

First real-time study of a BCI based on quasi-movements: Comparison to the MI BCI within a new hybrid eye–brain–computer interface paradigm

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ABSTRACT: We report the first real-time study of a brain–computer interface (BCI) based on quasi-movements (QM) and compare it with standard motor imagery (MI) within a novel hybrid eye–brain–computer interface (EBCI). Eighteen healthy participants used gaze to select on-screen objects and then activated EEG-based control to interact with a game requiring precise initiation and termination of sensorimotor-task execution. Online classification performance was comparable across conditions: mean balanced accuracy was 74.25% for QM and 74.63% for MI, with 13 of 18 participants exceeding 70% in each condition. No significant differences were found between QM and MI in classifier performance, game interaction measures, or subjective ratings. Nevertheless, marked interindividual variability was observed, with some participants clearly favouring one condition over the other. These findings demonstrate that QM can support stable online BCI control in a demanding hybrid gaze–EEG paradigm and may serve as a practical alternative to MI, potentially broadening accessibility of active sensorimotor BCIs.

INTRODUCTION

Kinesthetic motor imagery (MI), i.e., mental simulation of kinesthetic sensations associated with certain movements, is an especially popular method to issue a command via non-invasive brain-computer interfaces (BCIs). This mental task is associated with changes in EEG sensorimotor rhythms roughly similar to what is observed under real movements. However, MI BCIs are slow and often misinterpret the user's intentions. Some studies demonstrated improved BCI classification performance [1] and clinical outcome of BCI-based rehabilitation [2] in case of using an alternative to MI, attempted movements (AM). AM involve the effort to produce actual physical movement and elicit changes in the EEG with a pattern similar to changes during MI execution but not result in such movement due to paralysis. Unfortunately, studying AM in healthy subjects is complicated. Limb constraint (e.g., [3]) is associated with strongly increased sensory input, which may significantly alter the effects under study. Blokland et al. in their study of AM [1] used neuromuscular block to create temporal paralysis, an approach which cannot be widely used. Experimentation in paralysed and amputee

participants is limited by ethical issues.

Nikulin et al. [4] discovered a new motor phenomenon, quasi-movements (QM), and proposed to use it as a model for AM in healthy participants. QM are overt movements minimized to the extent that no muscle activation is detectable [4]. Similarly to attempted movements, QM elicit stronger event-related desynchronization (ERD) of sensorimotor rhythms compared to MI [4,5]. Previous studies, however, did not explore real-time control using QM.

We suggested previously that, because AM and QM are closer to real movements than to MI in the sense of intention [7], they could potentially be more compatible than MI with tasks requiring attention to outside world, such as receiving visual feedback from a BCI and, especially, sending commands to a computer using eye gaze [6,8]. So far, tight hybridization of noninvasive MI BCIs with gaze-based control (e.g., when the user has to do MI during intentional gaze fixation) has not been very successful [9,10]. Designs where gaze direction has been used to select an object for subsequent interaction via MI BCI seem more effective, although still prone to frequent errors [11, 12].

In the current study we, for the first time, explored real-time QM BCI control. Participants had to activate the BCI immediately after selecting an object on a screen using their gaze and stop performing QM or MI tasks at given moments as precisely in time as possible, based on visual feedback from the BCI. The need to use gaze intentionally for control and then to closely monitor visual feedback from the BCI had to increase external attentional focus. We expected that in such a hybrid eye–brain–computer interface (EBCI) paradigm QM would perform better than MI due to their hypothetically better compatibility with a task requiring external focus of attention (gaze-based control), and, as a result, better EBCI performance, as well as subjectively more successful and comfortable control, would be observed under the use of QM compared to MI.

Preliminary results from this study, with a focus on gaze data, have been reported at the ACM ETRA conference [13].

MATERIALS AND METHODS

Participants: 18 healthy volunteers (13 females and 5

males, aged 19–41 years; median age 24) participated in the study. Written informed consent was obtained from all of them.

All participants had prior experience with motor imagery (MI), and nine had experience with quasi-movements (QM) as they had taken part in one of our earlier studies. Experienced participants were intentionally recruited to ensure reliable contralateral event-related desynchronization (ERD) during sensorimotor tasks essential for BCI control.

Signal acquisition: EEG (64 electrodes) and EMG were recorded at 1000 Hz using an NVX136 DC EEG amplifier (Medical Computer Systems, Moscow, Russia). The ground electrode was placed at Fpz. Electrode impedance was kept below 20 k Ω . EMG electrodes were positioned on the participant's right palm of a participant: one over the belly of the *abductor pollicis brevis* muscle and the other near the proximal base of the phalanx.

