Motor-Imagery-Based Brain Computer Interface using Signal Derivation and Aggregation Functions

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Abstract—Brain Computer Interface (BCI) technologies are popular methods of communication between the human brain and external devices. One of the most popular approaches to BCI is Motor Imagery (MI). In BCI applications, the ElectroEncephaloGraphy (EEG) is a very popular measurement for brain dynamics because of its non-invasive nature. Although there is a high interest in the BCI topic, the performance of existing systems is still far from ideal, due to the difficulty of performing pattern recognition tasks in EEG signals. This difficulty lies in the selection of the correct EEG channels, the signal-to-noise ratio of these signals and how to discern the redundant information among them. BCI systems are composed of a wide range of components that perform signal pre-processing, feature extraction and decision making. In this paper, we define a new BCI Framework, named Enhanced Fusion Framework, where we propose three different ideas to improve the existing MI-based BCI frameworks. Firstly, we include an additional pre-processing step of the signal: a differentiation of the EEG signal that makes it time-invariant. Secondly, we add an additional frequency band as feature for the system: the Sensory Motor Rhythm band, and we show its effect on the performance of the system. Finally, we make a profound study of how to make the final decision in the system. We propose the usage of both up to six types of different classifiers and a wide range of aggregation functions (including classical aggregations, Choquet and Sugeno integrals and their extensions and overlap functions) to fuse the information given by the considered classifiers. We have tested this new system on a dataset of 20 volunteers performing motor imagery-based brain-computer interface experiments. On this dataset, the new system achieved a 88.80% of accuracy. We also propose an optimized version of our system that is able to obtain up to 90.76%. Furthermore, we find that the pair Choquet/Sugeno integrals and overlap functions are the ones providing the best results.

Index Terms—Brain-Computer-Interface (BCI); Motor Imagery (MI); Classification; Aggregation functions; Information Fusion; Signal Processing;

I. INTRODUCTION

Brain-computer interfaces (BCIs) provide a new interface between the human brain and the devices or systems to be controlled by the changes of brain dynamics [1], [2]. One popular BCI is Motor Imagery (MI) in which a person imagines a specific body movement (usually moving left or right hand). As imagining the movement, the Event-Related Desynchronization (ERD) in mu rhythm near motor areas has been widely reported in the previous studies [3], [4]. Therefore, correct ERD identification highly influences the performance of MI-based BCI. Recently, a lot of state-of-the-art algorithms, such as Common Spatial Pattern (CSP), support vector machines, or deep learning have been extensively used to identify the ERD in MI-based BCI [4], [5], [6].

BCIs use a wide range of techniques to extract features from the original raw data. Due to the volume-conduction effect, it is very difficult to extract information directly from the ElectroEncephaloGraphy (EEG) data [7], because the measures taken are affected by the conductance of the biological tissues that transmit the electrical signal. To cope with this, most algorithms use a procedure to extract features from the EEG data before feeding them to a classifier. Some of the most common procedures include using the Fast Fourier transform (FFt) to transform the EEG signals to the frequency domain [8], [9], [10] and the Meyer wavelet transformation [11], [12]. There have also been many different fuzzy approaches to the BCI problem [13], [14], [15].

A BCI framework is composed of signal pre-processing, feature extraction and control commands. The interactions among all of these elements take a crucial role in the final performance of the system. However, possible correlations and synergies among the different features are ignored in the command control phase in the classical BCI framework. In [16] the authors proposed a channel selection procedure to minimize the number of correlated components in the system. In [17] the authors use a time-window selection algorithm to choose the best time to collect the MI features, and the authors in [18] use the spatio-temporal information of the EEG signals to detect the optimal channels to discriminate between the MI tasks. In [19] the authors propose a new BCI framework, the Multimodal Fuzzy Fusion BCI Framework (MFF), that uses the fuzzy integrals [19], [20] to model these interactions, and a two-step decision making process that considers that combines the outputs of three classical classifiers.

Two of the most important fuzzy integrals are the Sugeno and the Choquet integrals. Both aggregate values using a measure that indicates how important are the different correlations among the data. Therefore, they are specially suited in applications where there are significant interactions among
the features to aggregate. Fuzzy integrals have been widely used in decision making \cite{21}, image processing \cite{20} and deep learning \cite{22}. As we have mentioned, Fuzzy integrals have already been used in a BCI framework in \cite{3}, obtaining better results than the classical aggregations. Many different generalizations of the Choquet integral have been proposed \cite{23}, \cite{24}, \cite{25}. The CF, \cite{26}, and \(C_{F1,F2}\) \cite{27} generalizations of the Choquet integral have proven to be very successful in classification systems. Ordered-Weighted-Averaging operators \cite{28}, \cite{29} (OW As) are a specific case of the fuzzy integrals. Some different types of them, we also describe the traditional BCI framework \cite{28}, \cite{29}, \cite{30}, \cite{31} (OW As) are a specific case of the fuzzy integrals. Some common examples of classical n-ary aggregation functions are the geometric and harmonic means. Generalized overlap functions have been proposed in \cite{33}. Some common examples of these generalized overlap functions are the geometric and harmonic means. Generalized overlap functions have been successfully used in Big Data \cite{34} and in fuzzy rule-based classifiers \cite{35}.

A closed concept to aggregation functions are the overlap functions, which were introduced in \cite{32} in the fuzzy community, as a way to represent the overlapping between two concepts. Since these functions were only defined for two elements, the generalized version of overlap functions for n-valued vectors were proposed in \cite{33}. Some common examples of these generalized overlap functions are the geometric and the harmonic means. Generalized overlap functions have been successfully used in Big Data \cite{34} and in fuzzy rule-based classifiers \cite{35}.

The most successful MI-based BCI framework using aggregation functions is \cite{3}. However, in the decision making process, it does not study:

1) The effects of new types of classifiers with the new integrals.
2) The possibility of using different aggregation functions in each step of the process.
3) It does not improve other areas of the BCI framework besides the decision making phase.

In this paper, we present a new BCI framework, named Enhanced Fusion BCI Framework (EMF). It includes a new differentiation signal phase, an additional wave band: the SensoriMotor Rhythm, and we add two additional types of classifiers to the ensemble of classifiers: Gaussian Process and Support Vector Machines. We also consider a wider set of aggregation functions to be used in the decision making phase that includes not only the Choquet and Sugeno integrals and their generalizations, but also Ordered Weighted Averaging operators and generalized overlaps. Finally, we also propose an Optimized version of the EMF (OEMF) in terms of accuracy by checking the most proper combinations of wave bands and classifiers.

