Classification of Functional Motions of Hand for Upper Limb Prosthesis with Surface Electromyography

Muhammad Asim Waris, Mohsin Jamil, Yasar Ayaz and Syed Omer Gilani

***Abstract*—** Significance of rehabilitation engineering is gaining popularity with the advancement in technology as more amputees desire to perform day to day tasks. Researchers are proposing designs and devices related to prosthesis which can achieve principle functions. Ideal upper limb prosthesis is one which can mimic actual hand. Control of Electromyography (EMG) based prosthesis is still in primitive stage as large number of channels is required even for the recognition of only few hand gestures. This study presents classification of essential hand movements for dexterous control of upper limb active prosthesis using surface Electromyography (EMG). Forearm muscles were used to detect these signals. Four pairs of surface electrodes were used with one reference electrode. Thus lesser number of channels used as compared to previous studies. Off-line analysis was used to figure out classification accuracy. Time domain feature extraction was done in the initial stage with support vector machine (SVM) analysis used for classification in the later stage. Results showed that hand movements were decoded accurately under latencies of 300ms. Five different movements were classified with the average accuracy between 84-90%.

***Keywords*—**Electromyography (EMG), Support Vector Machine (SVM), Prosthesis, Gesture Recognition

I. Introduction

Amputation is one of the most visible and psychological mortifying event that can happen to any person. According to extrapolated statistics there are more than 1.1 million amputees in Pakistan. Due to ongoing conflict this number is still increasing. Many of these disarticulations are upper limb which are below elbow. Most of these people are not provided with devices which can help them in their daily chores. Those provided with these prosthetics are having very low functionality and can perform very limited tasks. Trauma is the main cause of amputation [1]. Many high tech artificial limbs are available in the market with variable set of gestures such as *The Hand* with multiple grip patterns by RSL Steeper [2], trainable *Michelangelo* by Ottoback [3], *i-Limb ultra-revolution* with powered rotating thumb by Touch Bionics [4]. But the device which can mimic actual hand is still a long way to go. For EMG based control prosthesis it is basically a tradeoff between degrees of freedom attained by the limb and the number of channels used.

Electromyography (EMG) is field that deals with detection (from needle, surface and cup electrodes), signal processing (Power Lab or Lab view) and use of electrical signals generated by the voluntary contractions of muscles (for active prosthesis) [5]. This potential generated varies from 0-5 mV when they are flexed or neurologically activated. EMG surface activity stimulated by voluntary contraction of the targeted muscle is considered as the intention of myo-limb user. Comparisons of the predetermined threshold value of EMG signal with Mean Absolute Value (MAV) give us the intension of the user.

Human body consists of muscles, composed of fibers having motor points in it. These points when activated generate motor point active potential. Motor unit is the composition of anterior horn cell, its axon and muscle fibers innervated by the motor neuron. Motor unit action potential (MUAP) is a train of pulses or summation of a group of muscle fiber action potential (MFAP) where superimposed information of muscles and generated pulses is determined by each MFAP. As long as force is maintained or even increased motor unit generates pulses continuously and consequently muscle contracts [6]. Number of activated motor points will increase as human muscle apply more force, so we can drive that throwing a heavy stone activates more motor points than throwing a lighter stone. Greater number of activation of MUAP’s makes things difficult for the neurophysiologist to distinguish between individual signals of muscles. Decomposition and careful grouping of these potentials can provide useful information which can lead neurophysiologist to the diagnoses of many neuromuscular disorders.

MUAP’s is the symptom of muscle control of human body that incorporates the data of user’s intent to flex his muscle. Recent studies have shown that human muscle generates repeated patterns of EMG signals before the intension to perform a certain movement [7].So the importance of these signals increase many fold because the control of active prosthesis is based on the intension of user.

