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Chapter 12

Recent Trends in EMG-Based Control Methods for Assistive Robots

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Additional information is available at the end of the chapter

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1. Introduction

Any person would like to spend his or her entire life time as an individual without becoming a dependant person by any means. Nonetheless, there are several instances where a human being would fail to achieve this due to physical problems which preventing him/her from acting as an individual. In most cases, after a stroke, brain or orthopedic trauma, brain damage due to an accident or a cognitive disease the victim will definitely have to undergo physical or cognitive rehabilitation in order to get him used to changed body conditions. In modern society, a considerable percentage of population is physically weak due to aging, congenital diseases, physical diseases and occupational hazards [1, 2]. Such people need a dexterous assistive methodology to regain the normal activities of daily living (ADL). Not only they, those with a missing limb (e.g. due to an amputation), should also be furnished with necessary aids which would enable them to regain the individuality. The development of proper devices for the purpose of rehabilitation, human power assistance and as replacements to body parts has a long history [3, 4] which has reached a high point due to recent developments in technology, such as robotics, biomedical signal processing, soft computing and advances in sensors and actuators over the past few decades. With many advances, capabilities and potential, still biological signal based control has a long way to go before reaching the realm of professional and commercial applications [5].

Most of the studies [5-7] that considered the integration of biomedical signal processing with robotics have achieved tremendous development in the area of assistive robotics. Assistive robots can mainly be classified into three areas: orthoses, prostheses and other types. An orthosis is worn as an external device to the existing body part, while a prosthesis is used as

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a replacement for the lost body part [5, 8]. The meal assistive robot [9], assistive wheel chair [10] and assistive humanoid robot [10] are some examples of the other types of assistive robots. Both orthoses and prostheses directly interact physically and cognitively with the wearer. Therefore, they are expected to provide physiological and mental comfort to the user, without letting the user feel a difference while functioning/assisting correctly to perform the required motion. However, the controlling of the robot according to human motion intention is not an easy task [11, 12]. Therefore, in the integration of the human with a robot, the selection of a proper control input signal to reflect the correct motion intention would be very important. So far research is being carried out considering different biological signals such as Electromyography (EMG), Mechnanomyogram (MMG), Electroencephalography (EEG) Electrooculography (EOG) and Electrocorticogram (EcoG) [13, 14, 15] as the main input signal to the robot controller. Among them, the EMG signal, which is the measurement of the electrical activity of muscles at rest and during contraction, has obtained promising results in the case of controlling robotic prostheses and orthoses by correctly interpreting the human motion intention [16, 17]. Basically, EMG based control is a sophisticated technique concerned with detection, processing, classification and application of EMG to control assistive robots. EMG can be applied to control assistive robots in various manners by considering data acquisition, feature extraction and classification [18]. Some of the available exoskeleton robots controlled based on EMG are the orthotic exoskeleton hand [19], exoskeleton robot for tremor suppression [20], SUEFUL-7 [6] etc. In addition, DEKA Arm [21], Saga Prosthetic Arm [22], and Manus Hand [23] are some of the available prosthetic devices with EMG based controlling. Many researchers from different institutions have been working on EMG based control methods over several decades and their contribution has greatly influenced a new era of EMG based control of assistive robots [5, 24, 25].

This chapter presents a comprehensive review of EMG based control methods of recent upper-limb orthoses and prostheses. Initially, it explains the detection and processing of EMG and available EMG extraction systems. Next, ways of categorization of EMG based control methods are explained. Here EMG based control methods are categorized in detail, based on the structure of the controller algorithm, as pattern recognition based controls and non-pattern recognition based controls. Most of available control methodologies used with assistive robots are pattern recognition based controls [18, 19, 24, 26, 27]. The control methods belonging to non-pattern recognition based controls [28-30] are rare. Further, comparison of EMG based control methods of upper-limb exoskeleton robots and upper-limb prostheses are presented considering the features of the control method. In addition, the conclusion and future directions of EMG based control methods of assistive robots are described.

The next section focuses on the procedure of EMG detection and processing. Section 3 describes the categorization of EMG based control methods. The review of EMG based control methods of upper-limb exoskeleton robots and upper-limb prostheses together with a comparison of control methods are presented in section 4. The final section briefly outlines the conclusion and future directions.

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2. Procedure of EMG detection

Detection of EMG signals can be done mainly in two ways, namely non-invasive and invasive [5]. Surface EMG (sEMG) electrodes are used for the former, while intramuscular EMG (iEMG) electrodes are used for the latter. Placement of surface EMG electrodes is comparatively easier than intramuscular EMG electrodes. However noise and other disturbances are inherent in surface EMG detection [5]. Intramuscular EMG electrodes are placed close to the Motor Unit Action Potentials (MUAP), and as a result the influence of other disturbances is not dominant. It provides a better accuracy and repeatability of the EMG signal [25]. As shown in Fig. 1, the EMG extraction process includes several steps. The initial step is the selection of the most significant muscle of the human body relevant to the required motion. After the muscle is selected, the next important step is the placement of electrodes. In the case of sEMG, the electrodes should be placed in the belly area of the muscle for maximum signal extraction.

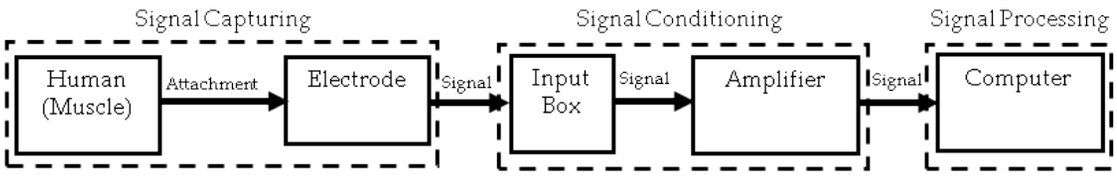


Figure 1. EMG signal extraction process

The electrode should be placed onto the relevant muscle after cleaning the skin surface. There are a few types of surface electrodes, some of which need a gel [31] to be applied between the skin and the electrode and some [32] which instead use an adhesive tape to ensure proper contact between the muscle and the electrode. Signals from several electrodes are then fed into the input box and subsequently passed to the amplifier. The output of the amplifier can be fed into a computer via data cards or any other data communication interface and can be recorded or manipulated in the required way. In most EMG based control methods a raw EMG signal is processed to extract the features of the signal. Several feature extraction methods are available for this purpose [5]: mean absolute value, mean absolute value slope, waveform length, zero crossings, root mean square value, *etc*. The features of the raw EMG signal have to be extracted in real time to use EMG as input signals to the controller of the assistive robots. Most robots use Root Mean Square (RMS) as the feature extraction method of raw EMG mainly due to ease of analyzing real time information of EMG signal.

There are a number of commercially developed EMG acquisition systems available [31-34] (see Fig. 2). They could be used for both medical and research purposes. Some of the leading EMG acquisition system manufacturers are Nihon Kohden Co. [31], Delsys [32], BioSemi [33], and Cambridge Electronic Design [34]. The Delsys EMG system shown in Fig. 2(a) is widely used in research, whilst the Nihon Kohden EMG system shown in Fig. 2(b) is widely used for medical applications. Nevertheless, there are other models in Nihon Kohden which also support for research [31]. The BioSemi EMG system shown in Fig. 2(c) could also be used in research applications. The next section will explain the classification of EMG based control methods



Figure 2. Available EMG acquiring systems

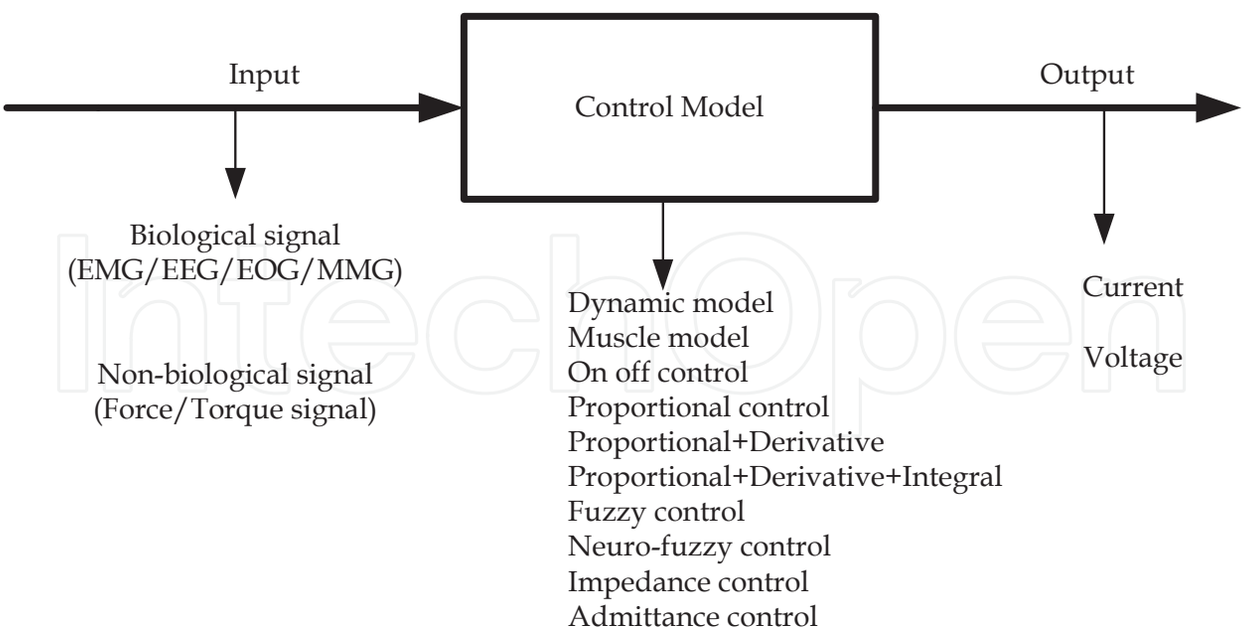


Figure 3. Control method classification for assistive robots

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Figure 4. EMG processing sequence in pattern recognition based control

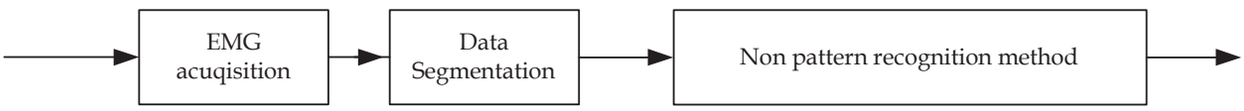


Figure 5. EMG processing sequence in non-pattern recognition based control

3. Categorization of EMG based control methods

Control methods of assistive robots based on EMG can be categorized mainly according to the input information to the controller, architecture of the control algorithm, output of the controller and other ways. Figure 3 shows the ways of categorization of EMG based control methods. In this chapter, the EMG based control methods of assistive robots are categorized based on the architecture of the control method. Considering the EMG signal processing method in the architecture of the controller the EMG based control methods can be categorized mainly as pattern recognition based and non-pattern recognition based [5, 25]. Control methods of many assistive robots are designed with pattern recognition based control methods and it provides an accurate control action compared to non-pattern recognition based EMG based control [5]. However, several intermediate steps (see Fig.4) are applied with a pattern recognition method such as data segmentation, feature extraction, and classification [5, 25]. The accuracy of pattern recognition based control is greatly improved by methods of feature extraction and classification [5, 25]. Robots such as, SUEFUL-7 [6], NEUROExos [27], W-EXOS [11], DEKA Arm [21], Saga Prosthetic Arm [22], Manus Hand [23] are on pattern recognition based control. The non-pattern recognition based control method involves only a few steps (see Fig.5).

