

MOTOR-UNIT CONTINUITY IN WEARABLE ELECTROMYOGRAPHY DURING RESISTANCE EXERCISE: DETECTION, IDENTITY, AND MECHANICAL TIMING

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ABSTRACT

Movement changes the electrical signatures that high-density surface electromyography uses to identify motor units. An interruption in a discharge train therefore requires separate assessment of recording quality, event detection, and unit identity before it can support a physiological interpretation. In controlled ankle contractions, applying separation filters across movement velocities identified more than 92% of the units detected at the highest velocity in both lower-velocity recordings. In biceps simulations with known firing times, Kalman-based separation achieved 95.6% mean sensitivity and 96.5% mean precision during 2-s flexion-extension cycles. These findings demonstrate that detected unit number depends on the analysis as well as on neural activity. An interval record specifies channel usability, accepted discharges, and identity decisions; its interpretation distinguishes verified missed events, cessation conditional on detection sensitivity, ambiguous identity, and unavailable observation. Probability identities define the effects of selective inclusion on unit counts and discharge-rate means. A participant-weighted comparison retains the same eligible units across mechanically comparable intervals. Accurate exercise interpretation requires verified timing, unit correspondence, and explicit sampling denominators; acceptance of a later train cannot establish activity during an intervening unobserved interval.

Keywords: high-density surface electromyography; wearable electrodes; motor-unit tracking; resistance exercise; discharge sensitivity; neuromechanical delay.

INTRODUCTION

Wearable high-density surface electromyography (HD-sEMG) combines spatially distributed electrodes with discharge separation to examine the neural control of muscle. A stretchable 64-electrode sleeve permits conformal recording over a moving limb (Varghese et al., 2024); convolutive blind source separation estimates the firing times of individual motor units from multichannel electrical activity (Negro et al., 2016). For resistance exercise, the relevant measurement is a sequence of identified discharges linked to the contraction phase, force, and joint motion.

Movement changes the relationship between muscle fibres and the electrode array. Consequently, the action-potential waveform used for identification can change while the motor unit continues firing. Cyclic-contraction decomposition (De Luca et al., 2015), repeated-movement identification (Glaser and Holobar, 2019), and velocity-matched unit analysis (Oliveira and Negro, 2021) address different parts of this problem. Adaptive separation during changing force or posture further reduces the dependence on a fixed electrical signature (Chen et al., 2020; Yeung et al., 2024; Mendez Guerra et al.,

2024). None of these operations makes an absent accepted train equivalent to derecruitment.

The Consensus for Experimental Design in Electromyography (CEDE) single-motor-unit matrix specifies acquisition, decomposition-quality, and tracking requirements (Martinez-Valdes et al., 2023). During resistance exercise, these requirements must be applied to the interval in which a train becomes unavailable. A successful match at the beginning and end of a repetition establishes correspondence between those observations; it leaves firing during the intervening interval undetermined unless independent timing evidence is available.

The analysis below concerns voluntary contractions in adults without diagnosed neuromuscular transmission disorders. It separates four decisions: whether the recording permits detection, whether discharges are present, whether they belong to the same unit, and which units contribute to the exercise estimate. Controlled ankle, wrist, and biceps measurements establish the relevant acquisition and validation conditions. Transfer to fatiguing multi-joint exercise requires direct assessment under the intended load, movement, and contact conditions.

ACQUISITION, DECODING, AND MOVEMENT CONDITIONS

ELECTRODE CONFORMITY AND DISCHARGE SEPARATION

The stretchable-sleeve evaluation used two men for forearm gestures and one man for tibialis-anterior decomposition at 20% maximal voluntary contraction (MVC) (Varghese et al., 2024). These are distinct tests: gesture classification evaluates separation of movement classes, whereas motor-unit analysis evaluates individual discharge trains. A wearable electrode configuration therefore needs its own unit-level verification during the intended exercise.

Oliveira and Negro examined eleven participants at 10% and 25% maximal voluntary isometric contraction (MVIC), with ankle movement at 5, 10, and 20° s^{-1} (Oliveira and Negro, 2021). Approximately 14 units per participant were matched across velocities. Applying the 20° s^{-1} filters to the slower contractions identified more than 92% of those units in both recordings. Under these controlled conditions, a unit's appearance in a separately decomposed recording did not establish additional recruitment.