Recent development in electronics and computer technology made automated EMG signal analysis possible. Many studies have been done on able as well as disable bodies to authenticate the expediency and performance of different classification algorithms. These techniques used EMG signal taken from forearm. Variable number of electrode pairs was used ranging from 4-12. Shenoy et al presented a technique to classify eight different motions (griping, opening of hand, rightward, leftward, upward, downward movements of hand, angular motion of hand) with the help of artificial neural network (ANN). Eight pairs of surface electrodes were used and placed on selected muscles with real time data acquisition [8]. These patterns can be linked to prosthesis to control the dedicated moves. Zecca at el in their review demonstrated that EMG signals can be used for active prosthesis control [9]. Zhang et al extracted multiple motor unit action potentials from the subjects having neuromuscular disease for rehabilitation purposes [10]. Hargrove et al determined muscles re-innervation with the help of electromyography using adaptive pattern recognition [11]. A strategy has been presented by Liu et at for rehabilitation of the subject having incomplete cervical spinal cord injury using surface electromyography [12]. Kanitz et al [13] has decoded 12 different finger gestures using 16 surface electrodes. Support vector machine (SVM) was used for classification.

All the above mentioned studies used high density surface electromyography which require more than 6 electrode pairs, Although utilization of data form greater number of electrode pairs provide elaborated information but also require large surface area to place them on given amputee. Due to this impulsion routine EMG clinical procedures and checkup are still not possible. Large set of gesture must be discriminated if small number of surface electrodes is used. A study has shown that classification accuracy drops by 3% if the number of electrode pair used are restricted to 8 [14].

In this paper, we classified five different functional motions of hand using low density EMG signal, acquired from targeted muscles. The main goal of this proposed system is to automatically discriminate five motions. These motions were griping, upward, downward, leftward and right ward motion of hand. Four EMG channels were used, which were lesser in number as compared to previous studies. Subjects performed these mentioned gestures. Surface EMG electrodes were used to record data. Four time domain features were extracted from each channel data which is then followed by feature classification with the help of support vector machine (SVM).

II. Proposed System

System consists of EMG data acquisition unit, Signal analysis unit, feature extraction unit and classification unit.

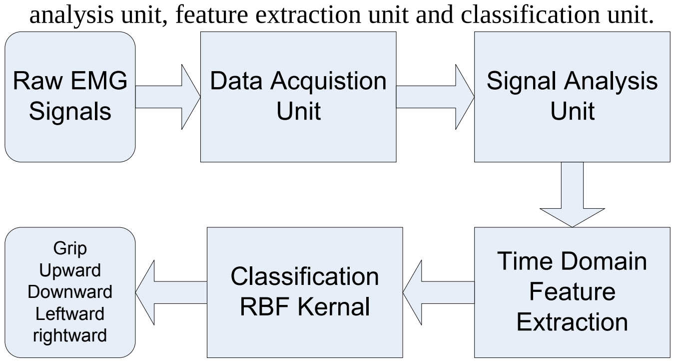

Fig.1 Flow chart of EMG based gesture recognition system.

Raw EMG signal is fed in to data acquisition system taken form the subjects. In this phase amplification and filtering of raw signal is being done, with the help of notch and band pass filter. For sampling purposes careful selection of sampling rate of EMG signal has been done. This recorded data is then fed in to unit where features were extracted from each channel's data. Feature vector is then classified using RBF kernel based support vector machine (SVM) with a 10-fold cross validator.

III. Noise reduction technique

Electromyographic signal has very low signal to noise (SNR) ratio, one of the main reason of low SNR is disturbances. These disturbances are caused by many factors and one of the main factors is cardiac artifacts. Ratio between electromyographic signals and cardiac artifacts keep on changing due to non-stationary nature of EMG signals.

A method has been devised to cater for these cardiac artifacts in which referencing is done with respect to ECG signals ,digital filter is applied to reduce the power line disturbances.

