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Mahalanobis Distance-Based Classifiers Are Able to Recognize EEG Patterns by Using Few EEG Electrodes

Fabio Babiloni[1], Luigi Bianchi[2], Francesco Semeraro[1], José del R. Millán[3], Josep Mouriño[3], Angela Cattini[4], Serenella Salinari[4], Maria Grazia Marciani[2,5] and Febo Cincotti[5]

[1] Dip. Fisiologia umana e Farmacologia, Università "La Sapienza", Rome, ITALY [2] Dip. Neuroscienze, Università "Tor Vergata", Rome, ITALY, [3] ISIS, Joint Research Center of the EC, Ispra (VA), ITALY, [4] Dipartimento Informatica e Sistemistica, Università "La Sapienza", Rome, ITALY, [5] IRCCS, Fondazione Santa Lucia, Rome, ITALY.

Abstract- **In this paper, we explore the use of quadratic classifiers based on Mahalanobis distance to detect EEG patterns from a reduced set of recording electrodes. Such classifiers used the diagonal and full covariance matrix of EEG spectral features extracted from EEG data. Such data were recorded from a group of 8 healthy subjects with 4 electrodes, placed in C3, P3, C4, P4 position of the international 10-20 system. Mahalanobis distance classifiers based on the use of full covariance matrix are able to detect EEG activity related to imagination of movement with affordable accuracy (average score 98%). Reported average recognition data were obtained by using the cross-validation of the EEG recordings for each subject. Such results open the avenue for the use of Mahalanobis-based classifiers in a brain computer interface context, in which the use of a reduced set of recording electrodes is an important issue.**

I. INTRODUCTION

Usually, the EEG was recorded by using an array of electrodes, regularly disposed on the scalp surface, according to the international 10-20 standard and its successive extension [1-2]. Nowadays, neuroscientists set the requirements for an high number of electrodes (64-128) for the appropriate processing of scalp high spatial frequency components of evoked and event-related potentials [3-7]. However, there is a research field involving the EEG in which the use of an increased number of electrodes is not a critical issue. In fact, in the context of Brain Computer Interface (BCI), the use of many EEG electrodes represents a drawback for the final user, due to the time-consuming procedures needed to appropriately set such electrodes and to decrease the contact impedance between them and the scalp. In this particular framework, the research focuses on the use and selection of an appropriate and reduced set of EEG electrodes [8-11]. To now, several interesting results for EEG classification procedure have been produced by using particular electrodes array, preferably disposed along the centro-parietal scalp areas, that roughly overlying the sensory-motor cortices [8-11]. Another key factor in the BCI researches is to develop methods for reliable EEG classification that do not involve lengthy training procedures, in order to reduce the time spent by the user in the unsuccessful interactions with the final device. In this respect, many algorithms involving non linear and linear classifiers have been suggested in literature [11-15]. With these problematic in mind, we explored the possibilities offered by simple quadratic classifiers, based on the concept of Mahalanobis distance, for the recognition of EEG patterns sampled with a low number of scalp electrodes (2 or 4). The rationale at the base of the classifier's choice was to avoid the relatively training procedure needed when neural-network based classifiers have to be employed. We analyzed the performance of such quadratic classifiers on EEG data gathered from a group of 8 healthy subjects performing two motor-related mental tasks, namely imagined right and left hand movements. Furthermore, we compared the performance of Mahalanobis-based classifiers against a linear classifier recognized known to be useful in the detection of EEG patterns when at least 9 electrodes are used [16].

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II. METHODOLOGY

A. Data Collection

Eight healthy subjects participated voluntarily in experiments where they performed different tasks, including the imagination of the movement of the right middle finger (RI) as well as the left middle finger (LI).

Four EEG electrodes are placed over the centro-parietal scalp areas of both hemispheres, namely in the position C3, P3, C4 and P4 of the 10-20 international system.

EEG data sampling frequency was 400 Hz, and signal was bandpass filtered between 0.1 and 100 Hz before digitization. At the beginning of a recording session, subjects remained in a resting state—relax with eyes opened—for 60 s. The EEG activity of this period is used as a baseline for subsequent analysis of the mental tasks. Then, subjects started performing the task immediately after the operator instructed them to do so, and they maintained that task for more than 10 s. Every subject executed eight times each task during the recording session, with a resting period of 10 s between each. After removal of time segments contaminated with EMG in the arms it remains about 80 seconds of EEG signals for each task for every subject.

