Global Journal of Engineering and Technology Advances
eISSN: 2582-5003
Cross Ref DOI: 10.30574/gjeta
Journal homepage: https://gjeta.com/

(RESEARCH ARTICLE)

SEVEN-CLASS LOWER-LIMB ACTIVITY RECOGNITION USING THREE-CHANNEL SEMG

Javier Rodríguez-Herrejón *, Enrique Reyes-Archundia, Jose A. Gutiérrez-Gnecchi, Marco V. Chávez-Báez and Jonathan A. Sanchez Trujillo

Division for Postgraduate Studies, Technological Institute of Morelia, Morelia, Mexico.
* Corresponding Author

ORCID Details
Javier Rodríguez-Herrejón: https://orcid.org/0000-0002-9767-425X
Enrique Reyes-Archundia: https://orcid.org/0000-0003-3374-0059
Jose A. Gutiérrez-Gnecchi: https://orcid.org/0000-0001-7898-604X
Marco V. Chávez-Báez: https://orcid.org/0000-0002-6294-2074

Global Journal of Engineering and Technology Advances, 2026, 29(02), 001–011

Publication history: Received on 22 September 2026; revised on 29 October 2026; accepted on 31 October 2026

Article DOI: https://doi.org/10.30574/gjeta.2026.29.2.0313

Copyright © 2026 Author(s) retain the copyright of this article. This article is published under the terms of the Creative Commons Attribution License 4.0

ABSTRACT

Three-channel sEMG recordings may contain different signatures of lower-limb activity, but separating movements is less straightforward when they recruit some of the same muscles. We examined this problem in seven right-leg activities using the conditioned envelopes recorded over rectus femoris, vastus lateralis, and semitendinosus. The experiment comprised five repeated movements and two sustained postures, each recorded for 40 s during one session with a 25-year-old participant without amputation. We divided the recordings into 300-ms windows with 60% overlap, extracted seven time-domain descriptors, and used them in a support vector machine (SVM). The stored test matrix contains 464 windows and 401 correct assignments, corresponding to 86.42% accuracy. The findings describe the discrimination achieved with the selected channels and indicate aspects of electrode placement and cycle labeling that warrant further testing.

Keywords: Lower-limb activity recognition; EMG; Support Vector Machine; Movement classification.

1 INTRODUCTION

Knee flexion and hip extension are different actions, yet they both involve the semitendinosus. An active posterior-thigh channel is therefore not, on its own, enough to distinguish the two. What matters is the pattern observed across the available recording sites, including the activity they have in common. With only three channels, electrode placement has a direct bearing on the recognition task.

Surface EMG has been used as an input in several forms of lower-limb assistance [1], [2], [3], [4]. Obtaining a recording is only one part of that process. Differences associated with each activity also need to remain identifiable after

conditioning and segmentation, when the information finally reaches the classifier. We examined this issue at two levels: the envelopes produced at the three thigh sites and the activity labels assigned by the SVM.

The three recordings used for this study are the sensors' envelope outputs (ENV), not broadband EMG waveforms. In the MyoWare 2.0 modules, the muscle potentials had already been conditioned before acquisition. We could therefore examine changes in the envelopes over time, but not the frequency content of the unprocessed signals. These acquisition considerations are also discussed in [5], [6], [7].

Work on lower-limb EMG recognition for prosthetic applications provides context for this experiment. Zhang et al. [8] studied movement intention in participants with transfemoral amputation, while Dhanush Babu et al. [9] and Vergara et al. [10] addressed other prosthetic tasks. The participants, movements, acquisition procedures, and classifiers in those studies are not the same as ours. We therefore discuss their findings as related work rather than rank the reported accuracy values against our SVM. The present evaluation concerns the muscles, activities, and temporal features defined in our protocol.

Before acquiring the classification records, we examined where to place the posterior-thigh sensor. In initial knee-extension trials, Channel 3 was positioned over biceps femoris and showed a stronger response than anticipated. We then repeated the instructed movement with the channel over semitendinosus. The knee-extension peaks were more evident on the two anterior channels in these subsequent traces. We retained this second arrangement for classification, although the preliminary trials were not a controlled comparison of electrode locations.

The seven recordings cover five repeated movements and two sustained postures. We examined their EMG envelopes alongside the SVM confusion matrix. The traces show how the three channels responded during each activity, whereas the matrix shows which activity labels the classifier recovered and which it confused. Together, they give an account of the evaluation that cannot be obtained from overall accuracy alone.

The goal here is to examine recognition with the selected three-channel configuration, not to present a new SVM architecture. We identify the activities that were separated in the original evaluation and the movement pairs that were not consistently distinguished.

2 MATERIALS AND METHODS

2.1 sEMG acquisition system

For acquisition, the ENV outputs of three MyoWare 2.0 sensors were connected to a RedBoard microcontroller's analog inputs. The board digitized the signals and sent the readings over a serial link to a computer, where Python was used for storage and analysis. The experimental report gives a sampling frequency of 1.2 kHz. Figure 1 shows the electrode positions used to record the seven activities.

The right rectus femoris, vastus lateralis, and semitendinosus were monitored through Channels 1, 2, and 3, respectively. Time is plotted in seconds in the retained figures, while amplitude remains in ADC counts. The records contain neither a calibration for the individual channels nor a documented conversion based on reference voltage. We have consequently left the amplitudes on the digital scale in which they were acquired, rather than expressing them in millivolts.

