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IDENTIFYING HAND GESTURES USING SEMG FOR HUMAN MACHINE INTERACTION

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ABSTRACT

Surface Electromyographic signals (sEMG) have emerged as a normal gadget for rehabilitation functions, medical analysis, and likewise as a source for manipulate of prosthetic and assistive instruments. It can be determined that EMG alerts showcase certain patterns for specified hobbies of the muscle. The right recognizance of the sample helps in greater manipulate of assistive gadgets for helping movement. This paper offers the growth of a neural networks classifier for classifying the one-of-a-variety hand moves of human forearm. Experiments are performed on the extensor digitorum and flexor digitorum superficial muscle of the right hand. Ten subjects are asked to participate in voluntary contractions with admire to the concerned muscle. From the obtained sEMG data, six parametric feature extraction techniques are used as function extracted and cascade forward back propagation neural network (CFBPNN), pattern recognizance network are utilized to gestures identifications. The classifier is learned to discriminate the patterns with an average classification accuracy of 95.13% for pattern recognizance network using auto regressive burg. The offline results showed that bit transfer rate (BTR) achieved highest value of 37.71 bits/sec.

Keywords: surface electromyographic, cascade forward back propagation neural network, pattern recognizance network, bit transfer rate.

1. INTRODUCTION

Human machine interface (HMI) techniques are described in as self-discipline which goals to make humans control or communicate with desktops or other instruments by using biosignals. On this sort of HMI methods, electrical activity of the muscular tissues are obtained by means of a biopotential amplifier then processed and categorized to generate easy commands to manipulate the prosthetic gadget [1]. Disabled men and women may experience severe challenge while using assistive prosthetic devices or robots which has natural person interfaces. HMI systems which might be managed by myoelectric alerts provide an opportunity for disabled individuals to make use of devices which facilitate their life.

After the discovery of electromyographic (EMG) sign, it has been generally used in biorobots manipulate and every other fields comparable to rehabilitation, human body motion detection and athlete training [3, 4]. The character feature of the EMG sign, which directly represent for the activation potentials of skeleton muscle, makes it very handy and direct in representing popularity of muscle groups. The analysis of EMG helps to a specified extent, to become aware of the human intention for action, and hence can be used as a supply of manipulate signal to force assistive mechanisms, for supporting the disabled and the elderly for their everyday movements and for rehabilitation functions [5, 6].

There are two forms of EMG: intramuscular EMG and surface EMG (sEMG). Intramuscular type involves the insertion of needle electrode or first-rate-wire by means of the dermis into the muscle; whereas surface sort includes putting of electrodes on the dermis over the muscle, to realize its electrical exercise. Though intramuscular EMG is incredibly touchy, files single muscle exercise with little cross-talks, and has entry to deep musculature, several factors like need of a medical expert to acquire EMG, problem in making a choice on detection field consultant of the entire muscle, and impossibility of repositioning of electrodes, make it complex to use for data acquisition. For that reason, floor EMG is preferred for EMG sign acquisition as it is non-invasive, riskless, and effortless to manage with minimal discomfort and without scientific supervision, although it has pass-talk issues. A couple of varieties of noises may just have an effect on the measurement of EMG signals. Fundamental types of noise, artifacts and interference in the recorded floor EMG signal are electrode and cable motion artifacts, ac power line interference and different noises such as broadband noises from digital devices, and so forth [7, 8 and 9].

2. sEMG SIGNAL FEATURES

The forearm myogram signals are generated by acquiring muscles counting on the dimensions of skeletal muscle or skeletal muscle unit, that the signal amplitude vary and frequency vary are wide and unsure. The everyday amplitude of associate myogram signal vary is between 0 mV and 10 mV (peak-to-peak). The everyday frequency of associate myogram signal is between 0 Hz and 500 Hz. However, the ability of forearm myogram signal is focused within the band between 30 Hz and 150 Hz [2].

