Bridging Clinical Needs and AI in Post-Stroke Rehabilitation: Patient Grouping, Adaptive Interventions, and Prognostic Assessment

Adriano Scibilia[1,†], Giorgia Gatto[2,†], Alessandro Brusaferri[1], Matteo Lancini[2] and Marco Caimmi[1,*]

[1]National Research Council of Italy, Via Alfonso Corti, 12 - 20133 Milano, Italy
[2]University of Brescia, Via Branze 43 - 25123 Brescia, Italy

Abstract

The integration of AI into robotic rehabilitation holds promise for enabling adaptive and personalized therapy protocols based on individual motor and cognitive profiles. This paper outlines the conceptual design of an AI-enhanced assessment and rehabilitation framework for stroke built on the TIAGo robotic platform. The protocol guides patients through functional gestures—such as reaching and hand-to-mouth movements—while collecting multimodal data via onboard sensors, depth cameras, and vocal interaction. AI applications are envisioned in three key domains: patient clustering and classification based on motor and cognitive indicators; real-time movement analysis for dynamic task adaptation based on parameters such as reaction time, range of motion, and spatial patterns; and outcome prediction using integrated kinematic, EMG, and EEG data. Although still under development, the proposed framework incorporates realistic patient clustering examples, grounded in clinical experiences, to illustrate potential stratification strategies and adaptation pathways. The paper aims to contribute to the ongoing discussion on how AI can enhance rehabilitation robotics by informing protocol development and supporting future clinical research.

Keywords

Artificial Intelligence, AI in neurorehabilitation, Machine Learning, ML in neurorehabilitation, stroke rehabilitation, robotic assessment, motor function, cognitive evaluation, eye tracking

1. Introduction

Stroke is one of the leading contributors to long-term disability in industrialized nations, often resulting in persistent motor deficits, particularly in the upper limbs. Studies estimate that approximately 70%–80% of stroke survivors experience impairments that limit their ability to perform Activities of Daily Living (ADLs) [1]. Even six months after the acute event, a considerable percentage—ranging from 25% to over 50%—remains partially dependent in everyday tasks [2].

In recent years, a wide range of interventions has been explored to support upper-limb recovery; however, clear evidence on their comparative or combined efficacy remains limited. One of the major challenges in rehabilitation is the heterogeneity of post-stroke clinical pictures — patients differ in lesion location, severity, motor and cognitive impairment profiles, and recovery trajectories. As a result, a one-size-fits-all approach is suboptimal, and personalized rehabilitation strategies are increasingly advocated [3].

The integration of Artificial Intelligence (AI) with robotic platforms can enhance assessment and intervention by enabling continuous, multimodal, and adaptive analysis of patient performance. AI models can support individualized treatment by identifying patient subtypes, adapting exercises in real-time based on sensor-derived metrics, and predicting recovery trajectories.

Workshop on Social Robotics for Human-Centered Assistive and Rehabilitation AI (a Fit4MedRob event) - ICSR 2025

*Corresponding author.
†These authors contributed equally.
adriano.scibilia@cnr.it (A. Scibilia); giorgia.gatto@unibs.it (G. Gatto); alessandro.brusaferri@cnr.it (A. Brusaferri); matteo.lancini@unibs.it (M. Lancini); marco.caimmi@cnr.it (M. Caimmi)
0000-0002-1521-2108 (A. Scibilia); 0009-0001-4662-7584 (G. Gatto); 0000-0003-0838-9826 (A. Brusaferri); 0000-0002-2301-876X (M. Lancini); https://orcid.org/0000-0001-9756-888X (M. Caimmi)

In this context, we propose an AI-enhanced rehabilitation and assessment framework for stroke built on the mobile bimanual TIAGo robotic platform (PAL Robotics, Spain). The system guides users through goal-directed tasks, such as reaching and hand-to-mouth gestures, while collecting kinematic, visual, and physiological data via integrated depth cameras, eye tracking, and voice interaction.

We identify three key AI application areas: (1) patient classification into functional clusters based on integrated motor and cognitive features, (2) real-time analysis of performance metrics to dynamically adapt task parameters, and (3) outcome prediction using multimodal sensor data (e.g., kinematics, EMG, EEG) to inform individualized rehabilitation strategies. By presenting realistic examples of patient's clustering and AI-driven adaptation strategies—drawn from clinical experience—the approach illustrates possible directions for developing intelligent, personalized rehabilitation protocols.

