Studies in Classification, Data Analysis,
and Knowledge Organization

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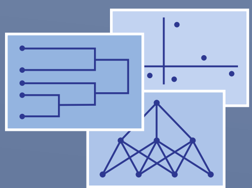
Classification and Data Science in the Digital Age



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Springer

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ISSN 1431-8814 ISSN 2198-3321 (electronic)
Studies in Classification, Data Analysis, and Knowledge Organization
ISBN 978-3-031-09033-2 ISBN 978-3-031-09034-9 (eBook)
https://doi.org/10.1007/978-3-031-09034-9

Mathematics Subject Classification: 62H30, 62H25, 62R07, 68T09, 62H86, 68T10, 94A16, 68T30

This Springer imprint is published by the registered company Springer Nature Switzerland AG
The registered company address is: Gewerbestrasse 11, 6330 Cham, Switzerland

Emotion Classification Based on Single Electrode Brain Data: Applications for Assistive Technology

Duarte Rodrigues, Luis Paulo Reis, and Brígida Mónica Faria

Abstract This research case focused on the development of an emotion classification system aimed to be integrated in projects committed to improve assistive technologies. An experimental protocol was designed to acquire an electroencephalogram (EEG) signal that translated a certain emotional state. To trigger this stimulus, a set of clips were retrieved from an extensive database of pre-labeled videos. Then, the signals were properly processed, in order to extract valuable features and patterns to train the machine and deep learning models.There were suggested 3 hypotheses for classification: recognition of 6 core emotions; distinguishing between 2 different emotions and recognising if the individual was being directly stimulated or merely processing the emotion. Results showed that the first classification task was a challenging one, because of sample size limitation. Nevertheless, good results were achieved in the second and third case scenarios (70% and 97% accuracy scores, respectively) through the application of a recurrent neural network.

Keywords: emotions, brain-computer interface, EEG, supervised learning, machine and deep learning

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P. Brito et al. (eds.), *Classification and Data Science in the Digital Age*, Studies in Classification, Data Analysis, and Knowledge Organization,
https://doi.org/10.1007/978-3-031-09034-9_35

1 Introduction

Emotions are a part of our lives, as humans we know how to identify the tiniest of microexpressions to unveil what someone is feeling, but also how to use them to express our hearts. From the youngest of ages we see and interact with others and build a database of patterns of, for example, what joy is and how different it is from fear or sadness. Computers, on the other hand, do not have any idea of what an emotion is or how to recognize it. Or do they?

The Artificial Intelligence and Computer Science Laboratory (LIACC) established 2 projects where emotion recognition can be of the utmost importance. The first project, the "IntellWheels 2.0" [1], intends to develop an interactive and intelligent electric wheelchair. This innovative equipment will have a diverse set of features, such as an adaptive control system (through eye gaze, a brain-computer interface, hand orientation, among others) and a personalized multi-modal interface which will allow communication to multiple devices both from the patients and the caregivers. In this case, having information about the mood of the patient is very beneficial, because the interface can give updates to the nursing staff of the emotional condition of the patient. The second project, the "Sleep at the Wheel" [2], focuses on the research of an interface that can sense and predict a driver's drowsiness state, being able to detect if he fell asleep while driving and, consequently, support an alarm system to provide safer routing and driving. Here the state of mind of the driver is a very important aspect, as different emotions, like anger or fear, can provoke dangerous situations or unpredictable scenarios, making the driver less attentive to his surroundings.

In this work, emotions will be sensed through a brain-computer interface (BCI). These are commercial devices that allow to acquire a surface electroencephalogram (EEG). This signal is used to measure the electrical activity of the brain, that fluctuates according to the firing of the neurons in the brain, being quantified in micro-volts. In this research, the BCI used was the "NeuroSky MindWave2" which possesses one single electrode on the forehead, from which it collects a signal from the activity of the frontal lobe. This brain area is responsible for the higher executive functions, including emotional regulation, planning, reasoning and problem solving [3].

The study of emotion recognition started with psychologist Paul Ekman that defined, based on a cross cultural study, six core emotions - Fear, Anger, Happiness, Sadness, Surprise and Disgust [4]. Later, psychologist Robert Plutchik established a model called "Wheel of Emotions", a diagram where every emotion can be derived from the core 6.

