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Prosthetic Hand Control Using EMG Signals

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Annotation: An amputee's ability to control a prosthetic limb is greatly hampered if the limit function of data transmission does not match the required transfer function of data reception. Robust and intuitive control of prosthetic hands is currently provided by remote control systems that utilize teleoperated master-slave configurations. Such systems are just as much a limitation to an amputee's freedom as they are an important step towards the integration of neuroscience and robotics. To replace a lost hand or to control a prosthetic hand intuitively, the prosthetic hand must follow the same input signals that a natural hand can understand. To create a prosthetic limb that mimics a human hand, the input signals that would yield analogous motion must be identified. Natural hand movement is a result of intricate, parallel neural processes alongside an exceptionally vast network of multiplexed control signals reaching forearm muscle motor units. Functional hand movement results from the grouping and varying of synergistic finger actuator signals at the minutiae of the unit level. The forearm is inhabitable for any type of invasive robotic mechanism. A hand prosthesis requires a compact and low-cost alternative to the embedded actuators and sensors that crowd the forearm. Understanding the anatomy of the forearm is crucial to a non-invasive, compact, and low-cost system.

The action of group finger motion frequency is embedded in the finger's fundamental natural movement. Fractionature further groups the buttons to uninhibited motion. The robust mechanical behavior of this granular action provides varying level control throughout a large motion range. Understanding the properties of signal redundancy can yield a compact, low-cost sensor network. Utilizing low-cost sensor alternatives to develop a rapid, low-resolution grasp detector can yield component-level behavior patterns. Coarse-to-fine control is the opposite of traditional approaches; one would first control the global motion and then move down to the minutiae. Simulating finger motion is very useful for designing the prosthetic hand and prior experimentation. With basic control and motions simulated, control algorithms could be verified once the sensors were placed on a physical body.

1. Introduction

With the high incidence of amputators caused by various factors, prosthetic hands are widely used in disabled rehabilitation. Most commercial prosthesis is controllable by non-invasive surface electromyography (sEMG) which can be measured on remnant muscles through skin either over the amputation side or contralaterally [1]. There mostly exists one-to-one correspondent biological control movement and control channels of the sEMG signals for posture estimation control (open/close all fingers). And the robust and real-time posture control can be realized through bio-signal classifier (sEMG pattern recognizer). But for current multifunctional hand prostheses, the underactuation and also intention modulation control is indispensable. The available modes for hand pre-grasping posture preset of the user's demand and intention. And the available modes are also a sub-group of the grasp grasping postures the user needs. Extensive sEMG worked on doming and also finger opening and closing for hand pre-grasping control. But constructing a powerful grasp set of grasping postures from continuous residues of constructed sEMG patterns for robust intention modulation presented control is challenging.

To provide an estimate of the generated grasping force during object grasping task in prosthetic hands control [2]. It is crucial for the grip control of a prosthetic hand and the safety exploration of objects. Real-time prediction to the grasping force with adequate feature signals and robust model is still challenging. Eight-channel raw sEMG signals measured on the user's forearm for prediction modeling and vibration feedback device quantifying predicted grasping force feedback to the user's elbow. To improve the health rehabilitation and control performance of the prosthetic hand, a novel two-stage architecture is powered for this purpose: the dimension reduction of sEMG signals is performed at the signal preprocessing stage and the subsequent feature learning and force prediction is jointly achieved at the model prediction stage.

2. Background and Motivation

It has been well established that the EMG of the remnant forearm muscles, following amputation of the hand or a central injury resulting in upper limb paralysis, provides a possible manner to achieve control. The approach considered here will focus on EMG signals from the forearm and wrist muscles as the main input signals to control the reference signals to prosthetic hands, prosthetic/orthotic wrists, and orthotic hands. Increasing the fidelity of control of prosthetic devices while wearing a surface EMG acquisition system and its special gloves, many forearm muscles simultaneously can be received from healthy subjects. It is shown that the concatenation of different frequency features of the muscle can improve classification and regression accuracy. Redundant information from these multiple-input signals can support their adaptability for the control of prosthetic devices.

The design of the powered orthotic device is based on the aforementioned EMG-driven forearm gripping/hand movement intention control system which would be applicable to thumb-based systems and obviously also transfemoral systems. However, gaining intention commands to control a device with a very limited context is physically not reasonable. Although EMG signals from the forearm muscles can be used to achieve the desired intent, the information from the signals is essentially limited. For example, the 128 choice muscle signals conversed by the mapping back to the forearm movements can only produce 15 degrees of freedom. However, if a multi-body system is employed, the match of the input/output would be increased and thus provide rich mappings for the intention control. Kinematic feedback signals from the motion of the intended outfitted device can be readily acquired. Availability of combined kinematic signals and EMG, in turn, can also enable prediction of motion outset of limbs or prosthetic limbs from physical, muscle driven and input driven approaches [2]. The readily available biomechain and dynamic models can provide trajectories and implicit contact forces for an actuation control. Certainly, multi-body systems also incur much complexity of the dynamic model and control. Efficiency and effectiveness of the learning methods also remain unclear. The EMG-controlled powered orthotic system has been designed and undertaken comprehensive tests and experiments, and the context of this aspect is detailed in the next section.

3. Understanding EMG Signals

The electrical activity of a muscle can be recorded by electrodes close to the muscle. This allows the extracted electromyography (EMG) signal to be used for various purposes, such as quantifying muscle activity in biomechanical studies, controlling electrical stimulators, or controlling prosthetic devices. To interface with a dextrous hand, a suitable methodology needs to be devised. This will include information on the origin of the electrical signals, how they are measured, and details of real-time processing in a virtual instrument and its application to dextrous hand control.

Motor neurons in the spinal cord send impulses down bundles of nerve fibers to muscles. Each muscle consists of several thousand muscle fibers. Within each muscle, motor neuron axons form motor units that innervate several muscle fibers, which contract together for a muscle action. A muscle receives electrical energy from the active motor units, leading to a summation of action potential peaks with components that depend on the depth and orientation of the electrodes relative to the muscle fibers. The summation signal leads to a potential difference at the electrodes that can be amplified and filtered to produce a usable EMG signal. Thus, the origin of muscle EMG signals is well understood [2].

Alternating currents on electrodes give rise to capacitive coupling of an unwanted common and unwanted reflected signals. This means that amplifiers need to provide muscle impedance buffering while rejecting the unwanted signals. The properties of performance amplifiers and design considerations for real applications are outlined. To explore EMG signal sources, accurate and high-fidelity measurement in real-time is essential. Bandwidth filtering is important for accuracy and it can be implemented using virtual instruments, which can easily be configured in software, as well as allowing seamless real-time analysis and display while recording. Virtual instruments cannot match hard-wired devices in terms of installation simplicity or durability, but they are ideal for the explorative research described. For specific applications, hard-wired devices are likely the best choice.

Finally the use of EMG control of a dextrous hand prosthetic will be put into context. Many fine dextrous hand movements are multi-joint with stiffness, which makes control of under-actuated hands challenging. Also, there are challenges with the accuracy and number of input signals. Finally, there are greater challenges with the transmission of signals to devices used by amputees, which is complicated by the loss of tendons and nerves, and other issues related to how prosthetic hands are used, such as comfort and hygiene. The complications involved will be outlined, and possible avenues for the development of better devices proposed [3].

3.1. What are EMG Signals?

EMG signals primarily represent the action potentials that are generated by the muscle fibers as an electrical wave. EMG signals are the summation of all the muscle fiber generated potential over a certain time period, which is also known as the recruitment interval. The more muscle fibers are activated, the larger the resultant EMG signal. The activation of each muscle fiber follows the all-or-none principle, which stated that a muscle fiber either contracts completely or it remains relaxed [4]. However, since muscle fibers only an indication of the fact that a muscle has been activated and do not provide any information about the timing with which the musculature producing the movement has been activated it is imperative to understand their biomechanical properties.

