Riemannian Geometry on Connectivity for Clinical BCI
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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 Log-Suissen distance via the Frobenius norm:

\[ d_F(A, B) = \| \log(A) - \log(B) \|_F \]

Functional connectivity

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

Coherence (Coh):

\[ \text{Coh}(f) = \frac{\text{Im}(\text{FRF}(f))}{\text{FRF}(f)} \]

Phase-locking value (PLV):

\[ \text{PLV}(x, y) = \frac{\text{cov}(x, y)}{\text{std}(x) \cdot \text{std}(y)} \]

For an illustrative purpose, we represented the values obtained by averaging the FC estimators in each task separately in a data obtained from one patient.

Ensemble classifier

Spatial covariance (CoC), coherence (Coh) and phase-locking value (PLV) are estimated from electroencephalographic (EEG) signals. A first level of classification was performed by FyGMDM classifiers that yielded 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/sylvieno/BCI-xgcrn.

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>Sampling rate 512Hz</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 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 9 different countries spread 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 74.99% 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


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