EMOTIONS RECOGNITION AND ARTIFICIAL SIGNAL GENERATIONS

Authors: Alberto Padilla Nieto and Marco Antonio Hernani Chavez

1. Introduction:

Using datasets containing a collection of signals read by receptors placed in different parts of the brain on subjects watching different videos that made them feel positive, negative, or neutral emotions. The main objective is to generate new artificial signals that contain the same properties as the real ones. As an optional goal, we also aim to create a recognition model capable of distinguishing to which emotion each set of signals belongs.

To achieve this objective, the content of the files containing each dataset was explored and studied, they were separated properly to facilitate the achievement of our objectives, and different methods were used to achieve them. The main objective was achieved without the use of any model and with the use of one.

To achieve the optional goal, the methodology of a study (Duan, Zhu, & Lu, 2013) and authorship methodologies were tried to be implemented.

2. Context:

Emotions are an important part of our lives. They affect how we experience it and this is one of the main reasons for their study. Understanding how we feel can help us understand ourselves and help others understand us better.

There are many techniques and tools used to obtain information about what is happening in our minds. One of them is the capture of the electrical impulses produced by the brain (electroencephalogram or EEG).

Using a non-invasive tool (which does not require any type of surgical intervention), the Shanghai Jiao Tong University collected the electrical signals captured by 62 receptors located in different parts of the brain as a result of repeated experiments in which subjects watched videos tagged as positive, negative, and neutral.

The motivation for the proposed objectives arises from the desire to help generate more data to facilitate the study of emotions, as it is a new field and there is still a scarcity of such datasets. Having more data could help, among other things, facilitate the creation of better models for recognizing emotions. This can help us understand how those who have problems communicating feel.

3. Methodology:

To achieve the proposed objectives, the next methodology was followed:

Data collection: We requested the data from Shanghai Jiao Tong University (https://bcmi.sjtu.edu.cn/home/seed/contacts.html). Once they grant us access to all the requested datasets We download the data in our personal computers.

Preprocessing: The data was preprocessed for further use. This preprocessing consisted into filtering the signals in different frequency bands, normalization to adapt all signals to the same time scale and separation of the data of each file in the dataset, so there is one file for each stimulation (one subject watching one labeled video).Finally, these resulting files were saved in 3 different folders according to their emotion. (Positive, Negative and Neutral).

Generate synthetic stimuli (without model): Using the preprocessed data, We developed a way to create new signals without using any model. First by grouping all the stimuli by duration and emotion and creating a new stimuli for each group . In a second attempt We group them by emotion and equalize the duration of all the stimuli and use them to create new stimuli.

Feature extraction: Using the preprocessed data relevant features were extracted: signals in the different frequency bands, entropy differential (DE) and power spectral density (PSD).

Feature selection: To prepare the data to train our models using the extracted features. Those selected features were and the idea to use them for the emotion recognition model training are taken from the article (Bands Frequencies - Position and Signals by Channels - DE - PSD):
https://link.springer.com/article/10.1007/s11571-021-09751-5

Model development: Finally two models were created to meet the objectives. A CNN model, whose function is to recognise whether the input stimulations are positive, neutral or negative emotions. And a GAN model, whose objective is to generate synthetic stimuli.

4. Data:

Data consisted of EEG signals collected with the 62-channel ESI NeuroScan System. The datasets were shared for the Shanghai Jiao Tong University (more information at https://bcmi.sjtu.edu.cn/home/seed/) for research purposes.

The data was divided into 6 datasets. Only 4 of those (SEED, SEED_V, SEED-GER,SEED-FRA) are used, due to time limitations and format:

SEED: EEG of 15 subjects. The data were collected while watching film clips. The videos were carefully selected to induce different types of emotions: positive, negative and neutral. https://bcmi.sjtu.edu.cn/home/seed/seed.html

SEED_V: EEG of 20 subjects. Evolution of the original SEED dataset. The number of emotion categories changes to five: happy, sad, fear, disgust and neutral. https://bcmi.sjtu.edu.cn/home/seed/seed-v.html

SEED_GER: EEG of 8 German subjects with positive, negative and neutral emotional labels. https://bcmi.sjtu.edu.cn/home/seed/seed-GER.html