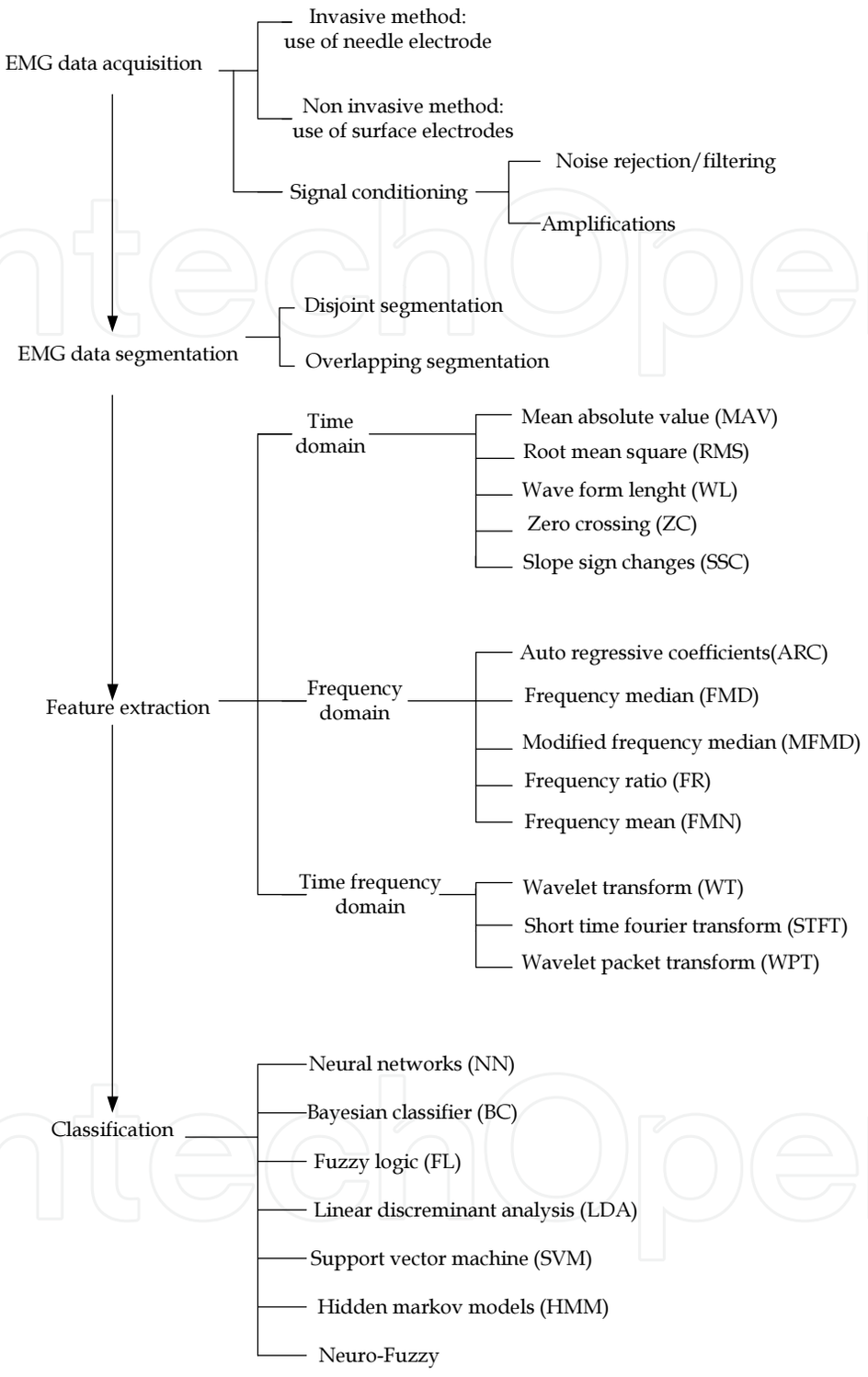


Figure 6. Steps of pattern recognition based EMG processing

EMG processing in pattern recognition based control [5] and non-pattern recognition based control are further illustrated in the next subsections.

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3.1. Pattern recognition technique

The different steps coming under pattern recognition such as data acquisition, data segmentation, feature extraction and classification can be further broken down into sub areas considering available options as shown in Fig. 6. Next subsections present further categorization of data segmentation, feature selection and classification respectively coming under the pattern recognition based EMG based control method.

Data segmentation: The EMG signal has two states: transient and steady. In the transient state, the muscle goes from rest to a voluntary contraction level [5]. Constant contraction of the muscle can be seen under the steady state. In addition the EMG signal in the transient state shows a large deviation of error compared to the steady state level. Therefore, in many cases, the steady state signal is used for the analysis of EMG. For the better result of data segmentation, the selected time slot should be equal to or less than 300ms. This includes segment length and processing time to generate the control command. In addition bias and variance of features can be minimized by selecting adequately a large time slot and it contributes to better classification performance [5, 12, 19]. Data segmentation is carried out with two major techniques: overlapping segmentation [5, 25], and disjoint segmentation which uses segments with predetermine length for feature extraction. Also processing time is a small portion of segment length and thus processor is idle for remaining time of the segment. The new segment slides over the current segment and has small incremental time for overlapping segmentation technique. According to [25], overlapping segment method increases processing time and hence better for the data segmentation [5].

Feature selection: Due to the large number of inputs and randomness of the signal, it is impractical to feed the EMG signal directly to the classifier [6, 18]. Therefore, it is necessary to create the feature vector, where sequence is mapped into a smaller dimension vector. Success of any pattern recognition problem depends almost entirely on the selection and extraction of features. According to the literature, features fall into one of three categories: time domain, frequency domain and time scale domain [25]. Many assistive robots use time domain analysis for feature extraction and in most cases, RMS calculation is adapted for feature extraction [6, 35]. Assistive robots based on frequency domain and time frequency domain were scarce.

Classification: Extracted features need to be classified into distinctive classes for the recognition of the desired motion pattern [5]. Several external factors, such as fatigue, electrode position, perspiration and posture of the limb may causes changes in the EMG pattern over time. Therefore, this leads to large variations in the value of a particular feature. The important feature of the classifier is the ability to identify the unique feature throughout the varying pattern due to other influences. The speed of the classifier is an important aspect for generating required output from the controller. Further, training of the classifier is another way to improve the response of the control system of the assistive robot. Depending on the performance of the subject, practice required for rehabilitation etc can be customized through a training of the classifier and it produces the expected rehabilitation training for the patient too. According to the literature, several methods are used for EMG classifications. Some of them are Neural network [5, 35], Fuzzy logic [25], Neuro-fuzzy logic [5, 25], Probabilistic approach etc.

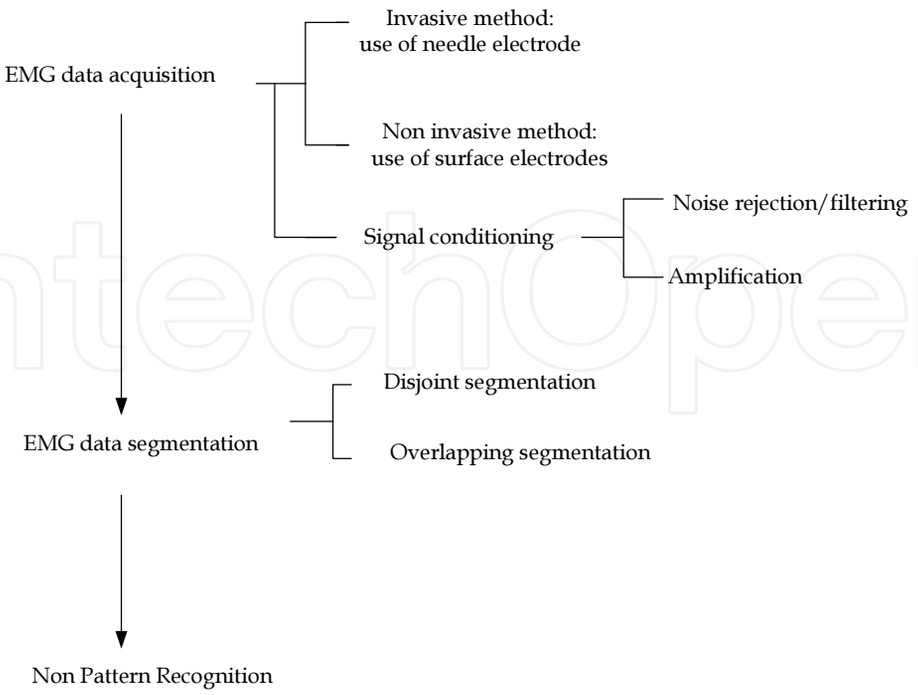


Figure 7. Steps of non-pattern recognition based EMG processing

3.2. Non Pattern recognition technique

In the non-pattern recognition based method accuracy is not as high as the pattern recognition based method. The two main steps coming under non-pattern recognition based method can further be broken down into sub areas considering available options as shown in the Fig. 7. Typically, non-pattern recognition based method includes proportional control, threshold control etc. This is a simple structure and in most cases it uses ON/OFF control [5]. During the review, control methods of assistive robots based on non-pattern recognition based control were hardly found. This may be due to poor accuracy, low level of response, etc.

4. Review of EMG based control method of assistive robots

This section presents a review of EMG based control methods of upper-limb exoskeleton robots and prostheses. For this review, several databases including IEEE explorer, Science direct and Google scholar were used. In total, more than forty five numbers of conferences and journal papers are included and reviewed. Further, EMG based control methods of upper-limb exoskeleton robots and prostheses are compared considering their country of origin, input signals, structure of the controller and special features. Table 1 shows the comparison of EMG based control method of assistive robots.

