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A Review of EMG-Based Prosthetic Arm Systems and their Control Techniques

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Abstract: Electromyography (EMG)-based prosthetic arms have emerged as an effective solution for restoring functional hand movements in upper-limb amputees by utilizing bioelectrical signals generated during muscle contraction. This review paper presents a comprehensive analysis of EMGcontrolled prosthetic arm systems, with particular emphasis on low-cost prototype development and the progressive transition toward advanced, intelligent prosthetic solutions. The paper reviews fundamental principles of EMG signal acquisition, conditioning, and processing, along with commonly used control strategies ranging from simple threshold-based methods to machine learning and deep learning-based pattern recognition techniques. Hardware implementations involving low-cost microcontrollers, EMG sensors, and servo actuators are discussed, followed by an overview of recent advancements in 3D-printed prosthetic designs, embedded intelligence, and sensory feedback mechanisms. Key challenges such as signal variability, electrode placement, noise susceptibility, and limited degrees of freedom are critically examined. The review also highlights current research trends focused on adaptive algorithms, multimodal sensing, and closed-loop feedback systems that aim to improve control accuracy and user comfort. This study serves as a technical guide for students and researchers, providing a clear pathway for developing affordable EMG-controlled prosthetic arms while identifying future directions toward more robust and high-performance systems.
Keywords: Electromyography (EMG), Prosthetic Arm, Myoelectric Control, EMG Signal Processing, Low-Cost Prosthetics, Machine Learning, Biomedical Engineering.

I. INTRODUCTION

Upper-limb amputation significantly limits an individual's ability to perform daily activities and affects overall quality of life. Prosthetic arms are designed to restore lost functionality; however, conventional prostheses often suffer from limited dexterity, lack of intuitive control, and high cost. These limitations have motivated research into more accessible and user-friendly prosthetic solutions. Electromyography (EMG)-based control has emerged as an effective approach for prosthetic arm operation, as it utilizes bioelectrical signals generated during muscle contraction. Surface EMG signals acquired from forearm muscles can be processed and translated into control commands for actuators, enabling natural and voluntary control of prosthetic movements. With advancements in low-cost microcontrollers, EMG sensors, and open-source platforms, it has become feasible to develop affordable EMGcontrolled prosthetic prototypes suitable for basic hand functions.

At the same time, recent research has focused on advanced EMG-based prosthetic systems incorporating machine learning, multi-degree-of-freedom control, and sensory feedback to improve accuracy and usability. This review paper presents an overview of EMG-controlled prosthetic arm systems, highlighting signal acquisition methods, control strategies, hardware implementations, and recent advancements, while outlining future directions toward more intelligent and high-performance prosthetic solutions.

II. BACKGROUND AND PROBLEM DEFINITON

Upper-limb prosthetic technology has evolved significantly over the past few decades, yet many existing solutions remain inaccessible due to high cost, mechanical complexity, and limited adaptability to individual users. Conventional body-powered prosthetic arms rely on mechanical cables and harnesses, which often result in unnatural movements, user fatigue, and restricted degrees of freedom. Although electrically powered prostheses provide improved motion control, their high cost and maintenance requirements limit widespread adoption, particularly in developing regions. Electromyography (EMG)-based prosthetic control offers a promising alternative by enabling intuitive interaction between the human neuromuscular system and artificial limbs. EMG signals are generated by motor unit activation during muscle contraction and can be acquired noninvasively using surface electrodes placed on residual muscles. These signals contain valuable information about user intent, which can be processed to control prosthetic joints and fingers. Despite their potential, EMG signals are inherently low in amplitude and susceptible to noise, motion artifacts, and electrode displacement, making reliable signal acquisition a major challenge.

Another critical issue in EMG-controlled prosthetic systems is the trade-off between performance and affordability. Advanced prosthetic arms employ complex signal processing, machine learning algorithms, and sensory feedback mechanisms to achieve multi-degree-of-freedom and simultaneous control. While these approaches significantly improve accuracy and usability, they require high computational resources, expensive hardware, and extensive user training. In contrast, low-cost prosthetic systems often rely on simple threshold-based control techniques, which are easier to implement but limited in terms of functionality and robustness.

