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REVIEW

Myoelectric control of prosthetic hands: state-of-the-art review

Purushothaman Geethanjali

School of Electrical Engineering
Department of Control and Automation VIT University, Vellore, Tamil Nadu, India

Correspondence: P Geethanjali
School of Electrical Engineering,
Department of Control and Automation,
Katpadi-Thiruvalam Road, VIT University,
Vellore-632014. Tamil Nadu, India
Tel +91 994 498 0194
Email pganjali78@hotmail.com

Abstract: Myoelectric signals (MES) have been used in various applications, in particular, for identification of user intention to potentially control assistive devices for amputees, orthotic devices, and exoskeleton in order to augment capability of the user. MES are also used to estimate force and, hence, torque to actuate the assistive device. The application of MES is not limited to assistive devices, and they also find potential applications in teleoperation of robots, haptic devices, virtual reality, and so on. The myoelectric control-based prosthetic hand aids to restore activities of daily living of amputees in order to improve the self-esteem of the user. All myoelectric control-based prosthetic hands may not have similar operations and exhibit variation in sensing input, deciphering the signals, and actuating prosthetic hand. Researchers are focusing on improving the functionality of prosthetic hand in order to suit the user requirement with the different operating features. The myoelectric control differs in operation to accommodate various external factors. This article reviews the state of the art of myoelectric prosthetic hand, giving description of each control strategy.

Keywords: EMG, assistive device, amputee, myoelectric control, electric powered, body powered, bioelectric signal control

Introduction

Today, the development of science and technology has led to prosthetic devices with promising functional capabilities and esthetic appearance in research domain in favor of commercialization. The design of prosthetic hand is multidisciplinary, compelling knowledge of physiology, anatomy, electrical and electronics, mechanical design, software, and so on, depending on the nature of control. Still, most of the research is in the laboratory and the issue is lack of integration with the technology due to its multidisciplinary nature and the non availability of funds. There have been different types of prosthetic hands ranging from body-powered prosthetic hand to neural interface-based prosthetic hand, which are being manufactured and attempted in the market and for the purpose of research. The choice of prosthetic hand is based on the requirement of the user.

In general, the prosthetic devices could be body powered, pneumatic powered, or electric powered.[1] The body-powered devices harness energy from muscles to operate the cable through a link. The advantages of body-powered devices are that they are of low cost and are less expensive to repair. However, these devices are not cosmetically appealing and are difficult to operate with body power by some users. The electric-powered prosthetic devices that are operated with battery are desired by most of the users due to their cosmetic appearance. However, these devices are expensive, heavy, and expensive to repair. Nevertheless, there has been a major breakthrough in the operation of electric-powered prosthetic devices. These externally powered devices may be operated from pressure, switch, strain gauge, myoelectric signals (MES), and electroencephalogram signals. There is a possibility of hybrid control strategy to improve the operation of the devices. Regardless of the operation of devices, typically, the prosthetic hands are available with the mechanical design of hooks, prehensors, artificial hands, and special type of terminal devices, depending on the user-specific activity.

Hooks are devices with good durability, less maintenance, low weight, and good gripping capability. The hooks are made out of metals such as aluminum, stainless steel, and titanium. Aluminum has less weight and lower strength, and stainless steel has more weight and strength. Titanium hooks have good strength with less weight. But hooks are not cosmetically appealing. They are used for body-powered control. Prehensors are between hooks and artificial hands. Prehensors are available with/without tension feedback in the market. Similar to hooks, prehensors are not cosmetically appealing and are body powered. The special types of terminal devices made to suit user interest in recreational or sports activities like playing golf, climbing mountain, and so on are also body powered.

Artificial hands are cosmetically pleasing, but functionally inferior to hooks and prehensors. These artificial hands may be controlled using MES, reflecting the intention of the user. Attempts are being made to control the hand through restoration of function of the nerves of arm with targeted muscle reinnervation (TMR) surgery to actuate the hand and through the neural interface. Current state of the art is to control the prosthetic hand using MES with various control schemes to interpret the muscle signals. Figure 1 shows the commercially available body-powered prosthetic hand and myoelectric prosthetic hand from Otto Bock HealthCare GmbH (Duderstadt, Germany).[2]

Attempts are also being made to control the joints of fingers in order to improve the dexterity. The i-limb hand has been developed with the articulation of each finger separately or simultaneously, depending on the capability of the user. Therefore, this review focuses on the state of the art of control of myoelectric-controlled prosthetic hands, giving details of various control strategies and briefing about the mechanical design in commercial and research study.