Gaze data were acquired through the EyeLink 1000 Plus eye tracker (SR Research, Canada) in remote mode (without a chin rest) at 500 Hz from the dominant eye, determined using the Miles and Porta tests. Eye tracker calibration was performed every 10 minutes (before each second game), ensuring validation error not exceed 1.0°.

Software: Signal acquisition and real-time processing were performed using the Resonance platform. The EBCI game was implemented in Unity 3D game engine, gaze data were processed online in Python, offline classification was conducted in MATLAB (MathWorks, USA), and surveys were administered using PsychoPy.

Offline Data Processing: The EEG classification pipeline followed [14]. Individual μ -rhythm frequency bands were identified by computing Common Spatial Pattern (CSP) filters in overlapping sub-bands (7–9 to 14–16 Hz) and manually selecting the band showing contralateral and/or ipsilateral ERD. EEG signals were then spatially filtered using two CSP components (typically those with the smallest eigenvalues). Spectral features were extracted using a short-time Fourier transform (1-s window, 90% overlap), and Fisher's Linear Discriminant with 5% covariance regularization was applied to obtain optimal frequency-bin combinations for class separation. Feature vectors consisted of power values from the selected spatial components within the individual frequency band. A Naïve Bayes classifier was trained on these features and applied online.

Online Data Processing: For real-time control, features were extracted from the ongoing EEG signal, and the trained classifier was applied every 100 ms to estimate the probability of sensorimotor task execution over the preceding 1-s window. To reduce the impact of classifier errors, these outputs were aggregated into one decision per second: a positive decision (task detected) was made if more than half of the ten consecutive classifier outputs exceeded 0.5.

EBCI algorithm: Gaze was used to select objects on

the screen, triggering the BCI-controlled phase. Classifier decisions then generated on-screen feedback. At the end of each trial, BCI control was blocked until a new object was selected. Thus, the gaze and BCI components operated sequentially and complementarily.

Experiment design: Two conditions corresponding to sensorimotor tasks (MI or QM) were presented in random order. Each condition comprised three stages: training, calibration, and EBCI interaction.

During training, participants were instructed how to perform MI or QM. EEG data were then recorded while participants performed the sensorimotor and counting tasks during the calibration session to obtain two classes of data for training an individual classifier. The resulting model enabled BCI control in the game AstroSync, which was played three times by each participant during the EBCI interaction session. After the calibration session, after the first and third games in each condition, and at the end of both conditions, participants completed questionnaires assessing their user experience.

We further describe training, calibration, and EBCI interaction stages in reverse order, as it helps to clarify the relations between them.

EBCI interaction session: Participants played AstroSync, a game designed in this study for testing combined gaze- and BCI-based control. The game field consisted of 10 constellations, each comprising a central star surrounded by multiple mini-stars (Fig. 1a). Maintaining gaze fixation on a constellation for 0.5 s caused it to be outlined by a circular frame; after an additional 1.5 s of continuous fixation, the central star turned yellow (Fig. 1b), signaling that it is time to start interaction via the BCI.

During this period, one of eight concentric zones, invisible to the player, was activated every second from the center towards the periphery. Mini-stars within the active zone were illuminated in green and awarded points when the EEG classifier detected execution of the sensorimotor task; otherwise, they were illuminated in red and points were deducted (Fig. 1c).

If the sensorimotor task execution was detected before the center star turned yellow, the player was prompted to relax: the constellation disappeared and a distractor counting task was presented (Fig. 1d). In such cases, the participants were required to enumerate mini-stars within the triangles and squares. Failure to terminate the sensorimotor task after completion of the circular sequence resulted in point deductions per outer zones (up to four zones).

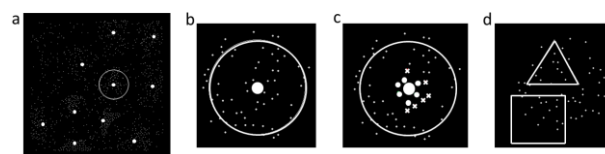


Figure 1: AstroSync gameplay features. (a) Star selection, (b) interaction with a constellation, (c) blocked interaction.

Calibration session: Each calibration trial followed the

sequence of phases in the EBCI interaction session's trials; however, as no classifier was available at this stage, all interactions were predefined as successful. No interaction was blocked, all mini-stars were illuminated in green, zone by zone, and the outer zones were not activated. The session comprised 40 trials presented in random order: 20 sensorimotor-task and 20 counting-task trials.