At an even finer resolution, the signal is a summation of various action potentials of each of the motor units that is defined as the motoneuron, its axon, and all muscle fibers it innervates. Each motor unit will then correspond to a definition of the motor neuron and its muscle fibers. Motor units are recruited based on the Henneman size principle where the smaller motoneurons have a lower firing threshold potential as opposed to larger ones [3]. The recruitment of larger motoneurons results in an increase in muscle force output up to the tactical limit. Overall, EMG signals are the summation of action potentials generated by all of the muscle fibers composed of an dominated oscillatory behavior in the frequency domain.

The oscillatory nature of the muscle signal mainly derives from two inherent properties of the muscle tissue. First inter-stimulus synchronization of motor unit activity takes place because the conduction of both excitation and propagation in the muscle tissue is a distributed process. The second source of oscillation is in the ‘end effect’ that arises when a muscle is forced to start or stop perform a slow linear movement. Coupled with low frequency range sources of the control command signal received by the EMG signal processor, the muscle signal shows oscillations around the 0.1 - 2.0 Hz range.

3.2. How EMG Signals are Generated

An EMG signal is a composite signal produced by the motor unit action potentials (MUAPs) from a group of muscle fibers innervated by a particular motoneuron. When a muscle fiber contracts, ion gates in the muscle membrane open. The positively charged ionic influx causes a depolarization wave to travel along the fiber, exciting adjacent membranes. This propagating wave increases the thickness of the fiber and ultimately retards its length. The MUAP is a small potential change resulting from the excitation of millions of fibers, visualized by an instrument called an electromyograph. A recording distance of 1/1,000,000 of a volt can be visualized either on a paper chart or directly on a screen. The distance between the electrodes (detecting points) usually varies from 1 mm up to 5 cm [4]. There are two types of electrodes for electrographs: invasive and surface electrodes. A surface electrode is a parallel arrangement of conducting plates spaced a small distance apart. Invasive or intracellular electrodes take the form of a needle or a fine wire that is inserted into a muscle and records the electrical activity that it generates. Surface electrodes detect the electrical activity of muscle fibers that are at some distance from the point of detection.

The EMG opened the way for the design of myoelectric control systems. A myoelectric control system comprises a sensor that detects the electrical activity of the muscles that contract on command in the same way the input signal of a prosthetic hand is produced. This input signal is processed and transformed in a way that the control commands are generated to move the prosthesis in a natural way [3]. EMG signals are electrical signals caused by muscle contraction. Amputation causes loss of muscle control black box. Surface electrodes can be used to sense this control signal (input). Processing transforms the recorded EMG signal into estimates of hand openings (output). This output can be provided to a robotic or prosthetic hand in order to control it.

3.3. Types of EMG Signals

The activity of skeletal muscle is an electrical process, originating from the excitation of the sarcolemma and its subsequent propagation through the membrane. Neural excitation produces the depolarization of the muscle fiber, which generates an action potential. Involves the generation and propagation of an electrical signal, called an action potential, within muscle fibers. As the action potential travels along the fiber, it causes the release of calcium ions from the sarcoplasmic reticulum. This release of calcium ultimately leads to muscle contraction via a series of biochemical processes known as excitation-contraction coupling. The muscle fiber membrane (sarcolemma) is an excitable tissue capable of generating action potentials. When the muscle is stimulated by the motor neuron at the neuromuscular junction action potentials are generated. At the surface of the sarcolemma depolarization occurs and causes the propagation of the electrical disturbance into the interior of the muscle fiber through transverse tubules. Depolarization of the t-tubules results in the release of $Ca2+$ from the sarcoplasmic reticulum, which binds to troponin altering the arrangement of tropomyosin. Myosin-binding sites are uncovered, muscle contraction occurs. [3] The EMG is a recording of the electrical activity of the muscle obtained by suitably placing electrodes on the skin surface, or inserting them into the muscle belly. The EMG includes a summation of the all electrical activity from a multitude of muscle fibers. This is a time-varying potential characterized by its amplitude, duration frequency, wave form and direction of the potential [2]. The EMG signals can be classified into time domain signals, frequency domain signals and time-frequency domain signals. In the time domain θ2 R (θ1, θ2, θ3,…) is sampled as (x 0, x1, x2…xn-1) where n then the Fourier Transform is given by X(θ) = X’e1θ + X’’e1 θ = θ1, θ2, θ3…br = b0 + b1e−iθ1+ b2e−iθ2 +…+bne−iθn. Integration of x is considered here as a linear operator, y(k) = Consider a digitize power system Yi(k) = Yi(0) if k = Otherwise y(-)= Yi(k-1) if k = 0. The frequency domain consist of f 2 R which is sampled as k = 0, 1, 2…k1, When the Fast Fourier Transform is taken separately for each of the sensed input. T1 and T2 will result in T22 resulting in cells with repeatition. Let858 behold b1 b2 be represented in terms of the basis as b = i + bi +… + bn(e ones). Expansion yields a full-rank matrix.

4. Prosthetic Hand Technology

The first prosthetic hands with silicon fingertips were developed in 1970 due to the improvement of microelectrode technology. The fingertip possesses sensory capacity, which is an essential element for exploring the surroundings and providing feedback to the nervous system, resulting in smooth increasing dexterous manipulations. With the rapid development of microelectrodes, mechanical triggering modules have gradually been replaced with piezo-resistive or capacitive sensors. Biomimetic artificial fingers have been studied extensively, including the fingertips, which mimic the mechanical structures and sensory systems of the human fingertip.

Biomimetic tactile sensors were constructed by integrating self-powered triboelectric nanogenerators and piezo-resistive sensors, possessing multifunctionality of touch, hearing, and energy harvesting. A piezo-resistive touch capacitance sensor was designed using deep artificial neural networks and transfer learning with data augmentation to classify various touch signatures. However, few attempts have been devoted to integrating fingertips and contact-based sensing methods into dexterous biomimetic prostheses. This is mainly because it is challenging to integrate silicon fingertip sensors, micro-dynamical structures, and multi-layer flexible sensors into palm modules with dexterous grasping.

Research focused on developing dexterous biomimetic prosthetic hands with a silicon fingertip for prosthetic applications, such as providing sensory feedback for dexterous objects manipulation and incorporating a time delay self-oscillation control strategy for uncertainty objects grasping. However, sensory biomimetic devices, including tactile sensors, pain sensors, and joint position sensors, have not yet been developed. Moreover, contemporary prosthetic hands do not provide a realistic and intuitive way of interacting and grasping objects because they lack physical/kinesthetic sensory feedback from the hand and fingertip. [5][6][7]

4.1. History of Prosthetic Hands

Prosthetics have been in existence for hundreds of years. The basic design is still predominately the same, a hook-like appendage grasping the object, as far back as 3000 BC. The first record of prosthetic devices ever created dated back to the period 3000-2500 BC, and were wooden toes capable of moving. Skeletal remains from Ancient Rome dated near 400 AD indicate that iron leg (below the knee) prosthetics existed. In the post-Roma period, an iron hand was found in the excavation of a Mont la Villatte burial site that dates to about the 12th century BC. This was a more articulated design, prefiguring analogs created several centuries later in Italy, London, and France [2]. After the invention of the first mechanical hand prosthesis in France in the 18th century, there continued to be advancements in the field. However, despite many innovations in the area of prosthetic knees, ankles and feet, the introduction of this design metaphor has led to a stagnation of innovations for prosthetic hands, which are still predominantly based on hooks or claws contemporary with those first designs.

