

HD-EMG-Based BCI for Control and Assessment in Post-Stroke Hand Paresis: A Proof of Concept

Gian Maria Velardi^{1*}, Thien N. Le^{1*}, Andrea Cimolato¹, Bernhard Fasching², Wolfgang Serles²,
Stanisa Raspopovic^{1†}

¹Center for Medical Physics and Biomedical Engineering, Medical University of Vienna, Vienna, Austria

²Department of Neurology, Medical University of Vienna, Vienna, Austria

* These authors contributed equally to this work

† Corresponding author. E-mail: stanisa.raspopovic@meduniwien.ac.at

ABSTRACT: Brain–computer interfaces (BCIs) offer a promising avenue for restoring motor function after stroke, but conventional BCIs are often limited by lengthy calibration or invasive implantation. High-density electromyography (HD-EMG) enables non-invasive decomposition of surface muscle signals into individual motor unit (MU) spike trains, providing a direct readout of neural drive to muscle, even when corticospinal transmission is impaired (e.g., after stroke). However, the blind source separation algorithms used for decomposition typically require approximately 15 seconds of sustained contraction, a demand that many stroke survivors cannot meet due to post-stroke fatigue and reduced motor endurance. Here we present a new HD-EMG processing pipeline that extracts movement intention through motor unit decomposition using repeated brief contractions rather than a single sustained effort. We evaluate this calibration strategy in both simulated signals (with ground-truth MU activity) and stroke-participant recordings. Our repeated-contraction approach maintains the same number validated motor units compared to sustained contraction (~6.75–6.95 MUs), indicating that our approach preserves decomposition sensitivity of state of art approaches. Furthermore, using two selectively recruited motor units, we demonstrate real-time classification capability of two distinct hand movements with high accuracy. Importantly, we identify a satellite potential in the motor unit action potential waveforms. This is a biomarker of corticospinal reorganization not previously observed with non-invasive recordings of stroke patients. These findings establish a clinically feasible calibration paradigm for HD-EMG-based BCIs in neurological populations and suggest that motor unit analysis may simultaneously serve both real-time control and longitudinal monitoring of recovery.

INTRODUCTION

Stroke is a leading cause of long-term disability, with approximately 12 million new cases annually worldwide [1]. Upper limb motor impairment is among the most common sequelae, affecting up to 80% of patients in the acute phase and persisting in close to 40% at the chronic stage [2]. Recovery of hand dexterity, grasping, and reaching is critical for independence in daily activities

such as feeding, dressing, and object manipulation, and is a significant predictor of health-related quality of life. Yet, only approximately half of survivors regain upper limb functional use within six months [3].

Brain–computer interfaces (BCIs) have been investigated as adjuncts to upper limb rehabilitation after stroke [4][5]. Muscles act as biological amplifiers of motor commands originating in the cortex, therefore Electromyographic (EMG) signals provide an indirect but accessible window into the neural control of movement, which can be used to interface with external computational systems [6]. However, when the corticospinal pathway is damaged, as in stroke, the descending drive to muscles is weakened, and conventional surface EMG may fail to capture meaningful activity [7].

High-density EMG (HD-EMG) addresses this limitation by enabling decomposition of the interference signal into individual motor unit action potentials and their discharge trains, providing direct access to the neural drive to the muscle. Critically, motor unit decomposition remains feasible even when corticospinal transmission is impaired. Studies in individuals with spinal cord injury [8][9] and Stroke [10] have shown that HD-EMG decomposition can extract motor unit activity despite reduced descending input, even from muscles that do not produce visible force. Among available decomposition methods, blind source separation (BSS) algorithms are the most widely validated [11]. These algorithms rely on the statistical properties of the signal accumulated over a sufficient observation window, typically requiring approximately 15 seconds of sustained contraction for reliable decomposition [11][13]. However, such trivial motor action for a healthy participant, could be problematic in stroke participants, as fatigue affects approximately 50% of the survivors [13]. To address this constraint, we propose a decomposition strategy that acquires the necessary signal information through multiple repetitions, accommodating the limited endurance of neurological patient. This modification may improve the clinical feasibility of HD-EMG-based systems for motor assessment and neurorehabilitation.

