International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878, Volume-8 Issue-3, September 2019

Emotion Classifications in Electroencephalogram (EEG) Signals

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Abstract*: When students are performing bad in their academics or sports activities, there are underlying causes as to why they are unable to concentrate during class and training. This paper describes the method used to obtain, identify and classify emotions from EEG signals captured from students. As the focus on this paper is on military cadets' performance, the signals are acquired during classes and military training. The acquired signals are pre-processed using artifact removal techniques before sent for feature extraction and finally signals classification based on the valence-arousal emotion model system. The output of the classification will be able to determine if the students are having positive or negative emotions during class thus effecting their concentration level. This paper analyses the current available methods on artifact removals, feature extractions and the training model for the signal classification. Each method is analyzed in accordance to their accuracy, adaptability and the method that results in the least amount of lost data.

***Index Terms*: Feature extraction; Artifact removal; EEG signal classification; Emotion classification**

I. INTRODUCTION

The human brain is made up of multiple electrical signals working at the same time to perform certain actions in the human body. The electrical signals are called neural signals and is produced by the neuron's cells. The neurons functions as the communication central of the brain as it is able to receives, process and transmits information in the form of electrical signals. Each section of the brain produces a corresponding neuron signals in relation to the action needed. This isn't limited to the physical actions but emotional actions as well. By analyzing each neural signal produced by the brain and at which section it's being produced at will make it easier to understand a person's mental and physical state.

Manuscript published on 30 September 2019
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The human brain is divided into multiple parts that are able to perform tasks needed by the human body. The frontal lobe is located on the front of the head below the forehead and its main function is to control intellectual activities such as organization, personality, behavior and emotions. [11] Emotions can be defined as a feeling or a perception that occurs during a certain circumstance that a person is in or with the interactions of people surrounding them. Depending on the circumstances, whether it's a positive or negative, the emotions produced will corresponds to it. By analyzing the asymmetry of the EEG signals from the frontal lobe, it is possible to determine the emotional state of a person. The brain activity obtained from the left frontal lobe are usually connected to positive emotions while the brain activity from the right frontal lobes are connected to negative emotions. [12] Due to this, the focus of this research will be on the EEG signals obtained from the frontal lobe. In order to classify the EEG signals in accordance to the emotions, the Valence-Arousal emotion model is used as depicted in Figure 1.1. The arousal scale shows whether the person is calm/bored or excited/stimulated while the valence scale shows if the person is unhappy/sad or happy/joyful. [5] Therefore, the EEG signals obtained will need to undergo a pre-processing to remove signal artifacts, feature extraction and finally signal classifications in accordance to the Valence-Arousal emotions model.

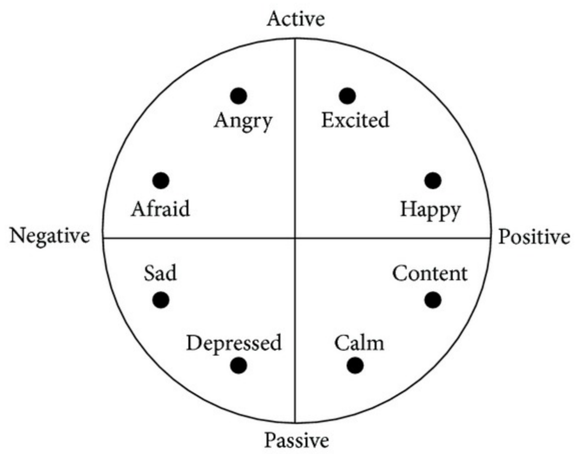

Figure 1: The Valence – Arousal emotion model

Retrieval Number: B2650078219/2019©BEIESP
DOI:10.35940/ijrte.B2650.098319
Journal Website: www.ijrte.org

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II. LITERATURE REVIEW

To determine the emotions in EEG signals, most of the current available algorithms are dependent on an EEG training data. The data is obtained by subjects that are experiencing certain emotions during a training session. The recorded EEG data will then need to be pre-processed to remove signal artifacts that affects the quality of the data. The processed data is then subjected to feature extraction to extract numerical feature vectors and finally the extracted features are fed into a classifier for the training that is done by machine learning.

