ElectroEncephaloGraphic signal processing & classification for Brain-Computer Interfaces

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From ElectroEncephaloGraphy (EEG)…

EEG signals acquisition

Example of EEG signals

Berger, H., *Ueber das Elektroenkephalogramm des Menschen*, Archiv für Psychiatrie und Nervenkrankheiten, 1929,
…to Brain-Computer Interface (BCI)

System translating measures of brain activity into commands or messages for an interactive application

Ex: Motor Imagery BCI-based [Bonnet, Lotte, Lécuyer, 2013]

EEG-based BCI: a promising technology

Communication & control

Gaming

Stroke rehabilitation

Neuroadaptive technologies

BCI principle

BCI are promising but not reliable enough

High error-rate
[Guger 2003]
[Blankertz 2010]

\~10-30\% of users cannot control a BCI
[Allison 2010]

⇒ We need more reliable BCI!
Making BCI reliable at the signal processing level

Brain activity pattern production → Measurement of brain activity → Brain signal processing → Decision → Sensory feedback

Challenges in EEG signal processing for BCI

- Noisy data [Goncharova 1999]
- Limited amount of training data [Lotte 2015]
- Within-user variability [Grosse-Wentrup 2013]

Outline

1. Standard EEG signal processing in BCI
2. Dealing with between-user variability
3. Dealing with noise
4. Dealing with limited training data
5. Dealing with within-user variability
6. Conclusion & perspectives
Standard EEG signal processing for BCI
Standard signal processing for Mental Imagery-based BCI

- **Spatial filtering**
- **Frequency filtering**
- **Features**
- **Classifier**

Raw EEG signals e.g., corresponding to imagined movements

Ex: Laplacian filters

e.g., 8-30 Hz for motor imagery

Standard: Band Power

Standard: Linear Discriminant Analysis (LDA)

\[ x' = \sum_i w_i x_i = wX \]
Basic spatial filters

Bipolar filters
- \( C_3' = FC_3 - CP_3 \)

Laplacian filters
- \( C_3' = 4*C_3 - FC_3 - C_5 - C_1 - CP_3 \)

Emphasize localized activity and reduce diffuse spatial activity

Band power features

Signal power in a given frequency band (here $\mu=8$-12Hz)

1s of raw EEG at C3 (left motor cortex)

1 feature: $\mu$ band power for channel C3 ($P_{C3-\mu}$)

Band-pass filtering in 8-12 Hz ($\mu$)

Temporal average

Power estimation (squaring)
Classification

- Linear Discriminant Analysis (LDA)
  - Need for « training » examples

Performance examples

- BCI competition IV, data set IIa (Tangermann et al, Frontiers, 2012)
  - 9 users, Left vs right hand motor imagery
  - 72 trials per class for training and testing
  - different spatial filters + 8-30 Hz band power + LDA

⇒ Still modest performances, huge between-user variability

Average Accuracy:

- C3-C4: 60,7%
- Bipolar C3-C4: 70,5%
- Laplacian C3-C4: 68%
Dealing with between-user variability
Using user-specific, data driven spatial filters: Common Spatial Patterns (CSP)

- Find spatial filters $w$ such that the variance of the filtered signal is maximal for one class and minimal for the other

$$J(w) = \frac{wx_1x_1^Tw^T}{wx_2x_2^Tw^T} = \frac{wc_1w^T}{wc_2w^T}$$

Features = variance of the spatially filtered signals = $\log(wxx^Tw^T) = \log(wcw^T)$

$w$: spatial filter to optimize
$X_i$: multichannel EEG signals from class $i$
$C_i$: covariance matrix from class $i$

CSP performance examples

- BCI competition IV, data set IIa
  - 9 subjects, left vs right hand motor imagery
  - 8-30 Hz band power+LDA, different spatial filters

Average Accuracy:

- C3-C4: 60.7%
- Bipolar C3-C4: 70.5%
- Laplacian C3-C4: 68%
- CSP: 78.1%
Using user-specific frequency bands: The Filter Bank CSP (FBCSP)

