Control of Upper Extremity Prosthetics

B.M.Oscar De Silva
201070588
Faculty of Engineering and Applied Science
Memorial University of Newfoundland

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Abstract

An Upper Extremity Prosthetic is a device that is worn by an amputee, to restore the missing functions of the limb. These devices which used to be simple structures mounted to the body, has evolved in to electrically powered robotic devices. Such prosthetics are already available in the market but controlling of these devices pose a major challenge. This report outlines the current research in the field of intelligent upper limb prosthetic control. A review on the control strategies, its alternate forms and hardware are discussed, outlining the directions of future research.

KEY INDEXING TERMS: Upper Limb Prosthetics, Myoelectric Control, Electro Myography (EMG), Artificial Intelligence (AI), Targeted Muscle Reinervation (TMR)
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1  Introduction

Upper extremity (UE) amputees are the class of amputee patients who have lost an upper limb. This would be due to reasons varying from disease to trauma. The devices available for these patients are traditionally body powered, which consists cables and hooks. In the past few decades these prosthetics has evolved in to externally powered devices with improved dexterity. This constitutes a challenging control problem which attempts to imitate the rather complex biological system. The report presents a review of different methods of control of these devices, elaborating heavily on myoelectric control and its advances.

1.1 The control problem

The controller of an upper limb prosthetic attempts to interface the biological control system of the human body to a mechanical device. In the ideal case, it should convert the users intentions in to control signals which drives the prosthetic; at the same time it should provide feedback of the exteroceptive and proprioceptive senses to the user. So this two way communication link between the user and the prosthetic is necessary. Also the controller should allow for the fact that; Motion of the human hand in a natural arm is controlled both at conscious and subconscious levels. The user is only required to initiate strategic level decisions such as picking an object or pressing a button. The control of joints, grasp geometries and natural reflexes required to achieve the task, are all handled at a subconscious level of the biological control system. So to fully address the control problem it is necessary to;

• Establish forward communication link between the user and the prosthetic. i.e: implement user intended task in a multi degree of freedom prosthetic system.
• Establish backward communication link between the user and the prosthetic, i.e: exteroceptive proprioceptive feedback
• Artificial subconscious level control to minimize cognitive burden

1.2 Control vs Level of Amputation

Figure 1 illustrates the levels of amputations that is performed on the class of patients under discussion. The controller for the prosthetics becomes complex and highly constrained as the amputation level is higher in the arm. The higher the level of amputation, the higher the
number of DOF's the patient looses, thus higher the functionality of the prothetic that should be in place to restore it. Such a prosthetic with higher functionality requires more control input sources. But as the level of amputation becomes higher the control input sources (muscles, nerves) reduces drastically. This is termed as the paradox of myoelectric control, where as more control signals is needed due to level of amputation, only few sources are available [5] [6][7]. For example a transradial amputee has the muscles which control the wrist, which can be used as sensing sites but transhumeral amputee looses this set of muscles with the amputation leaving no direct physiological muscles to sense the users intention of moving the wrist.

2 Recent advances in UE Prosthetic control

There are many branches in which UE prosthetic controllers has evolved. EMG control and its developments ,are the most clinically significant with availability in the market and considered to be most physiologically natural form of control to date [8] [6]. Work in alternate methods of control are also progressing which mostly attempts to establish brain machine interfaces using neurons. These alternate control forms and device hardware of prosthetics are summarized in the final sections of the report. This section focuses specifically on the mainstream research (EMG control) that's underway as a control methodology of UE prosthetics.

In his comparative study Lake et al. identifies 3 generations of upper limb prosthetic control. In the first generation of control there was no proportional controlling of the arm. The devices relied on on/off control with single rate; more often single DOF operation. The most common input devices used were harness switches, which are triggered by applying tension on the straps which hold the prothetic to the body. Other forms like chin operated switches and switches operated with the sound hand were also used[9]. With the advent of Electro Myography(EMG), electrodes were used to measure electrical signals generated from muscle activity and these were also used as on/off control signals in the first generation upper limb prosthetics.

