

Real-Time Classification of Hand Movements from Surface Electromyography Signals Using Feature Engineering and an Ensemble of Machine-Learning Classifiers for Rehabilitation

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Abstract - Myoelectric control of prostheses and biosignal-driven rehabilitation require hand-movement recognition that is simultaneously accurate, computationally light, and fast enough for real-time operation on embedded hardware. This paper presents an end-to-end methodology for classifying object-interaction hand movements from surface electromyography (sEMG) signals. Four contributions are combined into a single deployable pipeline: (i) a real-time active-potential onset/offset detection algorithm based on rectified-signal variance thresholding (threshold = $\mu + h\sigma$); (ii) an optimal, low-dimensional feature vector obtained through feature engineering in the time, frequency and time-frequency domains; (iii) a real-time algorithm for automatically building the training set during signal acquisition; and (iv) an ensemble classifier that fuses k-Nearest Neighbours, Support Vector Machine and Random Forest decisions with a confidence gate and temporal confirmation. Two datasets were recorded - a single-channel BITalino dataset (20 subjects, 4 movements) and a five-channel BTS FreeEMG dataset (42 subjects, 7 movements). The proposed onset detector achieved the lowest mean error (15.45 samples) among six competing methods. A six-feature time-domain vector (SSI, ACC, IEMG, WL, RMS, MAV) reached up to

99% accuracy with a 223 ms response time, and the overall real-time accuracy for object-interaction movements was 94.6%. When embedded in a low-cost hardware-software complex and deployed for the rehabilitation of spinal-cord-injury (C5-C8) patients, the method increased the number of elicited hand movements by a factor of 2-3 and shortened the rehabilitation course by roughly threefold.

Keywords: surface electromyography; hand-movement classification; feature engineering; machine learning; ensemble classifier; real-time; myoelectric prosthesis; rehabilitation; spinal cord injury.

Introduction

The number of people whose motor function is fully or partially impaired continues to grow worldwide, driven by congenital disability, vascular and diabetic disease, and traumatic injury. According to the World Health Organization, tens of millions of people currently require prosthetic assistance, yet commercial myoelectric prostheses remain prohibitively expensive (on the order of tens of thousands of euros) while typically reproducing only two or three grasp patterns. This mismatch between clinical need and affordable, multifunctional technology motivates research into low-cost, sensor-efficient systems that recover as much hand function as possible.

Human movement originates in the motor cortex; descending impulses travel through the spinal cord to skeletal muscles, whose contraction generates the electromyography (EMG) signal. Decoding hand movements from this signal underpins both myoelectric prosthesis control and biosignal-based physiotherapy, and additionally supports the detection of neuromuscular pathologies. Surface EMG (sEMG) is attractive because it is non-invasive, but the raw signal is stochastic, low-amplitude (0.1-5 mV), band-limited (20-500 Hz), and highly sensitive to electrode placement, fatigue and motion artefacts. Consequently, raw sEMG cannot be classified directly with acceptable accuracy or latency; informative **feature engineering** and an appropriately chosen classifier are essential.

For any device that must respond to the user in real time, three requirements dominate: the **response time** (the sum of data-collection and data-analysis time), the **classification accuracy**, and the **computational cost** of the features and classifier. These requirements are frequently in tension: richer feature sets and larger sensor arrays can raise accuracy but inflate latency and hardware demands. The central question addressed in this work is therefore how to reach high accuracy for a useful repertoire of hand movements while using as few sensors and as light a feature set as possible.

This paper makes the following contributions, each validated experimentally and integrated into a single deployable system:

- 1) A real-time algorithm that determines the active-potential threshold of the EMG signal from the variance of the rectified signal, locating movement onset and offset more accurately than five established alternatives.
- 2) An optimal, low-dimensional feature vector derived through systematic feature engineering, which maximises classification accuracy while remaining cheap to compute on embedded hardware.
- 3) A real-time algorithm that automatically assembles a labelled training set during signal acquisition, removing the manual effort usually required to build sEMG corpora.
- 4) A real-time ensemble classifier that fuses k-NN, SVM and Random Forest decisions, embedded in a low-cost hardware-software complex and validated clinically on spinal-cord-injury patients.

