

FROM CUE-BASED TO SELF-PACED MOVEMENT DETECTION: INFLUENCE OF THE CUE ON TRAINING DATA

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ABSTRACT: The utilization of a visual cue plays a significant role in enhancing the operational efficiency of brain-computer interface (BCI) systems for individuals with Locked-In Syndrome (LIS). This significance arises from the absence of a reliable method to discern the actual initiation of attempted movements in these patients. First, the decoders for identifying or classifying self-initiated movements need to be trained on cue-based paradigms. However, these cues can elicit neural activity (e.g., visual/auditory evoked potentials, cognitive processing, etc.) that obscures the neural dynamics of movement, thus negatively influencing the performance of the decoder. Therefore, we implemented four novel visual cues with the intention to reduce these effects to a minimum. Our research findings indicate that the effectiveness of classification performance in self-paced EEG recordings when the decoder is trained on cue-based data for movement tasks, is significantly impacted by the design of the cue.

INTRODUCTION

A brain-computer interface (BCI) is a sophisticated system designed to facilitate communication between the human brain and external devices. This is achieved by capturing and interpreting bioelectrical signals, which are indicative of the user's intentions. These signals can be obtained through non-invasive methods such as electroencephalography (EEG) or invasive techniques like electrocorticography (ECoG). The BCI serves as a bridge, translating the user's cognitive intentions into actionable commands for seamless interaction with external technologies [1],[2]. We aim to make use of four different gestures and movement-related cortical potentials (MRCPs) elicited by these gestures to decode the user's intention. The rationale for incorporating different gestures in this study was to anticipate their potential use in the INTRECOM Project (<https://intrecom.eu/>) where we aim to use them for a four directional control of a speller [3]. The MRCP, a crucial EEG signal tied to voluntary movement preparation and execution, has been extensively studied for its insights into neural processes governing motor planning and control [4], [5]. Comprising components such as the readiness potential (RP) and the movement-related potential, MRCPs offer

a window into the mechanisms of movement-related neural events. In case of paralyzed participants, the movement itself cannot be measured to retrieve the time point of movement onset. In such cases cues seem unavoidable. The challenge arises when the cues essential for the precise timing of a paradigm elicit visual or auditory evoked potentials (V/AEPs) after their stimulus. Such V/AEPscan can inadvertently interfere with the analysis of MRCPs, especially in experimental paradigms involving self-initiated neural patterns such as voluntary movements or attempted movements [6], [7], [8] in an asynchronous BCI application in a later stage. Meaning, in the realm of BCIs, asynchronous configurations pose challenges to decoding performance because the classifier is trained on MRCPs influenced by cue-related potentials, which are absent in asynchronous usage. This underscores the need to refine and optimize the visual cue to produce MRCPs minimally influenced for training a classifier that can detect self-paced movement.

Therefore, the primary motivation for this study is to address a fundamental question: can visual cues be designed to exert minimal impact on MRCPs during movement attempts? While past research has compared cue-based and self-paced MRCPs and explored the influence of visual, auditory and vibrotactile cues [9], [10], [11], [12], [13] limited attention has been given to strategies mitigating the impact of visual cues on MRCPs. To fill this gap, we draw inspiration from previous work by Ofner et al. [7], who introduced a gradually appearing visual cue gradually appearing to minimize abrupt changes. Consequently, this gradual adaptation aims to mitigate the interference of cues on EEG signals. Building on this foundation, we propose three new cues designed with the principle of exerting minimal influence on signals associated with movement execution. By rejecting or minimizing cue-induced effects, our goal is to ensure that signals recorded during cue-based activities closely mirror those generated during self-initiated movement attempts.

