International Journal of Software Innovation
Volume 12 • Issue 1

Evaluating an Elevated Signal-to-Noise Ratio in EEG Emotion Recognition

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ABSTRACT

Predicting valence and arousal values from EEG signals has been a steadfast research topic within the field of affective computing or emotional AI. Although numerous valid techniques to predict valence and arousal values from EEG signals have been established and verified, the EEG data collection process itself is relatively undocumented. This creates an artificial learning curve for new researchers seeking to incorporate EEGs within their research workflow. In this article, a study is presented that illustrates the importance of a strict EEG data collection process for EEG affective computing studies. The work was evaluated by first validating the effectiveness of a machine learning prediction model on the DREAMER dataset, then showcasing the lack of effectiveness of the same machine learning prediction model on cursorily obtained EEG data.

KEYWORDS

Affective Computing, Arousal, BCI, Data Analysis, Data Integrity, Emotion Classification, Machine Learning, User Study, Valence

INTRODUCTION

The recognition of human emotions from electroencephalography (EEG) signals has been a steadfast research topic within the field of affective computing. In the past two decades, many valid techniques to interpret human emotional states from EEG signals have been documented, and a standardized workflow has been established. This standardized process involves EEG signal collection, band separation, feature extraction, and emotion classification. Information about proper EEG data collection processes, however, is scarce. There are no commonly accepted guidelines for proper EEG data collection techniques. As such, this scarcity of information leads to an artificial bottleneck for new researchers seeking to incorporate EEGs within their research workflow.

EEG signals are extremely vulnerable to external artifacts, and a controlled environment is essential for obtaining usable EEG signal data. While there are techniques that can be used to remove artifacts and noise from EEG data, these techniques are limited in their efficacy. A participant's

DOI: 10.4018/IJSI.333161

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involuntary movement, a random sound emitted near the participant, or a distracting conversation can easily be enough to compromise the data being collected. Furthermore, the collection of data could also be compromised by factors not easily controlled by an experiment's facilitator, such as the participant's hair type, length, or density or a psychoactive medication being taken by the participant.

In this paper, an EEG user study is presented in which external artifacts, such as noise or involuntary movement, accumulated within the EEG data collected due to an uncontrolled testing environment. From there, the results of multiple different machine learning prediction models on the established DREAMER dataset are compared to the results of the same prediction models on the EEG data obtained in the aforementioned poorly controlled environment. This study demonstrates the importance of a meticulous and methodical approach to EEG data collection by showing the ineffectuality of validated data analysis techniques when applied to EEG data with a high signal-to-noise ratio.

The remainder of this paper is structured as follows: the second section presents a brief background of the concepts of valence and arousal within affective EEG studies and the related techniques utilized during the study, the third section provides details of the experiment methodology, the fourth section showcases a comparison between the analysis of the EEG data collected during the experiment and the analysis of the EEG data from the DREAMER dataset, the fifth section provides a brief discussion of the experiment and EEG data collection, and sixth section wraps up the paper with the conclusion and planned future work.

BACKGROUND

Valence–Arousal Model

Russell's valence–arousal model (Russell et al., 1979) is a human emotion classification model consisting of two dimensions: valence and arousal. *Valence* represents the positivity of the emotion being felt, with positive emotions existing on one side of the axis and negative emotions on the other side. *Arousal* represents the degree of stimulation of the emotion being felt, with high-stimulation emotions being placed on one side of the axis perpendicular to the valence axis and low-stimulation emotions on the other side. The combination of these two axes allows emotions to be categorized into four unique quadrants: high valence with high arousal, high valence with low arousal, low valence with high arousal, and low valence with low arousal. These quadrants provide a convenient way to group similar emotions. With the quadrants drawn out, discrete emotions can then be placed in their associated quadrants, as seen in Figure 1.

Pre-Processing

The goal of pre-processing EEG data is to remove noise from the signals, thereby yielding a higher signal-to-noise ratio. EEG electrodes are highly prone to artifacts and interferences. Notch filtering is often used to remove alternating current power line interference from EEG signals, most commonly at 50 Hz or 60 Hz. Bandpass filtering is used to remove frequencies outside of the useful range. Signals can also be detrended to compensate for the dehydration of wet electrodes over the course of a recording. This dehydration would lead to signals becoming weaker over time, so detrending seeks to compensate for that. Artifacts originating from the wearer's movement, including facial muscle movement and speech, can only be removed with limited success depending on the severity of the movement. Regression analysis is an effective approach to remove artifacts, but this technique requires a reference channel. Both EEG devices used in this study provide a reference channel, so this approach was utilized. Artifactual segment rejection involves removing artifacted sections of EEG data (Islam et al., 2016). This segment rejection can be performed manually by searching for large spikes in EEG signal activity or automatically by removing sections that contain signal outliers that are many standard deviations from the mean. A visualization of EEG signal pre-processing can