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A Study onControl of Myoelectric Prosthetic Hand Based on Surface EMG Pattern Recognition

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ABSTRACT

As robots come closer to humans, an efficient human–robot control interface is an utmost necessity. In this paper, electromyographic (EMG) signals from the muscles of the human upper limb are used as the control interface between the user and a robot arm. An accurate and computationally efficient means of classifying surface myoelectric signal patterns has been the subject of considerable research effort in recent years. This paper presents a method of using SVM for classification, and examines overlappedsegmentation toimprove controller performance. In order to improve the classification an Artificial -euro-Fuzzy inference system (A-FIS) has been used by the researchers. Secondly, some recent applications of myoelectric control of human arm prosthesis by using machine learning algorithms are compared. Finally, characterization of EMG for human arm prosthesis has been discussed.

Keywords*:*EMG, SVM, MUP, MES, TMR

I. INTRODUCTION

Robots came to light approximately 50 years ago.However, the way humans can interface with and finally control robots is still an important issue. The human–robot interface plays a role of the utmost significance, particularly since the use of robots is increasingly widening to everyday life tasks (e.g., service robots, robots for clinical applications). More than 100 neuromuscular disorders that influence the spinal cord, nerves or muscles are present. Early finding and diagnosis of these diseases by clinical examination and laboratory tests is crucial for their management as well as their anticipation through prenatal diagnosis and genetic counselling. Such information is also valuable in research, which may leadto the understanding of the nature and eventual treatment of these diseases Motor unit morphology can be studied by recording its electrical activity, known as electromyography (EMG)[1]. In clinical EMG motor unit potentials (MUPs) are recorded using a needle electrode at slight voluntary contraction. The design of prosthetic hand is multidisciplinary, compelling knowledge of physiology, anatomy, electrical and electronics, mechanical design, software, and so on, depending on the nature of control. Still, most of the research is in the laboratory and the issue is lack of integration with the technology due to its multidisciplinary nature and the non-availability of funds. There have been different types of prosthetic hands ranging from body-powered prosthetic hand to neural interface-based prosthetic hand, which are being manufactured and attempted in the market and for the purpose of research. The choice of prosthetic hand is based on the requirement of the user. In general, the prosthetic devices could be body powered, pneumatic powered, or electric powered. The body-powered devices harness energy from muscles to operate the cable through a link. The advantages of body-powered devices are that they are of low cost and are less expensive to repair. However, these devices are not cosmetically appealing and are difficult to operate with body power by some users. The electric-

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powered prosthetic devices that are operated with battery are desired by most of the users due to their cosmetic appearance. However, these devices are expensive, heavy, and expensive to repair. Nevertheless, there has been a major breakthrough in the operation of electric-powered prosthetic devices. These externally powered devices may be operated from pressure, switch, strain gauge, myoelectric signals (MES), and electroencephalogram signals[2].

Artificial hands are cosmetically pleasing, but functionally inferior to hooks and prehensors. These artificial hands may be controlled using MES, reflecting the intention of the user. Attempts are being made to control the hand through restoration of function of the nerves of arm with targeted muscle reinnervation (TMR) surgery to actuate the hand and through the neural interface. Current state of the art is to control the prosthetic hand using MES with various control schemes to interpret the muscle signals[3]. Fig. 1 shows the commercially available body-powered prosthetic hand and myoelectric prosthetic hand from Otto Bock HealthCare GmbH (Duderstadt, Germany).

Attempts are also being made to control the joints of fingers in order to improve the dexterity. The i-limb hand has been developed with the articulation of each finger separately or simultaneously, depending on the capability of the user. Therefore, this review focuses on the state of the art of control of myoelectric-controlled prosthetic hands, giving details of various control strategies and briefing about the mechanical design in commercial and research study[4].

The myoelectric prosthetic hand is based on electromyographic (EMG) signals generated in skeletal muscles, which reflect the intention of the user. The EMG signals generated by the intention are used to control the prosthetic hand using various deciphering schemes such as proportional control, on–off control, finite state machine, pattern recognition, and postural control. Researchers are attempting to decipher more information from EMG to improve the dexterity of prosthetic hand. On the other hand, some researchers are attempting on EMG signal interfacing techniques to improve the dexterity[5].

II. DETECTION OF EMG SIGNALS

The body-powered prosthetic hand does not mimic the natural human hand movement. The user intention-controlled devices mimic the natural human movement. The user intention for the control of hand may be obtained from physiological control signals acquired throughsensors. The sensor technology interfaces the human control signals to the artificial hand. Modern prosthetic hands incorporate surface electrode to interface artificial hand through myoelectric control signals to human[6]. The surface EMG signals for artificial hand control are sensed from the surface of the skin and are preferred due to their ease of access and the procedure being noninvasive.

