A Brain-Switch using Riemannian Geometry

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Abstract

This paper addresses the issue of asynchronous brain-switch. The detection of a specific brain pattern from the ongoing EEG activity is achieved by using the Riemannian geometry, which offers an interesting framework for EEG mental task classification, and is based on the fact that spatial covariance matrices obtained on short-time EEG segments contain all the desired information. Such a brain-switch is valuable as it is easy to set up and robust to artefacts. The performances are evaluated offline using EEG recordings collected on 6 subjects in our laboratory. The results show a good precision (Positive Predictive Value) of 92% with a sensitivity (True Positive Rate) of 91%.

1   Introduction

Asynchronous BCIs are of major interest in order to set-up practical BCI system in real-life conditions. Such BCI attempts to detect predefined brain pattern during operation and the user can send a command at any time. This is the most natural way but also the more difficult since one has to discriminate specific brain patterns with respect to the ongoing brain activity. A particular case of asynchronous BCI is called a brain-switch when only one brain state is to be detected in the ongoing brain activity [1]. A brain-switch could allow the user to indicate the system s/he is ready for an action [2] or simply sends a binary command very much like an electrical switch. The false rate should be kept as low as possible to let the communication system silent, when the user does not intend to communicate. Different brain-switches have been proposed based on different sources of BCI control, such as the post-imagery beta ERS [3].

Motor Imagery (MI) is a mental simulation or rehearsal of a movement without motor output, which results in the activation of dedicated cortical areas (somatosensory cortex) in given frequency bands. MI is often used in BCI applications since the brain patterns and areas involved are well known. Moreover, from the user point of view, it is also a natural way to interact. It has been observed that spatial covariance matrices are central to the detection process and that the respect of their topology using Riemannian geometry can improve the problem at hand. In this paper we propose to build a brain-switch based on direct manipulations of spatial covariance matrices using concepts of distance and geometric mean using a Riemannian metric. The classifier is first trained using a self-paced motor imagery BCI system and then evaluated offline on test recording which follows the same paradigm.

2   Methods

In the proposed approach, spatial covariance matrices are the features of interest for the brain-switch detection task and they are manipulated by doing computations within the manifold of symmetric positive-definite (SPD) matrices. The brain-switch is implemented on a sliding trial manner, where each trial is detected as a (specific) brain pattern and the result is aggregated within time to activate or not the brain-switch.

2.1 Riemannian Metric

Let $\mathbf{X} \in \mathbb{R}^{C \times N_t}$ be a short-time segment of EEG signal, which corresponds to a trial of motor imagery: C is the number of channels and N_t is the number of samples in a trial. We assume further that $\mathbf{X}$ has been band-pass filtered in a pre-processing step, and that the spatial covariance matrix of the trial is estimated by the Sample Covariance Matrix (SCM) :

$$\mathbf{P} = \frac{1}{N_t - 1} \mathbf{X}\mathbf{X}^T \tag{1}$$

A key observation is that SCMs are symmetric positive-definite (SPD) matrices that belong to the manifold $P(C)$. Using Riemannian geometry, it is possible to define precisely the distance between any two SPD matrices $\mathbf{P}_1$ and $\mathbf{P}_2$ as :

$$\delta_R(\mathbf{P}_1, \mathbf{P}_2) = \left[\sum_{c=1}^{C} \log^2 \lambda_c \right]^{1/2} \tag{2}$$

with $\{\lambda_c, c = 1 \ldots C\}$ the eigenvalues of $\mathbf{P}_1^{-1}\mathbf{P}_2$ [4]. This formula has some reminiscence with the common spatial pattern technique as demonstrated in [5].

If we are now given a set of M covariance matrices, it is possible to estimate the (Frechet) mean of this set using :

$$\mathfrak{G}(\mathbf{P}_1, \ldots, \mathbf{P}_M) = \underset{\mathbf{P} \in P(C)}{\arg\min} \sum_{m=1}^{M} \delta_R^2(\mathbf{P}, \mathbf{P}_m) \tag{3}$$

Although no closed-form expression does exist, this (geometric) mean can be computed efficiently using an iterative algorithm [6].

