

An Adaptive AI-Integrated Smart Prosthetic Limb for Real-Time Personalized Motor Learning Using EMG Signal Processing

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ABSTRACT

Limb prosthetics have evolved from passive mechanical devices to advanced myoelectric and sensor-driven systems. However, achieving natural, intuitive control and functional mobility after amputation remains a significant challenge.

Although modern prosthetic systems utilize electromyographic (EMG) pattern recognition and embedded sensors, most commercial devices rely on fixed classification models calibrated during clinical sessions. These systems do not continuously adapt to the user-specific motor patterns. This limits the prosthesis's ability to function as a seamless extension of the user's neuromuscular system.

Recent research shows that deep learning models such as Long Short-Term Memory (LSTM) networks and transformer-based models have been used to estimate continuous arm/hand kinematics from EMG signals, enabling improved temporal modeling. Adaptive frameworks, including reinforcement learning and temporal techniques, have also shown promise in enabling systems to refine motor output through iterative feedback.

This study proposes developing an AI-integrated smart prosthetic limb capable of adaptive motor learning through real-time EMG signal analysis. The system will incorporate surface EMG sensors to detect residual muscle activity, inertial measurement units (IMUs) to monitor limb orientation, and embedded deep learning machine learning algorithms designed for continual adaptation. Using a reinforcement-learning-based adaptive feedback loop, actuator responses will be adjusted based on muscle intensity patterns, signal frequency characteristics, and contextual motion data. Over time, the model will refine predictive accuracy.

By integrating continuous learning mechanisms into prosthetics, this approach aims to effectively bridge the gap between static myoelectric systems and intelligent assistive devices that evolve with the neuromuscular profile. Ultimately, improving functional independence for amputees with prosthetics.

Keywords: Electromyography (EMG), Adaptive Prosthetics, Motor Learning, Reinforcement Learning, Deep Learning

INTRODUCTION

1.2 Million people globally experience major limb amputation every year and this number continues to grow. About 3 million people worldwide currently live with upper limb amputations, with the demand for upper limb prosthetic devices increasing alongside the need for advanced assistive technologies. Beyond the physical loss, amputation not only affects a person's mobility significantly, but also their independence and psychological well-being, making the quality of prosthetic rehabilitation a major topic of importance.

Most modern prosthetic technologies have advanced considerably over the past few decades. Devices have evolved from simple passive, body-powered mechanical systems to sophisticated myoelectric prosthetics that can detect electrical signals generated by residual muscles (known as electromyographic (EMG) signals) to drive motorized limb movement.

A myoelectric signal is an electrical activity generated when a muscle fiber contracts. When this activity is recorded non-invasively through electrodes on the skin's surface, rather than inserted into the muscle itself, it is referred to as surface electromyography or sEMG (Scheme & Englehart, 2011). A classifier, in this context is that which is trained to map a window of these recorded sEMG features onto a predicted hand or wrist gesture, which is then used to drive the prosthetic's actuators (Scheme & Englehart, 2011; Windrich et al., 2016). 'Myoelectric prosthetics' refers to any device that uses this signal-to-gesture pipeline for control, as opposed to earlier body-powered designs that relied on mechanical cables and harnesses (Windrich et al., 2016).

These myoelectric systems represent a major step forward, offering users with much greater functionality and a more intuitive means of control as compared to the earlier designs (Windrich et al., 2016). Despite this progress, a fundamental problem remains. Current prosthetic systems are still widely rejected by their users. Biddiss and Chau (2007) reported upper-limb prosthesis abandonment rates range from 23% to 45% (rejection rates of 45% for body-powered and 35% for electric prostheses in pediatric populations, with lower but still significant rates of 26% and 23% in adults.), with users most frequently citing limited functionality, discomfort and the absence of natural and intuitive control as key reasons for rejection.

The root of this problem lies in how most commercial prosthetics are designed. The majority of myoelectric devices rely on fixed classification models, meaning the system is trained and calibrated during a short clinical session and then remains static. The fixed classification model does not update or learn how the user's muscles actually behave over time. This is a substantial limitation because EMG signals are inherently variable. Factors like muscle fatigue, changes in electrode placement, perspiration and long-term physiological shifts in the residual limb all cause the EMG signals to drift and change in ways that a fixed model cannot account for (Scheme & Englehart, 2011). Research (Pradhan et al., 2022), which tracked sEMG signals from participants across three separate sessions spanning a month, confirmed that signal characteristics changed significantly over time, resulting in a measurable drop in

classification accuracy when using a static prosthetic model. This signal drift problem is also supported by Vidovic et al. (2016), who demonstrated that fixed classifiers' performance degrades over time and that adaptive algorithms employing covariate shift correction substantially improve robustness. Together, these findings make it clear that the clinical standard for training a prosthetic once and deploying it permanently is fundamentally misaligned with the amputee's neuromuscular system.

Recent developments in artificial intelligence and machine learning offer a more promising path. Deep learning architectures, particularly Long Short-Term Memory (LSTM) networks and transformer-based models, have demonstrated strong capability in decoding continuous limb movement from EMG signals by modeling temporal dependencies in sequential data (Bethausen et al., 2024). In parallel, reinforcement learning (RL) frameworks have shown potential to enable systems to refine their motor output in response to real-time feedback, thereby gradually improving performance without requiring repeated clinical recalibration (Berman et al., 2024). However, these approaches remain largely confined to research settings. They have not been meaningfully integrated into widely available clinical prosthetic devices, creating a significant translational gap between what is scientifically possible and what amputees can actually use and access.

This paper proposes a conceptual framework for an AI-integrated smart prosthetic limb capable of real-time, personalised motor learning through the continuous analysis of EMG signals. The proposed system would incorporate surface EMG sensors to capture residual muscle activity, inertial measurement units (IMUs) to monitor limb orientation and motion context and embedded deep learning models designed for continual on-device adaptation. A reinforcement learning-based feedback loop would dynamically adjust the prosthetic's actuator responses in response to evolving muscle signal patterns, progressively refining predictive accuracy and reducing the cognitive effort required of the user over time.

The objective of this study is to bridge the gap between the static myoelectric systems currently dominating clinical use and a new generation of intelligent assistive devices that adapt to the user's neuromuscular profile. By doing so, it aims to meaningfully improve functional independence, reduce device abandonment, and bring prosthetic technology closer to functioning as a true extension of the human body.

LITERATURE REVIEW

Evolution of Prosthetic Limb Technology The development of particularly upper limb prosthetics has progressed from merely passive body-powered mechanical devices to the now widely available in the market sophisticated static myoelectric systems that can detect residual muscle electrical activity through the use of surface electromyography to drive limb movement. (Windrich et al., 2016) Despite this progress, user satisfaction has been low and prosthetic rejection and abandonment rates have been high. Beddiss and Chau (2007) reported that upper limb prosthesis abandonment rates range from 23 to 45 %, where users normally cite limited functionality, lack of intuitive control, and discomfort as primary reasons. Cordella et al. (2016) further identified that users consistently prioritize the naturalness of

movement and reduce cognitive effort, which current commercial devices are failing to provide to a certain level.

