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RESEARCH ARTICLE

Identifying User Suitability in sEMG Based Hand Prosthesis Using Neural Networks

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Abstract: ***Background***: Identifying user suitability plays a vital role in various modalities like neuromuscular system research, rehabilitation engineering and movement biomechanics. This paper analysis the user suitability based on neural networks (NN), subjects, age groups and gender for surface electromyogram (sEMG) pattern recognition system to control the myoelectric hand. Six parametric feature extraction algorithms are used to extract the features from sEMG signals such as AR (Autoregressive) Burg, AR Yule Walker, AR Covariance, AR Modified Covariance, Levinson Durbin Recursion and Linear Prediction Coefficient. The sEMG signals are modeled using Cascade Forward Back propagation Neural Network (CFBNN) and Pattern Recognition Neural Network.

Methods: sEMG signals generated from forearm muscles of the participants are collected through an sEMG acquisition system. Based on the sEMG signals, the type of movement attempted by the user is identified in the sEMG recognition module using signal processing, feature extraction and machine learning techniques. The information about the identified movement is passed to microcontroller wherein a control is developed to command the prosthetic hand to emulate the identified movement.

Results: From the six feature extraction algorithms and two neural network models used in the study, the maximum classification accuracy of 95.13% was obtained using AR Burg with Pattern Recognition Neural Network. This justifies that the Pattern Recognition Neural Network is best suited for this study as the neural network model is specially designed for pattern matching problem. Moreover, it has simple architecture and low computational complexity. AR Burg is found to be the best feature extraction technique in this study due to its high resolution for short data records and its ability to always produce a stable model. In all the neural network models, the maximum classification accuracy is obtained for subject 10 as a result of his better muscle fitness and his maximum involvement in training sessions. Subjects in the age group of 26-30 years are best suited for the study due to their better muscle contractions. Better muscle fatigue resistance has contributed for better performance of female subjects as compared to male subjects. From the single trial analysis, it can be observed that the hand close movement has achieved best recognition rate for all neural network models.

Conclusion: In this paper a study was conducted to identify user suitability for designing hand prosthesis. Data were collected from ten subjects for twelve tasks related to finger movements. The suitability of the user was identified using two neural networks with six parametric features. From the result, it was concluded thatfit women doing regular physical exercises aged between 26-30 years are best suitable for developing HMI for designing a prosthetic hand. Pattern Recognition Neural Network with AR Burg extraction features using extension movements will be a better way to design the HMI. However, Signal acquisition based on wireless method is worth considering for the future.

Keywords: Surface electromyography, autoregressive, AR Burg, AR Yule Walker, AR Covariance, AR modified covariance levinson durbin recursion, linear prediction coefficient, cascade forward backpropagation neural network, pattern recognition neural network.

1. INTRODUCTION

Upper limb amputation is a major problem in India and rest of the world. Most frequent causes of upper limb amputation are due to traumatic accidents, congenital,

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tumour followed by vascular complications of diseases. After severe accidents, amputees are unable to perform hand motion and individual finger movements properly. Individual finger motion control is important for the performance of intricate tasks in modern life, such as using a computer mouse, typing on a computer keyboard, operating a mobile phone, or operating other electronic and domestic devices. In order to give rehabilitation to amputees, prosthetic hand with excellent HMI is one of the best solutions ever. The HMI is a system that establishes a connection between human and machines. The communication channel provided by HMI can help people manipulate a machine. sEMG based prosthetic hand is a kind of typical HMI device for the people with upper limb amputation. Prosthetic hand can help them recover some of its functions [1, 2].

2. RESEARCH BACKGROUND

(Ahsan *et al.*, 2012) proposed seven feature extraction techniques for feature extractions like MAV, RMS, VAR, SD, ZC, SSC and WL. Hand motion was acquired from forearm muscles. BPANN with Levenberg-Marquardt training algorithm was deployed for pattern classification. Highest classification accuracy of 89.2% was obtained from BPANN [3]. (Arnav Gupta *et al.*, 2012) used WT and NN for detection of myopathic signal. WT was used to extract the features from an EMG. It included decomposing the EMG signal into different levels to generate the coefficients. Signals were obtained from 6 myopathic patients and 10 normal subjects using needle electrodes. Elbow flexion and forearm supination were extracted from biceps brachii muscles. SOFM and LVQ neural networks were constructed for pattern identification from extracted coefficients. LVQ fared better between the two with a lowest accuracy of 83.33% whereas SOFM had accuracy as low as 40.00% [4].

