Classification in Riemannian space: an application to sleep EEG.

Decoding the brain activity of dreamers and non-dreamers.

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Introduction

Riemannian approaches for EEG signal decoding are currently attracting increasing attraction[9].

Sleep data analysis provides a good application for machine learning methods and can be used to classify sleep related phenomena[3], [4].

The aim of this study was to explore the feasibility of classification in Riemannian manifolds to distinguish between sleep EEG data in individuals with high versus low dream recall.

Methods

Subjects and data[2], [6]

High dream recallers (HR): dream recall at least 3 mornings per week. (18 subjects)

Low dream recallers (LR): dream recall on less that 3 mornings per month. (18 subjects)

Data composed of EOG, EMG and 19 scalp-EEG channels placed according to the International 10–20 System. EEG channels are visually scored in 30s windows (according to the R&K guidelines).

Data analysis

Classification of HR vs LR

Features:

- Power Spectral Densities* (PSDs)
- Cross-spectrum** matrices
- Covariance matrices

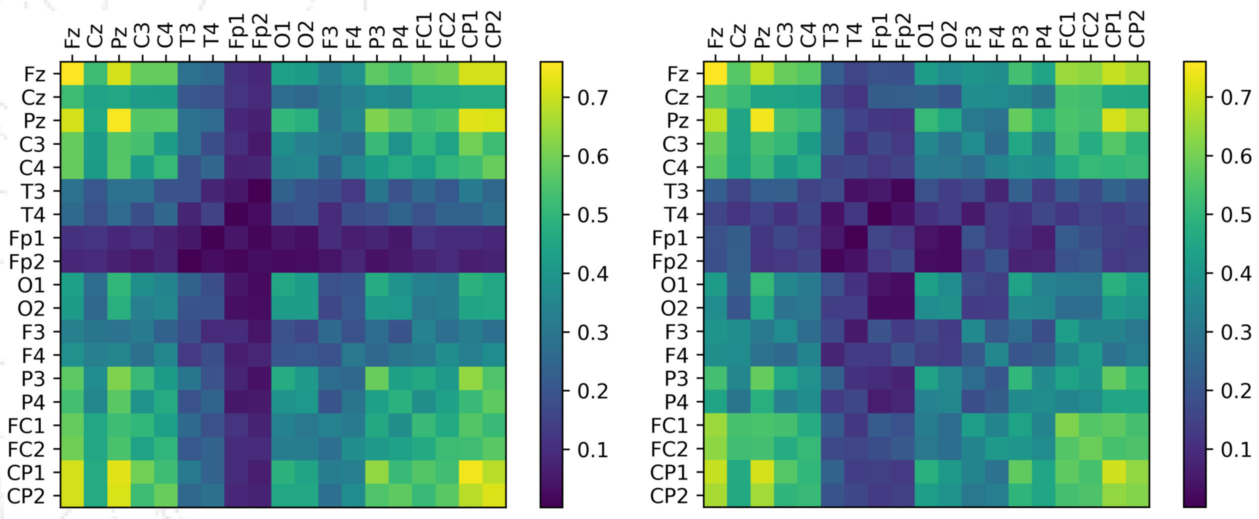

Figure 1: Normalized cross-spectrum matrices (S2 sleep stage, Sigma frequency band) of random subjects of each condition (LR on the left and HR on the right).

Algorithms:

- Linear Discriminant Analysis (LDA) for the PSDs.
- Tangent Space LDA (to a Riemannian manifold) for the cross-spectrum and covariance matrices.

