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OPTIMIZING SPATIAL FILTER PAIRS FOR EEG CLASSIFICATION BASED ON PHASE-SYNCHRONIZATION

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ABSTRACT

Brain-Computer Interfaces (BCI) aim at translating brain signals, typically ElectroEncephaloGraphy (EEG), into commands for external devices. Spatial filters are powerful tools for EEG classification, able to reduce spatial blurring effects. In particular, optimal spatial filters have been designed to classify EEG signals based on band power features. Unfortunately, there are other relevant EEG features for which no optimal spatial filter exists. This is the case for Phase Locking Value (PLV) features, which measure the synchronization between 2 EEG channels. Therefore, this paper proposes to create such a pair of optimal spatial filters for PLV-features. To do so, we optimized a functional measuring the discriminability of PLV-features based on a genetic algorithm. An evaluation of our algorithm on a motor imagery EEG data set showed that using optimized spatial filters led to higher classification performances, and that combining the resulting PLV features with traditional methods boosts the overall BCI performances.

Index Terms— Brain-Computer Interfaces, EEG signal processing, Phase Locking Value, Spatial Filter, Genetic Algorithm

1. INTRODUCTION

Brain Computer Interfaces are communication systems able to process brain signals in order to detect specific mental states or events. The decoded brain activity can be used to command an external device allowing communication with the external world, notably for people with motor disabilities[1]. Measuring brain activity is the first step in the design of a BCI, and is most commonly achieved using electroencephalography (EEG), which offers the best compromise between affordability, availability and low invasiveness.

One of the major challenges in the design of BCI is to robustly decode the noisy EEG signals in order to recognize the occurrence of two or more different mental states. With the rapid recent development of BCI, several EEG signal processing techniques were developed to improve mental state classification. Among the different instruments proposed in the literature, spatial filtering proved to be particularly useful to maximize the signal-to-noise ratio (SNR). The first used spatial filters were Common Average Reference (CAR) and Laplacian, both constructed for reducing the effect of spatial blurring. CAR subtracts the average value of the entire electrode montage to each channel while Laplacian is an approximation of the second derivative of the instantaneous spatial voltage distribution that operate as a high pass spatial filter able to emphasize localized activity [2].

Moreover in the last years, more adaptive spatial filters were developed to optimize the SNR of specific features, in particular to make the features extracted from the spatially filtered signals as discriminative as possible. One of the most useful such spatial filter is the Common Spatial Pattern (CSP), which is the optimal spatial filter for band power features [3]. It has notably been used successfully for the classification of BCI based on motor imagery [3]. In particular CSP is constructed in order to maximize the variance of the band-pass filtered EEG signal (i.e., the signal band power) recorded under one condition while minimizing the variance of the band-pass filtered signal during a second condition [4].

The success of CSP highlighted the usefulness of optimal spatial filters for maximizing the discriminative power of EEG features. Unfortunately, there are several EEG features for which no optimal spatial filter has been proposed. This is notably the case for connectivity features such as the phase locking value (PLV), which measures the synchronization between the signals from two different EEG channels and thus between different brain areas [5], [6]. Such features have indeed been shown to be promising to classify EEG signals for BCI [7], [8].

Thus, the purpose of our work was to fill this gap by optimizing spatial filters for PLV features. The PLV was introduced in the 1999 as a statistics for detecting synchrony in a precise frequency range between two different recording sites [5]. For calculating the PLV the variability of phase difference between two signals is measured across trials making this statistics unusable for online EEG-classification. In the same year was introduced a variant of PLV, the single trial-PLV (S-PLV), in which synchrony is compared across samples [6]. Based on this feature we constructed a new functional in order to find the best two spatial filters able to maximize the discriminative power of

the S-PLV feature between two conditions of EEG signals (e.g., left hand motor imagery versus right hand motor imagery).

In order to find the optimal filters we chose to combine a genetic algorithm (GA) with a local minimum search. Each chromosome of the GA represents the two spatial filters, using this evolutionary methods we were able to explore a large space of solutions, and then the best chromosome was taken as a starting point for the local search.

2. MATERIALS AND METHODS

A. *Single Trial Phase Locking Value*

The feature that we have chosen for the classification of EEG traces is the single trial phase locking value, which, has we have mentioned earlier, has been identified as a promising feature for EEG classification [7], [8].