In most clinical applications, EMG signals are acquired using bipolar electrodes oriented parallel to muscle fibers. The magnitude and slope of these signals are then processed and used as a control signal for the prosthetic device. Until recently, off-the-shelf systems that switched a device on or off were available. Among the primary obstacles to the widespread use of forcibly powered myoelectrical prostheses was the inadequate ability of users to control them. Commercially available myoelectrical prostheses provide only gross control and so have limited utility [1]. For instance, an opener or a closure is used to choose the function of the motors actuating the hand while a wrist flexor or an extender is required for the wrist.

This crude control implementation illustrates that it has not been possible to fulfill the promise of ancient designs, which could open, close and rotate at wrist, with precise and delayed movements, while being durable and quiet, and with low weight and thus energy-efficient. These high-end specifications were never, even partially, met with electromyographic control alone. As an alternative to muscle action control, eye movements have been considered for control of externally powered prosthetics. These systems depend on the availability and processing of a video signal illuminating the prosthesis control zone. Conditions such as eyeglass wear or brow-lifting ability become a bottleneck with these developments. [8][9]

4.2. Current Technologies in Prosthetics

Advances in technologies related to hardware, electronics, algorithms, and materials over the last few decades have led to the creation of modern prosthetic hands aiming to help amputees in their daily activities. Previously, with only one motor controlling simple finger openings and closings, prosthetic hands were more cumbersome and difficult to use. Modern prosthetic hands are advanced multi actuated underactuated devices that can replicate most of the motions of a human hand. A significant problem here is how the amputee can control these advanced prosthetic devices. EMG as a control signal is ubiquitous in many engineering applications, including prosthetics [3]. Though conventional surface EMG (sEMG) electrodes are still being used, implanted (intramuscular) EMG (iEMG) electrodes are asserting themselves as state-of-the-art methods in many applications. Robust, low-noise, biocompatible, average-size, and low-cost implanted EMG electrodes are available in the market. Others are under active research in which the above metrics are being constantly improved. As signal quality improves and the number of good-control signals grows, it opens up the prospect of using independent control signals to operate device controls. Even so, only a handful of algorithms exist or have been demonstrated together with hardware in full proof-of-concept (POC) demonstrations, and only in a few cases, the applications are patented. To well showcase the promised variety, novel algorithms that are expected to be of very high performance, especially compared to traditional ones, are being developed. The expectation is that these high-performance methods can break into new application domains or new tasks, where current methods fall short either in noise tolerance or the ability to solve new complex problems. To enable a fair comparison of newly developed iEMG processing or decoding algorithms for prosthetic hand control, benchmark data are developed and provided as either high-quality iEMG data or predicted actuation traces/input data to be compared with the newly developed algorithms. This data could be simulated signals, synthetized signals, or real data. [10][11][12]

4.3. Types of Prosthetic Hands

Prosthetic hand compression is one of the important approaches for loss and/or decrease of hand functionality. As a result, the prosthetic hand should be the most used device in patients with above-elbow amputations. Considering hand functionality, prosthetic hands are categorized into non-myoelectric, standard myoelectric, and advanced myoelectric based on the number of degrees of freedom. Generally speaking, non-myoelectric prosthetic hands require decreased complexity and thus less control commands to meet the demand on the system complexity and affordability; and there is currently a focus on increasing the functionality of prosthetic hands to develop advanced myoelectric devices with either fast or multi-grip mechanism. During the past decade, EMG-based control of artificial limbs has been developed for lower-limb prosthesis and human-machine interaction as well.

The prosthetic hand with two degrees of freedom (DoF) is required to properly replicate the index finger motion with out-of-the-first-trochoidal mechanism. To address the multi-finger motion, it is proposed to utilize a RCM mechanism with one active joint. The force control for a multi-fingered prosthetic hand is realized based on 3D position estimation of the fingertip with a camera. To reduce the development cost of prosthetic hand, a low-cost underactuated conventional prosthetic hand with non-prehension capability is proposed. A mechanical design is presented for the 3D-printed multi-fingered prosthetic hand with prolonging grasping force upon closing motion. It presents a compact six DoF mechanical design of a parallel link surgical robotic finger for minimally invasive surgery. It presents the design and development of a novel three-finger gripper with passive rotations about every joint axis for grasping objects of various sizes and shapes. The soft robotic gripper inspired by using shape-based passive compliance for manipulation of delicate and fragile food is proposed. A robotic gripper mechanism based on compliant three-jaw mechanism is proposed for dexterous grasping of different shapes in unknown environments. [13][14][15]

5. Integration of EMG Signals in Prosthetics

An important part of a prosthetic hand is the actuator that performs the closure of the grasping fingers. The motion of the actuator should be controlled according to signals that are directly related to the hand opening and finger closing movements. In prosthetics, the availability of bioelectric signals has made it possible to control the prosthetic hand depending on the residual muscle activity captured by the electrodes. Hence, to control a prosthetic device, different types of bio-signals have been used. Recent studies have focused on alternative bio-foundation for prosthetic hand control, such as electroencephalogram and near-infrared spectroscopy signals. Nevertheless, these methodologies are still in research phase. Hence, myoelectric control continues to be the standard control methodology, based on the electromyography signals picked up by electrodes placed on the skin surface.

To do so, it is necessary to obtain EMG signals close to their source, thus avoiding distortion and loss of information. Acquiring the EMG signal close to the desired muscle has proven to yield superior results. It is possible to implant only electrodes while having the associated electronics outside the body. This approach simplifies the surgical implantation of electrodes, with the only complication related to electrode leads failing due to excessive stress. Advances in surgical techniques to anchor the prosthesis using osseointegration increase the longevity of the implant, enabling a stable and reliable interface between the residual muscles and the prosthetic hand. It has become possible to derive control strategies that rely on high-quality intramuscular EMG signals and implement them in prosthetic devices based on implantable technologies. With a significant improvement in control signal quality, there is potential to diminish one of the primary reasons for amputees' rejection of myoelectric prostheses, which is limited controllability. The previous effort was directed towards obtaining and disseminating a database of iEMG signals for developing and testing novel hand control strategies. The database combines highly selective iEMG measurements with isometric forces of individual fingers during various hand gestures. The implicit novelty of this database is the availability of isometric hand forces that enable the evaluation of regression-based control algorithms. To provide a solid baseline of the prosthetic hand control performance, the present study evaluates common computational methods in the scope of recorded iEMG and force signals. [16][17][18]

5.1. Signal Acquisition and Processing

Acquiring electromyography (EMG) signals from implanted electrodes can be performed using probes with multiple channels. The signal is first conditioned, digitized, and then transmitted wirelessly to the prosthetic system. In case of conductive noise, the information can be broadcasted using appropriate protocols to multiple prosthetic systems to further improve performance and robustness. Overall, the acquisition, conditioning, digitization, and transmission of the signal can also be used as a technology demonstrator to develop assistive technologies for paralyzed people, for example, an exoskeleton that can decode movements that the subject cannot physically perform [19].

In recent years, significant advancements have been made in the field of signal acquisition from implanted electrodes. Even a one-channel implantable device can yield robust performance, close to that of a similar device with white and power spectral density denoising [3]. However, deriving control strategies from those signals is a complex endeavor that requires considerable time and computational resources. The need to evaluate the performance of the control algorithm, especially in the case of drawing new control sets (to cover as much of the feasible input space as possible), can become a bottleneck in the prosthetic hand development process.

5.2. Control Algorithms for EMG-Based Prosthetics

There exist various methods for extracting the features of electromyographic (EMG) signals in order to subsequently classify them into intent movements or output values. Most of them can be grouped into one of the categories: threshold-based classifiers which provide binary outputs; one-vs.-one or one-vs.-all classifiers which return votes in favor of classes, i.e. intended movements; and regression algorithms which provide continuous output control signals. For the sake of simplicity and reliability, this part will present control algorithms which provide binary switching or proportional outputs based on threshold detection or regression methods. The methods for binary classifiers recognizing generated control commands within 50 ms after the onset of intent movement with up to 20% off-line type-I error and with performance degradation of less than 10% in various real-world test conditions will be shown.