This work presents a conceptual framework for integrating AI into robotic rehabilitation, with the aim of exploring its potential to enhance assessment, task adaptation, and outcome prediction. Rather than offering definitive answers, this contribution seeks to stimulate discussion within the research community about the opportunities, challenges, and methodological considerations involved in applying AI to neurorehabilitation

The paper is organized as follows: Section 2 reviews recent literature on the application of AI in upper-limb rehabilitation; Section 3 details the proposed assessment and rehabilitation protocol; Sections 4 presents the envisioned AI modules and example use cases; finally, Section 5 briefly discusses the approach and draws conclusions.

2. Background

AI is gaining traction in stroke rehabilitation for supporting assessment, personalizing therapy, and improving outcomes. Its ability to process large, complex datasets enables pattern discovery that aids clinical decision-making. Applications include diagnosis, treatment planning, real-time adaptation, and outcome prediction [4, 5].

Yet, significant challenges persist. Clinical datasets are often small and highly variable, limiting model generalizability [4, 6]. Stroke is inherently heterogeneous, with wide variations in motor and cognitive impairments linked to lesion characteristics and comorbidities. This complicates data standardization and feature selection [4].

Evidence for AI effectiveness is still limited. Reviews highlight inconsistent results, data scarcity, and low clinical adoption [5]. Small, heterogeneous cohorts restrict robustness and raise uncertainty about which features best reflect function and recovery potential [4, 6].

Some propose prioritizing features tied to specific goals, such as motor or cognitive outcomes, over large datasets [7]. Advanced strategies like transfer learning, self-supervised learning, and synthetic data may help but are underused in this field [4].

In summary, AI offers strong promise, but further work is needed to handle patient variability, leverage multimodal data, and ensure clinical relevance.

3. Operational Clinical Context

In this section, we briefly present the assessment and rehabilitation protocol that provides the experimental framework for our work. A detailed description of the protocol is available in [8]. This overview is included to orient the reader, as it sets the stage for how we later propose to apply AI techniques for (i) patient classification based on motor and cognitive features, (ii) real-time adaptation of task parameters, and (iii) outcome prediction from multimodal data. The protocol described here is based on structured interaction with the Tiago-Pro robotic platform. It builds upon prior work on upper-limb functional assessment [9] and robot-assisted rehabilitation [10, 11], and extends it by incorporating cognitive evaluation through eye tracking alongside motor assessment, enabling real-time, integrated monitoring of both motor execution and attentional focus [8].

The upper-limb assessment protocol on which our approach is based includes a limited set of frontal reaching and hand-to-mouth movements performed in the frontal plane [9]. Despite the small number of tasks, this protocol has proven effective in capturing the patient's clinical picture. It enables the evaluation of shoulder function, which is essential for orienting the arm in space, and elbow function, which is required to extend the arm and reach for objects. At the same time, it assesses whether movements are performed with sufficient speed and supported by adequate motor control.

The extracted parameters include: (i) execution time; (ii) maximal shoulder flexion; (iii) maximal elbow extension during forward reaching; (iv) maximal elbow flexion during hand-to-mouth movement; (v) movement repeatability, assessed through the Coefficient of Periodicity of Acceleration (CPA); and (vi) movement smoothness, evaluated using the Normalized Jerk index (NJ).

The protocol comprises distinct phases: i) structured assessment sessions—conducted pre-intervention, post-intervention, and at a six-month follow-up to evaluate retention of motor gains—and, ii) a series of 12 intervention sessions held three times weekly over the course of one month.

THE ASSESSMENT SESSIONS include the execution of 10 frontal reaching movements and 10 hand-to-mouth movements, following the original protocol in [9]. To enhance the evaluation, we have introduced 10 additional reaching tasks involving medial and lateral directions, as well as a set of spatially guided pointing movements within the peripersonal space. These movements are indicated by the Tiago robot and are specifically designed to assess cognitive aspects such as attentional state and potential signs of spatial neglect.

Masured kinematic parameters include: **i) Speed and timing:** Duration of individual movement phases and total execution times; **ii) Joint dynamics:** Shoulder and elbow angular displacement to estimate functional range of motion; **iii) Movement quality:** Measures of smoothness (e.g., normalized jerk), consistency, and periodicity to assess motor control.