The rest of our paper is organized as follows. In section \textbf{II}, we remind the concept of is an aggregation functions and different types of them, we also describe the traditional BCI framework \cite{36} and the MFF BCI framework \cite{3}. In section \textbf{III} we explain the the new Enhanced Multimodal Fusion BCI Framework. In section \textbf{IV} we show our experimental results for our own BCI dataset, and in section \textbf{V} we discuss our results for the BCI IV competition dataset \cite{37}. Finally, in section \textbf{VI} we give our final conclusions and remarks for this work.

\section*{II. Preliminars}

In this section we recall some basic notions about aggregation functions (Section \textbf{II-A}), the traditional BCI framework (Section \textbf{II-B}) and the MFF BCI framework (Section \textbf{II-C}).

\subsection*{A. Aggregation Functions}

Aggregation functions are used to fuse information from n sources into one single output. A function \(A: [0,1]^n \rightarrow [0,1]\) is said to be a n-ary aggregation function if the following conditions hold:

- A is increasing in each argument: \(\forall i \in \{1, \ldots, n\}, i < y, A(x_1, \ldots, x_i, \ldots, x_n) \leq A(x_1, \ldots, y, \ldots, x_n)\)
- \(A(0, \ldots, 0) = 0\)
- \(A(1, \ldots, 1) = 1\)

Some examples of classical n-ary aggregation functions are:

- Arithmetic mean: \(A(x) = \frac{1}{n} \sum_{i=1}^{n} x_i\)
- Median: \(A(x) = x_i : \{a : \forall x_a < x_i\}, \{b, \forall x_b > x_i\}, |a| = |b|\)
- Max: \(A(x) = max(x_1, \ldots, x_n)\)
- Min: \(A(x) = min(x_1, \ldots, x_n)\)

Other types of aggregation functions are the following ones:

1) \textbf{T-norm} \cite{38}: A T-norm is an aggregation function \([0,1]^2 \rightarrow [0,1]\) that satisfies the following properties for \(a, b, c \in [0,1]\):

- \(T(a,b) = T(b,a)\)
- \(T(a,T(b,c)) = T(T(a,b),c)\)
- \(T(a,1) = a\)

Some examples of T-norms are the product or the minimum.

2) \textbf{Choquet integral} \cite{20}: Having \(N = \{1, \ldots, n\}\), a function \(m : 2^n \rightarrow [0,1]\) is a fuzzy measure if, for all \(X,Y \in N\), it satisfies the following properties:

- \((m1)\) Increasingness: if \(X \in Y\), then \(m(X) \leq m(Y)\).
- \((m2)\) Boundary conditions: \(m(\emptyset) = 0\) and \(m(N) = 1\).

The discrete Choquet integral of \(x = (x_1, \ldots, x_n) \in [0,1]^n\) with respect to \(m\) is defined as \(C_m : [0,1]^n \rightarrow [0,1]\) given by

\[
C_m(x) = \sum_{i=1}^{n} (x_{\sigma(i)} - x_{\sigma(i-1)}) \cdot m(A_i) \tag{1}
\]

where \(x_\sigma\) is an increasing permutation of \(x\) such that \(0 \leq x_{\sigma(1)} \leq \cdots \leq x_{\sigma(n)}\). With the convention that \(x_0 = 0\), and \(A_i = \{i, \ldots, n\}\).

3) \textbf{CF} \cite{29}: It is a generalization of the Choquet integral that replaces the product used in Eq. \textbf{1} for a more general function \(F\). In \cite{39}, the authors detail the required properties for \(F\) so that the CF is an aggregation function, and conclude that the best \(F\) in their experimental results is the Hamacher T-norm. For this reason, we have chosen it for our experimentation, as detailed in the following expressions:

\[
T_H(x,y) = \begin{cases} 
0, & \text{if } x = y = 0 \\
\frac{x y}{x + y - x y}, & \text{otherwise} 
\end{cases}
\]

\[
CF(x) = \sum_{i=1}^{n} T_H(x_{\sigma(i)} - x_{\sigma(i-1)}, m(A_i))
\]
4) $C_{F_1,F_2}$ [27]: The original product of the Choquet Integral can be decomposed on two product functions using the distributive property of the product. Therefore, the Choquet integral can be written as:

\[ C(x) = \sum_{i=1}^{n} x_{\sigma(i)}m(A_i) - x_{\sigma(i-1)}m(A_i) \]

Then, the product functions are substituted for two more generic functions: $F_1$ and $F_2$. In [27] the authors explain the properties that must hold $F_1$ and $F_2$ so that the $C_{F_1,F_2}$ is an aggregation function. Consequently, the expression for the $C_{F_1,F_2}$ is the following:

\[ C_{F_1,F_2}(x) = \sum_{i=1}^{n} F_1(x_{\sigma(i)}), m(A_i)) - F_2(x_{\sigma(i-1)}), m(A_i)) \]

5) Sugeno integral [19]: Let $m : 2^N \rightarrow [0, 1]$ be a fuzzy measure. The discrete Sugeno integral of $x = (x_1, \ldots, x_n) \in [0, 1]^n$ with respect to $m$ is defined as a function $S_m : [0, 1]^n \rightarrow [0, 1]$, given by:

\[ S_m(x) = \max \{ \min \{x_{\sigma(i)}, m(A_i)\} | i = 1, \ldots, n \} \quad (2) \]

6) Sugeno Hamacher [3]: If we consider using the Hamacher T-norm instead of the minimum in Eq. 2 we obtain the following expression:

\[ S(x) = \max \{ T_H(x_{\sigma(i)}, m(A_i)) | i = 1, \ldots, n \} \]

7) Ordered Weighted Averaging operators (OWA) [28]: $\overline{w} = (w_1, \ldots, w_n) \in [0, 1]^n$ is called a weighting vector if $\sum_{i=1}^{n} w_i = 1$. The OWA operator associated to $\overline{w}$ is the mapping $OWA_{\overline{w}} : [0, 1]^n \rightarrow [0, 1]$ defined for every $(x_1, \ldots, x_n) \in [0, 1]^n$ by:

\[ OWA(x_1, \ldots, x_n) = w_1 x_{\gamma(1)} + \cdots + w_n x_{\gamma(n)} \]

where $\gamma : \{1, \ldots, n\} \rightarrow \{1, \ldots, n\}$ is a permutation such that:

\[ x_{\gamma(1)} \geq x_{\gamma(2)} \geq \ldots \geq x_{\gamma(n)} \]

