Stress recognition using Electroencephalogram (EEG) signal

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Abstract. The electroencephalogram (EEG) is a device for measuring the electrical activity of the brain; it has the ability to detect the waves at various frequencies. The device uses a small electrode to record the measurements. The EEG waves can be used to detect many activities in the brain, such as stress. This study identifies stress using EEG signals. Stress causes a certain range of frequencies in the range to change their activities, in which the changes can be analyzed. Test results were filtered properly, and the frequency bands measured. The data shows the difference in the ratio of beta waves and alpha waves in the brain as a result of stress. The changes in the ratio will be able to show the degree of stress encountered.

1. Introduction

The body undergoes changed when in stress and tries to bring back itself to its normal condition when the stress is gone [1]. Stress can affect the performance of people in the workplace, it doesn’t only cause discomfort to the person, but it can cause other issues. The stress in the workplace has a very high number, with 20% of adults in the workplace suffer great deal of stress, and with a staggering 52% suffer from relatively high levels of stress, with only about 29% having very mild stress [2]. Diseases that are related to stress have the highest mortality rate in the world [3], a system for analyzing stress has to be constructed, that can provide feedback in real-time. The system would use the EEG data in order to determine the state of the patient.

EEG is a device for measuring the conductivity in the brain. Although the skull has a conductivity of its own, it has about only 1/80 of that of the brain. Use of some fluid between the scalp and the device helps the signal receiver, the fluid acts as a conductivity medium [4]. EEG brainwaves are divided into 4 bands which are Delta, Theta, Alpha and Beta [5] as seen in Table 1).
Table 1. The Band Waves of EEG

| The brain waves | Frequency band | Nature of the wave |
|-----------------|----------------|--------------------|
| Delta wave      | 0.5Hz to 4Hz   | Slowest frequency band in the brain. |
| Theta wave      | 4Hz to 8Hz     | Observed in a state of drowsiness. |
| Alpha wave      | 8Hz to 12Hz    | Observed in a state of relaxation. |
| Beta wave       | 12Hz to 30Hz   | Observed in a state of active thinking. |

The power spectrum of the beta waves over the alpha waves has a correlation with the level of stress, the numerical equation of the ratio was given to indicate the state of the subject directly [6, 7]. A single band of waves can be used to detect stress in a human being; the alpha band was used to do so. The patterns had a symmetric motion in which the anomalies were taken as indications of stress [8].

The frontal brain activity is suggested to be associated with the emotional part of human beings, as in it changes accordingly. The analysis of EEG signals was to determine negative and positive feelings by assessing the waves of the brains in the frontal lobe. By using the direct values from the EEG signals and reducing the mean of the data from it, we can find the variance of the data. Using deviations from the brain signals to indicate arousal, which was identified with any extreme emotion, while submissive signals were associated with calm states [9]. It is proven that there is a huge correlation with physiological stress and brain activity, which can be measured and analysed [10]. Beta bands seemed to be of higher value than alpha and theta bands, under stress. An increase of beta power and decrease of alpha power seemed to indicate stress. The difference can be found by minimization [11].

EEG signals seem to have a direct relationship with the emotional alterations in the brain, in which it can identify and measure the amount of arousal in the brain. The waves that the brain produces can be analysed and filtered in a manner that will enable us to make a deduction.

A stable EEG machine can be used to reduce any noise that may arise from movement of the subjects participating in the study, with a standard emotional stimulus to engage the brain waves. If the data from the EEG was collected at specific timelines, a proper understanding of the waves of the brain can be achieved.

2. Methodology
This section will cover the explanation of the methodology that will be used in completing the study. The process is based on the general view of similar evaluations, with certain changes. There are four major steps to be taken in order to complete the study, which are the data acquisition, pre-processing, feature extraction of the data, and finally, the decision-making algorithm.