3. BACKGROUND

Many researchers area unit engaged on EMG-based devices vogue, like Christian Antfolk projected a distinct between 3 pattern matching algorithms for cryptography finger motions exploitation sEMG. Twelve electrodes were settled on the superficial flexor muscles. Four electrodes were positioned on the superficial extensor muscles of the higher arm. Thirteen hand movements were

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categoryified during this study like rest class, thumb flexion, thumb extension, index finger flexion, index finger extension, middle finger flexion, middle finger extension, ring finger flexion, ring finger extension, pinkie finger flexion, pinkie finger extension, thumb opposition and thumb abduction. Feature extracted by using Mean Absolute Values (MAV) and LDA (Linear Discriminate Analysis), k-nn, MLP (Multi-layer perceptron) were used as classifiers. Highest classification accuracy of 80.66% was achieved by LDA [10].

Jingdong Zhao presents sEMG based five-fingered under actuated prosthetic hand controlled. sEMG signals were measured through 3 electrodes mounted on the flexor digitorum profundus, flexor pollicis longus and extensor digitorum. sEMG motion pattern classifier which combines variable learning rate (VLR) based neural network with parametric Autoregressive (AR) model and wavelet transform. This motion pattern classifier can successfully identify flexion and extension of the thumb, the index finger and the middle finger. Furthermore, via continuously controlling single finger's motion, the five-fingered under actuated prosthetic hand can achieve more prehensile postures such as power grasp, centralized grip, fingertip grasp and cylindrical grasp. The experimental results show that the classifier has a great potential application to the control of bionic man-machine systems because of its fast learning speed, high recognition capability [11].

Ali H proposes classification of finger movements for dexterous control of prosthetic hands. sEMG channels were recorded from ten intact-limbed and six below-elbow amputee persons. The results show that high classification accuracies achieved time domain-auto regression feature extraction with orthogonal fuzzy neighborhood discriminate analysis. It was also found that highest accuracy of 98% over ten intact limbed subjects for the classification of 15 classes of different finger movements [12]. Pradeep Shenoy investigates the use of forearm surface EMG signals for real time control of a robotic arm. Eight electrodes were placed in the form arm to acquired signals. Data collected from 3 subjects over 5 sessions each. Subjects were performed grasp-release, left-right, up-down, and rotate task to generate EMG signals. RMS amplitude used as a feature and Linear Support Vector Machines used as a classifier. Classification-based paradigms for myoelectric control to obtain high accuracy 92-98% [13].

A. Phinyomark presents the findings of a comparative study of classical LDA and extended LDA methods. Four EMG channels were placed on the extensor carpi radialis longus muscle, extensor carpi ulnaris muscle, extensor digitorum communis muscle and flexor carpi radialis muscle of the right forearm. Each subject generated eight different movement classes: forearm pronation, forearm supination, wrist extension, wrist flexion, wrist radial deviation, wrist ulnar deviation, hand open and hand close. From the results extended LDA methods achieved maximum classification accuracy of 95.2% compare to classical LDA [14].

This paper, investigated the possibility of recognizing twelve hand gestures using two classification algorithms namely pattern recognizance neural network and cascade forward back propagation neural network. Performances of the six parametric feature extraction techniques are compared using two neural networks to validate the results.

4. MATERIALS AND METHODS

sEMG based hand prosthesis system consists following four step such signal acquisition, signal preprocessing, feature extraction, classification as shown in Figure-1.

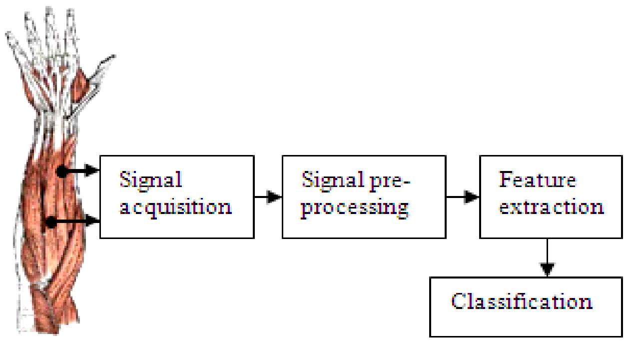

Figure-1. Over review of sEMG recognized system.

A. Signal acquisition

1) Gestures for arm control: The following tasks were performed by each subjects such as opening hand, closing hand, thumb extension, thumb flexion, index extension, index flexion, middle extension, middle flexion, ring extension, ring flexion, little extension and little flexion which are shown in Figure-2.