MATERIALS AND METHODS

A. EEG recordings: cue-based and self-paced data

In this research, 22 individuals in good health,

averaging 26.2 ± 4.2 years of age, participated in EEG activity recording. Each participant willingly gave written consent after receiving detailed information from the researchers regarding the study's goals, content, and procedures. Participants were assured the autonomy to cease their involvement at any point without obligation to provide a reason. The experimental protocol obtained approval from the ethics committee at TU Graz before initiation. Additionally, the recorded data for each participant underwent anonymization. Participants engaged in the recording of EEG activity as they executed four distinct hand movements (gestures) using their right hand while seated in front of a computer screen. The EEG signals were recorded using a 64-channel actiCAP system (Brain Products GmbH, Gilching, Germany) at a sampling rate of 500 Hz. EEG signals were collected from all cortical areas through 60 electrodes positioned based on the 10-10 electrode system, while the remaining four electrodes served as electrooculography (EOG) electrodes. EOG electrodes were strategically placed at the outer canthi of both eyes and above and below the left eye to monitor saccades and blinks. The ground electrode was situated at the right mastoid, and the reference electrode was positioned at FCz. To identify actual movement onsets in both cue-based and self-paced sessions, we utilized a motion capture system developed in the institute with a sampling frequency of 30 Hz. A marker was positioned at the nail of the participant's pointer finger. The data output provided spatial information along the x, y, and z axes.

The gestures (Fist, Pincer, Y, Pistol) were chosen based on classification results of previously performed studies [7], [14], [15] in light of the assumption that gestures can differ significantly due to variations in involved joints and rotation thus producing variations in the EEG movement-related dynamics. The experiment consisted of two parts: (i) cue-based data collection applying different cues and gestures. (ii) a self-paced phase where participants were instructed to freely execute corresponding gestures at any time. Data recorded during this phase were used to evaluate the performance of an offline asynchronous decoder, trained on the data of (i).

For the cue-based part participants were instructed to execute four specific hand movements precisely at predetermined start times, signaled by various visual cues. Six successive movements of all four gestures were performed resulting in 5-minute runs, followed by a 30-second rest period. The cue was constant throughout this period, while the presentation order of the gestures was randomized for each trial. This process was repeated over 32 separate runs, each with a randomly shuffled cue, resulting in a cumulative total of 192 trials for each individual gesture (48 trials per cue and per gesture). The core concept underlying these cues is their gradual appearance; they do not appear abruptly but transition smoothly to their initial positions through methods like shrinking, rotating, or fading. A single trial, exemplified on the reference cue [7], has the

following sequence (Fig. 1): the gesture was displayed for 1s, followed by a fixation cross positioned in front of a filled green circle ('ready cue'). After a variable period (2-3s), the green circle would gradually shrink. This phase was designed to function as a preparatory period for participants, serving as a smooth visual transition between cues and minimizing visual cue effects on EEG. The preparation phase was succeeded by the 'go cue,' signaling the initiation of movement execution (3s of execution and holding the end position of the gesture). After that a rest phase with a blank screen was presented for 1.5s. In this study, alongside the reference cue, three novel visual cues were introduced which are based on the same principle (see Fig. 2) the fading cue, the rotation cue, and the star cue.

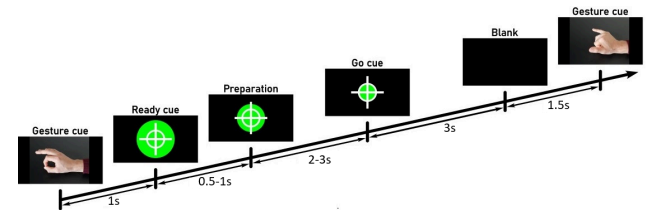


Figure 1: Timings of the different phases during one gesture trial. Starting with the gesture presentation, followed by the ready cue, thereafter the preparation phase, then the go cue and at last the blank (rest) phase.

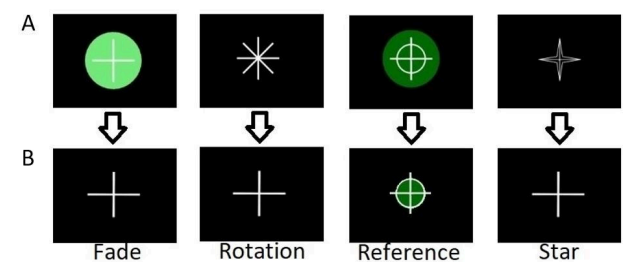


Figure 2: Four cues. A. Initial position/shape of the different cues. B. End position/shape.

