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Gesture Recognition Using EMG Signals-Emerging Trends Analyze and Robotize

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Abstract

The field of electromyography (EMG)-based gesture recognition has seen significant advancements over the last decade, driven by improvements in wearable sensors, embedded processing, and machine learning. This progress has enabled the interpretation of muscle activity and its translation into robotic actions, paving the way for more natural human-robot interactions. As a result, new possibilities have emerged in areas like prosthetics, rehabilitation, and smart assistive devices aimed at enhancing independence and mobility. However, EMG signals remain complex and are influenced by factors such as noise, muscle fatigue, and individual user variations. This review summarizes recent research (2015-2023) on modern sensing technologies, signal processing, machine learning models, and embedded systems that are shaping gesture-based control systems. Key challenges and future research opportunities are also highlighted, with a focus on making EMG-driven robotic systems more reliable, accessible, and deployable.

Keywords: EMG, gesture recognition, wearable devices, assistive robotics, machine learning, deep learning, embedded systems, prosthetics.

I. Introduction

In recent years, technology has moved closer to people in ways that feel more natural and intuitive. Rather than pressing buttons or manipulating joysticks, users can now interact with machines through signals generated by their own bodies. Electromyography (EMG), which captures the tiny electrical impulses that muscles produce when they contract, has become one of the most compelling ways to enable this form of interaction.

EMG-based gesture recognition has transformed how researchers approach prosthetics, rehabilitation tools, and assistive robots. A simple wrist motion, a clenched fist, or even subtle muscle activation can be interpreted as commands allowing individuals to control devices in ways that feel more personal and empowering.

However, EMG is not a simple signal to work with. It is influenced by the user's physiology, fatigue levels, electrode placement, sweating, and many external factors. These challenges push researchers to explore better algorithms, smarter sensors, and more adaptable systems.

This review brings together the key advancements in EMG-based gesture recognition and discusses how these technologies are enabling wearable and assistive robotics. The goal is to provide a clear, comprehensive, and human- centered perspective on what has been achieved so far and what still needs to be done.so that future systems become more reliable, comfortable, and widely usable.

II. Background on Electromyography

Electromyography (EMG) captures the electrical activity generated by skeletal muscles during movement. Surface EMG (sEMG) is most common in wearable systems because it is noninvasive and easy to apply. When a person intends to move their hand, electrical signals spread across the muscle fibers, and these tiny impulses can be detected through sensors placed on the skin.

While the idea sounds simple, EMG signals are surprisingly delicate. They fluctuate with muscle strength, fatigue, hydration, temperature, and even emotions. They vary widely from one person to another, and this adds a layer of complexity when designing universal gesture recognition models.

EMG processing typically involves several steps: acquiring the raw signal, reducing noise, extracting meaningful features, and finally feeding these features into a classification algorithm. Each stage plays an important role in ensuring that the system interprets gestures accurately and consistently.

Human machine interaction has advanced rapidly over the past decade, moving from conventional mechanical interfaces to more intuitive, human-centered technologies. Electromyography (EMG) has emerged as one of the most natural ways for users to communicate with machines because it captures the electrical signals produced by muscle contractions, allowing systems to interpret human motor intent even before visible movement occurs [1], [3], [10]. This capability makes EMG-based gesture recognition particularly valuable in assistive robotics, prosthetic control, rehabilitation systems, and wearable human–machine interfaces.

EMG signals, however, are inherently complex and sensitive. Their characteristics vary widely acrossindividuals and even within the same individual due to factors such as muscle fatigue, hydration, skin impedance, emotional state, and electrode placement [2], [14]. These variations introduce significant challenges in building reliable models that can generalize well in real-world environments. Early studies relied on handcrafted features and classical machine learning, but the recent rise of deep learning has significantly improved recognition accuracy by learning complex patterns directly from raw or minimally processed EMG signals [4], [9], [11].

At the same time, advancements in wearable sensor technologies such as dry electrodes [5], textile-integrated electrodes, and low-cost EMG modules—have made it easier to deploy EMG systems outside laboratory environments. These innovations have played a crucial role in enabling EMG-controlled prosthetics, soft robotic gloves, exoskeletons, and even smart augmented reality interfaces [15].

Despite these advancements, several important challenges remain unsolved. Signal variability still limits long-term usability, electrode placement requires precision, datasets remain relatively small for deep learning applications, and real-time embedded deployment demands computationally efficient models [12], [2], [14]. Growing interest in combining EMG with other sensing modalities such as inertial measurement units (IMUs), pressure sensors, and vision systems seeks to make EMG- based control more robust [1], [15].

