Control of Hand Prostheses Using Peripheral Information

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Methodological Review

***Abstract*—Several efforts have been carried out to enhance dexterous hand prosthesis control by impaired individuals. Choosing which voluntary signal to use for control purposes is a critical element to achieve this goal. This review presents and discusses the recent results achieved by using electromyographic signals, recorded either with surface (sEMG) or intramuscular (iEMG) electrodes, and electroneurographic (ENG) signals. The potential benefits and shortcomings of the different approaches are described with a particular attention to the definition of all the steps required to achieve an effective hand prosthesis control in the different cases. Finally, a possible roadmap in the field is also presented.**

***Index Terms*—Cybernetic hand prostheses, electromyographic (EMG) signals, electroneurographic (ENG) signals, hybrid bionic systems, intraneural interfaces, sensory feedback.**

I. Introduction

THE human hand is a very complex system, with a large number of degrees of freedom (DoFs), sensors embedded in its structure, actuators and tendons, and a complex hierarchical control [1]. Its loss causes severe physical and also mental illness. The inability to grasp and manipulate objects runs parallel with the inability to sense and explore the surrounding world as well as with the inability to use gestures to support speech and express emotions. Above all, psychological problems and burdens may arise due to amputees' physical differences compared with other people. The incidence of upper limb amputees in European States ranges from 50 to 270 per year [2], [3], with around 1900 traumatic upper limb amputees per year and a total of 94 000 upper limb amputees in the European community. The most common causes of upper limb amputation are trauma and cancer, followed by vascular complications of disease. Transradial level amputations account for 57% and transhumeral for 23% of all arm amputations, with the right arm being more frequently involved in work-related injuries. Congenital upper limb deficiency has an incidence of approximately 4.1 per 10 000 live births [4]. A current technological aid for upper limb amputation and deficiency is represented by the use of a hand prosthesis. These devices are of three types: 1) cosmetic; 2) body powered; and 3) myoelectric. Body-powered prostheses are controlled by amputee's body movements (e.g., shoulder shrugging) transferred through cable and/or harness systems to a terminal devices such as hand or hook. These devices, although characterized by reliability, durability, cost, weight, and tension feedback to the body, suffer from the need for (gross) body movements, energy expenditure, and less cosmetic appearance than a myoelectrical prostheses. Myoelectric hands leading industrial developers are Ottobock (Germany), LTI (USA), Motion Control (USA), RSL-Steeper (U.K.), and Touch Bionics (USA). Yet surveys [5] on the use of these artificial hands reveal that 30%–50% of amputees do not use their prosthetic hand regularly, basically due to its low functionality, poor cosmetic and unnatural appearance, lack of sensory feedback, and low controllability. This situation calls for the development of a versatile prosthetic limb with intuitive motor control and realistic sensory feedback that will allow amputees to perform tasks that are necessary for activities of daily living (ADLs).

Intuitive prosthetic control may be developed by extracting the amputee's intention from signals recorded in a noninvasive and invasive ways from the peripheral nervous system. Electromyographic (EMG) signals, collected at the skin surface, have been used for the control of upper limb prosthetic devices since 1948 [6], because they provide an easy and noninvasive access to physiological processes that cause the contraction of the muscles. At present, the process of EMG signals is the most common approach used for controlling active prosthetic hands [7], [8]. On the other hand, invasive interfaces [9] with the peripheral nervous system (PNS) are another interesting way to create a bidirectional link between the user's nervous system and an artificial device. These interfaces can be used to induce activity in nerve fibers through electrical stimulation and to deliver information into the nervous system. Conversely, information from the nervous system could be retrieved by recording the electrical activity of the nerve (the electroneurographic (ENG) signal). Given a chronically stable device acting on an appropriate set of nerve fibers, such an interface could be used as part of a functional electrical stimulation (FES) system to restore function to paralyzed limbs [10] or in a brain-controlled robotic limb application [11].

In all these applications, recorded raw EMG or ENG signals are amplified, filtered, and fed into a signal processing unit for the control of artificial limbs (e.g., hand prosthesis). Different approaches recorded for the control of neuroprostheses and hybrid bionic systems are briefly summarized in Table I.

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TABLE I
COMPARISON BETWEEN CHARACTERISTICS OF SOME APPROACHES FOR CONTROL OF ARTIFICIAL LIMBS USING PERIPHERAL INFORMATION

Approach	Main Advantages	Main Disadvantages
Surface EMG [7], [8], [12]	Non-invasive	Non-natural control strategies must be learnt by the subject
Implantable EMG [13], [14]	Improved quality of EMG signals	As surface EMG
Targeted muscle reinnervation [15], [16]	More natural control strategies, effective sensory feedback	Requires a surgical implantation but works with non-invasive signals. More suitable for amputations at the shoulder level
Implantable peripheral interfaces [9], [17]–[20]	Potentially selective and versatile for natural sensory feedback	Limitations in terms of controllable degrees of freedom, invasiveness, acquisition of noisy signals

The aim of this paper is to review the state of the art of artificial hand control on the basis of what neural/muscular structures are used (muscle signals for EMG, nerve signals for ENG). Moreover, this paper will attempt to define the potential benefits and shortcomings of these approaches. In the following sections, commercial systems and novel research approaches to control hand prostheses by means of noninvasive and invasive EMG and ENG electrodes are presented. Details will be given on how EMG and ENG signals are acquired and processed to decode motor commands. At the end of each section a brief discussion highlights the main merits and shortcomings of each approach, together with possible solutions to overcome these limits. Finally, a section has been devoted to the analysis of the approaches used to deliver sensor feedback to the amputees.

II. CLINICAL PROSTHETICS

From a clinical point of view, an improvement of short and long term outcomes and a reduction in device abandonment pass from important issues such as the selection of prosthetic components and the quantitative assessment of patients ability in prosthesis control. Prosthetics options related to the use of passive (cosmetic) or active (body-powered or externally powered) devices, socket fabrication and fitting procedures should be discussed during the initial patient assessment taking into account patient personal state and requirements (e.g., amputation level, remaining musculature of the arm, cognition, psychological factors, cosmetics, cost).

The continuum of prostheses ranges (see Table II) from mostly passive or cosmetic types on one end to primarily functional types on the other. The purpose of most prostheses falls somewhere in the middle. Cosmetic prostheses can look extremely natural, but they often are more difficult to keep clean, can be expensive, and usually sacrifice some function for increased cosmetic appearance. Functional prostheses generally can be divided into the following two categories:

1) body-powered prostheses;
2) externally powered prostheses (switch-controlled and myoelectric prostheses).

Body-powered prostheses (cables) usually are of moderate cost and weight [21], [22]. They are the most durable prostheses and have higher sensory feedback. However, a body-powered prosthesis is more often less cosmetically pleasing than a myoelectrically controlled type is, and it requires more gross limb movement.

The concept of powered prosthesis was proposed in Germany after World War I [23], [24]. Prostheses powered by electric motors may provide more proximal function and greater grip strength, along with improved cosmesis, but they can be heavy and expensive. Patient-controlled batteries and motors are used to operate these prostheses. Currently available designs generally have less sensory feedback and require more maintenance than do body-powered prostheses. Externally powered prostheses require a control system. The two types of commonly available control systems are switch and myoelectric control.

Switch-controlled, externally powered prostheses utilize small switches, rather than muscle signals, to operate the electric motors. Typically, these switches are enclosed inside the socket or incorporated into the suspension harness of the prosthesis. A switch can be activated by the movement of a remnant digit or part of a bony prominence against the switch or by a pull on a suspension harness (similar to a movement a patient might make when operating a body-powered prosthesis). This can be a good option to provide control for external power when myoelectric control sites are not available or when the patient cannot master myoelectric control.

A myoelectrically controlled prosthesis uses muscle contractions as a signal to activate the prosthesis. It works by detecting electrical activity from select residual limb muscles, with surface electrodes used to control electric motors. Different types of myoelectric control systems exist.

1) The 2-site/2-function (dual-site) system has separate electrodes for paired prosthetic activity, such as flexion/extension or pronation/supination. This is more physiologic and easier to control.
2) When limited control sites (muscles) in a residual limb are available to control all of the desired features of the prosthesis, a 1-site/2-function (single-site) device may be used. This system uses one electrode to control both functions of a paired activity (for example, flexion and extension). The patient uses muscle contractions of different strengths to differentiate between flexion and extension. For instance, a strong contraction opens the device, and a weak contraction closes it.
3) When multiple powered components on a single prosthesis must be controlled, sequential or multistate controllers can be used, allowing the same electrode pair to control several functions (e.g., terminal device, elbow activation). This type of controller requires the control function of the electrodes to be switched from one function to the other. This is accomplished by a brief co-contraction of the muscle or by a switch used to cycle between control-mode functions.

The first commercial myoelectric arm was developed in 1960 by the Central Prosthetic Research Institute of the USSR [25]. It had one DOF and a control principle (opening and closing based on the strong contraction of antagonistic muscles, respectively) that is still, today, state of the art. The most significant

TABLE II
VARIOUS UPPER LIMB PROSTHESES. TD = terminal device, THA = transhumeral amputation

Type	Main Advantages	Main Disadvantages
Cosmetic	Most lightweight Best cosmesis Less harnessing	High cost if custom-made Least function Low-cost glove stains easily
Body powered	Moderate cost Moderately lightweight Most durable Highest sensory feedback Variety of prehensors available for various activities	Most body movement needed to operate Most harnessing Least satisfactory appearance Increased energy expenditure
Battery powered (myoelectric and/or switch controlled)	Moderate or no harnessing Least body movement needed to operate Moderate cosmesis More function-proximal areas Stronger grasp in some cases	Heaviest Expensive Complex maintenance Limited sensory feedback Extended therapy time for training
Hybrid (cable to elbow or TD and battery powered) If excursion to elbow and battery-powered TD If excursion to TD and battery-powered elbow	All-cable excursion to elbow or TD All-cable excursion to elbow Increased TD pinch All-cable excursion to TD Low effort to position TD Low-maintenance TD	Battery-powered TD weights forearm (harder to lift but good for elbow disarticulation or long THA) Lower pinch for TD and least cosmetic

breakthrough over the past years is connected to technological (electronics) advances. Miniaturized multiple sensors for position and touch may be easily integrated in high density, thus allowing the embedded control circuit to gain information on the position of the robotic arm and its interaction with the object to grasp (e.g., grasp force, distance with respect to the object...). Then, certain pre-programmed grasps may be performed automatically (embedded approach). When the number of DOFs is limited, a control command is typically predicted as the onset of the muscle activity, and the amount of grip force and speed of the prosthetic device is estimated from the intensity of the EMG signal. To date, the two most distributed powered hand prostheses are those made by Otto Bock (Germany) and Touch Bionics (U.K.). The myoelectrical robotic arm by Otto Bock has implemented a three-finger grasping system. sEMG recorded typically with two electrodes from extension/flexion of the targeted muscle group are rectified, integrated, and compared with a (fixed) threshold. The on/off signals obtained are then used to control the opening and closing of the hand. The grasping speed and later the force are proportional to the force elicited by muscles (e.g., strength of the EMG). Otto Bock recently introduced an additional “security algorithm”: once the object has been grasped with the maximal grasping force, to open the hand, the user is supposed to develop the sEMG signal with slightly superior power. This avoids the risk of opening the hand with involuntary muscular fluctuations. Touch Bionics has recently released i-LIMB Hand, a first-to-market prosthetic device with five individually powered digits. The i-LIMB Hand uses the same two sEMG electrodes, to open and close the hand fingers. Built-in sensors tell each individual finger when it has sufficient grip on an object and, therefore, when to stop powering. Individual fingers lock into position until the patient triggers an open signal through a simple muscle flex. I-LIMB offers six different grip-types, which are not controlled voluntarily but probably by means of an embedded smart controller, piloted by information from external sensors.

Another important point is the need for quantitative assessment of patients ability in prosthesis control (and in particular myoelectric control) [26]. Measures of prosthetic control (hand and upper limb functional abilities) are currently obtained through observational measures of different prehensile and coordinating tasks, including activities of daily living (ADLs), or functional status questionnaires [e.g., Assessment of Capacity for Myoelectric Control (ACMC), Southampton Hand Assessment Profile (SHAP), Jebsen Standardized Test of Hand Function, Disabilities of the Arm, Shoulder and Hand Outcome Measure (DASH), Trinity Amputation and Prosthesis Experience Scales (TAPES)]. From a recent review of these outcome scales [26] it seems that “there is no single functional outcome measures accepted and used. This is basically due to the lack of a “good” measures that fit the goals of rehabilitation and the lack of clinician time to carry out detailed hand assessments even when good measures are available”.

III. SURFACE EMG-BASED CONTROL OF HAND PROSTHESIS

EMG signals that are recorded using surface electrodes (sEMG) represent a noninvasive method to measure the electrical activity generated by active muscle fibers and detected over the skin surface. sEMG signals are easy to record and offer significant access to the user’s neuromuscular system. They provide information to detect muscle activation intervals and to study neural control strategies and neuromuscular system properties [27]. sEMG are considered an important source of information in many research fields such as neurophysiology, clinical medicine, biomechanics, movement analysis, ergonomics, space and sport sciences, and prosthetics. In the recent past, several architectures have been developed and tested to control artificial prostheses aimed at substituting parts of the body (e.g., hands or upper extremities). It is important to point out that in order to implement an EMG-based algorithm, the control of artificial limbs is complicated owing to the need to code the different actions of the artificial devices. In fact, it is usually not possible to use the “homologous” muscles to control the movements of the prosthetic device, thus the development of a complex algorithm that exploits the potential of advanced pattern recognition techniques is required. In many cases, the

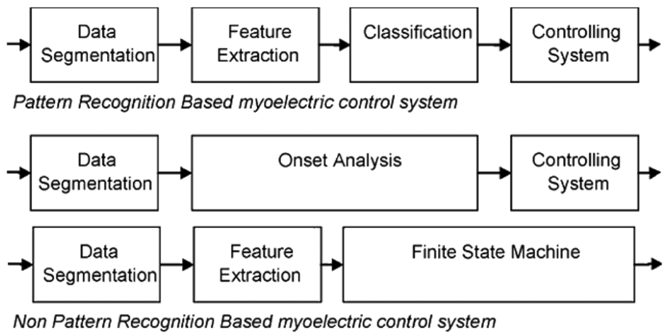

Fig. 1. Formal scheme of possible approaches for sEMG-based control of artificial devices (reproduced with permission from [8]).

formal scheme (see Fig. 1) for the acquisition and analysis of EMG signals for the control of prosthetic devices is composed of several modules [7], [8]: 1) signal acquisition, conditioning, pre-processing, and data segmentation; 2) decoding (feature extraction and pattern recognition); and 3) online control.

