ROBUST ELECTROENCEPHALOGRAM CHANNEL SET FOR PERSON AUTHENTICATION

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ABSTRACT

In electroencephalogram (EEG) based biometrics, the determination of the right channel set helps improve accuracy and usability, while reducing the required number of electrodes and hence the complexity and cost of the EEG system. In this work we find a reduced set of channels designed to enhance human authentication accuracy regardless of changes in the mental task. The study shows that the resulting eight EEG channels outperform previous state of the art studies. Also the experiments and quantitative comparison are conducted in a database significantly larger (106 subjects) than the ones used previously. The suggested set half total error rate (HTER) is 14.69%.

Index Terms— Electroencephalogram, Authentication, Reduced Channel Set.

1. INTRODUCTION

One of the main challenges of any successful biometric modality is its immunity against spoofing. This explains the increasing interest in using EEG in biometrics [1]. Recent discussions show how to spoof face recognition security [2], and also how to spoof fingerprint security [3]. This implies that two of the main currently used biometrics are vulnerable to spoofing, and many more may be added, like hand print, iris and speaker recognition. Improving the methods of recording these modalities may reduce the spoofing threat, such as adding liveness detection procedures. However the effectiveness of these procedures is directly related to the cost and the degree of user inconvenience [4]. Bioelectric signals like EEG may provide a solution for spoofing by using them solely or use them with other biometric modalities either as liveness detectors or fused to make multimodal biometric system.

EEG has shown information related to human identity [5, 6] and many recent studies show interest in using EEG as a biometric modality [7–16]. Also recent years have witnessed a revolution in the technology that measures the EEG, it becomes more usable, cheap, and does not need lab environment. This may be due to widely used applications of EEG signals in Brain Computer Interface (BCI) for both entertainment and medical application such as helping paralyzed people [17].

EEG has many advantages *e.g.* confidentiality, high immunity to forgery and promising recognition accuracy among people. However, it still faces serious problems [18]. Among these problems are: the high noise content in the EEG signal, large dependency on mental task, high signal variation between EEG recording sessions and the cumbersome procedure of the EEG electrodes placement on the client's scalp. Reducing the number of used channels will make the EEG electrodes placement easier. Moreover this will reduce the EEG number of electrodes and the complexity of the EEG recording system, which will lead to a smaller size and more affordable EEG recording system.

EEG is known to be highly affected by the user's mental task [19]. This may still be acceptable in an authentication problem, where the cooperation of the users is assumed for them to be authenticated, but this will highly affect its usability as a biometric modality in identification problem where the users' cooperation should not be assumed. In this work, the suggested EEG channel subset is less affected by the change of mental task, which indicates it may be used in identification or authentication problems. The full EEG number of channels ranges from 32 to 64 channels in most of the cases and to 256 channels if needed.

In this work the signal Power Spectral Density (PSD) was considered as a feature, as it was noted in [20] that the EEG signal periodogram (which is a method of estimating the PSD) lead to better or similar performances than more elaborated features such as parameters of autoregressive (AR) models and wavelets.

In order to study channels that are less affected by mental task, we measured the between mental task distance for the same channel and person, and measured the between person distances for the same channel and mental task. The channels that have their between tasks distance less than the between persons distance are given priority to be used in authentication problem. Mahalanobis distance was used for distance measure [21].

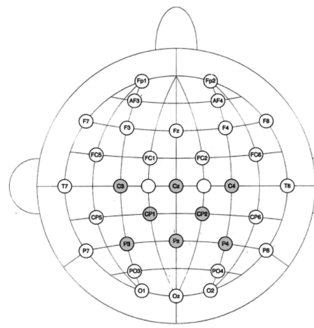
2. RELATED WORKS

Many studies examined the accuracy of EEG signals as a biometric modality, some used the full EEG channel set *e.g.* [12, 22], and some used a subset of the EEG channels with lack of justification *e.g.* [1, 7–11, 13, 23]. To the best of our knowledge, few studies justify using a subset of EEG channels in biometric.

