Bionic Hand

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Abstract:

This paper presents an integrated approach to improving prosthetic bionic hand control for children, focusing on the challenges of interpreting electromyography (EMG) signals obtained from the MyoWare sensor. By addressing both the biological intricacies of forearm muscle and nerve activities and the application of machine learning techniques for signal interpretation, we aim to develop a more responsive and intuitive prosthetic hand that closely mimics natural hand movements.

Note that this paper is the independent work of the author, developed for personal understanding and to systematically compile research on enhancing prosthetic bionic hand control. It remains a work in progress, with updates planned as new findings emerge. The project is expected to be completed by April 2024, reflecting ongoing advancements.

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CHAPTER I

INTRODUCTION

1.1 Outline

The context for the Bionic Hand project is set against the backdrop of an urgent global need for affordable prosthetic technologies, especially for children in economically disadvantaged regions. High costs and technical limitations significantly restrict the functionality and accessibility of prosthetic hands. The motivation stems from a desire to bridge this gap by leveraging innovative solutions and advanced software algorithms, making efficient, cost-effective prosthetic hands a reality for children worldwide, fostering inclusivity and community support.

1.2 Background

In our venture at "Give A Hand," my team and I are revolutionizing prosthetic technology for children by creating an affordable, high-functioning bionic hand for under $70. This initiative not only makes advanced prosthetics accessible to families globally, such as in regions like Mexico and Saudi Arabia, but also sets a new benchmark in compassionate engineering. Our multidisciplinary team leverages the latest in software and hardware integration, employing innovative design principles such as Dielectric Elastomer Actuators (DEAs). These actuators, utilizing a thin polymer film coated with compliant electrodes, exemplify revolutionary advancements in artificial muscle technology. By applying a voltage difference, we induce electrostatic pressure, enabling precise movement and mimicking the natural motion of human hands. Our fabrication process, made for efficiency, incorporates monolithic and folded actuator designs to enhance performance while simplifying production. This project embodies our commitment to giving back, inspiring change, and fostering inclusivity in technological development.

1.2.1 Objectives

Address the significant challenge of signal noise in prosthetic bionic hands, thereby enhancing the efficiency and functionality of the device. By innovating a cost-effective solution that reduces production expenses, we aim to make advanced prosthetic technology accessible worldwide. This endeavor not only seeks to refine electromyography (EMG) signal interpretation through advanced software algorithms and machine learning integration but also to inspire a broader impact on community aid and technological inclusivity in prosthetic development.

CHAPTER II

BIOLOGICAL INSIGHTS

The control of a prosthetic hand through signals detected in the forearm involves understanding the biological processes behind muscle activation and the generation of electromyographic (EMG) signals.

2.1 Section

The forearm contains a complex arrangement of muscles and nerves. When a person decides to open or close their hand, the brain sends signals through the nervous system to the muscles in the forearm. This process involves several key steps with the first being motor cortex activation.

Motor cortex activation, (MCA), involves the decision to move the hand which originates in the motor cortex of the brain. This area of the brain generates neural impulses that travel down the spinal cord to the peripheral nerves that innervate the forearm muscles.

The next step in the process involves neural transmission. The neural impulses, or action potentials, are electrical signals that travel along motor neurons. These motor neurons exit the spinal cord and branch out through the peripheral nervous system to the specific muscles involved in hand movements.

The neural impulses reach the neuromuscular junctions, which are the interfaces between motor neurons and muscle fibers. The arrival of an action potential at the neuromuscular junction triggers the release of neurotransmitters, specifically acetylcholine, into the synaptic cleft (the gap between the neuron and the muscle fiber).

The acetylcholine binds to receptors on the muscle fiber's surface, leading to a series of biochemical events that result in the muscle fiber's depolarization. This depolarization, if strong enough, triggers an action potential in the muscle fiber itself.

The muscle fiber's action potential initiates the sliding filament mechanism, causing the muscle to contract. This contraction pulls on tendons connected to the bones of the hand, leading to movement (either opening or closing the hand, depending on which set of muscles is activated).

The electrical activity generated during muscle contraction can be detected on the skin's surface as electromyographic (EMG) signals. The MyoWare sensor and similar devices detect the electrical activity associated with muscle contractions through a process known as electromyography (EMG).