MATERIALS AND METHODS

Decomposition pipeline overview

We developed a motor unit decomposition pipeline designed to operate on short, repeated contractions rather than prolonged sustained efforts—a key practical requirement when recording from patients with severe motor impairment who cannot sustain isometric contractions for extended periods. The pipeline introduces two principal methodological contributions relative to the standard offline CBSS workflow [11]: (i) a segmentation and concatenation strategy that constructs a pseudo-continuous signal from repeated contraction plateaus, making the signal duration sufficient for reliable source separation without requiring a single long contraction; and (ii) recalibration of the offline separation filters for causal, peel-off-free deployment in a real-time streaming context.

The processing pipeline consists of the following

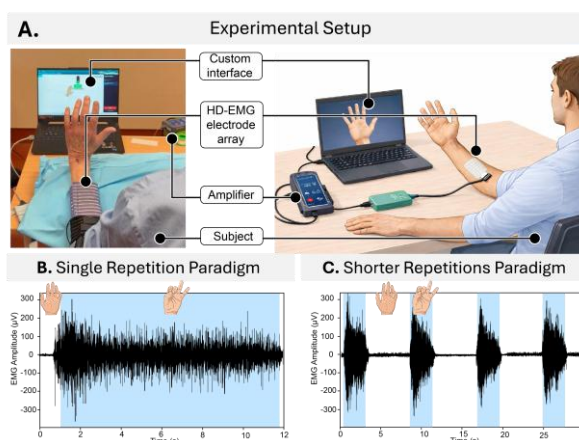


Figure 1. Experimental setup and calibration paradigm. (a) Custom recording interface providing animated visual cues for movement and rest periods. (c) Comparison of calibration conditions: a single sustained contraction (B) versus concatenated segments from multiple brief repetitions (C) regions shaded in blue correspond to the signal being decomposed.

subsequence. First, HD-EMG signals recorded during the repeated-movement condition are segmented into individual repetition windows corresponding to the plateau phase of each contraction. Second, the segmented windows are concatenated to form a single continuous signal of sufficient length for source separation. Third, CBSS [11] is applied to the concatenated signal to extract individual motor unit spike trains and action potential waveforms. Fourth, the decomposed motor units are evaluated on the basis of waveform morphology and firing-rate statistics to distinguish physiologically plausible units from decomposition artifacts [10]. Lastly, the motor unit filters derived during this calibration phase are recalibrated and applied to simulate real-time streaming conditions, using signals recorded during the same experimental session [14].

To validate the pipeline before applying it to patient data, the full workflow was first evaluated on simulated HD-EMG data with known ground-truth spike trains allowing objective quantification of decomposition accuracy. The

validated pipeline was then applied to recordings from a stroke patient to demonstrate feasibility in a clinical setting.

Signal processing

Raw HD-EMG signals were preprocessed offline as follows. The DC offset was removed from each channel, followed by band-pass filtering (4th-order Butterworth, 20–500 Hz) and notch filtering at 50, 100, and 150 Hz ($Q = 30$) to suppress power-line interference and its harmonics. Impulsive artifacts exceeding 8 standard deviations were removed by linear interpolation, and 0.5s of edge-contaminated samples was discarded at each signal boundary.

For the repeated-movement calibration condition, video footage was used to identify the sustained isometric phase of each contraction, excluding movement onset and return. These segments were extracted, concatenated across repetitions, and processed using the decomposition pipeline described below.

Motor unit decomposition

Motor unit decomposition was performed using a convolutive blind source separation (CBSS) framework [11] as implemented in MUniverse [15]. Prior to source separation, preprocessed signals were extended by a factor of $R = 16$ to capture delayed channel replicas and whitened using Zero-phase Component Analysis (ZCA) to enforce statistical decorrelation. FastICA was subsequently applied to extract the activity of the single MUs.

Spikes in this source activity were detected using a peak-finding algorithm with a 20ms refractory period, followed by k-means clustering ($k = 2$) to discriminate active peaks corresponding to spike firing from background peaks caused by noise. Motor units were retained only if they satisfied a silhouette score (SIL) > 0.85 between the two clusters, indicating good separation of the peaks from the baseline noise.

Units with sufficiently regular Inter Spike Interval (ISI) (Coefficient of Variance (CoV) < 0.4) were peeled off from the signal as they were found. Duplicate units sharing more than 50% of common discharge times within a ± 0.5 ms tolerance window were discarded; the duplicated unit with the higher SIL score was kept.

The output of the decomposition comprised, for each identified motor unit, the estimated motor unit action potential (MUAP) waveform and its corresponding binary spike train.

