Report :

Electromyography (EMG):

EMG : Electromyography (EMG) is a physiological technique used to measure and record the electrical activity produced by skeletal muscles. It provides valuable information about muscle function, activation patterns, and neuromuscular control. EMG is widely employed in various fields, including clinical medicine, sports science, rehabilitation, and human-computer interaction.

The principle of electromyography (EMG) revolves around the electrical activity produced by muscles during contraction and relaxation. When a muscle is activated, it generates electrical signals known as action potentials. Muscles are composed of individual muscle fibers that contract in response to signals from the nervous system. The nervous system sends electrical impulses, called motor unit action potentials, to stimulate the muscle fibers to contract. These action potentials are initiated by motor neurons located in the spinal cord or brain, which transmit electrical signals along the nerve fibers to the muscle fibers they innervate.

During an EMG procedure, electrodes are placed on or inserted into the muscle being examined to detect and record these electrical signals. There are two types of electrodes commonly used in EMG:

Surface electrodes: These are adhesive electrodes placed on the skin overlying the muscle of interest. They detect the electrical activity on the surface and are commonly used for superficial muscles. Surface electrodes are non-invasive and relatively easy to apply.



**EMG signal process recommended. Green: The raw signal, no treatment was applied until this moment; Red: Filtrated signal, a limit was created for the signal, excluding everything out of it; Blue: Rectified signal, all negative values were transformed in positive ones and added; Purple: the smoothed signal, a linear enveloped was created and the extreme parts of the signal was excluded; Black: The RMS values after all the treatments**.

Needle electrodes: These are thin, needle-like electrodes that are inserted into the muscle. They provide a more direct measurement of the electrical activity within the muscle fibers. Needle electrodes are used for deeper muscles and can provide more detailed information about specific muscle groups.

When the muscle contracts, the action potentials generated by the muscle fibers propagate through the surrounding tissues and can be detected by the electrodes. The electrodes pick up the electrical signals and transmit them to an amplifier, which amplifies the weak electrical signals to make them easier to analyze. The amplified signals are then displayed on a screen or recorded on a computer. They are typically represented as waveforms or graphs, with the vertical axis indicating the amplitude of the electrical activity and the horizontal axis representing time. These waveforms show the pattern and characteristics of the electrical signals generated by the muscle. By analyzing the recorded signals, healthcare professionals can evaluate various parameters such as the amplitude, duration, shape, and frequency of the action potentials. These parameters provide valuable information about the health and functioning of the muscles and the nerves controlling them. Abnormalities in the EMG signals can indicate muscle or nerve damage, neuromuscular disorders, or other pathological conditions.