Therefore, the primary problem addressed in EMG-based prosthetic research is the development of systems that balance cost, control accuracy, and usability. There is a strong need for scalable prosthetic solutions that can begin as affordable, functional prototypes and be progressively upgraded with advanced control algorithms, improved hardware, and feedback mechanisms. Addressing these challenges is essential for creating prosthetic arms that are not only technically effective but also accessible and practical for real-world use.

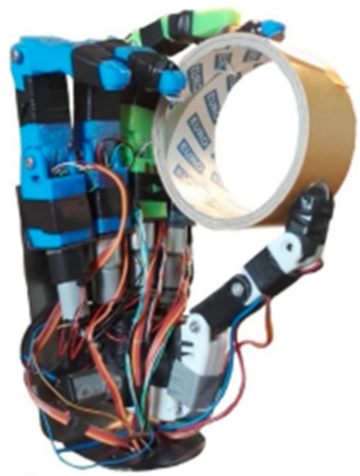

Fig.1.Prototype of the Prosthetic hand.

III. REVIEW OF RESEARCH WORK ON EMG-CONTROLLED PROSTHETIC ARMS

Over the past several decades, extensive research has been conducted on the design and control of prosthetic arms using electromyographic (EMG) signals. Early EMGcontrolled prosthetic systems primarily focused on demonstrating feasibility using simple signal conditioning and threshold-based control techniques. Sudarsan *et al.* [1] presented one of the foundational works in this domain, where surface EMG signals acquired from upper-arm muscles were amplified and processed to drive servo motors for basic limb movement. Although effective for simple actions, the system suffered from noise sensitivity and limited motion precision.

With the advancement of low-cost embedded platforms, several studies have explored affordable prosthetic solutions aimed at improving accessibility. Selvan *et al.* [2] developed a low-cost prosthetic hand using Arduino and surface EMG sensors to perform basic hand opening and closing actions. The study highlighted the role of open-source hardware and simple control algorithms in reducing system cost, though the control mechanism relied primarily on fixed thresholding and lacked adaptive capability.

To overcome the limitations of threshold-based systems, researchers have introduced pattern recognition and machine learning approaches for EMG signal classification. Xu *et al.* [3] proposed an EMG pattern recognition-based prosthetic arm using Linear Discriminant Analysis (LDA) with multichannel EMG inputs. Their system achieved high classification accuracy and enabled multi-degree-of-freedom control, demonstrating a significant improvement over conventional method. However, the increased computational complexity and hardware requirements posed challenges for real-time embedded implementation.

In addition to control accuracy, user interaction and feedback have become important research areas. Borisov *et al.* [4] developed an EMG-controlled prosthetic hand integrated with sensory feedback mechanisms, including force and position sensing. The inclusion of vibrotactile feedback improved grip control and enhanced user confidence, bringing prosthetic behavior closer to natural limb functionality. Despite these improvements, such systems remain relatively expensive and complex.

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Ahmed *et al.* [5] investigated EMG-based prosthetic arm control using single-channel signal acquisition and analog signal conditioning. Their work validated that even minimal EMG information could be effectively used for real-time prosthetic control, reinforcing the feasibility of low-cost designs. More recently, Hasan *et al.* [6] proposed an opensource, wearable prosthetic arm incorporating sensor feedback and modular design, emphasizing scalability and future integration of intelligent control techniques.

Recent studies (2019–2024) have increasingly focused on deep learning-based EMG classification, multimodal sensing (EMG combined with IMU or force sensors), and adaptive control strategies. Convolutional Neural Networks (CNNs) and recurrent architectures have shown improved robustness against signal variability and electrode displacement. However, these methods often require large datasets, higher processing power, and careful training, which limits their applicability in cost-constrained systems.

Overall, the reviewed literature demonstrates a clear evolution of EMG-controlled prosthetic arms—from simple threshold-based prototypes to intelligent, feedback-enabled systems. While advanced methods achieve superior performance, low-cost EMG prosthetic designs continue to play a crucial role in education, early rehabilitation, and accessibility. This highlights the need for scalable prosthetic architectures that allow gradual enhancement from basic control to intelligent, adaptive systems.