Detected signal comprised of both mayo graphic $p_l(t)$ as well as cardio graphic $h_l(t)$

$$\mathrm{F}(t)=\sum_{l=1}^{M}[p_l(t)+h_l(t)]$$

$$\mathrm{F}(t)=\sum_{l=1}^{M}p_l(t)+\sum_{l=1}^{M}h_l(t)] \qquad \text{(i)}$$

Here

$p_l(t)=$ Detected mayo-graph

$h_l(t)=$ Detected cardio graph

M= Electrodes placed on limb

Autocorrelation function is given as

Placing eq (i) in (ii)

$$\Gamma_{FF}(\tau)=E[\mathrm{F}(t)\,\mathrm{F}(t-\tau)] \qquad \text{(ii)}$$

$$\Gamma_{FF}(\tau)=E\left\{\left[\sum_{l=1}^{M}p_l(t)+\sum_{l=1}^{M}h_l(t)\right]\left[\sum_{l=1}^{M}p_l(t-\tau)+\sum_{l=1}^{M}h_l(t-\tau)\right]\right\}$$

$$\Gamma_{FF}(\tau)=\sum_{b,c}^{M}\Gamma_{p_bp_c}(\tau)+\sum_{b,c}^{M}\Gamma_{p_bh_c}(\tau)+\sum_{b,c}^{M}\Gamma_{p_ch_b}(\tau)+\sum_{b,c}^{M}\Gamma_{h_bh_c}(\tau)$$

As variables b and c has no co-relation, so those parts having both EMG and ECG combined together in one function will be cancelled out and remaining functions will be as follows.

$$\Gamma_{FF}(\tau)=\sum_{b,c}^{M}\Gamma_{p_bp_c}(\tau)+\sum_{b,c}^{M}\Gamma_{h_bh_c}(\tau)$$

As $b\neq c$ so

$$\Gamma_{FF}(\tau)=\sum_{l=1}^{M}\Gamma_{p_bp_b}(\tau)+\sum_{b,c}^{M}\Gamma_{p_bp_c}(\tau)+M^2\Gamma_{hh}(\tau)$$

$$\Gamma_{FF}(\tau)=M^2\Gamma_{hh}(\tau)+M\Gamma_{pp}(\tau)+\sum_{b,c}^{M}\Gamma_{p_lp_m}(\tau)$$

Derived equation shows that by increasing number of surface electrodes placed on the targeted muscles will increase signal to noise ratio SNR N times.

IV. Experimental Methods And Procedures

A. Data Acquisition Protocol

1. Participants

Low density EMG signals were acquired from right forearm of nine intact limbed subjects. All were male aged between 22-28 years. No subject had the history of any neuromuscular diseases. This research was approved by Bio-medical engineering department of school of mechanical and manufacturing engineering (SMME). Data were collected at human system lab (NUST), Pakistan. All participants gave their consent before participating in the study.

2. Electrodes Placement

Skin of the subjects was properly prepared before conducting these experiments. Alcoholic swaps were used to remove dead skin from the targeted muscles, to improve conduction of these signals preparation gel was applied on all the subjects. 4 EMG channels were used with self-adhesive passive Ag-Cl electrodes. Elbow joint is used as reference point for the placement of electrodes on the subjects. The established location of electrodes is between innervation zone and the tendinous insertion [15].

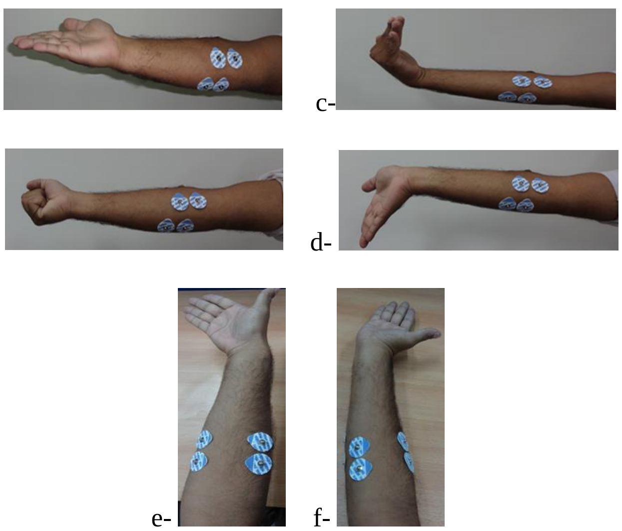

Fig.2 Pictures of movements discriminated by the proposed system (a) relaxed position, (b) flexion of hand, (c)upward movement of hand, (d)downward movement of hand, (e) leftward movement of hand, (f) rightward movement of hand.