The ADC traces are useful for examining the timing and persistence of responses within a recording. They also show which sections contain the most visible changes. Because the channels lack physiological calibration, however, differences between their plotted values cannot be interpreted as differences in absolute muscle activation.

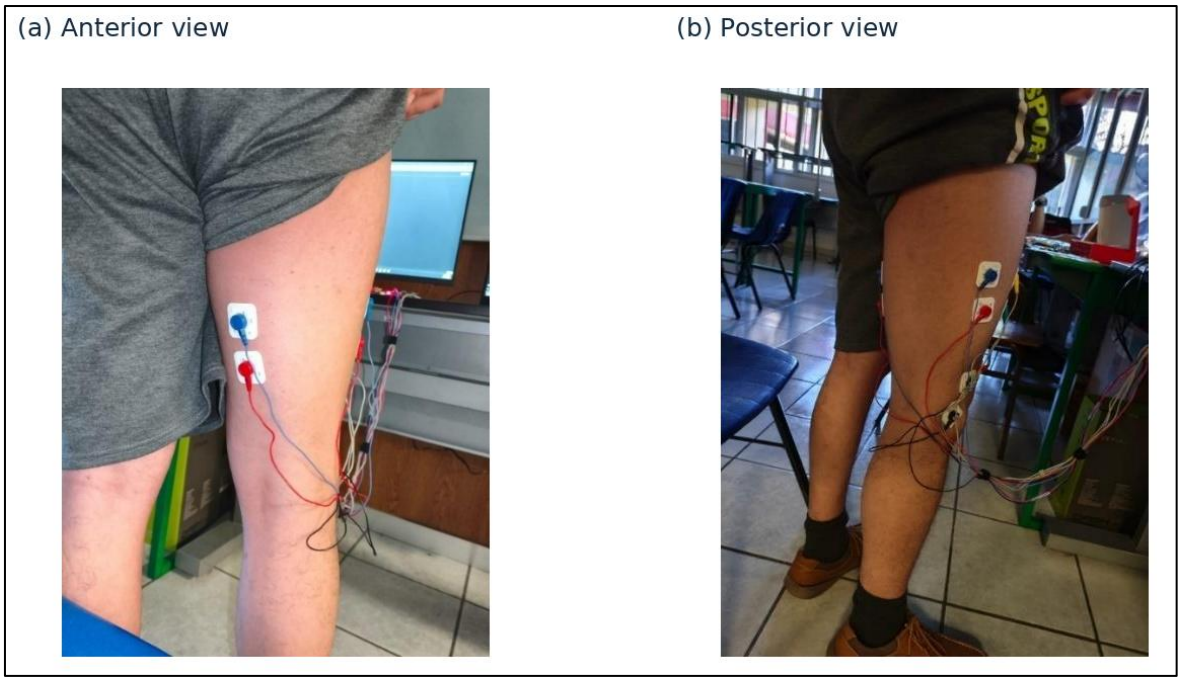


Figure 1: Placement of the three recording channels on the right thigh: anterior and posterior views.

2.2 Participant and experimental protocol

The recordings were collected in one session from the right leg of a 25-year-old participant without amputation. Each of the seven activities occupied a 40-s record. In five of them the participant completed 20 repetitions, approximately two seconds per cycle, returning to the initial position each time. For the two remaining records, the participant held a standing or sitting posture rather than repeating a movement.

Four of the repeated movements were performed standing. For knee extension, the participant began with the knee flexed and then straightened it. Knee flexion started from an extended knee and brought the heel backward. Knee elevation consisted of raising the thigh forward as the hip and knee flexed together. In hip extension, the thigh moved backward while the knee remained flexed. The limb returned to its initial posture at the end of every repetition.

Seated knee extension completed the set of five dynamic activities. From an initial knee angle of approximately 90° of flexion, the participant extended the lower leg forward and returned it. The resulting activity labels followed these complete repetitions; they did not specify only one direction of movement.

2.3 Selection of the posterior-thigh channel

An unexpected response during the first standing knee-extension trials led us to reconsider the posterior-thigh recording site [11]. With Channel 3 over biceps femoris, its activity was conspicuous relative to the anterior channels (Fig. 2a). Local electrode adjustments did not sufficiently change that pattern. The sensor was therefore transferred to semitendinosus, and the same instructed movement was recorded again.

After the sensor was moved, peaks associated with the same instructed task were more apparent on Channels 1 and 2 (Fig. 2b). The two panels do not use the same vertical range, so they document a change in the visible recording pattern rather than a measured gain in signal amplitude. The observations also do not separate possible effects of cross-talk, coactivation, and electrode contact; no independent test of those mechanisms was made.