Validation of the extracted MUs is performed by visually inspecting the motor unit action potential (MUAP) waveforms, using the criteria mentioned in [10]. Only those motor units with clear, well-defined waveforms that are distinguishable above baseline noise, such as the in Figure 2 are considered physiologically plausible motor units and retained for subsequent analysis.

Simulated online processing

To simulate Real Time signal analysis and control, the

HD-sEMG signals recorded during the experimental session were divided in 50 ms chunks and streamed to the online decomposition algorithm via the Lab Streaming Layer (LSL) framework [16]. Each chunk was individually preprocessed in real time in the same manner as the offline preprocessing.

The offline separation filters, derived from decomposition of only the first four repetitions, were recalibrated via spike-triggered averaging on the raw HD-EMG to reintroduce temporal overlaps removed during the offline peel-off step, adapting the filters for causal, non-peel-off spike detection [17].

Because each movement type was recorded separately during calibration, a unified whitening matrix was computed by concatenating preprocessed HD-EMG segments across all movements. Spike and noise centroids, obtained offline, were then recalibrated against this unified matrix, eliminating the need for real-time peel-off or k-means clustering [17].

The incoming HD-EMG signal was processed with each chunk spatially extended and projected onto the pre-computed whitening matrix before applying the separation matrix necessary to obtain the source signal corresponding to the activities of the single motor units. The resulting source signal was normalized using offset and scale parameters estimated during the offline calibration and clipped to the unit interval [0, 1]. Spike events were identified by comparing the normalized source against the recalibrated centroids in Euclidean space; values closer to the spike centroid were classified as spikes. The instantaneous firing rate of each motor unit was estimated at every sample using a sliding rectangular window of 1 s duration. The pipeline updated every 50ms as the data chunks arrived.

We selected 2 motor units with the most distinctive firing rate for the tripod pinch and digit 4+5 flexion to use as control signal. Thresholding of the firing rate were used to determine the controller's output. We computed a confusion matrix between the 2 action and rest to evaluate the accuracy.

Validation on simulated HD-EMG data

In order to validate the proposed calibration approach against a controlled ground truth, the pipeline was first applied to simulated HD-EMG data. Simulated datasets were generated using Neuromotion [18], an integrated neuromusculoskeletal simulation framework that produces motor unit action potential waveforms and their corresponding spike trains from prescribed movement inputs.

We generated two datasets corresponding to a hand-closing movement: (1) a single sustained contraction of 10 s duration and (2) eight repetitions of 2 s held contractions. For each dataset, the simulation produced motor unit spike trains and action potential waveforms, which were convolved to generate HD-EMG signals representative of recordings obtained from a surface electrode grid.

Both datasets were processed through the full decomposition pipeline described above, including

segmentation and concatenation for the repeated-movement condition. Decomposition accuracy was evaluated using the Rate of Agreement (ROA) metric. The ROA is defined as:

$$\text{ROA} = (C / (C + O + I)) \times 100\%$$

where C is the number of common spikes identified in both the ground-truth and decomposed spike trains, O is the number of spikes present only in the ground-truth, and I is the number of spikes present only in the decomposition output. Decomposed MUs with ROA greater than 30% with any ground truth unit were retained as valid.

Patient recruitment

This study was approved by the Ethics Committee of the Medical University of Vienna (approval number: EK-2280/2024). One participant with stroke affecting upper limb motor function was recruited from the Department of Neurology at the Vienna General Hospital (AKH Wien). Inclusion criteria required a diagnosis of ischemic or hemorrhagic stroke, at least 2 weeks from the last event, ability to sit in up-right position, motor Fugl-Meyer-Upper Extremity Scale between 10 and 66, age between 18 and 80 years. The participant provided written informed consent in accordance with the Declaration of Helsinki prior to any study procedures. All recordings were carried out under the supervision of a licensed physiotherapist.

Experimental setup

High-density electromyographic (HD-EMG) signals were recorded using two monopolar electrode arrays (GR08MM1305, OT Bioelettronica) with an inter-electrode distance of 8 mm and 32 channels. One grid was placed longitudinally along the muscle belly of the flexor and the second on the extensors, on the forearm as required by the target movement. Signals were amplified and digitized at 2 kHz through a Grapevine Trek Amplifier (Ripple Neuromed).

