A method for studying how much time of EEG recording is needed to have a good user identification

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***Abstract*— Recently, several researchers have tried to develop reliable biometric systems based on biological signals; brainwave signals, like Electroencephalograms (EEG), are unique for each person, and they are harder to steal and replicate than traditional biometrics. This paper presents a method for the development of biometric systems based on EEG signals, which allows to analyze the impact of the duration of the recorded signals in user identification accuracy. The proposed method uses a Discrete Wavelet Transform (DWT) to extract relevant features, and a hyperparameter selection for adjusting the base models following a greedy strategy. In the task of user identification, using five classifiers as base models, the experiments show that just 2 seconds of recording reach an accuracy of approximately 90% and with 20 seconds the accuracy increases to 99%.**

Keywords — Biometric, Electroencephalograms, Hyperparameter Selection, Discrete Wavelet Transform, Recording Time

I. INTRODUCTION

The development of robust biometric systems is a constant need, as it is possible to break security on traditional methods like username/password, face or voice recognition [1]. Brain activity captured by electroencephalograms (EEG) have showed good results as biometric; EEGs are unique for each person and any disruption in the subjects behavior can lead to significant changes on the signal, resulting in authentication failure [2]. However, a question arises: how much EEG recording could achieve a robust system. This paper introduces a method for developing biometric systems, based on EEG signals recorded during the sentiment reaction to an external stimulus [3]. The aim of this work is to provide a further perspective of EEG recordings duration effect on the accuracy of the biometric system.

Electroencephalography is a non-invasive electro-physiological monitoring method that records the electrical activity of the brain. The EEG recording procedure uses contact electrodes placed on the scalp surface; following the 10-20 International System as standard montage, each electrode produces a signal called channel [4]. This monitoring method has been widely used in medicine and psychology because it can be seen as a neuroimaging technology that helps to diagnose certain diseases or disorders [5][6].

Recently, the research of biometric systems based on EEG signals has become an area of interest; roughly the methods could be placedº in few groups. A group of methods start preprocessing the signals, then decompose each channel and analyze traditional features like mean, energy, standard deviation and entropy [7]–[10]. A second group of methods extract less traditional features such as the gamma-band spectral power ratio [11][12]. Finally, a third group of methods tries with reduction techniques like principal component analysis (PCA) with linear discriminant analysis (LDA) to improve classification [13][14]. All these methods exhibit good results, but they do not analyze the impact of time recording in the accuracy, and do not establish how to define the hyper-parameters of their base models.

The main scheme for working with EEG recordings includes preprocessing, feature extraction and classification [7][8]. In the proposed method, the EEGs pass through a common preprocessing including: common average reference, high pass filters and removing eye artifacts [3][4]. Feature extraction constitutes a crucial step for EEG classification because it impacts directly on the classifiers performance [6][15]. The proposed method decomposes the EEGs in band frequencies, using a Discrete Wavelet Transform (DWT); those correspond with the brain functioning bands. From each band, the proposal extracts the energy as distinctive feature. For the classification, the method analyzes a set of five classification models; a greedy strategy optimizes the hyper-parameters of each base model. Using the proposed method, this work studies the relation of different recording durations with the accuracy achieved in the user identification task.

The rest of the paper is organized as follows: Section II presents a brief review of previous works. Section III presents the materials and methods used for this study. Finally, in Section IV, we present our experimental results with its corresponding discussion.

II. Related work

EEG signals have been used in very diverse applications like prediction systems [16], classification of brain signals [17], sentiment analysis [3][18], medical diagnosis [19][20], etc. In this section, we are going to focus on the previous works about biometric systems based on EEG signals.