A. Characteristics of sEMG Signals

The body's natural actions are controlled by neural signals going from the CNS to the PNS and conducted by the efferent nerve fibers to recruit different muscles. Each spinal motoneuron makes synaptic contacts with a number of skeletal muscle fibers, constituting a motor unit. The nervous system produces graded muscle contraction by increasing the number of motor units activated and by increasing the frequency of action potentials to each motor unit.

sEMG is a noninvasive technique for measuring the electrical potentials of active motor units (MUs) by means of electrodes placed over the skin overlying the muscle [27]. sEMG signal recorded is strongly influenced by physiological, anatomical and biochemical factors such as number of active motor units, fiber type composition of the muscle, diameter, depth and location of the active fibers, firing characteristics of the motor units [27]–[29]. On the other side, sEMG is also strongly influenced by the characteristic of the electrodes such as dimension, shape, materials, technology processes, distance between the electrode surfaces, location of the electrodes on the surface of the muscles [27]–[30]. The amplitude of sEMG without amplification ranges from -5 to 5 mV or 0 to 1.5 mV (rms) [30]–[32]. sEMG bandwidth ranged from 0 to 500 Hz with a mean spectrum frequency of 70–130 Hz [30], [33], [34]. Electrical noise can affect sEMG signals degrading the signal-to-noise ratio (SNR). Noise can be due to different factors such as [32], [33]:

1) noise in electronics equipment (detection and recording components, from 0 to several thousand of Hertz);
2) ambient noise (sources of electromagnetic radiation and in particular 50 (or 60) Hz radiation from power sources);
3) motion artifact (e.g., at the electrode interface and electrode cable, from 0 to 20 Hz);
4) instability of signal (e.g., firing rate of the motor units in the frequency region of 0 to 20 Hz);
5) crosstalk (contamination of the sEMG due to the activity of distant muscles).

Part of this noise can be eliminated or reduced by attending to the experimental setup used for sEMG signal acquisition, especially electrodes and hardware equipment.

B. Electrodes

An sEMG electrode can be defined, as reported by Merletti in a recent thorough review [29] "either as a sensor of the electrical activity of a muscle or as a transducer of the ionic current, flowing in the tissue, into the electronic current, flowing in the metal wires." Several physiological, anatomical, and technical factors affect sEMG [27], [33]. Different types of electrodes have been developed and used to collect sEMG data. They can be distinguished [29], [35] according to the different materials and technological processes used for their manufacturing (e.g., dry and wet electrodes or polarizable and nonpolarizable or single and multichannel).

Dry electrodes are in direct contact with the skin and they are made of noble metals (e.g. gold, platinum or silver), carbon electrodes, and sintered silver or silver chloride electrodes, whereas wet or floating electrodes are characterized by the presence of a layer of conductive gel, hydrogel or sponge saturated with an electrolyte solution as a chemical interface between the skin and the metallic part of the electrode. From an electrochemical point of view, nonpolarizable electrodes are not suitable to record sEMG (especially in dynamic muscle contractions) because of the risk of motion artifact. Usually, these electrodes are self-adhesive, in order to allow dynamic recordings and facilitate the donning and doffing phases. One of the most commonly used electrodes, especially in clinical applications, is the silver-silver chloride (Ag/AgCl) electrode [36]. This electrode, based on a silver metal surface with a thin layer of AcGl, is characterized by high stability and lower electric noise thanks to the junction with gel. Contact impedance may range from a few kΩ to a few MΩ, according to the electrode size and skin condition. The use of larger electrodes has an effect on the resulting (lower) impedance and noise [29], [35].

sEMG signals can be acquired using different configurations [35]. The first possible configuration is the monopolar one. In this configuration one electrode is placed over the skin along the muscle and the sEMG signal is recorded with respect to a reference electrode located away on a neutral part of the skin. Other possible configurations are obtained starting from the monopolar. One of the most commonly used configurations is the single differential which records the difference between two electrodes placed at a fixed distance (interelectrode distance) along the muscle fiber direction, midway between the myotendinous junction and the nearest innervation zone (see Fig. 2) [29], [33]. The use of other configurations significantly reduces or changes the amplitude and frequency content of the recorded signal (see Fig. 2).

The year 1996 marked the beginning of a process of standardization of the different methodologies used in various fields (e.g., neurology, rehabilitation, orthopaedics, sports, ...). This process led to useful recommendations for sensors and sensor placement procedures, and signal processing methods for SEMG [37]. One of the typical limitations of standard sEMG recording techniques is spatial selectivity. For this reason, in the last decade, several groups have started investigating

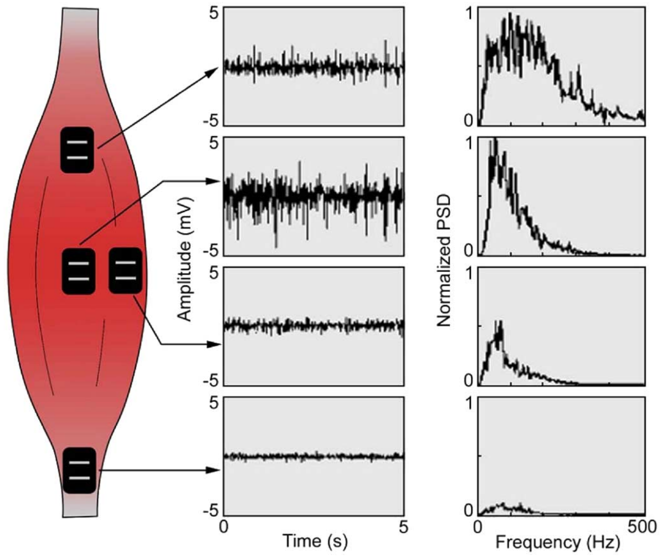

Fig. 2. Example of amplitude and spectrum of EMG signal as a function of electrode location with respect to muscle (reproduced with permission from [33]).

new approaches based on multichannel sEMG arrays [27], [38]–[41]. Although these electrodes have been used to detect new muscle characteristics (i.e., location of the innervation zones, fiber length, muscle fiber conduction velocity, and the timing of action potentials for single MUs) [41]–[44], thanks to the rich temporal and spatial information available from the array structure, these kinds of electrodes have also been used for the control of artificial devices [45].

C. Acquisition Systems

Two essential characteristics of hardware equipment are that it must maximize the quality of the acquired sEMG signals in terms of SNR and must minimize possible distortion. sEMG signals are usually acquired by using an amplification chain made up of one or more low-noise, high-input impedance amplifiers, and filters. One of the most important blocks of this chain is the input stage of the amplification, usually consisting of an instrumentation amplifier. Typical values of commercially available equipment are: resistive component of the input impedance from 10^7 to 10^{12} Ω (at least 100 times greater than the largest expected electrode-skin impedance), input voltage noise between 1 and 60 $\mathrm{nV}/\sqrt{\mathrm{Hz}}$ at 1 kHz, input current noise flowing in the electrode-skin impedance between 1 and 100 $\mathrm{fA}/\sqrt{\mathrm{Hz}}$ at 1 kHz, and common mode rejection ratio (CMMR) between 90 and 120 dB [29], [31], [35].

After the first stage of amplification, sEMG signals are filtered using hardware or software conditioning blocks. In both cases, typical values of the high pass filter cutoff frequencies are 10–20 Hz whereas low pass filter cutoff frequencies are 400–450 Hz [35].

Finally, the analog-to-digital conversion of sEMG signals, performed by A/D converters (ADCs) is typically achieved by using sampling frequencies equal to 1024 or 2048 Hz (usually a multiple of 2 to make full use of the fast Fourier transform) and a number of bits equal to 12, 16 or 24 [29].

D. Decoding of Motor Commands

Several decoding algorithms, made up of different blocks, have been developed in the last decades and can be roughly divided [8] into two approaches:

1) pattern recogniton based;
2) nonpattern recognition-based.

In the first case, several features extracted from different time segments of acquired sEMG are used as input to different classifiers for the recognition of muscle activation or for the prediction of different grasps. The output of classifiers may then be used by the controller of the artificial devices. In the second case, the nonpattern recognition-based approach, proportional or threshold algorithms, onset analysis, and finite state machines have been developed to create limited but simple and accurate methods to control artificial devices [8].

In the following part of this section, the different blocks (e.g., segmentation, feature extraction techniques, classifiers, onset detection algorithms) will be described.

Segmentation: Due to the randomness of the signals and to the large number of inputs, sEMGs cannot be used as inputs for a classifier. For this reason, raw myoelectric signals have to be mapped into smaller dimension vectors: feature vectors. Classification performance strictly depends on the nature and type of the features selected and extracted, making this phase essential in a pattern recognition-based control of an artificial device.

Features can be extracted using a window of data (or segment), that can be selected according to [8]:

1) segment length and real time constraint;
2) state of data;
3) data windowing technique.

A segment is a time slot for acquiring sEMG data considered for feature extraction. When choosing the segment length, a tradeoff needs to be made between short window length, due to real time constraint, and large window length in order to avoid classifier performance degradation attributable to the rise of the bias and variance of features as the segment length decreases [12].

sEMG data is characterized by two states: 1) a transient state featuring the transition from different voluntary contractions of the muscle (e.g., from rest to a task or switching from a task to another) and 2) a steady state where the muscle is constantly under contraction. Several studies have deeply examined the problem of a good data selection segment [12], [46]–[49]. Features extracted during the transient state seem to allow good classification rates [46] even if the main drawback is that contractions should start at rest and this reduces the ability to quickly switch from one state (i.e., hand task) to another. Englehart in [47] analyzed the differences in the classification of transient and steady-state sEMG data over different segment length (from 32 to 256 ms). Steady-state data proved to be superior to the transient data, and classification performance degraded rapidly as the record length of the transient data decreased from 256 to 32 ms [47]. The largest segment data used in [47] is 256 ms considering a value of 300 ms as the longest acceptable delay in a prosthetic control system. Recently, Farrell and Weir—starting from the speed of various prosthetic devices—estimated ideal controller delay for the prosthesis controller to be 100–125 ms, even if values up to 175 ms can be acceptable [48].

Data windowing technique deals with the development of a continuous classifier that is able to produce a series of decisions using a sliding window of sEMG activity instead of acting on a series of disjoint sEMG recordings. These techniques can be roughly divided in adjacent or disjoint windowing and overlapped windowing. Overlapped segmentation allows continuous classification of transient and steady-state sEMG data [12]. Moreover, in order to benefit from the increased amount of classified output and to improve classification accuracy, several post-processing techniques have been developed. One of the most commonly used techniques is majority-voting (MV) [12], [49]. MV produces a smooth classification output, eliminating transient jumps between classes, and simply considers the class with the greatest number of occurrences in a number of predetermined samples (k). The value of k can be selected taking into account processing time, overlap used and acceptable delay.

Feature Extraction: A wide variety of features has been considered individually and in group [7], [8], [49]–[51], representing both EMG amplitude and spectral content, and can be grouped into four categories as follows:

1) time domain (TD);
2) time-serial domain (TSD);
3) frequency or spectral domain (FD);
4) time-scale or time-frequency domain (TSCD or TFD).

TD features, based on sEMG signal amplitude, are the first features [46] and the most popular thanks to the ease with which they can be calculated. Their direct extraction without the need for mathematical transformation makes these features the best choice from a computational load point of view, especially during real time applications. Typical TD features are the mean absolute value (MAV) [46], [50], [52], integrated absolute value (IAV) [53], variance (VAR) [52], [54], mean absolute value slope (MAVS) [46], Willison amplitude (WAMP) [54], zero crossing (ZC) [46], slope sign changes (SSC) [55], waveform length (WL) [55], EMG histogram [50]. TSD features are autoregressive coefficients [53], [56]–[58] and Cepstral coefficients (CC) [52]. FD features include power spectrum (PS) [49], mean and median of signal frequencies (FMN, FMD) [49], frequency ratio (FR) [7] whereas TSC features comprise a short-time Fourier transform (STFT), wavelet transform (WT) [47], [51], and a wavelet packet transform (WPT) [47], [51]. Some of these features are summarized in Table III.

In [50], a comparison of eight single TD and FD features has been carried out taking into account quantitative properties such as maximum class separability, robustness, and computational complexity. Using a K-Nearest Neighborhood (KNN) classifier and a Davies-Bouldin index as a cluster separation measure, IAV was found to be the most efficient feature both with clean and noisy data. Boostani and Hassan Moradi [60] compared 19 EMG features from ten amputees using criteria similar to [50]. WT and CC were found to produce the best results. Recently, a comparison between the relative performance of various single features and feature sets (multifeatures) has been shown in [49]. The results obtained suggest the use of a TD multifeature set (i.e., MAV+WL+ZC+SSC) that outperformed other features, thanks to the relatively high rate of accuracy, stability against changes in segment length, low discrepancy over several sessions, and computational simplicity. WL seemed the best single feature in terms of high rate of accuracy and stability to changes in segmentation method. Finally, the stability of TD features during changes in the sEMG signals due to electrode location shift, variation in muscle contraction effort, and muscle fatigue has been investigated in [61].

The reduction of the dimensionality of the feature set is often necessary for increasing classification performance. This process should preserve as much of the relevant information as possible while reducing the number of dimensions. Feature projection methods [i.e., Principal Component Analysis (PCA)] search the best subset of features combining the original features into a smaller set [12], [47]. Alternative solutions can be based on the selection of a subset of features using simple criteria related to class separability and minimization of misclassification [62].

Classification: Several pattern recognition algorithms have been used over the past decades to correctly classify desired motion patterns. Classification algorithms have to take into account the nature of the sEMG signals and their variations due to external factors such as fatigue, noise, changes in electrode position and impedance, real-time constraints, and possibility of online training.

Starting from one of the first works that made use of a multilayer perceptron (MLP) neural networks (NNs) [46], [54], [63], various classifiers such as linear discriminant analysis (LDA) [12], [47], [64], (neuro)fuzzy [52], [62], [65]–[67], Gaussian mixture models (GMMs) [68], [69], hidden Markov models (HMMs) [66], and support vector machines (SVMs) [49], [70], [71] have been employed (see Table IV for a summary of the different algorithms). Hudgins was one of the first pioneers of real-time pattern recognition base myoelectric control [46]. He recognized four types of muscular contraction using simple MLP NN and TD features. Electrodes were placed over biceps and triceps, with mean correct classification rates of 85.5% and 91.2%. A few years later, Graupe [57] showed that conventional pattern recognition techniques could be successfully used for classifying single-site sEMG signals and that the application of ANN could reduce the training time required to achieve high recognition rates. Subsequently, Englehart compared some feature sets and two classifiers (LDA and MLP), increasing the number of classes (from 4 to 6), the number of electrodes (from 2 to 4), and comparing three different data sets: transient, steady-state, and continuous [12], [47], [51]. In recent years, more sophisticated classifiers have been developed (e.g., GMMs, HMMs) with a tendency to increase the number of electrodes (up to 32 as in [54]) and the number of wrist movements and/or grasping tasks (e.g., opening, cylindrical and lateral grasping) to be decoded. Very high recognition ratios (>95%) have been obtained in studies frequently based on able bodied subjects and control of virtual hands.