The weight vector can be computed used a quantifier function, $Q$. For this study, we have used the following one:

\[ w_i = Q\left( \frac{i}{n} \right) - Q\left( \frac{i-1}{n} \right) \]

\[ Q_{a,b}(i) = \begin{cases} 0, & \text{if } i < a \\ 1, & \text{if } i > b \\ \frac{i-1}{b-a}, & \text{otherwise} \end{cases} \]

where $a, b \in [0, 1]$. Depending on the value of the parameters $a$ and $b$, different weight vectors can be obtained. We have used three different ones:

- OWA$_1$: $a = 0.1, b = 0.5$
- OWA$_2$: $a = 0.5, b = 1$
- OWA$_3$: $a = 0.3, b = 0.8$

8) Overlap functions [33]: A $n$-dimensional overlap, $G$, is a $[0, 1]^n \rightarrow [0, 1]$ function that holds:

- Is commutative.
- If $\prod_{i=1}^{n} x_i = 0$, then $G(x) = 0$.
- If $\prod_{i=1}^{n} x_i = 1$, then $G(x) = 1$
- $G$ is increasing.
- $G$ is continuous.

The minimum function, for example, is an overlap function.

We have also considered three more:

- Harmonic Mean (HM): $\sum_{i=1}^{n} \frac{1}{x_i}$
- Sinus Overlap (SO): $\sin \frac{\pi}{2} (\prod_{i=1}^{n} x_i)$
- Geometrical Mean (GM): $\sqrt[\prod_{i=1}^{n} x_i]$

B. Traditional BCI Framework

The traditional BCI system structure includes four parts:

1) The first step is acquiring the EEG data from the commercial EEG device and performing band-pass filtering and artefact removal on the collected EEG signals.

2) The second step is EEG feature transformation and feature extraction. Usually, the FFT is used to transform the EEG signals from the into different frequency components [40]. The FFT analysis transforms the timeseries EEG signals in each channel into its constituent frequencies. Following the procedure in [45], [18], we cover the frequencies range 1-30Hz. We study for the delta ($\delta$) wave band the 1-3 Hz frequencies, for the theta ($\theta$) wave band the 4-7 Hz frequencies, for the alpha ($\alpha$) 8-13 Hz frequencies, for the beta ($\beta$) the 14-30 Hz frequencies and All 1-30Hz frequencies [41] using a 50-point moving window segment overlapping 45 data points.

3) Subsequently, the CSP was used for feature extraction to extract the maximum spatial separability from the different EEG signals corresponding to the control commands. The CSP is a well-known supervised mathematical procedure commonly used in EEG signal processing. The CSP is used to transform multivariate EEG signals into well-separated subcomponents with maximum spatial variation using the labels for each example [42], [43], [44].

4) Last, pattern classification is performed on the CSP features signals using an ensemble of classifiers to differentiate the commands. Each base classifier is trained using a different wave band (for instance, if the base classifier is the LDA, the ensemble would be composed of: $\delta - LDA$, $\theta - LDA$, $\alpha - LDA$, $\beta - LDA$, and $\text{All} - LDA$) and the final decision is taken combining all of them. The most common way of obtaining the final decision is to compute the arithmetic mean of the outputs of all the base classifiers (each one provides a probability for each class), and take the class with higher aggregated value. The most common classifiers used for this task are the Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA) and k-nearest neighbours classifier (KNN) [45].
C. Multimodal Fuzzy Framework

The Multi-modal Fuzzy Framework (MFF) is proposed in [3]. It follows a similar structure to the one in the traditional BCI framework: it starts with the EEG measurements, it computes the FFT transformation to the frequency domain and it uses the CSP transform to obtain a set of features to train the classifiers.

However, in the MFF it is necessary to train not one, but three classifiers for each wave band: a LDA, a QDA and a KNN. We name the classifiers according to their type of classifier and the wave band used to train it. For instance, for the δ band we would have $\delta - LDA$, $\delta - QDA$ and $\delta - KNN$.

Then, the decision making phase is performed in two phases:

1) Frequency phase: since we got a LDA, QDA and KNN for each wave band, the first step is to fuse the outputs of these classifiers in each wave band. For example, in the case of the LDA classifiers, we have a $\delta - LDA$, $\theta - LDA$, $\alpha - LDA$, $\beta - LDA$ and $All - LDA$ that will be fused using an aggregation function to obtain a vector, $FF - LDA$. That is, the same process explained for the traditional framework is applied but without making the final decision. We do the same with the QDA and KNN classifiers. The result of this phase is a list of collective vectors (one for each type of classifier).

2) Classifier phase: in this phase, the input is the list of collective vectors given by each different kind of classifier ($FF - LDA$, $FF - LDA$, $FF - KNN$) computed in the frequency phase. We fuse the three vectors according to the classes, and the result is a vector containing the score for each class for the given sample.

As in the traditional framework, the decision is made in favour to the class associated with the largest value. We must point out that the same aggregation is used for both the frequency phase and the classifier phases.

The aggregation functions tested in the MFF are the Choquet integral, the CF integral using the Hamacher T-norm, the $CF_{min, min}$ generalizations, the Sugeno integral and the Hamacher Sugeno integral. We used the cardinal fuzzy measure for all of them [46].

III. Enhanced Fusion Framework

Our aim with the Enhanced Multimodal Fusion Framework (EMF) is to build upon the foundations of the MFF in order to improve its experimental results. Starting from the MFF, we add a new band as well as a new signal pre-processing phase known as differentiation. Furthermore, we considered more classifiers and a wider set of aggregation functions for the decision making process. Finally, we give more flexibility to the decision making process because we allow the aggregation function to be different in each stage.

A schematic view of the whole EMF classification process is in Fig. [9]. The new components compared to the MFF in [3] can be seen in the figure: the SMR in the FFT phase, the differentiation phase, and the two new classifiers (SVM and GP). In the following sections we present in detail each component added in the EMF framework.

A. Wave bands

For the EMF we have considered all the wave bands used in the traditional BCI framework: $\delta$, $\theta$, $\alpha$, $\beta$ and All. However, we have also added the SensoriMotor Rhythm (SMR), which covers the $13 - 15$Hz frequencies [47].