The classical approach, followed by its high accuracy, has four main steps: preprocess the signal, decompose each channel in frequency bands, extract traditional features like mean, energy, standard deviation, etc., and select a classification model to person identification. For example, Hu [7] applied a band-pass filter of 2–40 Hz as preprocessing and then he extracted the autoregressive (AR) coefficients, linear complexity (LC), energy spectrum density (ESD), energy entropy (EE) and phase locking value (PLV) as features. Shedeed [9] and Gui, Jin and Xu [10] also applied the same preprocessing technique using different frequencies, but in addition Shedeed used a Discrete Fourier Transform (DFT) and a 5 level Wavelet Packet Decomposition (WPD) while Gui, Jin, Xu just applied a 4 level WDP for decomposing the channels in frequency bands. In both cases, the authors extracted the mean, standard deviation and entropy as features, Sheeded also extracted the minimum and maximum coefficient. For the classification stage, all the authors trained a multilayer perceptron (MLP) neural network using standard backpropagation. The identification accuracy obtained by them [7], [9], [10], was 85%, 93% and 94.04% respectively.

Other researchers are trying to find new features that lead to higher identification accuracy. For this reason, a study by Fraschini, Hillebrand, Demuru, Didaci, and Marcialis [11] proposed a method based on band-pass filtering, functional connectivity estimation, brain network reconstruction and characterization of brain network topology. They used a public and freely available dataset and applied band-pass filtering to extract the delta [0.5-4 Hz], theta [4-8 Hz], alpha [8-13 Hz], low beta [13-20 Hz], high beta [20-30 Hz], and gamma [30-50 Hz] frequency bands. They estimate the functional connectivity between sensors and compute the eigenvector. The highest recognition rates of 95.6% were observed in the gamma band.

Zhang, Zhou, and Zeng [12] made a comparison between EEG and ECG signals. A Butterworth band-pass filter was applied for preprocessing the two signals. In the case of ECG, the filter was of 2-50 Hz while for the EEG it was of 30-50 Hz. For ECG feature extraction, eleven features from multi-domains were extracted and for EEG signals the gamma-band spectral power ratio was used as feature. For classification, they use MLP, K-NN, Bagging, Random Forest (RF), and AdaBoost (AB), but they got higher accuracy using ECG instead of EEG. RF reached the best accuracy in both cases.

The amount of data which needs to be processed during the developing of a biometric system based on EEG signals can be very huge. For this reason, some authors include dimensionality reduction techniques to reduce the computational cost and to extract the most relevant information among all the available data. Koike-Akino et al. [14] developed a biometric system applying Principal Component Analysis (PCA) and Partial Least Squares (PLS) to the preprocessed EEG signals. They made a comparison between several classifiers: Linear Discriminant analysis (LDA), Quadratic Discriminant Analysis (QDA), Nave Bayes (NB), Decision Trees (DT), K-nearest neighbor (K-NN), Support Vector Machine (SVM), Logistic Regression (LR) and MLP. The best accuracy was 96.7% and it was reached with QDA using the result of PLS.

A method for EEG based biometric system proposed by Campisi, La Rocca and Scarano [13] first preprocess the signal dividing it into frames of 10 seconds with a 50% overlap. Then an anti-aliasing low pass filter with cut-of set at 41 Hz and a Common Average Reference filter were used for each frame. Power spectral Density was then computed as feature, PCA was performed to obtain a compact feature representation while retaining relevant information for recognition purposes and LDA was applied to improve classification rates. K-NN was selected as classifier for two main tasks: classification using the whole EEG frequency range and classification on EEG sub bands; obtaining 97.01% for the whole frequency range and 97.68% on the theta beta sub band.

As we can see, researchers focus their attention on investigating which is the best preprocessing technique, feature and classifier. These are crucial parts for the development of secure biometric systems, but another important thing that remains without being investigated is the duration of the EEG recordings. If a system needs long signals, its usability can be affected because a good biometric does not require too many time for recognizing a person.

III. Materials and methods

The proposed scheme is based on the relationship of EEG signals with the sentimental reaction of a user to an external stimulus. This system can be very secure because even if someone tries forcing a user to obtain his EEG signals, the emotional stress will cause a failure in the identification process. The scheme workflow follows dataset acquisition, data preprocessing, feature extraction and user identification. The details of each phase are discussed in the following subsections.