2.1. Data acquisition
In this study, 39 volunteers, all-males, were tested by using the Neurosky Mindwave Mobile EEG device. The purpose of this data acquisition is to get EEG data from two different states of mind. The first state would be in a calmed state, and the second would be under stress. The EEG device would be placed on the heads of the participants, with minimal movement to prevent too much noise in the signal. The device uses one electrode to collect its data; the electrode is to be placed on the forehead. The electrode measures the EEG data from the right side of the frontal lobe of the brain, which is considered to have a correlation with emotional changes. The testing has to be very simple as not to engage the subjects in any movement. Heavy movements of the volunteers will interfere with the data collected and might produce data that is flawed. The participants will be in a calmed state when the testing starts.

The stressed state of the volunteers is our main concern. The data acquired from the second phase will be compared with the first state to see the difference in the waves of the brain under stress. After
the first 60 seconds, which engulf the calmed state, the video of the stressed state will start. The EEG device would still be recording from the beginning of the calming video until the end of the stress-inducing video.

2.2. Pre-processing
The data would be analyzed by the algorithm at different timings. The data has to be cut into 3-second samples, with an intersection of two seconds between them, in order to get a full reading. Although the EEG data is independent of previous outputs, the data can’t be sampled at different timings without intersection, since this may cut a rise or a fall in the signal that might indicate a variation in the level of stress, thus the sampling technique is to be used. Each sample would be processed independently; the same filters would be used for each sample. The data would be divided into two sections, one for the alpha waves, which range from 8 to 12 Hertz, and the beta waves which would range from 13 to 30 Hertz. The band power of each of the filtered products would be computed.

2.3. Feature extraction
The data from the pre-processing would be analyzed in this stage; it would be in sets of time intervals, where each time interval will have to be analyzed. The band powers of the alpha, beta, and beta over alpha (B/A) will have to be compared. The alpha and beta power would be taken from each sample. The final value of the data is the power of beta over the power of alpha. This will be expressed as in Equation (1).

\[
\text{power of Beta / power of Alpha}
\]

(1)

The alpha waves would be collected by putting the raw EEG data through a low-pass Butterworth filter with a cut-off frequency of 12 Hz, then a high-pass Butterworth filter with a cut-off frequency of 8 Hz. On the other hand the beta waves would be collected by putting the raw EEG data through a low-pass Butterworth filter with a cut-off frequency of 35 Hz, then a high-pass Butterworth filter with a cut-off frequency of 13 Hz. The same system will be used in order to determine whether the eye-blinks of the volunteers will affect the results. A sample with an eye-blink will be tested, and then the same sample will be edited to remove the time range with the eye-blink, this will produce the same signal, but without the eye-blink amplitude rapid movement. The two results will be analyzed, and the rate at which the signal will differ from the eye-blink will be determined.

2.4. Decision making
The variation of the change from the stressed state to the calmed state would be considered as an indication for stress. The data would then be made in order to try and get a number that can be used for real-time applications, at which a single stressed state would be indicated using only the data available on hand.

3. Experimentation and results
The isolation of the data consisted of filtering the signal with both a low-pass Butterworth filter and a high-pass Butterworth filter, each with the specific cut-off frequencies. After the experimentation, the effects of eye blinks on the EEG data were tested; this was done by testing the sample with the algorithm, by finding the final value of both the original signal and the signal that has the eye blink time removed. The full algorithm was used to test the EEG data of 39 volunteers. A survey has been handed out to all the volunteers to express the levels of stress that they had experienced at both the calmed and the stressed states. The volunteers were all male of ages between 18 and 30; all of them were of good health and a median body mass index (BMI).
3.1. The isolation of the frequency band
A sample of ten seconds was taken for testing, and the value of the signal in millivolts fluctuates between 400 to -300. However, most of the power would be confined between the values of 200 to -200 millivolts, which is to be expected from an EEG signal. For acquiring the clean beta waves, which are isolated between the frequencies of 13 to 35 Hz, the data has to be filtered. The data was first put through a low-pass Butterworth filter with a cut-off frequency of 35 Hz; which marks the highest end of the frequency in a beta wave. The same signal that was filtered for a low-pass filter of 35 Hz is then passed through a high-pass Butterworth filter. The high-pass filter has a cut-off frequency of 13 Hz, which is the lowest end of the frequency range for a beta wave.