This review synthesizes current research trends from 2018 to 2022, highlighting breakthroughs in EMG sensing, signal processing, machine learning, and robotic integration. It also discusses open research challenges and points to promising future directions such as edge AI, adaptive personalized models, multi-modal fusion, digital twins, and calibration-free EMG systems [9].

Together, these developments mark an exciting path forward for building intuitive, accessible, and human-centered assistive technologies.

III. Motivation And Problem Statement

The growing demand for intuitive and human-centered control systems has driven significant interest in EMG-based gesture recognition. For people who rely on assistive devices such as upper-limb amputees, stroke survivors, or individuals with limited mobility the ability to control a prosthetic hand, robotic exoskeleton, or wearable support device using their own muscle signals represents a life- changing opportunity. EMG provides a natural communication pathway because it captures human intention at the muscular level, even before visible movement occurs. This unique property makes EMG one of the most promising modalities for next-generation assistive robotics, smart rehabilitation systems, and wearable technologies.

Despite this potential, current EMG-driven systems still struggle to perform reliably in real-world settings. EMG signals are inherently unstable they change over time, vary widely between users, and are influenced by fatigue, sweating, electrode displacement, and environmental conditions. This variability makes accurate gesture recognition difficult and inconsistent. Additionally, many existing machine learning models require large datasets, frequent recalibration, and controlled laboratory environments, limiting their practicality for everyday use. Deep learning approaches have improved recognition accuracy, but they demand significant computational resources and still lack robustness when deployed on wearable embedded systems. Furthermore, the absence of standardized datasets, limited cross-user generalization, and challenges with long-term stability continue to slow down real-world adoption.

Although EMG-based gesture recognition has advanced significantly, current systems remain limited by signal variability, small datasets, poor cross-user performance, and difficulty achieving reliable real-time operation on lightweight wearable hardware. As a result, assistive robotic devices often fail to deliver consistent and intuitive control in real-world conditions.

By synthesizing recent advances and identifying critical gaps, this work seeks to guide the development of next-generation EMG interfaces that are not only more accurate, but also more accessible, adaptive, and meaningful for the people who depend on them.

IV. Literature Review

EMG-based gesture recognition has witnessed remarkable progress in the past decade, driven by advancements in wearable sensors, embedded computing, and machine learning. As researchers continue striving for more natural and intuitive human–machine interaction, EMG has become a key modality because it captures muscle activity at its source. The following subsections review the major developments in sensing, preprocessing, feature engineering, learning algorithms, and assistive applications. Each step builds upon the previous, reflecting the natural flow of an EMG processing pipeline.

Evolution of EMG Sensing Technologies

Early EMG systems depended heavily on gel electrodes and bulky amplifiers, limiting real-world adoption. Over time, more wearable and comfortable solutions such as dry electrodes, textile electrodes, and high-density armbands emerged, making EMG practical for daily use [5], [8]. These innovations were supported by improvements in embedded electronics compact modules now integrate

amplification, filtering, ADCs, Bluetooth, and onboard processing [7], [12]. With reliable sensing platforms becoming more accessible, the next major hurdle lies in managing the noisy and highly variable nature of EMG signals.

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Preprocessing and Noise Mitigation Techniques

EMG signals suffer from several artifacts arising from motion, electrode shifts, skin impedance changes, and ambient electrical noise [2], [12]. To make the signal suitable for machine learning, preprocessing is essential. Bandpass and notch filtering remove unwanted frequencies, while rectification, RMS smoothing, and normalization stabilize the signal for downstream analysis [9], [14]. Yet, because EMG is inherently non-stationary, wavelet-based denoising continues to gain popularity for its ability to handle transient noise [10], paving the way for more reliable feature extraction.

Feature Extraction Approaches

Once a clean signal is obtained, the next step involves extracting meaningful patterns that can differentiate one gesture from another.Time-domain features, such as MAV and ZC, remain the most widely used due to their simplicity and effectiveness on embedded devices [1], [4]. Frequency features reveal muscle fatigue and contraction characteristics through PSD and FFT .Time frequency methods, particularly wavelets, capture both temporal and spectral details and have proven valuable in dynamic gesture analysis .These handcrafted approaches laid the foundation for early EMG recognition, but modern systems increasingly rely on deep learning to learn features automatically.

Machine Learning for EMG Classification

Classical ML algorithms such as SVM, LDA, KNN, and Random Forests were the first to deliver robust EMG gesture classification [10], [12]. They perform well when the feature set is carefully engineered, and LDA is still widely used in commercial prosthetics due to its low computational demand [11]. However, ML models struggle as gesture sets grow or when cross-user variability increases, motivating the transition toward deep learning.