A. *Dataset acquisition*

The dataset used in this work is an open-access dataset of EEG signals recorded during sentiment reaction to YouTube videos provided by Koelstra et al. [3]. The dataset is available at https://www.eecs.qmul.ac.uk/mmv/datasets/deap/. The subjects in the dataset were 32 healthy participants (50% female), aged between 19 and 37; each record has 32 EEG channels, 12 peripheral channels, 3 unused channels, and 1 status channel. Each subject was recorded during 60 seconds trials and 3 seconds pre-trial baseline; during each trial, subjects scored the level of valence, arousal, dominance and liking based on each video. In total, there were 40 trials for each subject.

B. *Data preprocessing*

For this research, the preprocessed version of the DEAP dataset was utilized. In this version the EEG signals were downsampled to 128Hz and passed through a band-pass frequency filter from 4.0-45.0 Hz to improve signal-to-noise ratio; the electrooculographic (EOG) artifacts were removed. In addition, the data was segmented into 60-second trials and a 3-second pre-trial baseline that was removed. Finally, the data was averaged to the common reference.

Additionally, we applied a discrete wavelet transform (DWT) since it is frequently used for the analysis of biomedical signals [5][6][21][22], especially in the analysis of non-stationary signals. Since EEG signals have non-stationary characteristics, DWT can be perfectly applied for its analysis. The wavelet technique applied to the EEG signal will reveal features related to its nature, which are unobvious for the Fourier transform. In general, it must be said that no time-frequency regions but rather time-scale regions are defined [23].

The fundamental idea of wavelet analysis consists of expressing a signal as a linear combination of a particular set of functions, obtained by shifting and dilating one single function called mother wavelet [23]. In this work, the Daubechies-4 (db4) wavelet was used as mother wavelet due to its smoothing feature which made it more appropriate to detect changes in EEG signals [24]. DWT decomposes a signal into a set of sub-bands through successively high-pass and low-pass filtering in combination with two down samplings of two.

The high-pass filter (g) is the discrete mother wavelet, while the low-pass filter (h) is the mirror version. The output of the low-pass filters is called approximation coefficient (A) and the output of the high-pass filters is referred to as detail coefficient (D). The maximum level of decomposition can be computed as:

$$log_2(M) - 1 \quad (1)$$

where M represents the length of the signal [5][6][21]. In the present study, we perform two different DWT decompositions. The first one with five levels of decomposition to get the following frequency bands: 32-64 (D1, γ); 16-32 (D2, β); 8-16 (D3, α); 4-8 (D4, θ); 2-4 (D5, δ) and <2 (A5) [24].

These frequency bands correspond to five main brain rhythms related to specific functions [4]. On the other hand, the second DWT was performed with four levels of decomposition as many authors proposed [5][15][21][22]. The aim of these different decompositions is making a comparison between them to recognize the best level of decomposition for biometric systems based on EEG signals.

C. *Feature extraction*

The extracted wavelet coefficients show the energy distribution of the EEG signals in time and frequency in a compact representation. However, the choice of the features represents a critical step in all classification systems because of its direct influence on classification performance. Some authors use the coefficients directly as their feature vectors [5][22][25]. Nevertheless, other authors try decreasing the dimensionality of the feature vectors extracting higher level features such as: the maximum, minimum, mean, standard deviation, entropy or relative energy of the wavelet coefficients in each sub-band [6][15][21][23][24]. For the present work, relative wavelet energy was chosen as a feature because it has been shown to be very useful in classification tasks [14]. The energy of each sub-band was computed using the following equations:

$$E_{D_i} = \sum_{j=1}^{N} \left|D_{ij}\right|^2, \; i = 1,2,3,\ldots,L \quad (2)$$

$$E_{A_L} = \sum_{j=1}^{N} \left|A_{Lj}\right|^2 \quad (3)$$

N is the length of the coefficient vector and L is the maximum level of decomposition. Using (2) and (3), the total energy is defined as:

$$E_T = \left(\sum_{i=1}^{L} E_{D_i}\right) + E_{A_L} \quad (4)$$

Finally, the relative wavelet energy (RWE) was computed as follows:

$$E_R = \frac{E_i}{E_T}, \text{ where } E_i = E_{D_{j=1,\ldots,L}} \text{ or } E_{A_{j=L}} \quad (5)$$

At this stage, only 32 EEG channels were used to compute the RWE features for all subjects. Also, all the feature vectors were scaled using min-max scaling to obtain values between 0 and 1.

