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Subject identification through standard EEG signals during resting states

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***Abstract*—In the present work, we used the brain electroencephalografic activity as an alternative means to identify individuals. 50 healthy subjects participated to the study and 56 EEG signals were recorded through a high-density cap during one minute of resting state either with eyes open and eyes closed. By computing the power spectrum density (PSD) on segments of 10 seconds, we obtained a feature vector of 40 points, notably the PSD values in the standard frequency range (1-40 Hz), for each EEG channel. By using a naive Bayes classifier and K-fold cross-validations, we observed high correct recognition rates (CRR) at the parieto-occipital electrodes (~78% during eyes open, ~89% during eyes closed). Notably, the eyes closed resting state elicited the highest CRRs at the occipital electrodes (92% O2, 91% O1), suggesting these biometric characteristics as the most suitable, among those investigated here, for identifying individuals.**

I. Introduction

Biometrics (in ancient Greek: bios = "life", metron = "measure") consists of methods for uniquely recognizing humans based upon one or more intrinsic physical or behavioral traits.

Many techniques has been used to this end, relying on fingerprints, DNA, retina, hand geometry, voice, odor, signature and face [1]. Other methods based on human physiologic signals, like heart (ECG) or brain activity (EEG) have been rapidly investigated during the last decade due to the high security-level (i.e. a hard reproducibility) of their potential application [2-5].

Our aim in this paper is to provide further information on the possibility of EEG based person identification. With the perspective to maximize the ease and the portability of a possible future device, we investigated the classification properties of the EEG signal for each single sensor on the scalp, either during resting states with eyes closed and open.

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II. Methods

A. EEG Recordings

Fifty healthy volunteers have been recruited for this experiment. During the experiment, the participants were comfortably seated in a reclining chair with both arms resting on a pillow in a dimly lit room. They were simply asked to perform two consecutive tasks, i.e. 1 minute of resting state with eyes closed (CE) and 1 minute of resting state with eyes open (OE). During the OE task subjects were asked to avoid ocular blinks. Brain activity was recorded with a 56-channel system (Brain Amp, Brainproducts GmbH, Germany) with a sampling rate of 200 Hz. Finally, EEG signals have been band pass filtered at 0.1-45 Hz. The electrode positions on the scalp followed an extension of the standard 10-20 montage.

B. Feature extraction

The filtered EEG signals were segmented into sub-epochs of 10 seconds. For each sub-epoch we computed the power spectrum density (PSD) according to the Welch's modified periodogram by averaging the PSD values obtained from smaller overlapping (50%) Hamming-windowed sections. The PSD values are then converted into decibel values ($20*\log_{10}(PSD)$), which is commonly used to represent the spectrum shape. Thus, each subject is characterized by a dataset of 6 feature vectors, containing 40 numbers, i.e. the PSD decibel values corresponding to the standard physiological frequencies 1-40 Hz, which cover the standard neurophysiological bands, namely Delta, Theta, Alpha, Beta and Gamma.

For each task (CE, OE), the whole dataset consisted in 300 (50 subjects * 6 PSD vectors) features. For each subject 5 vectors were used as training, while the remaining one was used as validation. Thus, the 83.3% of the whole dataset was used as training set, while the remaining 16.6% as testing set.

C. Identification

A simple probabilistic Naive Bayes classifier, with a diagonal covariance matrix, was used to classify the testing set and perform the identification of the subjects from their PSD vectors in each single EEG sensor. Notably, this classifier was found to give the highest performances in this study (data not shown here).

A K-fold cross-validation procedure was applied for assessing how the results of the statistical analysis will generalize to an independent data set. To reduce variability, 6 rounds of cross-validation (6-fold) are performed using different partitions, and the validation results are averaged over the rounds.

III. Results

Fig. 1 and 2 show the mean correct recognition rates (CRR) obtained from each single electrode in the CE and OE task, respectively. In general, the CRR values tend to

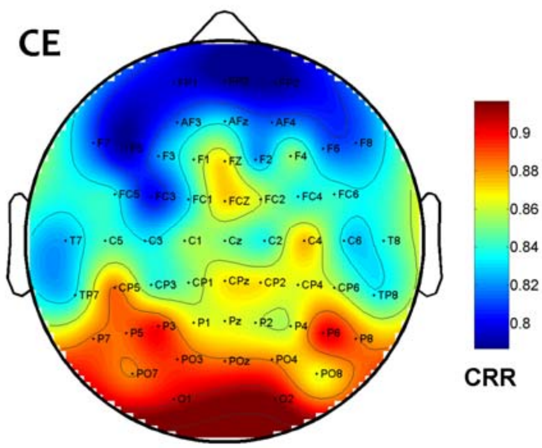

Fig. 1. Map of the EEG sensor positions over the scalp. Blue markers indicate the position of the 8 electrodes excluded in the study.

increase when moving longitudinally from the frontal to occipital areas of the brain. In particular, the correct recognition rates in the CE task are significantly higher than those obtained in the OE task. The maximum values for the

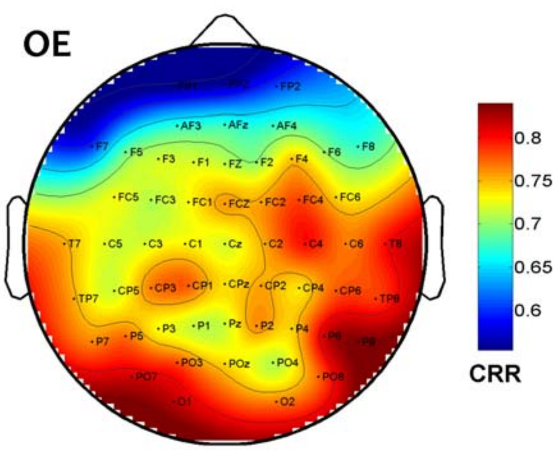

Fig. 2. Mean CRR values. Electrode labels are displayed on x-axis. Solid blue lines represent rates from eyes closed resting states (EC). Dashed red lines represent rates from eyes open resting states (EO).Vertical bars denote standard deviations.

