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Low Valence Low Arousal Stimuli: An Effective Candidate for EEG-Based Biometrics Authentication System

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Abstract. Electroencephalography (EEG) has recently gained popularity in user authentication systems since it is unique and less impacted by fraudulent interceptions. Although EEG is known to be sensitive to emotions, understanding the stability of brain responses to EEG-based authentication systems is challenging. In this study, we compared the effect of different emotion stimuli for the application in the EEG-based biometrics system (EBS). Initially, we pre-processed audio-visual evoked EEG potentials from the 'A Database for Emotion Analysis using Physiological Signals' (DEAP) dataset. A total of 21 time-domain and 33 frequency-domain features were extracted from the considered EEG signals in response to Low valence Low arousal (LVLA) and High valence low arousal (HVLA) stimuli. These features were fed as input to an XGBoost classifier to evaluate the performance and identify the significant features. The model performance was validated using leave-one-out cross-validation. The pipeline achieved high performance with multiclass accuracy of 80.97% and a binary-class accuracy of 99.41% with LVLA stimuli. In addition, it also achieved recall, precision and F-measure scores of 80.97%, 81.58% and 80.95%, respectively. For both the cases of LVLA and LVHA, skewness was the stand-out feature. We conclude that boring stimuli (negative experience) that fall under the LVLA category can elicit a more unique neuronal response than its counterpart the LVHA (positive experience). Thus, the proposed pipeline involving LVLA stimuli could be a potential authentication technique in security applications.

Keywords. Audio-visual evoked potential, Biometric authentication, Electroencephalography, Time and frequency features, XGBoost

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1. Introduction

Electroencephalography (EEG)-based biometrics is an emerging technology that utilizes brain signals to identify and authenticate individuals [1]. EEG signals can vary significantly depending on the user's mental task, as different areas of the cortex are activated and deactivated accordingly. The human mental state has a substantial impact on the brain's neuronal firing, making it highly sensitive to both external environmental stimulation and endogenous autonomous regulation [2]. Because of this, researchers consider EEG to be an ideal biometric system, as it can generate distinctive signals for each individual based on their brain's neural pathways and cognitive patterns [2]. Moreover, Electroencephalography based biometric systems (EBS) have the potential to surpass the limitations of conventional biometrics. The conventional biometric modalities have some security disadvantages such as the face, fingerprint and iris information that can be photographed, voice can be recorded, and handwriting can be mimicked. Moreover, individuals may lose or change their biometric characteristics such as finger or face in certain circumstances: changes may occur due to injury [3,4]. Further, EBS can provide a precise, non-intrusive, and dependable solution that can be used for a variety of applications, such as access control, medical diagnosis, and user authentication [5]. Despite current advances in EBS technology, there remain significant challenges in the selection of suitable paradigms for enrollment, universality, and user-friendliness in real-world EEG authentication scenarios. Out of these challenges, selecting the optimal paradigms is one of the most pronounced difficulties in EBS [2]. Many of the EEG-based biometric researches have used motor imagery [6], cognitive tasks [7], and response to visual stimuli [8] during enrollment in EBS identification and verification processes. However, each of these protocols has its own drawbacks. The performance of motor imagery and cognitive tasks is difficult and calls for extensive user training [8]. As suggested in [2], choosing a suitable induction paradigm will have a great impact on the recognition results. Recently, emotion-eliciting stimuli have been used for EBS applications, as a distinct brain neuronal firing pattern influenced by mood, stress, and mental state can be used as a possible biometric identifier [5,9]. Thus, in this study, we attempted to identify the optimal emotional eliciting stimuli required for developing credible EEG-based biometrics for usage in real-life scenarios.