B. Data Pre-Processing

Time varying spectrograms of EEG data by estimating the Power Spectral Density (PSD) of 2-second long epochs, each starting 1 s after the previous one were computed. The Welch periodogram algorithm to estimate the PSD was applied. Epochs are divided into segments of 1 s, with a Hann window of the same length applied to each segment, and 50 % overlapping between the segments. This gives a frequency resolution of 1 Hz. Finally, the power components are

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referred to the corresponding values of the estimated PSD of the baseline and transformed in dB—i.e., we take the logarithm of the division. The spectral values were considered in a frequency band from 8 to 30 Hz, since those band was recognized to be useful for the recognition of mental pattern in previous papers [15,16]. Three separate sets of feature vectors are prepared, one referring to all the electrodes used (C3, P3, C4, P4) another relative to the data of only two electrodes (C3 and C4), and the last one referred to the data from the electrodes montage C3-P3 and C4-P4. The rationale was to investigate the eventual degrade of the performance of the classifiers when data from only two electrodes were used.

C. Mahalanobis distance-based classifiers

Let us indicate the n-dimensional measured spectral vector x from the EEG data in the frequency band of 8-30 Hz during the mental tasks analyzed. The mean vector $\mathbf{m}_R$ ($\mathbf{m}_L$) is the average of the x vectors computed during the right (left) movement imagination during a particular time period (training). Now, we define a quantity *d* called Mahalanobis distance that is computed as follows

$$d = (x - m_I)^T C_I^{-1} (x - m_I) \qquad (1)$$

where C_I is the covariance matrix for the particular imagined movement considered, left or right (C_L and C_R, respectively) and T stands for the transposition operator. The Mahalanobis distance is used in a minimum-distance classifier as follows: Let $\mathbf{m}_R$, $\mathbf{m}_L$ be the means for the right and left imagined movement classes, and let C_R, C_L be the corresponding covariance matrices. We classify a feature vector **x** by measuring the Mahalanobis distance d from **x** to each of the means, and assigning **x** to the class for which the Mahalanobis distance is minimum.

Two particular distance based classifiers have been used in this paper. The first was the diagonal Mahalanobis classifier (MD), that relies on the use of a diagonal covariance matrix C for both left and right imagined movements. The second was the full Mahalanobis classifier (M), that relies on the estimation of the full covariance matrix.

D. Signal Space Projection

The Signal Space Projection method is here used as a linear classifier shown to be useful for the recognition of mental EEG patterns [16].

E. Cross validation.

For recognition purposes, we applied to the all classifiers the k-fold cross-validation, with k = 10. Hence, we divided the EEG data set for each subject (80 seconds of imagined right and left movement) into k subsets of equal size. The SSP, MD and M classifiers were recomputed k times, each time leaving out one of the EEG data subsets from the training, and using the omitted subset to compute the recognition rate. Then, the results presented here are an average of the recognition rate obtained for each one of the k subset of EEG data not used by the classifiers for the estimation of the class means (training).

F. Statistical analysis

A two-way Analysis of Variance (ANOVA) was performed on the average values of the recognition scores obtained by the cross-validation technique. The first main factor was METHODS with three levels (SSP MD, M) for the classifiers used in the present work, while the second main factor was ELECTRODES, with three levels (2 electrodes C3 and C4; 2 channels C3-P3 and C4-P4; and 4 electrodes, C3, P3, C4, P4). Greenhouse-Gasser correction has been used [17] for the ANOVA computation. The Scheffe's test was used as post-hoc test, at the 5% level of significance.

III. RESULTS

Table 1 reports the average true positive rates between the experimental subjects with the use of the SSP, MD and M classifiers.

