



**Marta Pereira
Neves**

TÍTULO DA TESE (MÁXIMO 130 CARACTERES)

THESIS TITLE (MAX 130 CHARACTERS)

PROPOSTA DE TESE



**Marta Pereira
Neves**

TÍTULO DA TESE (MÁXIMO 130 CARACTERES)
THESIS TITLE (MAX 130 CHARACTERS)

Projeto apresentado à Universidade de Aveiro para cumprimento dos requisitos necessários à obtenção do grau de Licenciatura em Engenharia Biomédica, realizado sob a orientação científica da Doutora Susana Brás, Professora Auxiliar do Departamento de Eletrónica, Telecomunicações e Informática da Universidade de Aveiro, e investigadora do Instituto de Engenharia Eletrónica e Informática de Aveiro (IEETA).

o júri / the jury

presidente / president

Prof. Doutor João Antunes da Silva
professor associado da Universidade de Aveiro

vogais / examiners committee

Prof. Doutor João Antunes da Silva
professor associado da Universidade de Aveiro

Prof. Doutor João Antunes da Silva
professor associado da Universidade de Aveiro

Prof. Doutor João Antunes da Silva
professor associado da Universidade de Aveiro

Prof. Doutor João Antunes da Silva
professor associado da Universidade de Aveiro

Prof. Doutor João Antunes da Silva
professor associado da Universidade de Aveiro

**agradecimentos /
acknowledgements**

Agradeço toda a ajuda a todos os meus colegas e companheiros.

palavras-chave

texto livro, arquitetura, história, construção, materiais de construção, saber tradicional.

resumo

Um resumo é um pequeno apanhado de um trabalho mais longo (como uma tese, dissertação ou trabalho de pesquisa). O resumo relata de forma concisa os objetivos e resultados da sua pesquisa, para que os leitores saibam exatamente o que se aborda no seu documento.

Embora a estrutura possa variar um pouco dependendo da sua área de estudo, o seu resumo deve descrever o propósito do seu trabalho, os métodos que você usou e as conclusões a que chegou.

Uma maneira comum de estruturar um resumo é usar a estrutura IMRaD. Isso significa:

- Introdução
- Métodos
- Resultados
- Discussão

Veja mais pormenores aqui:

<https://www.scribbr.com/dissertation/abstract/>

keywords

textbook, architecture, history, construction, construction materials, traditional knowledge.

abstract

An abstract is a short summary of a longer work (such as a thesis, dissertation or research paper).

The abstract concisely reports the aims and outcomes of your research, so that readers know exactly what your paper is about.

Although the structure may vary slightly depending on your discipline, your abstract should describe the purpose of your work, the methods you've used, and the conclusions you've drawn.

One common way to structure your abstract is to use the IMRaD structure. This stands for:

- Introduction
- Methods
- Results
- Discussion

Check for more details here:

<https://www.scribbr.com/dissertation/abstract/>

**acknowledgement of use of
AI tools**

**Recognition of the use of generative Artificial Intelligence
technologies and tools, software and other support tools.**

I acknowledge the use of [insert AI system(s) and link] to [specific use of generative artificial intelligence or other tasks]. I acknowledge the use of [software, codes or platforms] to [specific use software, codes or platforms or to other tasks].

Example 1: I acknowledge the use of ChatGPT 3.5 (Open AI, <https://chat.openai.com>) to summarise the initial notes and to proofread the final draft and the use of Office365 (Microsoft, <https://www.office.com>) for text writing and productivity.

Example 2: No content generated by AI technologies has been used in this Thesis.

Contents

Contents	i
List of Figures	ii
List of Tables	iii
Glossary	iv
1 Introduction	1
1.1 Motivation	1
1.2 Work Objectives	2
1.3 Pain	2
1.4 Pain Description	2
2 Methods and Procedure	3
2.1 Database Acquisition	3
2.2 Feature Extraction	4
2.2.1 ECG Data Exploration	5
2.3 Data Analysis	6
3 Results and Discussion	9
References	11
A Additional content	11

List of Figures

2.1	Processing pipeline.	3
2.2	Scheme of the protocol applied to obtain the database. (Adapted from [10])	4
2.3	Section of the ECG signal of a participant.	5
2.4	Section of the standardized ECG signal of a participant.	5
2.5	Daubechies-4 Wavelet Decomposition - level 2.	6
2.6	Standardized features' time series.	7
2.7	Histograms of the features.	7
2.8	Features normalized in time after interpolation.	8