The remainder of the paper is organised as follows. Section 2 reviews related work. Section 3 describes the two datasets, the signal-processing chain, the active-potential detector, the feature-engineering procedure and the ensemble classifier. Section 4 reports the experimental results, including a comparison with the state of the art. Section 5 presents the clinical deployment, Section 6 discusses the findings, and Section 7 concludes.

Related Work

EMG-based movement recognition has been studied extensively. Early myoelectric systems relied on artificial neural networks (ANN, BPNN) and their probabilistic variants (LLGMN, RLLGMN), as well as hidden Markov models and Bayesian networks. Reported accuracies range widely - from around 70% for cursor-control tasks using back-propagation networks to about 94-95% for specific architectures - but neural approaches generally require multi-layer structures, long training, careful stochastic-parameter tuning, and are sensitive to small mislabelled movements, which limits their suitability for latency-critical embedded control.

A parallel body of work has concentrated on **feature engineering**. Time-domain features such as mean absolute value (MAV), waveform length (WL), zero crossings (ZC), slope-sign changes (SSC), root-mean-square (RMS) and Willison amplitude (WAMP) are computationally cheap and well suited to real-time use, whereas frequency-domain and time-frequency features (power-spectral-density descriptors, autoregressive coefficients, wavelet transforms) capture complementary information at higher computational cost. Comparative studies have repeatedly identified WL, MAV and RMS as among the most discriminative and noise-robust individual descriptors, and the Hudgins set (MAV, WL, ZC, SSC) as an effective compact combination. Feature-selection and reduction techniques - the Davies-Bouldin index, the ReliefF algorithm and principal component analysis - are commonly used to prune redundant descriptors.

Compared with neural networks, classical machine-learning (ML) classifiers - k-Nearest Neighbours (k-NN), Support Vector Machines (SVM) and Random Forests (RF) - offer faster training, few hyper-parameters, and straightforward integration with pre-computed features, which is why they are increasingly preferred in myoelectric control. However, most publicly available sEMG datasets either lack sufficient movement repetitions, or are recorded in a single session, both of which undermine the reliability of the trained model. The present work addresses these gaps by combining a robust onset detector, an engineered compact feature vector, an automatically generated multi-session training set, and an ensemble classifier, and by validating the whole pipeline both offline and in a real embedded deployment.

Materials and Methods

The complete recognition pipeline comprises seven stages - signal acquisition, pre-processing and band-pass filtering, active-potential detection, feature extraction, feature selection, ensemble classification, and command actuation (Figure 1). Each stage is designed so that the cumulative data-collection and data-analysis time remains compatible with real-time control.

Real-time hand-movement recognition pipeline



Figure 1. Real-time hand-movement recognition pipeline. Shaded blocks denote the novel components proposed in this work.

Data acquisition and datasets

Two datasets were recorded from healthy volunteers who took part voluntarily and in a positive psychological state. Before each session, participants completed a questionnaire covering sex, age, weight, health history, smoking and sporting activity, and the forearm and elbow diameters were measured. Signals were recorded from the forearm muscles responsible for grasping using non-invasive Ag-Cl surface electrodes placed over the muscle innervation zones. Recording was carried out gradually to avoid stress and fatigue and to obtain clean, low-artefact signals. The two corpora are summarised in Table 1.

Property	Dataset I (single-channel)	Dataset II (multi-channel)
Device	BITalino (Plux, Portugal)	BTS FreeEMG
Channels	1 (extensor carpi radialis)	5 (innervation zones)
Subjects	20 healthy	42 healthy (5 F, 37 M), 19-37 y
Movements	4 (3 active + rest)	7 (6 active + rest)
Repetitions	20 per movement	up to 30 per movement
Sessions	2 (over 1 week)	2 (over 2 weeks)
Sampling rate	1 kHz	1 kHz
Band-pass filter	band-pass, 20-500 Hz	band-pass, 20-500 Hz
Window length	200 ms (sequential)	256 ms
Samples	1 600 (20×4×1×20)	multi-session, multi-subject

Table 1. Characteristics of the two recorded surface-EMG datasets.

