

First Real-Time Use of Quasi-Movements for Exoskeleton Control: Comparison with MI-BCI in Healthy Participants and Pilot Application in Stroke Rehabilitation

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ABSTRACT: Quasi-movements (QM) are movement attempts minimized to produce no overt movement or muscle activation. Unlike kinesthetic motor imagery (MI), they may not require mastering an abstract mental skill; unlike conventional attempted movements, they may reduce risks of abnormal motor synergies. QM-based BCI training may therefore be a useful clinical alternative for sensorimotor BCI rehabilitation. We evaluated QM for real-time control of a hand-exoskeleton BCI. First, 19 healthy participants completed QM- and MI-based control sessions with online three-class EEG classification and post-session ratings. QM achieved performance comparable to MI in online accuracy and subjective ratings, although it required closer muscle-tension monitoring. Preferences for QM versus MI were split evenly, indicating inter-individual variability. Second, four chronic stroke patients completed repeated QM-BCI training over multiple days. Patients quickly understood the instructions and produced classification accuracies consistently above a nominal three-class chance reference. Clinical changes were heterogeneous but generally favorable. QM may therefore provide a promising additional strategy for exoskeleton-based BCI rehabilitation.

INTRODUCTION

Motor imagery (MI) with feedback from the brain-computer interfaces (BCIs) has repeatedly been shown to be a promising supplement to post-stroke rehabilitation. However, despite encouraging results, MI-BCI training is still rarely used in clinical practice [1-3]. One major limitation is the difficulty of teaching patients to perform MI reliably enough to activate an MI-BCI within the limited training time available in clinical settings [1,3]. Attempted movements or movement attempts (MA) represent a potentially more natural task for paralyzed patients. Attempting to perform a familiar motor action may require less training than MI, or no training at all;

thus, reliable BCI control can be achieved faster. Previous studies reported that MA can produce more pronounced EEG effects than MI [4,5] and may enable higher BCI classification accuracy [5]. Moreover, BCI training based on MA has been associated with improved clinical outcomes compared with MI-based training [6]. However, it could be argued that encouraging patients with paresis or plegia to repeatedly attempt overt movements may lead to undesirable side effects, including increased spasticity, activation of pathological motor synergies, or frustration caused by repeated failure to produce movement.

One possible alternative is the use of quasi-movements (QM). QM are movement attempts which are so weak that they produce no overt movement and no detectable electromyographic (EMG) activity [7]. In this task, participants attempt to perform the instructed movement while intentionally minimizing the strength of the attempt. Importantly, QM elicit EEG changes that were found to be even stronger than MI-related effects in offline EEG studies [7,8], suggesting that patients may be able to activate BCIs through such minimized movement attempts.

Because QM do not involve overt movement or detectable muscle activation, they may reduce the risk of side effects associated with overt movement attempts.

However, to our knowledge, QM have not yet been applied to online BCI control of rehabilitation devices.

In this study we, for the first time, investigate the feasibility of using quasi-movements for real-time BCI control of a rehabilitation hand exoskeleton:

- First, we compare QM-based and MI-based BCI control in healthy participants.
- Second, we perform a pilot clinical evaluation of QM-BCI in chronic stroke patients.

MATERIALS AND METHODS I

Participants: The experimental comparison of QM and MI was conducted with 19 healthy volunteers (15 f,

4 m; 14 right-handed; age range 19-33 years, median = 22 years) who provided written informed consent. All experimental procedures had local ethical approval.

Equipment and signal acquisition: EEG and EMG signals were acquired at a sampling rate of 500 Hz with 24-bit resolution, using a 0-300 Hz bandwidth, via a DC-coupled NVX136 EEG amplifier (Medical Computer Systems, Moscow, Russia).

EEG was recorded from 64 built-in gel-based Ag/AgCl electrodes arranged according to the international 10-10 system. For online classification, data from 52 electrodes were used. Signals were recorded in a unipolar montage, with the ground electrode positioned at Fpz. Surface EMG electrodes were placed on both forearms. On each forearm, one electrode was positioned over the belly of the *m. extensor digitorum communis*, and the second was placed 2-3 cm distal to it, along the longitudinal axis of the muscle. The signals were converted into two bipolar EMG channels and processed using the Teager-Kaiser energy operator for online visualization. EEG and EMG electrode impedances were kept below 20 k Ω .

