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G. Orrú, M. Garau, M. Fraschini, J. Acedo, L. Didaci, D. Ibáñez, A. Soria-Frish, G.L. Marcialis,
"Personal identity verification by EEG-based network representation on a portable device."
Computer Analysis of Images and Patterns: 18th International Conference, CAIP 2019,
Salerno, Italy, September 3–5, 2019, Proceedings, Part II 18.
Springer International Publishing, 2019, pagg. 164-171.

The publisher's version is available at:

https://doi.org/10.1007/978-3-030-29891-3_15

When citing, please refer to the published version.

Personal identity verification by EEG-based network representation on a portable device

Giulia Orrù¹, Marco Garau¹, Matteo Fraschini¹, Javier Acedo², Luca Didaci¹,
David Ibáñez², Aureli Soria-Frish², and Gian Luca Marcialis¹

¹ Department of Electrical and Electronic Engineering, University of Cagliari,
Cagliari, Italy

m.garau@gmail.com, fraschin@unica.it, { giulia.orrù, luca.didaci,
marcialis}@diee.unica.it

² Starlab Barcelona S.L., Barcelona, Spain

{javier.acedo, david.ibanez, aureali.soria-frish}@starlab.es
<https://www.starlab.es/>

Abstract. EEG-based personal verification was investigated so far by using mainly standard non-portable device with a large number of electrodes (typically, 64) constrained to heavy headset configuration. Despite this equipment has been shown to be useful to investigate in depth EEG signal characteristics from a biomedical point of view, it may be considered less appropriate for designing real-life EEG-based biometric systems. In this work, EEG signals are collected by a portable and user-friendly device explicitly conceived for biometric applications, featured by a set of 16 channels. Investigated feature extraction algorithms are based on modelling the EEG channels as a network of mutually interacting units, which was shown to be effective for personal verification purposes when brain signals are acquired by standard EEG devices. This work shows that, even using a reduced set of channels, these approaches still remain effective. The aim of this paper is intended to stimulate research on the use of light and portable EEG headset configurations by adopting network-based representations of EEG brain signals, since a light headset represents a precondition in order to design real-life EEG-based personal verification systems.

Keywords: EEG · person verification · portable device.

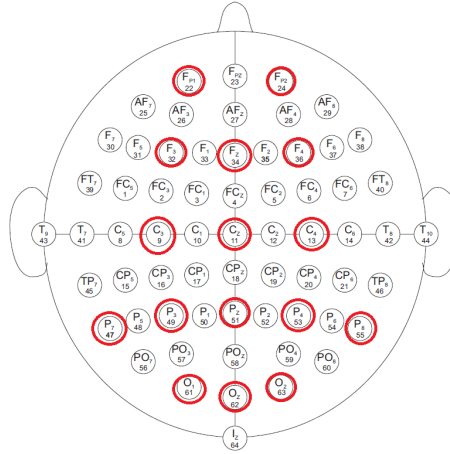
1 Introduction

The electroencephalogram (EEG) signal detected at scalp level has been proposed in the last decade as a biometric trait for personal recognition purposes [1–5], beside other well-known biometrics [7]. Despite its great potential, confirmed by the encouraging experimental results over different approaches [1–5], its main limitation relies on the large number of channels that strongly hinder the use in practical applications. Furthermore, the standard EEG devices used so far are expensive, cumbersome and unfriendly. These devices require a heavy headset configuration of a large number of electrodes (64, in most cases) distributed

over the scalp by means of which it is possible to acquire the time-variant EEG signals.

In this paper, we implemented a recently proposed feature extraction method for personal authentication [1], based on EEG network characteristics, by adopting a realistic, portable and low cost EEG device explicitly conceived for this application. In particular, the device is characterized by a small number of channels (only sixteen), considerably less than the number channels used for standard configuration (typically sixty-four) [1, 2, 5]. The feature extraction method allows to measure the importance of network nodes (EEG channels) estimating the network centrality (eigenvector centrality) from patterns of EEG phase synchronization between recordings sites. The network configuration is supposed to be unique from person to person and previous studies [1, 4, 5] have shown that a noticeable degree of individuality is embedded into the EEG signal and this can be exploited thanks to this representation.

