Effect of Auditory Stimuli on Electroencephalography-based Authentication

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Abstract—In contrast with standard authentication methods based on credentials, biometric-based authentication has lately emerged as a viable paradigm for attaining rapid and secure authentication of users. Among the numerous categories of biometric traits, electroencephalogram (EEG)-based biometrics is recognized as a promising method owing to its unique characteristics. This paper provides an experimental evaluation of the effect of auditory stimuli (AS) on EEG-based biometrics by studying the following features: i) general change in AS-aided EEG-based biometric authentication in comparison with non-AS-aided EEG-based biometric authentication, ii) role of the language of the AS and ii) influence of the conduction method of the AS. Our results show that the presence of an AS can improve authentication performance by 9.27\%. Additionally, the performance achieved with an in-ear AS is better than that obtained using a bone-conducting AS. Finally, we verify that performance is independent of the language of the AS. The results of this work provide a step forward towards designing a robust EEG-based authentication system.

Index Terms—Authentication, biometrics, electroencephalography, machine learning, neural networks.

I. INTRODUCTION

At present, it is mandatory to effectively protect personal data and secure information from cyber attacks. This includes being able to identify and authenticate users of digital systems. Several user authentication methods are known, involving credentials represented by something you 1) possess, 2) know, or 3) are. The first form of authentication exploits some type of physical token or key (card). The second approach leverages passwords and passkeys for authentication. The third method, involving biometrics, is instead based on physical, anatomical or functional traits of the human body.\[1\].

The usage of credentials based on the first two techniques (either tokens or passwords) is inherently exposed to the risk of theft and loss of the credentials. Techniques based on biometrics mitigate these risks and provide a legitimate alternative to owned or known credentials. Biometric data cannot be forgotten or lost since they are naturally with the owner, such as fingerprints and iris print\[2\], and are also consequently difficult to be copied or stolen. Biometric credentials are usually defined by means of seven terms\[3\]: universality, uniqueness, permanence, collectability, performance, acceptability and circumvention, as defined next.

1) Universality: It means that every individual should own the biometric data. This guarantees that the biometric data might be utilised by most people.

2) Uniqueness: It is the most significant factor for identification and indicates that the biometric traits cannot be shared by two or more persons.

3) Permanence: It refers to the steadiness over time. The biometric data cannot be modified from time to time.

4) Collectability: Defines how straightforward is to measure the biometric parameters in a quantitative manner.

5) Performance: Reflects how efficient is to execute identification based on biometrics in terms of accuracy and complexity.

6) Acceptability: Reflects how individuals are willing to use biometrics in practice and how happy they are with the system.

7) Circumvention: It is linked to spoofing resistance. In other words, some biometric features could be mimicked easily while for others it is considerably harder.

Traditional biometric features like fingerprints, iris recognition, and signatures can be copied or extracted from a corpse. In contrast to these methods, brain waves provide more difficult-to-forge biometric signals. For this reason, systems based on electroencephalography (EEG) have already been considered in the field of cybersecurity, as a basis for authentication\[4\], \[5\]. The main advantage of EEG-based authentication is that EEG signals are generated exclusively by living beings and are mood-dependent. As a result, they cannot be extracted from a dead brain or through force or threat, which makes them more robust than other biometric signals\[1\]. Nevertheless, there are still many challenges to be faced in order to obtain practical EEG-based authentication.

Designing secure and efficient EEG-based authentication systems basically is an open challenge, and the design process must follow the steps presented in Fig. 1, as described in\[3\]:

1) Definition of the requirements of the information system and the accompanying security requirements.

2) Choice of the biometric features that include sufficient identity information, especially those covering the uniqueness requirement.

3) Data collection and feature extraction. For better outcomes, the collected dataset should involve enough
participants to guarantee universality. Since gathered data often contain far more information than needed, feature extraction is required to focus on identity-related information and reject other forms of information that could be deceptive.

4) Classification through matching algorithms based on the comparison with a template, employing a mathematical model or artificial intelligence and machine learning methods.

5) Assessment of authentication performance to improve the design with the purpose of obtaining some desired performance target in terms of authentication accuracy.

In [7], [8] the use of a brain-computer interface with authentication systems in the presence of a musical stimuli has been studied. The results showed that auditory-evoked response carries subject discriminating features, which can be potentially used as a biometric. Another effort in this field was conducted in [9], where the participant in EEG-authentication was exposed to three different genres of music. The experiments were repeated over 6 weeks. The results showed that the reaction of the brain is different when exposed to a familiar music genre. This means that the brain develops specific features after repetition, regardless of the genres of the music. Based on these premises, it seems legitimate to investigate whether the language has a similar effect or not. Moreover, auditory stimuli can be conveyed through in-ear or bone-conducting headphones, thus one may also wonder if the conduction method affects the performance of EEG-based authentication. The aim of this paper is to study the effect of the auditory stimuli on the performance of EEG-based biometric authentication, focusing on these aspects. In particular, we aim at identifying whether there is an effect of auditory stimuli on the performance and practical feasibility of EEG-based authentication. Additionally, this work investigates the effect of language of the auditory stimuli on the authentication performance.