(Mohammed Z. Al-Faiz *et al.*, 2013) proposed discriminant analysis for human arm motion prediction and classification. EMG data were simulated as the subject underwent seven distinct limb motions: hand open, hand close, supination, pronation, wrist flexion, wrist extension, and rest. These data were simulated from simulation of seven sites on the forearm and one site on the bicep. The first four autoregressive coefficients and the root mean square value were used as the feature vector. A comparison between the LDA and KNN algorithm was made for the classification of upper arm motions. The obtained results demonstrated superior performance of LDA to k-NN. The average accuracy obtained was 65% [5]. Body-powered prosthetic hands control was proposed by (Fathia H. A. Salem *et al.*, 2013). They collected the EMG signal from the residual limb muscle of amputees. The collected signals were treated as sounds and saved as MAT files. Absolute value was used for feature extraction. The collected data was classified using fuzzy control method and downloaded to the Digital Signal Processor (DSP) [6].

(Mehmet RecepBozkurt *et al.*, 2016) compared AR parametric methods with subspace-based methods for EMG signal classification using neural network models. EMG was recorded from the biceps brachii muscle using a concentric needle electrode and an EMG measurement system. The signal was sampled at 20 kHz. EMG collected from 7 healthy, 7 Myopathic, and 13 neurogenic disordered people. AR parametric methods (Burg, Covariance, Modified Covariance and Yule- Walker) and subspace-based methods (MUSIC, Eigenvector) were used as extractors. Feed-Forward Error Back-Propagation Artificial Neural Network (FEBANN) and Combined Neural Network (CNN) were used for classification in which success rate was slightly higher in CNN. Within the different AR and sub-space methods that were used in this study, the highest performance was obtained using Eigen Vector method.

From the survey, it can be clouded that many of researchers have analyzed classification based results only. In this study, we explore the suitability of user based on network, subject, age group, gender for designing hand prosthesis using neural networks.

3. METHODOLOGY

sEMG signals generated from forearm muscles of the participants are collected through an sEMG acquisition system. Based on the sEMG signals, the type of movement attempted by the user is identified in the sEMG recognition module using signal processing, feature extraction and machine learning techniques. The information about the identified movement is passed to microcontroller wherein a control is developed to command the prosthetic hand to emulate the identified movement.sEMG recognition system is shown in Fig. (**1**).

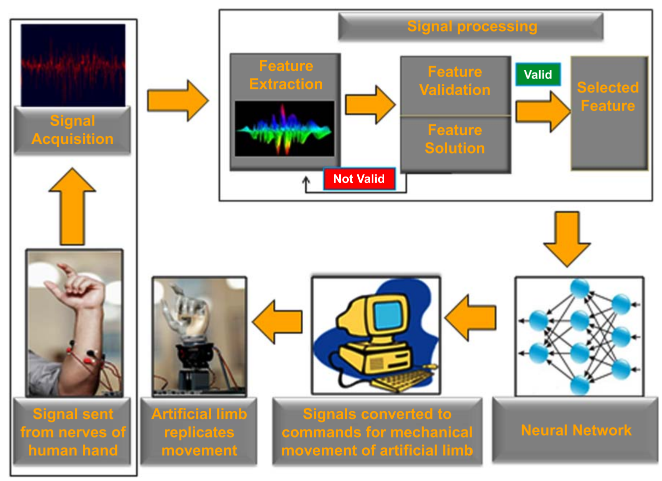

Fig. (1). sEMG recognition system.