IV. FUNDAMENTALS OF EMG-BASED PROSTHETIC CONTROL

Electromyography (EMG) is a technique used to measure the electrical activity produced by skeletal muscles during contraction. These electrical signals originate from motor unit action potentials generated when the nervous system activates muscle fibers. In EMG-controlled prosthetic systems, these bioelectrical signals are interpreted to infer user intent and translate it into mechanical movement of an artificial limb.

A. EMG Signal Characteristics

EMG signals are stochastic and non-stationary in nature, with amplitudes typically ranging from a few microvolts to several millivolts. The useful frequency content of surface EMG signals generally lies between 20 Hz and 450 Hz. The signal amplitude increases with muscle contraction intensity, making EMG suitable for proportional and gesture-based control. However, EMG signals are highly sensitive to noise caused by power-line interference, motion artifacts, skin impedance, and electrode displacement, which necessitates careful signal conditioning.

B. Types of EMG Acquisition

EMG signals can be acquired using either intramuscular or surface electrodes. Intramuscular EMG involves inserting fine-wire electrodes directly into the muscle, providing high signal selectivity but at the cost of invasiveness and user discomfort. Surface electromyography (sEMG), on the other hand, uses electrodes placed on the skin surface and is noninvasive, safe, and widely used in prosthetic applications. Due to its ease of use and suitability for daily wear, sEMG is the preferred choice for most low-cost and wearable prosthetic arm systems.

Fig. 2. Scheme of the prosthesis control system

C. Electrode Placement and Muscle Selection

Proper electrode placement is critical for reliable EMG signal acquisition. Electrodes are typically positioned over forearm muscles responsible for hand and wrist movements, such as the flexor and extensor muscle groups (see Fig. 3 & Fig. 4.). Incorrect placement can lead to cross-talk from adjacent muscles, reduced signal quality, and inconsistent control. Therefore, careful muscle selection and repeatable electrode positioning are essential for achieving stable prosthetic performance.

D. Basic EMG-Based Control Principle

The fundamental principle of EMG-based prosthetic control involves detecting muscle activation, conditioning the acquired signal, and mapping it to actuator commands. After amplification and filtering, the EMG signal is processed to extract an envelope that represents muscle activation intensity. This processed signal is then compared against predefined thresholds or used as input to classification algorithms to determine the intended motion. The resulting control command drives actuators such as servo or DC motors to perform prosthetic movements like finger flexion or hand opening.

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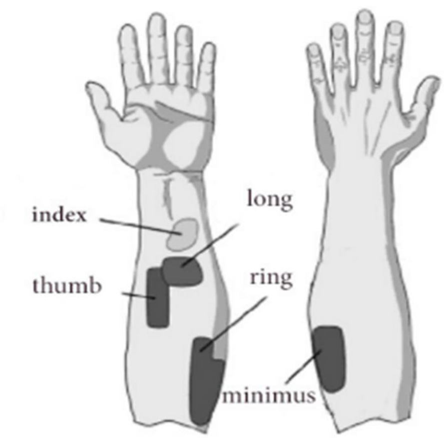

Fig. 3.EMG Sensor Installation Scheme.

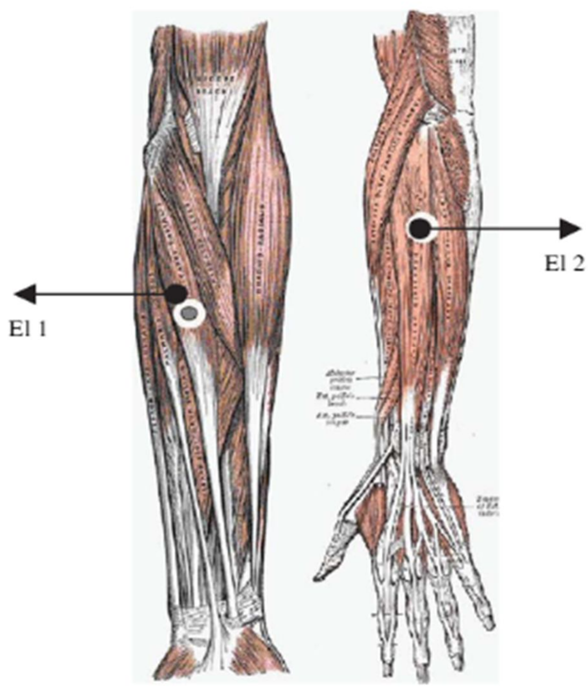

Fig. 4. Position of two Electrodes.