Chen and colleagues tested adaptive separation during non-stationary force production using known simulated discharges and signal-quality assessment of human recordings (Chen et al., 2020). Yeung and colleagues used concurrent fine-wire discharges to assess adaptation in extensor carpi radialis brevis during low-force isometric contractions at different fixed wrist positions (Yeung et al., 2024). Mendez Guerra and colleagues assessed continuous wrist movement over 80° ; sensitivity, precision, and timing agreement reached at least 90% in at least 80% of the tested cases using two-source verification (Mendez Guerra et al., 2024). Fixed-position and moving-joint tests must remain distinguishable when interpreting these results.

For 2-s biceps flexion-extension cycles with known firing times, CKC identified 7.1 ± 2.0 units, cyclostationary CKC 18.9 ± 2.0 , and Kalman-based CKC 21.3 ± 1.8 (mean $\pm$ SD) (Kramberger and Holobar, 2021). Figure 1 gives discharge sensitivity and precision. Concurrent surface/fine-wire recordings (Bradford et al., 2023) and ultrasound-transparent electrodes (Martinez-Valdes et al., 2022) provide separate means of checking discharge timing and muscle mechanics.

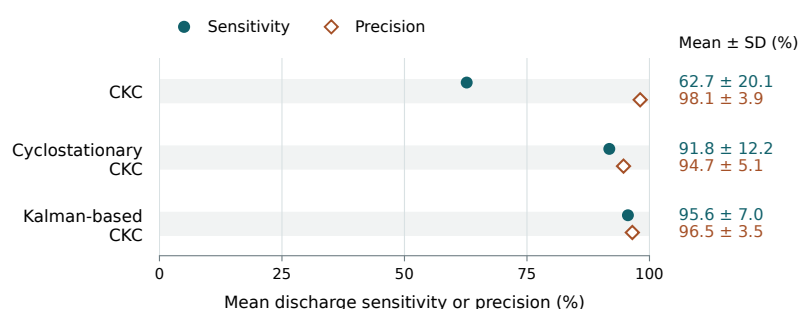


FIGURE 1. DISCHARGE IDENTIFICATION DURING SIMULATED BICEPS FLEXION-EXTENSION CYCLES LASTING 2 S. POINTS DENOTE MEAN SENSITIVITY OR PRECISION; ADJACENT VALUES GIVE MEAN $\pm$ SD IN PERCENT. VALUES ARE FROM KRAMBERGER AND HOLOBAR (2021), WHOSE TESTS COMBINED KNOWN FIRING TIMES WITH MEASURED ACTION-POTENTIAL SHAPES. CKC, CONVOLUTION KERNEL COMPENSATION.

IDENTITY AND MECHANICAL TIMING

Longitudinal waveform matching (Martinez-Valdes et al., 2017) and comparisons of separation filters with waveform cross-correlations (Goodlich et al., 2023) address whether two trains represent the same unit. Acceptance of both trains

on discharge-quality criteria does not establish that correspondence. Electrode number and spacing also change the sampled unit population (Caillet et al., 2023); additional detected units cannot be treated as complete coverage of the motor-neuron pool.

Martinez-Valdes and colleagues measured cumulative discharge activity, fascicle length, and ankle torque concurrently (Martinez-Valdes et al., 2022). Correlations were 0.60 for discharge-length association (range 0.31–0.85) and 0.71 for discharge-torque association (0.31–0.88). Discharge activity preceded fascicle-length changes by approximately 75 ms and torque changes by approximately 150 ms ($P < 0.001$ for the delay comparison). These isometric measurements establish that joint torque and muscle shortening have different temporal relationships with discharge activity.

During dynamic exercise, recruitment and cessation must therefore be indexed to synchronized joint angle, movement direction, velocity, and force. The mechanically associated event may occur after the electrical discharge, and the delay can affect the angle or force assigned to that event. Fixed joint position also does not guarantee fixed fascicle length.

Bradford and colleagues' concurrent surface, fine-wire, and ankle recordings permit direct timing comparisons in seated static and dynamic contractions (Bradford et al., 2023). Fine-wire selectivity confines verification to units present in both recordings. A discharge from a surface unit outside that reference sample cannot be declared erroneous solely because the fine-wire recording does not contain it.