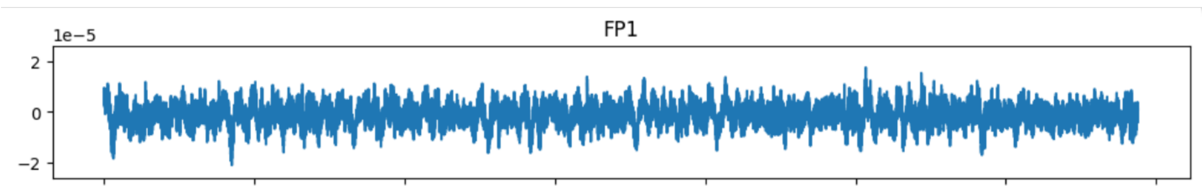
SEED_FRA: EEG of 8 French subjects with positive, negative and neutral emotional labels. https://bcmi.sjtu.edu.cn/home/seed/seed-FRA.html

The data was stored in cnt files that contained a raw object from the MNE library. This object is made to work with EEG and has useful methods, attributes and information.
For example the name of the channels (receptors), the sample rate of the signal, etc. .Also in the datasets there were some files with additional information about when each stimuli begins and ends in each cnt file and the label of those stimuli.

5. Results:

5.1 For the generate synthetic stimuli (without model):

For the first attempt we get one stimuli for each group of stimulus with the same emotion and duration made. This is a visualization of one of the 62 signals for one of the stimuli. The x-axis indicates de time, and the y-axis indicates de value in volts readed by the receptor in that instant. The best way to test this result is reproducing these signals in a brain with the inverse tool (one that stimulates the brain). But We don't have it. We are not experts in this field so we can just display the result but not check if it's correct and We successfully created a synthetic stimuli for an emotion.



For the second attempt We equaled the duration of all trials for the same emotion and got only one synthetic stimuli. Similar to the previous attempt We can't check if We succeeded.

5.2 For the emotion recognition model:

We got an accuracy of 37,25% and a loss of 1.0998 for the created CNN model, which indicates that our model has an accuracy of 37,25% classifying the test data.

5.3 For the model made to generate artificial stimuli:

We trained a GAN model and obtained a D_loss of 1.95, an accuracy of 53.125 and a G_loss of 1.57.

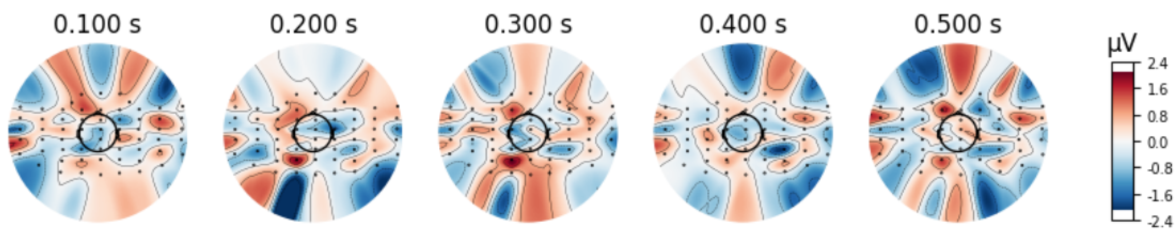
Notes:

G_loss: A high value indicates that the generator needs to be improved.

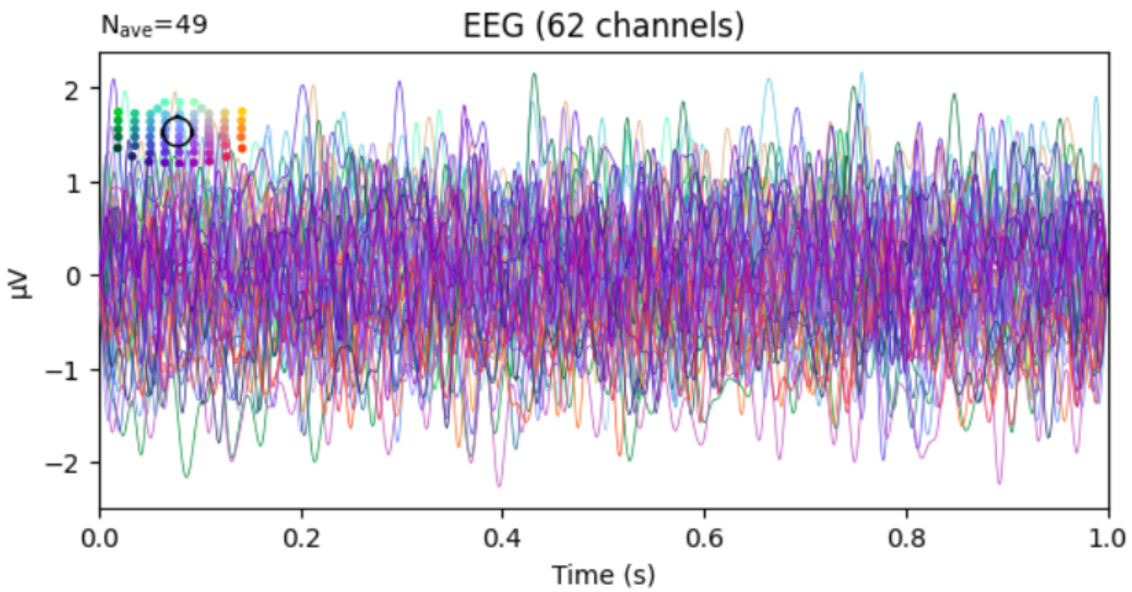
D_loss: A low value indicates that the discriminator performs well in classifying the input data as true or false.