To provide kinesthetic feedback, we used a hand exoskeleton system for both hands with two degrees of freedom and external software control (ExoHand-M; Fig. 1A). This system is an extension of a setup previously employed in post-stroke rehabilitation using kinesthetic motor imagery [9]. The exoskeletons were mounted on supports positioned on either side of a comfortable chair in which the participant was seated (Fig. 1B). Participants' hands were secured in the exoskeletons.

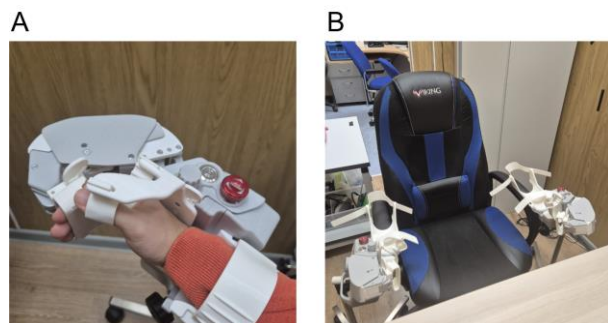


Figure 1: (A) Fixation of the hand in the hand exoskeleton; (B) the experimental chair with hand exoskeletons mounted on both sides.

Design: After electrode placement and before the main part of the experiment, participants completed a training phase in both quasi-movements (QM) and kinesthetic motor imagery (MI). The main part of the experiment comprised three conditions: (1) controlling the hand exoskeletons using QM; (2) controlling the exoskeletons using MI; and (3) a passive-movement condition, in which participants performed no task and the exoskeletons opened automatically with simulated classifier operation. The passive-movement condition was included for EEG-analysis outside the scope of the present paper. The order of the three conditions was randomized across participants. Each condition comprised two sessions, each lasting approximately 6 minutes. After each session, participants completed a

questionnaire.

Procedure: The QM training protocol followed procedures previously described in the literature [7,8]. Relative to earlier studies, we used a different target movement – hand opening (extension of four fingers) – and participants performed QM with both hands. When interacting with participants, QM were referred to as “micro-movements.” This terminology was adopted to reduce suspicion: participants were not informed that, under ideal performance, the EMG signal during micro-movements is indistinguishable from rest.

Training comprised three stages: (i) gradually reducing the amplitude of the overt movement in the dominant hand while monitoring EMG, (ii) refining small movements into QM under experimenter supervision, and (iii) transferring the skill to the non-dominant hand. Training in MI was also conducted in multiple stages: (i) working with a finger-extension resistance device to elicit and label kinesthetic descriptors using the dominant hand, (ii) synthesizing a kinesthetic image based on these descriptors, and (iii) repeating the procedure with the non-dominant hand. Total QM training lasted approximately 15 minutes as did MI training.

Each session in each condition consisted of four blocks of trials. The first block was used for initial classifier training, whereas the remaining three blocks involved online BCI operation. After each block, the classifier was updated using the data accumulated up to that point, so online control did not rely solely on the first block. Each block contained eight trials: in half of the trials participants were instructed to rest, and in the other half they were instructed to interact with one of the two exoskeletons (motor trials). Trial type was cued visually using three arrows presented on the screen (Fig. 2): an upward arrow indicated a rest trial, a leftward arrow indicated the left exoskeleton, and a rightward arrow indicated the right exoskeleton. Each rest trial was always followed by a motor trial; within each block, the order of left- versus right-hand commands was randomized. Arrow color indicated the current task phase: blue corresponded to preparation and green corresponded to execution. The preparation phase lasted 2 s and the execution phase lasted 9 s.



Figure 2: Visual arrow cues used during the sessions. (A) a blue arrow indicating preparation to perform the task with the left hand; (B) a green arrow indicating active task execution; (C) Illumination of a circle indicating successful BCI classification.

During online BCI blocks, successful detection of a command triggered opening of the corresponding exoskeleton. Opening speed depended on the estimated

probability of the target class: opening occurred during those time intervals within a trial in which the classifier output favored the target class among the three classes. In addition, a circle presented at the center of the screen provided visual feedback; its brightness reflected classification confidence for the current command. At the end of each trial, the exoskeleton closed and the on-screen circle disappeared. Participants were instructed to perform micro-movements or MI regularly, without compromising task quality and without inducing excessive muscle tension. Muscle activity was monitored using EMG signals.

