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Empirical Analysis of Artificial limb for Trans Radial Amputation People with the support of advanced machine learning strategies

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Abstract

For the improvement of performance of trans radial amputees, there will be identification of hand gestures using electromyogram. Whatever the data retrieved from the electrode will be used for controlling the prosthetic hands. In this paper, we are proposing the systematic hand gestures to improve the performance of the trans radial amputation people using the 2-channels amplifier. Different hand gestures like hands up, hands open, hands down, hands close are represented by the different variants and all these gestures will be preprocessed by the discrete approach. Extraction of the features will be done using the combination of ML Strategies. For identifying the pattern, LVQ mechanism is used. By this 2-Channel amplifier the identification of outcome can be evaluated effectively.

Index Terms — *Prosthetic Hand, Neural Network, Machine Learning, Hand Gestures*

I. INTRODUCTION

Electromyography (EMG) may be a process to assess the health of muscles and therefore the nerve cells that management them (motor neurons). In medicine, a restorative is a synthetic device that replaces a missing part. Prosthetics square measure supposed to revive the conventional functions of the missing part [1]. Upper limb amputations tend to be less common than lower limb amputations however will have an effect on individuals of all ages. The foremost common causes of higher limb amputation are accidents, infection or burns, tumors or illness, conditions gift at birth [2 &3].

(Adhiti Gupta et al., 2012) classified completely different hand movements as flexion, extension, adduction, abduction for hand control using NN. The information was collected from five subjects and the sEMG signal was acquired using an in-house built amplification and acquisition system. A custom-built Lab View application was used to store and record the data. The four selected muscles were flexor carpiulnaris, palmarislongus, extensordigitorum and extensor carpi radialis. From the result it was noticed that the finger movements are largely controlled by flexor digitorum and extensors digitorum muscle systems [4]. (Satyajit Bhowmick et al., 2013) used control of a robotic arm using ANN. EMG extracted from forearm by using instrumentation amplifier AD620 and surface gelled disposable electrodes. Participants performed following tasks: right-left, forwards- backwards and up-down movements. RMS was used as feature extractor. FFNN with sigmoid hidden neurons was used for pattern identification. Network identified the pattern well, validation and test set is found to be 0.999 [5]. Muscle fatigue detection using Multi-Layer Perceptron Neural Network (MLPNN) was proposed by (Subasi A et al., 2010). Vector elements were extracted by STFT, Smoothed Pseudo Wigner-Ville Distribution (SPWVD), and CWT. Signals were recorded from Right biceps brachii muscles. MLPNN with Levenberg- Marquardt and gradient descent algorithms were used for classification. Feature dimensionality reduction was done by Independent Component Analysis (ICA). Identification accuracy of 90%, 91% was obtained for Levenberg-Marquardt and gradient descent algorithms respectively [6].

(AlexandreBalbinot et al., 2012) applied neuro-fuzzy system for characterization of arm movements. 8-channel system used for signal acquisition. Seven forearm muscles were used for signal acquisition. Hand contraction, wrist extension, forearm rotation, wrist flexion, and forearm flexion were recorded. Feature extracted by RMS. Extracted features were applied to neuro-fuzzy system. The highest rate of 86% accuracy was achieved for 7 different movements [7]. (J. Senthil Kumar et al., 2013) created a low cost prosthetic arm operated by the sEMG signals. Two bipolar sensors were placed on the skin. AR model was used for feature extraction and ANN with Back Propagation (BP) algorithm was used for pattern classification. Output of the system was effective [8].

From the literature survey, we concluded that more number of electrodes is used to increase hand gestures which is decline the efficiency and also creates inconvenient to subjects. In this paper we propose only

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two channel system to extract two hand gestures.

II. MATERIALS AND METHODOLOGY

Proposed hand gestures system contains following five parts which is shown in figure.1.