	Delta	Theta	Alpha	Sigma	Beta	Gamma1	Gamma2
fmin	2	4	8	11	13	30	60
fmax	4	8	13	16	30	60	90

Table 1: Frequency bands used for PSD computation, values in Hertz (Hz)

** PSD computed with sliding windows of 1s on the 30s sub-trials using the frequency band values of table 1.*
*** Covariance matrices computed between electrodes on the PSD values to get a cross-spectrum matrix.*

Results

LDA Classification with PSD values

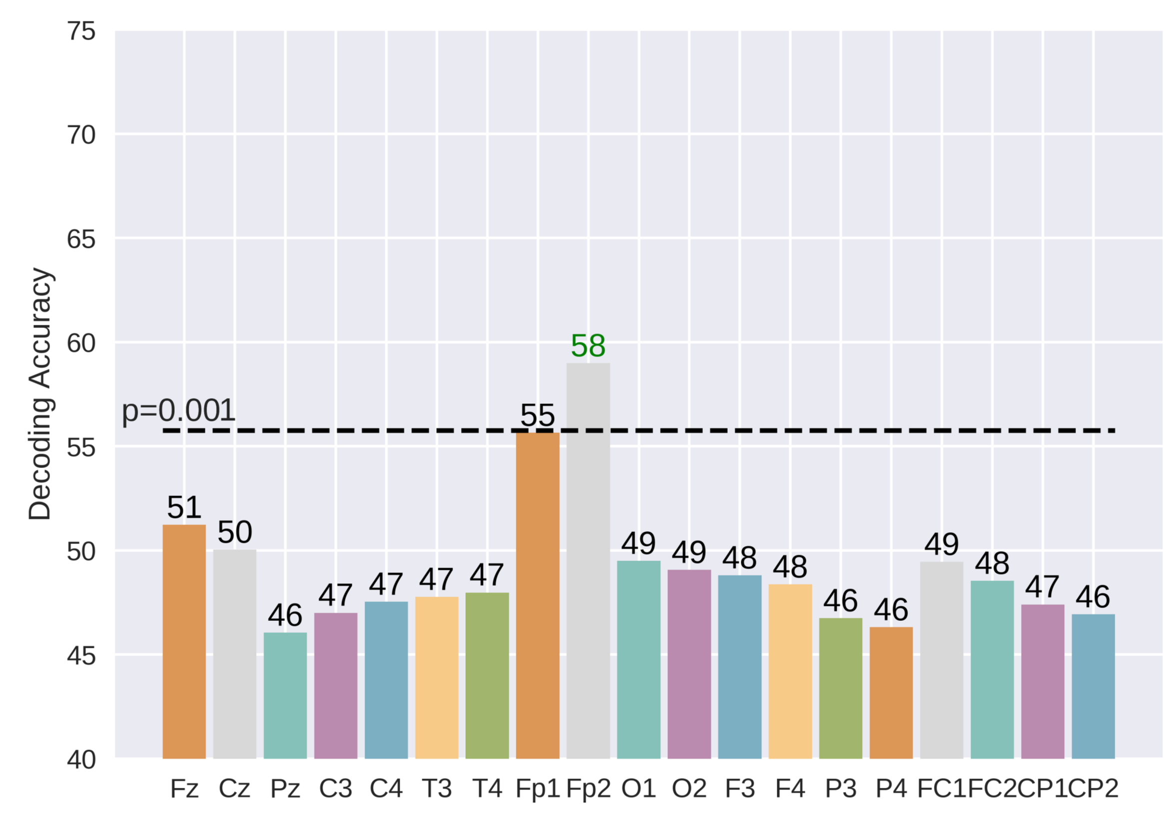

Figure 2: results in the Alpha band. Significance tested with a permutation test (1000 permutations).

