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Recognition of sEMG for Prosthetic Control Using Static and Dynamic Neural Networks

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ABSTRACT

Several experiences were applied highlighting some great benefits of utilizing muscle sign in order to manage rehabilitation contraptions. This paper offers an investigating surface electromyography (sEMG) signal for classification of hand gestures to manipulate a prosthetic hand using neural networks. We assess the use of two channel surface electromyography to classify twelve person finger gestures for prosthetic control. sEMG alerts have been recorded from extensor digitorum and flexor digitorum superficial muscular tissues for ten subjects. Energy feature extraction techniques such as Plancherel's theorem, Singular Value Decomposition (SVD) are used as perform extracted and nonlinear autoregressive network with exogenous inputs (NARX), fitting neural network are utilized to gestures identifications. The high classification accuracies accomplished kind nonlinear autoregressive network with exogenous inputs using Plancherel's with accuracy of 92.04%. From the outcome it is determined that dynamic community outperformed than static network. Investigation moreover proved that recognition accuracy of sEMG alerts had been greater for women when evaluate to men. It is also found from the outcome that subjects in the age of 26-30 years had higher muscle flexion in comparison with the other age businesses studied. We also located that bit transfer rate (BTR) achieved best possible worth of 35.04 bit/min for Plancherel's.

Keywords: Surface electromyography, plancherel's theorem, singular value decomposition, autoregressive network with exogenous inputs, fitting neural network, bit transfer rate

1. INTRODUCTION

Upper limb amputation one of the increasing challenge in India and leisure of the world which can arise by way of trauma, health problem or inborn defect [1, 2, 3 and 4]. After a tragedy incident disabled men and ladies need assistive contraptions comparable to prosthetic arm to participate in their every day endeavor. Prosthetic arm is a man-made gadget that restores a misplaced body section. This approach helps to improve quality level of the amputee folks which is controlled with the aid of surface electromyography (sEMG). sEMG is an investigation of electrical undertaking of skeletal muscle tissue which is recorded on the surface of the skin. sEMG is commonly utilized for rehabilitation, prosthetic arm manipulate, clinical detection and analysis of muscle tissue tiredness. sEMG can be operated with the aid of knowledgeable people or a health care provider with minimal hazard to the participants. One of the vital advantages of sEMG is non invasive [5, 6, 7, 8 and 9].

Prior study tried to classify finger actions for hand prosthesis manipulate equivalent to Ali H. Al-Timemy proposed a system for the classification of finger movements for dexterous manage of prosthetic hand. sEMG channels were recorded from 10 intact limbed and 6 below-elbow amputee folks. The 12 character finger actions carried out by means of each amputee persons and intact-limbed topics are: little flexion, ring flexion, middle flexion, index flexion, rest position, little extension, ring extension, middle extension, index extension, thumb flexion, thumb extension, thumb abduction. The other three finger movement combinations performed only by the intact-limbed subjects are little and ring fingers flexion,

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flexion of the ring, middle and index fingers and finally the flexion of the little, ring, middle and index fingers. Time Domain-Auto Regression (TD-AR) used as feature extractor and Orthogonal Fuzzy Neighborhood Discriminate Analysis (OFNDA) for characteristic discount. Classification was carried out with the aid of Linear Discriminate analysis (LDA). From the empirical outcome it was determined that 98% accuracy over 10 intact-limbed subjects for the classification of 15 courses of distinct finger actions and 90% accuracy over 6 amputee folks for the classification of 12 classes of individual finger actions. It was additionally found that thumb abduction used to be decoded efficaciously by using all subjects [10].

Antfolk projected a unique between three sample matching algorithms for cryptography finger motions exploitation sEMG. Twelve electrodes have been settled on the superficial flexor muscle tissue. 4 electrodes had been positioned on the superficial extensor muscle tissues of the better arm. 13 hand actions had been categoryified during this study like rest classification, thumb flexion, thumb extension, index finger flexion, index finger extension, core finger flexion, core 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. Best possible classification accuracy of 80.66% used to be finished by LDA [11]. Xueyan Tang proposed multi-channel sEMG for identification of Hand gestures, six male subjects have been picked for performing 11 forms of hand gestures. Six-channel sEMG electrode arrangement was once used for recording. Features were extracted by using energy ratio and concordance correlation. Cascaded-structure classifier was once used to identify hand gestures. Empirical results confirmed that absolute best identification rate of 89% [12].