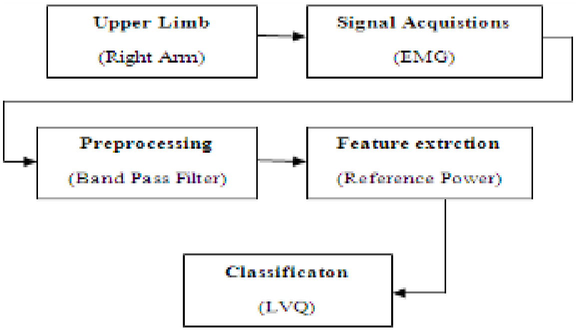

Figure 1. Methodology for sEMG system

Upper limb: Two right arm muscles are opted for signal acquisition**.**
Signal acquisition: An AD T26 instrument is used for extracting two hand gestures.
Preprocessing: Band pass filter is applied to remove unwanted noise from the acquired signals.
Feature extractor: Value information about two hand gestures are extracted by Reference power technique.
Classification: LVQ neural network is used for identify hand gestures.

2.1 Protocol

The protocol for signal acquisition for two tasks is elaborate below:
Hand Close (HC): The subjects were requested to flex all
their fingers to form a fist. Skeletal muscle digitorum superficialis muscle is concerned during this task.

Hand Open (HO): The subjects were requested to open the clenched fist. Extensor digitorum muscle is concerned during this task.

(a) (b)

Figure 2. Hand open and hand close Gestures

2.2 Muscles

The two muscles of forearm - flexor digitorum superficialis and extensor digitorum are responsible for flexion and extension of two hand gestures [10].

2.3 Signal Acquisition

sEMG signals of the two hand movements were non inheritable employing a 2 channel AD Instrument bio-signal electronic equipment. 5 gold plated, cup formed electrodes were placed on top of digitorum superficialis muscle, skeletal muscle digitorum muscle of the correct forearm and ground conductor was placed on the bony surface. 10 subjects (7 Males, 3 Females) participated within the experiment. All subjects who participated within the experiments were university students and workers aged between 21 to 40 years who voluntarily participated within the study. Participated subjects are divided into 2 teams supported gender are shown in Table 1 and that they are divided 3 teams supported age are shown in Table 2 respectively.

TABLE.1. GENDER BASED SUBJECTS GROUPING

Gender Group	Male	Female
Subjects	S3, S5, S6, S7, S8, S9, S10	S1, S2, S4

TABLE.2. AGE BASED SUBJECTS GROUPING

Age Group	21-25 years	26-30 years	31-40 years
Subjects	S3, S4, S5, S6, S7, S9	S1, S2, S10	S8

ISSN (Print): 2204-0595
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Figure 3. Equipment setup during signal acquisition

Consent was taken before the study. All subjects were healthy and free from health problem throughout the study period. Subjects were sitting during a comfy chair and requested to not create any visible movements throughout information acquisition which is shown in figure.3.

Subjects were explained regarding the two hand movement tasks (hand open, hand close) and were executed by moving their hand as per the protocol. sEMG signals were sampled at 400 Hertz [11,12]. Throughout signal acquisition a notch filter was applied to get rid of the 50 Hertz power cable artifacts. Acquired EMG signals are shown in figure 4 & 5.