Second generation takes a step forward utilizing proportional control of the upper limbs along with better signal amplification and threshold control. It was achieved using servo controls like linear potentiometers and force sensors(FSR's) inside the socket of the prosthetic. Proportional EMG control is the dominant form of control in second generation systems such as Utah Arm and Pro control 1(Motion Control Inc. The devices are controlled in a sequential manner being able to control only one DOF at a time; and most used packaged electronics with little or no programmability.

The third generation attempts to overcome sequential control and achieve simultaneous control of the prothetic, utilizing microprocessors as the main controllers of the system. So the systems were reprogrammable easily to suit each patient and was able to control multiple DOFs. Pro control II, The Boston III (Liberating Technologies), ErgoArm (Otto Bock),and Vasi-Pediatric(Variety Ability Systems Inc.) are some prosthetics which falls in this category [9].

2.1 The EMG Signal

Myoelectric control and its advances are based on the identification and understanding of the electrical signals generated during muscle activity termed EMG signals. These signals are generated as a result of the neurological signals that are received by the muscle.

Human muscles comprise thousands of tiny muscle fibres. Motor neurons at the spine are responsible for transmitting the signals from the brain to these muscles via a series of pulses named innervation pulse train(IPT). These IPT's causes the corresponding muscle fibres controlled by the neuron to contract and, at the same time, produce a measurable electrical potential, termed
Motor Unit action potential (MUAP). Since a muscle is controlled by a number of motor units, a summation of such MUAP’s form a time varying electrical signal to propagate. It emerges at the middle of the muscle body, and propagate along the fibres to both directions towards the muscle tendons[1]. This electrical activity can be harvested using either invasively using needle electrodes or at the surface using surface electrodes.

EMG signal in the context of UE prosthetics are mostly acquired non invasively using surface EMG electrodes (sEMG’s). These record electrical signals of the underlying muscle fibres termed as Muscle fibre action potentials (MUAP) through the skin. So the signals from sEMG’s has a superimpose of motor unit action potentials of underlying set of muscle fibres, measured at an arbitrary position in space from signal source. It does so through a passive electric media (i.e skin, blood..) which acts as an low pass filter causing a reduction in amplitude and increase in time of the signal [1]. Later studies identified the myoelectric signal carries information of the task at hand in distinct electrical patterns[10]. So an EMG signal is a complicated stochastic signal controlled by the neurological system which carry information on;

- level of activity of the particular muscle as a whole
- level of activity of individual motor units (MUAP’s) that control the muscle
- distinct tasks performed by the muscle.

### 2.2 Non Pattern based Myoelectric control

EMG control of UE prosthetics are broadly classified in to two, pattern recognition based myoelectric control and non pattern recognition based myoelectric control [3]. Non pattern recognition based methods include threshold control and Finite State Machines (FSM) by analyzing the EMG signal level. The Basic process of EMG signal processing for Threshold Control is illustrated in figure 3. This processed signal can be compared with a threshold representing the noise, to control a single device (DOF). So for controlling multiple devices (multifunctionality), a number of independently controlled muscles are required along with patient training to control the device using the muscles. Other methods such as Signal mean value, signal envelop mean value and MarpleHovart and Gilbey algorithm are used instead of the low pass filter for extracting muscle activity from EMG [3].
2 RECENT ADVANCES IN UE PROSTHETIC CONTROL

2.3 Pattern based Myoelectric control

The previously discussed method of control has some drawbacks especially when extended to control of more than one device (DOF). This is due to:

1. Unavailability of myoelectric sites for controlling multiple DOFs. (i.e. not multifunctional)
2. The patient has to sequentially control each joint with much concentration, which becomes difficult. (i.e. sequential)

So research in myoelectric control was geared towards multifunctional simultaneous EMG control of prosthetics. A breakthrough in this area dawned with work of [10], where they studied that there is considerable structure in the myoelectric signal during the onset of a contraction. Furthermore, the structure is distinct for contractions which produce different limb functions. Consequently, the actual structure of the myoelectric signal over time can be used to discriminate limb function. So the aim was to identify these natural patterns present in the EMG signals which are naturally produced at the onset of the limb function. With this, the control problem became one of pattern recognition and classification, where different methods were appreciated with varying classification accuracy.

