Riemannian Geometry on Connectivity for Clinical BCI
Camille Noûs, Marie-Constance Corsi, Sylvain Chevallier, Florian Yger

To cite this version:
Camille Noûs, Marie-Constance Corsi, Sylvain Chevallier, Florian Yger. Riemannian Geometry on Connectivity for Clinical BCI. ICASSP 2021, Jun 2021, Toronto / Virtual, Canada. 10.1109/ICASSP39728.2021.9414790 . hal-03202349

HAL Id: hal-03202349
https://hal.science/hal-03202349
Submitted on 27 Apr 2021

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L’archive ouverte pluridisciplinaire HAL, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d’enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.
Remannian geometry

The diffusion of Riemannian geometry for motor imagery BCI has strongly increased in the past decade [3]. This method consists in the extraction of Symmetric Positive Definite (SPD) matrices, usually the covariance matrices among sensors, for each trial and in considering this as a curved space. Here, to estimate the distance between two matrices A and B, we used the LogEuclidean distance via the Frobenius norm:

$$d_L(A, B) = \| \log(A) - \log(B) \|_F$$

Functional connectivity

Two main estimates were computed within the alpha-beta frequency band (8-30 Hz): the coherence (Coherence) and the phase-locking value (PLV).

Coherence (Coherence)

$$\text{Coherence}(f) = \frac{\text{Im}(\mathbf{A}^H \mathbf{B})}{\sqrt{\text{Im}(\mathbf{A}^H \mathbf{A}) \text{Im}(\mathbf{B}^H \mathbf{B})}}$$

Phase-locking value (PLV)

$$PLV = \frac{\mathbf{A}^H \mathbf{B}}{\| \mathbf{A} \|_F \| \mathbf{B} \|_F}$$

Ensemble classifier

Spatial covariance (Cov), coherence (Coherence) and phase-locking value (PLV) are estimated from electroencephalographic (EEG) signals. A first level of classification was performed by Fishers Discriminant Machines (FgMDM) classifiers, that yield output decision probabilities to train a second-level classifier, a ridge regression classifier, that provided the final decision. The associated code is available at https://github.com/sylvienec/2018-ieee.

IEEE WCCI BCI Competition dataset

<table>
<thead>
<tr>
<th>Item</th>
<th>Information</th>
</tr>
</thead>
<tbody>
<tr>
<td>Participants</td>
<td>8 stroke patients</td>
</tr>
<tr>
<td>EEG dataset</td>
<td>12-channel montage</td>
</tr>
<tr>
<td>Tasks</td>
<td>6 trials for each subject</td>
</tr>
<tr>
<td>Training/Testing set</td>
<td>80/40 trials</td>
</tr>
</tbody>
</table>

Proof of concept

To assess the performance of our approach, we conducted a comparison of the estimators both at the individual and at the group level. For that purpose, we directly applied our approach to an EEG dataset obtained from 8 stroke patients in the frame of the IEEE WCCI Clinical BCI Challenge. There were 14 submissions to the competition from 12 different institutions around the world across 3 continents.

Our approach got the first position on this task with a substantial margin, the following teams having respectively kappa scores of 0.49 and 0.47 and accuracies of 74.69% and 73.75%. The kappa score obtained on validation is close to 0.68 and to the value obtained on training data with a 5-fold cross-validation. Our hypothesis is that this result is due to the robustness provided by a classification based on multiple sources.

Using FC estimators associated with an ensemble classifier gives the possibility to take into account the users’ specificity. After participating to the competition, we identified different approaches to improve our method. Further investigation should be done regarding the follow-up to the MDM and the dimensionality reduction. We plan to refine the selection of the frequency band of interest. Another promising lead would be to extract for each epoch several PSD matrices, each on a different frequency band, and to consider this set as a trajectory on the manifold.

References


Acknowledgements

The authors would like to thank the organizers of the WCCI BCI competition for giving them the opportunity to start this promising collaboration. EY thanks F. Lotté for suggesting several years ago the use of connectivity features in Riemannian classifiers.