A Review of EEG Emotion Recognition

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Abstract *— Emotion recognition is an important aspect of HMI (Human Machine Interface) Field, EEG (Electroencephalography) allows a simple and effective elicitation of those emotions, increasing the accuracy of the EEG signals is the focus of many researchers from across the globe, some are intending to improve the signals by focusing on the signal processing techniques, some are focusing on statistics or machine learning techniques. In this paper, we will discuss the most common techniques, especially the studies that are yielding to the best result, but we also are going to highlight the novel ways of classifying the emotions even if the results weren't the best. Also reviewing the common steps of making the emotion elicitation experiment setup, we will discuss the different techniques of collecting the signals, then extracting the features then selecting the features, as well as discussing some standing problems in the field and future growth areas.*

Keywords—*EEG,Emotion Recognition, Emotion Detection,HMI,BCI*

I. INTRODUCTION

If the machine is conscious about the current user emotion, it can drive it to take more informed decisions that will be appreciated by the user, and reduce the user frustration, resulting in enhancement of the user machine communication, hence driving the HMI (Human Machine Interaction) field forward.Humans emotion detection can be approached from a number of angles, and number or rational. Researchers were trying to detect the emotions from different angels like text, speech, facial images or videos, facial depth images, skin conductivity, temperature, EOG (Electrooculogram), heart rate, Eye blinking, Heart Rate Variability (HRV), and now EEG.The biometrics reflects a high correlation between the readings and the human emotions,especially the brain signals. Brain signals can be measured by different techniques, there are several invasive and non-invasive techniques for collecting the brain signals such an EEG (Electroencephalogram), fMRI (Functional Magnetic Resonance Imaging), MEG (Magneto Encephalography), NIRS (Near-infrared Spectroscopy), PET (Positron Emission Tomography), EROS (Event-related optical signal). In this work, we will focus on EEG Emotion Recognition. EEG signals are the voltage fluctuationsmeasured by placing sensitive electrodes on the scalp measuring the voltage by microvolt (mV) with a certain frequency Ex. 100 Hz. The EEG signals could be monopolar or bipolar. Monopolar is measuring the pure voltage readings,bipolar is measuring the voltage difference between twoelectrodes, there are different techniques for specifying which two. Although the monopolar recording is more popular. The most famous placement of the electrodes is called 10-20 position system, which is proposed by the International Federation of Societies for Electroencephalography and Clinical Neurophysiology. [25],[30]

II. REVIEW EXPERIMENTSETUP

EEG Emotion Recognition is a still standing problem and it has been for a long time. There is a lot of studies in this area, most of the studies have a similar experimental setup to extract the emotion from the user and then classify it,the steps look like this:

1- Emotion elicitation: by using an external stimulusfor example (images, videos, audio, game) the studies could develop their own stimulation material or they can choose from a readymade dataset to trigger a studied range of emotions
2- Collecting SAM (Self-Assessment Manikin): The same image could trigger a happy feeling in one subject but a sad feeling on the other, that's why we need to ask the subjects after the experiment to tell us what is the feeling that they experienced, the depth or the magnitude of the emotion may differ as well that's why most of the studies are using variations of SAM to rate pleasure, arousal, and dominance.
3- Feature extraction and feature selection of the EEG data.
4- Machine Learning Classification:the most common classifier is the SVM but depending on the study researchers tend to use the otherclassifierbased on their data.

It's not clear in this field (EEG Emotion Recognition) on the range of emotion that can be detected or on how to detect certain emotions, so each study is trying to either focus on one or two emotions and describe the best approach for it, but there are no well-proven standards, studies examples:

1- Distinct emotion: (happy, sad …) in this type of studies researches focus on a single emotion or a handful of emotions to recognize.
2- Positive vs Negative emotion detection.
3- Arousal, Valancestate:high arousal high valence (HAHV),low arousal high valence (LAHV), high arousal low valence (HALV).