2. Methods

The processing pipeline adopted in this study is shown in Figure 1. The EEG signals and subjective ratings of emotion experience from the 'A Database for Emotion Analysis using Physiological Signals' (DEAP) dataset were used in this investigation [10]. The EEG signals of 32 participants were recorded while they watched 40 emotion-eliciting music video clips. The data was collected across 32 channels with 8064 data points each. Participants rated each video in terms of the levels of arousal, valence, like/dislike, dominance and familiarity. Using subjective ratings, we segregated the video clips into four groups: High valence high arousal (HVHA), Low valence high arousal (LVHA), High valence low arousal (HVLA) and Low valence Low arousal (LVLA) according to the average valence and arousal ratings from all participants, keeping 5 as the threshold. The HVHA relates to amusing stimuli, LVHA can be scary stimuli, HVLA relates to relaxing stimuli, while LVLA is concerned with boring stimuli. The preprocessed data from the DEAP dataset was used in this study, which had already been downsampled to 128Hz, EOG artifacts were removed, a 4.0-45.0Hz band-pass frequency filter was applied, data were averaged to the common reference, data was segmented into 60-second trials and a 3-second pre-trial baseline was removed [11].

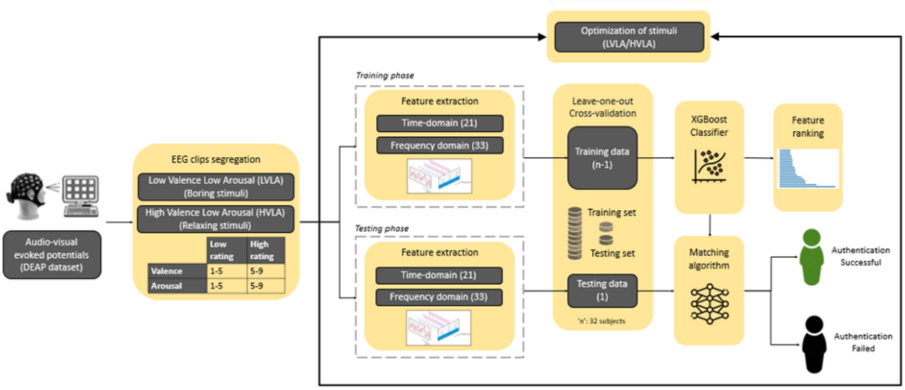


Figure 1. Proposed pipeline for EEG-based biometrics system

We extracted 21 time-domain and 33 frequency-domain features using data points for each user, each clip averaged out on all 32 channels resulting in a dataset with instances for user and clip combination [12]. The final dataset was split into a train and test set using leave-one-out cross-validation (LOOCV) where each instance was predicted, training on all other instances. The classification result was obtained using the eXtreme gradient boosting (XGBoost) classifier [12]. Two models were trained: one for LVLA, consisting of stimuli-based EEG segments corresponding to 11 video clips, and one for LVHA, consisting of stimuli-based EEG segments corresponding to 9 video clips. The performance parameters such as binary accuracy, multiclass accuracy, precision, recall and F-measure were calculated. We evaluated the model using two performance metrics for calculating classification accuracies: binary accuracy and multi-class accuracy. We have performed multiclass classification accuracy to remove bias induced due to true negatives and to get actual performance from the model. The feature ranking was then obtained using the feature importance method of the XGBoost algorithm [12].

3. Results and Discussion

Figure 2 shows the comparative performance of the XGBoost model built using LVLA and HVLA stimuli categories. It can be seen that multiclass accuracy for correctly identifying the user was 80.97% and 72.97% for LVLA and HVLA, respectively. The LVLA stimuli-based EEG segments yielded higher average classification accuracy than HVLA. It indicates that LVLA stimuli were better at eliciting the emotion required for EEG-based biometrics application as compared to the HVLA. F-measure, recall and precision were also high using LVLA stimuli-based EEG segments. However, the binary class accuracy is similar in both cases.

