Online processing for motor imagery-based brain-computer interfaces relying on {EEG}

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Online processing for motor imagery-based brain-computer interfaces relying on EEG

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***Abstract*—This manuscript reports a comparison among three possible strategies for online processing of electroencephalographic signals, in terms of their impact on the online classification accuracy. The comparison was carried out in the framework of brain-computer interfaces based on motor imagery. *Filter bank common spatial pattern* was exploited as a standard feature extraction technique along with a support vector machine for classification of the brain signals. This machine learning-based algorithm was trained offline and evaluated on independent evaluation data by means of the online processing strategies. Benchmark dataset were used, so that the online processing performance was compared to reference offline performances compatible with literature (at least $74\,\%$ classification accuracy). Results suggest that it is convenient to use the bigger part of the imagery period in training the algorithm prior to online classification accuracy. Moreover, using an enlarging window for evaluation appeared to be the best strategy to remain close to reference mean accuracy.**

***Index Terms*—Electroencephalography; online processing; signal processing; brain-computer interfaces; motor imagery.**

I. Introduction

Brain activity in a human subjects exhibits peculiar spatio-temporal features when imagining a movement [1], [2]. Measuring this brain activity enables the usage of motor imagery in control applications [3], [4] or in improving motor performance [5], without actually requiring a movement execution. Therefore, brain-computer interfaces (BCI) relying on motor imagery appear especially suited for disabled people [6], but they are addressed to able-bodied people as well [7].

A BCI involves building blocks like brain signals acquisition, signals processing, and translation into commands for an application (Fig. 1). Notably, electroencephalography (EEG) is widely considered for data acquisition [8], [9]. Indeed, EEG allows wearability, portability, and low cost for measuring the surface electrical activity of the brain [10], [11]. As a consequence, several EEG processing approaches have been investigated too [9], [12], [13].

Common spatial pattern (CSP)-based algorithms are common and effective for processing motor imagery-related EEG signals [14]. These rely on a linear transformation that translates the EEG signals acquired from different channels into a new spatial domain, so that the variance of a class of signals is maximized while the other class(es) variance is minimized. Then, the CSP ultimately extracts power features and, together with a bank of filters, it is capable of extracting spatio-temporal features for different frequency bands [15].

Although relatively old, recent literature has demonstrated that such approaches are still effective for features extraction in motor imagery BCI [16]–[18]. Then, features selection and classification are conducted, in order to associate a class the multi-dimensional input EEG signal. In these steps, deep learning approaches are greatly investigated, but traditional machine learning approaches are efficiently used as well [19].

Despite the specific approach, processing blocks generally require a first identification phase (named *training* in the machine learning jargon), and an actual usage phase (named *inference* in the machine learning jargon). In this last phase, a practical application would require that the trained algorithm processes EEG signals online to translate brain activity into application commands [20]–[22]. In principle, BCI applications demand continuous processing of EEG signals and the algorithm must return the classification output with a certain pace.

As a representative case, neurofeedback involves online EEG processing to deliver a sensory feedback to the user as he/she performs motor imagery [23]. In these regards, researchers are currently investigating how often the neurofeedback should be provided [24] and suggest that misclassification of EEG data is disengaging for the user [25], [26]. Hence, the online algorithm implementation must be carefully designed to achieve a performance compatible with a validated offline version.

A peculiar aspect for online processing concerns the choice of the time window to adopt during online classification. As a representative example, EEG signals were processed in [26] by considering an enlarging time window, which starts at a cue, enlarges as acquisition progress, and then stops at the trial end. Another option is, instead, the possibility to use a sliding window of fixed duration [27].