[27], [28]

Study	Purpose of the study	Technique	Observations and result
[1] 2017	To detect the emotions (Excited, Relax, Sad, Average (neutral))	***Channels***: AF3, T7, T8, AF4 with 128 Hz, ***feature extraction***: Wavelet***Classifier***: Support Vector Machine (SVM) and Learning Vector Quantization (LVQ)	Run on 10 subjects, using emotion database, (morning, noon, and night), window is 10s, the accuracy (Excited 88%, Relax 90%, Sad 84%, Average 87%)
[2] 2016	Anger, Surprise, Other	***Channels***: (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 and AF4) with 128Hz. ***feature extraction***: Short-Time Fourier Transform (STFT) and (mRMR), and 1sec window, ***Classifier***: Random Forests (RF) and SVM. they used the DEAP dataset to trigger the emotions	RF better than SVM
[3] 2016	Valence, Arousal	***Channels***: (Fp1, Fp2, F3 and F4), ***feature extraction***: Wavelet + Basic Statistics Higher Order Crossing (HOC), ***Classifier***: SVM as a classifier. 32 participants involved, and they used the DEAP.	Valence 82%, Arousal 76%
[4] 2016	Happy, angry, sad, neutral	***Channels***: 10-20 system, ***feature extraction***: Principal Component Analysis (PCA) Fourier Transform (FT), Short-time Fourier Transform (STFT) slow cortical potential (SCP) and Wavelet Packet Transform (WPT) Discrete Wavelet Transform (DWT), ***Classifier***: radial basis function neural network (RBFNN) and SVM. 5 subjects	HOC is the best
[5] 2017	- high arousal, high valence x - low arousal, high valence x - low arousal, low valence x - high arousal, low valence	***Channels***: 32, ***feature extraction***: Statistical Feature, Hjorth Features, Non-Stationary Index, Higher Order Crossings, ***Classifier***: Relief algorithm, Bhattacharyya distance, DEAP, 32 subjects, 40 Music videos	the statistical feature is more powerful
[6] 2016	positive or negative	***Channels:*** 32 128Hz, ***feature extraction***: spatial filter of common spatial pattern (CSP)**,** ***Classifier***: ElasticNet, LDA, QDA, SVM, set of movie clips, 23 subjects	spatial filters better than conventional methods (CSP)
[7] 2012	low arousal low valence (LALV), low arousal high valence (LAHV), high arousal high valence (HAHV), and high arousal low valence (HALV)	***Channels***: 3 channels, ***feature extraction***: adaptive way (AsI-based algorithms), ***Classifier***: quadratic discriminant analysis (QDA), Mahalanobis distance (MD), -nearest neighbour(-NN), support vector machine (SVM), 16 subjects, IAPS	AsI-based algorithms introduced performing better than simple SVM
[8]2015	happy, calm, sad, and scared	***Channels:***Fpl, Fp2, C3, C4, F3, and F4 ***feature extraction***: No Extraction ***Classifier***: Three layers of restricted Boltzmann machines (RBMs), 21 subjects	better recognition accuracy than KNN, SVM, ANN
[9] 2014	(LALV), low arousal high valence (LAHV), high arousal high valence (HAHV), and high arousal low valence (HALV)	***Channels:*** 64**,** ***feature extraction***: Wavelet ***Classifier***: kernel Fisher's discriminant analysis (KFDA) kernel eigen-emotion pattern (KEEP) 10 volunteers	Novel feature extraction method KFEP better than normal classification
[10] 2012	Arousal detection (strong vs. calm), and valence detection (positive vs. negative).	***Channels:*** FP1/FP2, F7/F8, F3/F4, FT7/FT8, and FC3/FC4. ***feature extraction***: asymmetric features and filter bank common spatial pattern (FBCSP) as a benchmark and proposing Recursive Fisher linear discriminant (RFLD) ***Classifier***: K-nearest neighbor (KNN), Naive Bayes (NB), and support vector machine (SVM) ,video clips, lasts for less than 20 minutes, 4	Novel feature extraction method