The myoelectric prosthetic hand is based on electromyographic (EMG) signals generated in skeletal muscles, which reflect the intention of the user. The EMG signals generated by the intention are used to control the prosthetic hand using various deciphering schemes such as proportional control, on–off control, finite state machine, pattern recognition, and postural control. Researchers are attempting to decipher more information from EMG to improve the dexterity of prosthetic hand. On the other hand, some researchers are attempting on EMG signal interfacing techniques to improve the dexterity. Nevertheless, the prosthetic hand control depends on the mode of sensing the signals as well as deciphering the intention from EMG signals. This section presents an overview of literature pertaining to improving myoelectric hand control.

Detection of EMG signals

The body-powered prosthetic hand does not mimic the natural human hand movement. The user intention-controlled devices mimic the natural human movement. The user intention for the control of hand may be obtained from physiological control signals acquired through sensors. The sensor technology interfaces the human control signals to the artificial hand. Modern prosthetic hands incorporate surface electrode to

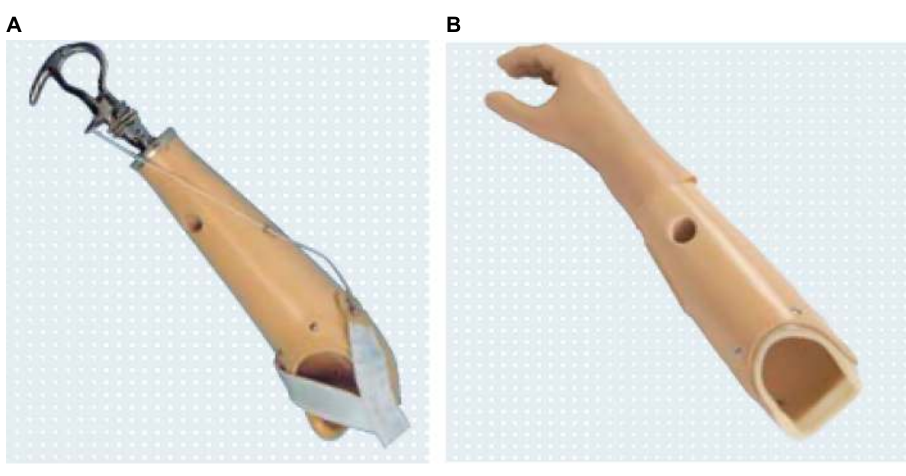

Figure 1 (**A**) Body-powered prosthetic hand; (**B**) myoelectric controlled prosthetic hand.

interface artificial hand through myoelectric control signals to human. The surface EMG signals for artificial hand control are sensed from the surface of the skin and are preferred due to their ease of access and the procedure being noninvasive. The dexterity of prosthetic hand is less in surface EMG due to limitation in identifying the locations to acquire signals. Using surface electrodes, it is possible to identify three to four possible locations from the residual limb to acquire signals for sequential control. However, collecting the intramuscular EMG signals[3–5] is an invasive technique and requires surgical skill for using the implantable myoelectric sensor. But the intramuscular EMG signals provide access for collection of EMG signals from multiple locations to offer multiple degrees of control to prosthetic hand. It could be possible to achieve simultaneous control of prosthetic hand with the intramuscular EMG signals using an implantable sensor.

TMR[6] surgical procedure has been recently used to rewire the nerves to different muscle sets which can be measured from the surface for the control of artificial hand. The use of TMR is effective for transhumeral amputees, and this technique provides access to utilize user intention.

Myoelectric control schemes

The EMG signal has been used in prosthetic hand actuation since 1948.[7,8] Producing commercial prosthetic hand using MES began in 1957 at the Central Prosthetic Research Institute, Moscow to drive stepper motor.[9] This was later upgraded with permanent magnet DC motor and electromagnetic relays. Later, the myoelectric control strategy had been widely analyzed and a simple on–off control scheme was developed. In this myoelectric control scheme, the amplitude of EMG is used to decode the information in the acquired EMG signals to on/off state of the motor. The command to actuate the prosthetic device is determined by comparing the amplitude calculated using the root mean square or mean absolute value (MAV) with the preset threshold. A wide variety of control schemes have been developed to translate the information in the EMG and are typically classified based on the nature of control as sequential control and simultaneous control. Most of the control schemes employed in user's prosthetic hand are of sequential control, and research is now being conducted to employ simultaneous control of the hand. In sequential control schemes, the EMG signals are translated using the following schemes: 1) on–off control, 2) proportional control, 3) direct control, 4) finite state machine control, 5) pattern recognition-based control, 6) posture control schemes, and 7) regression control schemes.