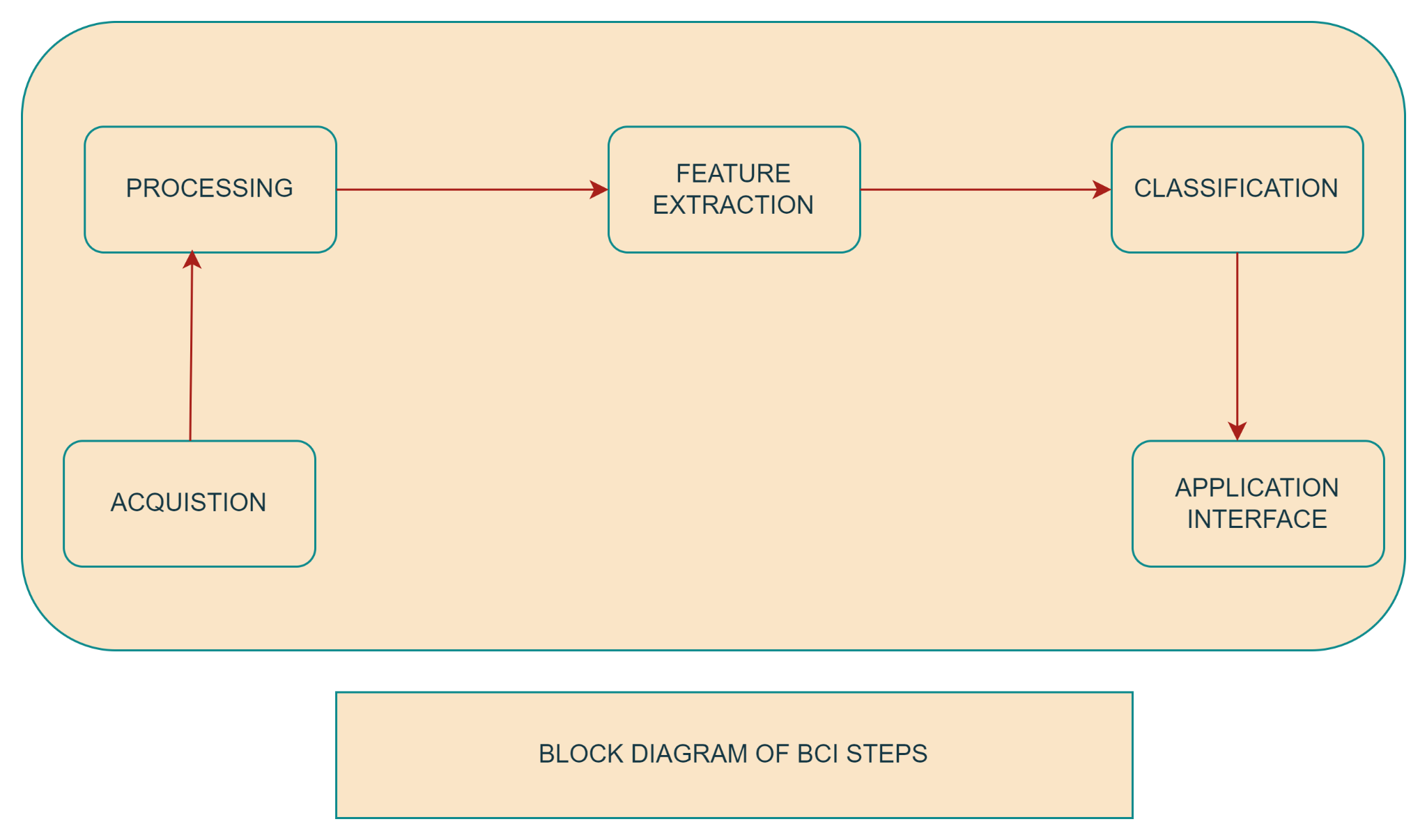
sEMG signals can be explained in terms of a rainbow analogy. Most know that a rainbow appears when the sunlight hits the raindrops. The sunlight, also known as white light, is made up of several components. These components are other types of light, which are red, orange, yellow, green, blue, violet, and indigo. The combination of these seven lights produces sunlight. When the sunlight hits a raindrop, the raindrop reflects the components of sunlight differently, and that makes them visible to the human eye. We see the rainbow, the seven lights that make up the sunlight. sEMG signals, like sunlight, consist of many components put together. These components are other electrical signals. The different sunlight components are identified by a measurement called wavelength. sEMG components are identified by frequency, which is measured in Hertz (Hz). Various academic studies have shown that the sEMG frequency of its combined components ranges from 20 to 450 Hz. 20 to 500 Hz , 30 to 400 Hz , or 40 to 450 Hz. In most research, it is standard to assume the 20 to 500 Hz range. Unfortunately, when electrodes measure sEMG, they might also pick up noise signals. For instance, if an electrode is not firmly attached on the arm, the electrode will move against the arm, creating another action potential. This type of noise is referred to as motion artefact, and it is made up of components with frequency below 20Hz , which can be separated from sEMG. Another common type of noise is called power line interference, an electrical signal generated by the interaction between nearby electrical devices and the electrodes. Unlike motion artefact, the components of this noise have frequencies that are approximately multiples of 60 Hz. Since these components and sEMG directly overlap, they are much harder to separate from each other. The industry has dedicated a lot of research to learn how to separate noise signals from sEMG signals. The second most common characteristic of an sEMG signal is its strength. For example, the strength of sunlight is measured by its intensity. Since, sEMG is an electrical signal, we use voltage, the most common measurement, to determine sEMG strength. Just as intensity of sunlight can vary, so can the strength of an sEMG signal. Research shows that typical peak strength of sEMG is anywhere from a few tens of micro-Volts (µV) to 1 or 2 milli Volts (mV), 0 to 6mV, and even as high as 10 mV.The electricity strength needed to charge an iPhone is 5 Volts. Thus, for researchers to have the ability to analyze an sEMG signal, its strength needs to be increased by using a circuit device called an amplifier. This device has very specific hardware requirements such that it does not add noise to the electrode measurement.