E. Relevance to Low-Cost and Advanced Systems

In low-cost prosthetic prototypes, EMG control is commonly implemented using simple threshold-based methods due to their low computational requirements and real-time performance. In contrast, advanced prosthetic systems utilize multi-channel EMG acquisition combined with pattern recognition and machine learning techniques to enable simultaneous and multi-degree-of-freedom control. Understanding these fundamental EMG principles is essential for designing scalable prosthetic systems that can evolve from basic prototypes to intelligent, high-performance devices.

F. Discussion Summary

The experimental results confirm that EMG signals can be effectively utilized for real-time control of prosthetic limbs through simple, low-cost embedded systems. The system demonstrates reliable and consistent behavior under normal operating conditions. With further optimization in signal processing and mechanical design, such prosthetics can become a practical solution for upper-limb amputees seeking affordable rehabilitation technology.

V. EMG SIGNAL PROCESSING AND CONTROL STRATEGIES

Effective control of EMG-based prosthetic arms depends heavily on accurate signal processing and robust control strategies. Raw EMG signals acquired from surface electrodes are low in amplitude and highly susceptible to noise and artifacts, making preprocessing an essential step before control decisions can be made. This section reviews commonly used EMG signal processing techniques and control strategies employed in both low-cost and advanced prosthetic systems.

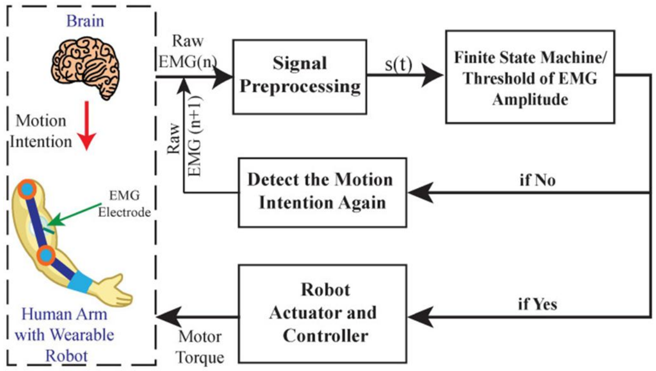

Fig. 5. Conceptual block diagram for threshold-based (On–Off/Finite State Machine) myoelectric control system.

A. EMG Signal Processing Techniques

The first stage of EMG processing involves amplification of the weak bioelectrical signals to voltage levels compatible with embedded controllers. Instrumentation amplifiers are commonly used due to their high gain and noise rejection capabilities. Following amplification, bandpass filtering is applied to retain the useful EMG frequency range, typically between 20 Hz and 450 Hz, while eliminating motion artifacts and high-frequency noise.

After filtering, the EMG signal is rectified and smoothed using low-pass filtering to obtain the signal envelope, which represents muscle activation intensity. This envelope is widely used for control purposes in real-time systems. In more advanced approaches, feature extraction techniques are applied to the processed signal to reduce data dimensionality and enhance discrimination between different muscle activities. Common time-domain features include mean absolute value (MAV), root mean square (RMS), zero crossing (ZC), and slope sign changes (SSC). Frequencydomain and time–frequency features, such as median frequency and wavelet coefficients, are used in systems requiring higher classification accuracy.

B. Threshold-Based Control Strategies

Threshold-based control is one of the simplest and most widely used methods in low-cost EMG prosthetic systems. In this approach, the processed EMG signal is compared against predefined threshold values to determine muscle activation. When the signal exceeds the threshold, a corresponding actuator command is generated, such as closing or opening the prosthetic hand. This method offers low computational complexity, fast response, and ease of implementation, making it suitable for microcontroller-based prototypes. However, its performance is sensitive to electrode placement, muscle fatigue, and environmental noise, limiting its scalability.