Pradeep Shenoy investigates the use of forearm surface EMG signals for actual time control of a robotic arm. Eight electrodes were positioned in the form arm to obtained 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]. Francesco V. G. Tenor proposed decoding of individuated finger actions using sEMG. Six subjects, 4 male and 2 females aged 23–26 were participated in this experiment and flexions, extensions of all the fingers individually performed by all subjects. sEMG data were got using sixty four-channel amplifier. Mean and variances used as feature extractor and feed forward multilayer perceptron was once used determine the patterns. Experimental outcome confirmed that it was possible to decode individual flexion and extension movements of each finger (ten movements) with greater than 90% accuracy in a transradial amputee using only noninvasive surface myoelectric signals [14].

In the previous research as a minimum 4 pairs of electrodes to assess the performance of the pattern recognition algorithms. The proposed system uses most effective two channels for signals acquisition and processes these signals with artificial neural networks for recognition of carried out hand gestures; this is cut down the inconvenient to subjects, as good as growing the classification accuracy.

2. 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.

2.1. sEMG Data Acquisition

1) *Participants:* sEMG signals were recorded from the right forearm of ten healthy subjects (seven males and three females) aged 21- 40 years. The data from subjects were collected at Karpagam University, India. All subjects were asked to read the participant information sheet and to give their written informed consent

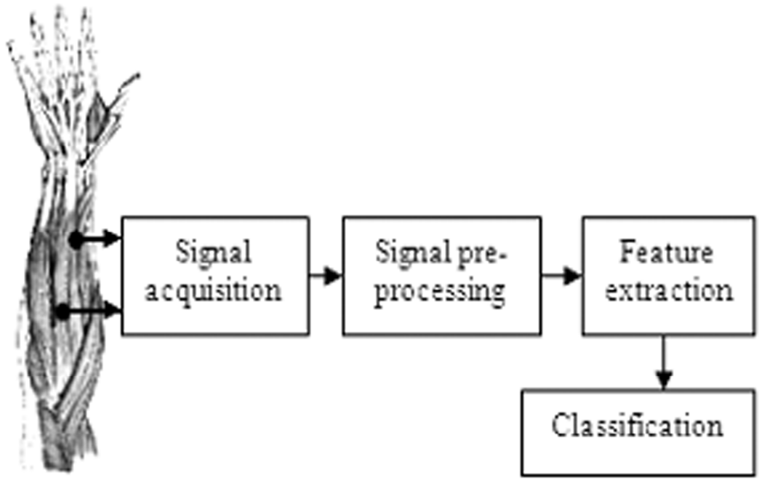

Figure1: Over review of sEMG recognized system

to participate in the study. It was ensured that all participants were healthy and free from medication during the course of the study. All the Subjects participated voluntarily in the study.

2) *Electrode Placement:* Before placing the electrodes, the skin was prepared with 70% alcohol wipes and sensors were adhered using medical-grade adhesive tapes. sEMG signals were extracted using AD Instrument bio signal amplifier. The electrode locations were chosen to maximize the quality of recording. 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.2.

3) *Experimental protocol:* Subjects were informed prior about the twelve different hand movements tasks to be executed by changing their hand position. The following gesture 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.3. Participants were asked to produce finger movements with a moderate, constant-force and non-fatiguing contraction to the best of their ability. During the recording, each participant sat on a chair in front of a computer with the Lab view interface screen to see all the EMG channels in real-time while performing the movements. 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