The proposal of the present work is thus to compare three different strategies, exploiting either fixed or enlarging time windows, for implementing an online processing of EEG in the framework of motor imagery-based BCIs. In the remainder of the paper, Section II presents the methodology and the data used to carry on such a comparison, while Section III presents and discusses the inherent results. The work has taken

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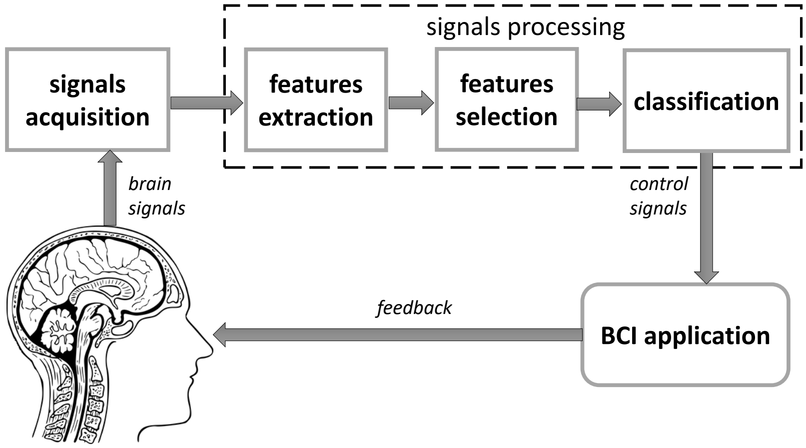

Fig. 1. Architecture of a brain-computer interface, from data acquisition to data processing and application control.

into account four (public) benchmark datasets and a standard processing approach to ease reproducibility and generalization of the results.

II. Materials and methods

The present study deals with online processing of EEG signals associated with motor imagery. To this aim, three different strategies were tested on four benchmark datasets from BCI competitions. In the following, the filter bank CSP is briefly recalled as a standard processing approach. Next, the strategies to compare are described. Finally, the adopted benchmark datasets are introduced.

A. Filter bank common spatial pattern

To process motor imagery EEG data, the filter bank common spatial pattern (FBCSP) algorithm was used for features extraction in combination with the support vector machine (SVM) classifier. Previous works demonstrates that this is an effective (and popular) algorithm introduced to optimize the subject-specific frequency band for CSP [15], [19], [28]. In details, the specific pipeline involved four main stages: (i) a filter bank with 4-8 Hz, 6-10 Hz, ..., 36-40 Hz pass-band filters, (ii) a CSP for feature extraction, (iii) a features selection with "mutual information-based best individual feature" (MIBIF) algorithm, and (iv) an SVM to classify the selected CSP features. More details on the implementation can be found in [15], [28]. In the training phase, the CSP, the MIBIF, and the classifier were trained with labeled EEG data. Then, the models identified in this first phase were used to classify the EEG per each trial during the inference (i.e., the phase corresponding to actual usage).

B. Online processing strategies

Motor imagery BCIs typically rely on synchronous paradigms, namely the timing for resting and imagining movement are externally paced [19]. Notably, the current study considers a limited period for each trial (some seconds), during which the user has to imagine a movement according to an external indication. The specific timings are detailed in the following section because they necessarily depend on the dataset. However, different strategies for online processing can be discussed independently of the exact window length.

By relying on the FBCSP architecture, three strategies for online data analysis were taken into account in the comparison:

1) *strategy 1:* a $1.0\,\mathrm{s}$-long sliding window with a shift of $0.5\,\mathrm{s}$ was used for both training and inference; therefore, a classification model was identified for each possible window within the motor imagery period, and each model could be used to classify the corresponding window of the evaluation data thanks to the synchronous paradigm, which allows to univocally identify the pace for changing the classifier;
2) *strategy 2:* the whole motor imagery period on training EEG signals was exploited to identify a single classification model, while a $1.0\,\mathrm{s}$-long sliding window with a shift of $0.5\,\mathrm{s}$ was exploited during inference;
3) *strategy 3:* the whole motor imagery period on training EEG signals was exploited to identify a single classification model, and the inference was conducted using an enlarging time window, which started from a $1.0\,\mathrm{s}$ width and progressively widened by $0.5\,\mathrm{s}$ steps until the entire motor imagery period was reached.

For strategies 2 and 3, it is worth remarking that the length of the feature vector for both the training and inference phases is not influenced by the different lengths of the time windows. Indeed, when using the CSP, the number of features extracted from the data is defined a priori by fixing the number of components to extract. Instead, training the algorithm with more information on the EEG time series implies that the noise is lowered for the projection matrices of the CSP.

