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Towards automated quality assessment measure for EEG signals

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ABSTRACT

EEG signals provide the means to understand how the brain works and they can be used within a wide range of applications; especially BCI applications. The main issue that affects the performance of such applications is the quality of the recorded EEG signal. Noise produced during the recording of the EEG signal impacts directly on the quality of the acquired neural signal. BCI applications performance is susceptible to the quality of the EEG signal. Most BCI research focuses on the effectiveness of the selected features and classifiers. However, the quality of the input EEG signals is determined manually. This paper proposes an automated signal quality assessment method for the EEG signals. The proposed method generates an automated quality measure for each EEG frequency window based on the EEG signal bands characteristics as well as their noise levels. Six scores were developed in this research and the quality of the EEG signal is postulated based on these scores. This EEG quality assessment measure will give researchers an early indication of the quality of the signal. This research will help in testing new BCI algorithms so that the testing could be made on only high quality signals. It will also help BCI applications to react to high quality signals and ignore lower quality ones without the need for manual interference. EEG data acquisition experiments were conducted with different levels of noise and the results show the consistency of our algorithms in estimating the accurate signal quality measure.

1. Introduction

Neurons communicate with each other using electrical spikes that carry the information required for a specific activity. Electroencephalogram (EEG) is the standard means by which we record neural signals that includes different waves and spikes with varying amplitudes and frequencies [1–5]. These signals are recorded by placing a set number of electrodes on the human scalp [6]. Billions of neurons communicate together with electrical pulses, forming a huge complicated neural network [7,8].

There are many challenges in recording the EEG signal [9,10]. Some sources other than the brain produce unwanted electrical interference, which is recorded with the cerebral activity and increases the noise in the recorded EEG [11]. Sometimes the signal can be fully corrupted and needs to be reacquired [12].

The noise affecting the quality of the EEG signals originates mainly from the non-cerebral activities taking place at the time of recording. Non-cerebral activities can be divided into two categories. The first category is the physiological activity, which is generated by organs in the human body, other than the brain, such as muscles and limbs. The second category is external environmental factors. Fig. 1 shows the effect of an eye blink on the quality of the acquired EEG signal.

Many feature extraction and classification techniques have been developed in the past few years to improve the performance of the BCI applications [13,14]. However, the EEG data recording process has a significant impact on the resulting performance of the BCI algorithms. The traditional method is to observe the recorded signal and discard the highly corrupted parts that are clearly contaminated with noise. However, there are some inherent noise features within the signal that cannot be clearly observed. Having means of measuring the quality of the recorded EEG signal will be of a great importance to detect these features and highlight only the reliable parts of the signal [15–17].

The main objective of this section is to generate an automated quality assessment measure for an input EEG signal through generating automated scores that evaluate the quality of the signal while recording. These scores are based on biological and mathematical features where signal processing techniques are needed. This idea has many benefits such as:

- Online quality assessment: While recording the EEG signal, our system will give an online alert when any channel has abnormal behavior. This will help researchers decide whether to stop recording and resolve the noise-generating issues, or continue recording.
- Important factor in BCI applications: The proposed scores can be used as input to BCI applications. This will increase the accuracy of BCI applications, as the brain commands will be handled with different levels of confidence based on the quality of the signal.

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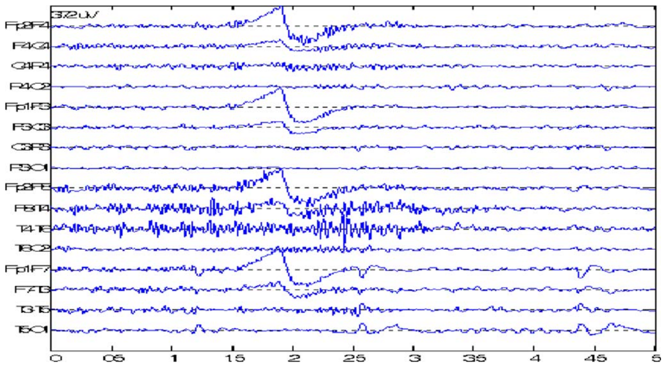

Fig. 1. Eye blinking/movement effect on the EEG signal.

Earlier research has been made to analyze, diagnose or even remove the noise from EEG signals as in [18–21]. However, this research is not about diagnosis, analysis or noise removal. This research is mainly about giving an automated online indicator of the reliability of the acquired signal. Suggesting means to remove the detected noise which is outside the scope of this paper. As an example, an alert will appear to the researcher while recording the data if the data is corrupted with an indication of the degradation in the quality of the signal [22,23].

