A Preliminary Case Study: Predicting Postoperative Pain Through Electrocardiogram

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Abstract. Currently pain is mainly evaluated by resorting to self-reporting instruments, turning the objective evaluation of pain barely impossible. Besides the inherent subjectivity due to these reports, the perception of pain is influenced by several factors. Moreover, cognitive impairments and difficulties in expressing pose a burden difficulty in pain evaluation. Beyond less efficient pain management, the consequences of an incorrect pain assessment may result in over or under dosage of analgesics, with potentially harmful consequences due to the undesirable side-effects of wrong doses. Therefore, a quantitative and accurate assessment of pain is critical for the adaptation of healthcare strategies, providing a step further in personalized medicine. Thus, the analysis of Autonomic Nervous System (ANS) reactions, which can be assessed continuously with minimally invasive equipment, offers an excellent opportunity to monitor physiological indicators when in the experience of pain. The goal of the proposed work is to classify the presence of pain in postoperative records. The results show accuracy and precision of around 85%, and recall and F_1-score of 92%, indicating that the experience of postoperative pain can be classified by relying on physiological data.

Keywords: Postoperative pain · ECG · Signal processing · Prediction problems · Machine learning · Decision support

1 Introduction

Pain involves dysregulations in the Autonomic Nervous System (ANS), a primary behavioral regulation system [20]. As the experience of pain induces reactions in the ANS, and, as it functions without conscious control [4], the study of such reactions is a feasible way to assess pain.

The ANS controls various organ systems inside the body, namely muscles, glands, and organs within the body. While maintaining the equilibrium of the body's systems according to both internal and external stimuli, many physiological signals reflect the activity of the ANS. The activation of the ANS can suppress or, in pathological states, aid pain.

Due to the lack of quantified pain measures, currently, pain is mainly evaluated by resorting to self-reporting instruments. Besides the inherent subjectivity due to these types of reports, the perception of pain is influenced by several factors. Moreover, cognitive impairments and difficulties in expressing pose a burden hazard in pain evaluation.

An incorrect assessment of pain may lead to undertreatment or overtreatment of pain [5,16], difficult the overall recovery [9,18], and lead to adverse psychological and cognitive effects [7,15]. Moreover, in postoperative pain, the correct management of pain is a critical task of utmost relevance to ensure patient comfort. Thus, researchers have been using statistical inference to describe and characterize the experience of pain and proposed machine learning models to identify pain and/or classify pain levels.

Considering that it is of utmost importance to proper assess pain, there are recent studies showing that common symptoms associated with pain seem to induce a broad heightened sympathetic branch activation of the Autonomic Nervous System (ANS), including increased electrodermal and respiratory activities, cardiac acceleration and heightened muscle contraction [3,6,8,11–13,19,20].

In [11], the authors agree that the severity of postoperative pain significantly influences SC (skin conductance). From a sample of 25 patients subjected to surgery (11 general surgical patients, 9 orthopedic, and 5 plastics cases), they demonstrated a correlation between NFSC (number of fluctuations within the mean SC per second) and self-assessed pain measured using a NRS (numeric rating scale), concluding that changes in levels of patient-rated postoperative pain on a NRS are reflected by corresponding changes of NFSC as a parameter of SC.

A total of 180 children within 3 different age groups (with valid pain assessments in 165 patients), undergoing elective surgery, had participated in the study [6]. The authors proposed using changes in the NFSC as a biomarker to assess acute postoperative pain, being able to predict moderate to severe postoperative pain from NFSC.

Based on the relationship between lowered heart rate variability (HRV) and poor health, the authors of [3] proposed HRV as a biomarker. Participants included 104 healthy control children and 48 children with chronic pain, aged from 8 to 17 years, and laboratory sessions involved four pain induction tasks (evoked pressure, cold pressor, focal pressure, and a conditioned pain modulation task).

1.1 Motivation, Goals, and Structure

The above studies sustained the importance of an accurate assessment of acute pain as an essential component of postoperative care, improving pain control, avoiding undesirable side-effects from under/overdosage, and promoting health-care.