The four movements of Dataset I - making a fist (grip), pinch grip with the fingers, opening the hand, and a rest (motionless) state - represent the primary object-interaction functions of the palm. Dataset II extends this to six active movements (finger grip, fist, hand opening, and flexion

of the index, middle and ring fingers) plus the rest state. Signals were split 85% for training and 15% for testing.

Pre-processing and active-potential detection

Raw sEMG was recorded in differential mode and band-pass filtered (low cut-off 20 Hz, high cut-off 500 Hz) with a sixth-order Butterworth filter to remove baseline drift, motion artefacts and out-of-band noise. Because features must be computed from the muscle-active portion of the signal, robust detection of activation onset and offset is critical for both accuracy and speed. The proposed detector operates on the rectified signal and compares the windowed variance against a data-adaptive threshold

$$threshold = \mu + h \cdot \sigma, \quad \sigma = \sqrt{(1/N) \sum (x_i - \bar{x})^2} \quad (1)$$

where μ and σ are the mean and standard deviation of the EMG values, h scales the threshold level, and N is the number of samples. Starting from the onset point, the loop advances until the windowed variance of the rectified signal exceeds the product of the threshold and the noise variance. In the resulting indicator signal, a 0→1 transition marks activation onset and a 1→0 transition marks offset. The detector was compared with the single-threshold, double-threshold, Komi, sign-change and Teager-Kaiser energy operator (TKEO) methods (Section 4.1).

Feature engineering and the optimal feature vector

Features were extracted from three domains: the time domain (TD), the frequency domain (FD) and the time-frequency domain (TFD). Each descriptor was first evaluated **individually** and then in **combinations**, and the most discriminative descriptors were retained. Candidate selection was guided by three criteria - class separability, robustness to noise, and low computational complexity - and supported by the Davies-Bouldin index, the ReliefF weighting algorithm and principal component analysis for dimensionality reduction.

Individual descriptors reached only 40-60% accuracy on average, with WL the strongest single feature (87% with k-NN, $k = 3$) and ZC the weakest (33%). Accuracy improved sharply once several energy-related time-domain descriptors were combined. The retained optimal vector consists of six descriptors defined in Table 2: simple square integral (SSI), average amplitude change (ACC), integrated EMG (IEMG), waveform length (WL), root-mean-square (RMS) and mean absolute value (MAV).

Feature	Definition	Physiological meaning
SSI	$\sum x_i^2$	Signal energy index
ACC	$(1/N) \sum x_{i+1} - x_i $	Mean waveform-length change
IEMG	$\sum x_i $	Summed activation over the window
WL	$\sum x_i - x_{i-1} $	Cumulative waveform length
RMS	$\sqrt{(1/N) \sum x_i^2}$	Amplitude / contraction level
MAV	$(1/N) \sum x_i $	Rectified mean; contraction degree

Table 2. The six-descriptor optimal time-domain feature vector (x_i = sample; N = samples per window).

Machine-learning classifiers and the ensemble strategy

Three classical supervised classifiers were used. **Random Forest (RF)** aggregates the votes of many decision trees, each trained on a bootstrap sample using a random subset of m features per node; it is efficient on large data, resists over-fitting and provides feature-importance estimates. **Support Vector Machine (SVM)** constructs the maximum-margin separating hyperplane, using kernels (radial-basis-function or polynomial) for non-linearly separable data and either a one-against-one or one-against-all strategy for the multi-class problem. **k-Nearest Neighbours (k-NN)** is a non-parametric rule that assigns the majority class among the k closest training samples under the Euclidean distance.

For deployment the three classifiers were combined into a real-time ensemble (Figure 1, final block). Each incoming 25 ms sliding-window feature vector is normalised ($z = (x - u)/s$) and passed to all three models; the movement command is issued only when the mean of their class probabilities exceeds 0.85 and the same class is confirmed over four consecutive windows ($h = 4$). This confidence gate and temporal confirmation suppress spurious activations, which is essential when the output drives a physical actuator. The training set required by these models is generated automatically during acquisition: once the device connection is established and the active region is detected, the onset-to-offset segment is written to the corpus with a fixed array size, ensuring uniform training samples.