There are numerous Pattern base control techniques in literature. The report focuses on the most cited methods found in popular scientific journals which are neural network based, fuzzy based, statistical technique based and linear discriminant classifiers. The genetic algorithm based, support vector machine and other forms are referenced for interested readers. In each
2 RECENT ADVANCES IN UE PROSTHETIC CONTROL

the pattern recognition control problem is appreciated in 4 main aspects which are feature extraction, data segmentation, classification and learning.

2.3.1 Artificial Neural Networks

Hudgins et al. with his finding; that the transient myoelectric signal of a muscle has a wealth of information with regard to the activity its about to perform, progressed his work to decompose 2 EMG channels acquired from biceps and triceps in to 4 tasks performed. A feature set of 6 basic time domain features were selected feeding in to a Multi Layer Perceptron (MLP) based Artificial Neural Network (ANN) with 3 layers. A simple Backpropogation algorithm was used with 10 training data sets to train the network where 90% average classification accuracy was observed with 10 subjects. The work deduced several findings with numerous different experiments performed on the system. A hidden layer of eight neurons trained on features from 5 time segments of the transient EMG signal, seems to improve accuracy on all users. Some general important observations in these experiments were;

- Due to the muscle recruitment during amputation and the uniqueness of each user the classifier should be trained for each user for acceptable results. Yet a large 5% additional error is present initially due to the lack of user training to the device.

- In order to meet the real time constraint the delay of the system should be less than 300ms. This includes the time for data collection to final response from the prosthetic.

- Widely spaced electrode configuration was used for each muscle, where the classifier accuracy was insensitive to small changes in electrode placements.

- The system adjusts to gradual feature drifts by training it self. So a proficient user can adopt own styles of controlling the system with time rather than maintaining the same strategy

With the success of the system in laboratory setup it was further developed to a microprocessor based system [12].

Figure 4: myoelectric control system based on pattern recognition [3].
Following Hudgins work, many key research in the area was performed specifically focused on overcoming the following shortfalls in the proposed system:

- Using of custom electrodes which are seldom used in clinical applications
- Feature selection to be rather systematic
- Classification error of 10%
- Using transient signal which forces the user to initiate each operation from rest.

Kurunganti et al. confirmed in his studies that using a bipolar electrode pair instead of a wide spaced electrodes improves the classification accuracy in method developed by Hudgins et al. Along with this more exhaustive studies were performed by [13] which ultimately reduced the average classification accuracy to 0.5% in the 4 class classifier and upto 2% in a 6 class classification. The experiments deduced the following results:

- Using *Principal component analysis* (PCA) to reduce feature set improves classifier accuracy. Using a wavelet packet transform (WPT) feature set with PCA instead of the time domain feature set by [12] drastically improved the results.
- Changing the classifier from MLP to *Linear Discriminant Analysis* (LDA) performed better with the WPT feature set.
- Using the steady state myoelectric signal instead of the transient signal improves accuracy and at the same time enabling record lengths of the input EMG signal to be reduced upto 64 ms without considerable effect on the classifier.
- Use of steady state signal also allows a Continuous Classification strategy to be implemented removing the requirement of starting every operation from rest.
- Improvement in packaged electronics enabled use of 4 EMG channels which further reduces classifier error to 0.5% in 4 class classification and 2% in 6 classes.
- Highest classification error occurs during the transition between states since the classifier is operating between two states. But prosthetic response to this misclassification is unlikely due to the intrinsic inertia of the device.