4. MATERIALS AND METHODS

4.1. Experimental Protocol

In order to validate the protocol, a preliminary study was conducted. In this initial study, five subjects were recruited. Sixteen movements (12 hands, 4 wrists) were chosen for an initial experimentation. Preliminary studies showed that the wrist movements like wrist flexion, wrist extension, ulnar deviation and radial deviation are quite difficult to be performed by some subjects. Therefore, twelve hand movement tasks namely hand opening, hand closing, thumb extension, thumb flexion, index finger extension, index finger flexion, middle finger extension, middle finger flexion, ring finger extension, ring finger flexion, little finger extension and little finger flexion are performed by each subject during the signal acquisition which are shown in Fig. (**2**).

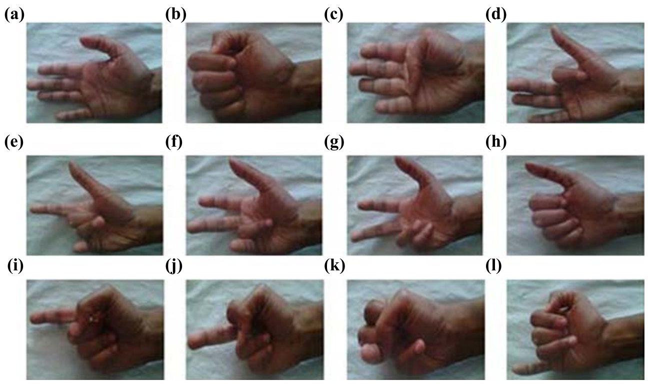

Fig. (2). Twelve different finger movements (**a**) open, (**b**) close, (**c**) thumb flexion, (**d**) index flexion, (**e**) middle flexion, (**f**) ring flexion, (**g**) little flexion, (**h**) thumb extension, (**i**) index extension, (**j**) middle extension, (**k**) ring extension, (**l**) little extension.

After the skin was cleaned, five gold plated cup shaped surface electrodes were placed above right forearm (flexor digitorum superficial and extensor digitorum muscles) to detect hand and ground electrode was placed on the bony surface of forearm which is shown in Fig. (**3**). The subjects were instructed to execute twelve different movement tasks which are given below. Subjects were seated in a comfortable chair in front of a computer with the Lab View interface screen, to see all the sEMG channels in real-time while performing the movements [7-9]. The room used for the experiment did not have any special acoustic control. During signal acquisition, a notch filter was applied to remove the 50 Hz power line artifacts.

All subjects who participated in the experiments were healthy university students aged between 21 to 40 years who voluntarily participated in the study. The protocol for signal acquisition for twelve tasks is detailed below.

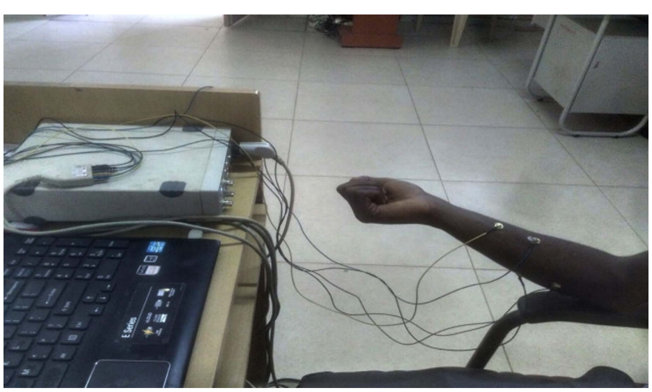

Fig. (3). Equipment setup during sEMG signal acquisition.

Thumb flexion: The subjects were asked to move their thumb towards their palm while keeping other fingers in open position. Flexor digitorum superficialis muscle is involved in this movement.

Thumb extension: From the folded position, the subjects were instructed to outstretch their thumb while keeping other fingers relaxed. Extensor digitorum muscle is accountable for this movement.

Indexfinger flexion: This movement is accomplished by moving the index finger towards their palm while keeping other fingers in open position. Flexor digitorum superficialis muscle is responsible for this movement.

Index finger extension: From the folded position, the index finger was unfolded while keeping other fingers in open position. Extensor digitorum muscle is accountable for this movement.

Middle finger flexion: The subjects were asked to move their middle finger towards their palm while keeping other fingers in relaxed. Flexor digitorum superficialis muscle is involved in this movement.