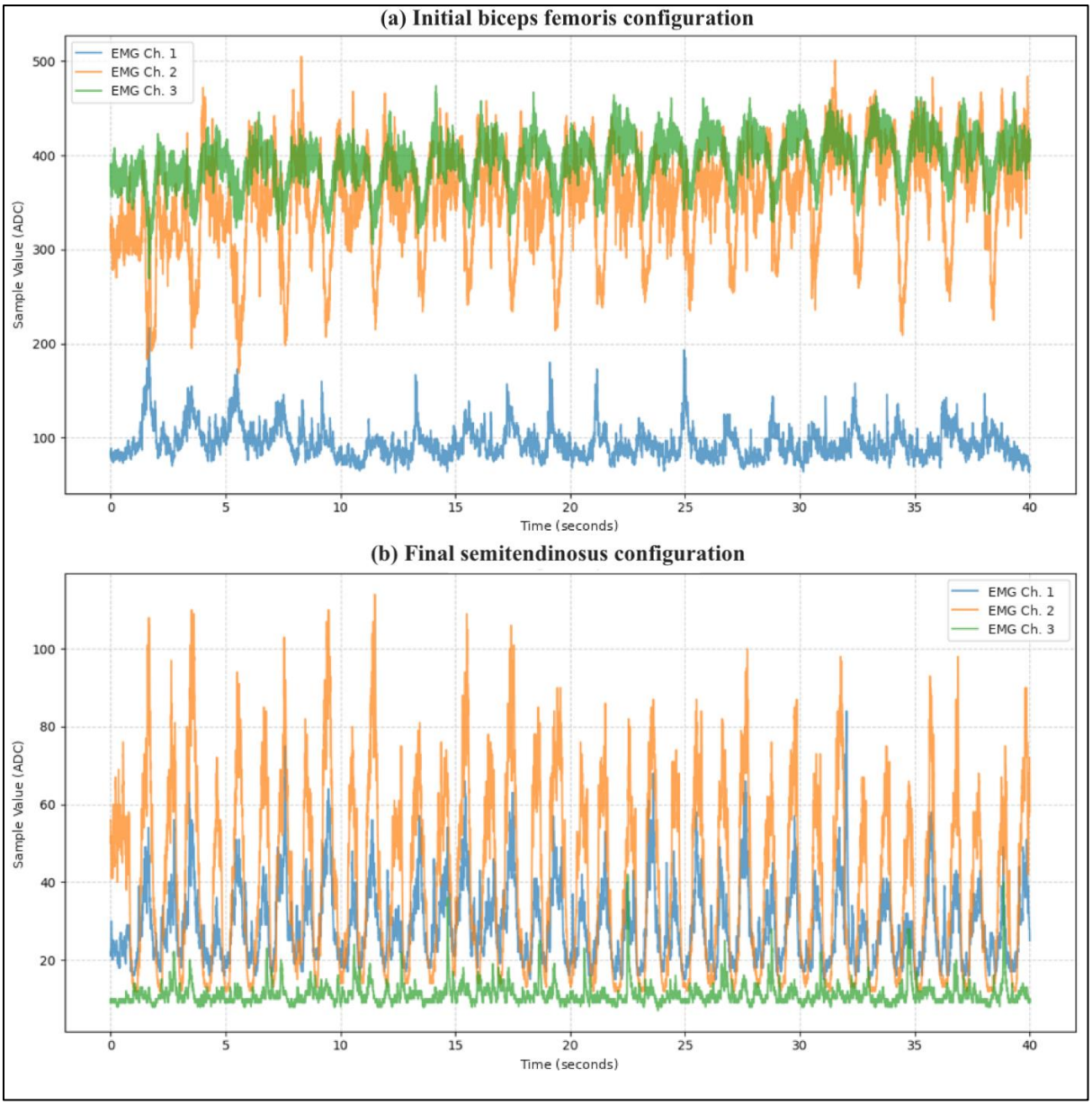


Figure 2: Standing knee-extension recordings obtained with Channel 3 over (a) biceps femoris and (b) semitendinosus. The ADC scales differ.

2.4 Signal segmentation and feature extraction

Each ENV recording was segmented into 300-ms windows. With 60% overlap, consecutive windows began 120 ms apart [12], [13]. We calculated seven time-domain descriptors for every channel: root mean square (RMS), mean absolute value (MAV), waveform length (WL), integrated EMG (IEMG), peak-to-peak amplitude, variance, and arithmetic mean. These descriptors served as the SVM inputs [14]. They characterize the conditioned envelopes delivered by the sensors, not the broadband EMG waveforms before conditioning.

During each 40-s movement recording, one label identified the instructed activity from beginning to end. It also covered the return to the starting position, which was not treated as another class. A window predicted as knee flexion, for example, refers to the labeled movement cycle rather than to a particular direction of joint motion. We use that same interpretation when discussing the errors in the confusion matrix.

2.5 SVM classification and evaluation

The laboratory report gives the training–test allocation as 80% and 20%. The team recalls that, for the five dynamic activities, complete repetitions were allocated before the overlapping windows were generated. Sixteen of the twenty repetitions per activity were selected at random for training and four for testing. Standing and sitting were recorded continuously, rather than as separate repetitions. The available documentation does not specify how windows from those posture recordings were assigned to the two sets.

The available files do not allow us to establish whether that sequence was followed in the original code: neither the feature dataset nor the SVM script was preserved. The size of the test set is also compatible with a different procedure. With windows of 300 ms and a step of 120 ms, a 40-s recording yields approximately 331 windows. Selecting 20% of the windows from seven records would produce about 464 test examples, as in the saved confusion matrix. This agreement does not establish a window-level division, however, and it cannot rule out the repetition-level division recalled by the team. The results reported here were calculated from the integer entries of that confusion matrix; the SVM was not retrained. We obtained accuracy, precision, recall, and F1-score from those counts. The original kernel, hyperparameters, feature-scaling procedure, and random seed remain unspecified because they could not be recovered.