List of Tables

Glossary

ECG Electrocardiogram
NPS Numerical Pain Scale

VAS Visual Analog Scale

Introduction

Face your life, its pain, its pleasure, leave no path untaken. - Neil Gaiman

1.1 MOTIVATION

Pain is unpleasant. No one enjoys experiencing it, whether it's the muscle soreness from working out or the more severe pain from a broken bone. In fact, it might even represent a significant burden on a person's quality of life. The unpleasant feeling it provokes may result in functional disability or even a change of behaviour, making an individual feel anger and frustration [1]. However, pain serves a valuable purpose: it alerts us to potential dangers and helps us adapt to situations that could harm us, helping us avoid further injuries [2]. Nevertheless, when it interferes with the way people typically live their lives, it's important to find ways to attenuate it. This burden is particularly profound for patients suffering from chronic pain conditions, for whom discomfort becomes a persistent and debilitating element of life.

Attempts of measuring pain surged with the intent of improving quality of pain management [3]. For this reason, scales like the Numerical Pain Scale (NPS) and the Visual Analog Scale (VAS) have been used since 1950 [4]. Although these are the most used methods, they're very subjective, depending on a patient's own perspective of pain. Moreover, some patients might undermine the severity of their pain or be unwilling to share their experience. For those with cognitive difficulties, these methods of verbal report may not even be appropriate, especially for non-verbal individuals [5].

The challenge of measuring pain makes prescribing pain medication a difficult job for healthcare providers since the only comparison they have is a patient's previous results. This means that the prescription can be excessive and the organism will grow accustomed to it quicker or, if the patient minimizes the severity, they will continue to experience pain as their tolerance increases. This highlights the importance of finding an objective way of describing pain.

1.2 WORK OBJECTIVES

1.3 PAIN

According to its duration, pain can be classified as acute or chronic. Acute pain is induced by the activation of nociceptor sensory neurons, which occurs in the presence of actual or potential damaging stimuli, such as intense heat or cold and excessive mechanical force, or due to inflammation [6]. On the other hand, chronic pain is defined as lasting more than three months [7] and can be classified into nociceptive, neuropathic or nociplastic pain. Nociceptive pain results from continuous stimuli associated with tissue injury, while neuropathic pain results from damage to the peripheral or central nervous system. Lastly, nociplastic pain is a broader term, that is applied to chronic pain when it can't be described by the other two terms [8].

The Numerical Pain Scale is one of the most widely used traditional methods for assessing pain. It typically involves asking patients to rate their pain on a scale from 0 to 10, where 0 represents no pain and 10 signifies the worst pain imaginable [3]. While simple and easy to administer, this method relies entirely on the individual's subjective interpretation of their pain, which can be influenced by factors such as mood, stress and gender. Besides this, the difference between pain scores may not be comparable in scaling the intensity of pain [9]. Finally, its verbal component is a limitation for non-verbal patients who may not be able to describe their pain using this method.

Another traditional method for assessing pain is the Visual Analogue Scale. This scale represents a continuous range of values, and it mainly uses a horizontal line measuring exactly 100 mm (10 cm). The patient is asked to make a mark on the line according to their level of pain, then, the distance of the mark is measured and recorded in millimetres or centimetres [4]. However, even though it's non-verbal, a minimum level of motor abilities is necessary to correctly use the VAS, which makes it inadequate for scaling pain in some patients with motor impairment, for example. This method, although it seems to be more detailed in values than the NPS, is still very subjective, not allowing for an accurate pain description and comparison. This method can also be used for assessing other symptoms, however. For example, in the dataset used in this project, it was used to assess the level of anxiety, happiness, fear and stress that the participants felt, on a scale of 0-100%, and the arousal and valence states in a -5 to 5 scale [10].

Other similar scales, that also depend on a patient's perception of their own pain, end up also being subjective [9][11]. Due to this, researchers have attempted to find objective ways to describe pain using physiological signals.

1.4 PAIN DESCRIPTION

In this project, ECG was the physiological signal chosen for analysis.

Methods and Procedure

In figure 2.1, the processing pipeline for this project is shown.

