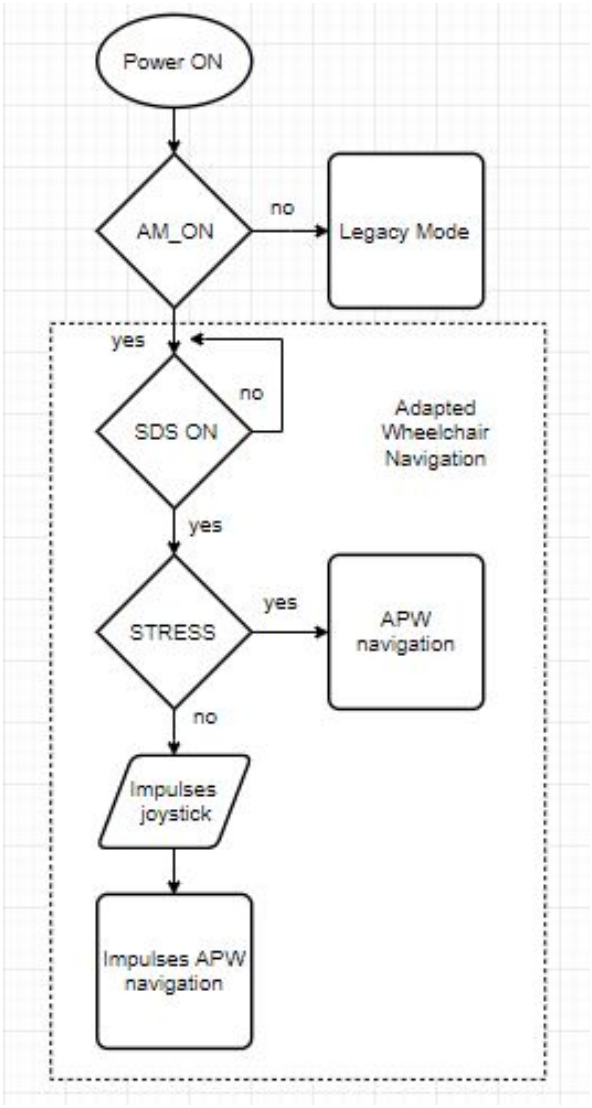


Figure 4.4: The overall operation of the proposal APW

The hierarchical FSM of the APW operation is defined by four states: the Legacy mode (Lm), the Legacy Adapted mode (LA), the Semi-transfer Adapted mode (SaT) and the Alert mode (AL) as depicted in the figure 4.5 and the respective conditions are defined in the table 4.1.

The default mode is the Legacy mode. The APW user can choose between the three states, Legacy, LA and SaT modes by using a switch, and the APW controller can only be in one of the selected modes at any time.

The APW controller enters in the alert mode when the SDS detects a high user APW

stress emotional state.

- m_a is a Boolean variable indicating if the LA mode is ON or OFF.
- m_b is a Boolean variable indicating if the SaT mode is ON or OFF.
- m_c is a Boolean variable indicating if the Alert mode is ON or OFF.

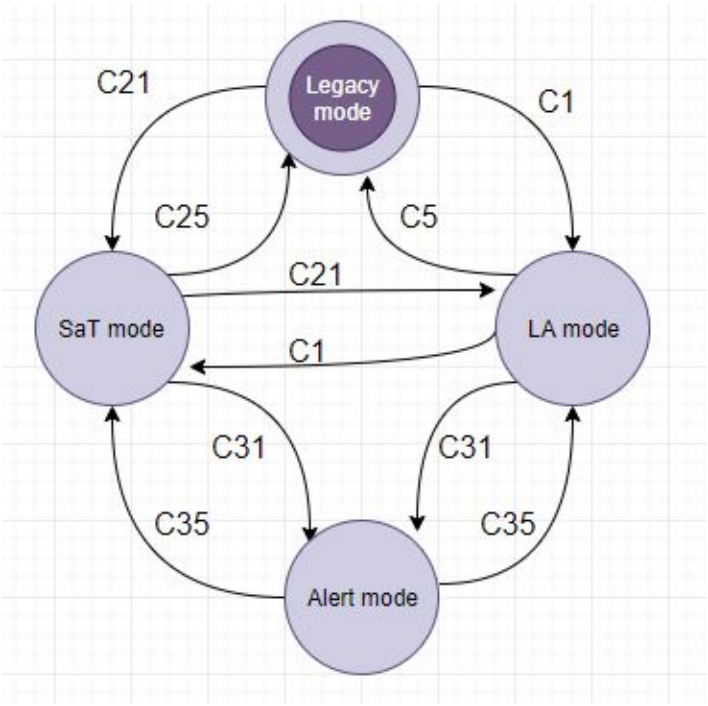


Figure 4.5: APW operation Finite State Machine

Table 4.1: APW transition conditions

Condition	Transition Condition
C1	m_a = ON
C5	m_a = OFF
C21	m_b = ON
C25	m_b = OFF
C31	m_c = ON
C35	m_c = OFF

4.3 The APW assistive mode

According to the clinicians of Center, the ideal solution for the problem of people who have reduced handling ability would be to navigate the wheelchair without the need of a continuous driving force. They also agree that an autonomous wheelchair is not the best

solution for these patients. They argue that, if there is a way to allow these patients to navigate the wheelchair by using the joystick, they are doing some physical exercise which, for them, is considered as rehabilitation. This reasoning was used as the starting point to define the three modes of operation of the adapted mode.

To address the problem of the reduced strength in the hands and arms, a commercial joystick was adapted. This joystick was physically changed to turn it more manageable, as shown in figure 4.6: a foam ball replaced the top of the joystick. Also the normal operation of the joystick was changed in such a way that the user only gives single touches on the joystick to identify the navigation direction, as explained in section 4.6.

Besides that, and because the inability of manoeuvring the joystick can cause fatigue and consequently changes in the user emotional state, the proposed navigation system will be supported by a stress detection system (SDS) as referred previously.

Figure 4.6: Commercial adapted joystick

The assistive mode is a general designation as it, in effect, provides three different modes of operation: the Legacy Adapted Mode (LAM), the Semi-autonomous Transfer Mode (SaTM) and the Autonomous Transfer Mode (ATM).

- LAM is appropriate for users who have the strength to give some impulses of pushing and pulling the joystick and some precision in issuing the desired direction. So they can make some manoeuvres like, for example, going along a corridor and they are also able to make the necessary corrections to the trajectory and to avoid obstacles.

- SaTM is targeted for users that can give stimuli (e.g. touches) to the joystick but are not able to provide successive touches in the joystick or keep them steadily, like, for example when it is necessary to correct the trajectory of the wheelchair in a reduced space.

- In the ATM mode, the APW controller responds to generic commands issued by the user. The commands are encoded, e.g. the number of impulses given in the joystick refer to the place for where the user wants to go (e.g. 1- dinner room, 2-kitchen,...)

The selection among different operation modes can be made manually by the wheelchair user and depends on the:

- Initial skills of the patient,
- The manoeuvre to execute
- The improvement of those skills after training

As we can see in figure 4.7, the degree of autonomy of the APW depends on the skills of its user.

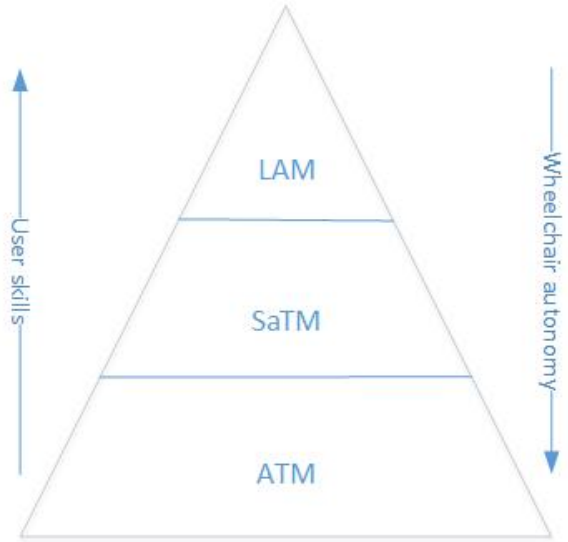


Figure 4.7: Wheelchair autonomy / user skills

In all modes of operation, if, for any reason, the wheelchair collides with some obstacle, it will stop immediately due to the action of bumpers and, automatically, it returns to legacy mode.

The LA mode of operation is described in the next section. Its implementation in simulation environment and in a commercial powered wheelchair is described in sections 5.2.2 and 5.2.4.

Section 4.3.3 describes the SaT mode operation and, section 5.2.3 its implementation on Stage.

The ATM mode of operation was not an object of study in this work since its simulation or implementation enters the area of the trajectory planning. In this mode, the APW is entirely autonomous in terms of path selection, obstacle contouring and manoeuvring like passing a door and for this, it is necessary to implement algorithms of trajectory planning. This was not a part of the general objectives of this work so it is not discussed further.

4.3.1 The legacy adapted mode (LAM)

Concerning the legacy adapted mode of operation, we propose an interface in which the user gives a non continuous touch to the joystick in order to indicate the start and stop of the wheelchair and the displacement direction. The stroke is defined by two variables:

- t_{stroke}: a touch during a specified duration t_{stroke}=t_r-t_a where $t_r > t_a$ and t_a is the instant in which the joystick is actuated in any direction and t_r is the instant in which the joystick is released.
- α_{stroke} the angle of the joystick stroke measured from 0°, being 90° the wheelchair movement direction at the instant of the stroke.

During the navigation, the distance from obstacles is computed from sensor fusion:

- d_{obs}: minimum distance from an obstacle among the distances obtained from different obstacle detection sensors positioned in the movement direction.
- m_a: a Boolean variable indicating if the LAM is ON or OFF. This is done by the user and the system command can also switch to off if a safety critical situation occurs.

In what concerns constants or parameters, defined before run-time operation, we have:

- T_{start}: The minimum duration of a joystick stroke to be interpreted as a command to start the wheelchair movement (protects the system from noise spikes or from spasms or other involuntary strokes in the joystick).
- T_{stop}: the minimum duration of a stroke to be interpreted as a "panic" stop command.
- D_{obsd}: boundary distance bellow which an obstacle in the movement direction starts being taken into account.
- D_{saf}: the minimum safety distance to an obstacle, i.e., the distance bellow which the wheelchair must be stopped for safety reasons (even if bumpers are also used for impact protection).

The hierarchical FSM shown in figures 4.8 and 4.9 describes the LAM operation and the transition conditions defined in the hierarchical FSM are presented in table 4.2.

1. When the wheelchair is powered ON, it starts in legacy mode, where it operates as usual, reacting to an also usual driving from the joystick.

2. To switch to LAM mode, the transition condition C_1 must be true.

3. When the user gives a touch in the joystick, condition C_2 force a transition to the acceleration state where the wheelchair will start moving after t_r and the velocity will increase until a final velocity, v_{final}, that depends on the distance to the nearest obstacle. The increase of the velocity in these circumstances depends of a stair shaped function where temporal constant T_{acc} defined off-line represents the time the wheelchair will stay in a velocity (or in a power level) before it changes to the next one.

4. If, during its movement, the wheelchair will stay beyond the D_{obsd} of any obstacle (which is determined by the sensors) then the velocity may attain the steady state value v_{ss}, which is chosen by the user.

5. If the user wants to stop the wheelchair, condition C_9 or C_{10}, then the decrease of the velocity depends also on a stair shaped function where T_{dacc} is a temporal constant defined off-line. It represents the time the wheelchair will stay in a velocity before it changes to the next one.

6. If, during the displacement, the wheelchair must change its velocity according to the condition C_8, then the wheelchair velocity may be changed depending of the value of d_{obs}.

7. When the wheelchair reaches zero velocity (it stops), condition C_4 is true. Once in the stopped state, the LAM system waits for another command given by the user.

8. If, for some undesirable reason, the wheelchair enters in the danger distance from an obstacle and the condition transition that triggers C_3 becomes true then the transition to the legacy state must occur.

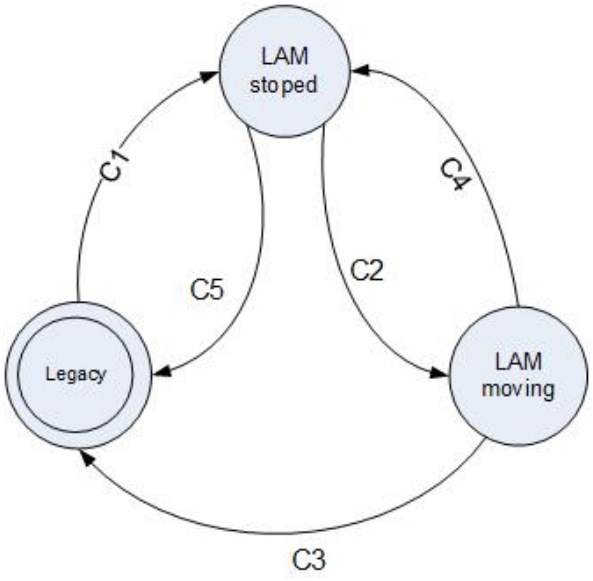


Figure 4.8: LAM operation FSM

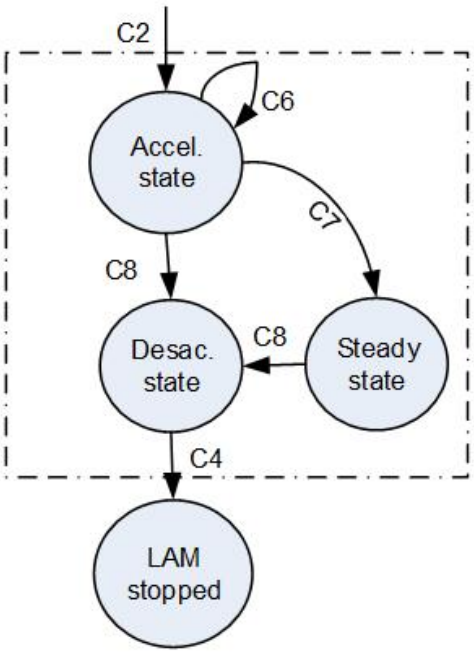


Figure 4.9: LAM moving state

4.3.2 A novel adaptation of LAM

As referred previously, LAM was used by patients who could define a direction with different degrees of precision. However, during our work at the Center we found a significant number of patients with more severe impairments, namely we identified a problem related

Table 4.2: LAM mode transition conditions

Condition	Transition Condition
C1	m_a = ON
C2	$T_{start} < t_{stroke} < T_{stop}$
C3	$d_{obs} < D_{saf}$
C4	v_w=0
C5	m_a = OFF
C6	t $< t_{stroke} + kT_{acc}$
C7	t $> t_{stroke} + kT_{acc}$
C8	$D_{saf} < d_{obs} < D_{obsb}$
C9	$(T_{start} < t_{stroke} < T_{stop}) \wedge (180^\circ < \alpha_{stroke} < 360^\circ)$
C10	$T_{stroke} > T_{stop}$

with the manipulation of the CPW joystick by patients with insufficient strength in the hands. From those, we worked with three patients. One of them was a woman that has become a C4 (this is an indication of the disability [3]) in the right arm and a C6 in the left arm. Because she can't extend the left hand and she hasn't flexion of wrist and fingers, she pushes the joystick with the back of the hand. She had already done some training in manoeuvring the wheelchair but she feels tired quickly. The other patient was a man that is now a C3 and a C4 in the left and right arms respectively. He has great difficulty to operate the joystick not only because of inadequate positioning but also because he has not enough strength to drive it continuously. He made a few tests but he also felt very tired soon. The last one was a man that is a C5 and a C6 in the right and left arms respectively. He can drive his powered wheelchair but he feels tired quickly.

These cases, and the knowledge of similar ones, led us to learn that these patients have two kinds of problems in operating the joystick: the inadequate position of the hand and the reduced strength in the hand and arm. The inadequate position of the hand can be compensated with adaptations that may vary from case to case. Weakness is more difficult to solve and, even if they are able to operate the joystick quite a while, they feel tired soon.

These patients are not able to indicate directions. In fact, in the universe of these people, there are some able to spin to the front, others to spin to the left and to spin to the right. That means, there are some able to move the hand to the front, others to the left or right. Normally, they are able to do the movement to the back but not in a continuous way. If, for example, someone is just able to spin to the left, the only movements that he/she is able to do are to give some impulses in the joystick to the left and to the back. So, he/she should be able to navigate the wheelchair by giving some impulses in the joystick just in those two directions, that is left and back. According to the clinicians, the ideal solution for the problem

of these people would be to navigate the wheelchair without the need of continuous driving force.

So, we considered a new version of LAM in which the same movement in the joystick commands the wheelchair in two different ways: go forward or change direction. The distinction between the two movements, is done by manually switching between them (cd is ON or OFF, condition C11 in table 4.3). This means that the patient will define the future wheelchair movement direction with the wheelchair stopped that is, just rotating without linear movement. This is done by successive interaction with the joystick using their abilities, for example spinning left as in the case described above. After the direction is defined, then the movement is performed, in front or back, using the two joystick movements that the patient is able to perform (for example, spinning left to go in front or pushing the joystick back to go back). It should be noticed that these patients are used to take some time in their displacements and that this solution was considered to be the most adequate by the medical doctors with whom we are working.

Concerning the novel legacy adapted mode of operation (LAM), an new interface in which the user gives a non continuous touch to the joystick in order to indicate the start and stop of the wheelchair and the displacement direction is proposed. So we define a new set of variables and constants, some are the same as defined above in LAM mode operation and others are new:

- m_a: a Boolean variable indicating if the LAM is ON or OFF. This is done by the user and the system command can also switch to off if a safety critical situation occurs.

- c_d: a Boolean variable indicating if the change direction is ON or OFF.

  The stroke is defined by two variables:

- t_{stroke}: a touch during a specified duration $t_{stroke} = t_r - t_a$ where $t_r > t_a$ and t_a is the instant in which the joystick is actuated in any direction and t_r is the instant in which the joystick is released.

- α_{stroke}: the angle of the joystick stroke measured from 0^o, being 90^o the wheelchair movement direction at the instant of the stroke.In this case we can just define two very coarse values for α_{stroke}, for example 180° and 270° for patients that spin left.

  In what concerns constants or parameters, defined before run-time operation, we have:

- T_{start}: The minimum duration of a joystick stroke to be interpreted as a command to start the wheelchair movement (protects the system from noise spikes or from spasms or other involuntary strokes in the joystick).

- T_{stop}: the minimum duration of a stroke to be interpreted as a "panic" stop command.

- D_{obsd}: boundary distance bellow which an obstacle in the movement direction starts being taken into account.

- D_{saf}: the minimum safety distance to an obstacle, i.e., the distance bellow which the wheelchair must be stopped for safety reasons (even if bumpers are also used for impact protection).

- $\triangle$: the delta precision is defined as the number of direction angles that the wheelchair can rotate. A small delta indicates more directions but implies a larger number of impulses in the joystick to attain a specific direction.

The hierarchical FSM shown in figures 4.10 and 4.11 describes the novel LAM operation mode. In table 4.3 the transition conditions defined in the FSM are presented.

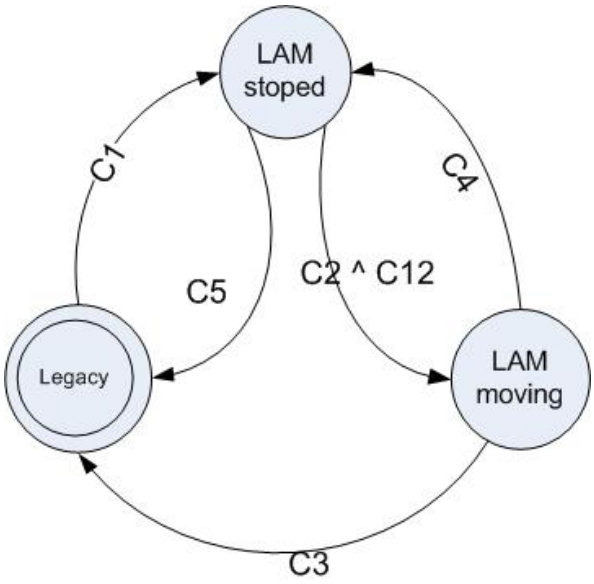


Figure 4.10: Novel LAM operation FSM

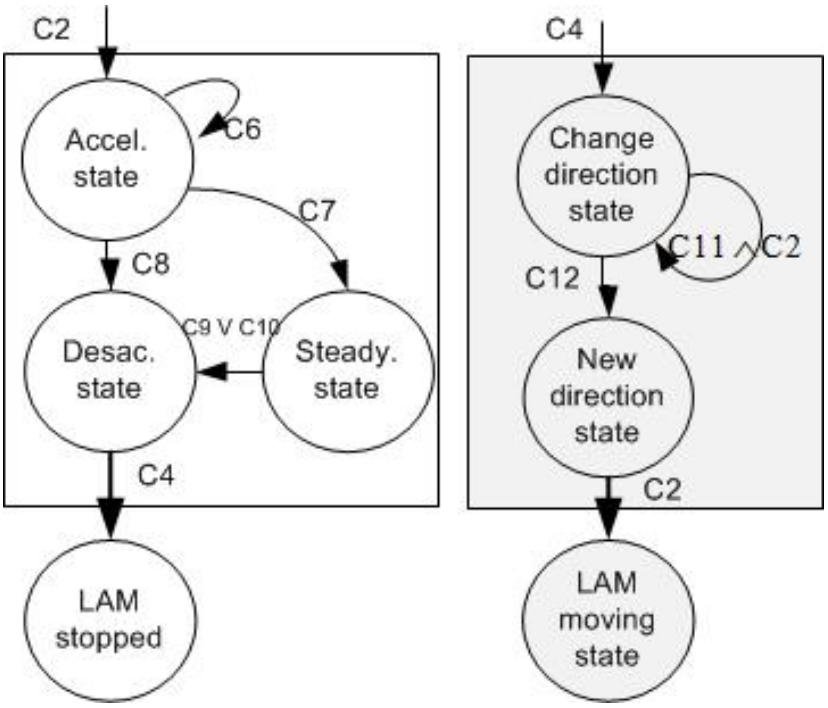


Figure 4.11: Novel LAM moving and stopped states

In table 4.3 , the transition conditions defined in the hierarchical FSM are presented.

Table 4.3: Novel LAM transition Conditions

Condition	Transition Condition
C1	m_a = ON
C2	$T_{start} < t_{stroke} < T_{stop}$
C3	$d_{obs} < D_{saf}$
C4	v_w=0
C5	m_a = OFF
C6	t $< t_{stroke} + kT_{acc}$
C7	t $> t_{stroke} + kT_{acc}$
C8	$D_{saf} < d_{obs} < D_{obsb}$
C9	$(T_{start} < t_{stroke} < T_{stop}) \wedge (180° < \alpha_{stroke} < 360°)$
C10	$T_{stroke} > T_{stop}$
C11	c_d = ON
C12	c_d = OFF

1. When the wheelchair is powered ON, it starts in legacy mode, where it operates as usual, reacting to a usual driving from the joystick.

2. To switch to LAM mode, the transition condition C1 must be true.

3. When the user gives a touch in the joystick and the user wants to go ahead, condition C2 and C12 become both true, the system will start in the acceleration state while

condition C6 is true.

The increase of the velocity in these circumstances depends of a stair shaped function depicted in figure 4.12. The temporal constant T_{acc}, defined off-line, represents the time the wheelchair will stay in a velocity (or in a power level) before it changes to the next one. These different values for the velocity belong to a set of discrete velocity values V:

$$V = \{0, v_1, v_2, ..., v_i, v_{N_max}\} \tag{4.1}$$

where N_{max} is the maximum number of velocities imposed to or available at the commercial wheelchair.

4. If, during the wheelchair movement, condition C7 becomes true and if the wheelchair will stay beyond the D_{obsb} of any obstacle (which is determined by the sensors) then the velocity may attain the steady state value v_{ss}, which is chosen by the user.

5. If the user wants to stop the wheelchair, condition C9 or C10, then the decrease of the velocity depends also on a stair shaped function depicted in fig. 4.13 where T_{dacc} is a temporal constant defined off-line. It represents the time the wheelchair will stay in a velocity before it changes to the next one.

6. If, during the displacement, the wheelchair must change its velocity according to the condition C8, then the wheelchair velocity may be changed depending of the value of d_{obs}.

   (a) It should be noticed that the wheelchair is moving, and then the d_{obs} is decreasing with the time. In this case, we have v_w=f(d_{obs},v_k) where v_k is the velocity of the wheelchair when it enters in the boundary distance, D_{obsb}.

   (b) If we have a number of intervals k and d_k is the dimension of each interval and is given by:

   $$d_k = \frac{D_{obs} - D_{saf}}{k}. \tag{4.2}$$

   and the velocity that corresponds to a certain distance, d_{obs} is given by:

   $$v_{obs} = \frac{(d_{obs} - D_{saf}) * k}{D_{obsb} - D_{saf}} \tag{4.3}$$

   (c) For example, if the wheelchair moves with the highest velocity, v_{ss}=v_5 a gradual

decrease in velocity such as in the figure 4.14 can be imposed, according to the number of intervals k=5.

7. When the wheelchair reaches zero velocity (it stops), condition C4 is true. Once in the stopped state, the LAM system waits for another command given by the user: go ahead or change direction.

8. If in the stopped state, condition C11 is true and the user gives a touch in the joystick, condition C2, then the wheelchair changes direction according to the delta precision defined in the initial configuration.

9. If in the stopped mode and if conditions C12 and C2 becoming true also, then the wheelchair enters in the LAM moving state.

10. If, for some undesirable reason, the wheelchair enters in the danger distance from an obstacle and the condition transition that triggers C3 becomes true then the transition to the legacy state must occur.