In the self-paced part, participants were instructed to execute the same gesture and hold it for 3s (same procedure as in the cue based part) at approximately 10-second intervals over the course of a 5-minute run. The timing of one run can be seen in Fig. 3. This protocol was repeated across a total of 8 runs, leading to 60 trials for each distinct gesture. It is worth mentioning that the amount of movement trials for each subject differ slightly, since the self-paced paradigm instructs the participants to do the movements approximately every 10s, leading to some variation between subjects.

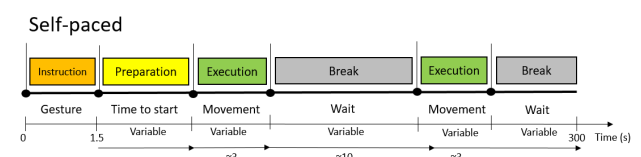


Figure 3: Timing of the self-paced paradigm and different steps during one 5-minute run.

B. Processing of recordings

The recorded signals underwent offline processing and analysis using MATLAB R2019a and the EEGLAB toolbox ([16]). For the offline analysis, the EEG signals from 60 channels in a standard 10-10 setup underwent preprocessing steps. Initially, a zero-phase band-pass filter, implemented as a third-order Butterworth filter was applied to the signals within the frequency range of 0.3 to 70 Hz. To eliminate power line interference at 50 Hz, a notch filter was employed. Independent component analysis (ICA) was utilized to remove artifacts related to eye and muscle activity. A common average reference (CAR) was then applied. As we concentrate specifically on MRCPs for this study, we bandpass filtered the data in the low-frequency range of (0.5 - 5 Hz) by using a 3th order IIR filter and thereafter we resampled the whole signal at 10 Hz to decrease computational workload. Temporal alignment of all trials occurred with respect to the cue onset, within a window spanning from -2 s to 2 s. After a thorough visual inspection, epochs exceeding the threshold of ± 50 μV were excluded. Kinematic data related to gestures were used to calculate the velocity of participants' hand movements. Movement onset was determined when the hand's velocity surpassed a predefined threshold (which was set to the same velocity value for all participants) between the "go" cue and the cue for the break, ensuring accurate detection while minimizing false positives (FP) for small movements during rest. We had to exclude one participant's dataset due to exceptionally poor signal quality and kinematic tracking.

C. Training a classifier on the different cues and applying it on self-paced data

In this study, our main goal was to develop an MRCP-based classifier capable of predicting when a gesture occurs regardless of the specific gesture itself. We therefore combined, for each participant, trials from all four gestures into a single class, labeled as 'movement' (4 gestures x 48 trials = 192 trials). Data from the rest condition (independently of the cue type) were utilized as a 'rest' class (4 cues x 4 trials = 192 trials).

To identify the point of maximum discrimination between the two classes around the cue onset, we employed a 2-class shrinkage linear discriminant analysis (sLDA) [17], [18], using overlapping 1.2-second window segments of current and past EEG lags within each participant. We experimented with various window lengths and selected the one that yielded the highest accuracy. The input of the classifier included EEG data (band-pass filtered between 0.5 - 5 Hz, as described in section B.) from both gesture (i.e., 'movement') and resting (i.e., 'rest') trials, which were aligned around one of the four previously mentioned visual cues. To evaluate the performance of the classifier within each window, we applied a trial-based 10x1 fold cross-validation approach. Subsequently, we

selected the window with the highest cross-validated accuracy to train the final classifier, utilizing data from all trials. This classifier was then used to predict offline movement instances during the self-paced paradigm.