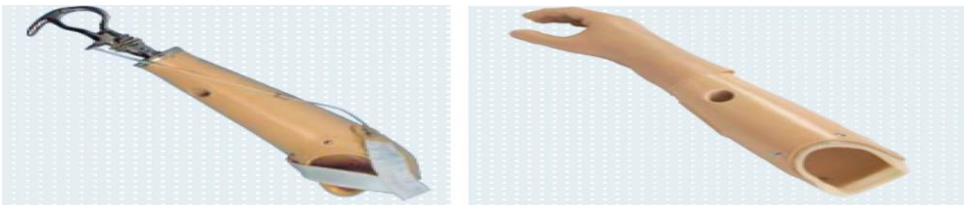

Fig.1(a) Body-powered prosthetic hand (b)myoelectric controlled prosthetic hand[7]

Using surface electrodes, it is possible to identify three to four possible locations from the residual limb to acquire signals for sequential control. However, collecting the intramuscular EMG signalsis an invasive technique and requires surgical skill for using the implantable myoelectric sensor. But the intramuscular EMG signals provide

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access for collection of EMG signals from multiple locations to offer multiple degrees of control to prosthetic hand. It could be possible to achieve simultaneous control of prosthetic hand with the intramuscular EMG signals using an implantable sensor. TMR surgical procedure has been recently used to rewire the nerves to different muscle sets which can be measured from the surface for the control of artificial hand. The use of TMR is effective for trans humeral amputees, and this technique provides access to utilize user intention.

III. MYOELECTRIC CONTROL SCHEMES

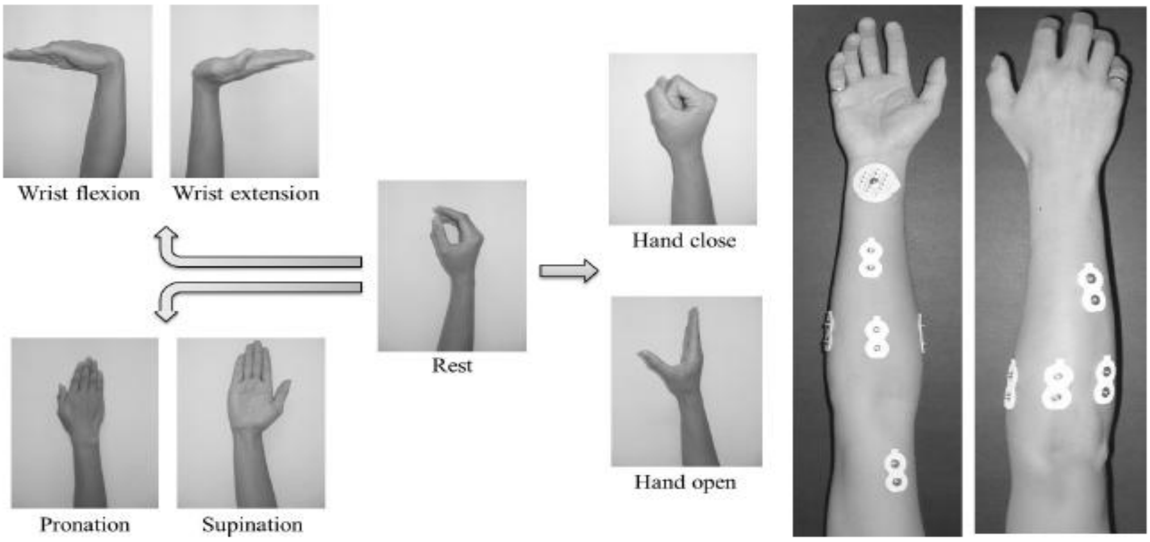

Fig.2 Seven upper limb motion and Eight Channel of muscle on the right hand of the subject

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

The flowchart for implementation of different types of typical myoelectric scheme with the signal processing stages is presented in Fig 3. Furthermore, proportional control is used in combination with direct control, finite state machine, and posture control for effective decoding of information from the MES. The MES signals acquired from the surface of the skin in these schemes are amplified and preprocessed before analog-to-digital conversion. The acquired EMG data are processed to decipher the user intention and communicate with the motor controller in

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order to actuate the appropriate motor to achieve the user-intended activity. Signal processing of the various modules is described subsequently[10].