Results

Active-potential detection performance

Table 3 and Figure 2 compare the six onset-detection algorithms in terms of mean error and mean deviation, together with the number of signal samples each method processes. The proposed variance-threshold detector achieved the lowest mean error (15.45) and the lowest mean deviation (18.9), clearly outperforming the single-threshold method (31.0 / 32.2) and the classical Komi algorithm (29.5 / 32.8). Accurate onset localisation matters because features extracted from the correct activation instant improve both the speed and the accuracy of the downstream classifier.

Algorithm	Mean error	Mean deviation	Samples
Proposed	15.45	18.9	352
TKEO	20.2	27.5	402
Double threshold	25.6	22.6	156
Sign changes	24.8	25.8	718
Komi	29.5	32.8	956
Single threshold	31.0	32.2	98

Table 3. Comparative accuracy of active-potential (onset) detection algorithms (lower is better).

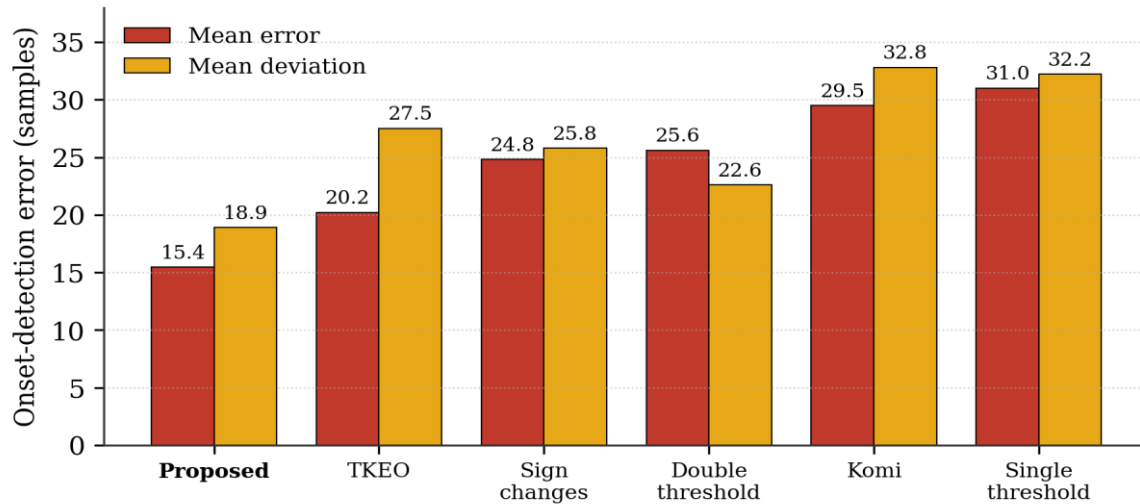


Figure 2. Mean error and mean deviation of the six onset-detection algorithms. The proposed method yields the smallest values.

Comparison of feature domains

Table 4 and Figure 3 summarise the mean classification accuracy and response time obtained with each feature domain on the four-movement task. Time-domain features gave the highest accuracy (95%) at the shortest response time (223 ms), of which 200 ms is the sequential-segmentation window and 23 ms is spent on pre-processing, feature extraction and classification. Frequency-domain and time-frequency features achieved 91% and 93% respectively but at two-to-four times the latency, because their computation is markedly more expensive - a decisive disadvantage for real-time control.

Feature domain	Mean accuracy (%)	Response time (ms)	Rank
Time domain (TD)	95	223	1
Time-frequency (TFD)	93	708-856	2
Frequency domain (FD)	91	443-556	3

Table 4. Mean accuracy and response time by feature domain (four-movement task).

