MCSoC 15th IEEE International Symposium on Embedded Multicore/Many-core Systems-on-Chip (MCSoC-2022)
Universiti Sains Malaysia, Penang, Malaysia, December 19-22,2022

Title

Movie Oriented Positive Negative Emotion Classification from EEG Signal using Wavelet Transformation and Machine Learning Approaches

Authors

Abu Saleh Musa Miah
Jungpil Shin
Md. Al Mehedi Hasan
Yuichi Okuyama
Tomioka Yoichi
School of Computer Science and Engineering
The University of Aizu
Aizuwakamatsu, Japan
jpshin@u-aizu.ac.jp

Md. Khademul Islam Molla
Computer Science and Engineering
University of Rajshahi
Rajshahi, Bangladesh

Pattern Processing Lab

Overview

- Introduction
- Related work
- Research gap
- Our objective
- Proposed Methodology
  - Dataset
  - Preprocessing
  - Feature extraction
  - Classification
- Performance accuracy
- Discussion
- Conclusion

Introduction

- Human have various emotions, which can now be recognized by AI and ML.
- It is important to understand human psychological behavior, making decisions.
- Positive emotions provide better living standards,
- Negative emotions can cause physical and psychological problems.
- Diagnosis depression and dementia by using different modality.
- To develop a communication system for the deaf-mute community.
- AI model for emotion recognition for social service agencies,
- Hospitals and healthcare institutions, pre-stroke situation and epilepsy.
- It can also be a tool for occupational therapy for health prediction, identifying signs of non-motor stage 1/2/3 symptoms for depression, anxiety and/or cognitive decline.

Related work

- ❖ Many research work has been done for emotion recognition
- ❖ Facial images, Facial temperature, and EEG signals [1-3].
- ❖ Facial temperature reactions used to classify **joy**, **disgust**, **anger**, **fear** and **sadness** emotion [1]
- ❖ Thermal images based landmark to classify children emotions [2,3]
- ❖ Seven emotions namely: **surprise**, **sadness**, **happiness**, **fear**, **anger**, **neutral**, and **disgust** achieved 65% average accuracy [2,3].
- ❖ **Speech** signals containing neutral, anger, sadness, surprise, fear, disgust, and happiness and achieved 78.89% accuracy [4,5].
- ❖ Lacking of the dataset due to high cost infrared camera. **Difficult to identify exact emotion of the human by seeing on the facial expression**
- ❖ Some people always have smile face but they are thinking negative thing and may have in depression and we can extract exact thinking information through EEG signals.

Related work

- To overcome the challenges researchers used EEG signal [22]
- Tree structure approach [24], Emotion wheel [25], Valence-arousal scale [26]
- Li et al. applied a model to recognize emotion using particle **swarm optimization feature based on the multi-stage linearly-decreasing inertia weight (MLDW)** classification algorithm [27].
- Using 4 class emotion-based EEG dataset and achieved 76.00% average accuracy.
- Few studies classify emotion using a **single electrode** [28-29].

Research Gap

- Few research have been done for channel wise performance calculation.
- Performance accuracy of the EEG based emotion classification is not satisfactory.

Our Objective

- To classify the positive-negative emotion during the movie based on EEG signal
- Knowing which electrode is most effective for carrying actual brain activity is essential

Proposed methodology

- Figure shows the working flowgraph
- Firstly we applied a db5 wavelet transform, after preprocessing
- Secondly, we calculated SD, MAV, and AVP statistical feature.
- Applied 3-machine learning algorithm, ETC, RF and SVM.

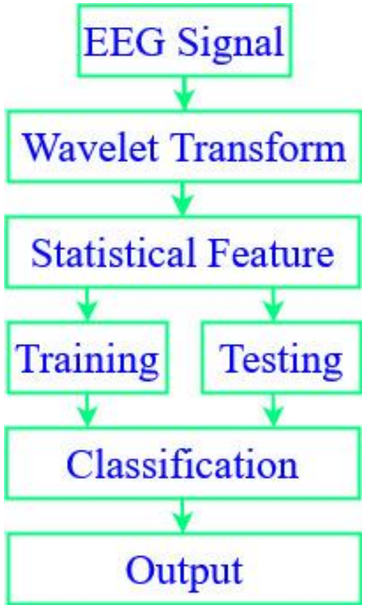

Figure: Working Architecture

EEG Dataset

- Dataset collected from the our laboratory in the University of Aizu
- During viewing the Horror and Funny movie
- In total 30 people whose age range was 19-38.