3.1. On–off myoelectric control

The conventional on–off control is appropriate for maximum of two degrees of freedom. In on–off/crisp/binary/bang–bang control, the prosthetic hand is operated with a constant speed in clockwise and counterclockwise directions with a full stop[11]. There are various control schemes for on–off control. The simplest on–off control is based on a threshold of EMG to make a choice of direction of control of the hand. In this control scheme, the hand is operated at a constant speed that is independent of the level of contraction. The simultaneous motion control is possible with motors turned on and off and run at a constant speed.

3.2. Proportional myoelectric control

In proportional control scheme, the voltage applied to the motor is proportional to the contraction level/intensity of EMG signals. This enables fast grasping for gross movement, and the suitability of the control in upper limb is still under study. Researchers have been focusing on simultaneous proportional control recently. This simultaneous control is against sequential control schemes such as state machine. Other control schemes areused along with proportional control to improve the dexterity in myoelectric control schemes.

3.3. Direct myoelectric control

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

3.4. Finite state machine control

In case of finite state machine control, the postures of thehands are predefined as states and transition among states is also predefined or decoded from the inputs. This is suitable for a fixed number of postures and may not be suitable for multifunctionality. Furthermore, the state change occurs from the EMG command till the desired posture function is selected. These limitations can be overcome using pattern recognition approach. Many researchers have developed various algorithms for identification of information from the signals using pattern recognition approach.

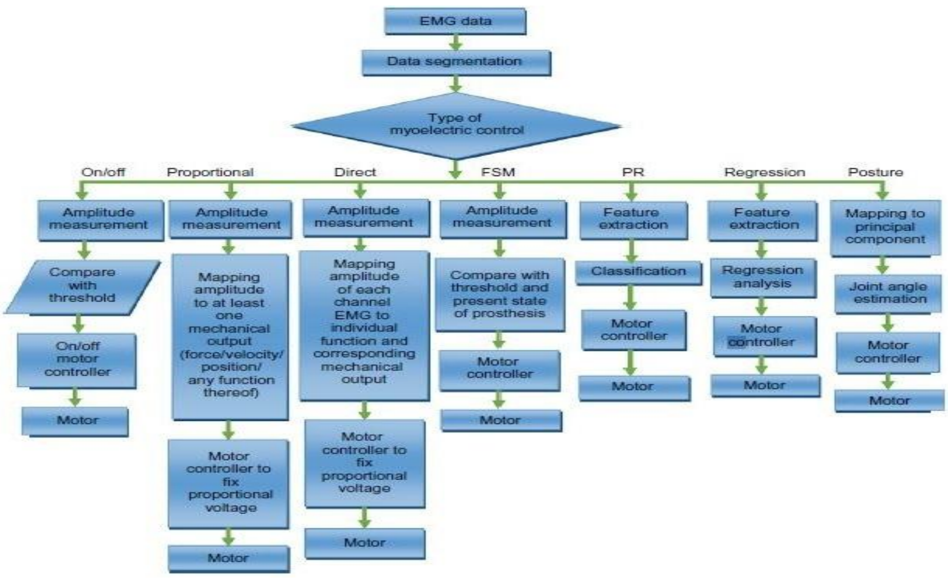

Fig.3 Type of Myoelectric Control Scheme

IV. SIGNAL CLASSIFICATION TECHNIQUES

For the past decade, the problem of signal classification has been addressed by a large number of engineering researchers, undoubtedly because a robust combination of signal processing and classification algorithms is vital to a functional, dexterous, and anthropomorphic electrode-based prosthetic hand. Improved classifiers allow for more functions of the hand, a quicker response time, and a more reliably accurate system. While the problem of obtaining an adequate number of degrees of freedom (DOF) is largely a design concern, signal classification is equally important. Without an advanced signal classifier, an electrode-based prosthetic hand would be incapable of reliably or accurately performing grasp patterns. The components of a signal classifier can be broken into the basic stages of feature extraction (including dimensionality reduction) and pattern recognition, along with online and offline learning. An example of a typical classifier is shown in Fig. 4. Much research has been dedicated to optimizing feature extraction and pattern recognition, and various techniques for each of those classifier steps will be discussed in the following sections.

