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Improved Time-Frequency Features and Electrode Placement for EEG-Based Biometric Person Recognition

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ABSTRACT This paper introduces a novel feature extraction method for biometric recognition using EEG data and provides an analysis of the impact of electrode placements on performance. The feature extraction method is based on the wavelet transform of the raw EEG signal. Furthermore, the logarithms of wavelet coefficients are processed using the discrete cosine transform (DCT). The DCT coefficients from each wavelet band are used to form the feature vectors for classification. As an application in the biometrics scenario, the effectiveness of the electrode locations on person recognition is also investigated, and suggestions are made for electrode positioning to improve performance. The effectiveness of the proposed feature was investigated in both identification and verification scenarios. The identification results of 98.24% and 93.28% were obtained using the EEG Motor movement/imagery dataset (MM/I) and the UCI EEG database dataset, respectively, which compares favorably with other published reports while using a significantly smaller number of electrodes. The performance of the proposed system also showed substantial improvements in the verification scenario, when compared with some similar systems from the published literature. A multi-session analysis is simulated using with eyes open and eyes closed recordings from the MM/I database. It is found that the proposed feature is less influenced by time separation between training and testing compared with a conventional feature based on power spectral analysis.

INDEX TERMS Biometrics, feature extraction, EEG.

I. INTRODUCTION

Biometric person recognition technologies have become an active area of research in recent years, leading to significant deployments in a range of application domains. However, despite some considerable successes, important challenges still hinder their widespread adoption and acceptance [1], because of this the search for new biometric modalities continues. Using the electroencephalographic (EEG) signals for biometric recognition has been receiving increasing attention in recent years. The EEG signals have been widely employed in clinical applications (such as the epileptic seizure events detection [2]). However, as a relatively new biometric modality, they were first used for person identification in 1999 [3]. After years of research, it is now experimentally established that EEG signals indeed contain biometric information [4]. However, the usage of EEG for person recognition is still mainly restricted to laboratory environments; most of the reported EEG-based scenarios could not be adapted for real-life scenarios due to usability issues. For example, many proposed EEG biometric systems require a large amount of electrodes to achieve an acceptable recognition performance [5].

Feature extraction is a critical step in developing EEG biometric systems. After nearly 20 years of research, most of the proposed systems are still using one or both of the following features for classification: Power Spectral Density (PSD) [6], [7] and Autoregressive Model (AR) coefficients [8], [9]. These features on their own, however, do not seem to be able to convey enough biometric information while using a limited number of electrodes.

Recently, Bai *et al.* [10] reported a system using the visual evoked potential for person identification. A series of techniques, including Genetic Algorithm, Fisher Discriminant Ratio and Recursive Feature Elimination were employed to reduce the number of electrodes for less intrusive

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user experience. Data from 32 out of 64 electrodes were tested using a database of their own comprising 20 subjects. The best identification rate of 97.25% was achieved using a Support Vector Machine classifier.

Phung *et al.* [11] proposed using Shannon Entropy (SE) as the feature for fast EEG-based person identification. Their database consisted of 40 subjects and EEG data captured from 23 electrodes were used for feature extraction. It was found that using SE was 2.3 to 2.6 times faster than the method based on AR, while a comparable accuracy was achieved (97.1% for SE versus 97.2% for AR).

Gui *et al.* [12] proposed to use Euclidean Distance (ED) and Dynamic Time Warping (DTW) for the EEG data matching. Their proposed methods were tested with a database having 30 subjects using a 74-channel EEG cap. Only the data obtained from four electrodes (Pz, O1, O2, Oz) were used. It was found that the ED method had an accuracy of over 80% whereas the accuracy achieved by the DTW method was about 68%.

Ruiz-Blondet *et al.* [13] reported an identification system based on the Event-Related Potential (ERP) using a discriminant function for classification, a 100% identification accuracy was achieved in a pool of 50 users. Using the ERPs as features, a longitudinal study of EEG biometrics was also investigated [14]. EEG recordings from three different sessions of 50 subjects were employed for analyzing its repeatable characteristics. Deep convolution neural networks have also been used for EEG biometrics [15]. Using the open-source database (Physionet EEG Database), an Equal Error Rate (EER) of 0.19% was reported. In terms of EER, it surpasses by far all the previous reports using the same database in a verification scenario.

The efforts in developing a user-friendly EEG biometrics device recently received much attention in the community. Nakamura *et al.* [16] reported a two-sensor In-Ear EEG biometric system, tested in both the verification and identification scenarios. Fifteen subjects participated in two temporally separate sessions. Depending on the subject, the time intervals between the two sessions ranged from 5 to 15 days. Three trials of recording were obtained for each session, each trial lasted for 180 seconds. The PSD and AR features were trained by linear discriminant analysis (LDA) and support vector machine classifiers. The best recognition rate was 87.2% while using the data from the trials in the same day; whereas when the data from the trials performed in a separated day were used for testing, the recognition degraded to 67.8%.

The affective (emotional) state of an individual also play a role in the EEG-biometrics ability to identify individuals. For example, in [45], Arnau-Gonzalez et al. reported that the identification accuracy is consistently higher when EEG recordings are from the same emotional state. Their experiment found a drop in accuracy of about 5-11% due to the affective states depending on the feature types and classification algorithms explored. A more significant reduction in accuracy occurred when data were picked from different recording sessions. Key issues that emerge from this brief survey of relevant literature include the need for reducing the number of electrodes for more usable biometric recognition systems while improving accuracy rates for large cohorts of users, as well as an understanding of the stability of EEG-based biometric features over time.

In this paper, a novel feature extraction method based on the Wavelet Transform is introduced for biometric recognition using EEG data. The effectiveness of the proposed feature was investigated in both identification and verification scenarios. The paper is organized as follows: Section II introduces the proposed feature extraction algorithm. A brief introduction of the databases used in this study is presented in Section III, including parameter estimations such as the window size and the electrode placement. In Section IV, both identification and verification tests are conducted to evaluate the biometric performance of the proposed system. In Section V the experimental results are compared with other systems. Conclusion and suggestions for future work are presented in Section VI.