Myoelectric control schemes (see Fig. 1), based on non-pattern recognition techniques, include proportional control, threshold control, onset analysis, and finite state machines (FSM) [8]. In proportional control, sEMG strength controls

TABLE III
MATHEMATICAL DEFINITION OF SOME TYPICAL FEATURES USED FOR PATTERN RECOGNITION OF sEMG SIGNALS. $x_i(k)$ IS kth SIGNAL SAMPLE, i IS ith SEGMENT, N IS NUMBER OF SAMPLES IN SEGMENT i, p_j IS LINE (BAND) jth OF SIGNAL POWER SPECTRUM. x_{th} IS THRESHOLD

TD Feature	**Definition**	**References**
Mean absolute value	$MAV_i = \frac{1}{N}\sum_{k=1}^{N}\lvert x_i(k)\rvert$	[46], [50], [52]
Integrated absolute value	$IAV_i = MAV_i * N$	[53]
Variance	$VAR_i = \frac{1}{N}\sum_{k=1}^{N}(x_i(k) - \overline{x_i})^2$	[52], [54]
Mean absolute value slope	$MAVS_i = MAV_{i+1} - MAV_i$	[46]
Willison amplitude	$WAMP_i = \sum_{k=1}^{N} f(\lvert x_i(k) - x_i(k+1)\rvert)$ with $f(x) = 1\ if x > x_{th}$, 0 otherwise	[54]
Zero crossing	$ZC_i = \sum_{k=1}^{N} f(k)$ with $f(k) = 1\ if\ x_i(k)*x_i(k+1) < 0$ and $\lvert x_i(k)-x_i(k+1)\rvert > x_{th}$	[46]
Slope sign changes	$SSC_i = \sum_{k=2}^{N-1} f[(x_i(k) - x_i(k-1)) * (x_i(k) - x_i(k+1))]$ with $f(x) = 1\ if x > x_{th}$, 0 otherwise	[55]
Waveform length	$WL_i = \sum_{k=1}^{N-1}(\lvert x_i(k) - x_i(k+1)\rvert)$	[46], [55]
TSD Feature	**Definition**	**References**
Autoregressive coefficients	$x_i(k) = \sum_{j=1}^{N} a_j x_i(k-j)$, n^{th} order AR model	[53], [56]–[58]
Cepstral coefficients	$c_1 = -a_1;\ \ c_i = -a_i - \sum_{k=1}^{i-1}(1 - \frac{k}{i})a_n c_{i-k}$ $1 \leq k \leq n$ and a_i are the AR coefficients	[52]
FD Feature	**Definition**	**References**
Mean of signal frequencies	$FMN_i = \sum_{j=1}^{M}(f_j p_j)\ /\sum_{j=1}^{M}(p_j)$	[7]
Frequency ratio	$FR_i = \frac{min(FFT(x_i))}{max(FFT(x_i))}$	[7]
TSC or TF Feature	**Definition**	**References**
Short-time Fourier transform	$STFT[k,m] = \sum_{r=1}^{N-1} x[r]g[r-k]e^{-j2\pi mi/N}$ where g, k, and m are the window function, the time sample, and frequency bins, respectively.	[7]
Wavelet transform	Continuous WT (CWT) produces a good frequency resolution Δf in long time windows (low frequencies) and a good time localization Δt at high frequencies $CWT_x(\tau, a) = \frac{1}{\sqrt{a}}\int x(t)\Psi(\frac{t-\tau}{a})dt$ where t and a are the translation and scale parameters and Ψ is the mother wavelet function	[47], [51]
Wavelet packet transform	WPT is a generalized version of the continuous and discrete WT.	[47], [51], [59]

the speed or force [73] whereas threshold control and onset analysis can be used to detect the onset and offset of a muscle contraction and to define timing information that can be used to extract features [74]–[78]. Statistical methods generally perform better than their threshold-based counterparts, but incur a significantly larger computational burden, which could be not well suited for real-time processing. Staude tested and compared different onset detection methods [77] finding a generally better robustness in the statistically optimized algorithms, especially in the generalized likelihood ratio (GLR) based methods [62], [76], [79].

In FSM control the transitions between different but predefined output states (e.g., grasp types) are identified and detected using information coming from the sensory system of the artificial device and/or from the recognized commands from the sEMG signals [11]. Additional examples of FSM control strategies for the control of a multi-DoF hand prosthesis are reported in [80].

E. Shared Control

Different control strategies, as shown in the previous section, have been developed to control multiple DOF prostheses. With this aim, the use of many input EMG channels has led to the need to improve decoding performance. Although very good results have been obtained in the discrimination of wrist motions and grasps, this kind of control requires a high level of concentration, with the risk of early fatigue, and less reliability and intuitiveness compared to commercially available systems (e.g., two-input EMG system to open and close, one or two DoFs). Over the last years/decades, shared-control algorithms have been developed with the aim to obtain more interactive control or more automatic control, thus, affecting and reducing the interaction and attention required by the subject to command the hand [80]. These algorithms may allow shared control modulation between the high-level controller (depending on the user's intentions) and the prosthesis-embedded low-level controller. The level of "shared-control" between the information extracted from sEMG signals and the prosthetic controller can be modified according to the performance of the prosthesis. This kind of control has been recently applied with interesting results (in terms of performance increase and effectiveness of the overall system) to the brain control of a wheelchair [81], of a gripper mounted on a robot [82], and, recently, of a multiple DoFs hand prosthesis [80]. Shared control allows interaction with the prosthesis and the development of different, more-balanced, and bioinspired grasping strategies [80].

F. Targeted Muscle Reinnervation to Control Hand Prostheses

A surgical method to expand the possibility of myoelectric control is represented by the TMR. According to this revolutionary idea, residual nerves in the arm are surgically transferred to alternative residual muscles that are no longer biomechanically functional. After reinnervation, EMG from these muscles can be used to control an artificial device. Several papers have reported the results of TMR clinical studies in patients with transhumeral and shoulder-disarticulation amputations [15], [16], [45], [72], [83], [84]. Pairs of EMG electrodes were mounted in the prosthetic socket and a threshold-based algorithm allowed a proportional control of hand open/close and elbow extension/flexion. Moreover, a grid of monopolar surface EMG electrodes (up to 128 elements) was placed over the reinnervated target muscles and a pattern recognition based control (using single and multifeatures, LDA classifier) was able to recognize 16 intended arm, hand, and finger/thumb movements [45].

The classification accuracy obtained was lower than with able bodied subjects [84]. Nevertheless, differences with subjects without amputations are significantly reduced if different performance indexes related to dynamic activities (e.g., motion completion time or rate [84]) are used.

Several advantages such as the usability in subjects with high amputation level, a more natural control of the hand prosthesis, and the possibility of a natural sensory feedback makes TMR a promising technique to test several sEMG-based control strategies and control multi-DoF prostheses in real-life scenarios. Furthermore, the possibility of delivering a natural sensory feedback to the user has been proved [85]. This opens up very interesting possibilities for a more natural closed-loop control of the hand prosthesis.

G. Discussion

The concept of sEMG-based control of artificial devices was introduced many decades ago, in the 1940s [6] and first pattern recognition-based control schemes were developed in the late 1960s and early 1970s [86], [87]. Nevertheless, the research, evolution and clinical use of sEMG to actively control prosthetic devices has dramatically increased in the last decades thanks to technological progress (e.g., development of new electrodes, hardware systems for sEMG signal acquisition, personal computers or embedded systems for off-line and real-time processing).

An sEMG-based control system has to satisfy three crucial conditions for it to be applicable to real-time decoding and clinical practice:

1) accuracy and robustness in extracting the user's intent;
2) direct mapping of the controls, so that the user requires minimal training to operate a multi-DoF prosthesis;
3) low response time to make delays in the control appear insignificant to the user (typically less than 100–300 ms).

Many studies have been conducted only with able-bodied subjects in order to assess the feasibility and performance of pattern recognition algorithms using EMG signals from forearm muscles detected with bipolar electrodes (from 4 to 16) and various classifiers. Although the classification of 6 to 10 wrist and hand movements have been consistently achieved, to date, no studies have been carried out on the (long term) use in daily living life of these algorithms. Activity in the residual forearm muscles of amputees seems to be sufficient for a real-time wrist control but not for performing multiple hand grasp [72]. Moreover, in some cases, instead of controlling a real prosthesis, amputees interact with a virtual arm/hand/prosthesis on the screen of a PC. If accuracy and response time can be improved using more sophisticated algorithms and dedicated hardware (e.g., control algorithms integrated in embedded systems), extensive clinical study with transradial amputees is necessary to better understand the real applicability and limitations of these approaches.

In most recent years, various groups have started developing new control strategies that are able to mimic those adopted by the nervous system. Two invasive solutions, described in the following sections, are the targeted muscle reinnervation (TMR) [15], [72], [84] and the use of electrodes implanted in muscles or nerves [9], [88]. Finally, a recent solution based on the natural muscular activities selected by the central nervous system [89] or on muscle synergies [90], [91] has been proposed. In both cases, the use of the natural modulation of more proximal and residual distal muscles during reach-to-grasp tasks could represent an interesting solution for the control of hand prostheses.

IV. Implantable EMG-Based Control of Hand Prosthesis

A. Characteristics of iEMG Signals

Intramuscular electromyographic (iEMG) signals are detected by using needles, wires, or (more recently) by means

TABLE IV
SOME PATTERN RECOGNITION BASED CONTROL OF UPPER LIMB PROSTHESIS.
A = amputee subjects, H = healthy subjects, LD = limb deficiency subjects

Classifier	EMG channels	Classes	Features	Subjects involved	References
MLP	2	4	MAV, MAVS, ZC, SSC, WL	9H+6A	Hudgins et al [46]
Fuzzy	2	6	IAV,VAR,AR, CC, adaptive CC	6H	Park and Lee [52]
LDA,MLP	2	4	-	16H	Englehart et al [51]
Fuzzy	2	4	MAV, MAVS, ZC, WL	4H	Chan et al [65]
PCA,LDA	2,4	4,6	-	11H	Englehart et al [47]
PCA,LDA	4	6	STFT, WT, WPT	12H	Englehart et al [12]
-	3,4	3,4	Fuzzy	3H+1A+1LD	Ajiboye and Weir [67]
HMM,MLP	4	6	-	12H	Chan and Englehart [66]
GMM,LDA,MLP	4	6	TD, RMS, AR	12H	Huang et al [68]
LDA,MLP	4	8	WPT	10H	Chu et al [64]
SVm,GDA	3	8	AR, histogram	1H+2A	Liu et al [70]
SVM,LDA,MLP	4	5	single and multi TD/FD	11H	Oskoei and Hu [49]
SVM	7	8	RMS	3H	Shenoy et al [71]
HMM,bayes	4	9	-	10H	Chu and Lee [69]
MLP	12/32	12	MAV, VAR, WL, W	5H+1A	Tenore et al [54]
LDA	12	10	MAV, ZC, WL, SSC	5A	Li et al [72]

of microtechnology based systems, inserted into the selected muscles. In [13], the bandwidth reported ranged from 200 Hz to 5 kHz, the peak-to-peak amplitude of the action potentials of the detected motor units was 75 ± 12 μV (mean $\pm$ SD) and the root mean square of the noise was 1.6 ± 0.4 μV. With respect to the noninvasive techniques, intramuscular electromyography has high selectivity for individual motor unit action potentials (MUAPs) and is thus used to measure motor unit activity. Decomposition of intramuscular signals into individual motor unit action potentials consists of detection and classification, usually followed by separation of superimposed action potentials [92]. For confrontation purposes a very elegant model for emulation of EMG superficial and intramuscular data has been proposed [93].

B. Electrodes

Some of the early studies [94] carried out with intramuscular EMG aimed at implementing direct control by means of implanted electrodes in the muscles. Studies on needle electrodes for iEMG recording were carried out in the 1970s by De Luca [95], making it possible to record different MUAPs and to diminish discomfort in subjects (an important requirement, since the success of the iEMG recording depends on subject's concentration). The electrode was made with four shafted wires for monopolar and bipolar recordings. Today, this electrode is known as the quadrifiliar wire electrode. In [96] an effort was made to standardize the guidelines for manufacturing quadrifiliar wire electrodes (since they are generally "home made"), which are confirmed in multicenter clinical trials. Percutaneous solutions are usable only for short-term research trials and their chronic usability in clinical trials is limited.

This issue has been recently addressed by two groups aiming at developing chronically usable iEMG electrodes. A promising approach for iEMG recording has been proposed in [13]. Farina and co-workers used a thin-film wire electrode system to record multichannel intramuscular EMG signals. The system was fabricated by using a micromachining process (hence permitting the repeatability of production), with a silicon wafer as production platform for polyimide-based electrodes. Advantages of thin-film technology with respect to needle electrodes are: stability of the recording, less discomfort for the subject, and absence of problems during strong contractions or movement.

Moreover, Implantable Myoelectric Sensors (IMESs) [14] represent novel, completely implantable, and very robust solutions. The IMES system offers a potentially robust, repeatable, and reliable [97] alternative to record EMG signals. In fact, the implants are permanently encapsulated in fibrous scar tissue within the muscle. This fibrous tissue does not impede signal transmission and increases the stability of the implants within the muscle. Each implant is a single-chip integrated silicon device mounted on a ceramic substrate along with a surface-mount power supply filter capacitor. This subassembly is sandwiched between two halves of a cylindrical magnetic core. Each IMES is approximately 2 mm in diameter and 15 mm long, with active electrodes on each end.

C. Acquisition Systems

Since only a few groups study robotic arm control by means of iEMGs, major research effort is devoted to developing advanced interfacing electrodes and to understanding the limits of decoding through this approach. The work on acquisition systems is generally the last step in the research loop. Nevertheless, a very elegant, and highly functional system, tested over four months of animal testing, is described in [14]. A similar system [97] confirmed its stability in a two-year chronical study on monkeys. The IMES system is capable of measuring raw EMG at 8-bit resolution of up to 32 implants/sites at a sample rate of roughly 1000 samples/s/channel. Completely functional and *in vivo* and *in vitro* tested telemetry is implemented. EMG signals generated by the residual muscles at each implant site are amplified and digitized by the implants. Each implant is a single-chip integrated silicon device mounted on a ceramic substrate along with a surface-mount power supply filter capacitor. The completed IMES is attached to a carrier printed circuit board using silicone rubber ties. The telemetry controller passes data from the implants directly to the prosthesis controller. The prosthesis controller is where high-level decisions are made as to operation of the telemetry controller, where the reverse telemetry data are processed to determine user intent, and where the motor control signals originate to drive the appropriate components in the prosthesis. The external power coil, receiving antenna, telemetry controller, and prosthesis controller are all housed in the prosthetic socket used to mechanically interface the user to the prosthetic components. Implants are powered transcutaneously, via the external coil, with magnetic field. This powering magnetic field is modulated to send control signals to the addressable implants. The telemetry controller within the prosthesis orchestrate RF transmissions from each implant so that data from all implants may be sequentially collected by a receiver in the prosthesis. The telemetry controller demodulates the received signals and passes the multichannel EMG data to a prosthesis controller. The user's intention should be decoded within the prosthesis controller. This issue will be addressed in the next section.

D. Decoding Algorithms and Performance

Generally, the iEMG signal is used for clinical studies (e.g., neuromuscular disorders). Therefore, data analysis is often taken from these applications. Since the MUAPs are short events and have a characteristic shape, which is affected by the distance between the electrode and the MU generating it, it is natural that the major part of signal processing paradigms is based on "shape-recognition" wavelet analysis. Furthermore, since there is general overlapping of different MU areas within the same recording site, the most natural and most used second step to be taken is ICA or PCA analysis. Finally, similar as in sEMG analysis, some classifier is used. In [98], the authors investigated the capacity of selective single-channel iEMG recordings to represent the grasping force with respect to the use of sEMG. The goal was to assess whether iEMG can be effectively used to proportionally control hand prostheses. This study investigated whether power grip force was better described by a global measure of intensity (sEMG) or by a local muscle area (iEMG), using linear correlation coefficients as measure. The results showed that the two approaches are comparable and that iEMG can be used to control hand prostheses, in the same way as sEMG. This is a very important issue for justifying the invasiveness of this approach. A comparative analysis between sEMG and iEMG is performed in [99]. Pattern recognition-based myoelectric controllers were applied, which use information extracted from sEMG to the same controllers which use information extracted from fine-wire iEMG. In making this comparison, six different state-of-the-art pattern recognition-based myoelectric control approaches were investigated. The results suggest that information extracted from either surface or intramuscular EMG inputs yield excellent classification accuracy; however, there was no significant difference in classification accuracy for any of the six control schemes investigated for this particular experiment. Both recording techniques yielded classification accuracies between 95% and 99%. One of the main problems related to iEMG recordings is the need for additional procedures during the implantation such as ultrasound guidance. Thus, it is important to understand whether a very precise position of the electrode is essential to obtain good classification performance. In [100], dedicated decoding experiments (for up to 12 different grasp types) were carried out to analyze this issue for a targeted versus a nontargeted implant of electrodes. The results, obtained in healthy subjects, suggested that there is no difference in classification performance both for sEMG and iEMG with targeted and nontargeted placement if a sufficiently large feature set is used. A recent study [97] analyzed the ability of chronic decoding of single finger movements in monkeys when using the IMES sensors. Offline parallel linear discriminant analysis (LDA) was performed to decode finger activity based on features [12] extracted from continuously presented frames of recorded EMG. The most interesting aspect of this study is that offline parallel LDA was run on intraday sessions as well as on sessions where the algorithm was trained on one day and tested on following days. The performance of the algorithm was evaluated continuously by comparing classification output by the algorithm to the current state of the finger switches. The algorithm detected and classified seven different finger movements, including individual and combined finger flexions, and a no-movement state (with chance performance $= 12.5\%$). When the algorithm was trained and tested on data collected during the same day, the average performance was 43.8% $(n = 10)$. When the training-testing separation period was five months, the average performance of the algorithm was 46.5% $(n = 8)$. Nevertheless, the decoding performance for the single fingers was reasonably high, considering that the classifiers were tested several months after their training.