Reference	Country of origin	Input signal	Structure of controller	Special features
Hand exoskeleton [27]	Germany	EMG	Uses blind source separation to recover the original EMG signal	Developed for hand rehabilitation. Adding force sensors will increase the complexity of blind source separation. increased when combined force sensors
Neuro-fuzzy exoskeleton robot [18]	Japan	EMG and force signal	Multiple neuro-fuzzy controllers are used to take the effect of posture changes during motion	Mean absolute value (MAV) of EMG signal used to controller. Force sensor signals are used to control robot at low muscle activity
Exoskeleton hand [19]	USA	EMG	Uses binary, variable and reaching control algorithms	Suitable control algorithm is needed to provide accepted level of rehabilitation
Hand rehabilitation robot [24]	Italy	EMG	Input signals are fed to the microcontroller via serial connection	Motor speed varies according to joint angle variation of fingers
SUEFUL-7 Upper limb exoskeleton [6]	Japan	EMG and force sensor signal	Neuro-fuzzy controller with muscle model oriented control method. Impedance controller is applied to change the impedance parameters	Joint torques and weights of muscle-model matrix are changed according to posture changes.
Proportional EMG control upper limb exoskeleton [27]	Italy	EMG	EMG based proportional controller. Proportional control gains, K_{bic} and K_{tric} are used to determine the output	Exoskeleton provides extra torque when it works at high proportional gains. This provides better assistance according to level of EMG activity
W-EXOS [35]	Japan	EMG and force signal	EMG based fuzzy-neuro controller. Fuzzy rules are used to determine torque required according to motion intention	Allows flexible and natural motion to user according to motion intention.
Saga Arm [22]	Japan	EMG and Kinematic signal	EMG based fuzzy controller and a kinematic based controller	Transhumeral Prosthetic Arm developed for predefined daily activities
Manus Hand [23]	Spain	EMG	Based on EMG signal of three levels	A command language was developed for the 3-bit input signal of EMG
Finger Prosthesis [46]	AUS	EMG	Post-processing Classification using LIBSVM and kNN	An improved control algorithm has being proposed
EMG based Robotic Hand [36]	Japan	EMG	Based on ANN classification	Together with motion capturing data, joint angles can be calculated for controlling purposes
DEKA arm [21]	USA	EMG/ pressure signals	Uses TMR controlling with pressure signals from the foot	Modular based controlling could be realized

Table 1. Comparison of EMG based control method of assistive robots

A considerable numbers of literature of EMG based control methods show the usage of different methods for EMG processing. This may give a number of options to researchers to conduct experiments for EMG processing in different angles. Most of EMG based assistive robots use surface EMG electrodes for EMG signal detection and few robots use needle electrodes [8, 13]. It was found that all methods of EMG processing belong to one of three main categories: time domain, frequency domain and time-frequency domain [5]. Another important aspect of an EMG based control method is signal classification. Generally, accuracy of EMG based control method highly depends on method of classification and which helps to identify muscles to generate the required output from the EMG based control method [18]. Different robots use different techniques for signal classification and many of them are based on neuro-fuzzy, fuzzy logic and neural network. All assistive robots considered for this review used an EMG signal as its main input signal and the architecture of the controller varies from one type to other. Some of them are based on proportional control and others use advanced control methods such as PID control. In another way, controllers can be classified based on its model as dynamic model [25], muscle model or other method. EMG based control methods of upper-limb exoskeleton robots and prostheses are respectively presented and reviewed in the next subsections. The authors make every possible effort to include all recent EMG based control methods of assistive robots in the next section. The logic for selecting particular control method is its key features and novelty.

4.1. EMG based control methods of upper-limb exoskeleton robots

Different approaches have been proposed by various researchers in the past in order to estimate the muscle torque starting from EMG activation. These methods include neural networks, neuro-fuzzy classifier, hill model *etc* [27]. In the next subsections, several EMG based control methods of upper-limb exoskeleton robots are reviewed.

4.1.1. EMG based control of hand exoskeleton

The hand exoskeleton robot with EMG control has been developed by researchers from the University of Berlin, Germany [26]. This mainly focuses to use by patients who have limited hand mobility. Figure 8 shows the EMG control method for a hand exoskeleton with blind source separation. The construction of the design allows controlling the motion of finger joints. Researchers have presented the difficulties in the application of EMG algorithms. One such drawback is the identification of the correct muscle responsible for a particular motion. In other words, only a subset of muscles responsible for hand movement is sampled by the surface electrodes [26]. Another difficulty is the EMG signal separation for relevant motion. This needs a suitable process to recover the underlying original signals. Armin *et. al.*, have proposed a blind source separation method to recover the underlying original signals developed by a particular motion of muscle [26]. Initially signals are filtered by a weighted low pass differential filter. Then an inverse demixing matrix which, results from an iterative algorithm [4] approximates the separation about 1.5dB for close proximity sensors. Subsequent to the separation, the signals are used for control purposes. However, integration of additional sensors and additional DoF complicates the separation and further, the position of electrodes increases the complexity. Therefore, blind source separation has practical limitations in working with EMG sensors with force sensors.

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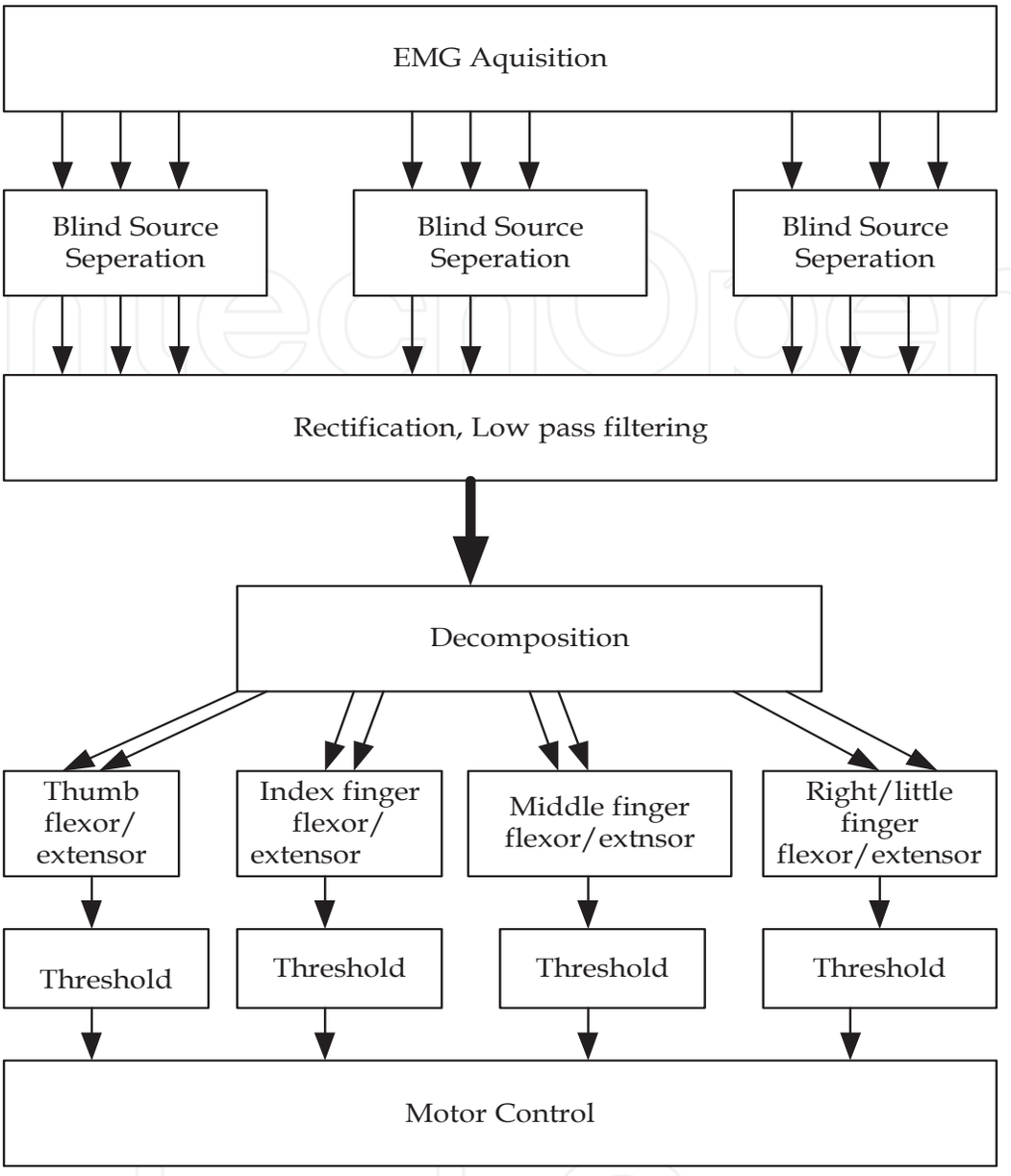


Figure 8. Structure of the control method with blind source separation [26]

4.1.2. EMG based neuro-fuzzy control method

Kiguchi *et al*. [18] have developed an exoskeleton robot and it is controlled based on EMG signals. The robot is used to assist the motion of physically weak persons such as elderly, disabled and injured [37-39]. Although EMG signals directly reflect the human motion intention, it is difficult to control the robotic exoskeleton since the strength of EMG varies with factors like physical and physiological conditions, placement of electrodes, shift of electrodes and high nonlinearity of muscle activity for a certain motion. Therefore, Kiguchi *et al* proposed a neuro-fuzzy controller with EMG signals which provides flexible and adaptive nonlinear control for the exoskeleton robot in real time. The architecture of the controller is shown in the Fig. 9. Mean absolute value (MAV) is used to extract the features of the EMG signal due to its