During the postoperative period, the pain that the patient is being subjected to, and the pain reported, varies a lot according to the overthrow of the anesthesia and the effects of analgesics administered. Thus, these changes may be rendered by physiological signals, such as the ECG.

The purpose of the present study is to go beyond the characterization of postoperative pain, proposing the classification of postoperative pain through features computed from Heart Rate (HR), which render the influence of pain in ECG.

Regarding the evaluation of postoperative pain, assessed in the recovery room, the goal of this work is to address the classification of pain experience through HR-based features. To the best of our knowledge, this is the first attempt to classify postoperative pain experience through physiological data.

The remainder of this work is organized as follows: Sect. 2 describes the setup, the equipment, and the methodology of data collection and physiological monitoring, as well as the methods used for data analysis. In Sect. 3 the results are presented and discussed. Final remarks and future research lines are presented in Sect. 4.

2 Dataset Description and Methodology

This section describes the setup and data collection, as well as the ECG processing techniques for feature extraction, and provides a description of the data used for postoperative pain prediction. The machine learning methodology applied to classify pain in postoperative scenarios is also explained. Data analysis was performed in MATLAB [14] and Python, using the NeuroKit2[1], which provides biosignal processing routines.

2.1 Setup and Data Collection

The study was conducted in accordance with the Declaration of Helsinki, and under the approval of the Ethics Committee for Health of Centro Hospitalar Tondela-Viseu (CHTV), with document number 894, 30/11/2018, and the Ethics and Deontology Council of the University of Aveiro, with document number 36/2018, 03/04/2019.

This study required the participation of adults patients who underwent elective neck and thorax surgeries at CHTV, recruited on a volunteer base after written informed consent. The exclusion criteria applied included the presence of major systems diseases, congenital syndromes, pacemakers, and psychological/psychiatric/mental disorders. The data used in this study was collected in the recovery room, after surgery, during the standard clinical practices of analgesia, fulfilling all the clinical aspects, and without compromising the patient's well-being.

During data monitoring, through the Vital Jacket® [1], with a sampling rate 500 Hz, and using two electrodes placed on the right and left side of the participant's ribcage and a reference electrode placed above the pelvic bone, the patients' health and well-being was always the first concern.

All the procedures were explained to the voluntary participants, as well as being informed that there were no risks involved in participating and that they could decline from participating in the study at any time.

[1] https://neurokit2.readthedocs.io/en/latest/.

Besides the ECG signals, this dataset contains information on patient age, gender, type of surgical intervention, and type of anesthesia protocol. The procedures performed during the postoperative recovery of patients were also registered, including self-reports of pain, pain relief therapeutics, and other medical interventions, such as patient repositioning. These procedures are associated with time triggers that mark the event occurrence in the ECG signal. The evaluation of pain was based on self-report instruments (Numerical Rating Scale - NRS [21]) and several assessments, as necessary accordingly to the clinical team, were obtained until discharge.

Of the twenty patients in the dataset, one patient was withdrawn from the study because of the lack of pain assessment annotations during the ECG recording, resulting in a total of nineteen patients (60 ± 21 years old), ten females.

2.2 Feature Extraction

The ECG signals are affected by noise, such as skin-electrode interference (low-frequency noise, which is amplified by motion, movements, and respiratory variation), powerline (with a frequency 50 Hz), and electronic devices (high-frequency noise) namely from the clinical apparatus that concern this specific clinical scenario [2,10]. To attenuate the effects of noise and improve the quality of the signal, the raw ECG was low-pass filtered at a cut-off frequency 40 Hz, as the useful band of frequencies for these research purposes, without clinical relevance, varies between 0.5 Hz and 40 Hz. Afterward, the baseline wander was removed with a moving average filter, and Heart Rate was computed using the distance between R peaks locations.