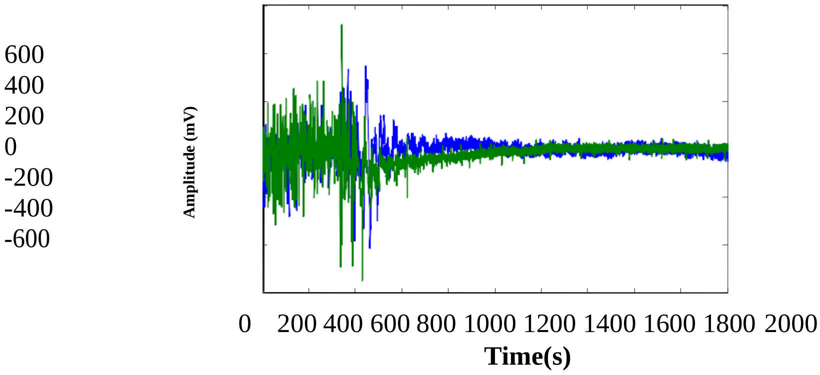

Figure 4. Hand open gesture from right arm

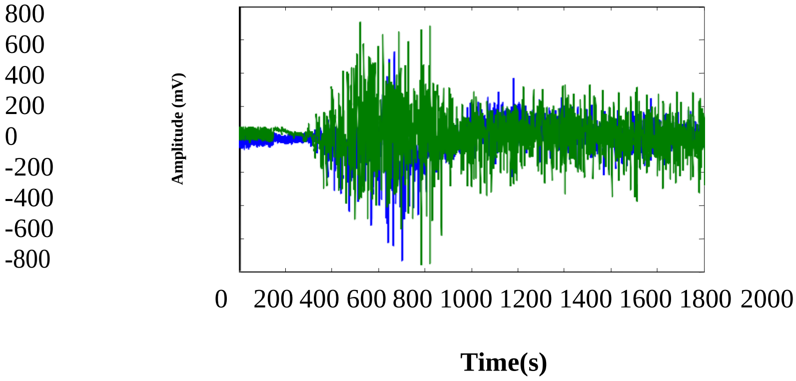

Figure 5. Hand close gesture from right arm

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ISSN (Online): 2203-1731

III. PREPROCESSING AND FEATURE EXTRACTION

3.1 Spectral Analysis

The spectrum of the raw signals is studied using Short-Time Fourier Transform (STFT) to see the frequency elements for every movement. STFT algorithm is employed to see the sinusoidal frequency and phase content of a signal as it changes over slender time intervals (Marcelo Bigliassi et al., and Hema.C.R et al., 2014). From the spectral analysis, the frequency components for two tasks are inferred, the spectrum for two signals is shown in figure 6 for subject 10. From the figure6, it can be observed that dominant frequency range is from 0.1- 150 Hz for two hand movements of the subject 10.

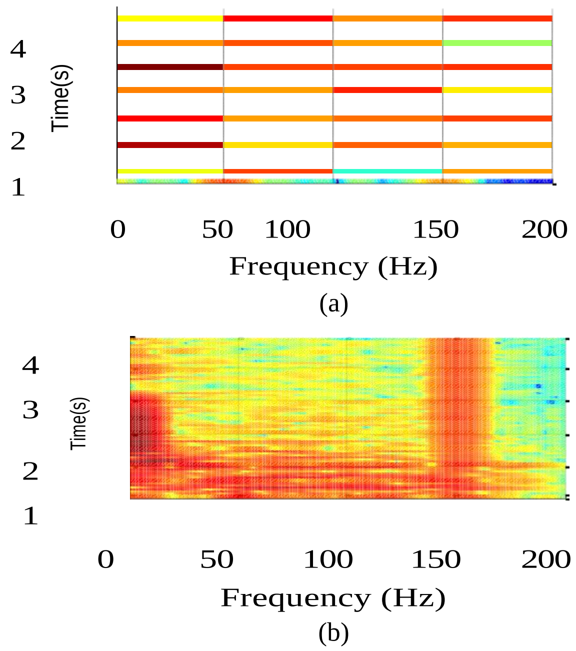

Figure 6. Spectrogram of Subject 10 for Two Different Finger Movements (a) Hand Close, (b) Hand Open.

3.2 Preprocessing

Five frequency bands area unit extracted employing a Chebyshev bandpass filters by split the signal within the vary of forty Hertz to filter the noisy information. The five frequency ranges are (0.1-40) Hz, (40-80) Hz, (80- 120) Hz, (120-160) Hz, (160-200) Hz.

3.3 Reference Power Technique

The feature extraction method proposed was the reference power technique which states that the difference between reference signal X(t) and task signal E(x) is summed, squared and performed logarithmic transform to the band power data [13].

$$S = \sum_{n=0}^{n-1}[X(t) - E(x)] \quad (1)$$

$$R = 20 * \log(S^2) \quad (2)$$

Where S is the sum of the difference between two signals and R is the power density of the signal. Sixteen features are extracted for each task per trial. The features are extracted for ten such trials for each task. 200 data samples for one subject are obtained. The feature sets obtained from the above feature extraction methods are individually applied to neural networks as input features to identify the signals into two hand movements.