II. THE PROPOSED WAVELET-LOG-DCT FEATURE

EEG signal is considered a non-stationary modality [17], which is, to some extent similar to human voice signals [18]. It is reported by Kawabata [17] that for EEG signals (during both the eyes-open and the eyes-closed states), some stepwise changes in the amplitude together with rapid changes in the center frequency were observed. It has been claimed that these characteristics of EEG signals are similar to human speech [19], and therefore, it is justifiable that some well-established feature extraction algorithms in the voice recognition field can also be explored for EEG-based recognition. Nguyen *et al.* [19] conducted a preliminary investigation using the conventional Mel-frequency Cepstral Coefficients (MFCC) features for biometric person identification. Tested using a population of 20 subjects (subset of a public database of 122 subjects), 92.8% identification rate was achieved using data from eight electrodes. Their work suggests MFCC feature which transferred directly from voice recognition is also effective in revealing the biometric information of EEG signals.

The notion of combining Wavelet Transform (WT) and Fourier Transform (FT) has also been reported in the speaker recognition field [20], [21]. In the work presented in our paper a new wavelet-based feature is proposed. Figure 1 shows the main steps of the proposed feature extraction method. Previously reported algorithms, however, follow the order of computing Fourier Transform-Mel Log Powers per Window-Wavelet Transform [20, [21] for feature extraction. This newly proposed scheme for EEG-based biometric recognition, on the other hand, performs the wavelet transform first, then the logarithm of the wavelet coefficients is computed. Finally, the Discrete Cosine Transform (DCT) is computed. A subset of the resulting coefficients for each wavelet band are then used as the feature for pattern classification.

The main feature extraction process is divided into four steps. The first step is to perform the Wavelet Transform of

TABLE 1. Statistical comparison between two types of features: with and without the logarithm step. The Fisher's linear discriminate ratios between the 12-dimensional features from Subject 1 and Subject 2 (from the MM/I database) are computed to illustrate the effectiveness of the logarithm step in the proposed feature extraction method.

Fisher's linear discriminate ratio						
Band (Hz)	0-20	20-40	40-60	60-80	0-10	10-20
With log	**1.7709**	0.0524	**0.2928**	**0.2694**	**11.9517**	**1.3647**
Without log	0.0016	0.9955	0.2582	0.1415	0.0028	0.0789
Band (Hz)	20-30	30-40	40-50	50-60	60-70	70-80
With log	**2.7129**	**0.1056**	**16.1299**	0.1381	**3.6337**	1.0775
Without log	0.9323	0.0063	0.2851	2.4055	0.1289	1.6665

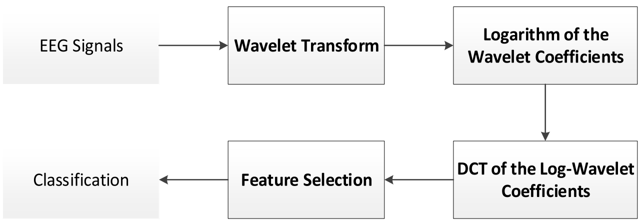

FIGURE 1. Overall process of the proposed Wavelet-Log-DCT approach to biometric identification.

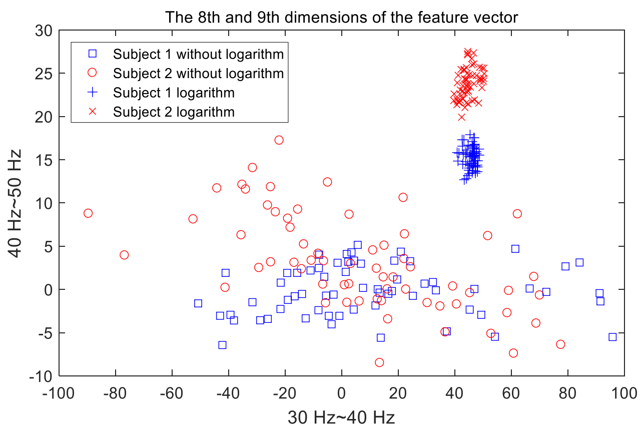

FIGURE 2. Two dimensions of the WLD feature vectors from Subject 1 and 2, with and without the logarithm step. The data used to generate this illustration is from the MM/I dataset for an epoch size of 15 seconds (Cz electrode).

the EEG data: here Wavelet Packet Decomposition (WPD) is employed [22]. The wavelet coefficients encapsulate both the time and the frequency properties of the signal. The Daubechies 4 wavelet function is used to decompose the windowed signal into four levels (Level 0 to Level 3).

Similar to the conventional computation of the cepstrum in the field of speech/speaker recognition [23], the second step is to compute the logarithm of the resulting WT coefficients for each wavelet band. The resulting WT coefficients may contain both positive and negative values. In our implementation, we took the absolute magnitudes of the WT coefficients prior to the calculation of the logarithms. It is found that the resulting logarithmic wavelet coefficients are better separated in the feature space than without performing the log step as illustrated in the Figure 2. Only two sets of features (extracted from the Cz channel recordings of the MM/I database) are presented for visual comparison, one including the logarithm step, and the other without are shown in the same feature space. The two elements of the feature vectors (8th and 9th) plotted corresponds to two wavelet bands (30-40 Hz and 40-50 Hz respectively). It can be seen that inclusion of the logarithm step results in feature points of each class to be much more compact and better separated.

To statistically further analyze the effectiveness of the logarithm step, a series of comparisons are presented in Table 1. The proposed EEG feature vector contains 12 dimensions extracted from the subbands in Level 2 and Level 3. The classical Fisher's linear discriminate (FLD) ratios [24] of the features for each dimension are computed; these results are compared with the ratios obtained from the features obtained without the log step. It is found the FLD ratios from most of the bands with the log step were significantly higher revealing better clustering for classification. It can be seen that for some dimensions from the proposed feature produced lower FLD ratios, however, the overall quality of the feature as a vector (of 12 dimensions for the proposed method) still out performed the features without including the log step.

