Third International Conference on "Materials, Computing and Communication Technologies"
in association with International Journal of Scientific Research in Science,
Engineering and Technology
Print ISSN: 2395-1990 | Online ISSN : 2394-4099 (www.ijsrset.com)

Hand Gestures Recognition Using Fractional Fourier Transform and KNN Classifier

Abira, Mary Vasanthi
Department of Electronics and Communication Engineering, St. Xavier's Catholic College of Engineering, Chunkankadai, Nagercoil, Tamil Nadu, India

ABSTRACT

Hands are the most crucial organs and they play a major role for human activities. Therefore amputee people experience many difficulties in daily life. To overcome these difficulties, prosthetic hand is an effective solution. In order to automate the control of prosthetic hands, surface Electromyogram (sEMG) signals and machine learning techniques play a vital role. In this work, a novel Fractional Fourier Transform (FrFT) based iterative feature extraction method is proposed. The proposed FrFT based hand gestures recognition method consists of feature selection by using 2 levelled feature selection method and classification using KNN classifier. The proposed method is tested using a sEMG dataset, which are collected from amputee participants. Based on the evaluations, the proposed FrFT based hand gestures recognition achieved 88.2% accuracy rate by using K Nearest Neighbor (KNN) classifier.

Keywords- Electromyography (EMG), Fractional Fourier Transform, Feature selection, Classification

I. INTRODUCTION

Electromyography (EMG) refers to the collective electrical signal from muscles, which is controlled by the nervous system and produced duringmuscle contraction. EMG is used as a diagnostics tool for the diagnosis of neuromuscular or motor control pathological conditions. EMG is acquired from electrodes mounted directly on the skin, the signal is a composite of all the muscle fiber action potentials occurring in the muscles underlying the skin. Surface EMG is a method of recording the information present in these muscle action potentials. The signal represents the anatomical and physiological properties of muscles; in fact, an EMG signal is the electrical activity of a muscle's motor units, which consist of two types: surface EMG, and intramuscular EMG. A muscle is composed of bundles of specialized cells capable of contraction and relaxation. The amplitude range of EMG signal is 0-10 mV (+5 to -5) prior to amplification. The EMG signals acquire noise while travelling through different tissues. It is important to understand the characteristics of theelectrical noise associated with the EMG signal.

The body-powered prosthetic hand does not mimic the natural human hand movement. The user intention-controlled devices mimic the natural human movement. The user intention for the control of hand may be obtained from physiological control signals acquired through sensors. The sensor technology interfaces the human control signals to the artificial hand. Modern prosthetic hands incorporate surface electrode to interface artificial hand through myoelectric control signals to human. The surface EMG signals for artificial hand control are sensed from the surface of the skin and are preferred due to their ease of access and the procedure being non-invasive. The dexterity of prosthetic hand is less in surface EMG due to limitation in identifying the locations to acquire signals.

The remainder of the paper is organized as follows. Section II presents the related work. The proposed method is described in Section III. The obtained results are reported in Section IV. Conclusions are drawn in Section VI.

II. RELATED WORK

Ahmed Ebied et al [1]proposed a Constrained Tucker Decomposition (ConsTD) method for efficient synergy extraction building onthe power of tensor decompositions. This method is proposed as a direct novel approach for shared and task-specific synergy estimation from two biomechanically related tasks. Our approach is compared with the current standard approach of repetitively applying non-negative matrix factorization (NMF) to a series of movements. The results show that the consTD method is suitable for synergy extraction compared with PARAFAC and Tucker. It provides more direct and data driven estimation of the synergies in comparison with NMF based approaches.

Abdulhamit Subasi et al. [2]proposed an ensemble model for hand movement recognition based on the tunable Q-factor wavelet transform (TQWT). Bagging and Boosting ensemble classifiers is assessed for the basic hand movement recognition to construct a prototype system with the aim of controlling hand. TQWT is used for feature extraction from the sEMG signals, then, statistical values of TQWT sub-bands are calculated. Performances of the Bagging and the Boosting ensemble classifiers are compared in terms of different performance measures Ensemble classification method applymultiple classifiers for the same classification problem.

