Development of Prosthetic Robotic Hand Using EMG Sensor for Upper-Limb Amputees

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Abstract. Conventional body-powered systems eventually suffer from the limitations of the relatively low force and dexterity these can offer while requiring strenuous exertion to operate, and advanced myoelectric systems tend to rely on complex algorithms and expensive hardware and calibration routines. These challenges present significant barriers to access of functional prosthetic hands for upper-limb amputees. This paper presents an EMG-controlled three-fingered prosthetic robotic hand based on non-invasive surface electromyography signals from healthy distal residual forearm muscles. The proposed system integrates analog signal conditioning, time-domain feature extraction (Mean Absolute Value) and threshold-based classification to enable Arduino-based real-time processing for servo-driven mechanical actuation. The system achieves 92.5% single-gesture and 88.4% multi-gesture accuracy, with a total average response time of 290 ms, confirming that simplified embedded control can deliver performance and reliability for practical prosthetic functionality in a daily-assist device.

Keywords: Prosthetic Robotic Hand, Upper-Limb Amputees, Myoelectric Control, Signal Processing, Arduino Microcontroller, Low-Cost Prosthesis.

1 Introduction

Upper-limb amputation has a profound effect on one's ability to perform activities of daily living, with implications for independence, employability, and overall quality of life. A prosthetic hand serves the common task of replacing lost motor properties, yet the current solutions do not possess a satisfactory trade-off between functionality, usability and costs. Conventional hook body-powered prostheses have limited fine control and no natural operation, whereas modern myoelectric prosthesis operates on complex electronics and software with higher cost and maintenance [1].

EMG-based prosthetic systems have developed as a favourable option, allowing intuitive control using the muscle signals produced during voluntary motion. Improvements of the embedded systems, low-cost sensors and compact actuators have made possible the development of affordable assistive technologies [2]. EMG-controlled prosthetic robotic

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hands can offer a feasible solution to provide necessary hand functions to upper-limb amputees, especially in low-resource countries.

The development of an EMG-controlled prosthetic robotic hand is mainly motivated by the wide gap between efficacious but costly commercial prostheses and affordable but underperformed mechanical substitutes [3]. A lot of amputees, particularly in low-income countries, cannot access existing prosthetic systems because of cost problems and unavailability of technical support. Moreover, more complicated prosthetic systems can necessitate significant training, calibration, and specialized maintenance, hindering long-term adoption [4].

The aim is to construct an inexpensive EMG-driven prosthetic robotic hand, which can grasp and release basic objects in real time. The system is designed to collect muscle activation signals via non-invasive surface EMG sensors and then utilize signal conditioning and classification algorithms for real-time processing followed by motorized actuation of prosthetic components [5]. The work has achieved a practical and affordable EMG-based prosthesis that balances integrity with simplicity.

The novelty of the present work lies in the development of a reduced EMG controlled prosthetic robotic hand which paid attention to reducing the cost, with low computation requirements and responsiveness in real-time. In contrast to many of current generation prosthetic systems, which employ machine learning models and high-performance embedded processors where the proposed design employs a low-cost threshold classification approach on a low-cost Arduino Microcontroller. These can be used to have a viable real-time-control at low hardware cost and power consumption. The combination of the non-invasive EMG sensing, the effective signal conditioning and the modular mechanical actuation contributions is linked to the development of a low-cost solution that can be applied in low resource setting.

2 Related Work

Real time performance and robust control of the EMG-controlled prosthetic hand were two main purposes on which hands design for experimental studies have been based. Studies emphasized on the significance of response uniformity, individualized response and biomechanical possibility, which proved that practical convenience for daily activity can be maintained with simplified control strategies [6].

Several wider challenge studies addressed technical developments in upper-limb prostheses, aimed at overcoming shortcomings in mechanical complexity, control accuracy, fit and comfort. EMG control has been presented as an excellent contribution for intuitive operation but remains plagued by issues including calibration requirements and low signal variability leading to challenges in real-world implementation [7].