The PLV is a statistic used to investigate synchronization of neural activity from EEG data and expresses a measure of connectivity. The equation that we used for this measure is:

$$S_{PLV} = \frac{1}{N} \sum_{k=1}^{N} e^{j|\varphi^1(k) - \varphi^2(k)|} \tag{1}$$

Where N is the number of samples in the considered time window, φ^1 and φ^2 are the phase values of the two signals that we want to compare [6]. The computed S-PLV is a number between 0 and 1 that reflects how the two channels are synchronized to each other. The phase value is computed using the Hilbert Transform [6], [9].

B. *Spatial filters optimization*

Considering that S-PLV is the result of a comparison between two channels we had to find two spatial filters that will create two new channels, each one a different combination of all the recorded ones. Indeed, as mentioned before, the EEG signals from individual channels is prone to have a low SNR, due to spatial blurring and volume conduction effects. In order to obtain better PLV features for EEG classification, it thus seems relevant to compute the PLV between two spatially filtered channels (thus with a higher SNR), rather than between two original channels. We therefore propose an algorithm to optimize these two spatial filters in order to maximize the resulting PLV feature discriminative power.

We represented EEG traces with a 3D matrix $X \in \mathbb{R}^{Nc \times Ns \times Nt}$ (with Nc the number of channels, Ns the number of samples and Nt the number of trials), the two spatial filters w_1 and w_2 were two vectors in $\mathbb{R}^{Nc \times 1}$. The two new channels $\hat{X}^1, \hat{X}^2$ were computed as follows:

$$\hat{X}^1 = w_1^t X \tag{2}$$

$$\hat{X}^2 = w_2^t X \tag{3}$$

where t denotes transpose. The idea for optimizing the spatial filters was to maximize the difference of the S-PLV between the two new filtered channels during two different conditions, hence maximizing the following functional:

$$Diff = |S\_PLV(w_1^t X_1, w_2^t X_1) - S\_PLV(w_1^t X_2, w_2^t X_2)| \tag{4}$$

where X_1 were the EEG traces recorded under one condition and X_2 were the EEG traces recorded during the second condition. In other words, this functional amounts to optimizing spatial filters such that the resulting S-PLV value is maximally different between the two conditions.

To avoid obtaining two identical spatial filters, which would be useless (a signal is necessarily synchronized with itself), we proposed to enforce the orthogonality of the two spatial filters by introducing a regularization term expressed as:

$$Ort = \frac{|w_1^t w_2 * Diff|}{dim(w_2)} \tag{5}$$

In this way the orthogonality value was scaled according to the value computed in $Diff$. Combining the two members gives the final functional which was maximized by the GA:

$$fitness = Diff - \alpha * Ort \tag{6}$$

where α was a parameter between 0 and 1 indicating how the second member weighs, i.e., how much we want to enforce the spatial filter orthogonality

The PLV value is meaningful only if it is computed in a certain frequency band, thus the first operation of our research process was a frequency filter, and specifically we chose to filter the signal between 8-24Hz, which contains both the Mu (8-12 Hz) and Beta (12-24 Hz) rhythms, which are involved in motor imagery [10]. For searching the solution we developed a Genetic Algorithm working on a population of random chromosomes, each containing the weights of the two spatial filters. The GA evolves using elitism, tournament-k selection, single point crossover maintaining gene integrity, and mutation [11]. The GA was set to evolve the population for a predefined number of generations. The fitness function for evaluating each chromosome was computed according to Equation(6).

The best solution found by the GA was then used as an initialization point for the *fminsearch* function of the MATLAB Optimization Toolbox, in order to obtain a better local solution. For using this functionality we had to search a minimum, thus we decided to minimize the inverse of (6):

$$fun = \frac{1}{fitness} \tag{7}$$

C. *Evaluation*

Our approach was evaluated on data set 2a from BCI competition IV [12], provided by the Graz group [13]. This set comprises EEG signals from 9 subjects who performed left hand, right hand, foot and tongue Motor Imagery (MI). The EEG signals were recorded using 22 EEG channels.

TABLE 1

CLASSIFICATION ACCURACIES (MEAN, MEDIAN AND STANDARD DEVIATION (STD) IN %) OBTAINED
FOR EACH SUBJECT FOR DIFFERENT APPROACHES. BEST PERFORMANCES ARE DISPLAYED IN BOLD.