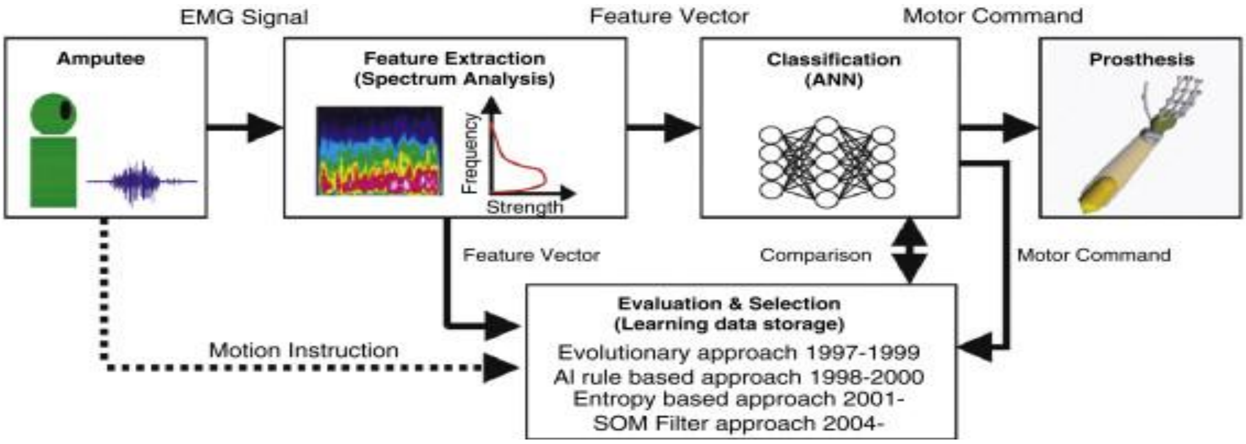

Fig. 4 Typical control classifier[12]

V. FEATURE EXTRACTION

The purpose of the feature extraction stage is to identify and select the most useful components of the processed signal. An intelligent choice of features is a highly important step in the signal classification process; by choosing features which separate patterns of movement most distinctly, a higher level ofaccuracy can be obtained. Choosing the optimal number of extracted features is also important for creating a balance between the reliability and computational burden of the system.

The extracted portion of the signal is contained in thetransient part of the EMG signal[13]. There are numerous features that have been chosen and employed for extraction, and they are separated into several main categories. The two most commonly extracted features are time domain features and time-frequency domain features. Among the most popular time domain features are mean absolute value (MAV), zero crossing (ZC), waveform length (WL), root mean square (RMS) and slope sign change (SSC). Liu et al. tested combinations of the MAV, ZC, WL, and SSC time domain features for the classification of eleven different hand movements and concluded that three time-domain features (regardless of the feature) and a sixth order autoregressive (AR) model provide optimal feature extraction[14]. Using linear discriminant analysis (LDA), a pattern classifier was created which achieved accuracy similar to an artificial neural network (ANN). Huang and Chiang used a combination of time domain features, including integral of EMG (IEMG), variance, ZC, SSC, an AR model, Cepstrum analysis, WL,

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and Willison Amplitude (WAMP) to determine which time domain features would produce the highest classification rate. Those features were extracted and used as input for the classifier. Time-frequency domain features are more accurate than time domain features but are also more computationally expensive[15].

The most commonly used time-frequency domain features are wavelet transform (WT) and wavelet packet transform (WPT). Sometimes, it is useful to combine time and time frequency domain features. Combined the MAV, ZC, WL, and SSC time domain features with the extraction of the time-frequency wavelet features as the driving features for an ANN. A list of common time domain features and time-frequency domain features, along with their governing equations, can be found in another technique associated with the feature extraction stage is dimensionality reduction[16]. Dimensionality reduction is used to reduce the dimension of the feature vector, thereby alleviating some of the computational burden. One commonly used dimensionality reduction technique is principal component analysis (PCA). Using PCA, the original data is linearly mapped to a new, reduced set of uncorrelated features.

The mean square error between the original and projected feature sets is minimized. Employed PCA for dimensionality reduction, using MAV, Wilson Amplitude, and waveform length features. With a feed forward artificial neural network (ANN) and 32 surface electrodes, they were able to decode individual finger movements with a discrimination accuracy of 98%. While the system achieves a higher accuracy than most classification systems, the large number of EMG channels may increase the amount of concentration and effort required for the patient to control it. PCA is also used for feature reduction[17]. Extracting the time-frequency domain WPT feature from the transient portion of the signal, PCA is used for dimensionality reduction and compared to the performance when the feature vector is self-organizing feature map (SOFM). The use of PCA and SOFM are also considered together, and a multilayer ANN was used for pattern recognition. Results indicated a trade off when each method was used alone; the SOFM obtained much higher accuracy but also required a much larger computation time. A combination of the two results in an optimal compromise, achieving both low error rates and low processing time. All processes (9 motions) could be performed in less than 125 msec[18].