The importance of low-computational EMG gesture recognition schemes stems from their relevance for embedded prosthetic systems. Lightweight neural modeling and handcrafted features can be used with good performance while reducing energy consumption and hardware requirements, which is preferred for wearable prosthesis [8]. Real-time EMG-controlled prosthetic hand systems demonstrated that system confidence level was largely dependent on signal constancy and actuator synchronization [9].

Design and development of low-cost myoelectric prosthetic arms apply low-resolution EMG acquisition on a microcontroller, having few degrees-of-freedom to execute finger opening and closing movements. Results show that powerful functionality is naturally available without complex algorithms, though the repertoire and resolution of gestures are limited [10]. Studies also explored the possibility of controlling a prosthetic limb based on

EMG and concluded that surface EMG can provide simple functional control of the hand even when limited muscle availability occurs [11,12].

Targeted muscle reinnervation prosthetic systems have displayed higher degrees of freedom, resulting in improved hand dexterity and near-natural movement. While these systems perform well, the complexity and high cost of production prevents widespread usage, indicating a need for simplified alternatives [13,14]. Transfer learning approaches for EMG-based motion recognition show good adaptation to new subjects but increase computational load and require large amounts of data, making them unsuitable for low-cost embedded prosthesis systems [15,16]. Although previous studies have demonstrated that EMG analysis can be classified with high accuracy based on the machine learning or deep learning, these systems frequently require high computing power, large training data and complex hardware architecture. Such requirements increase the cost of the system and limit the use in a portable or resource-constrained environment. In contrast, the proposed system emphasizes a light implementation of the system that reduces the complexity of the solution in order to still address the problem with good gesture recognition and acceptable response time. Therefore, the research gap that will be overcome by this work is the lack of a simplified, low-cost EMG prosthetic control framework that enables a balance to be reached between performance and practical aspects of implementation.

3 Methodology

The proposed system specifically addresses the overall design of a low-cost EMG-controlled prosthetic robotic hand, for rehabilitation and functional therapy to provide independent use of missing fingers for upper-limb amputees. Common systems include body-powered mechanical prostheses and advanced commercial myoelectric prostheses. Mechanical prostheses provide limited degrees of freedom and low intuitiveness, while commercial myoelectric prosthetic hands rely on intricate EMG signal processing and multiple sensor-fusion algorithms, coming at high cost and maintenance barriers for users in low-resource settings [3].

The proposed system relies on the surface EMG sensors attached to the stump muscles of the forearm connected with the volitional intent. Amplification and filtering operations condition signals so that to maximize the signal-to-noise ratio (SNR) and to have a high probability of reliable detection of muscle activity. A low-cost Arduino microcontroller platform that was selected due to its low cost, ease of programming, and ubiquity relays the conditioned signals and is used to implement education, clinical, and assistive applications.

The classification of the muscle contraction states is performed by a threshold classifier, which enables one to detect in real-time user intended actions such as gripping or releasing. This process cuts down the computer costs and power and overheads significantly to enhance reliability and consistency. The mechanical design is four fingers and one thumb with the simple fingers open and close movements that can be performed due to the servo and DC motor actuation.

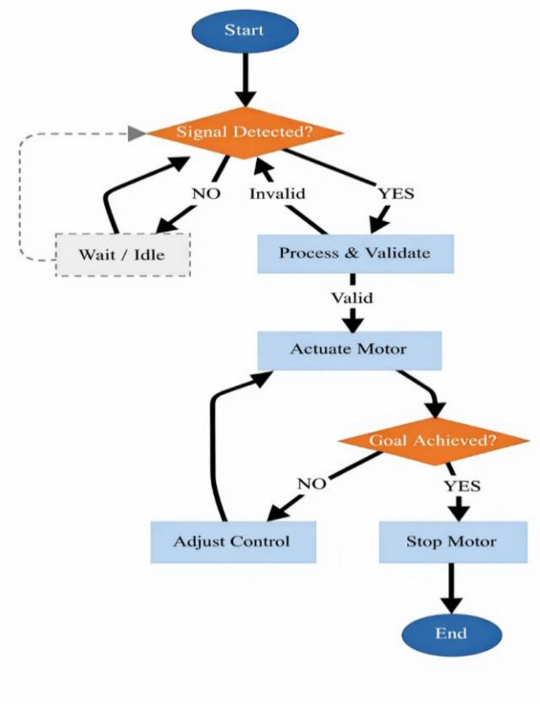

Fig. 1. Adaptive EMG-Based Motor Control.