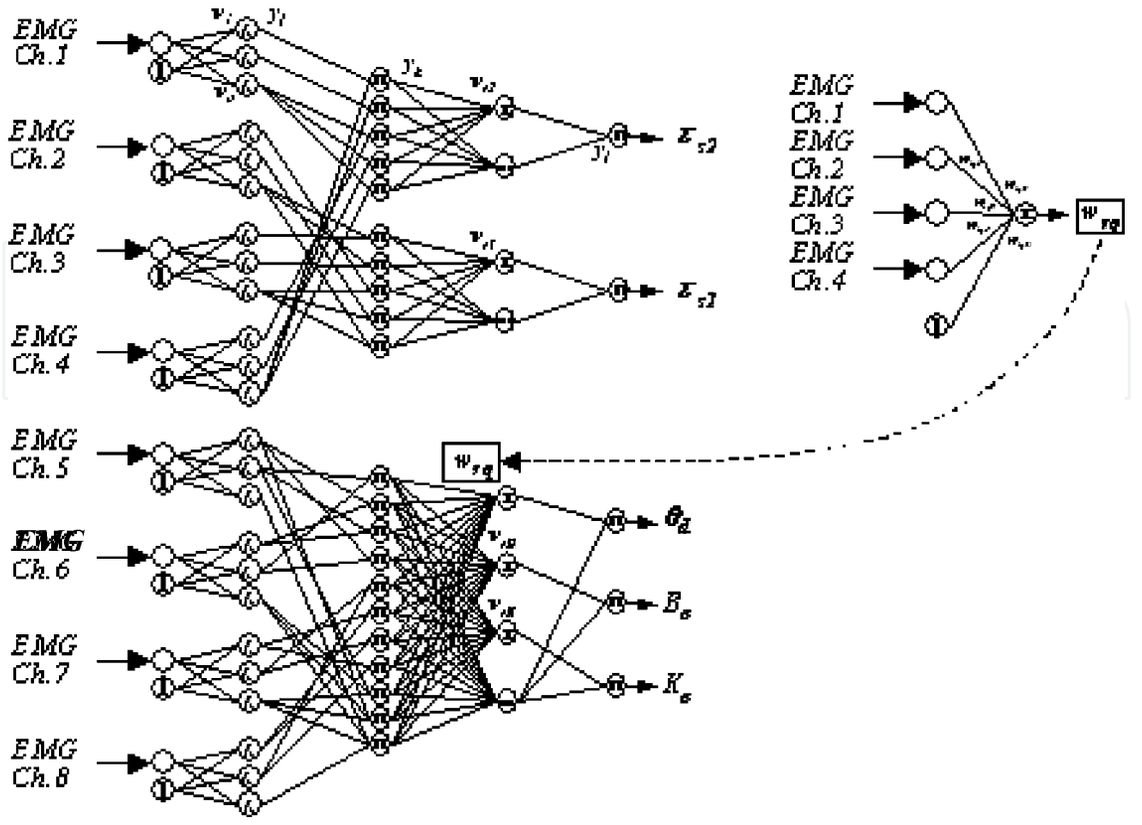


Figure 9. Architecture of neuro-fuzzy controller [18]

effectiveness in real time control compared with other methods such as mean absolute value slope, zero crossing, slope sign changes or wave form length [16, 18]. The hierarchical controller consists mainly of three stages: input signal selection stage, posture selection region stage and neuro-fuzzy control stage. The first stage consists of EMG based control according to the muscle activity levels of the robot and the second stage consists of neuro-fuzzy control according to the motion of the human and finally the controller determines desired torque command for each joint via neuro-fuzzy controller. This helps to realize the effective motion assistance for the robot user. In the first stage, input information to the controller is selected in accordance with the user's muscle activity levels. The control is carried out based on EMG, however, when muscle activity is low, the control signal is generated by force sensors. The second stage of the controller basically works in accordance with the user's arm posture. Different postures may cause different control rules and this leads to complexity of controller. In this situation, multiple neuro-fuzzy controllers have been proposed. The desired torque commands are finally generated by the neuro-fuzzy controller in their last stage.

This EMG based control method employed controller adaptation to realize the desired motion assistance for any subject. Further, the controller is capable of adapt itself to physical and physiological condition of any user of robot. However, this adaptation of the controller imposes training prior to use the assistive robot and it may take a considerable time resulting in a lack of motivation.

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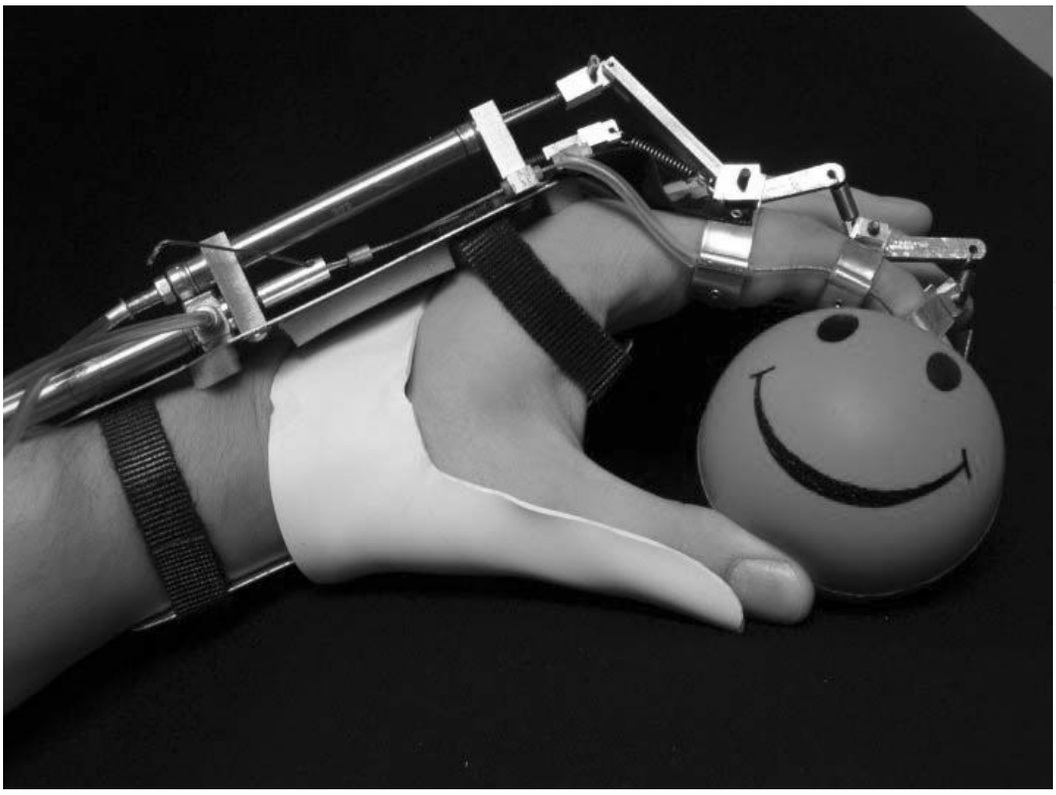


Figure 10. Orthotic exoskeleton hand control by EMG [19]

4.1.3. EMG controlled orthotic exoskeleton hand

Researchers from Carnegie Mellon University, USA have developed a light weight, low profile orthotic exoskeleton (see Fig. 10) which is controlled by using EMG signals [19]. Matsuoka *et al*. further extended their research on discovering the best control methodology for EMG based control of exoskeleton robots. Their observations are presented through conducting experiments under three control scenarios [19]. According to [19], they have conducted EMG based control through Binary control algorithm [40], Variable control algorithm [19] and Natural reaching algorithm [19].

The binary control algorithm provides either 'ON' or 'OFF' states to the outputs or actuators based on EMG activity. This is a more primitive type of control method and it does not cover any intermediate state of function. This problem is overcome when adopting a variable control algorithm which defines the intermediate state and guarantees the smooth function of robotic actuators via an EMG signal. The natural reaching algorithm is suitable for subjects who are paralyzed completely in one of the arms. Authors concluded that the suitable control algorithm is one of the important aspects for better control of the exoskeleton robot with an EMG signal. This determines the type of object being carried by user and the type of interaction needed for it. Therefore, identification of the control algorithm enhances the effective use of the EMG signal for exoskeleton robot control. However, the experiments have not been carried out to determine the effectiveness of the natural reaching algorithm.



Figure 11. Hand exoskeleton [24]

4.1.4. EMG based controlled exoskeleton for hand rehabilitation

Giuseppina *et al* from Italy have worked on developing a hand exoskeleton system (see Fig. 11) which is also controlled by EMG signals [24]. This is mainly developed for hand rehabilitation where people have partially lost the ability to correctly control their hand movements. Figure 12 shows the control flow chart of the hand rehabilitation robot. During the research they have selected the relevant muscle to capture the finger motion and EMG electrodes are placed in order to minimize the noise due to the movements. This is one of the important factors to be considered when placing dry electrodes on the skin. The control system of the robot consists of microcontroller and EMG acquisition systems. Processed EMG signals are communicated with the microcontroller via serial connection. Finally the microcontroller generates the command signal required to drive the actuator and control real positions by means of sensory inputs. Threshold is defined in order to distinguish the real electric activity of the muscle from other interferences. According to [24], the relationship between motor speed, $v(t)$ and joint angle position, $\theta(t)$ is obtained as in equation (1).

$$v(t) = A\{1 - \theta(t)\} \tag{1}$$

where A is defined as an opportunely chosen factor.

According to (1), they are able to control the motor speed which is proportional to the hand opening and progressively it reaches zero when the fingers are flexing. This control method is more suitable for advanced rehabilitation processes. At the same time it takes the effect of natural variability of the EMG signal into account.

4.1.5. Muscle-model-oriented EMG based control of an exoskeleton robot

The SUEFUL -7 is an upper-limb exoskeleton robot mainly developed to assist motion of physically weak individuals. In the robot EMG signals are used as the main input signal to the