EEG classifier: Classifier training used EEG data band-pass filtered from 5 to 30 Hz. The signal was segmented into non-overlapping 250 ms epochs; epochs with at least 10% artifacts were excluded. Covariance matrices were estimated from the remaining data separately for each class.

For each pair of classes, Common Spatial Pattern (CSP) spatial filters were computed from the corresponding covariance matrices. Four CSP components were selected per class pair. Components were first selected if the variance ratio of the corresponding CSP component for the given class pair fell within 0.65-0.95. If fewer than four components were obtained by this criterion, the remaining components were selected from the unused set by the absolute value of the log variance ratio. Spatial filters selected across all class pairs were then combined and used to construct feature vectors.

Each feature vector was computed from a 1 s window advanced in steps of 250 ms; features were the log-variances of the selected CSP components. Feature vectors were classified using regularized Linear Discriminant Analysis (shrinkage LDA). The classifier was updated after each block. During online feedback, classifier outputs were also generated from 1 s windows advanced in 250 ms steps.

Questionnaires: Participants completed a set of questionnaires throughout the experiment. After each session in the QM and MI conditions, participants completed several scale items. Using a 0-1 scale, they rated Task Success (“How successful were you at performing micro-movements [imagining movements]?”), from “Could not do it at all” to “Could do it well”), Difficulty (“How difficult was it for you to perform micro-movements [imagine movements]?”), from “Not difficult at all” to “Extremely difficult”), Tension Monitoring (“How closely did you monitor muscle tension while the exoskeletons were opening?”), from “Did not monitor it at all” to “Monitored it constantly”), Compatibility (“How well did micro-movements [motor imagery] fit with the opening of the exoskeletons?”), from “Did not fit at all” to “Fit well”), and their sense of control over the left and right exoskeleton movements (“Did not control it at all” to “Controlled it completely”). For follow-up questionnaires within the same condition, participants were shown their previous responses on the scales, enabling them to evaluate the new session relative to earlier sessions in the same mode.

At the end of the experiment, participants completed comparative scale items: PerformDiff (“In which condition were you better able to open the exoskeletons?”, from “Micro-movements” to “Motor imagery”), ComfortDiff (“Which condition felt more comfortable?”), and CompatDiff (“Which task fit better with opening the exoskeletons?”). They also provided open-ended responses describing their preferred condition and the perceived advantages of the two control conditions. Questionnaires were presented on a computer screen using PsychoPy [10].

Statistical analyses: The following quantitative dependent variables were analyzed: (1) EEG-classification accuracy during interface operation and (2) numerical questionnaire ratings. Classification accuracy was computed for each session as the proportion of correct recognitions of the target command class (left/right command and “rest”) based on online blocks, with the distribution of misclassifications across classes additionally inspected using the confusion matrix. When interpreting recognition quality, we used 1/3 (≈ 0.33), the theoretical chance level for a balanced three-class task, as a nominal reference for evaluating whether the feedback loop produced task-contingent responses. Questionnaire outcomes were values on continuous rating scales with two verbal anchors.

For the two sessions in the MI condition and the first two sessions in the QM condition, a two-way repeated-measures ANOVA was conducted with factors Condition and Session number; computations were performed in Python using the SciPy library. Post-hoc analyses used t-tests with FDR correction for multiple comparisons; statistical significance was determined after correction (p-values are reported as p_{FDR}). Open-ended responses were treated as qualitative data to support interpretation of the quantitative findings.

RESULTS I

Classification accuracy: Mean three-class EEG classification accuracy was comparable between the QM and MI conditions. In the MI condition, mean accuracy was 0.49 ± 0.10 in Session 1 and 0.50 ± 0.09 in Session 2; in the QM condition, the corresponding values were 0.49 ± 0.10 and 0.54 ± 0.10 (Fig. 3). The two-way repeated-measures ANOVA for the first two sessions showed no statistically significant effects of Condition, $F(1, 18) = 3.138$, $p = 0.093$, Session, $F(1, 18) = 3.635$, $p = 0.073$, or their interaction, $F(1, 18) = 1.884$, $p = 0.187$. Overall, classifier performance remained broadly stable across tasks and sessions.