Training: Prior to the calibration session participants were trained approximately 15 minutes per condition. First, they were familiarized with the target action, thumb abduction. This movement was chosen following previous studies [4-8], because the muscle activity related to it could be readily monitored using EMG to verify the absence of muscle activation in the QM condition. For this purpose, the EMG signal was monitored online using Teager-Kaiser Energy Operator (TKEO), which highlighted bursts in the signal.

QM training was adapted from the standard protocol described in the original QM study [4] and used in our previous work. Participants watched their transformed EMG at a computer screen and were instructed to gradually reduce the amplitude of right thumb abduction until the visualized signal approached noise level. They were then guided to transit to QM. Unlike in previous studies, we explicitly defined QM for the participants as motor attempts that produce no visible muscle contractions. Also specific to this study, participants were instructed to focus on generating an "impulse" or motor "command" to the thumb, rather than on muscle sensations or somatosensory feedback.

Although all participants were familiar with the MI task, they received brief instructions on kinesthetic MI. First, they performed full-amplitude thumb abductions while attending to the associated sensations, such as the feeling of movement, muscle tension, and a sense of heaviness or warmth in the hand. They were then instructed to mentally rehearse these movements while keeping the hand completely relaxed.

Performance evaluation: Online EEG classifier performance was evaluated using balanced accuracy to account for class imbalance. In addition to overall performance, we examined how accurately the classifier detected task execution. The true positive rate (TPR) reflects how often the classifier correctly identified periods when participants were performing the sensorimotor task, whereas the true negative rate (TNR) reflects how often it correctly identified periods when the task was not being performed.

BCI interaction performance was quantified using several measures. The primary metric was the percentage of successfully completed constellations, with success defined as achieving >50% correct classifier predictions per constellation. Because the classifier is sensitive to the timing of task execution, additional metrics assessed participants' ability to start and stop tasks appropriately: the proportion of constellations activated without blocking, and a measure of how long participants remained in the active state after completing a task.

Surveys: After completing both conditions, participants rated how effective and comfortable each was, using scales anchored by QM on the left and MI on the right. They also reported how often they were able to interact with the game without consciously attending to the sensorimotor task, separately for QM and MI, using scales anchored by "never" on the left and "very frequently" on the right. Participants also rated, after each game in the QM condition, how much they attended to preventing quasi-movements from turning into actual movements, using a scale anchored by "constantly monitored" on the left and "did not monitor at all" on the right.

Statistics: To analyze classifier performance and game metrics, we used mixed-effects models with Geisser-Greenhouse correction, assessing the main effects of condition and game, as well as their interaction. Questionnaire data were analyzed using t-tests for the automation scales and one-way ANOVA for amplitude-tracking ratings.

RESULTS

EMG monitoring: Mean RMS EMG levels remained low and comparable between the QM and MI conditions during both calibration ($1.91 \pm 0.8 \mu\text{V}$ for MI; $2.04 \pm 0.78 \mu\text{V}$ for QM) and game sessions ($2.49 \pm 1.77 \mu\text{V}$ for MI; $2.37 \pm 1.27 \mu\text{V}$ for QM), indicating no systematic increase in muscle activity in the QM condition compared to MI.

Classifier performance evaluation: Fig. 2 summarizes online EEG classifier performance across conditions and games. Mean balanced accuracy was $74.63 \pm 6.52\%$ for the MI condition and $74.25 \pm 6.73\%$ for the QM condition. Notably, 13 out of 18 participants achieved balanced accuracy above 70% in each condition, indicating a confident level of interface control.

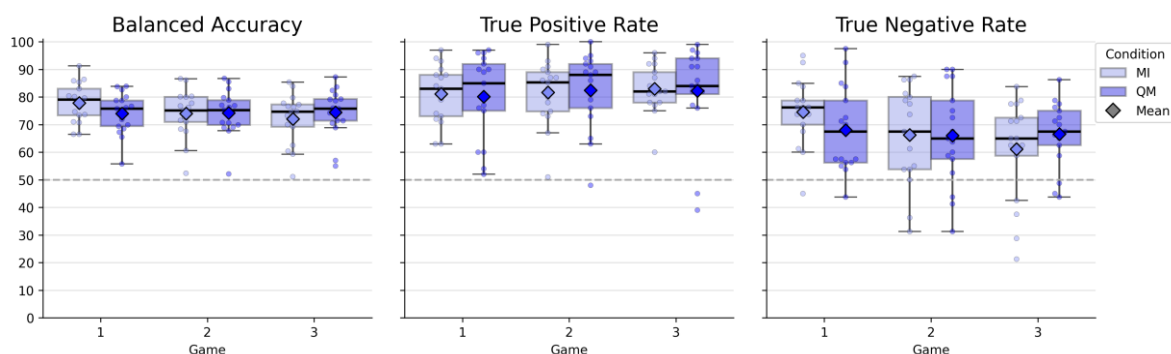


Figure 2: Performance of the online EEG classifier. Balanced accuracy, true positive rate (TPR), and true negative rate (TNR) in the MI and QM conditions across games.

