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Neural Signal Decoding for Prosthetic Control: Brain- and Muscle-Signal-Based Approaches

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Abstract:

Neural decoding technology has made great strides in the past two decades, transitioning from the lab to clinical applications. Brain signals and electromyographic (EMG) signals have emerged as two key information sources for prosthetic control: the former includes invasive and non-invasive neural electrical activity, and the latter leverages residual muscle and peripheral nerve signals. This paper reviews recent advances in prosthetic control from the perspectives of brain-signal-based control and muscle-signal-based control. This paper introduces the main signal types, decoding algorithms, and representative applications, provides a comparative analysis of these signals in terms of information capacity, stability, invasiveness, etc., and discusses current limitations and future prospects. By surveying the latest research, this review aims to offer valuable insights for future neuroprosthetics research and clinical applications. At a broader level, the development of neural decoding reflects the ongoing convergence of science, technology, and medicine, and its future progress will not only reshape prosthetic design but also expand our understanding of human–machine interaction, rehabilitation, and even the nature of human agency itself.

Keywords: Brain-Computer Interface (BCI); Neural Decoding; Electromyography (EMG); Prosthetic Control; Sensory Feedback.

1. Introduction

Brain-computer interfaces (BCIs) control external devices by decoding neural activity, and in the past two decades, they have progressed from proof-of-concept experiments to clinical applications. In the field of prosthetic control, two main technical approaches have emerged: the first is brain-signal-based control, which involves recording electrical signals from the central nervous system for decoding and aims for high spatiotemporal resolution and long-term reliability; the second is residual limb signal-based control, which entails capturing muscle and peripheral nerve activity from an amputee's limb stump

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(e.g., via electromyography electrodes). The former category includes methods such as implanted microelectrode arrays, cortical surface electrodes (electrocorticography, ECoG), and non-invasive electroencephalography (EEG) for directly reading motor intent from the brain. The latter utilizes residual muscle or nerve signals, often in conjunction with regenerative interfaces such as the Regenerative Peripheral Nerve Interface (RPNI), to provide natural and seamless control signals.

This paper reviews key advances in both of these approaches, introduces representative decoding algorithms and application examples, and discusses challenges in areas such as electrode hardware, intelligent algorithms, and closed-loop control. By comparing the advantages and disadvantages of brain-based versus muscle-based signals in prosthetic control, we hope to inform future research and clinical practice in neuroprosthetics.

2. Brain Signals and EMG Signals

Neural signals originating in the brain are an important information source for prosthetic control. Among these, invasive intracortical spike signals offer the highest spatial resolution and richest information content, but they require implantation of microelectrode arrays in the cerebral cortex. Such signals contain rich motor intent information and have enabled high-rate decoding of speech [1]. However, long-term implants elicit tissue reactions and material degradation, causing signal quality to deteriorate over time: experiments in primates found that approximately 79% of intracortical microelectrodes failed within one year, and after a few years the signals could disappear completely [2]. Electrocorticography (ECoG) electrodes are placed beneath the dura on the cortical surface; with millimeter-scale electrode spacing, they provide intermediate spatial resolution and can cover almost the entire cortical surface. Because ECoG electrodes do not penetrate brain tissue, they have low maintenance requirements and good biocompatibility. ECoG has been shown to stably record and decode fine motor intentions over long periods [3]. In contrast, electroencephalography (EEG) measures brain activity from the scalp. EEG is entirely non-invasive and easy to use, but the filtering effect of the skull leads to very low spatial resolution and signal-to-noise ratio, often necessitating many repeated trials to obtain reliable control signals. High-frequency details in EEG are severely attenuated, and its information throughput is far lower than that of invasive interfaces; EEG signals are also easily contaminated by muscle activity and environmental noise, and they have poor reproducibility across sessions. In summary, each brain-signal acquisition method has its trade-offs: invasive interfaces provide information-rich signals but suffer from stability issues, whereas non-invasive interfaces are safe and easy to access but limited in signal quality and reliability.

Residual muscle and peripheral nerve signals from an amputee's limb stump likewise carry substantial motor intent. Surface EMG (sEMG) signals, recorded non-invasively from the skin, have low amplitude, are easily disturbed, and can vary greatly between sessions, requiring frequent recalibration. High-density EMG (HD-EMG) uses arrays of electrodes to increase spatial resolution and information content. HD-EMG, combined with advanced algorithms, can decode a greater variety of gestures and achieve smoother control than conventional EMG; for example, it has enabled decoding of over a dozen distinct hand gestures. In contrast, invasive peripheral nerve interfaces—such as RPNI and the Transverse Intrafascicular Multichannel Electrode (TIME)—directly acquire neural signals from peripheral nerves via surgical implantation, trading a higher level of invasiveness for high-quality multichannel recordings. RPNI has demonstrated stable signals over multiple years in initial trials [4], indicating potential for long-term stable control. TIME electrodes have been used to control multi-finger prosthetic hands and to provide sensory feedback, via nerve stimulation, from prosthetic fingers back to the user [5]; however, to date TIME interfaces in humans have only been shown to function continuously for a few months [6]. Overall, sEMG is completely non-invasive but the signals are relatively weak and unstable; HD-EMG increases the information throughput of non-invasive methods; and RPNI and TIME, while requiring surgical implantation, provide high-quality multi-channel signals—especially RPNI, which has shown promise for long-term stable control [4]. In practice, different amputees can choose appropriate combinations of interfaces depending on their residual limb condition.