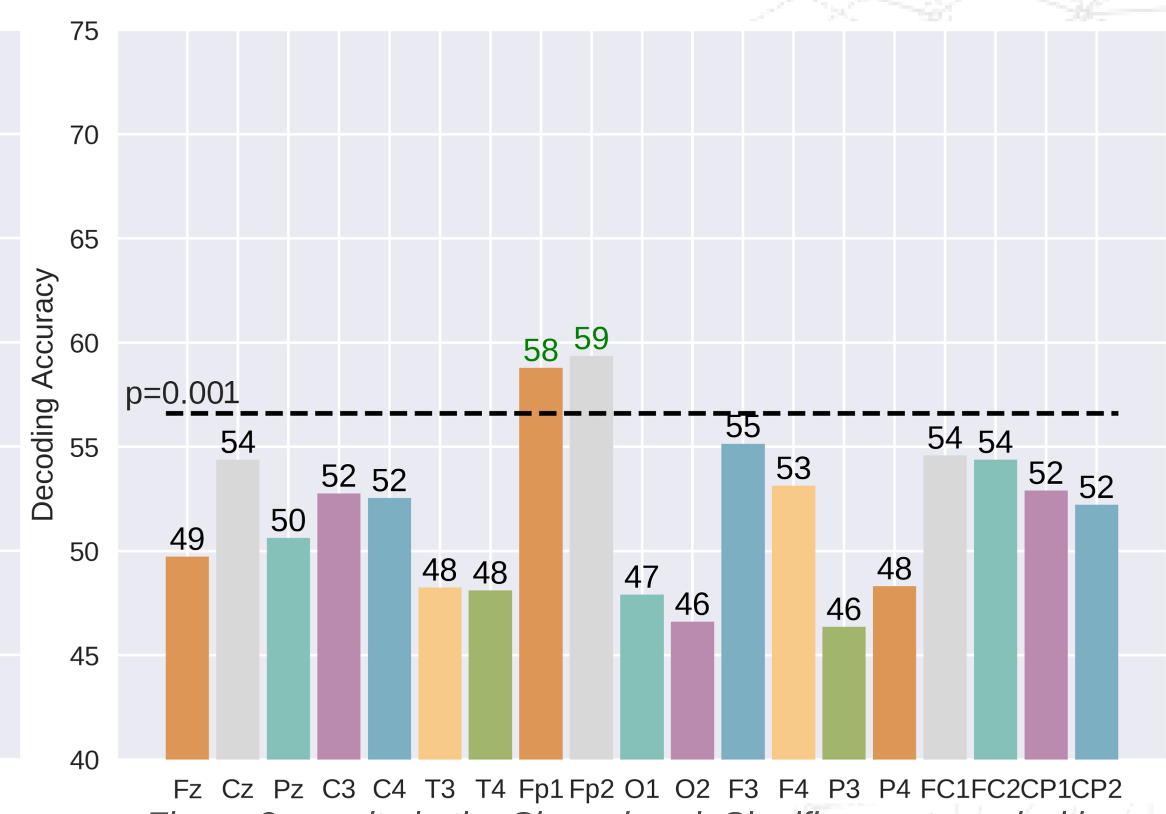

Figure 3: results in the Sigma band. Significance tested with a permutation test (1000 permutations).

Significant results in S2 only, in the Alpha and Sigma frequency bands on Fp1 and Fp2. We are currently investigating if these results are due to difference in eye movements. Previous results showed significant differences in S2 and Sigma and Alpha frequency bands but in the occipital area[5],[7].

LDA Classification in the Riemannian space

Cross-spectrum matrices allow to get much better and more significant results:

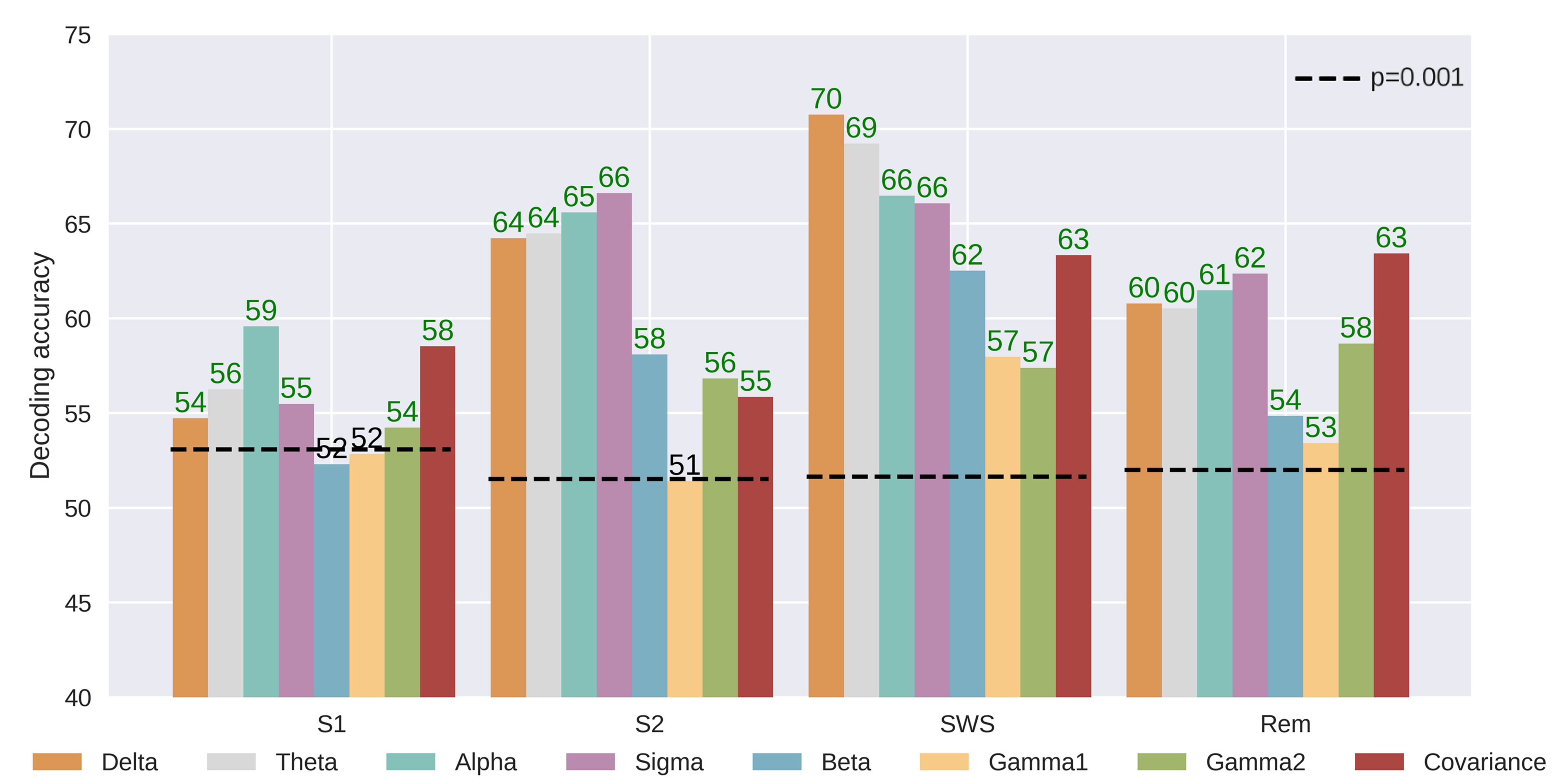

Figure 4: Decoding accuracy of cross-spectrum matrices and covariance matrices using TSLDA. Significance tested with the binomial law.

Best significant results: in S2 and SWS which seems to confirm previous research[4], [7], [8]. The variation in decoding accuracies between Fig. 4 and Fig. 2-3, could be explained by the added connectivity information which lies in the cross-spectrum matrices.

Conclusions

Our results confirm that the Riemannian classification, that had already proven to deliver high classification results for BCI problems[1], [9]., gives better results for the classification of HR vs LR in sleep EEG,

As demonstrated here, classification in Riemannian manifolds is a very promising machine-learning techniques for EEG data. One of its strengths is that it incorporates cross-channel information in the time or frequency domain[1].

References

1. Congedo et al, Brain-Computer Interfaces, Taylor & Francis, 2017
2. Eichenlaub et al, 2012, 2014
3. Lajnef et al, J Neuroscience Methods, 2015.
4. Lajnef et al, Front Hum Neuroscience, 2015.
5. Niielsen et al, Sleep Spindles & Cortical Up States, 2017
6. Ruby et al., 2013a,b.
7. Toneni et al, Nature Neuroscience, 2017
8. Vallat et al, Frontiers in human neuroscience, 2017
9. Yger et al, IEEE Transactions on neural systems and rehabilitation engineering, 2017