The HR-features used for postoperative pain prediction had been proposed by [17] for early classification of mortality prediction based on ECG information, with F1-score around 93%. Thus, based on the reasoning provided for that problem, the proposed work attains to predict postoperative pain using the same features. Considering that postoperative pain can be assessed within the time-period before ('pain') and after ('no pain') analgesia administration, ECG-epochs of 1 min before and 1 min after the administration of analgesia for pain relief were used. For the ECG data after the administration of pain, it was considered different time epochs with a duration of 1 min, however with different initial times regarding the administration of analgesia. Namely, one, two, and three minutes after the administration of pain relief drugs. This strategy, besides assessing pain, will also allow reasoning on the time-effect of analgesia. Thus, using sliding windows of 10 s, HR-features were computed for these different epochs and, thereafter, were normalized before the classification task. To describe useful insights about the distribution of HR, after the signal processing methodology, 12 quantitative features were computed:

- Maximum: maximum value of HR;
- Minimum: minimum value of HR;
- Mean: mean value of HR;
- Median: median value of HR;

- Mode: mode of HR;
- Standard deviation: standard deviation of HR;
- Variance: HR's variance;
- Range: HR's range;
- Kurtosis: thickness of the tails of HR's distribution;
- Skewness: symmetry of HR's distribution;
- Energy: HR's averaged power;
- Periodogram Power: the periodogram power spectral density (PSD) estimate of HR;

2.3 Data Analysis Methodology

For performance comparison, using a 5-fold cross-validation strategy, 6 classifiers were used: decision tree, linear discriminant, random forest, boosted trees, Gaussian support vector machine (SVM), and k-nearest neighborhood (kNN), with the default hyperparameters.

The performance of classification models was assessed through several metrics, such as *accuracy*, *precision*, *recall*, and F_1-*score*. *Accuracy* gives the ratio between the corrected classified examples and the total examples to be classified. *Precision* measures the ratio between the correct predictions and all the predictions of a given class (usually, denoted as positive), while *Recall* is the ratio of correct predictions and all the examples that actually belong to that class. In the case both metrics get high values, then the different classes are properly handled by the classifier.

Precision and *recall* are closely related to the concepts of type I and type II errors: a classifier with high recall has a low type II error rate, which means that it misses few detections. While a classifier with high precision has a low type I error rate, which means that is resilient to false alarms. Combining both, the F_1-*score* is defined as the harmonic mean of these two evaluation metrics.

3 Results and Discussion

As detailed above, the workflow process for data analysis consisted of several steps, from the collection of data to the evaluation of the results, including the preprocessing of ECG data, the selection of 'pain' and 'no pain' epochs according to the reports and analgesia, the extraction of features and distribution's analysis, and the computation of machine learning models for pain prediction. This workflow is illustrated in Fig. 1.

The HR-features computed for the different pain epochs will be fed into different machine learning algorithms with the purpose of pain prediction and comparing the performance of the used models in the classification task. Also, different epochs of 'no pain' will be considered to infer the influence of time-effect of analgesia on the pain experience. Figure 2 shows the distribution of the 12 computed HR-features (for the 'no pain' features computed from 1-min interval of ECG recorded 1-min after analgesia administration). It can be observed that

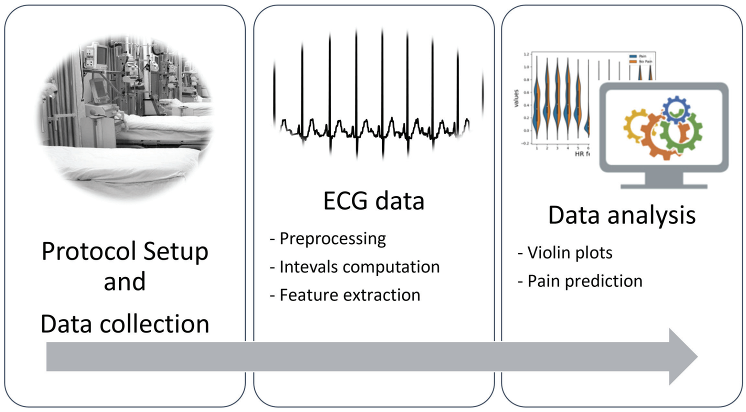

Fig. 1. Workflow for postoperative pain prediction.