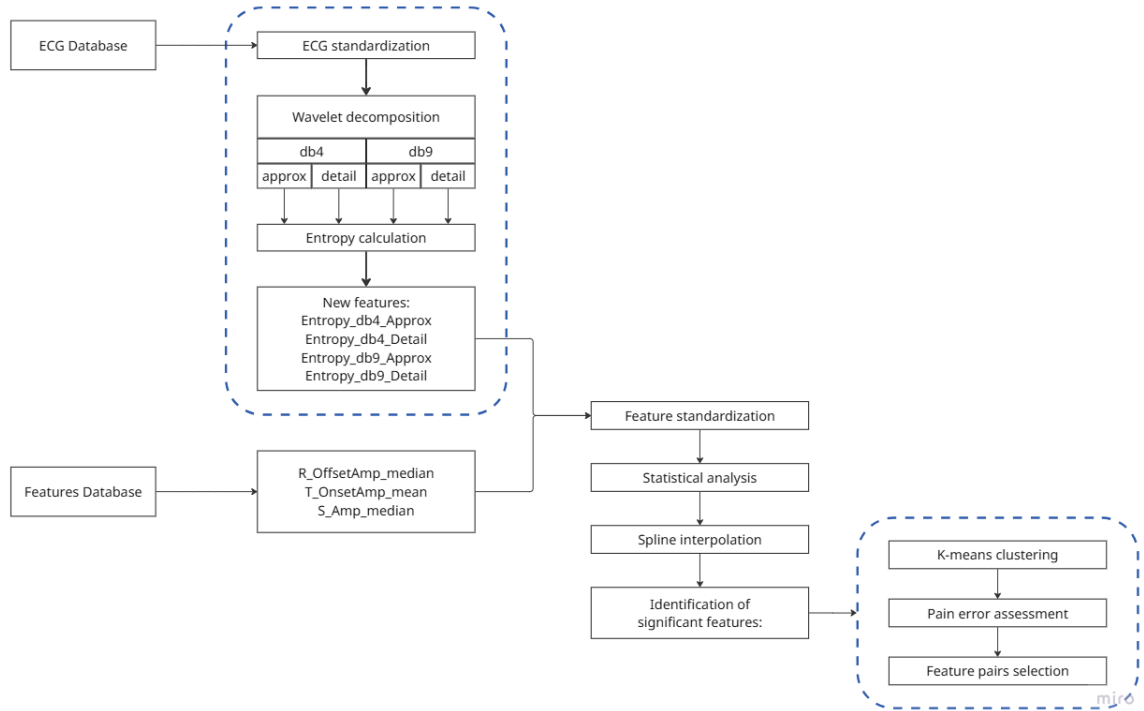


Figure 2.1: Processing pipeline.

2.1 DATABASE ACQUISITION

In this project, two databases were used: one has data from an Electrocardiogram (ECG) signal while the other contains features extracted from that ECG, as described in the article by Alves et al [10].

The data collection protocol followed a structured sequence designed to elicit and record both emotional and pain-related responses. It began with a 5-minute baseline period, during

which participants remained seated in a relaxed position without any external stimuli. During this time, only physiological signals were recorded to establish a baseline. Subsequently, participants watched a 10-minute video, composed of excerpts from comedy, horror, or documentary films, aimed at inducing positive, negative, or neutral emotional states, respectively. This was immediately followed by a second 5-minute stimulus-free period, allowing for recovery and stabilization of physiological responses. Next, participants underwent a Cold Pressor Test (CPT), in which they immersed their non-dominant hand in a tank of cold water maintained at $7 \pm 1^\circ\text{C}$. This procedure aimed to induce pain, and participants reported their experience using the Numerical Pain Scale (NPS) at four key time points: (1) before immersing the hand, (2) at the moment pain was first perceived (Pain Threshold), (3) when the pain became unbearable (Pain Tolerance), and (4) three minutes after hand removal. The CPT phase concluded either when the participant reached their pain tolerance or after a maximum of 2 minutes, whichever occurred first. Finally, the protocol concluded with a third 5-minute period without stimuli, serving as a rest phase to observe post-task physiological responses. This process is depicted in figure 2.2.

