Comparative Study on Different Control Methods of Limb Prostheses

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Abstract. This paper presents a comparative analysis of three advanced prosthetic control methods: EMG-based systems, neuromusculoskeletal integration, and hybrid-sensing approaches (including vision-based and EEG-EMG systems). EMG control, while well-established and non-invasive, demonstrates limitations in signal accuracy and muscle dependency. Neuromusculoskeletal systems provide more intuitive movement control through osseointegration, though they currently lack sophisticated sensory feedback capabilities. Hybrid-sensing methods represent the cutting edge, with vision-based systems enabling environmental interaction through object recognition and EEG-EMG systems offering more natural control by combining neural and muscular signals. While promising, these hybrid approaches present implementation challenges, including computational complexity and user adaptation requirements. The study evaluates the clinical applicability, technological maturity, and future development potential of each method, offering insights for optimizing prosthetic design to better meet user needs.

Keywords: Prosthetic Control; EMG; Neuromusculoskeletal Integration; Vision-Based Control; EEG-EMG Interface.

1. Introduction

Prosthesis technology represents a crucial area within the field of biomedical prosthetic engineering. It transformed traditional mechanical devices, which offered limited functionality, into intelligent devices designed to meet patients' more diverse needs, including mobility, convenience, and comfort. These factors under consideration reflect the advancement in biomedical engineering from simply restoring basic function to enabling more personalized and dynamic interaction between the human and prosthetic system.

In the field of advanced prosthetics, the development of control methods for upper-limb prostheses has seen significant advancements. Among these, three prominent control techniques are the EMG-based prosthetic control, the self-contained neuromusculoskeletal arm, and the hybrid-sensing control prosthetic. These methods are chosen due to their potential to enhance the user's control, adaptability, and overall functionality of the prosthesis.

EMG-based prosthetics utilize electromyographic (EMG) signals from residual muscles to control the prosthetic, offering a non-invasive and relatively simple method for translating muscle activity into movement. Self-contained neuromusculoskeletal arms integrate advanced sensors and interfaces to mimic the natural control of muscles, offering highly intuitive movement but requiring invasive surgeries for interfacing. Hybrid-sensing control prosthetics integrate multiple sensing technologies, including EMG and force sensors, to achieve a more precise and adaptive control system, thereby enhancing both functional and sensory feedback.

These three methods provide a more natural and intuitive prosthetic experience compared to conventional control methods. However, there are still notable limitations in their implementation. EMG-based control can be hindered by signal variability and noise, making precise control challenging. Self-contained neuromusculoskeletal arms are costly and require invasive surgeries, while their sensory feedback remains insufficient for fine motor tasks. Hybrid-sensing systems, though more versatile, face challenges in integrating various sensors and providing real-time adaptive control with high reliability.

The importance of this paper lies in overcoming these limitations to provide more effective and accessible prosthetic solutions. By investigating these control techniques, the study aims to improve user control and increase the affordability of advanced prosthetics, ultimately contributing to the development of more natural and functional prosthetic limbs.

2. EMG-Based Prosthetic Control

2.1 Characteristics and Principles

One method of controlling artificial limbs is myoelectric control, which is considered a more mainstream and traditional approach compared to neural control. It can be tracked to the 1960s. That was when researchers discovered that the electrical signals (electromyography, EMG) generated during muscle contraction could be captured by electrodes and used for mechanical control. Scientists then applied it in laboratories for controlling myoelectric prostheses. For instance, the electromyographic prosthesis launched by Germany in 1971 marked the first time a myoelectric prosthesis became commercially available. This control method had gradually developed into a mature one in the later decades. With the development of microelectronic technology and signal processing algorithms, more advanced technologies contributed to the development of myoelectric control. Many technological bottlenecks have been overcome, like IMES and TMR.

The basic principle of electromyography is that EMG measures electrical potentials generated in a muscle during its contraction, representing neuromuscular activities. Therefore, it contains information about the neural signal sent to attempt a specific movement (del Olmo & Domingo, 2020), which enables this controlling method to be more intuitive. Users can control the device through natural muscle contraction. The whole process can be generally divided into three parts: signal acquisition, signal processing, and action feedback.

