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A protocol for Brain-Computer Interfaces based on Musical Notes Imagery

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***Abstract*—The application of Brain-Computer Interfaces is expected to become a matter of daily life. For this purpose, several efforts are being developed to ensure that users can employ this technology without difficulties. A large amount of studies consider motor imagery, which implies the usage of sensorimotor rhythms produced when imaging motor actions. However, previous works have shown that from a sample of population, a portion of users (15∼30%) is unable to efficiently control a BCI based on such paradigm. The roots of this issue have been partially located to different factors related to the training protocol that users follow to learn how to use the system. Thus, in order to extend the applicability of BCIs, training procedures must consider different approaches. Musical imagery is another mental task that may be used to control BCIs and requires users to have music related thoughts or imagine specific notes and even songs. In this work, we propose a protocol to explore the properties of Musical Imagery based training procedures. For this, we developed both offline and online experiments, where the last one consisted of 4 sessions. The data-processing steps include filtering the data using a FIR filter to later extract features using PCA, and classify such features with a multi-class SVM. Our results show that the offline classification is comparable to motor imagery based BCIs as the accuracy is between 80% to 95%. Moreover, we found that the online setup results point to up to 64% of accuracy for the third session with feedback.**

***Index Terms*—Brain-Computer Interface, Mental Task, Musical Imagery, Training Protocol**

I. Introduction

A Brain-Computer Interface (BCI) measures central neural activity to then transform such signals into control variables that are used to interact with the environment through different devices or means [1]. The attention to this technology has grown exponentially and different approaches to develop them are being studied [2]. The functional structure of a BCI system involves different elements, some of them refer to the user, which explicitly involves psychological states and personality traits [3]. Further, other elements point to the algorithmic or data-processing steps in charge of decoding neural signals [4], [5].

While there is a vast diversity of neural signals acquisition methods [6], the development of BCIs based on electroencephalography (EEG) is very attractive due to its portability, non-invasiveness and affordability properties [7]. Nevertheless, despite the acquisition technique that may be used, any BCI additionally involves an appropriate user training protocol and a task paradigm which are related to both the type of signals to be employed and the system-user's goal [3].

For EEG-based BCIs, several paradigms have been proposed as exposed in [7]. Their characterization, on the other hand, may follow the active, passive or reactive description [8]. The key characteristic between all of them relies on the type of signals that the system analyzes and tasks that the user must develop. Passive and reactive paradigms are linked to P300 and Steady-State Somatosensory Evoked Potentials (SSSEP). Further, sensorimotor rhythms and slow cortical potentials are related to Motor Imagery (MI) [9]. While passive and reactive BCIs rely on non-entirely intentional neural mechanisms, active BCIs require the user to modulate his/her brain rhythms at will. From the user's perspective, an active BCI seem more intuitive as it makes the interaction more natural.

The applicability and effectiveness of a paradigm is a result of different factors that involve user's psychological traits [10], and also appropriate algorithms for data processing [11]. As a matter of fact, while there have been several reports of inter- and intra-variability which decrease the accessibility of BCIs [12], there is a clear need for more online studies and with different approaches to address BCI illiteracy [13]. One of them is to consider different mental tasks modalities for different population sections, which means to use almost tailored paradigms or protocols according to users' characteristics.

Besides MI, other modalities include Auditory Imagery (AI), in which users evoke characteristic sounds like cat's meow [14], and Imagined Speech, that implies a more natural way of communication [15], [16]. However, the complexity of the inner speech and languages' differences makes difficult to establish a universal protocol [17]. Because of that, Music Imagery, defined as the imagination of musical elements, is an attractive alternative given that music, at a psychological level, produces similar effects despite differences in origins [18] and provides a good framework for neuroplasticity [19]. Furthermore, previous research showed that the music training level does not significantly influence on brain responses [20].

