A Review on Hybrid Myoelectric Control Systems for Upper Limb Prosthesis

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***Abstract*— Prosthesis is a device extension which is used to replace a missing body part. Amputees who lost all or part of the upper limb may use a prosthesis depending on their requirement. Externally powered prosthesis holds an importance since it is capable of imitating natural limb motions. However, the way they are controlled stand way back from the natural limb. Myoelectric control systems which uses electromyographic signals holds an important role in controlling prosthesis. This paper reviews the myoelectric control systems for upper limb prosthesis. At first control methods based only on myoelectric signals are briefly reviewed. The main focus is given to review hybrid myoelectric control systems. Hybrid myoelectric control methods are categorized and each category is compared and reviewed. Finally feasibility of using vision as an added sensor was discussed with examples from literature.**

***Keywords*— prosthesis;myoelectric;electromyography;pattern recognition;**

I. Introduction

It is difficult to replace a human limb by an artificial device, however in case of loss of limb or part of the limb it is required to replace the missing limb with an artificial device. This device is called a prosthesis which return the amputee to their pre-amputation functional state. These prosthetic devices can be controlled in several ways. Among them myoelectric control systems have taken the interest of the researchers. This paper discusses the available myoelectric control systems, hybrid myoelectric control systems and use of vision as an added sensor to control upper limb prostheses.

Prostheses that are used to replace a missing upper limb can be categorized in two ways. One way is the categorization them by the level of amputation, such as hand prosthesis, transradial prosthesis, prosthesis for elbow disarticulation, transhumeral prosthesis and prosthesis for shoulder disarticulation. Second way is the categorization as cosmetic prosthesis, body powered prosthesis and externally powered prosthesis. The cosmetic prosthesis is worn just for the appearance and body powered prosthetic devices use the wearer's body power to operate. For example, upper limb prosthesis can use the amputees healthy limb shoulder power to operate the elbow, hand and wrist using cables and mechanical locks [1]. Externally powered prosthetic devices are powered by an external power source such as batteries. These devices use different types of input signals for controlling. Biological signal such as Electromyography (EMG), Electroencephalography (EEG), and Electrocorticography (ECoG) can be used as an input signal to control prosthesis. Furthermore external sensory inputs from switches, foot pressure sensors, cameras, inertial measurement units (IMU), etc. can also be used to control the prostheses.

EMG signals are the signals extracted from the muscles, which gives information related to muscle activity. Loss of muscles due to amputations makes EMG signals unavailable which in turn affect the controllability of the prostheses. EEG can be used to extract motion intentions of the human from the surface of the head [2]. ECoG uses electrodes placed on surface of the brain (under the skull) to capture signals related to motion intentions [3].

Currently prosthetic developers are experimenting with different combinations of sensory signals and biological signals to achieve smooth and reliable control of the prosthesis but still these prosthetic devices stand way back from the natural limb. This study is focusing on hybrid myoelectric control systems with main focus given to evaluate the possibility of using vision as an added sensor. This paper conveys the conclusions made as a preliminary study of the research work towards, vision aided task planning and control of a robotic prosthetic limb.

Myoelectric signals are discussed in section II. Section III explains about available myoelectric control systems. Section IV presents the hybrid myoelectric control systems and applications. Section V discuss about the use of vision as an added sensor for prosthesis control and available vision aided prosthetic systems.

II. Myoelectric Signals

Human motion intentions are generated in the brain and transferred to the muscles through the nervous system. EMG are the signals that represent the current generated by the ionic flow across membranes of the muscle fibers. Muscle fibers are in groups called motor units (MU) where the activation of MU creates a motor unit action potential (MUAP). Continuously firing of muscle fibers creates a motor unit action potential train (MUAPT). EMG signal is the summation of these MUAPTs. EMG signals contain rich information regarding limb motions and can be used to control prosthetic devices. EMG signals can be extracted in two ways. Under first method surface electrodes are used to extract EMG signals non-invasively from the surface of the muscles. This signal is called as surface EMG. Second method is to extract EMG signals by inserting needle electrodes

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into the muscle which is an invasive process. These EMG signals are called as intramuscular EMG [4][5].