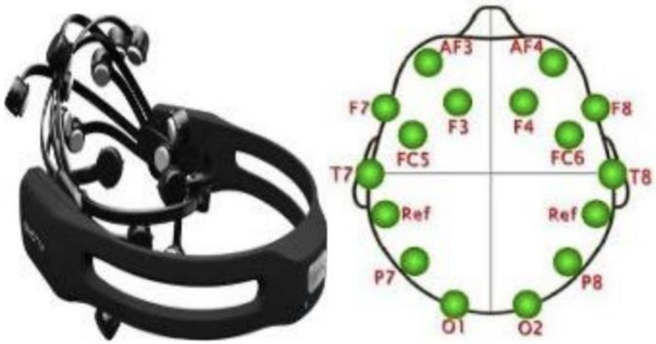

Figure 1. Experimental recording system to record EEG signals. Epoch plus, Channel positions.

EEG Dataset

- 5 seconds before the started movie to the end.
- Total of 672 trials for 14channels,
- Each trial contained a 65s signal for the funny movie and a 92s signal for the horror movie.
- Name of 14 channels are: AF3, F7, F3, F4, F8, FC5, FC6, P7, P8, T7, T8, O1, O2, and AF4.
- Sampling frequency is 64 Hz.
- The International 10-20 system is used to arrange the electrode in the cap for EEG measurement.

Methodology

Feature extraction method

- Discrete wavelet transform (DWT) to extract the frequency band of the emotion EEG signals.

- DWT is a very effective way to extract actual information from the signal because of the oscillating frequency bands and time information.

- From the same EEG segment, DWT produces different degrees of multiple mother wavelets, which finally helps to generate multiple detection results have used a band-pass Butterworth filter to pass the EEG signal.

- We extracted DWT for five levels and extracted features considered as follows D1, D2, D3, D4, D5 and A5.

Methodology

➢ Statistical Features

- ❖ Average power (AVP)
- ❖ Mean absolute value (MAV)
- ❖ Standard deviation (SD)

$$MAV = \frac{1}{s}\sum_{i=1}^{s}|x_i| \qquad (4)$$

$$AVP = \frac{1}{s}\sum_{i=1}^{s}|x_i|^2 \qquad (5)$$

$$SD = \sqrt{\frac{1}{s-1}\sum_{i=1}^{s}(x-\mu)^2} \qquad (6)$$

Methodology (Cont.)

- Classification
  - To classify the emotion, based on EEG signal data-
  - We have employed three distance-based machine learning classification algorithms and fed the feature data:
    - Support vector machine (SVM) in one to one scheme,
    - Random Forest Algorithm
    - Extra Tree Classifier(ETC)
  - Each classifier is used here with 10 fold cross-validation.
  - Thus observed data classify into class.

Performance Accuracy

	SVM	RF	ETC
AF3	63.00	75.00	75.00
F7	75.00	75.00	75.00
F3	63.00	75.00	88.00
FC5	75.00	88.00	88.00
T7	75.00	75.00	75.00
P7	63.00	75.00	75.00
P8	75.00	88.00	75.00
T8	88.00	75.00	88.00
FC6	63.00	88.00	88.00
F4	55.00	75.00	75.00
F8	55.00	75.00	88.00
AF4	63.00	75.00	88.00

Table-1: Classification accuracy (%) is based on different classifiers for each electrode.

Discussion

- F3, FC5, T8, FC6, F8, and AF4 electrodes achieved 88.00% with ETC.
- F3, FC5, T8, FC6, F8, and AF4 are most useful electrode among the 12 electrodes.
- Our model will be useful for selecting EEG channels during the EEG signal processing spatially positive negative emotion classification tasks.