INTERPRETING AN INTERRUPTED DISCHARGE TRAIN

RECORDING QUALITY, DETECTED EVENTS, AND CORRESPONDENCE

A physiological discharge, a detected electrical event, and assignment to a unit identifier are separate observations. Their relationship can be written as

$$x_c(t) = \sum_{u=1}^U \sum_k h_{cu}(t - t_{uk}; t) + \varepsilon_c(t), \quad (1)$$

where $x_c(t)$ is the signal at electrode c , t_{uk} is discharge k of unit u , h_{cu} is its channel-specific action potential, and ε_c contains residual activity and noise. The second time argument of h_{cu} allows the electrical waveform to change during movement. A separation filter adapted to one waveform may consequently fail to detect later discharges from the same unit.

For each identified unit, partition recording time into intervals $W_j = [a_j, b_j)$ with stated boundaries. Preserve contraction phase and movement transitions rather than averaging shortening and lengthening together. Each interval contains three records: channel usability, accepted discharge times, and unit correspondence.

The channel record identifies excluded electrodes, clipping, contact interruption, movement artefact, preprocessing, and changes in spatial coverage. Electrode exclusion changes the input to separation and matching; its effect must be assessed in that configuration. An amplifier trace within its voltage range does not by itself establish the detectability of the target unit.

The discharge record retains separated electrical traces, accepted and rejected event times, editing decisions, and pulse-to-noise ratio (PNR). In Holobar and colleagues' tests, nearly all units with PNR above 30 dB had sensitivity above 90% and false-alarm rates below 2% (Holobar et al., 2014). Discharge inspection and physiological interpretation require additional checks (Del Vecchio et al., 2020). PNR assesses a recovered train: a satisfactory value before an interruption supplies no score for the empty interval itself.

The correspondence record identifies the earlier train, common channels, waveform or filter comparison, competing candidates, and the acceptance decision. CEDE describes waveform-correlation assessment with visual inspection (Martinez-Valdes et al., 2023). During movement, compatibility with one candidate and discrimination from other candidates must both be assessed. Similar firing rates or recruitment times do not establish unique identity. When more than one candidate remains plausible, the correspondence is unresolved.

EVENT VERIFICATION AND INTERVAL DECISIONS

Interpretation begins by checking whether the target unit can be observed during the interval. If surface contact fails while an independently matched fine-wire train continues, its discharge times identify specific missed surface events. If both recording routes are unavailable, no firing-rate value can be assigned. The validity of an observation route must cover the interval being interpreted, not just its endpoints.

Next, assess correspondence for each accepted train. A train that cannot be distinguished from a competing unit is retained with an ambiguous identifier. Event timing is compared only after the identity relation has been established. One-to-one matching within a prespecified tolerance prevents a single reference discharge from validating several detections.

Table 1 states the four possible conclusions. Recording and identity uncertainties can coexist. An interval containing a verified event followed by contact failure should be divided at the change in evidence; the first observation cannot determine the remainder.

TABLE 1. DECISIONS FOR A SPECIFIED MOTOR UNIT AND INTERVAL. RECORDING, DISCHARGE, AND CORRESPONDENCE RECORDS REMAIN SEPARATE EVEN WHEN ONE DECISION DESCRIBES THE INTERVAL.

Decision	Required observation	Interpretation
Verified missed discharges	The same unit has reference-confirmed events absent from the accepted surface train, or events recovered through independently validated reanalysis. Timing matches use a stated tolerance.	Identify the missed event times. Other portions of the interval remain undetermined unless they have their own evidence. Algorithm agreement is weaker than an independent electrical recording.
Cessation conditional on detection sensitivity	No accepted events; a secure identity relation; an observation route valid throughout the interval; sensitivity assessed under comparable conditions; a continuation model making zero detections sufficiently unlikely.	Continued firing is unsupported under the stated detection and timing assumptions. The physiological cause of cessation is not identified.
Ambiguous identity	Valid trains exist but more than one candidate remains compatible, discrimination is inadequate, or comparison across channel sets lacks validation.	Do not calculate a within-unit change across this interval. Retain candidate identifiers and comparison values.
Unavailable observation	Recording quality, detection sensitivity, event evidence, or reference coverage cannot establish firing or cessation.	Retain missing activity and its cause. Do not enter zero discharge rate or interpolate surrounding discharges as observations.