III. Myoelectric Control Systems

Myoelectric control systems are based on EMG signals and first developed in late 1950s and early 1960s [1]. Surface EMG is mostly used in myoelectric control systems.

There are two types of myoelectric control systems; pattern recognition and non-pattern recognition. Fig. 1. shows a pattern recognition based myoelectric control system. In pattern recognition based control systems the input signals are converted into output commands using features. Features are extracted from a signal of small duration which is called a segment. Moreover features can be categorized into the domain that they are being extracted from as time domain features, frequency domain features and time-frequency domain features [6]. Time domain features are the most commonly used features in prosthesis control. Some of the commonly used features according to [7][8][9] are: root mean square (RMS), mean absolute value (MAV), MAV slope, zero crossings (ZC), slope sign changes (SSC), and waveform length (WL). Depending on these features the segments are classified into different tasks using a classifier and those tasks are used to control prostheses [6][10].

The classification can be done in 3 stages for better accuracy (see Fig. 2.). These stages are preprocessing, classification, and post processing. Preprocessing is performed in most cases to get rid from the curse of dimensionality where the classification error will increase with too many features in the case of few training samples. Principle component analysis (PCA), linear discriminant analysis (LDA), and multiple discriminant analysis (MDA) are the mostly used methods in preprocessing [11][12]. In classification, these inputs (feature vector) are classified into classes using artificial neural networks (ANN), Bayesian networks, LDA, fuzzy inference systems (FIS) or fuzzy-neuro classifier [8]. Post processing on these classified outputs are performed to reduce misclassifications and increase classification accuracy. Post processing techniques such as majority voting, moving average and fuzzy logic have used after classification for improved accuracy [13][14].

Non-pattern recognition control systems do not use classification. Some of the non-pattern recognition control methods are proportional control, onset analysis, and threshold control [6][15]. As an example, in proportional control, speed or torque of a prosthetic joint is determined to be proportional to the amplitude of EMG signals [16][17]. In threshold control, output command is generated if amplitude of EMG signal is greater than a threshold [15]. Non-pattern recognition control algorithms are simple to implement compared to pattern recognition based control algorithms, but the number of functions that can be controlled is limited [6]. Behavior of non-pattern recognition control systems depends on characteristics of the data acquisition system, anatomy and physiology of muscles, position of sensors on the skin and muscle fatigue [15]. It is most effective to use non-pattern recognition methods alongside pattern recognition control systems [6].

Both methods discussed above require the existence of muscles to extract the EMG signals, however as a result of amputations there are only few muscles available to extract signals. In the case of transhumeral prosthesis, all the forearm muscles and part of the biceps brachii and triceps brachii are not available. In order to control the prosthesis, the available muscle segments of biceps brachii, triceps brachii and shoulder muscles are used. In most cases the prosthesis is controlled using an agonist and antagonist muscle pair, such as biceps brachii and triceps brachii. The user of prosthesis is capable of activating these muscles with different intensities and patterns. So that the prosthesis developers can take this into account when developing prostheses. The different patterns of those two muscle signals are used to achieve the required DOF [18]. However this method of controlling prosthesis requires higher amount of training to adapt to the system and the user need to perform several contractions to get a single task done[18].

Myoelectric based control system is used in [19] for a 9 year old girl with a transhumeral amputation. Biceps brachii and Triceps brachii are used to control the prosthesis. Two motions of prosthesis are controlled: elbow flexion/extension and hand open/close [19]. Two methods of controlling is discussed in [19]: three-level method and contraction rate detection. In three-level method, contraction level is used in controlling 2 motions where slight contractions of muscle activate open/close of the hand and higher contractions activate flexion/extension. In second method, the contraction rate gives hand open/close in slow contractions and flexion/extension in faster contractions [19]. In [20], flexion/extension and pronation/supination of healthy humans are classified using EMG signals. Biceps, medial head of triceps and posterior deltoid were the muscles used for surface EMG extraction. Intramuscular electrodes were used to extract signals from brachialis. The algorithm could predict simultaneous elbow flexion/extension and pronation/supination. 16 myoelectric signals were used in a prosthetic hand designed for transradial amputees in [21].