D. *User Identification*

A classifier is an algorithm that takes features as inputs and predicts the corresponding class of the independent variable. A classifier has many hyperparameters that need to be adjusted for the working data. When the classifier is trained, it represents a model of the association between the extracted features and the classes, in this case the classes are the subjects [6], e.g., for a given RWE vector of subject 1, the classifier can be seen as a function c that takes as input the RWE vector and predicts it belongs to subject 1.

To analyze the effectiveness of RWE as feature and to find the best classifier, five classifiers were modeled. SVM is a classifier that finds a hyper-plane within the features space, maximizing the margin between the nearest data point of each class and the hyperplane [24]. Despite being originally designed for binary classification problems [26], SVMs can be extended to multiclass problems. K-NN is a distance-based classifier because it predicts the output class based on the k nearest training classes to the input feature vector [17]. RF is an ensemble of decision tree classifiers, where each tree is

TABLE I
HYPERPARAMETER OPTIMIZATION

Classifier	Hyperparameter	Tested Values	Best Value
SVM	Penalty Parameter	0,5; 1; 10; 50; 200; 300	100
	Kernel	linear; rbf; sigmoid	rbf
	Tolerance	1e-7; 1e-6; 1e-5; 1e-3; 0,1; 1	0,001
K-NN	Number of neighbors	1; 5; 10; 20; 50; 100	1
	Distance metric	Euclidean; Manhattan	Euclidean
	Leaf size	5; 10; 30; 50; 100	10
RF	Number of estimators	1; 10; 50; 100; 200; 500; 750; 1000	100
	Min number of samples required to split an internal node	2; 5; 10; 50; 100	2
	Criterion	gini; entropy	gini
AB	Weak classifier	SVM; RF; K-NN	RF
	Number of weak classifiers	5; 10; 50; 100; 500; 800	100
	Learning rate	0,1; 0,5; 1; 5	1
	Boosting algorithm	SAMME; SAMME.R	SAMME
MLP	Net specifications (neurons per layer)	(106); (106,106); (106,106,106); (84,84); (127,127)	(106)
	Learning rate	1e-3; 5e-3; 0,01; 0,05; 0,1	0,01
	Batch normalization	True; False	True
	Dropout	True; False	False
	L2 regularization	True; False	False
	Epochs	10; 100; 500	500

constructed using a randomly selected group of features, independently sampled with an identical distribution for all trees [27]. For each input feature vector, each tree in the forest predicts a class and the output is the most voted class. AB is also an ensemble classifier as RF, but in this case, the weak classifier can be any of the previous classifiers. AdaBoost is adaptive in the sense that subsequent weak learners are tweaked in favor of those instances misclassified by previous classifiers [19]. MLP [12] is inspired by the brain structures where layer-wise neurons are organized in a way that can represent a high-level abstraction.

To select the hyperparameters of each classifier, the proposed method uses a greedy search optimization approach. Greedy search optimizes only one hyperparameter at a time while keeping other hyperparameters fixed [28]. It is based on an exhaustive searching through a manually specified subset of the hyperparameter space of a learning algorithm. In this work, tenfold cross-validation was used to guide the performance of the greedy optimization. The results of the hyperparameter optimization are shown in Tab. I.

E. *Experimental set-up*

Two tests were performed. In the first one, we applied the feature extraction process described before over the entire signals of the dataset, while in the second test we employed the previous process for different segmentations of the EEG signals. The segmentations were made at 0.25, 0.5, 1, 2, 4, 6, 8, 10, 20, 30, 40, 50, and 60 seconds, all of them starting at the beginning of the recordings. These tests were designed to identify from which time an EEG recording can be used for the development of a biometric system.