We aim to show that a networks-based EEG representation is still able to convey individual and discriminant information, even when EEG signals are captured by a cheap and portable device, equipped with a limited set of channels. The relevance of the reported findings is in line with the requirement to develop EEG-based personal verification systems that can be used in real-life applications. In order to support our claim, the reported experimental results have been compared with those of previous works [1–5] which used a publicly available EEG dataset with a standard 64-channel configuration. In both cases, EEG signals were acquired during eyes-open resting-state condition.



2 The Method

We replicated the approach proposed in [1], based on the Eigenvector Centrality (EC) measurement. Given, per each person, a sample of n EEG signals, where n represents the number of channels, we performed the following:

- we filtered each signal by using a band-pass filter to obtain the correspondent band-limited signal in the range between 30 and 40 Hz, namely the gamma band [1–5];
- we computed the adjacency matrix that describes a graph of the functional brain network, where each node corresponds to a channel location and the weights are expressed by the Phase Lag Index (PLI). The PLI [2] allows to estimate the interdependence between channels pairs, as a sort of co-variance matrix. In particular, the PLI is defined as:

$$PLI = | \langle \text{sign}[\sin(\Delta\phi(t_k))] \rangle | \quad (1)$$

Where $\Delta\phi(t_k)$ represents the difference between instantaneous phases of two signals at the time t_k ;

- from the adjacency matrix the importance of each node was computed by using the EC values as previously described in [1], which are, in summary, the eigenvalues of the diagonalized PLI matrix. According to [8], this approach is still highly competitive with respect to other feature extraction methods based for example on wavelet transform [9]. This is the first paper where it is shown its potentialities on a real, user-friendly device with a small number of channels.

In this way, starting from the raw EEG signals, we obtained, for each person, a feature vector consisting of n measurements, that is, the PLI matrix and the EC values of each node. The match score between two feature vectors is computed by using the Euclidean distance [1], where appropriate references to PLI and EC measurements can be also found.

3 Experimental Results

3.1 Data Set

A data set explicitly collected for testing EEG-based biometric systems has been provided by the Neuroelectronics Company. EEG data have been recorded by means of Enobio 20 [3], a wireless and easy to use system. This is characterized by a bluetooth connection, a resolution of 24 bit and a sampling frequency of 500 Hz. EEG signals were recorded by using 16 channels: P3, P4, P7, P8, O1, O2, C3, C4, F3, F4, FP1, FP2, Cz, Pz, Oz, Fz. An additional electrode was located on the earlobe as reference channel. Fig. 1 shows the correspondence with the 64 electrodes of the 10-20 standard montage system.

The dataset consists of EEG recordings from 22 subjects. For each subject, two EEG signals were acquired. Each acquisition consists of one-minute eyes-open resting-state and a session of P300 Visual Event Related Potentials, made

up of 10 trials, followed by 1 minute of Spontaneous EEG. The trials were organized as follows:

- the subject relaxes for one minute;
- the subject identifies a target image showed asynchronously in 4 different orders (10 images selected from the 15 image set) and push a button. This task is repeated 10 times;
- after this step, randomized images (selected from the 15 image dataset) are shown, using 3 different inter-stimuli interval (ISI): 100 ms, 750 ms, 1100 ms, with a random variation of ± 25 ms (uniform);
- the user is asked to count how many times he recognizes the target image.

In total, twenty one-minute trials for each person were captured.

We partitioned each one-minute long EEG sample in five non-overlapping epochs of 12 seconds each. This allowed us to simulate five different traces of the EEG signal per subject as done in [1]. We refer to this dataset as Enobio, in the following.

For sake of comparison, the Physionet dataset was also used. This is a publicly available dataset that has been previously used for biometric applications [1–5]. The main difference with the Enobio is related with the acquisition protocol: the resting-state condition has been evaluated only after several kind of external stimuli³, whilst in the Enobio dataset the resting state condition is evaluated before the external stimulus. In other words, subjects were free to concentrate themselves according to their own will. The Physionet dataset contains 109 subjects and the number of channels is 64.

Resting-state condition is considered as the ground-truth to evaluate the individuality of EEG signals of biometric applications, according to [4].