accuracy.: It is the accuracy of the discriminator in correctly classifying input data as real or fake.

Like in our attempts to generate synthetic stimulus (without use of models) there is no way to be certain that We succeeded. We can just display the synthetic stimuli obtained with the model:



Above we can observe a topography with the values readed by each receptor at different instants (0.1s, 0.2s, 0.3s, 0.4s, 0.5s).
Below there is a display of all the signals readed by each channel (receptor) in the first second. The values readed are in microvolts.



6. Conclusions:

The CNN model is very primitive and the expected accuracy value is not obtained. This is due to the structure of the model, since the article on which it is based also consists of a type of self-adaptive attention module made up of two sub-modules, the spatial attention module and the spectral attention module.

For the GAN model as we have seen in the results, the discriminator still identifies with some accuracy those that are false and real. On the other hand, the loss of the generator can still be improved. The big problem we have encountered at this point is that the data is so large and takes up so much space in memory to train both models. That is the reason why we have had to interpolate the time scale to 50 seconds for each file of each stimulus (range from 52s to 300s), losing a lot of information and making it harder for the generator to find a pattern.

7. Next steps:

- Improve the accuracy of the GAN Model.
- Improve the accuracy of the Model for Emotion Recognition.
- Transforming the stimuli into images and using them to train the emotion recognition model and the GAN.

8. Bibliography:

1. Ruo-Nan Duan, Jia-Yi Zhu and Bao-Liang Lu, Differential Entropy Feature for EEG-based Emotion Classification, Proc. of the 6th International IEEE EMBS Conference on Neural Engineering (NER). 2013: 81-84. [link] [BibTex]

2. Wei-Long Zheng, and Bao-Liang Lu, Investigating Critical Frequency Bands and Channels for EEG-based Emotion Recognition with Deep Neural Networks, accepted by IEEE Transactions on Autonomous Mental Development (IEEE TAMD) 7(3): 162-175, 2015. [link] [BibTex]

3. Wei-Long Zheng and Bao-Liang Lu, A multimodal approach to estimating vigilance using EEG and forehead EOG. Journal of Neural Engineering, 14(2): 026017, 2017. [link] [BibTex]

4. Wei-Long Zheng, Wei Liu, Yifei Lu, Bao-Liang Lu, and Andrzej Cichocki, EmotionMeter: A Multimodal Framework for Recognizing Human Emotions. IEEE Transactions on Cybernetics, Volume: 49, Issue: 3, March 2019, Pages: 1110-1122, DOI: 10.1109/TCYB.2018.2797176. [link] [BibTex]

5. Wei Liu, Jie-Lin Qiu, Wei-Long Zheng and Bao-Liang Lu, Comparing Recognition Performance and Robustness of Multimodal Deep Learning Models for Multimodal Emotion Recognition, IEEE Transactions on Cognitive and Developmental Systems, 2021. [link] [BibTex]

6. Wei Liu, Wei-Long Zheng, Ziyi Li, Si-Yuan Wu, Lu Gan and Bao-Liang Lu, Identifying similarities and differences in emotion recognition with EEG and eye movements among Chinese, German, and French People, Journal of Neural Engineering 19.2 (2022): 026012. [link] [BibTex]