Di Wu et al. [6] proposed Deep Dynamic Neural Networks (DDNN) for multimodal gesture recognition. A semi-supervised hierarchicaldynamic framework based on a Hidden Markov Model (HMM) is proposed for simultaneous gesture segmentation and recognition where skeleton joint information, depth and RGB images, are the multimodal input observations. The Gaussian - Bernoulli Deep Belief Network (DBN) is proposed to extracthigh level skeletal Joint features. It is used to estimate the emission probabilityneeded to infer gesture sequences. This purely data driven approach achievesa Jaccard index score of 0.81 in the ChaLearn LAP gesture spotting challenge.The performance is high with a variety of state-of- the-art hand-tuned feature-based approaches and other learning-based methods.

Eric J. Perreault et al. [8] proposed Myoelectric pattern recognition algorithms for the control of powered lower limb prosthesis but electromyography (EMG) signal disturbances remain an obstacle to clinical implementation. To address this problem, we investigated using a log likelihood metric to detect both simulated EMG disturbances and real disturbances acquired from EMG containing electrode shift. We designed a Linear Discriminant Analysis (LDA) classifier that uses log likelihood to decide between using combination of EMG and mechanical sensors. The LDA classifier had significant lower prediction errors and had a false positive threshold. The log likelihood threshold could be applied to determine whichEMG channel contains disturbances.

Ghulam Rasool et al.[10] proposed muscle synergy based TaskDiscrimination (MSD) Algorithm that incorporates information about muscle configurations. The synergy activation coefficients are modeled as the latent system state and are estimated using a constrained Kalman filter. These task- dependent synergy activation coefficients are estimated in real-time from the electromyogram (EMG) data and are used to discriminate between various tasks. The task discrimination is helped by a post-processing algorithm that uses posterior probabilities. The MSD algorithm is more robust todiscrimination errors than the widely used LDA. The proposed algorithm is computationally efficient, yielding a decision with >90% discrimination accuracy in approximately 3 ms.

III. METHODOLOGY

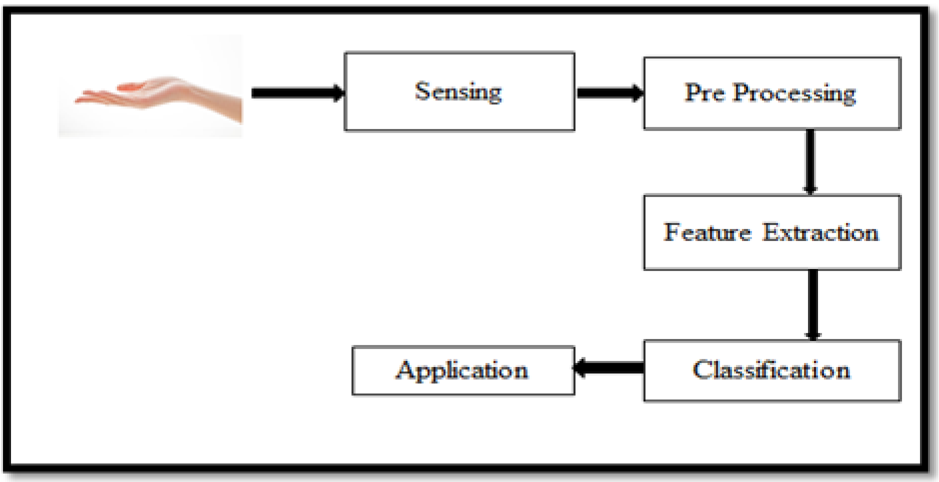

Figure 3.3 Block diagram of the proposed classification method

Figure 3.3 shows the block diagram of the proposed classification process. The novelties and the contributions of the proposed framework aregiven as follows:

- Pre-processing is done for the obtained sEMG signal that includes amplification and spatial filtering.
- Feature extraction is done using Fractional Fourier Transform (FrFT) from which real and imaginary parts of FrFT coefficients is obtained.
- A two level feature selection method, which uses windowing and t- test approach together to select the discriminative features.
- In the classification phase, a K Nearest Neighbor (KNN) classifier is used to demonstrate the strength of the extracted features. The results clearly indicate that the extracted features are distinctive.
- High success rates are achieved using the KNN based sEMG signal classification method for hand gestures recognition.

The sEMG signals are acquired from the muscles using sEMG sensors and then denoised to eliminate the artifacts. In the second phase, the informative features are extracted from the sEMG signals acquired from the previous stage to form feature vectors. In the third phase, Feature selection is done from the extracted features using Windowing and t-test method. Finally conventional classifier namely KNN classifier is selected to show discrimination of the developed method.