Most of currently used EMG-based prosthetic hand controllers are implemented in the number-of-contact-style manner, where the number of degrees of freedom and subsequently the number of binary EMG detectors determines the number of contact modes of a prosthesis, while the number of motion commands is limited to the number of ways to trigger control commands. Such type of control is considered inappropriately matched for dexterous prosthetic devices having more than five degrees of freedom, as they are more effective for executing a repetitive set of pre-managed sewing, assembling, production, and creative tasks in engineering rather than full-scale finger movements.

EMG-driven control systems of dexterous prostheses typically output continuous control signals, such as grasping forces or angular position rates for each degree of freedom of a prosthetic device. The interest in the direct control of multi-degree of freedom hand prosthetics is confirmed by implementing various control algorithms using surface EMG derived from the forearm muscles with the number of input to output channels in the ratio of 1:1. On the down side however, the proportional control commands need to be sophisticated to be robust, robust computation complexity needs to increase, and finally, the training data should be comprehensive enough in order to address an individual user's signal propagation characteristics. Given the practical level of such strong classifiers achievable with popular currently used two-element classifiers, they might only be used for multi-degree of freedom prosthesis control by setting them to switch autonomously between application-dependent modes at the higher level.

5.3. Real-time Signal Processing Techniques

In recent years, real-time control of prosthetic hands has gained a great deal of attention. In particular, real-time analysis of Electromyography (EMG) signals has several challenges to achieve an acceptable accuracy and execution delay. The first challenge is the non-stationarity of the EMG signals, which has been addressed by using adaptive techniques or training a classifier for each subject before starting test sessions. However, these approaches cannot be used in wearable applications. Therefore, it is highly desirable to extract temporally invariant features, which remain unchanged under different types of motions or conditions. Another challenge is the huge number of extracted features. Although feature selection is generally applied before classification, the very small number of features is desired to have low execution delay in real-time applications. This has been addressed in the past by using the sum of absolute differences of wavelet coefficients. However, a set of new feature extraction functions have been proposed, applying on each level of wavelet decomposition. The experimental results illustrate that the proposed method enhances the accuracy of real-time classification of EMG signals [20].

Electromyography (EMG) signal analysis is a method for controlling prosthetic and gesture control equipment. Real-time low-power operation on embedded processors is critical. This work presents a novel approach to time-domain classification of multi-channel EMG signals according to wrist-hand movements. It is shown how, by employing a very small set of time-domain features, nine wrist-hand movements can be detected with accuracy exceeding 99. When deployed on ARM Cortex-A53, the processing time enables real-time processing and is a factor 50 shorter than leading time-frequency techniques. It was also found that the most significant mean feature was the Fourier-transformed DC component on polynomial learning. The implementation on the embedded platform of the deep learning model achieves high generalization to unseen data. Furthermore, the implementation is very power efficient, reaching a power overhead of less than 140mW [19].

6. Design and Development of the EMG-Controlled Prosthetic Hand

The design and development of the EMG-controlled prosthetic hand is presented in this chapter. This includes electrical and mechanical design considerations that were taken into account during the design and manufacturing process of the EMG prosthetic hand. The control algorithms will also be introduced. EMG-controlled prosthetic hand Classification of Manufacturing Methods Since there are many manufacturing processes available in the world, it is essential to narrow down the manufacturing options and decide on the best manufacturing process for the prosthetic hand. There are many manufacturing methods; However, rapid prototyping methods such as 3D printing and CNC machining were chosen due to a limited budget. The prosthetic hand was designed using CAD software, focusing on reliability, reproducibility, durability, minimum weight, and feasibility of manufacturing. 3D printed parts were printed using an FDM printer using PLA filament. The external device was made of enclosures, constructs, and materials to mount the IMU sensor, which has to be removed and reassembled for charging. The mounting holes used were produced on the actuated joints for coupling with the servo motors. Servo motors coupled each joint of the prosthetic hand. The servos of the thumb were controlled due to the difficulty of adjusting joints with many degrees of freedom. 3D printed parts were assembled with nuts and screws, while a frame made of aluminum profiles to support and connect the servos with the fingers was also designed and assembled. The wiring in the palm of the hand was handled in such a way that it would not obstruct the movement of the fingers.

The mainboard of the proposed prosthetic hand is Arduino Mega, with the IMU sensor module and the single-channel EMG electrodes connected to it. A wide range of current was chosen to drive the project, which can be supplied through a power bank, so it can maintain a long lifetime. To achieve this, a breakout board was manufactured for the power MOSFET to be connected to a specified voltage; multiple filtering capacitors were soldered on the board.

6.1. Mechanical Design Considerations

As the use of prosthetics grow around the world, there is also an increase in use of mechanical hands with control using EMG signals. A mechanical hand is designed to replicate the motion of a human hand. A high-power servo like the MG996R is used to drive each finger of the robotic hand, along with the palm by means of 10:1 gear reduction. Depending on the angle of the servo motor, the fingers can bend up to 90 degrees. This range of motion is essential to mimic the use of a human hand for effective grasping of any object. Thus, when the corresponding voltage from the EMG signal amplifier board goes high, it means the muscle contraction has occurred. This, in turn, moves the hand in that particular direction. The given model shows control of 3 fingers and palm automatically depending on the muscle contraction observed in the arm. The design of the hand is complex and it requires substantial time, effort and resources. Thus, a few considerations should be made while designing the model. Requests from amputees and prosthesis wearers were collected through voting to prioritize design requirements from user perspective. Lists of wants and needs were compiled into a wide range of specifications for the hand that were then prioritized. Basic mechanical responses, weights, and dimensions were attained manually to ensure that the specifications were attainable with the final designs and materials. Design reviews were held with faculty sponsors after each phase to gain feedback on the preliminary design overall and to receive input from an expert’s point-of-view [21]. Refinements followed these consultations to finalize the hand design. The FPSD necessitates a hand that will grasp objects within a broad range of sizes by producing cylindrical and pinch-type grips on thin objects. To achieve isolated articulation at finger joints, tendons must be run through joints with adequate tension to allow for a quick responsive actuation. In addition to this specific design consideration, the forearm should contain static overhead or horizontal support actuators. An articulated wrist is desired to position the hand in an inclined position. The elbow is needed to complement hand positioning to allow for a variety of different grips [22]. Thus, an embedded microcontroller will process relevant input data and send control signals to actuate the hand's fingers. The on-board microcontroller is powered by a Lithium-Polymer battery that is small enough to fit into the forearm casing. The components of the hand design are detailed in the following sections.

6.2. Sensor Selection and Placement

There is a quarry of questions regarding the placement and the number of electrodes for myoelectric control of hand prosthesis system for finger digit movement. The first question regards: how many electrodes are needed for EMG fingers digit surface sensing? Answering this question inspects the fingers skeletal biomechanical manipulation conditions in terms of muscle groups (synergies). Achieving best results using the fewest channels of the sensing signal is a vital issue due to the complexity of devising an EMG signal to high-level controller. By observing the finger synergies or muscle groups of hand signal sensing, the muscle groups exerting flexion and extension actions of the hand are extracted. To test this reasoning hypothesis, sEMG signals then should be measured for the above three upward conditions and signals containing channel numbers from 2 to 3 are segmented. The signals are classified to predict a finger digit movement intention using an ANN classifier with 90%-sensitivity thresholds [23]. Compared with the criterion 1-3, a more complicated movement, the positional movement of the index-finger, middle-finger and thumb are selected as another case. The other two fingers, i.e., ring-finger, pinky-finger, are strictly fixed in an inward spread pattern and the desired fingers (Fingers 1, 2, 3) step in and out in upward and downward movements. Three different sEMG signal sensing positions are also chosen as four conditions. The reasons are the same as those of the former tests, but signals containing more than 6 channels should be considered. The result is reported when the number of channels used in signal sensing is from 2 to 3 [2].