		subjects	
[11] 2015	Regret, rejoice, other emotion	***Channels:*** 64 ***feature extraction***: Approximate entropy (ApEn) ***Classifier***: Fisher Linear Discriminant (FLD) 25 subject using gambling paradigm	Extracting the regret emotion from the signal
[12]	'anger', 'contempt', 'disgust', 'fear', 'sad', 'surprise', 'happy'.	***Channels:*** 14 channels ***feature extraction***: Wavelet ***Classifier***: Mel-frequency cepstral coefficient (MFCC) multilayer perceptron (MLP) IAPS	A human can have more than one emotion at a time
[13] 2018	positive/negative and the approach/withdrawal	***Channels:*** F8, FC2, FC6, C4, T8, CP2, CP6, and PO4, F7, FC1, FC5, C3, T7, CP1, CP5, PO3 ***feature extraction***: DEEP PHYSIOLOGICAL AFFECT NETWORK (Deep Learning model) ***Classifier***: multi-layer convolutional neural network (CNN), 1,280 videos, along with the 64 combinations of physiological signals per video.	Deep neural network for features extraction
[14] 2016	Normal, Abnormal	***Channels:*** 64 ***feature extraction***: Wavelet, Discrete wavelet transform (DWT) ***Classifier***: feed forward back propagation, 10 subjects	75% for normal and 65% for abnormal
[15] 2014	Valence, Arousal, Liking with Positive Negative for each	***Channels:*** 32 and 10 ***feature extraction***: Bandpower and PSD by Wavelet Transform ***Classifier***: Support Vector Machine (SVM), 32 participants DEAP	The best combination is one-minute EEG data using band power filter from 10-channel probes
[16] 2005	arousal, valence, dominance and liking	***Channels:*** 32-channel ***feature extraction***: Gaussian Mixture Model and wavelet ***Classifier***: linear ridge regression and support vector regression (SVR), 40 one-minute long music videos and let then score dominance (on a scale from 1 to 9) and familiarity (on scale 1 to 5). From DEAP dataset	unsupervised training have better results than traditional classification
[31] 2014	happy, sad and neutral)	***Channels:*** Twelve channels (AF3, F7, F3, FC5, P7, O1, O2, P8, FC6, F4, F8, and AF4) ***feature extraction***: short-time Fourier transform (STFT) 1sec window. differential laterality (DLAT) and differential causality (DCAU) ***Classifier***: Gaussian Naïve Bayes (GNB) Music listening (24 trials per day).	Comparing feature selection techniques

Table 1 Studies on emotion detection using EEG

III. EMOTIONS STIMULI DATASETS

There is a number of datasets that provide a studied emotion stimulus and metadata around each item in the dataset:

A. *International Affective Picture System: IAPS* consists of a set of pictures used to cause a wide range of emotional stimulations in the subject, every picture will contain the expected dimensions valence, arousal, and dominance, to be used as a reference. The dataset consists of a diverse number of pictures, snakes, accidents, contamination, insects, illness, attack scenes, loss, pollution, babies, puppies, and landscape scenes, among others. This dataset also contains metadata describing the dimensional aspects of the emotion that will be triggered by the picture. For example, heart rate and facial electromyographic activity differentiate negative frompositive valence, whereas skin conductance. The dataset also trying to attach distinct emotion with the picture (sadness, disgust,fear, happiness and nurturance) also contains valence and arousal readings, and that they can be distinguished by facial electromyographic, heart rate, and electrodermal. There is another dataset called International Affective Digital Sounds (IADS) which contain sounds stimuli instead of pictures. [16]

B. *Genevaaffective picture database: GAPED*usually the studies have multiple tries to get the measurement done, so if the subject saw the image they can't show it again as it will be well known by the subject and it will not trigger the stimuli again, that's why the GAPED has being introduced to offer an alternative to those images.This dataset also contains anumber of measures to give a view on the dataset images like facial expressions and physiological reactions. The downfallof this dataset is the limited number of Positive emotions compared to the negative ones. [17]

C. *Nencki Affective Picture System:*NAPS this dataset consists of 1,356 high-quality photographs. This pictureconsists of five different categories (faces, people,animals, objects, and landscapes). The dataset contains picture metadata, valence, arousal, and approach-avoidance dimensions using bipolar semantic slider scales using Self-Assessment Manikin (SAM). All the images in the dataset are1,600 by 1,200 in size. [18]

D. *Open Affective Standardized Image Set: OASIS*its consists of 900 pictures that are distributed into four categories (people, animals, objects and scenes). It's an open-access dataset, doesn't have copyright restrictions like IAPS Also the spread of the range of positive and negative images is reasonable.[19]

Images videos and sounds arethe only way to trigger emotions, there are other studies[11], that is conducting a gambling game to trigger two types of emotions *Regret* and *Rejoice*to isolate the emotion and increase the ability to identify the emotion. Other studies focused on Rage [26] the study didn't conduct a data collection sessions but they sued DEAP which is a premade data set to just identify that particular emotion.