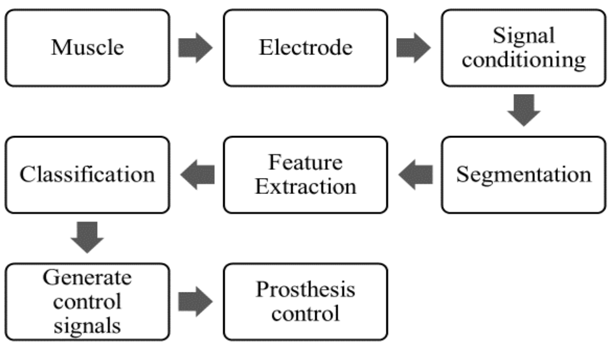

Fig. 2. Structure of a pattern recognition myoelectric control system

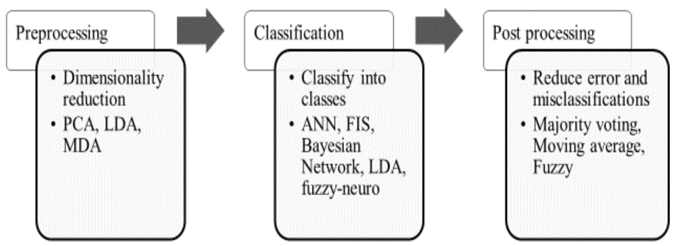

Fig. 1. Three step classification

TABLE I. COMPARISON OF PATTERN RECOGNITION BASED PROSTHESIS CONTROL SYSTEMS

Classifier	Prosthetic type	Ref.	Accuracy	Motions
ANN	transhumeral	[20]	RMS angle errors 15.7° and 24.9° for flexion/extension and pronation/supination respectively	Elbow flexion/extension and pronation/supination
Local approximation and lazy learning	transradial	[21]	86%	16 DOF including individual finger movements
AR model and ANN	transhumeral	[15]	91-98 %	Wrist flexion/extension, pronation/supination, and hand open/close
Conditional parallel approach based on Bayesian theory	transhumeral	[9]	96.4% for discrete motions 89.1 % for combinations	Hand open/close, wrist flexion/extension, pronation/supination, and combinations of two of above motions.
SVM	transhumeral	[6]	95.5 +/- 3.8 %	Five limb motions
LDA	transhumeral	[6]	94.5 +/- 4.9 %	Five limb motions
LDA and MLP	transradial	[22]	97.4%	4 DOF of the hand

In [21], EMG electrodes were placed on superficial extensor muscles on dorsal side and superficial flexor muscles on the volar side of the forearm. The subject could learn in less than 2 hours to perform intended tasks with the prosthetic hand. This includes power, lateral and precision grips. Fingers of the prosthetic hand were equipped with the force sensors to provide feedback to the user [21]. Surface EMG signals from biceps, triceps and pectoralis major were used to control a prosthetic arm designed for transhumeral amputees in [15]. This arm could achieve wrist flexion/extension, pronation/supination, hand open/close. Furthermore, the speed of opening and closing hand is able to be changed based on EMG signals according to [9]. Various motions of the arm and hand as well as combinations of the motions could be able classified in this research. For healthy subjects, 6 pairs of electrodes were placed 2 cm distal to the elbow around the circumference of the forearm in an equidistance manner. For amputees, eight pairs of electrodes were placed on the biceps and triceps. A motion classification system was suggested in [22] for transradial amputees. It is capable of identifying 9 kinds of hand motions: wrist flexion/extension, ulnar radial deviation, pronation/supination, opening and closing of the fingers, and relaxation [22]. Four channels of EMG signals were used for the classification process. Furthermore, [23] used a self-correcting pattern recognition method based on neural networks to control an upper-limb prosthetic device. The self-correcting post-processing algorithm detects potential erroneous classifications which in turn increases the classification accuracy by 30%. [24] researched about the effects on a prosthetic hand when changing its impedance. Both stiffness and damping could be changed in a virtual environment. Adapting for different conditions of the hand was seen to be increased after incorporating impedance control. D Farina *et al.* reviewed simultaneous control of multiple DOF in upper-limb prosthetic devices in [25]. [26] use a method based on quantum information processing for pattern recognition. In a virtual environment designed by the researchers, simultaneous movements of multiple DOF were simulated. Furthermore, authors discussed about the possibility of adapting the system or classifying surface EMG. Details of the work discussed are summarized in Table I.