### 2.3.2 Fuzzy Classification

Fuzzy classifiers have much advantages with processing specifically biomedical signals such as EMG. Fuzzy based systems can incorporate medical experts knowledge to its rule base. More importantly it can tolerate contradictions occurring due to low repeatability and stochastic nature of myoelectric signals. Similar to *Multi Layer Perceptron* (MLP) systems, fuzzy systems have the ability to train it self, which is a crucial requirement for myoelectric controllers [14].

Chan *et al.* compared a Fuzzy system to one of MLP proposed by Hudgins *et al.*. The work implemented a trainable (adaptive) fuzzy classification system proposed by Wang *et al.* [15] which updated both fuzzy set definitions and fuzzy rule weights with a back propagation algorithm. The study was conducted on 4 subjects using time domain feature set extracted from 6, 40ms segments from the EMG onset signal. The fuzzy classifier required initialization due to stability issues using an *Isodata* algorithm to cluster and predict the boundaries for fuzzy set initialization. The results were quite similar in terms of accuracy to the study of Hudgins *et al.*, but the author notes the consistency of the system is superior to the MLP classifier and that the fuzzy system has a lower overtraining risk [14].
2.3.3 Statistical Classification

EMG signal is a stochastic signal, so naturally classification with probabilistic approaches display much potential. Huang et al. studied on Gaussian Mixture Model (GMM) based EMG pattern classification. The motivation of using GMM for the task can be traced back to its extensive usage in text independent speaker recognition. The speaker recognition problem has much analogy with the myoelectric task classification [16]. In this approach various comparisons were made with the methods available to date for Electromyographic signals (EMS) classification. Different feature sets were assessed namely Time Domain (TD), Auto Regressive (AR) and Root Mean Square (RMS) features. The classification of the GMM was well compared between the MLP and LD classifiers discussed earlier.

An important study in the research was that because the GMM used a continuous classification strategy with overlapping window lengths, the classifier was able to give 8 classifications within the real time constraint set to 256ms. So an overall final result was possible within the time window with many inputs to a maximal voting (MV) post processing. Other findings of the research are summarized as follows:

- GMM classification matches or outperforms the TD and MLP classification methods.
- AR + RMS feature set gives the optimum results.
- Mode selection for GMM should be done for each patient and variance limiting strategies should be introduced with this classifier.
- Using overlapping window segmentation and maximal voting schemes improves the results significantly.

The author notes that with the exceptional success of the system, much more challenging control problems can be addressed. Such as simultaneous control of the UE prosthetics. Myoelectric pattern classification methods has much success in terms of multifunction control, specifically in forearm amputees. But simultaneous control of these devices and more importantly, addressing the control problem of upper extremity amputations with these classifiers pose many practical problems. The main problem with upper extremity cases such as above elbow or shoulder disarticulation, is the unavailability of physiologically appropriate Myoelectric sites to decode the user intentions for movements lower in the arm. Because the muscles controlling the wrist and fingers are unavailable for myoelectric classification in Upper extremity amputees, researchers are developing innovative methods to somehow access these missing muscle signals.

2.4 Targeted Muscle Reinervation

In this section an innovative surgical method which creates myoelectric sites otherwise inaccessible due to unavailability of residual limb muscles is discussed. The brain continues to send signals to the arm via the nerves even after the loss of a limb. But since the nerve signals are not directed to a muscle, there is no actuation and no useful myoelectric generation in the process. The surgical procedure termed Targeted Muscle Reinnervation (TMR) transfers remaining nerves to residual chest or upper arm muscles, which are no longer biomechanically functional due to loss of limb [4]. The reinnervated muscle acts as a biological amplifier for the nerve signals which can be harvested as myoelectric signals at that site. With this breakthrough myoelectric control is extended to TMR patients. Initial studies with EMG level threshold control schemes has exhibited that marked increase in prosthetic performance can be achieved even in the complex cases as shoulder disarticulation [17]. Latest studies implements the much more powerful EMG pattern recognition based controllers to these systems.
In EMG classification point of view, the method increases the myoelectric input sites. More importantly it enables physiologically appropriate signals which were unavailable before TMR, to be entered as inputs to the classifier. This increases the accuracy and enables to classify more classes of user intentions. [18] has studied ways in optimizing the electrode placement after TMR procedure. A electrode selection algorithm is developed which is used in many prosthetic control studies of TMR patients. 12 such optimized bipolar electrode placements were used in the studies which involved both shoulder disarticulation amputees and Trans-humeral amputees [4].