E. Discussion

An invasive EMG system is not affected by crosstalk, typical of sEMG, and provides more stable and independent control sites. Moreover, the problems related to sEMG recording (displacement of electrodes resulting in the need to retrain the system) would be overcome by using implanted electrodes. However, intramuscular recordings provide more local information due to their high selectivity and may thus be less representative of the global muscle activity with respect to sEMG. Although very promising classification results have been achieved, more extensive experiments (e.g., less grips, executed in free 3-D space, by amputees and normal bodied, and under nonisometric conditions…) are necessary to clearly identify the potential benefits and shortcomings of this approach (compared to sEMG). Particularly interesting is the

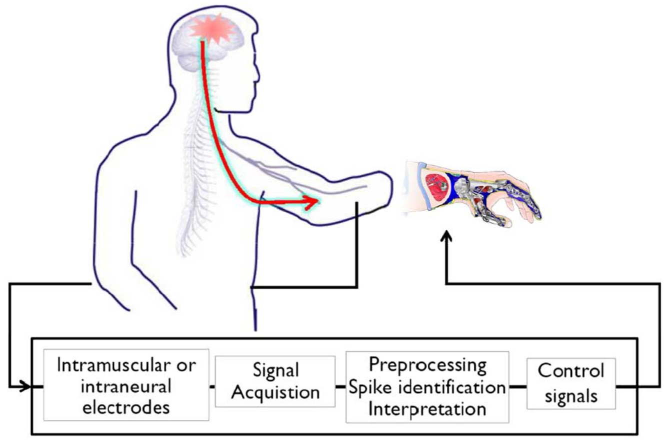

Fig. 3. Schematic representation of hand prosthesis control paradigm using implantable devices (modified from [88]).

study presented in [97], where the percentage of classification of seven finger movements is evaluated when the classifier is trained on day one and tested days and months after. Movement percentages were around 45%, yet the study provides several very important hints for future works. It shows that single fingers can be decoded well, that there is no crosstalk between different IMES recordings and that the most limiting issue is the decoding of thumb movements for several reasons. Future studies with amputees are also necessary in order to determine the impact of residual muscle structural changes on the quality of iEMG signals and to understand the level of iEMG repeatability that can be obtained.

V. ENG-Based Control of Hand Prostheses

The principle underlying the use of neural signals for the control of artificial limbs is that, despite nervous reorganization following upper limb amputation, original neural pathways are still preserved and they can be exploited for interfacing prostheses. The movement-related activity in M1 and S1 cortical areas controlling the hand and finger may still be found even years after amputation [101], [102]. The fact that amputation does not eliminate the peripheral nerve connections or their CNS relay makes them excellent candidates for reestablishing an almost physiological control of an artificial prosthesis via a bidirectional intraneural electrode implant into the stump nerves [103]. Thus, the intent to move the amputated limb is still projected from the subject's brain to the peripheral nerves, although the movement cannot be executed. The neural signals projecting to the nerves above the amputation can be recorded and translated into a command signal for controlling an artificial limb (see Fig. 3).

Invasive recordings from nerves result in the detection of spike trains either from efferent and afferent nerve fibers. Contrary to noninvasive approaches, these recordings provide the direct measure of the neural drive to the muscles.

A. Characteristics of ENG Signals

The majority of somatic peripheral nerves are mixed nerves, providing motor, sensory, and autonomic innervations to the corresponding projection territory. Afferent sensory fibers convey a variety of sensory inputs, mainly mechanical, thermal and noxious stimuli; they can be unmyelinated or myelinated and terminate at the periphery either as free endings or in specialized receptors in the skin, muscles and deep tissues. Efferent motor fibers originate from motoneurons in the spinal cord anterior horn and end in neuromuscular junctions in skeletal muscles. Signals are transmitted by the corresponding axons in series of action potentials, with intensity of the signal mainly coded in impulse frequency along the peripheral axon. Most peripheral nerve interfaces use an electrical coupling method to detect the electrical activity of the nerve fibers and/or to induce their excitation. Peripheral nerves are organized somatotopically and functionally at the fascicular level. Nerve fibers are grouped in fascicles that eventually give origin to branches that innervate distinct targets [104]. Fascicular groups destined to the same target remain localized within the nerve for some long distances, thus facilitating the selective interface of different fascicles within a given common nerve [105]. Therefore, detection above background noise is easier for impulses propagated in large alpha motor and mechanoreceptive sensory fibers than in small sensory and sympathetic fibers. Ideal electrodes would be able to record unitary activity and selectively differentiate units by fiber size established on conduction velocity measurements. In this respect, intraneural electrodes have higher recording selectivity and better SNR and are able to stimulate axons with stimulus intensity considerably lower than with extraneural electrodes, since they are in closer contact with the axons and less affected by the insulating properties of perineurial and epineurial layers [106], [107]. The major studies on intraneural (intrafascicular) recordings are based upon the results gained from afferent activity recording, triggered either by distal electrical stimulation or by stimuli (generally touch and flexion) application on the animal limbs. In [108], the signal properties were characterized on the basis of the studies carried out on six cats implanted with longitudinally implanted intrafascicular electrodes (LIFEs). Neural recordings from LIFEs are multiunit in nature. These units appear as spikes with peak-to-peak amplitudes of about 20 μV. Frequency domain analysis shows that neural signals have a power spectrum lying between 500 Hz and 7 kHz, peaking at about 2 kHz. There are only new studies that focus on the efferent signal properties from human amputees [19], [109]. As reported in these studies, the signal obtained is very weak and prone to different noise sources (mainly due to the EMG). In an intraoperative study [19], six intrafascicular electrodes were inserted into the ulnar, radial, and median nerves in the stump of an amputee. The signal amplitude from the radial nerve was 5.5 μV $\pm$ 0.8, which was greater than the amplitudes from the ulnar (2.5 μV $\pm$ 0.4) and median (2.2 μV $\pm$ 0.3) nerves. In [109], the values in peak-to-peak were closer to 20 μV, as reported in the above animal studies.

B. Electrodes

Electrodes acting as interfaces with the peripheral nerves may be used for stimulating sensory nerve fibers and for recording neural impulses, allowing a bidirectional interface with the nervous system. A bidirectional interface for hand prosthesis control in amputees should allow on the one hand, recording of

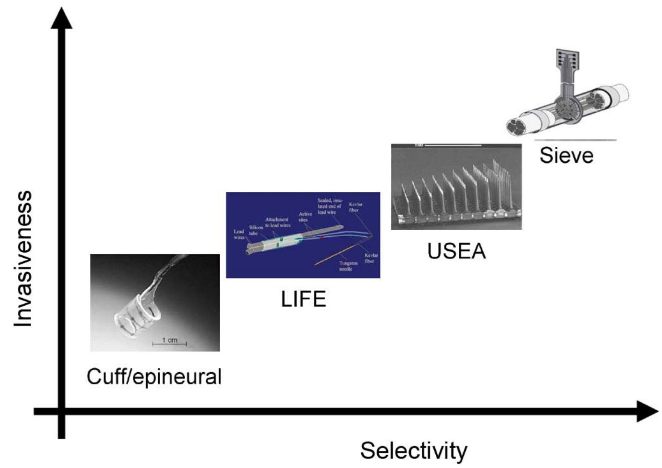

Fig. 4. Tradeoff between selectivity and invasiveness for different implantable electrodes (reproduced with permission from [118]).

neural efferent signals that can be used for controlling mechanical prosthesis motion [110], and on the other, providing sensory feedback from tactile and force sensors to the user through stimulation of afferent nerve fibers within the residual limb [111]. The action potentials detected by the extracellular electrodes are several orders of magnitude lower than the transmembrane potential and depend on several factors, among them, on the relative distance of the electrode from the active fiber and on the physical size of the detecting electrode [112], [113]. Since the conductivity of the electrode is orders of magnitude greater than that of the extracellular medium, an electrode acts as an isopotential boundary within the medium, averaging the extracellular action potentials of the fibers in its vicinity. Thus, the physical area of the electrode is directly associated to its selectivity. The second essential factor is the distance between electrode and the cells [114], since the neural signal recorded decays approximately with the square of distance between the active cells and recording sites. Most nerve electrodes are implanted close to, around, or even within a peripheral nerve trunk. Thus, recording selectivity and stimulation capability are enhanced but with the tradeoff of increased invasiveness (see Fig. 4). Although this coupling method is characterized by a certain level of invasiveness with the biological system, recent research in neuroprosthetics has devoted considerable attention to the development and test of interfaces able to reduce nerve damage [115]–[117] and to allow access to electrical activity or graded stimulation of selective groups of axons [9].

Among the electrodes (see Fig. 4) employed in current research activities on the bidirectional control of artificial limbs, the most used are: cuff, FINE and intrafascicular electrodes; although, the first two are more commonly used in FES systems.

C. Extraneural Electrodes

Cuff electrodes are composed of an insulating tubular sheath that completely encircles the nerve and contains two or more electrode contacts exposed at their inner surface that are connected to insulated lead wires. They have been fabricated in several configurations, the most common being split-cylinder and spiral cuffs [119]. Cuffs are the most widely used peripheral nervous interface in research and clinical applications. One design variation of the cuff electrode is the "flat interface nerve electrode" (FINE) developed by Durand and coworkers [120]. The FINE is an extraneural electrode designed to reshape peripheral nerves into a favorable geometry for selective stimulation and for recording. By flattening the nerve into a more elliptical shape, fascicles become more accessible and central fibers are moved closer to the stimulating electrode in comparison with cylindrical cuffs. The surface area of the nerve is also enlarged, therefore increasing the interface surface and allowing more contacts to be placed around the nerve. Recently, the use of cuff spiral electrodes in chronical neuroprosthetic applications for upper [121] and lower [122] extremities has proven to be very promising.

D. Intrafascicular Electrodes

Electrodes placed inside a peripheral nerve have been developed [106], [107] in order to allow enhanced selectivity with respect to extraneural electrodes and also to increase the SNR of recordings. Intrafascicular electrodes are placed within the nerve and are in direct contact with the tissue they are intended to activate or record from. Stimulation through them specifically activates the nerve fascicle in which they are implanted with little crosstalk to adjacent fascicles. Longitudinally implanted intrafascicular electrodes (LIFEs) offer a way to interface a restricted subsets of axons within fasciculated peripheral nerves. Single-channel intrafascicular electrodes started the LIFE studies and were useful in initial experiments that led to multichannel electrode applications. Flexible polymer filaments are preferred to metal wires because the stiffness of the latter presumably leads to motion of the electrode that elicits gradual decrease in the recorded amplitude of axon potentials. LIFEs have been implanted in severed nerves proximally to the stump of eight subjects with limb amputation [109]. Electrophysiological tests conducted for two consecutive days after the surgery indicated that it was possible to record volitional motor nerve activity associated with missing limb movements. Electrical stimulation through the implanted electrodes elicited graded sensations of touch, joint movement, and position, referring to the missing limb. This suggested that peripheral nerve interfaces could be used to provide amputees with prosthetic limbs that have a more natural feel and control compared to current myoelectric and body-powered prostheses. Regarding electrodes, the main problem is that the implantation procedure is blind, consequently, the SNR obtained from the recordings is stochastic. An innovative technological solution to overcome this issue is the use of actuated electrodes as proposed in [123], [124].

E. Acquisition and Stimulation Systems

Since the signals recorded by means of neural electrodes are very weak and prone to noise (e.g., EMG, thermal, capacitive couplings…), the acquisition circuit should be as close as possible to the electrode and should be optimized with respect to the input noise/power consumption tradeoff. It also needs to respect different biocompatibility constraints in order to be implantable. Since (in case of intrafascicular electrode signals)

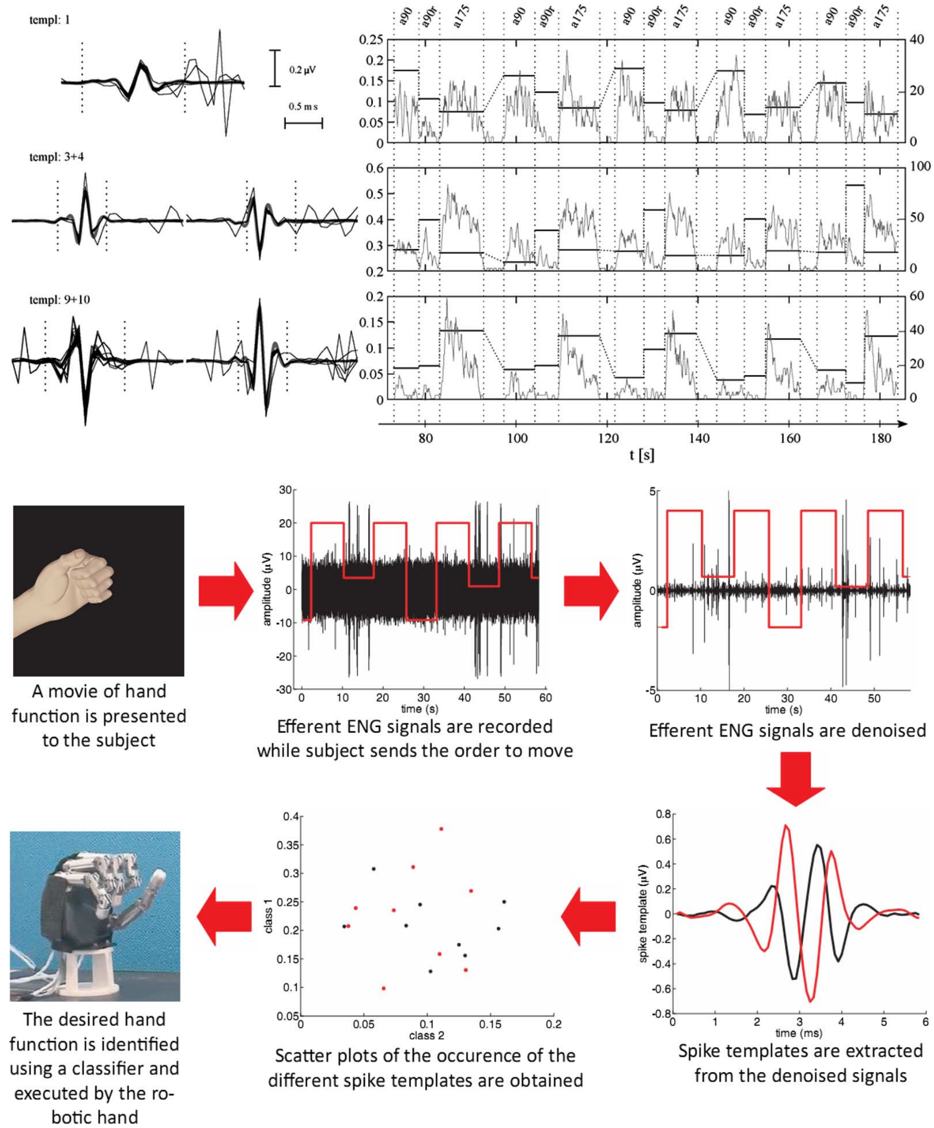

Fig. 5. Decoding algorithm proposed in Cyberhand project (top: reproduced with permission from [141]; bottom: modified from [140]).

