Analysis of factors that influence the performance of biometric systems based on EEG signals

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Abstract

Searching for new biometric traits is currently a necessity because traditional ones such as fingerprint, voice, or face are highly prone to forgery. A motivation for using electroencephalogram signals is that they are unique to each person and are much more difficult to replicate than conventional biometrics. This study aims to analyze the factors that influence the performance of a biometric system based on electroencephalogram signals. This work uses six different classifiers to compare several decomposition levels of the discrete wavelet transform as a preprocessing technique and also explores the importance of the recording time. This work proves that the decomposition level does not have a high impact on the system's overall result. On the other hand, the recording time of electroencephalograms has a significant impact on the classifiers' performance. It is worth mentioning that this study used two different datasets to validate the results. Finally, our experiments show that Support Vector Machine and AdaBoost are the best classifiers for this particular problem since they achieved a sensitivity, specificity, and accuracy of 85.94 ± 1.8, 99.55 ± 0.06, 99.12 ± 0.11 and 95.54 ± 0.53, 99.91 ± 0.01, and 99.83 ± 0.02 respectively.

1 Introduction

There are many types of biological traits used in the development of biometric systems. Nevertheless, many of them are susceptible to brute force attacks, forgery, or direct forcing on users [1]. Furthermore, a constant problem of most biometrics is that they cannot guarantee that the user is alive [2]. To overcome these problems, the electroencephalogram (EEG) signals are an excellent choice as biometric traits; the main advantages of EEG as a biometric include [3]: Universality, Distinctiveness, Permanence, and Circumvention.

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This work aims to provide a detailed analysis of the Discrete Wavelet Transform (DWT) as a preprocessing and feature extraction technique. Besides, this paper investigates the impact of recording time on the classifier's performance and the DWT. Moreover, this study aims to establish a comparison between different classification algorithms to select the most suitable to develop this kind of system. This work's main contribution is the analysis of some of the fundamental components required in the development of a biometric system based on EEGs; this analysis will improve the understanding of the factors that can affect the system performance.

2 Methodology

The EEG signals used in this study correspond to two different datasets. The first one is the open-access *DEAP Dataset* [4], and the second one called *BIOMEX-DB*[1], which is a private dataset recorded in the "National Institute of Astrophysics, Optics and Electronics (INAOE)". The goal of working with two different datasets is to validate the results with different data sources.

This work compares four different decomposition levels of DWT to analyze their impact on the system's performance. First one, a five-level decomposition was applied to get the following frequency bands: 32-64Hz (D_1, γ); 16-32Hz (D_2, β); 8-16Hz (D_3, α); 4-8Hz (D_4, θ); 2-4Hz (D_5, δ) and <2Hz (A_5). These frequency bands correspond to five main brain rhythms related to specific functions [5]. The second DWT was performed with four decomposition levels because many authors proposed it as a reduction of the amount of data [6, 7, 8]. Additionally, three and two levels of decomposition were also applied to analyze their impact on the biometric system. This research uses Relative Wavelet Energy (RWE) as a feature because it has been proven to be useful in other EEG-applications.

This study followed a closed set strategy in the recognition problem, meaning that at training time, the classifiers saw examples of all testing classes [9]. Additionally, a multi-class classification approach was followed, where for each dataset, the number of classification categories was equal to the number of subjects. The following classification algorithms were evaluated to make a comparison among them and to choose the best one for this specific problem and datasets: Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Random Forest (RF), Gaussian Naïve-Bayes (GNB), AdaBoost (AB), and Multilayer Perceptron (MLP). The reason for choosing these classifiers was that each is based on a different criterion to perform the classification. The Average accuracy (Acc), Macro-averaging Sensitivity (Se), and Macro-averaging Specificity (Sp) were used to measure the performance of the classification algorithms in this multi-class scenario [10].

3 Results and Discussion

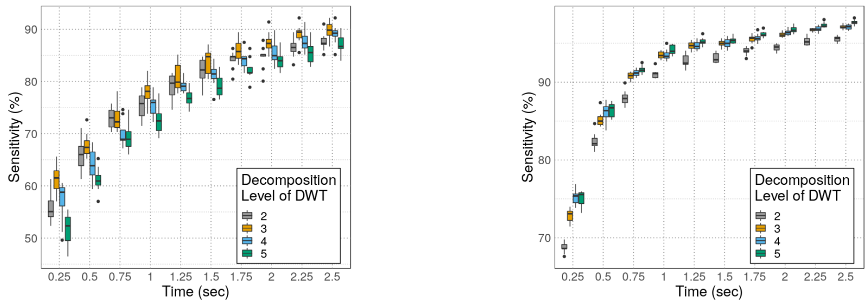
Figure 1 shows the sensitivity, in each level of DWT, achieved by the best classifier for each dataset. The boxplot is based only on the sensitivity because this was the lowest performance metric. Furthermore, the behavior of specificity and accuracy was the same as that of sensitivity. A Hotelling's T^2 test was applied to verify if there was a significant difference between each time segment concerning the maximum time used, i.e., 2.5 seconds. This test showed that from 1.75 seconds of recording, there is no longer a significant difference in the performance of the classifiers. Moreover, a MANOVA was applied using all classifiers' data in all-time segments regarding the decomposition level. The *p*-value obtained in this test was 0.1, demonstrating that the difference in performance between the different decomposition levels is not significant. Furthermore, the same analysis was performed without considering the data corresponding to the two-level DWT, and the *p*-value increased to 0.85, verifying that, in this case, three-levels of DWT can be considered as the best decomposition level.

4 Conclusions

The experimental results obtained using different levels of decomposition during preprocessing with DWT showed that although the state-of-the-art recommends using five or four levels of decomposition, fewer levels can be used and obtain significantly similar results. Moreover, the multivariate statistical

[1] A detailed description available at: `http://inaoe.repositorioinstitucional.mx/jspui/handle/1009/1604`

analysis demonstrates that there is a point from which it does not matter if the available time increases, the performance of the system does not vary significantly. Finally, using 1.75 seconds of EEG recording can be proposed as the recommendation for future studies because of the quality of results achieved with this time.



(a) SVM with DEAP dataset

(b) AB with BIOMEX-DB dataset

Figure 1: Boxplots of the sensitivity of the best classifiers for each dataset grouped by decomposition level of DWT.

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