A classifier with 12 classes was implemented with Linear discriminant analysis, accepting 4 time domain features from 12 EMG channels. The data was segmented in 100ms overlapping windows. So for this initial classification studies the improved classifier configurations discussed earlier [16] [13] was not fully implemented, despite a mean classifier accuracy of 88% was achieved in this setting. It is important to note the use of control participants in this study which recorded a 99% mean average classification accuracy. This gives a good comparison on classifier performances, when transferred to amputated arms and more specifically to reinnervated muscle systems from normal subjects with intact limbs.

The study initially tested the controllers in a virtual platform as part of protocol. This
enabled extraction of more number of performance metrics with more insight which was missing in many myoelectric pattern classification studies discussed so far. Apart from pattern classification accuracy the classifier speed, motion completion time were analyzed for both controlled participants and amputee patients. The motion classification time for hand movements were relatively slow with 380ms response time which is detectable by the user. Since this delay is due to sufficient data acquisition for classification, improvements would be only possible through stronger classification methods rather than computational speed.

The patients were tested on two prosthetic systems, one developed at John Hopkins University and another developed through the Defence Advanced Research Project Agency (DARPA), which is a 10 DOF arm termed the DEKA arm. The systems used EMG classification for elbow and hand movements and EMG signal levels for humeral rotation, while the shoulder flexion/extension and adduction/abduction were both controlled by a rocker switch detecting the shoulder movements. Simultaneous control of shoulder and elbow were observed however patients tend to control one degree at a time. So further studies are required to establish whether this is an efficient method of addressing the simultaneous control problem.

The controller performance degrades when transferred from the virtual platform to the physical system. This is mostly affected by poor electrode contact and effect of tissue loading. So improvements in the surface electrodes and EMG recording method is necessary for the robustness of these systems and to reduce or eliminate daily training of the classifier. Author also points out the use of hierarchical control for improving the robustness of the system [16].

Myoelectric control after TMR procedure has addressed much functionality and has potential to progress. It approaches to fully establishing the complete forward communication required between the user and the prosthetic. Currently research is progressing specifically focusing on the robustness of the interface and simultaneous control.

<table>
<thead>
<tr>
<th>Reference</th>
<th>Year</th>
<th>Feature set/Segmentation</th>
<th>Classifier</th>
<th>Channels /Classes</th>
<th>Classifier Error</th>
<th>Delay</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hudgins et al.[10]</td>
<td>1993</td>
<td>TD 5 feature set,40ms 5 segments of onset signal</td>
<td>ANN-MLP</td>
<td>2 channel 4 class classifier</td>
<td>16-2%</td>
<td>250ms</td>
</tr>
<tr>
<td>Chan et al.[14]</td>
<td>2000</td>
<td>TD 4 feature set,40ms 6 segments of onset signal</td>
<td>Adaptive FUZZY</td>
<td>2 channel 4 class classifier</td>
<td>10-1.3%</td>
<td>&lt;300ms</td>
</tr>
<tr>
<td>Englehart et al.[19]</td>
<td>2002</td>
<td>WPT feature set with PCA,256ms 50% overlap continuous on steady state signal</td>
<td>LD</td>
<td>4 channel 6 class classifier</td>
<td>7.9-1.1%</td>
<td>&lt;300ms</td>
</tr>
<tr>
<td>Huang et al.[16]</td>
<td>2005</td>
<td>TD+AR+RMS,256ms 32ms overlap continuous on steady state signal</td>
<td>GMM</td>
<td>4 channel 6 class classifier</td>
<td>6.7-1.1%</td>
<td>&lt;300ms</td>
</tr>
<tr>
<td>Kuiken et al.[4]</td>
<td>2009</td>
<td>TD feature set,150ms 50ms overlap continuous on steady state signal</td>
<td>LD</td>
<td>12 channel 11 class classifier</td>
<td>96.3-1.1% elbow</td>
<td>220ms</td>
</tr>
</tbody>
</table>