Regarding the nature of ERD/ERS, movement or preparation for movement is typically accompanied by a decrease in mu and beta rhythms, particularly contralateral to the movement [48] to control sequence. This phenomenon has been named event-related desynchronization or ERD [49]. Its opposite, rhythm increase, or event-related synchronization (ERS), occurs after movement and with relaxation [50]. So, we suppose that the activity present in this band will be closely related to the studied task.

B. Signal pre-processing and feature extraction

The data acquisition process is similar to the rest of the BCI frameworks. First, we obtain the EEG data, second, we apply the FFT. Then, we add a new component, the differentiation for the signals. Finally, we compute the CSP of 25 components to extract the features from which we will train the classifiers from the differentiated signals.

The idea to apply the differentiation comes from a related area, neuroscience. In [51] the authors measure the activations of a moving C.Elegans, using the luminescence of each neuron during a series of trials. Alongside the paper, the corresponding dataset was released. This dataset was composed of real numbers that quantified the luminescence of each neuron, instead of a neuron activated/deactivated classification, since a straightforward method to compute if a neuron was activated or not was not found. Authors in [52], based on this same C.Elegans dataset, stated that the real activations of the neurons should be computed not using the absolute value of the luminescence, but only the spikes of the signal. They attributed the big changes in the tendency of the temporal series to artefacts in the measures. So, they performed a low-pass filter to the signal (Fig. [2]).

EEG data and the neuron luminescence, although different in nature, are both time series data [53]. Temporal series are composed of three components: tendency, seasonal component and the random component [54], which can be observed for the average of all of our wave bands in Fig. [9]. The high pass Butterworth filter used in [52] is a way to remove the tendency from the time series while keeping the spikes. We have decided to do something similar to the EEG signal in order to extract the spikes in the wave bands, which are similar to the random component in the temporal series. However, instead of using the high pass Butterworth filtering, we have used a simpler procedure, the differentiation, to avoid having to tune additional parameters for the filtering. In Fig. [4] we show the resulting signal of the differentiation process.

C. Classifiers

In the MFF the classifiers types are LDA, QDA and KNN. They are chosen because they are “weak” classifiers, and it is when using the aggregation process that the “strong” decision is obtained.
In the EMF we have decided to test two more types of classifiers: Support Vector Machines (SVM) \cite{55} and Gaussian Processes (GP) \cite{56}. These classifiers are by themselves generally more accurate than the three classifiers used in the MFF, which may increase the final accuracy of the system. However, it makes the decision making process less diverse, because the higher the accuracy for each individual classifier, the less novel info each one of them will give to take the final decision.

### D. Decision Making

In the original MFF, authors studied the effects of the arithmetic mean operator and the following aggregation functions:

- Choquet Integral and two generalizations: $CF_{\text{min},\text{min}}$ and $CF$ using the Hamacher T-norm.
- Sugeno Integral and Sugeno using the Hamacher T-norm.

The same aggregation function was used both in the frequency-phase and in the classifier phase fusion steps.

For the EMF we have considered a wider set of aggregation functions, more precisely, all the aggregation functions presented in section \cite{11}. That includes the classical ones, Choquet and Sugeno Integrals alongside their generalizations, OWA operators, and n-ary overlap functions.
We have also added an extra degree of freedom to this process: the frequency fusion phase and classifier fusion phase can use a different aggregation function. We allow it because we aim at each phase is different. In the case of the frequency fusion phase, we are using outputs of classifiers from the same type, so their predictions are of the same nature and we are building a new collective vector. In the case of the classifier fusion phase, we are using different types of classifiers (even if the outputs are normalized in the [0, 1] scale) and we want to make the final decision, not only building another collective vector.

IV. EXPERIMENTAL RESULTS FOR THE ENHANCED MULTIMODAL FUSION FRAMEWORK ON THE UTS MI DATASET

We have evaluated the EMF using the MI dataset collected by the University of Technology Sidney (UTS) using the same procedure as in [3]. This dataset consists of twenty participants. Each one of them performed a total of forty trials in which they were asked to imagine to move the left or right hand. Half of them corresponding to right, and the other half to left, consisting in a total of 800 trials. EEG data was taken from the channels C3, C4, CP3 and CP4. We have used a CSP with 3, 4, 6, 15, 3 and 25 components, respectively, for the δ, θ, α, β, SMR and All (1 – 30 Hz) wave bands. These values have been chosen empirically (Fig. 5).

We have applied a five-fold cross validation scheme to evaluate our results: we have taken the 800 available trials, and divided it into 5 different 80/20 train-test splits, denoting the final accuracy as the mean of the accuracy for each test split. Although results here shown only show the performance of the EMF for the totality of the dataset, results for each individual subject are available online at: [https://github.com/Fuminides/BCI_Results](https://github.com/Fuminides/BCI_Results).

In Table I we compared the results for the traditional framework, the MFF and our new proposal, the EMF. For the traditional framework we have used the 5 classifiers considered in this work (LDA, QDA, KNN, SVM and GP), and in the case of both the MFF, the EMF we have reported the result of the best aggregation (we will show their influence later). Looking at these results, we can observe that we have obtained a remarkable improvement using the EMF compared to any of the other frameworks, since we improve in almost 12% the MFF and more than 15% the best traditional framework (Trad. QDA).

The EMF offered two main differences compared to the MFF and the traditional approaches: the differentiation phase and the enhanced frequency and classifier fusion phases. To test how much percentage of improvement comes from each one, we have computed the traditional BCI framework using the differentiation signal phase. We named this configuration “Diff-traditional” Framework. In the traditional framework,

| Framework       | Accuracy for the trad. SVM Framework | Accuracy for the Diff-traditional Framework | Best Frequency Fusion |
|-----------------|--------------------------------------|--------------------------------------------|-----------------------|
| Trad. SVM       | 67.07                                | 79.98                                      | 80.67                 |
| Trad. LDA       | 72.24                                | 72.13                                      | 83.25                 |
| Trad. QDA       | 73.82                                | 86.06                                      | 86.06                 |
| Trad. KNN       | 68.87                                | 85.95                                      | 86.51                 |
| Trad. GP        | 72.47                                | 85.95                                      | 86.51                 |
| MFF             | 76.96                                | 98.06                                      |                       |
| EMF             | 88.86                                | 98.06                                      |                       |

TABLE I: Performance for each BCI framework in the UTS dataset.