the aim is to detect and transmit the spiking data, as well to carry out electrical stimulation (analog to microstimulation in CNS), the circuit architectures proposed are similar to those proposed in works pertaining to CNS implantable systems [125]. The main difference is the presence of strong EMG couplings, together with the fact that PNS data flow should be reduced (e.g., arrays with more than 100 electrodes used for the CNS are currently not available for the PNS). EMG couplings can be approached digitally (e.g., filtering), or, with passive networks, as in [126]. Schematically, the integrated circuits proposed in literature are composed of: multichannel low-noise, low-power amplifiers (excellent examples have been developed for CNS [127], and PNS recordings [128]) connected to low-power multiplexers [129], with digitalized output by means of ADC. Finally, either the raw data are directly wireless-transmitted [130], or basic data processing is performed [131] (e.g., spike sorting) that permits less data flow for the telemetric interface (e.g., just spike times). The stimulation circuit is also important to obtain a bidirectional control of the robotic arm. It is supposed to transmit in a reliable (charge balance is important to prevent nerve injury) and repetitive way different waveforms enabling stimulation of different axonal subpopulations. A promising solution is proposed in [132]. An advantage of silicon-based microdevices is the ability to monolithically integrate electronic circuits for recording and signal processing. The passivation and packaging of silicon-based devices should be carefully considered to ensure long-term stable behavior of electrodes with integrated electronic devices. Implantable systems for PNS and spinal cord stimulators are generally within the silicon rubber, where different constraints have to be respected [133], [134]. If parts of standard electronic processes were to be directly transferred for implant passivation, degradation during implantation would deteriorate not only the insulation layer but also the functional integrated structures within 1 year [135]. Despite the amount of research carried out in this field, to date there are no fully integrated and implantable acquisition/stimulating systems for PNS (such as those available for CNS) which are able to answer basic research questions that are still open, such as the decoding of information carried by nerves.

F. Decoding Algorithms

Decoding algorithms represent the critical point of ENG-based hand prosthesis control. In the field of extraneural electrodes, algorithms have been generally developed to decode ENG signals for the closed-loop control of FES systems. Nonetheless, these findings can provide an insight into the information that can be decoded from these signals and hints about the algorithms to use. The main problem and the reason for the development of ENG algorithms with afferent signals is the difficulty to obtain voluntary efferent ENG activity (most of the experiments are carried out in anesthetized animals). For cuff electrodes, higher order statistics algorithms have been developed for switching off/on the stimulation [136] or the continuous decoding of afferent signals by means of power-based features and support vector machine classifiers [137]. In the case of FINE electrodes two interesting approaches have been proposed, which could be used in closed-loop prosthetic devices. They exploit blind source separation [138] and beamforming algorithms [139] for signal separation, but, unlike the above cuff electrodes ENG decoding, the algorithms are based on simulated data. Intrafascicular electrodes have been used to develop and test algorithms for the neurocontrol of hand prostheses in amputees [17]–[19], [109], [118], [140]. Decoding algorithms developed for this purpose (see Fig. 5) are developed in three steps: firstly the ENG signals are denoised, then spike sorting is performed and finally sorted spike templates are used to classify the amputee's intention.

The approach used to denoise the signals is based on a work in the field of microneurography [142]. It uses wavelet-denoise techniques to eliminate the noise from ENG signals, leaving just the informative, spiking activity. This idea was enhanced in a work on the decoding of afferent rabbit signals [141], as for the use in natural sensors applications. After denoising, spike sorting is performed and, finally, SVM classification is conducted based on different spike template frequency. Spike identification is performed with the goal of increasing the performance of the approach and making it also more similar to the natural situation [141].

In fact, the shape of the spike, as recorded by an extracellular electrode, is determined, for example, by:

1) distance between the fiber and the electrode (the tissue in between acts as a low-pass filter: the longer the distance, the smoother, smaller, and longer the spike shape);
2) relative orientation of the nodes of Ranvier in the nerve fiber;
3) inhomogeneity of the intrafascicular space.

Thus, the signals related to different nerve fibers can be identified and extracted on the basis of the shape recorded from a multiunit recording. Since different nerve fibres carry different information (e.g., which motor units to activate to perform a given grasp), spike sorting can be used to infer the grasp selected by the user. Finally, the same algorithm, with small modifications, has been exploited in amputees trials [118], [140], showing for the first time the possibility to decode specific grip types and also finger movements. In a study regarding afferent neural activity decoding [143], the multiscale continuous wavelet transform was exploited outperforming the simple amplitude thresholding method, especially in low SNR cases, typical in real ENG recording systems. Interestingly, all above decoding studies showed:

1) that spike denoising and recognition algorithms outperform classical amplitude thresholding and Rectified Integral Bin studies;
2) enhancement in performance when using several independent channels on LIFEs.

The basic drawback of this denoising and decoding solution is the high computational burden which becomes a critical factor when aiming to develop a real-time controller. Other algorithms for spike sorting can also be applied as done for CNS intracortical signals [144], [145]. However, it is important to point out that intracortical signals have much higher absolute values, while in PNS signals the spikes are more difficult to observe and generally have lower SNR.

G. Discussion

After several decades of research efforts to develop highly sophisticated hand prosthesis controlled by processing EMG signals, in very recent times, an interesting alternative has been found in PNS neural interfaces. Their pros, compared to "classical" EMG based paradigms, are several.

1) In high amputees (or muscle degenerative diseases) the number of muscles at disposal, or the quality of the signal that can be obtained, for controlling purposes can be too low. Yet neural signals conveying information even to lacking muscles should be present.
2) Several studies [146] have shown the importance of feedback for a more robust control of prosthetic devices. The peripheral neural interfaces represent the confirmed and most natural choice for delivering feedback, as shown in [17], [18], and [140].
3) The feasibility of this signal for proportional and different grip state control has been shown in preliminary studies [17], [140].

Their greatest drawback is the invasiveness of the implantation procedure, which is directly linked to a second issue: the current lack of long-term chronical studies. If the results from these studies confirm good performance of this approach, these implants could enter clinical practice in the future, as in the case of cochlear implants, pacemakers and bladder stimulators.

VI. Sensory Feedback to Control Hand Prostheses

Various studies have shown the great importance of delivering feedback to the user to achieve an effective control of the prosthesis [146], [147]. In this section, the possible approaches to achieve this goal are described and analyzed.

A. Sensory Feedback in Clinical/Commercial Systems

In clinical applications the feedback is achieved in a quite simple way. In body-powered applications the feedback is simply delivered by means of the sensation elicited by the prosthesis movement on the rest on the amputee arm (or on the shoulder pressure, if it is included into the movement generation). Body-powered prostheses (cables) usually have higher sensory feedback, with respect to other clinical solutions. Currently available externally powered prostheses generally

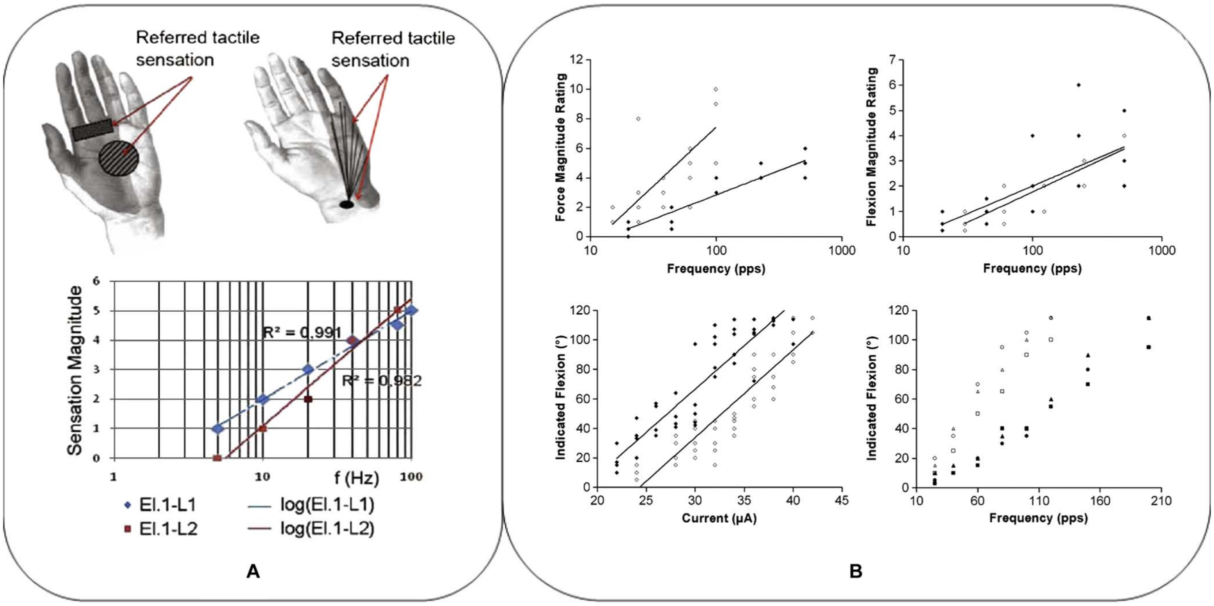

Fig. 6. (a) Positions of referred sensation on phantom limb and modulation of refereed sensation (reproduced with permission from [140]); (b) in [18], multi-subject study touch and proprioceptive sensation were elicited. As in (a), touch is modulated linearly with respect to log of frequency, when using psychometric sensory magnitude rating (reproduced with permission from [18]).

have less sensory feedback and require more maintenance than body-powered prostheses. In present commercial solutions, there is no dedicated device to deliver sensory feedback.

B. Sensory Feedback in EMG-Based Systems

One of the main problems of current myoelectric hand prostheses is the lack of sensory feedback. Amputees depend almost entirely on vision for positioning the limb and grasping objects. As a consequence, reaching and grasping tasks demand more and continuous attention, often leading to fatigue, frustration, and dismissal of the prosthesis [146]. Several techniques have been developed in order to provide noninvasive tactile or proprioceptive information to the amputees [148]. Electrical [149]–[151] and mechanical skin stimulation [80], [152], [153] are two of the most commonly used techniques for tactile feedback. They are based on the mapping of information coming from the sensors embedded in the prosthesis onto mechanical or electrical stimuli delivered to the subject's skin. Less work has focused on haptic proprioceptive feedback for prostheses. The delays associated with the feedback (50–250 ms, depending on the modality [154]) indicate that it is difficult to enclose this in real-time control. Nevertheless, the addition of proprioceptive feedback creates a closed-loop system that may make the prosthesis a more intuitive extension of the user [155]. The use of such feedback techniques usually presents several drawbacks such as need for long training, sensory adaptation, low resolution, interference, and unpleasant sensations [148]. For this reason, there is no clear clinical evidence in literature that this kind of feedback can really provide benefits or advancement in the control of myoelectric prostheses. Nevertheless, both mechanical or electrical stimulation can increase both users' acceptance of the prosthetic hand and their ability to control it [80], [156]–[159].

TMR also allows the transfer of sensations (e.g., perception of the missing hand) by means of mechanical or electrical stimulation of the reinnervated chest [160]. It is worth noting that in this case a natural sensation can be delivered.

C. Sensory Feedback in ENG-Based Systems

Several studies [146], [147] have shown the importance of feedback providing more robust control of prosthetic devices. Peripheral neural interfaces have been shown to be an effective and natural approach to deliver sensory feedback in [17], [109], and [140].

In [18], the authors enrolled eight amputees, and all of them reported either tactile or proprioceptive sensations from one or more electrodes (wire electrodes were used in this study). In half of the subjects, both types of sensations could be elicited (through different electrodes). Electrical stimulation usually resulted in unimodal (i.e., touch, movement, or static joint position) sensations that showed stable topography. In all cases, the sensations were in the fascicular projection territories of the implanted nerve, suggesting a stable electrode position, and stimulated a small cluster of neurons. The same finding, regarding stable positioning versus fascicular territories, is confirmed in a single-case study [140], performed with multi-polar tfLIFEs (see Fig. 6(a) upper panel). In 20% of the cases [18], sensations were confused as to being either movement or pressure, vibration in a digit, and a mixture of tugging and movement localized to the palm or the fingers. The majority (70%) of the cases resulted in stable sensations of touch/pressure or joint position/movement sense that were localized to the digits. In general, sensations were discrete, unimodal, repeatable, and could be painlessly elicited over the duration of the study. With increasing stimulus current, sensations of touch/pressure usually spread from distal (digit tip) to proximal locations. By modulating stimulus frequency, the magnitude estimation, but not the

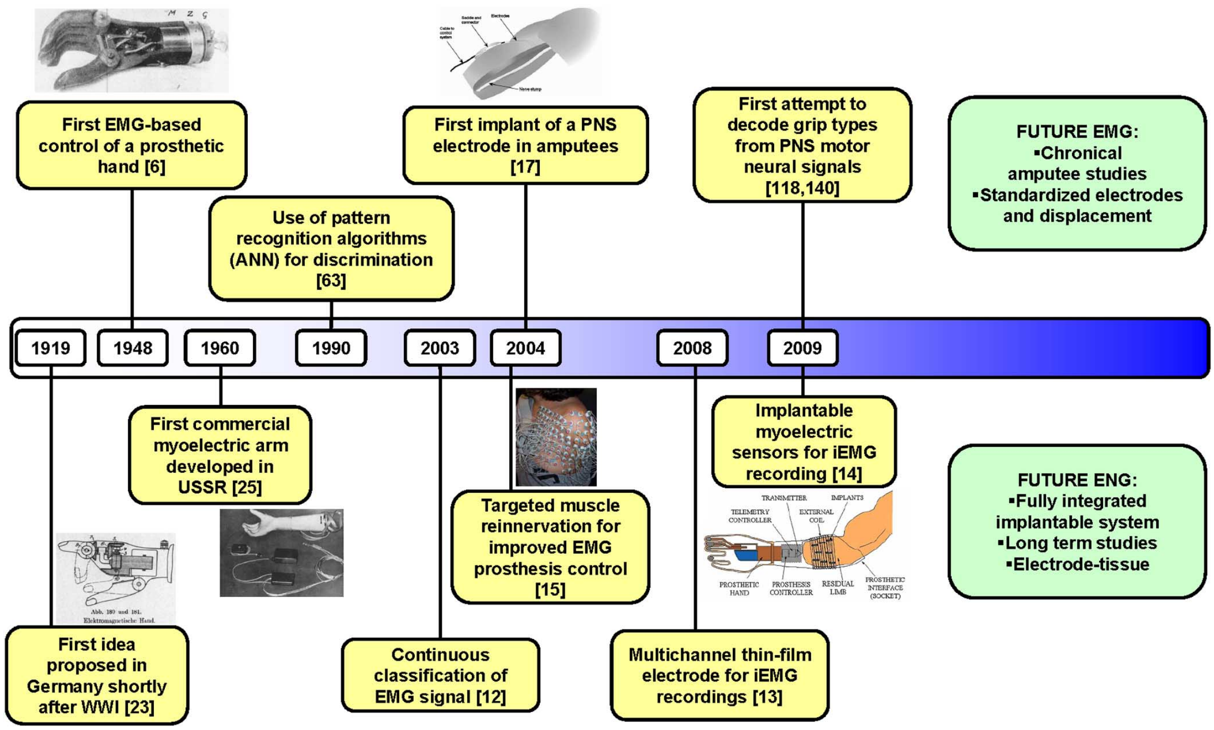

Fig. 7. Milestones in the history of EMG- and ENG-based control of prosthetic hands.

modality or the topography, of referred sensations of touch/pressure or proprioception could be varied systematically: a logarithmic regression gave the best fit for the ratings of magnitude of sensation (psychometric sensory magnitude rating) versus frequency of nerve stimulation (see Fig. 6(b) upper panel). Similar results are also reported in [140], where a psychometric sensory magnitude rating was used (see Fig. 6(a), bottom panel). However, indicating perceived finger position by matching it with the contralateral finger produced a more linear relationship between both stimulus amplitude and frequency and reported phantom finger position (see Fig. 6(b), bottom panel). The resting position of a given phantom digit was consistently reported in full extension by the amputees. At the upper limit of stimulus frequency, the terminal aspect of the finger would appear to dig into the palm, explained by the amputees as a clenched fist but involving only one digit. At the end of the impulse train, the digit would be perceived as having returned back into its original position (full extension). The authors reported that, in general, the higher the stimulus amplitude the lower the frequency required to produce the sensation of flexion to a given position.