It is also important to have a way to measure what someone is feeling or what emotion they are experiencing. An easy way to do this is through the "Discrete Emotion Questionnaire", a psychological validated questionnaire to verify the intensity of a certain emotion. This assessment presents the 6 core emotions to the subjects asking them to rate the intensity they felt, from 1 to 7 [5].

As a first approach in this area, the current work aims to be able to identify the core emotions using EEG signals collected with the BCI.

2 Experimental Methodology

In order to correctly identify the core emotions, the first step is to trigger them in an efficient way for the brain data collected to be as informative as possible.To do so, the emotions were prompted via a set of video clips, that lasted 5-7 seconds. These videos were selected from a certified database, where the videos were labeled according to the intensity and kind of emotion it caused in the subjects [6]. For each of the 6 core emotions, the 4 videos classified with the biggest intensity were selected to be presented to the participants of this research work.

For each of the 24 video clips (4 videos per each of the 6 emotions), 3 EEG samples are collected. The first is before the display of the video, where a fixation cross is presented, in order to collect the idle/blank state of the user, where he is asked to relax. The second sample is the EEG during the video (active visual stimulus); and the third sample is after the video finishes where the volunteer is processing the emotion triggered (higher level thinking), while getting back to the initial relaxed state, where the fixation cross is presented again. To confirm that the volunteers experience the same emotion defined in the pre-determined label, they are a prompted to answer the "Discrete Emotion Questionnaire", after the 3 EEG samples are collected.

Regarding the physiological signal processing, this step is important because the raw EEG signal that comes directly from the BCI has a low signal-to-noise ratio, as well as many surrounding artifacts that contaminate the readings, especially eye blinks and facial movements triggered by the various emotions. These interfering signals caused by the latter, denominated electromyograms (EMG), are characterized by high frequencies (50-150 Hz) that make the underlying signal very noisy. Every time a person blinks, the EEG signal shows a very high peak with a very low frequency (<1Hz). To remove these muscle artifacts, a 5^{th} order utterworth bandpass filter (this type of filter was chosen because it has the flattest frequency response, which leads to less signal distortion) with cut-off frequencies in 1 Hz and 50 Hz [7].The attenuation of very low frequencies is important to remove the eye blinks artifacts. Considering the top cut-off frequency, it is very convenient to use 50 Hz since it mitigates the effects of the power line noise and the EMG artifacts. Like this, no important brain data is lost. At this step, the EEG was segmented in the brain waves of interest, i.e., the alpha and beta brain waves. The best way to perform this is to apply bandpass filters (same filter type as before) in the corresponding bandwidths, 8-13Hz and 13-32 Hz, to have alpha and beta bands, respectively.

The EEG signals, at this stage possess the "emotional data" exposed allowing to extract the features. To do so, multiple mathematical equations were applied to obtain relevant information from the signals. Feature extraction methods depend on the domain, as will be seen ahead [8]. Most strategies to extract features from the EEG are formulas applied in the time domain, such as, the common statistical equations, the Hjorth statistical parameters, the mean and zero crossings (number of times the signal crosses these 2 thresholds) [8]. Besides these, there were applied more advanced feature extraction methods, based on fractal dimensions and entropy analysis (methods to assess the complexity, or irregularity, of a time-series) [9].

Regarding frequency domain approaches, these features can only be calculated in the filtered EEG and not in the brain waves, as their spectrum is very narrow. In terms of the pure frequency band, the only feature computed was the Power Spectral Density (PSD), based on the Welch method. These domains can be combined creating the time-frequency domain, leading to more sophisticated methods, like the Hilbert – Huang Transform, where the original signal is decomposed in intrinsic mode functions (IMF) [10].

The resulting number of features is too high to compute machine learning models, because the correlation between most of the features is very low, which means that between different classes the information is virtually the same. This would introduce uncertainty in the weights for each class in the models, thus the number of features needs to be reduced. To do this the "Min Redundancy Max Relevance" (MRMR) method was applied, with the objective of finding the optimal number of features to have a higher inter-class variability, in order to find distinct patterns between emotions [11]. The features were used raw, normalized or standardized to train the models.

