Evaluation of filtering techniques to extract movement intention information from low-frequency EEG activity

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***Abstract*— Low-frequency electroencephalographic (EEG) activity provides relevant information for decoding movement commands in healthy subjects and paralyzed patients. Brain-machine interfaces (BMI) exploiting these signals have been developed to provide closed-loop feedback and induce neuroplasticity. Several offline and online studies have already demonstrated that discriminable information related to movement can be decoded from low-frequency EEG activity. However, there is still not a well-established procedure to guarantee that this activity is optimally filtered from the background noise. This work compares different configurations of non-causal (i.e., offline) and causal (i.e., online) filters to classify movement-related cortical potentials (MRCP) with six healthy subjects during reaching movements. Our results reveal important differences in MRCP decoding accuracy dependent on the selected frequency band for both offline and online approaches. In summary, this paper underlines the importance of optimally choosing filter parameters, since their variable response has an impact on the classification of low EEG frequencies for BMI.**

I. INTRODUCTION

Brain-machine interfaces (BMI) have been proposed over the past years as a promising rehabilitative tool for patients who suffered stroke or spinal-cord injury. BMI-based therapies close the loop between the brain signals associated to movement intentions and the stimulation of paralyzed limbs, promoting neuroplasticity [1]. For that purpose, motor information is decoded from the brain and translated into control commands for controlling, for instance, prosthetic and robotic rehabilitative devices or virtual reality environments [2], [3]. The online detection of motor intentions is an important and challenging task in non-invasive (e.g., electroencephalogram–EEG–based) BMI, due to the low spatial resolution and signal-to-noise ratio of the signals. Different cortical signatures of movement have been proposed for decoding this information, such as the event related (de)synchronization (ERD/ERS) of sensorimotor rhythms [4] and the movement-related cortical potentials (MRCP) [5].

The MRCP consist of slow changes in the EEG amplitude beginning up to 1.5 s before the execution, attempt, and imagination of movements [5]. These potentials are especially relevant due to their good temporal precision for decoding the onset of movements or movement attempts [6], [7]. In fact, studies have demonstrated that, linking peripheral stimulation with the peak negativity of the MRCP can facilitate neuroplasticity [8], [9]. Furthermore, there is recent evidence showing that low frequencies in the EEG contain information to decode different movements of the same limb [10], [11].

Despite there is a large body of literature exploiting low EEG frequencies to decode movement information, there is not a consensus about the optimal methodology to filter and process these signals. Filtering is, however, a critical point in the classification results since most of the low-frequency-based decoders use temporal features for characterzing the waveform. Hence, optimizing filter characteristics like phase response could have an important impact in the decoding performance. Many studies have used zero-phase configurations (i.e., non-causal), filtering in diverse frequency ranges, to demonstrate that movement information can be decoded from low-frequency EEG: some of them using infinite impulse response (IIR) filters (e.g., Butterworth) [6], [7], [10], [12], and others with finite impulse response (FIR) filters [13]. However, these FIR filters are not valid for online applications since they require a high order to achive the specifications required (i.e. narrow transition band) that would induce a large delay (e.g., 5 seconds for the FIR with order N = 10 x sampling rate used in [13]). IIR filters have been successfully applied online with causal configurations, although their non-linear phase distortions can induce a drop in decoding performance (see [6] versus [14]).

An analysis comparing offline and online filtering techniques can help to better understand the viability of low frequencies for BMI systems. The objective of the current study is to compare these techniques to filter MRCP activity, and quantify their influence in the decoding accuracy. In this study, we used different commonly used metrics to extract more solid conclusions about how MRCP should be filtered in a real-time scenario.

II. METHODS

A. Dataset

1) Subjects: Six healthy right-handed subjects without any neurological disease history (three males and three females, mean age 24 years) participated in one recording session. Subjects were informed about the experimental procedure and signed a written consent form. The study was approved by the ethical committee of the Faculty of Medicine, University of Tübingen, Germany.

2) Experimental Setup: Subjects were seated in a comfortable chair with their right arm and hand wearing a 7 degrees of freedom (DoF) exoskeleton (Tecnalia, San

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Sebastian, Spain) to track their movement kinematics and an EEG cap with 32 electrodes. The task consisted of a center-out reaching movement from a starting position (rest position). Upon the presentation of an imperative auditory cue specifying the target, participants were asked to perform the movement and return to the starting position at a comfortable pace but within 3 seconds. The auditory cues and the EEG data were presented and acquired using BCI2000 software. The experiment was divided in 5 runs of 40 trials. Each of these trials consisted of a rest period of a random duration between 2-4 seconds, in which the subjects were asked to relax and try not to move. Right after, an auditory cue was presented and the subject had to prepare the movement. After 2 seconds, an imperative "go" cue was reproduced, and the subject had 3 seconds to reach the target and go back to the initial position.