Beside above discussed methods there is a surgical procedure known as targeted muscle reinnervation (TMR) for persons with low control input sites (muscles) [27]. In TMR the nerve endings of the amputated limb section is transferred onto a muscle where the activation level is low, for upper limb, muscles at the chest are used in most cases [27]. The reinnervated muscles are used to extract EMG signals for the prosthesis control. Also the persons who undergo TMR can get the sensations relevant to the missing limb from the surface of the reinnervated muscles [9][10]. TMR has some risks associated due to the invasive surgery that needs to undergo. They are permanent paralysis of the target muscles, phantom limb pain, development of painful neuromas, and standard risks of elective surgery.

IV. HYBRID MYOELECTRIC CONTROL SYSTEMS

A hybrid system is where it uses two or more control inputs to control the prosthesis [30]. For example a hybrid myoelectric prosthesis can have EMG signal inputs and some other inputs such as foot pressure sensors, switches, etc. which are used collaboratively to achieve the desired motions of the prosthesis. Furthermore, some research activities being carried out to fuse EMG signals with EEG signals to design prosthesis controllers [31].

Hybrid myoelectric control systems can be categorized into 3 (see Fig. 3.). In the first category the EMG signals are fused with other sensory inputs such as foot pressure sensors, IMU, and switches to reinstate the lost functionality of the human limbs. Vision aided myoelectric control systems are the latest addition to this category and discussed in a separate section (Section V). In the second category the myoelectric signals can be fused with any other biological signals such as EEG or ECoG. This field is still under development and not much literature can

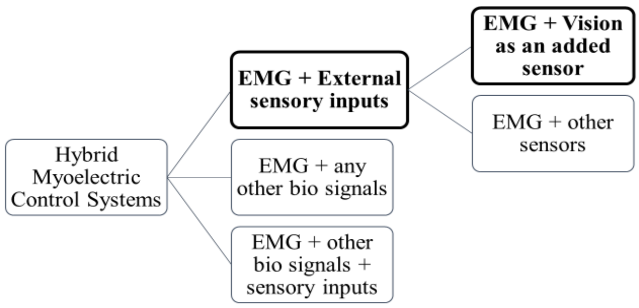

Fig. 3. Catagorization of hybrid myoelectric control systems

be found related to this category. Under third category the EMG signals can be fused with bio signals and external sensory inputs to build robust controllers and research related to this category needs more improvements.

A. EMG + External sensory inputs

Boston elbow and Utah arm are commercially available prosthetic devices which are equipped with hybrid myoelectric control systems fall under this category. These devices use mechanical switches to switch between motions [7]. In these devices the user needs to use the other hand or any other means to press the switches and activate the different motions. ACHILLE [32] is a foot pressure sensory wearable interface for prosthesis control. This device is equipped with 4 sensitive areas and can be worn inside a shoe. This is an instrumented insole and it can wirelessly transmit the signals to a prosthetic controller [32]. Signals from these kind of devices combined with EMG signals can be used to control a prosthesis. ACHILLE can be used even by an amputee who has lost both hands to control a prosthetic device. Moreover motion sensors such as accelerometers or IMU can be used as an added devices to control a prosthesis. The signals from the IMUs are combined with the EMG signals to achieve the prosthesis motions in [33]. A. Fougner *et al.* has used 8 EMG sensory inputs from muscles around the forearm and two 3-axis accelerometer inputs fitted near brachioradialis and biceps brachii, in a pattern recognition based control algorithm to distinguish hand motions [33].