The flowchart for implementation of different types of typical myoelectric scheme with the signal processing stages is presented in Figure 2. Furthermore, proportional control is used in combination with direct control, finite state machine, and posture control for effective decoding of information from the MES. The MES signals acquired from the surface of the skin in these schemes are amplified and preprocessed before analog-to-digital conversion. The acquired EMG data are processed to decipher the user intention and communicate with the motor controller in order to actuate the appropriate motor to achieve the user-intended activity. Signal processing of the various modules is described subsequently.

On–off myoelectric control

The conventional on–off control is appropriate for maximum of two degrees of freedom. In on–off/crisp/binary/bang–bang control, the prosthetic hand is operated with a constant speed in clockwise and counterclockwise directions with a full stop. There are various control schemes for on–off control. The simplest on–off control is based on a threshold of EMG to make a choice of direction of control of the hand. In this control scheme, the hand is operated at a constant speed that is independent of the level of contraction. The simultaneous motion control is possible with motors turned on and off and run at a constant speed.[10]

Proportional myoelectric control

In proportional control scheme, the voltage applied to the motor is proportional to the contraction level/intensity of EMG signals.[11,12] This enables fast grasping for gross movement, and the suitability of the control in upper limb is still under study. Researchers have been focusing on simultaneous proportional control recently.

This simultaneous control is against sequential control schemes such as state machine. Other control schemes are used along with proportional control[13–16] to improve the dexterity in myoelectric control schemes.

Direct myoelectric control

Direct control[17] is similar to proportional control and involves independent EMG sites to achieve individual control of finger movements. However, it is difficult to achieve independent control of hand due to crosstalk in EMG signals. This may be possible with intramuscular EMG signals using an implantable myoelectric sensor.[9]

Finite state machine control

In case of finite state machine control, the postures of the hands are predefined as states and transition among states is also predefined or decoded from the inputs.[18,19] This is