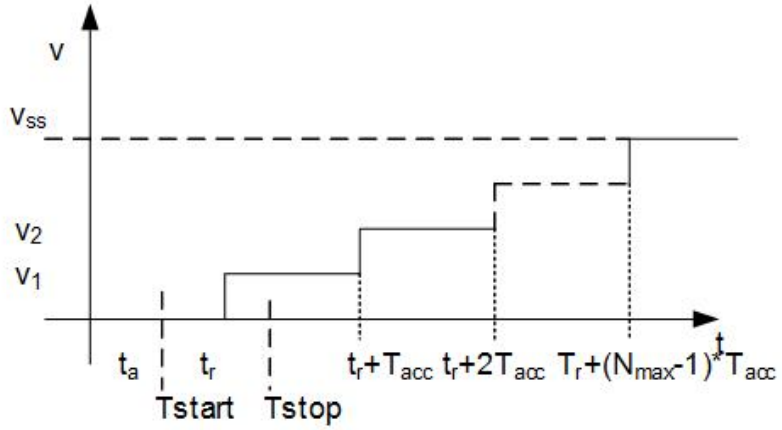


Figure 4.12: Example of a gradual increase in velocity considering k=5

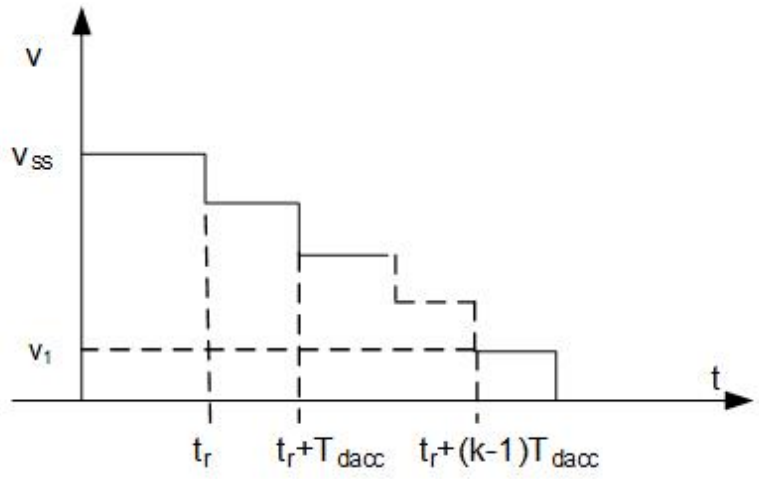


Figure 4.13: Velocity stair shaped function used to stop the wheelchair

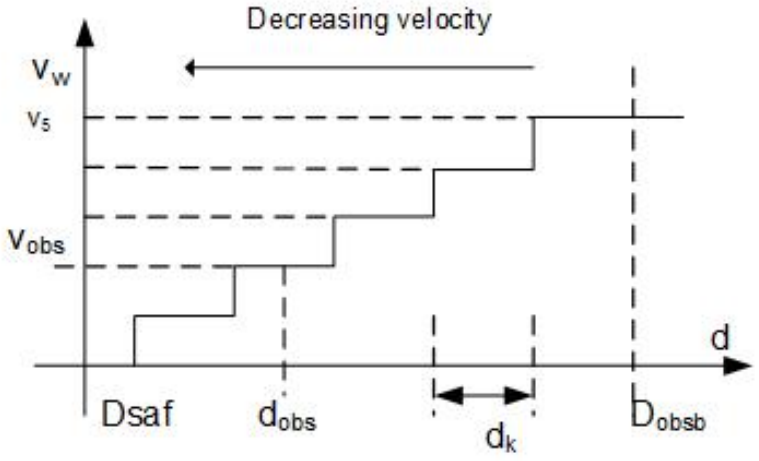


Figure 4.14: Example of a gradual decrease in velocity considering k=5

4.3.3 The Semi autonomous Transfer Mode (SaTM)

For those that are able to give stimuli to the joystick but are not able to give successive touches on the joystick or keep them steady, like passing a narrow door, the SaTM is proposed. Several autonomous operations are being considered, such as: drive through a door, park in front a table and park alongside of a bed. To illustrate one of those operations we choose the one corresponding to pass through a door. To open the door the wheelchair user will use the B-LIVE system [237]. This is a home automation solution to make the adaptation of conventional houses allowing people with severe impairments to have some autonomy in the daily life. It must be noticed that we are going to consider, in this first stage of the work, that the space surrounding the door is free of static obstacles.

The user conducts the wheelchair to a position near the door with the aim of driving through it. Two situations can occur: this position belongs or not to the acceptance area. The acceptance area is a space near the door defined by us where the wheelchair must be placed so that the command can be accepted and performed correctly. Also, the door must be completely open to allow the user to choose the SaT mode. Only in the case that these conditions are met, the command will be accepted and the navigation through the door will begin. Once started, the navigation will only stop when the APW controller concludes the maneuver or an obstacle is detected.

A set of assumptions need to be considered to perform the implementation of the SaT mode as well as variables and constants must be defined. These assumptions are based on the prerequisite that the sharing of the navigation APW should be made by the user through the joystick and by the APW controller, without the intervention of the APW user.

The sensorial system

The APW used in this proposed project is equipped with an external/environment sensor system, based on a set of ultrasonic range sensors, a wireless sensor receiver and a bumper. Because the number of the used sensors will influence the cost of the system, the dead zone and the system processing time, it must be bounded. The ultra sonar system is composed of nine sensors: the frontal system with five sensors guarantees that the APW will stop in a safety zone, i.e., without letting the bumper collide, independently of its velocity; the three sensors on each side of the wheelchair are necessary to plan a trajectory, in fusion with the wireless sensors, as explained next.

Wheelchair representation and the referential

To use SaT mode, some assumptions must be made:

- The APW is geometrically represented by a 2D shape, in particular, a rectangle with dimensions (L, W). All the parts and shapes of the APW and its passenger must be enclosed within this rectangle (see figure 4.16).
- The sensors are uniformly distributed along the length of the wheelchair: the left group (S1 to S3); the right group (S9 to S11) and the front group (S4 to S8).
- The wheelchair will move always with a pre-defined velocity V1.

- To perform the calculations of the trajectory planning, a referential must be defined: the middle point (Drx,Dry) of the door, taken from the line that joins the door corners was chosen, as depicted in figure 4.15, to have the (0,0) coordinates.
- The door width and thickness are known, D_w andD_t

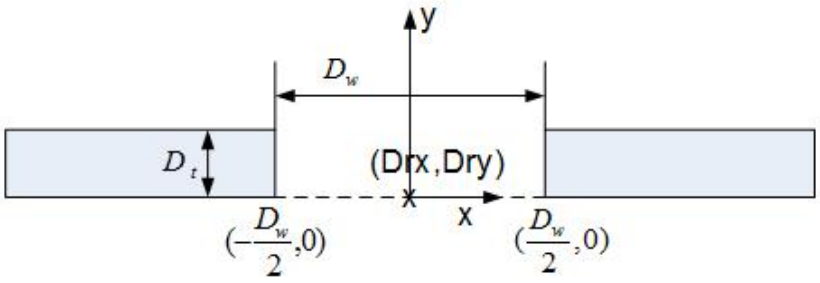


Figure 4.15: Door and referential

The acceptance area

In order to define the Acceptance Area (AA) it was decided to use an RF beacon with limited signal power in the middle point of the door.

The AA is defined then by the region where the RF signal is received in the wheelchair with a RSSI (Received Signal Strength Indication) above a pre defined threshold (K). This RF signal will also transmit to the APW controller some door parameters like for example the door width or its identification (kitchen door, room door) that will be used in the planning of the trajectory. The receiver is mounted in a point called p_{ilc} which corresponds to the inferior left corner of the wheelchair (see figure 4.16).

The position of the wheelchair, i.e., the position of p_{ilc} relatively to the middle point of the door is defined by:

$$p_{ilc} = (x_{ilc}, y_{ilc}) \tag{4.4}$$

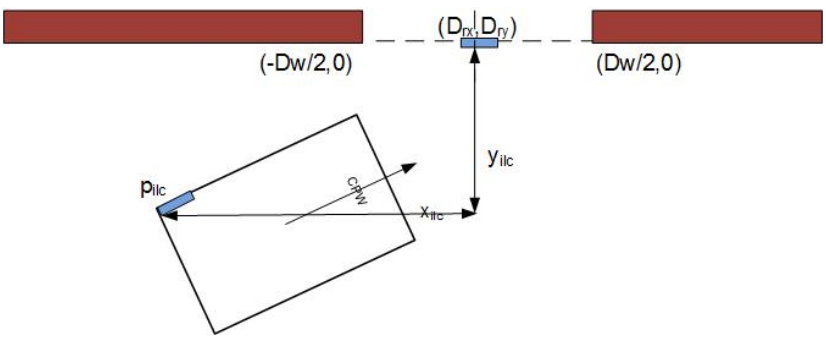


Figure 4.16: The wheelchair and the door

The wheelchair angle

Considering that the wheelchair was left with a leaning orientation, faced relatively to the door and inside the AA, its orientation will be calculated using the sonar sensors: depending on these values we can calculate the orientation wheelchair angle which is given by the equation 4.5. figure 4.17 depicts the wheelchair orientation angle.

$$\alpha = \arctan \frac{(d_2 - d_3)}{(D_3 - D_2)} = \arctan \frac{(d_1 - d_2)}{(D_2 - D_1)} \tag{4.5}$$

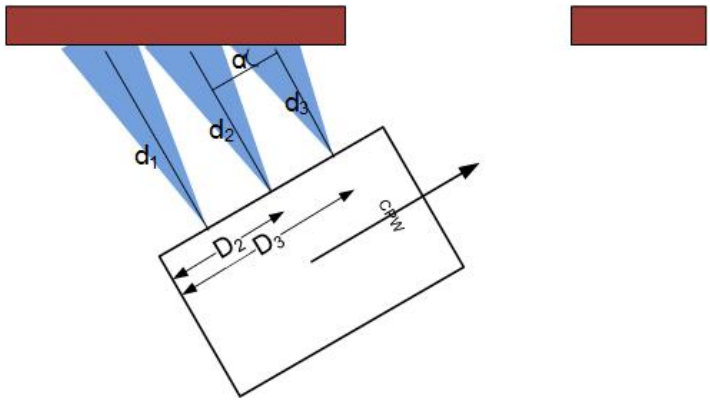


Figure 4.17: Wheelchair orientation angle

Concerning the SaT mode, the user gives a non continuous touch to the joystick in order to indicate that the APW controller can begin the moving ahead and rotate to execute the manouvre predefined. So, we define a set of variables and constants:

- x_{ilc}, y_{ilc}: Distances of p_{ilc} to the referential.
- d1, d2, d3: Distance of each sonar to wall door.
- α : the APW orientation angle.
- d_{RF}: Distance between the RF beacon to the p_{ilc}.
- t_{stroke}: The stroke definition
- m_{par}: The confirmation that the wheelchair is parallel to the wall door

In what concerns constants or parameters, defined before run-time:

- V1: the predefined SaT mode velocity.

- D1, D2, D3: the distances of p_{ilc} to each sonar sensor.
- D_w: the respective door width.
- D_t: the respective door thickness.
- D_{RF} : the predefined threshold to define the area of acceptance
- T_{start}, T_{stop}: the stroke definition
- PW_W: the powered wheelchair weight
- PW_L: the powered wheelchair length
- V_{man}: the manouevre velocity

The hierarchical FSM shown in figure 4.18 describes the SaTM operation to perform the passing a door manouevre. This mode of operation can be performed through two main states: the SaT moving where the APW moves ahead and the SaT stopped where the APW changes direction, both autonomously.

1. When the wheelchair is powered ON, it starts in legacy mode.
2. To switch to SaT mode, the transition condition C_{21} must be true. To navigate the APW in this mode, the powered wheelchair must be in the acceptance area, condition C22.
3. When the user gives a touch on the joystick, condition C2 becomes true and it will start the SaT autonomous change direction.
4. After the rotation of the wheelchair to a predefined position, condition C26 is true, the new direction is defined.
5. If, in the new direction state, C27 is true and C2 is true, then the wheelchair enters in the SaT moving state.
6. The increase of the velocity is smooth until a predefined velocity, condition C29.
7. After the APW reached the predefined positions given by the ultra sounds sensors and the predefined threshold for the RF signal, condition C28, the APW stops.

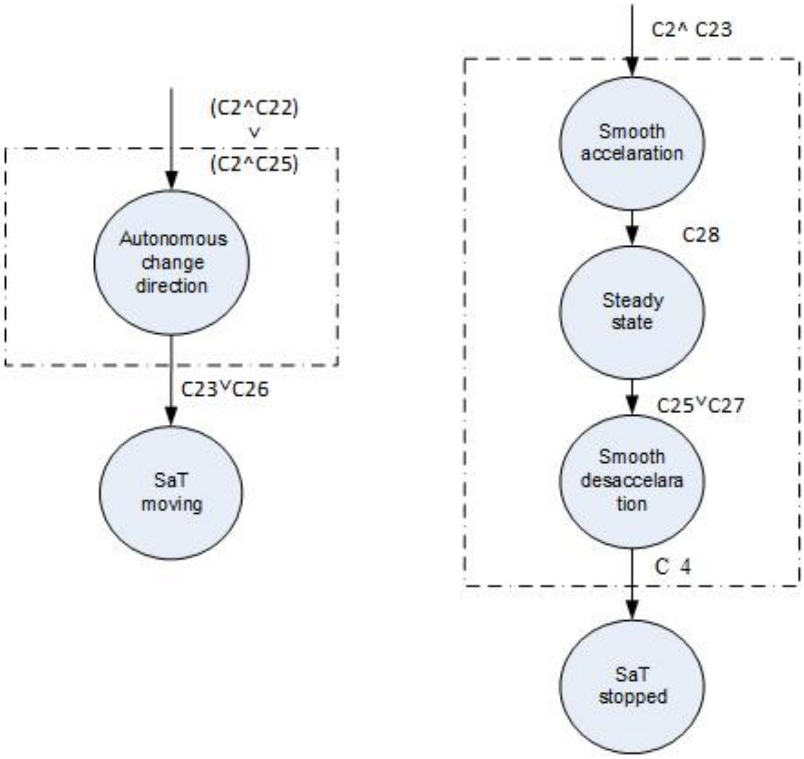


Figure 4.18: SaTM stopped and moving states

In table, the transition conditions defined in the SaT hierarchical FSM are presented.

Figure 4.19: SaTM transition conditions

Condition	Transition conditions
C21	m_b = ON
C22	m_{acc}=ON
C23	m_{par}=ON
C24	p'_{ilc}
C25	p''_{ilc}
C26	p'''_{ilc}
C27	p''''_{ilc}
C28	m_{vss}

4.4 The overall stress detection system model

4.4.1 Stress detection system (SDS) operation requirements

The proposed operating model of the stress detection system aims to determine the user emotional state. Some requirements for choosing sensor devices and the processing unit, have been considered according to the environment in which they will be used.

In which concerns the sensor devices, the following requirements were defined:

- Portable: small dimension and weight, easy to use, wireless and good lifetime battery.
- Non-invasive: so they do not cause pain and discomfort to their user.
- Low cost: the final APW is cost effective.

Another requirement, related to the development of the SDS, was to allow the recording of occurrences. This requirement arose when an analysis of a database, available in [238], was made: "this database, contributed to PhysioNet by its creator, Jennifer Healey, contains a collection of multiparameter recordings from healthy volunteers, taken while they were driving on a prescribed route including city streets and highways in and around Boston, Massachusetts".

This analysis was made by studying the GSR data on the different driving situations but, because there wasn't the occurrences marker it, was not possible to identify exactly when the driver started driving on the different prescribed route. Thus, it was difficult to justify whether or not a high GSR value was related to the event that had arisen in the meantime, such as overtaking a car or entering a roundabout.

So, it is essential that a SDS allows the register of occurrences on a friendly way. The purpose of register occurrences is to allow the cross analysis of data, that is, to understand which events can provoke higher stress levels and endanger the driver's safety.

Also, the processing unit must be able to receive data from several sensors via wireless communication protocol and to provide adequate data storage capacity. The data measured in real experiments must be saved in the processing unit for posterior off-line analysis.

4.4.2 The stress detection system architecture and operation

The main goal of this system is to detect in real time the emotional user state through the stress detection module as we can see in figure 4.3.

To achieve this goal, there must be a prior knowledge of the emotional behavior of each person that will use the system. Only after this the system is able to detect emotional behavior changes.

So, the SDS proposed is composed by two subsystems, as figure 4.20 illustrates:

- one for data acquisition, register occurrences and stress detection, named as Acquisition and Stress Detection subsystem (ASD). This ASD, in turn, is composed by two modules: the Acquisition and Register Module (ARM) and the Stress Detection Module (SDM).
- the second subsystem is intended for database analysis, to create the user emotional profile and select the best classifier algorithm and is named as Analyzing and Classification (AC subsystem.

The interaction between the different functionalities provided by the SDS have the following sequence:

1. Bio signals acquisition and recording of the relevant occurrences in the ARM: it is an online subsystem.
2. Send all acquired data to the AC data base.
3. Extract bio signals features and creation of the user emotional profile in the AC: it is an offline subsystem.
4. Selection of the best stress classification algorithm in the AC: it is an offline subsystem.
5. Detection, in real time, of the driver stress level in the SDM: it is an online subsystem.

The biosignals data base is created during real driving experiments. Using a developed bio-signals acquisition platform which is described in section 5.3, a continuous collection of data is made during real-world driving tasks and, at the same time, all events (stressors) that can occur are registered. So, with this data base it is possible to associate the different types of occurrences with the respective bio-signals data.

After that, a qualitative classification of the level of stress is made based in the normal activities occurred (see section n5.3). For example, we can assume that, during a real car driving, a low, medium high-stress conditions are associated to the rest, highway, and city segments or, during a CPW driving, a low, medium and high stress conditions are associated to rest, hallway and confined spaces segments.

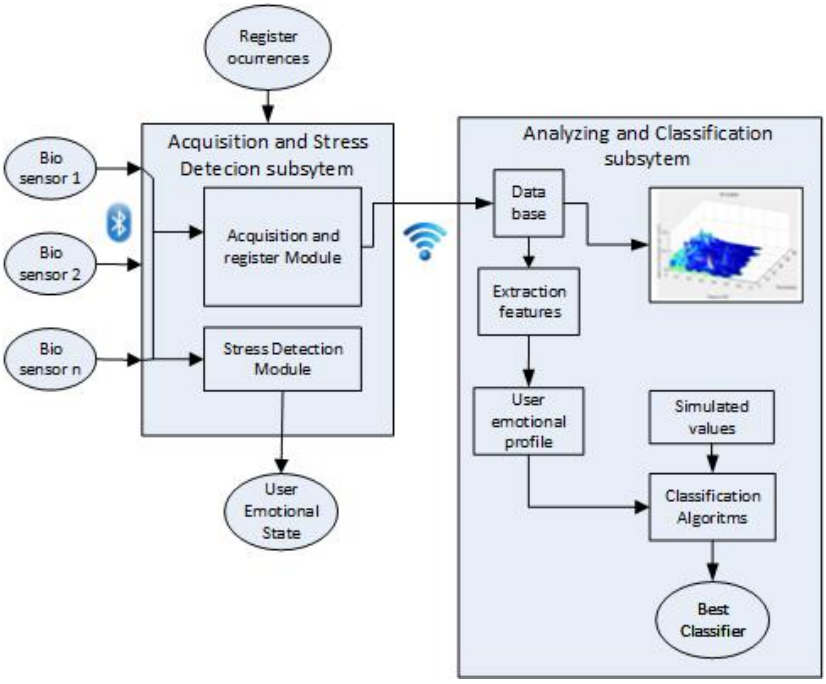


Figure 4.20: The Stress Detection System overview

For each segment of data, features extraction is done in an off line MATLAB interface specifically developed (see 5.3.2 and based on that, the user emotional profile is created.

Biosignals feature extraction consists in extracting the different features of each type of sensor. This reduces the amount of raw data but ensures the vital information for the pattern recognition.

The user emotional profile is built in table format identifying, for the three emotional state defined, the values of the respective features extracted earlier. Through this table, we can get to know for each user, what are her/his emotional characteristics, when she/he is in rest, normal or stress mode.

After being known the emotional user profile, several stress modeling techniques / classification algorithms are performed with simulated bio-signals values as is explained in section 5.3.2. The goal is to determine which algorithm has the best performance for each vector of features values. Several classification algorithms are performed since each individual has a variable response to stress, consequently, the degrees of correlations between the several feature values can be very different.

Thus, as results of off line stress detection system, we find out the user emotional profile and the respective best classification algorithm that characterizes stress.

The on line stress detection system is able, with these two results, to classify stress in real

time from the values measured. At every moment it is possible to know if the user is, or not, in stress state and send this information to the controller APW.

4.4.3 Integration of the user emotional state into APW

The integration of the user emotional state into the APW mode of operation is made by using the state Alert mode (see fig.4.5).

In this mode, see figure 4.21, two states were defined: the joystick OFF and the joystick ON. Two more Boolean variables more must be defined:

- m_d: Boolean variable indicating if the APW controller is in alert mode.
- w_{cd}: a Boolean variable indicating if the APW is in the change direction state (in LA or SaTM mode)

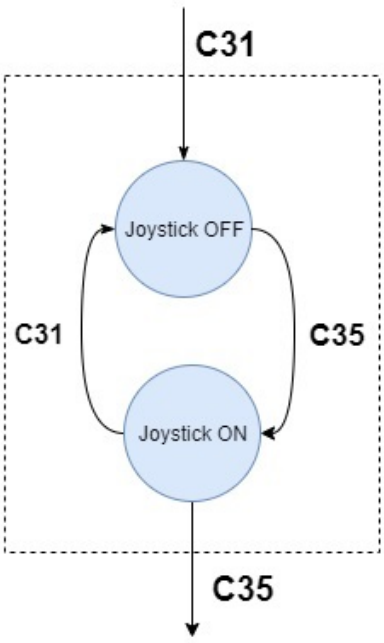


Figure 4.21: Alert mode operation FSM

The APW controller only considers that the controller is in joystick ON when it is detected that the user has reached a high level of stress and maintains it during some time (T1 time). Also, the APW controller only enters in joystick mode OFF if, after some time the user reached a low stress level and maintains it during some time (T2 time). This is described in the next temporal diagram.

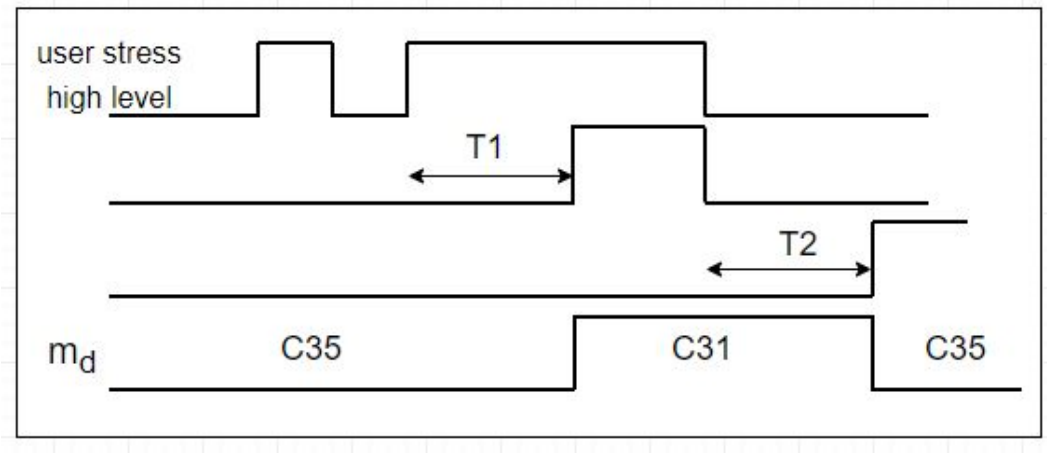


Figure 4.22: Alert mode temporal diagram

In the state joystick ON the commands given by the joystick are not considered and the APW moves autonomously until ending the manoeuver that is being executed. When in the state joystick OFF, the impulses given by the user in the joystick are considered and the user can manoeuver the APW or the wheelchair can navigate using the LA or SaT modes, as described before. This operation represents the APW alert navigation and is described in the next figure 4.23.

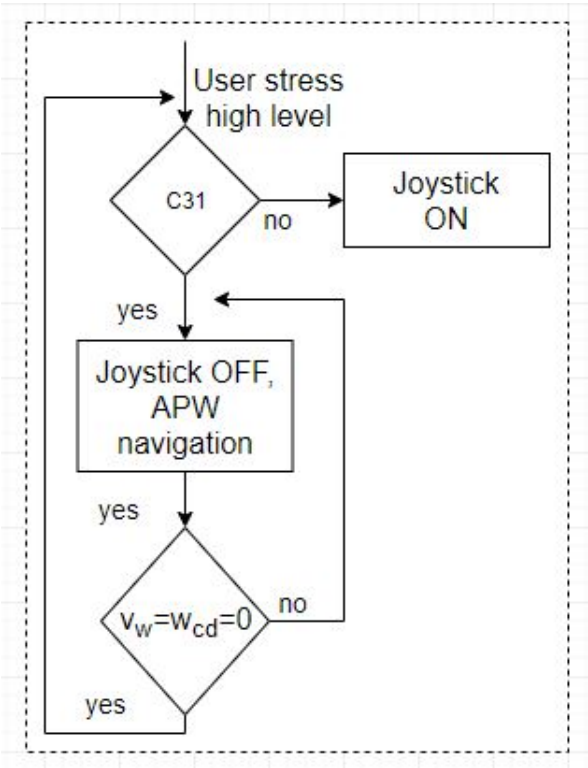


Figure 4.23: Alert APW navigation

In table 4.24 the transition conditions are presented.

Figure 4.24: Alert mode transition conditions

Condition	Transition conditions
C31	m_d=ON
C35	m_d=OFF

4.5 Conclusions

This chapter presented the overall architecture and the respective operation of the Assistive powered wheelchair (APW).

The architecture of the proposed Assistive powered wheelchair was inspired on the Artificial Recognition System project, leading to a solution where the assistive wheelchair navigation depends on the user emotional state. Thus, it is proposed a shared control between the user decisions and the user emotional state. To achieve a practical solution two main goals were defined: to maintain the legacy joystick and to create a stress detection system.

The operation of the legacy joystick was changed to control the navigation of the wheelchair through small impulses. The interpretation of these impulses is different and depends on the user decision. So, two of the three modes of operation proposed (Legacy Adapted and Semi autonomous Transfer) have been described and also the corresponding finite states machines were presented and explained.

In what concerns the Stress Detection System operation, the overall architecture is presented, including the description of its various components and their respective functionalities. Furthermore, the integration of the user emotional state into the APW controller is detailed.

In the next chapter, the implementation of two APW modes of operation is described. In addition, it is explained how the stress detection system was implemented.

Chapter 5

Support Tools

5.1 Introduction

This chapter is intended to describe all the work done in order to accomplish the implementation of the architecture and operation of the Assistive powered wheelchair.

Two of the proposed modes of operation are implemented, simulated and tested by using the robotics software simulator Stage.

The implementation of the stress system detection is also described. An Android platform is used to acquire the signal from the selected biometric sensors and to register occurrences. The software Matlab is used to perform the information processing like extracted data feature, create the user emotional profile and to choose the best classification model.

5.2 Using simulation for the validation of LAM

5.2.1 Introduction to the Stage Software

According to [239], an automated wheelchair is classified as a service robot for personal use. Simulators play an important role in robotics research as tools for robotic applications. The use of Stage enables the test of efficiency, safety, and robustness of new algorithms [240].

In our case, due to the variability of people with reduced strength in arms and hands, the APW must be able to translate the movements that the patient can perform in commands to drive the wheelchair. The translation must be specific for each patient, and so we will simulate and validate our proposal by using a robotic simulator.

For validation of the proposed APW modes of operation, and to justify our option for the Stage simulator, we first perform a review of some others robotics simulators. At the

time, the Cyberbotics professional mobile robot simulation [241], the Player/Stage and the SimRobot [242] from the Bremen University were considered. We chose Player/Stage since it was open free, run in Linux and it used C++. According to [240], Plater/Stage/Gazebo and Robot Operating System (ROS) are the two most popular open-source software for robotic simulation, what sustains our choice.

Stage is a 2D multiple-robot simulator from the Player project. Stage simulates a population of mobile robots, sensors and objects in a two-dimensional bit mapped environment. Stage is designed to support research into multi-agent autonomous systems, so it provides fairly simple, computationally cheap models of lots of devices rather than attempting to emulate any device with great fidelity. It provides configurable and composable device models like sensor and actuator models, including sonar or infrared rangers, scanning laser range finder, bumper and a versatile mobile robot base with odometry [243].

Stage is used during the research phase, that is:

- To evaluate the navigation algorithms.

- To evaluate the operational modes performance.

But we will use Stage also for operation, that is:

- To emulate the operation of the wheelchair by patients to determine the operational parameter values (set-up).

- To train patient skills without a real wheelchair, thus simplifying the rehabilitation.

Initially, we have introduced the architectural plant of the training house of the Rehabilitation Center as depicted in figure 5.1 and adapted Stage to read information from a joystick. Also, we incorporated eight sonar sensors to simulate the LAM moving state. Then, the user can choose, from the Mode Menu, the Legacy mode, the LAM mode and the SaTM mode as depicted in figure 5.2.