A. Artifact Removal of EEG Signals

Artifacts is a form of noise or disturbance that are commonly found in EEG signals during the recording session. The artifacts are divided into two categories which are physiological and non-biological artifacts.[7] Physiological artifacts are caused by non-brain related biological sources such as eye blinking, eye movements, muscle movements and head motions. Non-biological artifacts are caused by interference from non-body factors such as high-impedance electrodes, connectivity issues and physical problems with the device.

Table 1 Comparison of the Methods of Artifact Removal

Artifact removal methods	Advantages	Disadvantages
Data Removal	Simple and easiest method	Large loss of data
Regression Method	Can be used in either time domain or frequency domain	Good reference signal is needed to ensure that the wrong data is not eliminated
Independent Component Analysis	Most successful and common method used	Manual inspection and automatic identifications are needed to ensure an efficient identification of the artifacts

Multiple methods have been used to remove these artifacts without causing a loss of data. One of the most common method is data removal where some portions of the data that exceeds a certain pre-determined threshold are deleted. This causes a large loss of data from the EEG signals which might affect the ERP of the signals.[7] Another method is called the regression method where the artifacts are removed either in time domain or frequency domain. For this method, a good reference signal is needed to ensure that the wrong data isn't eliminated.[7] Alternatively, a method of using joint probability to determine the probability of artifact occurrence at a point in time in a specific channel and segment can be used to remove artifacts in the EEG signals .[2] The most successful and common approach for removal of artifact is the independent component analysis (ICA) method. ICA uses statistics to decompose the EEG recordings into a set of independent components that shows the statistical estimate of the source signals.[7], [2] However, to ensure that there is an efficient identification of artifact-related independent components, manual inspections and automatic identifications are used. Manual inspections are done using visual identification which is a time-consuming method as it involves a vast amount of knowledge of topographic patterns and time domain patterns. Automatic identifications are done using K-means clustering based on the similarity between each independent component obtained from the ICA.[7]

B. Feature Extraction of EEG Signals

After the signals has undergone the pre-processed stage, the signals will need to be studied using feature extraction to determine the distinct attribute that are corresponding to the values needed. The common methods of extracting features from signals are time domain and frequency domain. Time domain features includes sample entropy, approximate entropy, permutation entropy, fractal dimension, Hjorth parameters, Hurst components and Lyapunov components. [4] Whereas, the frequency domain features are done using the absolute and relative power in the EEG signals and comparing it with the power ratio in different bands. Alternatively, a combination of both time domain and frequency domain is the wavelet-based feature extraction method.

Discrete wavelet transforms (DWT) is a an extensively used method for analyzing EEG signals due to the non-stationary characteristics in the signals. [4] DWT uses a high pass and low pass filtering of the time series domain. It uses an ample time windows for low frequencies and a short time windows for higher frequencies. This results in a good analysis of the time-frequency signal analysis. Alternatively, another method of feature extraction is the empirical mode decomposition (EMD). This method decomposes a signal into a number of oscillatory components which is known as the intrinsic mode functions (IMFs). The signals that are decomposed into IMF has to satisfy two conditions which are the number of extrema or zero crossings must be equivalent or differ by the maximum of one. The second condition is the average value of the envelope defined by the local maxima and minima is equivalent to zero. [6] The extracted signals using the methods above are then ready for the classification stage.

Table 2 Comparison of the Methods of Feature Extraction

Feature Extraction Method	Advantages	Disadvantages
Discrete Wavelet Transform	Good analysis of the time-frequency signal analysis	The system is more complex
Empirical Mode Decomposition	The signals are decomposed into IMFs to have a more detailed extraction	The decomposed signals are difficult to work with

C. EEG Signals Classification

Once the signals have been pre-processed and the features are extracted, the signals are ready to be classified in accordance to their characterization.

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The feature classification methods are usually done using machine learning techniques that identify unknown samples by learning from previously known samples. The types of machine learning techniques commonly used for classifications are K-Nearest Neighbor (KNN), Support Vector Machine (SVM) and Artificial Neural Network (ANN).

KNN is a classification method that uses supervised learning to classify based on the closest training samples present in the feature space. [8] By inserting a test data into the classifier, the data is mapped to the class that is most common among the K neighbors. The KNN algorithm uses an integer value for K and a metric to measure the closeness.