Table 1: Summary of Myoelectric classifier performances

The next sections summarizes the alternate control forms along with the hardware thats used in the prosthetics.
2.5 Alternative control methods

While myoelectric control remains the most promising with commercial availability in upperlimb prosthetic control, there are many more potential control strategies for the devices. Although myoelectric control is praised as physiologically appropriate inherently it has many concerns regarding robustness of the sensors and simultaneous operation. This chapter briefly outlines neural cortical control strategies and some assisting strategies which may overcome issues faced with myoelectric control.

2.5.1 Brain Machine Interfaces (BMI)

Brain machine interfaces are tested on patients with spinal cord injury. It attempts to capture and decode the motor control signals at the signal source, the brain itself. Two challenges should be met in the process where the first being successful capturing of the signals. University of Utah has developed a cortical array inset records the brain signals emanating from different actions. Infection, complex surgical procedure and safety of these devices are prime concern. The second challenge is decoding the signals recorded at the brain. The insufficient understanding of the structure of neuron system has made the use of this method highly sophisticated and undeterministic.

2.5.2 Peripheral Nerve Interfaces

Peripheral Nerve Interfaces attempts to capture the same neuro signal at a different location; during transition. Small electrodes tap into the nerves carrying information to decode the neurological signal. Fragility of the nerves and infections are again prime concerns in the system. Additionally, capturing these small electrical activity among various other comparatively large signals such as EMG and ECG pose a very difficult signal processing task. Utah slant array inset is such an impartable peripheral nerve interfacing device being developed by University of Utah.

2.6 Hybrid control

Other candidate solutions for the control inputs have been studied some having great success. The shoulder position detection and using it to assist a myoelectric controller has been studied in the case of shoulder disarticulation. Using signals generated from different foot pressure positions has been employed in the preliminary studies of the DEKA arm. Some interesting methods employing cognitive vision has also been studied in improving the performance of myoelectric prosthetics.

While neuro signal control is in its infancy for prosthetic control, many other hybrid strategies which assist myoelectric control seems to bring upon a synergetic effect on the device performance. So it exhibits high research potential in UE prosthetic control.

2.7 Artificial Intelligence

Humans unconsciously adapt their grasp gait to suit the task at hand. For example when holding a glass the grip is controlled at a lower level not making the glass slip or too tight for it to break. The same type of low level control is highly beneficial for prosthetics [20]. This can be implemented for improving device performance as well as safety. Commercial implementations are seen in Otto Bock SensorHand Speed hand (Otto Bock Healthcare), where it detects slip and adjusts the grip force.
2.8 Sensory Feedback

Humans with intact limbs receive feedback of their task through a sensory process termed proprioception. Its basically the body’s internal sensation on the movement and position of its limbs. Exteroceptive sensors provide the sensation of touch, heat, etc. Visual feedback and force feedback on the body structure is the other auxiliary forms of feedback.

With amputation the individual looses the proprioception and the exteroceptive sensors. They have to mainly rely on the visual feedback for controlling the prosthetic. Research has been targeted to restore the feeling of touch to amputees.

In its basic forms the prosthetic hands transmits vibrations to the nearby tissues to signal the intensity of the grasp. This is done using force sensors on the hand controlling small vibrating motors attached to some skin area. More advanced approaches are in motion, where attempts are being made to fire signals to the sensing nerve to artificially restore the sensation. Most promising results have been achieved with targeted sensory reinnervation where similar to targeted muscle reinnervation procedure the nerve is transferred to tissue at the chest which restore the sensation of the missing hand, finger etc., at the reinnervated area. Little work has been done on this study area which resemble significant potential.