3 EXPERIMENTAL RESULTS

3.1 EMG envelope responses during the seven activities

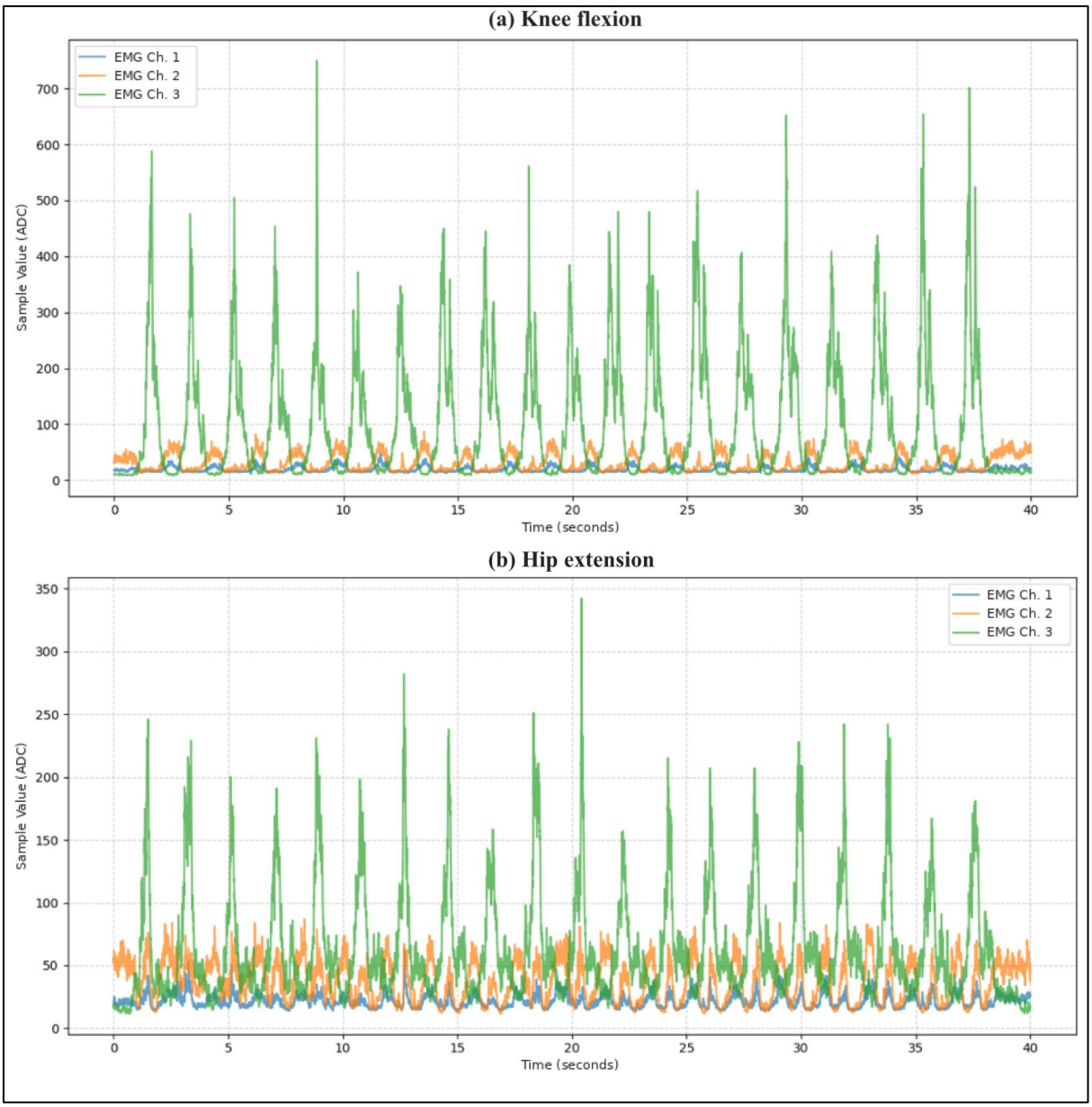


Figure 3: EMG envelope recordings during (a) knee flexion and (b) hip extension, with pronounced responses on Channel 3.

In Fig. 3, Channel 3 exhibits repeated responses during knee flexion as well as hip extension. The knee-flexion recording has particularly prominent peaks; the hip-extension trace occupies a smaller plotted range and follows a different sequence of local maxima.

Knee elevation likewise produces responses on this posterior-thigh channel (Fig. 4a). These activities are also involved in the most frequent classification errors. The plots show that connection at the level of the recorded signals, but they do not establish that overlapping feature values caused the errors.

The remaining recordings show other patterns. Repeated peaks are particularly visible on Channel 1 during seated knee extension (Fig. 4b).