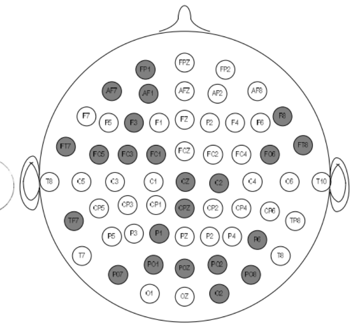
Marcel and Millan in [15] used all 32 EEG channels in the preprocessing stage, where they applied spatial filters: spherical splines and surface Laplacian. These filters increase the spatial resolution of the EEG and enhance the local signals coming directly from underneath the measuring electrode, and need to access all the available channel set to perform the interpolation [24]. In the feature extraction step, they considered the filtered signals coming from 8 channels, which are: C3, Cz, C4, CP1, CP2, P3, Pz, and P4. This subset was selected based on BCI experience that these channels are more appropriate for mental task classification. But there is no evidence that these channels are appropriate for person classification. Also the application of SS and SL spatial filters in the preprocessing step require more computation and need to access the total channel set (32 channels in their case). This indicates that there is no improvement in the process of EEG recording and no reduction in the EEG system cost. Furthermore, the selected channels known to be the best to detect mental tasks. This implies that they are highly affected by the change of mental tasks. Their suggested feature was the estimated power spectral density using welch method in the frequency range $8-30$ Hz with frequency resolution of 2 Hz, and they built a Gaussian Mixture Model classifier to measure their accuracy. Figure 1a shows the selected channel for their feature extraction.

Ravi and Palaniappan in [14] suggested channels subset based on genetic algorithm (GA). In the preprocessing they used elliptic band pass filter to get the γ band $30-50$ Hz. Gamma band energy only for each channel was considered as a feature. Linear discriminant classification was used to evaluate the fitness function for the GA algorithm because it is relatively fast. They found no statistical significance of the difference between using 23 channels and the total 61 channels with p-value=0.26. Their suggested channels FP1, F8, AF1, F3, FC6, FC5, FC1, Cz, PO2, PO1, O2, AF7, FT7, FT8, FC3, TP7, P6, C2, PO7, PO8, POz, P1, and CPz are shown in figure 1b. It is clear that the suggested number of electrodes still large (23) and more improvement may be reached. Moreover the suggested channels were found to be not significantly different from the full channel set, but using the full channel set does not guarantee to give the best authentication accuracy as it may confuse the classifier. Furthermore, their suggested channel set was tested using one mental task only, and the effect of different mental tasks was not measured.

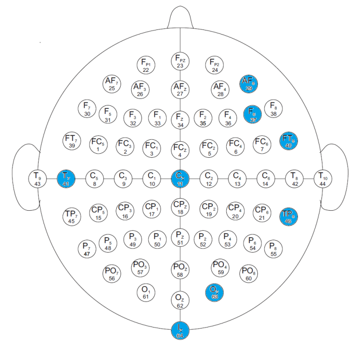
Palaniappan and Mandic in [16] ranked the EEG channels based on their Davis-Bouldin index (DBI) and selected them in the feature vector gradually. Maximum accuracy was reached after adding 35 channels. The suggested channel set still large and more reduction may be achieved. Moreover one mental task only is considered, and the effect of different mental tasks was not measured. Furthermore, it was noted in their results that many channels had reduced the recognition accuracy despite they had better DBI, and they were still considered in the final feature set.



(a) 8 channels suggested by [15]



(b) 23 channels suggested by [14]



(c) Our 8 suggested channels

Fig. 1: EEG Channel locations

3. PROPOSED METHOD

3.1. Dataset

We used the data described in [25], and it was downloaded from [26]. This data was selected since it contains large number of participants. Moreover the dataset contains 6 mental tasks, which makes it more appropriate to measure EEG channel stability in different mental tasks. The data contains EEG recordings for 109 persons with the following mental tasks: Task a: Idle (Baseline) with eyes open, Task b: Idle (Baseline) with eyes closed, Task c: Open and close left or right fist, Task d: Imagine opening and closing left or right fist, Task e: Open and close both fists or both feet and Task f: Imagine opening and closing both fists or both feet. The dataset contains recording of 64 EEG channels. The left earlobe and mastoid electrodes were used as reference and ground electrodes respectively. The data sampling rate is 160 samples/s. Three subjects of the 109 were disregarded because they contains data that were sampled at 128 sample/s. So in total we used EEG data for 106 subjects. Task a, b, c, d, e and f samples represent roughly 50%, 4%, 12%, 11%, 12% and 11% of the total samples number respectively.