Limitations of static EMG classification systems. The core limitation of the existing static myoelectric prosthetics lies in their dependence on fixed classification models calibrated during short clinical sessions. Scheme and Englehart (2011) identified EMG signal variability. This is normally caused due to the muscle fatigue, electrode displacement, perspiration, and the long-term physiological changes, which are a significant barrier to clinical translation of pattern recognition-based control. This variability produces the covariate shift, that is, the signal distribution a classifier was trained on diverges from what it actually encounters in the later sessions of the user. Vidovic et al. (2016) empirically confirmed that static classifiers degrade across sessions due to shift, while adaptive correction algorithms substantially restored robustness. Pradhan et al. (2022) also documented consistent intersession signal drift across 43 participants over approximately one month, providing further quantitative evidence that long-term static calibration is clinically insufficient.

Deep learning and adaptive frameworks. Deep learning approaches have demonstrated meaningful improvements over conventional classifiers for EMG-based control. Long short-term memory networks, in particular, have well-proven to be well-suited for sequential EMG data, achieving up to 91.7% motion estimation accuracy in prosthetic control tasks (Bethausen et al., 2024). To address signal drift specifically, adaptive reinforcement learning frameworks have shown considerable promise. Berman et al. (2024) applied an reinforcement learning-based policy to personalized EMG-driven musculoskeletal models, fine-tuning parameters iteratively to maximize motion estimation accuracy. This is directly analogous to the adaptive feedback mechanism that is proposed in this study. Despite such advances, these approaches remain largely experimental. As noted in recent literature, intelligent adaptive prosthetic systems are capable of real-time personalization, but remain absent from clinical markets (Chopra et al. and Emran, 2024), forming the central motivation for the proposed framework in this paper.

METHODOLOGY

The methodology is structured in two parts. The first describes the proposed system's architecture, outlining its hardware and software components of the AI-integrated adaptive prosthetic limb. The second presents a computational simulation that tests the paper's core argument: static EMG classifiers degrade over time due to intersession signal drift, and session-adaptive recalibration substantially preserves classification accuracy under the same drift condition.

3.1 Proposed System Architecture

The proposed system consists of a software component and three integrated hardware components working together for personalized motor learning.

Surface EMG sensors. The system would incorporate a range of surface electromyography sEMG sensors positioned over the residual limb of the amputee, that is, the user. These sensors would continuously capture electrical activity which is generated by the contraction of muscles, producing multi-channel time series signal data.

About 6 to 8 electrode channels are proposed, consistent with the channel count used by commercially available myoelectric pattern-recognition systems, which typically record from up to 8 muscle sites (Kanitz et al., 2024). Denser electrode arrays, such as the 12-channel configuration used in the NinaPro DB2 research benchmark (Atzori et al., 2014) have been shown to further improve classification accuracy, but at the cost of the setup complexity and electrode density that a wearable clinical device needs to minimise.

Inertial measurement units. Alongside these surface EMG sensors, the Inertial Measurement Units would be embedded within the prosthetic, which would capture limb orientation, acceleration and angular velocity. This IMU data would be essential for providing information that complements the EMG signal. For example, to differentiate between the same muscle contraction pattern performed at different arm positions, this is a known source of classification error in current static myoelectric systems.

Embedded Deep Learning and Adaptive Muscle Feedback Module.

To meet the real-time latency requirements associated with continuous myoelectric control (Scheme & Englehart, 2011), the classifier's parameters are stored and updated locally on the embedded microcontroller (Table S1) rather than on a remote server, as shown in the final stage of the system architecture flowchart ('Updated Model,' Figure S3.1). This avoids the round-trip delay that a cloud-dependent system would introduce between a muscle contraction and the corresponding actuator response. Where a wireless connection such as Bluetooth is included, it serves a secondary function, allowing a clinician to review performance logs, rather than participating in the real-time control loop itself. The precise memory footprint required to store and update the LSTM parameters on this class of embedded hardware has not been formally validated in this conceptual study and is noted as an open engineering question in Section 7 (Limitation).

The signal preprocessing and classification core of the system would also consist of this embedded deep learning and adaptive feedback module, specifically the long short-term memory network chosen because of its capability in modeling temporal dependencies in sequential EMG data. The LSTM network receives and processes EMG features, vectors, and IMU data as input and outputs a predicted gesture, which is then translated into actuator commands driving the prosthetic movement.

This module would incorporate the Reinforcement Learning-based adaptive feedback loop. For each movement, the system would evaluate the accuracy of the actuator response using either explicit feedback or implicit performance metrics such as signal consistency and update the model accordingly. This mechanism mirrors the approach demonstrated by Berman et al. in which Reinforcement learning policy was used to fine-tune musculoskeletal model parameters from EMG inputs, progressively improving the

motion estimation and accuracy without requiring repeated clinical recalibration. Over time, this feedback loop will help the system to almost "personalize" itself to the user's ever-changing neuromuscular profile.

3.2 Signal Preprocessing Pipeline

Prior to classification, the raw sEMG signals would have to undergo a standard preprocessing pipeline. This includes bandpass filtering between 20 to 450 Hz to remove motion artifacts and high-frequency noise, followed by full-wave rectification and feature extraction. Time-domain features like root mean square, mean absolute value, waveform length would also have to be extracted from the sliding windows of 200 ms with 50 ms overlap, consistent with the real-time prosthetic control requirements which were reported in the literature (Scheme and Engelhart 2011). Such features, combined with the IMU data, would help to form the input for the long short-term memory classifier.

3.3 Simulation design

To provide empirical grounding for the proposed adaptive system, a computational simulation was conducted using Python language in Google Colaboratory. Synthetic sEMG data was generated to model the intersession signal variability across the three time periods, day 1, day 8, and day 29, which are consistent with the recording protocol used in Pradhan et al. (2022) in which sEMG signals were collected from 43 participants across one month. This classifier was evaluated using a static random forest classifier, which was trained exclusively on day 1 data and then tested on all three sessions without any recalibration. This simulated the behavior of a conventional, fixed, static myoelectric prosthetic system. An adaptive classifier was retrained at each session using the updated signal data simulating the continual recalibration which is proposed in this paper. Classification accuracy was then recorded across all three sessions for both models and the distributional shift across the sessions was visualized to confirm the presence and the magnitude of the signal drift.

S1. Proposed Hardware Components

The table below outlines all the hardware components required to be integrated into the proposed adaptive prosthetic limb system. Each component is chosen/selected based on clinical literature findings in myoelectric prosthetic research.