VI. PATTERN RECOGNITION TECHNIQUES

The pattern recognition stage of signal classification uses the extracted features to predict the intended motion and, given this information, choose the resulting movement of the prosthesis. There are several common types of pattern recognition techniques used: Bayesian classifiers, linear classifiers such as linear discriminant functions, the least squares method, and support vector machines, nonlinear classifiers, commonly employing back propagation and neural networks (as well as nonlinear support vector machines), and the fuzzy optimization-based clustering algorithm, among others. As with feature extraction, it is important to strike a balance among computational burden, accuracy, and stability.

6.1 Bayesian Classifiers

Many pattern recognition methods in signal classification systems are based on the probability of an intended motion given the feature vector input. Therefore, the Bayes rule is useful for determining the conditional probabilities (and thus, the intended motion). There are numerous types of Bayesian classifiers. One interesting use of a Bayes classifier was produced by Kurzynski and Wolczowski, who developed a recursive method which would feed new parameters into a genetic algorithm after each iteration for better learning performance. A Bayes-optimal algorithm was used for feature extraction and compared to the performance of the RMS algorithm, and a

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Bayes classifier was compared to two different Markov models. The Markov model's consistently better performance shows that treating algorithms as decision tasks always produces a better result. In another study, a virtual model of a hand is created using a combination fuzzy-Bayesian classifier (called the Fuzzy Bayesian Inference System)[19]. An anticipatory pattern recognition technique with the k-nearest neighbor Bayesian classifier. Among input transient signals, the anticipatory pattern recognition identifies possible grasp patterns given prior knowledge about the probability of transitioning from the current grip to another grip. Across all subjects and trials, anticipatory pattern recognition combined with k-NN outperformed k-NN alone by an average of 6.7%.

6.2. Fuzzy Clustering Algorithms

Clustering methods, in general, are unsupervised and aim to identify groups (referred to as clusters) with similar patterns and to gain useful information from these clusters. The advantage of the optimization-based fuzzy clustering algorithm over other clustering methods is that it does not require an assumed probability density function (PDF) , Fuzzy inference systems (FIS) are effective tools for information processing[20].

6.3. Neural Networks

As a pattern classifier and a learning tool, neural networks have been widely used for controlling prosthetic hands. A neural network is meant to mimic the mapping patterns of the brain; based on the behavior of neurons, an artificial neural network (ANN) is a collection of nodes (to represent neurons) and the relationships among those nodes. Neural networks also typically involve a learning phase which allows the classifier to improve over time. A neural network is composed of an input layer, a series of hidden layers, and an output layer, as shown in Fig. 5, and it is one of the most popular pattern recognition techniques for prosthetic hand control applications. Neural networks effectively model nonlinear data; the drawback is that they tend to be unstable. Usually, neural networks are combined with other classifying strategies to improve stability. One common combination is the use of a NN with an AR model. The NN was based on the Levenberg-Marquardt or variable learning rate (VLR) methods.

The AR model performed dimensionality reduction on the EMG signals, and the coefficients were imported into a BP ANN which identified finger motions. Herle et al. used an AR model with a feed forward NN and a higher level hierarchical controller based on Finite State Machine (FSM) for classification. Tsuji et al.[21] used an ANN during two stages: one to discriminate the motion and one for impedance control by measuring the flexor and extensor contractions from the other ANN. Ito et al. improved the speed of ANN-based pattern recognition using considerations of entropy to determine movement vs. nonmovement and extracting features from an initial rise zone. A discrimination accuracy of greater than 90% was attained, and intended movements could be executed in approximately 70 ms, whereas most systems exceed 200 ms.Karimi et al.[22] extracted signals from 16 different forearm locations to discriminate 10 hand motions. The standard deviation of a WPT was used as the feature vector, a two-layer ANN performed the pattern recognition, and a GA optimized the algorithm. Discrimination rates exceeded 98%.

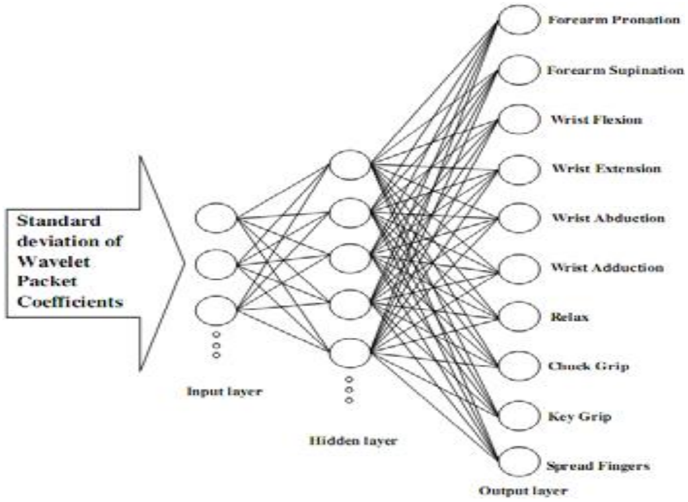

Fig. 5 ANN with example input and output reproduced from karimi et al. (2011)