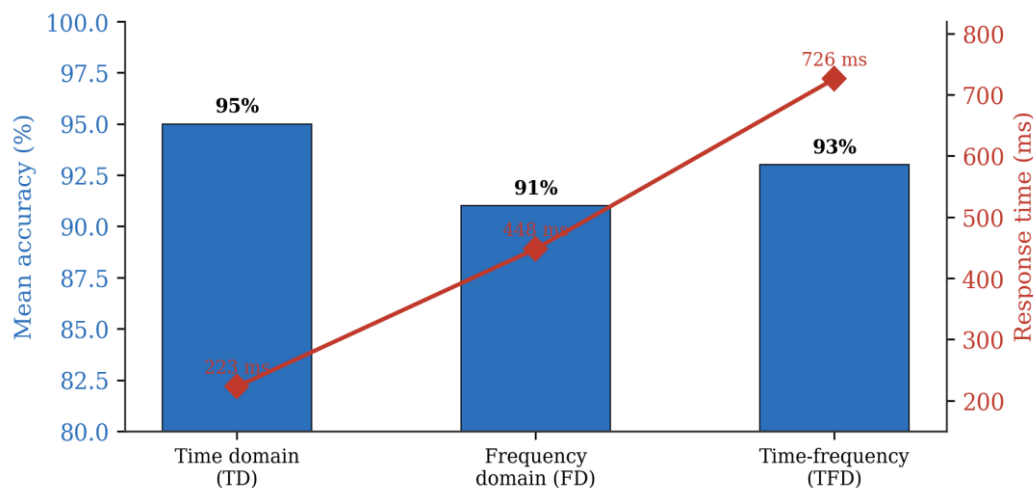


Figure 3. Trade-off between accuracy (bars, left axis) and response time (line, right axis) across the three feature domains.

Optimal feature-vector combination

Table 5 and Figure 4 trace how accuracy evolves as descriptors are added to the vector. Combining two features already lifts accuracy above the individual level, and results improve steeply from five features onward. The best result is obtained with the six-feature combination SSI + ACC + IEMG + WL + RMS + MAV, reaching 99% with k-NN, 99% with RF and 95% with SVM. Adding further descriptors (ZC, WAMP, log-detector) does not improve - and occasionally degrades - accuracy while increasing computational cost, confirming the six-feature vector as optimal.

Feature combination	k-NN (%)	RF (%)	SVM (%)
SSI + ACC	71	73	56
SSI + ACC + IEMG	86	87	70
SSI + ACC + IEMG + WL	94	97	89
SSI + WL + RMS	97	96	91
SSI + ACC + IEMG + WL + RMS	95	97	92
SSI + ACC + IEMG + WL + RMS + MAV	99	99	95
+ ZC	97	98	87
+ ZC + WAMP	98	95	89
+ ZC + WAMP + logDetect	98	97	90

Table 5. Classification accuracy as features are progressively combined; the highlighted six-feature vector is optimal.

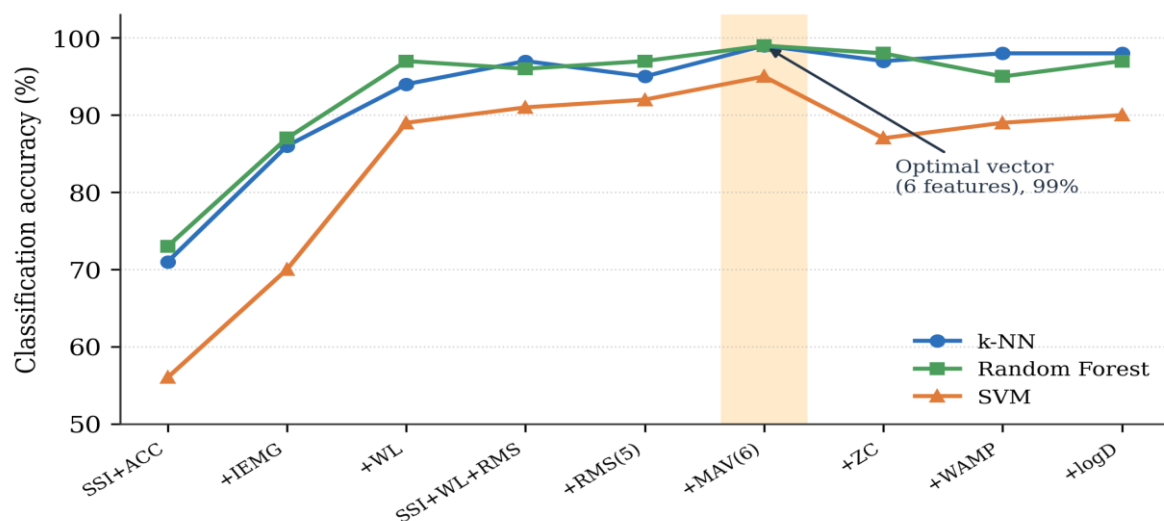


Figure 4. Accuracy progression of the three classifiers as descriptors are added. The six-feature vector attains 99%.