The logarithm of the wavelet coefficients for each EEG window (epoch) is subsequently fed into a discrete cosine transform filter bank [25], resulting in a series of Wavelet-Log-DCT (WLD) coefficients. Finally, the proposed feature extraction process selects the most information-bearing WLD coefficients obtained in the previous step. An empirical investigation was carried out (see Sec. IIIC for details) and for this particular implementation of EEG biometrics, only the first coefficients were selected for the feature vector construction. Note that, these coefficients are not related to the DC values of the time domain EEG signals due to the wavelet decomposition, except in the subbands 0-10Hz (Level 3) and 0-20Hz (Level 2). The DCT coefficients are derived from the wavelet transform, which have been frequency-banded in the wavelet domain and further compressed in the log-domain. The selected coefficients thus provide a time-frequency signature based on the information contained in the different wavelet bands.

This proposed feature extraction strategy has some similarity to the conventional MFCC algorithm [26], [27]. In the proposed method, the Wavelet Transform with its multi-scale decomposition characteristics is used instead of the Fourier transform to better distinguish the biometric information buried in the time domain signals.

III. EXPERIMENTAL SETUP AND ANALYSIS OF PARAMETERS

Data In the laboratory environment, a typical EEG-based biometric recognition system often requires the users to perform some activities, (e.g., viewing a series of pictures or making a movement) to trigger the signals of interest. The EEG signals are then recorded by a headset during this process.

To evaluate the effectiveness of the proposed feature, and compare the system performance with other existing reports, two publicly available databases namely "EEG Motor Movement/Imagery Dataset" [28] and "UCI EEG Database Dataset" [29] are employed in this study. For the sake of brevity, these two databases are referred as MM/I database and UCI database, respectively.

The MM/I dataset contains data obtained from 109 subjects, acquired using the BCI2000 instrumentation system: the headset contains 64 wet sensors acquired EEG at a sampling frequency of 160 Hz [30], [31]. Subjects involved in the data collection performed six different tasks: two resting state baseline tasks where there was no requirement for any specific activity (one with eyes open, one with eyes closed), and four motor movement/imagery tasks. Only the data from the resting states are utilized in this work. From the two baseline datasets, 105 out of 109 subjects were selected to ensure each recording contains at least 60 seconds of data.

The UCI database contains data obtained from 122 subjects, collected by a headset with 64 electrodes. 122 subjects were separated into two groups: alcoholic (77) and control (45). During the data collection, subjects were viewing a series of standard picture sets (banana, airplane etc.) [32] while their EEG signals were recorded. Each picture was shown for one second and the following one second's EEG data was recorded (at a sampling frequency of 256 Hz) as one trial. There were between 15 to 120 such one-second trials recorded for each subject. Therefore, the overall recording length varied a lot for different subjects. Further details of the data capture and preparation of the UCI database can be found in [29]. Due to the recording length variation between subjects, only 119 out of 122 subjects were selected for this analysis to guarantee adequate length of recordings (at least 60 seconds) from each individual. The distinction between two types of subjects (alcoholic and control) was ignored in these experiments and only the biometric performances were explored.

The raw signals were segmented into multiple time domain windows. For each window the WPD was performed [33]: for EEG analysis, the signals were decomposed into four levels (Levels 0 to 3) of wavelet bands and the wavelet coefficients of the 12 bands from Levels 2 and 3 are included in the feature vector. For the MM/I database (with 160 Hz sampling rate), the selected subbands used in the feature extraction are of 10 Hz and 20 Hz bandwidths as in [34].

TABLE 2. Impact of window size (samples) for feature extraction on identification accuracy: using MM/I database, Cz location.

	Window Size			
	800 (5s)	1600 (10s)	**2400 (15s)**	3200 (20s)
Maximum	70.95%	72.86%	**82.86%**	77.14%
Minimum	65.71%	69.05%	**66.67%**	72.38%
Mean	67.46%	71.11%	**76.66%**	75.24%

For the UCI database, with 256 Hz sampling, the corresponding smallest bandwidth after wavelet decomposition was 16Hz. For classification, a standard linear LDA classifier was used for training the MM/I and UCI databases respectively [35]. The following subsections describe the efforts towards the window size optimization, electrode subset selection, DCT coefficient selection, etc.

A. WINDOW SIZE ANALYSIS

The usability of EEG biometrics is becoming an increasingly important factor in designing a recognition system [16], [36]. The length of the time domain windows is one of the influential factors: since such window is used for feature extraction separately, user(s) must provide at least one continuous EEG recording with the length of the specified window size. However, for larger window sizes, longer time from the user is needed for testing. We did a series of analysis on the impact of the window size toward system performance. Only the data from sensor at Cz location was used for this parameter estimation (10-20 electrode placement [37]). The choice of this electrode was guided by our previous work [38]. A series of identification tests have been conducted using the proposed feature with a window size ranging from 800 samples (5 seconds) to 3200 samples (20 seconds). The identification accuracy performances based on the MM/I database are listed in Table 2. The results shown are the average of the leave-one-out cross-validation accuracies: each time one segment (i.e. the window in Table 2) of the available data is picked for test and the rest used to train the system. The classifications were conducted using MATLAB PRTools (pattern recognition toolbox [39]). The best identification rate achieved was 76.66% for a window size of 15 seconds. It is found the performance did not improve by further increasing the window size. Taken the real-world scenario into account, it is decided to use 15 seconds as the optimal parameter for the window size, which is used for the subsequent experiments reported here.

B. ELECTRODE PLACEMENT

Another critical factor that may affect the performance is the number of the adopted electrodes and their locations on the scalp. The goal is to reduce the number of electrodes while maintaining the biometric recognition performance. In this study, five different combinations of four electrodes were

TABLE 3. Identification rates for different four-electrode combinations, MM/I database is used for this four-electrode combination schemes.