Ang et al, « Filter Bank Common Spatial Patterns in Brain-Computer Interfaces », IJCNN, 2008
## FBCSP Results

<table>
<thead>
<tr>
<th>Method</th>
<th>Classification accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Data Set I (5 subjects)</td>
</tr>
<tr>
<td>CSP</td>
<td>86.6</td>
</tr>
<tr>
<td>FBCSP</td>
<td>90.3</td>
</tr>
</tbody>
</table>

Efficiency of FBCSP (from Ang et al, IJCNN, 2008)

Winning algorithm of BCI competition 2008 on all EEG data sets

Ang et al, Pattern Recognition, 2011
Deep Learning

- Shallow ConvNet:
  A (not so) deep Network to learn FBCSP-like features

Shallow ConvNet
[Schirrmeister et al, Human Brain Mapping, 2017]
Riemannian geometry for BCI

- Manipulating EEG oscillations as covariance matrices

\[ f = \log(wCw^T) \]

Note: we (indirectly) represent EEG with covariance matrices when using CSP.

F. Yger, M. Bérar, F. Lotte, "Riemannian approaches in Brain-Computer Interfaces: a review", IEEE Trans Neural System and Rehabilitation Engineering, 2017
Tools of Riemannian geometry

Riemannian Distance

\[ \delta_R(C_1, C_2) = \left\| \log \left( C_1^{-1/2} C_2 C_1^{-1/2} \right) \right\|_F \]

Invariant to full rank linear transformation!

F. Yger, M. Bérar, F. Lotte, "Riemannian approaches in Brain-Computer Interfaces: a review", IEEE Trans Neural System and Rehabilitation Engineering, 2017
Minimum Distance to the Mean (MDM) classifier based on Riemannian geometry

Min $\delta_R(C, \overline{C_x})$?

Riemannian classifiers won 5 international brain signal classification competitions!

F. Yger, M. Bérar, F. Lotte, "Riemannian approaches in Brain-Computer Interfaces: a review", IEEE Trans Neural System and Rehabilitation Engineering, 2017

Congedo, M., Barachant, A., & Bhatia, R. « Riemannian geometry for EEG-based brain-computer interfaces; a primer and a review ». Brain-Computer Interfaces, 2017
Comparing algorithms for workload & emotions estimation in EEG signals

A. Appriou, A. Cichocki, F. Lotte,
“Towards Robust Neuroadaptive HCI: Exploring Modern Machine Learning Methods to Estimate Mental Workload From EEG Signals”, ACM CHI Late Breaking Work, 2018
Dealing with Noise
Examples of noise

• ElectroMyoGraphy (EMG):
  • Measure of muscles activity

• ElectroOculoGraphy (EOG):
  • Measure of eye movements

EMG signals measured by an EEG sensor (Jaw clenching)

EOG signals measured by an EEG sensor (blinks)
Noise-robustness with a Regularized CSP (RCSP)

<table>
<thead>
<tr>
<th>CSP</th>
<th>RCSP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Goal: extremizing</td>
<td>Goal: maximizing</td>
</tr>
<tr>
<td>$wC_1w^T$</td>
<td>$w\tilde{C}_1w^T$</td>
</tr>
<tr>
<td>$wC_2w^T$</td>
<td>$w\tilde{C}_2w^T + \alpha P(w)$</td>
</tr>
</tbody>
</table>

with $\tilde{C}_i = (1 - \beta)C_i + \beta G_i$

Penalty term
Stabilization term

What prior knowledge to use?
Spatial knowledge to deal with noise

• Neighboring neurons are responsible for similar brain functions + EEG is smeared due to volume conduction
  => Spatially smooth filters

\[ P(w) = \sum_{i,j} G(i, j) (w_i - w_j)^2 \]

- proximity of two electrodes
- weight difference between electrodes

• For a given task, not all brain areas are involved

\[ P(w) = w^T D w \text{ with } D(i, j) = \begin{cases} \text{channel i "uselessness"} & \text{if } i = j \\ 0 & \text{if } i \neq j \end{cases} \]
Spatial filters obtained

