

Basic Emotion Recognition System for Persons with Amyotrophic Lateral Sclerosis Using Electroencephalography

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Article Info

Volume 83

Page Number: 4816 - 4823

Publication Issue:

March - April 2020

Article History

Article Received: 24 July 2019

Revised: 12 September 2019

Accepted: 15 February 2020

Publication: 27 March 2020

Abstract

Amyotrophic Lateral Sclerosis (ALS) is a progressive neurodegenerative disorder that causes the death of motor neurons making the person unable to speak and move. An EEG device will be used to record the brain activity of the user especially the emotions which were classified into three: the happy, sad and angry. The brain signals will be stored to be used as data. The method consists of pre-processing, amplification of the raw EEG signal and filtering. The filtered EEG signals will then undergo feature extraction to extract and determine the fundamental frequency components of the signal. The extracted frequency parameters will be the input for signal classification that will differentiate the three emotions. This study shows that the system achieved a 93.33% accuracy for happy emotion; 86.66% for sad; and 83.33% for angry detection, certainly proving to have a good score and beneficial utility for the recognition of emotion through EEG.

Index Terms: BCI, Brain Computer Interface, EEG, electroencephalography, emotion recognition, Fast Fourier Transform, FFT

I. INTRODUCTION

Amyotrophic Lateral Sclerosis (ALS) also known as Lou Gehrig's disease is a progressive neurodegenerative disorder that causes the death of the motor neurons. Motor neurons are cells that initiate and control movement by sending messages to the muscles of the body. With no motor neurons to receive brain signals to cause movement, patients become totally paralyzed. After a period with no input from motor neurons, the muscles become weak. The brain loses the ability to generate signals which cause involuntary movements of muscles [1].

Majority of the people with ALS experience a motor speech disorder. Initial symptoms may be limited to speaking rate reduction or change in voice quality. At some point in the disease progression, 80 to 95% of people with ALS are incapable to meet their daily

communication needs using their natural speech. In time, most become unable to speak at all [2].

When speech and movements are impaired, the communication between the persons with ALS and the caregivers and/or families also suffers. With such difficulties in communicating, the authors are developing a communication tool for patients with such conditions.

II. ALS AND EMOTION

Brain-Computer Interface (BCI) technology is a dominant communication tool among users and systems. It doesn't require any external devices or muscle intrusion to issue commands and complete the interaction [1]. The research community has primarily developed BCIs with biomedical applications in mind, leading to the generation of assistive machines [2]. They have facilitated rebuilding the movement ability for physically

challenged or locked-in users and returning lost motor functionality [3]. The promising future predicted for BCI has encouraged the research community to study the involvement of BCI in the life of non-paralyzed humans through medical applications.

Part of communicating with physically challenged patients is to monitor their feelings. They experience anxiety over both how to live and how to die and this was correlated with disease progression. There was a positive correlation between active coping strategies and lifespan. These coping strategies strengthen the sense of control, leading the patients to adopt a “fighting spirit”. ALS doesn't usually affect your bladder or bowel control, thinking ability or senses. It's possible to remain actively involved with your family and friends [3].

ALS has no remedy, and it progresses rapidly or gradually. Patients always die, even if they can live for years on ventilators and feeding tubes. The majority of ALS patients die within 3-5 years of diagnosis, but about 10% survive for ten years or more past their diagnosis, and 5% survive for twenty years after being diagnosed. Strong evidence claims that the brain is the last organ to be affected [4].

III. METHODS AND MATERIALS

The interrelation of the input, process and output of the system in the form of a glass box is shown in Fig 1. An EEG device will be used to record the brain activity of the user and stored to use as data. The process will undergo two classifications - the training phase and the actual phase. Pre-processing of the signal is necessary for both phases since raw EEG data is contaminated with noise from different forms and sources. This stage consists of amplification of the raw brain signal, analog to digital conversion, and filtering. Afterward, the filtered signal (data) will be transmitted to a system unit. The filtered EEG signals will then undergo feature extraction to extract and determine the fundamental frequency components of the signal such as theta (ranges from 0-4Hz), delta (4-8Hz),

alpha (8-16Hz), beta (16-32Hz), and gamma (32-64Hz). The extracted frequency parameters will be the input for signal classification that will differentiate the three emotions.