The Pre-processing of sEMG signals includes both amplification and filtering. The amplification is done by the factor of 1000. The amplification is done to improve the strength of the sEMG signals. The spatial filtering is done to remove the artifacts and noises associated with the obtained sEMG signal.

From the literature, multilevel feature extraction networks extract many features and parameters, settings of them is very hard. However, FrFT uses cognitive, light weight and effective algorithms together. Moreover statistical feature extraction method are very effective for signal processing. The FrFT relates a signal sampled in time or space to the same signal sampled in frequency.

The FrFT is an integral transform it is given by Equation (3.1)

$$f_{a}(u)=\int_{-\infty}^{\infty}(u, u')f(u')du' \qquad (3.1)$$

where, ka(u, u′) is the kernel function. The kernel function can be expressed as Equation (3.2)

(u,u′)=$A\alpha$exp [i($cot\alpha u$22csc$\alpha uu'$ +cotαu2)] (3.2)

where the amplitude $A\alpha$ is given by Equation (3.3)

$A\alpha$=√1 − $icot\alpha$ (3.3)

Where α is the multiple of , $\alpha = a\pi$ and a is the number of rotations on the 2 2 interval 0≤ |a|≤2 .Thus the Real and Imaginary parts of FrFt coefficients are extracted as features.

The Feature selection is done by using two techniques namely windowing and t-test approach. The Windowing technique is done by using the rectangular window of size 128 ms. It computes the mean and standard deviation of the FrFT coefficients.T-test approach computes the maximum of FrFT coefficients.

In the classification phase, K Nearest Neighbor (KNN) is used for hand gestures recognition, as K-NN is one of the simplest classifiers. The algorithm for the KNN classifier is given below

Algorithm 1 KNN based classification

Step1: Choose the number of K Neighbors K=5 Step2: Compute the K neighbors of the new data point according to some distance measure such as Euclidean st=[(x2 − x1) + (y2 − y1)] d2 2 Step3: Count the number of datapoints from each category among the neighbors in step2 Step4: The new datapoint is assigned to the category with most neighbour.

The above algorithm can be used to solve both regression and classification problems. It stores all available data and classifies new datapoint based on similarity.

IV. EXPERIMENTAL RESULTS

The muscular activity is gathered using 2 Thalmic Myo armbands. The database can be used to test the Myo armbands separately as well. The subjects in this database wore two Myo armbands one next to the other, including 16 active single–differential wireless electrodes. The top Myo armband is placed closed to the elbow with the first sensor placed on the radio humeral joint, as in the standard Ninapro configuration for the equally spaced electrodes; the second Myo armband is placed just after the first, nearer to the hand, tilted of 22.5 degrees.

A multi-channel EMG signal recording system was used to acquire the data at a sampling rate of 2000 Hz. Ten movements containing several finger and grasp movements were used. These movements are cylindrical grasp, tip grasp, hook grasp, palmar grasp, spherical grasp and lateral grasp. Figure 4.2 shows the input EMG signals for all the ten finger movements.

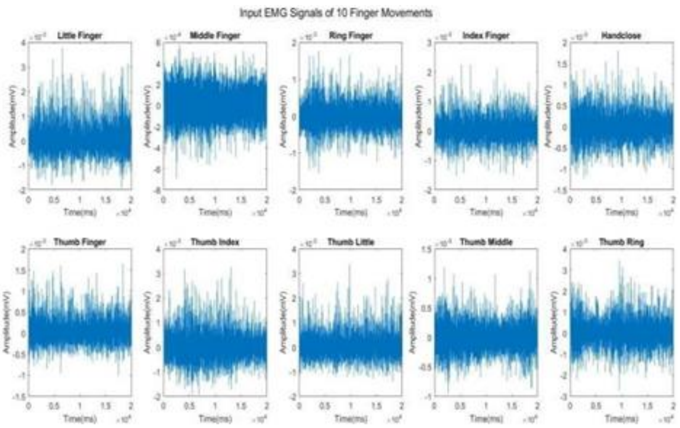

Figure 4.1 Input EMG signals for the ten finger movements

The input EMG signals are amplified to enlarge each information which can control the prosthetic hand of myo signal.