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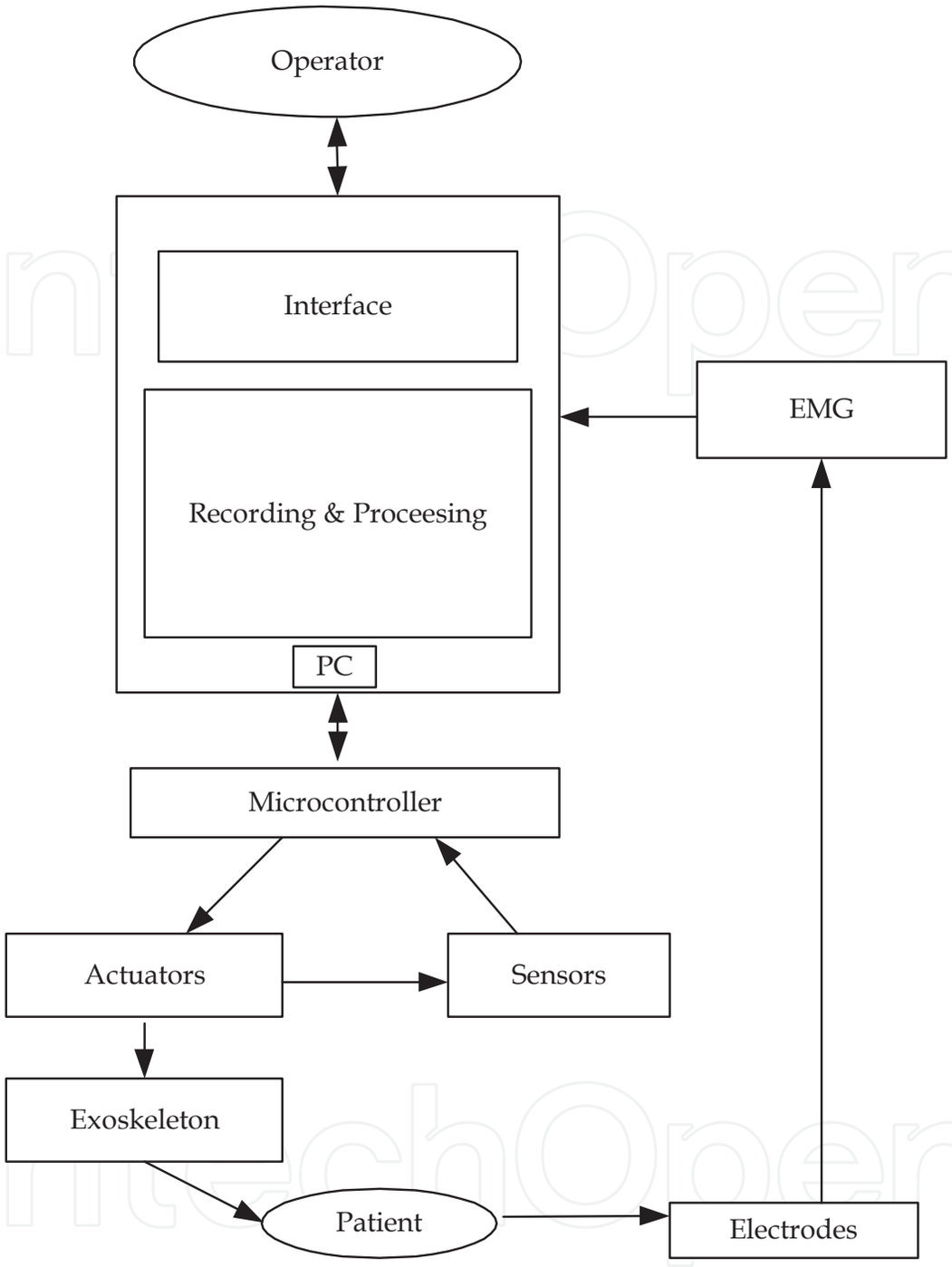


Figure 12. Control flow chart of hand rehabilitation robot [24]

controller (see Fig. 13). In order to obtain the real time control, a muscle-model-oriented control method has been proposed for the robot. This control method is more suitable compared to the fuzzy-neuro control method, where it needs a higher number of fuzzy rules in case of higher DoF. An impedance controller is applied with a muscle-model-oriented control method and impedance parameters are then adjusted in real time as a function of upper-limb posture and EMG activity level [6].

The controller of the SUEFUL-7 [6] uses EMG signals of the user as the primary input information. Also, forearm force, hand force and forearm torque are used as subordinate input information for the controller [6]. This hybrid nature of the control method is a guarantee to activate the SUEFUL-7 even with low EMG signal level. On the other hand, when EMG signals are high, the robot is controlled mainly by the EMG signal generated by user motion. The features of the raw EMG signal are extracted through RMS calculation. This RMS of EMG is fed to the controller. In order to identify the 7DoF motions the EMG signals of sixteen locations are measured with surface electrodes.

The correct joint torque is affected by the posture of the upper limb and it changes the relationship between EMG signals and generated joint torques. Further, this posture variation is nonlinear and stochastic [6]. Fuzzy reasoning is therefore applied to estimate the effect of posture change. Neuro-fuzzy modifier is then applied to modify the muscle model matrix by means of adjusting weights in order to take the effect of changes of posture of the upper limb effectively. Online adaptation of the neuro-fuzzy modifier is important if the robot is expected to be used for different uses. Therefore, the neuro-fuzzy modifier is trained for each user using relevant information. The overall structure of the controller (see Fig. 13) consists of two stages.

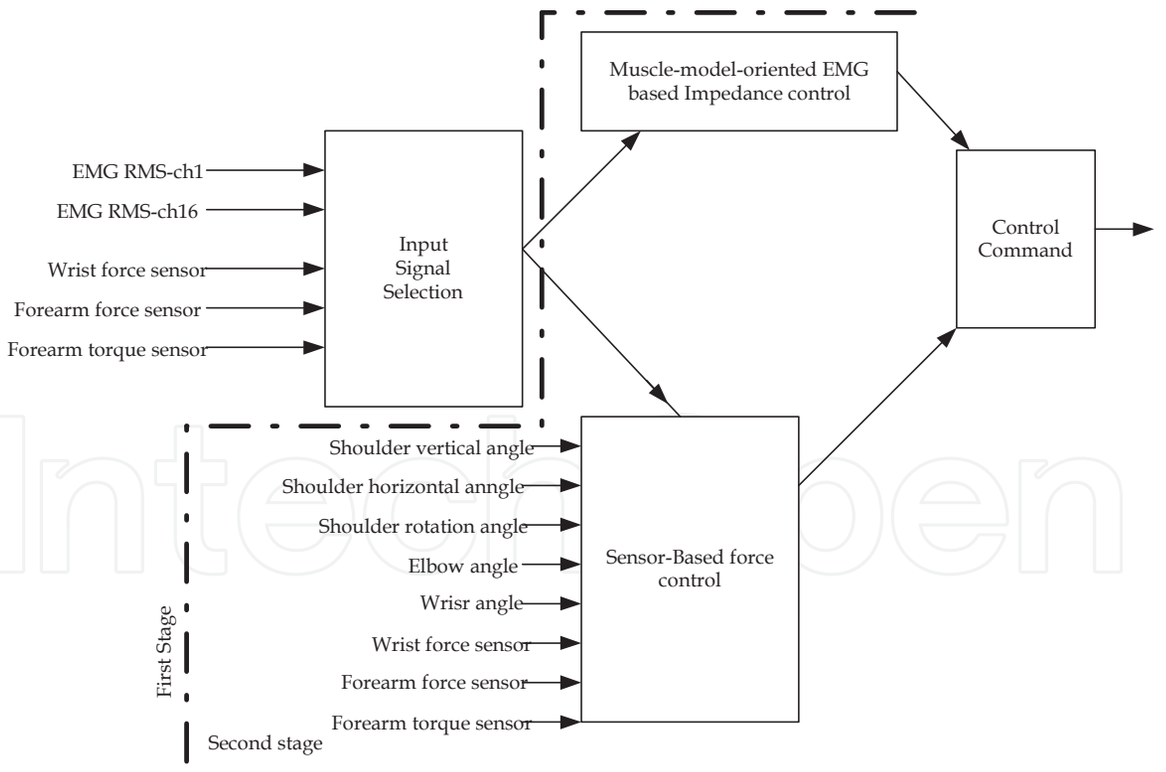


Figure 13. Structure of SUEFUL-7 controller [6]

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The first stage is the input signal selection and the second stage is muscle model oriented EMG based impedance control. Proper input information is selected to the controller according to muscle activity levels in the first stage. Depending on the RMS of the EMG signal, muscle model oriented EMG based control or sensor based force control is selected under the second stage and it is fed as a control command to the robot.

4.1.6. Use of EMG to tremor suppression control

Tremor is defined as the involuntary motion that may occur in various parts of the body, such as the leg or arm. An essential tremor is the most common tremor disorder of the arm and it may occur during a voluntary motion such as writing, painting, etc. If the essential tremor occurs in the arm, the person may not be able to achieve sensitive tasks properly with certain tools [20].

Saga University, Japan has developed an EMG based control method to suppress the tremor of the hand [20]. The features of the EMG signals are extracted from the RMS and fed to the controller. Sixteen EMG channels are selected to measure the muscle activity and they are used to determine the joint torque by knowing weight value for particular EMG signal. This weight depends on upper limb anatomy or result of experiment [20]. The essential tremor is a rhythmic motion and its vibrational component is extracted by using a band pass filter in the controller. Also, the user intention is extracted by using a low pass filter.

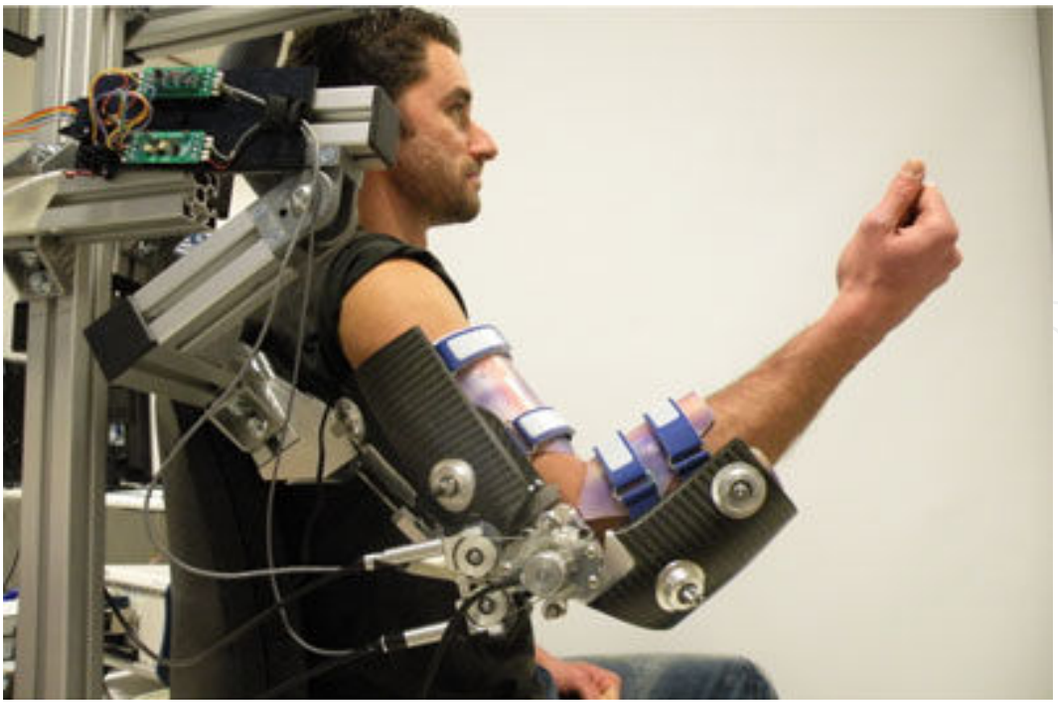


Figure 14. NEUROExos with a subject [10]

The desired hand position is then obtained considering the summation of the above two amplitudes. Therefore X_{avrg} represents the desired hand motion while suppressing the tremor.

$$X_{avg} = X_{usr} - X_{tre} \quad (2)$$

Where X_{avg}, X_{user} and X_{tre} are desired hand position, rhythmic motion and user intention respectively.