CE condition are reached by the occipital electrodes O1 (91% and O2 92%), whilst for the OE task the maximum values can be observed at the parietal electrode P8 (85%) and at the occipital O1 (83%).

Fig.3 shows the mean confusion matrices for the electrode with the highest CRR in the CE task, i.e. O2 (Fig. 3a) and in the OE task, i.e. P8 (Fig. 3b). These matrices contain the information about the actual and predicted classifications done by the classification system. Notably, the probabilities with which the classifier predicts correctly the actual subject are much higher in the CE condition than OE, as can be observed by tendency of the matrix to maintain high values (red colors) on its main diagonal.

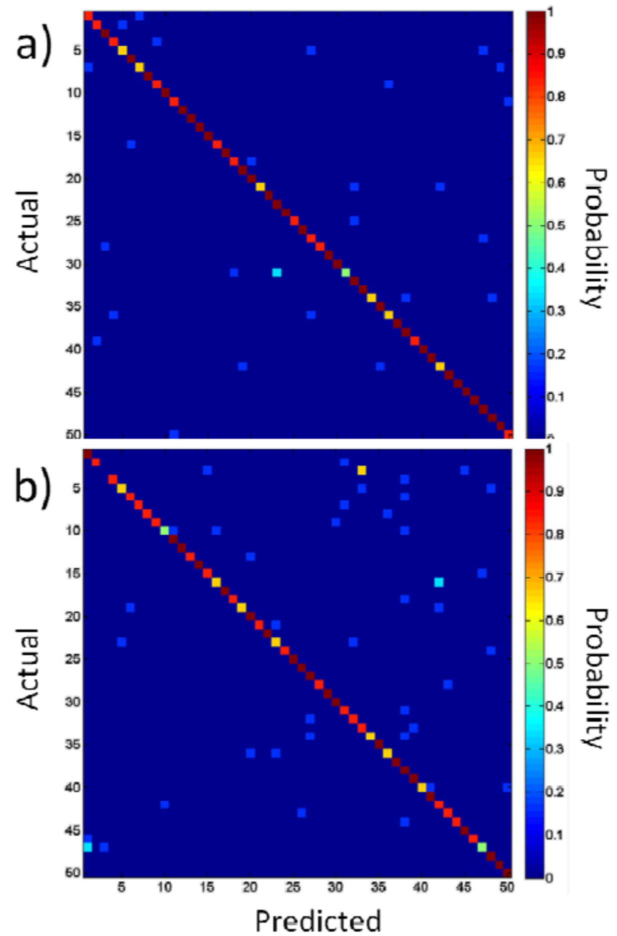

Fig. 3. Mean confusion matrices obtained from a) the O1 electrode features in the EC task ; b) the P8 electrode features in the EO task. The probability that an actual subject I (row) is predicted by the subject J (column) is coded by the color bar.

IV. Conclusions

The presents study supports the evidence that brain activity has the potential to play a crucial role in the development of biometrics systems [6,7]. In the light of a possible easy implementation of the system, our results suggest that the resting state with eyes closed generates individual EEG signals, which are more "identifiable" in terms of their power spectrum density. Moreover, by considering separate classifications for each single EEG sensor, we found that only the occipital electrodes, i.e. O1 and O2, were able to identify correctly about 45/50 (91%) subjects and about 46/50 (92%) subjects respectively. This result is in line with the fact that during periods of eyes closed the EEG waves appear more stable, especially the occipital alpha (8-13 Hz) ones [8]. Furthermore, it suggests a way to reduce drastically the number of EEG electrodes for biometric purposes.

We are aware of the fact that the presented results are just a initial step along the long way to arrive to a correct classification of subjects based only on EEG measurements, However, this work used a large number of healthy subjects to validate the results obtained, and the percentage obtained are encouraging. Other published studies in literature used a smaller EEG data set, presenting recognition percentage inferior to those reported here. It remains open the issue of if persons suffering from specific evolutionary brain diseases (such as Alzheimer Disease for instance) could be easily recognized, due to their EEG that will present probably a drastic evolution in time in terms of power spectra composition. In fact, it is well know as in the Alzheimer disease, a progressive slowing of the EEG power spectra is observed along the time. This will make the recognition of the persons on the base of EEG really problematic. Same lines of reasoning could be offered also for other type of Dementia, such for instance Vascular Dementia, that also it is know to lower the spectral contents of the recorded EEG in such patients.

At this time it is not clear if the use of advanced spectral features offered by high resolution EEG techniques [9-11] could be useful to increase the quality of the recognition process. EEG features derived from EEG spectra such as the network of the connectivity links between the electrodes or the property of the connectivity graphs derived from such links [12-15]

In conclusion, a procedure for the classification of healty subjects on the base of their EEG has been proposed and validated in a relatively large number of subjects. Such methodology could be not applied in the case of subjects with know progressive brain diseases, such as Alzheimer or Vascular Dementia that it is know to alter the frequency spectra of the EEG in the time evolution of the illness.

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