On the Invariance of EEG-based Signatures of Individuality
with Application in Biometric Identification

Yunqi Wang and Laleh Najafizadeh

Abstract—One of the main challenges in EEG-based biometric systems is to extract reliable signatures of individuality from recorded EEG data that are also invariant against time. In this paper, we investigate the invariability of features that are extracted based on the spatial distribution of the spectral power of EEG data corresponding to 2-second eyes-closed resting-state (ECRS) recording, in different scenarios. Eyes-closed resting-state EEG signals in 4 healthy adults are recorded in two different sessions with an interval of at least one week between sessions. The performance in terms of correct recognition rate (CRR) is examined when the training and testing datasets are chosen from the same recording session, and when the training and testing datasets are chosen from different sessions. It is shown that an CRR of 92% can be achieved based on the proposed features when the training and testing datasets are taken from different sessions. To reduce the number of recording channels, principal component analysis (PCA) is also employed to identify channels that carry the most discriminatory information across individuals. High CRR is obtained based on the data from channels mostly covering the occipital region. The results suggest that features based on the spatial distribution of the spectral power of the short-time (e.g. 2 seconds) ECRS recordings can have great potentials in EEG-based biometric identification systems.

I. INTRODUCTION

Biometric systems are recognition systems that are used to authenticate or identify individuals based on their unique physiological or behavioral attributes. A physiological or behavioral attribute can be accepted as the basis of a biometric identification scheme, if it satisfies a set of specific requirements [1]. These requirements include universality (possession by all human), collectability (has easy acquisition and feature extraction processes), distinctiveness (is discriminative among the population), performance (high accuracy) and invariance (exhibits invariance against time).

The use of brain activity as a physiological basis for biometric systems has been receiving increased attention in recent years [2], as it can offer attractive properties such as robustness against spoofing attacks and liveness detection [2], [3]. One imaging modality that can be used to acquire brain activity is electroencephalography (EEG) [4]. EEG is a non-invasive, portable system offering relatively inexpensive window into the human brain function with high temporal resolution. Therefore, compared to other functional brain imaging techniques such as functional magnetic resonance imaging (fMRI), it offers to be the best recording system choice when it comes to the implementation of biometric systems that are based on brain activity.

One of the main challenges in EEG-based biometric systems deals with identifying highly distinctive yet reliable traits of individuality in recorded EEG data. In general, to extract features, first, brain activities need to be recorded either in response to a particular task (task-based), or when the individual is at rest (resting-state). Second, data is processed and features are extracted. Previous methods for extracting features from EEG recordings include using activation characteristics of different brain regions either in time domain (by looking at event-related potentials [5] or regression coefficients [6]), or in frequency domain (by looking at absolute spectral power (ASP) [7], and power spectral density (PSD) [8]), and very recently, using characteristics of functional network topology (e.g. based on Phase Lag Index (PLI) [2] or spectral coherence [9]). For the choice of feature extraction and selection, there exists tradeoffs among easiness/reliability/repeatability of experimental conditions required for acquiring brain activity (e.g. rest or task, duration of the recording, number of channels used), processing time, and the obtained accuracy.

Majority of previous EEG-based biometric studies have extracted features and evaluated their performance based on recordings obtained in one session for each subject [10]. Given that in practical scenarios, there may exist variability in the recording setup (e.g. location of electrodes, noise) across different sessions, and individual’s brain state might not be the same on different days, one concern with EEG-based features in biometric systems is that how stable the extracted features are over time to meet the requirement of invariance. Few recent studies have considered longitudinal datasets (recordings obtained over different days) [10]. In [11]-[13] the training and testing datasets both consist of mixed-data taken from different acquisition sessions. [14], [15] have considered the training and testing datasets to be taken from different sessions, but features require recordings of at least 5 seconds.

In this paper, we investigate invariance of EEG-based features that are extracted based on the spatial distribution of spectral power of recordings, in different scenarios. EEG data are collected using a 128 channel system from 4 subjects on 2 different days with at least 1 week interval between the 2 sessions. To consider universality and collectability we extract features based on recordings during eyes-closed resting-state (ECRS). Task-based or eyes-open resting-state EEG recordings generally require visual/audio stimulus or physical responses from individuals, thereby are limited to groups of people capable of executing them. Motivated by the study in [16], which reports large inter-individual variability...
in the spectral power of $\alpha$ and $\beta$ bands of ERCS recordings, to meet the distinctiveness requirement, in this work, we propose a method for extracting EEG-based signatures of individuality based on the spatial distribution of the spectral power across different bands. We then investigate the invariance of the proposed features under two intra-subject testing scenarios: 1) the training and testing datasets are chosen from the same recording session, and 2) the training dataset is chosen from one session, and the testing dataset is chosen from another session. Furthermore, we examine the classification performance under the two intra-subject testing scenarios for the case where the number of recording channels are reduced to 48, as identified by employing principal component analysis (PCA).

This paper is organized as follows: in Section II the data acquisition procedure and methods for extracting the features are described. Experimental results based on 128 channels and reduced number of channels for two intra-subject testing scenarios are presented in Section III, and conclusions are given in Section IV.