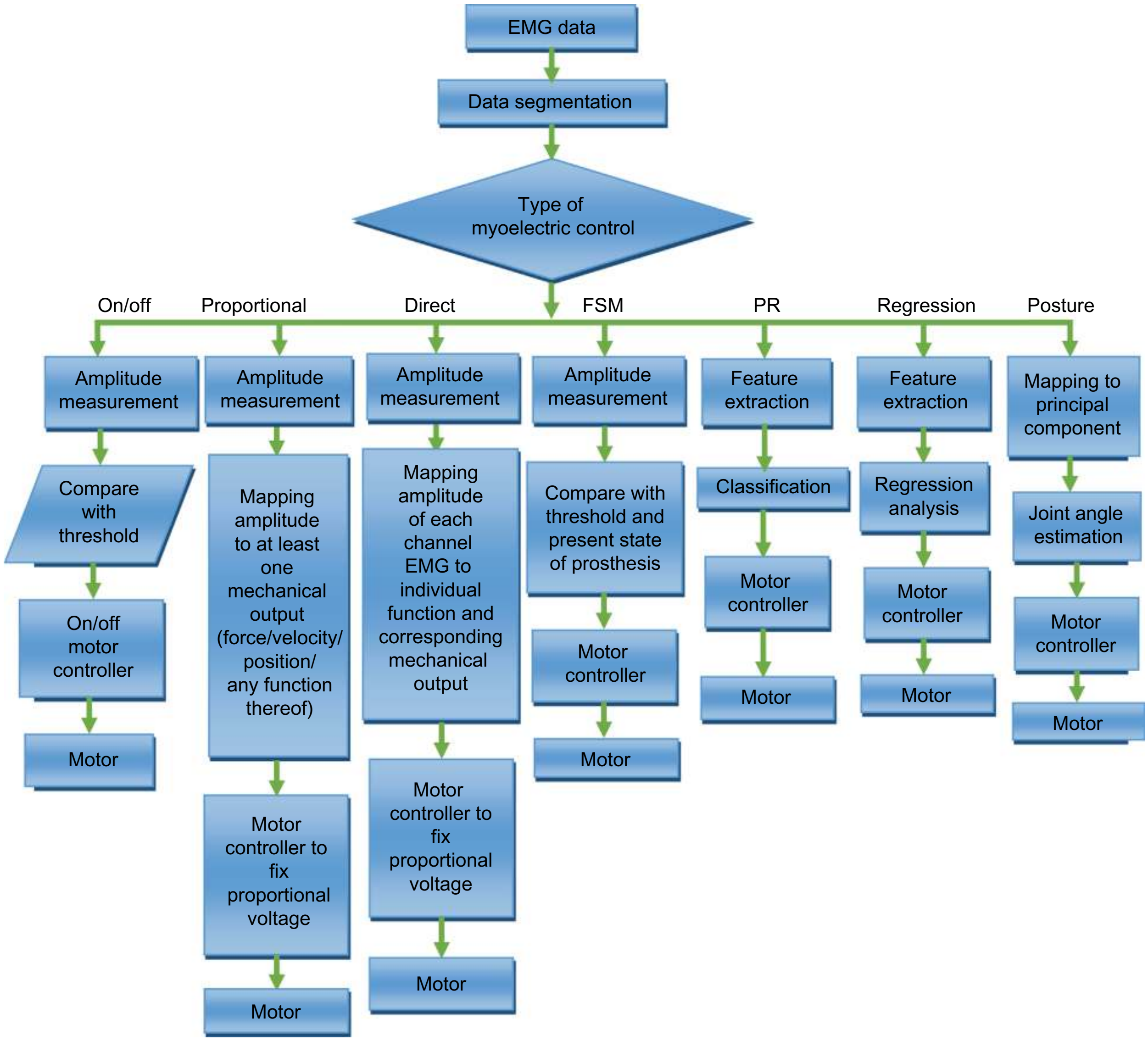

Figure 2 Type of myoelectric control schemes.
Abbreviations: EMG, electromyographic; FSM, finite state machine; PR, pattern recognition.

suitable for a fixed number of postures and may not be suitable for multifunctionality. Furthermore, the state change occurs from the EMG command till the desired posture/function is selected.

These limitations can be overcome using pattern recognition approach. Many researchers have developed various algorithms for identification of information from the signals using pattern recognition approach.

Pattern recognition-based myoelectric control

Pattern recognition-based myoelectric control typically consists of feature extraction and feature classification of segmented data in signal processing to command to the motor controller. Some signal processing may include feature reduction or feature selection (FS) between extraction and classification, depending on the number of features. In general, various features are extracted in time, frequency, and time–frequency to identify the information content of the MES.

Pattern-based recognition for myoelectric control involves an effective method of identification of information from the extracted features. Researchers widely used time domain features due to their simplicity. Sardis and Gootee[20] identified patterns of prespecified motion of the feature space of variance and zero crossing (ZC). Later, Lee and Sardis[21] used integral absolute value, also known as MAV, along with variance and ZC for the myoelectric control of the arm. Hudgins et al[22] investigated the information content in the transient burst of myoelectric activity using MAV, MAV slope, number of ZCs, number of slope sign changes, and waveform length. Because of the stochastic and nonlinear nature of EMG signals, a considerable amount of research has been carried out using autoregressive (AR) models[23–28] in order to describe feature sets to represent nonstationary nature of EMG signals. Liu et al[28] studied the classification accuracy is increasing more rapidly for AR model less than five. The increase in accuracy is low and attains saturation for AR model of five and more. Kang et al[29] and Chang et al[30] took advantage of the cepstral coefficients of EMG signal as the control command of man–machine interface. Many time domain features have been investigated and compared for their effectiveness in pattern recognition for myoelectric control.

In the frequency domain, the fast Fourier transform (FFT)[31–33] has been applied to the EMG signals for determining the frequency spectrum of the EMG signal. Farry et al[31] used the FFT in teleoperation of prosthetic hand. Sueaseenak et al[33] utilized FFT to extract the features from EMG signals of different hand and wrist motions.

More recently, time–frequency and time–space analysis methods have attracted the researchers, but lead to higher dimensional feature vectors and necessitate the use of feature reduction and FS methods to reduce the feature dimension. The short-time Fourier transform,[34] wavelet transform,[35–41] and wavelet packet transform[36,42,43] yield a high dimensional feature vector, and it is essential to employ dimensionality reduction techniques to reduce the burden to the classifier.

Other features such as zero moment, first moment, second moment, and spectral magnitude average from short-time Thompson transform and short-time Fourier transform are used as the features for classification and compared with the performance with temporal features, namely, the integral square, multiple Hamming windows, and multiple trapezoidal windows, for classification of EMG signals.[44] Feature extraction from EMG using moving approximate entropy,[45] hidden Markov model (HMM),[46] HMM-multivariate AR network,[47] fractal modeling,[48,49] statistical features about fractal dimensions for classification,[50] and higher order statistics[51] are some of the feature vectors that were attempted in pattern recognition.