Denoising stands for the process of removing the noise, i.e the unwanted information present in the signal. The wavelets are used for noise removal. The shrinkage methods for noise removal have led to a variety of approaches to signal denoising

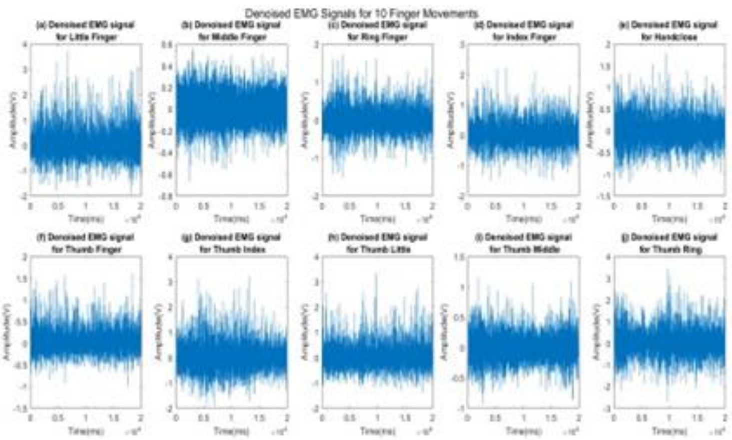

Figure 4.2 Denoised EMG signal for 10 finger movements

The experiment was implemented using the proposed Fractional Fourier Transform (FrFT) feature extraction network, 2 layered feature selection and the classification using the K-Nearest Neighbor (k-NN) classifier. Figure 4.3 shows the features selected for the ten finger movements after the T-test Approach. The selected features are

- The maximum of the FrFT Coefficients.
- The standard deviation of the FrFT Coefficients and
- The mean of the FrFT Coefficients.

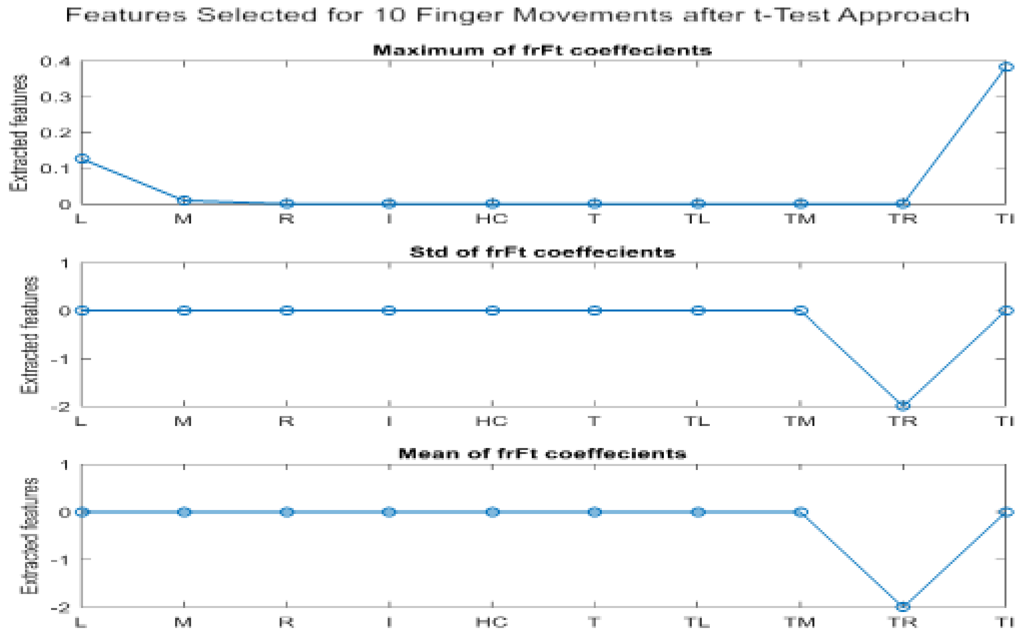

Figure 4.3 Features selected for the ten finger movements after the T-test Approach

Figure 4.4 shows the features selected for the six hand grasps after the T- test Approach.