In this work, we propose a protocol for BCI systems based on musical notes imagery. The methodology is inspired on the Graz protocol [21] and common procedures used for similar modalities as MI. The effectiveness of the protocol is tested by implementing an offline framework and an online setup. The paper is structured as follows: section II outlines related works and reviews approaches of musicality or auditory based

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BCIs. Section III describes the inner working principles of the protocol implementation. Section IV presents our results and discussion towards analyzing our contribution critically. Finally, Section V concludes the paper.

II. Related Works

According to Gonzalez et al. [22], white noise is the best sound that can be imagined because its power is uniformly distributed in the whole spectrum. Thus, by focusing in a set of frequencies instead of only one, variables as the pitch or tone can be removed from the analysis. In this work, the experiment consisted of three phases: white noise perception (5 seconds), white noise imagery (5 seconds), and silence imagery (8 seconds as rest stage). Once signals were acquired, they were filtered in two bands: 8-30 Hz and 30-50 Hz, in addition, they were labeled according to the belonging phase, i.e., noise imagery was tagged as noise class, and silence imagery as silence class. For classification, a comparison between Multi Layer Perceptron (MLP), Linear Discriminant Analysis and Support Vector Machine was executed, finding SVM as the best classifier with an accuracy of 93% on cross-validation for an offline setup. This studied concluded that Auditory Imagery is a feasible and constitutes a low-cost alternative to Motor Imagery even considering low-density EEG headsets.

On the other hand, vowel reconstruction has been attractive considering its intonation and phonology. Rampinini et al. [23] showed how Italian vowels could be reconstructed through the integration of motor and auditory cortices activity. Their results are analyzed from different perspectives. From the formants and tones view, differences were found among pitch, key, and harmonic structure. Further, for the articulatory model, although the difference relies on phonology, data shows that the significant difference is mostly found on the acoustic model performance. A similar work was presented by Min et al. [24], in which Korean vowels were recognized through the application of a Extreme Learning Machine-based classifier, a pass-band filter (from 1-100 Hz), a reject-band filter (59-61 Hz), and a sparse-regression feature selection for statistical properties of windowed samples. The protocol to acquire the signals involved three types of phases: beeps, auditory cues, and imagery.

Other works focus on the rhythmic part of music, coordinating synchronic and asynchronic tasks with specific instruments [25] or looking for a piece's tempo through subject perception [26]. At a tone level, Chen et al. [27] analyzed high (C6 to C7) and low (C2 to C3) by observing alpha-band neural signals, and applying both Common Spatial Pattern (CSP) and LDA. Their results showed an accuracy of 60%.

The auditory paradigm was compared with others to verify its efficacy, showing promising results, near to those works that use motor or visual tasks [25], [28]. Nevertheless, the type of information that a given subject may consider as familiar and preferred is not considered [29]. Thus, the commitment of the subject towards the experiment may be seem diminished, producing lower results as noted in [3].

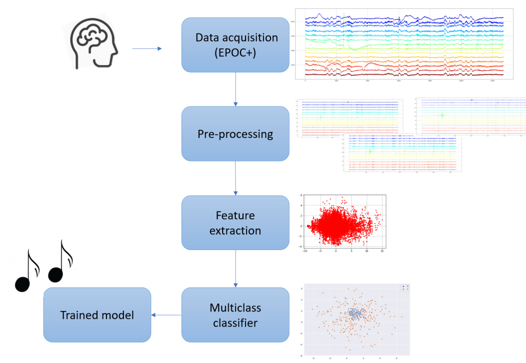

Fig. 1. Offline scheme showing four stages: data acquisition, preprocessing, feature extraction y multi-class classifier. It should be noted that the classifier trained in this setup will be used for the next session when using the online setup. These updates are periodic and run after each session.

