An EEG-Based Biometric System Using Eigenvector Centrality in Resting State Brain Networks

Matteo Fraschini, Arjan Hillebrand, Matteo Demuru, Luca Didaci, and Gian Luca Marcialis

***Abstract*—Recently, there has been a growing interest in the use of brain activity for biometric systems. However, so far these studies have focused mainly on basic features of the Electroencephalography. In this study we propose an approach based on phase synchronization, to investigate personal distinctive brain network organization. To this end, the importance, in terms of centrality, of different regions was determined on the basis of EEG recordings. We hypothesized that nodal centrality enables the accurate identification of individuals. EEG signals from a cohort of 109 64-channels EEGs were band-pass filtered in the classical frequency bands and functional connectivity between the sensors was estimated using the Phase Lag Index. The resulting connectivity matrix was used to construct a weighted network, from which the nodal Eigenvector Centrality was computed. Nodal centrality was successively used as feature vector. Highest recognition rates were observed in the gamma band (equal error rate (EER) $= 0.044$) and high beta band ($\mathrm{EER} = 0.102$). Slightly lower recognition rate was observed in the low beta band ($\mathrm{EER} = 0.144$), while poor recognition rates were observed for the others frequency bands. The reported results show that resting-state functional brain network topology provides better classification performance than using only a measure of functional connectivity, and may represent an optimal solution for the design of next generation EEG based biometric systems. This study also suggests that results from biometric systems based on high-frequency scalp EEG features should be interpreted with caution.**

***Index Terms*—Biometrics, centrality, EEG, networks.**

I. Introduction

A BIOMETRIC system can be defined as a pattern recognition system that aims to authenticate or identify a person exploiting physiological and/or behavioral personal characteristics. Biometric systems can be implemented on the basis of different characteristics, yet they need to satisfy requirements of universality, distinctiveness, permanence and collectability. Although research on biometrics has noticeably increased in recent years, to date no single physical or behavioral feature is able to satisfy all the necessary constraints for authentication or identification in real life applications. For comprehensive surveys on biometric systems see [14], [18].

Recently, there has been growing interest in the use of brain activity as a physiological characteristic for next generation biometric systems. It has been reported [4] that brain signals have some interesting properties, in terms of privacy compliance, robustness against spoofing attacks, continuous identification and liveness detection, that make their use in biometric systems particularly attractive.

Due to its high temporal resolution, portability and low-price (with respect to other systems that measure brain waves), electroencephalography (EEG), seems to be the most appropriate technique to acquire brain activity with the aim to develop biometric systems, and researchers have started to investigate the use of the distinctive biometric traits in EEG recordings (see [4] for a comprehensive survey).

Nevertheless, scalp EEG potentially suffers from some important limitations, such as volume conduction, common sources, signal spread, active reference and contaminations from, for example, muscle artifacts, that should be carefully taken into account.

So far, experimental protocols and EEG features that have been commonly used for the design of EEG biometric systems aimed to identify activation characteristics of spatially limited sets of brain regions. However, during the last decade, the idea that the brain can be seen as a complex system [21], with functionally interconnected units, has contributed to the understanding of how communication in the brain is organized. There is considerable evidence that the healthy human brain is characterized by a topology that resembles those of small-world networks [2], [33], yet also displays an evident hierarchical modularity [19] and has a relatively high prevalence of high-degree nodes (hubs) [1], [12], [27]. Although there is no universally accepted definition of a hub, in general terms it indicates that a particular node is of importance in the whole network. Measures that quantify this importance [24] include the degree (number of connections), betweenness centrality (indicating the fraction of shortest paths that go through a node) and eigenvector centrality (EC) [3], [17]. An advantage of EC is that it is much faster to compute than, for example, betweenness centrality, yet it captures more information about the network topology then a straightforward measure such as the degree.