Calibration must be done before recording muscle signal, by capturing signal between maximum voluntary contractions (MVC) as well as in the time of muscle relaxation. Low quality data will be acquired even if a single electrode is misplaced. Signal to noise ratio (SNR) must be greater than 10 to record data. During recording of data each subject sat on the chair in front of the computer and followed the directions (grip, upward, downward, leftward, rightward motion of hand) coming on the monitor. Elbow is stationary during experiment. Subjects were asked to perform each required motion for 10 seconds with 5 second of rest during each motion. 10 trials were taken from each subject.

Table.1 placement of EMG electrodes on the muscles

Channels	No of Electrodes	Muscles
EMG Channel 1	Ag-Cl Electrode pair	Flexor digitorum profundus
EMG Channel 2	Ag-Cl Electrode pair	Extensor carpi radialis longus
EMG Channel 3	Ag-Cl Electrode pair	Flexer carpi ulnaris
EMG Channel 4	Ag-Cl Electrode pair	Extensor digitorum cummunis

In order to remove common mode noises and cross talk from nearby muscles bi-polar EMG electrodes were used. 12mm distance was maintained between two individual sensors. Hairs were not removed from the forearm on the request of all subjects.

3. Data acquisition and signal processing

EMG electrodes were fed in to data acquisition and signal processing unit. For this purpose ML8456 Power Lab 26T (LTS) data acquisition system has been used for the investigation of spectral characteristics of EMG signals, which is their dominant frequencies, amplitude and Mean absolute values. It has two isolated biological inputs approved for human connection. External trigger was used for data recording. The integrated EMG signal was digitized at a sampling rate of 1 kHz using a 24 bit ADC of Power lab 26T.

Figure.3 Analysis of EMG signals through ML8456 Power Lab 26T (LTS) for flexion and extension of hand.

Table.2 Specification used, ML8456 Power Lab (LTS)

Parameter	Value
CMMR	110 dB
Bio-Amplifier	Input no 3 and 4
Low pass cut off	1kHz
High pass cut off	10 Hz
Notch filter	50 Hz
ADC resolution	24 bit
Maximum Bandwidth	25 Hz
Inter Channel cross talk	>90 dB
Signal noise ratio SNR	>110 dB
Input leakage current	<4uArms

As offline analysis was done, data that was collected from each subject was converted into a mat file and further used for feature extraction and classification.

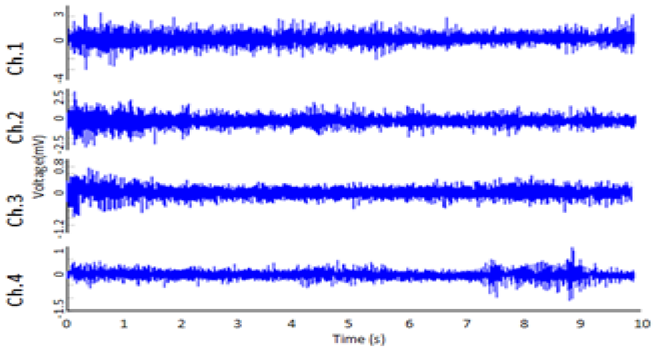

Fig.3 Data recorded from four EMG channels, contraction of forearm muscles for griping, at a sampling rate of 1 kHz. Single sample recorded for 10 seconds.

V. Feature Extraction And Selection

In the process of getting low dimensional feature vector, which will provide us distinguishing information, four frequently recommended time domain features were accessed from each channel.