3) Data acquisition: Brain activity was recorded with multi-channel EEG amplifiers (Brain Products GmbH, Germany) using 32 channels at a sampling frequency of 2500 Hz. The cap contained the electrodes FP1, FP2, F7, F3, Fz, F4, F8, FC5, FC1, FC2, FC6, T7, C3, Cz, C4, T8, TP9, CP5, CP1, CP2, CP6, TP10, P7, P3, Pz, P4, P8, PO9, O1, Oz, O2 and PO10, using AFz and FCz as ground and reference, respectively. Kinematic data of the 7 DOFs exoskeleton was recorded at 18 Hz and then resampled to 2500 Hz using cubic interpolation to match the EEG signals. Additionally, horizontal and vertical electrooculogram (EOG) signals, were recorded.

4) Preprocessing: In order to reduce the computational cost, EEG data was downsampled to 100 Hz after applying an antialiasing filter (Butterworth 4th order low-pass filter at 45 Hz). An automated method for reducing EOG artifacts [15] was applied. Finally, in order to re-reference the EEG signals, we applied a common average reference (CAR), where the average across all the motor cortex channels (FC1, FC2, C3, Cz, C4, CP1, CP2) was subtracted for each channel for each time sample.

B. Spectral filters

FIR filters introduce a large delay (several seconds), making IIR filters (i.e., Butterworth or Chebyshev) the only option for an online BMI application. Unlike the other IIR filters, Butterworth filters present a maximally flat frequency response and a more linear phase response. For this reason all or analyses are generated using Butterworth filters only. We studied several lower (0.01, 0.05, 0.1, 0.2 and 0.3 Hz) and upper (1, 2, 3, 5, 10 Hz) cut-off frequencies, following [13]. The order of the filter was not evaluated in the present study since orders above 2 would lead to an unstable IIR filter for most of the proposed bands. Therefore, all the filters analyzed were 2nd order Butterworth.

C. Feature extraction and classification

The preprocessed and filtered EEG data was aligned to the movement onset obtained from the kinematics recorded with the exoskeleton. Then, we extracted two one-second epochs per trial. The epoch from -4 to -3 seconds (being 0 the movement onset) will be used for characterizing the rest brain state, and the epoch from -1 to 0 seconds, for the movement intention state. Time features were extracted from channel 'Cz', subsampling each epoch to 20 Hz, resulting in a set of 20 features.

A block-based N-fold cross validation was applied in order to evaluate the performance using all available epochs, but avoiding overfitting. Feature vectors corresponding to the training epochs were standardized according to the z-score procedure: first, the mean of each feature was subtracted and then those features were divided by their standard deviation. A support vector machine (SVM) with a radial basis function (RBF) kernel was trained using these standardized feature vectors. Posteriorly, feature vectors corresponding to the test epochs were normalized using the mean and standard deviation obtained from the training data and then classified using the previously trained SVM model.

D. Metrics

The grand averages of the filtered EEG trials were computed to observe the waveshape differences produced by each analyzed filter. All the trials were aligned to the kinematic onset. Then, a baseline correction was applied by subtracting the mean of the time samples between -3 and -2 seconds.

We computed two different metrics in order to evaluate the influence of the filtering. Firstly, the accuracy of the decoder was evaluated as the percentage of epochs well classified divided by the total number of epochs. For this metric, only two epochs per trial were considered: [-4, -3] s as the rest class and [-1, 0] s as the movement class. Secondly, the percentage of correct trials was computed. This metric represents the number of executions that would provide an accurate detection of the movement onset without false positives before the movement starts [7]. Hence, a trial is considered correct if no movement detection is produced during the interval between [-4. -2] s, and at least one detection is produced in the [-2, 0] s interval. In this analysis, we evaluated the performance using one-second epochs between -4 and 0 seconds, with a sliding step of 50 ms.

III. Results

A. Grand Averages

Figure 1 shows the grand averages of channel 'Cz', varying both lower and upper cut-off frequencies, for causal and non-causal filtering.