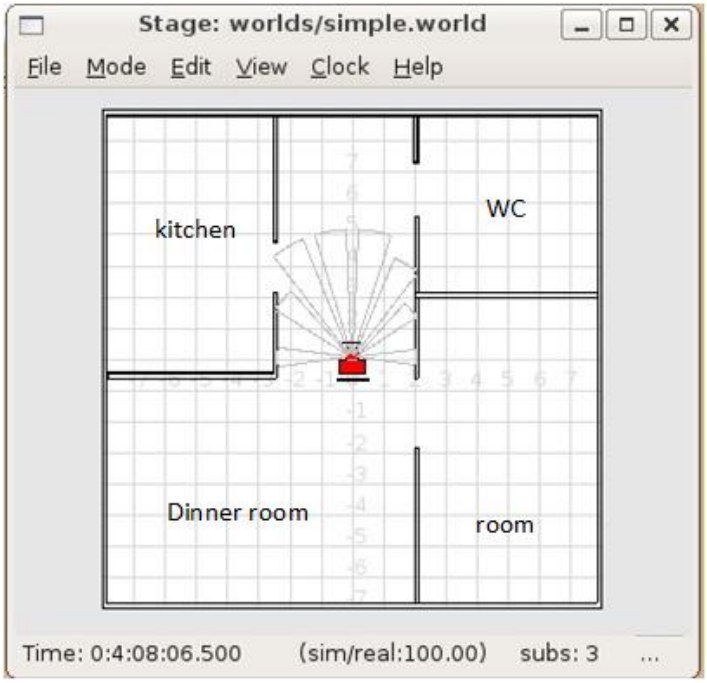


Figure 5.1: The architectural plant of the training house at the CMRRC-RP Center

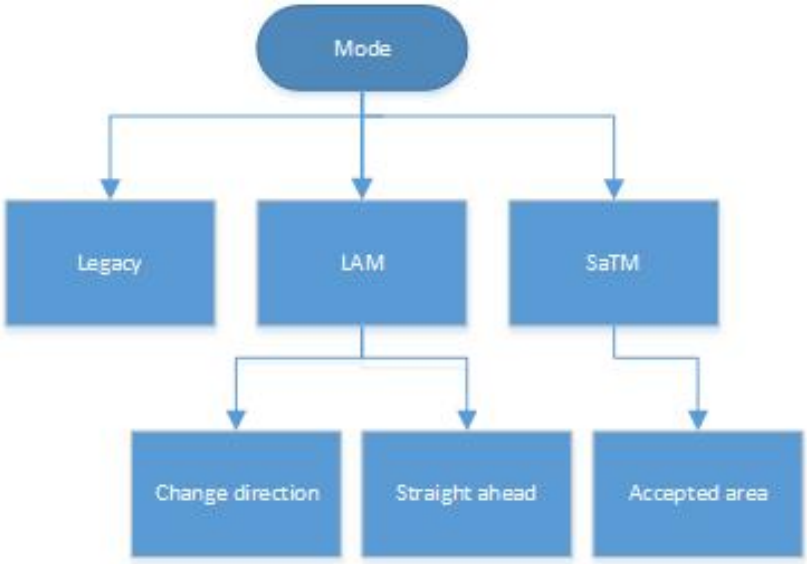


Figure 5.2: The Stage APW mode operation implementation

If the Legacy mode is chosen, the CPW is driven as it comes from the factory.

If LAM mode is selected, two meanings can be defined for the pulse given in the joystick: change direction or straight ahead. The APW navigation is made According to the novel adaptation explained in section 4.3.2.

If the APW user chooses SaT mode, that means that the APW controller will be responsible for the APW navigation according to what is explained in section 4.3.3.

5.2.2 Implementation of the LAM mode

After the LAM mode is chosen, with a group of menus, we can input the off-line parameters like T_{start}, T_{stop}, the v_{ss} and $\triangle$, such as defined in section 4.3.2.

Also, the user can choose if he/she wants to navigate the wheelchair as a spin left, spin right or spin front, that means if the wheelchair goes straight head or change direction with a push to the left, to the right or forward in the joystick. The acceleration and deceleration states are implemented with the use of the eight sonar sensors. The menu User Parameters is depicted in the next figure 5.3.

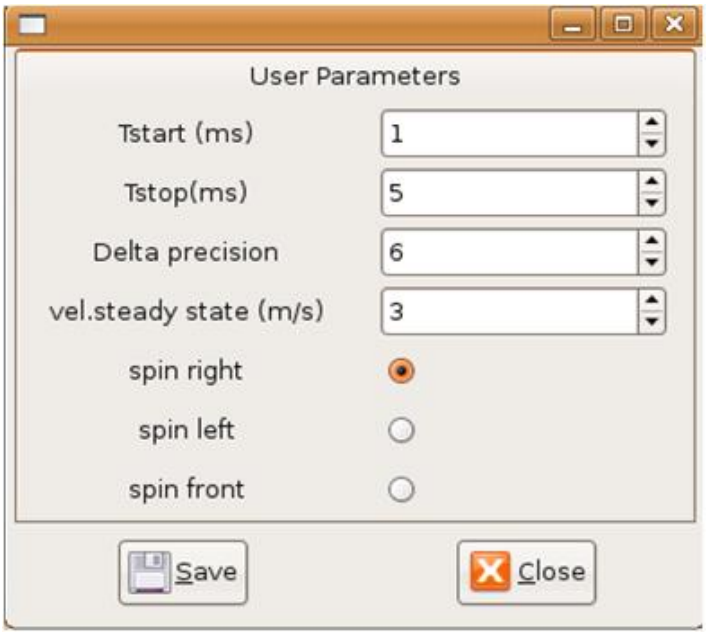


Figure 5.3: User parameters on STAGE

A very important aspect in this mode of operation is that the same movement in the joystick commands the wheelchair in two different ways: go forward or change direction. The distinction between the two movements, at Stage, is made by an option that can be selected in the LAM mode. In a real implementation, this can be performed by two large buttons that can be pushed by the patients.

After that, the user can simulate the navigation of the Assisted powered wheelchair. The implementation of this simulation was based in the next flowchart.

- if a change direction command is selected, for each impulse given in the joystick by the APW user, the wheelchair rotates the corresponding to the angle defined in $\triangle$.
- when the selected direction is reached, the APW user can select to move ahead.

- if the move ahead command is selected and the joystick impulse has the correct duration, the APW will start moving ahead.
- if the APW is moving ahead, the distance to any obstacle is measured in real time. If this distance is larger than the predefined safety distance, the APW will accelerate until it reaches the pre defined steady state velocity.
- when the APW is near an obstacle, the APW decelerates until it stops.
- if, for some reason, the APW user wants to stop the wheelchair, he / she should push the joystick backwards, condition C9.

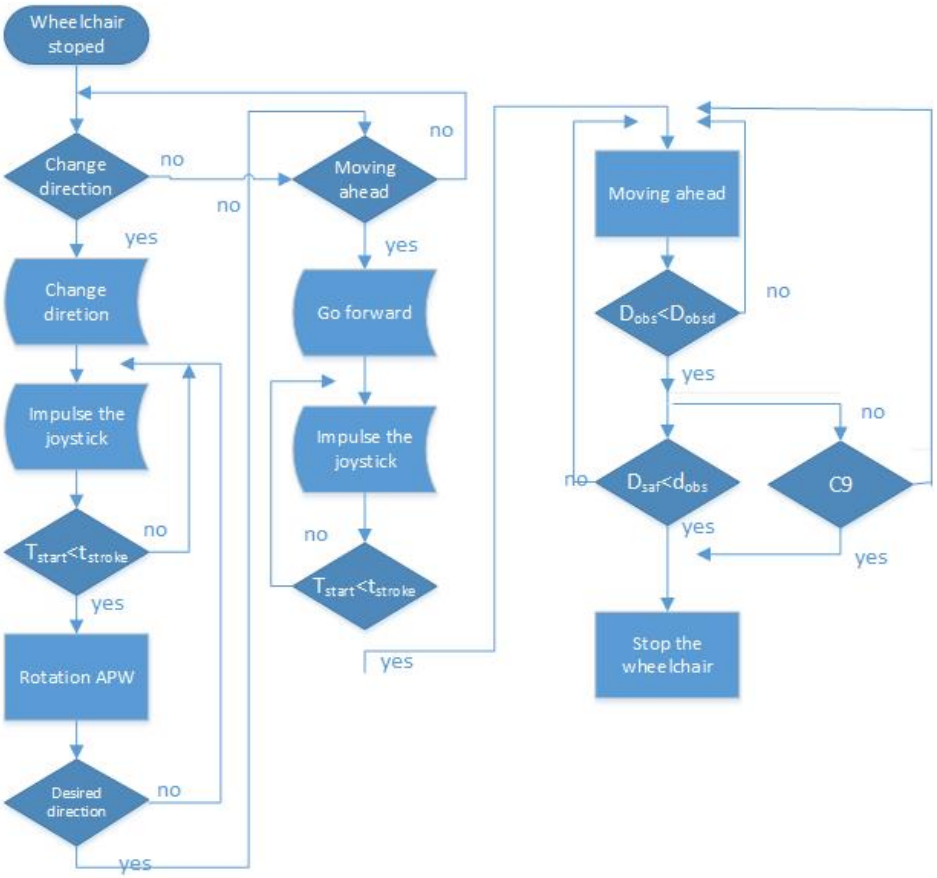


Figure 5.4: The LA mode operation implemented on STAGE

5.2.3 Implementation of the SaT mode on STAGE

Before choosing the SaT mode, the user places the APW in the predefined area as AA, by operating the APW with the LA mode.

To simulate this mode, the user must choose the SaT mode, see figure 5.2 and selected accepted area.

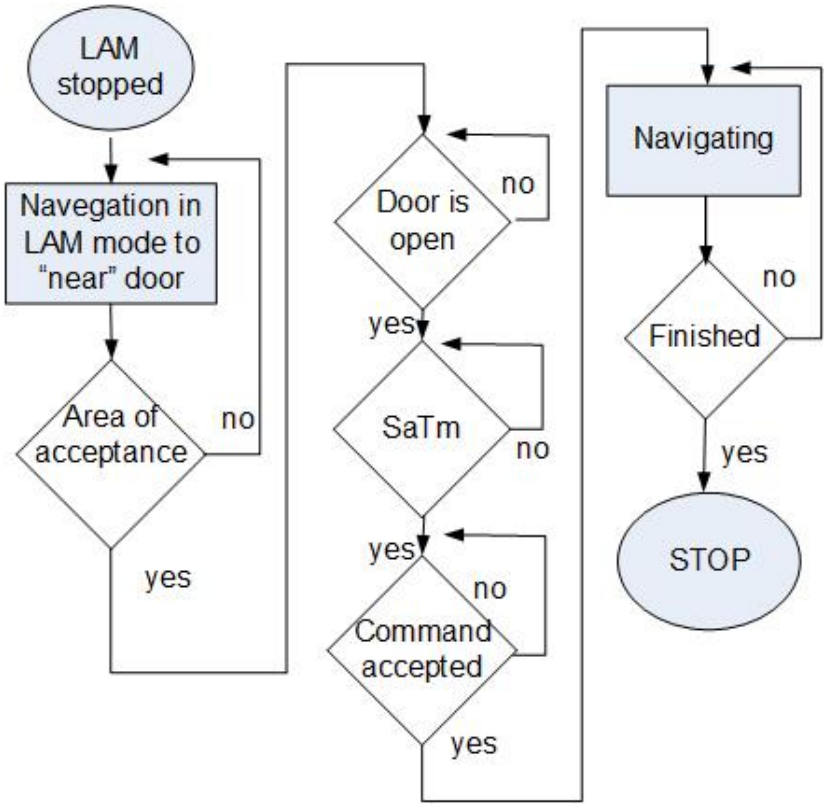


Figure 5.5: SaTM navigation flowchart

The algorithm that implements the SaT operating mode was developed so that it could be executed in the Stage simulation environment, and thus it could be used by the Rehabilitation Center patients.

The main focus when implementing this algorithm was the adaptability of the operating mode of the joystick. It has not having given a great focus to the autonomous driving of the APW. It was developed essentially with the goal of analyzing the ease of changing the modes of operation by tetraplegic people rather than developing an algorithm that would implement the wheelchair navigation in an autonomous indoor real environment. Therefore, the planning trajectory is made only based on information of the simulated ultrasonic sensors in the Stage software.

Of course, if this algorithm was to be implemented in a real environment, it would have integrate other types of sensors, making sensory fusion, and in consequence, making it more complex and with improved performance.

The trajectory planning

With the target being that the wheelchair will drive through the door in a safe way, a trajectory must be planned. This trajectory is based in some predefined values for (x_{ilc},y_{ilc}) which correspond to the different positions that the wheelchair's left inferior corner will take during its movement. The wheelchair movement begins with a command given by the user as explained in section 4.3.2 here:

$$T_{start} < t_{stroke} < T_{stop} \tag{5.1}$$

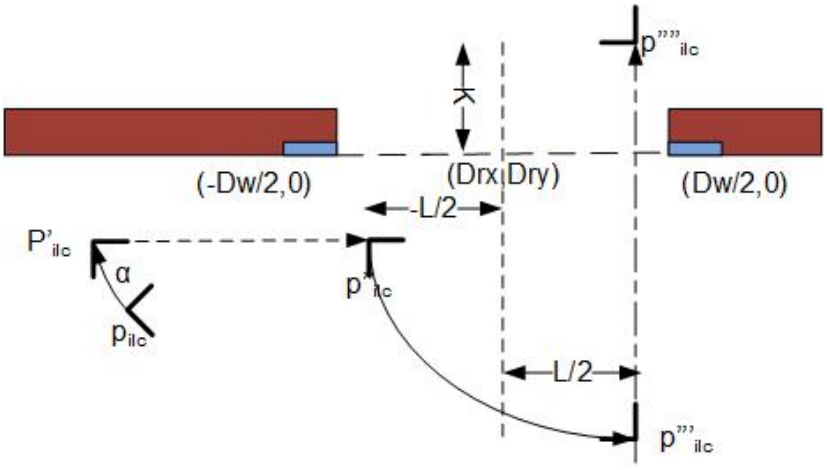


Figure 5.6: p_{ilc} positions

The wheelchair trajectory, as we plan to do it, is described below. To begin, the idea is just to use simple rotations and navigation in line to simplify the algorithm. A more complex approach will be needed if it was to operate in real environment.

The values for p_{ilc} (see 5.2.3 are updated during the wheelchair movement as we can see in figure 5.6. Initially we don't know the position of the wheelchair relatively to the door (p_{ilc} and p'_{ilc}).

After the wheelchair begins to move with a speed V1, at a given instant, one of the sonar sensors that was detecting the door, failed to detect it. When this occurs, p''_{ilc} and the others are calculated relatively to the referential. The value K, a predefined threshold for the RF signal that guarantees that the wheelchair is in the vicinity of the door, is again used, now to decide that the door has been passed.

In this implemented simulation solution, the different points are calculated based on the ultra sound measures and on specific Stage software instructions that control the rotation

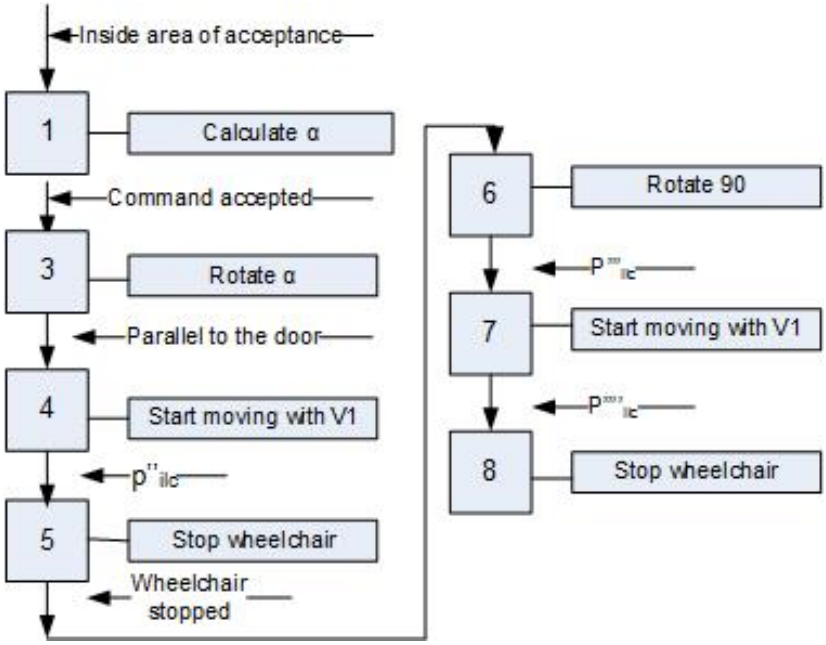


Figure 5.7: The trajectory planning

and position of the simulated APW. The APW position is known at every moment. When the APW is near one of the doors, through the lateral side sensors, it is determined whether the door is to the left or right and the respective angle of inclination with respect to the door wall. The table 5.1 explains how each point was calculated in the simulated environment for the case when the door is on the left.

Table 5.1: trajectory planning transition conditions

Condition	Variable	Calculation (simulated)
C22	m_{acc}	choose Accepted area / $d_{RF} < D_{RF}$
C23	m_{par}	d1=d2=d3
C25	$p“_{ilc}$	D_w-D3
C26	$p“‘_{ilc}$	Stage rotation instruction
C27	$p““_{ilc}$	Stage position instruction

If in real environment, what is proposed is:

- the accepted area is given by $d_{RF} < D_{RF}$
- $p“_{ilc}$= (x''_{ilc}, y''_{ilc})=$(x'_{ilc}$+$PW_w, y'_{ilc})$
- $p“‘_{ilc}$= $(x“‘_{ilc}, y“‘_{ilc})$=$(PW_L/2, y''_{ilc}$+PW_L)
- $p““_{ilc}$ is given by $d_{RF} > D_{RF}$

5.2.4 Implementation of the LAM mode in a CPW

The novel legacy LAM mode was studied and implemented in a master degree thesis entitled "Cadeira de Rodas Eléctrica Adaptada a Tetraplégicos" [244]. This subsection presents a summary and some of the conclusions of this work, which had as main goal, the implementation of the LAM mode in a CPW.

The CPW that served as a test platform integrates a DX System control of Dynamics Control, whose communication between the Joystick and the Power Module is based on the Controller Area Network (CAN) protocol. More specifically, the communication solution used is called DXBus and interconnects the calibration module of the joystick with the power module, see figure 5.8.

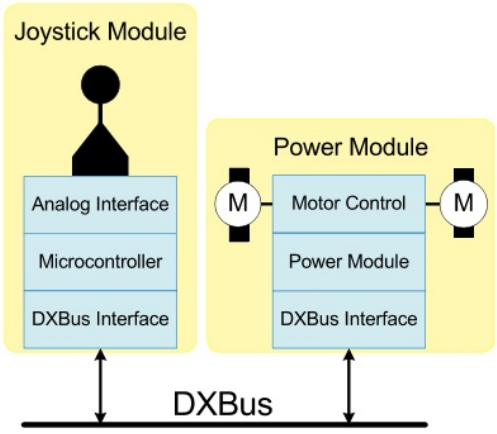
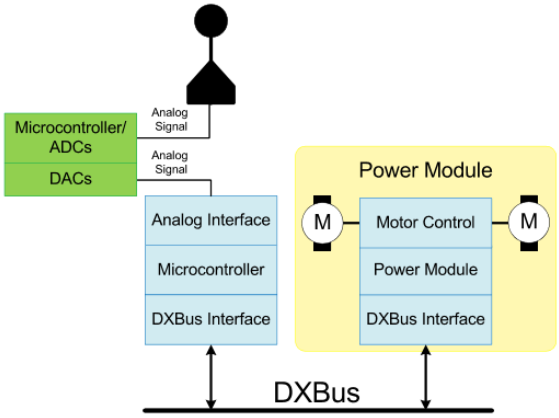


Figure 5.8: CPW architecture

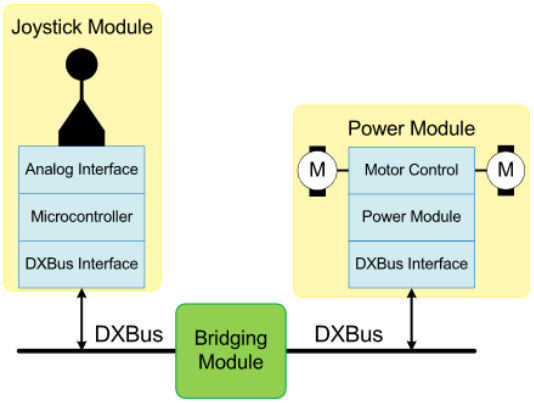
Two possible ways of implementing the LAM mode were studied: to process directly the analog signal at the output of the joystick or to intercept the messages on the bus to manipulate them (see figure5.9). The second option was chosen and a complete knowledge of the DX BUS behavior was necessary. This study was made by sniffing the CAN bus messages. After that, the new bridging module was conceived based in a time-trigger bridging module so as not to cause delays in the natural sequence of messages.

Some tests were carried out and it was verified that:

- The bridging module does not affect the legacy joystick operation.
- The module interprets well the messages given that the wheelchair has the expected behavior.
- The turn by turn and the forward commands were accomplished through two dip



(a) Direct analogic signal treatment



(b) Insert bridging module

Figure 5.9: Two possible ways of implementing the LA mode

switches.

- After a T_{start} command there is a smooth starting of the CPW as well as after the stop condition there is also a smooth decrease in speed.

So, as a conclusion of the LA mode implementation, the solution of using bridging module does not interfere with the normal bus operation and the new mode of operation was implemented as it was proposed.

Another goal was to equip the CPW with a obstacles detection system as explained in [244].

According to the size of the CPW and the characteristics of the selected ultrasound sensors, it was decided to place five sensors on the front of the CPW. These sensors are spaced 15 cm apart. This layout ensures that the area covered by the sensors is 75 cm, which is larger than the width of the wheelchair and that any obstacle more than 18,12 cm apart

is detected (see figure 5.10)

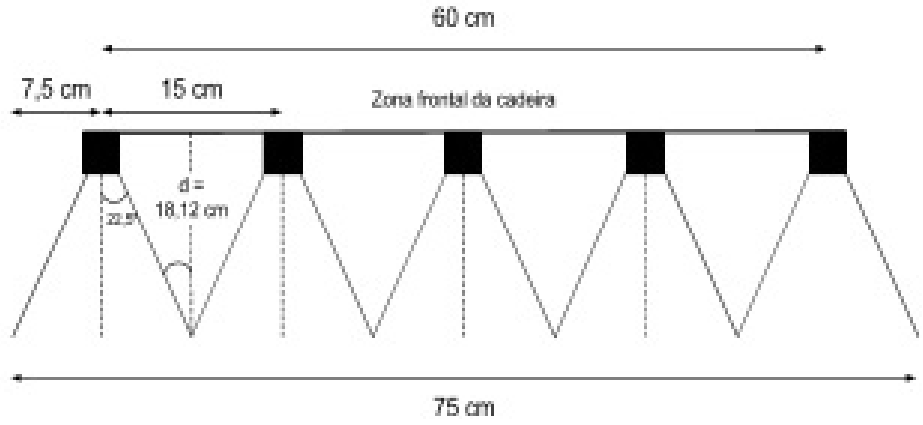


Figure 5.10: sensors US CPW layout

The acquisition of the sensors signals is performed sequentially at intervals between readings of 50 ms. Each sensor gives then origin to a measurement every 250 ms. With the various tests carried out, it was verified that with obstacles at a distance of 3 m the sensors have a maximum error of 3 cm. However, as the distance decreases, the associated measurement error also decreases.

5.3 Stress detection system implementation

The stress detection system (SDS) proposed in this work has, as its main feature, to be customizable. To fulfill this main goal, this system must have the ability to evaluate how each person reacts emotionally when facing daily life situations. That means, the SDS must have the the ability to define an emotional profile for each of its users.

After the emotional profile characterization, it will have to be able to detect emotional state changes and signalize those emotional states that are considered as stress states.

Although it was originally intended to be used in car or powered wheelchair navigation, it can also be used in other situations like for example, when someone is playing computer games or when performing school exams.

Next, it is explained how the Acquisition and register module and the functionalities of the Analyzing and classification system were implemented.

5.3.1 Acquisition and Register Module

This module was developed and implemented according to a set of requirements that should lead to a good degree of user friendless and ease of installation. In order to facilitate the installation it was decided to develop a wireless solution, Some advantages of a system with such characteristics are:

- The use of a wireless network enables the easy addition of other sensors.
- The data acquisition will help to create a larger and consistent database for subsequent stress analysis.
- It can be adapted to various applications besides wheelchair navigation as referred before.
- It will make possible that the person uses the devices during daily routines without concerns.
- It will allow that more persons use it on their own.
- The user himself can register occurrences, in a friendly way.
- It will be possible to associate the recorded occurrences with stress levels.

The implementation of this module was the focus of a master degree work and it can be viewed in detail in [245].

So, the platform developed is illustrated in figure 5.11. It is a mobile application (Android based) running in a tablet Asus Nexus, which communicates via Bluetooth with two different sensors placed on the driver: Galvanic Skin Response and Electrocardiogram.

These sensors were selected according to the state of art made in chapter 2 and, after research into the different trademarks of biometric sensors, the selection fell on those developed by Shimmer-Research, model Shimmer 2R. Each sensor also includes a 3-axis accelerometer for mobility situations, but it is not used given the type of application. Figure 5.12 shows the ECG and GSR sensors application.

The initial menu of the Android application developed, called Stress measurement, has a set of functionalities as depicted in Figure 5.13.

- Connect Sensors: to connect sensors via Bluetooth

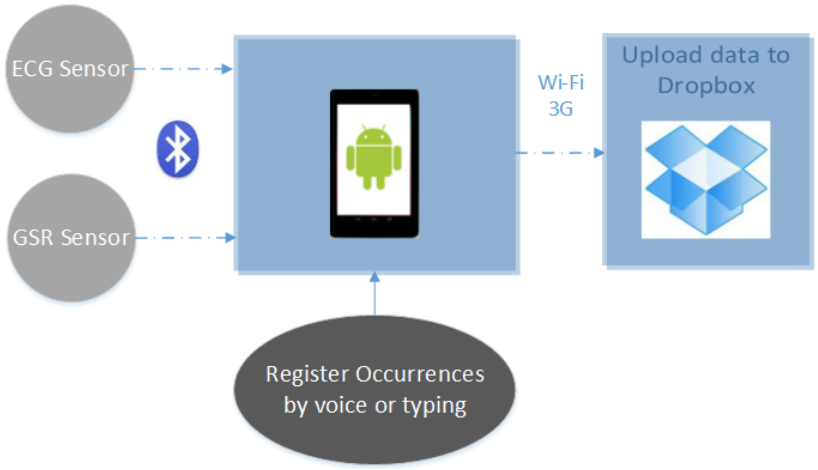


Figure 5.11: Acquisition and register platform overview

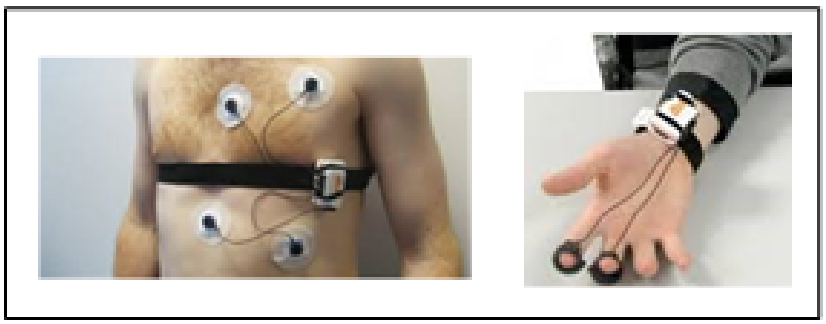


Figure 5.12: Shimmer ECG and GSR sensors applications

- Register New Patient: insert the name of the person that will be doing the experimental test. A folder will be created, containing all data acquired.
- Start Reading: to start reading sensors information.
- Begin Activity: to mark occurrences which have a beginning and an end. For example, driving in a city or driving the powered wheelchair through a corridor are normal activities.
- Spontaneous: to mark spontaneous events that will occur during the activity that is currently going on. For example, braking the car/powered wheelchair suddenly because a pedestrian is crossing the road/corridor is a spontaneous event.
- Upload to Dropbox: after the experimental test is over, and with internet connection, the user can send all acquired data to the user space account that makes it easy to access data "everywhere".

