Implications of EEG-based Developments in Artificial Intelligence

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Abstract. Researchers have been developing Brain-Computer Interfaces (BCIs) systems with Electroencephalography (EGG) and have been quite successful in modeling brain signals for various applications such as emotion recognition, user identification, authentication, and control. Despite several developments in EEG, the field is still growing slowly as compared to other AI-based developments such as user identification, authentication, and control using facial, fingerprint, signature, and gait data. One such reason is the availability of EEG data. Images and videos can be recorded through low-cost cameras, however, EEG sensors are very expensive. Moreover, EEG sensors are not handy, it takes efforts to correctly place the sensor electrodes on the head. Several reasons reducing the gradient of developments with EEG. This paper discusses the recent EEG-based AI developments and their limitations.

Keywords: Electroencephalography (EEG) · Brain-Computer Interface (BCI) · Emotion Classification · Authentication and Control.

1 Introduction

Electroencephalography (EEG) is the study of the electrical activity of the brain. The invasive technologies record the EEG signals by surgically implanting the EEG electrode on the surface of the brain or even at a certain depth within the brain. Such invasive methods are used in medical treatment. However, noninvasive technologies record the EEG signals by placing the EEG electrode onto the scalp over the head. The non-medical developments use noninvasive EEG sensors like EEG Emotiv [2] (a), ActiCHamp [9] (b). Typical Emotiv and ActiCHamp Plus EEG headset hardware are shown in Fig. 1.

These EEG headsets use a standard 10-20 system for the placement of the EEG electrode over the head. The typical positioning of an EEG headset with 32 electrodes is depicted in Fig. 2.

2 EEG-Based Developments and Their Implications

EEG has been used in emotion recognition [11, 1], user identification [7, 5, 10], authentication [7], and control [8].

Fig. 1. EEG headsets: (a) Emotive Epoc+ (14 electrode) [2] (b) ActiCHamp Plus (32-160 electrode).

In order to record EEG signals, a user is supposed to wear the EEG headset over the head. First, the reference EEG electrodes are supposed to be placed correctly onto the scalp of the head and placing the EEG electrodes and then the rest of the electrodes. Doing this is a cumbersome task and gets more complicated as the number of electrodes increase. The hair density might also affect the EEG signals. Many EEG headsets [2] require electrodes to be wet with saline water for better conductivity which at times bothers the user. The new headsets [3] do not require any saline water or glue, however, implanting issues might be there too. The noise gets added to the EEG signals due to the physical movements of the users and EEG electrodes get displaced which affects the EEG signals.

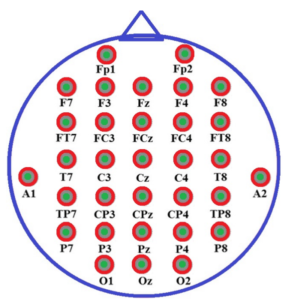

Fig. 2. The positioning of an EEG headset with 32 electrodes with their names as per 10-20 system standards.

Pham et al. [7] used EEG as biometrics for user authentication with the advantages of being unique and difficult to fake or mimic. Autoregressive and power spectral density-based features were used for authentication. Kaur et al. [5] proposed a user identification framework while listening to music where they used wavelets with hidden markov model for identification. The user identification performance changed with different emotions; highest at the calm state and lowest at scary state. Thus, emotions introduce confusion while modeling the

EEG signals. Thus, it is important that users are in a calm state and it might take time.

The researches [5, 6] are based on EEG signals recorded in a single session. The mental state and the response to an event might change next time. Thus, the model should not be biased towards sessions. To do that EEG signals should be recorded at sessions with an appreciable gap of hours, days, or months. Wang et al. [11] recorded EEG signals in different sessions and used disjoint sessions to train and test the support vector machine based classifiers. However, it was not clear if the EEG signals of a user (from different sessions) were in training and testing. If so, then the model is biased and might be learning users and not emotions. It is also important to see the impact of gender in EEG-based developments. Though not related to the main theme of this paper, another serious concern is the security of BCIs. Ienca and Haselage [4] studied the vulnerability of BCIs that could lead to hacking brain signals.

3 Conclusion

This short paper briefly discusses the issues that are faced in AI and machine learning developments with EEG. Implanting EEG electrodes on the head of a user with high hair density might affect the recording. The noise gets added to the signals due to the physical body movements while recording. Thus, models should be robust against noise. Models should be less biased and session, and user independent. User/Session independence can be achieved by *leave one user/session out* training protocol. User identification problems require better techniques to eliminate the effect of emotions and improving performance. Most of the studies are done on less than 100 users. It would be good to develop robust systems with data from more users.

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