In this study, all the models implemented are based on supervised learning and fully depend on the data that is inputted. Concerning emotion classification there is not a specific machine learning approach that is optimal, thus 9 different types of models were implemented to verify which has the best performance. These models are designed to be able to adapt to various kinds of input data, through the definition of hyper-parameters. Hence, to tune them to the best possible configuration, it was performed a GridSearchCV. This method exhaustively searches over a given list of possible parameters applying cross validation between them. In the end, the model with the best performance is chosen to be trained with the resulting feature matrix.

A deep learning model was also implemented, based on recurrent neural network (RNN), a very common architecture in classification problems using EEG. A particularity of this network is that it has a GRU, i.e., a layer that helps to mitigate the problem of vanishing gradients (common issue on artificial neural networks), giving long term memory to the model [12].

3 Evaluation and Discussion of Results

In this experiment, 12 subjects volunteered to participate. Each EEG recording is labeled according to the emotion registered in the original database, as well as if it was before video, during or after the video. The answers of the “Discrete Emotion Questionnaire” were used to validate if the emotion triggered by the video was as expected and, if so, the data was used. With this dataset structure, 3 hypotheses were tested and their results are discussed ahead.

An important aspect to have in consideration is that the EEG collected while the subject is relaxing, i.e., while the fixation cross presented before the video, does not have relevant cognitive information regarding emotions. Therefore, these segments were not considered to train any of the models.

3.1 Core Emotions Classification

This first hypothesis describes the main goal of the project where a model was developed to classify 6 emotions.

First, the feature extraction was computed. At this step, the optimal number of features to get selected was tested, iterating from 5 to 50, 5 at a time. The best number found was 30, which gave the best accuracies, with a balanced computation time and power. This value was chosen for the 3 feature matrixes (raw, normalized and standardized). The dataset was then divided into training and testing with an 80% ratio and fully independent of one another. Each model was then trained and assessed, by computing the accuracy in the test dataset. Table 1 presents the results for each model.

Table 1 Results of the 6 Core Emotions Classification.

Classification Models	Raw Features	Normalized Features	Standardized features
	Accuracy (%)		
Gaussian Naïve Bayes Classifier	12.07	12.93	10.34
Support Vector Classifier	12.07	12.93	16.38
Decision Tree Classifier	18.96	18.10	18.10
Random Forest Classifier	24.13	18.10	20.69
K Nearest Neighbors	21.55	18.96	16.38
Logistic Regression	**25.00**	14.66	18.10
Linear Discriminant Analysis	24.13	14.65	18.96
Linear Support Vector Classifier	18.10	13.79	19.82
Multi-Layer Perceptron	20.69	13.79	12.93
Recurrent Neutral Network	13.79	20.69	23.27

When comparing the various models, the average accuracy is around 16-18%, logically due to the number of classes in the problem (100%/6 = 16,6%). Despite this, the best result reached was 25% accuracy, with the features in their raw state, since the magnitude information was not lost, so patterns in different emotions could be more easily identified due to the high discrepancy in the values. These results are not discouraging since the main objective of the study is very ambitious, as we are trying to create a model to define universally what an emotion is. There is no work more subjective or abstract, and the only way to achieve this universal standardization would be with a sample population as wide and diverse as possible with different beliefs, nationalities, age groups, etc. Although this is an initial study, it shows that it is possible to register and identify differences in the electrical changes of the prefrontal cortex and, with that information, categorize what someone is feeling.

3.2 One vs One – Dual Emotion Classification

As the results in the previous hypothesis could not precisely identify an emotion when compared to the other 5, the problem was narrowed down and a new hypothesis was tested, to continue the proposed research. In this experiment, the model was trained to discern between only 2 emotions, decided *a priori*. For demonstration purposes, a concrete example can be seen in Table 2 where it compares "fear" vs "surprise".

Table 2 Results of "Fear vs Surprise" Classification.