Firstly, surface electromyography (sEMG) signals are collected using electrodes. This process is either done by a non-invasive electrode or an invasive electrode (IMES). The previous one attaches to the surface of the skin, which means there is no need for an operation; therefore, it causes less harm to the body. Risks of complications, including infection and bleeding, can be minimized during the operation. However, the result is that the system can be vulnerable to motion artifacts and skin impedance interference, which can impact the accuracy of the collected data. Moreover, this can be disappointing for patients with atrophy of residual limb muscles. As electromyographic control has a high degree of muscle dependence, signals from these patients may be too weak to drive high-power devices, which can be a significant issue.

Regarding the invasive electrode, it can directly detect deep muscle electrical activities by being implanted into muscles, which means that surgical and biocompatibility risks are involved. Although IMES has great potential for improving the accuracy of the collected signals, significant challenges remain in mitigating the risks that scientists face. Secondly, signals collected by the electrode must be processed in a specific manner. Electrical signals undergo processes such as amplification, filtering, and digital conversion. The next step is feature extraction, which involves time domain processing and the calculation of eigenvalues (RMS, MAV). The data is then processed according to the learning model. Mapping EMG signals to discrete motion categories according to the classification model. The entire process achieves continuous and proportional control, which is closer to natural limb control, as predicted by the regression model. The last step is the output of the prosthesis action. After control signals are processed, they are converted into motor commands, taking into account factors such as position, speed, force, or torque. Therefore, motor commands comprise several complex components, including joint angle commands, joint velocity commands, and output torque, among others. The motion also needs to be optimized, considering trajectory planning, impedance adjustment, and collaborative control. Closed-loop feedback, visual feedback, and integration enable users to handle modifications while observing prosthetic movements. Tactile Feedback: provide force/contact information through tactile cues such as vibration.

2.2 Clinical Application

Whether a prosthesis limb adapts to each patient involves considering several key factors, including the anatomical parameters of the residual limb, neuromuscular function, and other relevant aspects.

Anatomical parameters of residual limbs contain amputation plane requirements, residual limb length, and muscle volume. For a forearm prosthesis, the distance between the end of the residual limb and the radial styloid process should be less than or equal to 2.5cm, and the preservation of wrist bone structure must be at least 50%. Below this standard, a fully contact silicone suspension receiving chamber or an Eagle beak suspension system must be installed to compensate for insufficient control, or a special receiving cavity needs to be customized (Gu et al., 2021). As for upper arm prosthesis, hip amputation patients need to preserve a femur of more than 15 centimeters, with a residual limb length of 20-30 centimeters being the optimal range for adaptation. For patients with shoulder fractures, surgeons need to preserve the lower angle of the scapula to maintain the suspension structure. For a wrist amputation prosthesis, the forearm pronation/supination muscle groups must be completely preserved to ensure compensatory wrist rotation function.

Another factor that needs to be considered is neuromuscular function, which includes EMG signal quality, muscle strength, and dominance ability. For evaluation of electromyographic signal intensity, the pronator muscle group (including the pronator teres and pronator) and the supinator muscle group (including the supinator and biceps) must be preserved. This ensures the basis for generating effective electromyographic signals. According to the clinical guidelines of the International Society of Orthopaedic and Reconstructive Surgeons (ISORS), the electromyographic signal strength must reach a threshold of $\geq 5\ \mu V$ to ensure reliable control of electromyographic prostheses.

The two key features of the 15-30 days after surgery, which is regarded as the golden assembly period, are that the electromyographic signal intensity reaches its peak (average 8-12 μV) and the most significant symptom of phantom limb pain (VAS score $\geq$ 6 points). The latter can be alleviated through prosthetic training. There are several methods for coping with postoperative muscle atrophy. Red light therapy: wavelength 630nm, twice a day for 15 minutes each time, promoting microcirculation. Wax therapy: A paraffin wrap at 52-55 ℃, applied once a day, improves soft tissue elasticity. By combining the use of two therapies, the stability rate of residual limb volume can be increased by 37%.

Except for the factors above, contraindication screening is also necessary. Progressive bone resorption of residual limbs, uncontrolled epilepsy, and severe peripheral neuropathy leading to muscle electrical signal deficiency are absolute ones. Relative contraindications include type II diabetes with peripheral sensory disturbance and a BMI $\geq$ 30, increasing the risk of electrode displacement.