Due to the multichannel approach used for acquisition of signals, the extracted feature vector dimension can become large. Also, wavelet transforms generate many coefficients to represent time scale features. Thus, dimensionality reduction can be achieved using either FS or feature projection (FP) method. FS requires a search strategy that selects a candidate subset and an objective function that evaluates these candidates. There are many search strategies for FS such as Davies–Bouldin,[52–54] genetic algorithm,[55,56] Kohonen's self-organizing map,[57] particle swarm optimization (PSO),[58] mixture of PSO and the concept of mutual information,[59] mutual information,[60] rough set theory,[61] and multivariate analysis of variances[62] for selection of features. An important factor that limits the applicability of FS methods to EMG classification problems is the large variance of EMG signals.[63] Increased number of features can also be reduced by channel selection as proposed by the researchers. The FS algorithms cannot provide powerful performance when the features are dispersed. On the other hand, projection-based methods are more effective than selection-based methods.[64]

Several methods of FP such as principal component analysis (PCA),[32,65–67] a linear–nonlinear FP composed of PCA and a self-organizing feature map,[68] simple Fisher linear discriminant analysis (LDA),[69] LDA-based FP,[63] uncorrelated LDA,[70] combination of Fisher LDA, fuzzy logic, and differential evolution,[71] orthogonal fuzzy neighborhood discriminant analysis,[72] supervised discretization coupled with PCA,[73] and individual PCA[74] have been attempted to compress a number of features.

The pattern recognition (classification) maps the feature vectors from extracted features into specific classes of motion. Many literature reports highlight the success of neural networks (NNs) and their ability to learn the distinction between different conditions in pattern recognition. The advantage of NN is its ability to learn linear and nonlinear relationships directly from the data being modeled. As pioneers in developing real-time pattern recognition-based myoelectric control, Kelly et al[75] used Hopfield NN to calculate the time series parameter and perceptron network to classify the MES signals. Several researchers used a multilayer perceptron (MLP) NN and various NNs are reported in the literature to classify time domain EMG features for myoelectric control[33,48,76–82] to classify time domain features.[33,48,76–82] Wang et al[67] applied back-propagation NN with AR coefficients. Zhao et al[78] applied Levenberg–Marquardt-based NN with parametric AR model and integral of EMG. Tsuji et al[79] proposed an NN that combines a common back-propagation NN with recurrent neural filter in order to classify EMG. Other classification techniques are support vector machine,[83–85] Bayesian classifier,[86] evidence accumulation,[87] fuzzy logic,[88–90] Gaussian mixture model classifier,[63] Morse code-based classification,[91] canonical discriminations,[92] directed acrylic graph support vector machine classification,[93,94] simple logistic regression,[95] *k* nearest neighbor,[96] LDA,[35,83] and so on. Furthermore, hybrid classification techniques such as

HMM–MLP,[97] HMM–genetic algorithm–MLP,[98] and neuro-fuzzy,[99,100] were attempted to improve the performance of myoelectric control. It is essential to perform signal processing in order to maintain the optimal delay in the controller.[101] The performance of the pattern recognition method is studied in real time with virtual myoelectric hand control.[102]

But the pattern recognition methods need training to identify the intention of the user, and also, proportional control is deficient. Most of the pattern recognition control strategies are of sequential control. Researchers are now attempting to simultaneously control using pattern recognition method.[103,104]

Posture myoelectric control

In posture myoelectric control, the EMG signals are mapped to control parameters in the principal component domain.[105] The principal component domain coordinates are linearly transformed into the joint angle to represent target postures. This posture myoelectric control provides simultaneous myoelectric control of prosthetic hand.

Regression myoelectric control

Regression strategy is one of the control strategies developed recently to provide simultaneous as well as proportional control. In this control scheme, simultaneous control signals such as various joint angles would be obtained. Researchers attempted using nonnegative matrix factorization,[13,14] NN,[15] and other techniques.

Discussion and conclusion

In this paper, various myoelectric control schemes related to sequential and open loop control in research and not developed as a product have been reviewed. It is essential to develop products based on these schemes. Another milestone in myoelectric control is providing good gripping capability with the joints of digits actuated using motor to mimic human hand gripping.[106] Furthermore, closed loop control with integration of sensory motor is another thrusting area of research, in addition to simultaneous and proportional control. Researchers are attempting with tactile feedback to close the loop of myoelectric control.[107] Closed loop control is one of the areas that need to be addressed vehemently. Furthermore, research on implantable myoelectric sensor and TMR is progressing well in developed countries. But these studies should also start in developing countries in order to fill the gap.

Considerable research has been conducted in various parts of the world and it is necessary to measure the viability of myoelectric control strategies from the clinical perspective. In addition to control, other strategies such as mechanical design of hand to improve the dexterity, and providing battery with long life. This also necessitates the integration of experts from various disciplines to make the research clinically viable.

Disclosure

The author reports no conflicts of interest in this work.

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