Questionnaire analyses: For **Task Success** (Fig. 4A), the ANOVA revealed no main effect of Condition, $F(1, 18) = 0.487$, $p = 0.494$, and no Condition $\times$ Session interaction, $F(1, 18) = 0.004$, $p = 0.953$. The main effect of Session was significant, $F(1, 18) = 6.287$, $p = 0.022$, reflecting higher perceived success in S2 than in S1. However, FDR-corrected post-hoc tests did not yield significant pairwise differences. For **Task Difficulty** (Fig. 4B), there was no main effect of Condition, $F(1, 18)$

= 0.160, $p = 0.694$, and no Condition $\times$ Session interaction, $F(1, 18) = 0.001$, $p = 0.977$. The main effect of Session was significant, $F(1, 18) = 6.655$, $p = 0.019$, reflecting lower perceived difficulty in S2 than in S1. No FDR-corrected post-hoc comparison reached significance. For **Tension Monitoring** (Fig. 4C), the ANOVA revealed a significant main effect of Condition, $F(1, 18) = 7.878$, $p = 0.012$, reflecting higher tension monitoring in the QM condition than in the MI condition. The main effect of Session and the Condition $\times$ Session interaction were not significant, $F(1, 18) = 0.841$, $p = 0.371$, and $F(1, 18) = 3.300$, $p = 0.086$, respectively. FDR-corrected simple-effects analyses showed that the between-condition difference was significant in S2, $t(18) = -3.763$, $p_{\text{FDR}} = 0.006$, but not in S1. For **Task-Device Compatibility** (Fig. 4D), no significant effects were observed: Condition, $F(1, 18) = 0.003$, $p = 0.957$; Session, $F(1, 18) = 0.101$, $p = 0.755$; and Condition $\times$ Session, $F(1, 18) = 0.394$, $p = 0.538$. For **Perceived Control of the Exoskeleton**, averaged across the two hand-specific scales (Fig. 4E), no significant effects were observed: Condition, $F(1, 18) = 0.031$, $p = 0.863$; Session, $F(1, 18) = 0.726$, $p = 0.406$; and Condition $\times$ Session, $F(1, 18) = 0.016$, $p = 0.902$.

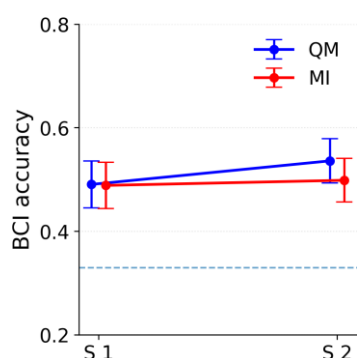


Figure 3: Group average three-class EEG classification accuracy for QM and MI in Sessions 1 and 2 (M with 95% CI). The dashed line indicates the nominal chance reference for a balanced three-class task (1/3).

In the final questionnaire, participants compared the two active conditions on three comparative scales: **PerformDiff**, **ComfortDiff**, and **CompatDiff** (Fig. 4F). On all three scales, 0.5 indicated no preference, values below 0.5 favored QM, and values above 0.5 favored MI. Mean PerformDiff was 0.45 ± 0.31 (M $\pm$ SD) and did not differ from 0.5, $t(18) = -0.653$, $p = 0.522$. Mean ComfortDiff was 0.47 ± 0.34 and also did not differ from 0.5, $t(18) = -0.420$, $p = 0.679$. Mean CompatDiff was 0.37 ± 0.28 and did not significantly differ from 0.5, $t(18) = -2.030$, $p = 0.057$.

Open-ended responses indicated marked inter-individual variability: 9 participants preferred QM, 9 preferred MI, and 1 reported no preference. Participants who favored QM often described them as easier to execute ($n = 6$), whereas four participants who preferred MI noted that it reduced the need to regulate muscle tension compared to QM.