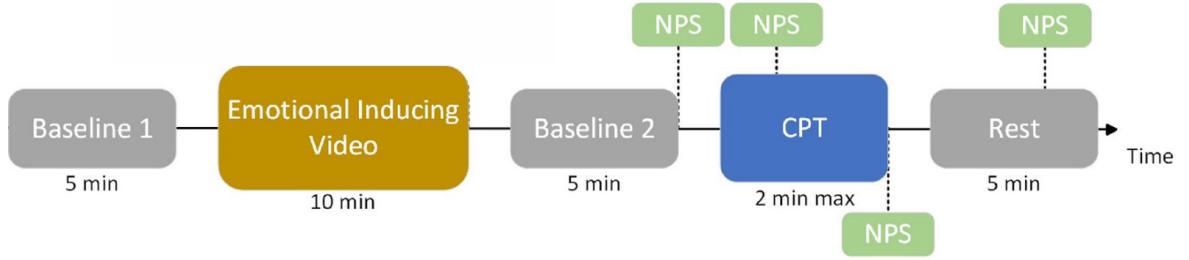


Figure 2.2: Scheme of the protocol applied to obtain the database. (Adapted from [10])

During the study, three physiological signals were recorded: electrocardiogram (ECG), electrodermal activity (EDA), and electromyography (EMG), with EMG signals collected specifically from the trapezius and triceps muscles. Among these, the ECG data were stored in a dedicated database, which was subsequently used in the present project. From the ECG signals, several time series were extracted, including heart rate (HR), amplitude of wave peaks, amplitude of onsets and offsets, and the intervals between consecutive onsets, offsets, and peaks. These features were computed using 10-second sliding windows with a 50% overlap. For each window, a set of statistical metrics—namely the mean, median, and variance—was calculated, resulting in a total of 237 features. These were compiled into a features database, which was also employed in the current project.

(Não percebi a parte de colocar já aqui as features)

2.2 FEATURE EXTRACTION

Four of all the extrated features revealed to be more related to pain assessment, by the use of a Random Forest classifier as the estimator and the median as the threshold [10]. So, under the scope of this project, the median of the R wave offset amplitude, the median of the T wave onset amplitude, and the mean and median of the S wave peak amplitude were

used as a base for subsequent analysis. Considering that the previously described features are examples of the state of the art features in ECG analysis, and knowing that the pain quantification or identification is still an open area, this work wants to understand and find out other possible features that may describe the pain process. So, to accomplish such goal, an exploratory analysis to the collected ECG was performed.

2.2.1 ECG Data Exploration

When looking at the time series of the signal, in figure 2.3, it's noticeable that the range of amplitudes of the QRS complex is way bigger than that of the P and T waves. To tackle this, the ECG signal was standardized according to equation 2.1, where X is the original ECG, μ is the mean, σ is the standard deviation and Z is the standardized signal, which has mean zero and standard deviation one. This means the range of values is the same for all participants, reducing the intervariability that is induced by the initial state of the participant, since it is an uncontrolled variable.

$$Z = \frac{X - \mu}{\sigma} \quad (2.1)$$

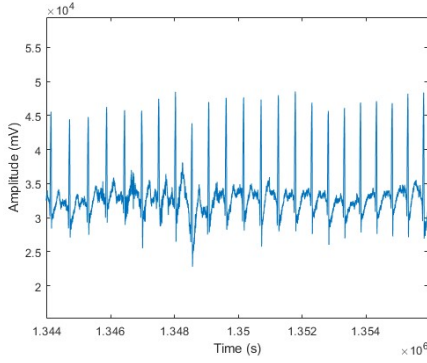


Figure 2.3: Section of the ECG signal of a participant.

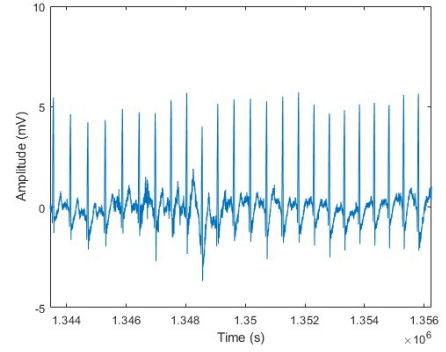


Figure 2.4: Section of the standardized ECG signal of a participant.