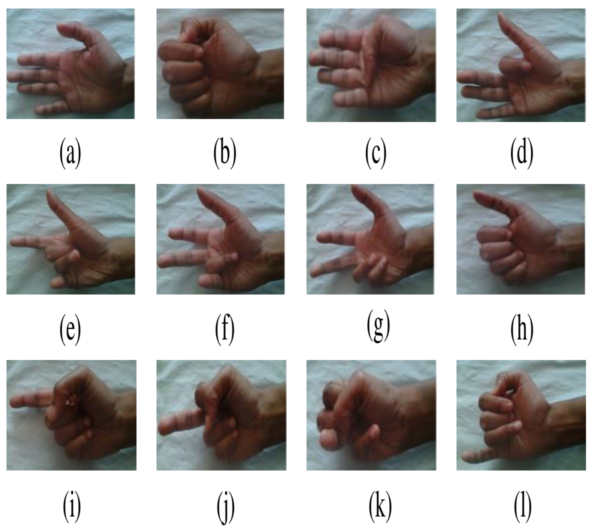

Figure-2. Twelve different finger movements (a)open, (b)close, (c)thumb flexion, (d)index flexion, (e)middle flexion, (f)ring flexion, (g)little flexion, (h) thumb extension, (i) index extension, (j) middle extension, (k) ring extension, (l) little extension.

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2) Electrode placement: sEMG signals were extracted using AD Instrument bio signal amplifier. The sEMG signal was acquired from flexor digitorum superficialis and extensor digitorum muscle of the healthy Subject by five gold plated, cup shaped Ag-AgCl electrodes are placed the over the right forearm[15, 16]. Each electrode was detached from the other by 2 cm. Ground electrode was located in bony surface. Forearm electrode placement is shown in Figure-3.

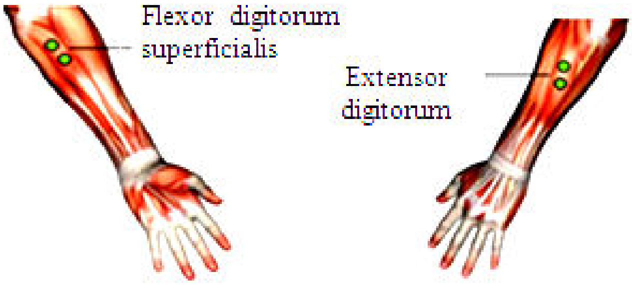

Figure-3. Electrode placement for sEMG system.

3) Data collection: sEMG signals evoked through the twelve tasks were recorded. Each recording trial lasted for 5seconds. Ten trials were recorded for each task. Subjects were given an interval of five minutes between the trials and data collected in two sessions. Each session lasted five trials per each task. 120 data sets were acquired per each subject and a total of 1200 data samples from 10 subjects. Seven of the ten subjects were male while three were female. The EMG signals was sampled at 400 Hz. All subjects who participated in the experimental study were karpagam University students and faculty members aged between 21 and 40 years. All the Subjects participated voluntarily in the study. It was ensured that all participants were healthy and free from medication during the course of the study. During the signal acquisition, a notch filter was applied to eliminate the 50Hz power line noise.

B. Spectral analysis

The spectral of the raw signals is studied using Short-Time Fourier Transform (STFT) to identify the frequency components for hand movement. STFT algorithm is applied to identify the phase content and sinusoidal frequency of a signal as it changes for different time intervals [17]. From the Figure-4, it was observed that dominant frequency range is from 0.1-150Hz for twelve different hand movements of subject10.