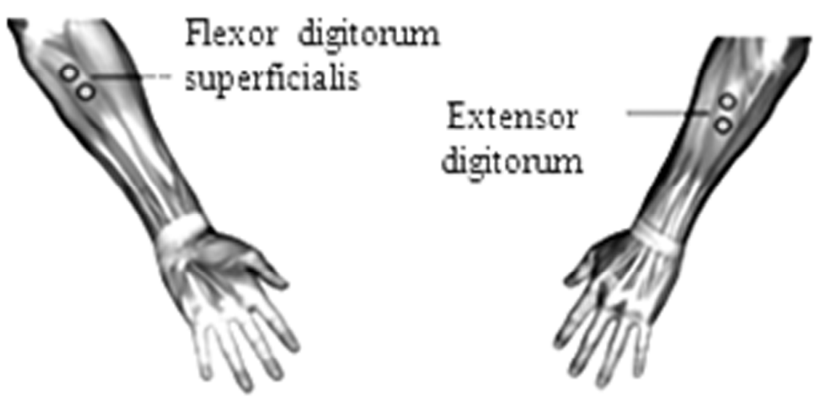

Figure 2: Electrode placement for sEMG system

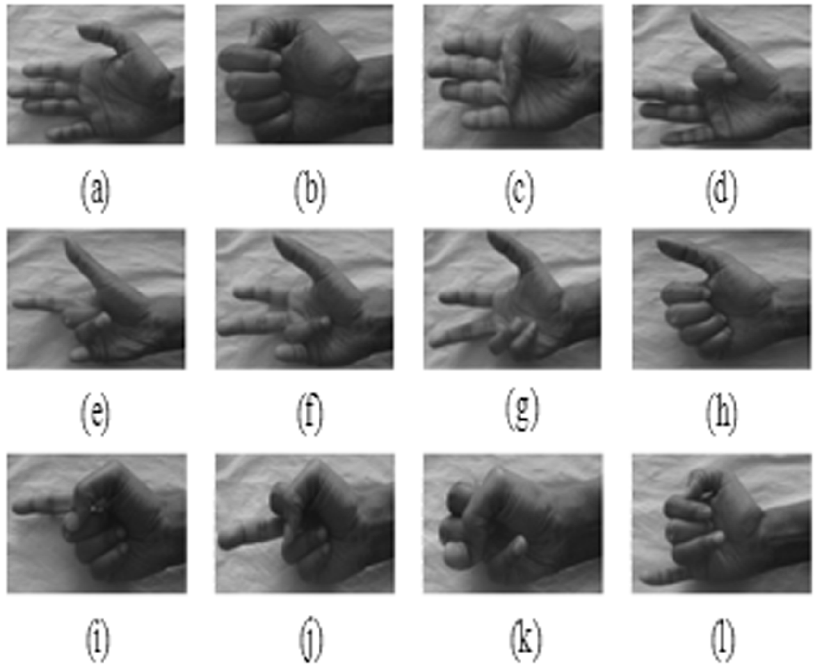

Figure 3: Twelve different finger movements (a) open, (b) close, (c) thumb flexion, (d) index flexion, (e) middle flexion, (f) ring flexion, (g) little flexion, (h) thumb extension, (i) index extension, (j) middle extension, (k) ring extension, (l) little extension

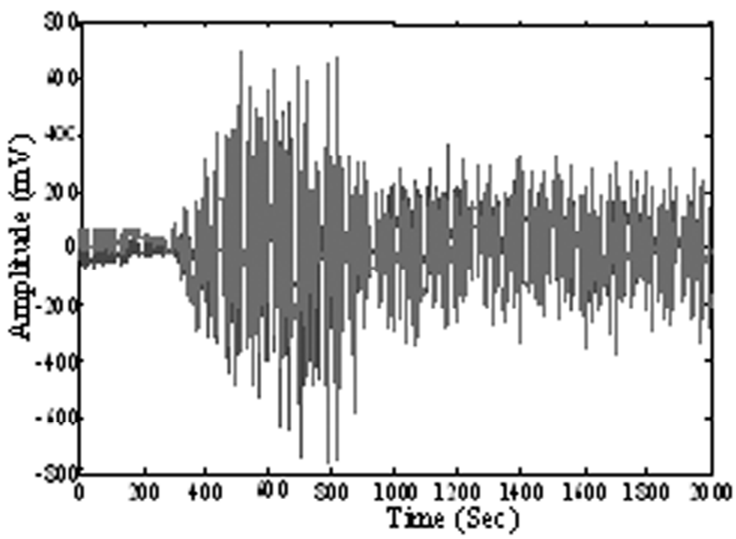

Figure 4: Raw sEMG signal for close movement

total of 1200 data samples from 10 subjects. During the signal acquisition, a notch filter was applied to eliminate the 50Hz power line noise and also sEMG signal was sampled at 400 Hz. Raw sEMG signal for close movement is shown in figure 4.