6.4. Hierarchical Control

One alternative to the traditional pattern recognition approach is to implement hierarchical control. Hierarchical control is an event-driven process which uses sensory information and causes the limb to switch among states and which generally simplifies the task of posture selection. The concept of hierarchical control was first implemented in the design of the MARCUS prosthetic hand. Initially, hierarchical control was used to transition among states such as touch, hold, squeeze, and release[23].

Classification With Linear Support Vector Machines

Linear support vector machines (SVMs) for classifying the feature vectors generated from the EMG data into the respective classes for the gestures. SVMs have proved to be a remarkably robust classification method across a wide variety of applications.

Binary Classification

Consider a two-class classification problem. Essentially, the SVM attempts to find a hyperplane of maximum "thickness" or margin that separates the data points of the two classes. This hyperplane then forms the decision boundary for classifying new data points. Let w be the normal to the chosen hyperplane. Then, the classifier will label a data point x as +1 or -1 , based on whether w*x+b is greater than 1, or less than -1. Here, (w.b) are chosen to maximize the margin of the decision boundary while still classifying the data points correctly. This leads to the following learning algorithm for linear SVMs. For the classifier to correctly classify the training data points $x_1,\ldots,x_n$ with labels $y_1,\ldots.y_n$ drawn from ± 1 , the following constraints must be satisfied(1).

$$y_i(w * x_i + b) \geq 1 - \xi_i \quad \forall i \; \xi_i \geq \forall i (1)$$

This set of constraints ensures that each data point xi is correctly classified, allowing for some small amount of error ξ_i since real-life data are noisy. The optimization goal for the noisy classification case is to minimize $(1/2)w*w + C\sum_i \xi_i$, where C is a user-specified cost parameter. Intuitively, the criterion is trading off the margin width with the amount of error incurred[24].

Multiclass Classification and Probabilities

The two-class formulation for the linear SVM can be extended to multiclass problems. System uses the following generic method for combining binary classifiers for multiclass classification: for each pair of classes, a separate binary classifier is trained on data from the two classes. In order to classify a test data point, the datapoint is

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classified by each binary classifier, and each result is counted as a vote for the respective class. The output of the classifier is the class label with the maximum number of votes.

VII. EQUIPMENT FOR AQUIRING AND ANALYSING THE EMG SIGNAL

1.g.USBamp

g.USBamp is a multimodal biosignal amplifier for any type of electrophysiological signals like EEG, ECG, EOG, EMG, ECoG, and external sensors as shown in Fig. 6. It has an integrated 24-bit ADC and a floating point DSP and can be connected directly to the PC via USB. It is a CE and FDA certified medical device. g.USBamp comes with 16 analog input channels, one trigger channel which is scanned with the analog inputs, 2 digital inputs and 2 digital outputs.

Fig.6 g.USBamp with 4 input channels[25]

2. GAMMAsys

g.GAMMAsys is g.tec's latest and high –end active electrode system for non-invasive electrophysiological derivations. The system allows the acquisition of biosignal channels such as EEG (Electroencephalogram), EOG (Electrooculogram), EMG (Electromyogram) and ECG (Electrocardiogram) using g.tec's genuine active electrodes. The system is designed for use with biosignal amplifiers with monopolar (unipolar) or bipolar (differential) inputs.

G.GAMMAbox is the interfacing unit between the electrodes and USB amplifier fig. 7(a).

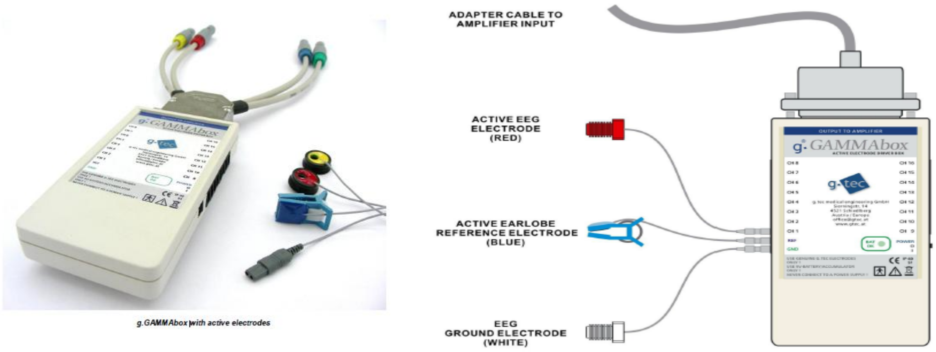

Fig. 7 (a)g.GAMMAbox with active electrodes (b)g.GAMMAbox connection scheme[26]