Effect of movement count and sensor count

Because Dataset I uses a single channel, the relationship between the number of target movements and accuracy was quantified (Figure 5a): a single-channel device can reliably classify at most three-to-four movements before accuracy falls below a usable level. On the multi-channel task (Figure 5b), accuracy peaks around five sensors and then plateaus or even decreases, because additional channels enlarge the real-time data stream and the feature-computation load. Random Forest slightly outperformed k-NN on the six-movement multi-channel task (94% versus 92% mean accuracy), and time-domain features again gave the highest per-movement accuracy. Across the three domains the overall figures were TD 95%, FD 91% and TFD 93%.

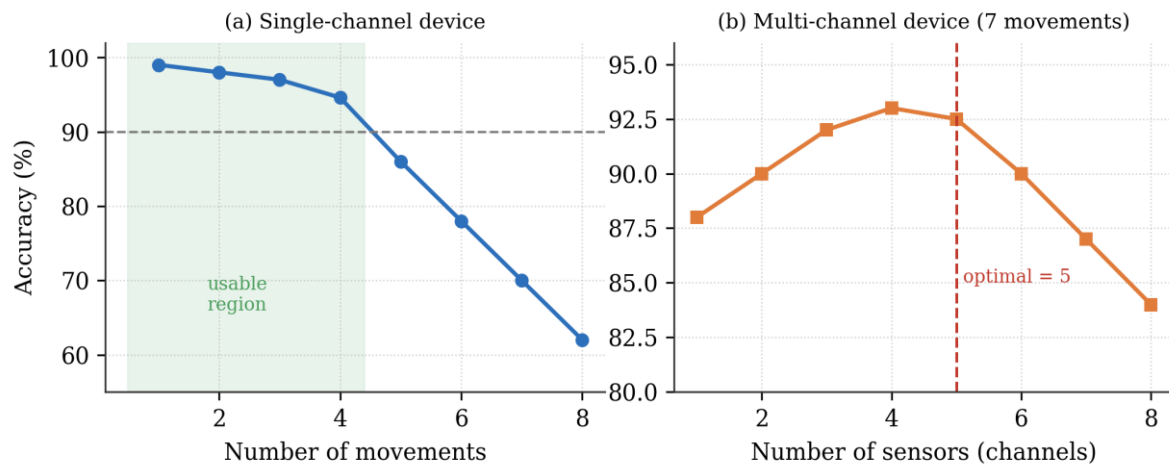


Figure 5. (a) Accuracy versus number of movements for a single-channel device; (b) accuracy versus number of sensors for the multi-channel device (seven movements).

Comparison with the state of the art

Table 6 places the two configurations of this work (marked * and) alongside twelve previously published systems. The comparison uses the number of movements, the number of sensors, the summed data-collection and data-analysis time (DCT + DAT), and the offline and real-time accuracies. Both configurations were tested on embedded systems** rather than on a PC. Using only one sensor for four movements, the proposed system reached 98% offline and 94.6% real-time accuracy at 223 ms; using five sensors for seven movements it reached 99% offline and 92.5% real-time at 232 ms. The distinguishing feature of this work is the deliberate minimisation of DCT + DAT and sensor count while keeping real-time accuracy above most reported systems.

Study	Movements	Sensors	DCT+DAT (ms)	Offline (%)	Real-time (%)	Platform
[1]	5	8	1029.4	90.7	85.3	PC
[2]	6	8	137.9	99.0	89.6	PC
[6]	10	4	250.2	94.0	85.0	Embedded
[7]	7	8	300.0	97.9	83.0	PC
[9]	9	8	254.5	99.0	90.2	Embedded
[12]	8	32	205.0	98.2	92.3	Embedded

Study	Movements	Sensors	DCT+DAT (ms)	Offline (%)	Real-time (%)	Platform
This work *	4	1	223	98.0	94.6	Embedded
This work **	7	5	232	99.0	92.5	Embedded

Table 6. Comparison with representative published sEMG hand-recognition systems (selected rows; DCT + DAT = data-collection + data-analysis time).