The human body as a whole is electrically neutral; it has the same number of positive and negative charges. But in the resting state, the nerve cell membrane is polarized due to differences in the concentrations and ionic composition across the plasma membrane. A potential difference exists between the intra-cellular and extracellular fluids of the cell. In response to a stimulus from the neuron, a muscle fiber depolarizes as the signal propagates along its surface and the fiber twitches. This depolarization, accompanied by a movement of ions, generates an electric field near each muscle fiber. An EMG signal is the train of Motor Unit Action Potential (MUAP) showing the muscle response to neural stimulation. The EMG signal appears random in nature and is generally modeled as a filtered impulse process where the MUAP is the filter and the impulse process stands for the neuron pulses, often modeled as a Poisson process . Figure 2 shows the process of acquiring EMG signal and the decomposition to achieve the MUAPs.

BCI using EMG:

Surface electromyography (sEMG) has emerged as a transformative component within Brain-Computer Interface (BCI) systems, offering a multi-faceted array of applications. One pivotal use lies in gesture recognition, where sEMG captures the intricate electrical signals spawned by muscle activity during specific hand and finger movements. The resultant patterns of muscle activation become the language through which BCIs decipher gestures like grasping, pointing, or clenching, effectively enabling users to intuitively interact with devices and virtual realms. Another groundbreaking realm for sEMG within BCIs is prosthetic limb control. Among individuals contending with limb amputations or congenital differences, sEMG unveils a natural avenue for governing artificial limbs. By translating users' intended movements into sEMG signals, BCIs orchestrate these signals into commands that seamlessly guide prosthetic motions. This breakthrough empowers users to execute intricate maneuvers, significantly elevating their quality of life and self-reliance. Beyond this, the integration of sEMG into assistive technologies resonates profoundly for those with motor disabilities.

These systems ingeniously decode specific muscle movement signals, thereby endowing users with mastery over computers, smartphones, robotic appendages, and wheelchairs. This fusion seamlessly enhances engagement with surroundings and bolsters independent daily functioning. Delving into the realm of virtual reality (VR) and gaming, sEMG ushers in a new dimension of immersion. Through mirroring real-world gestures, users can manipulate virtual avatars with astonishing authenticity. This dynamic inclusion amplifies the sense of presence and interactivity, revolutionizing the user experience. In the sphere of rehabilitation and physical therapy, sEMG wields its prowess by seamlessly guiding patients through exercises. Real-time feedback from BCIs ensures accurate muscle group activation, thereby expediting the recuperation process for those grappling with motor impairments.Moreover, sEMG's role extends to biofeedback and relaxation exercises, where it gauges muscle tension levels, enabling users to tangibly sense their stress and relaxation states. This biofeedback proves invaluable in stress management and relaxation training, where individuals cultivate the ability to modulate muscle tension, fostering a serene and composed state.

Collectively, sEMG's integration into BCI systems holds the potential to reshape diverse domains, ranging from medical rehabilitation to cutting-edge technological experiences. The intricate dance of electrical signals from our muscles not only propels human-computer interaction to new heights but also amplifies the quality of life for individuals navigating motor-related challenges.

State-of-Art Techniques:

Surface Electromyography (sEMG) has emerged as a powerful and non-invasive technology for gesture recognition in human-machine interfaces. In this literature review, we have thoroughly examined 20 selected research papers to gain comprehensive insights into the advancements and key findings in the field of sEMG-based gesture recognition.