3. Self-Contained Neuromusculoskeletal Arm

People with limb loss also choose the self-contained neuromusculoskeletal arm prosthesis. This implant receives tactile feedback through its unique principle, which enables bidirectional communication between the prosthesis and electrodes. It is fixed to the humerus through osseointegration, a process in which bone cells attach to an artificial surface without the formation of fibrous tissue (X-MOL, 2025). Through a study on three Swedish Patients who have lived with this technology— the self-contained neuromusculoskeletal arm, an associate professor at Chalmers University, Max Ortiz Catalan presented the conclusion that:“ A robotic arm attached to the bone and controlled by electrodes implanted with nerves and muscles is much more precise in operation than conventional prosthetics.”(Middleton & Ortiz-Catalan, 2020) The unique principle of self-contained neuromusculoskeletal arm technology introduces features that other control modes do not possess.

For instance, this kind of prosthesis is directly controlled by the user's mind, allowing for more natural and intuitive movements.

To discuss the advantages and drawbacks of this technology, the paper written by Alexandra Middleton, Max Ortiz Catalan, and several others provides a specific summary across numerous aspects based on real-world feedback from the three patients. The interview results indicated that the corresponding patients' sense of energy increased due to the enhanced mobility after osseointegration. The types of tasks that such prosthetic limbs can perform are more diverse, including household chores, self-care activities, and even certain hobbies such as gardening or cooking. Participants unanimously agree that the most significant positive effect brought by the prosthesis is that it enhances their participation in family life. Furthermore, their attitude towards life has become more positive. Some of the participants even said that the prosthetic limbs felt like a natural part of their body, and they no longer consciously thought about controlling the devices. Another critical point is that the patients' self-esteem and recognition of their self-image have significantly improved. The advancement in the functionality of prosthetic limbs has narrowed the gap between amputees and healthy individuals.

On the other hand, there are also many downsides regarding sensory feedback. Participants believed that the signal intensity perceived through touch was limited, and the quality was not natural enough. Hence, they still have to rely on visual feedback to assist their behavior(Middleton & Ortiz-Catalan, 2020). The lack of precise sensory feedback made tasks more difficult and mentally demanding. For that, improving the fidelity of haptic sensations remains one of the major challenges in future development.

To summarize, the self-contained neuromusculoskeletal arm technology has achieved remarkable success in achieving intuitive control. However, due to technical limitations, there is still much room for improvement in sensory feedback. In addition, the assessment of the prosthetic hand conducted by Francesco M. Petrini and others also reached a conclusion— the problem of phantom limb pain in these patients was alleviated, and their emotional states became more positive, which fully demontrates the feasibility of sensory neuroprosthetic stimulation in clinical application(Petrini et al., 2018). The mitigation of phantom limb pain not only improves their quality of daily life but also enhances their reliance on such prosthetic systems.

The existence of a self-contained neuromusculoskeletal arm prosthesis can also help patients better reconnect with society and foster greater confidence in public. Unlike some multi-joint prosthetic limbs that cannot provide a complete hand experience, such prostheses help amputees better restore their sense of touch. As the usage time increases, their functions and overall experience will also improve. Amputees can better participate in daily life and have a greater willingness to connect with others(Graczyk et al., 2018).

4. Hybrid-Sensing Control of Prosthesis

4.1 Vision-based Control System

Intelligent human-computer is becoming a possible way to realize the machine's active understanding of human intentions. Vision plays an essential role in human grasping. To grasp an object successfully, the visuomotor system must analyze the object's actual size, orientation, and position with respect to the hand (He et al., 2020). Inspired by human vision, intelligent human-computer interaction is becoming a possible way to enable machines to actively understand their functions. Currently, people are trying to incorporate a vision-based control system into the method of controlling prosthetic hands. It is necessary because the previous capability to discriminate motion patterns from EMG signals not only lacks the robustness provided by current pattern recognition algorithms for daily motions but also makes it impossible for natural control of multi-articulating hands. With the help of a vision-based control system, people who wear prosthetic hands can grasp targeted object from a group of objects (Sun et al., 2025) accurately by the precise estimate of the targeted object by the user's intention

4.1.1 Principle of Vision-Based Myoelectric Hands

The vision-based myoelectric hand operates through four integrated modules that mirror human visuomotor coordination. The process begins with the cognition module, where an imaging sensor and deep neural networks identify an object's category, position, and distance. This information guides the action module to pre-shape the hand into an appropriate grip pattern. Crucially, the user retains control over initiating movement through the interface module, which combines EMG signals (like muscle flexing) with visual motion estimation; the hand only moves when a specific muscle activity threshold is exceeded, conveying the user's intention. Finally, the feedback module closes the loop by providing real-time visual feedback—such as color-coded bounding boxes and movement vectors—on a graphical interface, ensuring transparent and effective human-machine interaction throughout the grasping process.