Once the signal was standardized, fluctuations were noticed in the time series. By removing high frequencies from the signal, by filtering for example, these would be alleviated. However, there could be information related to pain associated to those frequencies. A solution to these problems is to decompose the signal in wavelets. There are many wavelet families, but the selection should consider the characteristics of the signal and the decomposition we aim to achieve.

To choose the best type of wavelet, two criteria were established: one's format should be similar to that of the ECG wave, complementing the remaining features in gathering whether the QRS complex is relevant to describe pain, and the other should have a higher frequency, to understand if there's important information associated with the fluctuations of the signal, while still maintaining its smoothness. Accordingly, Daubechies-4 ('db4') and Daubechies-9 ('db9') were chosen. Regarding the number of levels of decomposition, as can be seen in figure 2.5, when there are two levels the R peak is noticeable in the first detail, which is not

something this project means to highlight. Therefore, only one level of decomposition was applied.

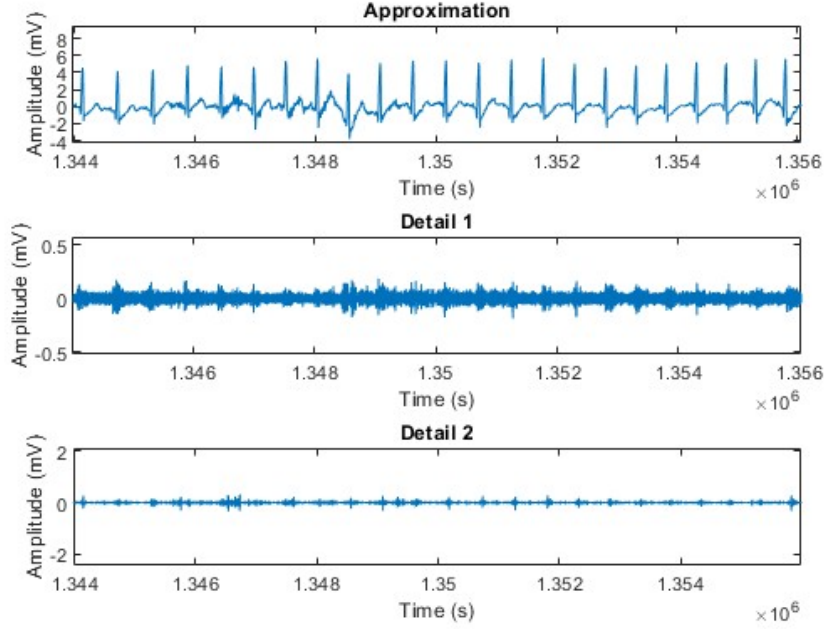


Figure 2.5: Daubechies-4 Wavelet Decomposition - level 2.

Entropy quantifies the order or disorder of information that a signal presents [12]. Since this quantity might be affected in the ECG when someone feels pain, it was extracted from the resulting wavelets, functioning as a new feature. In order to keep consistency with the other features, a same sized window was used, that is, 10 seconds with 50% overlap. Since the aim of the selected features is to

(Justificar tipo de entropia que escolhi? - approximation)

2.3 DATA ANALYSIS

To do the optimal processing of the features, fifteen participants were selected at random. After standardizing the features, so that they're comparable with each other, graphics of the time series of the features were plotted for each participant. An example can be seen in figure 2.6, in which a clear change can be seen when the participant dips their hand in water, feeling pain. Since the timeseries of the mean and median of the S wave amplitude were so similar, it was decided that only the median would be analysed.

Subsequently, a statistical analysis of the participants' features was conducted using histograms, as illustrated in Figure 2.7. The histograms revealed that the distributions of the features deviate from normality, justifying the use of the median and interquartile range (IQR) as measures of central tendency and dispersion, respectively. These values were computed for each feature and considered as derived features that will integrate the analysis.