Component	Specification / Example	Function in System	Role in Adaptive Loop
EMG Sensor	MyoWare 2.0 / AD8232	Captures residual muscle electrical activity	Primary input signal for gesture classification

Component	Specification / Example	Function in System	Role in Adaptive Loop
Microcontroller	ESP32 / STM32 / Arduino Nano	Processes EMG signals and runs embedded ML model	Executes adaptive recalibration algorithm
IMU Sensor	MPU-6050 (6-DOF)	Monitors limb orientation, acceleration, angular velocity	Provides contextual motion data to classifier
Servo Motors	MG996R / Hitec HS-645MG	Drive individual finger and wrist actuation	Actuator output responding to classified gesture
Motor Driver / PWM Controller	PCA9685 16-channel PWM	Translates classifier output to servo control signals	Bridges software command to physical movement
Power Supply	7.4V Li-Po battery + 5V regulator	Powers all electronic components	Ensures stable operation during continuous use
Signal Conditioning Circuit	Bandpass filter (20–450 Hz) + INA amplifier	Removes noise and amplifies raw EMG signal	Ensures clean signal input for accurate classification

Table S1. Proposed hardware components for the adaptive prosthetic limb system.

S2. Signal Acquisition Circuit — Description

The signal acquisition frontend will be responsible for capturing, conditioning, and digitising the raw surface EMG signal from the residual limb before it is passed to the embedded classifier. The circuit follows the standard instrumentation amplifier topology used in clinical EMG systems.

S2.1 Circuit Stages

Stage	Components	Description
Stage 1: Differential Input	Electrode pair (Relec_p/n, Celec_p/n)	Two surface electrodes placed over the residual muscle capture the differential EMG voltage. Electrode impedance

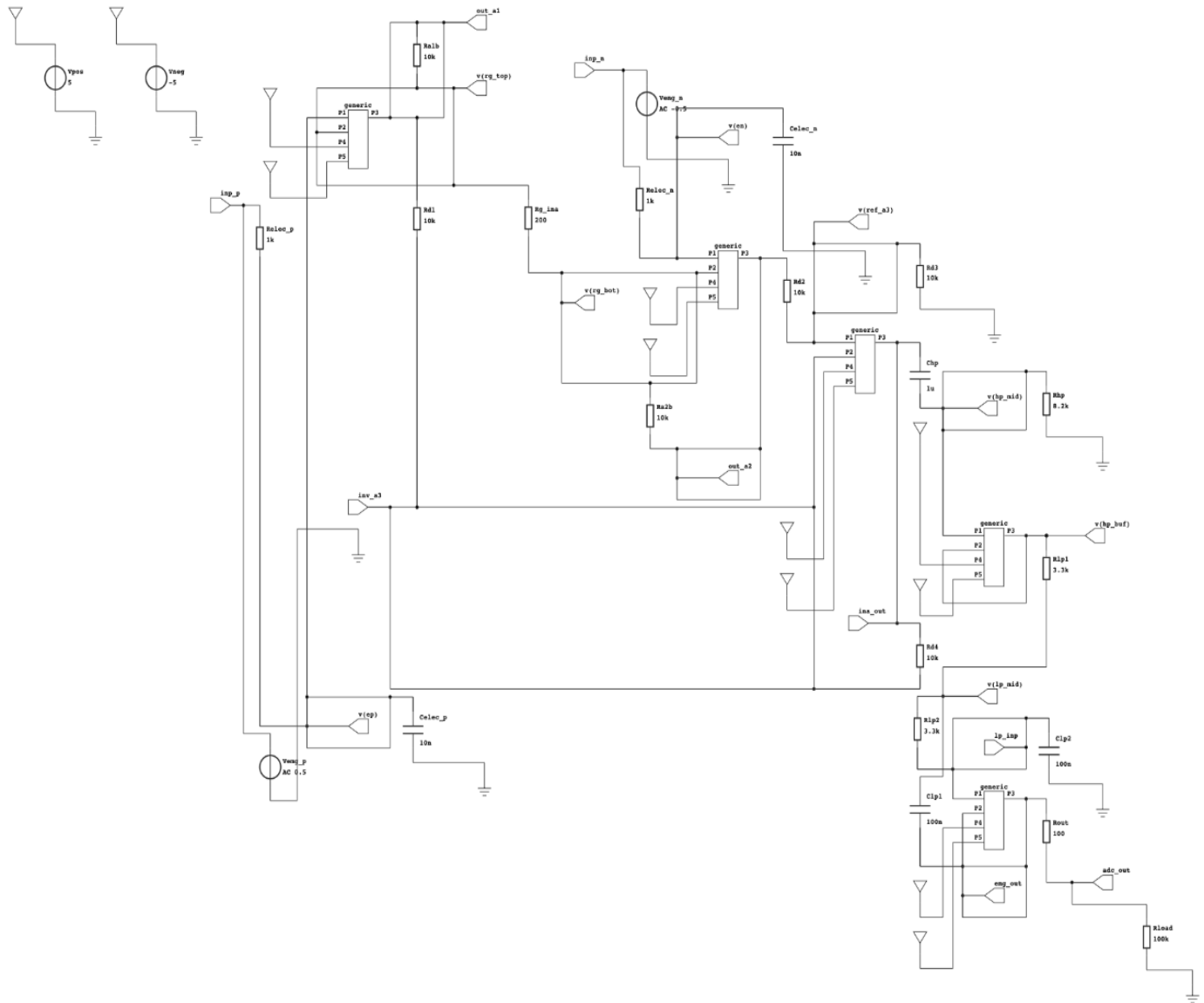
Stage	Components	Description
		modelled at $1\text{k}\Omega$ with 10nF coupling capacitors.
Stage 2: Instrumentation Amplifier	INA (R_{a1b} , $R_{g_ina} = 200\Omega$, R_{a2b})	A three op-amp instrumentation amplifier provides a high common mode rejection ratio (CMRR), amplifying the differential signal while rejecting 50/60Hz power line interference. Gain set by R_{g_ina} .
Stage 3: High-Pass Filter	$C_{hp} = 1\mu\text{F}$, $R_{hp} = 8.2\text{k}\Omega$ ($f_c \approx 19\text{ Hz}$)	Removes DC offset and very low-frequency motion artefacts below 20Hz, isolating the relevant EMG frequency band.
Stage 4: Low-Pass Filter	$R_{lp1/2} = 3.3\text{k}\Omega$, $C_{lp1/2} = 100\text{nF}$ ($f_c \approx 482\text{ Hz}$)	Second-order Sallen-Key low-pass filter removes high-frequency noise above 450Hz, completing the bandpass characteristic of 20–450Hz standard for sEMG.
Stage 5: Output Buffer	$R_{out} = 100\Omega$, $R_{load} = 100\text{k}\Omega$	Unity-gain buffer isolates the filter output from the ADC input impedance, ensuring accurate signal transfer to the microcontroller's analogue-to-digital converter.
Power Supply	+9V / -9V dual supply	Symmetric dual-supply powers the instrumentation amplifier and op-amps, enabling the circuit to process both positive and negative EMG signal excursions without clipping.