Analysis of TPR and TNR indicated that both task execution and non-execution periods were correctly classified in more than half of the trials. Mean TPR was $81.94 \pm 8.26\%$ for MI and $81.61 \pm 12.25\%$ for QM, while mean TNR was $67.32 \pm 11.21\%$ for MI and $66.89 \pm 11.72\%$ for QM. However, in the MI condition, two participants had TNR below 50%, and in the QM condition, one participant had TNR below 50%, suggesting that the classifier occasionally failed to correctly identify periods without task execution for some users.

A mixed-effects model with the Geisser–Greenhouse correction revealed no significant main effects of condition ($F(1, 32) = 0.026$, $p = .871$) or game ($F(1.78, 56.57) = 2.136$) on balanced accuracy. The interaction between condition and game approached significance ($F(2, 64) = 2.713$, $p = .074$). For TPR, there were no significant effects of condition ($F(1, 32) = 0.008$, $p = .928$), game ($F(1.601, 51.24) = 0.440$, $p = .603$), or their interaction ($F(2, 64) = 0.109$, $p = .897$). For TNR, no significant main effect of condition was observed ($F(1, 32) = 0.011$, $p = .916$), nor was there a significant

condition $\times$ game interaction ($F(2, 64) = 1.965$, $p = .148$). However, there was a marginal effect of game ($F(1.956, 62.58) = 3.123$, $p = .052$), suggesting a possible influence of game progression. Exploratory post-hoc comparisons indicated a difference between Game 1 and Game 3 in the IM condition.

Interaction evaluation: Game interaction measures are summarized in Fig. 3. For the percentage of successfully completed constellations, no significant effects were found for condition ($F(1, 32) = 0.017$, $p = .898$), game ($F(1.804, 57.52) = 0.246$, $p = .760$), or their interaction ($F(2, 64) = 1.469$, $p = .238$). Similarly, the proportion of constellations activated without blocking showed no significant effects of condition ($F(1, 32) = 0.047$, $p = .829$), game ($F(1.910, 61.13) = 0.732$, $p = .483$), or interaction ($F(2, 64) = 0.036$, $p = .965$). For the mean number of activated outer zones, no significant effects were observed for condition ($F(1, 32) = 0.073$, $p = .788$) or the interaction between condition and game ($F(2, 64) = 2.145$, $p = .125$). There was a marginal effect of game ($F(1.817, 58.13) = 2.707$, $p = .080$), suggesting a possible trend across games.

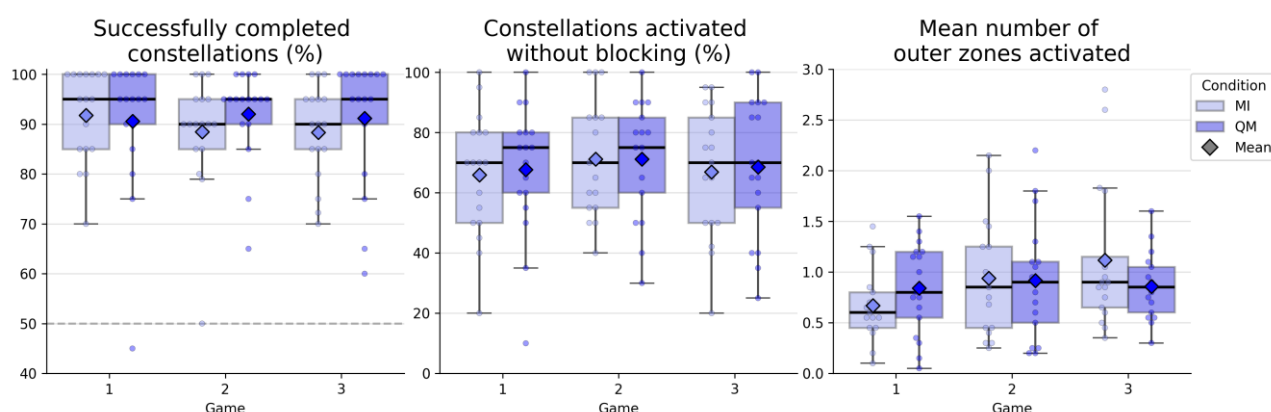


Figure 3: Game interaction performance in the MI and QM conditions across games.