Cognitive engagement, attentional state, and neglect are monitored through eye-tracking combined with spatial analysis, metrics include: **i) Pupil diameter:** An indicator of cognitive load and task difficulty; **ii) Saccades and blinks:** Frequency and temporal distribution provide information on attentional focus and fatigue; **Fixation patterns:** Used to assess visual scanning behavior, which combined to spatial analysis help to identify potential neglect-like symptoms.

THE INTERVENTION SESSIONS consist of four task guided by the Tiago, which robot provides visual, verbal, or demonstrative instructions and dynamically adjusts target positions and timing based on real-time motor and attentional performance: *i) Reaching training*, approx. 10 minutes,involves lateral, frontal, and medial reaching movements toward targets physically indicated by the robot's hand. This phase allows the robot to calibrate movement parameters and provides initial motor training for the subject; *ii) Repetitive reaching*, approx. 10 min., the subject performs a sequence of lateral, frontal, and medial reaching. The robot positions its hand to mark the target and provides verbal instructions, with the number of repetitions tailored to the subject's functional capacity. *iii) Hand-to-mouth training*, approx. 10 minutes, consists of self-directed hand-to-mouth movements. Tiago demonstrates the movement and gives verbal cues, adjusting timing to match the subject's execution speed, and, finally, *iv) Peripersonal reaching*, approx. 10 min., engages the subject in controlled movements within their peripersonal space, guided by the robot to explore various positions toward and away from the body.

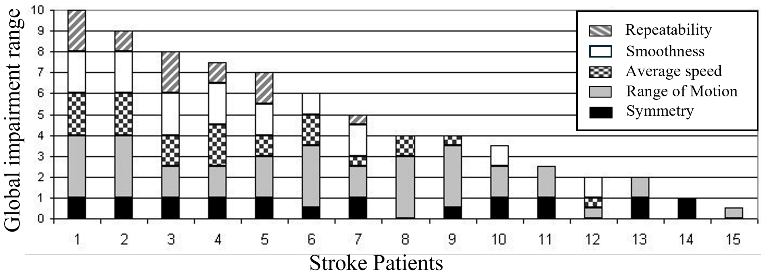
4. Using AI to Support Clinical Insight and Adaptation

While primarily supporting motor rehabilitation, the protocol also serves as a data pipeline for future AI models. In this context, we mainly target ML techniques for patient grouping, personalized interventions, and recovery prediction. Our approach will use supervised learning on labeled data (e.g., movement and clinical scores), extend the results with unsupervised methods to uncover hidden features, and eventually explore reinforcement learning for adaptive treatment, as detailed in the following sections.

4.1. Patient Classification

A key challenge in stroke rehabilitation is stratifying patients by the severity and nature of their impairments to guide treatment selection and personalization.

Our earlier study [12] demonstrated that even simple kinematic metrics can support effective patient grouping. In that work, 15 stroke patients and 10 controls performed a basic shoulder abduction task in the frontal plane. Despite its simplicity, the task revealed differences in symmetry, range of motion, speed, smoothness, and repeatability—parameters scored on a 0–10 scale using empirical thresholds based on standard deviations from healthy control group average score (Fig. 1b).



(a)

Parameter	Band 1	Band 2	Band 3	Legend
Symmetry	0	0.5	1	
Shoulder abduction	0	1	2	
Lateral bending	0	0.5	0.5	
Shoulder shrug	0	0.5	0.5	
Average speed	0	1	2	
Smoothness (JMN)	0	1	2	
Repeatability (CPA)	0	1	2	

(b)

Figure 1: Global impairment rating (0–10) based on shoulder abduction performance in the frontal plane (1a) and corresponding evaluation bands (1b).

Based on the data in Figure 1a, the 15 stroke patients can be empirically grouped into three clusters:

The cumulative score showed strong alignment with clinical video-based assessments, allowing the empirical identification of three patient clusters:

i) Mild impairment (7–10): Preserved control, smooth and repeatable movement; repeatability and smoothness are widely recognized as indicators of motor control performance [9, 13]. *ii) Moderate impairment (4–7):* Reduced speed and consistency. *iii) Severe impairment (0–4):* Limited range and poor performance.