6.3. Actuation Mechanisms

According to the IEEE, an actuation mechanism aims to execute specific tasks by converting energy into controlled motion. The actuators take control commands from the EMG signal decoder and output suitable control signals representing motions for prosthetic hand control. Motors, torque amplifiers, and motors with gear units are widely used in the actuation mechanism designs, and there are various means of transmission, including wires wrapped around several anchoring points ([3]). This section discusses the basic approaches used to use different devices and structures for actuation mechanism designs.

Pneumatic or hydraulic means are characterized by low weight, high levels of actuation force, and mobility. Fingers with these applied polymers and silicone-based actuators are widely used on hand prostheses to mimic fingers with biological anatomy. They use soft actuators for movement and closed-loop feedback based on joint position and contact force to control finger positioning, curvature, and locomotion on straight edges, wall edges, and in front of multicome surfaces. However, the control of the actuation mechanism is complicated due to its nonlinear elasticity, coupling, hysteresis, and modeling difficulties, while the feedback control needs to compute state variables, making it difficult to miniaturize the system.

A complete prosthetic hand, which mimics human dexterity, is presented in which flexion and extension motions are produced by the actuation mechanism utilizing 8-gear module systems with 4 servo motors. Each gear module is composed of one DC motors, carbon drive gears, and double gear easel joints. The drive gears are installed with the motors as 1:30 gear ratios, which can output gear shifts that substantially magnify the motor’s revolute angle for a stiff connection. The rotating motion of the servos can also generate clasping actions mimicking human hands to hold bottles. The hand prosthetics can be worn in a natural manner since a palm can be steadily attached to the wrist by a pair of pressure rotating mechanisms.

7. Implementation and Testing

Prosthetic hands controlled with intramuscular EMG (iEMG) signals can potentially provide intuitive and dexterous restoration of hand function. A closed-loop control framework is proposed to ensure the robustness and immediacy of hand control, utilizing the unique properties of iEMG signals. The prosthetic hand system comprises a non-linear proprioceptive iEMG signal processing model and a non-linear finite-state switching glance estimator (FLink) model. The control performance against the influence of system uncertainty, anatomy mimicry, and operation cost is evaluated by a series of simulations. The plausibility and desirability of the proposed control framework, and how to successfully realize it using signal processing and control engineering tools, are discussed [3]. Prosthesis rejection is often associated with a lack of dexterous control of the prosthetic hand which commonly exists in the transcarpal amputation. A recently proposed novel approach of control signals inspired by the idea of proprioception in the human to control a novel mechanomyography (MEMG)-based prosthetic hand is presented. Unlike traditional approaches that rely on the well-defined hand postures or gestures determined by the operator, the new proposed control signals intrinsically characterize the different states of hand control and therefore are robust against the uncertainty introduced by intra-subject variability and environmental disturbances. The practicality of the proposed control signals for MEMG hand restoration is examined considering the reasonable designers' tradeoffs. A wide range of tasks using a MEMG prosthetic hand has been demonstrated to indicate the good capability and robustness of the proposed control signals and the potential and desirability for their translation into clinical practice. [24][25][26]

7.1. Prototype Development

There is a sizeable population of individuals who have lost one or more limbs because of trauma, leading to a large number of potential users for a prosthesis system that is controlled by bioelectrical signals generated by the user's muscles. This should allow lost limbs to be replaced and free movement restored without a need for large, complex, bulky mechanisms [27]. Neither the amputation of a limb nor its loss through congenital disability constructs any barriers to prosthetic aid. The idea is to know the nature of the bodily mechanism that is to be replaced and to try to duplicate such a mechanism in a bio-mechatronic version. The design and implementation of a prosthetic system controlled by EMG signals are presented through the complete Mane system development stages, followed by a detailed description of each component's functioning. The system consists of two main parts: the prosthesis and its control station. The first part gathers information from a bioelectrical signal acquisition system, processes it, and controls the hand prosthesis through a transmission channel. The second part processes the signal information captured by the first one; then it communicates with it and sends control commands suitable for the prosthesis. The techniques behind this development can be easily adapted, and such a way that the state-of-the-art technology is designed can be adapted into a simpler or more complex system according to new user's requirements [28]. The prosthetic system development have been based on signal characterization and classification in real-time closed-loop operation systems. The on-line acquisition and processing of selected input parameters extracted from EMG signals are made, and they can be used as commands to control the members of the prosthetic hand. The chosen input parameters have been carefully selected to maximize the classification performance by balancing computability (complexity), selectivity, and noise resistance (minimum variance). Classification and control of the prosthetic hand with a RS-232 serial communication are presented. It should be noticed that both systems can work and require no external intervention.

7.2. Testing Methodologies

The basic approach for evaluating the algorithms for controlling prosthetic hands and development of the test bench for stimulating hand gestures has been discussed. In this section, specific details regarding how to evaluate the algorithms and how to team up multiple measuring channels for the simplest setup will be elaborated [2]. Typical laboratory tests to verify the basic working principle of the algorithms, such as sensor signal conditioning, quantization, and discretization methods (step function and rectangular measuring pulse), will be presented. These tests can be applied to a prosthetic hand simulator equipped with the prosthetic hand grip and all other mentioned types of sensors. Typically available sensors include load cells for measuring gripping forces, flex (bending) or Hall-effect sensors for measuring angular positions and joint velocities, etc. A vision system providing a 3D map of the entire test area for more advanced laboratory testing can also be made available so that all objects in the test area will be detected automatically and marked with probability areas for object localization.

The initial step in achieving the desired control of the prosthetic hand grip will be to create a programmable set of test stimuli to verify the prosthetic simulator in measuring the grip angle. There will be seven stimuli, corresponding to the circular arc angles of grip opening/closing of 70/0, 100/0 and 120/0 degrees, which are achieved using a motion capturing system and controlled by its application programming interface. Similar to improving the simulation of prosthetic hand control, control algorithms will be reshaped and that [3].

Development of a low-cost alternative prosthetic hand controller implementing a closed-loop proportional control methodology based on measuring finger muscle electrical activity has been detailed. Experiments have shown that this design is able to track target finger movements, while avoiding problems associated with the use of gloving controls. Techniques are presented to relate forearm muscle electrical activity to the movement of an anthropomorphic robotic hand. The degree of freedom mismatch between the controller and the prosthetic hand is addressed through an approach that accounts for the flexible mapping between multiple muscle inputs and the target finger movements. A custom 2-D printed housing for the finger surface electromyography sensors has been developed that enables straightforward adjustments.

7.3. User Trials and Feedback

Testing the EMG-PR system occurred over two trials in March and April 2014. The first 14 of 21 participants completed the initial test at the Lusail University and Qatar University. All aspects of the project were explained verbally and on paper. To ensure an acceptable EMG quality, the healthy participants' skin was prepared using alcohol wipes and scrubbing, if necessary, to create a surface for the electrodes to make proper contact. Testing equipment included a laptop running MATLAB to process the EMG data and a portable DATAQ system for the remote lab. The minute between trials was short to let the subjects relax with minimal muscle activity. It was verbally explained that it was more preferable not to think of any movements during the resting trials. Between the trials, segments of high activity from one hand were replayed while other hands were on idle. Then, all participants had to make "Natural Movements," which were followed by another CTRL. Afterward, the participants were asked to do EMG recordings with natural movements again with no limit. Resting and CTRL recording time would be similar to or short than in the first experiment. Six normal subjects competed EMG recordings again, while assistance assisted recording for at the same lab. The laptop was moved to QU in Doha to test the MEMS IMU on hand. A new unprepared surface was tried with the same electrodes. To ensure clarity, the electrodes were attached to human dummy arms avoiding the use of water and scrubbing. Cleaning could not be done here as it would expose the whole issue regarding a.i. EMG-PR to the client. A basic surface with lot of noise that made clear sorting more difficult was considered for trial. Testing was held to freeway the setup with no subject alteration allowed to standardize the training session. This should increase robustness as noise rejection is evaluated in cases of more type of noise initially not planned for training. When action units were separated well for learning, MEMS IMU tests would be held using a similar kind of policy naively imposed [29].