1. Mean Absolute Value (MAV)

It is defined as the calculation of all data values in the moving window and taking mean of the resultant value. In class separablity it has shown better results than other features [16]. Comparison can be done on class separablity in each case if we can find a suitable EMG subset. MAV is given as

$$MAV = 1/N\sum_{n=1}^{N}|x_n| \qquad (1)$$

In equation no.1 x_n represents the nth sample of the EMG signal and N is the number of samples in the window. Matrix with MAV features can be shown as below

$$V_{i,j}^{m} = \begin{pmatrix} v_{1,1}^{m} & \cdots & v_{1,10}^{m} \\ \vdots & \vdots & \vdots \\ v_{4,1}^{m} & \cdots & v_{4,10}^{m} \end{pmatrix} \qquad (2)$$

Where *v* is the value of MAV, *i* is the channel number (1-4), *j* is the number of trial (1-10) and m is the motion number (5), which goes as grip, upward, downward, leftward and rightward. Normalized samples were used ranging between 0-1 from each channel and motion. Average MAV value from each channel is given by

$$\overline{X}_i^{\,k} = \begin{bmatrix} \overline{x}_1^{\,k} \\ \overline{x}_2^{\,k} \\ \overline{x}_3^{\,k} \\ \overline{x}_4^{\,k} \end{bmatrix} \qquad (3)$$

Where $\overline{x}_i^{\,k}$ is

$$\overline{x}_i^{\,k} = 1/\mathrm{J}\sum_{j=1}^{\mathrm{J}} x^{k}_{i,j} \qquad (4)$$

2. Zero Crossing

This feature counts the number of times per unit time that the amplitude of the signal crosses the zero value of signal. The relative ease with which this feature can be measured made it very popular among researchers. Myopathic and normal muscles can simply be discriminated by using this feature. As muscle undergo sustained contraction, more motor point's fire and the number of motor unit action potential (MUAP's), also increases which consequently results in higher number of zero crossings as the frequency of the signal increases. This feature is very effective and small enough to be merged in other features without adding any significant computational burden. It is defined as

$$ZC = \sum_{n-1}^{N-1}\left[\operatorname{sgn}\left(x_n . x_{n+1}\right) \cap |x_n - x_{n+1}| \geq thres\right] \qquad (1)$$

Where sgn is

$$\operatorname{sgn}(x) = \begin{Bmatrix} 1, if x \geq thres \\ 0, otherwise \end{Bmatrix} \qquad (2)$$

If threshold is crossed, function sgn returns the value 1 and zero crossing counter increases by one.

3. Variance

Variances of EMG signal give us the power of the selected segment. It is defined as the mean value of the square of the deviation of that variable. It is based on assumption that EMG signal can be amplitude modulated Gaussian noise modeled. Small value of variance indicates that it is close to mean. Commonly the mean of the EMG signal is close to zero. It can also be used for augmenting the other features for a more powerful feature vector. Variance can be calculated as follows.

$$VAR = \frac{1}{N-1}\sum_{n=1}^{N} x_n^2$$

Where x_n represents the nth sample of surface EMG signal and N is the length of the signal.

4. Willison Amplitude

Willison Amplitude (WAMP) is defined as the number of times at which the difference between peak values of EMG signal and two consecutive segments of EMG signal exceeds the threshold value. It has the same effect as Zero crossing and slope sign change that is to reduce noise effect.

$$WAMP = \sum_{n-1}^{N-1}\left[\, f\,|x_n - x_{n+1}|\right]$$

$$f(x) = \begin{Bmatrix} 1, if x \geq thres \\ 0, otherwise \end{Bmatrix}$$

It has been experimentally determined that if we know the noise level then by keeping our threshold value above that

WAMP can accurately count the frequency of motor unit action potential (MAUP's) firing. So WAMP can be very useful and effective in temporal feature.

VI. Classification

Support vector machine (SVM) is the kernel based classifier in which it finds linear separating hyper plane with optimal margin by placing each training dataset into a higher dimensional feature space using a non-linear kernel[17]. It has the greater ability to generalize which is the primary goal in statistical learning. SVM was earlier developed to handle just classification problems but later on it was also used for regression. Linear kernel separating hyper plane is used for the classification of data, if the given data is linear. Some of the main reasons for choosing SVM are.