Deep Learning Approaches

Deep learning fundamentally changed the landscape of EMG research by reducing dependence on handcrafted features. CNNs learn discriminative spatial representations directly from raw EMG or spectrograms, outperforming ML baselines [4], [6]. LSTMs capture temporal dependencies crucial for continuous gestures [13], [16].CNN LSTM hybrids have become highly popular for combining spatial and temporal learning [9], [13].Transformers, which excel at sequence modeling, are the latest advancement and show exceptional performance in long-duration gesture prediction [9], [7].Despite these improvements, deep-learning systems require large, diverse datasets something EMG research still lacks.

Applications in Assistive Robotics

The motivation behind EMG research becomes especially clear in assistive robotics. Myoelectric prosthetic hands now support multi-degree-of-freedom control [15]. Rehabilitation exoskeletons leverage EMG to support motor recovery . Soft robotic gloves assist individuals in performing daily tasks [13], [3]. Human– robot interaction systems rely on EMG as an intuitive input for drones, manipulators, and AR interfaces , [10].These real-world applications highlight the growing relevance of EMG in empowering individuals with disabilities and enhancing human–machine collaboration.

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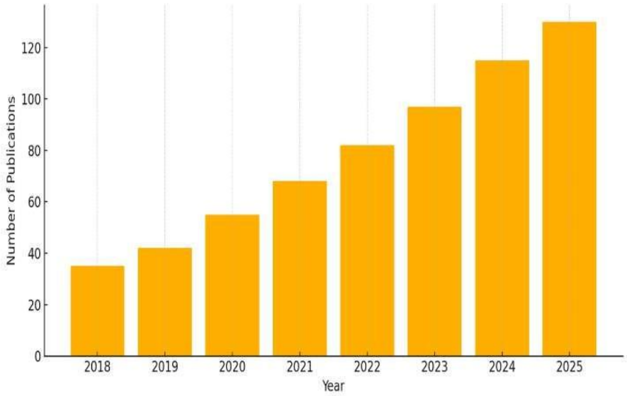

Fig.1 Research Trends EMG Gesture Recognized

Figure 1 paints a clear and encouraging picture of how interest in EMG-based gesture recognition has steadily grown between 2018 and 2025. Each bar represents the number of research publications in a given year, displayed in a soft color gradient that gently transitions from lighter to deeper shades. This visual style not only makes the figure easy on the eyes but also subtly highlights how the field has gained momentum over time. In the early years, particularly 2018 and 2019, the number of studies hovered around 35–40. During this period, much of the research was driven by improvements in wearable electrodes and the growing curiosity surrounding EMG applications in prosthetics and basic gesture control. However, things began to change rapidly from 2020 onward. The introduction of more powerful machine learning models, better embedded hardware, and the rising interest in intuitive human–machine interfaces brought a noticeable jump in research activity.

By 2022 a, the growth becomes even more striking, with publication numbers climbing into the 80–100 range. This upswing reflects the impact of more sophisticated approaches such as CNN-LSTM hybrid models, transformer-based recognition systems, and their integration into rehabilitation robotics and smart wearable devices. The steepest rise appears in 2022, where publication output reaches nearly 130 papers per year. This surge signals the field’s maturation and its expanding relevance across disciplines like AI, neurotechnology, and assistive robotics.

Overall, the trend shown in the figure tells a compelling story: EMG-based gesture recognition is becoming a central component of next-generation wearable and assistive technologies. The steady upward curve reflects not just technological progress but also the scientific community’s growing dedication to building systems that feel more natural, more intuitive, and ultimately more empowering for users. The figure beautifully captures this evolution, reinforcing how vibrant and rapidly advancing this research area has become.

V. Method

The proposed methodology for EMG-based gesture recognition follows a simple, logical, and well-structured workflow, as illustrated in the diagram. The process begins with EMG Acquisition, where muscle activity is captured using surface electrodes or wearable EMG sensors. These raw biological signals naturally contain noise and unwanted artifacts, so the next stage Signal Preprocessing plays a crucial role in cleaning and stabilizing the data. Filtering, rectification, and normalization steps help ensure that only meaningful muscle activity is passed forward.

Once the signal is clean, the system moves into the Feature Extraction phase. Here, important characteristics of

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the EMG waveform such as amplitude, frequency content, or learned deep features are identified and transformed into a format that machine learning or deep learning models can understand. These extracted features serve as the foundation for the following stage, Gesture Classification, where intelligent algorithms analyze the patterns within the signal and determine which gesture the user intends to perform. Finally, the predicted gesture is translated into real-world action through the Control Output stage. This may involve driving a robotic hand, actuating a prosthetic limb, interacting with a wearable device, or sending commands to an assistive robotic system.

