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State-of-the-Art Myoelectric Control for Prosthetic Hands: Technological Advances and Outstanding Clinical Barriers

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Abstract. Myoelectric control has been a cornerstone of new prosthetic hand development, enabling the world to be drawn towards more natural, personalized, and user-friendly technologies. The latest achievements in pattern recognition, feature extraction, signal acquisition, and machine learning have brought a major improvement to the capability of decoding motor intention based upon surface EMG signals. The high-density EMG arrays, adaptive machine learning algorithms, and neural networks, among others, have all contributed to the highest level of performance of the prosthetic systems with high-level features like real-time responses, multi-degree-of-motion capabilities, making prosthetic systems have more natural grasp patterns and high-quality results of rehabilitation. No matter how successful these technological advances are, there are still significant obstacles to successful clinical implementation. Lack of standard clinical evaluation protocols, signal variability, particularly during daily-life conditions, and electrode movement are still obstacles to its widespread use. This review will provide and summarize the state-of-the-art myoelectric control methodologies, highlighting the new human-advanced myoelectric control approaches which advance the prosthetic capability and functionality, and analyze the barriers of human-factor and placement to real-life application. Future research fields are discussed, including long-term feasibility, reliability, user-friendly design, and better rehabilitation pathways. These issues are important to reduce the divide between clinical and commercially viable solutions of prosthetic hands.

Keywords: Myocontrol, Prosthetic Control, Machine Learning, EMG Signals, Clinical Barriers

1. Introduction

The loss of the upper limb has a great influence on social participation, quality of life and functionality of hands. Millions of amputees, 35-40 million in the world, are currently using prosthetic technologies to restore the basic grasp and manipulation functions, whereas the current prostheses are hard to control and unintuitive to operate and do not have natural movement properties [1]. The rising need for upper-limb prosthetic solutions continues to rise as the recent epidemiological surveys showed evidence of the malformations of the upper limbs, and the amputation of the upper limbs due to vascular diseases [2]. Despite the continued development of commercially available prosthetic hands, which now have many degrees of freedom (DOF),

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enhanced actuation, and natural bionic shapes and designs, there are still limitations in the real-life applications and levels of acceptance [3]. Moreover, the rate of rejection of the prosthetic hand is still about 23 percent, which is mainly caused by dissatisfaction, and lack of functionality, such as poor performance in control, intuitiveness and fluidity [1].

The myoelectric control, which recognizes and deciphers electrical activity in the remaining muscles of the upper limbs in order to move the prosthetic device, has become a main consideration in ensuring human-machine interaction [3]. Surface electromyography (sEMG) came to be known in the 1940s, and the first myoelectric prosthetic apparatus was made in 1960. Within a couple of decades, the technology of sEMG has seen a significant advancement in terms of ability and technical state development. Certain improved features, like proportional control, pattern recognition and decoding motor intention, provide a more user-friendly experience and manipulation [4]. The increased magnitude in the research undertakings during the last 10 years shows an increased interest in the prosthetic hand systems, including detailed control structures [5]. Moreover, in the recent past, myoelectric control has been advanced with new features like high-density EMG arrays, motor unit decomposition, and adaptive deep learning algorithms, among others, which have made myoelectric control viable [6,7].

However, in spite of the very sophisticated achievements in the sphere of prosthetics, there is still a lack of clinical translation and adoption. A notable discrepancy between the good laboratory outcome and the workability in practical applications exists [8]. The experimental results of classification accuracy of EMG fail to match functional performance in real clinical settings. In many cases, laboratory accuracy measures, such as offline tests and tests to measure capability, are overconfident in real life because these metrics are not applicable to daily life [9]. Factually, the socket fit, pressure differences, customization to the user, and other environmental and human factors have a huge impact on clinical performance [10].