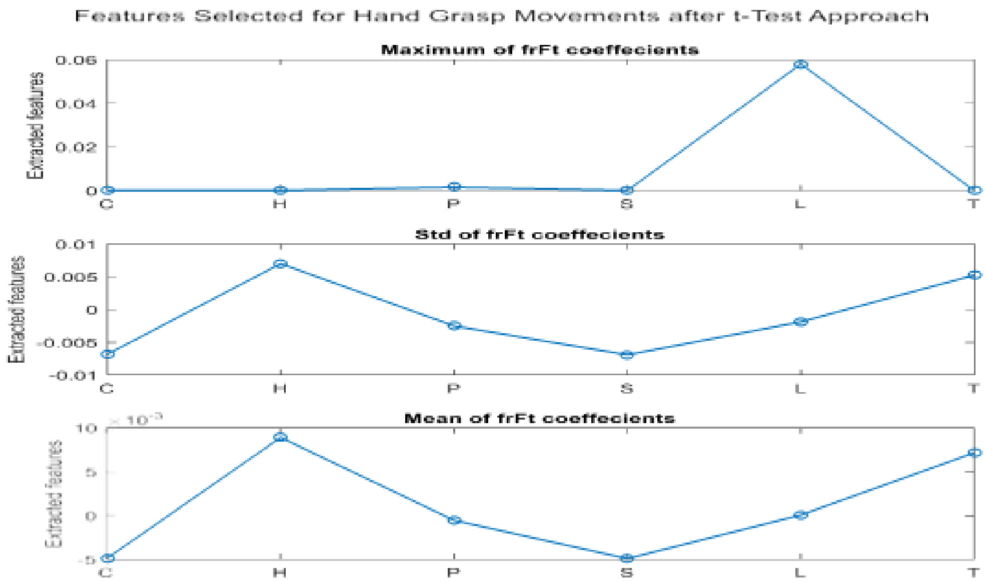

Figure 4.4 Features selected for the six hand grasps after the T-test Approach

In order to measure the performance of the proposed framework, accuracy, specificity and sensitivity were calculated. To evaluate these performance metrics, true correct classifications of each class, which are True Acceptance Rate (TAR), False Acceptance Rate (FAR), True Rejection Rate (TRR), False Rejection Rate (FRR) number of true positive (tp) andnumber of false negative (fn) were calculated. The Equations.(4.1) – (4.3) mathematically explain the performance metrics of the classifier.

$$\text{Accuracy} = \frac{TAR+FAR}{FRR+FAR+TRR+TAR} \quad (4.1)$$

$$\text{Specificity} = \frac{(\text{True Negativity})}{(\text{True Negativity}+\text{False Negativity})} \quad (4.2)$$

$$\text{Sensitivity} = \frac{t_p}{(t_p+f_n)} \quad (4.3)$$

Table 4.1 presents the performance of the proposed work in terms of accuracy, specificity and sensitivity. The proposed work achieved accuracy of about 88.2% , specificity of about 95.46% and sensitivity of about 89.5%

Table 4.1 Performance measures

Parameter	Value (%)
Accuracy	88.2
Specificity	95.46
Sensitivity	89.5

V. CONCLUSION

A lightweight, cognitive and highly accurate sEMG classification method is developed in this work. The developed sEMG signal recognition method employs FrFT based feature extraction network, 2-layered feature selection method and the KNN classifier. The utilized 2-layered feature selector selects three most discriminative features and those features are classified using KNN.The proposed method achieves an classification accuracy of about88.2%. Besides the classification accuracy, specificity and sensitivity of the results are given as well. These results clearly indicate that the developed method improved the success rates of the sEMG hand gestures recognition.In the future work, novel signal processing methods and Artificial Neural Networks can be proposed to enhance the classification accuracy.

VI. REFERENCES

[1]. Ahmed Ebied and Eli kinney-lang (2019), 'Muscle Activity Analysis Using Higher-Order Tensor Decomposition: Application to Muscle Synergy Extraction', IEEE Access, Vol. 7, No. 4, pp. 27257 – 27271.

[2]. Abdulhamit Subasi and Saeed Mian Qaisar (2020), 'Surface EMG signal classifcation using TQWT, Bagging and Boosting for hand movement recognition', Journal of Ambient Intelligence and Humanized Computing, Springer, Vol. 1, No. 2, pp. 1542–1552.

[3]. Ali Al-Timemy H., Ahmed Al-Ani, and Adel Al-Jumaily (2016), 'A Framework of Temporal-Spatial Descriptors based Feature Extraction for Improved Myoelectric Pattern Recognition', IEEE Trans. on Neural Systems and Rehabilitation Engineering, Vol. 25, No.10, pp. 1821 – 1831.