2.2. 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 [17]. 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.

2.3. Feature extraction

Feature extraction algorithms based on the Plancherels theorem and Singular Value Decomposition are proposed to extract the features from each band of sEMG.

1) Plancherel's: Plancherel's theorem which states that the integral of the squared modulus of a signal is equal to the integral of the squared modulus of its spectrum. Let be a signal and be continuous Fourier transform time signal so that [18]

$$\int_{-\infty}^{\infty} \left|E(x)\right|^2 dt = \int_{-\infty}^{\infty} \left|E_v\right|^2 dv \tag{1}$$

2) *Singular Value Decomposition (SVD):* The second feature extraction method proposed uses the singular value decomposition which states that a factorization of a real or complex matrix and expresses in the form of m-by-n matrix of non negative real numbers called singular value

$$M = U\Sigma V^* \tag{2}$$

Where U is a signal of m × m real or complex unitary matrix, Σ is an m × n rectangular diagonal matrix with non-negative real numbers on the diagonal and *V** is an n × n real or complex unitary matrix. The diagonal entries $\Sigma_{i,i}$ of Σ is known as the singular values of *M*. Such a factorization is called a singular value decomposition of *M* [19, 20, 21, 22, 23 and 24]

In Both feature extraction techniques 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.

2.4. Signal Classification

Artificial Neural Network (ANN) mainly is used to identify the muscle activation from sEMG signal. In this study, we use NARX, Fitting neural network to classify the sEMG data signals.

NARX neural system is the kind of recursive neural network which is dynamic network as shown in figure.5. When we intend to do multistage prediction, parallel NARX network has been selected as a classifier. In this case, prediction in each stage is being done based on outputs estimated by network in the previous stage. NARX has three nodes such as input node, hidden node and output node [25, 26, 27 and 28].

Fitting neural network is also a type of feed forward networks, which is used to fit an input output relationship [29, 30]. Fitting network is a static network which has three nodes such as input node, hidden node and output node as shown in figure 6.

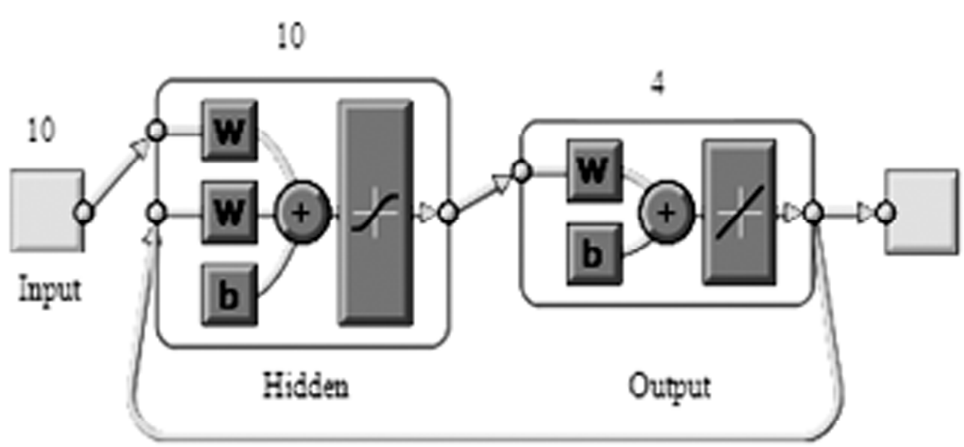

Figure 5: NARX neural network model for sEMG system

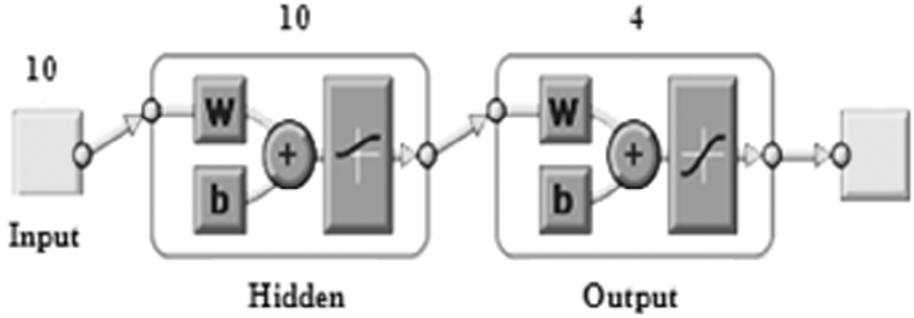

Figure 6: Fitting neural network model for sEMG system

In both networks for training and testing the neural networks 75% and 100% of data are used consequentially. The input, output and hidden neurons are namely 10,10,4 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.