Inspired by this work, we aim to replicate and extend stratification using ML on the movement data collected via the Tiago-based protocol (Section 3). Rather than relying on manual scoring, we will apply unsupervised and semi-supervised algorithms—such as k-means, hierarchical clustering, or self-organizing maps—to identify latent patient clusters based on a combination of motor features (e.g., range, smoothness, repeatability) and cognitive measures (e.g., engagement, attentional asymmetries).

By automating patients' grouping with ML, we seek to support clinically meaningful stratification that enables personalized rehabilitation and data-driven treatment planning.

4.2. Real-time Adaptation of Intervention Tasks

AI-driven adaptation is central to personalized rehabilitation. We aim to explore predictive modeling and reinforcement learning (RL) approaches to adjust task difficulty in real time based on patient responses.

In particular, predictive models — from traditional machine learning to deep learning architectures—will be investigated to forecast short-term performance evolution and guide the progressive scaling of task difficulty [14].

For **patients with severe impairment**, RL techniques will be deployed to properly adjust the robot target positions within the individual's reachable workspace, leveraging real-time estimates of range-of-motion (ROM). In **high-functioning patient**, the adaptation strategy will be developed to shift toward optimizing movement quality. Metrics such as spectral arc length (SAL), which is less sensitive to movement duration than jerk [15], will be computed in real time to assess smoothness and will be used to adjust execution speed, trajectory complexity, or precision requirements [16]. Besides RL methods, Bayesian Optimization based algorithms will be explored to balance smoothness with task timing [17].

Patients with cognitive impairments will be supported by adaptation logic that accounts for specific deficits. For instance, signs of hemispatial neglect—detected via asymmetric fixation patterns from eye-tracking data—will trigger adaptive cueing strategies. These may include spatial shifting of targets, visual or auditory prompts, or task rule modifications. This approach is supported by evidence from neglect rehabilitation studies [18], and we will investigate the use of contextual bandit models to personalize cue selection based on historical effectiveness for each patient [19].

This approach will enhance continuous personalization across both motor and cognitive domains, transforming the rehabilitation experience into an interactive and evolving process that remains sensitive to each patient's capabilities and progress.

4.3. Outcome Prediction from MultimodalData

Outcome prediction represents the final crucial component of our framework. To this end, we plan to develop predictive models on multimodal inputs—including three main signal sources from which relevant metrics can be extracted [20]: (1) upper-limb kinematics, (2) electromyography (EMG), and (3) electroencephalography (EEG). Kinematic features have been shown to be sensitive to rehabilitation-induced motor changes [21, 22]; EMG may reflect neuromuscular adaptations during training [23, 24]; and EEG has been associated with neuroplasticity potential and therapy responsiveness [25, 26]. These modalities could offer complementary insights into motor performance by capturing movement output, muscular activity, and cortical processes.

In addition to these measures, we aim to incorporate cognitive metrics—particularly related to attention—to monitor engagement and identify factors such as neglect, which could significantly affect recovery trajectories.

Combining these signals within AI-based models might support early outcome prediction and assist in patient stratification and resource planning [7]. Given the typically small sample sizes in neurorehabilitation, the integration of robust feature selection techniques (such as recursive feature elimination, LASSO regularization, etc.) within machine learning methods can prove crucial for isolating the most informative predictors and mitigating overfitting [6].

Moreover, recent studies suggest that multimodal fusion approaches based on deep neural networks—such as hybrid CNN-RNN pipelines or attention-based architectures—could be suitable for jointly modeling temporal (EEG, EMG) and spatial (kinematic) data [4]. Explainable AI approaches (such as SHAP, LRP, etc.) provide a further crucial ingredient to support the interpretability and transparency of machine learning models, enabling clinicians and researchers to better understand model decisions and build trust in AI-driven neurorehabilitation tools.

5. Discussion and Conclusions

Defining clear clinical goals for AI integration in stroke rehabilitation is crucial to ensure meaningful and effective application. By establishing well-defined objectives, we can better tailor AI tools to support clinical decision-making and patient-centered outcomes.

Due to the lack of widely acknowledged baselines in the literature for the target tasks, we plan to start with simple and interpretable machine learning models to establish robust benchmarks before implementing more flexible deep learning-based approaches to leverage the growing availability of datasets and meet clinical requirements.