| Framework       | Mean agg. | Best Frequency Fusion |
|-----------------|-----------|-----------------------|
| Diff-traditional SVM | 79.98     | 80.67                 |
| Diff-traditional LDA | 67.30     | 74.38                 |
| Diff-traditional QDA | 72.13     | 83.25                 |
| Diff-traditional KNN | 86.06     | 86.06                 |
| Diff-traditional GP | 85.95     | 86.51                 |

TABLE II: Performance for the traditional BCI frameworks using the differentiation. We compare the usage of the base aggregation (the arithmetic mean) against the best possible one.
(obviously also in the Diff-traditional), the final decision is taken fusing the information from each classifier using the arithmetic mean of all of them. Then, to see the improvement that can be achieved on the diff-traditional framework using different aggregation functions, we have tried all the aggregation functions considered in this paper and then we select the best one in terms of accuracy. The results of these tests are in Table II. In the first column we specify the classifier used for each diff-traditional framework configuration. In the second column we specify the accuracy if we use the arithmetic mean aggregation (Mean agg.), and in the third, we specify again the accuracy for the best possible aggregation function (Best Frequency Fusion). We have found that the differentiation alone is capable of boosting the performance in the case of SVM, KNN and GP more than 10%. In the cases where differentiation was not very successful (LDA and QDA), the aggregation phase obtained similar winnings in terms of accuracy as the differentiation did on the other cases.

In Table III we show the results for each pair of aggregations used in the frequency (rows) and in the classifier (columns) fusion phases using the EMF. Depending on the aggregations used, the accuracy can vary from ~ 85% to ~ 88%. Although there are some combinations which results in a really poor interaction between the frequency and the classifier function base. Therefore, we can conclude that in general, they provide competitive results since most of the combinations would allow to improve the results of the MFF (76.96%).

Then, we also test the best possible performance of each individual wave band, which is detailed in Table IV. The process is the same as in the standard EMF, but using only one wave band, so there is no classifier fusion-phase. In the first column we show the different wave bands used, in the second column the combination of classifiers that works best for this wave band, the third column is the aggregation used to fuse the information from the classifiers, and the last one shows the accuracy obtained. For example, in the case of the δ wave band, the best result is obtained using a SVM-δ and a KNN -δ classifier, and fusing their results using any aggregation function, as all of them result in the same accuracy for this case. We must stress that the β channels alone can lead up to ~ 86% accuracy using Gaussian Process and KNN classifiers and the All wave band can achieve a 89.77% using only a Gaussian Process classifier (so, no aggregation process is made). The good performance of the β band is in line with the results in [57] and [58]. The SMR band did not performed better than the alpha or beta wave bands, in spite of the results regarding MI reported in [47].

Finally, in Table V we show the resulting Information Transfer Rate (ITR) for the MFF, the EMF. The ITR measures the efficiency of the system, and it measured as bits/trial. It is computed using the following formulas [48]:

\[ B = \log_2 N + P \times \log_2 P + (1 - P) \times \log_2 \left( \frac{1 - P}{N - 1} \right) \]

\[ Q \left( \frac{\text{Trials}}{\text{Min}} \right) = \frac{S}{T} \]

\[ ITR = B \times Q, \]

where N is the number of target classes (2 in this case), S is the number of observations and P is the accuracy rate. So, the more accuracy and the less computing time, the better this index will be. From these results we can confirm again that the EMF, using the best combination of aggregations in terms of accuracy, surpasses the MFF.

A. Optimal Enhanced Motor Fusion: Classifier and wave band selection in the Enhanced Motor Fusion Framework

Diversity is an important part of an ensemble of classifiers [59]. As it seems logical, if a set of classifiers always give the same output, its combination will not give us new information. We are using a total of thirty classifiers in the EMF: five for each band (LDA, QDA, KNN, SVM and GP) and a total of six wave bands (δ, θ, α, β, SMR, All). To measure the diversity of this system we have used the Q-statistic [60], whose result is 0.99 meaning that the diversity in the output of these classifiers is scarce, which might be impacting the performance of the system.

One simple way to improve the system diversity, and reduce the Q-statistic value, is to erase components of the system, which is likely to improve the accuracy. Since there are only 30 classifiers, we can compute all the possible configurations of the system to see which combinations of classifiers and which wave bands are the most suited according to their accuracy. After computing all the possible 1860 combinations of wave bands and classifiers, we have determined which are the top configurations in terms of accuracy, which are shown in Table VI. As suspected, reducing the number of components has a good impact on the performance, since we can see that the best configuration is able to improve the EMF in almost 2%. It also improves the ITR compared to the previous tests, obtaining a value of 2007.47bit/min. We have named this optimal configuration of the EMF “Optimal Enhanced Motor Fusion” (OEMF).

V. COMPARISON ON THE BCI COMPETITION IV 2A DATASET

In this section we discuss the behaviour of our new approaches in the BCI competition IV dataset 2a, which is detailed in [61]. This dataset consists of four classes of imaginary tasks: tongue, foot, left-hand and right-hand performed by 9 volunteers. For each task, 22 EEG channels were collected. There is a total of 288 trials for each participants, equally distributed among the 4 classes.

For our experimental setup, we have used 4 out of the 22 channels available (8, 12, 14, 18). As features, we have used the FFT to obtain the δ, θ, α, β, SMR and All, and the CSP filters are the same in Section IV. From each subject, we have generated twenty partitions of the 288 trials consisting of 50% train (144 trials) and 50% test (144 trials) chosen randomly. Since we have 9 subjects, this produces a total of 180 different datasets. We do this in order to compute a population of accuracies for each classifier, which allow us to calculate the statistical significances among them.

We have studied this dataset from two different perspectives:

1) Taking the four classes to perform the classification task.
We can observe that the performance of EMF is statistically better than the rest of the frameworks. In this case, we have compared the same set of traditional frameworks as in the four classes case. As expected, the accuracy of all classifiers improves. The EMF increases almost 3% with respect to the four classes problem. In this scenario, the best pair of aggregations for the EMF is the Hamacher Sugeno and the Sin overlap. The rest of the results for each pair of aggregations can be seen in Table VII. The best configuration obtained by the OEMF (is using all the possible wave bands and QDA and KNN classifiers). This configuration presents a huge improvement of more than 12% over the EMF, reaching a total of 97.60%. We have also studied the statistical differences among the frameworks, using an analogue procedure to the one performed in the four-classes problem. We have found that the EMF and the OEMF are statistically better than the rest of the frameworks. In this case, the OEMF is also statistically better than the EMF.