3. RESULT AND DISCUSSION

3.1. Network Based Classification

The performance of the NARX is shown in figure 7, for two feature sets, from result it is observed that Plancherel's outdid SVD feature sets with the highest mean accuracy of 92.04% for subject 10 and the lowest mean accuracy of 89.46% for subject 7. Figure 8, depicts classification accuracy of Fit net for the two feature sets, from the result it is evident that Plancherel's again outperformed than SVD feature sets with the highest mean accuracy of 90.38% for subject 10 and the lowest mean accuracy of 87.88% for subject 7. In network based classification, NARX are identified pattern well than Fitnet this is because of NARX network is dynamic network.

3.2. Gender Based Classification

The gender based classification results for 2 neural networks are proven in figure 9, 10. From the outcome, it is found that the women carried out higher than adult males in the entire instances without performing any regular fitness coaching. Mean accuracy range for the female subjects with NARX varies from 89.90% to 91.50% and mean accuracy range for the male subjects with NARX varies from 89.46% to 90.71%. In

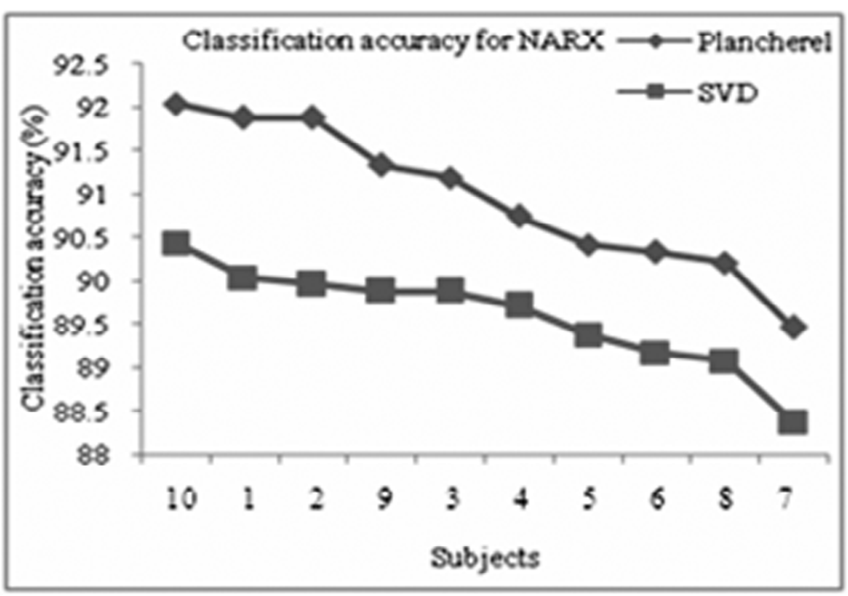

Figure 7: Classification results of NARX using energy features