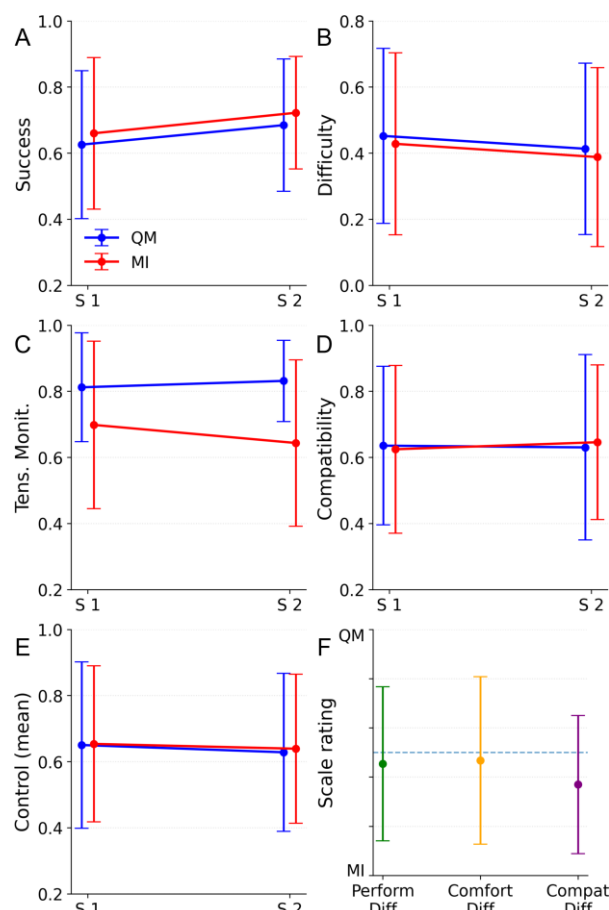


Figure 4: Group average questionnaire ratings (M $\pm$ SD).

MATERIALS AND METHODS II

Participants: The clinical sample comprised four patients with ischemic stroke (2 f, 2 m; all right-handed; age range 46-73, median 57) admitted to the Vladimirsky Moscow Regional Research and Clinical Institute (MONIKI). Time since stroke was 48, 11, 7, and 4 months for Patients 1-4, respectively. All patients were right-handed and had right-hemisphere lesions; two exhibited severe paresis and two moderate paresis. A local ethical committee approved the procedures. All patients signed informed consent.

Equipment and signal acquisition: Signal acquisition was identical to that used in the healthy sample, except that EEG was recorded with an NVX-52 amplifier from 32 scalp electrodes arranged according to the extended international 10-20 system (all used for classification). EMG was recorded from both the extensor muscles and the finger flexors (*m. flexor digitorum communis*).

Procedure: QM training in patients was shortened and generally adapted to reduce fatigue. Patients first performed overt hand-opening movements with the non-paretic hand and were asked to gradually reduce movement amplitude while observing the EMG signal. The EMG feedback was then hidden, and patients were instructed to further minimize muscle tension, although they were not required to suppress EMG activity completely. This was done to avoid excessive fatigue. Patients then performed the same minimized motor task

with the paretic hand, initially with EMG feedback available. The entire QM training procedure took only a few minutes. We did not use a repeated-measures QM–MI design in patients to avoid task-related confusion and potential disruption of the rehabilitation procedure. Although patients understood the instructions, they remained cognitively vulnerable, and introducing multiple motor tasks could have increased cognitive load. Patients completed QM sessions over 6–7 days (3–5 sessions per day depending on patient condition). Before and after the course of the procedures, patients underwent a clinical assessment that included the Mini-Mental State Examination (MMSE), the Montreal Cognitive Assessment (MoCA), the upper-extremity subsection of the Fugl-Meyer Assessment (FMA-UE), the Hospital Anxiety and Depression Scale (HADS), and the Barthel Index of Activities of Daily Living.

RESULTS II

Classification accuracy: Three-class classification accuracy across patient sessions is shown in Fig. 6. Mean accuracy across all sessions was 0.53 ± 0.12 for Patient 1, 0.50 ± 0.09 for Patient 2, 0.53 ± 0.10 for Patient 3 and 0.47 ± 0.09 for Patient 4.