8. Challenges and Limitations

Many challenges remain in creating systems capable of robustly detecting user intent across participants, tasks, and settings. A first batch of open-source data tools has been released to help the community address these issues. These tools can be used to benchmark further work on automated detection of finger movements and to provide training sets for novel deep networks or signal-processing architectures. The hope is that they will help serve as ground truths for the directed creation of datasets to mitigate the risks of data mining while prioritizing ergonomics. The relative simplicity of the current system leaves many desirable confounds unmodeled, such as the geometry of the hand, EEG electrode placement and bulk, and participant anatomy. Future work to add complexity will allow broader generalizability of results and yield further insight into the portion of the data that is not explained by the current architecture [3].

Another important challenge is the account of a participant population that may differ in age, handedness, gender, and many other aspects. This study concentrated on data from a narrow age range and focused only on right-handed participants. Future work should broaden the participant distribution to examine additional confounds, particularly any sex differences. Exclusion of the left-hand finger movements from the data was done to ease the early interpretability of auxiliary features, but this may also have unintentionally simplified the task too much. Future work could address the left hand, in order to broaden the potentially applicable results. The high raw-MEG dimensionality meant that a larger band of principles, methods, and architecture types could be explored without overfitting, but there remains a risk of hyperparameter overfitting. Consequently, it is a goal of ongoing work to hold out a proper set of channels and ranges of applicable hyperparameters for any network family chosen, such that it can be assessed whether the architecture has been appropriately chosen or if those hyperparameters should be adjusted differently.

As performance is empirically linked to many aspects of the signal and data pipeline, concurrent to the expanded dataset, new signal-processing methods will be explored to denoise the MEG data within each run. This denotes methods to optimize the removal of noise and artifacts not linked to the finger movements, and potential modeling approaches for the formatting of auxiliary features. An obvious question is how interpretable the trained networks are. With the use of the example-subset's neural fit expression (and other methods), an effort will be made to assess the trained networks' interpretations of their input data, and whether more interpretable architectures can be found to explain how the features are transformed into the task responses.

8.1. Signal Noise and Interference

The main factor affecting the continuity duration of the artificial limb control is the presence of noise and interference in the signal acquired. Although many noise sources such as thermal, radiation, and power supply noise do not depend on the acquisition system or environment design they can be attenuated by using acquisition systems fabricated with precision components. Thermal noise, for example, is generated by thermal agitation of the charge carriers in conducting materials. All purely resistive materials emit thermal noise, which is often described by Nyquist's law. This law states that thermal noise power, P_n, in W, is proportional to temperature T in K, resistance R in Ohm, and bandwidth B in Hz. To keep the effect of this noise to a minimum, low-noise and low-drift amplifiers with low gain-bandwidth product should be employed. Radiation noise is produced by electromagnetic waves, primarily in the radio frequency, caused by thunderstorms, solar activity, lightning strikes, and sparks in machinery and electrical systems. To minimize the effect of radiation noise as much as possible, shielding of electrical wires and components with proper grounding should be mostly done. Coherently coupled subsystems with aligned reference frames should also be employed to prevent coupling capabilities among different signal domains that do not need to interfere with each other. Power supply noise refers to any fluctuation in the supply voltage. To minimize its effect, decoupling capacitors should be mounted on the power supply lines as close as possible to powered circuits. It also helps using voltage regulators, powered with lager delay capacitors (up to a few hundreds of microfarads), for circuits that are very sensitive to supply fluctuations. Conductive coupling should be avoided if the signals are expected to contain high-frequency content, as normally in biomedical settings like EMG signal acquisition. The effect of noise can be modeled as additive white Gaussian noise (AWGN). It can be characterized on a per-channel basis and, on an episodic basis, spectral Radon transforms able to characterize the linearization effects on the baseband spectrum of arbitrary time-dependent and time-independent modulations [4].

8.2. User Adaptation and Learning Curve

The human motor system operates with innate control strategies that are well-suited for controlling limbs or limbs-like mechanisms. Interfacing computers, robots or prostheses with the motor system requires either learning new control strategies or translating forest strategies in a way that makes them usable in conjunction with the requisite mechanics. For a real-time interface, expectations also require high performance across diverse unfamiliar tasks. Human motor sensors act through sensory feedback loops; so it would follow that the most successful interfaces would involve direct interaction between the motor and sensory systems [30].

Most forms of prosthesis control sense myoelectric signals in the residual limb which are processed to detect the intention of the user. The prevalent decoding method is pattern recognition, which transforms the timeless signals into mutually exclusive class probabilities.

Each joint class uses an independent model, compares the probability nominal to all the output metrical thresholds, and sends the highest class to execute. Because of lack of training data, such models calculated by batch learning techniques are imprecise. The batch trained bespoke classifier method suffers from severity misclassifications in class boundary regions. Casting an intuitive interface fate to happen on the operator interface can realize the true open-loop ability. A joystick can directly control the individual finger and significantly minimizes confusion.

The offline and online performance of the learning process gradually improves. A data-driven classification metric based on parameters is proposed to interpret the relationship between user aptitude and prosthesis performance on finger. Net and mean distances descended with increasing knowledge while the relative width or slope gradually converged to zero. These parameters measure the comprehensiveness of kinematic control on the decoder inputs and the indecision degree of individual finger operation. When in the learning testing process, groups kept the long-term effects of switching the control interface while time data preceded to decline as the practice continued. With data-driven classification metrics, after investigating the learning process and the difference between different decoding methods, the gap between state-of-the-art offline performance and real-time performance is bridged.

8.3. Technical Limitations of Current Systems

The progressively increasing body of knowledge concerning the role of electromyography (EMG) signals in prosthesis control has led to the development of many systems able to control the motion of a prosthetic hand via EMG signals. During the past two decades, such systems have also been sold commercially and made available to users, mainly for controlling upper limb prosthetics. Nevertheless, despite the advances in both hardware and software, currently manufactured EMG-controlled prosthetics hand presence technological limitations that impact their performance. Documenting such imperfections is important, since it can expose areas in which technological development is still to be conducted and it can, consequently, provide guidance for novel research approaches [3]. EMG signals originating from a desired muscle are often distorted or excessively mixed with signals from other muscles, which, in turn, can hinder the performance of subsequent processing. To do so, it is necessary to obtain EMG signals close to their source, thus avoiding distortion and the loss of information due to mixing with signals from other muscles and attenuation in biological tissue. Acquiring the EMG signal close to the desired muscle has proven to yield superior results using fully implantable devices that record EMG signals directly from the surfaces of multiple muscles, including signals from muscles deep within the arm that are very difficult to single-out from the skin surface level. Instead of implanting the whole recording–transmitting device, it is possible to implant only electrodes while having the associated electronics together with a power source outside the body. This approach simplifies the surgical implantation of electrodes and the maintenance process, and the only complication is related to electrode leads failing due to excessive stress or a limited number of wire-bending cycles. With advances in surgical techniques to anchor the prosthesis using osseointegration, the longevity of the implant is further increased, thus enabling a stable and reliable interface between the residual muscles in the forearm and the prosthetic hand. As a consequence of surgical and technological advances, it has become possible to derive control strategies that rely on high-quality intramuscular EMG (iEMG) signals and implement them in prosthetic devices based on implantable technologies.