3.2. Preprocessing

The channel recording during each mental task was separated from other tasks based on the recorded annotation. So for each participant of the 106, the data for each channel was separated to 6 parts. Then, the data was segmented to one second segment. This segment length was chosen because there was no interest in very low frequencies, as the interest was in frequency range $4-52$ Hz, and we were considering frequency bins of size 8 as a feature, so no need to have high resolution spectrum.

Each segment was filtered to frequency range $4-52$ Hz, as it found in [1] that combining EEG rhythms (θ $(4-8)$ Hz, α $(8-15)$ Hz and β $(15-31)$ Hz) gives optimal result for recognition. Also some studies use the γ rhythm $(30-50)$ Hz as in [22] and claim very good identification accuracy. So we considered merging θ, α, β and γ rhythms for better results. No filtration was performed to reject EEG artifacts and all samples were considered.

3.3. Feature Extraction

The PSD of the frequency range $(4-52)$ Hz was selected as a feature, with frequency resolution of 8 Hz to reduce the size of the features and increase the learning speed of the model. So for a single channel, every segment have 6 features represent the frequency bins $(52-4)/8$. The features were normalized to the sum of all PSD bins in the same segment. When multiple channels are considered, their features were combined together.

3.4. Channel Selection Criteria

In this step we considered the data for 50 participant to avoid over fitting. For the same mental task, channel and person, the EEG feature vectors were assumed to have Gaussian distribution. In order to select stable channel subset among the available 64 two values were measured. The first is the average Mahalanobis distance between the means of the feature vectors distributions of the mental tasks for the same channel and person. So, the Mahalanobis distance between the distribution mean of *Task a* was measured against distribution mean of *Task b*, *Task c*, *Task d*, *Task e* and *Task f* for the same channel and person. This was repeated for all the other five tasks. This resulted in 30 distances per channel per person. Averaging these 30 distances for one person and over the 50 persons resulted in the "within person distance", which will be referred to as DW_i, where i refers to channel number. DW_i measures how far from each other the feature vectors distributions collected during different mental tasks within the same person for some channel i. The second measure was the Mahalanobis distance between the means of feature vectors distributions of the same mental task and channel but for different persons. So, the Mahalanobis distance was measured between the mean of *Task a* distribution against the other means for the same task and channel in different persons. This was repeated for all the other five tasks. This resulted in 49 distances per task per channel per person. Then we averaged over the 6 tasks and the 50 persons to find the "between persons distance", which will be referred to as DB_i, where i refers to channel number. DB_i measures how far from each other the EEG feature vectors collected using the same channel during the same mental task but in different persons.

The channels stability which will be referred to as S_i was measured as the difference between the "between person distance" DB_i and the "within person distance" DW_i as shown in equation 1

$$S_i = DB_i - DW_i \tag{1}$$

After finding the channel stability for all channels, they were ranked based on their stability value. In order to find the best channel subset, we run Sequential Forward Selection algorithm on the channels based on their stability value. Sequential Forward Selection is a simple greedy search algorithm, and so it does not guarantee to find the global minimum. The change of person authentication half total error rate (HTER) for the training set (50 persons) was set as an objective function. So, the channels that have higher stability were prioritized to be used in person authentication problem, as they give better between person separation. But this does not exclude other channels from being used as they may have different information that are related to person identity. Any added channel that did not improve the recognition accuracy by a certain threshold (set to 1% empirically) was considered non-informative or contains redundant information that exists in more stable channels, and thus was not considered in the feature vector. The details of the authentication experiment is described in section 4.