III. Proposed Method

A. General Considerations

The system implementation considered two setups: offline (Figure 1) and online (Figure 2). While the first one provides the data that is used to train the system, the second one provides the respective feedback to the user of how good the communication is being held between both the BCI and the user. It should be noted that the online setup uses a classifier that was trained with the data from the previous offline setup. However, the classifier is updated after each session. When the session is over, the obtained data was combined with the previous session, this way the BCI is constantly adapting to the user, and the user is constantly learning how to improve his or her BCI skills. Despite the fundamental differences between the setups, the signal processing pipeline is the same on them.

B. Data Acquisition

Initially, the procedure included three subjects, but only two remained in the study. Therefore, while we hold four sessions, only the two remaining participated in all of them. Each session lasted from 20 to 30 minutes to keep their

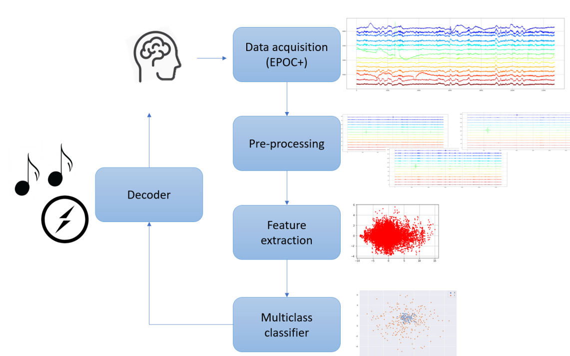

Fig. 2. Online scheme showing five stages: data acquisition, preprocessing, feature extraction, multi-class classifier and decoder. The classifier was trained with data from the previous session. Moreover, the decoder task is to present the appropriate imagined musical note to the user.

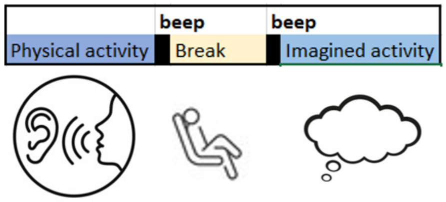

Fig. 3. Routines' elementary segment.

attention active [30]. All participant subjects belong to the musical field to some extent, being the differences on theoretical musical knowledge the primary distinction between them. The corresponding musical background for each subject is as follows: subject one - amateur (more than 25 years of experience), subjects two and three - professional (25 and 18 years of experience). The acquisition was performed using the 14 channel EEG EPOC+ device with 256 Hz as sampling frequency. The sessions comprised eight routines that included the audition and imagination of three different musical notes, which were chosen for each subject according to their preference. The instrument employed to play the musical notes was also picked by the user. Each routine is based on the elementary segment (Figure 3), which included the audition of a given note for five seconds, a break of ten seconds for the user to rest, and a period of five seconds for the user to imagine the musical note. It should be noted that users were asked to not blink during the first and third phases of the elementary segment. The overall scheme is based on the Graz protocol, replacing tasks of what is commonly motor imagery to musical notes imagery. For each musical note, ergo each class, four trials were executed using the listened note mode, and 6 trials using the imagined note mode. Nevertheless, if the researcher detected an inconsistency like unexpected blinks during any trial, it was discarded. Listened and imagined note modes represent different classes because, according to previous studies [23], there are less activation during imagery activity when is related to the auditory part. Imagined notes were used as reference for the subjects, also allowing a regulated scale for the routine.

The *beep* between activities consists of a short key hit to ease the musical note retention and make the interruption less annoying [31]. Furthermore, each subject had 15 minutes of previous preparation through meditation to achieve better performance [32].

C. Preprocessing

In this stage, we prepare data for feature extraction by applying three pass-band filters with cut-off frequencies of [(3.0-8.0), (8.0-12.0), (12.0-38.0)] Hz according to theta, alpha, and beta bands respectively [33]. Later, a Finite Impulse Response (FIR) filter of 6th order with Blackman-Harris was used as band-pass filter to minimize the levels of lateral lobes [34], [35]. FIR filters were applied individually to each channel through component convolution. The three resulting matrices from the band-filtering processes are then concatenated in a final matrix, which will be windowed for further processing. This process is shown in Figure 4.