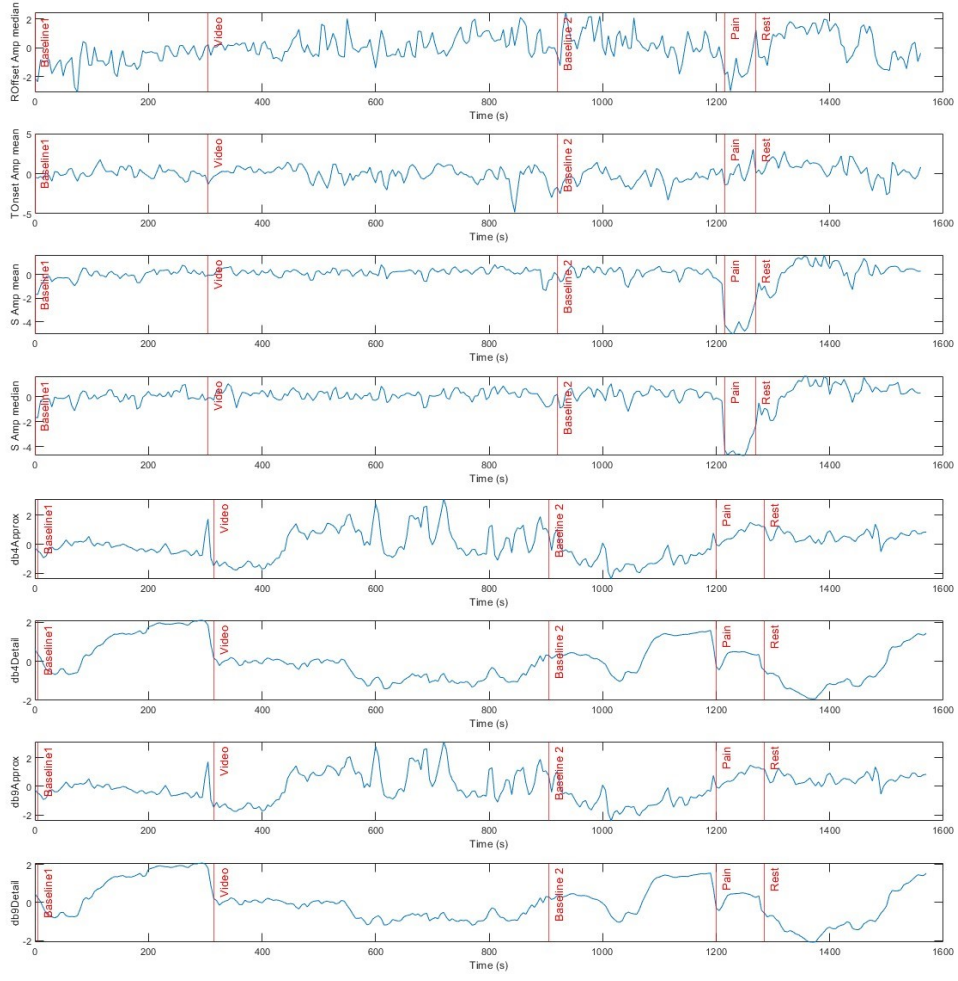


Figure 2.6: Standardized features' time series.

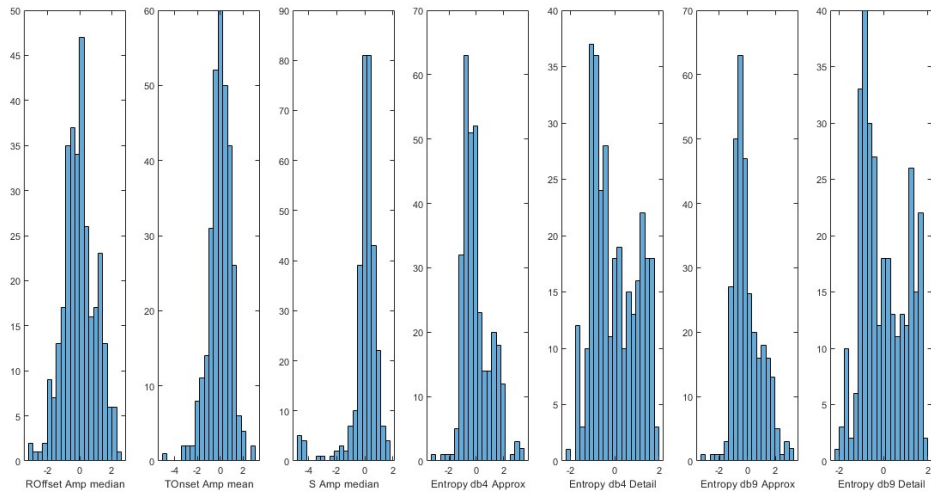


Figure 2.7: Histograms of the features.