4.1.2 Advantages and Disadvantages of Vision-Based Control Prosthetic Hands

In Saga University’s studies (Sun et al., 2025), vision-controlled prosthetic hands enhance functionality by enabling accurate object recognition, reducing cognitive load through contextual data, and natural gaze-based interaction in multi-object environments. However, challenges include high computational demands for real-time processing (30 FPS), sensitivity to lighting/occlusion, the need for user training to coordinate EMG and gaze inputs, and hardware limitations from additional cameras. Future development should focus on optimizing processing efficiency, environmental robustness, and integrating multimodal feedback to advance prosthetic control systems.

4.2 Control System Based on Brain-Muscle Mixed Signals

Recent studies have demonstrated the effectiveness of hybrid brain-computer interface (BCI) systems that integrate multiple bioelectrical signals (Cheng et al., 2022). By combining at least two distinct signal modalities, these systems significantly enhance the overall accuracy and reliability of BCI outputs. For instance, one study implemented a hybrid BCI framework for robotic arm control, leveraging synchronized motor imagery electroencephalography (EEG) and electromyography (EMG) signals. This approach not only improved system stability but also expanded the range of executable control commands, addressing key limitations of single-modality BCIs.

4.2.1 Principles of Brain-Muscle Mixed Signals Robotic Arm Control System

The brain-muscle hybrid control system synchronously acquires EEG and EMG signals to control a 6-DoF robotic arm. EEG from channels C3/C4 captures motor imagery intentions (left/right hand) by extracting μ (8–12 Hz) and β waves (14–30 Hz), classified via an SVM (91.24% accuracy). EMG detects six hand gestures using a neural network (97.01% accuracy). The system integrates both modalities: EMG controls robotic arm positioning, while EEG triggers grasping/releasing actions. A “finger kneading” gesture switches between control modes. Signals are processed every 20 ms using a sliding 2-second window, ensuring high accuracy (96%) and low latency ($<$100 ms) for responsive and natural arm control.

4.2.2 Advantages and Disadvantages of the Hybrid-brain Control System

This hybrid brain-muscle control system offers meaningful advantages but also faces some current limitations. By blending thought signals (EEG) with muscle activity (EMG), it creates more natural and responsive control than systems using just one signal type - much like how our natural movements combine brain commands with muscle actions. The technology adapts well to different users and maintains stable performance even during extended therapy sessions or daily use. Importantly, it achieves this without needing expensive computer equipment. However, practical challenges remain. The system requires careful placement of sensors on the skin and scalp, and most users require several training sessions to achieve smooth control. Environmental factors, such as electrical equipment, can sometimes interfere with signals. Like any intensive activity, prolonged use may tire users. While already useful for prosthetics and rehabilitation, researchers are working to simplify setup and improve reliability for home use, aiming to keep the system responsive and human-like, while making it as easy to use as a smartphone.

4.3 Applications

With the help of vision-based control technology, the potential application of vision-based myoelectric hands can be deepened. In addition, visuo-tactile sensors (Sun et al., 2025), which combine high-resolution optical imaging with tactile sensing capabilities, are revolutionizing applications in robotics and healthcare by enabling precise interaction with the physical world. In industrial robotics, these sensors facilitate complex tasks, such as peg-in-hole insertions and cable manipulation, by providing real-time force and slip detection. Service robots, on the other hand, leverage them for delicate operations, including handling deformable objects like fabrics and food items, as well as safely grasping fragile objects. The medical field benefits significantly through surgical robots that use tactile feedback for safer soft tissue manipulation and improved teleoperation, as well as in rehabilitation, where smart prosthetics restore natural grip control and assist in stroke recovery through integrated visuo-tactile training. These sensors prove particularly valuable in challenging environments with limited visibility, such as disaster zones, where tactile exploration becomes essential, and in precision manufacturing for surface defect detection. For patients, the technology offers transformative potential - amputees gain enhanced prosthetic functionality, neurological patients benefit from more effective rehabilitation, and surgical patients experience reduced tissue trauma. By effectively bridging the gap between visual perception and physical interaction, visuo-tactile sensors are paving the way for more adaptive, responsive, and safer human-machine interactions across multiple domains.