	Subj1	Subj 2	Subj3	Subj4	Subj5	Subj6	Subj7	Subj8	Subj9	Mean $\pm std$	Median
PLV	73.61	54.89	78.47	60.42	**54.17**	49.31	50.69	77.08	78.47	64.12 $\pm$12.59	60.42
PLV SP. FILT.	84.72	54.17	93.75	68.06	47.22	69.44	68.61	93.75	85.42	73.90$\pm$16.66	69.44
CSP	87.50	50	94.44	72.22	51.39	**74.30**	61.80	99.30	90.97	75.77$\pm$18.50	74.30
CSP (3 filter pairs)	84.72	**58.33**	91.67	68.75	53.47	63.88	**75.69**	97.91	89.58	76$\pm$15.83	75.69
PLV+CSP	**89.58**	57.64	**97.22**	**74.31**	51.39	73.61	66.67	99.30	**92.36**	**78.00$\pm$17.49**	74.31
PLV+CSP (3 filter pairs)	86.11	56.94	95.83	70.11	53.47	64.54	78.47	**99.31**	86.11	76.76$\pm$16.50	**78.47**

For the purpose of this study, only EEG signals corresponding to left and right hand MI were used. EEG signals were band-pass filtered in the 8-24 Hz frequency band using a 250th order Finite Impulse Response (FIR) filter used with Matlab *filtfilt* function. Indeed, this frequency band contains the mu (8-12 Hz) and beta (12-24 Hz) rhythms, i.e., the main frequencies involved in MI [10]. A training and a testing set were available for each subject. Both sets contained 72 trials for each class, the duration of a trial being 7 sec. Subjects performed MI within the time interval of t=3 to 7 sec of each trial. In this work, we only considered the discrete classification of the trials, i.e., we assigned a class to each trial and not to each trial sample. In order to do so, we extracted the features from the time segment t=3 to t=6 sec of each trial.

We used the available training set for the GA evolution and *fminsearch* computation. The initial population of the GA was set to 300 chromosomes and evolves for 300 generations. Then the two spatial filters were applied to the data and a feature value for each trial was computed as the S-PLV between the two new channels (i.e., between the two spatially filtered signals).Training trials were provided as input to an Support Vector Machine (SVM) [14] in order to train the classifier to recognize the two classes (left hand MI vs. right hand MI). Trials belonging to the test set were then classify with the trained SVM. For all evaluations and all subjects, we used α=0.8, which we found was a good default value. Moreover in order to compare our approach with those available in the literature, we also computed the performance obtained with CSP spatial filtering in the 8-24 Hz band, evaluating the performances with both one pair of CSP filters (i.e., as many filters as with our approach) and with three pairs of CSP filters (i.e., the standard way [4]). We also explored whether combining spatially filtered S-PLV features with CSP features was relevant. To do so, we concatenated the features extracted with CSP with the new ones derived from the proposed spatially filtered S-PLV and used them as input to the SVM classifier.

3. RESULTS

Table I presents the results in term of classification accuracy obtained on the test set by using the different signal processing approaches mentioned. The first row presented the best result obtained using the S-PLV computed between each pair of the available channels (i.e., without spatial filtering). Using a 5-fold-cross-validation we selected the best pair of channels for each subject in terms of classification accuracy on the training set.

In the second row is reported the classification accuracy obtained using the S-PLV between the two channels computed with the proposed spatial filters. The spatial filter algorithm outperformed the original S-PLV by about 9% in both mean classification accuracy and median classification accuracy. This confirms that our spatial filters improve the discriminative power of the S-PLV features.

The third and fourth row of Table I reports the performances obtained with the standard design, i.e., CSP features, with 1 pair and 3 pair of spatial filters respectively.

In the last two rows of the table are presented the results obtained on the test set combining the CSP approach and the spatially filtered PLV approach proposed in this work. Using one pair of CSP filters with the new PLV feature we improved the mean classification accuracy by 3%, as compared to CSP alone. Otherwise using three pairs of CSP filters with PLV led to an increase in median accuracy, but no increase in mean accuracy probably due to overfitting. Overall the best performances are still achieved combining CSP and PLV.

Figure 1 presents the spatial filters obtained for subject 3. The first two figures represent the solution found with the GA, while the last two the solution obtained by the local search (*fminsearch* function), after the GA. Comparing the 4 figures it is clear that *fminsearch* performed a local search around the solution of the GA. *Fminsearch* shapes the two spatial filters making them more specific by better identifying the cortical areas whose signals should be enhanced or suppressed to build two new channels whose signals are synchronized in one class and de-synchronized in

