

Myoelectric control systems for hand rehabilitation device: a review

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Abstract— One of the challenges of the hand rehabilitation device is to create a smooth interaction between the device and user. The smooth interaction can be achieved by considering myoelectric signal generated by human's muscle. Therefore, the so-called myoelectric control system (MCS) has been developed since the 1940s. Various MCS's has been proposed, developed, tested, and implemented in various hand rehabilitation devices for different purposes. This article presents a review of MCS in the existing hand rehabilitation devices. The MCS can be grouped into main groups, the non-pattern recognition and pattern recognition ones. In term of implementation, it can be classified as MCS for prosthetic and exoskeleton hand. Main challenges for MCS today is the robustness issue that hampers the implementation of MCS on the clinical application.

Keywords—myoelectric control system, hand rehabilitation device

I. INTRODUCTION

A myoelectric control system (MCS) is a control system that employs myoelectric signal from human muscle activity to create a smooth interaction between the machine and user. MCS empowers a rehabilitation device with an ability to predict the user intention so that the device works together along with human as if it is part of the human body. MCS has been implemented in many rehabilitation devices including hand rehabilitation device either for replacing a lost limb or recovering a limb functionality.

The review on general myoelectric control system was conducted by Oskoei and Hu [1]. They provided a comprehensive discussion on MCS in general and did not focus on specific rehabilitation devices. Meanwhile, Heo, et al. [2] reviewed the hand exoskeleton for rehabilitation and assistive device. They provided detail discussion on the hand exoskeleton. However, the focus is much on the mechanical and electrical point of view. To the best of author's knowledge, the review of the control system of hand rehabilitation device especially based on myoelectric signal does not exist yet. In fact, the well understanding of MCS on the hand rehabilitation device is needed to develop a rehabilitation device that can work together with the user seamlessly.

This article provides a comprehensive review on the implementation of MCS on the hand rehabilitation devices. In addition, it covers two main rehabilitation devices, the prosthetic and the exoskeleton. The hand rehabilitation device considered in this thesis is a wearable robot including the prosthetic and orthotic hand devices. The prosthetic hand

device is a wearable hand robot that can replace the missing hand and have the functionality of the hand replaced.

Nowadays, few dexterous and commercial prosthetic hands are available such as i-limb ultra from Touch bionic [3] and a bebionic hand from Ottobock [4]. Furthermore, a few low-cost prosthetic hands are available as well, such as prosthetic hands from Open bionics [5]. In addition, very few orthotics also available. One of the example is "hand of hope", a commercial exoskeleton hand by Rehab-robotics [6].

II. MYOELECTRIC CONTROL SYSTEM

A. Myoelectric signal

The muscles drive the limbs to generate electrical signals called electromyography (EMG) or myoelectric signal (MES). The EMG signal is a stochastic or random signal whose amplitude can range from 0 to 1.5 mV (root mean square) or 0 to 10 mV (peak-to-peak). The energy above the electrical noise level is in the range of frequency 0 – 500 Hz. Meanwhile, in the range of 50-150 Hz, the energy of the noise is dominant [7]. The noise can come from different sources such as noises from the electronic components, motion artefacts, the inherent instability of the signal, and ambient noise. The energy under the noise level is not reasonable for analysis.

The myoelectric signal may be collected in two ways, either invasive or non-invasive. Hargrove, et al. [8] shows that the control system using surface EMG is not too much different from invasive one. For further discussion, this article considers only surface EMG. Surface EMG electrodes are located on the subject's skin. Meanwhile, Fig. 1 describes the stages in the acquisition of the EMG signal. The source of EMG or myoelectric signal is the action potential generated by each of the motor units activated during a contraction. It is called a motor unit action potential (MUAP). The populations of motor units activated are asynchronous to allow smooth movements. The electrodes pick up the conducted signals generated by all activities involved.