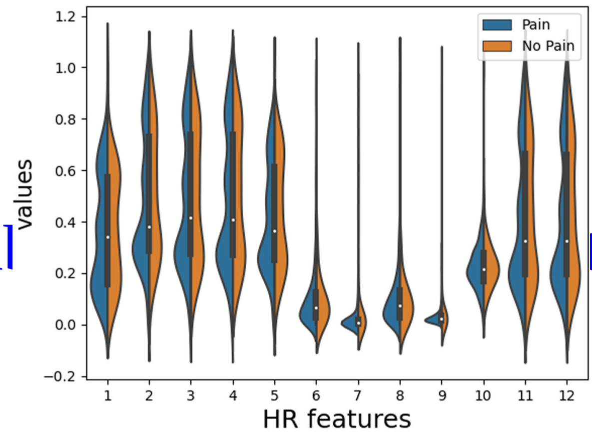

Fig. 2. Violin plots showing the HR-features distribution.

these features reveal distinct distributions among 'no pain' and 'pain' records, which supports the use of these features for pain prediction purposes.

Thereafter, the HR-features were used to compute classification models for pain prediction, and performance comparison was performed with different evaluation metrics. From Fig. 3 it can be observed that, with the exception of DT, the *accuracy* of the used classifiers are similar, reaching around 85%.

Figure 3 also shows that the 6 models get high and similar values of *precision* (around 85%). Regarding *recall*, except for the DT, the used models achieved almost 99%. For F_1-*score*, the performances of the 5 models (excluding DT) are quite the same, with values of almost 92%. For the four metrics used, the high values obtained sustain the feasibility of using these HR-features for postoper-

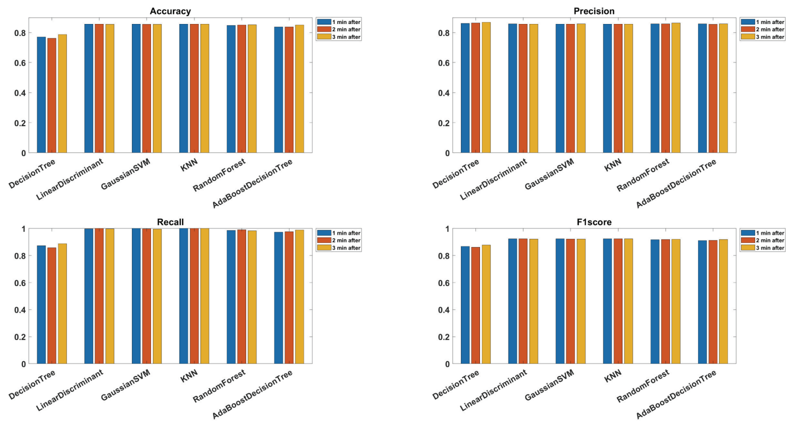

Fig. 3. Evaluation metrics of the 6 classification models.

ative pain prediction. Although the performance was slightly better than the remaining comparable models, the LDA achieved the best overall results.

4 Conclusions and Further Research

The obtained results indicate that the experience of postoperative pain can be predicted by relying on physiological data. Moreover, advancing classification models based on features computed from the ECG signal, which is continuously recorded through minimally invasive equipment, can help pave the way for future research in self-regulation strategies for pain management, i.e., biofeedback, promoting health, and well-being.

Through this preliminary study it is shown that the obtained results should be further explored and explained. This is critical for the adaptation of healthcare strategies, providing a step further in personalized medicine. Thus, future research should be concerned with the explanations of the contributions of these features to the experience of postoperative pain. Moreover, efforts should also be devoted to the exploration of the meaningful features for this purpose and the contributions of other physiological signals, attempting a multimodal classification approach. This designed future research, aiming at a more accurate pain assessment, can support therapeutic approaches, namely through a better dosage of analgesics, either by different pharmacological interventions or by cognitive-behavioral therapies.

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