The presence of a statistically significant increase in both the threshold and the upper limit for eliciting painless and unitary sensations of touch/pressure or joint movement is a critical aspect. Very similar results have been observed in [140], where, after 10 days, it was impossible (owing to the limited charge injectable through the multipolar LIFE electrodes used) to elicit any sensations. This could be due to the encapsulation answer from tissue, which increases electrode impedance over time. The two studies at issue, however, were relatively short; instead, in chronical stimulation studies with cuff electrodes [121] the changes in stimulation threshold currents were reported for the first 20 weeks after the implant, with values subsequently returning close to those found in acute conditions.

VII. General Discussion and Conclusion

EMG signals and more recently ENG signals have been used to develop more effective ways to control hand prostheses (see Fig. 7).

Processing sEMG signals to control hand prosthesis is a potentially interesting approach (achieving over 90% classification performance for several degrees of freedom as shown for example by Englehart and co-workers) but clinical applicability is currently still limited. To address this issue, several research groups are now working on implantable solutions (iEMG or ENG signals) or on "hybrid" solutions (TMR where sEMG signals are recorded and processed but after a surgical intervention). TMR is a very interesting approach; it is the most advanced clinical solution currently available and has the interesting advantage that the nerve function correlates physiologically to the function it is controlling in the prosthesis. Therefore, operation is more natural and thus easier than with other EMG-controlled devices. However, it presents two possible main drawbacks.

1) Although it requires a surgical intervention it also needs to use a grid of surface electrodes. As a result, invasiveness-related problems are not totally balanced by significant advantages in terms of usability and cosmetic appearance.
2) Because of the intrinsic characteristics of the surgical procedure it could be more effective for more proximal amputation levels (i.e., close to the axilla) which are less common than transradial amputations

This second issue must be investigated in order to completely characterize the potentials and shortcomings of this approach and its clinical applicability in different clinical situations. More specific surgical procedures should be developed to address the different neuroanatomical situation.

Focusing on implantable solutions, either iEMG and ENG signals can probably provide interesting performance for the decoding of motor commands, while PNS neural interfaces could have the advantage of providing natural (i.e., by using the existing neural "pathways") sensory feedback. Moreover, a very recent study [161] has pointed out the inherent limitations of the surface myoelectric signal, such as the lack of recording sites in high-level amputations, and the sensitivity to placement and impedance effects, and has proposed the ENG-based approach as future direction in this field.

When comparing iEMG and ENG signals as sources for artificial robotic hand prosthesis control, various assumptions (to be experimentally verified in the future) can be made.

1) The number of muscles—especially in case of severe amputations or extensive degeneration of the muscles—that can be used for EMG recording are lower, yet this does not reduce (to a certain extent) the possibility of signals recording.
2) In case of iEMG at least one electrode for each muscle must be implanted. This could not be necessary for PNS invasive electrodes which could record activities related to the control of different muscles from the same nerve. Moreover, it is also possible that a decoding based on ENG signal processing could be more robust than an EMG-based one with respect to 3-D spatial changes of the arm during the control of the hand prosthesis.
3) Displacement of electrodes, with consequent retraining of decoding algorithms, should be easier to address when using neural electrodes, which are fixed with encapsulation (fibrosis) tissue.

Obviously, the clear disadvantage of the ENG-based approach is its intrinsic invasiveness. However, starting from the interesting preliminary results achieved in the recent past, this approach should be exploited in new and more systematic experiments to better characterize the potentials and limits of this approach.

A very important issue to be addressed is the lack of uniformed metrics and of a testing experimental paradigm in order to compare different devices and algorithms. Particular attention should be paid to define training and testing dataset for evaluation purposes. The percentage of classification should be accompanied by a clear definition of training and testing dataset and by the evaluation criteria used (e.g., percentage of correct instances, leave one out, etc.). Regarding the experimental setup, it is often difficult to understand how different grasps (which make the decoding paradigm set) are performed. It is clearly not the same to decode three different grip types when the elbow is on the table or in different positions in the 3-D space.

Several actions could be carried out in order to improve this situation.

1) There should be a universally shared dataset for the different decoding algorithms, obtained from large intraclinical research with amputees. Then, each group, which offers innovative decoding algorithms should firstly be able to obtain high performance with the dataset by using clear training/testing division (e.g., training on 20% of data, and testing on the rest, or training on the first day, and testing on the sequents [97]).
2) Decoding algorithms for few (but important) grip types should be tested in more general situations [in 3-D space, uncontrolled (e.g., not isometric) situations] during extensive clinical trials.
3) The development of shared emulators (e.g.,http://www.cs.columbia.edu/cmatei/graspit/) is essential, as well as of databases for sharing the designs of different manipulators (http://openprosthetics.org/). This would allow groups which do not have the possibility to control robotic devices to test their decoding approaches with a "real" end-effector. Large, inter-laboratory, shared efforts, are necessary to allow the development of new, revolutionary steps enabling impaired individuals to enhance their everyday life capabilities. Recent EU-funded (e.g., CYBERHAND, NEUROBOTICS, TIME, or SMARTHAND projects) or international (e.g., the DARPA "Revolutionary Prosthetics" project) are good examples of this approach. This review aims to be another step ahead in this very important direction.

REFERENCES

[1] I. A. Kapandji, *Physiology of the Joints. The Upper Limb*. New York: Churchill Livingstone, 1982.
[2] S. Banzi, E. Mainardi, and A. Davalli, "Analisi delle strategie di controllo per protesi di arto superiore in pazienti con amputazioni transomerali o disarticolati di spalla," *ANIPLA—Biosyst.*, pp. 290–300, 2005.
[3] U.K. Prosthetics Services, "Upper Limb Amputations" Amputee Statistical Database for U.K.: 2005/06.
[4] M. P. LaPlante, Disability Statistics Rep., Chapter Disability in the United States: Prevalence and Causes National Inst. Disability Rehabilitation Res., 1996.
[5] D. J. Atkins, D. C. Y. Heard, and W. H. Donovan, "Epidemiologic overview of individuals with upper-limb loss and their reported research priorities," *J. Prosthet Orthot.*, vol. 8, no. 1, pp. 2–11, 1996.
[6] R. Reiter, "Eine neue elecktrokunsthand," *Grenzgebiete der Medizin*, vol. 4, pp. 133–135, 1948.
[7] M. Zecca, S. Micera, M. Carrozza, and P. Dario, "Control of multifunctional prosthetic hands by processing the electromyographic signal," *Crit. Rev. Biomed. Eng.*, vol. 30, no. 4–6, pp. 459–485, 2002.
[8] M. Oskoei and H. Hu, "Myoelectric control systems—A survey," *Biomed. Signal Proc. Contr. J.*, vol. 2, pp. 275–294, 2007.
[9] X. Navarro, T. B. Krueger, N. Lago, S. Micera, T. Stieglitz, and P. Dario, "A critical review of interfaces with the peripheral nervous system for the control of neuroprostheses and hybrid bionic systems," *J. Peripher. Nerv. Syst.*, vol. 10, no. 3, pp. 229–258, 2005.
[10] D. B. Popovic, R. B. Stein, K. L. Jovanovic, R. Dai, A. Kostov, and W. W. Armstrong, "Sensory nerve recording for closed-loop control to restore motor functions," *IEEE Trans. Biomed. Eng.*, vol. 40, no. 10, pp. 1024–1031, Oct. 1993.
[11] S. Micera, M. Carrozza, L. Beccai, F. Vecchi, and P. Dario, "Hybrid bionic systems for the replacement of hand function," *Proc. IEEE*, vol. 94, no. 8, pp. 1752–1762, Aug. 2006.
[12] K. Englehart and B. Hudgins, "A robust, real-time control scheme for multifunction myoelectric control," *IEEE Trans. Biomed. Eng.*, vol. 50, no. 7, pp. 848–854, Jul. 2003.
[13] D. Farina, K. Yoshida, T. Stieglitz, and K. P. Koch, "Multichannel thin-film electrode for intramuscular electromyographic recordings," *J. Appl. Physiol.*, vol. 104, no. 3, pp. 821–827, 2008.
[14] R. F. Weir, P. R. Troyk, G. A. DeMichele, D. A. Kerns, J. F. Schorsch, and H. Maas, "Implantable myoelectric sensors (IMESs) for intramuscular electromyogram recording," *IEEE Trans. Biomed. Eng.*, vol. 56, no. 1, pp. 159–171, 2009.

[15] T. A. Kuiken, G. A. Dumanian, R. D. Lipschutz, L. A. Miller, and K. A. Stubblefield, "The use of targeted muscle reinnervation for improved myoelectric prosthesis control in a bilateral shoulder disarticulation amputee," *Prosthet. Orthot. Int.*, vol. 28, no. 3, pp. 245–253, Dec. 2004.

[16] H. Huang, P. Zhou, G. Li, and T. A. Kuiken, "An analysis of EMG electrode configuration for targeted muscle reinnervation based neural machine interface," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 16, no. 1, pp. 37–45, Feb. 2008.

[17] G. S. Dhillon and K. W. Horch, "Direct neural sensory feedback and control of a prosthetic arm," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 13, no. 4, pp. 468–472, Aug. 2005.

[18] G. S. Dhillon, T. B. Krüger, J. S. Sandhu, and K. W. Horch, "Effects of short-term training on sensory and motor function in severed nerves of long-term human amputees," *J. Neurophysiol.*, vol. 93, no. 5, pp. 2625–2633, 2005.

[19] X. Jia, M. A. Koenig, X. Zhang, J. Zhang, T. Chen, and Z. Chen, "Residual motor signal in long-term human severed peripheral nerves and feasibility of neural signal-controlled artificial limb," *J. Hand Surg. Amer.*, vol. 32, no. 5, pp. 657–666, 2007.

[20] S. Micera, X. Navarro, J. Carpaneto, L. Citi, O. Tonet, P. M. Rossini, M. C. Carrozza, K. P. Hoffmann, M. Vivó, K. Yoshida, and P. Dario, "On the use of longitudinal intrafascicular peripheral interfaces for the control of cybernetic hand prostheses in amputees," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 16, no. 5, pp. 453–472, Oct. 2008.

[21] C. M. Fryer, G. E. Stark, and J. W. Michael*, Body Powered Components*, D. G. Smith, J. W. Michael, and J. H. Bowker, Eds., 3rd ed. Rosemont, IL: American Acad. Orthopedic Surgery, 2004, Atlas of Amputations and Limb Deficiencies.

[22] C. M. Fryer and J. W. Michael*, Harnessing and Controls for Body-Powered Devices*, D. G. Smith, J. W. Michael, and J. H. Bowker, Eds., 3rd ed. Rosemont, IL: American Acad. Orthopedic Surgery, 2004.

[23] G. Schlesinger*, Der Mechanische aufbau der kunstlichen glieder*, M. Borchardt, Ed. Berlin, Germany: Springer, 1919, vol. Ersatzglieder und Arbeitshilfen.

[24] D. Childress, "Historical aspects of powered limb prostheses," *Clin. Pros Orth.*, vol. 9, no. 1, pp. 2–13, 1985.

[25] A. E. Kobrinski, S. V. Bolkovitin, and L. M. Voskoboinikova, "Problems of bioelectric control," in *Proc 1st IFAC Int. Congr. Automatic Remote Control*, J. F. Coles, Ed., 1960, vol. 2, pp. 619–629.

[26] V. Wright, "Prosthetic outcome measures for use with upper limb amputees: A systematic review of the peer-reviewed literature, 1970 to 2009," *J. Prosthet. Orthot.*, vol. 21, no. 4S, pp. 3–63, 2009.

[27] D. Farina, R. Merletti, and R. M. Enoka, "The extraction of neural strategies from the surface EMG," *J. Appl. Physiol.*, vol. 96, no. 4, pp. 1486–1495, 2004.

[28] H. J. Hermens, B. Freriks, C. Disselhorst-Klug, and G. Rau, "Development of recommendations for semg sensors and sensor placement procedures," *J. Electromyogr. Kinesiol.*, vol. 10, no. 5, pp. 361–374, 2000.

[29] R. Merletti, A. Botter, A. Troiano, E. Merlo, and M. A. Minetto, "Technology and instrumentation for detection and conditioning of the surface electromyographic signal: State of the art," *Clin. Biomech. (Bristol, Avon)*, vol. 24, no. 2, pp. 122–134, 2009.

[30] R. Merletti, A. Rainoldi, and D. Farina, "Surface electromyography for noninvasive characterization of muscle," *Exerc. Sport Sci. Rev.*, vol. 29, no. 1, pp. 20–25, 2001.

[31] J. V. Basmajian and C. J. DeLuca*, Muscles Alive: Their Functions Revealed by Electromyography*, 5th ed. Baltimore, MD: Williams and Wilkins, 1985.

[32] M. B. I. Raez, M. S. Hussain, and F. Mohd-Yasin, "Techniques of EMG signal analysis: Detection, processing, classification and applications," *Biol. Proced. Online*, vol. 8, pp. 11–35, 2006.

[33] C. J. De Luca, "The use of surface electromyography in biomechanics," *J. Appl. Biomech.*, vol. 13, no. 2, pp. 135–163, 1997.

[34] C. J. De Luca, Surface Electromyography: Detection and Recording DelSys Inc., 2002.

[35] B. Gerdle, S. Karlsson, S. Day, and M. Djupsjöbacka*, Acquisition, Processing and Analysis of Surface EMG Signals*, H. Johansson and U. Winhorst, Eds. Hamburg, Germany: Springer Verlag, 1999.

[36] G. J. Janz and D. J. G. Ives, "Silver-silver chloride electrodes," *Ann. N.Y. Acad. Sci.*, vol. 148, pp. 210–221, 1968.

[37] H. J. Hermens, European Recommendations for Surface Electromyography: Results of the Seniam Project (SENIAM) Roessingh Res. Development, 1999.

[38] R. Merletti, D. Farina, and M. Gazzoni, "The linear electrode array: A useful tool with many applications," *J. Electromyogr. Kinesiol.*, vol. 13, no. 1, pp. 37–47, 2003.