Table S2. Signal acquisition circuit stages based on the EMG Signal Acquisition Frontend schematic.

Note: The circuit topology described above is consistent with the signal conditioning frontend used in published EMG prosthetic control systems (Scheme & Englehart, 2011). The bandpass characteristic of 20–450 Hz is the clinical standard for surface EMG acquisition. The complete circuit schematic is available in the attached PDF and is also pasted below.

 [EMG_Signal_Acquisition_Frontend_-_Prosthetic_Limb_Control.pdf](#)

An Adaptive AI-Integrated Smart Prosthetic Limb for Real-Time Personalized Motor Learning Using EMG Signal Processing



Oct 2026
Vol 12, No 3.

Figure S2.1 complete circuit schematic for proposed system.

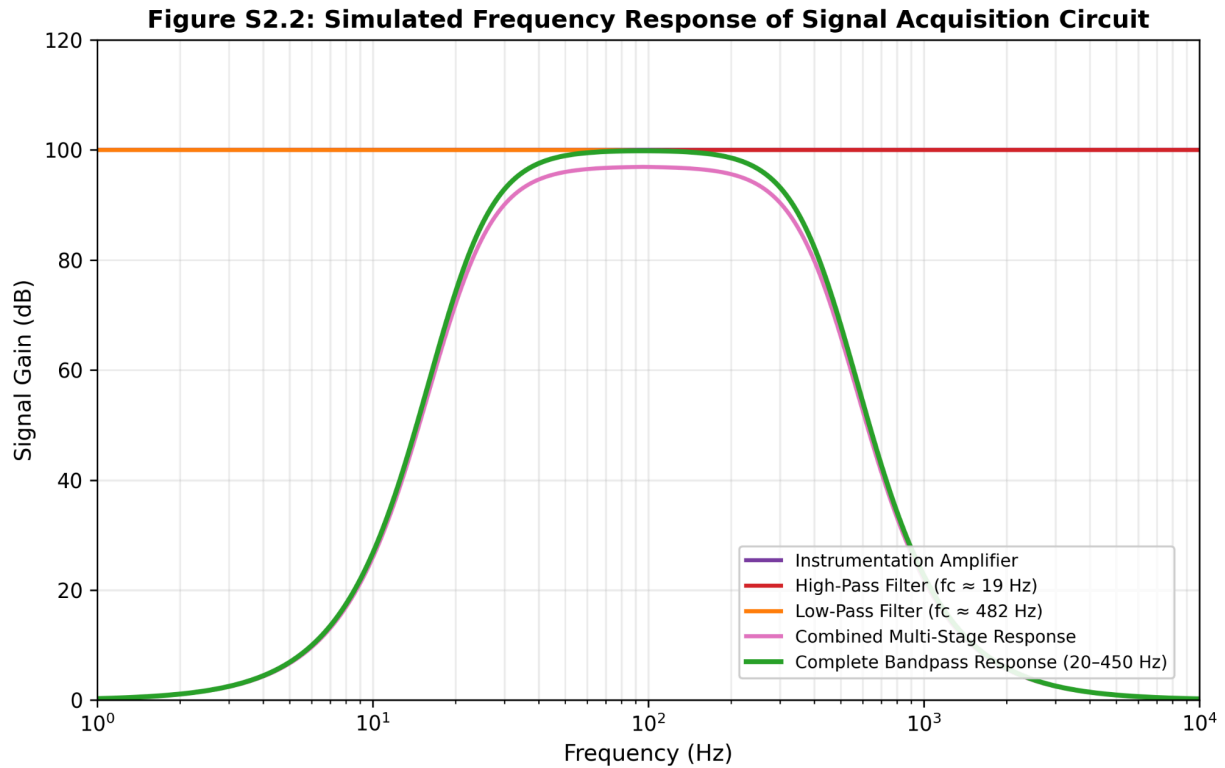


Figure S2.2 Simulated Frequency Response Plot for proposed system's circuit

The x axis is frequency in Hz (1 to 10,000) and the y axis is signal gain in dB (0 to 120).

Note: Green represents complete bandpass filter response, Purple represents instrumentation amplifier, Orange represents low pass filter, Pink represents combined response of multiple stages, Red represents high pass filter.

S3. System Architecture Flowchart

The following flowchart shows the complete signal processing and adaptive learning pipeline of the proposed system, from raw EMG acquisition through to actuator response and model update.