This review will analyze the latest state-of-the-art myoelectric control techniques, review the higher technical developments made to enhance the efficiency of their work, and critically analyze the clinical and user barriers that remain persistent and make their use in the field impossible. Combining the developments in engineering and the clinical view is essential in this paper to illuminate the emerging trends and views that could see better solutions to the problem of prosthetics, in addition to the gap between the lab and field practice.

2. Background and foundations of myoelectric control

2.1. Surface EMG physiology and signal characteristics

The signals in surface EMG are the combination of the action potentials of the motor unit, making voluntary contractions of the muscles. Upon the electrodes being placed on the skin surface, they gather composite signals which are affected by the activity of muscle fibers, the displacement of electrodes and other external sources of noise. This means that sEMG is nonlinearly behaved, and it is very vulnerable to noise [10]. Although it is used extensively in laboratory research, poor signal acquisition can result in poor control performance due to fluctuations in user applications, thus limiting its application in clinical practice [11]. Clinical reviews point to the fact that the interpretation of surface EMG is still an issue with which clinicians take on a difficult challenge; the instability of surface EMG remains a major detriment to clinical adoption [12].

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2.2. Amplitude-based threshold control

The simplest and oldest type of myoelectric control is amplitude-based control. In the pattern, the users control the prosthetic functionality like opening the hand or closing the hand, with a frequency higher than the EMG amplitude threshold. It is a relatively strong and computationally cheap method that helped to make it popular among early prosthetic systems. Nevertheless, it can only uphold one degree of freedom at a given time, thus having limited functional performance. These shortcomings are significant causes of dissatisfaction by users of the prosthetic hands, and the scientific analysis of studies on prosthetic hands reveals that the shortcomings are a primary cause of complaints and dissatisfaction by some who use the prosthetic hands [3]. Nevertheless, the increasing demands of the modern prosthesis users are to be much more dexterous and multi-DOF than can be provided by the systems which are based on the amplitude [13].

2.3. Proportional control

Proportional control is better than the threshold-based control system because the EMG signal is viewed as a continuous control signal that controls the speed or force with which the prosthetics move [3]. The intensity of muscular contraction directly controls the output of the actuator. This allows the users to make more natural variations of movement. Nevertheless, mode switching is still required to obtain different gestures, like wrist flexion or extension. According to customer feedback, proportional control can lead to jerky and unintuitive movement and longer training time [14]. Such limitations decrease the urge of an individual user to perform simple tasks or perform everyday opening and closing movements, limiting the functional capacity of the prosthesis.

2.4. Limitations of conventional myocontrol

Notwithstanding the technical improvements made in the last several decades, traditional myoelectric control still has significant challenges that precondition the limitation of its practical work and implementation. Due to the high sensitivity of the surface EMG to the displacement of electrodes, muscle fatigue, and physiological variability [10], reliability problems often occur with amplitude-based and proportional systems. Clinical research has recently demonstrated that instability in these systems necessitates frequent recalibration and poses a greater mental load upon their users [15]. Moreover, classical sEMG designs have very few independent control sites, and this leads to bad natural multi-joint movement [16]. More importantly, sequential mode switching is still slow, non-intuitive [17], and cannot be used with natural multi-DOF control. Moreover, there is also an inexplicable discrepancy between laboratory accuracy and clinical reality performance because the actual usability has been overestimated in offline classification accuracy [8]. These issues accentuate the necessity of more advanced myoelectric control strategies which allow more natural, simultaneous and strong functioning in real-life conditions.

3. Technological advances in myoelectric control

3.1. Multi-degree-of-freedom control

The multi-DOF operation of a prosthetic hand allows facilitating more types of grasps, wrist rotation, and smoother joint actions with the development of the prosthetic hands [3,13]. Several researchers have shown that classical amplitude-based or proportional-based control systems lack scalability as they need the use of a series of systems to alternate between functionalities. As an

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illustration, Segil et al. noted that the performance of multi-DOF and switching-based controllers is different with respect to the scalability limits of sequential control systems [18]. Besides that, the work done by Pilarski proved that multi-DOF control systems have the ability to facilitate smoother and coordinated motion [19]. These results prove that predictive modelling and real-time adaptive learning contribute greatly to the performance of the EMG real-time decoding [20]. This is the secret in obtaining natural multi-DOF control through the application of advanced decoding algorithms, which are able to offer sophisticated signal processing as well as enhanced sensitivity to real-world variability.