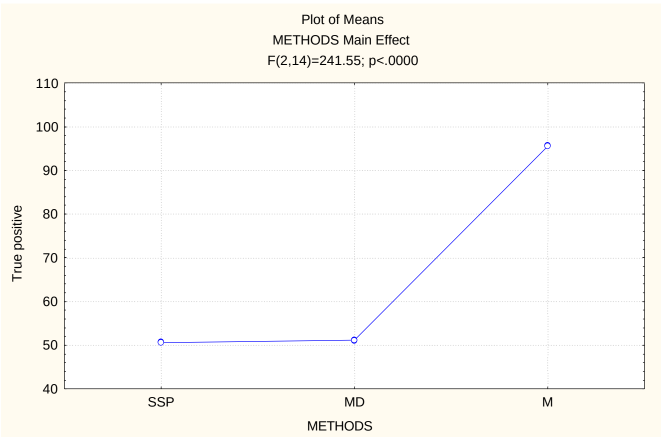

Figure 1. Average percentage recognition scores obtained for the population analyzed with the linear and quadratic classifiers described above. Methods employed are Signal Space Projection (SSP), diagonal Mahalanobis classifier (MD) and Mahalanobis-based classifiers with the use of full covariance matrix (M). Data are irrespective of the use of 2 or 4 recording EEG channels

The ANOVA demonstrated that the use of different classifiers improves significantly the values of recognition scores (METHODS main factor, F = 241.55, $p<0.000001$). Of note, the number of recording electrodes (2 or 4) was significant to increase the percentage recognition score of EEG imagined patterns with the different classification methods. (ELECTRODES main factor, F = 6.23, p = 0.0116). Furthermore, no interaction METHODS x ELECTRODES was found (F = .94, p = 0.45). The post-hoc statistical analysis performed with the Scheffe's test demonstrated that the recognition scores obtained with the Mahalanobis classifier using the full covariance matrix are higher (98% average recognition scores on all the population analyzed) than those obtained with the other classifiers here employed (SSP and Mahalanobis with diagonal covariance matrix). This result held at the statistical significance of $p < 0.00001$ for any combination of comparisons with different EEG recording electrodes configuration (C3 and C4, C3-P3 and C4-P4, or C3,C4,P3,P4). The recognition scores obtained by the Mahalanobis classifier with the use of the full covariance matrix (2 or 4) are statistically equivalent for any combination of the EEG recording electrodes (Scheffe's test, p = 0.12).

IV. Discussion

A. Pro and cons about the Mahalanobis distance-based classifiers

As known from the literature, the use of the Mahalanobis metric removes several of the limitation of linear classifiers based on Euclidean metric, since it automatically account for the scaling of the coordinate axes, as well as for the correlation between the different features considered. However, there is a price for these advantages. The covariance matrices can be hard to determine accurately, and the memory and time requirements grow quadratically rather than linearly with the number of features. These problems may be insignificant when only a few features are needed, but they can become quite serious when the number of features becomes large. In the present case, the use of EEG features from a low number of electrodes (2 or 4) makes possible the use of Mahalanobis-based classifiers.

B. Implication for the Brain Computer Interface

Results obtained in the present study suggest that the Mahalanobis classifier based on the use of the full covariance matrix of features is able to classify EEG patterns during imagination of left and right hand movements. Such recognition were performed by using data from few EEG electrodes at an high level of accuracy. Of note, the classification performance by using data from the C3 and C4 electrodes of such method are statistically equivalent to those obtained by using four recording electrodes (C3,C4, P3, P4). Instead, SSP and the other Mahalanobis classifier that used a diagonal covariance matrix (MD) presented recognition scores slightly above the chance level (in this case set to 50%). The decrement of performance of SSP is related to the decrease of recording electrodes, since higher recognition scores (on the order of 82%) were obtained by SSP using data from 9 electrodes of the 10-20 International System in another group of five healthy subjects [16].

Compared to neural networks [13,14], linear or quadratic classifiers are easier to train since they do not require non-linear minimization. With respect the recognition scores obtained here, other Authors have been able to perform successful recognition scores of patterns associated with the preparation of performed movements with linear classification technique based on the Common Spatial Patterns as high as 90% (CSP) [15] as well as non linear classifiers as high as 84% [11-13] in the Brain Computer Interface area. However, the use of CSP methods required the use of a larger set of EEG recording electrodes than those reported here.

In summary, results of the present work suggest that by using quadratic classifiers based on Mahalanobis distance, with the use of the full covariance matrix of the features it is possible to classify EEG mental patterns related to the imagination of hand movements by using just 2 scalp electrodes. Such electrodes were placed at C3 and C4 position of the international 10-20 system [1]. These results can open the avenue for an application of this classifier to the Brain Computer Interface area, in which the number of the electrodes to be used by the final user is a critical issue.

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