1. Kernel based SVM adds the advantage of handling threshold, which separates solvent from insolvency. It classifies even when data is non-linear or not having same functional form.
2. Having property of kernel implicitly, it contains non-linear transformation and no suppositions about the functional form of transformation, which makes the data linearly separable. SVM do these transformations without any human expertise verdict but on robust theoretical basis [18].
3. SVM ensures better generalization ability by selecting values of *C* and *r* appropriately. By careful selection of these parameters it improves robustness even when the training sample has some bias.
4. One of the aspects that give precedence to SVM over other classifiers is that it gives only one solution which makes it better classifier than multiple layer perceptron (MLP) neural networks (NN), which gives you more than solution depending upon local minima.

C and *r* are tuning factors for radial based kernel SVM. Here *C* controls the generalization ability of SVM. Higher the value of *C* higher will be the weight given to sample data misclassification and lower will be the generalization of the classifier. *r* control the radial basis of kernel reducing complexity of model selection.

In the study linear implementation of SVM was used for classification in which the complexity perimeter *C* was optimized for each subject. C was iteratively optimized between (0.001, 0.01, 0.1, 1, 10, 100, and 1000). To identify best classification scheme and its dependence on number of classes, following results were assimilated to distinguish five motions of hand.

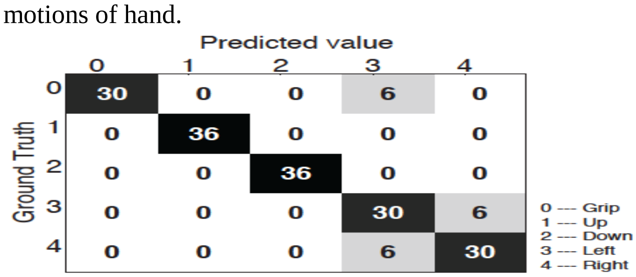

Fig.5 Class to class confusion matrix derived from classification results of nine subjects using SVM classifier. Results showed in the main diagonal matrix shaded in black shows correct classifications and those shaded in grey are wrong classifications.

One-vs-rest (OVR) is the strategy which is employed by during study, Library of libSVM is used to implement our classifiers. This was developed by Chang et al [20]. Training trials per subject were ten. Testing trials per subject were four. Total gestures recognized were five. Total training data was (subjects (9)*gestures (5)*training trial per subject (10)) =450, Total testing data was (subjects (9)*gestures (5)*training trial per subject (4) =180). Parameters C and r were optimized at the value of 8 and 0.5 respectively. Training data accuracy came out to be 95.55% whereas test data accuracy was about 90%.

Table.3 Recognition rate of each motion

Motions of hand	Average accuracy
Griping	84%
Upward motion	98%
Downward motion	98%
Leftward motion	84%
Rightward motion	84%

Misclassification was noticed in leftward, griping and rightward but these motion did not affect the classification of up and downward motion of hand, Misclassification occurred due to wrong positioning of surface EMG electrode, which is obvious as there are more than 20 muscles in human arm; some of them are overlapping which brings the effect of cross talk deteriorating the quality of signal. For actual active upper limb prosthesis these accuracies will be further reduced due to reliability issues of real-world control system in which the electrodes position on amputee arm and non-stationarity of EMG signal is going to affect the performance of artificial limb [21-23].Reproducibility is other constraint which is to be dealt. Much of the study has done on the classification and pattern recognition techniques but know there is a need of improving robustness of the fabricated system instead we keep on improving accuracies by small fractions. This can make EMG pattern recognition based system a real clinical procedure for diagnoses different neuromuscular diseases. Different amputees have different degrees of injury considering type of muscles and nerves damage for which he can perform only few motions with the help of rehabilitation device without any feedback. So before designing such device factors like number of channels, number of gestures and scheme for signal analysis must be personalized. Tackling with these issues will certainly help in increasing usability of EMG based pattern recognition controlled prosthesis and that will be the focus of our future work.