These processing strategies were applied to benchmark datasets from BCI competitions and they are graphically resumed in Fig. 2.

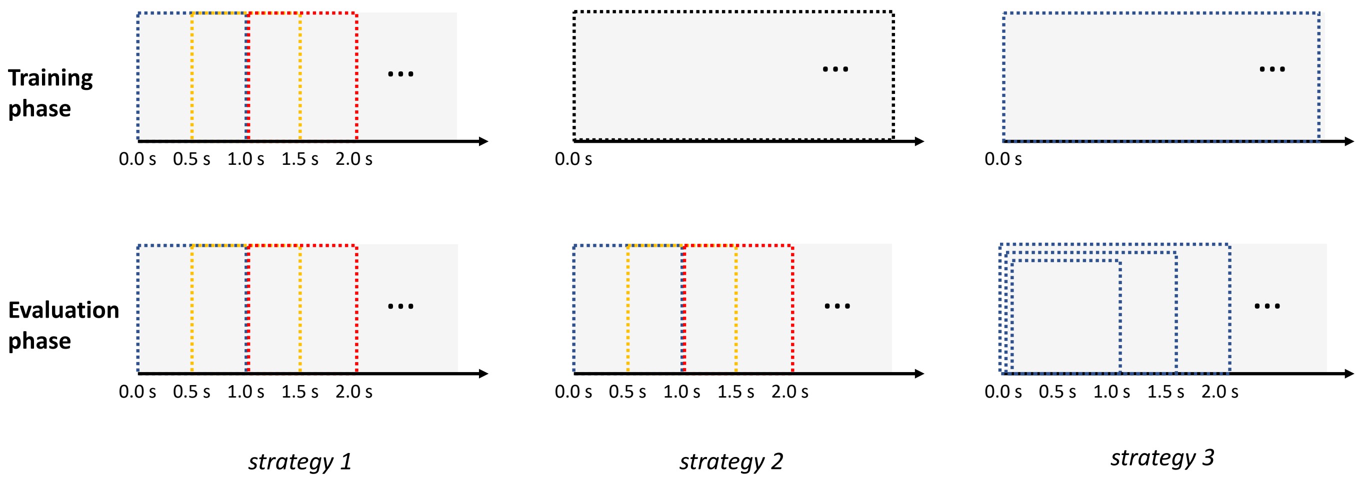

Fig. 2. Representative diagram of the three online processing strategies. The light gray area represents the EEG trace of a trial, windows are highlighted by dotted outlines. In case of sliding windows different colors are used for each new overlap.

C. Datasets

The four benchmark datasets exploited in the study were the datasets 2a [29] and 2b [30] from BCI Competition IV (2008), and the datasets 3a [31] and 3b [32] from BCI competition III (2006). The reader is addressed to the references for a detailed description of their, but useful aspects are briefly recalled below.

1) Dataset 2a from BCI competition IV: it consists of data from 9 subjects (A01...A09) recorded through 22 EEG channels and 3 electrooculographic channels. The synchronous paradigm consisted of four motor imagery tasks, namely imagining the movement of left hand (class 1), right hand (class 2), both feet (class 3), and the tongue (class 4). For every subject, signals were recorded in two sessions held on different days ("session T" and "session E", respectively). A total of 288 trials were recorded per each session. The motor imagery period for each trial lasted 3 s, it was preceded by a cue and followed by a relaxation period. In the current study, only trials related to left hand and right hand motor imagery were extracted.

2) Dataset 2b from BCI competition IV: it consists of data from 9 subjects (B01...B09) recorded through three differential EEG channels (C3, Cz, and C4) and three single-ended electrooculographic channels. The synchronous paradigm consisted of two motor imagery tasks, namely imagining the movement of left hand (class 1) and right hand (class 2). For each subject, signals were recorded in five sessions. The first two sessions comprise 240 trials without visual feedback. The last three sessions comprise 480 trials with visual feedback. The motor imagery period for each trial lasted 3 s, it was preceded by a cue and followed by a relaxation period. Note that also in this case only EEG data wee used.