EVIDENCE FOR CESSATION

An interval without detections supports cessation only relative to an explicit model of continued firing and observation. Let $N_R(W)$ be the detected event count in an independently assessed recording, H_{cont} the continuation model, and $\mathcal{C}$ the movement and acquisition conditions. A prespecified absence criterion is

$$\Pr\{N_R(W) = 0 \mid H_{\text{cont}}, \mathcal{C}\} \leq \alpha. \quad (2)$$

The firing-time distribution, local detection sensitivity, and decision threshold α must be justified before interpretation. A contact or separation failure can suppress consecutive events; independent miss probabilities cannot be multiplied when the failure affects the entire interval.

Eq. (2) states a conditional statistical requirement and has not undergone prospective validation as a cessation test. If slower firing makes zero events compatible with continued activity, the cessation decision is withheld. The same applies when detection sensitivity cannot be established for the current movement phase. Successful identification after the interval cannot supply missing event times within it.

Reanalysis retains the preceding accepted output, software identity, filter parameters, channel mask, edits, and correspondence map. Tools such as `openhdmg` permit train inspection (Valli et al., 2024), but agreement between analyses of the same electrical record is not an independent observation. Verification should state whether the event evidence comes from a second recording or from reanalysis.

Independent interval assessment by two analysts can test the consistency of these decisions. Record each analyst's initial classification and reason, then quantify agreement by class, undecided intervals, and the effects of boundary and matching choices. These evaluations are required before using the decisions to provide exercise feedback.

UNIT COUNTS AND DISCHARGE-RATE MEANS

DETECTION AND CORRECT IDENTITY

For unit u in interval W_j , define $A_{uj} = 1$ if at least one physiological discharge occurs, $D_{uj} = 1$ if at least one true discharge is detected, and $I_{uj} = 1$ if that observation is assigned to the correct identity. Correctly identified presence is

$$O_{uj} = A_{uj}D_{uj}I_{uj}. \quad (3)$$

Presence here denotes an event, not reconstruction of the complete train. A short interval may contain no event even when the unit remains part of an ongoing firing process.

The probability of correctly identified presence satisfies

$$\Pr(O = 1) = \Pr(A = 1) \Pr(D = 1 \mid A = 1) \times \Pr(I = 1 \mid A = 1, D = 1). \quad (4)$$

This conditional product requires no independence assumption. Spurious detections, duplicated trains, and incorrect identifiers are excluded from O and require separate counts.

The biceps comparison in Figure 1 held the simulated firing times fixed while changing the decoding method. Different detection yields therefore cannot be attributed to different neural activation. Similarly, units matched to an initial cohort and units found by independent decomposition at each velocity have different sampling denominators. Recruitment requires discharge evidence linked to the same unit and contraction phase.

SELECTIVE INCLUSION IN THE MEAN

Let Y be a discharge characteristic defined for a specified unit population and assessable interval. Let O indicate correct inclusion and $p = \Pr(O = 1) > 0$. Then

$$E(Y \mid O = 1) - E(Y) = \frac{\text{Cov}(Y, O)}{p}. \quad (5)$$

The identity follows from $E(YO) = pE(Y \mid O = 1)$. It specifies the difference between the included-unit mean and the population mean; it does not estimate the covariance from accepted trains or correct unavailable observations.

If detectability or correspondence varies with discharge properties, the detected mean can change when the set of included units changes. The direction depends on which units remain observable. High precision among accepted events consequently does not establish representative sampling. Discharge accuracy, unit retention, and population coverage must be assessed separately.

For comparisons across repetitions, give the number of initially identified units, units matched in both intervals, unmatched valid trains, rejected trains, and intervals without assessable activity. State these counts per participant and contraction phase. An aggregate unit number conceals whether loss occurs during shortening, lengthening, or the transition between them.

WITHIN-PARTICIPANT EXERCISE COMPARISONS

MATCHED-UNIT DISCHARGE CHANGE

For participant i , let S_i contain units securely matched and assessable in both intervals a and b under prespecified mechanical conditions. Let Y_{iua} and Y_{iub} be the corresponding discharge characteristics calculated over stated durations. A participant-weighted difference is

$$\hat{\Delta}_{\text{matched}} = \frac{1}{N_*} \sum_{i \in \mathcal{P}_*} \frac{1}{|S_i|} \sum_{u \in S_i} (Y_{iub} - Y_{iua}), \quad (6)$$

where $\mathcal{P}_*$ contains participants with at least one eligible pair and $N_* = |\mathcal{P}_*| > 0$.