EMG works in the context of detecting hand movements in a specific way. When a muscle fiber contracts, it generates electrical signals that propagate along the muscle and can be detected on the skin's surface. These signals are the sum of the action potentials from numerous muscle fibers within the muscle.

The MyoWare sensor, placed on the skin over the muscles of the forearm, detects these electrical signals. The sensor essentially captures the voltage changes caused by the underlying muscle fiber action potentials. The strength and pattern of these signals can indicate which muscle is contracting and how forcefully.

However, the forearm's muscles are layered and interwoven, making it a complex area for signal detection. Movements like opening and closing the hand involve multiple muscles, each contributing to the overall EMG signal. Additionally, the signal can be affected by factors such as sensor placement, skin conductivity, and external noise, complicating the interpretation of the data.

Understanding these biological and physiological processes is fundamental to improving prosthetic control systems. By integrating knowledge of muscle activity and neural control mechanisms with advanced signal processing and machine learning techniques, we plan to create more responsive and intuitive prosthetic devices that better mimic natural hand movements.

CHAPTER III

SIGNAL ACQUISITION AND PROCESSING

This section will detail the methodologies and technologies involved in capturing EMG signals, focusing on non-invasive techniques used for prosthetic control. It will discuss the importance of sensor placement, the types of electrodes used (surface vs. intramuscular), and the preprocessing steps necessary to obtain clean and usable signals for machine learning algorithms.

3.1 EMG Signal Acquisition Techniques

Electromyography (EMG) is a diagnostic procedure to assess the health of muscles and the nerve cells that control them. It has also found extensive application in controlling prosthetic devices, including bionic hands, by translating electrical signals from muscles into commands to move the prosthetic. The acquisition of these signals is a critical first step in the process, requiring precise techniques and technologies to ensure accuracy and reliability.

Surface EMG involves the use of electrodes placed on the skin overlying a muscle to detect the electrical activity of the muscle. This non-invasive method is preferred for prosthetic control due to its simplicity and ease of use. The sEMG sensors, such as the MyoWare sensor, are designed to pick up the electrical signals generated by muscle fibers during their contraction. These sensors are highly sensitive to changes in voltage that occur when muscle fibers are activated. For prosthetic applications, the placement of these sensors is crucial. They are typically positioned over the muscle groups that show the strongest signal during intended movements, such as flexing or extending the hand.

While less common in prosthetic control due to their invasive nature, intramuscular EMG techniques involve inserting a needle electrode directly into muscle tissue. This method provides a more direct measurement of muscle activity and can be useful in detailed clinical diagnostics or when surface EMG does not yield clear enough signals. However, its application in prosthetics is limited by the discomfort and the need for professional installation.

The effectiveness of EMG signal acquisition heavily relies on the technology of the sensors used and their placement on the body. Sensors must have high sensitivity and the ability to filter out noise from external sources, such as electrical equipment or other muscles' activity. Advanced materials and design innovations have led to the development of flexible, lightweight sensors that can conform to the skin, reducing artifacts from movement and improving signal quality. Proper sensor placement is determined through anatomical study and empirical testing to find the locations that provide the most robust signals for the intended movements.

Once acquired, the raw EMG signals undergo conditioning to improve their clarity and usefulness for control algorithms. This process typically involves amplification, to make the signals strong enough for processing, and filtering, to remove noise and artifacts that are not part of the muscle's electrical activity. Band-pass filters are commonly used to exclude signals outside the frequency range typical of human muscle activity, which is generally between 20 Hz and 500 Hz.

3.1.1 Noise Reduction and Signal Enhancement

An important aspect of EMG signal acquisition for prosthetic control is the calibration of the system to the individual user. Muscle strength, skin conductivity, and other factors can vary significantly between individuals, affecting the quality and characteristics of EMG signals. Calibration involves recording signals from the user during specific muscle movements to establish a baseline for interpreting future signals. This process may also include personalizing the control algorithms to match the user's unique physiology and movement patterns, enhancing the responsiveness and accuracy of the prosthetic device.