B. Myoelectric control system

The EMG signal can be employed in the control system of the hand rehabilitation devices either in EMG-based pattern recognition or non-pattern recognition system. The EMG-based pattern recognition (EMG-PR) or myoelectric pattern recognition (M-PR) consists of several steps from the pre-processing until the post-processing. The goal of M-PR is to recognise and classify the EMG patterns into classes or limb movements. On the other hand, the EMG-based non-pattern recognition (EMG-non-PR) system does not classify any limb

movement. It may estimate human physical parameters such as the angle of the elbow or the force exerted by the hand according to the EMG signals collected. Moreover, the EMG-non-PR may use EMG signals as a threshold control system or proportional control system. The following sections will explain M-PR and EMG-non-PR in detail.

C. Myoelectric pattern recognition (M-PR)

This section addresses the stages of myoelectric pattern recognition (M-PR) in detail by describing each component of M-PR as presented in Fig. 1.



Fig. 1. Myoelectric pattern recognition system

1) Filtering

The aim of filtering is to reduce the unwanted noises between 20 – 500Hz. A band-pass filter with upper bandwidth cut-off of 400 Hz was applied. The power line noise 50 Hz or 60 Hz may be removed using a notch filter of 50 or 60 Hz.

2) Data segmentation

The classification process lasts for a certain period called a window. In this window, the system extracts valuable information from the row of myoelectric signals. This information is called a feature. The quality of features greatly determines the performance of the system [8]. The feature is extracted in a data sequence bounded in this time slot or window. Based on the data in this window, the whole stages of the recognition system are performed.

EMG signals can be segmented either as an overlapped or disjoint windowing [9]. In the overlapped windowing, the segmented data is overlapped one another depending on the window increment. On the other hand, in the disjoint segmentation, no overlapped data.

3) Feature extraction

The next step of the myoelectric pattern recognition is a feature extraction. The feature extraction is a process that converts patterns to features. In the case of EMG signals, it means a process that converts the pattern of EMG signals, in particular, segments to a set of features that contains salient features of the signals [10].

In general, the feature extraction in EMG signal consists of time domain and frequency domain features. Time domain features have been used widely in EMG pattern recognition system [11]. The advantages of the TD features are quick, easy implementation, low computational complexity and having good performance in low noise environment [12]. However, it has a major disadvantage in dealing with non-stationary signals such EMG signals. The examples of these features are root mean square (RMS), mean absolute value slopes (MAVS) and mean absolute value (MAV). Other features such as slope sign changes (SSC), zero crossing (ZC), and waveform length (WL) can be added. Moreover, model parameters of Hjorth time domain (HTD) and autoregressive (AR) parameters may be utilized.

Beside time domain feature, frequency domain (FD) features that are mostly obtained from power spectral density (PSD) can be employed. Other FD features are median (MDF) and mean frequency (MNF). Furthermore, time and frequency domain feature can be combined to form time-frequency domain (TFD) features. TFD features provide more accurate

description of the physical phenomenon than the time domain and frequency domain features separately [13]. However, the TFD transformation needs heavy computation; somehow, it will not be reasonable for clinical application.

4) Dimensionality Reduction

The extracted features from the previous step are joined to form a set of features. However, this process increases the feature dimension. Therefore, the size should be reduced without compromising the main features. The feature reduction can be made either using feature selection (FS) or feature projection (FP) [13]. The FS selects a subset of best features that give the best performance of the system. On the other hand, the FP transforms the original feature space to a new feature space with smaller dimension. In the EMG signals cases, the feature projection is more favourable than the feature selection due to the characteristic of the EMG signals, i.e. whose variance is large [13].

The feature projection can be classified into an unsupervised and supervised method. In the unsupervised method, the feature space is projected into a new space with smaller size and without compromising the class information. Principle component analysis (PCA) [14] is an example. On the other hand, the supervised method includes the class knowledge into the projection. Linear discriminant analysis (LDA) [15] is as an instance. Inevitably, the class inclusion can enhance the accuracy of the myoelectric pattern recognition. One of the drawbacks of the LDA is a singularity problem that happens when the number of samples is smaller than the number of classes. Some methods can be used to overcome this singularity problem such as uncorrelated LDA (ULDA) [16] and orthogonal fuzzy neighbourhood discriminant analysis (OFNDA) [17].

