Optimizing a Weighted Moderate Deviation for Motor Imagery Brain Computer Interfaces

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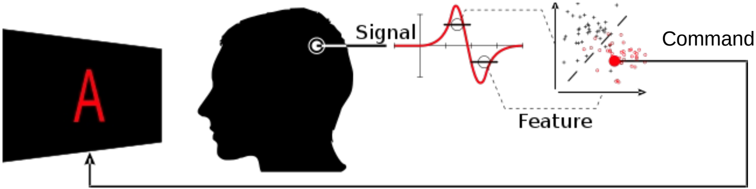
Introduction

1. Brain Computer Interfaces (BCIs)
2. Motor Imagery (MI)
3. Enhanced Multimodal Fusion Framework MI-BCI framework
4. Multichannel Weighted Moderate Deviations
5. Application and Results

Brain Computer Interfaces

- They are means to communicate **brain signals** and a **computer**.
- The target: to **understand** commands to execute in a external device.



Motor Imagery

- An individual rehearses or **simulates** a given **action**.
- We measure the **ElectroEncephalogram signal** while the simulation happens.
- We try to **identify** the imagined movement.

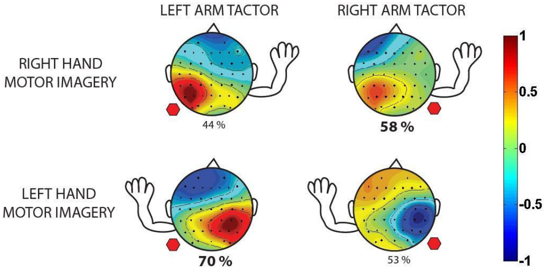


Image taken from: `http://www.traumatrucos.es/?p=395`

Enhanced Multimodal Fusion Framework

- A MI-BCI framework based on EEG signal[1].
- Tested on **left** hand, **right** hand, **tongue** and **foot** movement identification.
- Special focus on **signal derivation** and **decission making** based on the Multimodal Fuzzy Fusion framework[2].

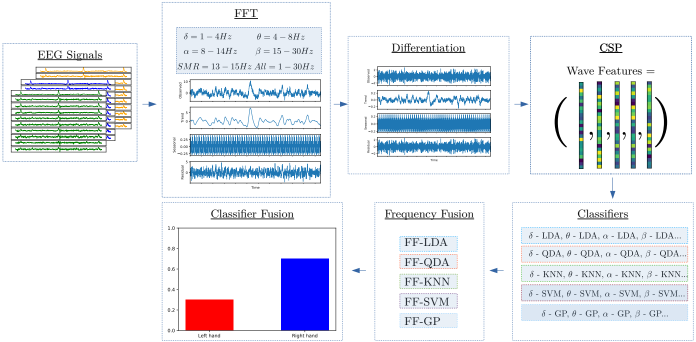
[1] Javier Fumanal-Idocin et al. "Motor-Imagery-Based Brain-Computer Interface Using Signal Derivation and Aggregation Functions". In: *IEEE Transactions on Cybernetics* (2021).

[2] Li-Wei Ko et al. "Multimodal Fuzzy Fusion for Enhancing the Motor-Imagery-Based Brain Computer Interface". In: *IEEE Computational Intelligence Magazine* 14.1 (2019), pp. 96–106.

Enhanced Multimodal Fusion Framework

1. EEG signal collection.
2. Fast Fourier Transform.
3. Differentiation.
4. Common Spatial Patterns.
5. Classifier training.
6. Extended Multimodal decision making phase.

EMF



Moderate Deviation-based aggregation

- Aggregation based on finding the point that minimizes sums of distances[3].
- Based on Darózcy means:
  A Darózcy mean is a mapping $M_D(\mathrm{x}) = y$, such that $\sum_{i=1}^{n} D(x_i, y) = 0, x_i, y \in R$.
- As D, we use a Moderate Deviation function. A mapping $I^2 \to R$ is said to be a Moderate Deviation function if and only if:
  (D1) for every $x \in I, D(x, \cdot) \to R$ is non-decreasing.
  (D2) for every $x \in I, D(\cdot, y) \to R$ is non-increasing.
  (D3) $D(x, y) = 0$ if and only if $x = y, x, y \in I$.
  Example: $D(x, y) = y - x$

[3] Abdulrahman H Altalhi et al. "Moderate deviation and restricted equivalence functions for measuring similarity between data". In: *Information Sciences* 501 (2019), pp. 19–29.

