

# A Brain-Switch Using Riemannian Geometry

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## INTRODUCTION

- **Asynchronous BCIs** are of major interest in order to set-up practical BCI system in **real-life conditions**.
- 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**.
- In this work we propose to build a brain-switch based on **direct manipulations** of spatial **covariance matrices** using concepts of distance and geometric mean in the **Riemannian manifold** of SPD matrices.

## MOTOR IMAGERY AND COVARIANCE MATRICES

- 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
- The spatial covariance matrix carries the spatial and band power information. In the context of motor imagery they can be used as EEG signal descriptors.
- 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**.

## RIEMANNIAN GEOMETRY

$\mathbf{X} \in \mathbb{R}^{C \times N}$  → EEG signal, N time samples and C electrodes.

$\mathbf{P} = \frac{1}{N-1} \mathbf{X} \mathbf{X}^T$  → Spatial covariance matrix

$\delta_R(\mathbf{P}_1, \mathbf{P}_2) = \left[ \sum_{c=1}^C \log^2 \lambda_c \right]^{1/2}$  → Distance between two covariance matrices with  $\lambda_c$  the eigenvalues of  $\mathbf{P}_1^{-1} \mathbf{P}_2$

$\mathfrak{G}(\mathbf{P}_1, \dots, \mathbf{P}_M) = \arg \min_{\mathbf{P} \in \mathcal{P}(C)} \sum_{m=1}^M \delta_R^2(\mathbf{P}, \mathbf{P}_m)$

→ Geometric mean of M covariance matrices

## METHOD

The goal is to detect a **specific activity** in the ongoing (**unspecific**) brain activity.

### Training stage :

Given M covariance matrices  $\mathbf{P}_i$  with the corresponding labels  $y_i \in \{s, \bar{s}\}$  the training stage is three step:

1. Estimating the mean covariance matrix of the specific activity

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

2. Defining a region of interest which contains the majority of the covariance matrices corresponding to the specific activity.

$$\Omega = \{\mathbf{P} | \delta_R(\mathfrak{G}_s, \mathbf{P}) < \epsilon\}$$

3. Estimating the mean covariance matrix of the unspecific activity for the matrices within the region of interest:

$$\mathfrak{G}_{\bar{s}} = \mathfrak{G}(\mathbf{P}_i, i | y_i = \bar{s} \text{ and } \delta_R(\mathbf{P}_i, \mathfrak{G}_s) < \epsilon)$$

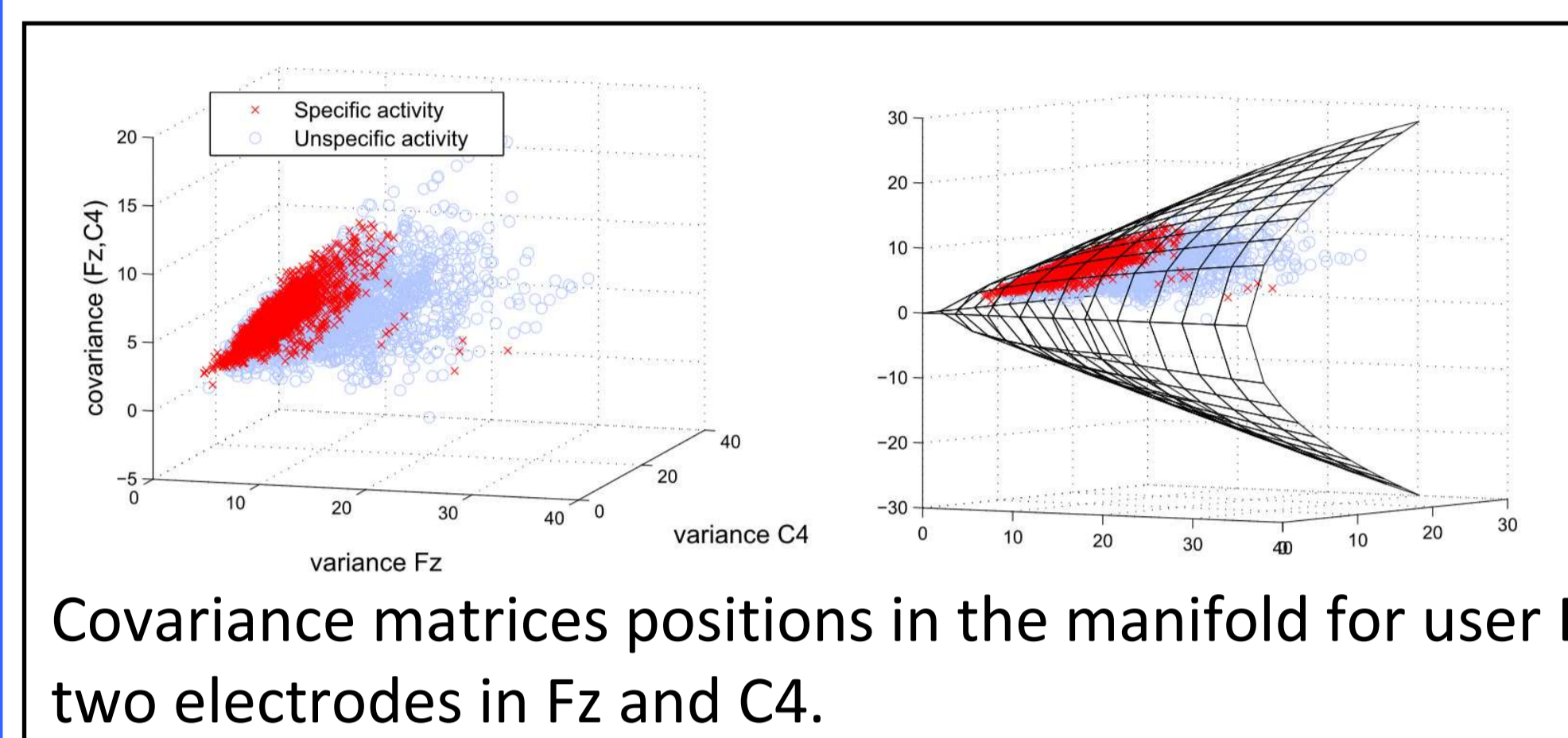
### Classification :