Further, a muscle-model matrix modifier is defined to take the changes of hand posture and minimize the effect of variation of EMG signal and hence torque variation. Also the amount of tremor is not uniform to all; therefore training of the muscle-model matrix is needed prior to use with the subject. Especially, in case of tremor, the training of the muscle-model matrix does not become easy, because the pattern of tremor is not uniform to all.

4.1.7. EMG based proportional control method of NEUROExos

NEUROExos [27] is an upper limb assistive robot designed to be controlled by EMG signals. The robot is shown in Fig. 14. Carrozza *et al* pointed the importance of understanding the accurate torque estimate for assistive robots. They have developed an EMG based proportional control method to estimate the required torque to operate the NEUROExos. [27]. In the control method, Raw EMG signals were processed to obtain the linear envelope (LE) profiles which resemble the muscle tension waveforms during dynamic changes of isometric forces [27]. These LEs were obtained on-line through full-wave rectification of band passed EMG signals and post-filtering by means of a second-order low-pass Butterworth filter with a cut-off frequency of 3 Hz [27].

The block diagram of EMG based proportional control method of NEUROExos is shown in Fig. 15. As in Fig. 15, two proportional controllers, K_{bic} (gain for bicep) and K_{tric} (gain for triceps) are set one after other starting from biceps. Both gains are initially set to zero and gradually increased while the subject moves the arm freely. This gain is increased until the subject feels a comfortable level of assistance. Once K_{bic} is set, the subject is instructed to repeat the same procedure for K_{tric} too. The experimental results of proportional EMG based control method of the NEUROExos shown in [27] are proved that the exoskeleton provides extra torque indicating effective reduction of effort spent by the subject for movement generation [27]. Therefore, proportional control of the EMG is one appropriate method to estimate the torque required to move the assistive robot. However, the amount of assistance given by the exo-skeleton depends on the subject.

The neuro-fuzzy modifier proposed by Kiguchi *et al* [6] can be applied with modifications for effective training for different subjects and hence it may possible to perform a task in minimum time.

4.1.8. EMG based fuzzy-neuro control method of W-EXOS

The W-EXOS is a 3DOF exoskeleton robot and its control method is an EMG based fuzzy-neuro control. The control method is illustrated in Fig.16. Surface EMG signals of muscles and sensors

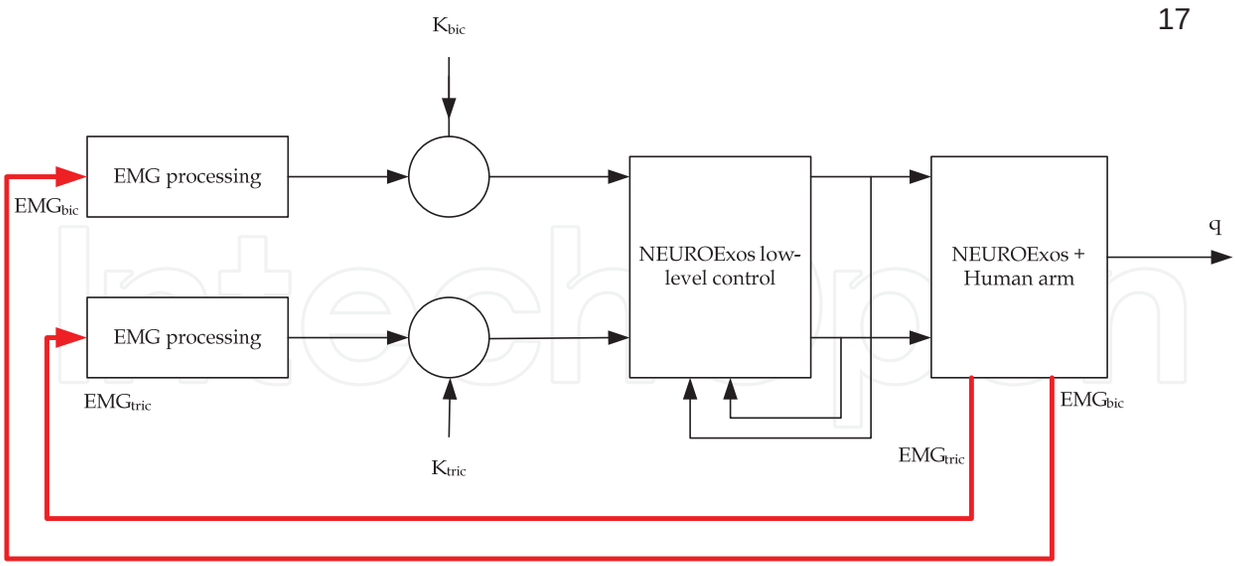


Figure 15. Proportional control block diagram of NEUROExos [27].

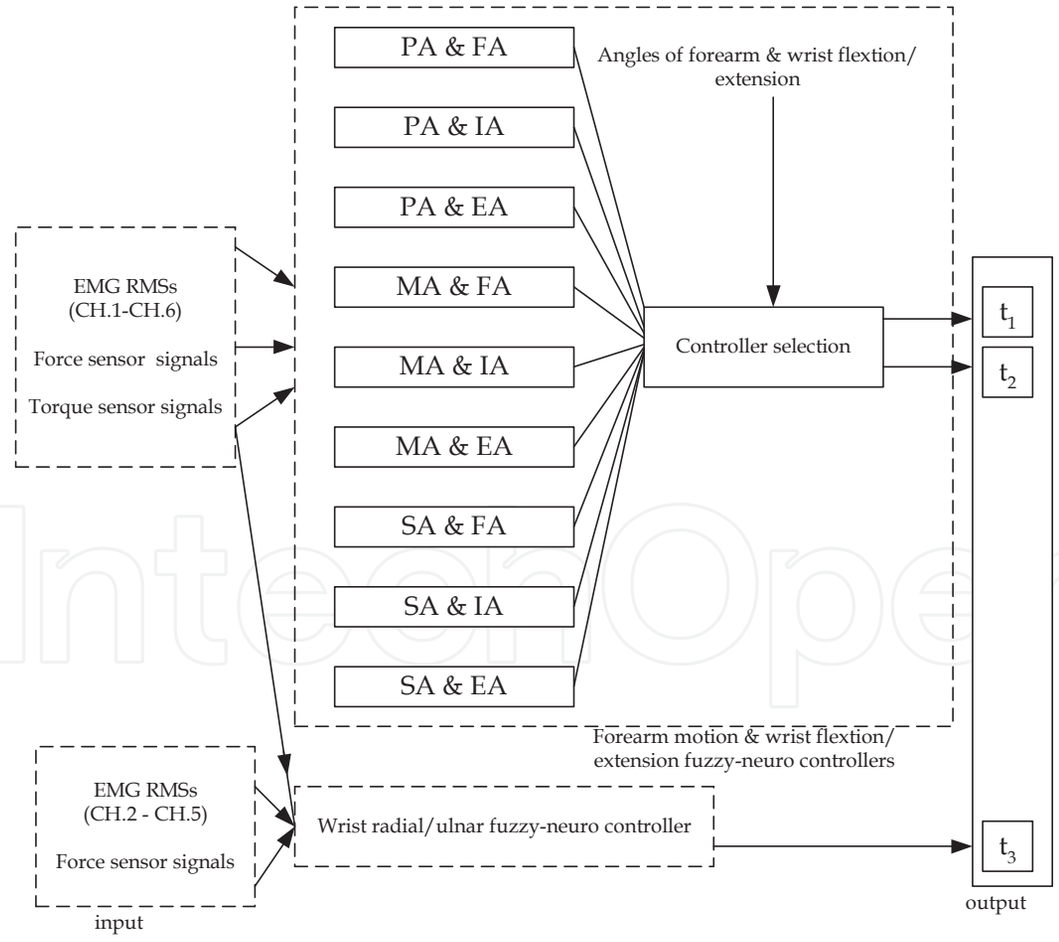


Figure 16. EMG-based fuzzy-neuro control method [35].

of the exoskeleton (hand force and forearm torque) robot [35] are used as input information to the controller. This fuzzy-neuro control method consists of a flexible fuzzy control and adaptive neural network control which is used to obtain natural and flexible motion assist. Fuzzy if-then rules have been constructed to determine the required torque to the motor according to the motion intention of the human. In total, nine fuzzy-neuro controllers are used and this allows operating the exoskeleton robot flexible with EMG signals. Depending on the subject and nature of power-assistance, training of the fuzzy-neuro controller is performed.

The main drawback of this kind of control method is the difficulty of defining the fuzzy if-then control rules when the controller is applied for exoskeleton robots with higher DoF. Further, training of the controller is essential even when the physical and psychological conditions change in the user.

4.2. EMG based control methods of upper-limb prostheses

This section reviews recent EMG based controllers of upper-limb prostheses. Controlling of a prosthetic device using EMG signals is cumbersome task compared to controlling an exoskeleton device using EMG signals, since already the person who wears the device has lost the best site of the body to get the required EMG signals for the controlling of the prosthesis. It makes the number of inputs for the control system to be less and obviously causes to underperform a conventional control system. So far researchers [21-23] have proposed different control methods to control prosthetic devices. In addition, the introduction of more advanced technologies such as targeted muscle reinnervation and implantable electrodes marks new boundaries in prosthesis controlling. The ensuing subsections review EMG based control methods of upper-limb prostheses. The logic for selecting a particular control method is its significance and novelty.

4.2.1. Control method of Saga university prosthetic arm

Saga University prosthetic arm is developed for the realization of 5DoF upper limb motions for a transhumeral amputee. The hand is controlled using a combination of an EMG based controller (EBC) and a task oriented kinematic based controller (KBC). Figure 17 shows an experimental setup of an EMG signal based controller of a Saga prosthetic arm. In a transhumeral amputee a part of the biceps and triceps are remaining. EMG signals of the amputee's biceps and triceps are used as the input information for the EBC to control elbow flexion/extension and hand grasp/release. Forearm supination/pronation, wrist flexion/extension and ulnar/radial deviation get controlled from the KBC. Motion intention of the amputee is identified via a task classifier using shoulder and prosthesis elbow kinematics. For the scope of this context only the EBC will be considered. EMG based fuzzy controller is the base for EBC. It proportionally controls the torque of the elbow and hand actuator according to the amount of the EMG signal. The activation of biceps generates the elbow flexion and the activation of triceps generates the elbow extension. Hand grasp is realized when both triceps and biceps are activated simultaneously. The release position of the hand is achieved when the both muscles are not working.