The goal of this project is to select features that distinguish pain from no pain. To do this, it's important to guarantee the synchronization between segments, so that they're comparable. To accomplish this goal, spline interpolation was done in each step, conducing to equalize the number of points to a 60 seconds intervals. The result of this method is portrayed in figure 2.8.

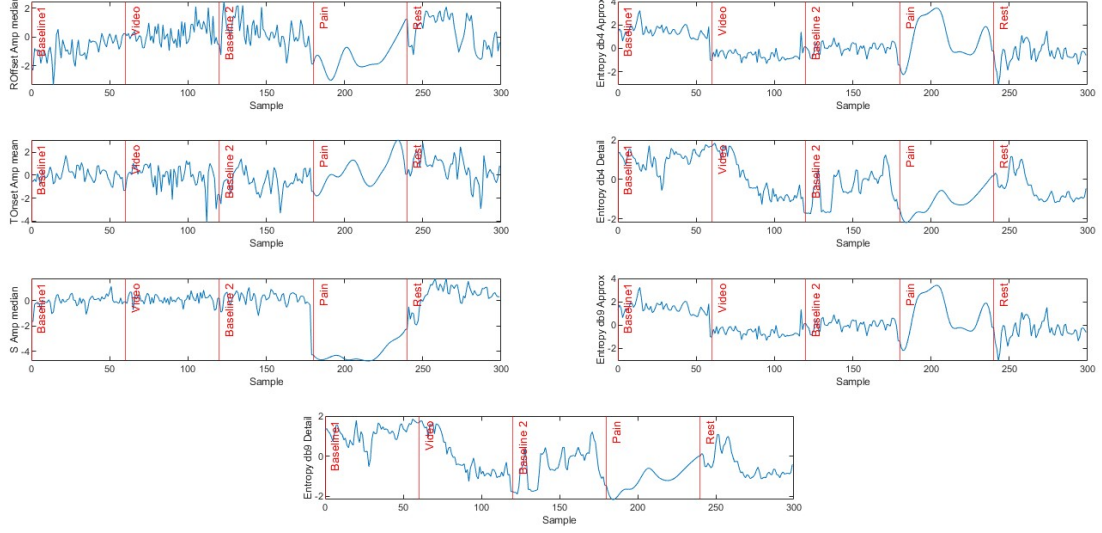


Figure 2.8: Features normalized in time after interpolation.

Results and Discussion

To identify the most relevant features for describing pain, this project employs unsupervised learning, specifically clustering. By using data from the baseline (no pain) and pain phases, the most relevant features are those that form clusters effectively separating the points corresponding to each condition.

In order to do this, there's the need to plot scattering graphics for each two features, as can be seen in figure AAAAA. Each point in the scatterplot represents one of the 15 participants in the study. The blue circles correspond to data from baseline 2 while the red circles represent data from the pain phase. In this example, the distribution of points reflects the relationship between two features – the median of the medians of S peak amplitude (x-axis) and R offset amplitude (y-axis) – in the two conditions. It's important to mention that this analysis was firstly done with baseline 1 but, comparing both options, the results were better using the second one, which may stem from the influence of the emotional stimuli in the pain felt by the participants.

Once this was done, k-means clustering was applied to all the data from baseline 2 and pain, with no distinction between them. In this case, the function 'kmeans' partitions data into two mutually exclusive clusters and returns the index assigned to them. Essentially, the function finds a partition in which objects within each cluster are as close to each other as possible, and as far from objects in other clusters as possible [13]. In this project, 'cityblock' was chosen as the distance metric. This metric measures the sum of absolute differences between data point coordinates, and assigns points to clusters based on this distance. Besides this, centroids are calculated as the component-wise median of points in each cluster. This metric was chosen because of the way centroids are calculated, that is, using the median, which is the measure that's been used during the course of this project. Moreover, this metric considers the absolute differences in each dimension separately, so it aligns well with datasets where feature relationships are independent, which is the case. The result of the clustering for the features in figure AAAAAAa is shown in figure AAAAAAb. Here, two clusters can be seen, one with blue circles and the other with yellow ones, as well as X's in the position of the

clusters' centroids.

To select the features that best distinguish pain from no pain, the success of the clusters was measured by calculating the percentage of points on the right that correctly correspond to the conditions on the left. In other words, it counts the number of blue circles on the right that are also blue on the left, and the number of yellow circles on the right that correspond to red circles on the left. Furthermore, only the graphics in which this percentage was over 80% were selected as being the result of a successful clustering.