[39] M. J. Zwarts and D. F. Stegeman, "Multichannel surface EMG: Basic aspects and clinical utility," *Muscle Nerve*, vol. 28, no. 1, pp. 1–17, 2003.

[40] B. G. Lapatki, J. P. V. Dijk, I. E. Jonas, M. J. Zwarts, and D. F. Stegeman, "A thin, flexible multielectrode grid for high-density surface EMG," *J. Appl. Physiol.*, vol. 96, no. 1, pp. 327–336, 2004.

[41] G. Drost, D. F. Stegeman, B. G. M. van Engelen, and M. J. Zwarts, "Clinical applications of high-density surface EMG: A systematic review," *J. Electromyogr. Kinesiol.*, vol. 16, no. 6, pp. 586–602, 2006.

[42] R. Merletti, A. Holobar, and D. Farina, "Analysis of motor units with high-density surface electromyography," *J. Electromyogr. Kinesiol.*, vol. 18, no. 6, pp. 879–890, 2008.

[43] K. Nishihara, H. Kawai, T. Gomi, M. Terajima, and Y. Chiba, "Investigation of optimum electrode locations by using an automatized surface electromyography analysis technique," *IEEE Trans. Biomed. Eng.*, vol. 55, no. 2, pt. 1, pp. 636–642, Feb. 2008.

[44] A. Holobar, D. Farina, M. Gazzoni, R. Merletti, and D. Zazula, "Estimating motor unit discharge patterns from high-density surface electromyogram," *Clin. Neurophysiol.*, vol. 120, no. 3, pp. 551–562, 2009.

[45] P. Zhou, M. M. Lowery, K. B. Englehart, H. Huang, G. Li, L. Hargrove, J. P. A. Dewald, and T. A. Kuiken, "Decoding a new neural machine interface for control of artificial limbs," *J. Neurophysiol.*, vol. 98, no. 5, pp. 2974–2982, 2007.

[46] B. Hudgins, P. Parker, and R. Scott, "A new strategy for multifunction myoelectric control," *IEEE Trans. Biomed. Eng.*, vol. 40, no. 1, pp. 82–94, Jan. 1993.

[47] K. Englehart, B. Hudgins, and P. A. Parker, "A wavelet-based continuous classification scheme for multifunction myoelectric control," *IEEE Trans. Biomed. Eng.*, vol. 48, no. 3, pp. 302–311, Mar. 2001.

[48] T. R. Farrell and R. F. Weir, "The optimal controller delay for myoelectric prostheses," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 15, no. 1, pp. 111–118, Feb. 2007.

[49] M. A. Oskoei and H. Hu, "Support vector machine-based classification scheme for myoelectric control applied to upper limb," *IEEE Trans. Biomed. Eng.*, vol. 55, no. 8, pp. 1956–1965, Aug. 2008.

[50] M. Zardoshti-Kermani, B. Wheeler, K. Badie, and R. Hashemi, "EMG feature evaluation for movement control of upper extremity prostheses," *IEEE Trans. Rehabil. Eng.*, vol. 3, no. 4, pp. 324–333, Aug. 1995.

[51] K. Englehart, B. Hudgins, P. A. Parker, and M. Stevenson, "Classification of the myoelectric signal using time-frequency based representations," *Med. Eng. Phys.*, vol. 21, no. 6–7, pp. 431–438, 1999.

[52] S.-H. Park and S.-P. Lee, "EMG pattern recognition based on artificial intelligence techniques," *IEEE Trans. Rehabil. Eng.*, vol. 6, no. 4, pp. 400–405, Aug. 1998.

[53] S. Micera, A. M. Sabatini, and P. Dario, "On automatic identification of upper-limb movements using small-sized training sets of EMG signals," *Med. Eng. Phys.*, vol. 22, no. 8, pp. 527–533, 2000.

[54] F. V. G. Tenore, A. Ramos, A. Fahmy, S. Acharya, R. Etienne-Cummings, and N. V. Thakor, "Decoding of individuated finger movements using surface electromyography," *IEEE Trans. Biomed. Eng.*, vol. 56, no. 5, pp. 1427–1434, May 2009.

[55] K. Farry, I. Walker, and R. Baraniuk, "Myoelectric teleoperation of a complex robotic hand," *IEEE Trans. Robot Automat.*, vol. 12, no. 5, pp. 775–788, May 1996.

[56] D. Graupe and W. Cline, "Functional separation of EMG signal via arma identification methods for prosthetic control purposes," *IEEE Trans. Syst. Man Cybern.*, vol. 5, no. 2, pp. 252–259, Feb. 1975.

[57] D. Graupe, J. Salahi, and K. Kohn, "Multifunctional prosthesis and orthosis control via microcomputer identification of temporal pattern differences in single-site myoelectric signals," *J. Biomed. Eng.*, vol. 4, no. 1, pp. 17–22, 1982.

[58] G. F. Inbar and A. E. Noujaim, "On surface EMG spectral characterization and its application to diagnostic classification," *IEEE Trans. Biomed. Eng.*, vol. 31, no. 9, pp. 597–604, Sep. 1984.

[59] G. Wang, Z. Wang, W. Chen, and J. Zhuang, "Classification of surface EMG signals using optimal wavelet packet method based on davies-bouldin criterion," *Med. Biol. Eng. Comput.*, vol. 44, pp. 865–872, 2006.

[60] R. Boostani and M. H. Moradi, "Evaluation of the forearm EMG signal features for the control of a prosthetic hand," *Physiol. Meas.*, vol. 24, no. 2, pp. 309–319, 2003.

[61] D. Tkach, H. Huang, and T. A. Kuiken, "Study of stability of time-domain features for electromyographic pattern recognition," *J. Neural Eng. Rehab.*, vol. 7, no. 21, 2010.
[62] S. Micera, A. M. Sabatini, P. Dario, and B. Rossi, "A hybrid approach to EMG pattern analysis for classification of arm movements using statistical and fuzzy techniques," *Med. Eng. Phys.*, vol. 21, no. 5, pp. 303–311, 1999.
[63] M. Kelly, P. Parker, and R. Scott, "The application of neural networks to myoelectric signal analysis: A preliminary study," *IEEE Trans. Biomed. Eng.*, vol. 37, no. 3, pp. 221–230, Mar. 1990.
[64] J.-U. Chu, I. Moon, Y.-J. Lee, S.-K. Kim, and M.-S. Mun, "A supervised feature-projection-based real-time EMG pattern recognition for multifunction myoelectric hand control," *IEEE/ASME Trans. Mechatron.*, vol. 12, no. 3, pp. 282–290, 2007.
[65] F. H. Chan, Y. S. Yang, F. K. Lam, Y. T. Zhang, and P. A. Parker, "Fuzzy EMG classification for prosthesis control," *IEEE Trans. Rehabil. Eng.*, vol. 8, no. 3, pp. 305–311, Jun. 2000.
[66] A. D. C. Chan and K. B. Englehart, "Continuous myoelectric control for powered prostheses using hidden Markov models," *IEEE Trans. Biomed. Eng.*, vol. 52, no. 1, pp. 121–124, Jan. 2005.
[67] A. B. Ajiboye and R. F. Weir, "A heuristic fuzzy logic approach to EMG pattern recognition for multifunctional prosthesis control," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 13, no. 3, pp. 280–291, Jun. 2005.
[68] Y. Huang, K. B. Englehart, B. Hudgins, and A. D. C. Chan, "A Gaussian mixture model based classification scheme for myoelectric control of powered upper limb prostheses," *IEEE Trans. Biomed. Eng.*, vol. 52, no. 11, pp. 1801–1811, Nov. 2005.
[69] J.-U. Chu and Y.-J. Lee, "Conjugate-prior-penalized learning of gaussian mixture models for multifunction myoelectric hand control," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 17, no. 3, pp. 287–297, Jun. 2009.
[70] Y.-H. Liu, H.-P. Huang, and C.-H. Weng, "Recognition of electromyographic signals using cascaded kernel learning machine," *IEEE/ASME Trans. Mechatron.*, vol. 12, no. 3, pp. 253–264, 2007.
[71] P. Shenoy, K. J. Miller, B. Crawford, and R. N. Rao, "Online electromyographic control of a robotic prosthesis," *IEEE Trans. Biomed. Eng.*, vol. 55, no. 3, pp. 1128–1135, Mar. 2008.
[72] G. Li, A. Schultz, and T. Kuiken, "Quantifying pattern recognition based myoelectric control of multifunctional transradial prostheses," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 18, no. 2, pp. 185–192, Apr. 2010.
[73] H. B. Evans, Z. Pan, P. A. Parker, and R. N. Scott, "Signal processing for proportional myoelectric control," *IEEE Trans. Biomed. Eng.*, vol. BME-31, no. 2, pp. 207–211, Feb. 1984.
[74] P. Hodges and B. Bui, "A comparison of computer-based methods for determination of onset of muscle contraction using electromyography," *Electroenceph. Clin. Neurophysiol.*, vol. 101, pp. 511–519, 1996.
[75] P. Bonato, T. D'Alessio, and M. Knaflitz, "A statistical method for the measurement of muscle activation intervals from surface myoelectric signal during gait," *IEEE Trans. Biomed. Eng.*, vol. 45, no. 3, pp. 287–299, Mar. 1998.
[76] S. Micera, A. M. Sabatini, and P. Dario, "An algorithm for detecting the onset of muscle contraction by EMG signal processing," *Med. Eng. Phys.*, vol. 20, no. 3, pp. 211–215, 1998.
[77] G. Staude, C. Flachenecker, M. Daumer, and W. Wolf, "Onset detection in surface electromyographic signals: A systematic comparison of methods," *EURASIP J Appl. Signal Process*, vol. 2001, no. 2, pp. 67–81, 2001.
[78] S. Solnik, P. DeVita, P. Rider, B. Long, and T. Hortobagyi, "Teager-Kaiser operator improves the accuracy of EMG onset detection independent of signal to noise ratio," *Acta Bieng. Biomech.*, vol. 10, no. 2, pp. 65–68, 2008.
[79] G. Staude and W. Wolf, "Objective motor response onset detection in surface myoelectric signals," *Med. Eng. Phys.*, vol. 21, no. 6–7, pp. 449–467, 1999.
[80] C. Cipriani, F. Zaccone, S. Micera, and M. Carrozza, "On the shared control of an EMG-controlled prosthetic hand: Analysis of user-prosthesis interaction," *IEEE Trans. Robot.*, vol. 24, no. 1, pp. 170–184, Jan. 2008.
[81] F. Galan, M. Nuttin, E. Lew, P. Ferrez, G. Vanacker, J. Philips, and J. del R. Millan, "A brain-actuated wheelchair: Asynchronous and non-invasive brain-computer interfaces for continuous control of robots," *Clin. Neurophysiol.*, vol. 119, no. 9, pp. 2159–2169, 2008.
[82] H. Kim, J. Biggs, W. Schloerb, M. Carmena, M. Lebedev, M. Nicolelis, and M. Srinivasan, "Continuous shared control for stabilizing reaching and grasping with brain-machine interfaces," *IEEE Trans. Biomed. Eng.*, vol. 53, no. 6, pp. 1164–1173, Jun. 2006.
[83] L. A. Miller, K. A. Stubblefield, R. D. Lipschutz, B. A. Lock, and T. A. Kuiken, "Improved myoelectric prosthesis control using targeted reinnervation surgery: A case series," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 16, no. 1, pp. 46–50, Feb.. 2008.
[84] T. A. Kuiken, G. Li, B. A. Lock, R. D. Lipschutz, L. A. Miller, K. A. Stubblefield, and K. B. Englehart, "Targeted muscle reinnervation for real-time myoelectric control of multifunction artificial arms," *J. Amer. Med. Assoc.*, vol. 301, no. 6, pp. 619–628, 2009.
[85] T. Kuiken, P. Marasco, B. Lock, R. Harden, and J. Dewald, "Redirection of cutaneous sensation from the hand to the chest skin of human amputees with targeted reinnervation," *Proc Nat. Acad. Sci. USA*, vol. 104, no. 50, pp. 20 061–20 066, 2007.
[86] R. R. Finley and R. W. Wirta, "Myocoder studies of multiple myocoder response," *Arch. Phys. Med. Rehab.*, vol. 48, pp. 598–601, 1967.
[87] J. Lyman, A. Freedy, and R. Prior, "Fundamental and applied research related to the design and development of upper-limb externally powered prostheses," *Bull. Prosthetics Res.*, pp. 184–195, 1976.
[88] K. Yoshida, D. Farina, M. Akay, and W. Jensen, "Multichannel intraneural and intramuscular techniques for multiunit recording and use in active prostheses," *Proc. IEEE*, vol. 98, no. 3, pp. 432–449, Mar. 2010.
[89] C. Martelloni, J. Carpaneto, and S. Micera, "Characterization of EMG patterns from proximal arm muscles during object- and orientation-specific grasps," *IEEE Trans. Biomed. Eng.*, vol. 56, no. 10, pp. 2529–2536, Oct. 2009.
[90] S. A. Overduin, A. d'Avella, J. Roh, and E. Bizzi, "Modulation of muscle synergy recruitment in primate grasping," *J. Neurosci.*, vol. 28, no. 4, pp. 880–892, 2008.
[91] A. B. Ajiboye and R. F. Weir, "Muscle synergies as a predictive framework for the EMG patterns of new hand postures," *J. Neural Eng*, vol. 6, no. 3, p. 036004, 2009.
[92] R. Merletti and D. Farina, "Analysis of intramuscular electromyogram signals," *Philos. Transact A Math. Phys. Eng. Sci.*, vol. 367, no. 1887, pp. 357–368, 2009.
[93] D. Farina, A. Crosetti, and R. Merletti, "A model for the generation of synthetic intramuscular emg signals to test decomposition algorithms," *IEEE Trans. Biomed. Eng.*, vol. 48, no. 1, pp. 66–77, Jan. 2001.
[94] R. B. Stein, D. Charles, and M. Walley, "Bioelectric control of powered limbs for amputees," *Adv. Neurol.*, vol. 39, pp. 1093–1108, 1983.
[95] C. J. De Luca and W. J. Forrest, "An electrode for recording single motor unit activity during strong muscle contractions," *IEEE Trans. Biomed. Eng.*, no. 5, pp. 367–372, May 1972.
[96] O. I. Ahmed and R. M. Roark, "Hand construction of quadrifilar wire electrodes for electromyography," *Muscle Nerve*, vol. 40, no. 6, pp. 1036–1039, 2009.
[97] B. Greger, J. Baker, E. Scheme, K. Englehart, and D. Hutcinson, "Continuous detection and decoding of dexterous finger flexions with implantable myoelectric sensors," *IEEE Trans. Neural Syst. Rehabil. Eng.*, no. 99, p. 1, Feb. 2010.
[98] E. N. Kamavuako, D. Farina, K. Yoshida, and W. Jensen, "Relationship between grasping force and features of single-channel intramuscular EMG signals," *J. Neurosci. Methods*, vol. 185, no. 1, pp. 143–150, 2009.
[99] L. J. Hargrove, K. Englehart, and B. Hudgins, "A comparison of surface and intramuscular myoelectric signal classification," *IEEE Trans. Biomed. Eng.*, vol. 54, no. 5, pp. 847–853, May 2007.
[100] T. R. Farrell and R. Weir, "A comparison of the effects of electrode implantation and targeting on pattern classification accuracy for prosthesis control," *IEEE Trans. Biomed. Eng.*, vol. 55, no. 9, pp. 2198–2211, Sep. 2008.
[101] C. Mercier, K. T. Reilly, C. D. Vargas, A. Aballea, and A. Sirigu, "Mapping phantom movement representations in the motor cortex of amputees," *Brain*, vol. 129, pt. 8, pp. 2202–2210, 2006.
[102] K. T. Reilly, C. Mercier, M. H. Schieber, and A. Sirigu, "Persistent hand motor commands in the amputees' brain," *Brain*, vol. 129, pt. 8, pp. 2211–2223, 2006.
[103] G. D. Pino, E. Guglielmelli, and P. M. Rossini, "Neuroplasticity in amputees: Main implications on bidirectional interfacing of cybernetic hand prostheses," *Prog Neurobiol*, vol. 88, no. 2, pp. 114–126, 2009.
[104] J. Badia, A. Pascual-Font, M. Vivó, E. Udina, and X. Navarro, "Topographical distribution of motor fascicles in the sciatic-tibial nerve of the rat," *Muscle Nerve*, pp. 1–10, 2010.