Middle finger extension: From the folded position, the subjects were instructed to outstretch their middle finger, while keeping other fingers relaxed. Extensor digitorum muscle is involved in this task.

Ring finger flexion: This movement was accomplished by moving the ring finger towards their palm while keeping other fingers in relaxed state. Flexor digitorum superficialis muscle is responsible for this movement.

Ring finger extension: From the folded position, the subjects were instructed to outstretch their ring finger, while keeping other fingers relaxed. Extensor digitorum muscle is accountable for this movement.

Little finger flexion: The subjects were asked to move their little finger towards their palm while keeping other fingers in relaxed state. Flexor digitorum superficialis muscle is involved in this movement.

Little finger extension: From the folded position, the subjects were instructed to outstretch their little finger, while keeping other fingers relaxed. Extensor digitorum muscle is accountable for this task.

Hand close: The subjects were requested to flex all their fingers to make a fist. Flexor digitorum superficialis muscle is involved in this task.

Hand open: The subjects were requested to open the fist. Extensor digitorum muscle is involved in this task.

4.2. Data Collection

For each subject, a data set consisting of 120 sets (12 tasks x 10 trials per task) of sEMG signals were formulated. Acquired sEMG signal for close movement is shown in Fig. (**4**). The datasets of all the subjects were combined and a master data set consisting of 1200 trials of sEMG signals was created as shown in Table **1**.

4.3. Features Extraction

In this study, we have used six Power Spectral Density (PSD) feature extraction methods to extract the features from pre-processed raw sEMG signals. PSD features are Autoregressive (AR) Burg, AR Yule Walker, AR Covariance, AR Modified Covariance, Levinson Durbin Recursion, and Lin-

Table 1. Data collection details.

Subjects	Tasks	Sampling Frequency (Hz)	Time Duration (Seconds)	Trials	Data Sets	
					Per Subject	Total Dataset
10	12	400	5	10	12x10=120	10x120=1200

Table 2. Networks design model.

S. No.	Design Modelled Using	Transfer Function	Training Algorithm
1	AR Burg	Sigmoid Function	Levenberg-Marquardt back propagation
2	AR Yule-Walker	Sigmoid Function	Levenberg-Marquardt back propagation
3	AR Covariance	Sigmoid Function	Levenberg-Marquardt back propagation
4	AR Modified Covariance	Sigmoid Function	Levenberg-Marquardt back propagation
5	Levinson Durbin Recursion	Sigmoid Function	Levenberg-Marquardt back propagation
6	LPC	Sigmoid Function	Levenberg-Marquardt back propagation

ear Prediction Coefficient (LPC) [10, 11]. In all the six, the feature extraction techniques model order was fixed as 4 for better accuracy based on trial and error process and ten features were extracted for each task per trial. A total dataset consisting of 120 data samples for each subject was obtained to train and test the neural network.

4.4. Signal Classification

Exacted features are classified using two neural networks such as Cascade Forward Backpropagation Neural Network (CFBNN) and Pattern Recognition Neural Network [12-14]. Pattern net and CFBNN are modelled using six feature extraction methods which are shown in Table **2**. Both networks are designed ten input neurons, ten hidden neurons and four output neurons to identify the twelve hand movements. The learning rate is chosen as 0.0001. Training is conducted until the average error falls below 0.001 or reaches maximum iteration limit of 1000 and testing error tolerance is fixed at 0.1 [15].

4.5. Offline Analysis Using Graphical User Interface (GUI)

The performance of a twelve state HMI systems is verified through offline analysis to determine the accuracy of the HMI system using the GUI which is demonstrated in Fig. (**4**). Individual performance of designing a twelve state HMI is evaluated by using GUI. The tested and trained feature sets obtained from the ten trials for each task from each individual subjects are classified and categorized into twelve different hand movement tasks using the GUI to validate the possibilities of designing a twelve state HMI.