3) Dataset 3a from BCI competition III: it consists of data from 3 subjects (l1b, k3b, k6b) recorded through 60 EEG channels. The synchronous paradigm consisted of four motor imagery tasks (left hand, right hand, foot and tongue). For each subject, at least six runs with 40 trials each were recorded. The motor imagery period for each trial lasted 4 s, it was preceded by a cue and followed by a relaxation period. Again, only the left hand and the right hand motor imagery were taken into account.

4) Dataset 3b from BCI competition III: it consists of EEG recordings from 3 subjects. They performed two motor imagery tasks according to an external pace (i.e., the paradigm is synchronous): left hand and right hand. Data were recorded using two differential EEG channels at the C3 and C4 standard locations. Data were recorded during three consecutive sessions with online feedback for each subject. Each session involved four to nine runs. The motor imagery period for each trial lasted 4 s, it was preceded by a cue and followed by a relaxation period. Subjects were named S4, X11, and O3VR, and the number of trials for each of them were 1080, 1080, and 640 trials, respectively.

III. Results

The following paragraphs first present the results obtained through the FBCSP by exploiting all available data from the reference datasets. These were used as a reference for the subsequent analyses. Then, the results obtained with the three proposed methods are presented.

A. Reference results

For each dataset, the results of the cross-validation (CV) and the hold-out (HO) techniques are first provided in Tab. I, II, III, IV. Four folds were used for the cross-validation.The tables report the classification accuracy in percentage (%) per each subject together with the mean classification accuracy among subjects and its associated standard deviation (type A uncertainty evaluation).

It is pointed out that the CV is useful for estimating the performance of the algorithm when only the training set is available. Furthermore, before online experiments, it can be used to check the quality of just recorded training data. In contrast, HO can only be applied when a new data set is available. Thus, the classification is robust if the results of CV and HO are compatible.

For the dataset 2a from BCI competition IV, set T was used to train the algorithm, while set E was used for evaluation. Instead, data from the first three sessions of dataset 2b from BCI competition IV were used as training set while data from the last two sessions were used as evaluation set. Finally, for both dataset 3a and 3b from BCI competition III, half of the data were used to train the algorithm, while the other half were used for its evaluation.

TABLE I
CROSS-VALIDATION AND HOLD-OUT RESULTS FOR DATASET 2A.

Subject	CV	HO
A01	82	87
A02	54	55
A03	95	96
A04	66	65
A05	89	88
A06	57	61
A07	84	79
A08	94	89
A09	68	81
Mean	77	77
Uncertainty	5	5

TABLE II
CROSS-VALIDATION AND HOLD-OUT RESULTS FOR DATASET 2B.

Subject	CV	HO
B01	73	65
B02	63	59
B03	52	55
B04	89	95
B05	80	88
B06	75	82
B07	73	73
B08	69	88
B09	76	84
Mean	72	77
Uncertainty	3	5

To sum up the results in the tables, the mean classification accuracies among the subject using different dataset is at least $74\,\%$. Notably, the specific mean accuracy depends on the adopted dataset (i.e. the involved subjects) and the uncertainty for datasets 3a and 3b is lower because of the limited number of subjects. Nonetheless, results using CV and HO are compatible in each case and the HO mean classification accuracy is used in the following as a reference.

B. Results of online processing strategies

The results using the three strategies proposed in Sec. II-B are presented in Fig. 3, Fig. 4, Fig. 5, Fig. 6 per each respective dataset. On the x-axis, the exploited time window is reported, while the y-axis reports the mean accuracy among subjects in %. Each curve represents a different condition. The blue

TABLE III
CROSS-VALIDATION AND HOLD-OUT RESULTS FOR DATASET 3A.

Subject	CV	HO
l1b	83	97
k3b	98	96
k6b	44	50
Mean	78	81
Uncertainty	13	15

TABLE IV
CROSS-VALIDATION AND HOLD-OUT RESULTS FOR DATASET 3B.