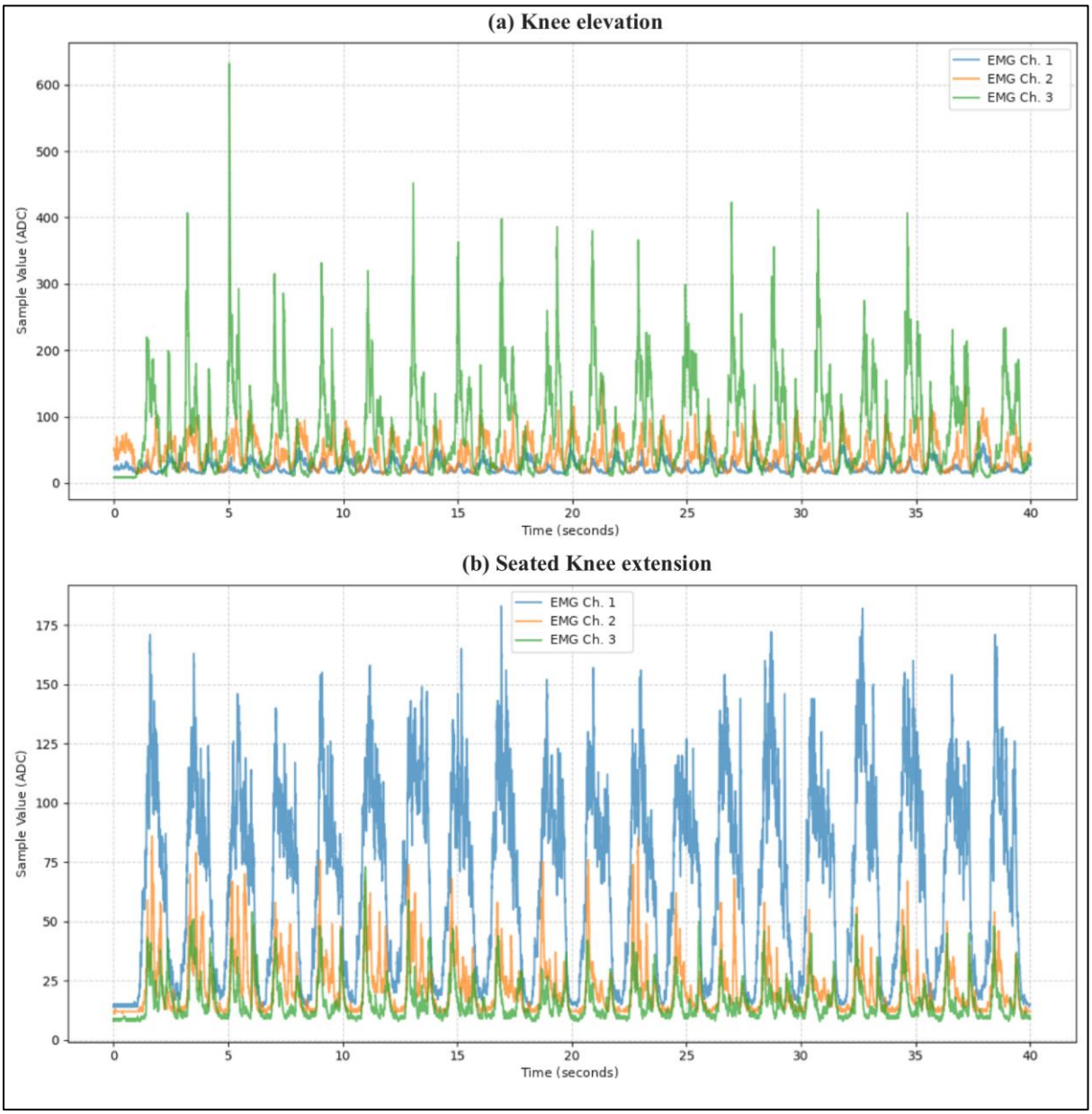


Figure 4: EMG envelopes during (a) knee elevation and (b) seated knee extension. The most prominent recording channel changes with the activity.

During standing, Channel 2 varies around a sustained level, whereas the sitting trace occupies only a few discrete ADC values (Fig. 5). Such differences may be useful for recognizing the recorded conditions. However, since each posture was represented by one continuous recording, the figures cannot establish whether the same patterns would appear in a new session or after electrode replacement.

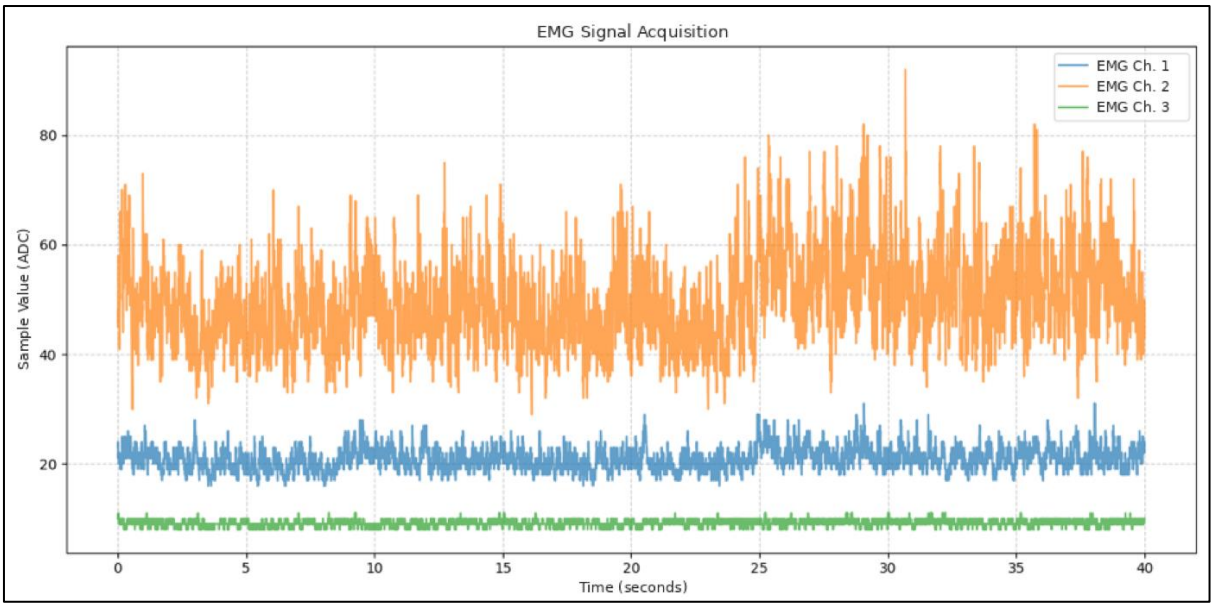


Figure 5: Recorded envelopes for standing. Amplitudes are shown as ADC counts.