The fingers are lightweight and modular which enables them to produce constant torque following repeated use of the fingers. The response times should be feasible considering the limitations of the human neuromuscular system of sensor input, processing delay, and the motor actuation. The design is cost-effective, simple to control logic, and resilient to daily use, which contrasts with high-end systems that use a deliberately limited number of degrees of freedom and complexity of gesture descriptions to solve a problem.

This could be made much easier with the use of low-cost and commercial microcontroller platforms and with standard electronic parts to make it much easier to repair and to scale up in areas where dedicated prosthetic services are less common. The EMG-driven intuitive control interface allows its users to operate the prosthetic hand soon after the initial testing, which makes it more acceptable and simpler to use. To sum up, the suggested system will provide a decent balance of functionality and implementation cost.

3.1 EMG Signal Acquisition

Signal acquisition starts with collecting the surface EMG signal of residual forearm muscles used for voluntary hand movement. Surface EMG detectors are chosen by virtue of their non-invasive mode of operation, safety, and the possibility of prolonged use. The electrode is applied over selected muscles to detect the differential voltages produced during muscle contraction and relaxation. Skin is prepared as cleaned and dried to minimize impedance and motion artifacts. The low-amplitude analog EMG signal in the vicinity of a few microvolts reflects how hard a muscle is driven to contract.

3.2 Signal Conditioning and Preprocessing

The purpose of signal conditioning is to improve the quality of the raw EMG signals. The obtained EMG signal contains inherent noise arising from power line interference, movement artifacts, and biological origins. An analog amplification stage amplifies the signal to a level adapted for microcontroller input. Active band-pass filtering is used, typically with cut-off frequencies at 20-450 Hz, to retain muscle activation frequencies and suppress undesirable drift and noise. A 50 Hz notch filter removes power-line interference. The moving average filter is used to carry out rectification and smoothing to offer a more stable envelope on which to perform threshold detection.

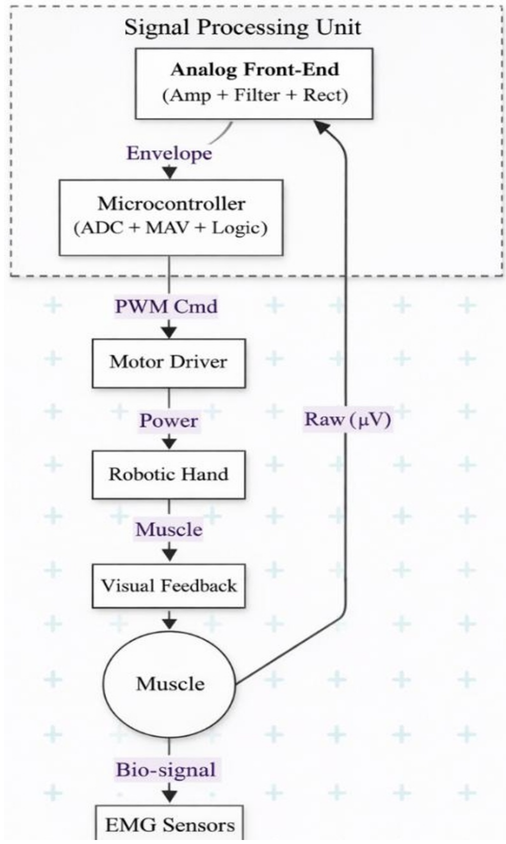

Fig. 2. Proposed EMG-Based Prosthetic Robotic Hand System Architecture.