Subject	CV	HO
S4b	81	81
X11b	76	79
O3VR	66	63
Mean	74	75
Uncertainty	4	6

curve refers to the mean accuracy among subjects using the HO technique. Then, red curve refers to mean accuracy among subjects and its associated type A uncertainty obtained from *strategy 1*. Similarly, the yellow and the magenta curves refer to results using *strategy 2* and *strategy 3*, respectively.

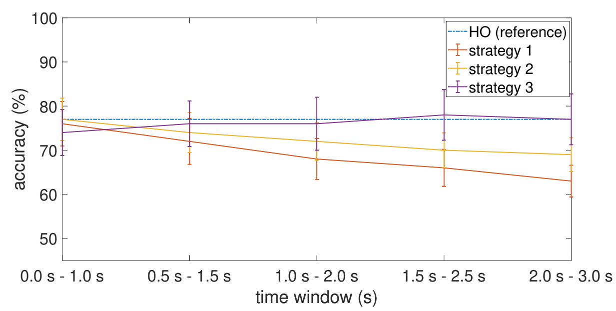

Fig. 3. Results of different strategies for dataset 2a.

For the dataset 2a from BCI competition IV, since the motor imagery task was recorded from $3.0\,\mathrm{s}$ to $6.0\,\mathrm{s}$, five one-seconds windows with a shift of $0.5\,\mathrm{s}$ were exploited. Results in Fig. 3 show that the best performance is obtained when considering an enlarging time window of the EEG signal. In this case, the classification accuracy even exceeds the HO accuracy from $1.5\,\mathrm{s}$ to $2.5\,\mathrm{s}$, i.e. when the window used is $2.5\,\mathrm{s}$ wide. In contrast, the other two curves decrease over time. Finally, the uncertainties associated with the classification accuracy in the 3 cases are comparable.

For dataset 2b from BCI competition IV, the motor imagery task was record from $4.0\,\mathrm{s}$ to $7.0\,\mathrm{s}$, thus five one-seconds windows with a shift of $0.5\,\mathrm{s}$ were exploited. As for dataset 2a, results in Fig. 4 show that the best performance was obtained when considering an enlarging time window of the signal. Moreover, the reference result was already reached during the time window from $1.0\,\mathrm{s}$ to $2.0\,\mathrm{s}$, thus with a window width of $2.0\,\mathrm{s}$.

Also for dataset 3a from BCI competition III, the motor imagery task was record from $4.0\,\mathrm{s}$ to $7.0\,\mathrm{s}$. Thus, five one-

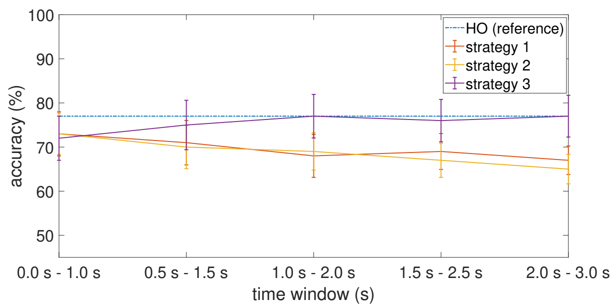

Fig. 4. Results of different strategies for dataset 2b.

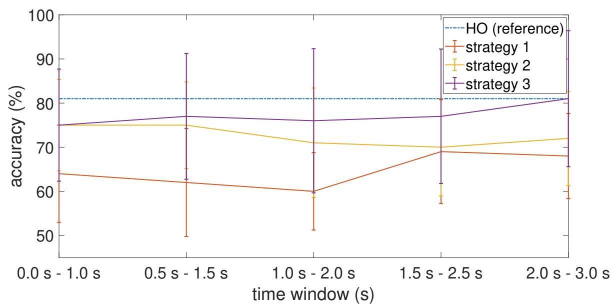

Fig. 5. Results of different strategies for dataset 3a.

seconds windows with a shift of $0.5\,\mathrm{s}$ were exploited. Results in Fig. 5 show that the best performance is again obtained when considering an enlarging time window of the EEG signal. Indeed, the classification accuracy increases as the considered time window widens. In this case, the uncertainty associated with accuracy is greater than in previous cases, due to the smaller number of subjects and their different performances.