It is also interesting to note that the different types of occurrences can be register by

Figure 5.13: Application Stress measurement principal view

voice or typing, depending if there is or not, internet connection and that the acquired data are saved in three different files, respectively, the ecg, the gsr and occurrences. A comma-separated values (csv) format was adopted for all these files.

5.3.2 Analyzing and classification subsystem

The AC subsystem has three main functionalities: to analyze the GSR and ECG database, to create the user emotional profile and to find the best stress classification algorithm for each user.

The ECG and GSR bio signals offline analysis is done in a MATLAB interface specifically developed and the other two functionalities are implemented using MATLAB built-in specific functions.

GSR and ECG offline analysis

This tool allows to visualize graphical data and to extract data features. The figure 5.14 presents the interface main screen, where the offline analysis of the GSR and ECG data acquisition from a real driver car experiment example is visualized.

It was made based in the GUIDE tool and the algorithms were developed by using two open sources software libraries: the *Biosig project* and the *LedLab*. All specifications of this implementation are explained in [245].

As depicted in the figure 5.14, the interface contains some sub-menus, necessary for the

extraction of the biosignals features.

- Importing data: to load the data previously acquired by the Android device and import the three files that contains the GSR data, the ECG data and the occurrences data.
- List of occurrences: after the loading data, the occurrences data information is updated. Each line of this list corresponds to the elapsed time (in milliseconds) from the beginning and the respective occurrence name.
- Choose a time interval and amplitude threshold: this sub-menu allows to show the acquired data and corresponding GSR and ECG features to a specific temporal range. The amplitude threshold is used to select only GSR peaks with an amplitude difference above this value.
- Graphical data: four charts are presented with the the GSR and ECG data obtained, since the start of reading of the sensors until the end.
- Measurements: in this sub-menu the GSR and ECG features are calculated based in the time range and the amplitude threshold previously chosen. Also, it allows the user to select what kind of data he/she wants to visualize: GSR, lead I, Heart rate; GSR, lead II, Heart rate among others as depicted in figure 5.14.

Using the open source *BioSig project* library, the instantaneous heart-rate and also its variability are extracted from the ECG signal.

To analyze the GSR signal, the interface uses the free software *Ledalab library* to extract the on-set and peak timings, allowing the measurement of relative amplitudes - difference between peak and on-set amplitudes - and their rising-times. As stated in [210], the amplitude is the most important clinical parameter of GSR due to its dependence on the surprise effect of the stress stimulus. Additionally, a filter can be applied to detect only relative amplitudes above a chosen threshold.

Analyzing the occurrences list, we can identify what type of event has occurred and when. So, for each time space between normal activities (between begin of: and ending of:) (see figure 5.15), the features of each biosignal are presented: maximum, minimum and average of HR and GSR are calculated to each of these temporal regions (see 5.16), allowing a better recognition of human stress in several contexts as, for example, driving in different cities.

Also, through the marking of spontaneous events in the graphs, it is possible to associate the event and its influence in the skin response, as we can see in the figure 5.17.

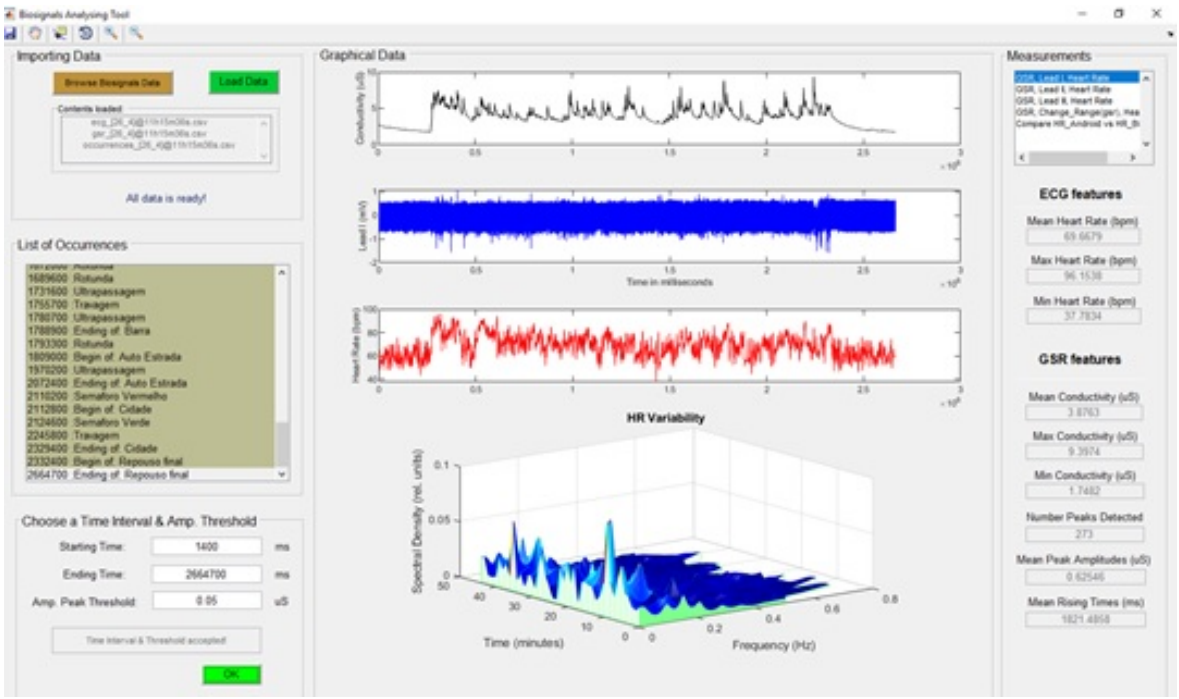


Figure 5.14: MATLAB interface principal screen

As an example of the features that can be extracted, table 5.2 presents the results for a vehicle driver experimental test. In this example, five normal activities have been defined. By using the interface and selecting the starting time and ending time of each normal activities, the respective GSR and ECG features appear in the right side window, and the table is filled with these values.

Table 5.2: GSR and ECG features

Features	Rest 1	City 1	Highway	City 2	Rest 2
Mean HR (bpm)	59.8	74.6	67.8	72.3	61.4
Max HR (bpm)	76.1	96.2	88.2	89.8	84.8
Min HR (bpm)	43.1	48.5	37.8	53.6	46.3
Mean Conductivity (μS)	2.1	4.4	4.2	4.8	2.4
Max Conductivity (μS)	2.9	7.5	8.9	9.4	4.8
Min Conductivity (μS)	1.8	3.2	2.8	3.5	1.8
Num. Peaks Detected	1	97	77	34	3
Mean Peaks Amplitude (μS)	0.12	0.74	0.79	0.85	0.14
Mean Peaks Rising Time (s)	3.2	2.1	1.9	1.6	2.2

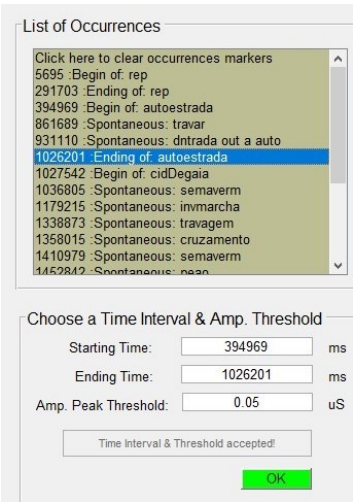


Figure 5.15: List of occurrences

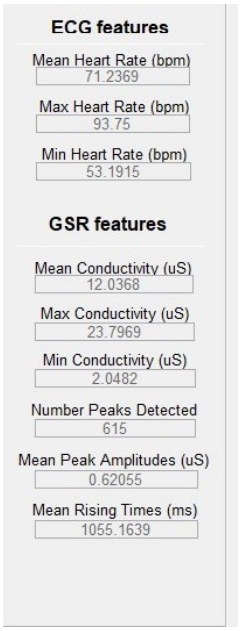


Figure 5.16: ECG and GSR features

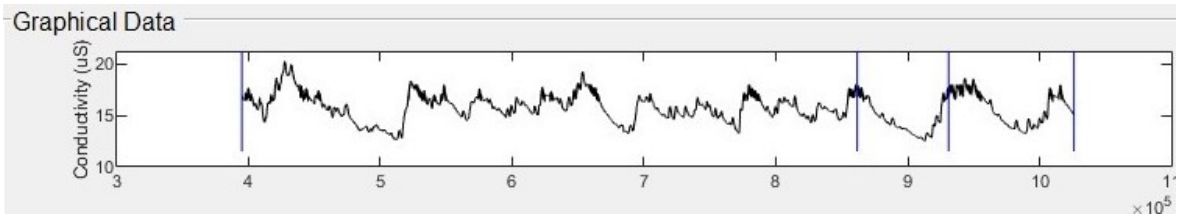


Figure 5.17: marked events in GSR signal

Creation of the user emotional profile

The idea underlying the creation of the user emotional profile is to identify each individual by using emotional features. Presently, and under the premise that each individual is unique and possesses distinct physical and behaviour characteristics, some of them, are widely used to accurately identify individuals.

Biometrics is the science of analyzing physical and/or behavioral characteristics specific to each individual in order to be able to authenticate their identity [163]. Fingerprint recognition and iris recognition are the most reliable biometrics technology. One of their applications, which has been most widely deployed, it is in the electronic passport technology [246].

As each individual is unique in terms of physical characteristics, it is also unique in terms of emotional reaction to stress [247]. As well, biometrics is used to uniquely identify each individual in physical terms; biometrics can also be used to identify each individual in emotional terms.

As already referred in this chapter, the individual emotional response can be measured with biometric signals like ECG and GSR [248]. As stated in [249], ECG has a great potential to be used in identification systems since they can not be falsely created or replicated.

One example of using the heart rate as biometric identification is the cardio watch that the majority of the athletes use in nowadays. Each user introduces his/her baseline heart rate or age and, during training, the heart rate is being monitored and an audible alarm sounds whenever it exceeds predefined limits.

These type of devices have a good market acceptance and this can be justified because the limits of the normal resting heart rate for adults are scientifically well known. And if someone wants to be sure of their baseline or maximum heart rate, for doing physical exercise for example, they can do a clinical protocol to calculate them more accurately.

Therefore, the user's emotional profile can also have the goal of identifying individuals, using the unique features of HR and of GSR.

The selection of the type of the emotional bio signals to integrate the user emotional profile will depend on the goal of its use as also the selection of the parameters or features of these biosignals. At the first stage of this work, we have selected the GSR and ECG bio signals and, as parameters to study the behavior of these bios signals, the HR mean and GSR mean parameters were chosen to integrate the user emotional profile. This selection was based in the following assumptions:

1. It is certain that GSR has high intra-personal fluctuations due to permanent variations in people's moods and changes of environmental factors.

2. There is no standard values for GSR response unlike HR response.

3. The main purpose is to study intra personal behaviours towards situations with different levels of stress.

4. Actually, inter personal is out of the scope of this work because the number of experimental tests done are not in sufficient number for doing it.

Three emotional states were defined: rest, medium and stress:

- rest: when the user is calm, it is a rest period where there is no emotional stressful situations.

- medium: when there are some stressful situations from time to time. When these situations already demand some concentration and time of response.

- stress: when there are more stressful situations and full concentration is mandatory as also the time of response is crucial.

This classification is made previously, during the planning of the experimental protocol which should include different activities with different sources of stress and, during the planning, each activity is associated to a stress level.

The creation of the user emotional profile is made based on the AS data base and is explained below:

- it is represented by a table.
- this table is drawn based in another table, the matrix table.
- this matrix table is created with the help of the Matlab interface.
- for each data segment, the GSR and HR mean values are calculated.
- each segment of data is classified with an emotional state defined previously.
- then, for each emotional state considered, the minimum and maximum values of each feature are calculated.
- the user emotional profile table is filled with these values.

The number of segments (n) will depend on the test duration, will depend on the amount of information given by the sensors but must be equal for each pre-established emotional states.

The selection of the duration of each segment must be a compromise between the number of segments and relevant information.

So, for each of the emotional states, we have a matrix table with n lines and two columns (GSR mean and HR mean).

The table 5.3 represents an example of a matrix table and it is created considering that, for each emotional state, there must be the same amount of information.

Emotional state	GSR mean	HR mean
rest	2,50	57,99
	2,25	59,66
	2,04	59,91
	1,89	60,10
	3,43	61,97
	2,57	61,35
	2,12	61,17
	2,02	60,96
medium	5,16	70,48
	4,23	62,05
	3,26	62,34
	3,13	63,92
	4,06	69,06
	3,77	62,04
	3,32	65,42
	4,22	66,76
stress	6,26	85,18
	5,42	81,37
	5,11	74,55
	3,81	70,34
	5,16	73,56
	4,17	67,56
	4,33	70,54
	5,16	72,41

Table 5.3: Example of a matrix table

After that, and using the matrix table, for each emotional state, the minimum and the maximum of the GSR mean values and the minimum and the maximum of the HR mean values are calculated.

The user emotional profile is created based in the minimum and maximum values features selected for each emotional state as table 5.4 shows. Both tables are created through programs built for this purpose in Matlab.

Emotional state	min / max	GSR mean	HR mean
rest	min	1,89	57,99
	max	3,43	61,97
medium	min	3,13	62,04
	max	5,16	70,48
stress	min	3,81	67,56
	max	6,26	85,18

Table 5.4: Example of a user emotional profile

So, if the emotional values that characterize each person are well known, new values of

emotional signals can be classified and the emotional state, in real time, can be predicted.

Choosing the best stress classification algorithm

This subsection will explain the two approaches followed in choosing the best algorithm for the classification model. The difference between these two approaches is related to the Matlab version. The first approach used the Matlab R2013b and the second the Matlab 2018b.

In both approaches, the main goal is to select the best algorithm for each user dataset, find the best algorithm for the classification model. So, several classification algorithms were implemented. This is justified because it is difficult to find a reliable single best classifier, for all data sets.

The first approach to the algorithms classification implementation was the creation of specific programs. These programs were written by using functions from the Matlab R2013b library. The second approach was to use Matlab R1018b dedicated applications to train models to classify data using supervised machine learning.

In the first one, three different classifier algorithms were selected based on the literature review made in 3.3.3: the LDA classifier, SVM linear and SVM quadratic kernel.

So, the procedure followed for the first approach is depicted in the next flowchart, see figure 5.18 and, is equal for the three emotional predefined states:

1. train and choose the best model for each algorithm
2. generate one hundred values for each state
3. classify these values with the three models
4. repeat the steps 1, 2 and 3 thirty times
5. calculate the mean of the correct instance

In this implementation, we have defined two classification groups: 'calm' and 'stress' and, a matrix classification table [24x1], where each line corresponds to a previous classification.

In this work, the LDA technique was used as a black box and, the main function used is *class = classify(sample,training,group,'type')* [250] where class indicates the group to which each row of sample has been assigned, and, is this case it will be 'calm' or 'stress'. So, the arguments used were:

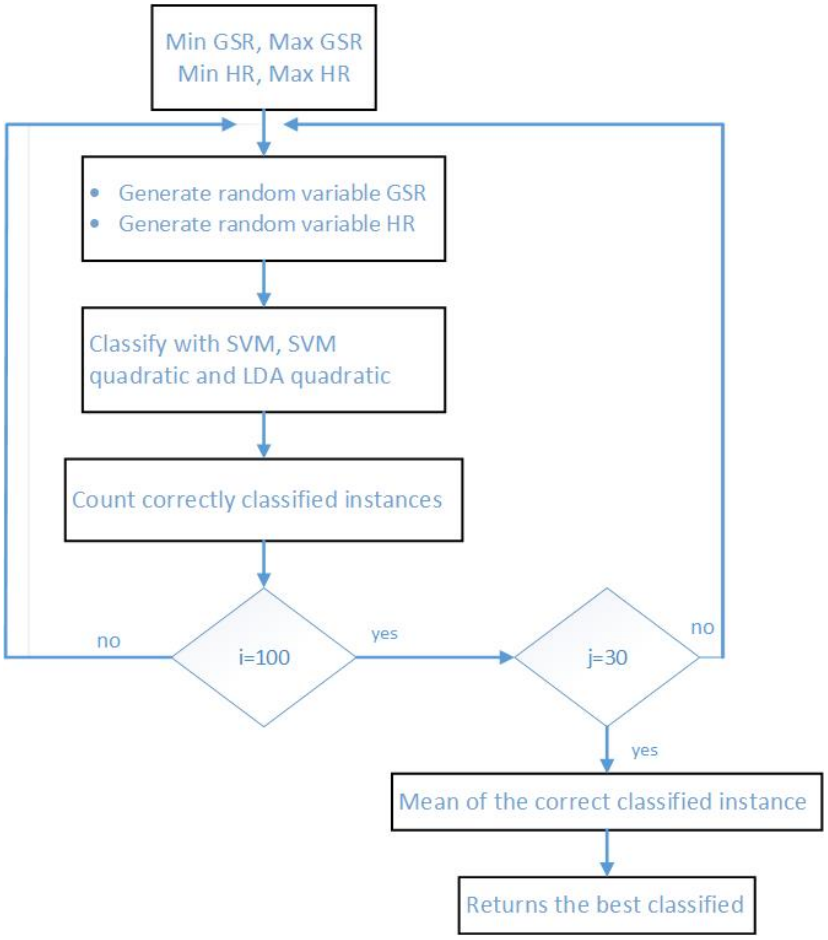


Figure 5.18: Classification procedure

- sample: a [2x1] vector of randomized values for GSR and HR
- training: is the matrix table [mxn] where m is the number of segments and n the number of features.
- group: is the matrix classification [24x1]
- type: quadratic discriminant function

Also, the Matab funtions that implement SVM were used as black box namely:

- the *SVMStruct= svmtrain(Training,Group,Name,Value)*
- the *Group = svmclassify(SVMStruct,Sample)*.

SVMStruct result contains information about the trained support vector machine (SVM) classifier where:

- Training: is a data set of the observations data, of the matrix table. This data set is built by a partition of half of the total of the observation data.

- Group: is the classification of each instance of the training data.

- Name: 'Kernel function'.

- Value: 'linear' for the SVM linear and 'quadratic' for the SVM quadratic.

Group result contains information about the classification of the test data set based in *SVMStruct* created with the *svmtrain*.

After the first classification, an classification error is calculated and a model of classification is obtained when a manually predefined threshold. After that, all data generated randomly are classified.

To compare the results of each classification algorithm, a table similar with the following was built:

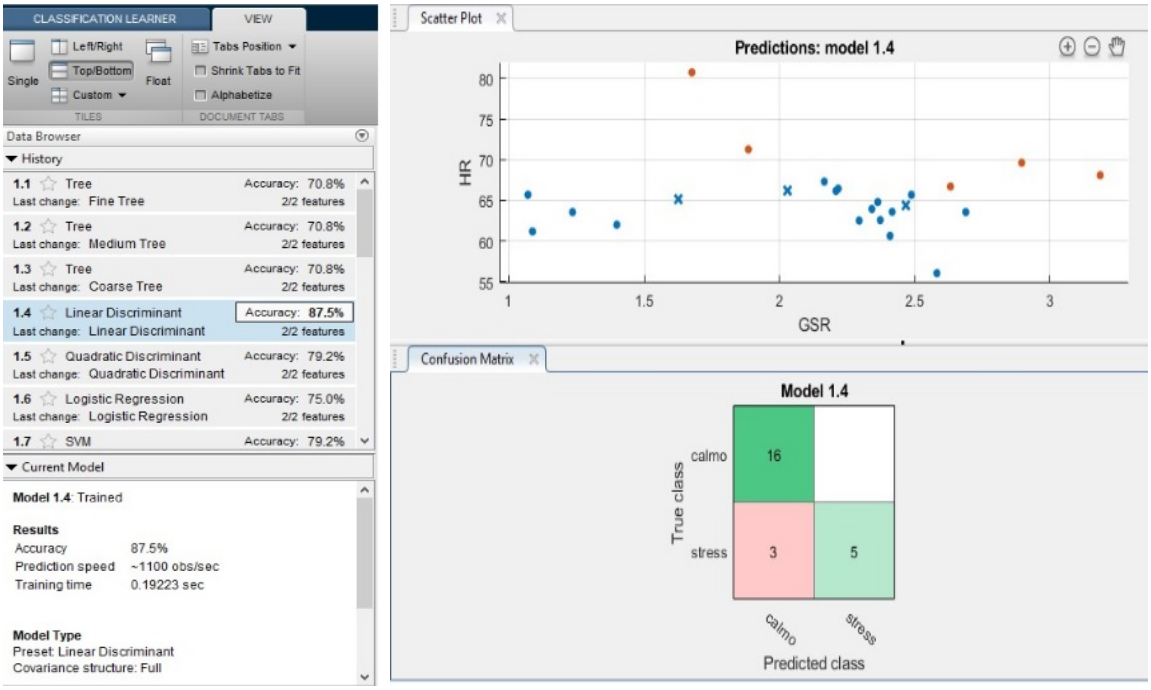
restLDA	mediumLDA	stressLDA
100%	77%	85%
restSVM	**mediumlinearSVM**	**stresslinearSVM**
100%	79%	92%
restquadSVM	**normalquadSVM**	**stressquadSVM**
100%	87%	84%

Figure 5.19: Comparison of classification algorithms

This table is filled with the results of the classification according to figure 5.18. In this example all three hundred values randomly generated for the emotional state rest are a hundred percent well rated by the three algorithms. For the three hundred randomly generated values for the medium emotional state, in the top rank is the SVM quadratic and, concerning the emotional stress state, the top-rated is the SVM linear with ninety-two per cent. This means that SVM linear has well classified 92 % of the generated stress values as stres and 8% were badly classified as calm.

Meanwhile, a new version of Matlab was used which integrates a dedicated application to train models to classify data using supervised machine learning. This application allows training models of several classifiers like decision trees, discriminant analyses, support vector machines among others. For more information about this application see [251].

The significant advantage of this application over the implementation of the individual algorithms is that several algorithms can be trained. After the training, for each model the accuracy and confusion matrix are calculated and displayed. Additionally taking account both features, a scatter plot is shown. Figure 5.20 shows the sequence of all training models, and for the selected training model, the accuracy, the scatter plot and confusion matrix.



(a) Classification learner history (b) Scatter plot and confusion matrix

Figure 5.20: Classification Learner App principal screen

To define which model is the best, some metrics must be calculated, like precision, recall, accuracy, true positive rate, false positive rate and F1Score. All these metrics are calculated based on the confusion matrix where the number of True Positive (TP), False Positive (FP), True Negative (TN) and False Negative (FN) are presented.

A confusion matrix summarizes the classification performance of a classifier with respect to some test data. It is a two-dimensional matrix, indexed in one dimension by the true class of an object and in the other by the class that the classifier assigns [252]. Table 5.21 presents an example for a two class classification example: rows reflecting the actual values and the columns reflecting the values predicted.

The following points are intended to explain how to calculate the metrics [253]:

1. true positive: when an instance is initially classified as true and the prediction is also true.

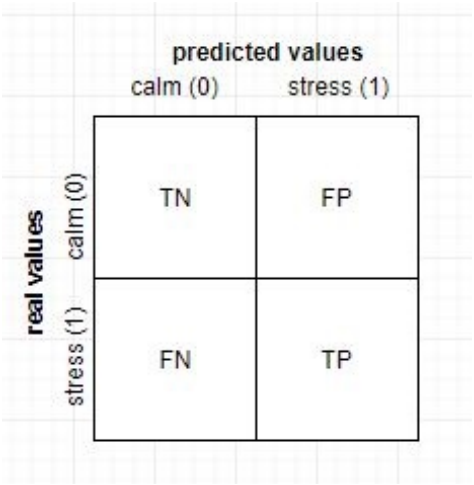


Figure 5.21: Confusion matrix

2. true negative: when an instance is initially classified as false and the prediction is also false.

3. false positive: when an instance is initially classified as false and the prediction is true.

4. false negative: when an instance is initially classified as true and the prediction is false.

5. true positive rate (TPR): is calculate by

$$\frac{TP}{TP + FN}$$

and is also designed as recall

6. false positive rate (FPR): is calculated by

$$\frac{FP}{FP + TN}$$

7. accuracy: is calculated by

$$\frac{TP + TN}{TP + TN + FP + FN}$$

8. precision: is calculated by

$$\frac{TP}{TP + FP}$$

9. F1score: is calculated by

$$2 * \frac{precison * recall}{precision + recall}$$

Accuracy give the percentage of the correctly values identified. Recall give the percentage of the values found, from the model, that are really positive and precision give the percentage of the values predicted as positive are really positive. F1-Score is a metric which takes into account both, precision and recall and identify the balance that exists between precision and recall.

Using only the accuracy metric may not be sufficient since for different confusion matrices the accuracy is the same, but as the distribution between FN, FP, TP and TN may be different, the calculated F1-Score value will also be different. These two metrics will be used to evaluate the classification algorithms.

The results from the vehicular navigation tests and powered wheelchair navigation experimental tests are presented in the next chapter.

5.4 Conclusions

In this chapter, the Legacy Adapted Mode (LAM) and Semi autonomous Transfer (SaTM) modes of operation of the proposed human machine interface implementation are detailed. The operating modes were developed based on a different interpretation of joystick impulses. The software Stage was used to implement these modes of operation, according to the finite state machines defined in the previous chapter.

Also, in this chapter, we explained how we had implemented the acquisition register module and the different functionalities of the analysis and classification sub-system. The AR module was developed for versatile use in an Android platform, to collect the several sensors' data and to register occurrences. The software Matlab was used to implement the functionalities of the analysis and classification sub-system like features signals extraction, creation of the user emotional profile and choosing the best classification model.

This chapter ends with the presentation of the concept of matrix confusion and how it is used to calculate the respective performance classification algorithms metrics.

The next chapter will present results from using Stage to validate the LAM and SaTM operation modes and results from the implementation of the proposed stress detection functionalities.

Chapter 6

Experimental Results

6.1 Introduction

This chapter aims to present some real experimental tests to validate some of the functionalities of the Assistive powered Wheelchair proposal, namely the Legacy adapted (LAM) and Semi autonomous transfer(SaTM) modes and the stress detection system (SDS).

The LAM model was tested by a tetraplegic patient during several and continued sessions, with the goal to configure the operational parameters values. The results shown below refer to the last experimental test performed, using the LAM operation mode final version.

Regarding the SaTM mode, no results are presented as it was not possible to test the operation of this mode with people with reduced handling skills, only by people without disabilities.

To ensure that the stress detection system was working correctly, we tested it during the car's driving tests. Thus, when experimental tests were performed at the Rehabilitation Center, with people with reduced handling skills, proper functioning and practical use of the system were already guaranteed.