Importantly, this new perspective strongly suggests that simple measures of activation may no longer be sufficient in order to fully characterize brain functioning [29]. Moreover, Smit and colleagues [26] have shown that certain brain network characteristics are viable markers of genetic differences in brain

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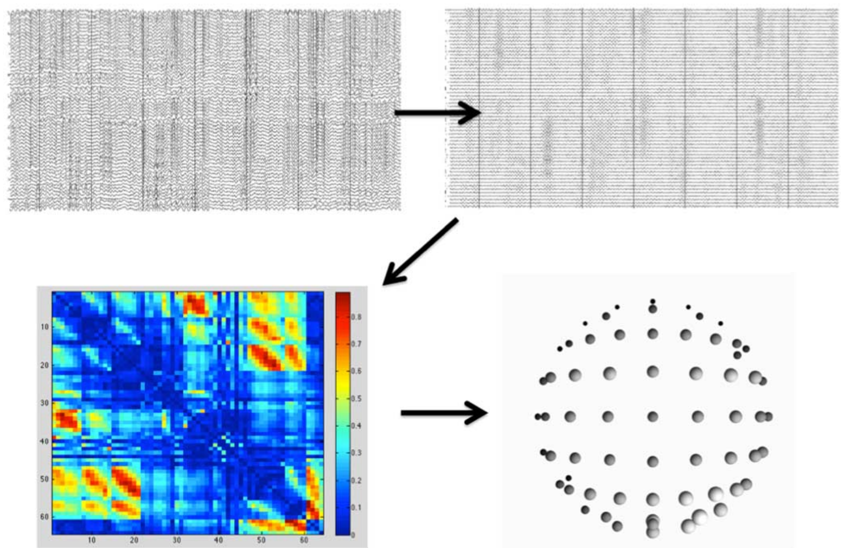

Fig. 1. A schematic view of the feature extraction procedure is represented. Panels respectively represent: raw EEG signals (upper left), band-pass filtered EEG signals (upper right), connectivity matrix containing PLI values (lower left) and role of each node in the network, where the size and colour of each node represent the importance of the nodes (lower right),. The EC values were used as feature vectors.

organization. Nevertheless, the use of the aforementioned topological characteristics of functional brain networks in biometric systems has not yet been reported, and their effectiveness to unveil distinctive personal physiological characteristics is as yet unknown.

Recently, La Rocca *et al.* [23] have proposed an interesting approach where they utilized a measure of functional connectivity as a biometric feature. They showed that functional connectivity patterns improve the performance of EEG-based biometric systems as compared to techniques based on power spectra.

In the present letter, we hypothesized that personal distinctive characteristics of functional brain organization can be effectively utilised in an EEG biometric system. We therefore proposed an approach that estimates the nodal importance (in terms of eigenvector centrality) within the whole functional brain network. These functional networks were based on a conservative measure of functional connectivity, namely the Phase Lag Index (PLI) [28], in order to avoid the above-mentioned problems associated with scalp EEG. Two recent reviews [25], [32] discuss the use of other possible solutions to these issues.

This study represents a first attempt to introduce the concept of functional brain network topology in the design of EEG-based biometric systems, also addressing the typical and underestimated (in the current biometrics literature) problems related to scalp EEG analysis and muscle contamination.

II. The Proposed Method

A schematic representation of the feature extraction procedure is shown in Fig. 1. The proposed method is based on four main steps: (i) band-pass filtering, (ii) functional connectivity estimation, (iii) brain network reconstruction, and (iv) characterisation of brain network topology.

The first step consists of band-pass filtering the raw (no data cleaning was performed) EEG signals in order to be able to study frequency-specific function brain networks. The procedure was performed using the eegfilt function which introduces no phase distortion [6].

The second step was performed by estimating pair-wise statistical interdependence between EEG time series using the PLI [13], [28]. The PLI, in contrast to the recently proposed approach based on spectral coherence [23], addresses the problems that are due to volume conduction, common sources and active reference, and therefore provides a more suitable estimate of functional interactions between brain regions. In particular, the PLI, which varies between 0 (no interaction, or interaction with zero-phase lag, referred to as volume conduction) and 1 (maximum interaction), evaluates the asymmetry of the distribution of instantaneous phase differences between pairs of channels in the following way:

$$PLI = |\langle sign\left[\sin\left(\Delta\phi\left(\mathrm{tk}\right)\right)\right]\rangle| \quad (1)$$

where $\Delta\phi$ is the difference between instantaneous phases for two time series, defined in the interval $[-\pi, \pi]$, t_k are discrete steps and $<>$ denotes the average over the time t. A functional connectivity matrix, containing the PLI values between each pair of electrodes is obtained.