Clinical Application

The hardware-software complex was designed around low-cost, widely available components (a BITalino acquisition board with an ATMEGA328P-AU micro-controller and a Bluetooth 2.0 link), a small number of sensors, and long battery life. It comprises five modules: signal acquisition, pre-processing, feature extraction, movement classification, and on-device testing. Beyond prosthesis control, the same system supports the rehabilitation of patients whose motor pathway is disrupted - most notably spinal-cord-injury (SCI) patients.

SCI arises predominantly from road accidents ($\approx 39\%$) and falls ($\approx 32\%$); injuries in the C5-C8 segments can disable the arm down to the shoulder, and the treatment course ranges from one month to several years at very high cost. In conventional physiotherapy a therapist forces muscle contraction with an electro-stimulator, typically eliciting only two movements. In the proposed method (Figure 6), the therapist's own hand movements are classified from EMG and the resulting commands drive stimulation of the patient's muscles, so the number of elicited movements scales with the number of acquisition channels.

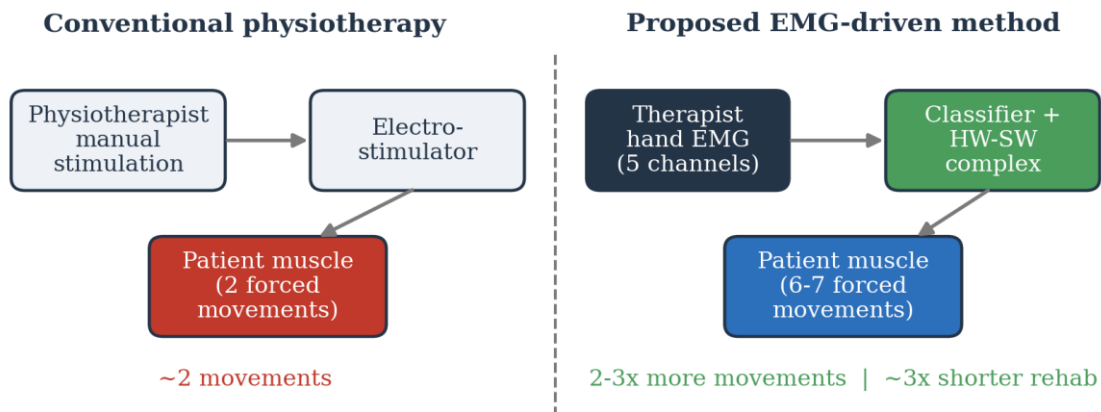


Figure 6. Conventional physiotherapy (left) versus the proposed EMG-driven rehabilitation scheme (right).

The method was deployed at the Kashkadarya Regional No. 1 Multidisciplinary Hospital and at the Kashkadarya Regional Rehabilitation and Physiotherapy Centre, and tested on SCI patients with C5-C8 injuries. In these trials the number of movements that could be elicited in the affected hand increased by a factor of two-to-three, giving the physiotherapy protocol greater multifunctionality, and the rehabilitation course was shortened by approximately threefold.

Discussion

The results support three main observations. First, accurate onset detection is a prerequisite for both speed and accuracy: by extracting features from the correctly localised activation segment, the proposed variance-threshold detector reduces onset error by roughly half relative to the single-threshold and Komi baselines. Second, for real-time embedded control, a compact engineered time-domain vector is preferable to richer frequency or time-frequency representations; the six-feature vector matches or exceeds their accuracy at a fraction of the latency. Third, sensor count must be matched to the movement repertoire - more channels are not automatically better, since they increase computation and can even reduce accuracy, with roughly five sensors sufficient for multifunctional operation and one sensor adequate for three-to-four movements.

Fusing k-NN, SVM and RF with a confidence gate and four-window temporal confirmation trades a small, bounded latency for markedly more stable output, which is critical when the classifier drives a physical actuator or a patient's muscle. The automatic, multi-session training-set generator further improves reliability by capturing the physiological variability and fatigue that single-session corpora miss. The principal limitations are that both datasets were recorded from healthy subjects and that clinical validation, while promising, involved a limited patient cohort; larger multi-centre trials and evaluation on amputees are natural next steps, together with closed-loop sensory feedback for the myoelectric-prosthesis use case.