3.3 Feature Extraction Technique

Feature extraction transforms conditioned EMGs into use of understandable parameters to provide control decisions. The time-domain feature is used as time-domain features have processing performance and muscle strength of activation. The key characteristics adopted are Mean Absolute Value (MAV) which is estimated with the help of a sliding window to measure motor activity of a muscle. The reason behind the selection of MAV is that it is noise immune, which is hardware friendly. The trade-off that is selected is the responsiveness versus stability trade-off which involves picking a window size. The features which come in as our input are then used as the input in the classification logic which has undergone hardening with threshold limits which are directly associated with the actuators.

3.4 Classification Algorithm

A threshold-based classifier is applied in order to make a difference between the desired hand gestures. The algorithm uses the extracted values of features of the EMG in comparison with the pre-established thresholds to determine the activation states. The reasons why it is chosen are its simplicity and clear behaviour about real-time embedded implementation. In contrast to machine learning classifiers, threshold-based logic does not need large training databases or require large computation time. The threshold values are empirically obtained using EMG during repetitive contracting and resting muscles. The classifier generates discrete control states (open or close commands) with a high level of reliability in the basic functions.

3.5 Microcontroller-Based Processing

Digital processing and control logic are applied to a microcontroller platform that has been determined with respect to low cost, availability and easy integration. Digitization of the EMG signals is done by the microcontroller and real-time feature extraction and classification takes place. Timer-based interrupts are engaged in the prediction of sampling intervals and additional predictability of the processing. The firmware is done in such a way that it has a low memory footprint, as well as low execution times. It is also directly related to the motor drives and does not need to process the controller in the outside. The embedded control system is based on Arduino Integrated Development Environment or Arduino IDE developed on the firmware. Embedded C/C++ libraries were employed in signal processing functions of feature extraction, threshold classification. This was done through the checking of EMG signal change and validation of the threshold levels with the assistance of the serial monitoring tools.

3.6 Actuation and Mechanical Control

The actuation of the robot is mechanically achieved with the system of servo and DC motors that move around to open and close the assembly of the robotic hand. Motor driver circuit involves current amplification and isolation to convey signals of the microcontroller to actuators. Control signals form the output of the classification, but in pulse-width modulation (PWM) format, which are the control commands of the position and speed of the motors. This rotary movement is mechanically connected with flexion and extension of the fingers. The machines are light, modular which ensures that there is low operator weariness and easy maintenance.

3.7 System Integration and Validation

Sensing, processing and actuating are as much system integrated as possible to reduce the latency between the acquisition ofEMG signal, digital processing and motor actuation. The end-to-end testing is method to ensure the response-time, repeatability of the trajectory and stability when used constantly. Signal-to-noise ratio, the activation delay, and mechanical accuracy are all performance measures. The safety requirements that have been sub-tested are low-voltage operation, and non-contact sensing compliance. The hail and hail mix reveals that the mechanism of the prostheses can be in the circumstances of working of the low cost and user-friendly style. It was carried out on the experimental EMG signals on the intact forearm's muscles of the volunteer subjects to simulate the case when a prosthetic will be operated. Surface EMG electrodes were applied on flexor and extensor each muscle groups on the forearm. To test the system, a number of experiments were recorded with the contraction and relaxation of the muscles, so as to get representative signal patterns. The data series represented in the sample were the repeated series of the trials of gestures of open hands and closed grip. These values of the measured signals were utilized in obtaining classification and stability and repeatability of the control system evaluation thresholds. The topic of ethics has also been taken into account when carrying out the experiment. The non-invasive electrodes were used in recording surface EMG signals, no medical procedure was performed and medical invasive procedure was not performed. Participants were made aware of the purpose of the experiment, and all the participants volunteered to participate in the experiment. No personal data were stored and thus privacy and confidentiality of the obtained data was secured.