B. EMG + any other bio signals

Possibility of using EEG and EMG based hybrid control approaches have being discussed in [31] for bio robotics applications which includes the control of prosthesis. They have drawn the conclusion that EEG and EMG combined control systems can perform well compared to the EEG only or EMG only control systems. The combined system can be formed in two ways as simultaneous and sequential in which the simultaneous control strategy outperforms. Furthermore appropriate fusion of EMG and EEG signals can improve the accuracy of the control system [31].

V. EMG + VISION AS AN ADDED SENSOR

Vision sensors can be used as an external input in order to control prostheses. Need for vision sensors arises due to the lack of capability of identifying the objects that the prosthesis needs to grasp. Moreover integrated vision systems can estimate the distance to the object, shape of the object and size of the object. Natural limb is controlled through the nerve system and those nerves are connected with the human vision system including eyes. External vision systems can fill the gap created by the loss of natural limb as the loss of natural limb breaks the link between the humans natural vision system with the limb. Vision systems such as stereo cameras, charge coupled devices (CCD), and complementary metal oxide semiconductor (CMOS) sensors can be integrated with prosthetic control systems.

One of the main objectives of a prosthetic device is grasping objects. When considering vision-based grasping, the first step is to identify and locate the target object. Secondly, the manipulator should be moved to an appropriate position to perform the grasp. Subsequently, identification of how to grasp the object is necessary. This includes identification and verification of grasping points on the target object. Finally, the grasp is being executed [34]. According to [34], grasping can be classified into two; blind grasps and visually guided grasps. In the former, the location of the object is determined. Then the manipulator is moved without any visual feedback. In the latter method, a visual feedback loop is established. This method is named as visual servoing [31]. Visually guided method is more accurate than the other method according to [34]. Number of cameras used is an important factor in designing a vision-based control system. Use of multiple cameras improves accuracy, and depth sensing can be achieved by using the stereoscopic vision of the cameras [36] but they need calibration. On the other hand, using a single camera reduces the need of calibration drastically [34]. However, additional depth sensing method must be deployed such as laser or ultrasound depth sensors [36]. In [37], two cameras have been used with a laser pointer for object recognition. It proposes a hat that consists of two web cameras and a laser pointer which should be worn by the user. The user points to the object with the laser pointer. The vision system calculated the distance to the object from cameras by comparing the two images taken by two cameras. Then it detects the object after a colour segmentation process and comparing the segmented image with a set of images stored in a database [37]. It uses tactile sensors which work alongside vision system to identify and recognize objects.

Cameras can be placed statically on a structure which does not move or they can be mounted on a moving part such as the manipulator itself (eye-in-hand) [34][36]. Similarly, combination of these two methods can be used [36]. If cameras are mounted statically, the manipulator might occlude the targeted object. Furthermore, camera to manipulator coordinate transformation has to be calibrated [34]. Mounting the camera in the manipulator eliminates these drawbacks, but introduces the problem of changing lighting conditions since the amount of light received by the camera changes due to its position being changed [34]. [36] employs LED illumination mounted on the hand to overcome this problem. [38], has used a web camera, ultrasound distance sensor and a laser pointer to control prosthetic hand along with an EMG interface. The user should move the arm so that the laser pointer points to the target object. Then it can be reliably identified by the prosthesis [38]. Camera and the accelerometer of [36] only turn on when the distance measured by the ultrasound depth sensor reaches some critical value (25 cm). According to [36] and [37], using the laser pointer will not benefit when the target object is of the same colour as that of laser. This will happen also when the target object is very bright, reflective or transparent [37]. [37], also suggests that inconsistent backgrounds and shadows can disrupt proper object recognition. If the visual data to be part of the feedback loop of the prosthetic control system, it should track the target object as the limb moves. In order to track the object, [34] suggests to use features corresponding to points on the perimeter of the object. [36] extracts image contour to estimate its shape.[38] and [36] have estimated the size of the target object taking distance to the object (obtained with the distance sensor), length of the object's short and long axes and focal length of the camera as inputs. Types of grip are decided based on the size of the object [38] [36]. The control system of [38] decides the grasping pattern named a Cognitive Vision System (CVS) and it is a rule-based approach. After grasp types are decided based on the size of the