Electrodes	Recognition rate
FCz-C1-C2-CPz	90.48%
FC1-FC2-CP1-CP2	89.52%
F3-F4-P3-P4	92.38%
F7-F8-P7-P8	96.19%
FPz-T9-T10-Iz	98.24%

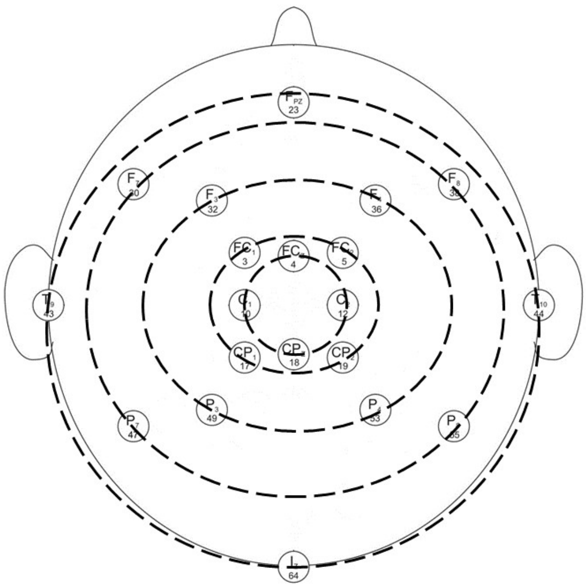

FIGURE 3. Five sets of electrode groups explored for optimal electrode placement reported in the Table 3.

evaluated and the corresponding performances analysed. The grouping of the electrodes is illustrated in Figure 3: there are five circles of electrode combination, the distances among these electrodes are increasing monotonically from inner to outer circles. For each of the combinations, we tested their recognition performances and found that the outer circles tend to perform better than the inner circle electrode placements.

The recognition results using the MM/I dataset are listed in Table 3. The results show a clear improvement of almost 9% when the distant electrodes were used. This indicates that the signals obtained from the isolated regions may contain more distinctive biometric patterns, than the signals obtained from nearby locations: the clustered electrodes may have collected redundant information.

To statistically investigate the evidence shown in Table 3, sensor-level functional connectivity in the time domain has been explored between the electrodes within each placement. For any given group in the Figure 3, the correlations of all possible feature vector pairs were computed. For example, for the most inner placement (FCz-C1-C2-CPz), the correlation coefficients of the feature vectors between FCz-C1, FCz-C2, FCz-CPz, C1-C2, C1-CPz, C2-CPz were computed for each subject. The mean of these coefficients was then calculated and used as the connectivity metric for all the electrodes within the placement. The full representations of these similarity values are shown in Table 4. It is found that the feature vector pairs from the inner placements tend to have higher correlations than the vectors from the outer placements, which indicates the features from distant electrodes are much less correlated to each other compared to the electrodes in the inner groups. This evidence suggests the distant electrodes appear to be able to capture less redundant information than the adjacent electrodes.

Based on the analysis in this section, the electrodes selected for MM/I are the FPz-T9-T10-Iz combination. For the case of UCI database, since the EEG signal was visually evoked, no empirical electrode selection was carried out and eight electrodes clustered near the occipital lobe were selected (i.e. the data from CPz, Pz, POz, Oz, PO3, PO4, PO7, PO8 were used) for the feature extraction in this study.

C. DCT COEFFICIENT SELECTION FOR FEATURE VECTOR

To further explore the effectiveness of the selection of the DCT coefficients as feature, a series of experimental analysis were performed. Table 5 illustrates the classification results using the first few DCT coefficients derived from MM/I database. The first DCT coefficient on its own is found to be most effective when used for biometric recognition. A gradual reduction in the classification accuracy was noticed while using additional coefficients in the feature vector. The second DCT coefficients onwards seems barely contain any biometric information on their own, as is indicated in Table 5. Therefore, only the 1st DCT coefficients from each band were selected to form the feature vector. The usage of only the 1st DCT coefficient as feature also provides the opportunity to significantly reduce the computational complexity of the proposed scheme.

IV. EXPERIMENTAL RESULTS

A series of investigations using the proposed WLD feature are presented in this section. The section is divided into two parts: Section IV.A is devoted to analyzing identification performance of the proposed feature, followed by a comparative analysis using the Cumulative Match Characteristic (CMC) curve [40] [41]. The verification performances are then reported and compared in Section IV.B using the Detection Error Trade-off (DET) curves.

In order to evaluate the performance of the proposed feature extraction algorithm, it is compared with similar features found in the literature. All these algorithms use either Fourier or Wavelet Transform to generate the initial coefficients, the dimensionality was subsequently reduced by a number of techniques. For example, Phung *et al.* [11] proposed to compute the Shannon Entropy of the time domain sequence as feature. Abdullah et al. [42] proposed to compute mean and standard deviation as features to achieve the dimension reduction after wavelet transform. Gupta *et al.* [43]

TABLE 4. Correlations of all the feature vectors from the selected electrode pairs, all of the five combination schemes (from the figure 3) are shown below.