VII. Conclusion

In this paper we presented initial study for the classification of functional motions of hand using low density EMG signal.4 channels of EMG has been used. Noninvasive 8 surface electrodes were employed for signal acquisition. Nine subjects were selected for data collection. Subjects were asked to perform five motor tasks which were griping of hand, upward, downward, leftward and rightward motion of hand as shown in figure 2. Four time domain (TD) features were carefully selected and used them for extracting required feature set. Standard support vector machine (SVM) has been used to classify motions on the basis of feature set. Testing data accuracy was 90%. This can be further enhanced by extracting more features and accurate placement of electrodes. Previous studies had more accuracy than this but they used more channels. Future work will be targeting more classification accuracy and developing a prosthesis design which can be personalized according to the type of amputation.

REFERENCES

[1] National Amputee Statistical Database (NASDAB). The Amputee Statistical Database for the United Kingdom 2006/2007 *ISD Publications*, Edinburg 2009.

[2] RSLSteepter, *Bebionic3 Product brochure* [online] Available on http://bebionic.com/the_hand/features, November 2013.

[3] Otooback Health care, *Michelangelo Technicon Brochure*, Available onhttp://www.ottobock.com/cps/rde/xchg/ob_com_en/hs.xsl/1929.html November, 2013.

[4] Touch Bionics. i-Limb ultra Data Sheet, Available on http://www.touchbionics.com/products/active-prostheses/i-limb-ultra/ November, 2013

[5] M. A. Waris H. Poor, *An Introduction to Signal Detection and Estimation*. New York: Springer-Verlag, 1985, ch. 4.

[6] S. Shahid, J. Walker, "Application of higher order statistics techniques to EMG signal to characterize the motor unit action potential", *IEEE Tans. Biomedical Engineering*, vol.52, no.57, July 2005.

[7] G. Li, A. E. Schultz and T. A. Kuiken, "Quantifying pattern recognition-based myo-electric control of multifunctional trans radial prosthesis," *IEEE Trans. Neural Systems. Rehab. Eng*. Vol.18, no.2, pp. 185-192, April 2010.

[8] P. Shenoy, K. J. Miller, B. Crawford and R. P. N. Rao, "Online Electromyogrphic control of Robotic Prosthesis," *IEEE Trans. Biomed. Eng.* vol.55, no.3, pp.1128-1135, 2008.

[9] M. Zecca, M. Micera, M. Carrozza, P. Dario, "Control of multifunctional prosthetic hands by processing the electromyographic signal," *Critical Reviews in Biomedical engineering*, vol.30, no.4-6, pp.459, 2002.

[10] X. Zhang, P. Zhou, "High-density myoelectric pattern recognition toward improved stroke rehabilitation," *IEEE Trans. Biomed. Eng*. vol.59, no.6, pp.1649-1657, 2012.

[11] L. Hargrove, P. Zhou, K. Englehart and T. Kuiken, "The effect of ECG interference on pattern-recognition-based myoelectric control of targeted muscle re-innervated patients," *IEEE Trans. Biomed. Eng*. vol.56, no.9, pp.2197-2201, 2009.

[12] J. liu, P. Zhou, "A novel myoelectric pattern recognition strategy for hand function restoration after incomplete cervical spinal cord injury," *IEEE Trans. Neural Systems. Rehab. Eng*. vol.21, no.1, pp.96-103, 2013.

[13] G. Kanitz, C. Antfolk, C. Cipraini, F. Sebelius, and M. Carrozza, "Decoding of individuated finger movements using surface EMG and input optimization and applying a genetic algorithm," *Proc. Ann. Int. Conf. IEEE. Eng. Med. Biol. Soc*, pp.1608-1611, Boston, Sep 2011.

[14] G. Li, A. E. Schultz and T. A. Kuiken, "Quantifying pattern recognition based myoelectric control of multifunctional transradial prosthesis," *IEEE Trans. Neural Systems. Rehab. Eng*. vol.18, no.2, pp.185-192, April 2013.