The training and actual phase consists of the same process. The only difference is that, in the training phase, it has a pre-defined input that will serve as the standard for comparison. The pre-defined input will be trained by using the algorithm for signal classification. The input brain signal in the actual phase will be compared with the pre-defined input in the training phase. If they have the same parameter, the corresponding result will then be indicated as an output.

The whole system will be processed by a certain platform that is responsible for accomplishing the functions indicated in the succeeding figure. The platform used by the authors was MATLAB.

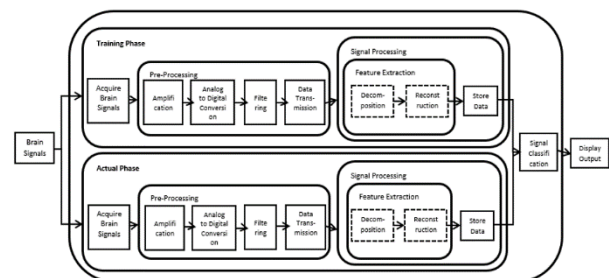


Figure 1 System Diagram

A. Emotion Elicitation Stimuli



Figure 2 MERS' Training Phase

In this work, the database of EEG signals is not created rather it is collected. EEG signals per each emotion are obtained by undergoing the training

phase as shown in fig 2. The user will choose an emotion that he/she wanted to demonstrate. After choosing an emotion, there will be a video that will automatically play which will trigger the user's emotion. Each video corresponds to what emotion the user will choose. While the video is playing, the system will record the user's brain signal and it will be placed in the database for the emotion chosen.

B. Amplification

The proponents used an instrumentation amplifier AD620 to amplify the very low amplitude signals of the raw EEG signal input. The AD620 is a monolithic instrumentation amplifier based on an alteration of the classic three operational amplifier approach. Absolute value trimming permits the user to program gain accurately (to 0.15% at $G = 100$) with just one resistor.

To determine what resistor will be used to manipulate the gain of the amplifier, the proponents used the gain equation below which is based on the datasheet of AD620.

$$R_G = \frac{49.4k\Omega}{G-1} \quad (1)$$

C. Filtering

The filtering algorithm will perform a bandpass filter to limit the allowable frequency the system will detect. There are a lot of frequency components that might enter the device, so its purpose is to limit the frequency to just the brain frequency, which is 0.3Hz to 42Hz.

This filter only lets the lowest and the highest frequencies through. This implies that it distinguishes itself quite a bit from the high-pass and the band-pass as it doesn't return to zero at all time, but instead follows the steady value of the signal.

The formula used for the band-pass filter was adopted from the band-pass filter formula used in other EEG signal acquisition systems. Meanwhile, the proponents just change the formulas required to limit EEG frequency into 0.3Hz to 42Hz range.

$$\text{EMA_S_low} = (\text{EMA_a_low} * \text{sensorValue}) + ((1 - \text{EMA_a_low}) * \text{EMA_S_low});$$

$$\text{EMA_S_high} = (\text{EMA_a_high} * \text{sensorValue}) + ((1 - \text{EMA_a_high}) * \text{EMA_S_high});$$

$$\text{bandpass} = \text{EMA_S_high} - \text{EMA_S_low};$$

(2)

D. Feature Extraction

Once the raw EEG signal is already amplified and filtered, the system will then transform the time into a frequency domain. The authors used the Fast Fourier Transform (FFT) algorithm of MATLAB to execute the function. Fast Fourier transform is a mathematical process for transforming a function of time into a function of frequency. It is sometimes described as transforming from the time to the frequency domain. It is very useful for analysis of time-dependent phenomena like in EEG.