C. Pattern Recognition and Machine Learning-Based Control

To overcome the limitations of threshold-based methods, pattern recognition techniques have been introduced for EMG signal classification. These methods involve extracting features from multi-channel EMG signals and classifying them using algorithms such as Linear Discriminant Analysis (LDA), Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Artificial Neural Networks (ANN).

Such approaches enable recognition of multiple hand gestures and support multi-degree-of-freedom control.

Recent advancements have explored deep learning techniques, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), which can automatically learn discriminative features from raw or minimally processed EMG signals. While these methods offer improved robustness and accuracy, they require larger datasets, higher computational resources, and more complex training procedures.

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D. Proportional and Simultaneous Control

Beyond discrete gesture classification, proportional control strategies utilize the amplitude of EMG signals to control the speed or force of prosthetic movements. This allows smoother and more natural interaction with the prosthetic arm. Advanced systems further support simultaneous control of multiple joints by interpreting combined EMG activations, enabling more complex and coordinated movements. Although effective, these strategies require precise calibration and advanced processing capabilities.

E. Applicability to Scalable Prosthetic Design

The choice of signal processing and control strategy plays a crucial role in determining the complexity, cost, and performance of a prosthetic system. Threshold-based methods are well-suited for low-cost educational and rehabilitation prototypes, while machine learning-based approaches provide a pathway toward intelligent and adaptive prosthetic arms. A scalable design approach allows gradual integration of advanced algorithms as hardware and computational resources become available.

VI. HARDWARE ARCHITECTURE AND SENSORY FEEDBACK MECHANISMS

The hardware architecture of an EMG-controlled prosthetic arm plays a critical role in determining system performance, cost, and usability. A typical prosthetic system consists of EMG sensors for signal acquisition, a processing unit for control logic, actuators for mechanical motion, and a structural framework to support the mechanical components. Recent advancements in embedded systems and additive manufacturing have enabled the development of compact, lightweight, and affordable prosthetic designs.

A. EMG Sensors and Data Acquisition Hardware

EMG signal acquisition is commonly performed using surface-mounted sensors due to their non-invasive nature and ease of use. Commercial EMG sensor modules such as MyoWare integrate amplification, filtering, and rectification circuitry, simplifying hardware design for low-cost systems. In advanced setups, custom-built acquisition circuits using instrumentation amplifiers provide greater flexibility and higher signal fidelity. The number of EMG channels directly affects control capability, with multi-channel systems enabling complex gesture recognition and multi-degree-offreedom control.

B. Processing Units and Embedded Platforms

Microcontrollers and embedded processors are responsible for interpreting EMG signals and generating control commands. Low-cost platforms such as Arduino are widely used in educational and prototype prosthetic systems due to their simplicity, low power consumption, and extensive community support. More advanced systems employ microcontrollers such as STM32 or embedded processors like Raspberry Pi to support higher sampling rates, complex signal processing, and machine learning algorithms. The choice of processing platform depends on computational requirements, power efficiency, and real-time constraints.

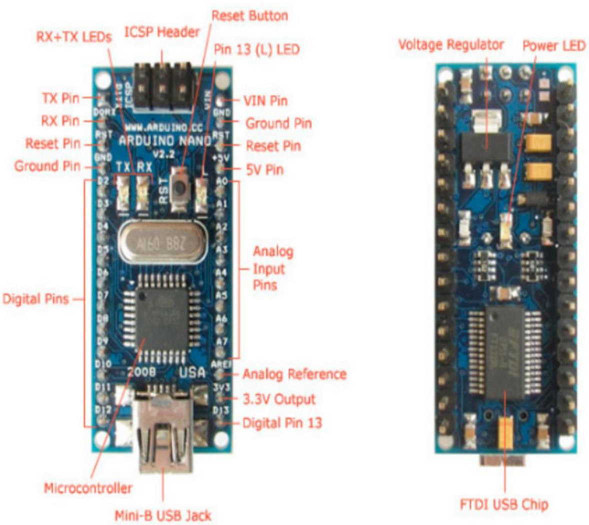

Fig.6.Arduino Uno.