2.2 Brain-switch based on covariance matrices

The estimate of the covariance matrix of the band-pass filtered EEG signal in the specific condition $y = s$, (e.g., left-hand or right-hand movement imagination) can be readily obtained using the previous section as :

$$\mathfrak{G}_s = \mathfrak{G}(\mathbf{P}_i, \, i \, | y_i = s)$$

It can be expected that all these points will be clustered in a very delimited portion of the manifold $P(C)$. This allows us to define a region of interest (ROI) in the manifold based on the intra-class covariance matrix and a threshold distance. The ROI is parameterized by the equation : $\Omega = \{\mathbf{P} \mid \delta_R(\mathbf{P}, \mathfrak{G}_s) < \epsilon\}$ where $\epsilon = m + 3s$ with m and s denote respectively the median and standard deviation of the point-to-center distances $\{\delta_R(\mathbf{P}_i, \mathfrak{G}_s), \, i \, | y_i = s\}$.

This simple criterion is very efficient to remove large amplitude EEG artifacts from the analysis. However, it may not be not specific enough during a brain-switch operation mode. To improve the specificity of the detection, a second step consists in estimating the geometric mean $\mathfrak{G}_{\bar{s}} = \mathfrak{G}(\mathbf{P}_i, \, i \, | y_i = \bar{s}$ and $\delta_R(\mathbf{P}_i, \mathfrak{G}_s) < \epsilon)$ of the covariance matrices corresponding to the unspecific activity restricted to the computed ROI. By definition, the unspecific activity class is composed by all the activities excluding the specific one. The restriction to the ROI reduces the diversity of the unspecific activity class and thus allows the estimation of the corresponding mean covariance matrix. Again a very simple criterion is to decide whether a test trial belongs to the class of the closest mean in terms of Riemannian distance. The whole algorithm can be described as follows :

$$y = \begin{cases} s & \text{if } \delta_R(\mathbf{P}, \mathfrak{G}_s) < \epsilon \text{ and } \delta_R(\mathbf{P}, \mathfrak{G}_s) < \delta_R(\mathbf{P}, \mathfrak{G}_{\bar{s}}) \\ \bar{s} & \text{otherwise} \end{cases} \tag{4}$$

This classification output is then integrated along time to improve robustness. As a consequence, the brain-switch will be triggered ON when the specific activity is detected continuously for a given period of time T_s, typically 1 s. After being triggered, the brain-switch remains halted until the unspecific activity is detected continuously for another period of time $T_{\bar{s}}$, typically 1s.
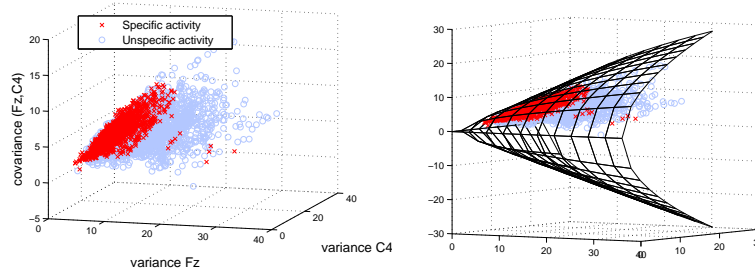
Figure 1: Covariance matrices positions for user E, channel *Fz* and *C4*. Training stage

3 Results

The brain-switch precision and sensitivity is now evaluated using EEG recordings collected on 6 subjects in our laboratory. These datasets have been recorded before the development of the algorithm presented in this paper, with an adaptive implementation of spatial filtering by CSP and classification by LDA. For this reason, the results presented hereby are related to offline processing of these measurements. For each subject, 16 active electrodes (from g.tec) are disposed on the whole scalp according to the 10/20 system (Fpz F7 F3 Fz F4 F8 T7 C3 Cz C4 T8 P7 P3 Pz P4 P8). A sampling frequency of 512 Hz and a general band-pass filter between 8 and 30 Hz were used. The training stage consists in a self-paced motor imagery paradigm and lasts up to 15 min. The user is sited in front of a computer screen and a continuous visual feedback is provided. It consists in a blue vertical bar which evolves jointly with the detection output. The user strokes a key to indicate the system that s/he wants to begin a specific mental task. Each mental task is performed until the switch is triggered ON, with a maximal duration of 10 s. The algorithms are continuously adapted. The testing phase of 5 min is done on a self-paced operation mode similarly to the training stage, but without the adaptation of algorithms. It is important to notice that the unspecific activity corresponds to a concentrated resting state and does not reflect the whole diversity of the unspecific activity, which can be seen during long-term EEG recording.