3 Device Hardware

UE prosthetics are primarily divided to two types based mainly on their power source. Body powered systems use cables and harnesses to transfer the movements of the body in to controlling the arm. However the discussion developed so far is based on the second type, externally powered prosthetics which are basically controlled by motors or some other form of externally powered actuator. This section briefly discuss the structure of these powered devices and current state of the art.

3.1 Power Source

The hardware system viewed from a mechatronics approach can be divided mainly in to the input power source and user interface, the output actuators and transmission, and the feedback which are sensors. The hardware system, while required to perform the task also should meet the design constraints of weight, size, appearance and safety. Main contributors to the weight and size are the power sources, actuators and the structure. So sources with more energy to weight density and actuators with high power to weight densities are appealing in the context. But high power to weight systems like hydraulics loose their advantages in the sizes required by prosthetics, more appealing piezo electric actuators fail to meet the required power output at the current levels of development. So electrically powered motors are the leading actuator in powered prosthetics [20].

Traditional lithium ion batteries which were used in the applications are gradually replaced by lithium polymer batteries. These have higher power densities while requiring less packaging and with custom shape. But newer technologies such as methanol fuel cells have the potential to replace lithium polymers with advancement [20].

3.2 Actuators and Transmission

Actuators and transmission has traditionally been DC motors with epicyclic or helical gear reductions. But [20] describes how Ikona gears and harmonic drives are employed in recent commercial devices such as the LTI Boston Digital Arm System (Liberating Technologies Inc.).
A more interesting design is seen in Otto Bock DynamicArm (Otto Bock Healthcare), where a new mechanical transmission architecture termed "cobot" is used. Initially studied for the automotive industry, it leaves a central motor to spin continually and allow tiny motors to tap in to the central power source to achieve simultaneous control of multiple devices. This consumes less energy while much power is available to each joints.[21] discusses how cobotic architecture improves the dynamic range, weight reduction and energy savings in prosthetic applications.

3.3 Input devices

The input devices or the sensors are the main interface the system has with the environment. The input devices can be identified in to two categories, set of sensors support to detect the users intention another set improves the device functionality by supporting artificial intelligence of the device. for the basis of this discussion these are termed user interface sensors and AI support sensors.

**EMG sensors** EMG sensors/electrodes are the enabling factor in the mainstream advance in upper limb control. There are different electrode configurations but surface bipolar electrodes has been the most utilized due the non invasive nature. but the advantage it self is heavily noted as a degrading factor on the robustness of the device due its movement on skin, sweat etc, [4]. Some research is focused in implanted EMG sensors to overcome these shortcomings. for TMR applications same EMG sensors in array configuration is used[18]. Optimum array placements are designed using algorithms developed for best classifier performance [18].

**Force sensors** There are couple of forms of force sensors, Force sensitive resistors (FSR) which change its resistance based on the load on the surface. Force sensitive arrays which can pickup the pressure distribution on the surface. Load cells which measures 3 dimensional forces at a location. FSR has the highest application specifically in prosthetic hands, also used to measure applied force in the socket, so its used as both user interfacing sensors and supporting sensors to the AI system.

**Switches** The simplest of sensors, switches are utilized in applications for robust control. but they lack the intuitiveness present inn other systems. the powered shoulder prosthetic used chin switches to cycle between the different degrees of freedoms controlled by myo electric signals. rocker type switches were used in John Hopkins University powered shoulder to detect the remnant shoulder movement of the amputee[4]. the initial design of the DEKA arm used switches in the shoe insole to control different movements of the arm[22].

**Encoders** Encoders are extensively used in robotic applications for revolution measurement of the motors. these help to implement low level controllers such as motor position/speed control, also important information on the current state of the prosthetic can also be extracted.

**Other sensors** There are many other options for controller inputs for example temperature sensors for safety of the device and proximity sensors to improve artificial intelligence in manipulation tasks. Cognitive vision is another area with considerable potential as inputs to controller.