C. Actuation Mechanisms and Mechanical Design

Actuators convert electrical control signals into mechanical motion. Servo motors are commonly used in low-cost prosthetic arms due to their ease of control, compact size, and precise angular positioning. DC motors with gear assemblies and brushless motors are preferred in high-performance systems for improved torque and durability. The mechanical structure of prosthetic arms increasingly utilizes 3D-printed components made from lightweight materials such as PLA or ABS, allowing rapid prototyping, customization, and cost reduction.

D. Sensory Feedback Mechanisms

One of the major limitations of conventional prosthetic arms is the absence of sensory feedback. To address this, researchers have introduced feedback mechanisms that provide users with information about grip force, position, or contact. Common approaches include vibrotactile feedback using small vibration motors, electrotactile stimulation, and force sensors integrated into the prosthetic fingers. These feedback systems enable closed-loop control, improving precision, reducing object slippage, and enhancing user confidence.

E. Integration and Scalability Considerations

A scalable hardware architecture allows gradual enhancement of prosthetic systems without complete redesign. Low-cost prototypes can initially employ basic sensors and microcontrollers, while future upgrades may incorporate higher-resolution EMG acquisition, advanced processors, wireless communication, and feedback modules. Modular hardware design ensures flexibility, maintainability, and adaptability to different user requirements, making it suitable for both academic research and practical deployment. VII. Comparative Analysis, Challenges, and Limitations

A comparative evaluation of EMG-controlled prosthetic arm systems reveals a clear trade-off between system cost, control complexity, and functional performance. Low-cost prosthetic systems typically employ threshold-based control with a limited number of EMG channels and simple actuators. These systems are lightweight, affordable, and suitable for basic hand movements such as grasping and releasing. However, they offer limited degrees of freedom, reduced adaptability, and lower robustness to signal variability.

In contrast, advanced prosthetic systems utilize multi-channel EMG acquisition combined with machine learning or deep learning algorithms to achieve higher accuracy and multidegree-of-freedom control. Such systems demonstrate improved gesture recognition, proportional control, and simultaneous joint movement. Additionally, the integration of sensory feedback mechanisms further enhances user interaction and control precision. Despite these advantages, high-end systems require greater computational resources, extensive training data, and significantly higher costs, limiting their accessibility for widespread use.

Several challenges remain common across EMG-based prosthetic systems. EMG signals are highly sensitive to electrode placement, muscle fatigue, and environmental noise, leading to variations in signal quality over time. Fixed threshold-based systems suffer from calibration drift, while machine learning-based approaches require frequent retraining to maintain performance. User dependency and inter-subject variability further complicate system generalization. Mechanical limitations, such as limited actuator torque and durability in low-cost designs, also restrict functional capabilities.

Overall, the comparative analysis highlights the need for scalable prosthetic architectures that balance affordability with performance. While low-cost systems serve as effective entry-level solutions, addressing the identified challenges is essential for transitioning toward reliable and user-friendly advanced prosthetic arms.

VII. FUTURE DIRECTIONS AND CONCLUSION

Future research in EMG-controlled prosthetic arms is focused on improving adaptability, robustness, and user experience while maintaining affordability. Adaptive and online machine learning algorithms are being explored to automatically adjust control parameters in response to signal variability and muscle fatigue. Multimodal control approaches combining EMG with inertial measurement units (IMUs), force sensors, or ultrasound signals offer improved reliability and richer interpretation of user intent.

Advancements in embedded systems and edge computing are enabling the deployment of lightweight deep learning models directly on prosthetic hardware. Wireless EMG sensors and wearable designs are also gaining attention for improved comfort and ease of use. Furthermore, the integration of closed-loop sensory feedback through haptic or tactile interfaces is expected to significantly enhance prosthetic embodiment and functional performance. Emerging research in brain–computer interfaces and bio-integrated electrodes may further expand control capabilities in the long term.

In conclusion, EMG-based prosthetic arms represent a promising solution for restoring upper-limb functionality. This review has examined the evolution of EMG-controlled prosthetic systems, covering signal acquisition, processing techniques, control strategies, hardware architectures, and recent advancements. Low-cost EMG prosthetic prototypes play a vital role in accessibility and early rehabilitation, while advanced intelligent systems define the future of prosthetic technology. A scalable development approach that bridges these two domains is essential for creating practical, affordable, and high-performance prosthetic solutions.

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