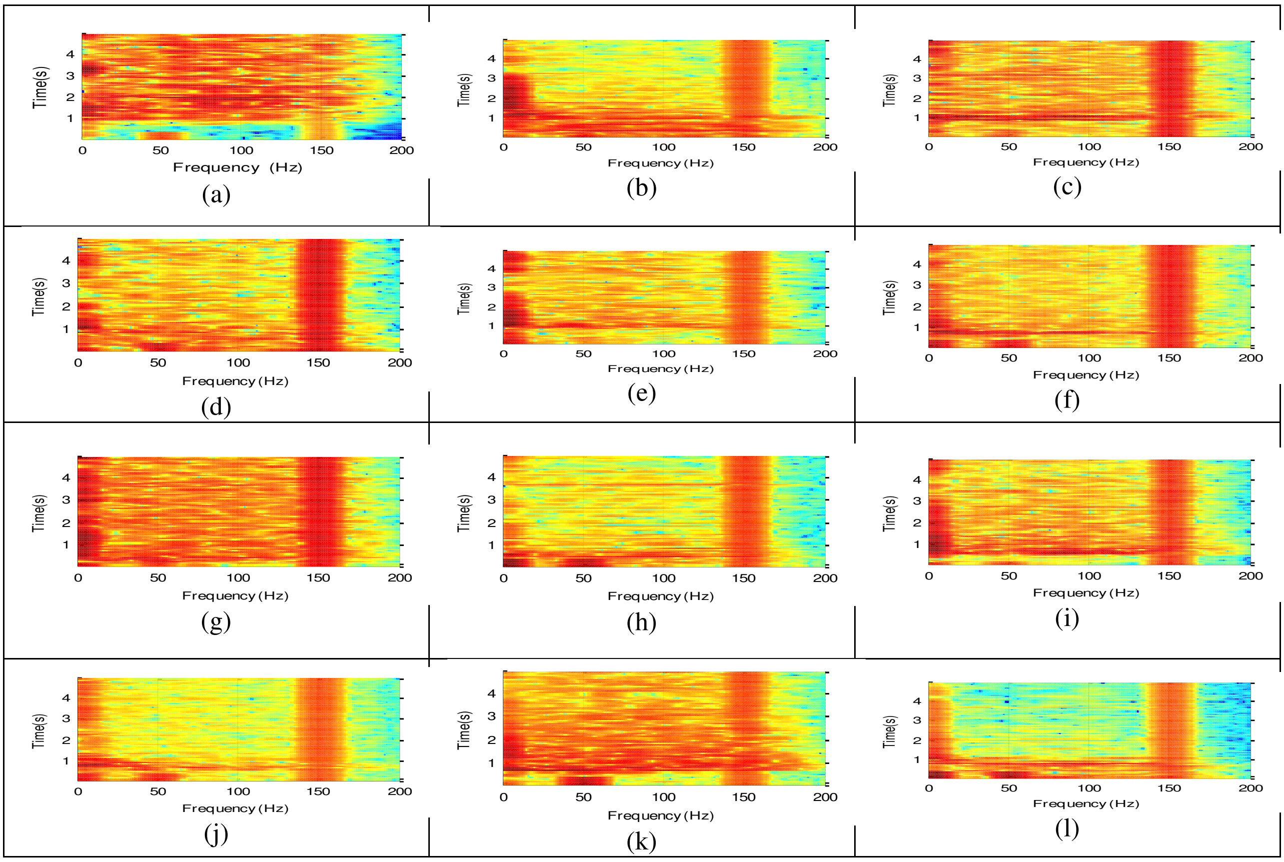

Figure 4. Spectrogram of subject 10 for twelve different finger movements (a) close, (b) open, (c) thumb flexion, (d) thumb extension, (e) index flexion, (f) index extension, (g) middle flexion, (h) middle extension, (i) ring flexion, (j) ring extension, (k) little flexion, (l) little extension.

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C. Preprocessing

The raw sEMG signals are processed to extract the features. sEMG signals related to this study falls in the range of 0-500 Hz, however the predominant frequency lies in the interval of 10-150 Hz [18]. A band pass filter is used to extract the frequency. This process also removes the artifacts due ambient noise, transducer noise. Five frequency bands were extracted using chebyshev filter to split the signal in the range of 45 Hz. The five frequency ranges are (0.1-45) Hz, (45-90) Hz, (90-135) Hz, (135-180) Hz, (180-199) Hz. The preprocessed sEMG signals are then applied to the feature extraction stage.

D. Power spectral density features and their estimation

The parametric spectrum estimation (PSD) depends on the previous information of the system. Generally used parametric method is the AR method. For the AR method the coefficient of a signal at particular instance is derived by adding the coefficient of the past samples and summing the error estimation [19, 20, 21 and 22]. pth model order of Autoregressive (AR) process is given by

$$x[n] = -\sum_{k=1}^{p} a_k \ x[n-k] + e(n) \tag{1}$$

Where a_k indicates AR coefficients, *p* indicates the model order, x(n) represents sEMG signal at the sampled point n and e(n) indicates the error term independent of previous samples [23, 24]. Thus, in order to obtain the estimates of AR coefficient a_k we have used six feature extraction algorithms such as AR Burg, AR Yule Walker, AR Covariance, AR Modified Covariance, Levinson Durbin Recursion and Linear Prediction Coefficient.