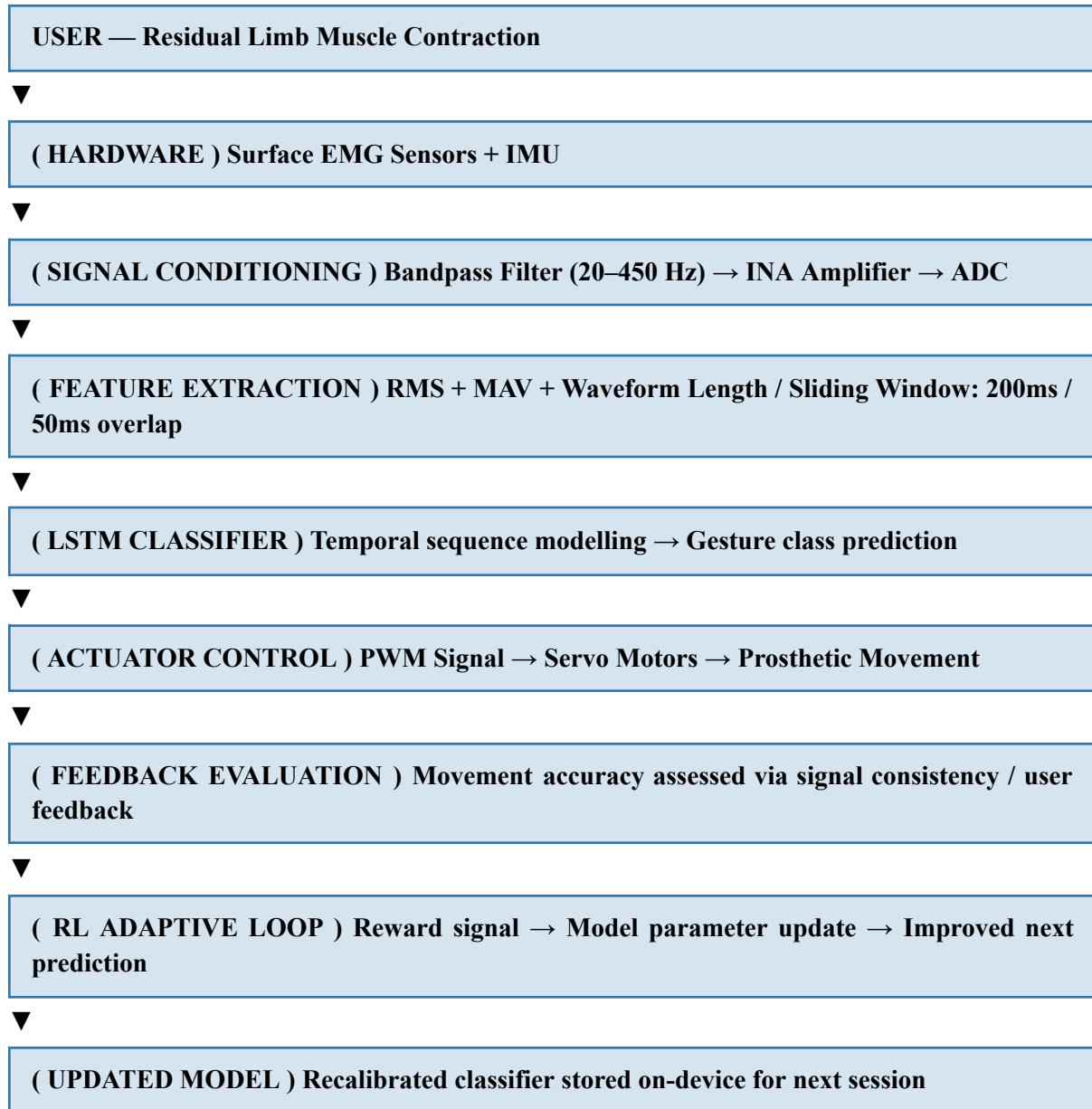


Figure S3.1 End-to-end system architecture flowchart showing signal acquisition, processing, classification, actuation, and adaptive feedback loop.

The key differentiator from existing commercial systems is the feedback loop between actuator output and model update (stages 6–8 above). In conventional myoelectric prosthetics, the pipeline terminates at stage 5. The classifier is fixed and never updated after deployment. The proposed system closes this loop through a reinforcement learning-based mechanism that continuously redefines the classifier parameters

based on real-world performance, enabling the device to ‘personalise’ itself to the user's evolving neuromuscular profile over time.

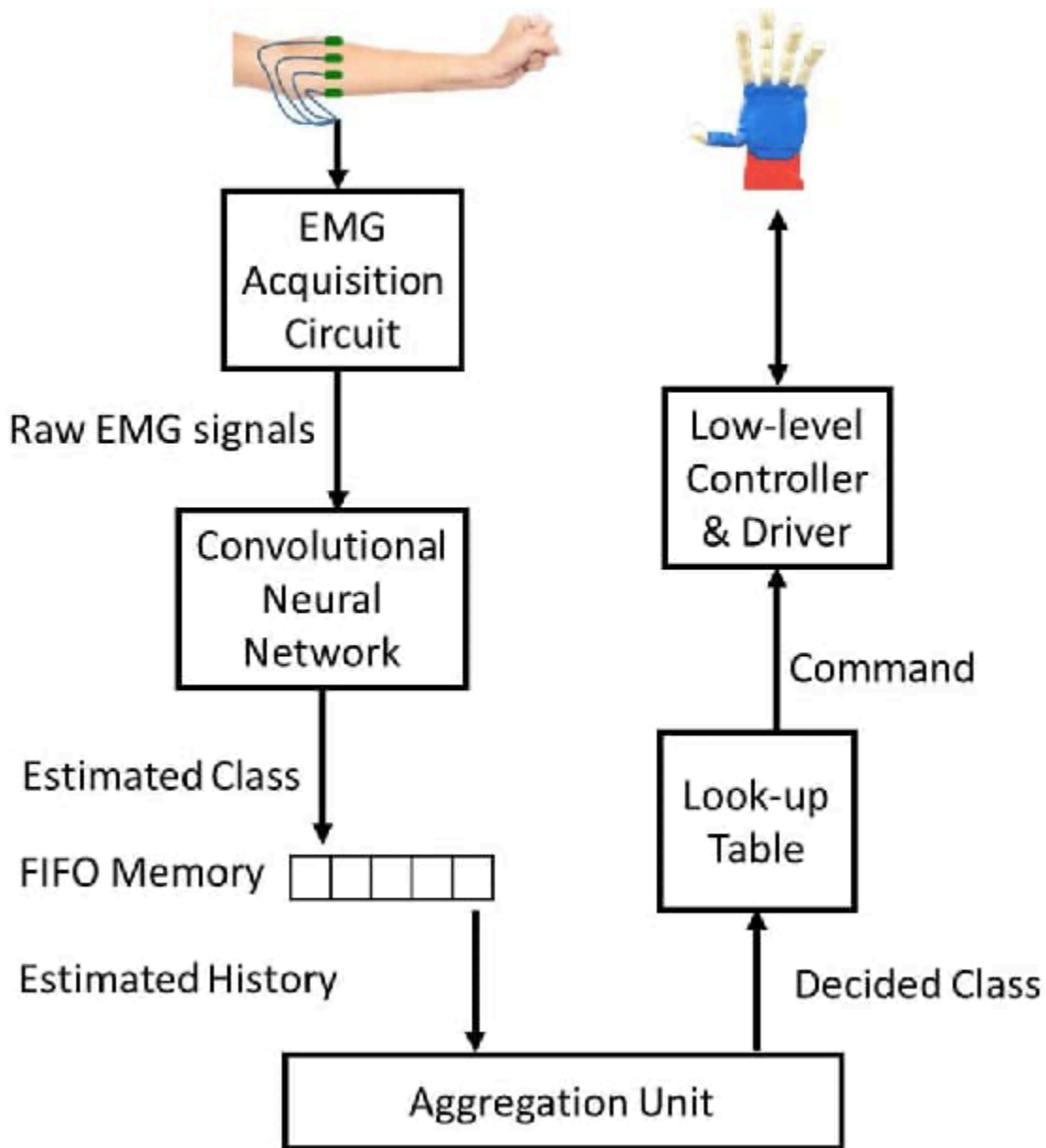


Figure S3.2 Reference image of end-to-end system architecture flowchart showing signal acquisition, processing etc. as mentioned in the above image.

S4. Model Architecture Comparison

The following tables showcase the key machine learning architectures considered for the proposed system, with their configurations and benchmark performance data from published research on EMG based prosthetics.

S4.1 Classifier Architecture Comparison

Architecture	Key Characteristics	Reported Accuracy	Temporal Modelling	Suitable for Real-Time Embedded
Support Vector Machine (SVM)	Linear/kernel-based, feature-dependent	85–92%	No	Yes
Random Forest (RF)	Ensemble of decision trees, robust to noise	88–94%	No	Yes
Convolutional Neural Network (CNN)	Spatial feature extraction from signal windows	91–95%	Limited	Moderate
LSTM (Long Short-Term Memory)	Recurrent architecture, models temporal dependencies	91.7–96.1%	Yes (core strength)	Moderate
CNN-LSTM Hybrid	Combines spatial + temporal feature learning	91.26–92.74%	Yes	Challenging
Transformer	Attention-based, strong long-range dependencies	93–97%	Yes (strong)	No (computationally heavy)

Table S3. Comparison of machine learning architectures for EMG gesture classification. Accuracy values drawn from published works (Betthausen et al, 2024; Scheme & Englehart, 2011).