The derivation for the Fast Fourier Transform formula is as follows:

$$\begin{aligned} X[k] &= \sum_{n=0}^{N-1} x[n]W_N^{nk} = \sum_{\substack{n=0 \\ \text{even } n}}^{N-1} x(n)W_N^{kn} + \sum_{\substack{n=0 \\ \text{odd } n}}^{N-1} x(n)W_N^{kn} \\ &= \sum_{r=0}^{N/2-1} x(2r)W_N^{2kr} + \sum_{r=0}^{N/2-1} x(2r+1)W_N^{k(2r+1)} \\ &= \sum_{r=0}^{N/2-1} x_1(r)W_{N/2}^{kr} + W_N^k \sum_{r=0}^{N/2-1} x_2(r)W_{N/2}^{kr} \\ &= X_1(k) + W_N^k X_2(k) \end{aligned} \quad (3)$$

E. Signal Processing

When the filtered digital EEG signal is already transmitted to a personal computer, it will undergo several processing techniques. A platform or software will be used to program the system. In most of the current studies about feedback devices, MATLAB is the most common tool for signal processing. A built-in libraries such as EEGlab, graphics makes it easy to visualize and gain insights from data. It also has a Graphical User Interface (GUI) maker for the user's to easily create their anticipated design for their system. The authors create their own GUI of their system (see fig 3)

which can help the user to easily navigate inside the program.



Figure 3 System's Homepage

F. Signal Classification

The researcher used an algorithm to classify the prominent features of the EEG signal being extracted. Support Vector Machine offers the most effective algorithm for this system since it can be used for both classification and regression challenges like classifying emotions by the user. In this algorithm, each data item was plotted as a point in n-dimensional space (where n is the number of features you have) with the value of each feature being the value of a particular coordinate.

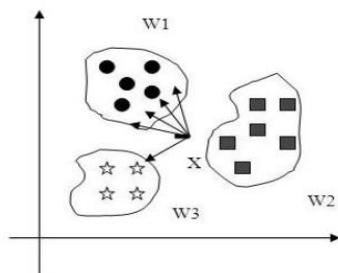


Figure 4 Sample data plotting

It is based upon the theory of the structural risk minimization principle that estimates a function by minimizing the upper boundary of the generalization error. K-Nearest Neighbor (KNN) training sample is compared with the testing data, the closest or nearest emotion-related features are identified, and the majority vote related features are grouped into the particular same class. KNN can be slow for real-time prediction if there are a large number of training examples. Linear Discriminant Analysis (LDA) is used to find the optimal hyperplane to

separate classes of emotion. LDA operates at a dimensionality subspace wherein classes are separated.

Shown in fig 5 is the detailed program flowchart of the system. The first step is gathering some general information about the user that will help the authors with the research based on their records of the data by different users.

After filling the required information, the program will then direct the user to choose what mode he/she will be using. If the information were not correctly provided, the system will not proceed, and an error dialog box will be displayed.

The system is composed of two modes, namely the training mode and the actual mode. In training mode, the user will be watching some video stimuli with respect to what emotion he/she has chosen in order for the user to concentrate and internalize the certain emotion to be saved in the database of the system. The system can now be closed after saving the data.

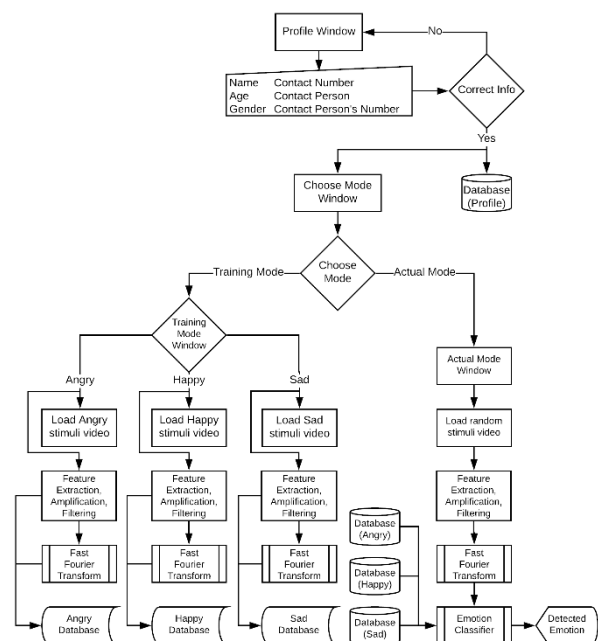


Figure 5 Program Flowchart

Meanwhile, the actual mode compares the gathered data from different emotions to the current reading of the brain signal. In addition, after extracting the brain signal and have gone through the process of amplification and filtering, the system will display an image of the current emotion the user acquired from the actual phase. The system can now be closed after saving the data.