3. Brain-Signal-Based Prosthetic Control

For brain-derived signals, researchers have developed various algorithms to decode neural activity into prosthetic control commands. Early approaches employed linear models and manual feature classification. For example, intracortical spike activity has been decoded using linear regression or Kalman filters, and field potential signals (such as ECoG or EEG band-power features) have been classified using algorithms like Linear Discriminant Analysis (LDA) or Support Vector Machines (SVM). These traditional methods offer good real-time performance but have limited accuracy when dealing with complex movements or multiple intention classes. In recent years, deep learning approaches (including Convolutional Neural Networks, Recurrent Neural Networks, and Transformers) have been introduced to further improve decoding performance. These models can automatically extract spatiotemporal features and model long-term dependencies in the neural data, enabling more accurate decoding of complex motor intentions.

Leveraging advanced algorithms and high-performance neural sensors, brain-signal-based prosthetic control has achieved several breakthrough results. For example, an implanted microelectrode array in a bidirectional BCI allowed a tetraplegic patient to control a robotic arm by thought and simultaneously receive tactile feedback via sensory cortical stimulation, significantly improving control accuracy [7]. In another demonstration, a 128-channel ECoG implant enabled a patient to independently control each finger of a prosthetic hand without lengthy training; the accuracy of finger control improved from around 76% initially to about 88% after further optimization [3]. Overall, brain-signal-based control has progressed from concept validation to initial practical use. It can output complex movement commands and, when combined with sensory feedback, form a closed-loop system that greatly enhances the practicality and functionality of prosthetic control.

4. EMG-Based Prosthetic Control

Myoelectric and peripheral nerve signals are convenient to acquire and directly reflect the movement intent of the residual limb, so they are widely used in prosthetic control research. Traditional schemes mainly employ EMG pattern recognition for a set of discrete hand gestures. In laboratory settings, classification accuracies for common hand gestures can exceed 90%. However, these methods are limited to predefined movements, and factors such as signal non-stationarity and electrode shift can lead to performance drops, necessitating frequent recalibration or adaptive updating. To address these issues, recent studies have explored using deep learning to directly decode continuous movements from EMG. For example, CNN and LSTM (Long Short-Term Memory) models applied to high-density EMG have reduced prediction error by over 30% compared to linear methods, and one Transformer-based model was able to classify up to 65 distinct hand gestures with about 92% accuracy [8]. Furthermore, even subtle, fine movements of individual fingers in transradial amputees have been decoded accurately from surface EMG signals in real time [9].

Currently, most commercial prosthetic arms rely on surface EMG for control, allowing many forearm amputees to regain basic grasping functionality. However, typical commercial prosthetic hands often provide only a single predefined grasp pattern, and users must continuously contract specific muscles to maintain a grip. When the muscle contraction ceases, the prosthetic hand relaxes and releases the object. This control scheme is not as intuitive or flexible as desired. With the development of multi-joint bionic hands and the integration of pattern recognition algorithms, users can now switch between multiple grasp postures. Some prosthetic hands also include built-in pressure sensors that automatically stop the closing action when an object is detected, to avoid excessive force (an early form of closed-loop force control). Despite the practicality and convenience of surface-EMG control, users report that it does not feel entirely natural. Considerable practice is often required, and users must pay constant attention to their muscle signals to avoid unintentional activations. For instance, when lifting a cup, the user must continuously exert muscle force; otherwise the prosthetic hand may loosen its grip on the cup.

Invasive peripheral nerve interfaces have shown exceptional performance in recent trials. For example, one amputee, after receiving four RPNI implants, was able to individually control multiple fingers and grip patterns of a prosthetic hand. Over 20 months of daily use, the control performance showed virtually no drift, with a grasp success rate of about 95%, and no recalibration was ever needed [4]. In another study, researchers implanted multiple TIME electrodes into the median and ulnar nerves of several amputees. These intraneural electrodes recorded nerve signals to control a multi-digit prosthetic hand, and also delivered tactile information from the prosthetic fingers back to the nerves via electrical stimulation. Over a 6-month trial, each stimulation elicited a clear sensation in the corresponding phantom hand finger, enabling subjects to adjust their grip force without visual feedback; long-term use of the system also significantly reduced phantom limb pain [5]. These results demonstrate that implanted peripheral nerve interfaces, by providing multi-channel motor control signals and sensory feedback, can substantially enhance prosthetic function while maintaining a reasonable level of invasiveness. Such interfaces are expected to become effective components of future bionic prosthetic control systems.