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To perform recordings with more than 16 channels with active electrodes multiple units of g.GAMMAbox can be used. For this purpose one standard g.GAMMAbox has to be used to connect the ground and reference electrode as shown in Fig. 7(b)

VIII. DISCUSSION AND CONCLUSION

This review study has presented comparison different algorithms used characterization of EMG signals for myoelectric control of human arm prosthesis.The most distinct advantage of surface myoelectric control is that it does not require an invasive procedure. The tradeoff is that signals from the nervous system must be obtained through muscle contractions, resulting in unnatural movement. A patient with a myoelectric prosthesis must learn a set of unnatural movements to operate it successfully. If only two or three EMG channels are used for control, excess concentration is not a large concern, but when more channels are included for increasing the reliability of the classification system, the prosthesis can become difficult to use. Consequently, amputated patients will often choose a simpler and less functional prosthesis. However, the main drawback of myoelectric hands is their inability to provide sensory feedback to the user. Sensory feedback is highly important for effective control, and in its absence, the wearer must rely heavily on visual cues to determine whether an object will slip or break within a grasp. This is problematic because it requires concentration from the user.

SVM has a high potential for application as a core for classification in myoelectric control systems, and appear to be capable of recognizing patterns that are more complex. This could lead to an expansion of the functionality of myoelectric control, as well as the development of advanced online training schemes to support long-term operation.

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

REFERENCES

[1] Chiharu Ishii, Akitoshi Harada, Takashi Nakakuki Hiroshi Hashimoto, “Control of Myoelectric Prosthetic Hand Based on Surface EMG”, IEEE International Conference on Mechatronics and Automation, Beijing, China, pp. 761-766, Aug. 7 – 10, 2011.

[2] W. D. I. G. Dasanayake, R. A. R. C. Gopura, V. P. C. Dassanayake, G. K. I. Mann,“Surface EMG Signals Based Elbow Joint Torque Prediction″, IEEE 8th International Conference on Industrial and Information Systems, Sri Lanka, pp. 110-115, Aug. 18-20, 2013.

[3] Jun Liu, Fan Zhang, He (Helen) Huang, “An Open and Configurable Embedded System for EMG Pattern Recognition Implementation for Artificial Arms”, International Conference of the IEEE Engineering in Medicine and Biology Society,pp. 4095-4098, 2014.

[4] BekirKarlık, “Machine Learning Algorithms for Characterization of EMG Signals”, International Journal of Information and Electronics Engineering, Vol. 4, No. 3, pp. 189-195 May 2014.

[5] BiswarupNeogi, SoumyajitMukharjee, SoumyaGhosal, Dr.Archintya Das, D.N. Tibarewala, “Design and implementation of prosthetic arm using gear motor control technique with appropriate teting”, International

IJARSE
ISSN (O) 2319 - 8354
ISSN (P) 2319 - 8346

Journal of computer applications in engineering and technology(IJ-CA-ETS), Vol. 3, Issue 1, pp. 281, Oct '10 – March '11.

[6] Oskoei, MohammadrezaAsghari, and Huosheng Hu. "Support vector machine-based classification scheme for myoelectric control applied to upper limb," IEEE transaction on biomedical engineering, Vol. 55, No. 8, pp. 1956-1965, 2008.

[7] Otto Bock HealthCare GmbH; 2002. Available from: http://www.ottobock.com. Duderstadt (DE).

[8] Shital B. SOnone, and G. D. Dalvi, "Real Time Control of Robotic Arm Using Electromyogram (EMG) Signals", International Journal of Science and Research (IJSR), Vol. 5, No. 1, pp. 797-800, February 2014.

[9] S. Sudarshan, and Dr. E. Chandra Sekaran, "Design and Development of EMG Controlled Prosthetics Limb", Proceeding of International Conference on Modeling and Optimization and Computing, pp. 3547-3551, 2012.

[10] SatyajitBhowmick, Rajesh Bag, SK Masud Hossain, Subhajit Ghosh, Shanta Mazumder, and Sauvik Das Gupta, "Modeling and Control of a Robotic Arm Using Artificial Neural Network", ISOR Journal of Computer Engineering (ISOR-JCE), Vol. 15, No. 2, pp. 42-49, December 2013.