Electrodes	FCz-C1	FCz-C2	FCz-CPz	C1-C2	C1-CPz	C2-CPz	Mean
CorrCoef	0.9913	0.9887	0.9834	0.9918	0.9899	0.9880	**0.9889**
Electrodes	FC1-FC2	FC1-CP1	FC1-CP2	FC2-CP1	FC2-CP2	CP1-CP2	Mean
CorrCoef	0.9724	0.9635	0.9603	0.9834	0.9790	0.9924	**0.9752**
Electrodes	F3-F4	F3-P3	F3-P4	F4-P3	F4-P4	P3-P4	Mean
CorrCoef	0.9856	0.9713	0.9654	0.9690	0.9644	0.9904	**0.9577**
Electrodes	F7-F8	F7-P7	F7-P8	F8-P7	F8-P8	P7-P8	Mean
CorrCoef	0.9737	0.9540	0.9420	0.9476	0.9389	0.9770	**0.9555**
Electrodes	FPz-T9	FPz-T10	FPz-Iz	T9-T10	T9-Iz	T10-Iz	Mean
CorrCoef	0.9001	0.9034	0.8828	0.8920	0.8484	0.8479	**0.8791**

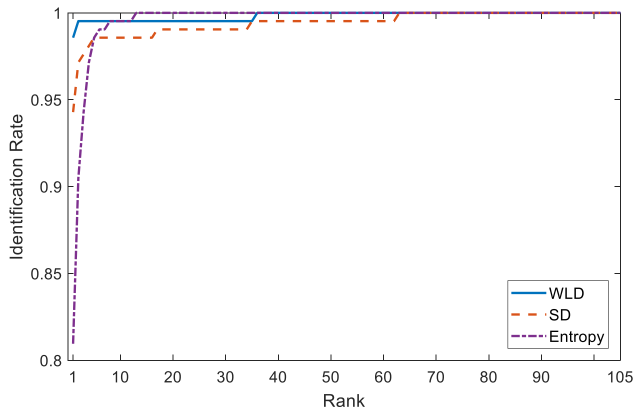

FIGURE 4. CMCs of biometric systems incorporating three different features using 105 subjects from the MM/I dataset.

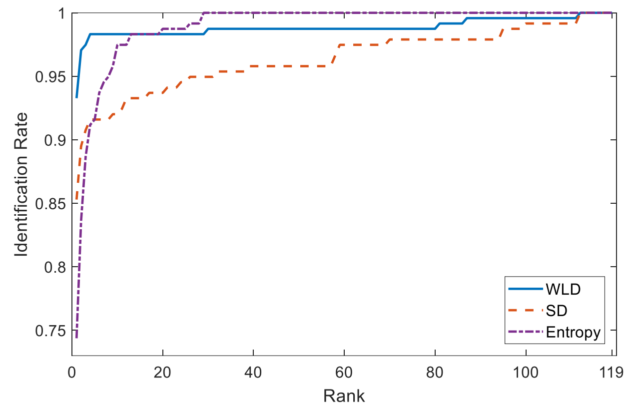

FIGURE 5. CMCs of several features, using 119 subjects from UCI database.

TABLE 5. Impact of the classification performance of the selected DCT coefficient(s) using the MM/I database (105 subjects).

DCT coefficient(s) retained as feature	Classification accuracy
1st	98.24%
2nd	1.00%
3rd	3.24%
4th	1.38%
5th	3.62%
1st - 2nd	96.86%
1st - 3rd	94.81%
1st - 4th	89.10%
1st - 5th	84.14%

proposed using the energy of resulting wavelet coefficient as feature. For this study, similar features were extracted by the authors from the two chosen databases and compared their biometric recognition performances against the proposed WLD feature.

A. IDENTIFICATION SCENARIO

The identification accuracy, when using the proposed WLD feature set, have been investigated using the MM/I dataset using the leave one out protocol as described in Section III.A. The CMCs shown in Figure 4 are for 15 seconds of EEG segments. Besides the proposed feature, two other conventional wavelet-based features were explored for comparative analysis. The Wavelet-SD scheme, proposed by [42], uses the standard deviation of the wavelet coefficients as feature whereas Wavelet-Entropy scheme uses Shannon Entropy of the time domain sequence as feature. The proposed WLD feature produced a rank-1 identification rate of more than 98%; the Wavelet-SD provided the second-best identification rate.

Figure 5 shows the CMCs while using the UCI database in the identification scenario. It can be seen that the proposed WLD feature again provided the highest identification rate (more than 93%). The second-best rank-1 performance of about 85% is achieved by using the SD feature. The proposed method reached 97% accuracy after rank-1. In comparison, the 'Wavelet-Entropy' reached 97% at rank-10.

B. VERIFICATION SCENARIO

The effectiveness of the proposed WLD feature is also investigated in the verification scenario using the MM/I dataset and the UCI database. The DET curves were used to illustrate the comparative performances. A publicly available curve plotting package by National Institute of Standards and Technology (NIST) [44] had been used to generate these DET curves.

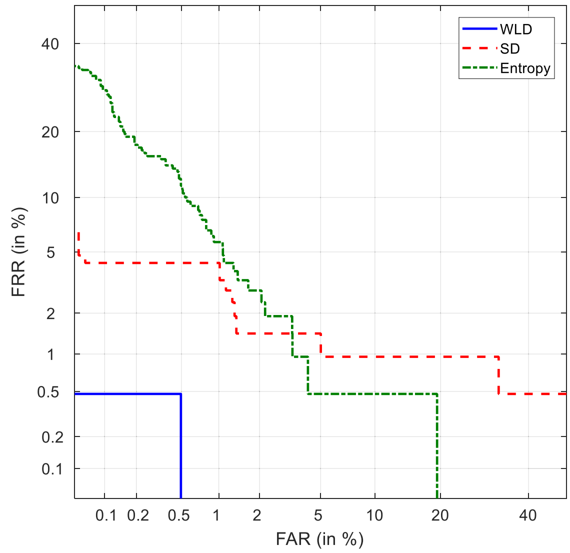

FIGURE 6. DET curves for the MM/I dataset (using 105 subjects, 15 sec. EEG window).