3.2 Overall classification performance

The confusion matrix in Fig. 6 contains 464 test windows, 401 of which were classified correctly; the resulting accuracy is 86.42%. Macro-averaged precision was 87.06%, macro recall 86.39%, and macro F1-score 86.08%. Overall accuracy and macro recall are close numerically, but neither describes the pronounced differences among the individual activity categories (Table I).

3.3 Performance across activities

Table 1: Class-specific precision, recall and F1-score calculated from the original confusion matrix.

Movement / posture	Precision (%)	Recall (%)	F1-score (%)	Test n
Standing	91.67	100.00	95.65	66
Knee elevation	81.03	71.21	75.81	66
Hip extension	67.05	89.39	76.62	66
Knee extension	93.65	88.06	90.77	67
Seated knee extension	94.12	96.97	95.52	66
Knee flexion	84.78	59.09	69.64	66
Sitting	97.10	100.00	98.53	67
Macro average	87.06	86.39	86.08	464

Every standing window (66/66) and every sitting window (67/67) was correctly labeled. Seated knee extension followed with 64 correct predictions among 66. The lowest counts of correct decisions were found for knee flexion (39/66) and knee elevation (47/66). Hip extension presents another aspect of the same test: the SVM recognized 59 of its 66 true windows, yet used the hip-extension label 88 times altogether. Of those predictions, 29 were false positives. Precision for hip extension was consequently 67.05%, despite a recall of 89.39%.

3.4 Distribution of classification errors

A small number of movement pairs account for much of the misclassification. In particular, 19 windows from knee flexion and ten from knee elevation received the hip-extension label. Together, those 29 cases represent 46.03% of all 63 errors. The confusion was directional: the model assigned other activities to hip extension substantially more often than the reverse pattern indicated by those cells. These counts convey something that is not apparent from the overall accuracy alone.

Other off-diagonal entries were smaller. Seven knee-flexion windows were labeled knee elevation, and four knee-elevation windows were labeled standing knee extension. From the matrix we know which labels were confused and how often, but not the position of a mistaken window within its movement cycle. Its features and location relative to the SVM boundary are also unavailable. The affected movement pairs can therefore be identified without assigning a measured physiological cause to the errors.

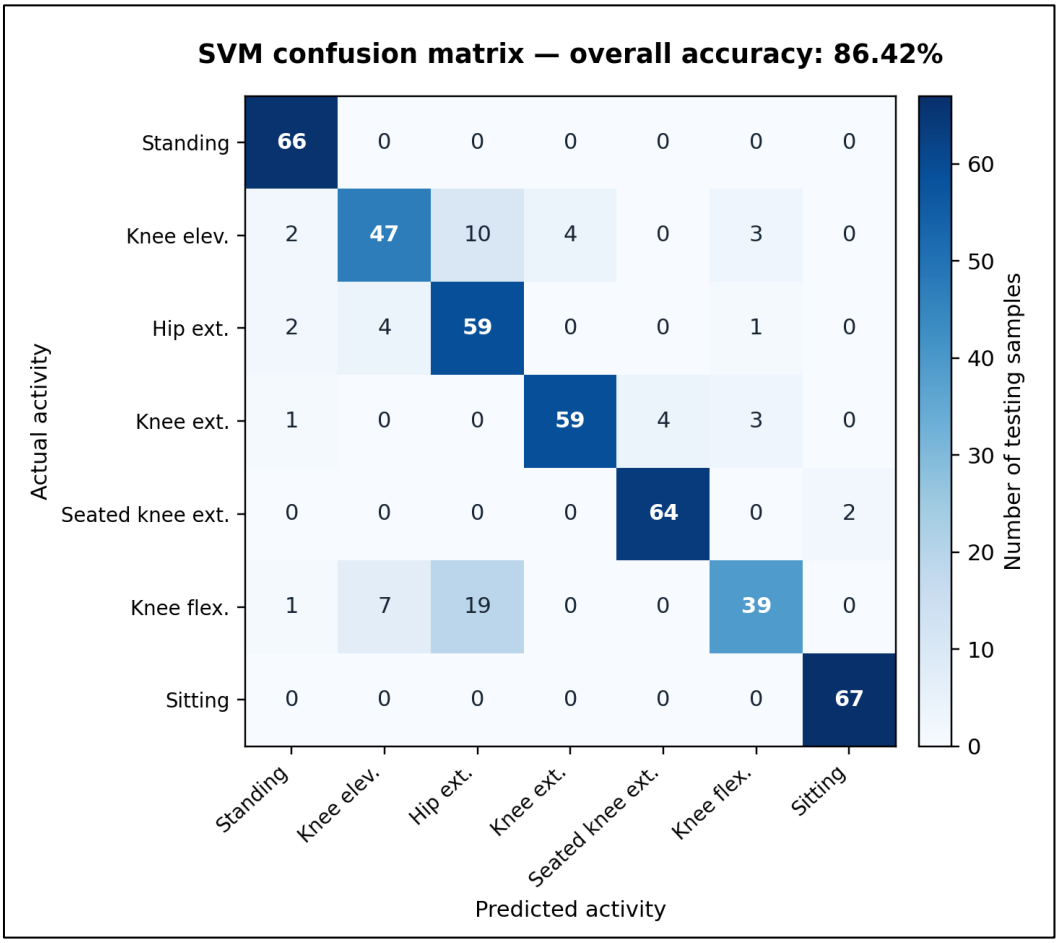


Figure 6: Seven-class SVM confusion matrix reconstructed from the recorded counts (401 correct predictions among 464 test examples).