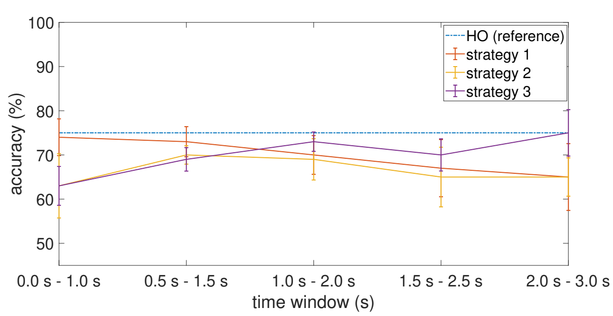

Fig. 6. Results of different strategies for dataset 3b.

Finally, Fig. 6 confirms that the best performance is obtained with the enlarging time window of *strategy 3* also for dataset 3b from BCI competition III.

C. Discussion

Analysing the results obtained with *strategy 1*, i.e. when a sliding window of $1\,\mathrm{s}$ was considered for both the training and evaluation datasets, it can be seen that the mean classification accuracy varies from one second to the next. Moreover, it decreases over time. Hence, the robustness of the algorithm is low if only trained on $1\,\mathrm{s}$ of the signal. Moreover, using multiple classifiers could introduce an unjustified complication, though it should be noted that a classifier with a state could be adopted in a practical real-time BCI.

Instead, using the *strategy 2*, namely all the available data from the training set and a sliding window of $1\,\mathrm{s}$ from the evaluation set, the results depended on the exploited dataset. For datasets 2a and 3a from BCI competition IV and III, respectively, the results were better with respect to the *strategy 1*. However, they again decreased over time. Instead, the results for datasets 2b and 3b BCI competition IV and III, respectively, are very similar to those obtained with *strategy 1*.

For all datasets, the best strategy was found to be *strategy 3*. Indeed, in all cases, a better average accuracy over time can be obtained by using the bigger part of the imagery period available for training and an enlarging window during the inference. In this way, the algorithm has an increasing amount of data for classification, becoming more robust over time. In many cases, the reference results were achieved starting from the middle of the widening window.

A statistical analysis was also performed for highlighting statistically significant differences between the strategies. In particular, an analysis of variances (ANOVA) was performed for each dataset with a significance level set a-priori at $\alpha = 5\%$. Test results suggest that, for the only case of dataset 2a, there is a significant difference between the *strategy 2* and the *strategy 1* or between the *strategy 3* and the *strategy 1*. This constitutes a (weak) evidence for avoiding strategy 1.

In future developments, the presented strategies could be also enhanced by considering different weighting windows. Indeed, in the present study, a rectangular windowing has been implicitly applied to derive the EEG parts for training and/or test. Instead, using a windowing like Hanning, Hamming, or Keiser could reduce the spectral leakage given by truncations in the time domain. A windows different from the rectangular one could thus reduce the artifacts of the spectral convolution.

IV. Conclusions

In this paper, a comparative analysis of three different strategies for the online processing of EEG signals associated with motor imagery has been carried out. In a synchronous BCI paradigm, the goal was to identify the best time window to adopt during online experiments when, for example, feedback is given to the user. In such cases, it is essential to employ a robust algorithm whose result improves over the course of the imaginative task.

Three strategies were taken into account, exploiting both fixed and enlarged time windows. They were tested on four benchmark datasets from BCI competitions. Moreover, for each dataset, the HO mean classification accuracy was used as a reference to evaluate the performance of the proposed strategies.

Results from all exploited datasets suggest that *strategy 3* outperforms the other strategies. It is the only strategy for which the accuracy increases over time. In some cases, the reference accuracy was already reached halfway through the trial. In contrast, the other two proposed strategies showed variable performance over time. In all cases, results dropped off at the end of the trial.

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