The windowing application considered 64 data points, which is equivalent to 1/4 of a second, due to the 256 Hz sampling frequency. The time also answers to the duration of a blink and is similar to what was used in [36], [37]. Additionally, this process extends the data set to avoid model overfitting [24].

D. Feature Extraction

Once signals are windowed, Principal Component Analysis was applied to, besides extracting features, reduce the dimensionality [38]. By using PCA, the classifier performance can be improved significantly. In fact, [39] showed that SVM classifiers perform better when PCA is included in the processing pipeline of a BCI.
Before applying it, the filtered time series were scaled between 0 and 1, this becomes the entry data set for PCA.
The method seeks to transform a data set **X** of dimensions n x m to a new data set **Y** of lesser dimension with the least loss of useful information possible. For this reason, the covariance matrix is used, which can be calculated from:

$$cov(X,Y)=\frac{\sum_{i=1}^{n}\left(X_i-\bar{X}\right)\left(Y_i-\bar{Y}\right)}{n-1} \tag{1}$$

After applying PCA, eight components were used according to the covariance criteria, but also considering the minimal number of data points that will be used for the online preprocessing stage. Data was scaled before extraction and once features were selected, the dimensionality was reduced in 98%.

E. Classification and Decoding

Considering that three musical notes must be listened and imagined, six classes are implied. However, by also taking into account the rest periods in which subjects blink, an extra class is introduced: blinks. To implement a multi-class SVM, we focused on the one vs one strategy, i.e., 21 models were developed to compare all classes individually. The final result is giving for the decision function "one vs one" of sklearn SVC classifier, which will take in count the higher value given,

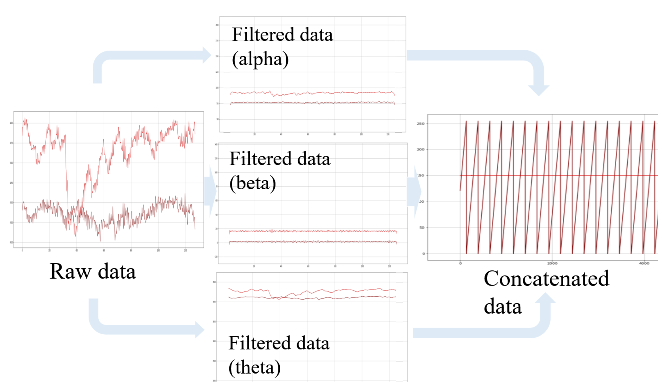

Fig. 4. Filtering diagram.

TABLE I
OFFLINE BCI PERFORMANCE. SESSIONS 1-3

ID	Session	Training	Validation	Testing
Subject 1	1	0.94	0.91	0.92
Subject 2	1	0.92	0.91	0.92
Subject 3	1	0.94	0.93	0.93
Subject 1	2	0.91	0.91	0.89
Subject 3	2	0.86	0.84	0.83
Subject 1	3	0.91	0.89	0.90
Subject 3	3	0.81	0.79	0.79
Subject 1	4	0.91	0.89	0.84
Subject 3	4	0.72	0.68	0.68

which represents the distance and side of the hyperplane. The implementation of these models is particular for each subject and each session.

Given the data distribution, we implemented a soft-margin SVM [40] and a Radial Basis Function (RBF) Kernel [41]. The values of gamma and C regularization were tuned through a grid search, each of them particular to each individual and session. Furthermore, data was randomly divided into: training, validation and testing following a 70%-15%-15% ratio. The SVM hyperparameter were selected using the training set as priority and validating these according the validation set. The test set was only used when reporting the corresponding results in Table I.