Let P a covariance matrix of unknown class y :

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

## RESULTS

- Offline processing of a dataset recorded in our laboratory. 6 subjects, 16 electrodes, 512 Hz, broadband filter 8-30Hz, g.tec amplifier.

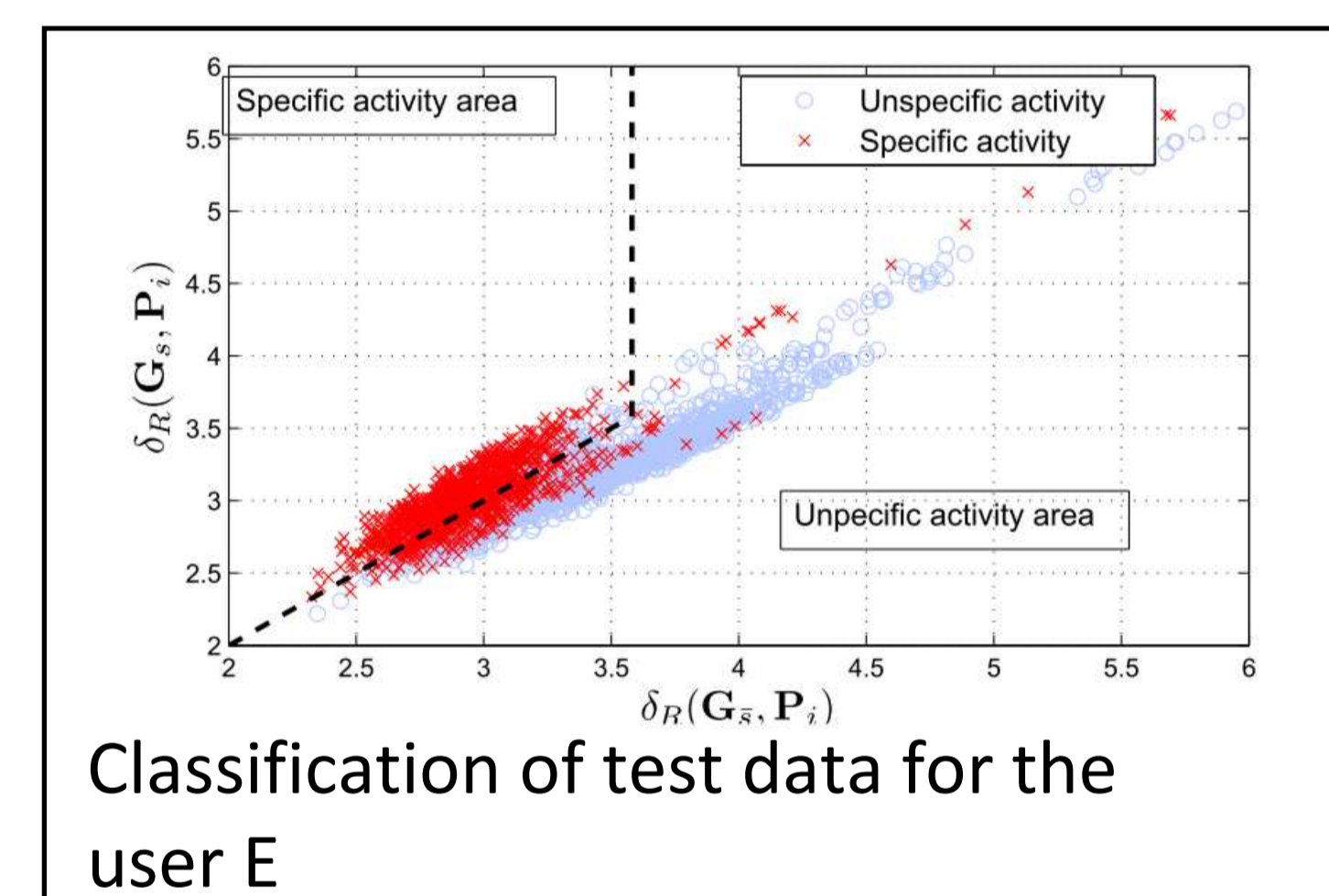