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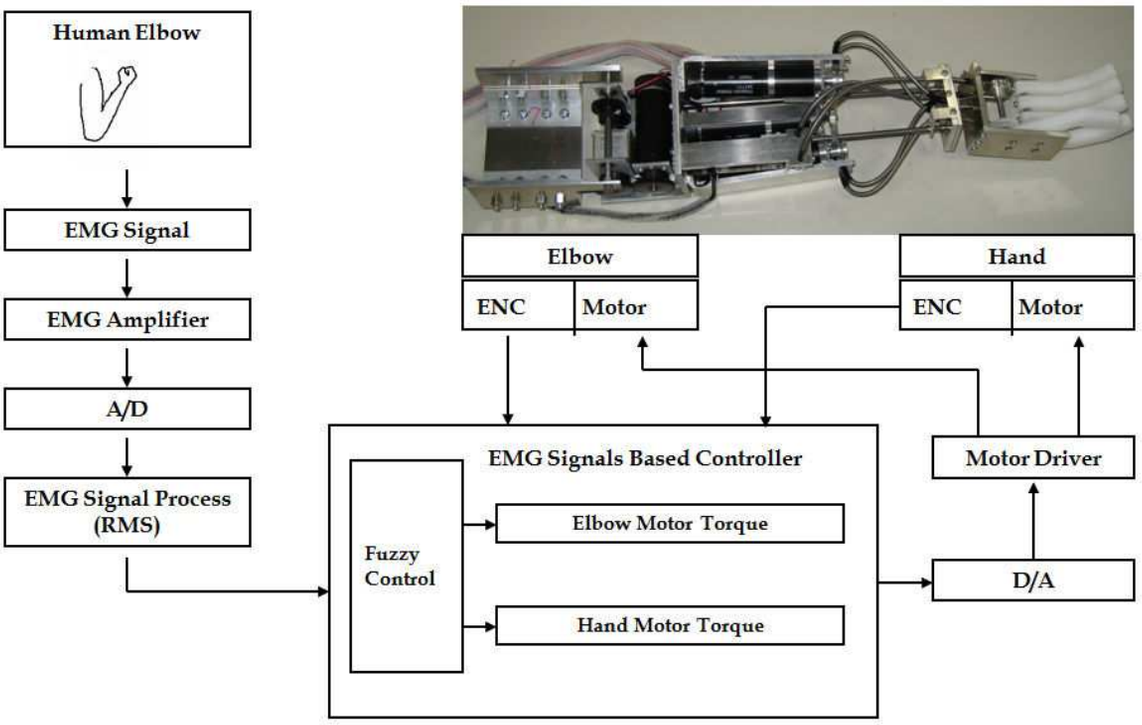


Figure 17. Experimental setup of EMG signals based Controller of Saga prosthetic arm [22]

Information from the raw EMG signals is extracted by taking the RMS value of the raw EMG signals. The RMS is determined as,

$$RMS = \sqrt{1/N \sum_{i=1}^{N} v_i^2} \tag{3}$$

where v_i is the voltage value at i^{th} sampling and N is the number of samples in a segment.

The EBC is provided with four EMG RMSs. Three kinds of fuzzy linguistic variables for each input were defined. Ten kinds of fuzzy if-then rules for elbow joint torque control and seven kinds of if-then rules for hand torque control were prepared. In addition, details on the KBC can be found in [22].

Even though the prosthetic arm is capable of catering to the human motion intension to a certain degree, still some improvements can be made. Since the KBC is trained to offline Vicon data for a given set of daily activities, the orientations of the limbs other than those trained for cannot be achieved using the KBC. Therefore, an inertial measurement unit (IMU) can be fixed to the stem arm of the amputee and used as an interface to read the real time kinematic data. By using the real time kinematic data as an input to the controller it can be improved to reach almost all the orientations of daily activities. In addition a hybrid control method - EMG coupled with EEG - can be used to enhance the performance of the controller by obtaining correct human motion intention.

4.2.2. EMG based control method with targeted muscle reinnervation

Targeted muscle reinnervation (TMR) is a surgical procedure which is developed to increase the number of psychologically appropriate control inputs available for use with a prosthetic device [42]. A surgical procedure is used to transfer the motor neurons of the residual limb to a remaining set of muscles. After denerverting, the target muscles motor nerves can be reinnervated. These reinnervated muscles are capable of providing EMG to a prosthesis controller with more accurate motion intention. For a transhumeral amputee, the goal is to transfer the median and distal radial nerves to target muscle segments creating hand open and close signals. For the shoulder/humeral neck disarticulated amputees all four brachial plexus nerves are transferred to the target muscles [42]. It should be noted that for cases with left shoulder disarticulation the interference of electrocardiogram (ECG) causes an effect to the TMR EMG signals [42]. This could be eliminated using a second-order high pass filter with 60Hz cutoff frequency, which results in 80% elimination of the ECG signals and 20% elimination of the EMG signals producing an improved law signal-to-noise ratio output.

Boston Digital arm [43], Otto Bock electric wrist rotator [44] and an electric terminal device (hook or hand, depending on subject preference) are fitted to six TMR subjects, three transhumeral (TH) amputees, two shoulder disarticulation (SD) amputees and one humeral neck transhumeral amputee. After attaching the patient with the prosthetic device the patient should be guided and continuously monitored to achieve better outcome from the TMR. Even though the training process of the prosthetic user with TMR EMG control is much more easily compared to the pre-TMR, EMG controlling since the TMR itself provides an initiative to the user for training. The control algorithm of the system is comprised of proportional controlling of velocity according to the amplitude of the EMG signal. Table 2 shows summary of information of TMR subjects in the experiment [42].

Even though TMR is capable of providing more sites to extract EMG signals, it is a surgical process and involves invasive procedures, which may cause user discomfort. Therefore, TMR should be replaced by a hybrid control mechanism developed using other signals such as EMG of residual muscles and the EEG signals.

4.2.3. EMG based control of prosthetic finger

Rami *et al* [16] have proposed an improved control algorithm for a control of a prosthetic finger. Using the developed controller different finger postures of the prosthetic hand can be controlled. The main EMG pattern recognition setup is shown in Fig. 18. The controller is mainly developed considering the main ten motions of the hand; flexion of each finger, pinching of thumb combined with each and every finger and clenching of the fist..

Data was collected using two EMG channels. For the feature extraction the windowing was done using a disjoint windowing scheme, which consumes less computer resources due to its simplicity. Various feature sets have been extracted; Waveform length, Hjoth Time Domain (TD) Parameters, Slope Sign Changes, Number of Zero Crossings, Sample Skewness and Auto Regressive (AR) Model parameters were selected [46]. The two feature sets from the two channels resulted in a large one feature set. Dimensionality reduction of the feature set has

been done using Linear Discriminant Analysis (LDA) and it provides nine features for the collected EMG data set. Then both k-Nearest Neighbor (kNN) and Library Support Vector Machine (LIBSVM) have been used for the classification. Use of majority voting technique has resulted in providing smoothed classification accuracies.

Subject identifier	Level of amputation	Elbow flexion	Elbow extension	Hand close	Hand open	Wrist rotation
SD-A	Shoulder Disartic.	Musculocutaneous N. to P.Major, Clav.Head	Redial N. to P.head Major, inf. Stemal	Median N. to upper stemal head	Median N. to upper stemal head*	Toggle between Hand Open/Close control using socket-mounted FSR
SD-B	Shoulder Disartic.**	Musculocutaneous N. to P.Major, Clav.Head	Native remnant triceps	Median N.to P.Major, stemal head and P.Minor	Distal Radial N. to Thoracodorsal N (Serratus Anterior)	Two-site control with two socket mounted FSRs
SD-C	Shoulder Disartic.	Musculocutaneous N. to P.Major, Clav.Head	Native remnant triceps/post. Deltoid	Ulnar N.to remnant P.Major stemal head segment	Radial N to P.Minor	Single-site control with one socket mounted FSR
TH-A	Trans-humeral	Native Biceps, long head	Native Triceps	Median N. to Biceps, short head	Distal Radial N. to Brachialis	Single-site control with harness linear potentiometer
TH-B	Trans-humeral	Native Biceps, long head	Native Triceps	Median N. to Biceps, short head	Distal Radial N. to Brachialis	Single-site control with harness linear potentiometer
TH-C	Trans-humeral	Native Biceps, long head	Native Triceps, long and medial head	Median N. to Biceps, short head	Distal Radial N. to Brachialis, lateral head	Single-site control with harness linear potentiometer

*Unexpected result: subject indicates opening hand with a movement of thumb abduction, a median nerve function

**Humeral neck level amputation clinically fit as a shoulder disarticulation level amputee

Table 2. Summary of TMR subjects including level of amputation, surgical sites used as inputs and any other prosthetic controls implements in the post-TMR prosthetic fitting [42]

4.2.4. EMG based control method of manus hand

Manus hand shown in Fig. 19 as a replacement to a lost hand for an amputee is capable of generating 3DoF, reproducing the grasping function for the user [23]. The hand is controlled via EMG signal of the residual muscle of the user. The simultaneous operation of the joints has been realized. It is achieved using a differently approached pattern recognition technique [23]. In this technique, single muscle EMG signal is used to generate the grasping commands. In order to do this a command language comprising of three EMG bits has been developed. Each

bit has defined three digital levels. Accordingly, an input comprises of three muscle contractions to generate three EMG levels and 27 different commands. From the practical point of view, 18 out of 27 commands were selected for the implementation. However, no information relevant to the pattern recognition has been published by the authors. Table 3 shows the main commands of the 3-bit command language extracted from [45]. According to the controller mechanism no simultaneous operation could be realized using the MANUS hand. Therefore instead of the 3-bit command language it would be better to use a proper pattern recognition method with a higher number of EMG inputs. This could also be coupled with an EEG or other biological signal, in order to achieve higher effectiveness from the controller.