5. RESULT AND DISCUSSIONS

5.1. Classification Result

From Pattern net classification result it is observed that AR Burg outdid the other feature sets with the highest mean accuracy of 95.13% for subject 10 and the lowest mean accuracy of 91.46% for subject 7. The next best performance was observed for the AR Yule feature set at 93.88% for subject 10 and the lowest mean accuracy for the same feature set was 92.50% for subject 7. Similarly, CFBNN for the six parametric features, from the result it is evident that AR Burg again outperformed other feature sets with the highest mean accuracy of 94.67% for subject 10 and the lowest mean accuracy of 90.50% for subject 7. In network based classification, Pattern net are identified pattern well this is because of good tolerance to input noise.

5.2. Gender Based Classification

It is observed that the mean accuracy range for the female subjects with Pattern Recognition Neural Network varies from 92.49% to 94.16% and mean accuracy range for the male subjects with Pattern Recognition Neural Network varies from 92.17% to 93.71% as shown in Fig. (**4**) and Table **3**.

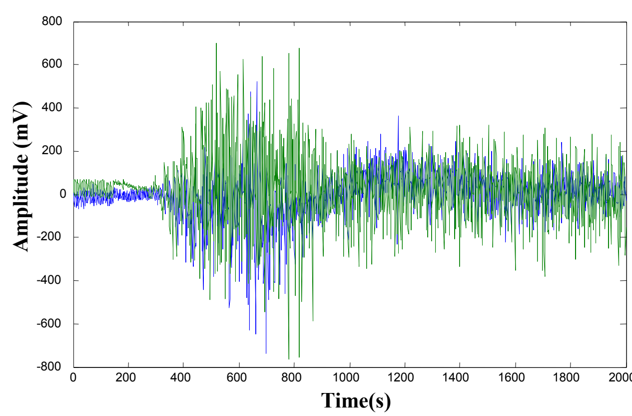

Fig. (4). Acquired sEMG signal for close movement.

Similarly, it is observed that the mean accuracy range for the female subjects with CFBNN varies from 91.85% to 93.99% and mean accuracy range for the male subjects with CFBNN varies from 91.35% to 93.50% to as shown in Fig. (**5**) and Table **4**.

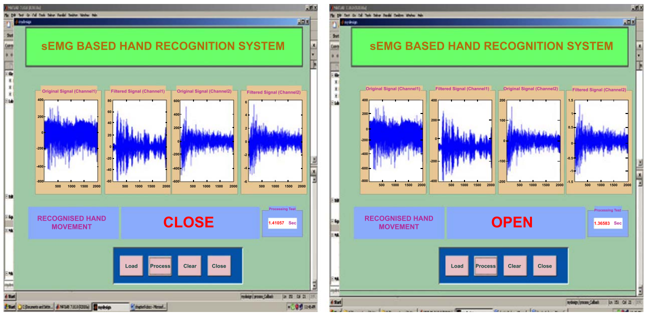

Fig. (5). Single trial analysis result evaluation using GUI for hand close and hand open movements.

5.3. Age Group Based Classification

The performance results are shown in Fig. (**6**) and Table **5**. From the Figure, mean accuracy range for the subjects in the age group 21-25 yrs with Pattern Recognition Neural Network were between 92.08% to 93.56%; age group 26-30 yrs between 92.78% to 94.66% and for age group 31-40 yrs between 91.79% to 93.12%. The highest performance accuracies were again observed for the AR Burg feature sets.

Table 3. Gender based classification rate of patten net neural networks using six PSD feature extraction methods.

Features	Gender Group for Patten Net (Mean Accuracy in %)	
	Female	**Male**
AR Burg	94.16	93.71
AR Yule-Walker	93.51	93.27
AR Cov	93.19	92.9
AR Mcov	93.06	92.7
Levinson Durbin Recursion	92.81	92.27
LPC	92.49	92.17

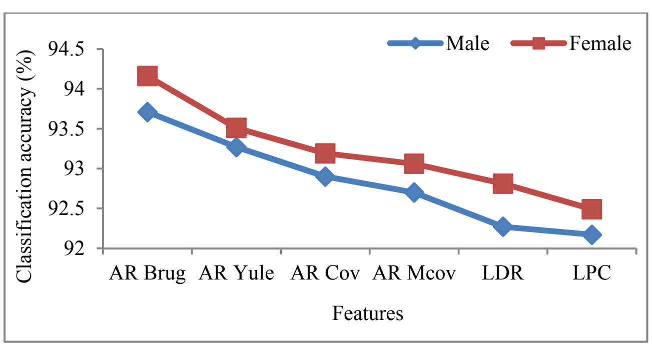

Fig. (6). Gender based classification for pattern recognition neural network using six PSD features.