This result is portrayed in the network map from figure BBBBB. This map was done with the help of Artificial Intelligence since it wasn't part of the taught contents in the Curricular Unit this project was developed for. In the figure, each circle corresponds to a feature and the connections between circles showcase the combinations of features that resulted in successful clustering. Additionally, the size of the circles is proportional to the numbers displayed above, highlighting the ones that were selected the most, specifically the median of the medians of the R offset amplitude and of the S peak amplitude. These are also the features whose graphics are shown in figure AAAAAAA.

References

- [1] D. D. Ridder, D. Adhia, and S. Vanneste, *The anatomy of pain and suffering in the brain and its clinical implications*, Nov. 2021. DOI: 10.1016/j.neubiorev.2021.08.013.
- [2] S. Coninx and P. Stilwell, “Pain and the field of affordances: An enactive approach to acute and chronic pain”, *Synthese*, vol. 199, pp. 7835–7863, 3-4 Dec. 2021, ISSN: 15730964. DOI: 10.1007/s11229-021-03142-3.
- [3] S. M. Nugent, T. I. Lovejoy, S. Shull, S. K. Dobscha, and B. J. Morasco, “Associations of pain numeric rating scale scores collected during usual care with research administered patient reported pain outcomes”, *Pain Medicine (United States)*, vol. 22, pp. 2235–2241, 10 Oct. 2021, ISSN: 15264637. DOI: 10.1093/pm/pnab110.
- [4] J. Bielewicz, B. Daniluk, and P. Kamieniak, “Vas and nrs, same or different? are visual analog scale values and numerical rating scale equally viable tools for assessing patients after microdiscectomy?”, *Pain Research and Management*, vol. 2022, 2022, ISSN: 12036765. DOI: 10.1155/2022/5337483.
- [5] J. Qin, *Entropy-based feature extraction method from wavelet coefficient for pain intensity assessment task*, 2022.
- [6] S. Jayakar, J. Shim, S. Jo, B. P. Bean, I. Singeç, and C. J. Woolf, “Developing nociceptor-selective treatments for acute and chronic pain”, *Science Translational Medicine*, vol. 13, 619 Nov. 2021, ISSN: 1946-6234. DOI: 10.1126/scitranslmed.abj9837.
- [7] S. Raman and P. Sharma, “Self-efficacy as a mediator of the relationship between pain and disability in chronic pain patients: A narrative review”, *Bulletin of Faculty of Physical Therapy*, vol. 27, 1 Dec. 2022, ISSN: 1110-6611. DOI: 10.1186/s43161-022-00101-y.
- [8] M. A. Fitzcharles, S. P. Cohen, D. J. Clauw, G. Littlejohn, C. Usui, and W. Häuser, *Nociplastic pain: Towards an understanding of prevalent pain conditions*, May 2021. DOI: 10.1016/S0140-6736(21)00392-5.
- [9] A. Adeboye, R. Hart, S. H. Senapathi, N. Ali, L. Holman, and H. W. Thomas, “Assessment of functional pain score by comparing to traditional pain scores”, *Cureus*, Aug. 2021, ISSN: 2168-8184. DOI: 10.7759/cureus.16847.
- [10] B. Alves, S. Brás, and R. Sebastião, “Decoding pain: Prediction under different emotional contexts through physiological signals”, *International Journal of Data Science and Analytics*, Oct. 2024, ISSN: 2364-415X. DOI: 10.1007/s41060-024-00649-z.
- [11] C. L. Robinson *et al.*, “Pain scales: What are they and what do they mean”, *Current Pain and Headache Reports*, vol. 28, pp. 11–25, 1 Jan. 2024, ISSN: 1531-3433. DOI: 10.1007/s11916-023-01195-2.
- [12] J. Ferreira, S. Brás, C. F. Silva, and S. C. Soares, “An automatic classifier of emotions built from entropy of noise”, *Psychophysiology*, vol. 54, pp. 620–627, 4 Apr. 2017, ISSN: 14698986. DOI: 10.1111/psyp.12808.
- [13] *K-means clustering*. [Online]. Available: <https://www.mathworks.com/help/stats/k-means-clustering.html>.

APPENDIX A

Additional content