The participant was seated comfortably in front of a screen with the forearm resting on a table. Four hand and wrist movements were tested: (1) wrist extension, (2) finger extension, (3) a three-digit pinch, and (4) flexion of the fourth and fifth digits. For each movement, two recording conditions were acquired. In the first condition, the participant performed a sustained contraction, limited to approximately 10s due to participant fatigue. In the second condition, eight repetitions of 3 s contractions were recorded, each initiated by cues from the recording interface. Between recordings the subject could rest to recover from fatigue.

A custom recording interface provided visual cues for movement and relaxation using an animated virtual hand. Cue timestamps were saved with the HD-EMG signals for alignment, and an external camera recorded the session to account for delays between cues and movement onset. Signals from both sustained and repeated conditions were then processed using the described decomposition pipeline.

RESULTS

The following results provide preliminary validation of the proposed approach. In simulation, repeated-contraction and sustained-contraction paradigms yielded comparable decomposition performance, supporting the validity of the proposed calibration strategy. We further applied this framework in a stroke participant, demonstrating that HD-EMG decomposition can enable two-degree-of-freedom external device control while also revealing candidate biomarkers relevant to recovery and rehabilitation.

Repetitions of a movement can be used in place of a single movement for calibration

In simulated signal, the decomposition algorithm yielded 43 MUs from the held contraction, of which 13 were validated against ground truth (69,81% Hallucination Rate) vs the repetition-based approach which yielded 40 MUs, of which 12 were validated against ground truth (70% Hallucination Rate).

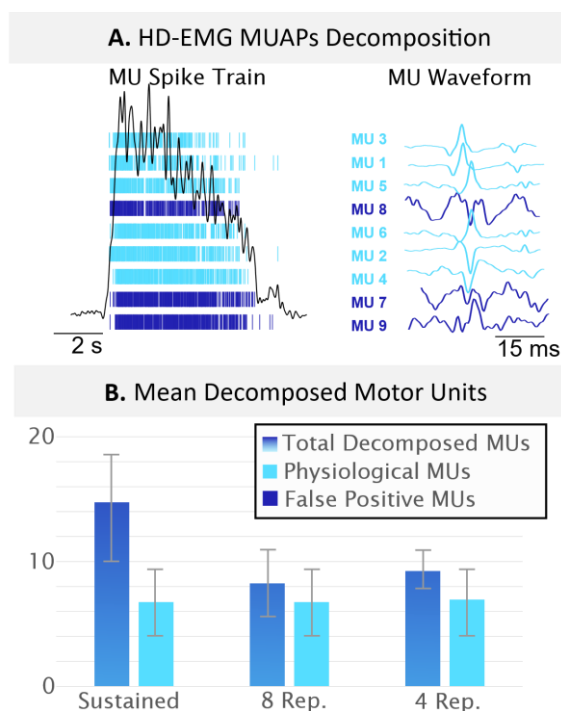


Figure 2. Repeated-contraction calibration preserves motor unit yield while suppressing spurious detections. A) Example of MUAPs Decomposition during 1 contraction of tripod pinch. Left: MU firing train corresponding to EMG envelop. Right: Decomposed waveform showing both physiological and false positive waveforms. B) total decomposed versus physiologically validated motor units across calibration conditions, averaged over four movements (N=4).

Although the yield and hallucination rate were similar in the simulations, a different pattern emerged from the data recorded from the subject (Fig. 2). Averaged across four movements, held contractions produced 14.5 ± 4.15

decomposed MUs of which only 6.75 ± 2.59 were validated (53.4% hallucination rate), whereas decomposition from repeated contractions yielded 8.25 ± 2.59 decomposed MUs with 6.75 ± 2.28 validated (18.2% hallucination rate).

Restricting the analysis to exactly four repetitions, in order to test the lower limit for effective decomposition, yielded similar results (9.25 ± 2.68 decomposed MUs, 6.95 ± 1.48 validated; 24.9% hallucination rate). Critically, the number of validated MUs remained stable across conditions (~ 6.75 – 6.95 MUs).

HD-EMG as BCI with 2 degrees of freedom

Motor unit filters and the whitening matrix were computed using four of the eight recorded repetitions.

From this first offline decomposition, two motor units with distinct activation profiles were identified. MU1 (Blue in Fig. 3) fired selectively during finger flexion (Movement 4), while MU2 (Orange in Fig. 3) was active during both tripod pinch (Movement 3) and finger flexion (Movement 4).