To prevent multiple detections during a movement period and to reduce the number of FP during the self-paced paradigm, we adjusted the threshold for the movement class probability and we additionally introduced a dwell time and a refractory period [13], [19]. The dwell time verifies whether there are consecutive detections within a specified timeframe, and only when this condition is met a movement is finally predicted. Once a movement has been predicted, the refractory period skips any further check for movement until a specified amount of samples have passed. For the classification of the asynchronous data the class probability, the dwell time and the refractory period were optimized individually for each subject and varied between 0.6 to 0.99, 0.5 to 2s and 2.5 to 4s, respectively. By adjusting these parameters, we ensured that multiple detections did not occur within a detection window (defined as [-0.5 1] seconds around an actual movement), while maintaining an overall FP count to 2 FP/min. Furthermore, considering that the gesture was performed for approximately 3s, an additional MRCP was produced when the participant returned to the resting state. Therefore, the refractory period was crucial to avoid detecting these movements upon returning to the resting state.

RESULTS

When assessing the effectiveness of visual cues, the discrepancy between the actual onset of movement and the onset signaled by the cue is of essential importance. Therefore, we defined 'temporal variability' as the difference between the movement onset and the cue onset for each movement performed by every subject. A negative time value indicates that the movement occurred before the cue onset, whereas a positive value indicates that the movement occurred after the cue onset. We investigated this variability for the four different cue types. The temporal variability is shown in the violin plots of Fig. 4. To evaluate statistically the differences between cues, we conducted for each pair of cues a Wilcoxon ranksum test and corrected for multiple comparisons using the Benjamini-Hochberg method. It is evident that the rotation and reference cues exhibit a narrower distribution, whereas the results for the fade and star cue are much more widely dispersed. In Fig.5 the grand average MRCPs produced by the different cues can be seen. The rotation and reference cues display significantly more distinct grand average MRCP patterns, whereas the fade and star cues yield notably more blurred results.

The cross-validated accuracy (%), averaged across all participants, for the 2-class classification task (i.e., 'Movement' vs 'rest') during the cue-based part of the experiment is depicted in Fig. 6. Fig. 6 essentially illustrates the temporal evolution of the accuracy around

the cue onset. The rotation cue achieves its highest accuracy of 68.1% at 0.97 second, matching the accuracy of the reference cue, which also peaks at 68.1% and occurs at 0.77 seconds. In comparison, the Star and Fade cues both demonstrate their peak accuracy at 0.56 seconds, achieving 65.2% and 64.85%, respectively.

The results of the classification comparison of the different classifiers trained on the specific cue and applied on the self-paced data to predict the self-paced movement can be seen in Fig. 7. We show the different true positive rates (TPRs) within the specified detection window (i.e., [-0.5 1] seconds) around the true movement onset for the four cue types. The highest median TPR was achieved with the reference cue and the rotation cue with a value of 60%, while the fade and star cue had a significantly lower TPR of 55%. The highest subject wise accuracy was achieved by the rotation cue with a value of 67%, while the lowest accuracy occurred for the star cue with a TPR of 48%. The accuracy of both rotation and reference cue shows a similar variation, ranging approximately from 67% to 55%. Similarly, the fade and star cue demonstrate accuracy levels ranging from 63.5% to 48% and 65% to 48%, respectively. We performed a Wilcoxon ranksum test and corrected for multiple comparisons using the Benjamini-Hochberg method to examine potential variations in results among the different cues. There were no significant differences between the fade and star cue, as well as between the rotation and reference cue. However, there was a significant difference ($p < 0.01$) between the fade cue and both the rotation and reference cue, as well as between the star cue and these two cues.

The rotation and reference cues exhibit similar ranges of accuracy, both in terms of lower and upper limits. Similarly, the fade and star cues also demonstrate comparable levels of accuracy across their respective lower and upper bounds. Notably, the rotation and reference cues generally show similar performance, as do the fade and star cue. Note that the overall FP count was maintained at 2 per minute for all participants. The median temporal disparity was for all cues the same and the difference between the predicted movement onset and the actual movement onset was 0.3s, indicating that, on median, the movement was forecasted 300 ms after the commencement of the actual movement.