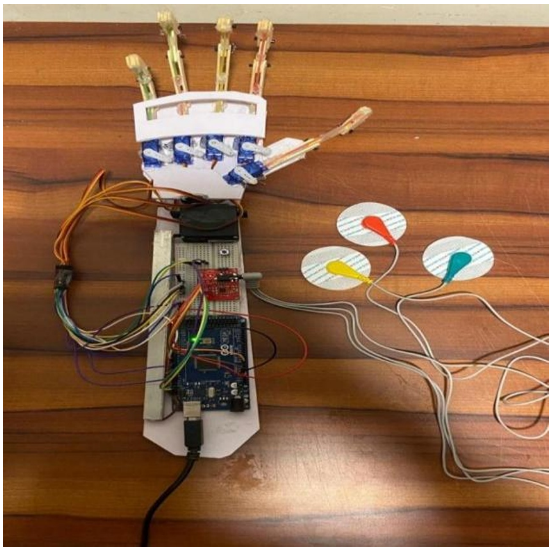

Fig. 3. Output Implementation of EMG-Controlled Prosthetic Robotic Hand.

Fig. 4. EMG-Based Prosthetic Hand in Open (Extension) State During Muscle Relaxation.

Fig. 4 demonstrates the hand prosthetic in the fully extended position. With the muscles of the forearm being relaxed, the sEMG signal amplitude will stay under the preset threshold and will cause all the servo motors to settle to their default position of 0, which will lead to full finger extension.

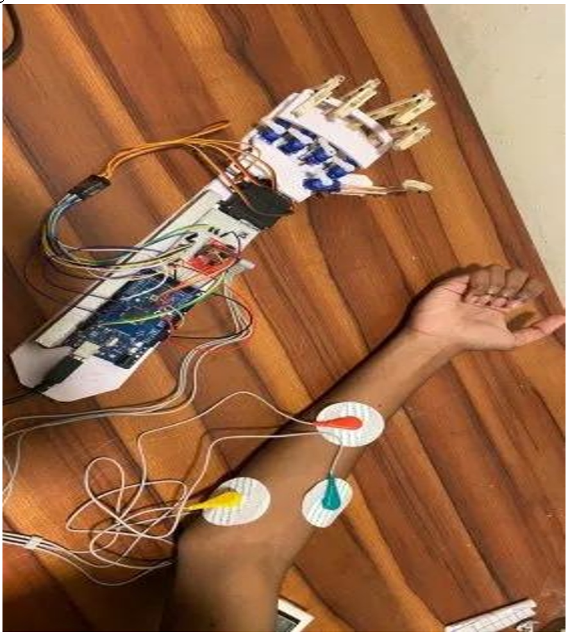

Fig. 5. EMG-Based Prosthetic Hand in Closed (Flexion) State During Muscle Contraction.

Fig. 5 demonstrates the prosthetic hand in closed grip position due to contraction of forearm muscles because of voluntary contraction. The sEMG signal exceeds the classification threshold, and the microcontroller sends two servo motors to approximately 90 degrees to generate simultaneous actions of the fingers in a similar manner as a normal grip. The latency of the system response was within the reasonable range of the prosthetic control of 150200 ms during testing.

4 Results and Discussion

The proposed EMG-controlled prosthesis hand performance was experimented and compared to two existing EMG-based control systems [8] and [9]. The areas of comparison include the accuracy of gesture recognition, system response time, and hardware cost-complexity trade-off to consider expediency, affordability, and real time application in amputees of the upper limbs. The classification method using threshold that is employed in the proposed system also drastically improves computational efficiency of the system as compared to computationally intensive machine learning models. The feature extraction and classification can be implemented to run on real time on a low-cost Arduino microcontroller with minimal memory and power requirements. Such lightweight implementation assists in minimizing the processing latency and ensures that it has a stable performance without external computing apparatus.

Table 1. Gesture Recognition Accuracy Comparison.

System	Single GestureAccuracy (%)	Multi-GestureAccuracy (%)
L. Lin et al. [8]	97.7	95.2
A. J. Kalita et al. [9]	96.1	93.8
Proposed System	**92.5**	**88.4**

The approach of system [8] has the best accuracy as it employs novel machine-learning based classification tailored to embedded systems. System [9] reports lower accuracy but shows good real-time performance. The proposed system achieves a competitive single-gesture accuracy of 92.5%, supporting the effectiveness of threshold-based EMG classification. The lower multi-gesture precision shows limitations of simpler algorithms, yet accuracy is adequate for basic daily activities