3.2. Pattern recognition control (PR control)

Pattern recognition control is also a significant improvement in that it increases intuitiveness and less use of turning models. The pattern recognition-based control signals are obtained from the multi-channel EMG recordings and recognised as the discrete motor intentions [3].

Nonetheless, Vujaklija et al emphasized that offline classification performance does not closely predict the real-world performance [8]. They have noted that in the absence of some evaluation strategies and a clinically meaningful evaluation standard, the results of the laboratory would overestimate actual usability [9]. Hargrove et al. displayed in a randomised clinical experiment an improvement of a statistically significant percent of functional task performance in a pattern-recognition-based control system over a direct control($p<0.05$) [7].

3.3. High-density EMG

High-density EMG measures muscle activity patterns by using electrode arrays to model the patterns of muscle activation located spatially. The technique gives more detailed spatial data in comparison with the use of conventional bipolar electrodes [6]. The review of EMG research indicates that the sphere of research is rapidly expanding with a high number of related studies, which can be explained by its greater resistance to the displacement of electrodes and the increase in the classification ability [6,21]. High-density EMG modes usually provide about 32-128 channels to record signals, whereas conventional system forms of bipolar EMG tend to only use 2-4 electrodes, which enhances spatial resolution and system performance [6].

In addition, high-density EMG research yields finer motor activation maps via advanced spatial filtering. Decoding accuracy of complex tasks is increased with this dimensional enhancement, and this makes it well-near to multi-DOF control. This is, however, still constrained by the complexity of hardware and the high requirements of computation to translate it to clinical prosthetic systems [21].

3.4. Deep-learning-based myocontrol

The most promising phenomenon in recent EMG studies is deep learning. In contrast to the classical myoelectric control systems that are based on artificially formulated characteristics, deep neural networks are automatic in their approach to understanding hierarchical characteristics of EMG using EMG signals [22]. According to the latest reviews, convolutional and recurrent neural networks are more effective than traditional classifiers since they are able to identify temporal and spatial dependencies within genuine EMG signals.

Meanwhile, Hahne et al demonstrated that deep-learning-based models display greater resistance to natural fluctuation, such as slight electrode movements [22]. Simultaneous multi-DOF control implemented by deep learning networks has also been reported to be better than the conventional solutions [7].

3.5. Motor-unit-based control and neural-drive system

Motor unit-level research, in contrast to global EMG amplitude analysis, is getting more and more popular. Neural-driven information is accessible through motor unit resolution, which could be useful in control [6]. Investigations on high-density EMG in the recent past have shown that high-density arrays yield much improvement in motor-unit decomposition, which enables a more accurate estimation of movement and force intention [6].

The neural-drive estimation is now emerging as essential in the process of accomplishing simultaneous and continuous multi-DOF control [23]. In the case of Fougner et al., a multi-grasp control algorithm, combining bio-inspired modelling with EMG decomposition, has better performance, robustness and user adoption [23].

4. Clinical barriers and future direction

4.1. Signal variation and environmental influences

One of the most commonly documented barriers to clinical adoption is the instability of surface EMG signals, caused by signal fluctuations due to perspiration, electrode displacement, variations in skin impedance, and prosthetic socket pressure [10]. These fluctuations lead to unpredictable control behaviour of the prosthetic hand. The clinical evaluation review by Santacaterina et al. indicates that electrode shift and unstable electrode-skin contact constitute primary contributors to poor myocontrol performance in rehabilitation settings, revealing that such variability creates significant barriers that conventional control systems are unable to compensate for effectively [12].