[105] X. Navarro, E. Valderrama, T. Stieglitz, and M. Schüttler, "Selective fascicular stimulation of the rat sciatic nerve with multipolar polyimide cuff electrodes," *Restor. Neurol. Neurosci.*, vol. 18, no. 1, pp. 9–21, 2001.

[106] N. Nannini and K. Horch, "Muscle recruitment with intrafascicular electrodes," *IEEE Trans. Biomed. Eng.*, vol. 38, no. 8, pp. 769–776, Aug. 1991.

[107] K. Yoshida and K. Horch, "Selective stimulation of peripheral nerve fibers using dual intrafascicular electrodes," *IEEE Trans. Biomed. Eng.*, vol. 40, no. 5, pp. 492–494, May 1993.

[108] K. Yoshida and R. B. Stein, "Characterization of signals and noise rejection with bipolar longitudinal intrafascicular electrodes," *IEEE Trans. Biomed. Eng.*, vol. 46, no. 2, pp. 226–234, Feb. 1999.

[109] G. S. Dhillon, S. M. Lawrence, D. T. Hutchinson, and K. W. Horch, "Residual function in peripheral nerve stumps of amputees: Implications for neural control of artificial limbs," *J. Hand Surg. Amer.*, vol. 29, no. 4, pp. 605–615, 2004, discussion 616-8.

[110] D. J. Edell, "A peripheral nerve information transducer for amputees: Long-term multichannel recordings from rabbit peripheral nerves," *IEEE Trans. Biomed. Eng.*, vol. 33, no. 2, pp. 203–214, Feb. 1986.

[111] R. R. Riso, "Strategies for providing upper extremity amputees with tactile and hand position feedback—Moving closer to the bionic arm," *Technol. Health Care*, vol. 7, no. 6, pp. 401–409, 1999.

[112] C. Gold, D. A. Henze, C. Koch, and G. Buzsáki, "On the origin of the extracellular action potential waveform: A modeling study," *J. Neurophysiol*, vol. 95, no. 5, pp. 3113–3128, 2006.

[113] F. Rattay, "Analysis of models for extracellular fiber stimulation," *IEEE Trans. Biomed. Eng.*, vol. 36, no. 7, pp. 676–682, 1989.

[114] G. Buzsáki, "Large-scale recording of neuronal ensembles," *Nat. Neurosci.*, vol. 7, no. 5, pp. 446–451, 2004.

[115] N. Lago, D. Ceballos, F. J. Rodrguez, T. Stieglitz, and X. Navarro, "Long term assessment of axonal regeneration through polyimide regenerative electrodes to interface the peripheral nerve," *Biomaterials*, vol. 26, no. 14, pp. 2021–2031, 2005.

[116] N. Lago, E. Udina, A. Ramachandran, and X. Navarro, "Neurobiological assessment of regenerative electrodes for bidirectional interfacing injured peripheral nerves," *IEEE Trans. Biomed. Eng.*, vol. 54, no. 6, pp. 1129–1137, Jun. 2007.

[117] N. Lago, K. Yoshida, K. P. Koch, and X. Navarro, "Assessment of biocompatibility of chronically implanted polyimide and platinum intrafascicular electrodes," *IEEE Trans. Biomed. Eng.*, vol. 54, no. 2, pp. 281–290, Feb. 2007.

[118] S. Micera, L. Citi, J. Rigosa, J. Carpaneto, S. Raspopovic, G. Di Pino, L. Rossini, K. Yoshida, L. Denaro, P. Dario, and P. M. Rossini, "Decoding information from neural signals recorded using intraneural electrodes: Toward the development of a neurocontrolled hand prosthesis," *Proc. IEEE*, vol. 98, no. 3, pp. 407–417, Mar. 2010.

[119] T. Stieglitz, M. Schuetter, and K. P. Koch, "Implantable biomedical microsystems for neural prostheses," *IEEE Eng. Med. Biol. Mag.*, vol. 24, no. 5, pp. 58–65, May 2005.

[120] D. J. Tyler and D. M. Durand, "Functionally selective peripheral nerve stimulation with a flat interface nerve electrode," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 10, no. 4, pp. 294–303, Aug. 2002.

[121] K. H. Polasek, H. A. Hoyen, M. W. Keith, R. F. Kirsch, and D. J. Tyler, "Stimulation stability and selectivity of chronically implanted multicontact nerve cuff electrodes in the human upper extremity," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 17, no. 5, pp. 428–437, Oct. 2009.

[122] L. E. Fisher, D. J. Tyler, J. S. Anderson, and R. J. Triolo, "Chronic stability and selectivity of four-contact spiral nerve-cuff electrodes in stimulating the human femoral nerve," *J. Neural Eng.*, vol. 6, no. 4, p. 046010, 2009.

[123] S. Bossi, A. Menciassi, K. P. Koch, K.-P. Hoffmann, K. Yoshida, P. Dario, and S. Micera, "Shape memory alloy microactuation of tf-lifes: Preliminary results," *IEEE Trans. Biomed. Eng.*, vol. 54, no. 6, pp. 1115–1120, Jun. 2007.

[124] S. Bossi, S. Kammer, T. Dorge, A. Menciassi, K. P. Hoffmann, and S. Micera, "An implantable microactuated intrafascicular electrode for peripheral nerves," *IEEE Trans. Biomed. Eng.*, vol. 56, no. 11, pp. 2701–2706, Nov. 2009.

[125] K. Najafi and K. D. Wise, "An implantable multielectrode array with on-chip signal processing," *IEEE J. Solid-State Circuits*, vol. 21, no. 6, pp. 1035–1044, Jun. 1986.

[126] I. Pachnis, A. Demosthenous, and N. Donaldson, "Passive neutralization of myoelectric interference from neural recording tripoles," *IEEE Trans. Biomed. Eng.*, vol. 54, no. 6, pp. 1067–1074, Jun. 2007.

[127] R. R. Harrison and C. Charles, "A low-power low-noise CMOS amplifier for neural recording applications," *IEEE J. Solid-State Circuits*, vol. 38, no. 6, pp. 958–965, Jun. 2003.

[128] R. Rieger, J. Taylor, A. Demosthenous, N. Donaldson, and P. J. Langlois, "Design of a low-noise preamplifier for nerve cuff electrode recording," *IEEE J. Solid-State Circuits*, vol. 38, no. 8, pp. 1373–1379, Aug. 2003.

[129] Z. Lertmanorat and D. M. Durand, "Integrated multiplexer for nerve electrodes," in *Proc. Fifth IEEE Int. Symp. Electronic Design, Test Application DELTA '10*, 2010, p. 237.

[130] K. D. Wise, D. J. Anderson, J. F. Hetke, D. R. Kipke, and K. Najafi, "Wireless implantable microsystems: High-density electronic interfaces to the nervous system," *Proc. IEEE*, vol. 92, no. 1, pp. 76–97, Jan. 2004.

[131] Y. Perelman and R. Ginosar, "An integrated system for multichannel neuronal recording with spike/lfp separation, integrated a/d conversion and threshold detection," *IEEE Trans. Biomed. Eng.*, vol. 54, no. 1, pp. 130–137, Jan. 2007.

[132] D. Andreu, D. Guiraud, and G. Souquet, "A distributed architecture for activating the peripheral nervous system," *J. Neural Eng.*, vol. 6, no. 2, p. 026001, 2009.

[133] P. E. Donaldson, "Aspects of silicone rubber as an encapsulant for neurological prostheses. Part 1. Osmosis," *Med. Biol. Eng. Comput.*, vol. 29, no. 1, pp. 34–39, 1991.

[134] P. E. Donaldson and B. J. Aylett, "Aspects of silicone rubber as encapsulant for neurological prostheses. Part 2: Adhesion to binary oxides," *Med. Biol. Eng. Comput.*, vol. 33, no. 3, pp. 289–292, 1995.

[135] H. Hämmerle, K. Kobuch, K. Kohler, W. Nisch, H. Sachs, and M. Stelzle, "Biostability of micro-photodiode arrays for subretinal implantation," *Biomaterials*, vol. 23, no. 3, pp. 797–804, 2002.

[136] B. Upshaw and T. Sinkjaer, "Digital signal processing algorithms for the detection of afferent nerve activity recorded from cuff electrodes," *IEEE Trans. Rehabil. Eng.*, vol. 6, no. 2, pp. 172–181, Apr. 1998.

[137] S. Raspopovic, J. Carpaneto, E. Udina, X. Navarro, and S. Micera, "On the identification of sensory information from mixed nerves by using single channel cuff electrodes," *J. Neuroeng Rehabil.*, vol. 7, no. 1, p. 17, 2010.

[138] W. Tesfayesus and D. M. Durand, "Blind source separation of peripheral nerve recordings," *J. Neural Eng.*, vol. 4, no. 3, p. S157, 2007.

[139] B. Wodlinger and D. M. Durand, "Localization and recovery of peripheral neural sources with beamforming algorithms," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 17, no. 5, pp. 461–468, Oct. 2009.

[140] P. M. Rossini, S. Micera, A. Benvenuto, J. Carpaneto, G. Cavallo, L. Citi, C. Cipriani, L. Denaro, V. Denaro, G. D. Pino, F. Ferreri, E. Guglielmelli, K.-P. Hoffmann, S. Raspopovic, J. Rigosa, L. Rossini, M. Tombini, and P. Dario, "Double nerve intraneural interface implant on a human amputee for robotic hand control," *Clin. Neurophysiol.*, vol. 121, no. 5, pp. 777–783, 2010.

[141] L. Citi, J. Carpaneto, K. Yoshida, K.-P. Hoffmann, K. P. Koch, P. Dario, and S. Micera, "On the use of wavelet denoising and spike sorting techniques to process electroneurographic signals recorded using intraneural electrodes," *J. Neurosci. Methods*, vol. 172, no. 2, pp. 294–302, 2008.

[142] A. Diedrich, W. Charoensuk, R. J. Brychta, A. C. Ertl, and R. Shiavi, "Analysis of raw microneurographic recordings based on wavelet de-noising technique and classification algorithm: Wavelet analysis in microneurography," *IEEE Trans. Biomed. Eng.*, vol. 50, no. 1, pp. 41–50, Jan. 2003.

[143] M. Djilas, C. Azevedo-Coste, D. Guiraud, and K. Yoshida, "Spike sorting of muscle spindle afferent nerve activity recorded with thin-film intrafascicular electrodes," *Comput. Intell. Neurosci.*, 2010.

[144] M. S. Lewicki, "A review of methods for spike sorting: The detection and classification of neural action potentials," *Network*, vol. 9, no. 4, pp. R53–R78, 1998.

[145] E. N. Brown, R. E. Kass, and P. P. Mitra, "Multiple neural spike train data analysis: State-of-the-art and future challenges," *Nat. Neurosci.*, vol. 7, no. 5, pp. 456–461, 2004.

[146] G. Lundborg and B. Rosén, "Sensory substitution in prosthetics," *Hand Clin.*, vol. 17, no. 3, pp. 481–488, 2001.

[147] M. C. Carrozza, G. Cappiello, S. Micera, B. B. Edin, L. Beccai, and C. Cipriani, "Design of a cybernetic hand for perception and action," *Biol. Cybern.*, vol. 95, no. 6, pp. 629–644, 2006.

[148] K. A. Kaczmarek, J. G. Webster, P. B. y Rita, and W. J. Tompkins, "Electrotactile and vibrotactile displays for sensory substitution systems," *IEEE Trans. Biomed. Eng.*, vol. 38, no. 1, pp. 1–16, Jan. 1991.

[149] T. W. Beeker, J. During, and A. D. Hertog, "Artificial touch in a hand-prosthesis," *Med. Biol. Eng.*, vol. 5, no. 1, pp. 47–49, Jan. 1967.

[150] G. F. Shannon, “Sensory feedback for artificial limbs,” *Med. Prog. Technol.*, vol. 6, no. 2, pp. 73–79, 1979.

[151] M. R. Mulvey, H. J. Fawkner, H. Radford, and M. I. Johnson, “The use of transcutaneous electrical nerve stimulation (tens) to aid perceptual embodiment of prosthetic limbs,” *Med. Hypotheses*, vol. 72, no. 2, pp. 140–142, 2009.

[152] B. Rosén, H. H. Ehrsson, C. Antfolk, C. Cipriani, F. Sebelius, and G. Lundborg, “Referral of sensation to an advanced humanoid robotic hand prosthesis,” *Scand. J. Plast. Reconstr. Surg. Hand Surg.*, vol. 43, no. 5, pp. 260–266, 2009.

[153] A. E. Schultz, P. D. Marasco, and T. A. Kuiken, “Vibrotactile detection thresholds for chest skin of amputees following targeted reinnervation surgery,” *Brain Res.*, vol. 1251, pp. 121–129, 2009.

[154] M. Kawato, “Internal models for motor control and trajectory planning,” *Curr. Opin. Neurobiol.*, vol. 9, no. 6, pp. 718–727, 1999.

[155] J. Wheeler, K. Bark, J. Savall, and M. Cutkosky, “Investigation of rotational skin stretch for proprioceptive feedback with application to myoelectric systems,” *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 18, no. 1, pp. 58–66, Feb. 2010.

[156] G. Lundborg, B. Rosén, K. Lindström, and S. Lindberg, “Artificial sensibility based on the use of piezoresistive sensors. Preliminary observations,” *J. Hand Surg. Br.*, vol. 23, no. 5, pp. 620–626, 1998.

[157] C. Pylatiuk, A. Kargov, and S. Schulz, “Design and evaluation of a low-cost force feedback system for myoelectric prosthetic hands,” *J. Prosthet. Orth.*, vol. 18, no. 2, pp. 57–61, 2006.

[158] A. Chatterjee, V. Aggarwal, A. Ramos, S. Acharya, and N. V. Thakor, “A brain-computer interface with vibrotactile biofeedback for haptic information,” *J. Neuroeng. Rehabil.*, vol. 4, p. 40, 2007.

[159] A. Panarese, B. B. Edin, F. Vecchi, M. C. Carrozza, and R. S. Johansson, “Humans can integrate force feedback to toes in their sensorimotor control of a robotic hand,” *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 17, no. 6, pp. 560–567, Dec. 2009.

[160] T. A. Kuiken, L. A. Miller, R. D. Lipschutz, B. A. Lock, K. Stubblefield, P. D. Marasco, P. Zhou, and G. A. Dumanian, “Targeted reinnervation for enhanced prosthetic arm function in a woman with a proximal amputation: A case study,” *Lancet*, vol. 369, no. 9559, pp. 371–380, 2007.

[161] R. Zhou, N. Jiang, K. Englehart, and P. Parker, “A computational model and simulation study of the efferent activity in the brachial nerves during voluntary motor intent,” *Med. Biol. Eng. Comput.*, vol. 48, no. 1, pp. 67–77, 2010.

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