Table 1. The Equal Error Rate (where FAR=FRR) and the FRR at 1% FAR for the investigated algorithms on the “light” device adopted in this paper and a standard “heavy” device [1, 4, 5].

Experimental condition: resting state at open eyes						
Feat. vect.	EER			FRR at 1% FAR		
	Enobio	Phy64	Phy16	Enobio	Phy64	Phy16
EC	5.1%	4.5%	11.9%	16.0%	8.0%	45.8%
SC	22.9%	9.9%	-	65.5%	43.0%	-
PLI	5.0%	3.8%	7.8%	10.5%	99.6%	99.7%
PSD	28.6%	22.0%	26.8%	99.6%	99.9%	99.9%

3.2 Results

In order to have an appropriate “ground truth”, we computed the so-called Power Spectral Density (PSD). This represents the basic measurement of the

³ See in particular the website <https://www.physionet.org/pn4/eegmmidb/>

variations along the EEG signal [6]. We selected the γ band which was the most representative for the subject identification, according to [1].

Moreover, we implemented the method proposed in [5], based on another connectivity measurement called Spectral Coherence (SC). We performed experiments using the method based on the PLI and EC as described in the previous section, and adapting the one based on the SC.

The Likelihood Ratio hypothesis verification test was used for estimating the performance of all methods. Let X be the match scores from a certain method, and $f_{gen}(x)$ and $f_{imp}(x)$ be the conditional joint densities given the genuine users class and the impostors class, respectively. The optimal test for deciding whether a score vector X corresponds to a genuine user or an impostor is the likelihood ratio test (LLR) [1]. It is possible to define the binary hypothesis that a match score is sampled from the genuine users distribution if the related likelihood ratio is greater than a predefined threshold η , otherwise it is concluded that the match score is sampled from the impostors distribution. The likelihood ratio test is optimal only when the marginal densities are totally known. Since in practice these densities $f_{gen}(x)$ and $f_{imp}(x)$ are estimated from the training set of genuine and impostor match scores, the performance of likelihood ratio test depends on the accuracy of these estimations. Accordingly, as in [5], we used 70% of subjects (15 subjects) for computing the matching scores and estimating $f_{gen}(x)$ and $f_{imp}(x)$. For each subject, 10 genuine match scores and 350 impostor match scores were computed (14 impostors x 5 traces x 5 genuine traces). In the case of impostors, we excluded those match scores obtained by the same couple of samples, thus obtaining $14 \times 25 \times 13 / 2 = 2,275$ values. The total number of genuine scores were 150. On the basis of these, we estimated $f_{gen}(x)$ and $f_{imp}(x)$. Densities were estimated by a kernel density estimation method. The remaining 30% of subjects was used for estimating the performance of the system. With regard to the Enobio dataset, a total number of 70 genuine match scores and $25 \times 6 \times 5 / 2 = 375$ impostor match scores were computed. This random partitioning was repeated 20 times and the mean performance is shown in Table 1.

Performance is given in terms of ROC curve (Fig. 2), which represent the percentage of wrongly accepted impostors (FAR) and the performance of wrongly rejected genuine users (FRR) in a unique plot, for each possible LLR threshold value. Two operational points in particular were pointed out: the Equal Error Rate point, where $FAR = FRR$, and the FRR correspondent to the threshold for which $FAR = 1\%$ (Table 1)⁴.

As it can be seen from Table 1 and Fig. 2, the performance of the PLI and EC methods is very high even using the Enobio light headset configuration, and totally surpass the one obtained by the PSD and SC. Worth noting, the performance of PSD did not significantly change when passing from 16 to 64 channels, thus maintaining the meaning of "ground truth" as expected. The performance of PLI is even comparable with that of EC when 64 channels are used on the Physionet data set, when FAR values less than 4% are taken into

⁴ The authors of this paper are available for any clarification concerning the source code and the protocol adopted in order to assure the repeatability of experiments.

account. This means that, although the FRR increases this is anyway less than that of the other investigated methods.