Next, the results concerning the use of the implementation of some of the proposed SDS functionalities, namely, those stipulated for the Acquisition and Register Module and the Analyzing and classification subsystem during the car and commercial powered wheelchair, are presented.

6.2 Results from using Stage to validate LAM and SaTM

The platform was tested by one patient in the Rehabilitation Center. This patient is a C5 and a C6 in the right and left arms, respectively, and he is only able to spin to the front. In his opinion, the LAM mode of operation proposed is very interesting because he has not to push the joystick continuously to drive the powered wheelchair, thus feeling much more comfortable. He was highly motivated when he was doing the tests. So, before each simulation, we have defined different pathways inside the apartment like, for example, going from the dinning room to the kitchen or the bedroom. Also, we have defined some metrics that we will use like:

- The time it takes to complete the pathways
- The time it takes to complete the pathways but with obstacles;
- The number of joystick interventions needed to change direction;
- The degree of fatigue;
- The time of reaction of each user.

As these were the first tests that took place, we have only considered all the possible pathways without obstacles. First of all, the patient was asked to train some movements such as moving forward, backward, turn the chair and pass doors. Then, he tested turning the wheelchair with different delta precisions, like two, four and six. First, he tried to make the simulation tests with a delta equal to two because, as he said, there is no need to touch the joystick so many times. But then he felt that he needed more experience using the experimental platform to position the wheelchair in the right place. So, he chose a delta precision equal to six. With this new configuration there is an augmentation of the number of direction angles and, consequently, he could move the wheelchair with greater precision in certain movements, like passing a door. The choice of this parameter is a compromise between the number of needed impulses given on the joystick and the direction angles.

We have defined six possible pathways:

1. dinner room to room
2. dinner room to bath room
3. dinner room to kitchen

4. room to bath room
5. room to kitchen
6. kitchen to bath room

He performed twelve simulation tests, two for each pathway and for each one we have used two of the metrics defined at the beginning of this section: the time it takes to complete the pathway and the number of joystick interventions needed to change direction. The metric degree of fatigue was not measured but it was observed by us when the patient has begun to show signs of tiredness. The other two metrics will be target of our future study and experiments. Table 6.1 presents the simulation results.

Simulation number	Pathway	Time (s)	Number of intervention
7	1	48	7
10	1	13	3
5	2	48	15
6	2	1'05	10
4	3	58	12
11	3	1'10	18
2	4	58	14
8	4	1'43	15
3	5	1'29	20
9	5	1'08	18
1	6	59	10
12	6	1'30	13

Table 6.1: LAM simulation results

These tests were made according to the wishes of the patient, which means that the order of these tests was not pre-defined but it was him that chose what he wanted to do each time. The tests took about two hours to be performed and, during this time, he was always navigating the wheelchair with success. Although the experimental platform allows to navigate the wheelchair in the legacy mode, this patient did not even attempt to do that because he is not able to do so. During the execution of these simulations, we have noticed that he has well learned the mode of operation and also that he showed, after some time, signs of tiredness. One of the symptoms that he was tired was that sometimes, when he pushed the joystick to the front to put the wheelchair in movement and when he dropped the joystick to making the arm movement to the back, he touched unintentionally in the joystick, thus triggering false stops.

So these results are not fully conclusive because the fatigue was making him a little nervous and he was also concerned because he begun to fail. At the end of these two hours

we have concluded, together with the clinician and the patient himself, that he needs to do some more training tests but not for so long time. The idea is to adapt the duration of each training session so that the learning process is not affected by the fatigue. With the learning process we want that he learns when he must exactly stop the wheelchair. When he does not stop the wheelchair in the right position he has, in some situations, to perform many more impulses in the joystick to reposition the wheelchair in the right pose.

6.3 Acquisition and Register Module validation

To validate the ARM android platform, four main experimental tests were done: check if it acquires and register occurrences properly, verify its reliability for long time experiments, check lifetime of sensors battery and the last one, to estimate the initial phase error. These all experimental test were made in the scope of the master degree thesis mentioned in 5.3.1 [244].

Only after this validation has been done and have the guarantee of the reliability of the system, all the following work, can be continued.

The conclusion is that this plataform works well and is credible although has a problem related with the time of the connection to the sensors, a limitation concerning ability of properly acquire data during only approximately 8 hours. A remark that confirms the state of art about GSR sensors, is that these ones are more susceptible to use than the ECG.

6.4 Vehicular navigation results

6.4.1 Experimental Procedure

Six vehicles with six different drivers were used during the experimental validation of the stress detection system. Four driving experiments were done on the city of Aveiro, all of them in different days but with the same route and with a duration of 45 minutes. The other two experiments were made in Porto, both with the same route and duration. The experimental procedure had the same sequence of phases: first, each driver stayed five minutes in a state of rest; then, he drove in the city; then, he drove on the highway; then he returned back, coming the inverse way, e.g., highway, city and rest again. During the driving, spontaneous events such as traffic lights changes, pedestrians suddenly crossing the road, and passing through roundabouts, were registered by the co-pilot. It is expected that the stress level of persons is

higher when driving in the city, lower in resting phases and medium in the highway.

6.4.2 Drivers matrix tables and their emotional profile

For each of the experimental driving tests, the matrix table was created with the help of the GSR and ECG offline analysis performed in the Matlab interface (see 5.3.2).

To guarantee that all emotional state levels have the same amount of information, for each emotional level, eight data segments were selected corresponding to eight minutes of data. Then, for each temporal data segment, the GSR mean and ECG mean is calculated by the Matlab interface sub-menus (see 5.16).

During each driving test, the data coming from the sensors were recorded and transferred to the analyzing unit. This was done using the interface developed. All data is divided into segments of one minute each. So each segment is characterized by the GSR and HR mean values, each corresponding to one minute.

All these segments were stored in a [24x2] matrix. As explained earlier, the driver's emotional profile was created based on the corresponding driver's matrix table.

The table 6.2 shows the emotional profile of the six drivers, with the GSR mean shown in microsiemens (μS) and the HR mean in beats per minute (bpm). It confirms the idea that different persons have different GSR and HR feature values when facing the same situation. For instance, the value of 3 μS for the mean GSR corresponds to a state of stress for the driver 4 and a state of rest for the driver 1.

Table 6.2: Drivers emotional profiles (GSR and HR)

		ID driver					
		1	2	3	4	5	6
GRS (μs)	minrest	1.9	7,7	0,9	1,1	8,4	3,1
	maxrest	3,4	11,4	2,8	2,6	15,4	8,4
	minmed	3,1	10,4	2,2	2,2	13,2	12,3
	maxmed	5,2	12,8	3,1	2,7	15,7	17,1
	minhigh	3,8	10,8	1,6	2,2	11,8	11,6
	maxhigh	6,3	12,7	3,1	3,2	15,5	15,8
HR (bpm)	minrest	58	63	57	56	78	64
	maxrest	62	69	61	66	82	70
	minmed	62	64	56	63	86	69
	maxmed	71	70	62	67	91	74
	minhigh	68	67	60	64	85	76
	maxhigh	85	79	68	81	89	76

6.4.3 Drivers emotional classification

The results of emotional classification of drivers presented are those performed by using the Classification Learner App of Matlab R2018b. This decision is justified because it has more potential compared with written programs. This advantage comes from the ability to train multiple algorithms such as decision trees, discriminant analyses, logistic classifiers, support vector machines and k-Nearest-Neighbor.

With this application, several models can be trained and, for each one, the respective accuracy is calculated. Then, for each model, the respective scatter plot is also displayed as also the respective confusion matrix. So, for each driver data set, this application was then used to train models and to find the best model. To find the best model for each classifier, the application allows us to select the predictors and to select the cross-validation k-fold. Cross-validation is a process for creating a distribution of pairs of training and test sets out of a single data set. In cross validation the data are partitioned into k subsets, called a fold [252].

Because one of the goals of this study is also to verify what are the best predictors, between GSR and HR, several iterations were made: some with GSR and HR as predictors, others with only GSR as predictor and others only with HR as predictor. All these iterations were performed with k-fold cross-validation with k=5 folds.

In this case, the goal is to have a reduced number of stress states classified as calm states: a stress state classified as a calm stress is a FN and the larger the number of false negatives, the greater the likelihood that the model will not recognize stress states. On the other hand, FP means that a calm stress is classified as a stress state and can be classified as false alarms. This balance between FP and FN is crucial to choose the model but from the user's point of view, it is more important to have a reduced number of false negatives.

For each driver, several classification algorithms iterations were made. First, these algorithms were trained considering the GSR and HR as predictors and, the classification model with the best accuracy was saved. Them, the same procedure was made, considering only the GSR as a predictor and, in the end, considering only the HR as a predictor.

So, for each driver, three confusion matrices will be presented: the first one represents the best model trained with the two predictors (GSR and HR), the second one the best model trained considering only the predictor GSR and the third one, the best model trained considering only the predictor HR. Also, a table with the respective metrics for each of these best models obtained, is presented.

Also, we will investigate the feasibility of using an emotional user profile by assessing the performance of the best classification algorithm found when training with individual user data.

Driver 1

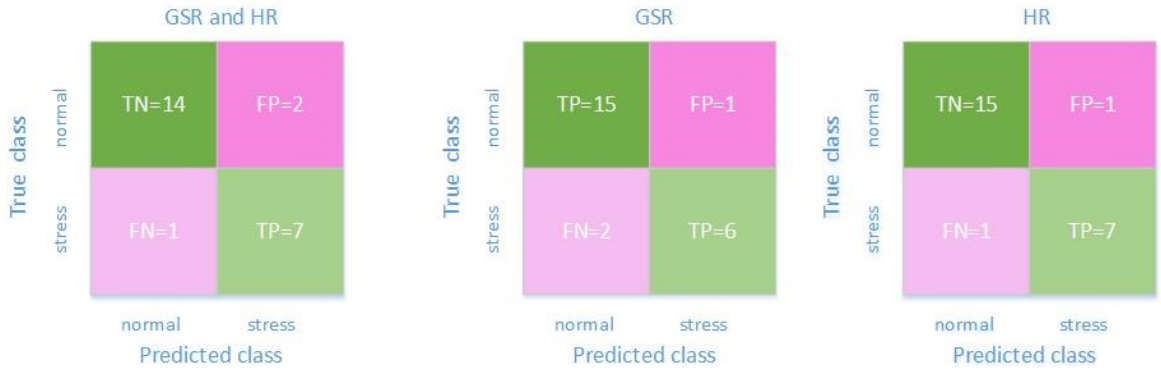


Figure 6.1: Confusion matrices for Driver 1

Table 6.3: Performance metrics for driver 1

Predictors	Model	Accuracy	Precision	Recall	F1-Score	FPR
GSR+HR	LDA	87,5%	78%	88%	0,82	13%
GSR	LDA	87,5%	86%	75%	0,80	6%
HR	LDA	91,7%	88%	88%	0,88	6%

For driver 1, the best classifier was the LDA regardless of the number and type of predictors. The model found by the classifier LDA, that only uses the HR as predictor, is the one with the best F1 score of 0.88. Analyzing the respective HR confusion matrix, there is only one FP which corresponds to one false alarm and one FN, which means that a true state stress is predicted as calm.

Driver 2

Table 6.4: Performance metrics for driver 2

Predictors	Model	Accuracy	Precision	Recall	F1-Score	FPR
GSR+HR	LDA, SVM	79,2%	80%	50%	0,62	6%
GSR	CubicSVM	79,2%	71%	63%	0,67	13%
HR	WeightKNN	87,5%	86%	75%	0,80	6%

For driver 2, the best classifier will depend on the type and number of predictors. The model found by the classifier LDA, that only uses the HR as predictor, is the one with the best F1 score of 0.80. Analyzing the respective HR confusion matrix, there is only one FP

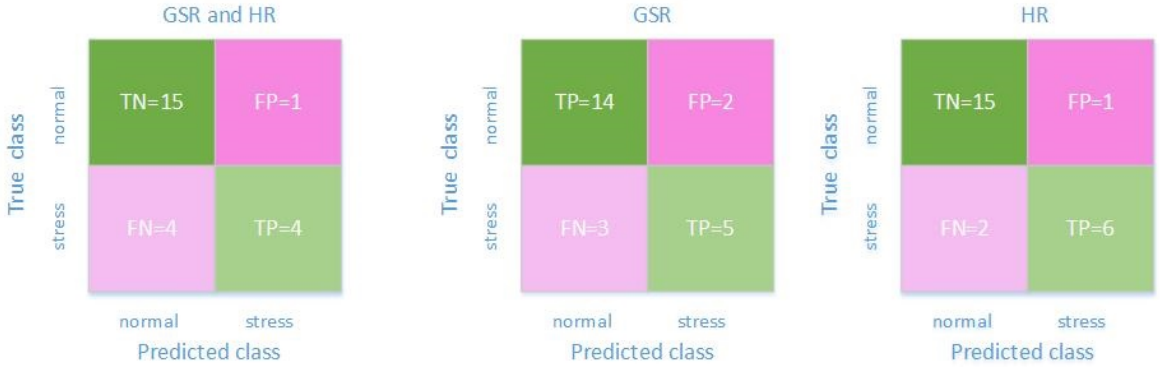


Figure 6.2: Confusion matrices for Driver 2

which corresponds to one false alarm, but there are two FNs which means that two stress states are predicted as calm.

Driver 3

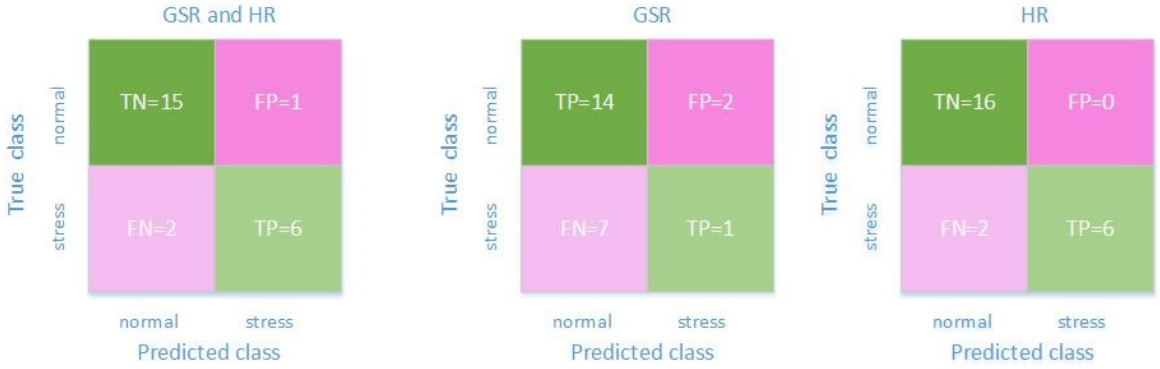


Figure 6.3: Confusion matrices for Driver 3

Table 6.5: Performance metrics for driver 3

Predictors	Model	Accuracy	Precision	Recall	F1-Score	FPR
GSR+HR	QDA, SVM	87,5%	86%	75%	0,80	6%
GSR	QDA	62,5%	33%	13%	0,18	13%
HR	QDA	91,7%	100%	75%	0,86	0%

For driver 3, the best classifier was the QDA regardless of the number and type of predictors. The model found the classifier QDA, that as also only uses the HR as predictor is the one with a better F1 score of 0.86. Analyzing the respective HR confusion matrix, there is two FNs which means that two stress states were predicted as calm state.

Driver 4

Figure 6.4: Confusion matrices for Driver 4

Table 6.6: Performance metrics for driver 4

Predictors	Model	Accuracy	Precision	Recall	F1-Score	FPR
GSR+HR	LDA	87,5%	100%	63%	0,77	0%
GSR	SVMCubic	83,3%	75%	75%	0,75	13%
HR	LDA	83,3%	100%	50%	0,57	0%

For driver 4, the best classifier was the LDA in both cases: when GSR and HR were used as predictors and when only the GSR was used as a predictor, when comparing the F1 Score. The first case is a little bit higher than in the second case but, on the other hand, in the second case, two FNs are comparing with the three of the first case.

Driver 5

Figure 6.5: Confusion matrices for Driver 5

Table 6.7: Performance metrics for driver 5

Predictors	Model	Accuracy	Precision	Recall	F1-Score	FPR
GSR+HR	QuadraSVM	78,3%	63%	71%	0,677	19%
GSR	Cubic SVM	70,8%	56%	63%	0,59	25%
HR	Cubic SVM	75%	60%	75%	0,67	25%

For driver 5, the best classifier was the SVM quadratic in the case where GSR and HR were used as predictors and it was the SVM Cubic when only the HR was used as a predictor when comparing the F1-Score. The second case is a little bit higher than in the first case but, on the other hand, it as four FN comparing with the three of the first case.

Driver 6

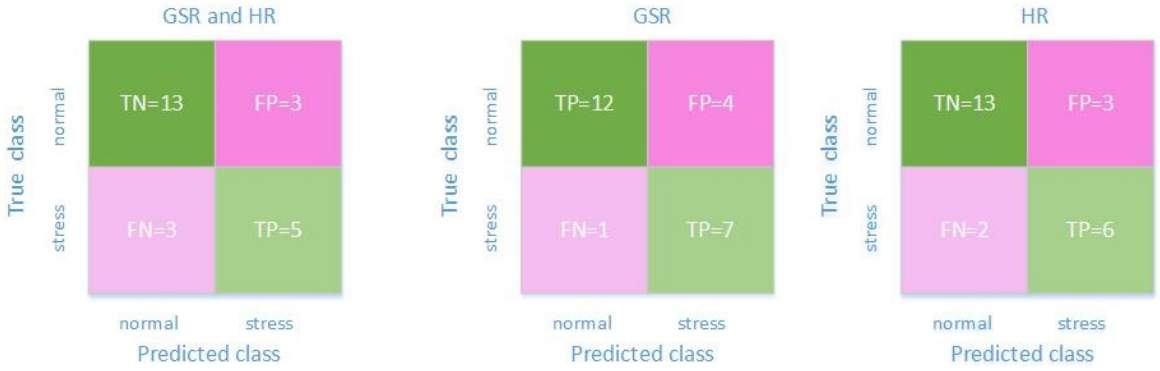


Figure 6.6: Confusion matrices for Driver 6

Table 6.8: Performance metrics for driver 6

Predictors	Model	Accuracy	Precision	Recall	F1-Score	FPR
GSR+HR	QDA, SVMMed	75%	63%	63%	0,63	19%
GSR	QuadraSVM	79,2%	64%	88%	0,74	25%
HR	FineKNN	79,2%	67%	75%	0,71	19%

For driver 6, the best classifier was the SVM quadratic in the case where GSR was used as a predictor and it was the Fine KNN when the HR was used as a predictor when comparing the F1-Score. In the first case is a little bit higher than in the second and it as one FN comparing with the two of the second case.

Classification Comparison drivers

The next three tables make a resume of the respective metrics for the best model found for each driver: table 6.9 when it was considered the two predictors GSR and HR, table 6.10

when it was considered predictors GSR and table 6.11 when it was considered the predictor HR.

Table 6.9: GSR and HR Metrics Models Comparison

Predictors	Model	Accuracy	Precision	Recall	F1-Score	FPR
GSR+HR	LDA	88%	78%	88%	0,82	13%
GSR+HR	LDA	79%	80%	50%	0,62	6%
GSR+HR	QDA	88%	86%	75%	0,80	6%
GSR+HR	LDA	88%	100%	63%	0,77	0%
GSR+HR	QuadSVM	78%	63%	71%	0,67	19%
GSR+HR	QDA	75%	63%	63%	0,63	19%

Table 6.10: GSR Metric Models Comparison

Predictors	Model	Accuracy	Precision	Recall	F1-Score	FPR
GSR	LDA	88%	86%	75%	0,80	6%
GSR	CubicSVM	79%	71%	63%	0,67	13%
GSR	QDA	63%	33%	13%	0,18	13%
GSR	CubicSVM	83%	75%	75%	0,75	13%
GSR	CubicSVM	71%	56%	63%	0,59	25%
GSR	QuadSVM	79%	64%	88%	0,74	25%

Table 6.11: HR Metrics Models Comparison

Predictors	Model	Accuracy	Precision	Recall	F1-Score	FPR
HR	LDA	92%	88%	88%	0,88	6%
HR	WeightKNN	88%	86%	75%	0,80	6%
HR	QDA	92%	100%	75%	0,86	0%
HR	LDA	83%	100%	50%	0,67	0%
HR	CubicSVM	75%	60%	75%	0,67	25%
HR	FineKNN	79%	67%	75%	0,71	19%

Comparing data from the three tables, and in particular the F1-Score, it can be concluded that this presents a higher average in the cases when it was used only the HR as a predictor and a lower average in the cases when it was used only the GSR as predictor.

When comparing the tables corresponding to the cases when it was used the GSR and HR as predictors and the cases where it was used only the HR as predictor, it can be noticed that the types of classification algorithms are different.

To try to find out if there is a single classification algorithm that can predict the state of stress for all drivers, several iterations on the classification learner application were made. The approach was the same when considering each data set individually: using the GSR

and HR as a predictor, only by using the GSR and only with the HR. A dataset has been constructed that groups all individual datasets, which will be called the global dataset.

The next table, table 6.12 resumes the results of the ten Application Classification Learner iterations that were made, to try to find a single classification algorithm for the global dataset.

Table 6.12: Global dataset classifications resume

Predictors	Model	Accuracy Average	F1-Score Average
GSR and HR	Tree (Coarse)	71%	0,56
GSR	Tree (Medium)	60%	0,32
HR	KNN (Cosine)	70%	0,6

While the results are overall lower than the user-specific models, the global model allows to generalize implementation to new users without the need to train a user-specific model first.

When comparing the global model performance with the scores achieved with individual models, we observed that, overall, the user emotional profile has a better ability to classify the users' stress state.

For new users, we thus suggest a strategy to apply the general model first (for a quicker deployment) and, if possible, train a user specific model for better performance.

6.5 Powered Wheelchair Navigation Results

6.5.1 Target Group

The experimental tests were carried out at the Rehabilitation Center.The centre has a set of training houses where patients are trained to use adapted facilities and assistive devices. Patients with spinal cord injuries attend the service of "Lesionados Vertebro Medulares" (LVM) essentially for two reasons: their need for rehabilitation in inpatient settings shortly after the accident, and, on a temporary basis, when they need rehabilitation sometime after the accident.

Obtaining permission from the Rehabilitation Center to carry out the experimental tests was necessary because it involved the co-operation of disabled people.

Afterwards it was necessary to schedule the tests. As mentioned above sometimes there are no tetraplegic patients hospitalized and some other times, even if there are, they may not be available to carry out the experimental tests. Depending on their health conditions, rest can be recommended by their physicians. So, scheduling the experimental tests depended

largely on the availability of patients and staff at the Rehabilitation Center. It should be emphasized that without the involvement and help of the head nurse at the LVM service, the tests would not have been carried out. Besides to schedule the tests, he helped in the patient preparation for the experimental test execution.

The tests of the study we conducted previously were carried out at the CMRRC-RP with tetraplegic patients with C5/C6 injuries, see 6.2. As this new study is a follow-up of the previous research, the target group still cervical spinal cord injured patients. Experience driving an electric wheelchair was one of the other criteria considered. Driving a wheelchair for the first time can be emotionally more stressful than it is for someone doing it regularly.

6.5.2 Experimental Procedures

Both the goal of the experimental test and the procedure were explained to the patients beforehand. First of all, we asked whether they were interested in co-operating by submitting to the experimental test. They all accepted the challenge and willfully participated. Some were more engaged than others, and the difference in their attitudes was mainly due to the way they were facing the reality of a new life. The experimental procedure follows 5 phases and is identical to the driver's experimental procedure.

- A five-minute rest;
- A five-minute wheelchair drive along a hallway;
- A ten-minute wheelchair drive in a dining room, around tables and chairs and along a wall;
- A wheelchair drive along a hallway;
- A five-minute rest.

It is always necessary to have someone to accompany the experimental procedures, to insert the events taking place, in the acquisition register module. During the CPW drive, spontaneous events such as turning around and approaching and going around the table were registered. A higher stress level when driving in the dining room, a lower stress level when resting, and a medium stress level when in the hallway are to be expected. Thirteen tests were carried out with ten patients with different spinal cord injuries. As tests were being carried out and results were being analyzed, the test was adjusted, namely in what concerns:

- the area of the body where to place the GSR electrodes;
- patients who repeated the test and
- the use of another GSR measuring system.

The first experimental procedure

The first test was carried out with a C4/C5 tetraplegic patient staying at the CMRRC-RP for temporary confinement. This patient had been injured five years previously and drove his wheelchair expertly as he had a three and a half years' experience.

The test was discontinued since no significant alteration in what concerns the skin conductivity values were detected. In discussion with the nursery staff, two possible reasons were identified. One involves the lose the perspiration function, that is, they are not able to sweat below the injury level, and some of them not even above. The second one concerns the fact that, as the patient already was an expert driving the wheelchair, nothing induced a change in his emotional state. Also, the different medication that patients take can be a justification.

Therefore, and according to the relevant literature, there are other areas on the body, namely dermatomes, which can be more effective than the fingers to read the skin conductivity. Thus, nursing staff and physicians at the CMRRC-RP having debated the issue, decided that the subsequent tests should be carried out with the GSR electrodes on the patients foreheads.

Subsequent tests

The following table, 6.13, shows a chronological summary of the tests carried out, identifying the type of injury for each patient, how long ago the injuries had occurred and for how long the patients had been driving their wheelchairs. It should be noted that the patient who carried out the first test repeated it to verify whether there were any differences in the GSR reading. The first test was carried out with the developed system and with the GSR electrodes on the patient's finger. As previously mentioned, the subsequent experiments were carried out with the same system but with the GSR electrodes on the patient's forehead.

After the 8th test another GSR acquisition system was used in order to compare the results. This system allows the placement of GSR sensors in two different areas of the body. One was placed on the finger; the other one was placed on the forehead. Thus the 8th, 9th and 10th tests were carried out with the two systems in order to compare the results. The 12th and 13th tests were carried out with the system we designed.

Table 6.13: Chronological experimental tests

ID test	**ID patient**	**Type of injury**	**Date of injury**	**Date of test**	**Experience driving wheelchair**	**Location of GSR electrodes**
1	1	C4/C5	07-2009	08-2014	4 years	Finger
2	2	C3/C4	03-2014	08-2014	1 month	front head
3	3	C5	2012	08-2014	1 month	front head
4	1	C4/C5	07-2009	10-2014	4 years	front head
5	4	C4	06-2014	10-2014	1 week	front head
6	5	C5/C7	08-2014	10-2014	First time	front head
7	6	C5	07-2014	10-2014	First time	front head
8	7	C5	02-2015	06-2015	1 week	front head
9	8	C4	12-2014	07-2015	1 week	Finger and front head
10	7	C5	02-2015	07-2015		Finger and front head
11	6	C5	07-2014	07-2015		Finger and front head
12	9	T11	07-2015	10-2015	Two weeks	Finger
13	10	T4	09-2015	10-2015	First time	Finger

6.5.3 Tests Results

Results of the first test

The GSR evaluation of the first test carried out is depicted in the next figure and in the next table. The first marking on the chart represents the beginning of the rest period; the second marking represents the beginning of the drive in a hallway; the third marking represents the drive in a room and the fourth marking represents the end of the drive in a room. As the GSR signal was no way identical to what was expected as can be seen in the Fig. 6.7 and table 2, it was decided to end the test and repeat it. The result was identical so it was decided to carry out the tests with the GSR electrodes on the forehead.