1) AR burg method: This method uses least squares sense techniques to minimize the forward and backward prediction errors for identifying AR coefficients by fitting AR model to the sEMG signals [19, 20]. The major benefits of the Burg estimation are high frequency resolution, stability and very efficient computation. The burg method generates the reflection coefficient automatically without the interference of autocorrelation function. The PSD is obtained by solving the normal equations.

$$\hat{p}_{burg}(f) = \frac{\hat{e}_p}{\left|1 + \sum_{k=1}^{p} a_k \exp(-j2\pi fk)\right|^2} \tag{2}$$

2) AR yule-walker method*:* This method uses least squares sense techniques to minimize the forward prediction errors for identifying AR coefficients by fitting AR model to the sEMG signals. Biased estimates of the signal's autocorrelation function are also used to calculate coefficients. AR yule walker techniques at all times gives a stable output for all pole model. The PSD is obtained by solving the normal equations [19, 20].

$$\hat{p}_{yule}(f) = \frac{\hat{\sigma}^2}{\left|1+\sum_{k=1}^{p} a_k \exp(-j2\pi fk)\right|^2} \tag{3}$$

3) AR Covariance method: This method uses least squares sense techniques to minimize the forward prediction errors for identifying AR coefficients by fitting AR model to the sEMG signals. Comparing to the Yule-Walker AR estimation Covariance AR estimation produces higher resolution spectrum for short data records. The linear equation is solved in order to obtain the results of the covariance techniques [19, 20],

$$\hat{p}_{cov}(f) = \frac{\hat{\sigma}^2}{\left|1+\sum_{k=1}^{p} a_k \exp(-j2\pi fk)\right|^2} \tag{4}$$

In this method, for calculating autocorrelation matrix windowing is not necessary.

4) AR modified covariance method: This method uses least squares sense techniques to minimize the forward and backward prediction errors for identifying AR coefficients by fitting AR model to the sEMG signals [19, 20]. The linear equation is solved in order to obtain the results of the modified covariance techniques.

$$\hat{p}_{mcov}(f) = \frac{\hat{\sigma}^2}{\left|1+\sum_{k=1}^{p} a_k \exp(-j2\pi fk)\right|^2} \tag{5}$$

5) Levinson-Durbin recursive algorithm: An alternative technique of evaluating the AR coefficients is provided by Levinson-Durbin recursive algorithm. The method utilizes the important property that the coefficient of an AR (k) process can be evaluated from the parameters of the AR (k-1) plus k value of the auto correlation function. First order AR coefficient of the signal is first obtained and from these, the algorithm proceeds recursively up to the order p [25].

6) Linear prediction coefficient analysis (LPC): In sEMG modeled LPC, every coefficient is evaluated as linear weighted sum of the previous *p* coefficients, where *p* indicates prediction order. If x (n) is the current coefficient, then it is foreseen by the previous *p* coefficients as

$$\hat{x}(n) = -\sum_{k=1}^{p} a_k \, x(n-k) \tag{6}$$

Levinson-Durbin recursive algorithm is used to calculate a liner prediction coefficient which is known as LPC analysis [26, 27].

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.

E. Signal classification

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Neural networks acquire knowledge of the environment through a process of learning which analytically changes the synaptic weights of the network to attain a desired design objective [28, 29]. In this study, we use cascade forward back propagation neural network, pattern-net neural network to classify the sEMG data signals.

Cascade forward back propagation model (CFBPNN) shown in Figure-5 is analogues to feed-forward networks, but include a weight connection from the input to each layer and from each layer to the successive layers. Cascade forward back propagation ANN model is similar to feed forward back propagation neural network in using the back propagation algorithm for weights updating, however the most symptom of this network is that every layer of neurons associated with all previous layer of neurons [30, 31, 32 and 33].