Furthermore, the feature projection can also be grouped into linear and non-linear feature projection. PCA and LDA are examples of the linear feature projection. As for the non-linear method, the non-linear version of PCA is as an example. It is a kernel PCA that employ a kernel instead of a linear function in the process. Another example of the non-linear method is a neural-network based feature projection such as unsupervised extreme learning machine (USELM) and Autoencoder [18].

5) Classification

The classifier is one of the main components of the M-PR system. It classifies the features into particular classes. The predicted class will be delivered to the robot to produce a certain hand posture accordingly. In the early stage of the M-PR system, multilayer perceptron (MLP) [19] or feed-forward neural networks (FNN) was frequently used [20]. The FNNs is a powerful classifier, but the training process is time-consuming. Therefore, some researchers preferred using linear discriminant analysis (LDA) than MLP because LDA is fast and performs as accurately as FNNs. In addition to MLP and LDA, a few researchers employed hidden markov model (HMM) [21] and k-nearest neighbour (kNN) [22].

Recently, support vector machine (SVM), which is used in many applications, promises better performance than LDA, FNNs, k-nearest neighbour (kNN) as long as the SVM parameters are optimized properly [23]. However, SVM is originally developed for binary classification. The recognition system should use several SVMs to deal with multi-class classification. Recently, a new machine learning originated from the artificial neural network was proposed and called

extreme learning machine (ELM) [24]. Not like FNNs, ELM omits iterative learning and does not need to tune the hidden-node parameters. Most recent classifier employed is convolutional neural network, a kind of deep learning neural network [25].

6) *Post-processing*

The aim of this stage is to smoothen the classification results. A majority vote is one of most common method that is employed by many researchers [26]. It makes a new result based on the output that appears most frequently from the current state and n previous states. This process yields a system that removes fake misclassifications.

D. *Myoelectric non-pattern recognition (M-non-PR) system*

The M-non-PR system has similar steps as the M-PR except in the classification stage. The M-non-PR does not have it. Instead, it has different processes, as depicted in Fig. 2.

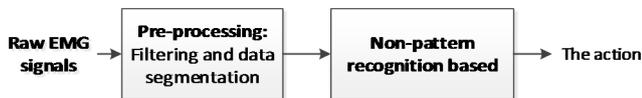


Fig. 2. The EMG-based non-pattern recognition

Among examples of EMG-based non-pattern recognition are the threshold myoelectric control, proportional myoelectric control, simultaneous and propositional myoelectric control and finite state machine (FSM) control [1].

a) *The threshold myoelectric control*

The threshold myoelectric control is a control system that utilizes a threshold value from the contraction level of EMG signal as a control source to activate or deactivate an action. It is also known as a binary on/off myoelectric control because the threshold value determines the on or off state of the assistive device [27]. The early stage of EMG controller in the prosthetic device employed this controller [28]. Besides, the majority of the current exoskeleton hands utilize the threshold controller instead of EMG based pattern recognition [29, 30].

b) *Finite state machine*

Finite state machine control consists of some states that the device should perform. The switching between states can be triggered by a timer or based on the level contraction of the EMG signals [1].

c) *The proportional myoelectric control (PMC)*

The PMC gives a more advanced control scheme than the threshold myoelectric control. In this control system, the control signal for the rehabilitation device is proportional to the contraction level of the EMG signal. The control system utilizes the EMG signal to estimate a specific physical parameter such as force or angle. Afterward, the control system treats those biofeedback values as the target that the device should achieve.

d) *The simultaneous and proportional myoelectric control (SPMC)*

The simultaneous and propositional myoelectric control is more advanced than the proportional one. This control system controls all joints proportionally and simultaneously from the EMG signal. To train the system, the amputees need a help

form their healthy hand to produce target movement. The control system should estimate all physical parameters recorded from the raw EMG signal. Therefore, this control system is also known as regression based myoelectric system [31].

III. MCS ON HAND REHABILITATION DEVICES

A. *EMG-based prosthetic hand*

This sub-section provides a review of prosthetic hands controlled by EMG signal. The discussion is focused on the hand movement excluding the arm movements such as shoulder, elbow and wrist movements.