The performance results are shown in Fig. (**7**) and Table **6**. From the Figure, mean accuracy range for the subjects in the age group 21-25 yrs with CFBNN were between 91.22% to 93.44%; age group 26-30 yrs between 92.24% to 94.36% and for age group 31-40 yrs between 90.96% to 92.75%. The highest performance accuracies were again observed for the AR Burg feature sets.

Table 4. Age Group based classification rate of CFBNN using six PSD feature extraction methods.

Features	Gender Group for CFBNN (Mean Accuracy in %)	
	Female	**Male**
AR Burg	93.99	93.5
AR Yule-Walker	92.89	92.51
AR Cov	92.75	92.33
AR Mcov	92.6	92.12
Levinson Durbin Recursion	92.27	91.87
LPC	91.85	91.35

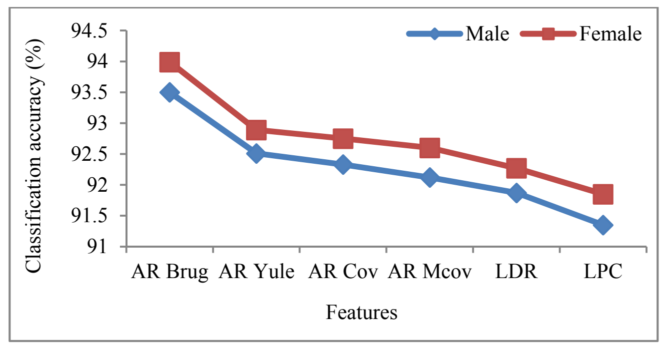

Fig. (7). Gender based classification for CFBNN using six PSD features.

Table 5. Age group based classification rate of pattern recognition neural network using six PSD feature extraction methods.

Features	Age Group (Mean Accuracy in %)		
	21-25 yrs	**26-30 yrs**	**31-40 yrs**
AR Burg	93.56	94.66	93.12
AR Yule-Walker	93.24	93.67	93
AR Cov	92.85	93.4	92.44
AR Mcov	92.63	93.35	92.29
Levinson Durbin Recursion	92.19	93.13	91.79
LPC	92.08	92.78	91.79

5.4. Single Trial Analysis

From the single trail result, it is observed that the mean accuracy range for the female subjects with Pattern Recognition Neural Network varies from 92.49% to 94.16% and mean accuracy range for the male subjects with Pattern Recognition Neural Network varies from 92.17% to 93.71% as shown in Fig. (**8**).

The gender based classification results for CFBNN are shown in Fig. (**9**). From the Figure, it is observed that the mean accuracy range for the female subjects with CFBNN varies from 91.85% to 93.99% and mean accuracy range for the male subjects with CFBNN varies from 91.35% to 93.50%.

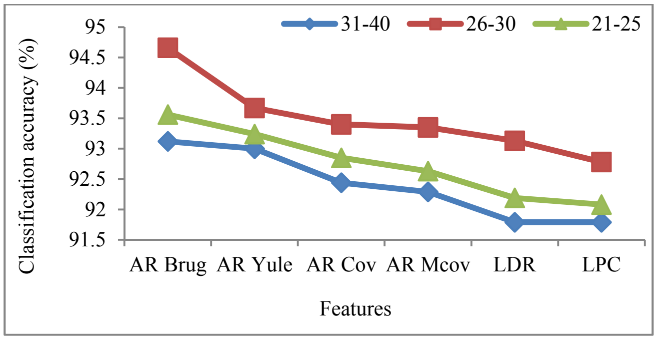

Fig. (8). Age group based classification for pattern recognition neural network using six PSD features.

Table 6. Age group based classification rate of CFBNN using six PSD feature extraction methods.