Moderate Deviation-based aggregation

Different **versions** of **Moderate Deviation**-based aggregation:

- For **numerical** data:
  Abdulrahman H Altalhi et al. "Moderate deviation and restricted equivalence functions for measuring similarity between data". In: *Information Sciences* 501 (2019), pp. 19–29.
- For **interval-valued** data:
  Javier Fumanal-Idocin et al. "Interval-valued aggregation functions based on moderate deviations applied to Motor-Imagery-Based Brain Computer Interface". In: *IEEE Transactions on Fuzzy Systems* (2021).
- For **multi-valued** data using **weights**:
  Martin Papčo et al. "A fusion method for multi-valued data". In: *Information Fusion* 71 (2021), pp. 1–10. ISSN: 1566-2535.

(We opted for the multi-valued data fusion)

Weighted Moderate Deviation-based aggregation

Defined as:

$$MD_{D,W} = \frac{1}{2}\left(\sup y \in I | \sum_{i=1}^{s}\sum_{j=1}^{t} w_{ij} D(x_{ij}, y) < 0 + \inf y \in I | \sum_{i=1}^{j}\sum_{j=1}^{t} w_{ij} D(x_{ij}, y) > 0\right) \tag{1}$$

Using as deviation function D:

$$D_\epsilon = (x+\epsilon)(y-x) \tag{2}$$

Then, we know the resulting MD:

$$MD_\epsilon(u,v) = \frac{u(u+\epsilon)+v(v+\epsilon)}{u+v+2\epsilon} \tag{3}$$

For example, for $I^4 \rightarrow R$ (2 x 2 patch):

$$MD_{\epsilon,w}(X) = MD_\epsilon(wX) = \frac{\sum_{i=1}^{2}\sum_{j=1}^{2} wx_{ij}(wxij+\epsilon)}{4w\epsilon + \sum_{i=1}^{2}\sum_{j=1}^{2} wx_{ij}} \tag{4}$$

Weighted Moderate Deviation-based aggregation

- Multimodal fusion scheme:

α Band - LDA

β Band - LDA

$\vdots$

All Band - LDA

Sample

(for each class c)

$$X_{LDA} = (x_{alpha}, x_{beta}, \ldots, x_{all})$$
$$X_{QDA} = (x_{alpha}, x_{beta}, \ldots, x_{all})$$
$$X_{KNN} = (x_{alpha}, x_{beta}, \ldots, x_{all})$$
$$X_{SVM} = (x_{alpha}, x_{beta}, \ldots, x_{all})$$
$$X_{GP} = (x_{alpha}, x_{beta}, \ldots, x_{all})$$

$$W_c = (w_1, w_2, w_3, w_4, w_5) \qquad w_{cf}$$

$$X = \begin{pmatrix} X_{LDA} \\ X_{QDA} \\ X_{KNN} \\ X_{SVM} \\ X_{GP} \end{pmatrix}$$

Weighted Moderate Deviation-based aggregation

- Multimodal fusion scheme:

α Band - LDA

β Band - LDA

⋮

All Band - LDA

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$X_{GP} = (x_{alpha}, x_{beta}, \ldots, x_{all})$

$W_c = (w_1, w_2, w_3, w_4, w_5)$ $\quad w_{cf}$

$$X = \begin{pmatrix} X_{LDA} \\ X_{QDA} \\ X_{KNN} \\ X_{SVM} \\ X_{GP} \end{pmatrix}$$

$$MD_{\epsilon}(X_{LDA}) = \frac{\sum_{i=1}^{N_{bands}} w_1 x_i (x_i \epsilon)}{N_{bands} w_1 \epsilon + \sum_{i=1}^{N_{bands}} w_1 x_i}$$

Weighted Moderate Deviation-based aggregation

- Multimodal fusion scheme:

(for each class c)

α Band - LDA

β Band - LDA

⋮

All Band - LDA

Sample

$X_{LDA} = (x_{alpha}, x_{beta}, \ldots, x_{all})$

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$X_{GP} = (x_{alpha}, x_{beta}, \ldots, x_{all})$