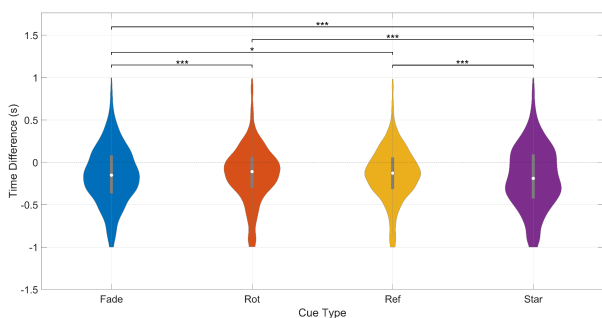


Figure 4: Violin plots depicting the time difference between movement onset and cue onset from all gesture

trials for each of the four cue types. Statistically significant differences between cues are indicated with stars ($*p < 0.05$, $**p < 0.01$, $***p < 0.001$). p-values were corrected for multiple comparisons using the Benjamini-Hochberg method.

MRCPs (Training classifier)

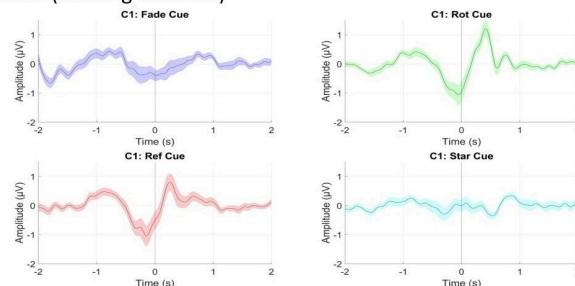


Figure 5: Grand average of MRCPs during different cues. MRCPs are aligned to the cue onset ($t=0s$).

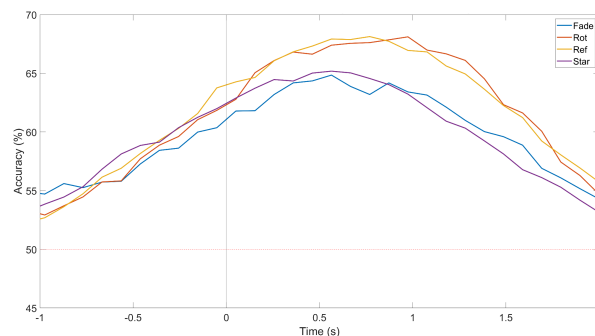


Figure 6: Grand-average cross-validated accuracy (%) for the 2-class classification task (i.e., ‘Movement’ vs ‘rest’) and for the different cue types within the duration of a trial ($t=0s$ corresponds to the cue onset).

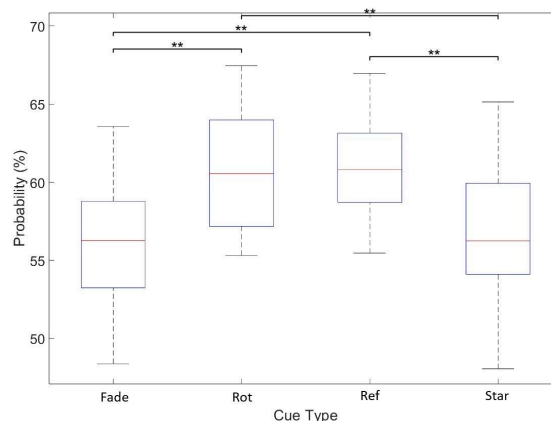


Figure 7: Boxplot showing the subject-specific TPRs in % for the different cue types. Statistically significant differences between cues are indicated with stars ($**p < 0.01$). p-values were corrected for multiple comparisons using the Benjamini-Hochberg method.

DISCUSSION

In this work we focused on movement onset prediction

during self-paced executed movement using classifiers trained on MRCPs triggered by four different visual cues.