The same holds for EC and PLI for the EER values (Physionet columns). This means that, at the state of the art, with such a number of channels, the degree of individuality is good when it is expected that, over 100 recognition trials, 5 are taken into account to be false acceptances or false rejections. On the other hand, the performance drops roughly when more conservative operational points, namely, the FRR is calculated at FAR= 1%. It is worth noting that the performance of the EC -based method on the Enobio and Physionet datasets is still much higher than that obtained using the SC-based method, even when all 64 channels are adopted for this last method. The EER is more than two times the one obtained on Enobio when the number of channels and the channels are exactly the same on the Physionet dataset (Physionet column) for the EC-based method, whilst a slight decrease of the performance is observed when using the PLI-based method. This is probably due to the differences in the protocol for data acquisition, and suggests that the resting-state condition evaluated after the external stimuli appears to be more susceptible to cause intra-subjects and inter-subjects variations influencing the captured EEG signal. This effect is partially overcome by the PLI method (PLI row), where we obtained a FRR value close to that of EC using 64 channels. A possible explanation is that PLI encodes the possible lags of all channels in more measurements: each PLI feature vector is made up of 120 values, whilst the correspondent EC feature vector is made up of only 16 values. However, the very good performance of PLI at EER when using 64 channels is worth noting. This performance is still high even with the Enobio device, and maybe some modifications of the basic algorithms could also allow decreasing the error rate in other operational points as well.

According to the reported evidences, this biometric application appears to be still immature and unsuitable for large-scale applications, that means, when the number of possible users rapidly increases. On the other hand, it can be a good method to vehiculate the identity and the will of resources access for a small group of users when a high level of security is not necessary. For example, opening an internal house door or accessing to the own laptop when the subject is unable to do this because she/he is constrained at bed or cannot move. In other words, we are referring to the design of an appropriate BCI [3].

The significant decrease of the processing time and the reduced memory storage, especially by considering the PLI and EC methods, are noticeable. The low number of channels leads to feature vectors made up of 120 and 16 values, respectively. The amount of information to be processed was not only notably reduced, but the templates can be easily stored in mobile devices with limited storage memory.

4 Conclusions

On the basis of the performance comparison between the results obtained in this paper and the ones reported in previous works, we noted that whilst methods

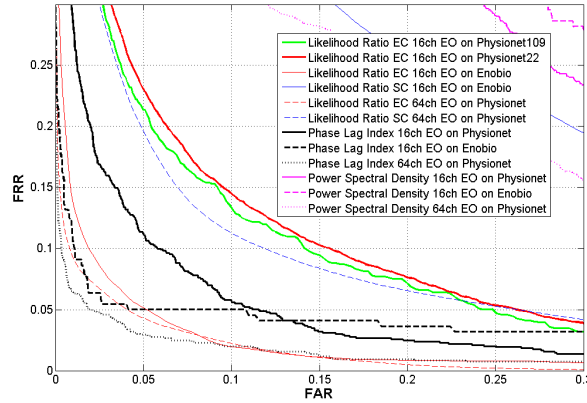


Fig. 2. ROC curves related to the Enobio data set for PSD, PLI, EC and SC methods. For sake of confirmation, we added the results obtained on the Physionet data set for the method at 16 and 64 channels. It is possible to see that Enobio and Physionet data sets led to similar results. However, the EER is more than two times the one obtained on Enobio when the number of channels and the channels are exactly the same (16) on the Physionet data set. This is probably due to some difference in the protocol for data acquisition.

based on the EC and PLI are robust enough with respect to the decreased number of available channels, the one based on the SC has an important loss in performance. In other words, estimating the PLI or EC still maintains a sufficient representation of the brain network even in the case of the lightweight configuration of 16 channel of the Enobio device. In short, the classification rate is almost equivalent to that obtained on the 64-channel datasets, especially when considering low FAR values.

Another point of interest was the significant decrease of the processing time, due to the lower number of channels: the amount of information to be processed was notably reduced.

Although this first set of experiments was done on an apparently small data set, let us consider that achieved results are still close to that obtained on larger benchmarks. Therefore, we may expect that reported performance is a good starting point, especially by considering that it is unlikely that a recognition system or a BCI based on the EEG signal is designed to be large scaled, due to the difficulties related to the interactions among electrodes and the high cooperation level required to reduce any external noise during the signal acquisition.

On the other side, what reported strongly encourages a deeper analysis and development of network-based brain signals representations and their use for personal recognition as a part of future personal verification systems and Brain-Computer Interfaces.

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