[11] Panagiotis K. Artemiadis, and Kostas J. Kyriakopoulos, "A Switching Regime Model for the EMG-Based Control of a Robotic Arm", IEEE Transaction on System, Man and Cybernetics, Vol. 41, No. 1, pp. 53-63, February 2011.

[12] Zhou, P. , Lowery, M. L., Englehart, K. B., Huang, H., Li, G., Hargrove, L., Dewald, J. P. and Kuiken, T. A., 2007, Decoding a new neural machine interface for control of artificial limbs. Journal of Neurophysiology, **98**(5), pp. 2974-2982.

[13] BiswarupNeogi, Soumyajit Mukherjee, SoumyaGhosal, Dr. Achintya Das and D. N. Tibarewala, "Design and Implementation of Prosthetic Arm Using Gear Motor Control Technique with Appropriate Testing", International Journal of Computer Applications in Engineering, technology and Science, Vol. 3, No. 1, pp. 281-285, March 2011.

[14] Crawford, Beau, Kai Miller, Pradeep Shenoy, Rajesh Rao, "Real-time classification of electromyographic signals for robotic control," Association for the Advancement of Artificial Intelligence (AAAI), Vol. 5, No.1, pp. 523-528, 2005.

[15] Han, Jianda, Qichuan Ding, AnbinXiong, and XingangZaho, "A state-space EMG model for the estimation of continuous joint movements." IEEE Transactions on Industrial Electronics, Vo.l 62, No. 7, pp. 4267-4275, July 2015.

[16] Renaud Ronsse, Nicola Vitiello, TommasoLenzi, Jesse Van Den Kieboom, Maria Chiara Carrozza, and Auke Jan Ijspeert, "Human–robot synchrony: flexible assistance using adaptive oscillators," IEEE Transactions on Biomedical Engineering, Vol. 58, No. 4, pp. 1001-1012, April 2011.

[17] Kazuo Kiguchi, and Yoshiaki Hayashi, "An EMG-Based Control for an Upper-Limb Power-AssitExoskelton Robot", IEEE Transaction on Man and Cybernetics, IEEE Transaction on Man and Cybernetics, Vol. 42, No. 4, pp. 1064-1071, August 2012.

[18] Mohammadreza Asghari Oskoei, and Huosheng Hu, "Support Vector Machine-Based Classification Scheme for Myoelectric Control Applied to Upper Limb", IEEE Transactions on Biomedical Engineering, Vol. 55, No. 8, pp. 1956-1965, August 2008

IJARSE
ISSN (O) 2319 - 8354
ISSN (P) 2319 - 8346

[19] Scheme, Erik J., Kevin B. Englehart, and Bernard S. Hudgins. "Selective classification for improved robustness of myoelectric control under nonideal conditions," IEEE Transactions on Biomedical Engineering, Vol. 58, No. 6, pp. 1698-1705, 2011.

[20] Subasi, Abdulhamit, Mustafa Yilmaz, and Hasan RizaOzcalik. "Classification of EMG signals using wavelet neural network," Journal of neuroscience methods, Vol. 156, No. 1, pp. 360-367, 2006.

[21] Tsuji, T., Fukuda, O., Shigeyoshi, H., Kaneko, M., 2000,"Bio-mimetic Impedance Control of an EMG-controlled Prosthetic Hand," 2000 IEEE/RSJ InternationalConference on Intelligent Robots and Systems, **1**, pp. 377- 382.

[22] Karimi, M., Pourghassem, H., Shahgholian, G., 2011, "A Novel Prosthetic Hand Control Approach Based on Genetic Algorithm and Wavelet Transform Features," 2011 IEEE 7th International Colloquium on Signal Processingand its Applications, pp. 287-292.

[23] Daley, Heather, Englehart, K., Hargrove, L., &Kuruganti, U. "High density electromyography data of normally limbed and transradial amputee subjects for multifunction prosthetic control," Journal of Electromyography and Kinesiology, Vol. 22, No .3, pp. 478-484, 2012.

[24] Pradeep Shenoy, Kai J. Miller, Beau Crawford, and Rajesh P. N. Rao, " Online Electromyographic Control of a Robotic Prosthesis", IEEE Transaction on Biomedical Engineering, Vol. 55, No. 3, pp. 1128-1135, March 2008.

[25] Dr. Christoph Guger, Dr.GuenterEdlinger, g.USB amp USB biosignalamplifier simulinkhighspeed on-line processing user manual v3.15.02

[26] g.GAMMAsys active electrode system Comparison of Active versus Passive Electrodes User Manual.