State of the Art Comparison

Paper	Method	Accuracy
Kasuga [30]	FFT	85.40
Proposed Method	Wavelet Transform	88.00

Table 2: State of the Art Comparison

Conclusion

- We developed a positive negative emotion classification system based on wavelet transform features in this study.
- First, we applied a wavelet transform to extract five bands’ information.
- From there, we extracted statistical parameters MAV, AVP and SD.
- Lastly, we applied an extra tree classifier (ETC) to the training and test data and got 88.00% accuracy for F3, FC5, T8, FC6, F8, and AF4 electrodes equally.
- We obtained a higher performance score compared with the existing work.
- In future we will include more than 2 class for the emotion recognition task.

Thank you for your kind attention

Any Question Please!

Reference

1. [6] Cruz-Albarran, I.A., Benitez-Rangel, J.P., Osornio-Rios, R.A., Morales-Hernandez, L.A., “Human emotions detection based on a smart-thermal system of thermographic images”. Infrared Phys. Technol. 2017, 81, 250–261. [CrossRef] [32]
2. [7] Goulart C., Valadão, C., Delisle-Rodriguez, D. Funayama, D. Favarato, A.; Baldo, G. Binotte, V. Caldeira, E. Bastos-Filho T., “Visual and thermal image processing for facial specific landmark detection to infer emotions in a child-robot interaction,” Sensors 2019, 19, 2844. [CrossRef]
3. [8] Chaitanya Sarath, S. Malavika, Prasanna Karthik, “Human Emotions Recognition from Thermal Images Using Yolo Algorithm,” In Proceedings of the IEEE International Conference on Communication and Signal Processing, Chennai, India, 28–30 July 2020. [CrossRef]
4. [9] Ko, Youjung, Insuk Hong, Hyunsoon Shin, and Yoonjoong Kim, "Construction of a database of emotional speech using emotion sounds from movies and dramas," In 2017 International Conference on Information and Communications (ICIC), pp. 266-267. IEEE, 2017.
5. [10] Zhu, Lianzhang, Leiming Chen, Dehai Zhao, Jiehan Zhou, and Weishan Zhang, "Emotion recognition from Chinese speech for smart affective services using a combination of SVM and DBN," Sensors 17, no. 7 (2017): 1694.
6. [11] Murugappan, Subbulakshmi Murugappan, “Human Emotion Recognition Through Short Time Electroencephalogram (EEG) Signals Using Fast Fourier Transform (FFT),” IEEE 9th International Colloquium on Signal Processing and its Applications, pp.289-294, Kuala Lumpur, Malaysia, 2013.
7. [12] Abu Saleh Musa Miah, M.K.I. Molla, M.E.Hamid. “Multiband Implementation of Tangent space Mapping for EEG signal,” Inter Academia Asia Conference-2017, Shuzuoka University, Japan.
8. [13] Abu Saleh Musa Miah, Saadaldeen Ahmed, Mohammed Ahmed, Adil Duru, Oğuz Bayat, Doaa Mraiza and Md.Khademul Islam Molla,” Motor-Imagery BCI task Classification using Riemannian geometry and averaging with Mean Absolute Deviation,” International Scientific Meeting of Electrical-Electronics & Biomedical Engineering & Computer Science EBBT’2019 held on Istanbul Arel University on 24-26 April 2019 at Kemal Gözükara Campus in Istanbul Arel University, Turkey.
9. [14] Abu Saleh Musa Miah, Md. Rabiul Islam, Md.Khademul Islam Molla, “Motor imagery classification using Subband Tangent Space Mapping,” International Conference on Computer and Information Technology-2017 held on University of Asia Pacific, Dhaka, Bangladesh.(Has been awarded as the Best Paper Award (1st Position))
10. [15] Abu Saleh Musa Miah, Md. Rabiul Islam, Md.Khademul Islam Molla ,“EEG Classification for MI-BCI using CSP with Averaging Covariance Matrices: An Experimental Study” International Conference on Computer, Communication, Chemical, Material and Electronic Engineering (IC4ME2-2019),Bangladesh.