We have also studied the impact of the pair of aggregations to be used in our new framework, since it seems to have an impact on the obtained results. There are some combinations which tend to perform always near the best possible performance, and others that do the opposite. Our results show that usually, the best combination is using a Sugeno/Choquet combination for each individual channel.
integrated in the frequency fusion phase and an overlap function in the classifier fusion phase, which can be appreciated in Tables III, VII, and VIII.

Finally, we have compared our results in the four classes task with three other kinds of BCI frameworks in Table IX. In [62] the authors combine Riemannian geometry with a Linear SVM. In [63] the authors optimize the time interval for each subject to obtain the optimal set of features to discriminate between tasks, and then apply a bio-inspired algorithm to optimize the CSP features and SVM parameters. And the authors in [64] use the Dempster–Shafer theory to fuse the output of different LDA classifiers. We found that the results obtained by the EMF are higher than the other three BCI frameworks.

VI. CONCLUSIONS

In this paper, we proposed a new BCI framework, named Enhanced Motor Fusion framework (EMF). The EMF proposes three new ideas to improve the Multimodal Fuzzy Fusion (MFF) BCI system performance:

1) A signal differentiation step.
2) Both a new wave band (SMR) and new types of classifiers: SVM and GP.
3) The usage of different aggregation functions in each phase in the decision making process.

Furthermore, we have also enlarged the number of aggregation functions used in the decision making process, like $C_{F1,F2}$, overlap functions and the OWA operators. We observe that the best results are obtained using a Sugeno/Choquet integral in the frequency fusion phase and an overlap function in the classifier fusion phase, which can be appreciated in Tables III, VII, and VIII.

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The performance of our new approaches is tested on two BCI datasets, where the suitability of our new methods is proven. Specifically, the EMF improves the results of the traditional framework as well as those of the MFF. The OEMF improves even more the obtained results, achieving statistical differences in one of the scenarios, which makes it a good option to tackle this kind of problems.

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REFERENCES

[1] Chin-Teng Lin, Ching-Yu Chiu, Avinash Kumar Singh, Jung-Tai King, Li-Wei Ko, Yun-Chen Lu, and Yu-Kai Wang. A wireless multifunctional ssvep-based brain–computer interface assistive system. IEEE Transactions on Cognitive and Developmental Systems, 11(3):375–383, 2018.

[2] Yu-Kai Wang, Tzyy-Ping Jung, and Chin-Teng Lin. Eeg-based attention tracking during distracted driving. IEEE transactions on neural systems and rehabilitation engineering, 23(6):1085–1094, 2015.

[3] Li-Wei Ko, Yi-Chen Lu, Humberto Bustince, Yu-Cheng Chang, Yang Chang, Javier Fernandez, Yu-Kai Wang, Jose Antonio Sanz, Gra-caliz Pereira Dimuro, and Chin-Teng Lin. Multimodal fuzzy fusion for enhancing the motor-imagery-based brain computer interface. IEEE Computational Intelligence Magazine, 14(1):96–106, 2019.

| Framework  | Accuracy      |
|-------------|---------------|
| Trad. SVM   | 60.67 ± 4.23  |
| Trad. LDA   | 69.94 ± 4.05  |
| Trad. QDA   | 47.93 ± 2.82  |
| Trad. KNN   | 60.56 ± 4.20  |
| Trad. GP    | 53.04 ± 4.60  |
| MFF         | 67.96 ± 2.19  |
| EMF         | 83.15 ± 3.02  |
| OEMF        | 85.40 ± 3.03  |

| Framework  | Accuracy      |
|-------------|---------------|
| Trad. SVM   | 73.97 ± 4.79  |
| Trad. LDA   | 80.75 ± 4.42  |
| Trad. QDA   | 67.15 ± 4.49  |
| Trad. KNN   | 71.41 ± 4.90  |
| Trad. GP    | 66.84 ± 4.32  |
| MFF         | 81.15 ± 1.32  |
| EMF         | 85.83 ± 1.68  |
| OEMF        | 97.60 ± 1.03  |

Fig. 6: Accuracy comparison for the BCI Competition IV dataset 2a using the four classes. * represents a p-value less than 0.001, favouring the framework in the row. + represents a p-value less than 0.001, favouring the framework in the column.

Fig. 7: Accuracy comparison for the BCI Competition IV dataset 2a using only the left-hand and right-hand classes. * represents a p-value less than 0.001, favouring the framework in the row. + represents a p-value less than 0.001, favouring the framework in the column.
four classes task.

TABLE VIII: Performance in the EMF for each pair of aggregations, for the BCI competition IV 2a dataset using only the classifier fusion phase.

| Framework | Accuracy |
|-----------|----------|
| EMF       | 83.15%   |
| KLRM + LSVM | 63% | 74.43% |
| CSP/AM-BA-SVM | 78.55% |
| Dempster-Shafer | 64% | 81.93% |

TABLE IX: Comparison of different BCI frameworks in the four classes task.

| Framework | Accuracy |
|-----------|----------|
| EMF       | 83.15%   |
| KLRM + LSVM | 63% | 74.43% |
| CSP/AM-BA-SVM | 78.55% |
| Dempster-Shafer | 64% | 81.93% |

TABLE VII: Performance in the EMF for each pair of aggregations, for the BCI competition IV 2a dataset using the four classes. Each row represents the aggregation function used in the frequency fusion phase, and each column the one used in the classifier fusion phase.

| Framework | Accuracy |
|-----------|----------|
| EMF       | 83.15%   |
| KLRM + LSVM | 63% | 74.43% |
| CSP/AM-BA-SVM | 78.55% |
| Dempster-Shafer | 64% | 81.93% |

[1] Yousef Rezaei Tabar and Ugur Halici. A novel deep learning approach for classification of electrocardiogram signals. In 2015 International Conference on Future Generation Communication and Technology (FGCT), pages 1–6, 2015.

[2] M. Mironova and J. Bila. Fast fourier transform for feature extraction and neural network for classification of electrocardiogram signals. In 2015 Fourth International Conference on Future Generation Communication and Technology (FGCT), pages 1–6, 2015.

[3] W. Zheng, W. Liu, Y. Lu, B. Lu, and A. Cichocki. Emotionmeter: A multimodal framework for recognizing human emotions. IEEE Transactions on Cybernetics, 49(3):1110–1122, March 2019.

[4] L. Xie, Z. Deng, P. Xu, K. Choi, and S. Wang. Generalized hidden- Markov models for classification of eeg signals in motor imagery bci. IEEE Transactions on Cybernetics, 49(3):1110–1122, March 2019.