This differential recruitment enabled a straightforward classification rule: when only MU2 exceeded the firing rate threshold (10 Hz), the output was classified as tripod pinch; when both MU1 and MU2 were concurrently active, the output was classified as finger flexion.

As shown in Figure 3, the raw HD-sEMG signal exhibits clear modulation aligned with the cued movements, with shaded regions indicating the timing of each action. The firing rates of both motor units reliably crossed the detection threshold during their respective movements, allowing a simple transfer function to map motor unit activity to discrete commands for virtual or robotic hand control with perfect precision.

HD-EMG analysis can provide bio-markers to track recovery

In the offline analysis phase, we investigated whether motor units extracted from the stroke patient exhibited unique firing characteristics or waveform features that could reflect underlying corticospinal pathway alterations. During each recorded action, we identified the presence of a distinctive oscillation that was temporally locked to the MUAP waveforms

This satellite peak was observed at a median delay of 22.2ms (IQR: 20.5–22.6ms) across all recorded movements (Fig. 4). The proportion of motor units displaying the satellite potential varied by task, ranging from 33.3% in tripod pinch (5/15 units) to 58.3% in wrist extension (7/12 units), with finger extension and 4th+5th finger flexion at 44.4% (4/9) and 42.9% (3/7), respectively.

DISCUSSION

The findings of this study address three interrelated challenges in deploying HD-EMG-based BCIs for neurological populations: calibration feasibility, real-time control, and longitudinal monitoring of recovery.

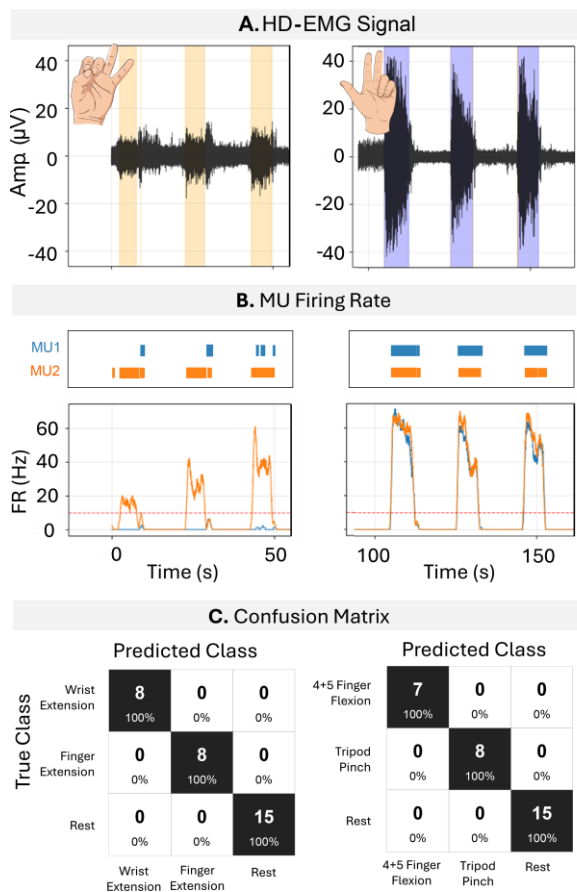


Figure 3. Real-time two-degree-of-freedom control driven by individual motor unit recruitment. (a) Raw HD-sEMG from a single channel during finger flexion and tripod pinch, with (b) instantaneous firing rates of MU1 (Blue) and MU2 (Orange) below. Selective recruitment — MU2 alone for tripod pinch, both units for finger flexion — enables discrete command encoding. (c) Confusion matrices confirming perfect classification accuracy using a simple firing-rate threshold rule.

The repeated-command calibration strategy addresses a fundamental barrier to the clinical deployment of HD-EMG decomposition in neurological populations. By concatenating signal segments from multiple brief contractions, the proposed approach preserves the statistical structure necessary for source separation while accommodating the reduced motor endurance characteristic of these populations.

Notably, the number of physiologically validated motor units remained stable across calibration conditions (~6.75–6.95 MUs), even as the hallucination rate dropped from 53.4%, with held contractions to 18.2% with repeated movements. This reduction in false-positive detections is particularly consequential for real-time applications, where spurious motor units would introduce erroneous control commands.