Lotte & Guan, *IEEE Trans. on Biomedical Engineering*, 2011

Average classification accuracy (%)  
(n = 12 subjects, 2 classes)

- **CSP**
  - Subject A1: 73.1%
  - Subject A5: 78.7%

- **SRCSP**
  - Subject A1: 78.7%
  - Subject A5: 77.6%

- **WTRCSP**
  - Subject A1: 77.6%
  - Subject A5: 78.7%
Dealing with Limited training data
Regularization terms to reduce calibration time

- Automatic covariance matrix shrinkage [Ledoit & Wolf 2004]
  \[ \tilde{C}_i = (1 - \beta)C_i + \beta I \]

- Using data from other users (previously recorded) as the stabilisation term [Lotte & Guan, ICASSP 2010 - Lotte, Proc. IEEE 2015]
Evaluation

Data Set 1 (Motor Imagery)

Data Set 2 (Workload)

Data Set 3 (Mental Imagery)

[Lothe, Proc. IEEE, vol. 103, no. 6, 2015]
Evaluation

Data Set 1 (Motor Imagery)

Data Set 2 (Workload)

Data Set 3 (Mental Imagery)

Dealing with non-stationarity
Non-stationarity in Brain-Computer Interfaces

- EEG signals/features distributions shift over time

- A solution: using adaptive classifiers, which updates their parameters as new EEG data are processed

Ex: Adaptive Riemannian Classifiers

- Retrain: incremental update of the prototype covariance matrix of each class

\[ \gamma \left( C_1, C_2, t \right) = C_1^2 \left( C_1^{-2} C_2^2 C_1^{-2} \right)^t C_1^2 \]

- Geodesic interpolation of the prototype covariance matrices
  - Supervised: we update the true class prototype
  - Unsupervised: we update the estimated class prototype

\[ C_{B_{\text{New}}} = \gamma \left( \overline{C_B}, C_i, \frac{1}{N_{\overline{C_B}} + 1} \right) \]
Rebias: projecting to a common reference point

\[ R_{i}^{Test} = \gamma \left( R_{i-1}^{Test}, C_i, \frac{1}{i-1} \right) \]

\[ C_{i}^{Rebiased} = R^{-\frac{1}{2}} C_i R^{-\frac{1}{2}} \quad R \in \{ R^{Train}, R^{Test} \} \]

Zanini, P., Congedo, M., Jutten, C., Said, S., & Berthoumieu, Y. Transfer learning: a Riemannian geometry framework with applications to brain–computer interfaces. IEEE Transactions on Biomedical Engineering, 2018
Performance of Adaptive Riemannian Classifiers

- Comparison on non-adaptive MDM, Retrain (supervised and unsupervised), Rebias and Retrain+Rebias

S. Kumar, F. Yger, F. Lotte, "Towards Adaptive Classification using Riemannian Geometry approaches in Brain-Computer Interfaces", IEEE Int Winter Conf on BCI, 2019
Conclusions & Perspectives
Summary

• BCI can decode EEG signals in real time

• Designed using Machine Learning and Signal Processing
  • Spectral & spatial filtering, feature extraction, classification

• Numerous EEG processing challenges
  • Between-user variabilities: using user-specific filters
  • Noise: using regularization
  • Limited data: transferring data across users
  • Within-user variabilities: using adaptive classifiers
Real-time EEG signals processing for everyone with OpenViBE!

OpenViBE is a software platform for

- Easily designing, testing and using BCI
- Real-time and online processing of brain signals acquisition, processing, visualization, …

Renard, Lotte, Gibert, Congedo, Maby, Delannoy, Bertrand, Lécuyer, *Presence*, 2010
Brain-Computer Interfaces: the books

Clerc, Bougrain, Lotte - ISTE-Wiley - 2016

Nam, Nijholt, Lotte
CRC Press, 2018
Perspectives

• Need for models explaining noise and variabilities

• Need for online studies with the designed algorithms

• BCI reliability can and should be improved at other levels
  • Brain activity sensors
  • Human-computer Interaction
  • User training
  ⇒ the ERC BrainConquest project

Thank you for your attention!

Any question?

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