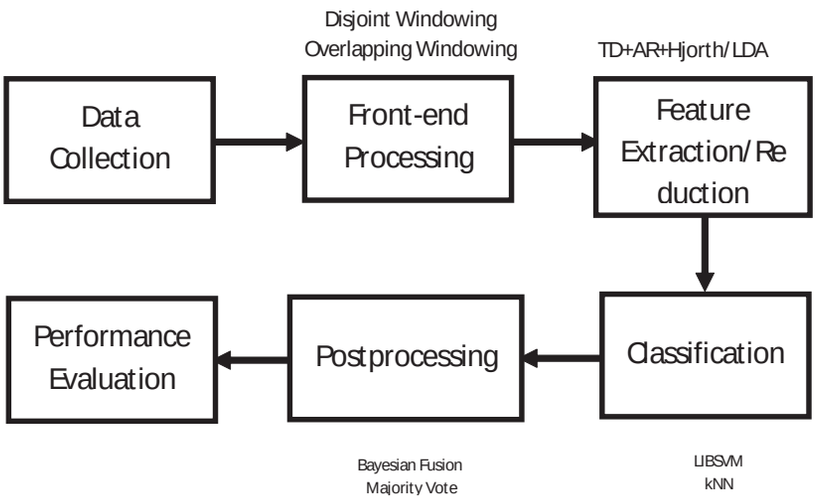


Figure 18. Block diagram of experimental evaluation of the EMG-pattern recognition system [46]

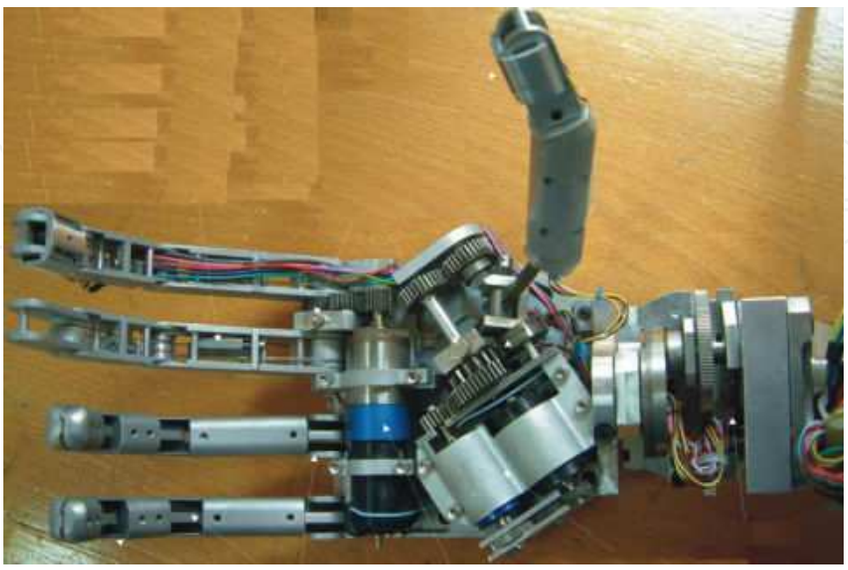


Figure 19. MANUS hand [23]

Functional command	3-bit pattern	Remarks
Stop	100	Constant, pre-set, compulsory
Default position	200	Constant, pre-set, compulsory
Calibration	212	Constant, pre-set, compulsory
Rotate to right, until "Default" or until "Stop"	210	Individually adapted, recommended "preset"
Close, gripping mode "1", Preset 0 to 250 gr. Total pressure, or until "Stop"	211	Individually adapted
Close, gripping mode "1", Preset 251 to 500 gr. Total pressure, or until "Stop"	221	Individually adapted
Close, gripping mode "1", Preset total pressure.500gr., or until "Stop"	222	Individually adapted
Rotate to left, until "Default" or until "Stop"	101	Individually adapted, recommended "preset"
Close, gripping mode "2", Preset 0 to 250 gr. Total pressure, or until "Stop"	120	Individually adapted
Close, gripping mode "2", Preset 251 to 500 gr. Total pressure, or until "Stop"	121	Individually adapted
Close, gripping mode "1", Preset total pressure.500gr., or until "Stop"	122	Individually adapted
Close, gripping mode "3", Preset 0 to 300 gr. Total pressure, or until "Stop"	201	Individually adapted
Close, gripping mode "4", Preset: arch, or until "Stop"	202	Individually adapted
Available	111	
Available	112	

Table 3. Summary of TMR subjects including level of amputation, surgical sites used as inputs and any other prosthetic controls implements in the post-TMR prosthetic fitting [45]

4.2.5. EMG based ANN controller for a transhumeral prosthesis

The EMG based Artificial Neural Network (ANN) controller was developed to realize elbow flexion/extension and forearm supination/pronation based on the artificial neural network (ANN) techniques using EMG signals as the input. Fig. 20 shows the basic concept of the design of the controller. EMG signals are fed into the controller from seven muscles: brachialis, biceps, medial head of triceps, posterior deltoid, anterior deltoid, clavicular and pectoralis major. Raw EMG signals from the muscles are amplified, alternating current coupled, low-pass filtered and recorded. Recorded EMG signals are processed offline. They are filtered, windowed and features extracted. Several features are extracted from 320 samples, 128ms sample time rectangular windows with 50 percent overlap between adjacent segments which provides a sample time of 64ms. The features, mean absolute value, waveform length, number of zero crossing and number of slope sign changes are extracted from each window, which generate a four-element feature set for each EMG channel. Simultaneously motion capturing data from the Optotrak Certus motion capture system is resampled such that its sample time matched that of the EMG data and average joint angles were extracted.

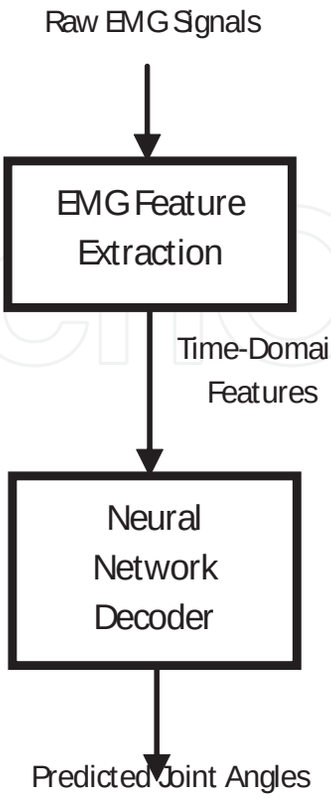


Figure 20. Block diagram of control strategy [36]

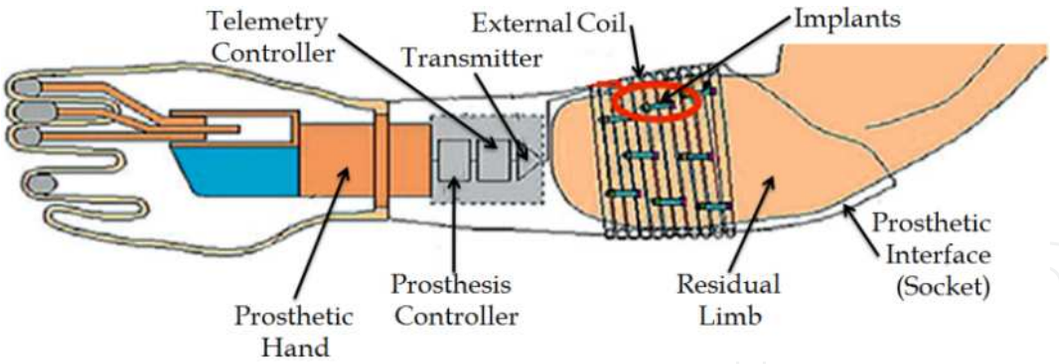


Figure 21. Schematic of the implantable myoelectric sensor system[8]

4.2.6. iEMG controlled prosthetic device

iEMG is capable of providing accurate EMG data to the control system. Use of implantable myoelectric sensor (IMS) would result in nullifying the problem of multiple-component EMGs, an inborn problem of surface EMG recording, as well as the nullifying the considerable amount of environmental effects caused for the changes in regular sEMG signal supply. Here the IMS receives commands and power from an external telemetry controller [8]. It drives a coil

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attached to the prosthetic socket as shown in Fig. 21. EMG data and digital information transmit between the implants and the telemetry controller forming a magnetic link through the coil. The data is then converted into analog form at the controller and can be used to control the prosthetic device. When the results from iEMG are compared with sEMG for the same user, iEMG results show a drastic improvement in providing the same motion of the natural hand. Even though iEMG is capable of providing better signals, it is an invasive process and may cause discomfort to the user. Therefore, a hybrid control method, EMG coupled with EEG would result in providing a better control for the prosthetic device. Further, it will not cause discomfort to the user.

5. Conclusion and future directions

In this chapter, recent EMG based control methods of assistive robots were comprehensively reviewed. As assistive robots, upper-limb exoskeleton robots and upper-limb prostheses were mainly considered here. At first, the detection and processing of the EMG was explained discussing available EMG extraction systems. Then ways of categorization of EMG based control methods as input information to the controller, architecture of the control algorithm, output of the controller and other ways were discussed. EMG based control methods were categorized based on structure of the control algorithm as pattern recognition based control and non-pattern recognition based control. Even though assistive robots with pattern recognition based control can be commonly found, control methods that belong to non-pattern recognition based control are hardly found. Recent EMG based control methods of upper-limb exoskeleton robots and prostheses were reviewed separately. In the review recent EMG based control methods of upper-limb exoskeleton robots and upper-limb prostheses were compared considering their features.

In addition to EMG signals, EEG, EOG and MMG signals also represent the human motion intention and these can be used as input signals to the controller of the assistive robots. Accordingly, in the future a hybrid control algorithm can be developed with a combination of two or more biological signals as inputs to the controller. Assistive robots are expected to function and appear as their biological counterparts. That is, an exoskeleton should ideally act as a second skin for the human and a prosthetic device the same as the natural limb. Accordingly, control methods of devices should be improved in the future.

Actuator technology also plays an important role of control methods of exoskeleton robot and prostheses. Actuators drive a robot interacting with human according to control inputs. Linearity, stability, correspondence between human motion and actuator actions are important terms for successful function of actuators and hence the control system too. New actuator technologies can be successfully used with exoskeleton robots and prostheses to improve its function.

In future developments, the aspect of control systems of the assistive robot can be extended to take the effect of microclimate conditions present around the user and take suitable control efforts to provide comfort to the user. Since exoskeleton robots and prostheses closely interact

with the human, safety conditions should be guaranteed at a maximum level. Although some safety features are connected with mechanical design through stoppers and emergency shutdown systems in an electrical system, proper software locks can be implemented in the control system of the robot to improve the safety features. Further, intelligent safety methods can be introduced to the assistive robot with the help of a feedback system of its control method. One of the human biological signals generated by eye ball movement called electrooculogram (EOG) can be used to generate the feedback signal to the controller. Therefore, when a person feels any unsatisfactory motion of the robot, a particular eye ball movement can be traced and used as a feedback signal and further it can be used to switch off the function of the robot. Since this type of safety method is directly connected with human function it gives maximum protection to the user.

The performance of the control methods is not only based on the controller; it may vary on selection of different components in the control loop. This includes selection of final control elements or actuators, instrumentation for feedback signal, disturbance rejection (inside control loop or outside to the loop), input signals etc. Therefore selection of actuators and sensors play an important role in exoskeleton and prosthesis control systems. In case of sensors, Micro-Electro-Mechanical System (MEMS) inertial sensors are very suitable to detect the changes in velocity, orientation and location of above assistive robots. This technology has made miniaturized sensors and provides low power consumption, low cost, low size and weight which can be used to enhance the function of control method of assistive robots.

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