The demonstration of two-degree-of-freedom control using only two selectively recruited motor units highlights the potential of HD-EMG to move beyond amplitude-based classification schemes that have traditionally constrained myoelectric interfaces. By exploiting the differential recruitment patterns of individual motor units, a simple thresholding rule

achieved perfect classification accuracy during simulated online decoding.

Beyond real-time control, our findings suggest that motor unit analysis may yield clinically informative biomarkers. We observed satellite potentials occurring 44.2 % of the decomposed motor unit, a feature that earlier intramuscular EMG studies attributed to collateral reinnervation and newly formed synaptic connections following upper motor neuron lesions [21].

To our knowledge, the present findings represent the first demonstration of such satellite potentials detected from surface HD-EMG recordings, extending prior needle-based observations to a non-invasive recording modality. If validated in larger cohorts, this feature could complement existing discharge-based biomarkers, such

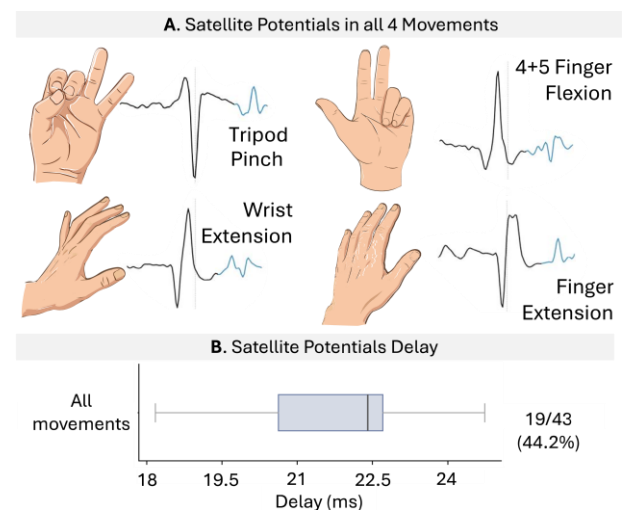


Figure 4. Surface-detected satellite potentials as candidate biomarkers of corticospinal reorganization. A secondary oscillation time-locked to the MUAP appears at a median delay of 22.2ms in 44.2% of decomposed motor units (N = 43).

as alterations in firing rate variability and motor unit synchronization [10][19][20] to provide a more comprehensive characterization of corticospinal recovery.

Several limitations should be acknowledged. The primary constraint is the small sample size, which precludes formal statistical inference and limits the generalizability of these findings.

The classification scheme, while effective, was designed for a controlled proof-of-concept setting; its robustness under conditions of fatigue, electrode shift, and variable contraction intensity remains to be established. Furthermore, the current two-degree-of-freedom paradigm, though clinically meaningful, falls short of the multi-joint control that would be required for functional neuroprosthetic applications, which will likely require decomposition of motor units across multiple muscles and the development of more sophisticated hardware pipelines [22]. Finally, the control was computed online but not in real time, owing to the computational cost of the decomposition step, which currently requires several minutes per movement. This processing time made it

impractical to keep the patient for the full duration, and we instead resorted to simulating the online control in the manner previously described.

CONCLUSION

This study demonstrates that a repeated-command calibration paradigm enables reliable HD-EMG decomposition in an acute stroke patient while substantially reducing spurious motor unit detections compared to sustained contractions. The stability of validated motor units across calibration conditions, combined with the successful real-time classification of two hand movements using only two selectively recruited units, supports the feasibility of motor unit-driven BCIs in neurological populations with limited motor endurance. Furthermore, the identification of satellite potentials in surface-recorded MUAP waveforms suggests that HD-EMG decomposition may serve a dual role: providing both real-time control signals and non-invasive biomarkers of corticospinal reorganization. While these findings are derived from a single participant and require validation in larger cohorts, they establish a foundation for clinically practical HD-EMG-based interfaces that accommodate the functional constraints of individuals with severe motor impairment.

ACKNOWLEDGEMENTS

Special thanks to our dear colleagues Anna Sparapani, and Hyunjeong Lee for their assistance with the experiment.