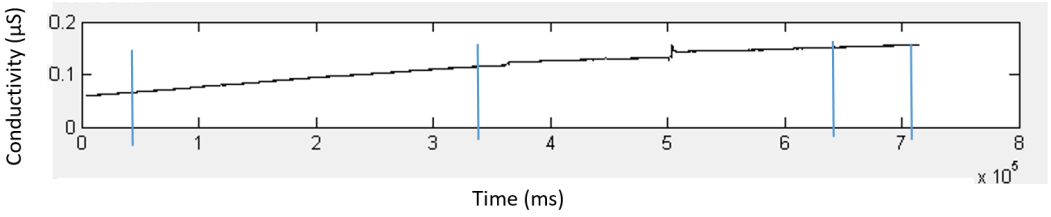


Figure 6.7: First experimental test GSR waveform

Table 6.14: GSR features with 0,01 threshold

Mean	**Max**	**Min**	**Number peaks**	**Mean Peak amplitude (μS)**	**Mean Rising Times (ms)**
0,11	0,16	0,06	1	0,022	585,94

Results of the subsequent tests

The result of the tests carried out with seven patients with the GSR electrodes on the forehead are shown on the following chart (ID test 2 to 8):

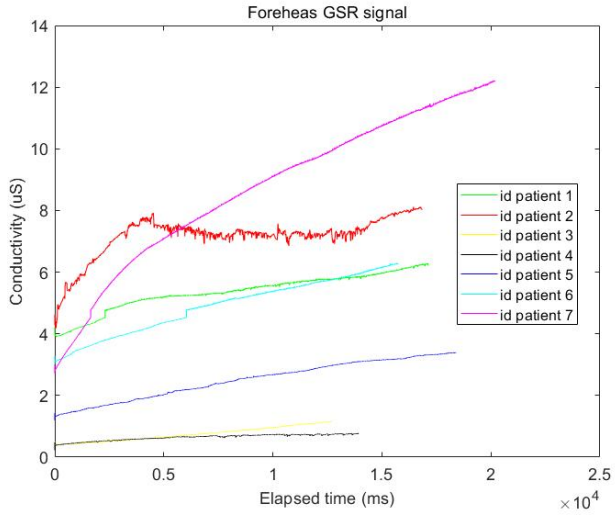
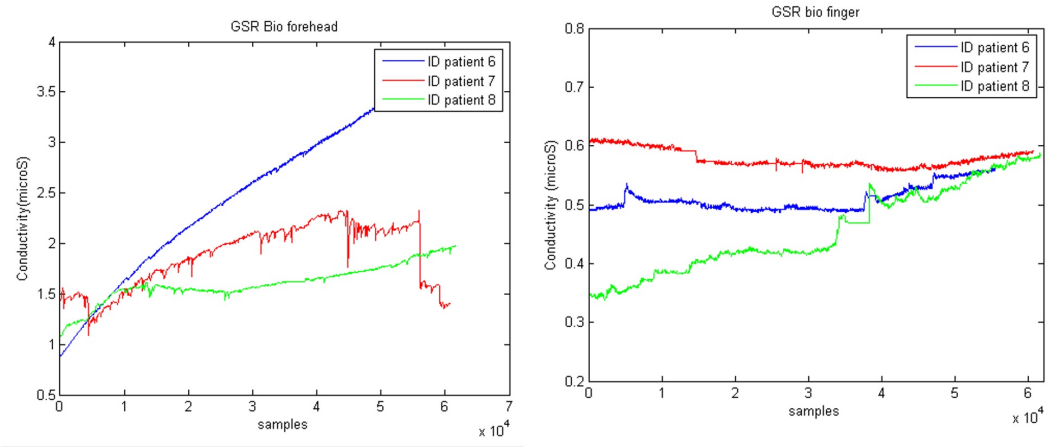


Figure 6.8: GSR signals with the electrodes in forehead

As one can see, the GSR signal with the electrodes placed on the forehead is also very different from the expected one, since it has no peaks and rises constantly. It has even the particularity of presenting higher values at the end of the test, during the last minutes when the patient was again in a rest period. Due to this unexpected result, we decided to investigate what would happen using another biosignals measuring system. This system, Biofeedback 2000 x-pert, incorporates two GSR sensors and, on the threee subsequent tests, one was located on the patient's finger and the other on the patient's forehead, in order to be able to compare the results obtainned with the Shimmer sensors.

Comparison between values drawn by the Shimmer sensor and by the Biofeedback 2000 x-pert system

Three tests were carried out with the Biofeedback system. The experimental procedure was the same as the other tests. The following figures represent the result of the three tests with the GSR signal on the patient's forehead (id test 9, 10 and 11) and the GSR signal on the patient's finger. From the first chart it is to be concluded that the geometry of the signal is identical to the signals of the tests previously carried out by the Shimmer sensor. From the second chart it is to be concluded that the GSR signal drawn from the patient's finger is also a signal geometrically identical to the Shimmer GSR signal: without peaks, practically constant.



(a) GSR Bio forehead

(b) GSR Bio finger

Figure 6.9: GSR Biofeedback results

It may be concluded that the patient's forehead is not a good dermatome to study the GSR behavior on tetraplegic patients. It was decided to carry out tests on patients with disabilities on the thoracic vertebrae, that is with type T injuries. Thus a test was carried out with a patient with a level T4 injury (a man) and a patient with a level T11 injury (a woman).

Results of the tests with patients with type T injury

As shown on the next chart and on the next table, the GSR signal on the patient with the level T4 injury has a higher number of peaks, a lower average rising time and a larger amplitude average as compared with the signal on a patient with a level C4 injury. In the case of the patient with the T11 injury the difference is even higher with a geometrical shape

identical to that of a patient without any injury. It must be emphasized that, at the end of each test, corresponding to the last phase of rest, there is an increase of skin conductivity. The reason for this was, in both cases, that due to their particular circumstances, the patients felt the need to talk and share the changes in their lives with the person carrying out the test and for that reason they aren't in a true rest state. The confrontation with the new reality after the trauma caused by the accident that made him/her paraplegic,is often very difficult and slow to overcome.

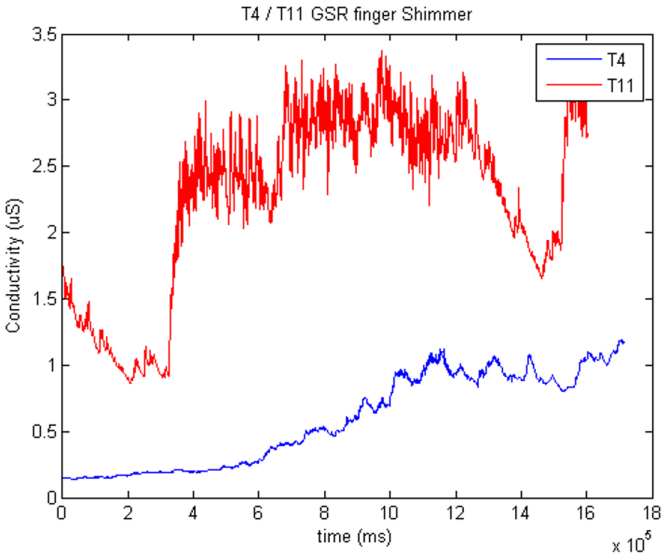


Figure 6.10: T4 and T11 GSR signal

Table 6.15: T4 and T11 GSR features (0,05 Threshold)

Type of injury	**Mean**	**Max**	**Min**	**Number peaks**	**Peak amplitude (uS)**	**Mean Rising Times (ms)**
T4	0,59	1,19	1,12	21	0,068	3534,23
T11	2,27	3,29	0,85	568	0,166	811,85

6.5.4 Powered wheelchairs drivers emotional classification

The some procedure used to classify emotion drivers will be used to classify emotion commercial powered wheelchair drivers.

A conclusion of work done in the section 6.5.3 is that, although the number of the experimental results is reduced, they corroborate the idea that the tetraplegia will not affect the heart rate as it affects the galvanic skin response. So, in this case, only the HR will be used as a predictor to execute the classification algorithms.

The information collected was divided into segments of 1 min each and thus the dataset corresponds to a matrix table [30x2] (instance, state). After that, the user's emotional profile is constructed.

The table 6.16 shows the emotional profile of the five powered wheelchair drivers, with HR mean in beats per minute (bpm).

Table 6.16: Powered wheelchair drivers emotional profiles (HR)

		ID patient				
		1	4	5	6	8
HR (bpm)	minrest	50	68	85	66	55
	maxrest	57	77	92	73	60
	minmed	54	73	89	67	61
	maxmed	57	76	95	76	63
	minhigh	55	74	91	71	57
	maxhigh	56	76	94	75	64

So, for each of the five patients drivers, the confusion matrix will be presented: it represents the best model trained with the predictor HR. Also a table with the metrics for each of the best models is obtained. The identification of the patients' drivers is according to the table 6.13.

Patient 1

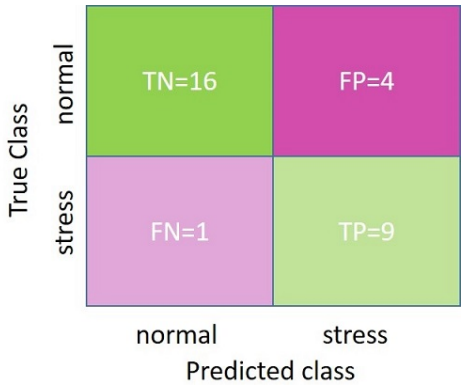


Figure 6.11: Confusion matrix - Patient 1

Table 6.17: Performance metrics for patient 1

Predictor	Model	Accuracy	Precision	Recall	F1-Score	FPR
HR	QuadraticSVM	83,3%	69%	90%	0,78	20%

Several iterations of classification algorithms were made. The SVM quadratic algorithm

has almost always the best accuracy in the several iterations. The best model chosen and save this one with 0.79 F1-Score.

Patient 4

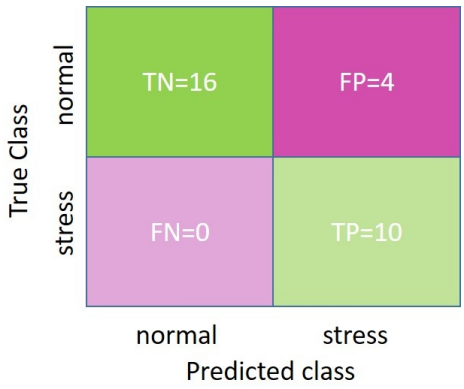


Figure 6.12: Confusion matrix - Patient 4

Table 6.18: Models metrics for patient 4

Predictor	Model	Accuracy	Precision	Recall	F1-Score	FPR
HR	WeightKNN	90,0%	82%	90%	0,86	10%

In this case, the Weighted KNN algorithm has almost always the best accuracy in the several classification iterations. The best model chosen was this one with 0.86 F1-Score.

Patient 5

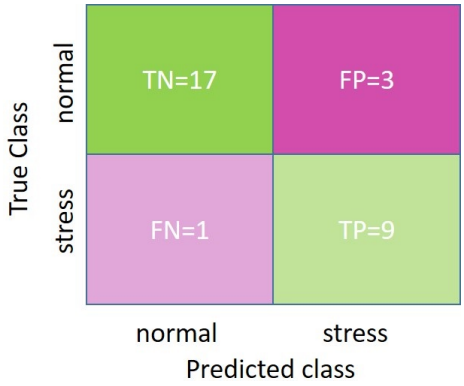


Figure 6.13: Confusion matrix - Patient 5

Table 6.19: Models metrics for patient 5

Predictor	Model	Accuracy	Precision	Recall	F1-Score	FPR
HR	FineTree	86,7%	75%	90%	0,82	15%

For patient 5, the Fine Tree and Fine KNN classifier algorithms were the ones with the best results for F1-Score. Because the Fine Tree has only has 1 false negative, it was the saved model.

Patient 6

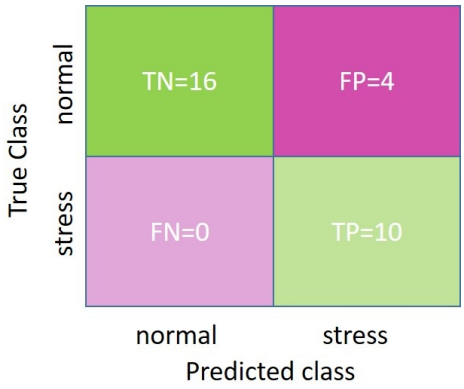


Figure 6.14: Confusion matrix - Patient 6

Table 6.20: Models metrics for patient 6

Predictor	Model	Accuracy	Precision	Recall	F1-Score	FPR
HR	FineTree	86,7%	71%	100%	0,83	20%

In this case, there are no doubts about choosing the Fine Tree model with zero false negatives and still have a good classify capability.

Patient 8

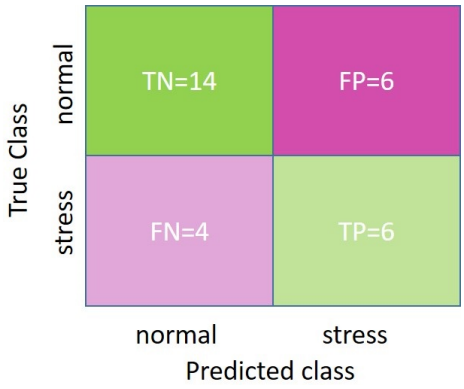


Figure 6.15: Confusion matrix - Patient 8

In this case, and after several models trained, the best found was the Fine Tree algorithm with a F1-Score of 0.55. This is the lower F1-Score found in all experimental tests.

To try to find out if there is a single classification algorithm that can predict the state of

Table 6.21: Models metrics for patient 8

Predictor	Model	Accuracy	Precision	Recall	F1-Score	FPR
HR	FineTree	66,7%	50%	60%	0,55	30%

stress for all patients drivers, several iterations on the classification learner application were made. A dataset has been build that groups all individual datasets, which will be called the global dataset.

At the end of iterations, it highlights three classification algorithms: the Fine Tree, the Fine Gaussian SVM, and the RUSBoostedTrees. Of these three, the RUSBoostedTrees performed the best accuracy as well as the best F1-Score. Next, it is presented the respective matrix confusion as well as the respective metrics for the selected model.

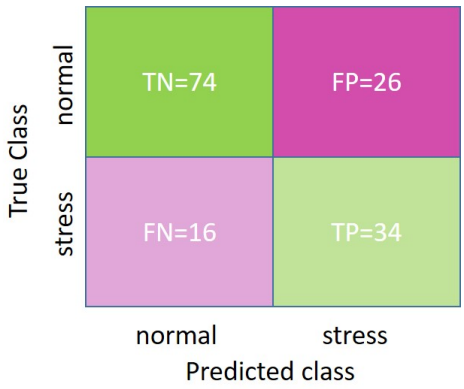


Figure 6.16: Confusion matrix - global dataset

Table 6.22: Models metrics for global dataset

Predictor	Model	Accuracy	Precision	Recall	F1-Score	FPR
HR	RUSBoostedTrees	69,3%	53%	62%	0,62	12%

The driver's classification global data set, as a result lower than all user-specific models, except for the patient eight. For this patient, it will be useful if the overall model was implemented.

The same suggestion is also made for the commercial powered wheelchairs users, to apply the general model first (for a quickerdeployment) and, if possible, train a user specific model for better performance.

6.6 Conclusions

In this chapter, results of using the Stage platform were presented, specifically, the results of using Legacy adapted mode by a tetraplegic patient. This mode of operation was well learned but, after some time, the patient showed signs of tiredness and stress because he begun to fail.

In order to get an idea about the operation of the stress detection system in persons without disabilities, we performed tests with drivers in different scenarios. After, we did additional tests with tetraplegic patients driving their powered wheelchair.

Using these tests, the behavior of the galvanic skin response and heart rate under different stress situations was also evaluated for both disabled and non-disabled people. For disabled people it was confirmed that the galvanic skin response cannot be used to detect stress.

In order to avoid the calibration of the system for each individual, we tried to obtain the respective user emotional profile. Then, based on the obtained profiles, the best stress classifier algorithm was selected.

For each user of the system, the respective user emotional profile was created and, based on these profiles, the best stress classifier algorithm was selected.

The results of the profile determination were displayed as well as the results for the best classifier found for a global data set comprising all the user-specific data. With these results, we concluded that, overall, the user-specific models classification has better performance comparing with the global data set classification. This conclusion empowered the concept of using the user emotional profile to detect stress.

Chapter 7

Conclusions and Future Work

The main proposal of the thesis supported by the present document claims that the autonomy and quality of life of users with severe disabilities can be substantially improved by adapting a commercial powered wheelchair joystick operation to the user disability and to enable the wheelchair navigation system to share the control between the own user decision and his/her emotional state.

This work resulted from the collaboration between the Rehabilitation Center Rovisco Pais and the University of Aveiro. The clinicians of this center have identified a problem related to the manipulation of the joystick by patients with reduced strength in arms and hands. They aren't able to manipulate the joystick continuously, so they have great difficulty to navigate their commercial powered wheelchair. Even in the situations that they can do it for a while, they get tired soon and thus they quickly become unable to perform the navigation.

During this work, that was carried on in close cooperation with the clinicians, it was found a huge diversity of patient capabilities within the available population of severely impaired persons. In consequence, a brief study was done on what causes can induce reduced muscle strength in the arms and hands. This study helped to define the target group of users who can profit from the idealized proposals for adapting wheelchairs.

As all these patients require an electric wheelchair, we performed a state of the art review concerning the research area of smart wheelchairs. We verified that, after a significant research effort, autonomous wheelchairs have been practically abandoned. But what is called adapted wheelchairs, that is evolution solutions for commercial wheelchairs where some elements are changed to better suit the patient needs and capabilities, have been object, afterwards, of interest of the academic and engineering communities and thus emerged as practical and adopted approaches. Based on the study about adapted wheelchairs, we defined an archi-

tecture for our solution, focusing on new proposals of navigation modes and novel ways of interpreting the joystick manipulation by patients.

In order to incorporate in the wheelchair control the user emotional state of the user it was considered to conceptualize a sub-system able to detect that state. In order to do that, a state of art review was made concerning the concept of stress and the correspondent biometric sensors used to detect this state. This study helped us to decide which sensors can be used to identify stress. We also evaluated the response of the biometric sensors selected when applied in the target group of impaired patients with whom we were working.

The proposed assistive wheelchair solution has been developed in order to facilitate its navigation by a user with reduced arm and hand strength, always ensuring his/her well-being. In our solution, once the detection system identifies that the user is in a stressful state that does not guarantee safe navigation, the assistive wheelchair controller takes charge of the wheelchair navigation. This situation should not, as it can be understood, have a binary behavior, that is, it should not just turn on or off. So, to facilitate the navigation operation, three modes were defined. The controller associated to these novel modes of operation should also be able to replace the original commands issued by a traditional joystick by an also novel interface unit that translates impulses provided by the joystick, depending of the user abilities, in intelligible speed and direction commands.

Going back to the modes of operation, the start of the navigation with them will depend on the initial skills of the patient, the maneuver to be executed and the improvement of those skills after rehabilitation/training. Selecting one of the navigation operating modes is the user's responsibility.

The adequacy and usability of two of these operating modes were validated by their implementation in simulation, using the software Stage and, in the case of the so-called legacy adapted mode (LAM), by its operation by tetraplegic patients, one of them having tested a final version that we consider satisfactory. However, the results of this experimental tests are not enough to conclude that this mode of operation can be a good solution but seem to be promising because, in the end, he had performed the wheelchair navigation with success. It should be noticed that the availability of members of this target population is very rare and the tests carried on are the result of a significant number of visits to the Rehabilitation Center and a large amount of hours of contact with the patients in order to obtain the mandatory agreements and to be able to proceed with the experimentation.

In the solution we proposed, in order to provide to the powered wheelchair user a good

degree of emotional well-being, we studied a stress detection system based on Galvanic Skin Response (GSR) and Heart Rate (HR) biometrics sensors. Using these sensors, we were able to define a user emotional profile and to evaluate the best classification model able to obtain it with a satisfactory degree of success.

In order to be able to validate the emotional profile detection solution, and as the number of available impaired patients was scarce, we decided to work in another use case that, in our opinion, is similar to our scenario. In this case it was chosen the driving of a car in roads with different stressful situations such as crowded roundabouts, zebra crossings, etc. So, we performed a battery of tests first in car drivers, in order to guarantee the robustness of the system and, after, in the few tetraplegic patients we could get access to.

From the results of the first experimental test group, we could conclude that different persons showed different galvanic skin responses and heart rate values when facing the same stressful situations. This could be confirmed by analyzing the various driver's emotional profiles. Also, and according to the results of emotional classification made, it could be concluded that the predictor biometric signal HR is more reliable than the predictor biometric signal GSR. A further conclusion is that each best model classifier will vary from driver to driver. However, if it is intended to choose a model classifier for all data sets, it is advised to use either the HR as predictor or the GSR and HR, but not only the GSR. Comparing the global model performance with the scores achieved by the individual's models, the user emotional profile has a better ability to classify the user's stress detection.

From the results of the experimental test with tetraplegic patients, we could conclude that best model classifier will vary from driver to driver and, overall, the user specific models classification as greater performance comparing with global data classification.

A significant additional future work is required to finish the validation of this novel adaptation of commercial powered wheelchairs. Three future lines are identified, namely, one related with the validation of the Assistive Powered Wheelchair (APW) mode operation, another for the implementation of the Legacy Adapted Mode (LAM) and Semi autonomous Transfer Mode (SaTM) modes, and a third line to the integration of the user emotional state on the APW controller.

First, in what concerns the validation of the APW mode of operation, more experimental tests must be made by using the software Stage. Patients with reduced strength in arms and hands must do several experimental tests, simulating the wheelchair navigation in the legacy adapted mode. These experimental tests must consider additional scenarios, like outdoor,

for example. Besides, the Semi autonomous Transfer Mode (SaTM) must be tested by these patients but, to do this in an effective manner , more autonomous wheelchair navigation algorithms to perform different operations like, for example, approaching a table must be implemented.

In what concerns the implementation of operational modes on a commercial powered wheelchair, several add-on units must be developed, namely a sensor module to detect obstacles and another one to adapt the wheelchair controller with the novel joystick command interpreter. Also, a set of adapted switches must be chosen to allow the change between the modes of operation.

Once this is done, we must integrate the user emotional state into the APW controller. To do this, the stress detection module must be implemented. This will be done by integrating the best model classification algorithms on the acquisition and stress detection sub system proposed.

Also future studies should investigate deeper a biometric sensor to replace the galvanic skin response when we are dealing with tetraplegic patients. We propose to implement a counter that will count the number of false commands given in joystick and introduce another non-intrusive sensor in the Stress Detection System (SDS). The first proposal is justified by the fact that, as the degree of tiredness increases, the number of false commands also increases because the person is no longer able to hold the joystick for the predefined time. Regarding the non-intrusive sensor, the first option is to try a sensor that will detect muscle activity on the face. This is justified by the fact that, from the moment the person begins to have difficulty manipulating the joystick, the person begins to perform involuntary contraction facial movements that can be detected through an electromyography sensor. Detecting pupil dilation is another solution as it is also the responsibility of the sympathetic nervous system. However, as it is more demanding in terms of both hardware and software requirements, it will be used at a later stage.

Finally, independently of the biometric sensor used in the detection of the emotional state, further investigation has to be done regarding the stress detection to evaluate if it possible to do it without the need to perform a calibration to the specific user, that means, without the need to obtain previously an user emotional profile.

Bibliography

[1] R.N. Marianne Belleza. Nervous system anatomy and physiology. Available: https://nurseslabs.com/nervous-system/. Last accessed 22 September 2019.

[2] Cindy Schmidler. Spinal nerves. Available: https://www.healthpages.org/anatomy-function/spinal-nerves/. Last accessed 29 June 2018.

[3] Spinal cord injury levels. Available: https://boneandspine.com/spinal-cord-injury-levels/. Last accessed 11 October 2019.

[4] Y Hu, C Converse, MC Lyons, and WH Hsu. Neural control of sweat secretion: a review. *British Journal of Dermatology*, 178(6):1246–1256, 2018.

[5] Mark J Shen and Douglas P Zipes. Role of the autonomic nervous system in modulating cardiac arrhythmias. *Circulation research*, 114(6):1004–1021, 2014.

[6] Sumit Desai, SS Mantha, and VM Phalle. Advances in smart wheelchair technology. In *Nascent Technologies in Engineering (ICNTE), 2017 International Conference on*, pages 1–7. IEEE, 2017.

[7] Jonathan Connell and Paul Viola. Cooperative control of a semi-autonomous mobile robot. In *Robotics and Automation, 1990. Proceedings., 1990 IEEE International Conference on*, pages 1118–1121. IEEE, 1990.

[8] H Hoyer, U Borgolte, and A Jochheim. The omni-wheelchair-state of the art. In *Proceedings of Conference on Technology and Persons with Disabilities, Los Angeles*, 1999.

[9] Machine Perception and Universidad de Málaga Intelligent Robotics (MAPIR). The sena robotic wheelchair. Available: http://mapir.isa.uma.es/mapirwebsite/. Last accessed 22 October 2017.

[10] RISE RESEARCH CENTER. Autonomous wheelchair project. Available: http://rise.smme.nust.edu.pk/projects/Wheelchair/, 2012. Last accessed 22 September 2017.

[11] Heidelberg University Automation Laboratory. Intelligent wheelchair. Available:https://healthengine.com.au/info/sweating-perspiration. Last accessed 22 September 2019.

[12] Richard Simpson, Edmund LoPresti, Steve Hayashi, Illah Nourbakhsh, and David Miller. The smart wheelchair component system. *Journal of Rehabilitation Research and Development*, 41(3B):429, 2004.

[13] Jeonghee Kim, Hangue Park, Joy Bruce, Erica Sutton, Diane Rowles, Deborah Pucci, Jaimee Holbrook, Julia Minocha, Beatrice Nardone, Dennis West, Anne Laumann, Elliot Roth, Mike Jones, Emir Veledar, and Maysam Ghovanloo. The tongue enables computer and wheelchair control for people with spinal cord injury. 5:213–166, 11 2013.

[14] Ericka Janet Rechy-Ramirez and Huosheng Hu. Bi-modal human machine interface for controlling an intelligent wheelchair. In *Emerging Security Technologies (EST), 2013 Fourth International Conference on*, pages 66–70. IEEE, 2013.

[15] Simon O'Regan, Stephen Faul, and William Marnane. Automatic detection of eeg artefacts arising from head movements using gyroscopes. In *Applied Sciences in Biomedical and Communication Technologies (ISABEL), 2010 3rd International Symposium on*, pages 1–5. IEEE, 2010.

[16] Lai Wei and Huosheng Hu. A multi-modal human machine interface for controlling an intelligent wheelchair using face movements. In *Robotics and Biomimetics (ROBIO), 2011 IEEE International Conference on*, pages 2850–2855. IEEE, 2011.

[17] Dora M. Kuntz. Basic ekg interpretation. Available: http://ekginterpretation.weebly.com/. Last accessed 22 September 2019.

[18] Natalie's Casebook Adventures in acute medicine. E c g basics. Available: http://www.nataliescasebook.com/tag/e-c-g-basics. Last accessed 22 September 2019.

[19] Roland Lang. A decision unit for autonomous agents based on the theory of psychoanalysis. *Ph. D. thesis at the Vienna University of Technology*, 2010.

[20] Jorn Bakker, Mykola Pechenizkiy, and Natalia Sidorova. What's your current stress level? detection of stress patterns from gsr sensor data. In *2011 IEEE 11th international conference on data mining workshops*, pages 573–580. IEEE, 2011.