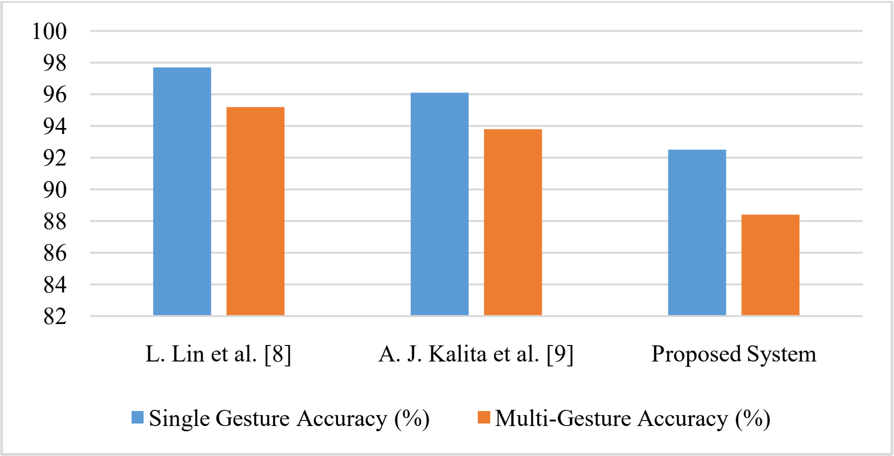

Fig. 6. Visual Plotted View for Accuracy Comparison.

Table 2. System Response Time Comparison (ms).

System	Single GestureAccuracy (%)	Multi-GestureAccuracy (%)
L. Lin et al. [8]	120	210
A. J. Kalita et al. [9]	140	250.8
Proposed System	**165**	**290**

The response time of the proposed system is slightly higher at 290 ms due to less complex microcontroller processing and mechanical servo delays. However, the delay is within human action limits for prosthetic use, confirming that real-time usability was preserved for simple grasping and releasing operations.

Table 3. Cost and System Complexity Comparison.

System	FPS (Real-Time)	Notification Latency (s)	Manual Intervention Reduction (%)
L. Lin et al. [8]	850	Embedded AI MCU	6
A. J. Kalita et al. [9]	720	ARM Processor	5
Proposed System	**180**	**Arduino Uno**	**3**

The proposed system makes use of control based on Arduino with a diminished number of actuators which makes it an extremely cost-effective platform at a cost of just 180 USD. It has more simple degrees of freedom and it also can perform simple hand operations in daily life. The trade-off is to the purpose of the research: to come up with a low-cost, scalable prosthetic that could be applied to people living in the low-resource environment.

The experimental findings demonstrate that the EMG-controlled prosthetic hand can be capable of transforming muscle activation signals into consistent mechanical work. The presented findings indicate that simplified algorithms that are correctly set could provide credible real-time control of vital hand movements. It is a low-cost training machine that can be used in everyday assistive tasks, rehabilitation, and instruction and has primitive gripping and releasing powers.

5 Conclusion

The proposed design of an EMG-controlled prosthetic robotic hand can potentially bring realistic and affordable hand functionality to upper-limb amputees by incorporating non-invasive EMG sensing, effective signal processing, embedded intelligence and motor-based actuation into a single unit. The current implementation demonstrates that it is possible to have reasonable control of prosthesis using simple algorithms with low-cost hardware that can deliver a robust real-time performance that can be applied to the daily life support.

The experimental tests indicate a consistent response, human like behavior of control and decent response-time that makes it worth practical on the way of implementation in a low resource. The threshold classification can only focus several contrastive gestures; the mechanical design is deficient of the capacity to execute complicated gestures or mild gestures. The difference in performance between users can be also associated with the difference in muscle signal sensitivity, fatigue and electrode position.

Adaptive or machine learning classification algorithms could be applied in the work in the future to identify more gestures and accommodate the behavior of a given user. Mechanical structure may be stepped up to give more degrees of freedom. Besides, application of sensory feedback modalities such as force and tactile feedback would enhance the engineering of the user experience and functional realism, and, thus, the prosthesis wearing and acceptance.

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