II. METHODS

A. Data Acquisition

EEG data were collected using a 128 channel EEG system (Brain Products) at the sampling rate of 250 Hz, from 4 right-handed volunteers (mean age of 22.2). Written informed consents approved by Rutgers IRB were obtained prior to experiments. The electrodes were positioned across the head based on the international 10–20 electrode placement system, with reference placed at location Cz. Each volunteer participated in 2 sessions, with at least 1 week interval between the 2 sessions. Each session consisted of 5 periods of 2-minute ECRS, separated by 5-minute relaxed intervals during which subjects had their eyes open (see Fig. II-A).

Prior to feature extraction, the recorded data were preprocessed. To remove artifacts such as eye movement, independent component analysis (ICA) was performed using the runica algorithm in EEGLAB toolbox [17], and components identified as eye movements, background noise and muscle artifacts were removed.

B. Feature Extraction

Features used for biometric systems should carry discriminatory information across individuals. For EEG, it has been shown that large inter-individual variability exists in the spectral field powers of $\alpha_1$, $\alpha_2$ and $\beta_1$ bands in recordings obtained during resting-state sessions [16]. The reported inter-individual difference ratios are 10 folds higher at the ECRS condition compared to eyes-open resting-state condition [16]. This result motivated us to focus on the spatial distribution of spectral power in different frequency bands for extracting features with large discriminatory power, and the possibility of using this information as a basis for biometric.

Continuous wavelet transform (CWT) (1) was used to analyze the preprocessed EEG data in time-frequency domain. In (1) $f(t)$ represents EEG signal recorded from one channel, $\varphi(t)$ is the mother wavelet, and $s$ and $\mu$ are the scaling and translation parameters, respectively.

$$W\{f(\mu, s)\} = \int_{-\infty}^{\infty} f(t) \frac{1}{\sqrt{s}} \varphi^*\left(\frac{t - \mu}{s}\right)dt. \quad (1)$$

Morlet wavelet was chosen as the mother wavelet. This choice was based on the high similarity (as measured by correlation coefficient) obtained between the signal and its reconstructed using this mother wavelet. Applying CWT on the preprocessed data from each channel for ECRS sessions results in a $F \times T$ matrix containing the power of continuous wavelet coefficients in $F$ frequency bins and $T$ sample points (here $F = 45$, $T = 150000$ (2 minutes per block, 5 blocks)). Including the information from all 128 channels ($C = 128$), a matrix, called the Coefficient Matrix, can then be constructed with the dimension of $C \times F \times T$.

To construct feature vectors based on the Coefficient Matrix, for each recording session, we divided the temporal domain into segments of $t$ seconds duration (here $t = 2$ seconds, and number of segments ($N$)$=300$) and computed the average spectral power across each temporal segment at frequency. The procedure results in $2N$ number of $C \times F \times 1$ features for each subject for the data recorded from the two sessions.

C. Classification

In the classification step, k-Nearest Neighbors ($k$NN) algorithm was used to design the classifier. For two feature vectors of length $m$, $X = [x_1, x_2, \ldots x_m]$ and $Y = [y_1, y_2, \ldots y_m]$, the Euclidean distance ($d(X, Y)$) is obtained as

$$d(X, Y) = \sqrt{\sum_{i=1}^{m} (x_i - y_i)^2}. \quad (2)$$

When a new feature vector arrives, $k$NN finds the $k$ neighbors nearest to the new feature vector from the training space based on suitable distance metric. To evaluate the classification performance for identification, we used the correct recognition rate (CRR) metric defined as

$$CRR(\%) = \frac{\text{number of correctly classified testing data}}{\text{total number of testing data}} \times 100, \quad (3)$$

for each subject and then averaged across subjects.

III. EXPERIMENTAL RESULTS

To investigate the invariance of the extracted features for identification systems, two intra-subject testing scenarios are considered: 1) intra-subject testing within a session, where the training and testing datasets are chosen from the data from the same session, and 2) intra-subject testing across sessions, where the training and testing datasets are chosen from different sessions. We performed these tests using all 128 channels as well as using a reduced number of channels, as identified by PCA. In the following we discuss the results obtained for each testing scenario.
A. Results Based on 128 Channels

1) Invariance within One Session: For this test the classifier was trained and tested using data from the same acquisition session. We considered 7 frequency bands: $\delta$ ($1 - 4$ Hz), $\theta$ ($4 - 7$ Hz), $\alpha_1$ ($7 - 10$ Hz), $\alpha_2$ ($10 - 12$ Hz), $\beta_1$ ($13 - 23$ Hz), $\beta_2$ ($23 - 31$ Hz) and $\gamma$ ($31 - 45$ Hz). For each of the 7 frequency bands, we did averaging across the corresponding spectrum, to obtain a total of 7 feature vectors ($C \times 1$) for each temporal segment. Each of these feature vectors corresponds to a contour map representing the spatial distribution of spectral power over the scalp for the corresponding frequency band. For the data from each session, we randomly selected half the data as the training samples, and the remaining half (from the same session) as the testing samples (i.e. for each individual, the number of training and testing samples for a given frequency band was $N/2 = 300$, for each session). For each frequency band, the identification classification was performed separately for the dataset of each session, and results were averaged. Table I summarizes the classification performance in terms of CRR. As can be seen, high CRR is obtained for the $\alpha$ and $\beta$ bands. This result is consistent with the large inter-subject variability that was observed in the field power amplitude of these frequency bands reported in [16].