TABLE II. COMPARISON OF AVAILABLE VISION AIDED PROSTHESIS CONTROL SYSTEMS

Task	**Method used**	**Ref**	**Advantages**	**Drawbacks**
Identify grasping points, determine grasping pattern	Single Camera mounted on the manipulator (eye-in-hand)	[34]	No need calibrate camera to manipulator coordinate system	Lighting conditions changes as hand moves Need other sensors to sense depth
-Do-	Use a camera mounted on static structures	[35] [37]	Lighting conditions do not change due to hand movements	Need to calibrate camera to manipulator coordinate system View of the camera can be disturbed by the manipulator
Locate target object	Use laser pointer with camera	[38] [37]	No ambiguous situations created	Difficulties in detecting objects which has the same colour as the laser and bright, reflective or transparent objects
Measure depth	Stereoscopic vision	[37]	No need sensors to measure depth	Need cumbersome calibration procedure
-Do-	Ultrasonic distance sensor	[36] [38]	Less complex calibration procedure with respect to cameras	The user has to point the sensor directly to the target object
Estimate orientation of manipulator	IMU	[36]	Low cost of equipment	Lack of feedback
-Do-	Stereoscopic vision	[35]	No need of additional sensors	Need larger processing power

object, CVS generates control commands for the hand control module, which in turn determined the appropriate finger positions and forces required. The user issues commands with the EMG interface for opening and closing hand [38]. [36], uses a rule based approach which relies on a set of if-then rules. Input for this system is the estimated size of the target object. Outputs are type of grip, aperture size of the prosthetic hand and control signals for wrist rotation to orient the hand appropriately.

Camera placement and their calibration are identified as the most daunting problems in vision-based grasping [34]. Table II summarizes the available vision aided prosthesis control systems.

VI. CONCLUSION AND FUTURE DIRECTIONS

Pattern recognition based algorithms for different limb motion classification have led to promising results in prosthetic control. Among them time domain features are the mostly used features due to the fact that they are able to perform well compared to the complexity and the computing power that is being demanded [6]. According to the literature the EMG only controllers did not able to classify the motions in full accuracy. As the level of amputation increases the classification becomes hard because the EMG signals also vanish. This problem was addressed using TMR and were able to control prosthetic limbs at a reasonable accuracy but TMR includes an invasive surgical procedure and it has some risks associated with.

In order to overcome the drawbacks of EMG only control systems and TMR, hybrid myoelectric control systems were developed. In hybrid myoelectric control systems, different sensory inputs are used in combination with EMG signals. Among them foot pressure sensors and mechanical switches are the easy to implement reliable methods. However, these types of control system have drawback of complexity and the user of the prosthetsis needs to press switches or foot against floor to perform the required task and this is very unnatural. Fusion of sensory inputs has a long way to go in order to reach the capabilities of natural limb.

Vision aided myoelectric control systems are considered as important since it has the ability to see things that needs to be grasped. Vision can be used in prosthesis for assisting grasp and taking feedback regarding the positions of prosthetic limb segments. Grasping assist was possible since the vision sensors can be equipped in the hand to see the object and trajectory can be planned depending on the vision feedback.

When the objects are close by it is difficult to differentiate and identify the intended object. These issues need more research effort in the future. Vision systems such as laser scanners and ultrasonic sensors can be evaluated in the problem domain and fusion may produce better results with reliable control options. In the way towards developing natural like prosthetic limbs the researchers needs to investigate different sensory combinations including EEG to overcome the problems present in the currently used combinations. In addition, vision signals can be combined with external sensory inputs like IMU which will not require the wearer's attention to switch between motions. Research can be conducted on camera fixation point, optimum frame rate (processing speed of images), new ways of distinguishing objects, identifying the object intended by the wearer of the prosthesis, and method to overcome the burden from the lightning condition of the environment. Feedback systems can be implemented using a visual servoying system so that the controller can predict whether the prosthesis is reaching towards the desired object.

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