3.4 Algorithm for Reference Power Technique

The feature extraction algorithm mentioned above consists of following steps:

Step 1: Collect sample data (S) of two channel sEMG signals for 5 seconds.
Step 2: Notch filter is applied to remove the 50 Hz power line artifacts.
Step 3: Band pass filters are applied to extract the five frequency bands from S.
Step 4: Apply Reference Power to the frequency band signal to extract the power features using Equations1 & 2.
Step 5: Repeat steps 1 to 4 for each trial for all tasks.
Step 6: Ten features are extracted for each task per trial and repeat for ten such trials for two tasks.
Step7: 200 data samples (20 x 10 trials = 20) for one subject is obtained to train and test the neural network.
Step 8: Do steps 1 to 7 for ten subjects to collect a master dataset.

IV. GESTURE IDENTIFICATION

Exacted features are identified using LVQ. LVQ

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neural network consists of two nodes. The first node maps input vectors into clusters that are found by the network during training section. The second node merges groups of first layer clusters into the classes defined by the target data [14, 15, 16, 17, 19 & 20]. Proposed network is designed two input neurons and four output neurons to identify the two hand gestures. LVQ designed model is shown in figure 7.

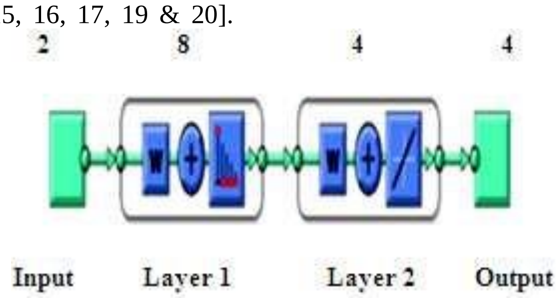

Figure 7. LVQ designed model

V. BIT TRANSFER RATE

The bit transfer rate for two hand gestures has been calculated from Equation.3.

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

n= Number of Hand Gestures p_a= Mean Accuracy

1- p_a= Mean Recognition Error

T_{act}= Action Period (in seconds) [18].

6.1 Network based results

VI. RESULTS AND DISCUSSION

The identification performance of the LVQ model using above mentioned features for the two hand movement tasks is shown in table 3. Table 3 comprises of mean testing time, training time, maximum, minimum, mean identification accuracy and standard deviation. From the tables, it was observed that the maximum mean identification accuracy of 93.08% for subject10 and minimum mean identification accuracy of 91.46% for subject7 were obtained. The mean training time and testing time for the network varied from 8.16 to 8.79 seconds and 0.50 to 0.93 seconds respectively. The standard deviation was 1.73 to 2.55.

TABLE 3: IDENTIFICATION PERFORMANCE OF LVQ NEURAL NETWORK USING REFERENCE POWER FEATURE EXTRACTION METHOD

Subjects	**ean Training Time (sec)**	**ean Testing Time (sec)**	**Recognition Performance (%)**			
			SD	**MAX**	**MIN**	**MEAN**
1	8.25	0.51	2.53	97.50	88.33	92.71
2	8.22	0.50	2.14	95.83	87.50	92.54
3	8.16	0.53	2.55	96.67	87.50	92.25
4	8.36	0.55	2.13	96.67	89.17	92.21
5	8.77	0.52	2.53	95.83	86.67	92.13
6	8.77	0.54	1.82	95.83	89.17	92.08
7	8.73	0.54	2.28	94.17	85.83	91.46
8	8.73	0.55	2.12	94.17	86.67	91.79
9	8.73	0.52	1.94	95.83	88.33	92.37
10	8.79	0.93	1.73	95.83	89.17	93.08

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ISSN (Online): 2203-1731

6.2 Identification Results for Subjects

Subject based identification using LVQ is shown in table A. From figure8, it was seen that the data from subject 10 had obtained the highest mean accuracy of 93.08% and the least performance mean accuracy was observed for subject 7 with a range of 91.46%.

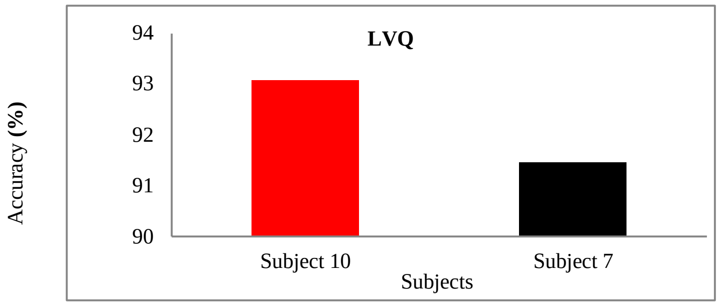

Figure 8. Subject based identification rate using LVQ neural network

6.3 Identification Results for Gender

The gender-based identification results for LVQ are shown in table B. From figure 9, it is observed that the mean accuracy range for the female subjects with LVQ 94.49% and mean accuracy range for the male subjects with LVQ 92.17%.