[5] D. Iacoviello, A. Petracca, M. Spezialletti, and G. Placidi. A classification algorithm for electroencephalography signals by self-induced emotional stimuli. IEEE Transactions on Cybernetics, 46(12):3171–3180, Dec 2016.

[6] L. Xie, Z. Deng, P. Xu, K. Choi, and S. Wang. Generalized hidden-classification transductive transfer learning for recognition of epileptic electroencephalogram signals. IEEE Transactions on Cybernetics, 46(12):3171–3180, Dec 2016.

[7] A. Jafariandam, M. A. Badamchizadeh, S. Khamomhaddad, M. A. Nazari, and B. M. Tazehkand. A new self-regulated neuro-fuzzy framework for classification of eeg signals in motor imagery bci. IEEE Transactions on Fuzzy Systems, 26(3):1485–1497, June 2018.

[8] P. A. Herman, G. Prasad, and T. M. McGinnity. Designing an interval-type-2 fuzzy logic system for handling uncertainty effects in electroencephalogram signals.
brain–computer interface classification of motor imagery induced eeg patterns. IEEE Transactions on Fuzzy Systems, 25(1):29–42, Feb 2017.

[15] T. K. Reddy, V. Arora, L. Behera, Y. Wang, and C. Lin. Multiclass fuzzy time-delay common spatio-temporal patterns with fuzzy information theoretic optimization for eeg-based regression problems in brain–computer interface (bci). IEEE Transactions on Fuzzy Systems, 27(10):1943–1951, Oct 2019.

[16] Jing Jin, Yangyang Miao, Ian Daly, Cili Zuo, Dewen Hu, and Andrezej Cichocki. Correlation-based channel selection and regularized feature optimization for mi-based bci. Neural Networks, 118:262 – 270, 2019.

[17] Jiankui Feng, Erwei Yin, Jing Jin, Rami Saab, Ian Daly, Xingyu Wang, Dewen Hu, and Andrezej Cichocki. Towards correlation-based time window selection method for motor imagery bcs. Neural Networks, 102:87–95, 2018.

[18] Feifei Qi, Wei Wu, Zhu Liang Yu, Zhenghui Gu, Zhenfu Wen, Tianyou Chen, Yufeng Gao, and Xingyu Wang. Spatiotemporal-filtering-based channel selection for single-trial eeg classification. IEEE Transactions on Cybernetics, 2020.

[19] Michio Sugeno. Theory of fuzzy integrals and its applications. Fuzzy Sets and Systems, 2:111–120, 1979.

[20] Claude Bidal, Pau D Gader. Generalized aggregated fuzzy integral fusion. Information Fusion, 3(3):50–59, 2002.

[21] Toshiaki Murofushi and Michio Sugeno. Fuzzy t-conorm integral with respect to fuzzy measures: generalization of sume integral and choquet integral. Fuzzy Sets and Systems, 42(1):57–71, 1991.

[22] Graçaliz Pereira Dimuro, Javier Fernández, Benjamin Bedregal, Radko Mesiar, José Antonio Sanz, Giancarlo Luca, and Humberto Bustince. The state-of-art of the generalizations of the choquet integral: From aggregation and pre-aggregation to ordered directionally monotone functions. Information Fusion, 57:27–43, 2020.

[23] Giancarlo Luca, José Antonio Sanz, Graçaliz Pereira Dimuro, Benjamin Bedregal, Humberto Bustince, and Radko Mesiar. C2-integrals: A new family of pre-aggregation functions with application to fuzzy rule-based classification systems. Information Sciences, 435/46:110–120, 2018.

[24] Graçaliz Pereira Dimuro, Giancarlo Luca, Benjamin Bedregal, Radko Mesiar, José Antonio Sanz, Chin-Teng Lin, and Humberto Bustince. Generalized c112-integrals: From choquet-like aggregation to ordered directionally monotone functions. Fuzzy Sets and Systems, 378:44–67, 2020.

[25] Ronald R Yager and Jianzhe Zhang. The ordered weighted averaging operator: theory and applications. Springer Science & Business Media, 2012.

[26] Ronald R Yager. Generalized owa aggregation operators. Fuzzy Optimization and Decision Making, 3(1):93–107, 2004.

[27] Laura De Miguel, Mikkel Selsa-Sara, Mikkel Elkano, M Asaïn, and Humberto Bustince. An algorithm for group decision making using n-dimensional fuzzy sets, admissible orders and owa operators. Information Fusion, 42:126–131, 2017.

[28] Jose M Merigo and Montserrat Casasnovas. The uncertain generalized owa operator and its application to financial decision making. International Journal of Information Technology & Decision Making, 10(02):211–230, 2011.

[29] H Bustince, J Fernandez, R Mesiar, Javier Montero, and R Orudna. Overlap functions. Nonlinear Analysis: Theory, Methods & Applications, 72(3–4):1488–1499, 2010.

[30] Laura De Miguel, Daniel Gómez, J. Tinguaro Rodríguez, Javier Montero, Humberto Bustince, Graçaliz P. Dimuro, and José Antonio Sanz. General overlap functions. Fuzzy Sets and Systems, 372:81 – 96, 2019. Theme: Aggregation Operations.

[31] Mikkel Elkano, Mikkel Galar, Jose Sanz, and Humberto Bustince. Fuzzy rule-based classification systems for multi-class problems using binary decomposition strategies: on the influence of n-dimensional overlap functions in the fuzzy reasoning method. Information Sciences, 332:94–114, 2016.

[32] Mikel Elkano, Mikkel Galar, Jose Antonio Sanz, Alberto Fernández, Edurne Barrenechea, Francisco Herrera, and Humberto Bustince. Enhancing multiclass classification in farc-hd fuzzy classifier: On the synergy between n-dimensional overlap functions and decomposition strategies. IEEE Transactions on Fuzzy Systems, 23(5):1562–1580, 2014.

[33] Shang-Lin Wu, Yu-Ting Liu, Tsung-Yu Hsieh, Yang-Yin Lin, Chih-Yu Chen, Chin-Hsiang Chuang, and Chin-Teng Lin. Fuzzy integral with particle swarm optimization for a motor-imagery-based brain–computer interface. IEEE Transactions on Fuzzy Systems, 25(1):21–28, 2016.

[34] Michael Tangermann, Klaus-Robert Müller, Ad Aertsen, Niels Birbaumer, Christoph Braun, Clemens Brunner, Robert Leeb, Carsten Mehring, Kai J Miller, Gernot Muller-Putz, et al. Review of the bci competition iv. Frontiers in neuroscience, 6:55, 2012.