In the third step, the functional network is represented as a (weighted) graph, where each electrode forms a node in the graph, and each functional connection an edge, where the PLI value is used as the strength of the connection.

The fourth step characterizes the functional brain organization, where we focused on a centrality measure in order to quantify the importance of each node in the network. Eigenvector Centrality (EC) [11], [15], [17] is a centrality measure based on the spectral decomposition of the weighted connectivity matrix. The EC of node i is equivalent to the i-th value of the eigenvector that corresponds to the largest eigenvalue of the weighted connectivity matrix. EC determines the importance of a node (within the network) by considering the quality of its connections (hence, not only how many connections it has, but also whether the connections are formed with important nodes). Furthermore, since EC is a normalized measure the comparisons between equal sized networks is much simplified. All the anal-

TABLE I
RECOGNITION RATES

Frequency Band	Resting state - eyes-open				Resting state - eyes-closed			
	EER	AUC	Rank-1	Rank-10	EER	AUC	Rank-1	Rank-10
Delta (0.5 - 4 Hz)	0.357	0.292	0.113	0.356	0.437	0.402	0.059	0.220
Theta (4 - 8 Hz)	0.348	0.328	0.077	0.294	0.387	0.347	0.075	0.283
Alpha (8 - 13 Hz)	0.328	0.260	0.157	0.416	0.312	0.247	0.199	0.469
Low Beta (13 - 20 Hz)	0.144	0.059	0.670	0.898	0.180	0.096	0.558	0.804
High Beta (20 - 30 Hz)	0.102	0.033	0.819	0.956	0.169	0.088	0.600	0.838
Gamma (30 - 50 Hz)	0.044	0.006	0.969	0.995	0.065	0.018	0.926	0.981

Recognition rates expressed as EER, AUC, rank-1 and rank-10 for each frequency band and for both eyes-open and eyes-closed resting state conditions.

ysis was performed using the Brain Connectivity Toolbox for Matlab [24].

Successively, a feature vector consisting of 64 elements, expressing EC values of each single node of the network, was used for classification. In the following, we investigated to which extent such features can indeed represent the unique characteristics of each individual when used for personal recognition and verification [14].

III. Experimental Results

A. Data Set

EEG signals from a public and freely available dataset (http://physionet.org/pn4/eegmmidb/) [8] were used in this study. EEG recordings were originally acquired using the 64 channels BCI2000 system (http://www.bci2000.org) with a sampling rate of 160 Hz, and EEG signals were referenced to the average of the ear-lobe electrodes.

The original dataset consists of fourteen different experimental runs including resting-state conditions (in both eyes-open and eyes-closed modes) and a set of imagery and real movements acquired from 109 subjects. Previous papers have used this dataset for both brain computer interface [7] and biometric system [23] design. Our analysis was performed on eyes-open and eyes-closed resting-state conditions, each single recording lasting 60 seconds in time. For each subject and each condition, five non-overlapping epochs of 12 seconds (2048 samples each; extracted from the entire recording) were separately analysed. EEG signals were band-pass filtered in the classical frequency bands: 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). However, since it has been shown that high-frequency components ($>$ 20 Hz) overlap with the spectral bandwidth of muscle activity [20], [34], [36], we only report high beta and gamma band results with the aims to allow comparison of our findings with previous studies, which did not exclude contaminated components [23], and to estimate the potential impact of such artifacts on the classification rate.