5. Comparative Analysis

Different types of neural signals each have distinct strengths and weaknesses in prosthetic control. In terms of information capacity: intracortical spike signals carry the richest information, supporting the highest precision and fastest response; ECoG and local field potentials

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are slightly lower, with each channel conveying a high amount of information, though not as much as spikes; EEG and conventional magnetoencephalography (MEG) have the lowest per-channel information content, generally only supporting a limited set of commands or low bitrate communication. EMG signals have a moderate information capacity, and HD-EMG combined with intelligent algorithms can recognize on the order of a dozen gesture types [8]. Peripheral nerve interfaces provide multiple independent channels of neural signals, with total capacity depending on the number of implantable electrodes and how well individual nerve fiber groups can be selectively accessed. In terms of signal stability: invasive central nervous system interfaces are limited by biological reactions and material longevity—intracortical electrodes often begin to fail roughly one year post-implantation [2]—whereas ECoG electrodes, not penetrating the brain tissue, tend to exhibit slower signal degradation and can function stably for several years. Non-invasive signals do not suffer biological degradation, but day-to-day electrode placement cannot be perfectly replicated and they are highly susceptible to external noise; as a result, non-invasive systems often require recalibration before each use to ensure reliability. Invasive peripheral nerve and muscle-derived interfaces, when the implant remains stable, generally offer better long-term reliability: RPNI has shown over 2 years of highly stable recordings in clinical use [4]; TIME electrodes have so far been stable for a few months in human trials [6]; by contrast, surface EMG is easily affected by physiological and positional changes and requires frequent recalibration to maintain performance.

Overall, no single signal source is superior in all aspects of accuracy, responsiveness, stability, and ease of use. Intracortical spikes can achieve the highest decoding accuracy and bandwidth, but with the greatest invasiveness and maintenance requirements. Non-invasive methods are the safest and easiest to deploy, but are limited by lower signal quality and stability. Peripheral nerve and muscle interfaces offer a compromise between performance and invasiveness, and are particularly notable for their potential long-term stability. In practical applications, it is likely that multiple interface technologies will be combined to complement each other, so as to fully exploit their respective advantages and optimize prosthetic control outcomes.

6. Current Limitations and Future Directions

Despite the significant progress in neuroprosthetic control, many challenges remain before prosthetic limbs can be controlled as naturally and fluently as biological limbs. The long-term stability of signals and the longevity of interfaces are pressing issues. Breakthroughs in more biocompatible electrode materials and adaptive algorithms will be required to maintain high-quality signals over extended periods [10].

Multi-modal information fusion and closed-loop sensory feedback are key directions for future development. Fusing central and peripheral signals can improve the robustness and granularity of control [11], and implanted electrical stimulation feedback has been shown to restore tactile sensation and alleviate phantom limb pain [5]. As interface durability and sensory feedback technologies advance, prosthetic control is expected to achieve true closed-loop operation, greatly enhancing the functionality and user experience of bionic limbs.

7. Conclusion

Research and innovations in neural signal decoding are driving bionic prosthetic control from a science-fiction vision toward practical reality. Ranging from neuronal spikes and field potentials to electromagnetic signals and hemodynamic imaging, multi-scale and multi-modal brain signals and peripheral nerve signals provide rich information sources for controlling prosthetic devices. Through appropriate decoding algorithms, these signals can be transformed into precise control commands for mechanical prostheses, making it possible for paralyzed or amputee patients to control external devices with their thoughts. Moreover, incorporating sensory feedback into the control loop makes prosthetic devices closer to biological limbs in both function and user experience—a qualitative leap forward.

However, each interface modality has its pros and cons, and there is not yet a “universal” solution that meets all requirements for accuracy, real-time responsiveness, stability, and ease of use. For the foreseeable future, researchers will need to continue seeking a balance between performance and practicality. This means, on the one hand, further improving decoding accuracy, reducing control latency, and increasing the controllable degrees of freedom; and on the other hand, ensuring long-term stability and reliability, convenient usability, and minimal burden on the user. Achieving these goals will require concerted progress on multiple fronts: from advances in signal acquisition hardware and the introduction of intelligent decoding algorithms to the integration of multi-modal information and optimization of user training and adaptation processes.

It is foreseeable that future neuroprosthetic systems will no longer be limited to any single interface or algorithm, but will integrate multiple advanced technologies. For example, people may envision comprehensive prosthetic control systems that combine implanted central and peripheral neural interfaces, incorporate AI-assisted decision-making, and provide adaptive sensory feedback—together enabling users to control prosthetic limbs almost as naturally as their original limbs. Realizing this vision will depend on continued breakthroughs in fundamental neuroscience and engineering. Nonetheless, neural decoding is certain to play a pivotal role as the hub of this process: only by accurately reproducing the user's movement intentions and timely conveying feedback from the environment and prosthetic device back to the user can the brain–machine–environment closed loop be truly completed, and the bionic prosthetic become a true extension of the user's body.

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