There are other studies [5, 6, 10] used the music to trigger the emotionsand collect the emotions by using SAM.

Other studies used different kind of datasets [29] but the its less common, with its own benefits and hazards.

IV. FEATURES EXTRACTION

In EEG Emotion Recognition field there is no clear understanding or agreement on which feature is describing which emotion [20], different studies are using differentfeature extraction techniques depending on their application and sometimes trial and error [22], based on the best result. Here is a list of common ways to pre-process the signal and remove the artefacts like eyes blinking.

Removing artefacts:

1) *Principal Component Analysis (PCA)*It is a techniquefor dimension reduction (noise reduction) of data without loss of information. The data is linearly transformed in such a way that only orthogonal components are retained.[21]

2) *Independent Component Analysis ICA*:The goal is to remove the artefacts, so after the PCA reduce the data to components then ICA will work on separatingthose components. Sothe distinction of the raw EEG data and the artefacts become clear. then those artefacts can be removed. But the problem is that the number of factors that are affecting the signal is not identified, so the assumption of EEG data and artefacts is specially fixed is not always right.

3) *Fractional Dimension*:fitting a minimum number of circles in an original value will help us represent the EEG data, by doing that we will be reducing the complexity of the signal.

4) *Other techniques*: like Common Average Referencing CAR, it will measure the potential of an electrode with respect to the average of all the other electrodes,this will reducethe noise by subtracting the commonbrain activity from the position of interest. There are also methods like (SL) Surface Laplacian or (CSP) Common Spatial Patterns. [23]

the first step was to clean the data from the artefacts, then we can continue with feature extraction:

E. Statistical

1) *(AR) Autoregressive:* it's a time series modelling and itrepresents the EEG signal and it's widely used. There are other modelsto calculate the randomness of a signallike a weighted moving average filter.

2) *ARMA and MVAM:* Autoregressive Moving Average and Multi-Variate Autoregressive,it's also a time series that can be used to analyze the signals.

3) *GARCH:* Generalized Autoregressive conditional heteroskedasticity, being autoregressive makes it a time series

model, it's used for time-varying volatility, the volatility here is the standard deviation.

4) Others like Burg Method and Durbin Recursion and Yule-Walker

F. Time domain

1) Event-related Potential *ERP*: it's not trivialto detect ERP linked to emotion

2) Hjorth features: Activity and Mobility and Complexity those are the three parameters (features) this model provides, the Activity represents the squared standard deviation in order to get the signal power.

3) Non-Stationary Index*NSI:* The signal is divided into smaller subsets and the average of each subset is calculated the NSI is the standard deviation for those averages by doing so, we are analyzing the variation of the local average over time, this will result in a measurement of the complexity.

4) Fractal Dimension*FD:*represents a measure of thecomplexity and there aremultipleways to calculateit.

5) Higher Order Crossings *HOS*: this method is one of the most solid methods, it's used in the pre-processingstep as a noise reduction technique.[4]

G. Frequency domain

1) Band power: it's a very common technique, the frequency bands can be as follow; delta (0-4 Hz), theta (4-8 Hz), alpha (8-16 Hz), beta (16-32 Hz), and gamma (32-64 Hz) used in this study [16] and the humming window is usually 1 second. widelyused with (DFT) Discrete Fourier Transform or (FFT) Fast Fourier Transform or(STFT) Short Time Fourier Transform or (PSD)Power Spectra Density. STFT is the most commonapproach.

2) Higher Order Spectra*HOS:*second-order measures assume that the signal has a Gaussian form (Normal distribution), so HOS is an extension of second-order measures. AnyGaussian signal will be characterized by its mean and variance. But the HOS of Gaussian signals are either zero or contain redundant information.

H. Time-frequency domain

1) Hilbert–Huang TransformHHT: the way it works is to break down the signal to intrinsic mode functions (IMF) with the trend, IMF is a function represent the signal part. HHT work well withdata that is nonstationary and nonlinear. it's more like an algorithm than a model, a set of steps need to be done sequentially.

2) Short Time Fourier TransformSTFT: this method can be considered as a bridge between the Fourier Transform and the Wavelet Transform.The FT does not provide time-frequencyanalysis so the signal is broken down into parts and the part signal is assumed to be stationary.