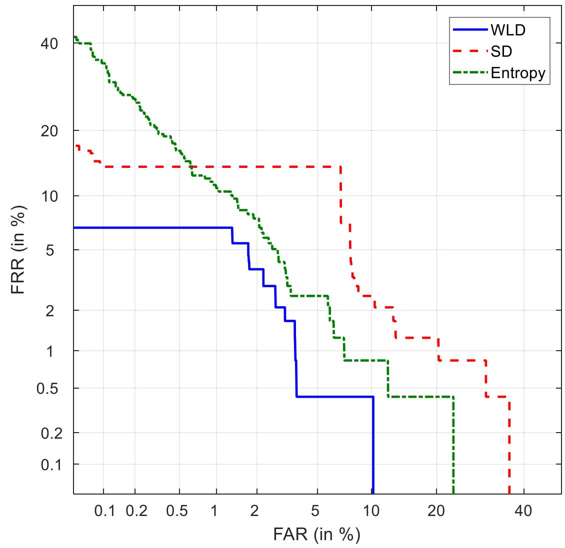

FIGURE 7. DET curves for the UCI database (119 subjects).

Figure 6 shows the resulting DET curves when using the MM/I database. The proposed WLD feature again produced the best verification performance, achieving an EER of about 0.5%. A higher EER about 1.3% was generated by the 'Wavelet-SD' feature. Similar to the results found in the identification scenario, the other wavelet-based features demonstrated worse performances than the proposed feature.

The verification performance using the UCI dataset is shown in Figure 7 which indicates that the proposed feature provided about 3% of EER. However, unlike the trend found in the MM/I database, the Wavelet-Entropy feature provided about 4% of EER, which is better than the Wavelet-SD feature. From the trends found in Figure 6 and Figure 7 for both the databases, it is clear that the proposed feature demonstrated both good and stable verification performance.

V. COMPARATIVE ANALYSIS

In this section, the proposed EEG biometric system is compared with other systems using non-wavelet-based features. All the results reported here are based on using either the MM/I database or the UCI database. The proposed system uses only a small number of selected electrodes, the WLD feature along with the LDA classification algorithm.

Table 6 shows the comparative results while employing the MM/I dataset using different features. Using only four electrodes for the proposed feature extraction, the classification rates outperformed similar schemes that are using many more electrodes. Table 7 shows the results obtained by different systems while using the UCI database. The PSD and the AR coefficients are the most commonly used features in EEG biometrics - high identification rates were reported by researchers using these features for this dataset. However, the large number of electrodes that were employed likely to have contributed towards such high recognition rates. Though provided somewhat lower recognition rate, the proposed 'WLD' feature extraction method used only eight electrodes (as described in Section III) and as such, the resulting Brain Computer Interaction (BCI) system would be much less intrusive.

TABLE 6. Feature sensitivity for identification scenario, MM/I eyes open subset.

Features	Spectral Coherence Connectivity [4]	Power Spectral Density [4]	Eigenvect or Centrality [45]	WLD
Subjects	108	108	109	105
Electrodes	56	56	64	4
Accuracy	75.86%	86.91%	96.9%	98.24%

TABLE 7. Feature sensitivity for identification scenario, UCI database.

	PSD & AR coefficients [46]	Univariate AR model [47]	Root Mean Square [48]	WLD
Subjects	20	120	116	117
Electrode	61	64	64	8
Accuracy	100%	98.96%	95.1%	93.28%

To address the impact of template ageing [36], we further selected two independent recordings in the resting state from the MM/I database for analysis. Data from the recordings with eyes open (R1) and eyes closed (R2) were used for training and testing the recognition system interchangeably. Conventional PSD (Welch's method) of five typical EEG bands (Delta, Theta, Alpha, Beta, and Gamma) were computed to show the comparative effectiveness of the proposed feature.

TABLE 8. The effectiveness of PSD in classification accuracy.

Train (Tr), Test (Te)	FCz-C1-C2-CPz	FC1-FC2-CP1-CP2	F3-F4-P3-P4	F7-F8-P7-P8	FPz-T9-T10-Iz
Tr 75% from R1, Te 25% from R1	69.9%	74.3%	76.1%	75.3%	**84.0%**
Tr 75% from R2, Te 25% from R2	68.0%	65.7%	72.4%	77.9%	**82.6%**
Tr from R1, Te from R2	42.9%	39.3%	35.3%	30.1%	**46.8%**
Tr from R2, Te from R1	41.3%	42.1%	35.7%	36.6%	**43.1%**

TABLE 9. The effectiveness of WLD in classification accuracy.

Train (Tr), Test (Te)	FCz-C1-C2-CPz	FC1-FC2-CP1-CP2	F3-F4-P3-P4	F7-F8-P7-P8	FPz-T9-T10-Iz
Tr 75% from R1, Te 25% from R1	91.2%	92.8%	96.0%	96.9%	**98.3%**
Tr 75% from R2, Te 25% from R2	88.0%	90.7%	93.7%	95.6%	**98.5%**
Tr from R1, Te from R2	70.1%	66.3%	62.3%	65.1%	**80.3%**
Tr from R2, Te from R1	70.9%	64.8%	59.6%	62.5%	**84.0%**

Table 8 shows the recognition rates using PSD features with two different setups: first two rows are based on using part of a single recording for training and the rest is used for testing; the last two rows are based on using data from one recording for training while the other recording used for performance test. Five electrode placements (placement 1 to placement 5 from inner to outer circle) are also included for analysis: the electrodes located in the outer circle are also found to provide better performance than the inner circle electrodes for PSD features. Even a short time lapse of a few minutes between the recordings used for training and testing results in significant degradation of the biometric recognition performance.

Table 9 shows the performance of the proposed WLD features. It is found that both the PSD and WLD features suffered significant reduction in performance while the training and test set were separated by a few minutes. However, the proposed WLD features' performance resulted in a much smaller drop in accuracy (14%) due to time separation compared with the PSD features (which were degraded by 41%). The results in Table 8 and Table 9 were obtained by averaging 10 runs. The MFCC and AR coefficients were also investigated and it was found that for the MM/I database the conventional MFCC and AR features are not as effective.