3.4 State of the Art

Table 2 summarizes the key hardware in research and in market. It is important to note the jump form 2-3 DOF’s to 22 DOF control with the dawn of Targeted Muscle Reinnervation method.
The latest and the most sophisticated "MPL arm" developed with collaboration with numerous universities and the US department of defense has entered clinical studies. The hardware capability is present to reproduce functional requirement of missing human hand but more development in controllers are necessary to address the prime concerns of robustness, simultaneous control and multifunctionality of the systems.

<table>
<thead>
<tr>
<th>Prosthetic</th>
<th>Manufacturer</th>
<th>Control</th>
<th>Specifications</th>
</tr>
</thead>
<tbody>
<tr>
<td>SensorHand</td>
<td>Otto Bock</td>
<td>EMG 2 channel</td>
<td>1 DOF, Slip detection(Auto Grasp), 15-300 mm/second</td>
</tr>
<tr>
<td>SPEED[23]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>iLimb[24]</td>
<td>Touch Bionics</td>
<td>EMG</td>
<td>5 DOF, modular</td>
</tr>
<tr>
<td>LTI Boston Digital Arm System[25]</td>
<td>Liberating Technologies Inc.</td>
<td>EMG control</td>
<td>1 DOF, use harmonic drives</td>
</tr>
<tr>
<td>Utah Arm Systems</td>
<td>Motion Control Inc.[26]</td>
<td>EMG control</td>
<td>1 DOF</td>
</tr>
<tr>
<td>Ergo Arm[27]</td>
<td>Otto Bock</td>
<td>EMG control</td>
<td>1 DOF</td>
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<td>Dynamic Arm[27]</td>
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<td>1 DOF</td>
</tr>
<tr>
<td>DEKA Arm[22]</td>
<td>DEKA R&amp;D, DARPA</td>
<td>EMG control, TMR</td>
<td>18 DOF</td>
</tr>
<tr>
<td>MPL</td>
<td>John Hopkins University, APL, DARPA</td>
<td>EMG control, TMR</td>
<td>22 DOF</td>
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</tbody>
</table>

Table 2: Current state of the art in prosthetic technology

4 Conclusion

Upper extremity prosthetics has come a long way from its body powered origins. The improvement has been gradual, where the technology available in the market today traceable in to lab experiments in the 1970’s. However the current control capability has come to a point where the devices are able to tap in to the biological brain control signals with considerable accuracy via muscles EMG. Hardware for these controllers are at the top end with the latest being the MLP arm which resembles the design and manufacturing capabilities of the latest technology. But much more is expected from the controllers to fully realize the capabilities of the developed hardware and fully address the control problem of these devices.

Research in myoelectric classification is exhaustive which has reached a ceiling performance level 90-98% (Refer Table1). A breakthrough is required for additional considerable development in terms of classification performance. But when the classification is done in realtime hardware the performance is considerably reduced. This is mainly due to difficulty in establishing a robust link between the skin and the socket containing the EMG electrodes. So studies attempts to identify robust interfacing with minimum training requirement for the patients.

Relatively complex interfacing such as neural interfaces has much potential in terms of establishing more natural forms of control. But it is with held due to the insufficient understanding of the neurological signal structure the brain emits. Much more interesting control methods will be available with breakthroughs in these alternate forms of control.

Targeted muscle reinnervation constitutes an effective solution to the multifunctional control problem, with the ability to create appropriate myoelectric sites required for the missing degrees of freedom. The inherent sequential decision making characteristic of EMG systems is identified as a barrier to establish natural coordinated control of an arm. To overcome this problem, Hierarchical control strategies and extracting tasks from the EMG signal rather than individual joint movements is performed. Making use of additional control signals simultaneously such as shoulder movement, force inside the socket are also attempted to arrive at the optimum configuration for performance. Studies combining the performance of myoelectric control systems with
other realizable biological signals pose a way forward in achieving simultaneous control with improved robustness. The research area is highly active in this decade and an exponential rise in research effort and funding is observed recently, ensuring the amputee community has much to expect in near future.

References


REFERENCES