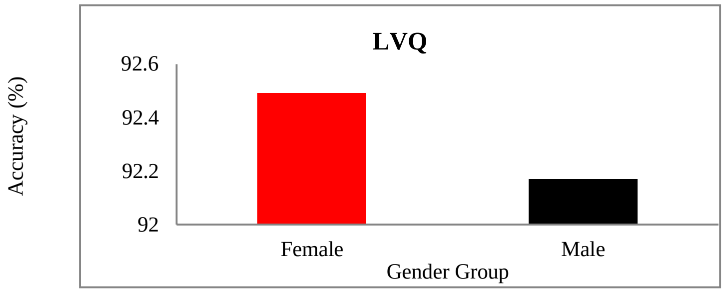

Figure 9. Gender based identification rate using LVQ neural network

6.4 Identification Results for Age Group

From the figure 10, mean accuracy range for the subjects in the age group 21-25 yrs with LVQ were 92.08%; age group 26-30 yrs 92.78% and for age group 31-40 yrs 91.79%.

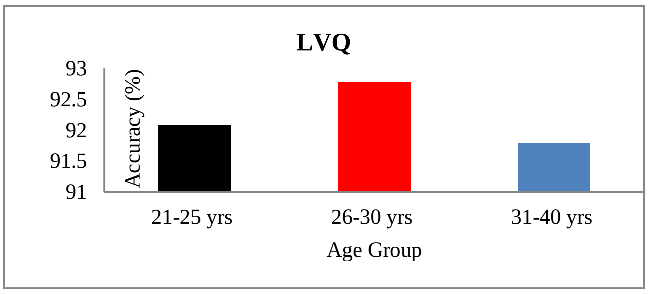

Figure 10. Age group based identification rate using LVQ neural network

6.5Identification Results Using Single Trail Analysis

The performance of the two states HMI designed for each subject is verified through a single trial analysis using LVQ. From the figure 12, it was observed that for subject 10 the acceptance rate was high and for subject 7 the acceptance rate was low using reference power features. From the results, it is observed that the feasibility of designing two states HMI is possible for some subjects using LVQ. Single trial analysis using GUI for hand close and hand open movements shown in figure.11.

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ISSN (Online): 2203-1731

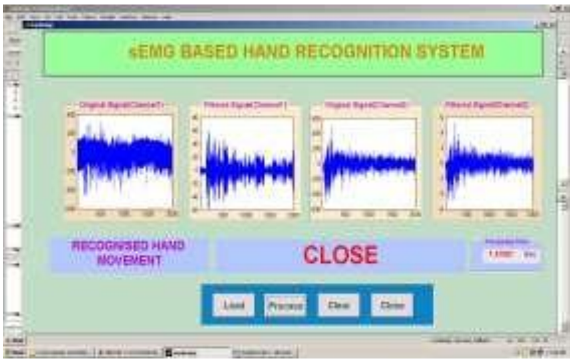

Figure 11. Single trial analysis result evaluation using GUI for hand close and hand open movements

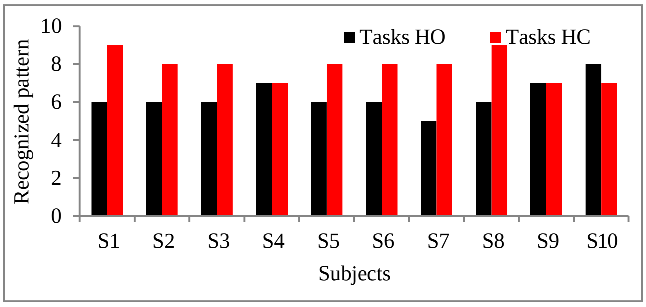

Figure 12.Single trial analysis using LVQ neural network

6.6Bit Transfer Rate Results

From the bit transfer rate results it is evident that maximum bit transfer rate of 35.91 bits/sec for subject 10 and minimum bit transfer rate of 34.56 bits/sec for subject 7 achieved. Bit transfer rate results using LVQ neural network is shown in figure 13.