1) *The Russian EMG controlled hand*

Historically, Rieter was the first person who developed an EMG controlled hand in 1948 [32]. In 1957, B Popov, a Russian researcher, began to develop a bioelectricity controlled prosthetic hand [28]. This prosthetic is designated for the upper extremity. The electrodes were located in the stump. There are two movements: grasp and release. The EMG signals were acquired from two contradictory muscles. The hand will grasp if the exerted voltage of the flexion muscle exceeds 30-40 mV. To release or open the hand, the system will detect the opposing flexing muscle. If the recorded voltage was more than the threshold value, then the hand will open. The prosthetic hand is controlled with a threshold control system. This is a very basic myoelectric control system because it considered the one degree of freedom (DOF) only.

2) *Suzuki 's system [33]*

In 1969, Suzuki and Suematsu [33] developed a more complex control system using EMG signals. They called it pattern recognition of multichannel myoelectric signals. The system classified seven kinds of hand motions using a spatial pattern collected from three EMG channels on the forearm. The system learned the pattern or the classes using the learning discrimination mechanism [33]. Compared to the Russian EMG controller, the EMG controller is more advanced. The indication is shown by involving more motions and employing a learning mechanism to learn the pattern of EMG signals. Even though it considered multi DOFs, there is no information about the clinical application.

3) *Uchida's system [34]*

Hiraiwa, et al. [20] employed a single channel EMG to classify five hand motions. They utilized the neural network to analyse and classify the EMG pattern to control a prosthetic hand. The work of Hiraiwa was continued and developed by Uchida, et al. [34] to deal with multichannel EMG. In their work, the electrodes were located on the forearm especially on the flexor digitorum superficialis (FDS) muscle. Five motions involved were the flexion of all fingers (A), the flexion of the index finger (B), the flexion of the middle finger (M), the flexion of the thumb (T) and relaxation of all fingers (N). Using two EMG channels, they extracted fast Fourier transform (FFT) features. The FFT of the EMG signals became the inputs of the feed-forward neural networks (FF-NN). The experimental results showed that the system able to classify five-finger movements and attain an accuracy of 67%. In the case of 2 EMG channels, they could improve the accuracy up to 86%. All experiments were conducted in the laboratory.

4) *Tsenov's system [19]*

Similar to Uchida, et al. [34], Tsenov, et al. [19] developed a recognition system of finger movement using multilayer

perceptron (MLP). MLP classified four finger movements: thumb, pointer, middle and hand closure. The electrodes were located on two groups of muscles, planaris longus (PL) and extensor digitorum (ED). They extracted time-domain (TD) features from EMG signals and put them on the input of the MLP. In the offline experiment, they achieved an accuracy of 93% and 98% using two and four EMG channels, respectively. Meanwhile, in the online classification, the system showed a promising performance by making 30 errors of 250 tested movements. These promising results were obtained in the laboratory environment.

5) Tenore's system [35]

Tenore, et al. [35], researchers from John Hopkins University developed a pattern recognition system using EMG signals to decode individual finger movements. The movements consisted of the flexion and extension of all individual fingers and the middle, ring, little fingers as a group. There are 12 classes involved in the experiment. The work involved five able-bodied subjects and one trans radial amputee. The experiments results show that the system achieved a high level of classification accuracy (approximately 90 %).

6) Cipriani

Cipriani, et al. [22] developed EMG pattern recognition for a prosthetic hand. Different from the previous researcher who employed MLPs or ANN, they utilized k-nearest neighbour (kNN). Features were extracted from nine EMG channels using time domain features. Moreover, they were acquired from five able-bodied and amputee subjects. There are seven hand movements classified including thumb flexion (A), index finger flexion (B), thumb opposition (C) middle, ring, and little finger flexion (D), long fingers flexion (E), tridigital grasp (F) and lateral grip/key grip (G).