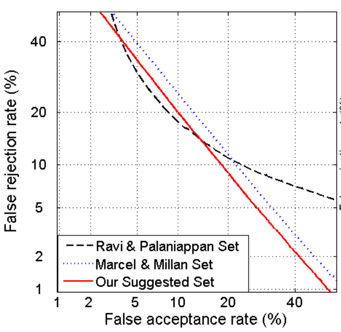
4. EXPERIMENT DETAILS

The EEG samples for each mental task per channel per person were collected together and apply feature extraction on each of them. In total we had $6 \times 64 \times 106 = 40704$ distributions. The mean and covariance were calculated for each distribution. After that, we measured the channels stability as described in section 3.4, and all channels were ranked based on their stability using the EEG data for 50 persons. Table 1 shows the stability value for each used channel. For the person recognition experiment, we built a person authentication framework based on Gaussian Mixture Model (GMM) classifier. Among the data of 50 persons, the data during all mental tasks for the first 30 persons were used to build a Universal Background Model (UBM) also known as the background model. The number of used mixtures in the GMM was set to 8 based on the best results of multiple trials. The remaining data of 20 persons were considered as clients. **All** samples from one mental task only (*Task a*) were used in training to build the client model, and **all** the remaining samples during the other five mental tasks were used in client /imposter testing. *Task a* samples represents around 50% of the total samples for each participant. In running the authentication experiment, we firstly considered the feature of one channel only, which is ranked 1 in table 1 (channel Iz), and the authentication accuracy was measured. Then, the second channel was added to the feature vector, and repeat the experiment to measure the accuracy. We continued adding channels sequentially according to their rank in table 1. We noticed that when some channels were added, they did not improve the accuracy, or in many cases they reduce the accuracy. So, if the added channel did not enhance the authentication accuracy, it will be removed from the feature set, as this indicates that this channel feature is redundant or does not fit well with the used feature vectors of the more stable channels. This continued until the accuracy of all 64 channels were tested. The best channel set that improve the authentication accuracy was considered as the optimal channel set. In order to verify this result, we run the authentication experiment using the optimized channel set considering all the data for all 106 persons. In this final testing, the data of the first 60 participants were used to build the UBM model, this includes the data for 50 participants that were used in verifying the optimal channel set. The remaining 46 participants were used in client /imposter testing. In both cases, the clients' data was not included in building the background model. Moreover the Gaussian mixtures were trained considering diagonal covariance, and the clients' mixtures' means were adapted using Maximum a Posteriori with the prior UBM model means. The adaptation was performed as described in [27]. The authentication was made such that the ratio between the probability density function (pdf) of a test feature vector measured by the client model and the pdf of the same feature vector measured by the background model should be greater than certain threshold. This threshold is changed according to the required False Acceptance Rate (FAR) and False Rejection Rate (FRR). Assuming independence for all feature vectors and a uniform class distribution, the likelihood that a certain feature vector $\bar{x} = x_1, x_2, x_3, ..., x_m$ belongs to a specific class λ which has n mixtures is measured by probability density function shown in equation 2.

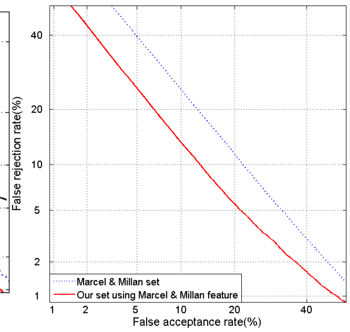
$$p(\lambda|\bar{x}) = \sum_{i=1}^{n} k_i N(\tilde{\mu}_i, \tilde{\Sigma}_i) \tag{2}$$

where, N: normal distribution with $\tilde{\mu}_i$ multivariate mixture mean and $\tilde{\Sigma}_i$ is multivariate mixture covariance matrix. k_i: the probability of the i^{th} mixture in the GMM model.

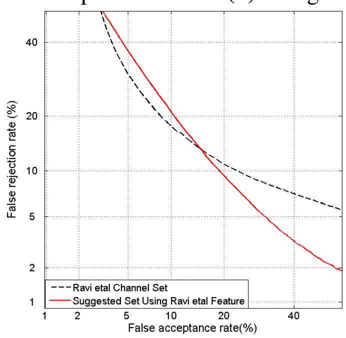
Moreover, the work done in [15] and [14] was repeated on the dataset in hand for quantitative comparison. This includes all their related preprocessing, features extraction and their selected channel sets. Also, since our preprocessing and feature extraction methods are different from those in [15] and [14], and in order to test how far our selected channels are affected by the preprocessing and feature extraction methods we chose, we applied the preprocessing and feature extraction methods described in [15] and in [14] on our suggested channel set, and verify its person authentication accuracy and



(a) DET curves comparison



(b) Using methods in [15].



(c) Using methods in [14].

Fig. 2: Authentication DET curves

compare it again with their work.