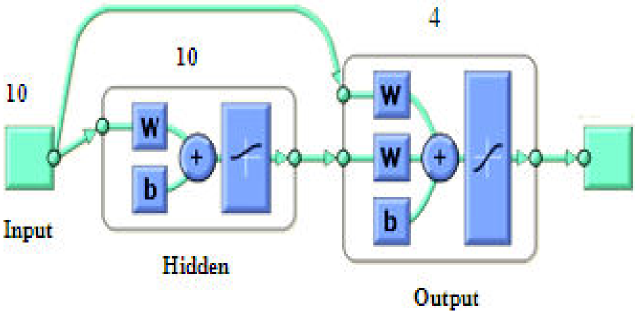

Figure-5. Cascade feed forward neural network model.

A feed forward back propagation based pattern recognizance neural network is used in this work for classifying and recognizing the twelve different hand movements as shown Figure-6. While a pattern recognition neural network (Pattern Net) can be created for pattern recognition problems, it is a feed forward network that can be trained to classify inputs according to target classes. The target data for pattern recognition networks should consist of vectors [34, 35].

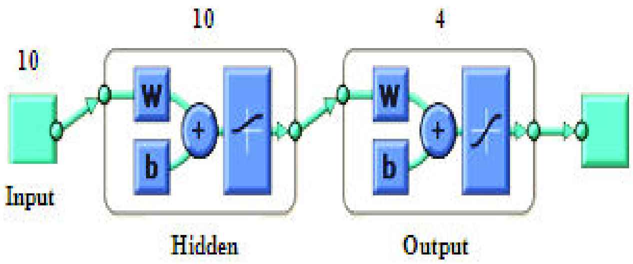

Figure-6. Pattern net neural network model.

In both networks, 75% and 100% of data are used for training and testing the neural networks consequentially. The input, output and hidden neurons are namely 10, 10, and 4 respectively to identify the hand movements. The testing error factor is set as 0.1 and the training error factor is set as 0.001.

5. RESULT AND DISCUSSIONS

A. Network based classification

The performance of the pattern net are shown in Figure-7, for the six parametric feature sets, from 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. Figure-8, depicts classification accuracy of CFBPNN 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.

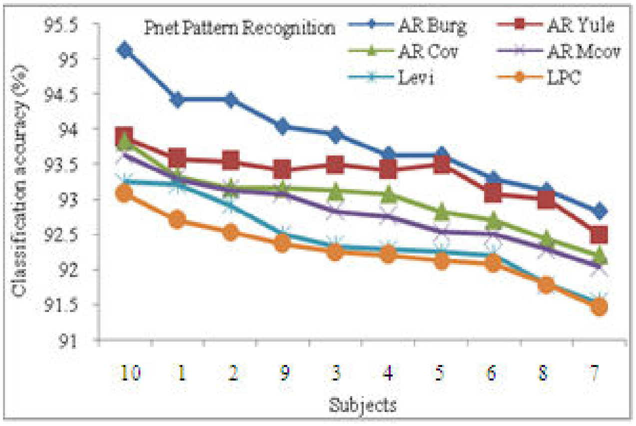

Figure-7. Pattern net neural network classification performance.

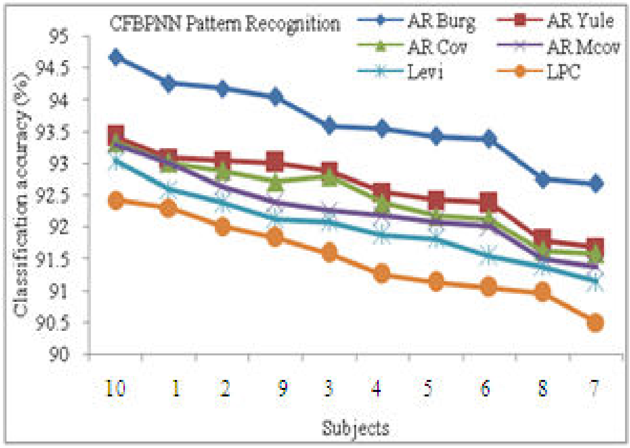

Figure-8. CFBPNN classification performance.

B. Subject based classification

From the 120 network models developed, it was seen that the data form subject 10 had obtained highest accuracy levels in the range of 92.42% to 95.13% as shown in Figure-9.