Alternatively, SVM is a common classification method that uses supervised learning to construct a separating hyperplane in a high dimensional space. [8][1] SVM is basically a linear machine that works in the k-dimensional space. The k-dimensional space is created by a n-dimensional input data X using non-linear mapping. This allows the data to be isolated normally by geometry and linear algebra. Therefore, by identifying a separating hyper plane, it is easy to obtain a linear classifier for any data points with labels.

Additionally, ANN is a method of classification with a set of connected input and output network where each weight is associated with each connection. ANN is made up of three layers which are input layer, hidden layer and output layer. ANN is based on the network structure of the human brain and it has a connected unit called nodes. The nodes form the input signals and transmit them to other nodes that are connected. [12] By adjusting the weight of the connection, the performance of the network improves. There are two types of ANN connection which are feed-forward network and recurrent network. Feed-forward network is a network connection that does not form into a cycle while recurrent network forms into a cycle. By modifying the weighted sum of input, the neurons of the neural network will be activated and the activation signals will be passed through transfer functions to produce one output of the neuron. To obtain a specified level of accuracy, the inter connection weight needs to be optimized during training.

Table 3 Comparison of the Methods of EEG Signals Classifications

Classification Method	Advantages	Disadvantages
K-Nearest Neighbor	Easy classifier and the most commonly used	Slow especially with large amount of data. Can result in low accuracy
Support Vector Machine	Strong classifier that is able to analyze multiple forms of data	The parameters Need multiple try and error method with the right parameters to obtain a high level of accuracy
Artificial Neural Network	Easy to use and high performance High accuracy compared to other classifiers	Need large amount of dataset to obtain accurate classification

III. RESEARCH METHODOLOGY

The research methodology for this research is chosen based on the quantitative research method. The research will be conducted on military cadets during their classes and military training to determine if the students are able to focus. The research will also need to determine what are the underlaying causes that are affecting the cadet's ability to focus. The EEG signals from the students will be taken during their classes. The signals will need to be pre-processed to remove the signals artifacts and sent to feature extraction and finally into the trained classification model. The trained model will be able to classify the signals according to the valence-arousal model. Figure 2 shows the steps taken in this research to obtain the output.

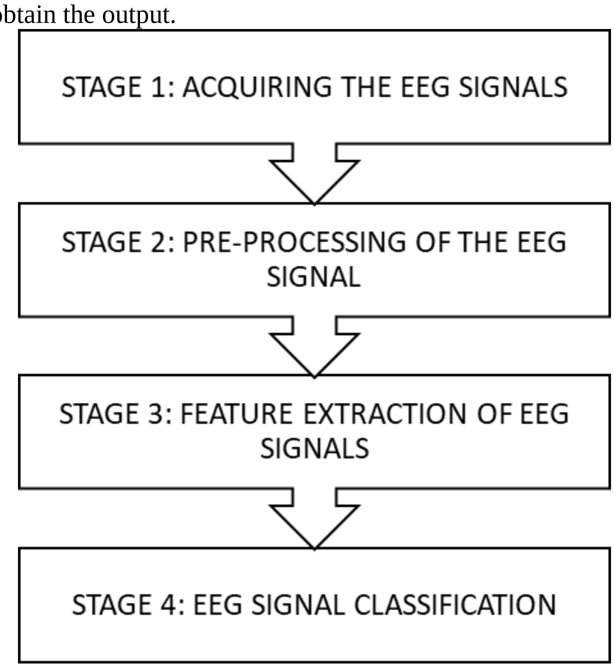

Figure 2: Stages required to obtain and classify the EEG signals.

A. Stage 1: Acquiring the EEG Signals

For this research, the focus will be on the military cadets during their university classes and military training. Therefore, the EEG signals will need to be taken during these situations without disrupting their lessons or activities. The EEG signals must have the least number of artifacts and noise to ensure that the output data is not affected. Due to this, the Mindwave Neurosky Mobile EEG headset is chosen as the device to obtain the RAW EEG signals from the students. The device was launched in the year 2010 and was designed to identify and monitor the electric signals generated by the neural activity in the brain. The device comprises of eight main parts which are the ear clip, sensor tip, sensor arm, battery area, power switch, adjustable head band and a Thinkgear chipset that is located inside the device. The sensor tip on the forehead detects electrical signals from the brain. The position of the forehead sensor is on the forehead above the eye which is in the FP1 position following the American Electroencephalographic Society's 10-20 system of electrode placement. However, the forehead sensor tip also picks up ambient noise from the surrounding environment.