For acquiring the clean alpha waves, which are isolated between the frequencies of 8 to 12 Hz, the data has to be filtered. The data was first put through a low-pass Butterworth filter with a cut-off frequency of 12 Hz, which marks the highest end of the frequency in an alpha wave. The same signal that was filtered for a low-pass filter of 12 Hz is then passed through a high-pass Butterworth filter. The high-pass filter has a cut-off frequency of 8 Hz, which is the lowest end of the frequency range for an alpha wave.

3.2. Testing the effect of eye-blink
Through the testing of the EEG data, it seems that the EEG raw data are affected in the form of a relatively rapid increase followed by a relatively large decrease in amplitude. The effect of this is not known, and the extent at which it might jeopardize the results. A sample of ten seconds was taken from the raw EEG data, with a blink amplitude rise and drop.

The sample had gone through the algorithm as in Eq (2.1) and delivered a final figure of 1.2111. This value represents the decision making value, and so, the difference in this value will determine how much the result be affected in the presence of an eye blink. The data without the eye-blink was then put into the algorithm as in Eq (2.1) with removed eye blink effect; the final value of the algorithm was 1.2172. The difference in the value is about 0.5 per cent, which is a very small value, and with an experiment that uses random input variables, the difference can be ignored. And a 0.5 % difference, which would amount to a maximum of 1.5 %, would be insignificant. The testing can be continued without the need to remove all the effects of eye-blinks manually from the raw EEG data.

3.3. Results of the experimentation
A total of 39 volunteers were tested using the finalized algorithm. The algorithm will find the final value of beta over alpha (B/A) for two different states. The first state was recorded in a calmed environment; the second was recorded in a stress-inducing environment. The two states are carried through 60 seconds each. The final decision-making result would be the difference of the stressed state from the calmed state; the difference of the values would form a percentage over the value of the calmed state.

The algorithm samples the raw EEG data 3 seconds at a time and increments one second after each sample. This process is used so that each sample is not built on random momentary value, as each sample would process 3 seconds (consisting of 1536 readings), since the EEG collection device samples at 512 Hz. The data collected is made up of 120 seconds, 60 seconds for calmed state and 60 seconds of a stressed state, which amounts to 61440 readings.

The average of the final value of all the volunteers was 34.207 %; all the volunteers had a positive final value, with the minimum at 6.91 % and a maximum of 91.85 %. The variation in the results is not surprising, since the raw data is random to a certain extent.

Most of the percentage difference is concentrated in the mid-region. About 77% of the volunteers had an increase in stress levels through the test in the range of 10% to 50% as can be seen in Figure 1. This shows that in most cases a similar rise in the B/A can be expected when encountering stress, to which there might be a correlation of stress to a rise of this size. The high density of volunteers between the reaction percentages of 10% and 50% is considerably higher than that of the rest of the volunteers, where a threshold range can be found from the samples.
The standard deviation of the sample is 18.5451, with a mean of 34.2. With these values, we can form a range of percentages of (B/A) that can be used. The lower point is \((34.2 - \text{standard deviation})\), and the highest point is \((34.2 + \text{standard deviation})\). This will enclose the threshold of (B/A) between 15.6% and 52.8%. Any raw EEG data that goes through the algorithm and has a final value that is within the range can be considered as a viable recognized stress in the volunteer.

4. Conclusion
The objective of this study is to investigate the reliability of the EEG signals detecting stress; through the results, a very clear proof of the reliability of the algorithm that collects data using EEG was confirmed. Stress causes an increase in the ratio of the power of the beta waves over the alpha waves; this was confirmed for all volunteers. The EEG device gives very clear and direct raw data that can be filtered properly, giving the parameters which allow the stress signal to be identified. The difference between the stressed state and the calmed state can be clearly seen from the filtered data, for each has a different beta to alpha ratio. The results obtained from the volunteer showed a proof of concept to the algorithm in which a clear change in the waves can be seen. Thus, the test can be used to recognize stress if the results fall into the range of 15.6% and 52.8% of (B/A). Therefore, EEG signal is viable for measuring stress.

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