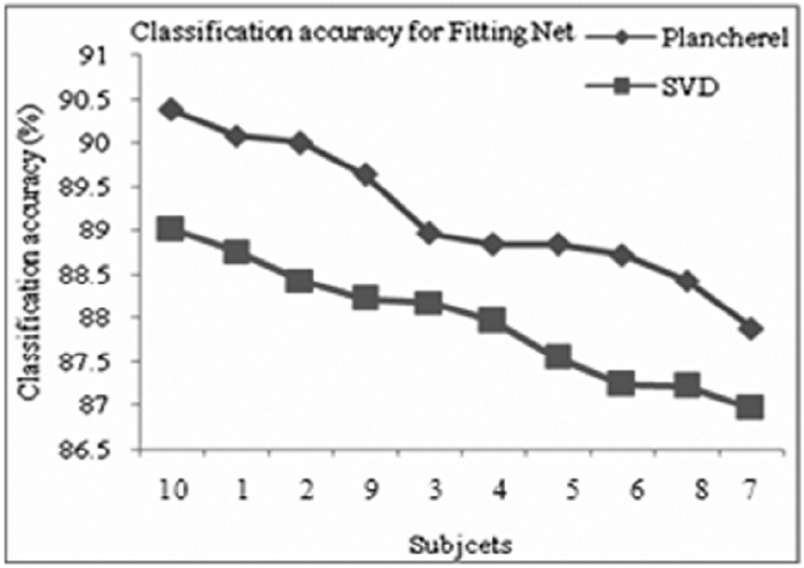

Figure 8: Classification results of Fit net using energy features

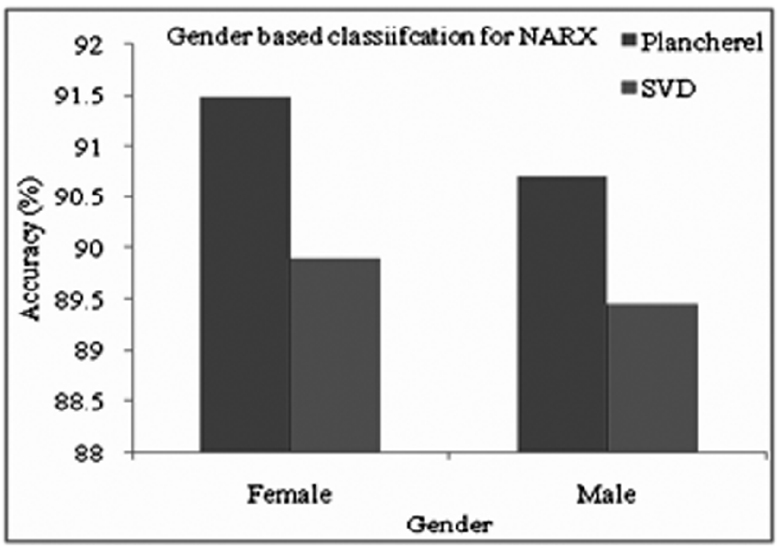

Figure 9: Gender based classification of NARX using energy features

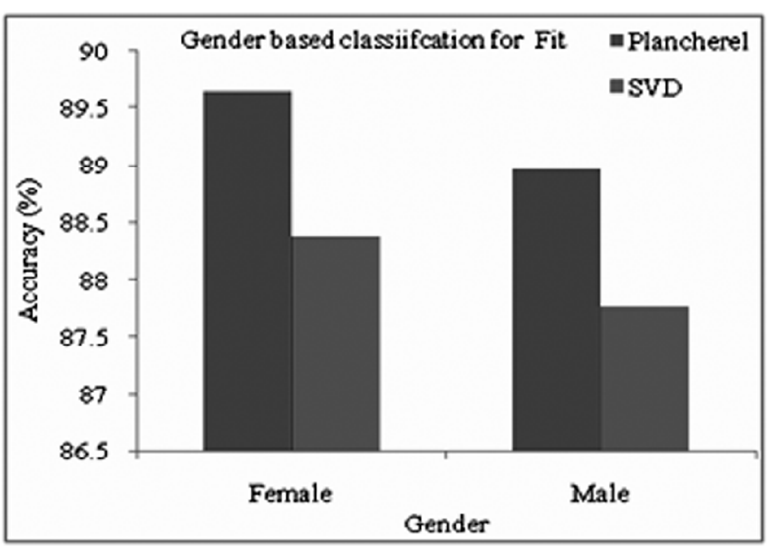

Figure 10: Gender based classification of Fit net using energy features

gender centered classification, women observed less complicated to manipulate the method than males this is given that females were significantly extra fatigue resistance than men and likewise they're able to preserve their venture longer than men [33].

3.3. Age Group Based Classification

An evaluation also done to look the variations in the performance of the algorithms proposed based on the age group of the subjects. The ten subject data are split into three categories specifically 21-25 years, 26-30 years and 31-40 years. From the results, it's located that sEMG data amassed from the subjects within the age workforce of 26-30 years has better performance accuracies in comparison with the other age corporations and this was visible in all two networks used. Easiest efficiency accuracies were once more found for the Plancherel's feature units for two networks. The efficiency outcome are proven in figure 11 to 12.