The second sensor is located at the ear clips and it functions as a ground and reference which allows the device to filter out the electrical noise. This device is able to read the raw signals, power spectrum signals, attention and meditation level, and blink detection. The raw signals are categorised into alpha, beta, gamma and delta signals. The raw signals are ready for the pre-processing stage.

B. Stage 2: Pre-processing of the EEG Signals

The raw signals obtained from the EEG headset is riddled with multiple artifacts and noise. This is caused by the situation the cadets are in when the signals are recorded by the device. In a class environment, the students will be experiencing both physiological and non-biological artifacts as there are multiple factors affecting the device connection. During the training environment, the student will be running and sweating which will cause interference during the signal recording. In order to remove the disturbance, the signals will need to undergo a pre-processing stage. The pre-processed stage involves a method of removing the artifacts without resulting in loss of data. For this research, the ICA method is chosen as the signals obtained after the artifact removal shows that it has the least amount loss of data and the signal quality is in a good condition. ICA method is done by decomposing the signals into independent components to ensure that there is no loss of data during the process. The independent components are then analyzed and combined together with the removal of artifacts at the end of the process. The processed signals are now ready for the next stage which is the feature extraction stage.

C. Stage 3: Feature Extraction of the EEG Signals

Once the signals have been subjected to the pre-processed stage, the signals are now ready for feature extraction. After the EEG signal has been filtered, the signal is then analyzed using feature extraction process where the feature of the signals is derived using multiple signal processing techniques such as Discrete Wavelet Transform, Fourier Transform and Empirical Mode Decomposition. The extracted features are then classified in accordance to their characterization. For this research, DWT is chosen as the feature extraction method due to its ability to adapt to features of the functions. DWT manipulates the low pass and high pass filter to obtain a good extraction analysis of the data. Once the feature of the signals is extracted, the signals are then ready for the classification stage.

D. Stage 4: EEG Signal Classification

The extracted features of the signals are then ready to be classified. The feature classification methods are usually done using machine learning techniques that identify unknown samples by learning from previous known samples. For this research, an already trained model is needed before using the data obtained from the students. The trained model has to be trained using available dataset that are given priority on emotions based on the valence-arousal model. Once the trained model is able to predict the data input accurately, the model is then used to classify the signals obtained from the students' data. For this research, the focus on the classification model is on the ANN technique. This is because ANN has the highest accuracy rating in comparison to the other machine learning techniques available. Furthermore, the ANN technique is easy to manipulate as it depends on the weight of each connection. By manipulating the weight, the performance of the network improves and the data accuracy increases. The output of the training model will verify if the students are experiencing positive or negative emotions.

IV. SUMMARY

The purpose of this study is to describe the multiple methods of performing emotions classification in EEG signals. In this research, the emphasis was given on military cadets' performance during class and military training. This paper divides the emotions classifications method in accordance to the steps in signal classification and comparing the output to the valence-arousal emotion model. The signals are first obtained from the military cadets using the EEG device called Neurosky Mindwave mobile headset. The acquired signals will then need to undergo artifact removal process. Multiple methods were analyzed for the removal process such as data removal, regression method and ICA. The chosen method for this research is the ICA method as it has the least amount of data loss. The raw signals will undergo feature extraction to ensure that the corresponding features are required for the classification. This paper analyzed the multiple methods available for feature extraction of an EEG signal such as DWT and EMD and decided on using DWT for the research. DWT is used as it has the ability to adapt to each features of the function. Once the features of the signals have been extracted, the signal are then classified in accordance to the valence-arousal emotions model using a training model. Multiple classification methods are analyzed in this paper such as KNN, SVM and ANN. Each method has its own advantages and disadvantages but ANN was chosen as the classification technique as it has the highest accuracy among the other training models.

ACKNOWLEDGMENTS

The research grant J0133 – UPNM/2018/GPJP/TK/2 supported this work. The National Defense University of Malaysia is acknowledged with gratitude.

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