In this context we observed that there is a significant difference in the decoding performance among the cues. Specifically the rotation and reference cue yielded the highest TPR in the self-paced data - a result that was expected since the shape of the grand average MRCPs was in general more pronounced for these cues. Additionally, the design of the cue considerably impacted the exact initiation time of participants' movement execution. As a result, we observed a higher temporal variability for the fade and star cue in the movement onsets, which led to blurring in the grand average potentials. These findings indicate the importance of the cue design, meaning that the starting period for the movement needs to be as precise as possible while the graduating period from the start to the 'go' position of the cue minimizes visual evoked potentials influencing the MRCPs.

Overall a TPR for the reference and rotation cue of 61% was obtained, while the fade and star cue achieved a significantly lower TPR of 56%. The total corresponding FP count amounted to 2 FP/min. These findings can be compared to the work done by [7][20], however, it's important to note that their investigations are based on attempted arm movement and motor imagery, respectively.

One reason for the low TPR and quite high FP count could be that the training of the classifier was based on MRCPs triggered on the cue onset, where the presence of temporal variability have adversely affected the MRCP patterns and thus the prediction performance. Additionally, the high imbalance of the dataset between the amount of movement and no movement instances poses a significant challenge.

In terms of movement onset detection we report a median temporal time delay of 0.3s for the movement onset prediction. This is expected since we use a non-causal filter, whereas in an online scenario the need of a causal filter would further increase this delay.

For the decoding performance, the correct settings of the hyperparameters class probability threshold, dwell time and refractory period proved as crucial for achieving the optimal balance between an overall low FP count and the highest TPR. In detail, we tuned the values of the movement class probability threshold between 0.5 to 0.99, the dwell time between 0.5s and 2s and for the refractory period between 2.5s to 4s for each subject. It is worth noting that the refractory period could be set up to 4s because we knew in advance how much time there would be between each movement. For a real world use the refractory period needs to be adjusted to a much lower time to allow a higher communication rate.

Although the study delivered interesting insights into the improvement of cue design in relation to synchronous and asynchronous BCI, there are some aspects to be considered for future work. First, in terms of the study design it would maybe be better to allow

participants to perform the gestures during the self-paced part at their own pace, meaning there is no condition like to hold the gesture for a certain amount of time. This could lead to a more consistent outcome in ignoring the movement offset MRCPs, since now it could be that the participants have a high variance in the time of hold when returning from the end position of the gesture to the rest position which is maybe not always covered by the refractory period. Second, upon analysis, both the rotation and reference cues consistently outperformed the fade and star cue across the evaluated metrics. However, further refinement of their design principles is necessary to enhance the precision of indicating the start of movement execution. Additionally the instructions and test runs for the participants could be improved to explain to them the importance of the exact starting time when they are indicated to do so. This would lead to more pronounced MRCPs on average when triggered on the cue onset. When analyzing the differences between cue onset and actual movement onset, the fade and star cue exhibited high temporal variability inflicted by the nature of their design. This suggests that these cues synchronize movement timing less effectively, which warrants consideration in future studies.

CONCLUSION

We demonstrated that the variations in MRCP shapes influenced by visual cue types play a crucial role in decoding performance when applying a cue-based decoder on self-paced data. Significantly, the rotation and reference cue yielded the most favorable results in terms of the true positive rate, whereas the fade and star cue exhibited comparatively poorer performance. This discovery aligns with the hypothesis that the rotation and reference cue, with their precise onset timing and more pronounced grand average MRCP patterns, are better suited for training classifiers in online scenarios. Future cue designs may be able to further improve the exact indication timing of the go cue for the movement to enhance the decoding performance even more. For the detection of executed movement in an asynchronous BCI there is a need for further improvements to lower the FP count and increase the TPR when the classifier is trained on MRCPs triggered on a cue onset. The tuning of the three hyperparameters is crucial but future considerations should also involve enhancing the methodological aspects of this work,

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