The left part of the figure (A and C) shows the results of applying causal filtering. On one hand, modifying the lower bound greatly impacts the slope of the MRCP: sharper slope of the MRCP for the smaller values (i.e., below 0.1 Hz) and an increase in the variance when decreasing the lower limit (see Figure 1.A). On the other hand, the upper bound of the bandpass range does not modify the resulting shape but influences importantly the time of the negative peak: the (0.1-1) Hz filtered grand average presents a delay of 160 ms with respect to the other upper limits studied (see Figure 1.C).

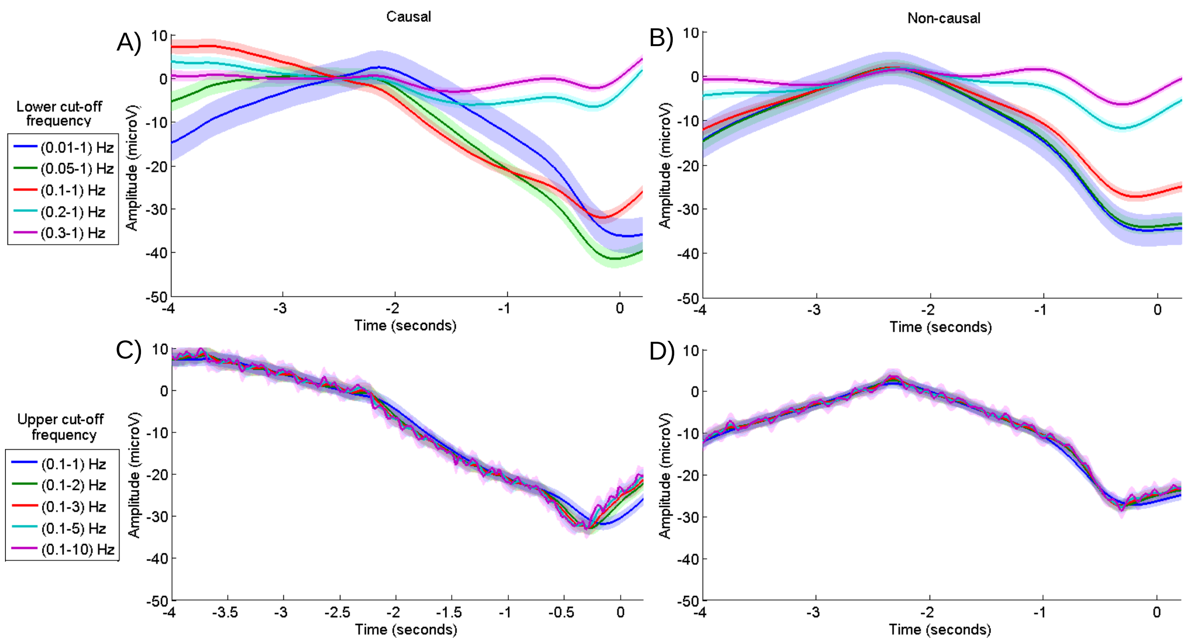

Fig. 1. Grand averages and standard errors, channel 'Cz'. (First row: varying the lower cut-off frequency, second row: varying the upper cut-off frequency. First column: causal filters, second column: non-causal filters)

Non-causal filtering shows less prominent differences for the studied bands. The upper bound of the filtered range does not affect the resulting shape (see Figure 1.D), while modifying the lower bound greatly impacts the slope of the MRCP, showing sharper shape and higher variance for the smaller values of the lower bound (see Figure 1.B).

B. *Influence on classification performance*

Figure 2 summarizes the single-window classification results obtained for the different filters. Both groups, causal and non-causal, present almost identical performance when modifying the upper limit. However, the lower limit has an impact on the classification accuracy. The lower cut-off frequencies above 0.1 Hz provide lower performances. Regarding the frequencies below 0.1 Hz, either in causal and non-causal approaches, the best accuracy values are obtained for the bands [0.05-1] Hz and [0.1-1] Hz.

The results obtained computing the metric of correct trials with a continuous decoding strategy are shown in Figure 3. The best results are achieved using the [0.1-1] Hz band, both in causal and non-causal filtering. However, these differences in performance are smaller in the causal approach, where the band [0.05-1] Hz has a similar performance to [0.1-1] Hz. Again, lower limits above 0.1 Hz show a decrease in performance. Upper limits above 2 Hz present also a drop in the performance.