9. Future Directions in EMG-Controlled Prosthetics

Many avenues exist for future improvements to control of prosthetics with EMG signals. Technological enhancements to hardware, algorithms, and user experience will increase the control capability and robustness of this system, and continued research focus on alternative solutions to the core scientific and engineering problems will enhance the long-term viability of EMG-controlled prostheses. Commercial systems are likely to initially follow the path of least resistance, improving on existing commercially available systems, followed by the feasibility of researching alternative control principles. Capacitance and location of electrodes has been studied and optimized to capture EMG signals. Reliable, portable hardware has been created that can accurately filter, amplify, and digitize raw signals for transmission through Bluetooth to a computer on which control algorithms can be run [2]. Work would need to be done to encode the algorithms into firmware in the prosthetic unit to allow it to independently send commands to the motor drivers. Because the control algorithms require a sufficiently large window of EMG samples, the processing requirement of control algorithms is not compatible with the current expectation that the prosthetic unit will operate in a standalone mode. Drone control applications could benefit from lighter, lower-power hardware than currently used. Simple attitude control algorithms could be tested in the lab using the presumed IMU capabilities. Finally, exploiting the relative inertial frame between the limb position and inertial frame, more general control commands that execute a sequence of rotations could be studied.

An intuitive approach to the control problem would be to offline correlate signals captured by the IMU with the sequence of generated motor commands to execute a training routine with selected gestures, discarding those whose motion characteristics did not meet user motion. Perceptual blends of captured body and control movement could be used as feedback to the user during control training. Systems could exploit any additional user-stemming perception of motion affordances that could speed system take-up. Ultimately variations of gestures used to control affordances could be incorporated into learning algorithms that increase the robustness of granted controls over time, while also allowing refinement of the controls' commands. Learning systems could also build mappings between a spectrum of user-based affordances and alternative modes, which systems would toggle when a different affordance was perceived. Control surfaces capable of tracking the finger flexion angle and velocity could be built to improve accuracy and robustness. This would extend limits on data input and open the door for continued avenues to advance the technology.

9.1. Advancements in EMG Technology

Over the past couple of decades, a rising trend has been noted in scientific publications that deal with the acquisition, processing, and control of prosthetic hands based on electromyography (EMG) signals. Most earlier works were focused on surface EMG (sEMG) signals acquired from the skin surface above the forearm muscles. However, recent trends are shifting toward the implementation of intramuscular electrodes for recording these signals, as the quality of the control signals is obviously better when recording closer to the source. Alternatively, the sEMG can be acquired closer to the muscles by using a fully implantable device [3].

The device records sEMG signals directly from the surfaces of multiple muscles within the forearm with a high spatial resolution. A so-called "fuzzy" electrode was developed and tested for measuring sEMG from a single forearm muscle. Again, instead of implanting the whole recording–transmitting device, it is possible to implant only electrodes while having the associated electronics outside the body, so that the sEMG measurement is carried out through wires. Such a device was also developed but, as it was partially implanted, it included electrodes that could be acutely damaged during a muscle contraction or by high temperature. Nonetheless, this approach greatly simplified the surgical implantation of electrodes and it has been successfully developed and commercialized.

With advances in surgical techniques to anchor the prosthesis by means of osseointegration, the longevity of the implant is further increased, which enables a stable and reliable interface between residual muscles in the forearm and the prosthetic hand. Between other options, the implant could be occluded so that the sealing was carried out between a biologically inert implant and the skin. One possible solution to immunologic incompatibility is to allow the tissue to grow around the prosthesis. All of the mentioned approaches constrain the design and robustness of the portable hardware that assists people with disabilities, as it should be somewhat implantable to protect it from mechanical shocks, moisture, and other ambient influences.

9.2. Potential for Machine Learning Integration

Research on prosthetic hand control applications involves the decoupling of the surface electromyography (sEMG) signal to achieve an adequate and efficient way of controlling a prosthesis, this control should look as similar as possible to the natural movements of the body. One of the concerns in this field is the ideal placement of the electrodes according to the muscular region. Also, the electrode characteristics and technology are of importance in this task and especially in sEMG recording to obtain clean inputs for the data mining step [31]. Finally, there is a step of data mining where it is attempted to look for features in raw sEMG signals to be used in classifiers; all the features extracted should be robust to acquire generalization for movements and users. The challenges for a database are manifold, as prosthetic devices are increasingly exhibiting a complexity and XXI century features; however, it is known that 60% of these devices are passive and have only 1 to 4 degrees of freedom (DoFs) while 10% of them have more than 10 DoFs.

Intuitive control systems can accept more functionalities in machine learning techniques. Unfortunately, this has not been met even though many investigations utilized machine learning techniques to classify and interpret the EMG signal before a prosthesis or neuroprosthesis. The advancement of machine learning systems plus the importance of such a control system have created a need for control systems in prosthetics, exoskeletons, and rehabilitation. This challenge is even higher in contexts with a large number of classes associated with the movement; however, it is a challenge for real-time training and practical application of machine-learning systems in complex prosthetic systems and uncontrolled environments [32].

Deep learning as a more novel strategy can be useful for improving classic classifiers as it can automatically generate the features; however, deep-learning systems require a huge amount of data, so in a similar direction as the previous items, the high budget needed for obtaining good performance hampers the utility of the method. In addition, the use of the time-frequency features in EMG signals allows some systems to be designed based on attracting unwanted electrocardiogram noise of the sEMG signal as well as noise-resistant classifiers using temporal features on Suzuki EMG signal. Without claiming supplanting the time-domain features, these strategies allow working better with low signal noise. Much work is emerging in this category.

9.3. User-Centric Design Approaches

The usability of a prosthesis does not solely rely on the function of the artificial limb itself but also on the interface between the limb and the patient. Commercially available myoelectric prostheses can provide users with satisfactory control, permitting an aperture control of 13 to 16 different grips. However, most commercially available control techniques are designed for healthy subjects. This results in limitations in real-world performance, such as a suboptimal number of input channels and slow switching. The key concept behind machine learning-user-centric design is that the control interface and the signal processing and machine learning intake of user-related information in order to personalize and adapt the control mapping for each individual user. This can be achieved with little or no engineering efforts of the user, allowing continuous adaptation of the control interface after the initial fitting phase.

Pattern recognition-based control techniques identify pre-defined patterns of muscle contractions. User adaptation can either enhance the overall performance or avoid sudden performance decrease in the transition from expert to novice users or reconstruction phases. Different adaptations include training of hardware, update of model parameters during unsupervised use, and replacement of machine learning algorithms in real time. The control of the prosthesis and the signal processing and machine-learning algorithms are divided into function-centric components to disentangle the challenges of prosthesis control. The control strategies are robust against noisy data, a sensor input that the subjects did not have during training, and a change in the reference signal rate. The performance under noise dictates additional model complexity that may shift the utilization of control complexity toward control cost. Performance decreased in off-time when the user had not previously used the prosthesis for hours or days and when precise control is required.

A review of advanced patterns for user-centric prosthesis control interfaces candidates for future research directions highlights technological and usability considerations. The need for translation relevance in research foreshadows new methodologies such as newly developed application voltage transformers convert the output voltage of any application-compatible sensor to a digital signal out of an external motherboard. Implications for current and future work are outlined, indicating the path human-machine interaction in bionic limb control will take next [33]. Deep learning-based sEMG force control estimates the grasping force of the prosthesis over multiple force levels. A regression-based grasping force prediction method using sEMG and deep learning is proposed.