11. [16] Mahmudul Haque Joy, Mohammad Hasan, Abu Saleh Musa Miah*, Abir Ahmed, Sadia Anwar Tohfa, Md. Farukul Islam Bhuaiyan, Md. Mamunur Rashid, Ashrafun Zannat, ”Multiclass MI-Task Classification using Logistic regression and Filter Bank Common Spatial Patterns,” Springer-Nature Singapore Pte Ltd. 2020, COMS2 2020, CCIS 1235, pp. 160–170, 2020. https://doi.org/10.1007/978-981-15-6648-6_13
12. [17] Abu Saleh Musa Miah1, Md. Mamunur Rashid1, Md. Redwanur Rahman1, Md.Tofayel Hossain1, Md. Shahidujjaman Sujon1, Nafisa Nawal1, Mohammad Hasan1,Jungpil Shin * “Alzheimer’s disease Detection using CNN based on Effective Dimensionality Reduction Approach” 3rd international conference on intelligent computing & optimization 2020, ICO 2020, December 17-18, 2020 (Accepted)
13. [18] Abu Saleh Musa Miah,Mumtahina Afroz Mouly,,Chandrika Debnath, Jungpil Shin,S. M. Sadakatul Bari, “Event-Related Potential Classification based on EEG data using xDWAN with MDM and KNN,“ Springer-Nature Singapore Pte Ltd. 2021, COMS2 2021, CCIS 1235, pp. 160–170, 2020. https://doi.org/10.1007/978-981-15-6648-6_13
14. [19] Talha Zobaed, Saadaldeen Rashid Ahmed ahmed, Abu Saleh Musa Miah, Salma Masuda Binta, Mohammed Rashid Ahmed AHMED and Md. Mamunur Rashid,” Real Time Sleep Onset Detection from Single Channel EEG Signal Using Block Sample Entropy,” ISCAU 2020, IOP publisher conference proceedings, Scopus indexed and has Cite Score 0.53 Q3,IRAQ.
15. [20] Hazarika, Neep & Chen, Jean & Tsoi, Ah & Sergejew, Alex. (1997). Classification of EEG signals using the wavelet transform. Signal Processing. 59. 89-92 vol.1. 10.1109/ICDSP.1997.627975.
16. [21] Wosiak, A.; Dura, “A. Hybrid Method of Automated EEG Signals’ Selection Using Reversed Correlation Algorithm for Improved Classification of Emotions,” Sensors 2020, 20, 7083. https://doi.org/10.3390/s20247083
17. [22] Koelstra, Sander, Christian Muhl, Mohammad Soleymani, Jong-Seok Lee, Ashkan Yazdani, Touradj Ebrahimi, Thierry Pun, Anton Nijholt, and Ioannis Patras, "Deap: A database for emotion analysis; using physiological signals," IEEE transactions on affective computing 3, no. 1 (2011): 18-31.
18. [23] Ekman, Paul, Wallace V. Friesen, Maureen O'sullivan, Anthony Chan, Irene Diacoyanni-Tarlatzis, Karl Heider, Rainer Krause et al, "Universals and cultural differences in the judgments of facial expressions of emotion," Journal of personality and social psychology 53, no. 4 (1987): 712.
19. [24] Parrott,W.G., “Emotions in Social Psychology: Essential Readings,” Psychology Press: Hove, UK, 2001.
20. [25] Plutchik, R., “The Nature of Emotions: Human emotions have deep evolutionary roots, a fact that may explain their complexity and provide tools for clinical practice,” Am. Sci. 2001, 89, 344–350. [CrossRef]
21. [26] Russell, J.A., “A circumplex model of affect,” J. Personal. Soc. Psychol. 1980, 39, 1161–1178. [CrossRef]
22. [27] Li, Zina, Lina Qiu, Ruixin Li, Zhipeng He, Jun Xiao, Yan Liang, Fei Wang, and Jiahui Pan, "Enhancing BCI-based emotion recognition using an improved particle swarm optimization for feature selection," Sensors 20, no. 11 (2020): 3028.
23. [28] Abu Saleh Musa Miah, Jungpil Shin, Md. Minhajul Islam, Abdullah, Md. Khademul Islam Molla, “Natural Human Emotion Recognition Based on Various Mixed Reality(MR) Games and Electroencephalography (EEG) Signals,” Taiwan conference, (Accepted) 2022.
24. [29] Spezialetti Matteo, Placidi Giuseppe, Rossi Silvia, “Emotion Recognition for Human-Robot Interaction: Recent Advances and