3.5 Recognition of static and dynamic activities

The static and dynamic categories can also be counted separately within the original seven-class matrix. Of 133 test windows from standing and sitting, all 133 fall on the diagonal, whereas the five dynamic activities account for 268 correct predictions among 331 windows (80.97%). These are two portions of the same evaluation, not results from independently trained classifiers. Each static posture was recorded in a single continuous trial, a condition that also matters when comparing these counts.

4 DISCUSSION

4.1 Interpretation of the main confusion patterns

Most windows recorded during hip extension received the correct label. The more noticeable difficulty was that the classifier also called many windows from other movements hip extension. In a system later used to inform control actions, accepting a different activity could be consequential even when the intended activity is usually recognized [15], [16]. This experiment, however, stopped at the classification of windows; actuator responses and command timing were not measured.

The semitendinosus recordings give this confusion a possible physiological context. The muscle contributes to knee flexion and hip extension, and the same channel also displayed pronounced responses during knee elevation. Still, a peak on that channel cannot explain a particular SVM decision. Classification used numerical features from all three

channels, while the original feature distributions and the information needed to examine the decision boundary were not retained.

4.2 Implications of complete-cycle labeling

The activity label remained fixed throughout each repetition, even though the limb traveled in opposite directions. During knee flexion, for example, one 300-ms window could contain the heel moving backward, another the reversal, and another the return toward extension. All were still assigned to knee flexion within a cycle lasting approximately two seconds. The classification target was therefore the instructed movement as a whole, not the joint direction at a particular instant.

This definition is appropriate for recognizing complete cycles, but different phases may contribute different muscle-activation patterns to the same category. The retained data cannot tell us whether the 19 knee-flexion windows classified as hip extension came from a particular part of the repetition. Recording joint angles in synchrony with EMG and marking the movement phases would allow that question to be examined separately from the possibility of shared muscle activation.

4.3 Relation to existing EMG recognition studies

Studies [8]–[10] address related EMG recognition problems under experimental conditions that differ from ours. The participants, movement definitions, acquisition procedures, and validation methods were not shared across the studies. We use those publications to place our work in context, rather than rank classifiers by accuracy values obtained from different evaluations.

The confusion matrix provides detail that is lost in a single accuracy figure. Although the envelopes differed across the instructed activities, windows from knee flexion and knee elevation were repeatedly assigned to hip extension. This pattern gives us a reason to revisit the electrode configuration and the use of one label for a complete movement cycle. It does not tell us how many recording channels would be optimal or which SVM settings would perform best.

4.4 Scope of the findings and future work

All seven activities were recorded from one participant with an intact right leg, in a single session and with one recording per activity. We have no measurement of how the same classifier would behave on another day, after the electrodes were replaced, or with another person. Changes in anatomy and sensor position are particularly pertinent when the intended application is assistive [17].

The confusion matrix is sufficient to check the reported classification metrics, since its integer entries were preserved. What cannot be checked is the training that produced it. We no longer have the original recordings, the features extracted for individual windows, or the SVM script, so neither the training procedure nor the allocation of data to the two sets can be reconstructed. The accuracy of 86.42% must therefore be read as the result of the original evaluation, not as an independently reproduced estimate of generalization.

The figures retain useful information about the timing and changes in the conditioned ENV responses, but their amplitudes are ADC counts rather than calibrated measures of muscle activation. Nor do the recordings contain synchronized labels for the phases of joint movement. Thus, the figures cannot establish absolute activation or show in which phase a particular misclassified window occurred.

For a subsequent acquisition, we would retain the ENV recordings together with electrode locations, repetition boundaries, the resulting windows, the extracted features, and the classifier code. The training and test sets should be defined and documented before overlapping windows are created; the two continuous posture recordings also need an explicit allocation procedure. Recordings from more participants and sessions, with joint-movement phases marked when appropriate, would then provide a way to test whether the same activity pairs remain difficult to separate under different acquisition conditions.

5 CONCLUSIONS

The original SVM classified 401 of 464 test windows correctly (86.42%) using three conditioned sEMG channels and seven activity labels. Both static postures were identified correctly in their retained test windows, and seated knee extension was recognized in most cases. Knee flexion and knee elevation had less consistent results. The differences among activities are substantial within the conditions examined.

Nearly half of the incorrect predictions involved knee flexion or knee elevation being assigned to hip extension. Shared muscular contributions and the use of one label for the outward and return portions of a cycle are compatible with that

pattern, although the retained measurements cannot isolate either effect. The distribution of errors is an observed result and also a point of departure for controlled follow-up experiments.

The envelope recordings and confusion matrix together offer an activity-level account of this three-channel sEMG recognition stage. They show what the original classifier distinguished and identify the categories for which the sensing and labeling arrangement still calls for further evaluation.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

Acknowledgments

The authors acknowledge the institutional support provided by the Tecnológico Nacional de México / Instituto Tecnológico de Morelia for the development of this research.

Funding Source

This work is partially supported by National Technological Institute of Mexico under project 24675.26-P.

Disclosure of conflict of interest

The authors declare no conflicts of interest regarding this manuscript.