B. Experimental Protocol

All possible genuine and impostor matching scores (1,090 and 147,150, respectively) were computed for each frequency band separately. The scores represent the Euclidean distance between each pair of feature vectors. Therefore, lower scores represent genuine matching (lower distance), while higher scores represent impostor matching (higher distance). The corresponding similarity score have been successively computed as $1/(1+\mathrm{d})$, where d represents the Euclidean distance. The performance of the proposed method was evaluated in terms of false acceptance rate (FAR) and false rejection rate (FRR) at different thresholds (that allow to accept or reject a match). FAR represents the error that occurs when the system accepts an impostor. FRR represents the error that occurs when the system rejects a genuine match. Receiver operating characteristic (ROC) curves were formed by plotting FAR and FRR at different thresholds. The area under the ROC curve (AUC) and the equal error rate (EER) were computed. The EER refers to that point where FAR equals to FRR. Lower AUC and EER values therefore indicate better classification performance. Furthermore, the rank-k performance, indicating the rate of correct identity occurring in the top k matches, were summarized using the Cumulative Match Characteristic (CMC) curve, where CMC curves were obtained using the FERET evaluation protocol [22]. Scikit-learn (version 0.14) for Python (version 2.7) was used for this analysis.

C. Results and Discussion

Recognition rates expressed as EER, AUC, rank-1 and rank-10 for each frequency band and for both eyes-open and eyes-closed resting state conditions are summarized in Table I. Higher classification rates were observed in gamma band, during eyes-open condition ($\mathrm{EER} = 0.044$) and eyes-closed condition ($\mathrm{EER} = 0.065$), and high beta band, during eyes-open condition ($\mathrm{EER} = 0.102$) and eyes-closed condition ($\mathrm{EER} = 0.169$). Slightly lower classification rates were observed in low beta band, during eyes-open condition ($\mathrm{EER} = 0.144$) and eyes-closed condition ($\mathrm{EER} = 0.180$), while poor classification rates were observed for the others frequency bands, irrespective of the experimental condition. The rank-1 and rank-10 indices followed a similar pattern. ROC and CMC curves for each frequency band in eye-open resting state condition are depicted in Fig. 2 and Fig. 3, respectively. The performance obtained using the average PLI for each node was worse for all frequency bands (best performance was achieved for the gamma band eyes-open condition, $\mathrm{EER} = 0.251$). The reported high rates of classification observed in the resting state

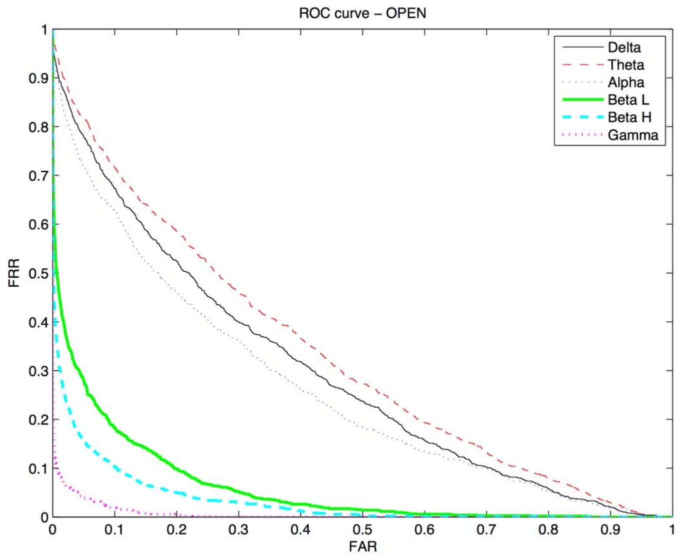

Fig. 2. ROC curves representing system accuracy for each frequency band in eye-open resting state condition.