Features	Age Group (Mean Accuracy in %)		
	21-25 yrs	26-30 yrs	31-40 yrs
AR Burg	93.44	94.36	92.75
AR Yule-Walker	92.48	93.18	91.79
AR Cov	92.29	93.07	91.62
AR Mcov	92.04	92.97	91.5
Levinson Durbin Recursion	91.76	92.67	91.37
LPC	91.22	92.24	90.96

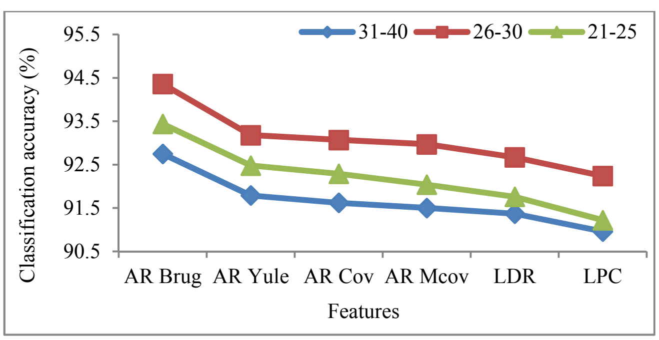

Fig. (9). Age group based classification for CFBNN using six PSD features.

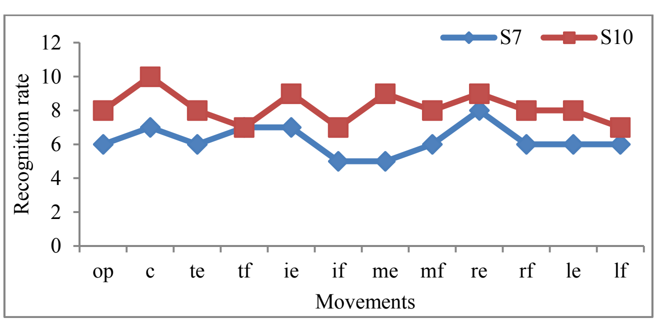

Fig. (10). Single trail analysis for pattern recognition neural network using AR burg features.

From the six feature extraction algorithms and two neural network models used in the study, the maximum classification accuracy of 95.13% was obtained using AR Burg with Pattern Recognition Neural Network. This justifies that the Pattern Recognition Neural Network is best suited for this study as the neural network model is specially designed for pattern matching problem [16]. Moreover, it has simple architecture and low computational complexity.AR Burg is found to be the best feature extraction technique in this study due to its high resolution for short data records and its ability to always produce a stable model. In all the neural network models, the maximum classification accuracy is obtained for subject 10 as a result of his better muscle fitness and his maximum involvement in training sessions. Subjects in the age group of 26-30 years are best suited for the study due to their better muscle contractions. Better muscle fatigue resistance has contributed for better performance of female subjects as compared to male subjects. From the single trial analysis, it can be observed that the hand close movement has achieved best recognition rate for all neural network models as shown in Fig. (**10**).

CONCLUSION

In this paper a study was conducted to identify user suitability for designing hand prosthesis. Data were collected from ten subjects for twelve tasks related to finger movements. The suitability of the user was identified using two neural networks with six parametric features. From the result, it was concluded thatfit women doing regular physical exercises aged between 26-30 years are best suitable for developing HMI for designing a prosthetic hand. Pattern Recognition Neural Network with AR Burg extraction features using extension movements will be a better way to design the HMI. However, Signal acquisition based on wireless method is worth considering for the future.

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

All the experimental procedures were carried out in Human Machine Interface Cluster of Karpagam Academy of Higher Education (Deemed to be University) after University Ethical committee's approval, and strictly followed the rules and regulations of the University and Government of India for performing safe Human trials.

HUMAN AND ANIMAL RIGHTS

All research procedures followed were in accordance with the ethical standards of the committee responsible for human experimentation (institutional and national), and with the Helsinki Declaration of 1975, as revised in 2008 (http://www.wma.net/en/20activities/10ethics/10helsinki/)

CONSENT FOR PUBLICATION

All participants provided informed consent.

AVAILABILITY OF DATA AND MATERIALS

Not applicable.

FUNDING

None.

CONFLICT OF INTEREST

The authors declare no conflict of interest, financial or otherwise.

ACKNOWLEDGEMENTS

Declared none.

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