Surveys: Ratings of perceived control effectiveness and comfort showed a bimodal distribution, with participants clearly favoring either QM or MI; none rated the conditions near the midpoint (Fig. 4). This pattern emphasizes strong individual differences in subjective preference, consistent with variability

observed in objective performance.

According to a one-way ANOVA, participants reported paying progressively less attention to the amplitude of QM as the games progressed (Fig. 3c), $F(2, 20) = 4.755$, $p = .0496$. Post-hoc comparisons indicated a significant difference between the “before” and “after” conditions

($p = .001$).

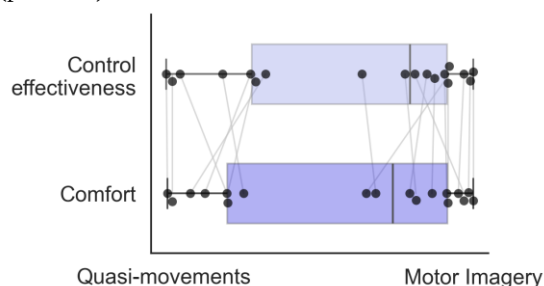


Figure 4: Final questionnaire results comparing the two conditions (MI and QM). Lines link responses from the same participant across conditions.

Ratings of control automatization revealed that participants were rarely able to interact with the constellation without focusing on the sensorimotor task in the QM condition ($t(17) = -2.598$, $p = .019$), whereas no significant deviation was observed in the MI condition ($t(17) = -1.584$, $p = .132$).

DISCUSSION

This study provides the first demonstration of online control using quasi-movements (QM) in an active brain-computer interface (BCI). Importantly, this control was implemented in a hybrid eye-brain-computer interface (EBCI) paradigm, in which participants had to combine gaze-based interaction with sensorimotor BCI control while continuously monitoring visual feedback. Despite this increased task complexity and the need to maintain attention to external stimuli, participants achieved stable BCI control.

Our results indicate that QM can support performance comparable to that of the standard motor imagery (MI) paradigm. Balanced accuracy remained consistently above chance, and many participants achieved reliable levels of BCI control in both conditions. Thus, QM appears to be a viable alternative control strategy for active BCI systems. Contrary to our initial hypothesis, however, the more externally oriented QM task did not outperform MI in either objective performance or subjective ratings. No significant differences between conditions were observed on any of the evaluated metrics. At the same time, substantial interindividual variability was evident: some participants performed markedly better in one condition than in the other. This pattern suggests that QM may be particularly useful for a subset of users, especially those who struggle with conventional MI-based control, a challenge often discussed in terms of BCI illiteracy.

Notably, this comparable performance was observed despite substantially lower prior familiarity with QM. All participants had previous experience with MI, whereas only about half had prior exposure to QM, and the revised instructions required even experienced participants to partially relearn the task. This finding suggests that QM can be learned sufficiently for online control even with limited prior training in healthy

participants, which supports its potential applicability in broader user populations.

QM has previously been proposed to offer practical advantages, including simpler training requirements [4] and a closer resemblance to natural movement [7]. However, in the present study only 7 of 18 participants reported preferring QM, while many described it as relatively difficult. One possible reason is the lack of somatosensory feedback from actual muscle activity, which may have reduced the subjective sense of control during QM. Visual feedback alone may not have fully compensated for the absence of proprioceptive cues, particularly given its limited congruence with the task and the approximately one-second delay imposed by technical constraints. This, in turn, underscores the importance of feedback design and temporal responsiveness for effective interaction with QM-based interfaces.

Taken together, these findings suggest that QM is a promising alternative control paradigm for sensorimotor BCI systems. By offering a control strategy distinct from traditional MI while achieving comparable performance, QM may help broaden the range of users who can effectively operate brain-computer interfaces.

CONCLUSION

This study demonstrates that quasi-movements (QM) can support stable online control in a brain-computer interface, achieving performance comparable to the standard motor imagery (MI) paradigm. The absence of systematic differences between conditions, together with strong interindividual variability, suggests that QM may serve as a useful alternative control strategy for some users, particularly those who struggle with MI. Overall, incorporating QM alongside traditional approaches may help broaden the range of available sensorimotor BCI control strategies.

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