Conclusion

This paper presented a complete, deployable methodology for real-time hand-movement classification from surface EMG. Its four integrated contributions - a variance-threshold active-potential detector (lowest mean error, 15.45), an optimal six-feature time-domain vector (up to 99% accuracy), a real-time automatic training-set generator, and a confidence-gated k-NN/SVM/RF ensemble - together achieved 94.6% real-time accuracy for object-interaction movements at a 223 ms response time on embedded hardware. Embedded in a low-cost hardware-software complex and deployed for SCI rehabilitation, the system increased the number of elicited hand movements 2-3-fold and shortened the rehabilitation course roughly threefold. By jointly optimising accuracy, latency and sensor count, the approach offers an affordable route to multifunctional myoelectric control and biosignal-driven physiotherapy. Future work will extend validation to amputees and larger patient cohorts and integrate sensory feedback.

Reference

1. Chen, Z., Min, H., Wang, D., Xia, Z., Sun, F., & Fang, B. (2023). A review of myoelectric control for prosthetic hand manipulation. *Biomimetics*, 8(3), 328.
2. Jiang, X., Liu, X., Fan, J., Ye, X., Dai, C., Clancy, E. A., Farina, D., & Chen, W. (2022). Optimization of HD-sEMG-based cross-day hand gesture classification by optimal feature extraction and data augmentation. *IEEE Transactions on Human-Machine Systems*, 52(6), 1281-1291.
3. Miah, A. S. M., Shin, J., & Hasan, M. A. M. (2024). Effective features extraction and selection for hand gesture recognition using sEMG signal. *Multimedia Tools and Applications*, 83, 1-25.
4. Aarotale, P. N., et al. (2024). Machine learning-based sEMG signal classification for hand gesture recognition. *arXiv preprint arXiv:2411.15655*.

5. Zhang, R., Zhang, X., He, D., Wang, R., & Guo, Y. (2022). sEMG signals characterization and identification of hand movements by machine learning considering sex differences. *Applied Sciences*, 12(6), 2962.
6. Junior, J. J. A. M., Pontim, C. E., Dias, T. S., & Campos, D. P. (2023). How do sEMG segmentation parameters influence pattern recognition process? An approach based on a wearable sEMG sensor. *Biomedical Signal Processing and Control*, 81, 104546.
7. Lv, X., et al. (2023). Gesture recognition based on sEMG using a multi-attention mechanism for remote control. *Neural Computing and Applications*, 35(19), 13839-13849.
8. Lee, K. H., Min, J. Y., & Byun, S. (2022). Electromyogram-based classification of hand and finger gestures using artificial neural networks. *Sensors*, 22(1), 225.
9. Trajdos, P., & Kurzynski, M. (2024). Application of context-dependent interpretation of biosignals recognition to control a bionic multifunctional hand prosthesis. *Biocybernetics and Biomedical Engineering*, 44(1), 161-182.
10. Trajdos, P. (2025). A noise-tolerant dual multi-classifier system with fuzzy model applied to the sEMG-based control of a bionic upper limb prosthesis. *Biomedical Signal Processing and Control*, 104, 107441.
11. Iqbal, H., Zheng, J., Chai, R., & Chandrasekaran, S. (2024). Electric powered wheelchair control using user-independent classification methods based on surface electromyography signals. *Medical & Biological Engineering & Computing*, 62(1), 167-182.
12. Bicer, Y., et al. (2024). User training with error augmentation for sEMG-based gesture classification. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 32.
13. Dai, Y., et al. (2022). MSEva: a musculoskeletal rehabilitation evaluation system based on EMG signals. *ACM Transactions on Sensor Networks*, 19(1), 1-23.
14. Mokri, C., Bamdad, M., & Abolghasemi, V. (2022). Muscle force estimation from lower limb EMG signals using novel optimised machine learning techniques. *Medical & Biological Engineering & Computing*, 60(3), 683-699.
15. Zhou, P. (2024). Surface EMG in China: a report on the 2023 surface EMG symposium. *Frontiers in Rehabilitation Sciences*, 5, 1353564.