[35] G Lucca, J A Sanz, Graçaliz Pereira Dimuro, Benjamin Bedregal, Radko Mesiar, Anna Kolesarova, and Humberto Bustince. Pre-aggregation Functions: Construction and an Application. IEEE Transactions on Fuzzy Systems, 24(2):260–272, APR 2016.

[36] Mehmet Akin. Comparison of wavelet transform and fft methods in the analysis of eeg signals. Journal of medical systems, 26(3):241–247, 2002.

[37] Michal Teplan et al. Fundamentals of eeg measurement. Measurement science review, 2(2):1–11, 2002.

[38] Benjamin Blankertz, Ryohta Tomokawa, Steven Lemm, Motoaki Kawanabe, and Klaus-Robert Müller. Optimizing spatial filters for robust eeg single-trial analysis. IEEE Signal processing magazine, 25(1):41–56, 2007.

[39] Christoph Guger, Herbert Ramsler, and Gert Pfurtscheller. Real-time eeg analysis with subject-specific spatial patterns for a brain-computer interface (bci). IEEE transactions on rehabilitation engineering, 8(4):447–456, 2000.

[40] Alexandre Gramfort, Martin Luessi, Eric Larson, Denís A Engemann, Daniel Strohmeier, Christian Brodbeck, Roman Goj, Mainak Jas, Teon Brooks, Laura Parkkonen, et al. Meg and eeg data analysis with mne-python. Frontiers in neuroscience, 7:267, 2013.

[41] S. Bhattacharyya, A. Khasnobish, S. Chatterjee, A. Konar, and D. N. Talwalkar. Performance analysis of lda, qda and knn algorithms in left-right limb movement classification from eeg data. In 2010 International Conference on Systems in Medicine and Biology, pages 126–131, Dec 2010.

[42] G Lucca, J. A. Sanz, G. P. Dimuro, E. N. Borges, H. Santos, and H. Bustince. Analyzing the performance of different fuzzy measures with generalizations of the choquet integral in classification problems. In 2019 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), pages 1–6, 2019.

[43] Santiago Arroyo, Ronald P Lesser, Barry Gordon, Sumio Uematsu, Darryl Jackson, and Robert Webber. Functional significance of the mu rhythm of human cortex: an electrophysiologic study with subdural electrodes. Electroencephalography and Clinical Neurophysiology, 87(3):76–87, 1993.

[44] Jonathan R Wolpaw, Niels Birbaumer, Dennis J McFarland, Gert Pfurtscheller, and Theresa M Vaughan. Brain–computer interfaces for communication and control. Clinical neurophysiology, 113(6):767–791, 2002.

[45] Claudio Babiloni, Filippo Carducci, Febo Cincotti, Paolo M Rossini, Cristina Neuper, Gert Pfurtscheller, and Fabio Babiloni. Human movement-related potentials vs desynchronization of eeg alpha rhythm: a high-resolution eeg study. NeuroImage, 10(6):658–665, 1999.

[46] Gert Pfurtscheller and FH Lopes Da Silva. Event-related eeg/meg synchronization and desynchronization: basic principles. Clinical neurophysiology, 110(11):1842–1857, 1999.

[47] Jeffrey Nguyen, Frederick Shipley, Ashley Linder, George Plummer, Mochi Liu, Sagar Setru, Joshua Shaveitz, and Andrew Leifer. Whole-brain calcium imaging with cellular resolution in freely behaving caenorhabditis elegans. Bulletin of the American Physiological Society, 2016.

[48] Miguel Aguillera, Carlos Alquézar, and Eduardo J. Izquierdo. Signatures of criticality in a maximum entropy model of the eegs brain during free behaviour. In Proceedings of the 14th European Conference on Artificial Life ECAL 2017, pages 29–35, 2017.

[49] Galka Andreas. Topics in nonlinear time series analysis, with implications for eeg analysis, volume 14. World Scientific, 2000.

[50] James D Hamilton. Time series analysis, volume 2. Princeton New Jersey, 1994.

[51] Georgios Cortes and Vladimir Vapnik. Support-vector networks. Machine learning, 20(3):273–297, 1995.

[52] David IC MacKay. Introduction to gaussian processes. NATO ASI Series F Computer and Systems Sciences, 168:133–166, 1998.
[57] Gunther Krausz, Reinhold Scherer, G Korisik, and Gert Pfurtscheller. Critical decision-speed and information transfer in the “graz brain–computer interface”. Applied psychophysiology and biofeedback, 28(3):233–240, 2003.

[58] Carmen Vidaurre, Reinhold Scherer, Rafael Cabeza, Alois Schögl, and Gert Pfurtscheller. Study of discriminant analysis applied to motor imagery bipolar data. Medical & biological engineering & computing, 45(1):61, 2007.

[59] Ludmila I Kuncheva and Christopher J Whitaker. Measures of diversity in classifier ensembles and their relationship with the ensemble accuracy. Machine learning, 51(2):181–207, 2003.

[60] Ludmila I Kuncheva, Christopher J Whitaker, Catherine A Shipp, and Robert PW Duin. Is independence good for combining classifiers? In Proceedings 15th International Conference on Pattern Recognition, ICPR-2000, volume 2, pages 168–171. IEEE, 2000.

[61] Clemens Brunner, Muhammad Naeem, Robert Leeb, Bernhard Graimann, and Gert Pfurtscheller. Spatial filtering and selection of optimized components in four class motor imagery eeg data using independent components analysis. Pattern recognition letters, 28(8):957–964, 2007.

[62] Pradeep Kumar Mishra, B Jagadish, MPRS Kiran, Pachamuthu Rajalakshmi, and D Santhosh Reddy. A novel classification for eeg based four class motor imagery using kullback-leibler regularized riemannian manifold. In 2018 IEEE 20th International Conference on e-Health Networking, Applications and Services (Healthcom), pages 1–5. IEEE, 2018.

[63] S. Selim, M. M. Tantawi, H. A. Shedeed, and A. Badr. A csp am-ba-svm approach for motor imagery bci system. IEEE Access, 6:49192–49208, 2018.

[64] Sara Razi, Mohammad Reza Karami Mollaei, and Jamal Ghasemi. A novel method for classification of bci multi-class motor imagery task based on dempster–shafer theory. Information Sciences, 484:14 – 26, 2019.

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