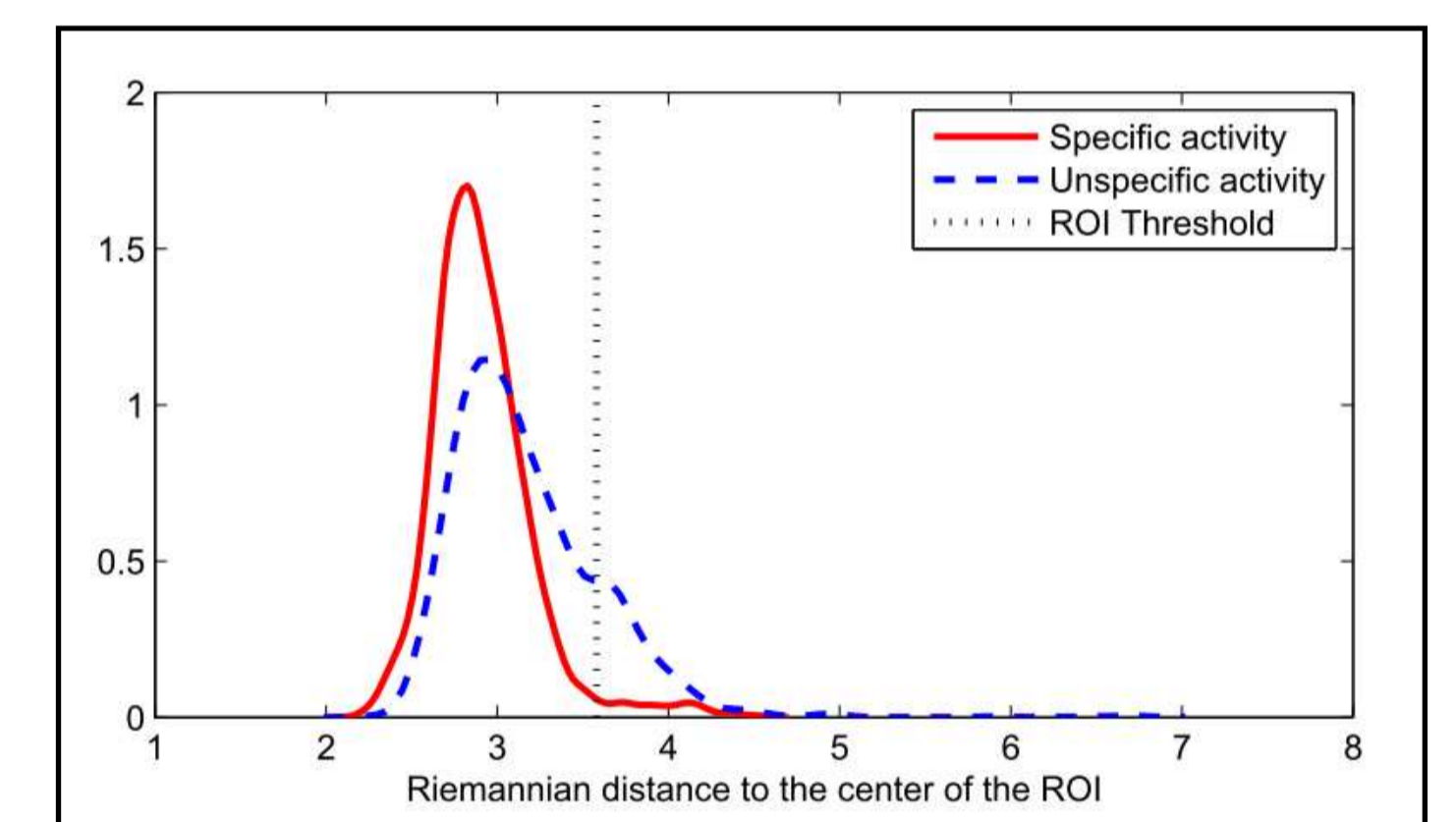


The matrices belonging to the specific activity class lie in a compact area while the other ones are spread over a larger area, theoretically completing the whole manifold.

Covariance matrices positions in the manifold for user E, two electrodes in Fz and C4.