4.2. Mismatch between laboratory and real-world performance

Another barrier to clinical translation is the mismatch between laboratory performance and practical functional outcomes. As revealed by Vujaklija et al., the offline classification accuracy often fails to predict reliable and effective performance in real-world tasks, usually overestimating system capabilities [8]. Laboratory testing is typically conducted under idealized and controlled conditions, such as maintaining a fixed limb position, ensuring stable electrode location, and using short testing intervals, all of which can influence the reported accuracy and may not accurately reflect daily prosthesis usage [15].

The review on motor learning and myoelectric interfaces highlights that natural prosthetic usage factors — including user adaptation, muscle fatigue, and task complexity — are rarely captured by traditional accuracy-based assessments, thereby limiting their clinical relevance [24]. In addition, the everyday prosthesis-use monitoring conducted by Vu et al. further confirms that real-world device usage rates are often lower and more inconsistent than laboratory expectations, underscoring the ecological gap between experimental evaluation and real-world performance [15].

4.3. Lack of long-term standardization and clinical adoption

Besides the technological limitations, systemic barriers within the clinical environment largely restrict the successful implementation of myoelectric prosthetics. The absence of standardized evaluation protocols and variable outcomes over extended periods results in a limitation to clinical

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adoption. The review of active upper-limb prostheses reveals that the outcomes obtained across clinics are difficult to compare due to variability in assessment procedures and device-specific training, thereby constraining the evidence-based adoption of control strategies [13].

Additionally, the bioelectric prostheses overview emphasizes that residual-limb condition and socket-fit variations over time are seldom monitored in experimental studies, despite these factors exerting a substantial influence on EMG signal stability and functional control performance [21]. In terms of human error, some clinicians receive insufficient training with the advanced sEMG system, resulting in inconsistent device setup and non-standardized rehabilitation pathways. As noted by Medved et al., limited education exposure and technical training frequently lead to inappropriate use of sEMG technologies in clinical environments [11]. These gaps in standardization, long-term monitoring, and clinical training all affect the effective integration of the myoelectric prosthetic hand.

4.4. Future directions

Research efforts in the future on control technologies based on EMG must focus on tackling the significant clinical limitations, which include signal variability, limited clinical reliability in practice, and the lack of long-term standardisation. To alleviate the variation of EMG signals due to the movement of the electrode, sweating, and physiological factors, recent works have demonstrated that deep-learning-formed models can boost the functionality of control systems based on learning invariant signal images, thus requiring less frequent recalibration [22]. Long-term monitoring and real-time closed-loop analysis are becoming a more considered and accepted approach to minimize the gap between laboratory performance and application in the field, providing more clinical performance evaluation [15]. Moreover, motor learning principles incorporated in myoelectric control have been demonstrated to improve the level of user satisfaction and achieve greater long-lasting performance [24]. Lastly, it is essential to pay more attention to standardized assessment and functionality during clinical implementation of the newest myoelectric control technology.

5. Conclusion

This review reviewed the latest developments in myoelectric control technology of upper-limb prostheses and described the most important technical developments and barriers to the practical application of these technologies. More traditional myoelectric control strategies, including amplitude modulation and proportional control, offer fundamental and easily available functionality but are limited to signal variations, reduced degrees of freedom, and large cognitive loads. Recent technologies, such as high-density EMG, pattern-recognition systems, deep-learning-based systems, and neural drive estimations, have shown significant gains in decoding accuracy, with more adaptable, multi-degree-of-freedom movements possible. Their feasibility and validity in practice in the short and long-term, however, remain constrained by the unstable nature of the environment and the continuing gap between the laboratory environment and the application of the prosthetic. It therefore follows that further research ought to concentrate on adaptive learning algorithms, multimodal sensing and user-centred design principles to enable better rehabilitation outcomes through offering more stable and intuitively and multi-functional prosthetic performance.

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