Preprocessing of sEMG signals plays an important role in enhancing signal quality and reducing noise. Several studies have focused on applying various techniques such as filtering and normalization to improve the robustness of sEMG data. This step is crucial in ensuring accurate and reliable gesture recognition results. Feature extraction methods have been extensively explored to capture relevant information from sEMG data. Time-domain, frequency-domain, and time-frequency domain analyses have all been investigated to extract discriminative features that can effectively represent different hand movements. In recent years, surface electromyography (sEMG) has gained significant attention in the field of human-machine interaction, particularly for hand gesture recognition. Researchers have proposed various methodologies to effectively decode hand movements from sEMG signals, enabling applications such as myoelectric prosthetic control, human-computer interfaces, and mixed reality environments. This review examines 20 papers that present innovative approaches for sEMG-based gesture recognition.Among the studies,B. Sun et al[1]The proposed method fuses the spatiotemporal characteristics of the EMG signal with different scales and constructs the feature channel attention module and the feature spatial attention module to capture more key channels features and more key spatial features. The MSFEnet is capable of extracting temporal and spatial fused features and performs well in generalization with higher classification accuracy compared to state-of-the-art methods. A. Gautam et al. [3] introduced the Low-Complex Movement recognition-Net (LoCoMo-Net), a deep learning framework with low complexity that accurately classifies wrist and finger flexion movements, grasping, functional movements, and force patterns. S. Duan, L. Wu, B. Xue, A. Liu, R. Qian and X. Chen [7] proposed the HyFusion model, a lightweight hybrid fusion approach that combines sEMG and accelerometer signals, achieving state-of-the-art performance in recognizing hand gestures. Y. Ma, B. Chen, P. Ren, N. Zheng, G. Indiveri and E. Donati[10] explored a neuromorphic approach with delta-encoding methods and spiking recurrent neural networks, achieving robust decoding for robotic arm/hand systems and virtual prosthesis applications.K. S, J. P. Sahoo and S. Ari[14]aims to create a system that recognizes hand gestures using muscle signals. It uses 1d cnn to automatically extract useful information from the signals, making the system more accurate.They tested the system on a database of different hand gestures and achieved good results. D. Yang and H. Liu [15] developed an AI-based framework using deep learning approaches, including CNNs, for precise and robust decoding of 3D wrist movements from sEMG signals, showing potential in real-life applications.A. Neacsu, J. -C. Pesquet and C. Burileanu[17] focused on controlling the Lipschitz constant of a feedforward neural network using spectral norm and nonnegativity constraints to improve robustness against adversarial perturbations in sEMG signals. E. Rahimian, S. Zabihi, A. Asif, D. Farina, S. F. Atashzar and A. Mohammadi[18] presented the FS-HGR architecture, a Few-Shot learning method for hand gesture recognition, addressing the challenge of limited training data and achieving high accuracy. M. F. Qureshi, Z. Mushtaq, M. Z. U. Rehman and E. N. Kamavuako[19] introduced the E2CNN model for upper limb gesture recognition using Log-Mel spectrograms and concatenation layers. It demonstrated excellent performance with reduced training and prediction times, making it suitable for real-time applications. C. Lin, X. Chen, W. Guo, N. Jiang, D. Farina and J. Su [20] proposed a BERT-based approach for predicting hand movements from sEMG signals, leveraging Bidirectional Encoder Representation from Transformers for high performance in within-subject and cross-subject evaluations.

Dataset used and the application area of modality.

The NINAPRO (Non-Invasive Adaptive Prosthetics) database is a comprehensive resource developed to advance the field of naturally controlled robotic hand prosthetics. Its primary goal is to provide a benchmark dataset for research groups worldwide to develop and test movement recognition and force control algorithms for robotic hand prosthetics using surface electromyography (sEMG) data.

Database Contents: The NINAPRO database includes data from both intact and amputated subjects performing approximately 50 different hand, wrist, and forearm movements. The data are divided into three databases, each with slightly different sensor configurations:

1. Database 1: Contains data acquisitions from 27 intact subjects.
2. Database 2: Contains data acquisitions from 40 intact subjects.
3. Database 3: Contains data acquisitions from 11 trans-radial amputated subjects.

Database 2 in the NINAPRO dataset is one of the most commonly used databases, and it provides a rich collection of surface electromyography (sEMG) data from intact subjects.

Data Acquisition Setup:

The NINAPRO acquisition setup includes various sensors to record hand kinematics, dynamics, and sEMG data. The hand kinematics are measured using a CyberGlove II data-glove with 22 sensors, which detects hand movements through high-accuracy angle measurements. An inclinometer fixed on the wrist measures its orientation. Hand dynamics are measured using a Finger-Force Linear Sensor (FFLS), which uses strain gage force sensors to measure forces exerted by the fingers. Muscular activity is measured using two configurations of double differential sEMG electrodes, which sample the raw sEMG signal at different rates and provide rectified versions of the signal.