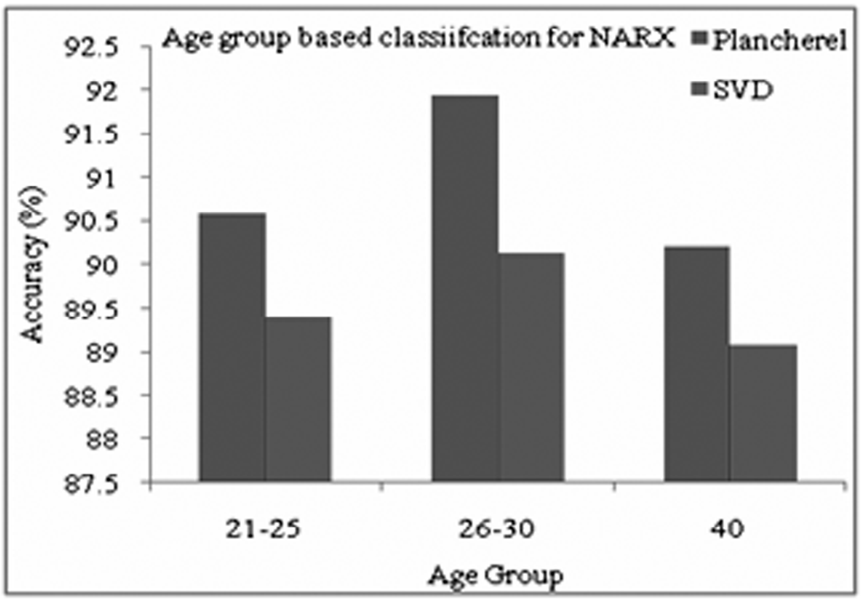

Figure 11: Age group based classification of NARX using energy features

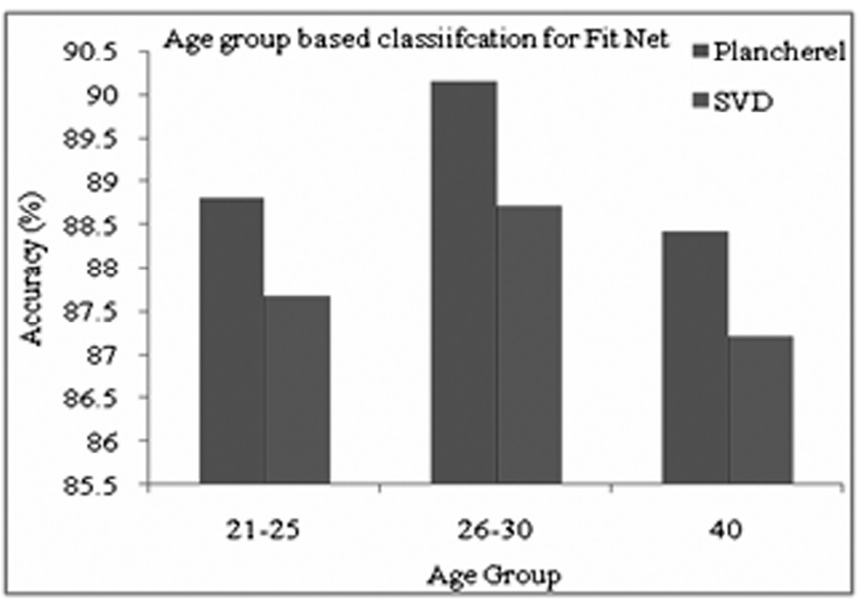

Figure 12: Age group based classification of Fit using energy features

3.4. 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 [31, 32]. 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 3.

$$BTR = \frac{60}{T_{act}}\left[\log_2 n + p_a \log_2 p_a + (1-p_a)\log_2 \frac{1-p_a}{n-1}\right] \tag{3}$$

Where, n = Number of Hand Movement

p_a = Mean Accuracy

$1 - p_a$ = Mean Recognition Error

T_{act} = Action Period (in seconds)

