Towards An Unified Analysis Framework for EEG-based Emotion Recognition

some people

ABSTRACT

some 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 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 [4] and [1] 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 base line based on previous 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. To the best of our knowledge, this is first time this methodology is used for this purpose.

After a empirical studty, our main findings are....

2. DATA SOURCES

hablar de las diferentes fuentes. comparar cualitativa y cuantitativa mente.. decir por que deap.

3. EEG BASED RECOGNITION MODELS

3.1 Takahashi method (2004)

In 2004, Kazuhiko Takahashi published his work called *REMARKS ON EMOTION RECOGNITION FROM MULTI-MODAL BIO-POTENTIAL SIGNALS* [7]. 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

[3] [9] [6] [5] [8]

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. RELATED WORK

7. CONCLUSIONS

8. ADDITIONAL AUTHORS

9. REFERENCES

[1] T. Judd, F. Durand, and A. Torralba. A benchmark of computational models of saliency to predict human fixations. In *MIT Technical Report*, 2012.

[2] S. Koelstra, C. Muhl, M. Soleymani, J.-S. Lee, A. Yazdani, T. Ebrahimi, T. Pun, A. Nijholt, and I. Patras. Deap: A database for emotion analysis ;using physiological signals. *Affective Computing, IEEE Transactions on*, 3(1):18–31, Jan 2012.

[3] Y. LeCun and Y. Bengio. Convolutional networks for images, speech, and time series. *The handbook of brain theory and neural networks*, 3361:310, 1995.

[4] O. Russakovsky, J. Deng, H. Su, J. Krause, S. Satheesh, S. Ma, Z. Huang, A. Karpathy, A. Khosla, M. Bernstein, A. C. Berg, and L. Fei-Fei. ImageNet Large Scale Visual Recognition Challenge. *International Journal of Computer Vision (IJCV)*, 2015.

[5] S. Stober, D. J. Cameron, and J. A. Grahn. Classifying eeg recordings of rhythm perception. In *15th International Society for Music Information Retrieval Conference (ISMIRâĂŹ14)*, pages 649–654, 2014.

[6] S. Stober, D. J. Cameron, and J. A. Grahn. Using convolutional neural networks to recognize rhythmï£ij stimuli from electroencephalography recordings. In *Advances in Neural Information Processing Systems*, pages 1449–1457, 2014.

[7] K. Takahashi. Remarks on emotion recognition from multi-modal bio-potential signals. In *Industrial Technology, 2004. IEEE ICIT '04. 2004 IEEE International Conference on*, volume 3, pages 1138–1143 Vol. 3, Dec 2004.

[8] Z. Xing, J. Pei, and E. Keogh. A brief survey on sequence classification. *ACM SIGKDD Explorations Newsletter*, 12(1):40–48, 2010.

[9] Y. Zheng, Q. Liu, E. Chen, Y. Ge, and J. L. Zhao. Time series classification using multi-channels deep convolutional neural networks. In *Web-Age Information Management*, pages 298–310. Springer, 2014.