VI. CONCLUSION AND FUTURE WORK

The work presented here explores the use of EEG data for biometric identification. There are two main contributions from this study: a wavelet-based feature is developed which is particularly suited for such applications and the role of electrode placement on recognition performance is investigated to establish optimal electrode configuration. The proposed scheme resulted in high accuracy rates using a reduced number of electrodes compared to other state-of-the-art schemes. The influence of time separation between training and testing with EEG data is also investigated to simulate template-ageing effect and it was found that while the conventional scheme shows a drastic drop in performance, the proposed scheme is significantly more resilient. Future work will investigate such template ageing effect more thoroughly using data with much longer time separation. It has also been reported that affective (emotional) state of an individual can play a detrimental role in the ability to identify individuals using their EEG recordings [45] especially in cross-session studies. Future work will also explore the effectiveness of the proposed feature in such scenarios.

REFERENCES

[1] A. K. Jain, S. Pankanti, S. Prabhakar, and A. Ross, "Biometrics: A grand challenge," in *Proc. 17th Int. Conf. Pattern Recognit., (ICPR)*, vol. 2, Cambridge, U.K., Aug. 2004, pp. 935–942.

[2] S. Aydin, H. M. Saraoğlu, and S. Kara, "Log energy entropy-based EEG classification with multilayer neural networks in seizure," *Ann. Biomed. Eng.*, vol. 37, no. 12, p. 2626, Dec. 2009.

[3] M. Poulos, M. Rangoussi, V. Chrissikopoulos, and A. Evangelou, "Person identification based on parametric processing of the EEG," in *Proc. 6th IEEE Int. Conf. Electron., Circuits Syst. (ICECS)*, no. 1, Pafos, Cyprus, Sep. 1999, pp. 283–286.

[4] D. La Rocca *et al.*, "Human brain distinctiveness based on EEG spectral coherence connectivity," *IEEE Trans. Biomed. Eng.*, vol. 61, no. 9, pp. 2406–2412, Sep. 2014.

[5] P. Campisi and D. La Rocca, "Brain waves for automatic biometric-based user recognition," *IEEE Trans. Inf. Forensics Secur.*, vol. 9, no. 5, pp. 782–800, May 2014.

[6] S. Marcel and J. D. R. Millan, "Person authentication using brainwaves (EEG) and maximum a posteriori model adaptation," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 29, no. 4, pp. 743–752, Apr. 2007.

[7] R. Palaniappan and D. P. Mandic, "Biometrics from brain electrical activity: A machine learning approach," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 29, no. 4, pp. 738–742, Apr. 2007.

[8] Q. Zhao *et al.*, "Improving individual identification in security check with an EEG based biometric solution," in *Brain Informatics* (Lecture Notes in Computer Science), vol. 6334. Berlin, Germany: Springer, 2010, pp. 145–155.