The classifiers were trained and tested for the extracted features using a tenfold cross-validation method. This method has the advantage that utilizes all of the instances in the dataset for both training and testing. The train-test split of the data was performed in a balanced way selecting 75% for training and 25% for testing of each subject. This process was replicated ten times using the same data for all the classifiers to obtain reliable results. The classifiers performances were computed using the accuracy as the evaluation metric and a receiver operating characteristic (ROC) curve was made to provide a graphic representation of it.

IV. Results and discussion

In this section, we present the experimental set-up, the experimental results, and discuss them.

A. *Experimental Results and Discussion*

The comparison between the five classifiers using five and four level DWT are shown in Tab. II. MLP reached the highest accuracy of 100% followed by SVM with 99.47%. On the other hand, the worst accuracy was given by K-NN classifier. A T-test was performed to evaluate if the accuracies between these decomposition levels were statistically different and another test was conducted to know if the differences presented for all the classifiers were statistically significant. Both tests were performed using a confidence level of 95%.

The first T-test showed that there was not a significant difference between using four or five level DWT, which means that for this specific application with this dataset, we can use a four-level decomposition because it is computationally faster and cheaper. The second test showed that the accuracy obtained by MLP and SVM was statistically higher than the accuracy obtained with the other classifiers, but there is not a statistical difference between them.

As a consequence of the previous T-tests, Tab. III shows the classification results for the different times, but only using a four-level DWT. In this table, we can appreciate how the duration of the EEG recordings produces a direct impact on the classification accuracies. With just two seconds, MLP achieved an accuracy higher than 90%. However, if we increase the duration of the EEG recording to 20 seconds an average accuracy of approximately 99% was reached.

TABLE II
COMPARISON BETWEEN ACCURACIES OF FOUR AND FIVE LEVELS DWT

Classifier	Level of decomposition	Accuracy (%)
SVM	4	99,47±0,28
	5	99,34±0,49
RF	4	98,00±1,17
	5	97,75±0,39
K-NN	4	98,31±0,83
	5	97,72±0,73
AB	4	97,94±1,05
	5	98,03±0,77
MLP	4	100,00±0,00
	5	99,81±0,16

TABLE III
COMPARISON BETWEEN ACCURACIES FOR DIFFERENT RECORDINGS DURATIONS

Time (sec)	SVM (%)	RF (%)	K-NN (%)	AB (%)	MLP (%)
0,25	59,88±2,55	53,25±2,23	37,00±2,40	52,69±2,69	61,97±2,40
0,5	70,25±2,13	59,09±2,24	45,19±3,49	59,84±2,77	73,78±1,79
1	79,34±2,79	70,91±1,58	58,81±1,60	70,38±1,94	83,63±1,31
2	88,31±1,66	79,69±2,42	72,38±2,23	78,84±2,16	92,25±1,92
4	93,75±1,41	87,72±1,77	82,91±1,88	87,31±1,63	96,47±1,37
6	95,44±0,81	90,31±1,55	86,25±1,56	90,59±1,33	97,81±0,93
8	96,69±1,00	91,81±1,56	89,13±0,92	92,31±1,06	98,47±0,45
10	97,66±0,82	93,16±1,12	89,97±1,85	92,44±1,28	98,56±0,37
20	98,94±0,61	95,25±1,10	95,53±0,84	95,06±1,55	99,72±0,23
30	98,88±0,40	96,47±1,04	95,97±1,01	96,22±0,88	99,53±0,37
40	99,31±0,48	96,81±0,94	96,81±0,52	96,84±0,71	99,75±0,25
50	99,47±0,42	97,66±0,68	97,75±0,56	97,88±0,87	100,00±0,00
60	99,50±0,35	97,97±0,89	98,38±0,23	97,88±0,72	99,97±0,10