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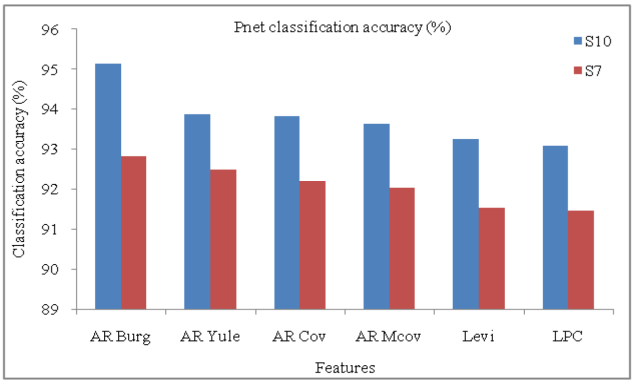

Figure-9. Classification performance for pattern net neural network using six parametric features.

The least performance accuracy was observed for subject 7 with a range of 92.83% to 90.50% as shown in Figure-10. Subject 10 had participated in the experiments for a longer period compared to other subjects. Also the muscular flexion was better in subject as he undergone fitness training on a daily basis. While subject 7 has a lanky physic. The other eight subjects are healthy subjects who did not have any regular fitness exercises.

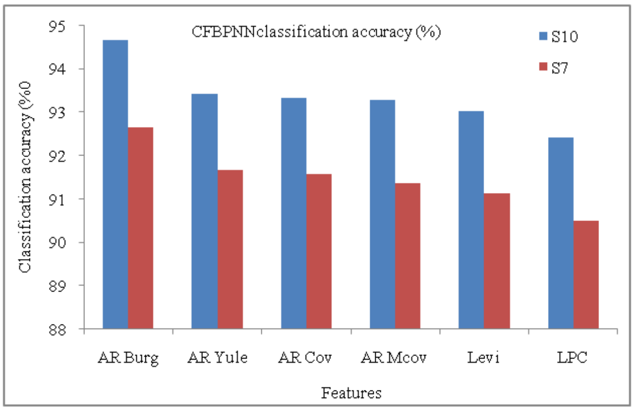

Figure-10. Classification performance for CFBPNN using six parametric features.

C. Specificity and sensitivity calculation

The true positive, true negative, false positive and false negative values are calculated; these parameters further used in calculating performance indices such as sensitivity, specificity using below equations. Results are shown in Tables 1 and 2 [36].

Specificity: Number of correctly detected negative patterns/total number of actual negative patterns.

$$\text{Specificity} = TN / TN + FP \times 100\% \quad (7)$$

Sensitivity: Number of correctly detected positive patterns/total number of actual positive patterns.

$$\text{Sensitivity} = TP / TP + FN \times 100\% \quad (8)$$

Where, TN = true negative
TP = true positive
FP = false positive
FN = false negative

From the result it is evident that highest sensitivity rate of 97% is achieved for pattern net using AR Burg for subject 10 and also highest specificity rate of 94% is achieved for pattern net using AR covariance for subject 6.

D. Bit transfer rate (BTR)

The classification accuracy was calculated in each block for each subject. Then BTR was calculated to evaluate the HMI system performance. The bit transfer rate is defined as the amount of information communicated per unit of time. This parameter encompasses speed and accuracy in a single value [37, 38]. The bit rate can be used for comparing the different HMI approaches and for the measurement of system improvements. The bit transfer rate has been calculated from equation (9).

$$\text{BTR}=\frac{60}{T_{act}}\left[\log_2 n + p_a \log_2 p_a + (1\text{-}p_a)\log_2 \frac{1\text{-}p_a}{n\text{-}1}\right] \quad (9)$$

Where, n= Number of Hand Movement
p_a= Mean Accuracy
1- p_a = Mean Recognition Error
T_{act}= Action Period (in seconds) proposed by

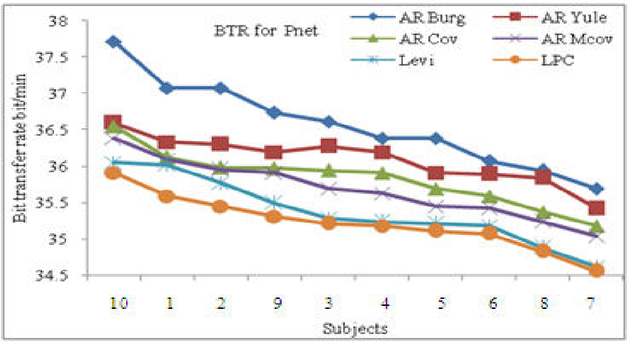

Figure-11. Bit transfer rate for pattern neural network using six parametric features.