[9] A. Riera, A. Soria-Frisch, M. Caparrini, C. Grau, and G. Ruffini, "Unobtrusive biometric system based on electroencephalogram analysis," *EURASIP J. Adv. Signal Process.*, vol. 2008, no. 1, 2008, Art. no. 143728.
[10] Y. Bai, Z. Zhang, and D. Ming, "Feature selection and channel optimization for biometric identification based on visual evoked potentials," in *Proc. 19th Int. Conf. Digit. Signal Process. (DSP)*, Hong Kong, Aug. 2014, pp. 772–776.
[11] D. Phung, D. Tran, W. Ma, P. Nguyen, and T. Pham, "Using Shannon entropy as EEG signal feature for fast person identification," in *Proc. Eur. Symp. Artif. Neural Netw. (ESANN)*, Bruges, Belgium, Apr. 2014, pp. 413–418.
[12] Q. Gui, Z. Jin, M. V. R. Blondet, S. Laszlo, and W. Xu, "Towards EEG biometrics: Pattern matching approaches for user identification," in *Proc. IEEE Int. Conf. Identity, Secur. Behav. Anal. (ISBA)*, Hong Kong, Mar. 2015, pp. 1–6.
[13] M. V. Ruiz-blondet, Z. Jin, and S. Laszlo, "CEREBRE: A novel method for very high accuracy event-related potential biometric identification," *IEEE Trans. Inf. Forensics Secur.*, vol. 11, no. 7, pp. 1618–1629, Jul. 2016.
[14] R. Das, E. Maiorana, and P. Campisi, "EEG biometrics using visual stimuli: A longitudinal study," *IEEE Sign. Process. Lett.*, vol. 23, no. 3, pp. 341–345, Mar. 2016.
[15] T. Schons, G. J. P. Moreira, P. H. L. Silva, V. N. Coelho, and E. J. S. Luz, "Convolutional network for EEG-based biometric," in *Proc. 22nd Iberoam. Congr. Pattern Recognit. (CIARP)* Lecture Notes in Computer Science, Valparaiso, Chile: Springer, Nov. 2017, pp. 601–608.
[16] T. Nakamura, V. Goverdovsky, and D. P. Mandic, "In-ear EEG biometrics for feasible and readily collectable real-world person authentication," *IEEE Trans. Inf. Forensics Secur.*, vol. 13, no. 3, pp. 648–661, Mar. 2018.
[17] N. Kawabata, "A nonstationary analysis of the electroencephalogram," *IEEE Trans. Biomed. Eng.*, vol. BME-20, no. 6, pp. 444–452, Nov. 1973.
[18] L. Parra and C. Spence, "Convolutive blind separation of non-stationary sources," *IEEE Trans. Speech Audio Process.*, vol. 8, no. 3, pp. 320–327, May 2000.
[19] P. Nguyen, D. Tran, X. Huang, and D. Sharma, "A proposed feature extraction method for EEG-based person identification," in *Proc. Int. Conf. Artif. Intell. (ICAI), Steering Committee World Congr. Comput. Sci., Comput. Eng. Appl. Comput. (WorldComp)*, 2012, pp. 1–6.
[20] Z. Tufekci and S. Gurbuz, "Noise robust speaker verification using mel-frequency discrete wavelet coefficients and parallel model compensation," in *Proc. IEEE Int. Conf. Acoust., Speech, Signal Process. (ICASSP)*, Mar. 2005, pp. 657–660.
[21] M. I. Abdalla and H. S. Ali. (2010). "Wavelet-based Mel-frequency cepstral coefficients for speaker identification using hidden Markov models." [Online]. Available: https://arxiv.org/abs/arXiv:1003.5627
[22] I. Daubechies, *Ten Lectures on Wavelets*, vol. 61. Philadelphia, PA, USA: Society for Industrial and Applied Mathematics, 1992.
[23] V. Tyagi and C. Wellekens, "On desensitizing the Mel-Cepstrum to spurious spectral components for robust speech recognition," in *Proc. IEEE Int. Conf. Acoust., Speech, Signal (ICASSP)*, Mar. 2005, pp. 529–532.
[24] R. A. Fisher, "The use of multiple measurements in taxonomic problems," *Ann. Eugenics*, vol. 7, no. 2, pp. 179–188, 1936.
[25] A. Jain, *Fundamentals of Digital Image Processing*. Englewood Cliffs, NJ, USA: Prentice-Hall, 1989.
[26] K. Aizawa, Y. Nakamura, and S. Satoh, Eds., *Advances in Multimedia Information Processing—PCM* (Lecture Notes in Computer Science), vol. 3333. Berlin, Germany: Springer-Verlag, 2004.
[27] M. Sahidullah and G. Saha, "Design, analysis and experimental evaluation of block based transformation in MFCC computation for speaker recognition," *Speech Commun.*, vol. 54, no. 4, pp. 543–565, May 2012.
[28] *EEG Motor Movement/Imagery Dataset*. Accessed: Apr. 20, 2015. [Online]. Available: http://www.physionet.org/pn4/eegmmidb/
[29] *UCI Machine Learning Repository: EEG Database Data Set*. Accessed: Apr. 22, 2015. [Online]. Available: https://archive.ics.uci.edu/ml/datasets/EEG+Database
[30] G. Schalk, D. J. McFarland, T. Hinterberger, N. Birbaumer, and J. R. Wolpaw, "BCI2000: A general-purpose brain-computer interface (BCI) system," *IEEE Trans. Biomed. Eng.*, vol. 51, no. 6, pp. 1034–1043, Jun. 2004.
[31] A. L. Goldberger *et al.*, "PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals," *Circulation*, vol. 101, no. 23, pp. e215–e220, Jun. 2000.
[32] J. G. Snodgrass and M. Vanderwart, "A standardized set of 260 pictures: Norms for name agreement, image agreement, familiarity, and visual complexity.," *J. Exp. Psychol., Hum. Learn. Memory*, vol. 6, no. 2, pp. 174–215, 1980.
[33] S. Mallat, *A Wavelet Tour of Signal Processing*. New York, NY, USA: Academic, 1999.
[34] S. Yang and F. Deravi, "Quality filtering of EEG signals for enhanced biometric recognition," in *Proc. Int. Conf. Biometrics Special Interest Group (BIOSIG)*, Darmstadt, Germany, Sep. 2013, pp. 201–208.
[35] R. O. Duda, P. E. Hart, and D. G. Stork, *Pattern Classification*. Hoboken, NJ, USA: Wiley, 2001.
[36] S. Yang and F. Deravi, "On the usability of electroencephalographic signals for biometric recognition: A survey," *IEEE Trans. Human-Mach. Syst.*, vol. 47, no. 6, pp. 958–969, Dec. 2017.
[37] R. W. Homan, J. Herman, and P. Purdy, "Cerebral location of international 10–20 system electrode placement," *Electroencephalogr. Clin. Neurophysiol.*, vol. 66, no. 4, pp. 376–382, Apr. 1987.
[38] S. Yang and F. Deravi, "Novel HHT-based features for biometric identification using EEG signals," in *Proc. 22nd Int. Conf. Pattern Recognit.*, Stockholm, Sweden, Aug. 2014, pp. 1922–1927.
[39] R. P. W. Duin, P. Juszczak, D. de Ridder, P. Paclik, E. Pekalska, and D. M. J. Tax. (2004). *PRTools*. Accessed: Apr. 21, 2015. [Online]. Available: http://37steps.com/prhtml/prtools.html.
[40] P. Grother, R. Micheals, and P. Phillips, "Face recognition vendor test 2002 performance metrics," *Audio-and Video-Based Biometric Person Authentication* (Lecture Notes in Computer Science), vol. 2688. Guildford, U.K., 2003, pp. 937–945.
[41] B. DeCann and A. Ross, "Relating ROC and CMC curves via the biometric menagerie," in *Proc. IEEE 6th Int. Conf. Biometrics, Theory, Appl. Syst. (BTAS)*, Arlington, VA, USA, Sep./Oct. 2013, pp. 1–8.
[42] M. K. Abdullah, K. S. Subari, J. L. C. Loong, and N. N. Ahmad, "Analysis of the EEG signal for a practical biometric system," *Int. J. Med., Health, Biomed., Bioeng. Pharmaceutical Eng.*, vol. 4, no. 8, pp. 364–368, 2010.
[43] C. N. Gupta, Y. U. Khan, R. Palaniappan, and F. Sepulveda, "Wavelet framework for improved target detection in oddball paradigms using P300 and gamma band analysis," *Int. J. Biomed. Soft Comput. Hum. Sci.*, vol. 14, no. 2, pp. 61–67, 2009.
[44] *NIST Evaluation Tools DETware_v2.1. DETware_v2.1*. Accessed: Apr. 21, 2015. [Online]. Available: http://www.itl.nist.gov/iad/mig/tools/DETware_v2.1.targz.htm
[45] P. Arnau-González, M. Arevalillo-Herráez, S. Katsigiannis, and N. Ramzan, "On the influence of affect in EEG-based subject identification," *IEEE Trans. Affect. Comput.*, to be published. doi: 10.1109/TAFFC.2018.2877986.

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