S4.2 Proposed LSTM Architecture

Parameter	Proposed Value	Justification
Input features	RMS, MAV, WL per channel (6 channels = 18 features)	Standard time-domain feature set for sEMG (Scheme & Englehart, 2011)
Window size	200ms with 50ms overlap	Balances temporal resolution with real-time latency requirements
LSTM layers	2 stacked LSTM layers (64 units each)	Sufficient depth for sequential EMG pattern learning without overfitting
Output layer	Softmax (4 gesture classes)	Probabilistic gesture classification across Hand Close, Wrist Flex, Thumb Extension, Hand Open
Training split	70% training / 15% validation / 15% testing	Standard split for sequential biosignal classification tasks
Optimiser	Adam (lr = 0.001)	Adaptive learning rate well-suited for recurrent networks
Adaptive update mechanism	RL-based parameter fine-tuning per session	Enables continual personalisation without full retraining (Berman et al., 2024)

Table S4. Proposed LSTM model configuration for the proposed adaptive prosthetic control system.

S4.3 Simulation Results (Static vs Adaptive Model)

Session	Static Accuracy	Model	Adaptive Accuracy	Model	Performance Gap
Day 1 - Baseline Calibration	98.3%		100.0%		1.7%
Day 8 - One Week Post-Calibration	91.0%		98.3%		7.3%
Day 29 - One Month Post-Calibration	67.3%		98.3%		31.0%
Total Accuracy Degradation (Static)	-31.0 percentage points		-1.7 percentage points		-

Table S5. Simulation results comparing static and adaptive classifier accuracy across three sessions. Synthetic data modelled after Pradhan et al. (2022). Static model trained on Day 1 only, adaptive model recalibrated at each session.

RESULTS

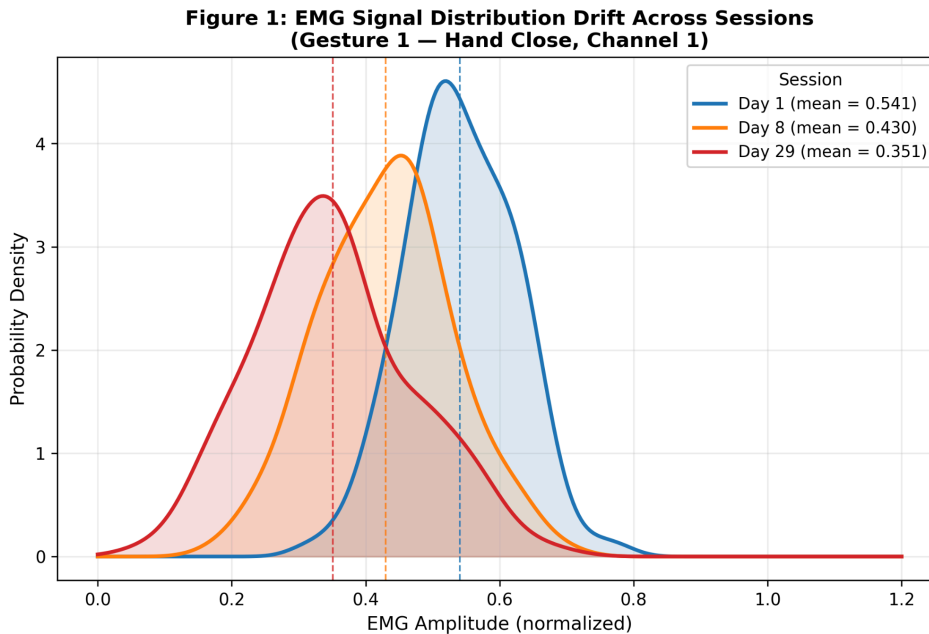
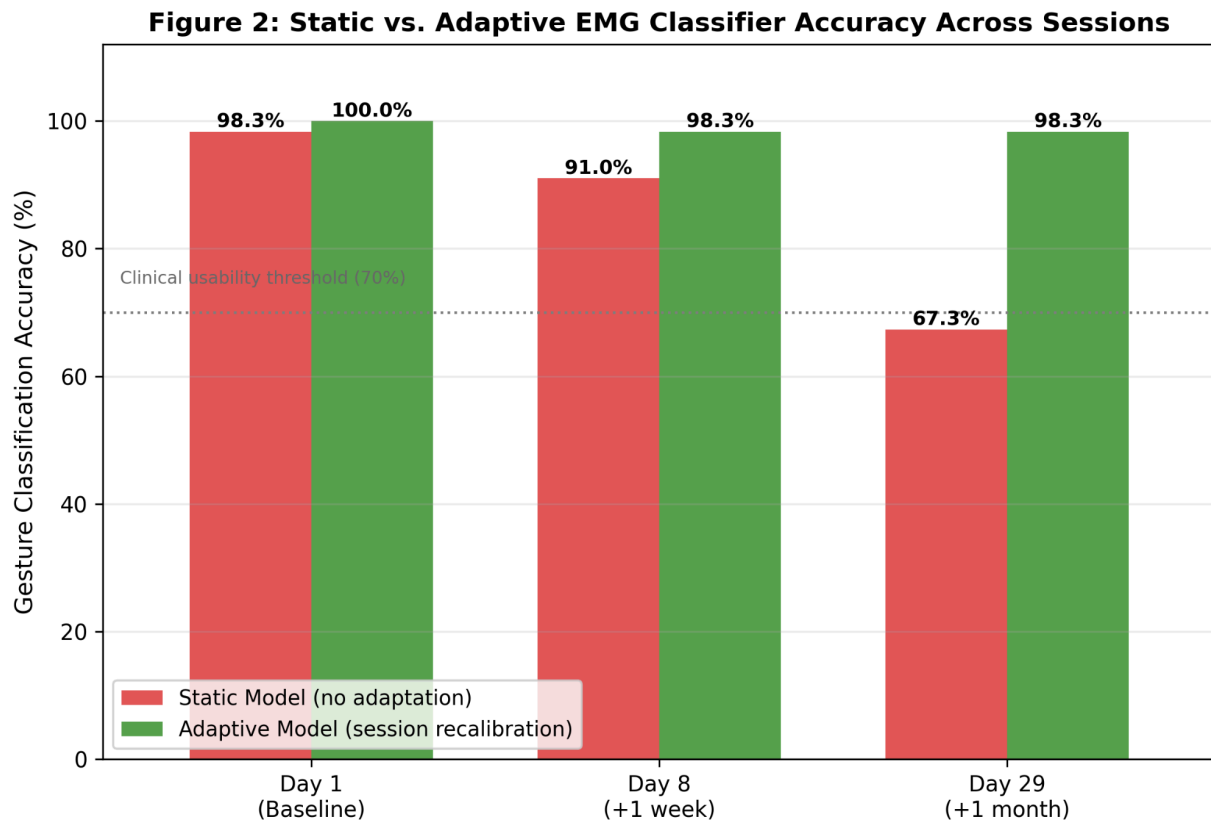
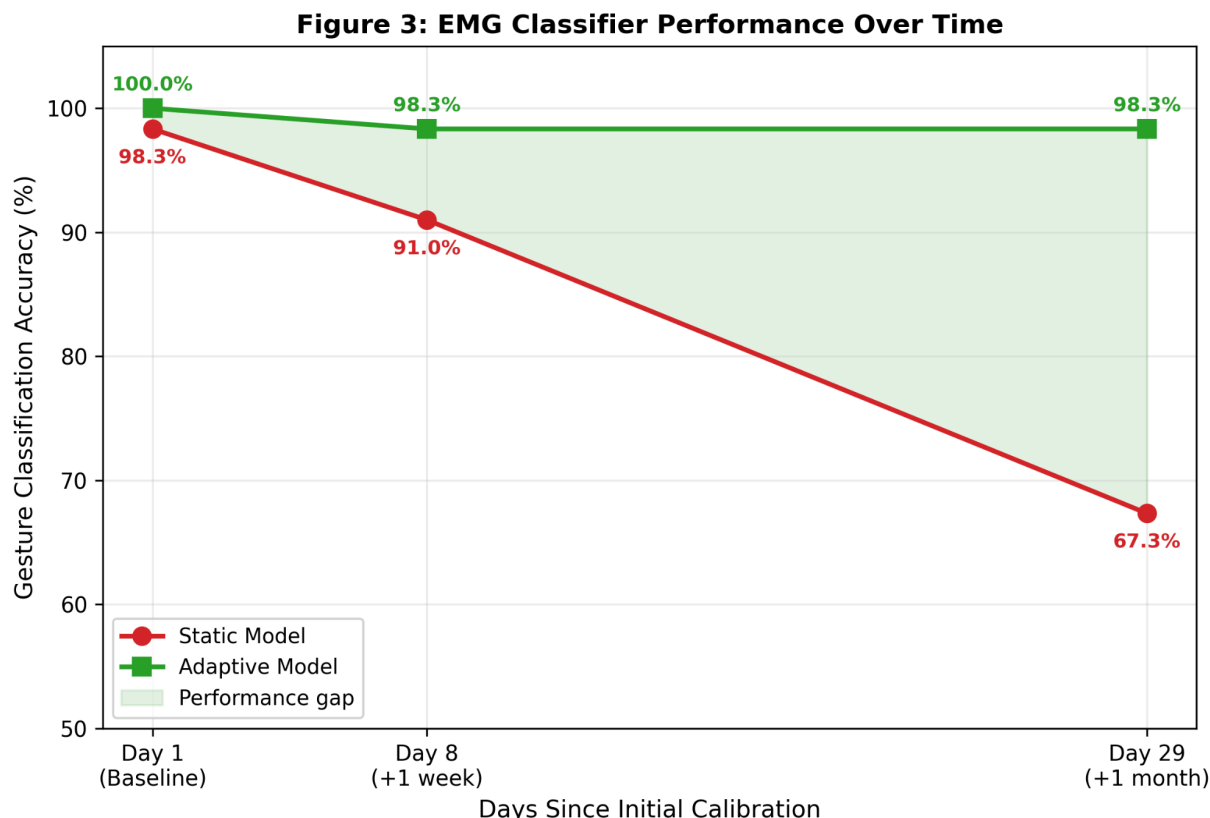