*3) Wavelet Transform:*we can use DWT or CWT Discrete or Continuous. We can perform multi-resolution analysis (MRA) also known as a multi-scale approximation (MSA) to balance time resolution and frequency resolution

I. Multi-layered neural network (deep learning) [8] in this researchthey run thedeep learning on the raw signal without hand- crafted feature extraction or feature selection techniques, they are relying on the layer of the deep learning to provide an abstraction layers and to play the role of the feature extraction and the features selection in a traditional model. Three layers of Restricted Boltzmann Machines (RBM) are introduced, and the results are rather acceptable, it's easy and straight forward to implement, but the accuracy variesmuch and the model takes a lot of data to be trained compared to traditional models.

V. FEATURES SELECTION

the importance of this step is to determine which subset of the features is actually matteredthe most, to get the best out of the classification. There is no general agreement on which features are better to identify which emotion. But we can use some techniques to be able to find the best features of our self's but the best feature will vary depending on the application and the data shape. we can list the most effective techniques in the EEG emotion recognition field:

1- *(mRMR)Min-Redundancy-Max-Relevance:*this method is trying to identify the features that correlate to the result, which is maximizing the relevance, at the same time reducing the redundancy, the feature could relate directly to the result but it's redundant.

2- *Relief*: the way that these algorithmworks are to draw instance randomly, then calculatethe nearest neighbours, then changethe feature weighting to give more weight to the features that discriminate the instance from neighbours of different classes.

3- *Bhattacharyyadistance*:this method is measuring the analogyof two discrete or continuous probability distributions. It isclosely related to the Bhattacharyya coefficient which is a measure of the amount of overlap between two statistical samples. [5]

4- *Comparison studies:* it's more or less trial and error, for example,the study [5] is trying to recognize theemotions from music listening. The best feature when it comes to channels are specific 3 channels, and the best wave bands are beta and alpha. By minimizing the number of featuresthey select the most relevant features to extract the emotions that they are targeting to classify.

VI. CLASSIFICATION

*1) Support Vector Machine SVM:*is the most frequently used classifier due to the high-quality classification results.[24]

2) k-nearest neighbours k-NN: it's a simple algorithm easy to be applied but poor runtime performance, the output is a class membership probability. *[24]*

*3) Learning vector quantizationLVQ:*it's related the kNN and it applies a winner takes all approach, it's a network which uses supervised learning [1].

4) Artificial Neural NetworksANN: it's a nonlinear classifier, the most commonversion of ANN is (MLPNN) Multi-Layer Perceptron Neural Network or (MLP)Multi-Layer Perceptron.

5) RestrictedBoltzmannmachines RBMs: This study [8] at el is using3 layers of RBM to recognize 4 deferent distinct emotions.

6) Others like: Linear Discriminant Analysis LDA assumes the features are Gaussian distributed and itfails if the discriminatory function is not in mean but in the variance of the data [23], also NBC Naive Bayes classifier, Hidden Markov Model (HMM), Gaussian Mixture Models(GMM).

VII. CONCLUSION AND DISCUSSION

After collecting the SAMresults it has to be mapped with the EEG data which is a lot of work that requires precision and carefulness, especially when tagging the EEG data with the SAM feedback, in the experiments that have been made by other studies, a lot of the collected data had to be dropped due to the low-quality data. Along with every subject had to tag his own data as the emotion tend to differ from subject to another. Cleansing the data and tagging it for the classification is a mandarin taskhence it's a progress hindrance.

Another issue is that there is no closed feedback loop to enhance the accuracy of emotion detection, by closed feedback loop we mean a method to show the subject the classified data and allow him to judge it and enhance his brain wave next time to get more accurate result, allowing the human mind to train with the model, it's a way to make the classifier and the mind to learn in real-time.

Another phenomena that will affect the result is peoplebrain signals are deferent from each other's [9]which meansthat the EEG data is unique per person and the tanning of the classifier has to be per person, the model is specific to each person, which can be a problem for the applications that require recognition directly without the possibility of doing the training session first.

Moreover, there is no general agreement on which feature is best to describe which emotion in other words (emotion to features mapping).Furthermore, humans can have more than one emotion at the same time [13] so currently, there is no way to classify more than one emotion, the state of the art struggle with classifying one.

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