IV. RESULTS AND DISCUSSIONS

During the development of the algorithm the researchers complied with the following functions that were essential to the system. For the function of acquiring the brain signals, the expected output is the acquired raw EEG signal of the user. The authors achieved this function by using a device called Neurosky Mindwave where it gets the raw signal.

After extracting the raw EEG signals from the user using the helmet, the signal will undergo preprocessing to filter the unwanted noises and improve the raw brain signal. For amplification, the raw EEG signal should be amplified to make the value of the voltage satisfy the required value needed. It amplifies the raw signal from microvolts to millivolt range. It has a high input impedance, high CMRR, and low output impedance to amplify the very low amplitude signals of the raw EEG. The researchers were able to achieve the function by creating an amplifier circuit. Meanwhile, the purpose of filtering is to limit the frequency that the system will read to avoid noise. It is also achieved by directly inputting the bandpass filter codes in MATLAB.

Feature extraction and signal classification were also accomplished through MATLAB. There are already existing functions or algorithms to make it work. Then lastly, after several processing techniques employed to the raw EEG data, an output display will be shown to recognize the current emotion of the user. It is also attained in MATLAB as an end process or result of the whole process.

A. Test Result for Signal Acquisition

The Neurosky Mindwave helmet will extract the raw EEG signal of the user. The expected result should be the raw voltage emitted by the brain waves. Shown in fig 6 is the waveform of the raw EEG signal in voltage with respect to time. That is the raw EEG signal of the user without undergoing any pre-processing.

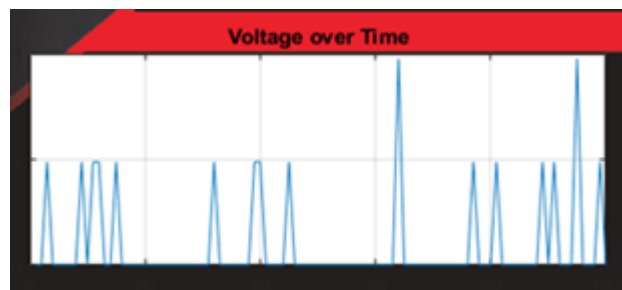


Figure 6 Sample waveform of raw brain signal

B. Test Result for Amplification

The raw EEG signal should undergo amplification for the very small signals to output much larger amplitude. The authors used an instrumentation amplifier using AD620 IC. Fig 7 shows the amplified waveform of the raw signal. Failure to amplify may also lead to failure in reading a prominent brain signal for it has to comply with the voltage requirements.

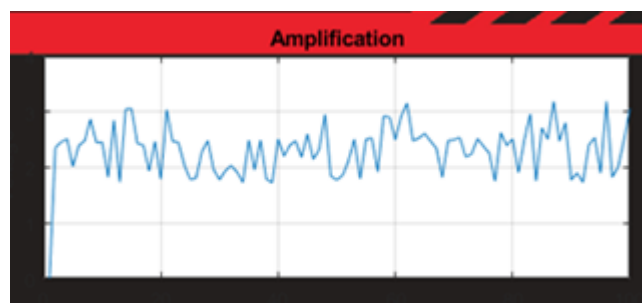


Figure 7 Sample waveform of the system with amplifier

C. Test Result for Filtering

When the raw signal was already amplified, the system must limit the entering frequency into the brain frequency requirement (0.3Hz to 42Hz) of the human. It prevents the system from getting other

unnecessary signals. Shown in fig 8 is the waveform of the filtered raw signal.