The ROI threshold is obtained from the class-dependent distribution of Riemannian distances.

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.

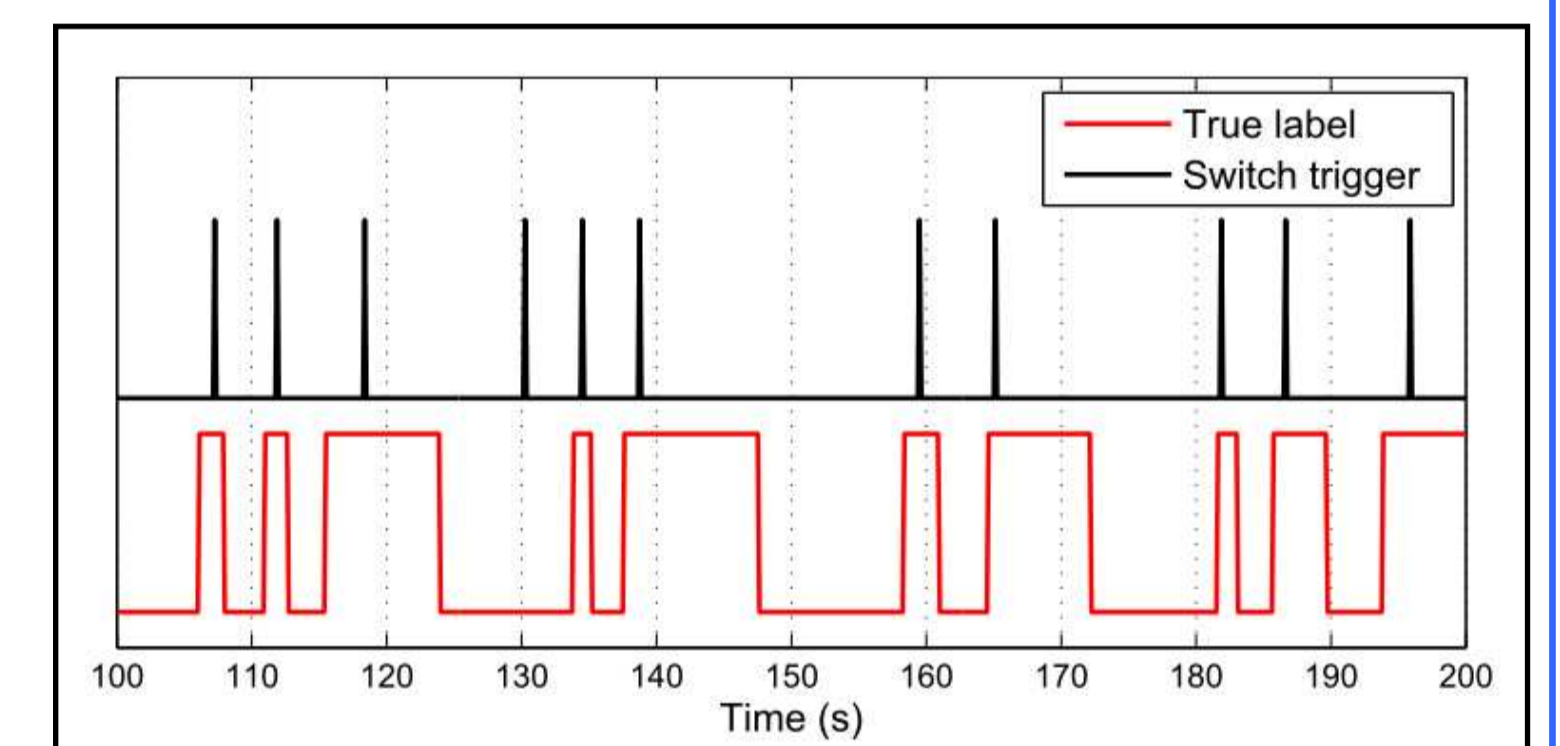


The decision rule is only based on the Riemannian distance to means. The region of interest rejects most of artifacts.

In this example, 85% of unspecific activities and 72% of specific activities have been correctly classified.

- This classification output is integrated along time to improve robustness :

- The brain-switch will be triggered ON when the specific activity is detected continuously during 1 s.
- The brain-switch remains halted until the unspecific activity is detected continuously during 1 s.



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	<b>91.8</b>	<b>91.3</b>	<b>5.5</b>	<b>0.4</b>

Table 1 : Results obtained offline for the 6 users.

The average performance is about 91% for both Positive Predictive Value (PPV) and True Positive Rate (TPR) with 0.4 False Positive (FP) per minute.

## CONCLUSION

- Simple method without spatial filtering using a distance based-classification
- The definition of a region of interest in the Riemannian manifold allows to handle artifacts natively.
- Can easily be made adaptive by the update of mean covariance matrices and region of interest.