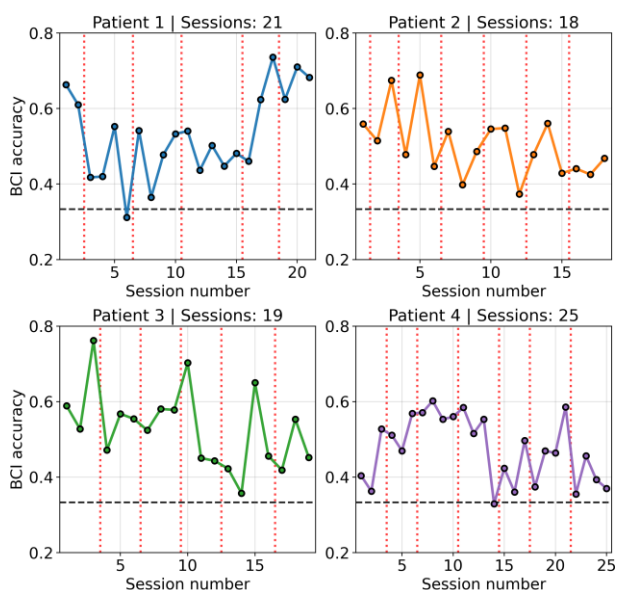


Figure 6: Three-class EEG classification accuracy across QM sessions for each patient. Points indicate session-wise BCI accuracy; the dashed horizontal line indicates the nominal chance reference for a balanced three-class task (1/3). Red vertical lines separate training days.

Clinical assessment: Descriptive inspection of the clinical assessments in the four patients indicated a heterogeneous but generally favorable pattern from admission to discharge (see Table 1). The most noticeable changes were observed in upper-limb motor function, while cognitive and functional measures showed only modest shifts overall. Notably, cognitive performance improved by an average of 2.75 points on the MoCA, allowing patients to move out of the

dementia range. Emotional status changed little, with no marked dynamics on the HADS scale.

Table 1: Clinical assessment results.

Assessment	At admission Mdn (range)	At discharge Mdn (range)
MMSE	25 (22-28)	n/a
MoCA	23.5 (18-25)	25 (23-28)
FMA-UE	29 (11-54)	35 (12-58)
HADS anxiety	8 (3-19)	7.5 (3-17)
HADS depression	5.5 (2-9)	5 (2-13)
Barthel Index	95 (70-100)	97.5 (95-100)

DISCUSSION

The present study had two main goals. First, we sought to determine, for the first time, whether quasi-movements (QM) can support real-time BCI control of a rehabilitation hand exoskeleton and how this control compares with conventional kinesthetic motor imagery (MI) in healthy participants, both in terms of classification accuracy and subjective experience. Second, we conducted a pilot clinical evaluation to examine whether QM-based exoskeleton training is feasible in chronic stroke patients.

Note that QM in this study did not follow the strict “classical” definition [7] that requires that no EMG activity was evoked. Interaction with a moving exoskeleton seemed to provoke some EMG activation even when participants did not report any muscle tension. However, we previously did not find a difference between EEG effects of such “quasi-quasi-movements” and “true” QM [8]. In the current study, therefore, we considered any movement attempt intentionally minimized up to the limit as QM. The relation between EMG and EEG in the new data will be further investigated and reported elsewhere.

Our results provide initial evidence that QM can serve as a viable sensorimotor task for exoskeleton-based BCI rehabilitation. In healthy participants, QM yielded online three-class classification accuracy and subjective ratings broadly comparable to those obtained with MI, suggesting that this task can support closed-loop BCI interaction without an evident loss of performance relative to the standard MI approach. At the same time, the higher ratings for monitoring of muscle tension indicate that QM is not simply interchangeable with MI at the phenomenological level, but places somewhat different self-regulatory demands on the user.

The comparative ratings and open-ended responses further point to substantial inter-individual variability. Preferences were divided almost equally between QM and MI, and participants described opposite advantages of the two modes: QM was often experienced as easier to execute, whereas MI reduced the need to regulate residual muscular effort. This pattern suggests that the main practical value of QM may lie not in universal superiority over MI, but in expanding the set of sensorimotor strategies available for BCI training. For

some users, especially those who struggle with purely imagery-based control, QM may provide a more accessible route to effective interaction with the exoskeleton.

The pilot clinical evaluation strengthens this interpretation. Although the patient sample was small and does not allow statistical inference, the descriptive findings indicate that repeated QM-based training was feasible in chronic stroke patients across multiple daily sessions and successive days of rehabilitation. The clinical scales showed a heterogeneous but generally favorable admission-to-discharge pattern, with the clearest changes observed in upper-limb motor function. At the same time, these clinical changes should be interpreted with caution, since the present pilot was not designed to isolate the specific therapeutic contribution of QM-BCI training. Importantly, patients understood the task instructions at the start of the course and consistently produced classification accuracies above the nominal three-class chance reference.