II. MATERIALS AND METHODOLOGY

In this section we describe the datasets we used for assessing the performance of EEG-based authentication along with the chosen authentication methods.

A. Local dataset

A local dataset, which has been made publicly available on Physionet [10], [11] was recorded at Marche Polytechnic University by enrolling 20 participants who performed the following 8 experiments:

1) Three minutes of resting-state, eyes open for three sessions.
2) Three minutes of resting-state, eyes closed for three sessions.
3) Recording EEG signal while hearing a song in the native language using in-ear headphone.
4) Recording EEG signal while hearing a non-native language song using in-ear headphone.
5) Recording EEG signal while hearing neutral music using in-ear headphone.
6) Recording EEG signal while hearing neutral music using bone-conducting headphone.
7) Recording EEG signal while hearing a song in your native language using bone-conducting headphone.
8) Recording EEG signal while hearing neutral music using bone-conducting headphone.

The EEG signals were captured from four channels, namely T7, F8, Cz, and P4, at a sampling rate of 200 Hz. The channel selection was subject to several factors:

1) The limit of choosing only four channels was due to available hardware, the OpenBCI ganglion Board [12].
2) Insights from literature aiming at finding the best channel locations were taken into account. In Fig 2 we show the channels used in [13], [14] and those we have chosen.
3) Diversity in the parts of the cortex (Temporal (T7), Frontal (F8), Central (Cz), and Parietal (P4)) covered. The used electrodes are passive, gold cup electrodes with TEN20 conducting paste used to stick EGG electrodes directly to the skin for secure connection.

Data preprocessing comprises a first-order bandpass Butterworth filter with a frequency range of 3 - 40 Hz. To ascertain the subjects’ level of comfort during the recording, they were asked to rank the experiments in order of their satisfaction. For the sake of simplification, the experiments were divided into four categories:

1) Resting-state: Eyes Open.
2) Resting-state: Eyes Close.
3) Auditory Stimuli using in-ear headphone.
4) Auditory stimuli using bone-conducting headphone.
B. Auditory stimuli analysis

The purpose of this analysis is to provide answers to the following three questions:

1) Do auditory stimuli affect the performance of EEG-based biometric authentication?
2) Does the auditory conduction method affect the performance of EEG-based biometric authentication?
3) Does the EEG-based biometric authentication performance differ between native, non-native, and neutral music?

These questions were addressed by using the locally recorded EEG dataset. To do this, we considered eight EEG-based biometric authentication systems based on the studies performed to collect the dataset. Following the EEG duration experiment conducted in [15], the EEG-epoch was split into 4-second segments; By EEG-epoch we mean a specific time-windows extracted from the continuous EEG signal. Instead, the features were extracted from the cluster map dataset in accordance with the results of a previous finding [6]. Three distinct classifiers were employed for classification: Multilayer Perceptron (MLP), K-Nearest Neighbors (KNN), and eXtreme Gradient Boosting (XGBoost). In order to assess the user satisfaction for each method, the subjects were asked to rank the four experiments’ types: In-Ear Auditory Stimuli, and Bone-Conducting Auditory Stimuli, Eyes Open Resting State, Eyes Closed Resting State.

C. Authentication methods

In this section we describe the tools used for performing authentication based on the considered EEG signals and assess the corresponding performance.

1) Multilayer perceptron (MLP): The MLP neural network architecture created using a trial and error approach. Five dense layers comprise the architecture utilized to classify the dataset. Each layer has 200, 150, 100, 57, and 48 neurons, respectively. Cross-entropy was employed as the loss function and the Adam optimizer was used in the architectures. Additionally, a batch size of 16 was chosen for training, and 1000 epochs were used. The MLP is summarized in Table I.

2) k Nearest Neighbours (KNN): KNN is a simple classifier that uses majority votes to determine class membership. The vote is limited to a specified number of nearest neighbours. We evaluated a range of neighbours from 1 to 20, with the greatest performance obtained when $K = 1$.

3) eXtreme Gradient Boosting (XGBoost): XGBoost is a cutting-edge classifier that was introduced in [16]. It is an ensemble method that enhances the performance of simpler models by combining them together. It is regarded as a promising method due to its great performance and short computing time [17].
against statistical oscillations. We then computed the average and standard deviation of performance measures.