During the EEG acquisition process, the electrodes record the signals which are generated by a specific number of neurons. The difficulty is that there is little control over the number of neurons captured in the recordings, so any unneeded number of spikes will decrease Signal-to-Noise Ratio (SNR) [24,25]. It is not possible to record the neural signals without the biological noise, but it is a relatively easy job to detect them or remove them after recording and analyzing the neural signal [22,25–27]. The effect of the technical factors can be minimized by knowing the amount of SNR. The difficulty in minimizing technical factors is due to the level of the SNR. To validate the accuracy of our scores, we recorded a normal signal carefully and then we added noise to the signal. We controlled the percentage on noise based on the SNR value as we already have the original clean signal.

Although it is not a difficult task to detect the occurrence of biological noise and a wide range of methodologies to remove this kind of noise is available. It is more challenging to remove the noise when the level and type of noise is unknown [28]. An example, it is an easy procedure to detect eye blinking artifact while recording the EEG signal and most EEG recording software has an eye blinking detection algorithms [29]. On the other hand, there are many factors that affect and sometimes destroy the recording such as electromagnetic signals, high power cables under the buildings and mobile phone signals. These factors are harder to detect [30,31].

In order to tackle the issue of minimizing the environmental noise we must be able to differentiate between the noise and the signal, and to avoid compromising the signal quality while removing the noise. One of the ways to remove the noise is through using the wavelet transform proposed in [32,33]. The main problem with this method is that it assumes that the signal's magnitude dominates the noise's magnitude in any wavelet representation. This assumption may not hold for many neural signal recordings. The target of this research is not to minimize the noise in an EEG signal, however, the target is to identify the quality of the EEG signal.

EEG signals have specific features that can provide more information about the quality of a signal's recording. These features are the biometric features of the signal bands which we use in this research. Each EEG signal consists of a range of signals within different frequency bands [5]. These bands are the Alpha, Beta, Theta and Delta as shown in Fig. 2 [34]. Different quality scores were created based on these bands. These scores show whether or not we can rely on the recorded EEG signal. To our knowledge, this is considered the first automated measure that assesses the EEG signal in terms of biological and statistical point of view. The rest of the paper is organized as follows: Section 2 is the Methodology which explains each quality score in details. Section 3 is the results section where the results of each score are shown and analyzed. Section 4 shows our system validation in BCI applications. Finally, the last section includes the conclusion and future work.

2. Methodology

The main idea for this research is to generate an automated quality assessment measure for an input EEG signal. Our model generates six scores which indicate the quality of the signal. The first score is calculated based on the general amplitude of the EEG channels. The second score is calculated based on which channel has the highest amplitude. The third score is based on calculating the dominant frequency for the channels. The last three scores depend on the

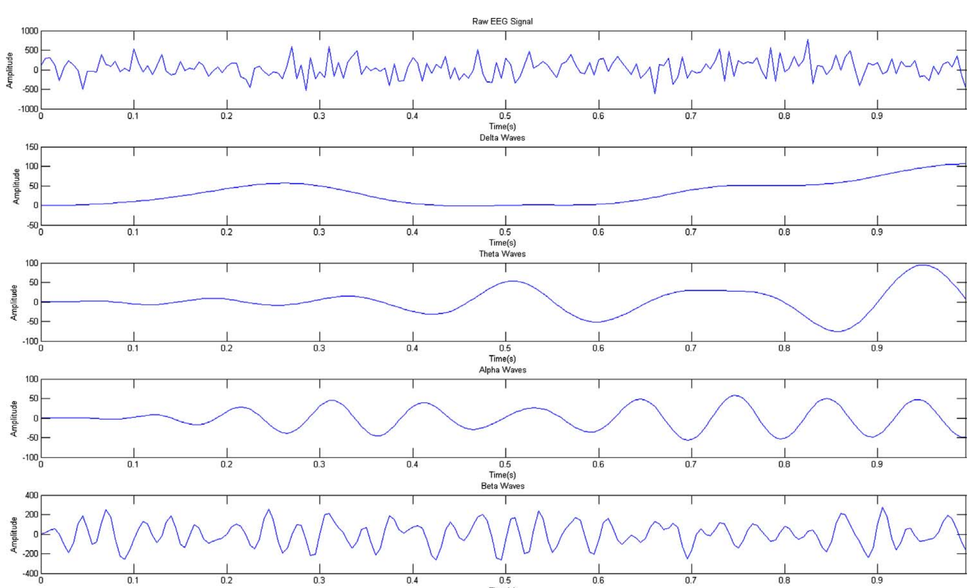

Fig. 2. EEG raw data is shown in the top figure, then the main frequency bands are shown in the rest of the figures. The main EEG frequency bands are Delta, Theta, Alpha and Beta as shown respectively.