REFERENCES

- [1] GBD 2021 Stroke Risk Factor Collaborators. Global, regional, and national burden of stroke and its risk factors, 1990–2021: a systematic analysis for the Global Burden of Disease Study 2021. *Lancet Neurol.* 2024
- [2] Lawrence ES, Coshall C, Dundas R, Stewart J, Rudd AG, Howard R, Wolfe CDA. Estimates of the prevalence of acute stroke impairments and disability in a multiethnic population. *Stroke.* 2001
- [3] Kwakkel G, Kollen BJ, van der Grond J, Prevo AJH. Probability of regaining dexterity in the flaccid upper limb: impact of severity of paresis and time since onset in acute stroke. *Stroke.* 2003
- [4] Chaudhary U, Birbaumer N, Ramos-Murguialday A. Brain–computer interfaces for communication and rehabilitation. *Nat Rev Neurol.* 2016
- [5] Biasucci A, Leeb R, Iturrate I, Perdakis S, et al. Brain-actuated functional electrical stimulation elicits lasting arm motor recovery after stroke. *Nat Comm.* 2018
- [6] Philipp Raggam, Manuel Eder, Alexia-Theodora Popa, Peter Fugger, Moritz Grosse-Wentrup, An EMG-based brain-computer interface for communication-impaired patients, 9th BCI Conference Graz, 2024.
- [7] Farina D, Holobar A, Merletti R, Enoka RM. Decoding the neural drive to muscles from the surface electromyogram. *Clin Neurophysiol.* 2010
- [8] Ting JE, Del Vecchio A, Sarma D, Verma N, Colachis SC 4th, Annetta NV, Collinger JL, Farina D, Weber DJ. Sensing and decoding the neural drive to paralyzed muscles during attempted movements of a person with tetraplegia using a sleeve array. *J Neurophysiol.* 202
- [9] Oliveira DS, Ponfick M, Braun DI, Osswald M, et al. A direct spinal cord–computer interface enables the control of the paralysed hand in spinal cord injury. *Brain.* 2024
- [10] Tacca N, Levine JT, Heimann MK, Schlink BR, et al. Leveraging neural drive to assess hand motor function in individuals with chronic stroke. *J Neuroeng Rehabil.* 2026
- [11] Negro F, Muceli S, Castronovo AM, Holobar A, Farina D. Multi-channel intramuscular and surface EMG decomposition by convolutive blind source separation. *J Neural Eng.* 2016
- [12] Holobar A, Zazula D. Multichannel blind source separation using convolution kernel compensation. *IEEE Trans Signal Process.* 2007;55(9): 4487–4496
- [13] Alghamdi I, Ariti C, Williams A, Wood E, Hewitt J. Prevalence of fatigue after stroke: a systematic review and meta-analysis. *Eur Stroke J.* 2021;6(4): 319–332
- [14] Barsakcioglu DY, Bräcklein M, Holobar A, Farina D. Control of spinal motoneurons by feedback from a non-invasive real-time interface. *IEEE Trans Biomed Eng.* 2021;68(3): 926–935
- [15] Pranav Mamidanna, Thomas Klotz, Dimitrios Halatsis, Agnese Grison, et al. MUniverse: A Simulation and Benchmarking Suite for Motor Unit Decomposition, Open Review, 2025
- [16] Kothe C, Shirazi SY, Stenner T, Medine D, et al. The lab streaming layer for synchronized multimodal recording. *Imaging Neuroscience.* 2025;3: IMAG.a.136
- [17] Grison A, Gibbs C, Rawji V, Gouveia Vila L, et al. Multidimensional motoneuron control using intramuscular microelectrode arrays in tetraplegic spinal cord injury. *medRxiv [Preprint].* 2025.
- [18] Ma S, Mendez Guerra I, Caillet AH, Zhao J, et al. NeuroMotion: open-source platform with neuromechanical and deep network modules to generate surface EMG signals during voluntary movement. *PLoS Comput Biol.* 2024
- [19] Oliveira DS, Carbonaro M, Raiteri BJ, Botter A, Ponfick M, Del Vecchio A. The discharge characteristics of motor units innervating functionally paralyzed muscles. *J Neurophysiol.* 2025;
- [20] Shandiz E, Gaskell A, Ingram M, Trajano GS, et al. Applying high-density surface EMG to the study of neuromuscular disorders: a systematic review. *Clin Neurophysiol.* 2025
- [21] Benecke, R., Berthold, A. & Conrad, B. Denervation activity in the EMG of patients with upper motor neuron lesions: time course, local distribution and pathogenetic aspects. *J Neurol.* 1983
- [22] Cimolatto A, Raspopovic S. Closing the sensory feedback loop is necessary for effective neurorehabilitation. *PLoS Biol.* 2024