Equal participant weights prevent a person with greater unit yield from dominating the estimate. Participants with no eligible pair require an explicit exclusion count. The target is the mean within-unit change among eligible participants and matched units. It does not represent unobserved units or participants without eligible observations.

Units are nested within participants and may be observed in several muscles or repetitions. A hierarchical model can represent this dependence, but it cannot recover unavailable units without assumptions about their inclusion. Give retained unit counts, rejection reasons, unobserved duration, and participant exclusions alongside interval estimates. Comparisons using different identity or quality thresholds must preserve the same physiological target.

STRENGTH ADAPTATION, FATIGUE, AND FORCE MATCHING

Del Vecchio and colleagues compared 14 participants undergoing four weeks of dorsiflexor training with 14 controls (Del Vecchio et al., 2019). In the training group, maximal voluntary force increased from 289 ± 64 to 329 ± 61 N. Plateau

discharge rate increased by 3.3 ± 2.5 pulses s^{-1} across participants and motor units during contractions at 35%, 50%, and 70% maximal voluntary force. Longitudinally matched units permitted assessment of discharge changes across the intervention.

These observations also identify the mechanical choices required for a training comparison. A contraction at the same percentage of a larger maximum uses a different absolute force. State whether force is matched in newtons, relative to each session's maximum, or relative to the maximum at the current joint position. Preserve direction, angle range, movement velocity, and analysis duration.

The relationship between motor-unit discharge and task failure has been examined in submaximal contractions (Martinez-Valdes et al., 2020). Angius and colleagues combined unit recordings with cortical, spinal, and neuromuscular assessment during sustained knee-extension tasks at 20% and 70% MVC (Angius et al., 2024). Such measurements permit fatigue interpretation within their tested contractions. Loss of surface trains alone cannot distinguish central drive limitation, contractile impairment, or failed detection.

Cumulative discharge activity represents the included units. Investigations of common synaptic input use summed trains from identified units (Negro et al., 2016); changing membership changes that sum even if the retained units maintain their discharge behaviour. Use a fixed matched set where the comparison concerns the same units. Normalization by detected unit number changes scale but does not reconstruct missing discharges.

ONLINE OUTPUT AND VERIFICATION DENOMINATORS

Real-time unit identification (Glaser et al., 2013) and I-Spin live (Rossato et al., 2024) permit immediate discharge displays. Computational feasibility has also been quantified: Yeung and colleagues measured 57.1 ± 14 ms for adaptation and spike estimation per 100-ms increment on an Intel Xeon W-2133 desktop (Yeung et al., 2024); Mendez Guerra and colleagues obtained approximately 22 ms per 100-ms batch (Mendez Guerra et al., 2024). These timings concern different implementations and tasks and do not establish comparative speed under identical conditions.

A live display must preserve the distinction between unavailable detection and a measured zero rate. Carrying a preceding rate into a failed interval makes the displayed value appear observed when it is not. The display should associate each rate with its analysis duration, quality status, and identifier decision.

For a reference-confirmed unit, discharge sensitivity is $TP/(TP + FN)$ and precision is $TP/(TP + FP)$, using one-to-one timing correspondence and a justified tolerance. Reference coverage defines where those counts are assessable. A selective fine-wire reference cannot classify an unmatched surface unit's events as false positives without establishing that the reference observes that unit.

Identity validation requires reference-confirmed unit-interval pairs. Give correct correspondences, swaps, ambiguous pairs, and unavailable pairs. The denominator among decided pairs and the denominator among all eligible pairs answer different questions; withholding difficult pairs can increase apparent accuracy among decisions. Analysis by movement phase and repetition position is necessary to identify late-exercise deterioration that a session-wide average would conceal.

CONCLUSIONS

Wearable motor-unit measurement depends on the conjunction of usable electrical recording, detectable events, and specific identity. Motion-dependent separation results demonstrate why detected unit loss cannot alone establish derecruitment. Concurrent mechanical measurements establish why force and angle must be synchronized to the electrical event. When either observation or correspondence is unavailable, the interval remains missing rather than becoming physiological silence. Exercise estimates are interpretable when their unit membership, participant weights, recording conditions, and discharge denominators are explicit.

DECLARATIONS

CONFLICT OF INTEREST

The author declares that there are no conflicts of interest related to this study.

DATA AVAILABILITY

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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