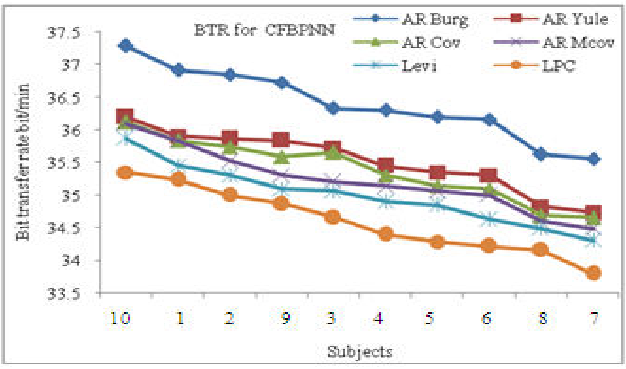

Figure-12. Bit transfer rate for CFBPNN using six parametric features.

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The bit transfer rates for CFBPNN and pattern net for six parametric features are shown in Figure-11 and Figure-12. From the results, it is observed that the highest BTR is achieved for pattern net using AR Burg with the rate of 37.71bits/sec to 34.56 bits/sec. Similarly CFFBNN is also performed well with BTR varies from 37.29 bits/sec to 33.80 bits/sec.

6. CONCLUSIONS

Identifying hand gestures using cascade feed forward neural network and pattern net are proposed in this study. Data was collected from ten subjects for twelve tasks related to finger movements. Six feature extraction algorithms namely the AR Burg, AR Yule Walker, AR Covariance, AR Modified Covariance, Levinson Durbin Recursion and Linear Prediction Coefficient were applied to the neural network for classification. From the empirical result, it was evident that the network model using pattern net and AR Burg feature is most suitable for recognizing all the twelve different finger movements with recognition rate of 95.13% and also subject 10 performed better than other subjects. It was also evident that maximum bit transfer rate of 37.71 bits/sec is achieved for Pattern net using AR Burg.

Table-1. Specificity and sensitivity calculation for six parametric features with pattern recognizance net.

S	Brug		Yule		Cov		Mcov		Levi		LPC	
	Spe (%)	Sen (%)	Spe (%)	Sen (%)	Spe (%)	Sen (%)	Spe(%)	Sen (%)	Spe(%)	Sen (%)	Spe (%)	Sen (%)
1	93	95	87	93	84	92	82	92	84	94	86	93
2	83	94	76	91	80	93	82	92	85	93	84	92
3	82	92	81	93	78	91	85	93	85	93	84	91
4	81	93	81	94	88	94	82	92	82	94	83	92
5	86	93	83	92	86	91	76	91	86	93	80	93
6	77	92	76	91	94	97	80	91	88	95	84	92
7	84	90	85	92	84	88	83	90	84	90	82	90
8	81	89	85	92	82	92	79	89	82	89	87	92
9	87	95	85	93	78	91	83	92	83	94	84	91
10	85	97	86	95	85	95	87	95	74	92	80	93

Table-2. Specificity and sensitivity calculation for six parametric features with cascade feed forward back propagation.

S	Brug		Yule		Cov		Mcov		Levi		LPC	
	Spe (%)	Sen (%)	Spe (%)	Sen (%)	Spe (%)	Sen (%)	Spe (%)	Sen (%)	Spe (%)	Sen (%)	Spe (%)	Sen (%)
1	68	89	85	93	85	93	83	92	82	92	88	95
2	75	90	88	95	88	95	81	94	84	94	87	93
3	88	93	84	92	84	92	83	90	87	94	86	91
4	86	93	83	92	83	92	83	90	81	91	83	92
5	86	93	83	92	83	92	79	93	80	91	83	92
6	91	96	81	90	81	90	90	94	89	95	83	92
7	91	94	78	88	78	88	86	91	81	89	80	86
8	83	92	82	91	82	91	82	89	88	93	83	92
9	81	91	84	92	84	92	79	93	80	91	82	92
10	88	96	86	94	86	94	88	96	82	92	80	94

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