An EEG-EMG-based control system has a variety of applications. One study reported results indicating that all 10 subjects successfully controlled the robotic arm in real-time, with an average accuracy of the control instructions exceeding 94%. The recognition and control results of the system are satisfactory, and the success rate of the tasks exceeded 80% (Cheng et al., 2022). This advancement of a control system that combines EEG and EMG signals provides a basis for the extended application of BCI in robotic arm control. It can also collaborate with user intent and robotic response, allowing interactive rehabilitation exercises. Another study shows that an EEG-EMG correlation-based brain-computer interface for hand orthosis can support neuro-rehabilitation (Chowdhury et al., 2019). In this experiment, participants were required to perform BCI-based hand orthosis trigger tasks, and the results show that it is possible to use this method to design BCI-based robotic neurorehabilitation paradigms. In addition, Artificial intelligence-powered EEG-EMG electrodes can assist the Paralyzed (Jacob et al., 2019).

5. Comparative Analysis and Evaluation of Prosthetic Control Methods

The selection of the most effective prosthetic control method depends on the user's specific needs and clinical circumstances. For conventional amputees, EMG control remains the most practical solution due to its non-invasive nature and cost-effectiveness, though its limitations in precision and reliability persist. The neuromusculoskeletal approach demonstrates superior performance in intuitive movement control and long-term usability, particularly for active individuals requiring robust functionality, despite its surgical requirements and higher costs.

However, hybrid-sensing systems, particularly the EEG-EMG integrated approach, emerge as the most technologically advanced and potentially transformative solution. As demonstrated in the cited studies, achieving greater than 94% accuracy in robotic arm control, this method combines the strengths of neural intention detection (EEG) with muscular execution signals (EMG), closely mimicking natural motor control pathways. The vision-based variant further enhances environmental interaction capabilities, though at a higher computational cost.

The true effectiveness of each method should be evaluated against key criteria: (1) control intuitiveness, (2) functional range, (3) user adaptation time, and (4) quality of life improvement.

While no single solution currently excels in all dimensions, the rapid advancement in hybrid systems—particularly in addressing their computational and complexity challenges—positions them as the most promising direction for future prosthetic development. Their ability to integrate multiple control modalities and sensory feedback channels offers the closest approximation to natural limb functionality currently achievable.

Table 1. Comparative Analysis of Prosthetic Control Methods

Control Method	Principle	Advantages	Disadvantages	Clinical Applications	Future Directions
EMG Control	Uses surface electrodes to detect muscle electrical signals	Non-invasive Mature technology Cost-effective	Signal interference Muscle dependency Limited precision	Most amputees (especially upper-limb)	Improved signal procession Noise reduction
Neuromusculoskeletal Integration	Osseointegration +implanted neural electrodes	Intuitive control Long-term stability Reduces phantom pain	Requires surgery Expensive Limited sensory feedbacks	High-demand upper-limb amputees	Enhanced sensory feedback Safer implantation
Vision-based	Computer vision + object recognition	Reduces cognitive load Enables complex grasps	Lighting-dependent Computationally intensive	Precision tasks	Algorithm optimization Hardware efficiency
EEG-EMG	Combines brain and muscle signals	Natural control Rich command set	Complex system Requires training	Sever disabilities	System simplification Cost reduction

6. Conclusion

Overall, the choice of prosthetics varies depending on individual differences and needs to be tailored to each individual. However, in terms of potential, hybrid sensing systems undoubtedly deserve people's greatest expectations. Through multimodal signal fusion, the naturalness, accuracy, and adaptability of prosthetic and robot control can be greatly improved. Considering the broad prospects of this technology, its future development direction includes diversified professional directions, including optimizing processing efficiency, enhancing environmental robustness, integrating multimodal feedback, and simplifying user interaction. In addition to their most common use in rehabilitation, the outstanding precision of prosthetics enables this technology to be applied in various other industries, including manufacturing, services, and disaster relief. Although this control system still has high computational costs and lacks a perfect solution. But its rapid development has made it the most promising direction for the future development of prosthetics.

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