Figure 1 shows the manifold of spatial covariance matrices in case of two channels. Each point represents an 2×2 SPD matrices estimated on a sliding windows of 1 second, either in specific condition (red points) or unspecific one (blue points). We note that the matrices belonging to the specific activity class lie in a compact area while the other ones are spread over a larger area. Moreover, we see that the points corresponding to the specific activity are close to the boundary of the manifold which is a cone. Such locations correspond to high correlations between the two chosen electrodes.

Figure 2 shows the class-dependent distribution of Riemannian distances from the center of the ROI during the learning stage for user E. In this example, 96.5% of the trials corresponding to the specific activity are within the ROI while 20% of the trials corresponding to the unspecific activity are outside the ROI. A visual inspection of the signal shows that most of rejected trials correspond to artifacts.

Figure 3 shows the classification process on the test data for user E. The threshold of detection given Eq. 4 is represented by the dashed line. In this example, 85% of unspecific activities and 72% of specific activities have been correctly classified.

Figure 4 shows the temporal output of the brain-switch for 10 realisations of specific mental tasks of various length after the integration along time. During this period, only one event is a false positive. We can also see that the switch triggered ON at the beginning of most trials, shows the reactivity of the brain-switch.

Finally, the results for the 6 subjects are given in Table 1. The average performance is about 91% for both PPV (Positive Predictive Value) and TPR (True Positive Rate) with 0.4 FP (False Positive) per minute, that is similar to the state of the art [3].
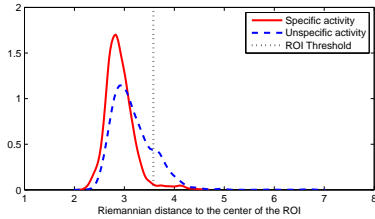
Figure 2: Distributions of the distance to the center of the ROI $\delta_R(\mathfrak{G}_s, \mathbf{P}_i)$ for the training data, user E.
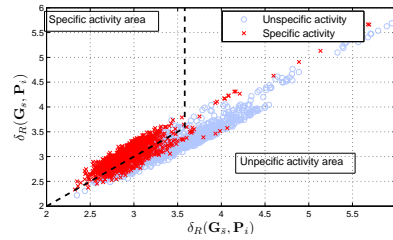

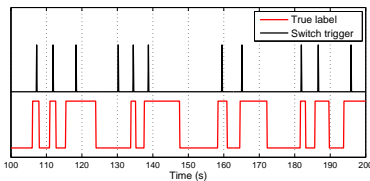
Figure 3: Classification of test data, user E

Figure 4: Temporal output of the brain-switch for test data, user E

$User$	PPV	TPR	TP/min	FP/min
A	100	84	4.8	0
E	94	100	6.4	0.4
G	94	100	6.8	0.4
I	80	64	2.6	0.6
J	83	100	5.2	1
M	100	100	7.2	0
mean	**91.8**	**91.3**	**5.5**	**0.4**

Table 1 : Results obtained offline for the 6 users.

4 Conclusions

The presented method is easy to set up in the EEG experiments. No parameters are needed to be set, and the large amplitude artifacts are natively handled. Offline results appear promising to go beyond the state-of-the-art. In addition, the training stage relies only on the estimation of class-related covariance matrices. The precision (PPV) could be improved by increasing the time T_s in return of losing sensitivity (TPR). Such an optimisation of timing should be done according to the application. This algorithm will be used in our next brain-switch experiments.

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