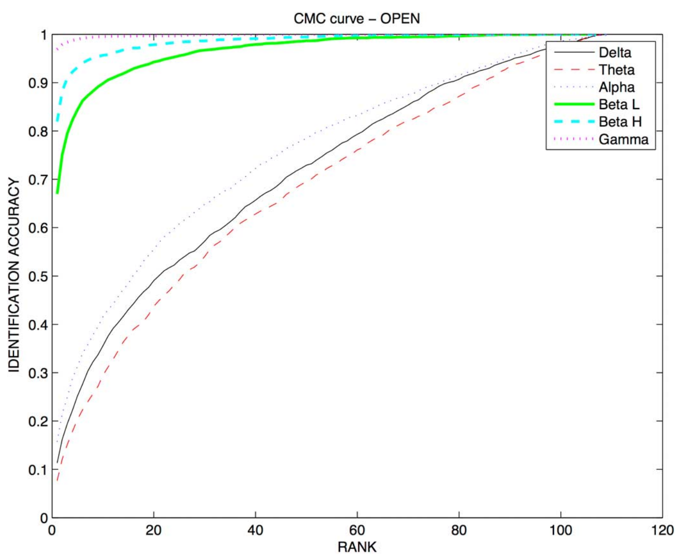

Fig. 3. CMC curves representing system accuracy for each frequency band in eye-open resting state condition.

conditions should not be surprising. Indeed, it has been reported previously that the resting state is not a static phenomenon [9]. Probably due to fluctuations in processes such as attention or spontaneous cognitive mechanisms, which imply changes in the functional network organization, resting state networks differ considerably between subjects [16]. Furthermore, the key role of the beta band is in agreement with experimental findings that show that beta rhythms correlate with individual-specific traits that are claimed to be genetically induced [31]. Moreover, it has also been suggested that beta band activity represent an index of spontaneous cognitive operations during conscious rest [16]. The variability of resting state activity across subjects and the role of the beta band in defining inter-individual traits may therefore represent the basis for the observed distinctive network characteristics.

A direct comparison with previous papers is hindered by several issues. The current literature is characterized by high variability in (i) experimental protocols, (ii) EEG systems/number of channels, (iii) dataset structure/number of subjects, (iv) features extracted from the EEG, (v) frequency components, (vi) sensitivity to methodological biases and (vii) performance measures. As previously observed [4], there is no evidence yet of reproducibility and stability in the plenitude of results reported in the last decade. However, our findings show that features of resting state functional brain networks, in terms of eigenvector centrality, may be used for the design of EEG-based biometric systems. This approach adds to the current methods, which are mainly based on more simplistic characteristics of brain activity and limited by the investigation of activation patterns of spatially circumscribed regions that are not representative of the complex functional interactions among brain areas. Indeed, it has been shown [23] that recognition performance from a connectivity-based approach leads to better performance as compared to classical power-spectrum measurements. Importantly, in this work we have shown that network topology further improves classification performance, as compared to using only information about functional connectivity (PLI). Importantly, since we used EC, which is a normalised measure, our results should not be simply due to methodological biases (induced by e.g. differences in average degree) that are inherent to weighted network analyses [35].

Importantly, erroneous estimates of functional relationships between EEG channels may be obtained due to incomplete demixing of brain sources, volume conduction and the use of an active reference. In this work these problems were addressed by using a conservative index of phase synchronization, the PLI, which strongly limits the effects of these often-overlooked issues. Finally, our results strongly suggest that results from biometric systems that are based on high-frequency (> 20 Hz) EEG features should be interpreted with caution. Indeed, although our results confirm that the investigation of high frequencies activity may provide good classification performance, it is difficult to estimate to what extent these results are induced by neural sources of activity or by muscle artifacts. The latter, when recorded from scalp-EEG, have spectral features that vary considerably across individuals [10], and hence may be partially responsible of the high accuracy in discriminating among different subjects. Alternatively, assuming that muscle artifacts vary along acquisition sessions, one could consider the use of a longitudinal dataset in order to extract features that are robust to noise, i.e. extract brain network topology that is repeatable and stable over sessions.

IV. Conclusions

The proposed method based on EEG functional brain network topology may represent an appropriate technique to develop EEG-based biometric systems, giving better classification performance than simple measures of brain connectivity. The results from biometric systems based on high-frequency scalp EEG features should be interpreted with caution though. Future studies should investigate whether classification performance can be further improved by using cleaner recordings of patterns of neural activity, using techniques such as magnetoencephalography (MEG), which is less susceptible to contamination from muscle activity [5], and by using unbiased reconstructions of network topology [30] to generate inter-individual distinctive features.

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