Due to the results obtained, we performed a post-hoc analysis evaluating the performance of the [0.05-2] Hz band. This filter showed a decoding accuracy slighly higher than the performance obtained using the [0.1-1] Hz and the [0.05-1] Hz band (see Figure 2). However, the percentage of correct

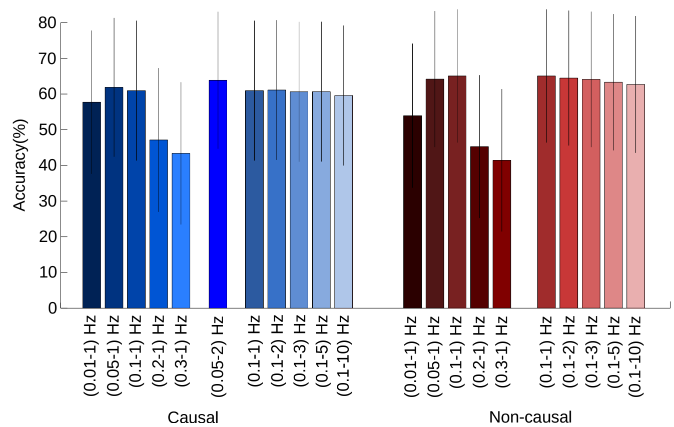

Fig. 2. Decoding accuracy (mean and standard error across the subjects) obtained for the different filters

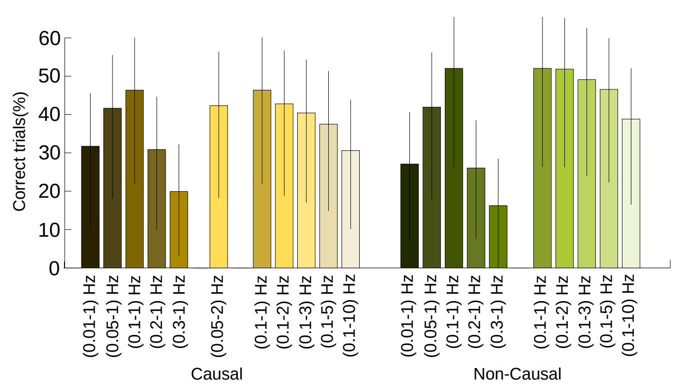

Fig. 3. Metric of percentage of correct trials for each filter (mean and standard error across the subjects).

trials using the [0.05-2] Hz band was lower than the result obtained using the [0.1-1] Hz (see Figure 3).

IV. Discussion and Conclusions

This paper studies the impact of an IIR filter frequency band on movement intention decoding based on EEG slow oscillations (MRCPs). In the non-causal approach, we found that a second-order Butterworth [0.1-1] Hz achieves the best performance results. Increasing the lower limit above 0.1 Hz has an important and negative impact in both performance results and grand average MRCP shape. Since the phase response of the filter does not play any role in the non-causal approach, this finding suggest the [0.1-1] Hz band as the spectral location of the MRCP. In the causal approach the results are slighly different. Firstly, a delay of 160 ms appears in the MRCP peak location between the 1 Hz upper cut-off frecuency and the higher values. This might be caused by the phase distortion introduced by the filter in the band edges (i.e., 0.1 and 1 Hz). Non-linear phase desynchronizes the MRCP harmonics, producing changes in the shape of the waveform. When increasing this upper limit to 2 Hz, the resulting phase response is more linear around 1 Hz, leading to smaller phase distorsion in the MRCP spectral location. This can be an important point in those studies where the feedback is coupled with this peak location [8], [9]. In addition, the differences between the [0.1-1] Hz and [0.1-2] Hz performances are almost negligible, proving this 2 Hz upper cut-off frequency as a more robust choice.

Regarding the lower cut-off frequency, although the [0.1-1] Hz filter got the best performance in the non-causal approach, the difference with the [0.05-1] Hz is small when a causal filtering was applied. Again, this might be due to the phase distorsion produced around 0.1 Hz, when the signal was filtered using the [0.1-1] Hz filter. Therefore, reducing the lower limit would produce a more linear phase around 0.1 Hz. However, observing the grand averages and standard errors, we found that when reducing the low-frequency limit below 0.05 Hz, the resulting signal presents a larger variance. This can be due to the variability introduced by the infra-slow oscillations (ISOs), present in the EEG signals below 0.1 Hz [13]. This may explain why the [0.01-1] Hz filter showed a much lower performance in terms of decoding accuracy.

In summary, for a real-time analysis, filtering the signal between [0.05-2] Hz can provide us with a good compromise between a precise temporal detection and an accurate decoding. Nevertheless, a [0.1-2] Hz filter has also to be considered in order to correctly attenuate the infra-slow oscillations mentioned above. Furthermore, our findings confirm previous studies [13] showing the [0.1-1] Hz filter as the most suitable choice for an offline analysis.

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