### III. RESULTS

The results of our study to determine if and how auditory stimuli impact EEG-based biometric authentication performance are reported in Fig. 3, 4, and 5. The figures compare the case of resting state with the case with an auditory stimuli. Comparisons are performed for accuracy, false acceptance rate (FAR) and false rejection rate (FRR). In order to statistically test whether there is a significant difference between the two cases, a t-test was performed between the mean values of resting-state and auditory-stimuli for all the classifiers and all the feature sets. The t-test showed that $P$-value < 0.05, meaning that a significant difference exists. From the accuracy analysis it results that auditory stimuli increase accuracy by 9.27%. After finding that auditory stimuli have a positive effect on performance, we investigate whether the conduction method has some effect. To do so, the paired t-test was utilised for the cases with in-ear auditory stimuli and bone-conducting auditory stimuli. The t-test showed that $P$-value < 0.05, meaning that a significant difference exists. The accuracy analysis shows that in-ear auditory stimuli increase accuracy by 1.73%. So far, our results show that the usage of auditory stimuli in the case of in-ear conduction provides a significant increase in performance. After this, it is also interesting to investigate whether the language of auditory stimuli has some effect. To do so, the ANOVA test was conducted on the following three cases: native language, non-native language, and neutral music. The ANOVA value showed that $P$-value > 0.05, meaning that no significant difference exists. This highlights that, in our experiments, performance was independent from the language of auditory stimuli.

### IV. DISCUSSION

Based on the previously described experiments and the relevant results, we can make the following observations.
a) Effect of the auditory stimuli on performance of EEG-based biometric authentication: As introduced in Section II-A, and in Fig. 3 compares resting state and auditory stimuli. Notably, the auditory stimuli instance exceeded the resting condition by a difference of 9.27 % in accuracy. Such a result comes inline with the findings of [7], [8]. This can be explained by the fact that the brain’s response to auditory stimuli generates distinct EEG oscillation patterns. As a result, the addition of auditory stimuli can improve authentication performance. In terms of implementability, as illustrated in Fig. 6, 52.63 % of subjects preferred auditory stimuli produced using bone-conducting headphones as their first choice for satisfaction, followed by 36.84 % as a second choice. While 42.11 % of subjects chose auditory stimuli via in-ear headphones as their primary source of satisfaction, 47.37 % chose it as a secondary source of satisfaction. This suggests that auditory stimuli are preferable in terms of performance and practical feasibility.

b) Effect of the auditory conduction method on the performance of EEG-based biometric authentication: The paired t-test was used to compare bone-conducting stimuli to in-ear auditory stimuli. \( P=0.0380.05 \) for accuracy, \( P=0.0460.05 \) for FAR, and \( P=0.0320.05 \) for FRR are the test results. As a result, there is a significant difference between auditory stimuli sent through the ear canal and auditory stimuli delivered through the bone. The average accuracy of the in-ear case (69.33 ± 8.92 %) is slightly greater than that of the bone-conducting case (67.60 ± 8.78 %). In terms of user satisfaction and implementability, according to the survey results shown in Fig. 6, 42.11 % of subjects preferred in-ear auditory stimuli, whereas 52.63 % preferred bone-conducting auditory stimuli. This trade-off between performance and implementability allows the system designer to prioritize either one or the other.

c) Differences in the EEG-based biometric authentication performance between native, non-native, and neutral music: The ANOVA test was used to determine whether there is a significant difference between the three groups. The statistical analysis produced a p-Value > 0.05, indicating that the difference is not significant. There is no correlation between EEG-based biometric authentication performance and the auditory stimuli’s language. This is consistent with the findings in [9], where it was concluded that EEG-based biometric authentication is genre-independent.

V. CONCLUSION

In conclusion, our experiments confirm that the use of EEG-based biometric authentication has the potential to represent a new cybersecurity tool with unique features. This work contributes to the study of the performance achievable by EEG-based biometric authentication with the following summary results:

1) Using auditory stimuli could improve the authentication performance by more than 9 %.
2) Using in-ear auditory stimuli is better than using bone-conducting auditory stimuli in terms of performance, despite bone-conduction turns out to be more acceptable by users than in-ear conduction.

3) Performance of EEG-based biometric authentication in the presence of an auditory stimulus is independent of the language of the auditory stimulus.

Finally, we observe that our results were obtained on a relatively limited dataset, involving 20 participants ad using 4 EEG electrodes. As a future work, repeating the experiments on larger datasets could give insights on the possibility of generalising our findings.

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