The feature importance plots corresponding to the XGBoost model built using LVLA and HVLA stimuli are shown in Figure 3a and Figure 3b respectively. We illustrated the top 10 most relevant features out of 54 features considered in the analysis. Skewness, Higuchi's fractal dimension and sample entropy are the best features for authenticating individuals using EEG signals, for both LVLA and HVLA.

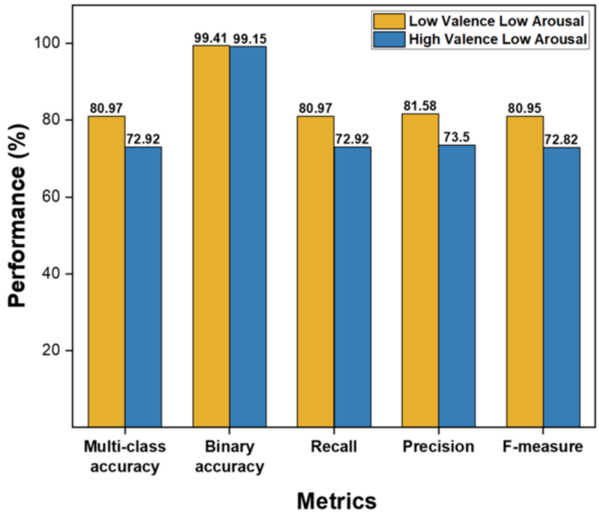
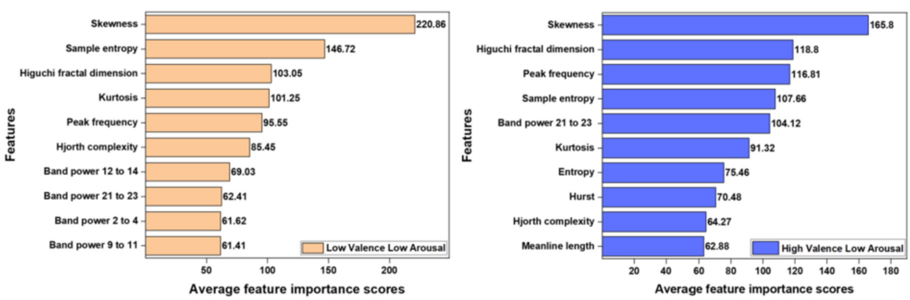


Figure 2. Comparison of classifier performance in two different stimuli: LVLA and HVLA



(a) LVLA (b) HVLA

Figure 3. Average feature importance scores (in descending order) achieved in each stimulus

4. Limitations and Future work

We have compared only LVLA and HVLA audio-visual stimuli to find the optimal stimuli for EEG-based biometrics; however, in the future, we could extend this study to other stimuli such as LVHA and HVHA to obtain more comprehensive results. Moreover, while this study has only used the XGBoost model, more complex models or other ensemble learning methods could be employed to obtain better predictive performance. Additionally, more sophisticated deep learning architectures could also be utilized to improve the classifier performance in authentication. It is essential to compare the performance of the model on multiple datasets and real-time persons from different demographics to increase the sample size and assess its generalizability.

Additionally, we have only utilized time and frequency domain features for authentication, however, the use of time-frequency domain features could provide intricate details that could improve the efficiency of the matching algorithms in the authentication. Furthermore, we were unable to find any exact literature that implements a similar approach using the DEAP dataset for EEG-based authentication. However, we will compare our results with other EEG-based authentication studies in the future.

5. Conclusions

The results of our study show that authentication using audio-visual evoked EEG signals can be performed successfully. Our model was validated with LOOCV, a low-bias method and achieved the highest multi-class classification and binary classification accuracies of 80.97% and 99.41%, respectively, with LVLA stimuli. Our analysis proved that the LVLA is a better candidate than HVLA for EEG-based biometrics applications. Further, the identification of best-performing features was analyzed, and the skewness was found to be the standout feature in both LVLA and HVLA stimuli. Our results suggest that with further development and refinement, EEG-based biometrics systems have the potential to revolutionize the way of biometric authentication.

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