[21] EU. Disability statistics-need for assistance. Available: http://ec.europa.eu/eurostat/statistics-explained/index.php/Disability_statistics_-_need_for_assistance. Last accessed 20 November 2017.

[22] Eurostat Statistics Explained. Disability statistics barriers to social integration. Available: http://ec.europa.eu/eurostat/statistics explained/index.php/Disability statistics barriers to social integration. Last accessed 5 April 2017.

[23] Mobility impairments. Avaiable:http://disability.illinois.edu/instructor-information/disability-specific-instructional-strategies/mobility-impairments.

[24] Linda Fehr, Ms W. Edwin Langbein, Phd Steven, and B Skaar. Adequacy of power wheelchair control interfaces for persons with severe disabilities: A clinical survey. *Journal of Rehabilitation Research and Development*, pages 353–360, 2000.

[25] Christian Brandstätter, Dietmar Dietrich, Klaus Doblhammer, Martin Fittner, Georg Fodor, Friedrich Gelbard, Matthias Huber, Matthias Jakubec, Stefan Kollmann, Daniela Kowarik, et al. Natural scientific, psychoanalytical model of the psyche. *Technische Universität Wien*, 2015.

[26] H. Zeilinger, R. Lang, and B. Muller. Bionic inspired information representation for autonomous agents. In *2009 2nd Conference on Human System Interactions*, pages 383–389, May 2009.

[27] Alexander G Reeves. *Disorders of the nervous system: a primer*. Imperial Company Printers, 1995.

[28] Kayvan Najarian and Robert Splinter. *Biomedical signal and image processing*. CRC press, 2016.

[29] Loss of strength / weakness. Available: https://nurseslabs.com/nervous-system/. Last accessed 22 September 2019.

[30] Janet L Taylor, Markus Amann, Jacques Duchateau, Romain Meeusen, and Charles L Rice. Neural contributions to muscle fatigue: from the brain to the muscle and back again. *Medicine and science in sports and exercise*, 48(11):2294, 2016.

[31] Kuen-Horng Tsai, Chun-Yu Yeh, and Hsin-Chang Lo. A novel design and clinical evaluation of a wheelchair for stroke patients. *International Journal of Industrial Ergonomics*, 38(3-4):264–271, 2008.

[32] Preeti Raghavan. Upper limb motor impairment after stroke. *Physical Medicine and Rehabilitation Clinics*, 26(4):599–610, 2015.

[33] Samar M Hatem, Geoffroy Saussez, Margaux della Faille, Vincent Prist, Xue Zhang, Delphine Dispa, and Yannick Bleyenheuft. Rehabilitation of motor function after stroke: a multiple systematic review focused on techniques to stimulate upper extremity recovery. *Frontiers in human neuroscience*, 10:442, 2016.

[34] Wei Pin Huang, Chia Cheng Wang, Jo Hua Hung, Kai Chun Chien, Wen-Yu Liu, Chih-Hsiu Cheng, How-Hing Ng, and Yang-Hua Lin. Joystick-controlled video console game practice for developing power wheelchairs users' indoor driving skills. *Journal of physical therapy science*, 27(2):495–498, 2015.

[35] Canning Brenda and Garret Sanchez. Manual versus power wheeled mobility for clients with ms. *International Journal of MS Care*, 7(3):87–92, 2005.

[36] Brain T Fay and Michael L Boninger. The science behind mobility devices for individuals with multiple sclerosis. *Medical Engineering and Physics*, 24(6):375–383, 2002.

[37] Ludmila Correa de Alkmin Silva, Fernanda Cristina Corrêa, Geraldo Gonçalves Delgado Neto, Vivianne V Delgado, and Franco Giuseppe Dedini. Canceling interference caused by tremors in joystick controller: study case in a power wheelchair. In *International Conference on Computers for Handicapped Persons*, pages 61–68. Springer, 2010.

[38] Pietro Mazzoni, Britne Shabbott, and Juan Camilo Cortés. Motor control abnormalities in parkinson's disease. *Cold Spring Harbor perspectives in medicine*, page a009282, 2012.

[39] Sheperd Center. Understanding spinal cord injury. Available: http://www.spinalinjury101.org/files/understanding-spinal-cord-injury.pdf, 2011. Last accessed 11 October 2109.

[40] Medscape William McKinley. Functional outcomes per level of spinal cord injury. Available: http://emedicine.medscape.com/article/322604-overview#a3, 2017. Last accessed 12 October 2017.

[41] BrainAndSpinalCord.org. Complete vs. incomplete. Available: http: http://http://www.brainandspinalcord.org/complete-vs-incomplete/, 2017. Last accessed 12 October 2017.

[42] Kemal Nas, Levent Yazmalar, Volkan Şah, Abdulkadir Aydın, and Kadriye Öneş. Rehabilitation of spinal cord injuries. *World journal of orthopedics*, 6(1):8, 2015.

[43] Gina Sprint, Diane J Cook, Douglas L Weeks, and Vladimir Borisov. Predicting functional independence measure scores during rehabilitation with wearable inertial sensors. *IEEE Access*, 3:1350–1366, 2015.

[44] Mohd Razali Md Tomari, Yoshinori Kobayashi, and Yoshinori Kuno. Development of smart wheelchair system for a user with severe motor impairment. *Procedia Engineering*, 41:538–546, 2012.

[45] SpinalHub. C5 complete. Available: http://www.spinalhub.com.au/what-is-a-spinal-cord-injury/how-do-i-move/c5-complete. Last accessed 13 June 2015.

[46] Katherine M Tsui, Holly A Yanco, David J Feil-Seifer, and Maja J Matarić. Survey of domain-specific performance measures in assistive robotic technology. In *Proceedings of the 8th Workshop on Performance Metrics for Intelligent Systems*, pages 116–123. ACM, 2008.

[47] Paul J. Rosch. Reminiscences of Hans Selye, and the Birth of "Stress". Available: https://www.stress.org/about/hans-selye-birth-of-stress. Last accessed 9 June 2017.

[48] Chang Won Kim, Kanghyun Ye, and Seung Kyu Park. Active safety system for personal mobility vehicles. In *Control, Automation and Systems (ICCAS), 2015 15th International Conference on*, pages 1271–1274. IEEE, 2015.

[49] Global Organization for Stress. Stress definitions from stress researchers. Available: http://www.gostress.com/stress-definitions-from-stress-researchers/. Last accessed 22 September 2019.

[50] George P Chrousos and Philip W Gold. The concepts of stress and stress system disorders: overview of physical and behavioral homeostasis. *Jama*, 267(9):1244–1252, 1992.

[51] Harvard Medical School Harvey Simon. Stress. Available:http://www.umm.edu/health/medical/reports/articles/stress, 2013. Last accessed 12 October 2017.

[52] American Psychological Association. Stress effects on the body. Available: http://www.apa.org/helpcenter/stress-body.aspx. Last accessed 12 October 2017.

[53] American Institute of Stress. Stress effects,50 common signs and symptoms of stress. Available:https://www.stress.org/stress-effects. Last accessed 12 October 2017.

[54] Institut universitaire en santé mentale de Montréal Centre for Studies of Human Stress. Understand your stress acute vs. chronic stress. Available:http://www.humanstress.ca/stress/understand-your-stress/acute-vs-chronic-stress.html, 2017. Last accessed 12 October 2017.

[55] American Psychological Association. Stress: The different kinds of stress. Available:http://www.apa.org/helpcenter/stress-kinds.aspx., 2017. Last accessed 12 October 2017.

[56] PsychJourn: General Psychology. The biological basis of behavior: Part 1 (nervous system). Available: http://psychjourngp.blogspot.pt/2013/10/the-biological-basis-of-behavior-part-1.html. Last accessed 4 March 2016.

[57] U.S.National Library of Medicine. How does the nervous system work? Available: http://www.ncbi.nlm.nih.gov/pubmedhealth/PMH0072574/. Last accessed 4 March 2016.

[58] Divisions of the autonomic nervous system. Available: https://opentextbc.ca/anatomyandphysiology/chapter/15-1-divisions-of-the-autonomic-nervous-system/. Last accessed 15 January 2019.

[59] Roberto Vetrugno, Rocco Liguori, Pietro Cortelli, and Pasquale Montagna. Sympathetic skin response. *Clinical autonomic research*, 13(4):256–270, 2003.

[60] Health Engine. Sweating (perspiration). Available: https://healthengine.com.au/info/sweating-perspiration. Last accessed 22 September 2019.

[61] Sanghyun Park, Tran Thi Thu Ha, Jadhav Yogiraj Shivajirao, Minsoo Hahn, Jaehyung Park, and Jinsul Kim. Smart wheelchair control system using cloud-based mobile device. In *IT Convergence and Security (ICITCS), 2013 International Conference on*, pages 1–3. IEEE, 2013.

[62] Jesse Leaman and Hung M La. A comprehensive review of smart wheelchairs: Past, present and future. *arXiv preprint arXiv:1704.04697*, 2017.

[63] Project adapt to develop new smart wheelchair and training programme. Available: https://sunfest.seas.upenn.edu/wp-content/uploads/2018/07/Catherine.pdf.

[64] Richard C Simpson, Edmund F LoPresti, and Rory A Cooper. How many people would benefit from a smart wheelchair? *Journal of rehabilitation research and development*, 45 1:53–71, 2008.

[65] Richard C Simpson. Smart wheelchairs: A literature review. *Journal of rehabilitation research and development*, 42(4):423, 2005.

[66] R. Madarasz, L. Heiny, R. Cromp, and N. Mazur. The design of an autonomous vehicle for the disabled. *IEEE Journal on Robotics and Automation*, 2(3):117–126, Sep 1986.

[67] Odile Horn. Smart wheelchairs: past and current trends. In *Systems and Computer Science (ICSCS), 2012 1st International Conference on*, pages 1–6. IEEE, 2012.

[68] Guy Bourhis and Y Agostini. The vahm robotized wheelchair: System architecture and human-machine interaction. *Journal of Intelligent and Robotic systems*, 22(1):39–50, 1998.

[69] Nikos Katevas. *Mobile robotics in healthcare*, volume 7. IOS Press, 2001.

[70] Gabriel Pires and Urbano Nunes. A wheelchair steered through voice commands and assisted by a reactive fuzzy-logic controller. *Journal of Intelligent and Robotic Systems*, 34(3):301–314, 2002.

[71] Holly A Yanco. Wheelesley: A robotic wheelchair system: Indoor navigation and user interface. In *Assistive technology and artificial intelligence*, pages 256–268. Springer, 1998.

[72] Ren C Luo, Kuo L Su, Shen H Shen, and Kuo H Tsai. Networked intelligent robots through the internet: issues and opportunities. *Proceedings of the IEEE*, 91(3):371–382, 2003.

[73] Catherine Lachance. The smart chair project: Reducing coding for the smart chair programmers. Available: https://sunfest.seas.upenn.edu/wp-content/uploads/2018/07/Catherine.pdf. Last accessed 28 September 2017.

[74] R. Gelin, J.M. Detriche, J. P. Lambert, and P. Malblanc. The sprint of coach. In *Systems, Man and Cybernetics, 1993. 'Systems Engineering in the Service of Humans', Conference Proceedings., International Conference on*, pages 547–552 vol.3, 1993.

[75] Lankenau A. Rofer Th. Architecture and applications of the bremen autonomous wheelchair. *Information Sciences*, 126(1-4):1–20, 2000.

[76] Richard C Simpson and Simon P Levine. Automatic adaptation in the navchair assistive wheelchair navigation system. *IEEE Transactions on Rehabilitation Engineering*, 7(4):452–463, 1999.

[77] G Bourhisa, O Horn, O Habert, and A Pruski. The vahm project: autonomous vehicle for people with motor disabilities. *IEEE Robotics and Automation Magazine Special Issue on" Research on Autonomous Robotics Wheelchairs in Europe*, 2001.

[78] Erwin Prassler, Jens Scholz, and Matthias Strobel. Maid: Mobility assistance for elderly and disabled people. In *Industrial Electronics Society, 1998. IECON'98. Proceedings of the 24th Annual Conference of the IEEE*, volume 4, pages 2493–2498. IEEE, 1998.

[79] E. Demeester, M. Nuttin, D. Vanhooydonck, and H. Van Brussel. Fine motion planning for shared wheelchair control: Requirements and preliminary experiments. In *in 11th International Conference on Advanced Robotics (ICAR 2003*, pages 1278–1283, 2003.

[80] Pierre Mallet and Jean-Marie Pergandi. Towards smart wheelchairs. *AAATE 2005*, pages 328–335, 2005.

[81] J Gonzalez, AJ Muaeoz, C Galindo, JA Fernandez-Madrigal, and JL Blanco. A description of the sena robotic wheelchair. In *Electrotechnical Conference, 2006. MELECON 2006. IEEE Mediterranean*, pages 437–440. IEEE, 2006.

[82] Joelle Pineau and Amin Atrash. Smartwheeler: A robotic wheelchair test-bed for investigating new models of human-robot interaction. In *AAAI spring symposium: multidisciplinary collaboration for socially assistive robotics*, pages 59–64, 2007.

[83] Rosalie H. Wang BSc(OT) PhD, Susan M. Gorski MHSc PEng, Pamela J. Holliday BSc(PT) MSc, and Geoff R. Fernie PhD PEng. Evaluation of a contact sensor skirt for an anti-collision power wheelchair for older adult nursing home residents with dementia: Safety and mobility. *Assistive Technology*, 23(3):117–134, 2011.

[84] Youcef Touati and Arab Ali-Cherif. Smart powered wheelchair platform design and control for people with severe disabilities. *Software Engineering*, 2(3):49–56, 2012.

[85] Patrice Boucher, Amin Atrash, Sousso Kelouwani, Wormser Honoré, Hai Nguyen, Julien Villemure, François Routhier, Paul Cohen, Louise Demers, Robert Forget, et al. Design and validation of an intelligent wheelchair towards a clinically-functional outcome. *Journal of neuroengineering and rehabilitation*, 10(1):58, 2013.

[86] Sarangi P Parikh, Valdir Grassi Jr, Vijay Kumar, and Jun Okamoto Jr. Integrating human inputs with autonomous behaviors on an intelligent wheelchair platform. *IEEE Intelligent Systems*, 22(2):33–41, 2007.

[87] Mohammed Hayyan AlSibai and Sulastri Abdul Manap. A study on smart wheelchair systems. *INTERNATIONAL JOURNAL OF ENGINEERING TECHNOLOGY AND SCIENCES (IJETS)*, 4(1):25–35, 2015.

[88] Brígida Mónica Faria, Luís Paulo Reis, and Nuno Lau. A survey on intelligent wheelchair prototypes and simulators. In *New Perspectives in Information Systems and Technologies, Volume 1*, pages 545–557. Springer, 2014.

[89] Nikos I Katevas, Nikitas M Sgouros, Spyros G Tzafestas, G Papakonstantinou, P Beattie, JM Bishop, Panayotis Tsanakas, and D Koutsouris. The autonomous mobile robot senario: a sensor aided intelligent navigation system for powered wheelchairs. *IEEE Robotics & Automation Magazine*, 4(4):60–70, 1997.

[90] Takashi Gomi and Ann Griffith. Developing intelligent wheelchairs for the handicapped. *Assistive Technology and Artificial Intelligence*, pages 150–178, 1998.

[91] A Civit Balcells and Julio Abascal González. Tetranauta: A wheelchair controller for users with very severe mobility restrictions. In *Proc. 3rd TIDE Congress*, pages 336–341, 1998.

[92] S. Fioretti, T. Leo, and S. Longhi. A navigation system for increasing the autonomy and the security of powered wheelchairs. *IEEE Trans. on Rehabilitation Engineering*, 8:490–498, 2000.

[93] Manuel Mazo. An integral system for assisted mobility [automated wheelchair]. *IEEE Robotics & Automation Magazine*, 8(1):46–56, 2001.

[94] A Pruski and H Knops. Infrared non-contact head sensor, for control of wheelchair movements. *Assistive Technology: From Virtuality to Reality: AAATE 2005*, 16:336, 2005.

[95] Richard C Simpson, Daniel Poirot, and Francie Baxter. The hephaestus smart wheelchair system. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 10(2):118–122, 2002.

[96] L Casimir Mostowy. Performance testing of collision-avoidance system for power wheelchairs. *Journal of rehabilitation research and development*, 48(5):529, 2011.

[97] OTR Mark Schmeler et al. Clinical evaluation of semiautonomous smart wheelchair architecture (drive-safe system) with visually impaired individuals. *Journal of rehabilitation research and development*, 49(1):35, 2012.

[98] Giulio Fontana Matteo Matteucci Andrea Bonarini, Simone Ceriani. Introducing lurch: a shared autonomy robotic wheelchair with multimodal interfaces. In *In Proceedings of IROS 2012 Workshop on Progress, Challenges and Future Perspectives in Navigation and Manipulation Assistance for Robotic Wheelchairs*, pages 1–6, 2012.

[99] Rodrigo Antonio Marques Braga, Marcelo Petry, Luís Paulo Reis, and Antonio Paulo Moreira. Intellwheels: Modular development platform for intelligent wheelchairs. *Journal of Rehabilitation Research & Development*, 48(9):1061–1077, 2011.

[100] Nicolas Ragot, Fadoua Bouzbouz, Redouane Khemmar, Jean-Yves Ertaud, Anne-Marie Kokosy, Ouiddad Labbani-Igbida, Patricia Sajous, Emmnanuel Niyonsaba, Daniel

Reguer, Huosheng Hu, et al. Enhancing the autonomy of disabled persons: Assistive technologies directed by user feedback. In *Emerging Security Technologies (EST), 2013 Fourth International Conference on*, pages 71–74. IEEE, 2013.

[101] DavidP. Miller and MarcG. Slack. Design and testing of a low-cost robotic wheelchair prototype. *Autonomous Robots*, 2(1):77–88, 1995.

[102] I. Mougharbel, R. El-Hajj, H. Ghamlouch, and E. Monacelli. Comparative study on different adaptation approaches concerning a sip and puff controller for a powered wheelchair. In *2013 Science and Information Conference*, pages 597–603, Oct 2013.

[103] Julio Abascal, Daniel Cagigas, Nestor Garay, and Luis Gardeazabal. Mobile interface for a smart wheelchair. *Human Computer Interaction with Mobile Devices*, pages 433–440, 2002.

[104] Jeong-Su Han, Z Zenn Bien, Dae-Jin Kim, Hyong-Euk Lee, and Jong-Sung Kim. Human-machine interface for wheelchair control with emg and its evaluation. In *Engineering in Medicine and Biology Society, 2003. Proceedings of the 25th Annual International Conference of the IEEE*, volume 2, pages 1602–1605. IEEE, 2003.

[105] Dmitry Sinyukov, Ross Desmond, Matthew Dickerman, James Fleming, Jerome Schaufeld, and Taskin Padir. Multi-modal control framework for a semi-autonomous wheelchair using modular sensor designs. *Intelligent Service Robotics*, 7(3):145–155, 2014.

[106] Eun Yi Kim. Wheelchair navigation system for disabled and elderly people. *Sensors*, 16(11):1806, 2016.

[107] Rama Mohana Reddy Kallam and Harish Kumar Sharma. Development of intelligent powerd wheelchair. In *Advance Computing Conference (IACC), 2017 IEEE 7th International*, pages 560–565. IEEE, 2017.

[108] Poornima Devi R Siva Bharathi K R Monisha B, Niranjana M. Intelligent wheelchair. *International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)*, 4(12), 2017.

[109] Jin Sun Ju, Yunhee Shin, and Eun Yi Kim. Vision based interface system for hands free control of an intelligent wheelchair. *Journal of neuroengineering and rehabilitation*, 6(1):33, 2009.

[110] M. Faezipour A. Al-Rahayfeh. Eye tracking and head movement detection: A state-of-art survey, 2013.

[111] Yoshihisa Adachi, Hiroyuki Tsunenari, Yoshio Matsumoto, and Tsukasa Ogasawara. Guide robot's navigation based on attention estimation using gaze information. In *Intelligent Robots and Systems, 2004.(IROS 2004). Proceedings. 2004 IEEE/RSJ International Conference on*, volume 1, pages 540–545. IEEE, 2004.

[112] Jae-Woong Min, Kyoobin Lee, Soo-Chul Lim, and Dong-Soo Kwon. Human-friendly interfaces of wheelchair robotic system for handicapped persons. In *Intelligent Robots and Systems, 2002. IEEE/RSJ International Conference on*, volume 2, pages 1505–1510. IEEE, 2002.

[113] Ericka-Janet Rechy-Ramirez, Huosheng Hu, and Klaus McDonald-Maier. Head movements based control of an intelligent wheelchair in an indoor environment. In *Robotics and Biomimetics (ROBIO), 2012 IEEE International Conference on*, pages 1464–1469. IEEE, 2012.

[114] Ikushi Yoda, Katsuhiko Sakaue, and Takenobu Inoue. Development of head gesture interface for electric wheelchair. In *Proceedings of the 1st international convention on Rehabilitation engineering & assistive technology: in conjunction with 1st Tan Tock Seng Hospital Neurorehabilitation Meeting*, pages 77–80. ACM, 2007.

[115] Tao Lu. A motion control method of intelligent wheelchair based on hand gesture recognition. In *Industrial Electronics and Applications (ICIEA), 2013 8th IEEE Conference on*, pages 957–962. IEEE, 2013.

[116] Diksha Goyal and Dr SPS Saini. Accelerometer based hand gesture controlled wheelchair. *International Journal on Emerging Technologies*, 4(2):15–20, 2013.

[117] G Schmeisser and W Seamone. An assistive equipment controller for quadriplegics. 145:84–8, 10 1979.

[118] Songfeng Guo, RA Cooper, ML Boninger, A Kwarciak, and B Ammer. Development of power wheelchair chin-operated force-sensing joystick. In *Engineering in Medicine and Biology, 2002. 24th Annual Conference and the Annual Fall Meeting of the Biomedical Engineering Society EMBS/BMES Conference, 2002. Proceedings of the Second Joint*, volume 3, pages 2373–2374. IEEE, 2002.

[119] Kyoobin Lee and Dong-Soo Kwon. Wearable master device for spinal injured persons as a control device for motorized wheelchairs. *Artificial Life and Robotics*, 4(4):182–187, 2000.

[120] A. Ruíz-Serrano, R. Posada-Gómez, A. Martínez-Sibaja, G. Alor-Hernández, and A. A. Aguilar-Laserre. Development of a magnetic control system for an electric wheelchair using the tongue. In *CONIELECOMP 2013, 23rd International Conference on Electronics, Communications and Computing*, pages 254–259, March 2013.

[121] Morten Enemark Lund, Henrik Vie Christiensen, Héctor A Caltenco, Eugen Romulus Lontis, Bo Bentsen, and Lotte NS Andreasen Struijk. Inductive tongue control of powered wheelchairs. In *Engineering in Medicine and Biology Society (EMBC), 2010 Annual International Conference of the IEEE*, pages 3361–3364. IEEE, 2010.

[122] R. S. Rao, K. Conn, S. H. Jung, J. Katupitiya, T. Kientz, V. Kumar, J. Ostrowski, S. Patel, and C. J. Taylor. Human robot interaction: application to smart wheelchairs. In *Proceedings 2002 IEEE International Conference on Robotics and Automation (Cat. No.02CH37292)*, volume 4, pages 3583–3588 vol.4, 2002.

[123] Fahad Wallam and Muhammad Asif. Dynamic finger movement tracking and voice commands based smart wheelchair. *International Journal of Computer and Electrical Engineering*, 3(4), 2011.

[124] Amit Ranjan Trivedi, Abhash Kumar Singh, Sundara Tejaswi Digumarti, Deepak Fulwani, and Swagat Kumar. Design and implementation of a smart wheelchair. In *Proceedings of Conference on Advances In Robotics*, AIR '13, pages 96:1–96:6, New York, NY, USA, 2013. ACM.

[125] Xiaodong Xu, Yi Zhang, Yuan Luo, and Dongyi Chen. Robust bio-signal based control of an intelligent wheelchair. *Robotics*, 2(4):187–197, 2013.

[126] Rafael Barea, Luciano Boquete, Manuel Mazo, and E López. Wheelchair guidance strategies using eog. *Journal of Intelligent & Robotic Systems*, 34(3):279–299, 2002.

[127] Masafumi Hashimoto, Kazuhiko Takahashi, and Masanari Shimada. Wheelchair control using an eog-and emg-based gesture interface. In *Advanced Intelligent Mechatronics, 2009. AIM 2009. IEEE/ASME International Conference on*, pages 1212–1217. IEEE, 2009.

[128] Brendan Z Allison, Elizabeth Winter Wolpaw, and Jonathan R Wolpaw. Brain-computer interface systems: progress and prospects. *Expert review of medical devices*, 4(4):463–474, 2007.

[129] Anas Fattouh, Odile Horn, and Guy Bourhis. Emotional bci control of a smart wheelchair. *Int. J. Comput. Sci*, 10(1):32–36, 2013.

[130] Tom Carlson and Jose del R Millan. Brain-controlled wheelchairs: a robotic architecture. *IEEE Robotics & Automation Magazine*, 20(1):65–73, 2013.

[131] Inhyuk Moon, Myungjoon Lee, Jeicheong Ryu, and Museong Mun. Intelligent robotic wheelchair with emg-, gesture-, and voice-based interfaces. In *Intelligent Robots and Systems, 2003.(IROS 2003). Proceedings. 2003 IEEE/RSJ International Conference on*, volume 4, pages 3453–3458. IEEE, 2003.

[132] Mohammed Hayyan ALSIBA, Hadi Bin Manap, and Abdul Adam Bin Abdullah. Enhanced face recognition method performance on android vs windows platform. In *Proceedings of International Conference on Electrical, Control and Computer Engineering, Malaysia*, volume 6, 2006.

[133] Vigneshwar Santhanam and Vignesh Viswanathan. Smartphone accelerometer controlled automated wheelchair. In *Proceedings of the 3rd International Conference on Electronics, Biomedical Engineering and its Applications*, pages 57–61, 2013.

[134] Mari Carmen Domingo. An overview of the internet of things for people with disabilities. *Journal of Network and Computer Applications*, 35(2):584–596, 2012.

[135] Cindy Wahyufitriyani, Susy Susmartini, and Ilham Priadythama. Review of intelligent wheelchair technology control development in the last 12 years. In *Industrial, Mechanical, Electrical, and Chemical Engineering (ICIMECE), International Conference of*, pages 201–206. IEEE, 2016.

[136] G Pacnik, K Benkic, and B Brecko. Voice operated intelligent wheelchair-voic. In *Industrial Electronics, 2005. ISIE 2005. Proceedings of the IEEE International Symposium on*, volume 3, pages 1221–1226. IEEE, 2005.

[137] Richard C Simpson and Simon P Levine. Voice control of a powered wheelchair. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 10(2):122–125, 2002.

[138] Masato Nishimori, Takeshi Saitoh, and Ryosuke Konishi. Voice controlled intelligent wheelchair. In *SICE, 2007 annual conference*, pages 336–340. IEEE, 2007.

[139] M Al-Rousan and Khaled Assaleh. A wavelet-and neural network-based voice system for a smart wheelchair control. *Journal of the Franklin Institute*, 348(1):90–100, 2011.

[140] Ali A Abed. Design of voice controlled smart wheelchair. *International Journal of Computer Applications*, 131(1), 2015.

[141] G Bourhis and M Sahnoun. Assisted control mode for a smart wheelchair. In *Rehabilitation Robotics, 2007. ICORR 2007. IEEE 10th International Conference on*, pages 158–163. IEEE, 2007.