$W_c = (w_1, w_2, w_3, w_4, w_5)$ $\quad w_{cf}$

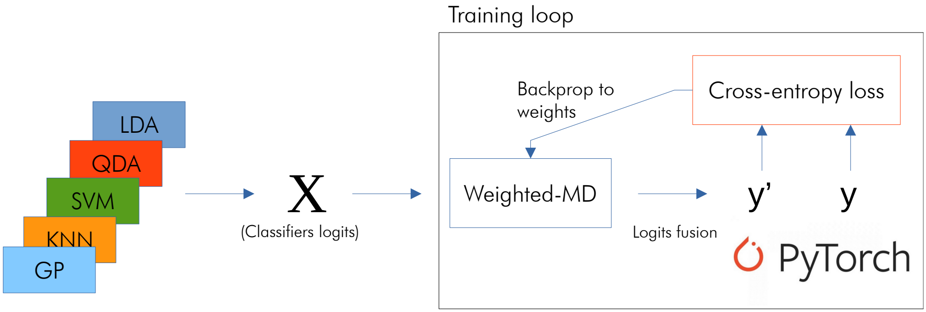
$$X = \begin{pmatrix} X_{LDA} \\ X_{QDA} \\ X_{KNN} \\ X_{SVM} \\ X_{GP} \end{pmatrix}$$

$$MD_\epsilon(X_{LDA}) = \frac{\sum_{i=1}^{N_{bands}} w_1 x_i (x_i \epsilon)}{N_{bands} w_1 \epsilon + \sum_{i=1}^{N_{bands}} w_1 x_i} \qquad MD_\epsilon(X_F) = \frac{\sum_{i=1}^{N_{classifiers}} w_{cf} x_i (x_i \epsilon)}{N_{classifiers} w_{cf} \epsilon + \sum_{i=1}^{N_{classifiers}} w_{cf} x_i}$$

Weighted Moderate Deviation-based aggregation

- Once we apply the weighted-MD:
  (1) **Fixing** the weights for all the channels to the same value.
  (2) **Learning** the weights using an optimization algorithm.

We tried both, using backpropagation with Pytorch in the second case:



Test performed

- We use the BCI IV 2a dataset to test the new aggregation proposal[4].
- We randomly generate 90 50%/50% train/test splits for evaluation.

Two classes: left/right hand.

Four classes: left hand, right hand, tongue, foot.

[4] Michael Tangermann et al. "Review of the BCI competition IV". In: *Front. in neuroscience* 6 (2012), p. 55.

Results for binary classification

Table 1: Results for the binary classification using the EMF with different configurations.

Aggregation	Accuracy	F1 Score
Weighted-MD learnt	$86.97\% \pm 3.98$	$86.95\% \pm 4.00$
Weighted-MD fixed	$85.80\% \pm 4.08$	$85.77\% \pm 4.09$
Arithmetic Mean	$85.80\% \pm 4.04$	$85.77\% \pm 4.04$
Choquet Integral	$86.39\% \pm 4.20$	$86.37\% \pm 4.21$
Sugeno Integral	$81.39\% \pm 4.39$	$81.37\% \pm 4.39$

Results for 4 classes classification

Table 2: Results for the four classification using the EMF with different configurations.

Aggregation	Accuracy	F1 Score
Weighted-MD learnt	$65.91\% \pm 13.15$	$65.91\% \pm 13.15$
Weighted-MD fixed	$72.93\% \pm 2.29$	$72.93\% \pm 2.29$
Arithmetic Mean	$72.22\% \pm 2.31$	$72.22\% \pm 2.31$
Choquet Integral	$72.93\% \pm 1.85$	$72.93\% \pm 1.85$
Sugeno Integral	$64.45\% \pm 2.66$	$64.45\% \pm 2.66$

Conclusions

- Multivalued MD-aggregations seem to be effective in this problem in any case.
- **Learning** the weights seem to be **effective** in the **binary** case, but not in the four classes. Probably **more data** is needed.
- Further learning algorithms for the weights should be studied.

References & Questions

Aggregations implementation library:
`https://github.com/Fuminides/Fancy_aggregations`

BCI frameworks implementation (WIP):
`https://github.com/Fuminides/athena`

Main references:

1. Javier Fumanal-Idocin et al. "Motor-Imagery-Based Brain-Computer Interface Using Signal Derivation and Aggregation Functions". In: *IEEE Transactions on Cybernetics* (2021)
2. Martin Papčo et al. "A fusion method for multi-valued data". In: *Information Fusion* 71 (2021), pp. 1–10. ISSN: 1566-2535