The experiment involved 10 participants, five trans-radial amputees, and five able-bodied subjects. Eight bipolar EMG electrodes were placed on the right arm of participants or the residual limbs. The recognition system was implemented online and able to classify seven finger movements with the accuracy of around 79 % and 89% on the amputee subjects and non-amputee subjects, respectively.

7) Khushaba

Khushaba, et al. [23] developed a new MPR system for finger movements using support vector machine (SVM). There were six time-domain features involved, i.e. ZC, WL, SSC, HTD, SS, and AR model parameters. Then, the size of the features was reduced using LDA. The experimental results indicated that the system achieved an accuracy of approximately 92% and about 90% in the offline classification and online classification, respectively. Regarding accuracy, Khushaba *et al.*'s recognition system was promising, but the system contains a natural shortcoming of SVM in dealing with the multi-classification problem. At least, the recognition system should use m SVMs to deal with m movement classes. Inevitably, this will add to the processing time of the system.

8) Al-Timemy

The most recent study of a pattern-recognition system on finger movement classification was undertaken by Al-Timemy, et al. [11]. They investigated several schemes for the EMG pattern recognition. The developed system extracted features from six up to twelve EMG signal using AR and TD features. There were four combinations of dimensionality reductions and classifiers employed. They are PCA-LDA,

PCA-SVM, orthogonal fuzzy neighbourhood discriminant analysis [17] (OFNDA)-LDA and OFNDA-SVM. Those systems classified 12 classes on six amputees. Meanwhile, it worked on and 15 classes on ten healthy subjects. The most accurate of the four combinations was the system with OFNDA-LDA. The experimental results showed that the proposed system achieved an accuracy of around 98% on the non-amputees and 90% on the amputees.

9) SPMC for MPR

The researchers realized that the existing MPRs did not consider many DOFs. SPMC is a solution that is being popular utilized nowadays. Jiang, et al. [36] employed SPMC to control 3-DOFs of the wrist. MLP was used to estimate the three joint angles of the wrist and send it to SPMC. The experimental results showed that the joint angle estimation from non-amputees was more consistent than the amputees. Other publications regarding the implementation of SPMC can be found in [37, 38].

10) Muscle synergy

The robustness issue of MPR, especially in clinical application, is the current problem of MCS. Muscle synergy was proposed to produce a robust feature to result in a robust MPR. The success of the implementation of the muscle synergy will lead to the success of SPMC. Ison and Artemiadis [39] evaluated the role of muscle synergy in the MCS. This publication has triggered other researchers implementing the muscle synergy on MCS [40] [41]. The experiments did not involve the amputee. However, the results indicate the big hope for the success of the muscle synergy on the clinical application.

B. EMG-based exoskeleton hand

This section presents a review on the current EMG-based exoskeleton hand.

1) Mulas's exoskeleton [29]

Mulas's exoskeleton is an exoskeleton hand that is designed for the hand recovery of a patient following stroke. The EMG electrodes were located on the subject's forearm. The signal was used to predict the user's intention to do a specific task or activity. The exoskeleton is composed of a glove with plastic support to guide the fingers to accomplish a natural movement and avoid getting an excessive load on the tips. It is actuated by two electric motors that are Hitec servos HS-8-5BB. One actuator is employed to move the thumb while the other were utilized to flex the four fingers simultaneously. Two springs on the dorsal side were put in to allow extension movements.

The main controller runs on the personal computer (PC) using MATLAB. The PC obtains the user's intention from the EMG signals acquired from two electrodes that capture the signals from the flexor digitorum superficialis and the Flexor flexor pollicis Longus. Then the output control from the PC was fed to the microcontroller to control the finger movements according to the intended position. In the hierarchical structure, the microcontroller behaves as a low-level controller while the PC behaves as a high-level controller. The controller utilized the threshold value of EMG to flex the fingers.

2) Wege's exoskeleton hand [42]

This exoskeleton hand was developed to support the rehabilitation process for the patient after a stroke or hand injuries. It has four degrees of freedom in each finger.