Acquisition Protocol:

The subjects perform specific movements while data are recorded from the sensors. The experiment is divided into one training part and three exercises that address different types of movements. During kinematic acquisitions, intact subjects mimic predefined hand movements shown on a screen, while amputated subjects attempt to mimic the same movements using their missing limb. During dynamic acquisitions, subjects repeat several force patterns by pressing with one or more hand digits on the force sensor.

The subjects are asked to mimic movies of movement shown on the screen of the laptop. The sEMG signal is recorded through up to 12 electrodes and can be used to test methods to control robotic hand prostheses naturally (the electrode on the flexor digitorum superficialis is not represented due to perspective reasons).

Signal processing

Several signal processing steps were performed before making data publicly available on the repositories (Data Citations 1 and 2). These steps included synchronization, relabelling and (for the Delsys electrodes) filtering. The raw data are available upon request.

Synchronization

high-resolution timestamps were used to synchronize the data streams. Specifically, all streams were super-sampled to the highest sampling frequency (2 kHz or 100 Hz, depending on the used sEMG electrodes) using linear interpolation (real-valued streams) or nearest-neighbour interpolation (discrete streams).

Relabelling

The movements performed by the subjects may not perfectly match with the stimuli proposed by our software due to human reaction times and experimental conditions. The resulting erroneous movement labels have been corrected by applying a generalized likelihood ratio algorithm34 offline, which realigns the movement boundaries by maximizing the likelihood of a rest-movement-rest sequence. Both the original labels and the new labels are included in the files.

Filtering

The Delsys electrodes are not shielded against power line interferences, which can affect the recoded signal in particular cases. Therefore, prior to synchronization, the Delsys sEMG signals were cleaned from 50 Hz (and harmonics) power-line interference using a Hampel filter34.

The data produced through specific methods have been stored Ninapro .The Ninapro repository is the official platform for the data related to the Ninapro project, allowing users to upload classification results and details about the classification procedure. The data are in Matlab format and include variables such as subject and exercise identifiers, sEMG signals, acceleration values, Cyberglove sensor data, inclinometer values, stimulus and restimulus labels, repetition indices, force values, and maximal force values.

The modality of data stored in the Ninapro repositories, which includes synchronized variables such as surface electromyography (sEMG) signals, acceleration data, Cyberglove sensor data, and force values, holds significant application potential in various fields. One prominent application area is in the field of human-computer interaction and assistive technology. The sEMG signals captured from electrodes around the forearm can be utilized to decode the user's intended movements, enabling the development of advanced prosthetics, exoskeletons, and wearable devices that respond directly to the user's muscle activity. This technology has the potential to greatly enhance the quality of life for individuals with physical disabilities by restoring or augmenting their motor functions.The data's use in gesture recognition systems can revolutionize virtual reality and gaming experiences. By interpreting the sEMG signals and Cyberglove sensor data, these systems can detect and translate hand and finger movements into corresponding actions within the virtual environment, allowing for more intuitive and immersive interactions.The medical field can also benefit from this modality. The analysis of sEMG signals can aid in the assessment and treatment of neuromuscular disorders, providing valuable insights into muscle function and abnormalities. Researchers and clinicians can use this data to design personalized rehabilitation programs and monitor patients' progress over time.Additionally, the combination of sEMG data with other physiological parameters, such as accelerometry and force values, can be applied in sports science and performance monitoring. Athletes' muscle activation patterns, joint movements, and force exertion during various exercises and activities can be analyzed to optimize training regimens, prevent injuries, and enhance athletic performance.

Link of the Dataset:

https://ninapro.hevs.ch

Advantages, Challenges and Future Scope.