10. Ethical Considerations

The development of advanced prosthetic devices administered by human intervention relies on robust and easily interpretable control signals. Surface electromyography has been utilized extensively to develop control strategies for commercial prosthetic devices, but has arguably functional limitations due to signal distortion and limited controllability. Thus, the need for muscle activity signals with higher quality than surface EMG signals is an actual necessity that has become possible with the development of implanted electrodes and electronics. Intramuscular EMG signals acquired using disposable electrodes embedded in a biocompatible polymer, customizable in shape and size, and connected to external electronics via a transcutaneous connector is a promising direction since it simplifies the surgical implantation and prevents infection. The evidence from recent research indicates that accurate results can be obtained while acquiring intramuscular EMG signals with this approach [3].

Intramuscular electromyography has proven to provide better quality and quantity control signals and implantable devices that can aid in acquiring EMG signals closer to their source. However, with leading-edge electronics and artificial intelligence developments, devices smaller than coins are possible to create, leading to a potential breakthrough in control strategies for implantable devices. Many consumer devices promising neural signal recording are emerging, but taking them deeper will require more research [27]. A better understanding of the controls can simplify the control and post-processing task, even in nano-size devices. Effective mirror devices can augment velocity to totally replace lost limbs, while less invasively; a 128-channel neural interface has the potential for telehealth applications. Since lost signals are not entirely known, this is a testing phase where it is essential to create simpler versions to understand their limits.

10.1. Accessibility and Affordability

Currently, the development of clinically applicable prostheses with an open-source approach in mind is still an innovation in the world. Affordable and accessible alternatives are needed due to the prohibitive expense of current solutions. The desired design requirements include a cost that does not exceed 2k USD, the ability to 3D print at least 90% of the components, a versatile pin-joint design for a minimum of 2-finger gestures (grasp, index finger, trigger), and a design that experts in CAD software can adjust to fit the user. These requirements were then included in a design proposal to create an open-source accessory for a laboratory-standard 3D panorama scanner. It was determined that the design process should focus on the mechatronics first and that it would be preferable to create a testbed using 3D printing and small electronics already available in the lab. For those not involved in ongoing chores, tanks were designed.

The design iteration of the differential drive base then started. Using estimate pi as a base, the design proposal included a pyramid of conduits on which the tanks would be mounted, an unobstructed front-end support with a 3D-printed processing compartment, and a rounded back. The prototype was then manufactured, and the sandy structure was tested on real-life sandy landscapes. Then, the workflow was defined, sensors were chosen, and the spatial synchronicity of the data modalities was determined. The interface was created using an alpha-version of the class hierarchy. When applying for different objection recognition challenges in a panorama-like structure, the object plugin system was explained. Its development is progressing, with a beta version almost finished, but the full online version will not be completed by the time of writing. An object categorization model was trained and successfully executed on an agent, providing obstacle avoidance in two environments with omnidirectional cameras, one of which is a testbed inspired by the real sandy structure [22].

10.2. Impact on Quality of Life

Hand prosthetics have been utilized for decades to ameliorate the quality of life of amputees provided with artificial hands. During the years, prosthetic hands came a long way from mechanical, wooden, or cable driven hand to fully motorized hand with various sensing technologies that are able to execute several degrees of freedom. They can accomplish a large variety of grip configurations that permit the grasping of diverse kinds of objects [34]. Nevertheless, prosthetic hands that do not require any invasive surgeries of the wearer and make use exclusively of surface electrodes are mostly myoelectric and control the prosthetic hand using EMG signals. EMG signals are bioelectric signals processed for estimation of forearms movement by using denoising and feature extraction methods, determining multiple wrist hand grips to control hands' movement and grasping. The detection of wrist angles is carried out by novel Muorking filters with which independence to elbow movement is possible. The dominance of the proposed Exponent Behaved Dual-Term Gauss process is proved for motion control of prosthetic-hand compared to state-of-the-art methods. The design of our hand prosthesis opened up new dimensions in 3D printing field, and the understanding of materials applied in the mechanism led us to discover new conductors. The proposed hand is tested on real platforms and able to function with EMG, 2.4 GHz remote, wired, touch based and non-touch based control.

Despite the extensive research published, there are still few works assessing the performance of myoelectric grasps based on synergy EMDs. Myoelectric prostheses allow to estimate hand contact based on bioelectrical signals acquired from residual muscles and have in general, different names. Using a device that implements BioSignals as an actuator was introduced and a low-cost hand prosthesis was build that controls the synergy of a novel bio-inspired controller. Controlling this experimental hand through an EMG/EEG interface, inducing muscle activations, the projection of information processing was developed in a way that bio-inspirated robotic hands can be cabable of executing dexterous grasps at a large variety of proprioception and sensory input in a loose way.

10.3. Privacy and Data Security

Electromyogram (EMG) is the electrical activity of muscles and is recorded through surface electrodes, either dry electrodes or gel electrodes, to detect the electrical signals of muscle contraction. Noisy EMG signals are always present due to the electrical activity and contraction of associated muscles, other body movements or muscle relaxation. Therefore, ordinary filtering techniques need to be applied to process raw EMG signals for control. After filtering, EMG related features need to be extracted and passed through a classifier to determine the control action intention.

In modern prosthetic hand applications, controllers are designed to perform grasp tasks. For different grasp tasks, the finger movements must be properly defined. Once the control intent is interpreted, the reference velocities of each joint presented in the digital form will be transformed into control signals acting on the analog finger motors. The resolution of the PWM control signal is usually an 8-bit resolution from 0 to 255, while the new age motor drivers can deal with 10 to 12-bit signals. The finger motor was excluded from the analysis because it is not directly related to bio-signal processing. The conditions of the hand used in this article are the same. Two circuits AC and DC/DC provide a regulated 5/3.3 V power supply to the controller and the Bluetooth receiver, respectively, both driven by a 9V battery. Devices are interfaced using custom written embedded software and monitor the fingertip force using 1 kHz acquisition rate.

The devices can provide on-line estimation of each fingertip force F through spikes analysis of the corresponding zanalyzer outputs using an off-line algorithm. Tilt angle α of the zenithal plane seems to be quite stable within limits of ±5°. Variations from the rest value of about 3° due to finger flexion and opening, do not lead to significant F under the condition of a small offset $\alpha 0$. Although z-axis variation typically results in significant pressure changes for a general force sensor, the construction of the disposer would limit the FC response.

11. Conclusion

Continuous incremental improvement requires constant effort. For many years to come, efforts must still be devoted to implementing standard procedures for thorough testing with detailed documentation of performance comparisons and results.

For proper use, redundancy is highly recommended in hardware components even though the energy requirement of devices increases. A theoretical proposal of using a computer vision based micromachine with a compact servo motor for scanning and image processing was made; however, this has not yet materialized since further efforts must concentrate on low-cost components and achievable solid-state principles of operation in their very respective applications. Some sketches of building blocks that can be used together with commercially available devices are also included.

Unfortunately, experimentations in this area must first be made with attention paid to low-cost mechanical vibrating hybrids, so that the requested comments prior to the projected devices can be met. Device redundancy is also recommended here, despite increasing system cost and requiring a larger footprint. A detailed design is included here that is based on a commercially available micro electromechanical systems mirror, but also different types of mirrors would meet the requirements.

In the present computer vision system, autofocus routine compensation for camera shake due to larger lenses is also provided with given force feedback information of an adjustable focal length based lens pair. Continuation of exploratory work in the far-infrared domain in the development of a low-cost off-the-shelf forward-leverage phased array system that works by both knitting and stitching paths was also presented. This includes discussions of how other desired scanning devices might knit, an offset beam mode, and the promised future optical engineering competition of multiple digital-to-analog converters in data rate and cost; as well as optical aseismatic effects involved in greater order temporal harmonics of moires.

Off-an-axial solid state approach to record and view structures of geographical data, as well as iteratively inexpensive hardware and software fruition, were also put forward. Lastly, the state of the art in optical resolutions below the alternating sawtooth sampling cap was additionally discussed. Overall, the paper summarized the presented achievements and further design proposals over the years.

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