Figure 1 shows the distributional shift in the EMG amplitude for gesture 1, which is the hand closed, across the three sessions. At Day 1, the signal mean is 0.541, consistent with the baseline calibration profile. By Day 8, the signal mean has shifted to 0.430, and by Day 29, it drifts to 0.351 - a decrease of approximately 35% from baseline. Moreover, the distribution also becomes notably flatter and more spread out over time, indicating the increased level of signal variance. This is consistent with the findings reported in the literature on another research conducted on intersession EMG non-stationarity, (Vidovic et al. 2016., Scheme and Engelhart, 2011), and visually confirms that this EMG signal of a prosthesis calibrated during the initial session will look meaningfully different weeks later.





Figures 2 and 3 present the classification accuracy of a static random forest classifier against a session adaptive classifier across the above mentioned three sessions.

The static model as seen, trained only and exclusively on day 1 data without any recalibration, achieves 98.3% accuracy on baseline session. However as inter-session signal drift accumulates, performance decreases sharply, falling to 91.0% on day 8 and further to 67.3% by day 29. This represents a total degradation of 31.0 percentage points approximately over the time span of one month. Notably, on day 29, the static model had fallen well below the commonly cited 70% clinical usability threshold for such myoelectric static prosthetic controls (Scheme and Engelhart 2011), meaning that a person, a real-world user, relying on the system would often experience misclassification of intended gestures directly impacting their day-to-day life and independence. In contrast, the adaptive model recalibrated at each session while using updated signal data maintains accuracy between 98.3% and 100% across the three time periods, substantially outperforming the static model without claiming perfect classification. The performance gap between the two models illustrated in figure three by the shaded region widens progressively with each session. This growing divergence shows the compounding nature of the signal drift. The longer a static system operates without adaptation, the more severely its performance degrades.

Oct 2026

Vol 12. No 3.

These simulated findings support the central argument of this paper that fixed classification models are fundamentally insufficient for the user for long-term prosthetic use. And session adaptive recalibration is more than just beneficial but necessary for them to have clinically viable control accuracy over the day-to-day work and hand gestures. While the present simulation uses only a random forest classifier as a proof of concept, the proposed system described in the paper would implement an adaptive mechanism through a reinforcement learning-based feedback loop that would operate on real sEMG and IMU data, as described in the above methodology section.

DISCUSSION

The above findings from the simulation present quantitative support to the problem outlined in this paper: the rejection of static myoelectric prosthetics have been well documented qualitatively been documented. However, it shows how it is fundamentally misaligned with the biological reality of the amputee for the long-term use of the prosthetic. In the simulation, the static classifier degrades from a baseline accuracy of 98.3% on Day 1 to 91.0% on Day 8 and 67.3% on Day 29, falling below the 70% clinical usability threshold by the end of the one-month observation period. This pattern is consistent with the findings reported by Vidovic et al. in 2016, who demonstrated that fixed classifiers experience a substantial measurable deterioration in performance due to the covariate shift in EMG signals across sessions and with the multi-session signal drift documented by Pradhan et al. (2022) across nearly one month.