EMG signal acquisition is a multifaceted process that forms the foundation of effective prosthetic control. Advances in sensor technology, signal processing, and machine learning have made it possible to translate the intentions of the user into precise movements of a bionic hand, offering new levels of functionality and freedom to individuals with limb loss.

3.2 Real-time Signal Processing Algorithms

When it comes to real-time signal processing, especially for applications like prosthetic control using EMG data, the goal is to achieve the highest possible accuracy in the interpretation of muscle signals. However, EMG signals are notoriously noisy, subject to interference from various sources including electrical noise, motion artifacts, and physiological factors like sweating. To address these challenges, especially in a resource-constrained environment like a Raspberry Pi, efficient algorithms and techniques can be employed to enhance signal quality before feeding it into machine learning models for prosthetic control. Python, with its rich ecosystem of scientific computing libraries, serves as an excellent platform for developing these algorithms.

Details on Noise Reduction and Signal Enhancement Techniques

The first step in processing EMG signals in real time is to apply filters that can reduce noise without significantly delaying the signal. High-pass, low-pass, and band-pass filters are standard tools used to eliminate frequencies that don't contain useful information. For instance, a high-pass filter can remove motion artifacts, which are typically low-frequency, while a band-pass filter can be configured to only allow frequencies within the expected range of EMG signals (usually between 20 Hz to 500 Hz).

In Python, the scipy.signal library can be used to implement these filters efficiently. For example, a Butterworth band-pass filter can be designed and applied to the data to retain only the frequency components of interest.

An additional technique could involve adaptive filters. Adaptive filters adjust their parameters in real time to dynamically respond to changes in the signal's noise characteristics. This is particularly useful for EMG signals, where the noise can vary widely depending on the user's movement and environment. The Least Mean Squares (LMS) algorithm is a common choice for adaptive filtering, due to its simplicity and effectiveness in many scenarios.

Wavelet transform provides a way to analyze the signal at various frequencies with different resolutions. It is particularly effective for non-stationary signals like EMG. Wavelet denoising involves decomposing the signal into wavelet coefficients, thresholding these coefficients to remove noise, and then reconstructing the signal. This method can effectively remove transient noise while preserving the sharp features of the EMG signal.

3.2.1 Machine Learning for Signal Quality Improvement

Machine learning models can be trained to detect anomalies in the EMG data, identifying segments that are too noisy to be useful. Once identified, these segments can either be discarded or subjected to further processing to try and salvage useful information. Techniques such as autoencoders, trained on clean EMG signals, can recognize when an input signal deviates significantly from the norm.

Before feeding EMG signals into a machine-learning model for prosthetic control, it's crucial to extract features that effectively represent the signal's characteristics. Features in both time and frequency domains, such as mean absolute value, waveform length, zero crossings, and power spectral density, can be calculated in real time. Machine learning algorithms can then be used to select the features that are most relevant for predicting the intended movement, reducing the dimensionality of the data and improving model performance.

For the actual control of the prosthetic, machine learning models can be trained to map the processed EMG signals to specific movements. For our specific task, we plan to explore Support Vector Machines (SVM), Random Forests, and Neural Networks. Specifically, these models can be made more robust against noisy data by training them on a diverse dataset that includes examples of noisy signals, effectively teaching the model to recognize the underlying patterns even in suboptimal conditions.

The Raspberry Pi, with its GPIO capabilities and support for Python, is a suitable platform for deploying real-time EMG signal processing and machine learning algorithms. However, we recognized that due to its limited computational power compared to a desktop computer, it's important to optimize the algorithms for efficiency. Perhaps this might involve simplifying models, reducing feature dimensionality, and implementing real-time data processing pipelines that minimize latency.

Libraries such as NumPy and SciPy can be used for signal processing, while scikit-learn and TensorFlow Lite offer machine learning capabilities that are optimized for performance on low-power devices. TensorFlow Lite, in particular, is designed to run lightweight deep learning models on edge devices like the Raspberry Pi, providing a balance between computational efficiency and predictive performance.

CHAPTER IV

MACHINE LEARNING FOR PROSTHETIC CONTROL

Work in progress (Coming soon as we advance more!)

4.1 More sections

4.2 More sections

4.2.1 Another subsection

REFERENCES

APPENDICES

Title of Appendix (Not Numbered)