Towards An Unified Analysis Framework for EEG-based Emotion Recognition

some people

ABSTRACT

Keywords
EEG, Machine Learning, Emotion Recognition

1. INTRODUCTION

Emotion is critical aspect of the human behavior that plays a significant role in activities such as communication and learning. Historically, researchers have focused on psycho physiological variables, such as posture, language (voice intonation), facial expression and gestures to identify and classify emotions and relate them to behavior patterns or decision making processes. The use of electroencephalography (EEG) to study the emotion recognition has allowed the support of disciplines such as Human Computer Interaction (HCI) and Brain Computer Interfaces (BCI). In this context, the vision proposed is that in the future, machines should have the ability to identify the emotional state of humans in order to provide an effective assistance. This could represent a relevant advance in fields such as health care and education.

EEG-based emotion recognition usually follows a sequence of steps, such as stimuli selection, feature selection and engineering, classification and evaluation. Literature reports a high level of heterogeneity on each of these steps, given the inherent richness of the data (usually captured through a sophisticated configuration of electrodes) , the multimodality of the stimuli and the wide range of analytical tools. Although this could be seen as a beneficial element, the recent increment in proposed approaches makes it difficult to perform a reliable comparison to assess the real impact , applicability and level of generalization that the current studies. Our vision is that, based on the collaborative work with other members of the community, in the future it will be possible to have a solid benchmark that could increase the performance and pace of the research in this area, similarly as benchmarks such as [6] and [3] have boosted the progress in the areas of image recognition and visual saliency, respectively.

In this paper, our goal is to firstly study the quality of the available datasets for EEG-based recognition, in terms of their level of generalization. After choosing one, select the current state of the art in terms of feature extraction and try to replicate the their results keeping in mind the unification as a primary goal.

After setting up a baseline based on the study of related work, we explored the use of a new paradigm based on Representation Learning: the use of Convolutional Neural Networks (CNN) for EEG-based emotion recognition. Our main motivation is try to generate an alternative to the feature engineering process present in EEG-based emotion recognition, which usually turns out to be difficult and excessively laborious. In that sense, we are interested in analyzing if an automatic feature extraction could be competitive compared to hand crafted features. Our main hypothesis is that the ability of CNN to generate hierarchical representations of the features could lead to an effective understanding of the relationship between signal patterns and the valence of emotions.

We performed an initial empirical study to compare the collected emotion classification methods based on an unified way. Our results show that...

The rest of the paper is structured as follows. Section 2 explores the publicly available EEG datasets for emotion recognition. Section 3 describes what we consider the most representative methods for emotion classification, along with a deep learning alternative. Section 4 sets a formal way to unify and compare the performance of the methods. Section 5 discusses the results and the limitations of the analysis. Finally, Section 6 outlines the conclusions and the future work.

2. DATA SOURCES ANALYSIS

Literature shows several attempts to provide robust dataasets for EEG based emotion recognition. These approaches differ in many factors, such as nature of the stimuli and number and type of participants. In this section, a detailed summary is provided, followed by a qualitative and quantitative comparison. The goal is to highlight the strengths and limitation in order to facilitate the selection, given a specific goal.

2.1 DEAP

Koelstra et al. [4] released the Database for Emotion Analysis using Physiological Signals (DEAP). This dataset contains electroencephalogram and peripheral physiological signals of 32 healthy participants (50% female), aged between 19 and 37 (mean age 26.9), while they were watching 40 one-minute long excepts of music videos. For each video, the dataset has a label for valence, arousal, dominance and liking levels according a process that combined Last.fm application and subjective annotation of subjects. The data is available include 48 channels (32 EEG channels, 12 peripheral channels, 3 unused channels and 1 status channel) at a sample rate of 512Hz. Due to different revision of the hardware, there are some minor differences in the format, mainly regarding to the order of the channels.

3. EEG BASED RECOGNITION MODELS

Based on the work of Jenke et al.[2], where a comprehensive survey on the features and models for emotion classification is presented, we performed a selection of the most representative in terms of the treatment of the data. These methods heavily rely on manually generated features, which basically represents the stat of the art in the field.[] We provide a detailed description of the steps involved and the replication efforts we carried out.

Additionally, we provide the an alternative based on ...

3.1 Takahashi method (2004)

In 2004, Kazuhiko Takahashi published his work called *REMARKS ON EMOTION RECOGNITION FROM MULTI-MODAL BIO-POTENTIAL SIGNALS* [9]. This research aimed to achieve a classification of 5 emotions (joy, anger, sadness, fear, and relax) using multi-modal biopotential signals such as brain signals, pulse and skin conductance. He did experiments in order to collect data and then make a posterior analysis using algorithms like Support Vector Machine and Artificial Neural Networks. His results reached a precision of 41.7% for 5 emotions and 66.7% for 3 emotions.

This work is one of the first that tries to use machine learning algorithms over biological signals features for emotion recognition. In order to see how this field has been growing over last decade, this research is a good candidate to start the list of included works in the benchmark.

3.1.1 Feature Extraction

To characterize the data this work used the next statistical features:

1. Mean (μ_X)
2. Standard Deviation (σ_X)
3. Mean of absolute differences

   $\delta_X = \frac{1}{N-1}\sum_{n=1}^{N-1} |X(n+1) - X(n)|$
4. Mean of normalized absolute differences ($\overline{\delta_X} = \frac{\delta_X}{\sigma_X}$)
5. Mean of absolute second differences

   $\gamma_X = \frac{1}{N-2}\sum_{n=1}^{N-2} |X(n+2) - X(n)|$
6. Mean of normalized absolute second differences ($\overline{\gamma_X} = \frac{\gamma_X}{\sigma_X}$)

3.2 Murugappan method (2010)

Murugappan et al. have quite an interesting story related to the emotion assessment through EEG analysis. Starting from 2008, several studies could be found in literature corresponding to this author, using different combinations of features, EEG channels and algorithms in order to classify discrete emotions such as disgust, happy, surprise, sad and anger.(CITAR los paper de muru).

For the present benchmark, we are centered in one of the mentioned Murugappan's works, where an experiment was conducted for collecting EEG data of 20 subjects, for the classification of five emotions, namely disgust, happy, surprise, fear and neutral. A wavelet-based approach was performed, three different features were proposed for the analysis and two classifiers were used, obtaining a maximimum average classification rate of 83.26% with KNN and 75,21% with LDA [**?**].

Since Murugappan is an active actor in the emotion recognition field, turns to be important to include this study in benchmark and see how those proposed features behave with the DEAP dataset.

3.3 Convolutional Neural Networks

The recent renaissance in Artificial Neural Network research through the so-called *deep learning*, has led us explore the use of these sets of techniques for EEG-based emotion recognition.

[1]

[5] [11] [8] [7] [10]

4. EMPIRICAL STUDY

4.1 How to compare

4.2 metric

4.3 evaluation Steps

4.4 remarks

5. DISCUSSION

5.1 threats to validity

6. CONCLUSIONS

7. ADDITIONAL AUTHORS

8. REFERENCES

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