While still exploratory, we believe AI holds strong potential to improve stroke rehabilitation outcomes. By using multimodal data and adaptive algorithms, it can enable personalized, responsive therapy that addresses the unique recovery trajectory of each patient. Future work will focus on validating these concepts in clinical populations and refining protocols based on empirical evidence.

Acknowledgments

This work has been partially supported by the Italian Ministry for Universities and Research (MUR) under the grant FIT4MEDROB (MUR: PNC0000007).
Part of this work was carried out with the support of the CNR Center of Excellence REDI.

Declaration on Generative AI

During this work, the authors used ChatGPT 4 for grammar and spelling checks. All content was subsequently reviewed and edited by the authors, who take full responsibility for the final version.

References

[1] E. C. van Lieshout, I. G. van de Port, R. M. Dijkhuizen, J. M. Visser-Meily, Does upper limb strength play a prominent role in health-related quality of life in stroke patients discharged from inpatient rehabilitation?, Topics in Stroke Rehabilitation 27 (2020) 525–533. doi:10.1080/10749357.2020.1738662.

[2] A. Pollock, S. Farmer, M. Brady, P. Langhorne, G. Mead, J. Mehrholz, van F. Wijck, Interventions for improving upper limb function after stroke, Cochrane Database of Systematic Reviews (2014). URL: https://doi.org//10.1002/14651858.CD010820.pub2. doi:10.1002/14651858.CD010820.pub2.

[3] L. G. Richards, S. C. Cramer, Therapies targeting stroke recovery, 2023. doi:10.1161/STROKEAHA.122.041729.

[4] F. Lanotte, M. K. O'Brien, altri, Artificial intelligence in rehabilitation medicine: opportunities and challenges, Annals of Rehabilitation Medicine (2023). Verificare dettagli esatti su titolo e rivista.

[5] J. Sumner, H. W. Lim, L. S. Chong, A. Bundele, Artificial intelligence in physical rehabilitation: A systematic review, Artificial Intelligence in Medicine 140 (2023) 102563. doi:10.1016/j.artmed.2023.102563.

[6] S. Rahman, S. Sarker, A. K. M. N. Haque, altri, Ai-driven stroke rehabilitation systems and assessment: A systematic review, IEEE Transactions on Neural Systems and Rehabilitation Engineering 31 (2022) 192–205. doi:10.1109/TNSRE.2022.3214567.

[7] A. White, M. Saranti, A. d'Avila Garcez, T. M. Hope, C. J. Price, H. Bowman, Predicting recovery following stroke: Deep learning, multimodal data and feature selection using explainable ai, NeuroImage: Clinical 43 (2024) 103638. doi:https://doi.org/10.1016/j.nicl.2024.103638.

[8] G. Gatto, A. Scibilia, M. Lancini, M. Caimmi, Preliminary motor assessment of a post-stroke rehabilitation and cognitive evaluation protocol using a service robot with eye-tracking, in: 2025 IEEE International Symposium on Medical Measurements and Applications (MeMeA), 2025, pp. 1–6.

[9] M. Caimmi, E. Guanziroli, M. Malosio, N. Pedrocchi, F. Vicentini, L. M. Tosatti, F. Molteni, Normative data for an instrumental assessment of the upper-limb functionality, BioMed Research International 2015 (2015). doi:10.1155/2015/484131.

[10] M. Caimmi, A. Chiavenna, A. Scano, G. Gasperini, C. Giovanzana, L. M. Tosatti, F. Molteni, Using robot fully assisted functional movements in upper-limb rehabilitation of chronic stroke patients: Preliminary results, European Journal of Physical and Rehabilitation Medicine 53 (2017) 390–399. doi:10.23736/S1973-9087.16.04407-5.

[11] M. Caimmi, C. Giovanzana, G. Gasperini, F. Molteni, L. M. Tosatti, Robot fully assisted upper-limb functional movements against gravity to drive recovery in chronic stroke: A pilot study, Frontiers in Neurology 12 (2022). doi:10.3389/fneur.2021.782094.

[12] F. Molteni, M. Caimmi, S. Maini, et al., Kinematic analysis of the upper limb movements on the frontal plane: the use in functional diagnosis in central nervous system lesions, Gait Posture 14 (2001) 4. doi:https://doi.org/10.1016/S0966-6362(01)00159-X.

[13] N. Hogan, D. Sternad, On rhythmic and discrete movements: reflections, definitions and implications for motor control, Experimental Brain Research 181 (2007) 13–30. doi:10.1007/s00221-007-0899-y.