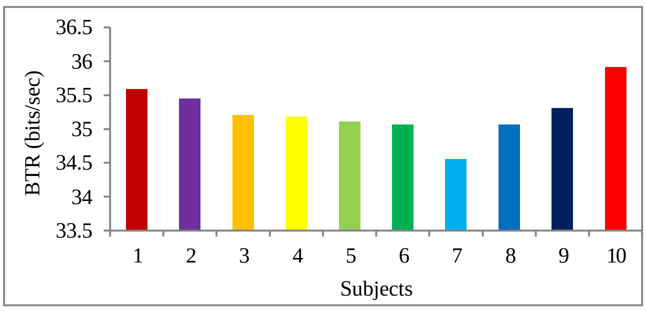

Figure 13. Bit transfer rate results using LVQ neural network

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ISSN (Online): 2203-1731

6.7 Discussion

From the Reference Power Technique feature extraction algorithmic program with LVQ neural network model employed in the study, the most classification accuracy of 93.08% was obtained. This justifies that the LVQ is best suited to this study because the neural network model is specially designed for pattern matching drawback. In projected methodology, most classification accuracy is obtained for subject 10 as results of his higher muscle fitness and his most involvement in work sessions. Subjects within the age group of 26-30 years are best suited to the study because of their higher muscle contractions. Higher muscle fatigue resistance has contributed for higher performance of feminine subjects as compared to male subjects. From the single trial analysis, it are typically discovered that the hand shut movement has achieved best recognition rate than hand open. Highest bit transfer rate of 35.91 bits/sec is achieved for subject 10.

VII. CONCLUSION

In this paper two states HMI were proposed for trans radial amputation people. Hand open and hand close signals were extracted from ten subjects and processed using band pass filter. Reference power used for feature extraction and LVQ applied for identification of two hand movements. From the results, highest identification accuracy of 93.08% and maximum bit transfer rate of 35.91 bits/sec is achieved for subject 10. From the output it concludes that the proposed two states HMI system is useful for improving performance of hand prosthesis.

APPENDIX A

TABLE A: SUBJECT BASED IDENTIFICATION RATE OF LVQ NEURAL NETWORK USING REFERENCE POWER FEATURE EXTRACTION METHOD

Features	**Subjects**	
	Subject 10 (Mean Accuracy in %)	**Subject 7 (Mean Accuracy in %)**
LVQ	93.08	91.46

TABLE B: GENDER BASED IDENTIFICATION RATE OF LVQ NEURAL NETWORK USING REFERENCE POWERFEATURE EXTRACTION METHOD

Features	**Gender Group**	
	Female (Mean Accuracy in %)	**Male (Mean Accuracy in %)**
LVQ	92.49	92.17

TABLE C: AGE GROUP BASED CLASSIFICATION RATE OF LVQ USING POWER FEATURE EXTRACTION METHOD

Features	**Age Group**		
	21-25 yrs (Mean Accuracy in %)	**26-30 yrs (Mean Accuracy in %)**	**31-40 yrs (Mean Accuracy in %)**
LVQ	92.08	92.78	91.79

TABLE D: SINGLE TRIAL ANALYSIS OF LVQ NEURAL NETWORK USING REFERENCE POWER FEATURE EXTRACTION METHOD

Subjects	**Tasks**	
	HO	**HC**
S1	6	9
S2	6	8
S3	6	8
S4	7	7

ISSN (Print): 2204-0595
ISSN (Online): 2203-1731

S5	6	8
S6	6	8
S7	5	8
S8	6	9
S9	7	7
S10	8	7

TABLE 8: BIT TRANSFER RATE OF LVQ NEURAL NETWORK USING REFERENCE POWER FEATURE EXTRACTION METHOD

Subjects	**BTR (bits/sec)**
1	35.59
2	35.45
3	35.21
4	35.18
5	35.11
6	35.07
7	34.56
8	35.07
9	35.31
10	35.91

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