[15] C. J. De Luca, "Surface Electromyography: Detection and Recording", *Delsys Incorporated*, 2002

[16] A. Phinyomark, S. Hirunviriya, C. Phukpattaranont, "Evaluation of EMG feature extraction for hand movement recognition based on Euclidean distance and standard deviation," *7th. Int. IEEE Conf. Elec. Elect. Comp. Telecom. IT*.pp.856-860, Chiang Mai, Thailand, 2010.

[17] C. J. C. Burges, "A tutorial on support vector machine for pattern recognition," *Data mining and knowledge discovery*, vol.2, no.2, pp.121-168, 1998.

[18] L. Auria, R. A. Moro, "Support vector machines (SVM) as a technique for solvency analysis," Discussion papers. German institute of Economic Research, no.811, 2008.

[19] Y. Guangying, Y. Shanxiao, "Emotion recognition of electromyography based on support vector machine," *3th. Int. IEEE Symposium on Intelligent information technology and security informatics*. pp.298-301, China, 2010

[20] C. Chang, C. J. Lin, " LibSVM, A library for support vector machines" *ACM. Trans. Intell. Syst. Tech*, vol.2, no.3, pp. 1-27, May, 2011.

[21] A. Fougner, E. Scheme, A. Chan, K. Englehart, O. Stavdhal, " Resolving the limb position effect in myoelectric pattern recognition" *IEEE Trans. Neural Systems. Rehab. Eng.* Vol.19, no.6, pp. 2537-2544, Sep 2011.

[22] Y. Geng, P. Zhou, G. Li, "Toward atteneuting the impact of arm positions on electromyography pattern recognition based motion classification in transradial amputees" *J. NeuroEng. Rehabil*. , vol.9, p.74, 2012.

[23] N. Jiang, S. Muceli, B. Graimann, D. Farina, "Effect of arm position on the prediction of kinematics from EMG in amputees" Med. Biol. Eng. Comput. , vol.51, pp-143-151, 2012.

Muhammad Asim Waris completed his bachelors in mechatronics engineering from College of Electrical and Mechanical engineering, National University of Science and Technology (NUST), Pakistan in 2011.He is currently pursuing his masters working on the rehabilitation project. His research interests include EMG based upper limb prosthesis, Devices based on gesture recognition and rehabilitation strategies.

Mohsin Jamil received his BEng Industrial Electronics degree from NED University, Pakistan, in 2004. He is MSc Electrical Engineering degree holder from *Dalarna* University Sweden and National University of Singapore in controls and automation. He completed his PhD degree at University of Southampton, UK. His research interests include digital control design for grid connected inverters and system identification of dynamic systems. He is an author of a book chapter and several IEEE publications. He is an author of a book chapter and several IEEE publications. He is currently working as Assistant Professor at NUST.

Yasar Ayaz is currently working at National University of Science and Technology (NUST) as the Head of the Department of Robotics and Artificial Intelligence. His research work on Humanoid Robot Footstep Planning, Navigation and Control has been cited by leading universities in more than eleven countries, including USA, Japan, France, Germany, Hungary, South Korea, China, Iran, Croatia, Singapore and Pakistan. HE is author of more than 35 International Publications in International Journals, Invited Book Chapters and International Conferences. The International Biographical Centre based in Cambridge, England (UK) has recently included Yasar Ayaz of NUST School of Mechanical and Manufacturing Engineering in their list of Top 100 Educators 2013.

Syed Omer Gilani received his BEng Computer Engineering degree from UET Taxila, Pakistan in 2003.He completed his MSc Electrical Engineering from Dalarna Univerisity Sweden in 2006 and then completed his PhD from National University of Singapore NUS, Singapore in electrical and computer engineering. He is currently working as Assistant Professor in Bio-Medical Engineering Department of NUST. His research interests include computer vision, gesture recognition and Digital image processing.

.