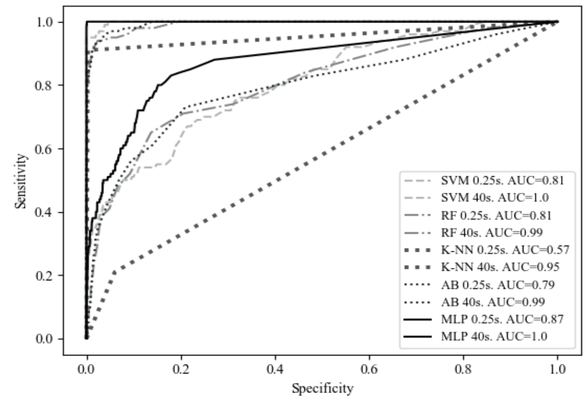

Fig. 1. ROC Curve for all classifiers at 0.25 and 40 seconds for subject 4.

In addition, the same T-test was applied on these results demonstrating that from 40 seconds, the difference in accuracy is not statistically significant, which means that it is unnecessary to obtain longer recordings. To acquire a clearer idea of this impact Fig. 1 also compares the classifiers using a ROC curve. ROC curve is used in binary classification problems, but in this study, the classification represents a multiclass problem; for this reason, we just use the EEG signals of the subject 4.

Creating a detailed comparison of the results in this study with the previous researches in EEG signals is complicated because of the variety of EEG datasets, types of decompositions, number of subjects and cognitive tasks used. However, a short comparison with the previous related studies is presented in Tab. IV. In this table the present work shows only the accuracy results of Tab. III corresponding to 60 seconds. Most of the studies have used MLP neural networks for the classification process, which are complex in nature and time consuming to build the classification model. In the present study, the best accuracy was achieved equally using MLP, but as the difference with SVM is not statistically significant, it can be used to the development of a biometric system.

TABLE IV
COMPARISON OF THE PRESENT STUDY WITH PREVIOUS WORKS RELATED TO BIOMETRIC SYSTEMS

Paper	**Year**	**Subjects**	**Electrodes**	**Feature**	**Classifier**	**Accuracy (%)**
[7]	2010	3	6	AR coefficients	MLP	85,00
				Linear complexity		
				Energy spectrum density		
				Energy entropy		
				Phase Locking Value		
[8]	2010	3	6	AR coefficients	MLP	92,80
[9]	2011	3	4	DFT and Wavelet mean, std and entropy	MLP	93,00
[10]	2014	32	6	Wavelet mean, std and entropy	MLP	94,04
[14]	2016	25	14	PCA and PLS	QDA	96,70
[25]	2017	70	14	Gamma-band features	HMM	95,65
[12]	2017	20	64	Gamma-band spectral power ratio	RF	86,00
					MLP	85,10
					K-NN	78,00
					AB	73,90
					Bagging	66,70
This work	2019	32	32	Relative wavelet energy	MLP	99,97
					SVM	99,50
					K-NN	98,38
					RF	97,97

AB	97,88

V. Conclusion

This research has presented the use of relative wavelet energy combined with different machine learning classifiers for the creation of a biometric system based on EEG signals. The EEG signals were split into sub-bands using DWT with db4 wavelets. The experimental analysis shows that for the proposed methodology, there is not a significative difference between four-level and five-level discrete wavelet transform.

The main contribution is the comparison and analysis between different times of EEG recordings. A viable biometric system based on EEG could be developed using only 2 seconds of recording, but if we use 40 seconds of recording the system becomes extremely secure.

Five different classifiers were employed for the classification process and their performance was evaluated for user identification. The classification results showed MLP and SVM were the best classifiers for this work. A relevant fact to highlight is that most of the literature says that a MLP tends to be better with at least two hidden layers, but nevertheless for this work a MLP of one hidden layer with 106 neurons allowed us to get higher accuracies.

We believe that the influence of sentiments in the capture of EEGs contributes to the good results obtained in this study. For this reason, we propose the study of this relationship as future work.

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