the other. Figure 2 reports the evolution of the fitness value during the generation of the genetic algorithm. In particular, it shows the evolution of both terms composing the fitness function. It is remarkable to see how in the last generation the term related to the difference ($Diff$, see Equation (4)) still increases while the term related to the orthogonality (Ort, see Equation (5)) decreases.
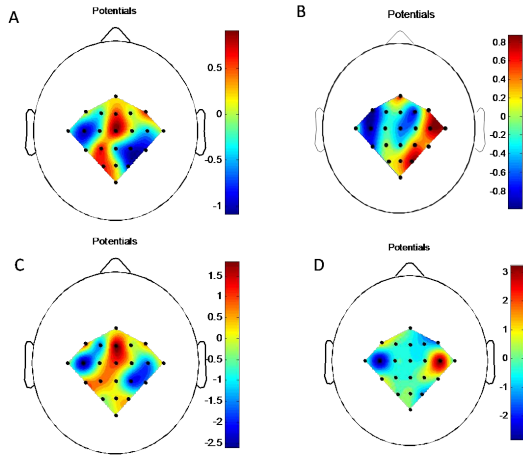

Figure 1 Spatial filters: image A and image B represent the two spatial filters found with the GA, C and D are the spatial filters optimized with *fminsearch*, following the GA use.
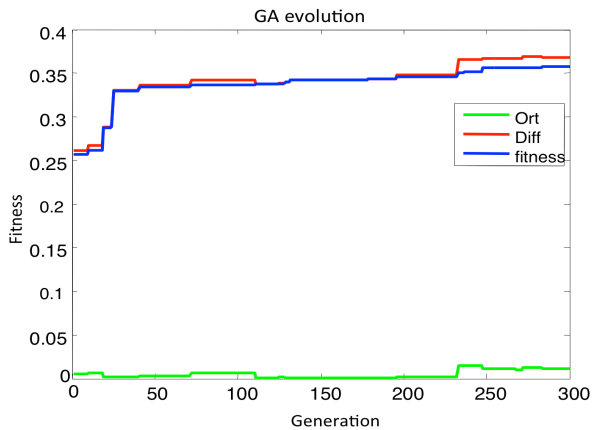

Figure2 Evolution of the fitness function during generation of the genetic algorithm for subject 3

4. DISCUSSION

The results obtained give several interesting insights. Concerning performances, they first show that computing a S-PLV-feature between two spatially filtered signals does lead to increased classification performances as compared to computing the S-PLV between two raw EEG channels. This further confirms the usefulness of designing optimal spatial filters for the different EEG features that are relevant for BCI design. Second, our results show that, at least for motor imagery-based BCI, spatially filtered PLV features do extract a different information than spatially filtered band power features (i.e., CSP features) since combining them

increases the overall classification performances. This makes optimally spatially filtered S-PLV features a valuable addition to the repertoire of features that can be used by EEG-based BCI designers.

In this work, we optimized a single pair of spatial filters which resulted in a single PLV feature. As such, our method might not have extracted all the relevant information, and maybe some other spatial filter pairs could have been used to increase the performances further. In the future, it may be useful to use, e.g., deflation approaches to extract several pairs of spatial filters from which computing PLV features. Furthermore GA generation takes time (several hours) then it could be useful to find an analytical solution to optimize the proposed functional.

From a neurophysiological point of view, it is worth noting that the obtained spatial filters can be interpreted to check the plausibility of the extracted features or to gain some insights about the brain dynamics. Here, as can be seen in Figure 1, one of the two spatial filters has strong weights on the brain motor areas (electrodes C3 and C4, images B and D), while the other one has strong weights on the brain frontal areas (electrodes FCz, Fz). This suggests that phase synchronization between the frontal and motor areas, in the Mu and Beta bands, might change during motor imagery and could be used to identify the type of motor imagery (left hand vs. right hand). However, since such spatial filters are "backward" models, this interpretation may be erroneous and should be considered with caution [15]. Nonetheless, this is in line with previous research on PLV-feature based BCI design [7], which confirms the validity and relevance of the proposed optimization algorithm.

5. CONCLUSION

In this paper, we proposed a method, based on a genetic algorithm, to create an optimal spatial filter pair for EEG signal classification with S-PLV-features. We demonstrated the validity of our method for classifying signal coming from BCI experiments based on motor imagery. We notably showed that our spatial filters led to higher classification performances, and that combining the resulting S-PLV features with CSP boosts the overall BCI performances.

Future work could aim at applying the proposed algorithm to different data sets and BCI tasks, to explore its scope of applicability. Moreover, we could optimize more pairs of orthogonal spatial filters in order to further increase classification performance and also it could be interesting to consider time as well. Overall, we hope our method could be a new and valuable addition to the repertoire of EEG signal processing tools.

6. ACKNOWLEDGMENTS

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