Statement of ethical approval

The experimental procedures involving a human participant were conducted in accordance with the ethical principles applicable to research involving human subjects. The study was reviewed and approved by the corresponding institutional ethics committee at the Tecnológico Nacional de México / Instituto Tecnológico de Morelia.

Statement of informed consent

Informed consent was obtained from the participant prior to data acquisition. The participant voluntarily agreed to participate in the study and authorized the collection and scientific use of the electromyographic recordings.

REFERENCES

[1] A. Cimolato, J. J. M. Driessen, L. S. Mattos, E. De Momi, M. Laffranchi, and L. De Michieli, “EMG-driven control in lower limb prostheses: a topic-based systematic review,” Journal of NeuroEngineering and Rehabilitation, vol. 19, art. 43, 2022. doi: 10.1186/s12984-022-01019-1.

[2] B. Ahkami, K. Ahmed, A. Thesleff, L. Hargrove, and M. Ortiz-Catalan, “Electromyography-Based Control of Lower Limb Prostheses: A Systematic Review,” IEEE Transactions on Medical Robotics and Bionics, vol. 5, no. 3, pp. 547–562, 2023. doi: 10.1109/TMRB.2023.3282325.

[3] A. Fleming, N. Stafford, S. Huang, X. Hu, D. P. Ferris, and H. Huang, “Myoelectric control of robotic lower limb prostheses: a review of electromyography interfaces, control paradigms, challenges and future directions,” Journal of Neural Engineering, vol. 18, no. 4, art. 041004, 2021. doi: 10.1088/1741-2552/ac1176.

[4] H. Huang, T. A. Kuiken, and R. D. Lipschutz, “A strategy for identifying locomotion modes using surface electromyography,” IEEE Transactions on Biomedical Engineering, vol. 56, no. 1, pp. 65–73, 2009. doi: 10.1109/TBME.2008.2003293.

[5] J. H. Sul et al., “Electromyography Signal Acquisition, Filtering, and Data Analysis for Exoskeleton Development,” Sensors, 2025. doi: 10.3390/s25134004.

[6] L. Cheng, J. Li, A. Guo, and J. Zhang, “Recent advances in flexible noninvasive electrodes for surface electromyography acquisition,” 2023. doi: 10.1038/s41528-023-00273-0.

[7] D. Farina, R. Merletti, and R. M. Enoka, “The extraction of neural strategies from the surface EMG: 2004–2024,” Journal of Applied Physiology, vol. 138, no. 1, pp. 121–135, 2025. doi: 10.1152/japplphysiol.00453.2024.

[8] Y. Zhang et al., “An Improved Extreme Learning Machine (ELM) Algorithm for Intent Recognition of Transfemoral Amputees With Powered Knee Prosthesis,” IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 32, pp. 1757–1766, 2024. doi: 10.1109/TNSRE.2024.3394618.

[9] R. Dhanush Babu, S. Siva Adithya, and M. Dhanalakshmi, “Design and development of an EMG controlled transfemoral prosthesis,” Measurement: Sensors, vol. 36, 2024. doi: 10.1016/j.measen.2024.101399.

[10] S. Vergara, G. Mosquera, V. Bonilla, M. Sánchez, and C. Rueda, "Diseño de un sistema de control de prótesis transfemoral basado en redes neuronales," Revista Mutis, vol. 13, no. 2, pp. 1–12, 2023. doi: 10.21789/22561498.2053.

[11] H. J. Hermens, B. Freriks, C. Disselhorst-Klug, and G. Rau, "Development of recommendations for SEMG sensors and sensor placement procedures," Journal of Electromyography and Kinesiology, vol. 10, no. 5, pp. 361–374, 2000. doi: 10.1016/S1050-6411(00)00027-4.

[12] J. J. A. Mendes Junior, C. E. Pontim, T. S. Dias, and D. P. Campos, "How do sEMG segmentation parameters influence pattern recognition process? An approach based on wearable sEMG sensor," Biomedical Signal Processing and Control, vol. 81, art. 104546, 2023. doi: 10.1016/j.bspc.2022.104546.

[13] L. H. Smith, L. J. Hargrove, B. A. Lock, and T. A. Kuiken, "Determining the optimal window length for pattern recognition-based myoelectric control: balancing the competing effects of classification error and controller delay," IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 19, no. 2, pp. 186–192, 2011. doi: 10.1109/TNSRE.2010.2100828.

[14] A. Phinyomark, R. N. Khushaba, and E. Scheme, "Feature Extraction and Selection for Myoelectric Control Based on Wearable EMG Sensors," Sensors, vol. 18, no. 5, art. 1615, 2018. doi: 10.3390/s18051615.

[15] E. Scheme and K. Englehart, "Electromyogram pattern recognition for control of powered upper-limb prostheses: state of the art and challenges for clinical use," Journal of Rehabilitation Research and Development, vol. 48, no. 6, pp. 643–659, 2011. doi: 10.1682/JRRD.2010.09.0177.

[16] K. Englehart and B. Hudgins, "A robust, real-time control scheme for multifunction myoelectric control," IEEE Transactions on Biomedical Engineering, vol. 50, no. 7, pp. 848–854, 2003. doi: 10.1109/TBME.2003.813539.

[17] B. Wang, J. Li, L. Hargrove, and E. N. Kamavuako, "Unravelling Influence Factors in Pattern Recognition Myoelectric Control Systems: The Impact of Limb Positions and Electrode Shifts," Sensors, vol. 24, no. 15, art. 4840, 2024. doi: 10.3390/s24154840.