[14] X. Chen, et al., Reinforcement learning for personalized rehabilitation, IEEE Transactions on Neural Networks and Learning Systems 33 (2022) 131–145. doi:10.1109/TNNLS.2020.3048700.

[15] S. Balasubramanian, A. Melendez-Calderon, E. Burdet, A robust and sensitive metric for quantifying movement smoothness, IEEE Transactions on Biomedical Engineering 59 (2012) 2126–2136. doi:10.1109/TBME.2011.2179545.

[16] A. Scibilia, N. Pedrocchi, M. Caimmi, Trajectory prediction in upper-limb robotic rehabilitation and its applicability to post-stroke patients: A preliminary analysis, in: 2025 IEEE International Conference on Simulation, Modeling, and Programming for Autonomous Robots (SIMPAR), IEEE, 2025, pp. 1–6.

[17] Y. Liu, et al., Personalized rehabilitation strategies using deep reinforcement learning, Nature Machine Intelligence 1 (2019) 44–52. doi:10.1038/s42256-018-0008-3.

[18] M. J. Bailey, J. Riddoch, Hemispatial neglect in stroke: assessment and rehabilitation, Progress in Brain Research 246 (2019) 239–271. doi:10.1016/bs.pbr.2019.01.010.

[19] M. Fumagalli, et al., A context-based bandit approach to adapt assistive cues for users with visuospatial neglect, IEEE Transactions on Human-Machine Systems 50 (2020) 485–495. doi:10.1109/THMS.2020.2994979.

[20] R. M. Maura, S. R. Parra, R. E. Stevens, D. L. Weeks, E. T. Wolbrecht, J. C. Perry, Literature review of stroke assessment for upper-extremity physical function via eeg, emg, kinematic, and kinetic measurements and their reliability, Journal of NeuroEngineering and Rehabilitation 20 (2023). URL: https://doi.org/10.1186/s12984-023-01142-7. doi:10.1186/s12984-023-01142-7, open Access under Creative Commons Attribution 4.0 International License.

[21] M. Pau, M. Porta, G. Spinicci, J. Frau, L. Lorefice, G. Coghe, E. Cocco, Change in upper limb function in people with multiple sclerosis treated with nabiximols: a quantitative kinematic pilot study, Neurological Sciences 44 (2022) 685–691. URL: http://dx.doi.org/10.1007/s10072-022-06456-3. doi:10.1007/s10072-022-06456-3.

[22] M. Caimmi, S. Carda, C. Giovanzana, E. S. Maini, A. M. Sabatini, N. Smania, F. Molteni, Using kinematic analysis to evaluate constraint-induced movement therapy in chronic stroke patients, Neurorehabil. Neural Repair 22 (2008) 31–39.

[23] K. Savoji, M. Soleimani, A. J. Moshayedi, A comprehensive review of electromyography in rehabilitation: Detecting interrupted wrist and hand movements with a robotic arm approach, EAI Endorsed Transactions on AI and Robotics 3 (2024). URL: http://dx.doi.org/10.4108/airo.7377. doi:10.4108/airo.7377.

[24] M. L. Harris-Love, E. Chan, A. W. Dromerick, L. G. Cohen, Neural substrates of motor recovery in severely impaired stroke patients with hand paralysis, Neurorehabilitation and Neural Repair 30 (2015) 328–338. URL: http://dx.doi.org/10.1177/1545968315594886. doi:10.1177/1545968315594886.

[25] P. Trujillo, A. Mastropietro, A. Scano, A. Chiavenna, S. Mrakic-Sposta, M. Caimmi, F. Molteni, G. Rizzo, Quantitative eeg for predicting upper limb motor recovery in chronic stroke robot-assisted rehabilitation, IEEE Transactions on Neural Systems and Rehabilitation Engineering 25 (2017) 1058–1067. doi:10.1109/TNSRE.2017.2678161.

[26] M. Caimmi, E. Visani, F. Digiacomo, A. Scano, A. Chiavenna, C. Gramigna, L. M. Tosatti, S. Franceschetti, F. Molteni, F. Panzica, Predicting functional recovery in chronic stroke rehabilitation using event-related desynchronization-synchronization during robot-assisted movement, BioMed Research International 2016 (2016). doi:10.1155/2016/7051340.