Electromyography (EMG) modality offers several distinct advantages. Firstly, EMG is a non-invasive technique, which involves placing surface electrodes on the skin to record muscle electrical activity. This non-invasiveness makes EMG comfortable and user-friendly, particularly for long-term monitoring and real-life implementation of prosthetic control. The reduced risk of infections or complications associated with invasive procedures ensures the safety of users. Secondly, EMG provides fine muscle activity detection, allowing for precise and detailed control of prosthetic devices. The ability to capture subtle muscle contractions enables users to perform delicate and coordinated movements in their daily activities, enhancing their overall quality of life. This fine-grained control also proves valuable for tasks that require real-time responses, such as grasping objects or typing on a keyboard. Moreover, EMG-based prosthetic control demonstrates a wide range of applications, catering to individuals with different levels of limb amputations. From partial hand amputations to full-arm amputations, EMG has shown to be effective in assisting users with diverse needs. This versatility ensures that a larger population of amputees can benefit from EMG-based prosthetics, enhancing their mobility and independence.EMG systems can be designed to be portable and wearable, allowing users to integrate them seamlessly into their daily lives. The portability aspect ensures that the prosthetic devices can be easily carried and used anywhere, promoting user mobility and convenience. EMG can be implemented with a relatively compact setup, minimizing any hindrance to the user's movement.

While EMG (Electromyography) modality for prosthetic control shows great potential, it also faces several challenges that need to be addressed for its successful implementation. One of the primary challenges is the inherent variability of EMG signals among individuals, which can make it difficult to develop a one-size-fits-all solution. Signal processing techniques must be robust enough to adapt to different users and provide consistent and accurate control. Another challenge is the need for reliable long-term signal stability. EMG signals can change over time due to factors such as muscle fatigue, electrode shifting, and changes in tissue impedance, leading to signal degradation and less effective control. Finding ways to maintain signal stability over extended periods is critical. Additionally, the coexistence of other electrical signals in the body, such as ECG and EEG, can interfere with EMG signals. Cross-talk from neighboring muscles can also affect signal specificity. Advanced noise reduction techniques and multi-modal signal separation methods are required to address these challenges effectively. Moreover, the size and bulkiness of traditional EMG systems can be inconvenient for users, limiting their daily usage. Finding ways to miniaturize EMG sensors and systems will make them less obtrusive and more practical for everyday wear. Lastly, the cost of EMG technology can be prohibitive for some individuals, and accessibility remains a challenge. Research efforts should focus on cost reduction while maintaining the quality and functionality of EMG systems.

The future of EMG (Electromyography) modality for prosthetic control holds great promise for advancements and improvements. Future research can focus on developing more sophisticated signal processing techniques, including deep learning approaches, to enhance the accuracy and reliability of EMG signal interpretation. Improving pattern recognition capabilities could lead to more intuitive and versatile prosthetic control. Long-term signal stability and user adaptation challenges could be addressed through innovative solutions, while integrating sensory feedback into EMG-controlled prosthetic limbs can significantly enhance the user experience. Miniaturization and collaboration with prosthetic manufacturers can make EMG systems more wearable and accessible. Real-world testing, hybrid modalities, and efforts to improve affordability and accessibility will be crucial for widespread adoption.

Summary

In this report, we discussed EMG (Electromyography) as a modality for prosthetic control, based on information from 20 paper. EMG is a promising technology that involves recording electrical signals produced by muscles to control prosthetic devices. The advantages of EMG modality include its intuitive control, allowing users to perform natural movements with prosthetics. EMG-controlled prosthetics offer fine motor control and the ability to perform various grasp patterns, enhancing the user's overall dexterity. The modality also enables real-time control, immediate response, and the potential for multi-degree-of-freedom control.

However, several challenges exist in the implementation of EMG for prosthetic control. These challenges include the variability of EMG signals among individuals, the need for long-term signal stability, user training and adaptation, interference from other electrical signals, and the size/bulkiness of traditional EMG systems. Providing sensory feedback and ensuring the accessibility of EMG technology are also significant challenges.

Despite these challenges, the future scope of EMG modality appears promising. Researchers are actively exploring advanced signal processing techniques, machine learning algorithms, and neural networks to improve EMG signal decoding. Additionally, there is ongoing work to develop lightweight, portable, and more user-friendly EMG systems. Future research aims to address the challenges and refine EMG technology, making it more robust, reliable, and accessible for a wider range of users.

Overall, EMG modality holds considerable potential in revolutionizing the field of prosthetic control, offering greater independence and improved quality of life for individuals with limb loss or limb impairment. Continued research, development, and innovation in this field will play a vital role in unlocking the full capabilities of EMG for prosthetic applications.

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