[142] Mohammed-Amine Hadj-Abdelkader, Guy Bourhis, and Brahim Cherki. Haptic feedback control of a smart wheelchair. *Applied Bionics and Biomechanics*, 9(2):181–192, 2012.

[143] Y Morere, MA Hadj Abdelkader, K Cosnuau, G Guilmois, and G Bourhis. Haptic control for powered wheelchair driving assistance. *IRBM*, 36(5):293–304, 2015.

[144] Sridhar P Arjunan, Hans Weghorn, Jay O'Connor, Dinesh Kumar, Sruthi Shahebjada, and Teodiano Bastos. Towards better real-time control of smart wheelchair using subtle finger movements via wireless (blue-tooth) interface. In *Intelligent Human Computer Interaction (IHCI), 2012 4th International Conference on*, pages 1–5. IEEE, 2012.

[145] Manju Davy. Hardware implementation based on head movement using accelerometer sensor 1. 2014.

[146] Vinay J Shetty, Maruti Laxman, Manjunath S Magdum, Shweta B Sidnal, and Soumya Paraddi. Head motion controlled wheel chair using mems. *International Advanced Research Journal in Science, Engineering and Technology*, 2(6):84–86, 2015.

[147] Sho Yokota, Hiroshi Hashimoto, Yasuhiro Ohyama, Jin-Hua She, Hisato Kobayashi, and Pierre Blazevic. The electric wheelchair controlled by human body motion. In *Human System Interactions, 2009. HSI'09. 2nd Conference on*, pages 247–250. IEEE, 2009.

[148] Christian Mandel, Thorsten Lüth, Tim Laue, Thomas Röfer, Axel Gräser, and Bernd Krieg-Brückner. Navigating a smart wheelchair with a brain-computer interface inter-

preting steady-state visual evoked potentials. In *Intelligent Robots and Systems, 2009. IROS 2009. IEEE/RSJ International Conference on*, pages 1118–1125, 2009.

[149] Cristina Urdiales, Blanca Fernandez-Espejo, Roberta Annicchiaricco, Francisco Sandoval, and Carlo Caltagirone. Biometrically modulated collaborative control for an assistive wheelchair. *IEEE transactions on neural systems and rehabilitation engineering*, 18(4):398–408, 2010.

[150] Kok Swee Sim, Lim Zheng You, and Kho Teck Kiang. Brainwave controlled electrical wheelchair. In *MATEC Web of Conferences*, volume 54. EDP Sciences, 2016.

[151] TM Nirmal. Wheelchair for physically and mentally disabled persons. *International Journal of Electrical and Electronics Research*, 2(2):112–118, 2014.

[152] Jordan S Nguyen, Steven W Su, and Hung T Nguyen. Experimental study on a smart wheelchair system using a combination of stereoscopic and spherical vision. In *Engineering in Medicine and Biology Society (EMBC), 2013 35th Annual International Conference of the IEEE*, pages 4597–4600. IEEE, 2013.

[153] David Balderas and Mario Rojas. Human movement control. In Pedro Ponce, Arturo Molina Gutierrez, and Luis M. Ibarra, editors, *Automation and Control Trends*, chapter 04. InTech, Rijeka, 2016.

[154] Mohammed Alshraideh, Basel A Mahafzah, Saleh Al-Sharaeh, and Ziad M Hawamdeh. A robotic intelligent wheelchair system based on obstacle avoidance and navigation functions. *Journal of Experimental & Theoretical Artificial Intelligence*, 27(4):471–482, 2015.

[155] S Adarsh, S Mohamed Kaleemuddin, Dinesh Bose, and KI Ramachandran. Performance comparison of infrared and ultrasonic sensors for obstacles of different materials in vehicle/robot navigation applications. In *IOP Conference Series: Materials Science and Engineering*, volume 149, page 012141. IOP Publishing, 2016.

[156] B Mustapha, A Zayegh, and RK Begg. Multiple sensors based obstacle detection system. In *Intelligent and Advanced Systems (ICIAS), 2012 4th International Conference on*, volume 2, pages 562–566. IEEE, 2012.

[157] Deepesh K Rathore, Pulkit Srivastava, Sankalp Pandey, and Sudhanshu Jaiswal. A novel multipurpose smart wheelchair. In *Electrical, Electronics and Computer Science (SCEECS), 2014 IEEE Students' Conference on*, pages 1–4. IEEE, 2014.

[158] Smile Smart Technology Ltd. Smile smart wheelchairs. Available: https://smilesmart-tech.com/assistive-technology-products/smile-smart-wheelchair/. Last accessed 27 November 2017.

[159] Nandita Sharma and Tom Gedeon. Objective measures, sensors and computational techniques for stress recognition and classification: A survey. *Computer methods and programs in biomedicine*, 108(3):1287–1301, 2012.

[160] P Karthikeyan, M Murugappan, and S Yaacob. A review on stress inducement stimuli for assessing human stress using physiological signals. In *Signal processing and its applications (cspa), 2011 ieee 7th international colloquium on*, pages 420–425. IEEE, 2011.

[161] Alberto de Santos Sierra, Carmen Sánchez Ávila, Gonzalo Bailador del Pozo, and Javier Guerra Casanova. Stress detection by means of stress physiological template. In *Nature and Biologically Inspired Computing (NaBIC), 2011 Third World Congress on*, pages 131–136. IEEE, 2011.

[162] Ke Ma, Joshua CT Khoo, and Thomas IH Brown. Development of an ambulatory multi-parameter monitoring system for physiological stress related parameters. In *Bioinformatics and Biomedical Technology (ICBBT), 2010 International Conference on*, pages 324–328. IEEE, 2010.

[163] Pankaj Sareen. Biometrics–introduction, characteristics, basic technique, its types and various performance measures. *International Journal of Emerging Research in Management & Technology*, 3, 2014.

[164] Jennifer A Healey and Rosalind W Picard. Detecting stress during real-world driving tasks using physiological sensors. *IEEE Transactions on intelligent transportation systems*, 6(2):156–166, 2005.

[165] Alberto de Santos Sierra, Carmen Sánchez Ávila, Javier Guerra Casanova, and Gonzalo Bailador del Pozo. A stress-detection system based on physiological signals and fuzzy logic. *IEEE Transactions on Industrial Electronics*, 58(10):4857–4865, 2011.

[166] Jacqueline Wijsman, Bernard Grundlehner, Hao Liu, Hermie Hermens, and Julien Penders. Towards mental stress detection using wearable physiological sensors. In *Engineering in Medicine and Biology Society, EMBC, 2011 Annual International Conference of the IEEE*, pages 1798–1801. IEEE, 2011.

[167] Ollander Simon, Christelle Godin, Sylvie Charbonnier, and Aurélie Campagne. Selection of the most relevant physiological features for classifying emotion. In *3rd International Conference on Physiological Computing Systems (PhyCS 2016)*, Lisbonne, Portugal, June 2016.

[168] Nandita Sharma and Tom Gedeon. Modeling a stress signal. *Applied Soft Computing*, 14:53–61, 2014.

[169] Mandeep Singh and Abdullah Bin Queyam. Stress detection in automobile drivers using physiological parameters: A review. *International Journal of Electronics Engineering*, 5(2):1–5, 2013.

[170] Yan Ge, Weina Qu, Caihong Jiang, Feng Du, Xianghong Sun, and Kan Zhang. The effect of stress and personality on dangerous driving behavior among chinese drivers. *Accident Analysis & Prevention*, 73:34–40, 2014.

[171] Feng-Tso Sun, Cynthia Kuo, Heng-Tze Cheng, Senaka Buthpitiya, Patricia Collins, and Martin Griss. Activity-aware mental stress detection using physiological sensors. In *International Conference on Mobile Computing, Applications, and Services*, pages 282–301. Springer, 2010.

[172] Rob Hoskin. The dangers of self-report. Available: http://www.sciencebrainwaves.com/the-dangers-of-self-report/. Last accessed 6 March 2018.

[173] Mitchel Benovoy, Jeremy R Cooperstock, and Jordan Deitcher. Biosignals analysis and its application in a performance setting. In *Proceedings of the International Conference on Bio-Inspired Systems and Signal Processing*, pages 253–258, 2008.

[174] Emran Mohd Tamil, NS Bashar, MYI Idris, and Azmi Mohd Tamil. A review on feature extraction & classification techniques for biosignal processing (part iii: Electromyogram). In *4th Kuala Lumpur International Conference on Biomedical Engineering 2008*, pages 117–121. Springer, 2008.

[175] Rüdiger Kramme, Klaus-Peter Hoffmann, and Robert Pozos. *Springer handbook of medical technology*. Springer Science & Business Media, 2011.

[176] Azian Azamimi Abdullah and Umida Hafsah Hassan. Design and development of an emotional stress indicator (esi) kit. In *Sustainable Utilization and Development in Engineering and Technology (STUDENT), 2012 IEEE Conference on*, pages 253–257. IEEE, 2012.

[177] Yong Deng, Zhonghai Wu, Chao-Hsien Chu, and Tao Yang. Evaluating feature selection for stress identification. In *Information Reuse and Integration (IRI), 2012 IEEE 13th International Conference on*, pages 584–591. IEEE, 2012.

[178] Jiliang Tang, Salem Alelyani, and Huan Liu. Feature selection for classification: A review. *Data Classification: Algorithms and Applications*, page 37, 2014.

[179] Yvan Saeys, Iñaki Inza, and Pedro Larrañaga. A review of feature selection techniques in bioinformatics. *bioinformatics*, 23(19):2507–2517, 2007.

[180] Thair Nu Phyu. Survey of classification techniques in data mining. In *Proceedings of the International MultiConference of Engineers and Computer Scientists*, volume 1, pages 18–20, 2009.

[181] Sagar S Nikam. A comparative study of classification techniques in data mining algorithms. *Oriental Journal of Computer Science & Technology*, 8(1):13–19, 2015.

[182] Mikhail Sysoev, Urban Sedlar, Andrej Kos, and Matevz Pogacnik. Stress-sensors classification and stress-analysis algorithms review/pregled senzorjev in algoritmov za dolocanje stopnje stresa. *Elektrotehniski vestnik*, 81(5):263, 2014.

[183] E. H. Jang, B. J. Park, S. H. Kim, and J. H. Sohn. Emotion classification based on physiological signals induced by negative emotions: Discriminantion of negative emotions by machine learning algorithm. In *Proceedings of 2012 9th IEEE International Conference on Networking, Sensing and Control*, pages 283–288, April 2012.

[184] MG Kumar and VR Dhulipala. Fuzzy logic based stress level classification using physiological parameters. *Asian Journal of Research in Social Sciences and Humanities*, 6(cs1):697–713, 2016.

[185] Feng-Tso Sun, Cynthia Kuo, Heng-Tze Cheng, Senaka Buthpitiya, Patricia Collins, and Martin Griss. Activity-aware mental stress detection using physiological sensors. In *International Conference on Mobile Computing, Applications, and Services*, pages 282–301. Springer, 2010.

[186] E-H Jang, B-J Park, S-H Kim, Y Eum, and J-H Sohn. Identification of the optimal emotion recognition algorithm using physiological signals. In *Engineering and Industries (ICEI), 2011 International Conference on*, pages 1–6. IEEE, 2011.

[187] L Vanitha and GR Suresh. Hybrid svm classification technique to detect mental stress in human beings using ecg signals. In *Advanced Computing and Communication Systems (ICACCS), 2013 International Conference on*, pages 1–6. IEEE, 2013.

[188] Virginia Sandulescu, Sally Andrews, David Ellis, Nicola Bellotto, and Oscar Martinez Mozos. Stress detection using wearable physiological sensors. In *International Work-Conference on the Interplay Between Natural and Artificial Computation*, pages 526–532. Springer, 2015.

[189] Bong Siao Zheng, M Murugappan, and Sazali Yaacob. Human emotional stress assessment through heart rate detection in a customized protocol experiment. In *Industrial Electronics and Applications (ISIEA), 2012 IEEE Symposium on*, pages 293–298. IEEE, 2012.

[190] Bong Siao Zheng, M Murugappan, Sazali Yaacob, and Subbulakshmi Murugappan. Human emotional stress analysis through time domain electromyogram features. In *Industrial Electronics and Applications (ISIEA), 2013 IEEE Symposium on*, pages 172–177. IEEE, 2013.

[191] Tatiur Rahman, Apu Kumer Ghosh, Md Maruf Hossain Shuvo, and Md Mostafizur Rahman. Mental stress recognition using k-nearest neighbor (knn) classifier on eeg signals. In *International Conference on Materials, Electronics & Information Engineering, ICMEIE-2015*, 2015.

[192] Jerritta Selvaraj, Murugappan Murugappan, Khairunizam Wan, and Sazali Yaacob. Classification of emotional states from electrocardiogram signals: a non-linear approach based on hurst. *Biomedical engineering online*, 12(1):44, 2013.

[193] Korbinian Frank, Patrick Robertson, Michael Gross, and Kevin Wiesner. Sensor-based identification of human stress levels. In *Pervasive Computing and Communications Workshops (PERCOM Workshops), 2013 IEEE International Conference on*, pages 127–132. IEEE, 2013.

[194] AS Anusha, Jose Joy, SP Preejith, Jayaraj Joseph, and Mohanasankar Sivaprakasam. Differential effects of physical and psychological stressors on electrodermal activity. In *Engineering in Medicine and Biology Society (EMBC), 2017 39th Annual International Conference of the IEEE*, pages 4549–4552. IEEE, 2017.

[195] U.S. Department of Health Bette Runck, Human Services Division of Communications, and National Institute of Mental Health Education. What is biofeedback? Available: http://psychotherapy.com/bio.html. Last accessed 3 Juin 2016.

[196] HeartMath. emwave2. Avaiable: http://store.heartmath.com/emwave2. Last accessed 7 Juin 2016.

[197] Christine Dunster. Treatment of anxiety and stress with biofeedback. *Global Advances in Health and Medicine*, 1(4):76–83, 2012.

[198] SCHUHFRIED. Biofeedback xpert – the multi-media system from schuhfried. Available: https:/https://www.schuhfried.com/biofeedback/biofeedback-xpert/. Last accessed 6 March November 2018.

[199] G. Schuhfried. Dt determination test. Available: https://www.schuhfried.com/test/dt. Last accessed 7 Juin 2016.

[200] National Center for Telehealth Technology. Available: https://science.dodlive.mil/2013/02/13/biozen-the-biofeedback-mobile-app/. Last accessed 02 October 2019.

[201] Shimmer Discovery in motion. Shimmer capture for android. Available:http://www.shimmersensing.com/products/shimmercapture-for-android. Last accessed 02 October 2019.

[202] Rajiv Ranjan Singh and Rahul Banerjee. Multi-parametric analysis of sensory data collected from automotive drivers for building a safety-critical wearable computing system. In *Computer Engineering and Technology (ICCET), 2010 2nd International Conference on*, volume 1, pages V1–355. IEEE, 2010.

[203] George Rigas, Yorgos Goletsis, and Dimitrios I Fotiadis. Real-time driver's stress event detection. *IEEE Transactions on intelligent transportation systems*, 13(1):221–234, 2012.

[204] J. Choi, B. Ahmed, and R. Gutierrez-Osuna. Development and evaluation of an ambulatory stress monitor based on wearable sensors. *IEEE Transactions on Information Technology in Biomedicine*, 16(2):279–286, March 2012.

[205] Sunghyun Yoon, Jai Kyoung Sim, and Young-Ho Cho. A flexible and wearable human stress monitoring patch. *Scientific reports*, 6:23468, 2016.

[206] Emre Ertin, Nathan Stohs, Santosh Kumar, Andrew Raij, Mustafa Al'Absi, and Siddharth Shah. Autosense: unobtrusively wearable sensor suite for inferring the onset, causality, and consequences of stress in the field. In *Proceedings of the 9th ACM Conference on Embedded Networked Sensor Systems*, pages 274–287. ACM, 2011.

[207] Owano Nancy. Ford explores call turnoffs for stressed-out drivers. Available: http://phys.org/news/2012-06-ford-explores-turnoffs-stressed-out-drivers.html., 2012. Last accessed 7 Juin 2016.

[208] Darren Quick. Smart steering wheel gives a health check while driving. Available: http://www.gizmag.com/smart-steering-wheel/20467/., 2011. Last accessed 7 Juin 2016.

[209] William Burns, PJ McCullagh, Chris Nugent, and Huiru Zheng. Evaluating the lifelog: a serious game for reminiscence. 2017.

[210] Jason J Braithwaite, Derrick G Watson, Robert Jones, and Mickey Rowe. A guide for analysing electrodermal activity (eda) & skin conductance responses (scrs) for psychological experiments. *Psychophysiology*, 49:1017–1034, 2013.

[211] Bernd Figner, Ryan O Murphy, et al. Using skin conductance in judgment and decision making research. *A handbook of process tracing methods for decision research*, pages 163–184, 2011.

[212] Paul A Iaizzo. *Handbook of cardiac anatomy, physiology, and devices*. Springer Science & Business Media, 2009.

[213] Diane R. Karius. Ecg primer: The leads of a 12-lead ecg. Available: https://courses.kcumb.edu/physio/ecg%20primer/ecgleads.htm. Last accessed 22 September 2019.

[214] Springhouse. *Nursing Know-how: Interpreting ECG's*. Lippincott Williams & Wilkins, 2009.

[215] PH King. Noninvasive instrumentation and measurement medical diagnosis. *IEEE Engineering in Medicine and Biology Magazine*, 21(4):131–133, 2002.

[216] S Karpagachelvi, M Arthanari, and M Sivakumar. Ecg feature extraction techniques-a survey approach. *arXiv preprint arXiv:1005.0957*, 2010.

[217] V Seena and Jerrin Yomas. A review on feature extraction and denoising of ecg signal using wavelet transform. In *Devices, Circuits and Systems (ICDCS), 2014 2nd International Conference on*, pages 1–6. IEEE, 2014.

[218] Noor Azuan Abu Osman, Fatimah Ibrahim, Wan Abu Bakar Wan Abas, Herman Shah Abdul Rahman, and Hua Nong Ting. *4th Kuala Lumpur International Conference on Biomedical Engineering 2008: BIOMED 2008, 25-28 June 2008, Kuala Lumpur, Malaysia*, volume 21. Springer Science & Business Media, 2008.

[219] Mikhail Sysoev, Urban Sedlar, Andrej Kos, and Matevz Pogacnik. Stress-sensors classification and stress-analysis algorithms review/pregled senzorjev in algoritmov za dolocanje stopnje stresa. *Elektrotehniski vestnik*, 81(5):263, 2014.

[220] Hindra Kurniawan, Alexandr V Maslov, and Mykola Pechenizkiy. Stress detection from speech and galvanic skin response signals. In *Computer-Based Medical Systems (CBMS), 2013 IEEE 26th International Symposium on*, pages 209–214. IEEE, 2013.

[221] Feng-Tso Sun, Cynthia Kuo, Heng-Tze Cheng, Senaka Buthpitiya, Patricia Collins, and Martin Griss. Activity-aware mental stress detection using physiological sensors. In *International Conference on Mobile Computing, Applications, and Services*, pages 282–301. Springer, 2010.

[222] Jing Zhai, Armando B Barreto, Craig Chin, and Chao Li. Realization of stress detection using psychophysiological signals for improvement of human-computer interactions. In *SoutheastCon, 2005. Proceedings. IEEE*, pages 415–420. IEEE, 2005.

[223] Rajiv Ranjan Singh and Rahul Banerjee. Multi-parametric analysis of sensory data collected from automotive drivers for building a safety-critical wearable computing system. In *Computer Engineering and Technology (ICCET), 2010 2nd International Conference on*, volume 1, pages V1–355. IEEE, 2010.

[224] Siao Zheng Bong, M Murugappan, and Sazali Yaacob. Analysis of electrocardiogram (ecg) signals for human emotional stress classification. In *International Conference on Intelligent Robotics, Automation, and Manufacturing*, pages 198–205. Springer, 2012.

[225] Hari Singh Dhillon and Navleen Singh Rekhi. The effect of emotions on electrocardiogram. *Academic Research International*, 1(1):280, 2011.

[226] Azian Azamimi Abdullah and Umida Hafsah Hassan. Design and development of an emotional stress indicator (esi) kit. In *Sustainable Utilization and Development in Engineering and Technology (STUDENT), 2012 IEEE Conference on*, pages 253–257. IEEE, 2012.

[227] Julian F Thayer, Fredrik Åhs, Mats Fredrikson, John J Sollers, and Tor D Wager. A meta-analysis of heart rate variability and neuroimaging studies: implications for heart rate variability as a marker of stress and health. *Neuroscience & Biobehavioral Reviews*, 36(2):747–756, 2012.

[228] Hye-Geum Kim, Eun-Jin Cheon, Dai-Seg Bai, Young Hwan Lee, and Bon-Hoon Koo. Stress and heart rate variability: A meta-analysis and review of the literature. *Psychiatry investigation*, 15(3):235, 2018.

[229] Jerritta Selvaraj, Murugappan Murugappan, Khairunizam Wan, and Sazali Yaacob. Classification of emotional states from electrocardiogram signals: a non-linear approach based on hurst. *Biomedical engineering online*, 12(1):44, 2013.

[230] Steven C Kirshblum, Stephen P Burns, Fin Biering-Sorensen, William Donovan, Daniel E Graves, Amitabh Jha, Mark Johansen, Linda Jones, Andrei Krassioukov, MJ Mulcahey, et al. International standards for neurological classification of spinal cord injury (revised 2011). *The journal of spinal cord medicine*, 34(6):535–546, 2011.

[231] Valentin Titus Grigorean, Aurelia Mihaela Sandu, Mihai Popescu, Mihai Aurelian Iacobini, Rares Stoian, Catalin Neascu, and Florian Popa. Cardiac dysfunctions following spinal cord injury. *Journal of medicine and life*, 2(2):133, 2009.

[232] P Serra-Añó, LL Montesinos, J Morales, L López-Bueno, M Gomis, X García-Massó, and LM González. Heart rate variability in individuals with thoracic spinal cord injury. *Spinal Cord*, 53(1):59, 2015.

[233] Marit Grønning Svein Faerestrand Ellen Merete Hagen, Tiina Rekand. Cardiovascular complications of spinal cord injury. Available: https://tidsskriftet.no/en/2012/05/cardiovascular-complications-spinal-cord-injury#reference-7. Last accessed 5 October 2019.

[234] E Heidbreder, A Ziegler, A Heidland, R Kirsten, and W Grüninger. Circulatory changes during mental stress in tetraplegic and paraplegic man. *Klinische Wochenschrift*, 60(15):795–801, 1982.

[235] Armin Curt, Christoph Weinhardt, and Volker Dietz. Significance of sympathetic skin response in the assessment of autonomic failure in patients with spinal cord injury. *Journal of the autonomic nervous system*, 61(2):175–180, 1996.

[236] Kubo T. Lee K. Katayama Y. Kira Y. Aramaki S. Ogura, T. Sympathetic skin response in patients with spinal cord injury. *Department of Orthopaedic Surgery.*, page 35–39, 2004.

[237] B-live. Available: http://www.microio.pt/en/b-live-2008/. Last accessed 4 March 2017.

[238] Glass L Hausdorff JM Ivanov PCh Mark RG Mietus JE Moody GB Peng C-K Stanley HE Goldberger AL, Amaral LAN. Physiobank, physiotoolkit, and physionet: Components of a new research resource for complex physiologic signals. Available: https://physionet.org/pn3/drivedb/. Last accessed 15 November 2018.

[239] International Federation of Robotics. Classification of service robots by application areas. https://ifr.org/img/office/. Last accessed 22 October 2017.

[240] Aaron Staranowicz and Gian Luca Mariottini. A survey and comparison of commercial and open-source robotic simulator software. In *Proceedings of the 4th International Conference on PErvasive Technologies Related to Assistive Environments*, page 56. ACM, 2011.

[241] Olivier Michel. Cyberbotics ltd. webots^{TM}: professional mobile robot simulation. *International Journal of Advanced Robotic Systems*, 1(1):5, 2004.

[242] University Bremen. Simrobot - robotiksimulator. Available: http://www.informatik.uni-bremen.de/simrobot/. Last accessed 22 October 2017.

[243] Brian Gerkey, Richard T Vaughan, and Andrew Howard. The player/stage project: Tools for multi-robot and distributed sensor systems. In *Proceedings of the 11th international conference on advanced robotics*, volume 1, pages 317–323, 2003.

[244] Pedro Daniel Marques. Cadeira de rodas eléctrica adaptada a tetraplégicos. Master's thesis, Universidade de Aveiro, 2010.

[245] Paulo Lopes Simão. Platform to acquire stress signals and register occurrences. Master's thesis, Universidade de Aveiro, 2013.

[246] Sean Farrell. Biometrics in air transport: no flight of fancy. *Biometric Technology Today*, 2019(1):5–7, 2019.

[247] Charles Stangor, Jennifer Walinga, et al. Introduction to psychology-1st canadian edition. 2018.

[248] Carmen Camara, Pedro Peris-Lopez, Juan E Tapiador, and Guillermo Suarez-Tangil. Non-invasive multi-modal human identification system combining ecg, gsr, and airflow biosignals. *Journal of Medical and Biological Engineering*, 35(6):735–748, 2015.

[249] Ala Abdulhakim Alariki, Sayed Mahmoud, Mohammad Reza Yousufi, Mohammad Tareq Aziz, and Christine Murray. A review study of heartbeat biometric authentication. *JCP*, 13(8):936–947, 2018.

[250] Matlab R2013b. classify discriminant analysis. Available: https://www.mathworks.com/help/releases/R2013b/stats/classify.html. Last accessed 6 March 2018.

[251] Matlab R2018b. Train classification models in classification learner app. Available: https://www.mathworks.com/help/stats/train-classification-models-in-classification-learner-app.html. Last accessed 16 August 2019.

[252] KM Ting. Confusion matrix. encyclopedia of machine learning, 2010.

[253] Marina Sokolova, Nathalie Japkowicz, and Stan Szpakowicz. Beyond accuracy, f-score and roc: A family of discriminant measures for performance evaluation. volume Vol. 4304, pages 1015–1021, 01 2006.

Acronyms

AA Aceptance Area, page 83

AC Analyzing and Classification, page 88

ASD Acquisition and Stress Detection, page 88

APW Assisted Powered Wheelchair, page 3

ARM Acquisition and Register Module, page 88

AT Assitive Tecnology, page 2

ARS Artificial Recognition System, page 3

ATM Autonomous Transfer Mode, page 70

CMRRC-RP Centro de Medicina e Reabilitação da Região Centro-Rovisco Pais, page 3

CPW Commercial Powered Wheelchair, page 1

ECG Electrocardiogram, page 23

EHSIS European Health and Social Integration Survey, page 1

EMG Electromyography, page 37

FIM Functional Independence Measure, 16

GSR Galvanic Skin Response, page 23

HR Heart Rate, page 46

HMI Human Machine Interface, page 3

ICT-TU Wien Institute of Computer Technology of the Vienna University, page 3.

IoT Internet of things

LAM Legacy Adapted Mode, page 70

SaTM Semi autonomous Transfer Mode, page 70

SCI Spinal Cord Injury, page 9

SiMA Simulation of the Mental Apparatus & Applications, page 4

SNS Sympathetic Nervous System, page 19

SoNS Somatic Nervous System, page 10

SDS Stress Detection System, page 23

PNS Parasympathetic Nervous System, page 19

PeNS Peripheral Nervous System, page 10

VAHM Véhicule Autonome pour Handicapé Moteur