Classification Models	Raw Features	Normalized Features	Standardized features
	Accuracy (%)		
Gaussian Naïve Bayes Classifier	48.27	55.17	53.44
Support Vector Classifier	51.72	51.72	53.44
Decision Tree Classifier	56.89	50.00	44.83
Random Forest Classifier	48.27	50.00	60.34
K Nearest Neighbors	46.55	44.82	50.00
Logistic Regression	50.00	53.45	53.45
Linear Discriminant Analysis	50.00	48.28	53.44
Linear Support Vector Classifier	50.00	51.72	55.17
Multi-Layer Perceptron	50.00	50.00	58.62
Recurrent Neutral Network	**69.23**	51.23	56.21

In this case, most of the machine learning algorithms have accuracies in the order of the 50-53%. This results are not ideal, as they are no better than a random choice between the two classes, however this can be justified by the low population sample, which is not high enough to bring to the surface concrete patterns on the features. Regarding the deep learning approach, the RNN has an advantage in this case, giving a final accuracy of 69%. This result shows that this model is reliable, and in the majority of the cases the 2 emotions can be distinguished. In this particular case, the facial expressions and their muscle activity, can induce big artifacts in the EEG. Someone who feels surprised has the tendency to raise their eyebrows and open the mouth. These movements can lead to a difference in the EEG and, consequently, in the patterns of the features, making the distinction between surprise and fear more noticeable. The same thinking applies to other emotions that trigger facial movement, like laugh, frowning, among others.

3.3 Stimulus vs No Stimulus Classification

Besides the good results presented in the last premise, one last hypothesis was assessed, regarding the difference between experiencing the emotion while watching the video (direct stimulus), and after, when the fixation cross is presented, while the volunteer is simply thinking and cognitively processing the emotion.

Table 3 summarizes the results of the various models.

Table 3 Results of Stimulus vs No Stimulus classification.

Classification Models	Raw Features	Normalized Features	Standardized features
	Accuracy (%)		
Gaussian Naïve Bayes Classifier	61.20	58.62	85.34
Support Vector Classifier	58.62	58.62	91.37
Decision Tree Classifier	39.65	58.62	89.65
Random Forest Classifier	39.65	58.62	91.37
K Nearest Neighbors	37.93	58.62	89.65
Logistic Regression	34.48	58.62	87.06
Linear Discriminant Analysis	29.31	37.06	80.17
Linear Support Vector Classifier	34.48	58.62	87.06
Multi-Layer Perceptron	31.03	58.62	88.79
Recurrent Neutral Network	**96.55**	61.20	88.79

As it can be seen, for this experiment, most models did fairly well using the standardized feature, being all accuracies higher than 80%. However, when testing the deep learning approach, this architecture revealed to fit almost perfectly to the testing data, with an accuracy higher than 96%. This hypothesis is the proof of concept that the characteristics of the signal collected during the stimulus itself are very different from the ones from a signal obtained when the person is simply thinking and cognitively processing the emotion (this change would be obvious if the EEG was collected from the occipital lobe, which is responsible for the visual perception, but is remarkable when spotted in the prefrontal cortex).

4 Conclusions

In conclusion, as a first approach, the results achieved are very satisfactory and reveal a high potential to be greatly efficient in the proposed applications both in "IntellWheels2.0" and "Sleep at the Wheel projects". Nevertheless by collecting more data the models will get more generalized resulting in more realistic patterns and, consequently, increasing the prediction's accuracies.

Comparing to the literature, using simple visual stimuli to distinguish six emotions, in a relaxed state, is a novel tactic. Most studies, complement the stimulus with forced facial expression, introducing different characteristics to the signal, leading to better results. Other studies use BCIs with more electrodes (channels), covering a wider cranial surface and, consequently, getting more EEG and information, which leads to more robust results.

As future work, the preprocessing of the data could be polished, improving the removal of artifacts and enhancing the underlying information of the EEG's. To obtain better results, it could also be used a transfer learning approach, by pre-training the models with another emotion related EEG databases.

Acknowledgements This work was financially supported by Base Funding - UIDB/00027/2020 of the Artificial Intelligence and Computer Science Laboratory – LIACC - funded by national funds through the FCT/MCTES (PIDDAC), Sono ao Volante 2.0 - Information system for predicting sleeping while driving and detecting disorders or chronic sleep deprivation (NORTE-01-0247-FEDER-039720), and Intellwheels 2.0 - IntellWheels2.0 – Intelligent Wheelchair with Flexible Multimodal Interface and Realistic Simulator (POCI-01-0247-FEDER-39898), supported by Norte Portugal Regional Operational Programme (NORTE 2020), under the PORTUGAL 2020 Partnership Agreement.

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