Therefore, in total, it supports up to 20 finger joints. The system is equipped with some sensors such as hall sensors, optical encoders, and force sensors. Other sensors are surface (EMG) sensors at the forearm. This exoskeleton hand employed the blind source separation to separate the information contained in the high-density surface EMG signals at the forearm into several signals related to specific finger movement. Ten electrodes were located in the forearm

3) Tong's exoskeleton [30]

This exoskeleton was designed as a hand robotic training device to help stroke patient in recovering the impaired hand function. This device is able to detect the user's intention from the user's muscles in the hand opening and closing training. The exoskeleton's structure fits the different finger lengths and aligns the virtual centre of rotation of the metacarpophalangeal (MCP) and the proximal interphalangeal (PIP).

The embedded controller is built to accompany the hand robot that drives the linear actuator and detect the user's intention by interpreting the EMG signals that are acquired from the abductor pollicis brevis (APB) and the extensor digitorum (ED). These signals were used to predict the hand closing and hand opening, respectively. The embedded controller was equipped with a wireless module to enable the therapist to configure the exoskeleton and the training module.

4) Ngeo's finger exoskeleton [43]

This finger exoskeleton is constructed of a four-bar linkage structure that is able to actuate the movement of finger joints. The Arduino Mega micro-controller was used to control the movement of the exoskeleton based on the motor command obtained from the processed EMG signals. The surface EMG from the flexor digitorum Superficialis (FDS), flexor digitorum profundus (FDP), extensor digitorum (ed) and extensor indicis (EI) muscles were acquired and processed to predict the motor intention of the continuously moving fingers.

Each surface EMG signal was converted to a muscle activation by using the so-called EMG-to-muscle activation model. The muscle activations from each muscle were fed to the artificial neural network (ANN) to predict the intended finger joint angle. The experimental result was good and promising even though it was only tested on a healthy subject. The drawback of this system is obviously working on one finger only. The complexity and density of the muscles in the forearm have not been considered yet. Another example of EMG controller for index finger was proposed by Anam, et al. [44]

IV. DISCUSSION

Myoelectric pattern recognition (M-PR) is used in most current prosthetic hands. On the other hand, myoelectric non-pattern recognition (M-non-PR) is widely used for exoskeleton hand, instead of M-PR. Furthermore, among M-non-PR, a myoelectric threshold controller is the most controller for the exoskeleton hands. As a result, the hand or finger actions involved are very limited. Most of them are the hand opening and hand closing only. In reality, the finger movements are not limited to two of those actions only. Therefore, the exoskeleton hand should consider more finger motions instead of just two fingers. This the main issue in the M-non-PR controller.

Different from the M-non-PR, the major issue emerging in the M-PR is the big gap between success of the laboratory experiments and the clinical applications. Farina, et al. [31] found that this is due to robustness of M-PR. The robustness issue can be overcome by following ways (Ning, et al. [45]). Firstly, the M-PR should be able to handle multi-degrees of freedom by using a simultaneous and proportional controller. Secondly, M-PR has to utilize sensors for movement feedback. Thirdly, M-PR should have adaptation mechanism on the changes of EMG signal characteristic. Finally, M-PR should integrate EMG with sensors to allow complex actions. To the best of author's knowledge, all reviewed system has not considered this gap properly.

The main metric to measure the success of the M-PR in the laboratory and clinical application is either an error or accuracy of the classification result. These measurements (error or accuracy) is used to judge the efficacy of the proposed M-PR as an attempt to reduce the gap between the laboratory experiment and clinical application. To the best of the author's knowledge, the majority of researchers have used this metric for years. Nevertheless, there is little improvement in the error metric by proposing incorrect active decisions instead of using wrong decision only, as proposed by Scheme, et al. [46]. Therefore, the error or accuracy are the primary measurement used to verify the efficacy of the M-PR.

V. CONCLUSION

This paper provides the review of the myoelectric control system (MCS) on the rehabilitation devices. MCS has been developed since the 1940s. This article has emerged some issues that should be considered in developing MCS for the hand rehabilitation devices. The main issue is the robustness of myoelectric signal. This issue should be addressed properly to achieve a reliable control system for hand rehabilitation device.

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