Once parameters are chosen for a given session, the model is kept to be loaded in the the next session during the online setup. As stated before, the purpose of the online BCI is to generate the sound in case the classifier that a given musical note has been imagined. This decoding process responds to a variation according to the accuracy percentage that the BCI computes:

- 0-20%: No sound
- 20-40%: Sound at 25% of intensity
- 40-60%: Sound at 50% of intensity
- 60-80%: Sound at 75% of intensity
- 80-100%: Sound at 100% of intensity

The variation of this value will allow the subject to identify if his or her brain activity is being appropriately classified, and the level of certainty the classifier has with respect to that data. This feedback strategy, eases BCI training for further sessions. For reference, we measured and averaged the time that the classification processes resulting in 0.6397 seconds, which represents $\sim$32% of the 2 seconds window time.

IV. RESULTS AND DISCUSSION

A. *Offline BCI*

After executing the grid search, we analyzed the accuracy of the different developed models to choose the values that secured good performance and do not tend to overfitting by taking a margin between 5 and 20% (variant between sessions). The performance of the best models through sessions and according to subjects can be found in Table I.

It can be seen that all accuracy results are higher than 80%, which, considering other works based on auditory imagery or similar, is significant. As a matter of fact, the approximate average of works, such as [24], [25], [27], [36], that used SVM is around 70%, which implies an improvement of over 20% in some cases. Furthermore, this study can be considered as a continuation to the tonal analysis presented by Chen et al. [27], with the implementation of five more classes and an improvement of up to 30% on classification accuracy.

B. *Online BCI*

Online BCIs are more complex to analyze and to summarize results given the lag times that can arise due to hardware and computational issues. Nevertheless, acquired data on the online setup was analyzed through the signal processing pipeline with the goal of verifying the data, given that these were still going to be consider for the next classifier training step. This result was compared with the ideal matrices considering that users were instructed to follow the same protocol of BCI training mentioned on the Data Acquisition section. Due to hardware limitations that did not allow entirely real-time performance, such comparisons took data through index-matching, i.e., the signal processing pipeline used data according to indices on temporal buffering rather than in a streaming manner. As for the feedback in the online setup, as noted in the Classification and Decoding section, this required approximately 2.6 seconds of data, which meant that users waited a brief amount of time prior to hear any feedback from the BCI. Unfortunately, the experiments that included the online BCI carried on only with two subjects and during three sessions as presented in Table II.

TABLE II
ONLINE BCI PERFORMANCE. SESSIONS 1-4

ID			
Subject 1		Subject 3	
Session	Accuracy	Session	Accuracy
1	-	1	-
2	0.41	2	0.36
3	0.54	3	0.41
4	0.59	4	0.51
5	0.64	4	0.54

We believe the online BCI accuracy is significantly lower than the offline's due to factors as intra-class variability, but also the time lag. Considering that our algorithms require at least the half of the time the phase is designed (2.6 of 5 seconds), the feedback may not be as effective as desired. Nevertheless, it is possible to detect the improvement on subjects' performances. Specifically, subject 1 improved more than 20%. Finally, a negative aspect is that none of the subjects were able to overcome the 50% signal intensity which seems to suggest the need of additional training sessions or the inclusion of positively biased feedback.

V. Conclusion

In this work, we have proposed a protocol for musical notes imagery based BCIs. As a proof-of-concept we implemented it on two setups: offline and online. Considering the offline performance, the proposed protocol is comparable to studies based on Motor Imagery, presenting a possible alternative to BCIs training which considers the importance of the user's preferences information and possesses musical background. On the technical perspective, the PCA and RBF-based SVM implementation shows satisfactory results (best accuracy on testing equal to 93%). Furthermore, considering the online performance, despite the low performance results, subjects' and system continuous learning can be observed. Nevertheless, current results are promising as the evolution of one of the subjects is significant. The application of these BCIs is diverse, while some may focus on making more intuitive brain based music composition as in [42], others might consider replacing motor imagery based BCIs for musicians, avoiding to train specificities as in [43]. Future work should focus on developing further tests seeking statistical significance of the protocol and better methods to provide real-time feedback.

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