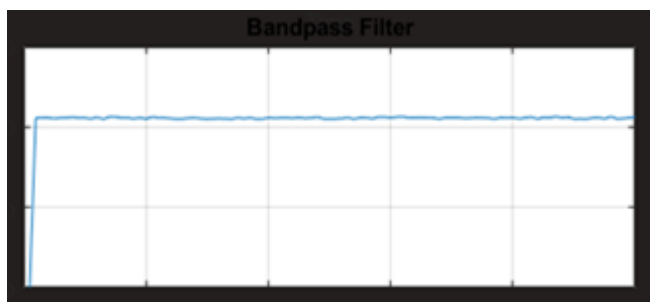


Figure 8 Sample waveform of the filtered data

A. Test Result for Signal Classification

Fig 9 shows the process of classification of data in the system. The pre-defined brain signals per emotion and the actual brain signal reading of the user will be compared, and whatever data matches the pre-defined data will become the output emotion of the user.

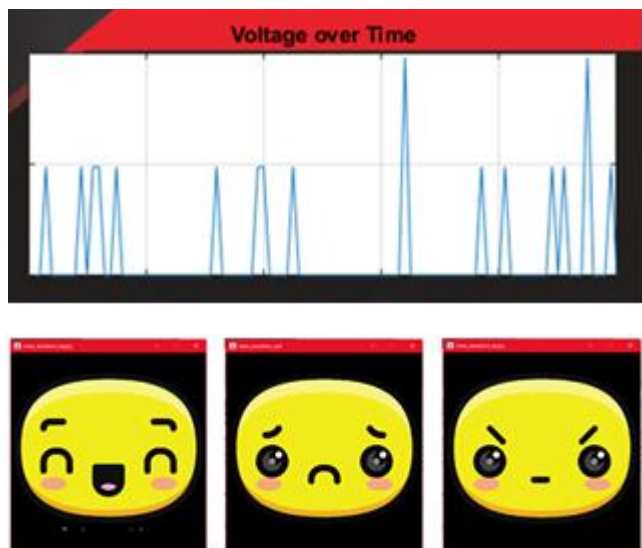


Figure 9 Sample output emotion after classification

TABLE I. CLASSIFICATION ACCURACY

Trials	Emotion Parameters		
	Happy	Sad	Angry
P1	100%	70%	80%
P2	90%	100%	70%
P3	90%	90%	100%
TOTAL	93.33%	86.66%	83.33%

The results in Table I were obtained by conducting 10 test samples per person (represented by P1, P2, and P3). Before performing the test, each person undergoes the training phase where they watched different emotion stimuli per a certain emotion. The obtained brain signals from the training phase were stored in the database and serve as pre-defined brain signals per emotion. The actual test will be classified by comparing the actual signals to the pre-defined values obtained from the training phase process.

CONCLUSION

The article presents the results of the accuracy of the EEG signal classification for three types of emotion. For a happy emotion, the system got a 93.33% accuracy which is the highest rating among the three classes. 86.66% accuracy was rated for the sad emotion classification and 83.33% for the anger.

Although the authors met the functions to be complied essentially by the system, they were not able to neither conclude nor identify the pattern and range of the voltage for the three emotions (angry, happy, and sad). Moreover, the reading also varies concerning to the person who has the greatest number of stored data to the training phase. Table I shows the variation of results based on the training phase and testing phase. P1 has the greatest number of brain signals in the happy signal database, the reason why he got 100% accuracy. Same with P2 who was trained in sad emotion and P3 in angry database.

There are several factors that the authors were able to identify. One of which is the environmental condition of the place where the training and actual phase will be conducted. They found out that the behavior of the brain signal varies depending on the place and time it was recorded. Recording the brain signals on the same place at the same time gives a more accurate reading. Thus, the accuracy of the system depends on the time and place the brain signals were acquired. The more training brain

signals fed in the database will also yield a more accurate system.

To the future researchers who wanted to improve the prototype, the team would recommend using sensitive EEG sensors that can produce higher voltage output or a better amplifier circuit where signals from different brain signal patterns can easily be recognized to avoid unnoticeable difference of the amplified signal from the raw signal.

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