5. RESULTS

Table 1 list the channel stability values after applying the channel stability described in section 3.4. In the table, the channels are listed in descending order from top-to-bottom and left-to-right.

The best results were noticed to be for channels O2, Iz, TP8, FT8, F6, AF8, T7 and Cz on the 50 persons training set. A map of the suggested channels and their location in the selected dataset is shown in figure 1c. Also to verify the effect of channel order in table 1, we consider adding the channels in in reversed order, which resulted in 11 channels instead of 8 and HTER value of 14.875% rather than 14.69%, which indicates that the order in table 1 is meaningful.

Figure 2a shows the Detection Error Tradeoff curve (DET curve) to verify our selected channels accuracy on all the dataset, compared with the accuracy of channel sets suggested in [15] and [14]. The HTER values was 14.69%, 17.48% and 14.66% respectively.

In order to measure the effect of the selected preprocessing and feature extraction on the suggested set, we applied the preprocessing and feature extraction methods described in [15] on our suggested channel set, and test its person authentication accuracy and compare it again with the one described in [15]. Figure 2b shows the DET curve of this comparison, with HTER value for our suggested set improved to 12.08%. Also we applied the preprocessing and feature extraction methods described in [14] on our channel set, and test its person authentication accuracy and compare it again with the one described in [14]. Figure 2c shows the DET curve of this comparison, with HTER value for our suggested set becomes 15.03%.

Table 1: Stability Result for 64 EEG Channels

Channel							
ID	S_i	ID	S_i	ID	S_i	ID	S_i
O2	4.034	T8	3.2872	FPz	2.9676	AF3	2.870
Iz	4.017	AF8	3.253	C2	2.965	CPz	2.868
TP8	3.987	AF4	3.238	P2	2.959	P7	2.862
O1	3.859	P8	3.236	FC3	2.953	CP5	2.861
Oz	3.858	P4	3.179	AF7	2.943	P1	2.858
FT8	3.807	CP4	3.178	F5	2.932	FC1	2.848
C6	3.672	P6	3.171	CP3	2.927	C1	2.837
F6	3.589	FP2	3.142	Pz	2.908	P5	2.812
T10	3.484	FC2	3.122	P3	2.895	CP1	2.811
C4	3.469	C3	3.095	FT7	2.888	Fz	2.787
FC6	3.443	FP1	3.086	F7	2.887	PO3	2.786
CP6	3.366	PO4	3.066	F2	2.886	AFz	2.775
FC4	3.338	CP2	3.033	POz	2.885	PO7	2.773
PO8	3.309	C5	3.024	FCz	2.884	F3	2.663
F8	3.300	F4	3.006	Cz	2.875	F1	2.643
FC5	3.290	T7	2.984	TP7	2.873	T9	2.557

6. CONCLUSION

In this work we suggested 8 EEG channels to be used in biometrics as an alternative to using the complete EEG channel set. The suggested set was justified based on its stability in different mental tasks. Channels with high stability values were given priority to contribute in the feature vector if they reduce the HTER. The suggested set was examined by a challenging experiment where the feature vectors during one mental task only were used for training, and the remaining feature vectors from other mental tasks were used for testing. These results were compared with other EEG channel sets suggested by [15] and [14]. Our suggested set has a smaller HTER and a better DET curve than the one suggested in [15], despite that the preprocessing used in [15] needs to access the total channel set. Also comparing our result with the work in [14], their suggested set achieved a smaller HTER, but the DET curve behavior shows that in cases where low false rejection rate (FRR) is required, our suggested set has better results, even though [14] used 23 channels and we used 8.

The accuracy of our suggested set may be enhanced further by using different preprocessing and feature extraction. As can be seen, when we applied the preprocessing and feature extraction in [15] to our suggested set, an improvement of the HTER of around 2.61% was achieved. Our suggested channel set needs to be tested further on different datasets that have different mental tasks, since the dataset used has six mental tasks, four of them related to imagery or actual movement which are related to motor cortex, and the other two idle tasks with eyes open and eyes closed. Also, in the dataset used, the EEG recording considered the left earlobe and mastoid electrodes as reference and ground respectively. Selecting a different reference electrode may lead to a different result, and this will be tackled in a future work. The Sequential Forward Selection algorithm does not guarantee to find the global minimum. Using other exhaustive methods like dynamic programming may lead to better results.

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