The healthy-participant study, however, support a personalized rather than one-size-fits-all view of choosing the patient's task in the BCI rehabilitation. One possible approach to be explored in future studies is to suggest patients, from time to time, choose between QM and MI according to their own preference. MI has certain advantages over MA, for example, it is possible to imagine complex movements at all their stages, while attempts are linked to the start of a movement, and this is applied to QM, which are a subtype of MA. Moreover, it is yet unknown if repeated training with QM-BCI is as beneficial for the post-stroke recovering as MI-BCI procedures. Nevertheless, our studies already indicate that QM is a good candidate for a task from which BCI-based rehabilitation can be started.

A key limitation of the clinical part of the study is that patients performed only QM tasks; future work will compare QM- and MI-based rehabilitation protocols in patient groups. Another limitation is that non-sensorimotor contributions to EEG classification cannot be fully excluded: the paradigm used abrupt visual arrow cues, no dedicated analysis separated sensorimotor activity from cue-onset visual responses, and ocular artifacts were handled only by the general amplitude- and distribution-based rejection procedure rather than by specific correction. Because CSP can in principle exploit any class-related variance, residual visual-evoked or ocular contributions remain possible. However, classification was restricted to the 5–30 Hz range during the execution phase, cues were centrally presented, and no gaze-dependent response was required.

CONCLUSION

Quasi-movements appear to be a feasible new control strategy for exoskeleton-based sensorimotor BCI rehabilitation. In healthy participants, they performed similarly to motor imagery in online accuracy and most subjective measures. The pilot clinical evaluation suggested that repeated QM-based training can be

implemented in chronic stroke patients and can support BCI control. While MI was not studied in patients, pronounced variability in performance and preferring QM vs. MI observed in healthy participants justify further patient-centered studies of QM as part of an individualized rehabilitation protocol rather than as a universal replacement for motor imagery.

REFERENCES

- [1] Simon C, Bolton DAE, Kennedy NC, Soekadar SR, Ruddy KL. Challenges and opportunities for the future of brain-computer interface in neurorehabilitation. *Front. Neurosci.* 2021;15: 699428
- [2] Colucci A, Vermehren M, Cavallo A, Angerhöfer C, Peekhaus N, Zollo L, Kim W-S, Paik N-J, Soekadar SR. Brain-computer interface-controlled exoskeletons in clinical neurorehabilitation: ready or not. *Neurorehabil. Neural Repair* 2022;36(12): 747-756
- [3] Mokienko OA, Lyukmanov RKh, Bobrov PD, Suponeva NA, Piradov MA. Brain-computer interfaces for upper limb motor recovery after stroke: current status and development prospects (review). *Sovrem. Tehnol. Med.* 2023;15(6): 63
- [4] Blokland Y, Spyrou L, Lerou J, Mourisse J, Scheffer GJ, van Geffen GJ, Farquhar J, Bruhn J. Detection of attempted movement from the EEG during neuromuscular block: proof of principle study in awake volunteers. *Sci. Rep.* 2015;5: 12815
- [5] Chen S, Shu X, Wang H, Ding L, Fu J, Jia J. The differences between motor attempt and motor imagery in brain-computer interface accuracy and event-related desynchronization of patients with hemiplegia. *Front. Neurobot.* 2021;15: 706630
- [6] Mansour S, Ang KK, Nair KPS, Phua KS, Arvaneh M. Efficacy of brain-computer interface and the impact of its design characteristics on poststroke upper-limb rehabilitation: a systematic review and meta-analysis of randomized controlled trials. *Clin. EEG Neurosci.* 2022;53(1): 79-90
- [7] Nikulin VV, Hohlefeld FU, Jacobs AM, Curio G. Quasi-movements: a novel motor-cognitive phenomenon. *Neuropsychologia* 2008;46(2): 727-742
- [8] Vasilyev AN, Yashin AS, Shishkin SL. Quasi-movements and “quasi-quasi-movements”: does residual muscle activation matter? *Life* 2022;13(2): 303
- [9] Frolov AA, Mokienko O, Lyukmanov R, Biryukova E, Kotov S, Turbina L, Nadareyshvily G, Bushkova Y. Post-stroke rehabilitation training with a motor-imagery-based brain-computer interface (BCI)-controlled hand exoskeleton: a randomized controlled multicenter trial. *Front. Neurosci.* 2017;11: 400
- [10] Pierce J, Gray JR, Simpson S, MacAskill M, Höchenberger R, Sogo H, Kastman E, Lindeløv JK. PsychoPy2: experiments in behavior made easy. *Behav. Res. Methods* 2019;51: 195-203