These numbers are significant because a prosthetic user whose prosthetic is calibrated on day 1 would by day 29 experience many misclassifications of intended hand gestures, roughly one in three times. Cooking, opening and closing of doors, gripping objects and other everyday tasks would hence become very difficult for the prosthetic user. This would not only reduce the independence of the prosthetic user, but also the functionality of the prosthetic itself, causing it to directly contribute to the device abandonment rates of 23% to 45 % as reported in the Biddiss-Chau 2007. Therefore, this simulation attempts to bridge the gap between the statistical degradation and its real human consequences.

The proposed adaptive model maintains accuracy between 98.3% and 100% across all three sessions, demonstrating the core value of the proposed recalibration mechanism in the prosthetic. By updating its parameters each session to reflect the current signal distribution, the adaptive classifier substantially neutralizes the impact of the drift, though not perfectly. While the simulation does use the random forest classifier, mostly for simplicity, in principle, it directly supports the integration of the LSTM-based model with the reinforcement learning feedback loop. The LSTM architectures are particularly suited to this application given their ability to model the temporal dependencies in sequential EMG data (Betthausen et al 2024) and RL-based parameter updating has already demonstrated success in refining the musculoskeletal model estimates from EMG inputs in clinical contexts, (Berman et al 2024)

It is also worth noting that we see the signal distribution in figure one, which not only shows the shift in the mean EMG amplitude across the three sessions from 0.541 at Day 1 to 0.351 at Day 29. We can also see the flattening and widening of the distribution itself. This shows that increasing variance is particularly problematic for static classifiers because it means that the signal space the model was trained on no longer updates the signal space it is being tested on. An adaptive system would continuously update its internal representation of each gesture class and would inherently account for this expanding variance, maintaining a robust classification boundary, even as the underlying characteristic signals evolve. Together, these findings reinforce the paper's central premise: that the prosthetic limb should not be treated as a device calibrated once during a short clinical period and then deployed permanently, but should instead function as an intelligent assistive system that learns and evolves alongside the user's neuromuscular profile. The shift from static to adaptive tools represents a meaningful direction for the next generation of prosthetic development.

A fair question is whether a clinician recalibrating the device periodically would simply outperform an on-device adaptive system, since both draw on similar underlying signal information to update the model. The relevant comparison, however, is not classifier performance under an idealized recalibration schedule, but the frequency and consistency of recalibration that current care-delivery pathways can actually sustain. Biddiss and Chau (2007), in their review of upper-limb prosthesis abandonment, explicitly recommend improved follow-up and repair services as a way of reducing rejection rates, indicating that inconsistent post-fitting many users. Scheme and Englehart (2011) similarly identify long-term EMG variability, driven by factors such as electrode displacement and muscle fatigue, as a central obstacle to moving pattern-recognition control out of the laboratory and into sustained clinical use; this variability accumulates between clinical visits regardless of how skilled the calibrating clinician is. An adaptive on-device model contact, which is of particular benefit to users for whom travel, cost, or appointment availability how often clinical recalibration can realistically occur.

CONCLUSION

This paper proposes a conceptual framework for an AI-integrated smart prosthetic limb, which is capable of personalized motor learning through the continuous analysis of surface EMG signals. The proposed system aims to combine the surface EMG sensors, inertial measurement units IMU and long short term memory (LSTM)-based deep learning classifier and a learning reinforcement-driven adaptive feedback loop to create a prosthetic system that evolves with the user's neuromuscular profile rather than just being fixed or static after the initial clinical calibration was done.

A simulation study modeled after the intersession variability documented by Pradhan et al. (2022) demonstrates how static classifiers experience significant accuracy degradation over time, that is, they decline from 98.3% to 67.3% in about a month, while an adaptive classifier maintains accuracy above 98% across all sessions through the continuous recalibration. These simulation findings are central to the

paper. The translational gap between the current static myoelectric prosthetics that are widely in circulation in the market and the adaptive intelligent systems proposed in recent literature is both real and consequential for prosthetic users. By addressing this gap through the integration of the above as a unified adaptive framework, this proposed system aims to reduce device abandonment and rejection, lower the cognitive burden for prosthetic users, and bring assistive technology meaningfully closer to functioning as a seamless natural extension of the human body. While the system is right now at the conceptual stage, the convergence in having prosthetics embedded with AI, real-time signal processing, and adaptive machine learning makes it very important in the field of prosthetic rehabilitation.

LIMITATIONS AND FUTURE RESEARCH

There are several limitations of the study that must be acknowledged.

First, the simulation conducted here uses the synthetically generated data rather than the actual sEMG recordings from amputee participants. While the drift parameters were modeled after the statistical properties reported in the study Pradhan et al. carried in 2022, synthetic data cannot fully capture the complexity and perhaps the variability of biological EMG signals which are influenced by a variety of factors which are difficult to simulate. Validation using real multi-session datasets such as NinaPro DB2, (Atzori et al. 2014) or Pradhan et al. (2022) dataset itself would be necessary before drawing stronger empirical conclusions.

Real multi-session datasets were not used as the primary basis for this proof-of-concept simulation for two reasons. First, NinaPro DB2 (Atzori et al., 2014) spans 49 distinct hand and wrist movements collected from 40 subjects, and the Pradhan et al. (2022) dataset spans 16 gesture classes collected from 40 participants; both are considerably higher in class complexity than the four-gesture task modeled here, and would require a classifier substantially more expressive than the Random Forest baseline used in this proof-of-concept to avoid confounding genuine signal drift with simple under-fitting to a larger label space. Second, using synthetic data allowed the drift parameters themselves to be directly controlled, isolating the effect of intersession drift on classification accuracy from other sources of variability such as inter-subject differences and electrode placement inconsistencies that are present but not separately controllable in real recordings. The three-session structure (Day 1, Day 8, Day 29) and general magnitude of intersession drift used in the present simulation were modeled on the Pradhan et al. (2022) protocol, but its full gesture set and raw recordings were not used directly. Full validation on both datasets remains necessary for future work, as noted above

Second, the Random Forest model was selected for this simulation because of its simplicity and interpretability. The proposed system, by contrast, relies on an LSTM architecture with reinforcement-learning-based adaptation, which is significantly more computationally demanding.

Whether such a model can run on embedded hardware within a prosthetic device has not been evaluated here and remains a separate engineering question for future work.

Lastly, the reinforcement learning feedback loop proposed in this system assumes a reliable reward signal, whether from explicit user feedback or implicit performance metrics such as signal consistency. Defining and reliably capturing such a signal in a wearable, real-world setting is a nontrivial open problem that the present conceptual study does not resolve, and is flagged here as a necessary direction for future work. Therefore, future research requires validation of adaptive classification frameworks using real-life multi-session EMG datasets for both able-bodied patients and upper-limb amputees, the investigation of perhaps lightweight LSTM architectures suitable to be embedded in the prosthetic itself, examining the cognitive load and functional performance of adaptive and static prosthetic over extended periods, and exploring more learning approaches that would allow the model to adapt and improve, that would work across different population of users while maintaining user privacy.

Ultimately, translating the proposed framework from simulation to a physical prototype represents a major direction for future research.

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