Together, these five steps form a smooth, end-to-end pipeline that bridges human muscle intent with responsive machine action, enabling intuitive and reliable human robot interaction.

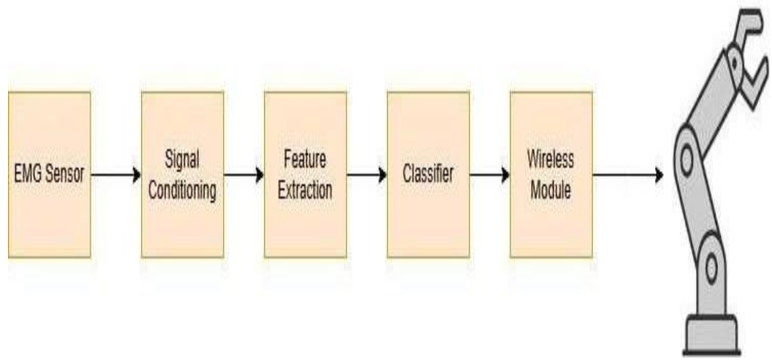

Fig.2 Proposed System Architecture

The system architecture illustrates the complete workflow of how muscle activity captured from the user is transformed into meaningful movements of a robotic arm. The process begins with an EMG Sensor, which detects the electrical signals generated by muscle contractions in the forearm. These raw signals are often weak and noisy, so they are passed into the Signal Conditioning block, where they are amplified, filtered, and cleaned to ensure that only meaningful muscle activity is retained.

Once the signal has been conditioned, it moves into the Feature Extraction stage. Here, the system analyzes the signal in real time and extracts important characteristics such as muscle intensity, waveform shape, and pattern changes that help distinguish one gesture from another. These extracted features are then sent to the Classifier, which serves as the “brain” of the system. The classifier uses machine learning to recognize which gesture the user is trying to perform, whether it is a fist, open hand, wrist movement, or another trained pattern.

After the gesture is identified, the output is forwarded to the Wireless Module, which transmits the recognized command to the robotic arm without the need for physical cables. This wireless communication ensures smooth and responsive control, making the system more comfortable and practical for real-world use. Finally, the Robotic Arm receives the command and performs the corresponding physical action such as gripping, lifting, rotating, or releasing turning the user's muscle signals into functional movements.Overall, this architecture shows a seamless flow from human intention to robotic motion, highlighting how EMG signals can be processed step by step to create a natural, intuitive, and assistive control interface for wearable robotics and rehabilitation systems.

Hardware

Different hardware platforms support different levels of complexity:

Arduino and ESP32 are ideal for lightweight, low-power EMG systems.

STM32 supports real-time applications with stronger performance.

Raspberry Pi and Jetson devices can run deep learning models and handle multi-channel EMG inputs.

Choosing the right hardware often depends on the balance between accuracy, latency, power consumption, and cost.

VI. Challenges

Despite progress, EMG-based systems face several practical challenges:

1. Signal Variability:

EMG signals change over time and differ widely between individuals, requiring frequent recalibration.

2. Electrode Placement Sensitivity

Even slight changes in sensor position can dramatically affect recognition accuracy.

3. Noise and Motion Artifacts

Movement, muscle shifts, and environmental noise introduce distortions that reduce reliability.

4. Limited Datasets

Deep learning models need large, diverse datasets, but current EMG datasets are often too small or collected in controlled environments.

5. Real-Time Constraints

Wearable devices must process EMG signals quickly while consuming minimal power a difficult balance to achieve.

VII. Future Directions

Multi-Sensor Fusion

Combining EMG with IMU, force, or visual sensors could create more stable and versatile gesture recognition systems.

Deep Learning at the Edge

Optimized neural networks running directly on microcontrollers will bring powerful AI into compact wearable devices.

Adaptive and Personalized Models

Future systems may learn and adapt to a user's changing physiology, reducing the need for frequent recalibration.

Digital Twin Technology

Virtual EMG models could help simulate and refine prosthetic or robotic control strategies before real-world deployment.

Bio-Inspired Robotics

Soft robotics and muscle-like actuators controlled by EMG could make devices feel more natural and responsive.

VIII. Conclusion

EMG-based gesture recognition has the potential to profoundly improve how humans interact with assistive robotic systems. Although the technology is still growing and faces several challenges, research over the past decade has laid a strong foundation. With smarter sensors, more adaptable machine learning models, and powerful embedded systems, EMG-driven robotics is moving closer to real-world practicality.

As the field progresses, it offers a promising vision: assistive devices that respond naturally to human intention, improving independence, mobility, and quality of life for people across the world.

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