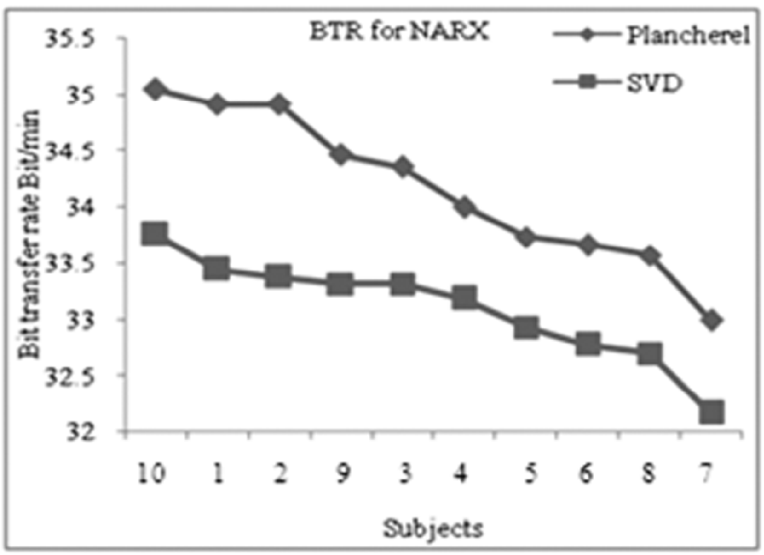

Figure 13: BTR rate for NARX using energy features

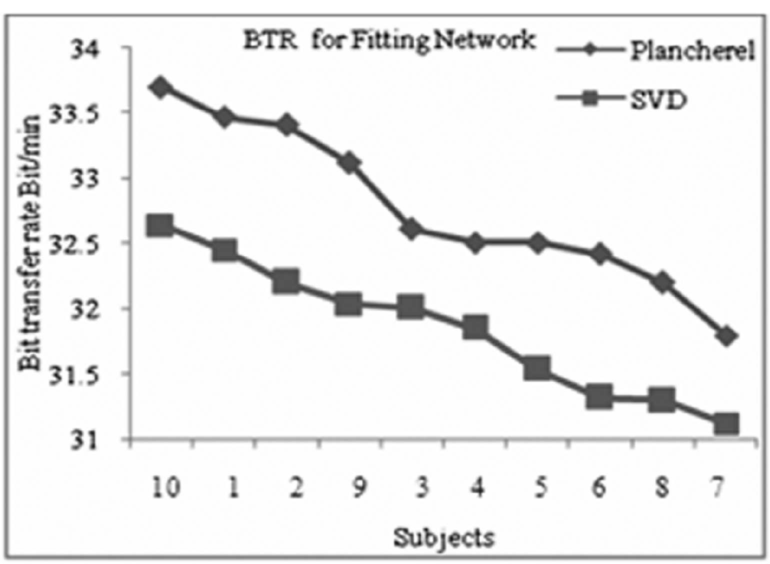

Figure 14: BTR rate for Fit net using energy features

The bit transfer rates for NARX and Fitting net using two energy features are shown in figure13, 14. From the results it is observed that highest BTR is achieved for NARX using Plancherel's with the rate of 32.99 bit/min to 35.04 bit/min and lowest rate achieved for SVD varies from 32.16 bit/min to 33.75 bit/min. Similarly Fitting net is also performed well with BTR varies from 31.80 bit/min to 33.70 bit/min for Plancherel's and 31.12 bit/min to 32.64 bit/min for SVD.

4. CONCLUSION

This article presented a study of the use of two-channel sEMG to classify individual finger movements for prosthetic control. We analyzed sEMG dataset from ten subjects. Two feature extraction algorithms and two neural networks are used to design algorithms for recognizing the twelve hand gestures. From the empirical results it was observed that the Plancherel's and NARX combination had the highest recognition accuracy rate of 92.04%. Investigation also proved that recognition accuracy of sEMG signals were better for females when compare to males. It was also observed from the results that subjects in the age of 26-30 years had better muscle flexion compare to the other age groups studied. However, for the study is required to verify the performance of the proposed algorithm in the online recognition of sEMG signals which can applied in prosthetic arm.

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