2) Invariance Across Two Sessions-Different Datasets: To examine the invariance of the extracted features, for each of the 7 frequency bands, we trained the classifier based on these features extracted from the data obtained through one session, and tested with the data obtained from another session. The average CRR results (session 1 as training-session 2 as testing, and session 2 as training-session 1 as testing) are summarized in Table I. As can be seen, the performance has significantly dropped compared to the case when the training and testing datasets are chosen from the same session.

To address this issue, we re-examined the feature extraction procedure. Realizing that a relatively high CRR was obtained for features extracted in $\alpha_1$, $\alpha_2$, $\beta_1$ and $\beta_2$ bands, we focused on these 4 frequency bands. Instead of spectral averaging, we used all the information available in these frequency bands for the training and testing procedures. We considered 4 frequency bands from $\alpha_1$ to $\beta_2$ range. Results are summarized in Table II. As can be seen, the classification performance in terms of CRR has significantly improved, suggesting that such an approach provides features with strong invariance.

B. Results Based on Reduced Number of Channels

To investigate whether we can reduce the number of channels without compromising the performance and invariance, we employed PCA to identify channels that contribute most in differentiating individuals.

PCA is a dimension-reduction technique that transforms a large number of possibly correlated variables into a smaller number of principal components. To identify the discriminatory channels, features from all 4 subjects were included into the matrix $F$ as

$$F = \begin{bmatrix} f_{1,1} & f_{1,2} & f_{1,3} & \ldots & f_{1,128} \\ f_{2,1} & f_{2,2} & f_{2,3} & \ldots & f_{2,128} \\ f_{3,1} & f_{3,2} & f_{3,3} & \ldots & f_{3,128} \\ f_{4,1} & f_{4,2} & f_{4,3} & \ldots & f_{4,128} \end{bmatrix},$$

where $f_{i,j}$ represents the spectral power of a given frequency band ($\alpha_1$, $\alpha_2$, $\beta_1$ and $\beta_2$) for a 2-second ECRS recording obtained from channel $j$ for subject $i$. PCA was then performed and principal components $V = [v_1, v_2, ..., v_{128}]$ were found. The obtained $v_j$ vectors associated with all 2-second segments were summed up to obtain the contribution vector $V_{\text{cont}} = [v_{\text{cont}1}, v_{\text{cont}2}, ..., v_{\text{cont}128}]$, where $v_{\text{cont}j}$ relates to the contribution of channel $j$ in discriminating feature vectors across different subjects. We assigned the inverse of channel contribution as the penalty level to channel $j$. It was observed that channels mostly covering the occipital region carry the most discriminatory information for differentiating individuals. Based on this outcome, for the following studies, we focused on the data obtained from identified 48 channels.

1) Invariance within One Session: Similar to the case of 128 channels, in the case of reduced number of channels, for each of the 7 frequency bands, we trained the classifier on features derived based on spectral averaging of a given frequency band, and tested using the data from the same session. Identification classification was performed separately for the data from each session, and results were averaged. Table III summarizes the classification performance in terms of CRR. As can be seen, similar to the case of 128 channels, a relatively high CRR is achieved for features related to $\alpha$ and $\beta$ bands, suggesting the channels placed on the occipital region carryout the most discriminatory information for ECRS across individuals.

2) Invariance Across Two Sessions-Different Datasets: Using features in 7 frequency bands although resulted in strong invariance within session, however, did not provide
similar performance for the case when the training and testing datasets are chosen from different sessions (Table III). However, for the 4 frequency bands when the information is used without spectral averaging, the CRR significantly improves (Table IV).

IV. CONCLUSION AND FUTURE WORK

In this paper we investigated the invariance of EEG-based measures of individuality against time with application to biometric identification. The considered measures of individuality were features based on the spatial distribution of the spectral power of EEG data corresponding to 2-second eyes-closed resting-state. To examine the invariability of these features against time, we considered two intra-subject testing scenarios. For the scenario in which the training and testing procedures use data from single session, features based on the “averaged” spectral power in $\alpha$ or $\beta$ bands provided very high CRR. For the scenario in which the training and testing procedures use data from different sessions, using features based on the spectral power (and not averaged spectral power) offered high CRR. To decrease the number of required recording channels, PCA was used to reduce the dimension of feature vectors. It was observed that high CRR can be obtained based on the data from channels that mostly cover the occipital region.

Table V compares our results with some of the previous EEG-based biometric works. As can be seen, our method provides an improved identification performance (in terms of CRR) based on only 2-second recording, when the training and testing data are from different sessions. Therefore, it is expected that the proposed method will have great potentials in EEG-based biometric identification systems. Future work will involve including more subjects, more recording sessions with longer between recordings intervals, and recordings under different mental states (e.g. stress, fatigue) to further evaluate the invariability of the extracted features.

REFERENCES