[4]. Ananda Sankar Kundu and Oishee Mazumder (2017), 'Hand Gesture Recognition Based Omnidirectional Wheelchair Control Using IMU and EMG Sensors', Springer Link, pp. 529–541.

[5]. Bo Hakansson, Max Ortiz-Catalan and Rickard Brånemark (2017), 'Real-Time and Simultaneous Control of Artificial Limbs Based on Pattern Recognition Algorithms', IEEE Transactions on Neural systems and rehabilitation Engineering, Vol.15, No.6, pp. 4366–4369.

[6]. Di Wu, Lionel Pigou, Joni Dambre, Jean-Marc Odobez,Ling Shao , Nam Le and Pieter-Jan Kindermans (2016), 'Deep Dynamic Neural Networks for Multimodal Gesture Segmentation and Recognition', IEEE Trans. on Pattern analysis and Machine Intelligence, Vol. 38, No.8, pp. 1583 – 1597.

[7]. Dingguo Zhang ,Jianwei Liu, Ning Jiang ,Xinjun Sheng and Xiangyang Zhu, Member (2018), 'Towards Zero Re-training for Myoelectric Control Based on Common Model Component Analysis', IEEE Transactions on Neural Systems and Rehabilitation Engineering, Vol. 24, No.4, pp. 444 – 454.

[8]. Edison Chung A. and Marco Benalcazar (2019), 'Real-Time Hand Gesture Recognition Model Using Deep Learning Techniques and EMG Signals', European Signal Processing Conference (EUSIPCO), pp.256-286.

[9]. Eric Perreault J.and John Spanias (2015), 'Detection of and Compensation for EMG Disturbances for Powered Lower Limb Prosthesis Control', IEEE Transactions on Neural Systems and Rehabilitation Engineering, Vol. 43, No. 8, pp. 226 – 234.

[10]. Ganesh Naik R. and Hung Nguyen (2015), 'Transradial Amputee Gesture Classification Using An Optimal Number Of sEMG Sensors: An Approach Using ICA Clustering' IEEE Transactions on Neural Systems And Rehabilitation Engineering, Vol. 22, No. 4, pp. 837 – 846.

[11]. Ghulam Rasool and Kamran kabal (2015),'Real-time Task Discrimination for Myoelectric Control Employing Task-Specific Muscle Synergies', IEEE Transactions on Neural Systems and Rehabilitation Engineering, Vol. 24, No:1, pp. 98 – 108.

[12]. Heung Suk and Ki-Hee Park (2015),'Position-Independent Decoding of Movement Intention for Proportional Myoelectric Interfaces', IEEE Transactions on Neural Systems and Rehabilitation Engineering, Vol. 29, No. 6, pp.928 – 939

[13]. Javier Escudero, Guido Bugmann, and Rami Khushaba (2015), 'Improving the Performance against Force Variation of EMG Controlled Multifunctional Upper- Limb Prostheses for Transradial Amputees', IEEE Transactions on Neural Systems and Rehabilitation Engineering, Vol. 24, No.6, pp. 650 – 661.

[14]. Jiaxin Ma and Nitish Thakor (2018), 'Hand and Wrist Movement Control of Myoelectric Prosthesis Based on Synergy', IEEE Transactions on Human-Machine Systems, Vol. 45, No. 2, pp. 74 – 83.

[15]. John Mc Allister and Sumit A. Raurale (2020), 'EMG Biometric Systems Based on Different Wrist-Hand Movements', IEEE Access, Vol. 9, pp. 12256 – 12266

[16]. Joseph Pancrazio J., Siddhartha Sikdar and Wilsaan Joiner (2015), ‘ Real-time Classification of Hand Motions using Ultrasound Imaging of Forearm Muscles’, IEEE Transactions on Biomedical Engineering, Vol.63, No.8, pp. 1687 – 1698.

[17]. Leila Wehbe Robert J. and Sclabassi Xuefan Zha (2020), ‘A Deep Learning Model For Automated Classification Of Intraoperative Continuous EMG’, IEEE Transactions on Neural Systems and Rehabilitation Engineering, Vol. 16, No. 6, pp. 44 – 52.

[18]. Lizhi Pan, Dingguo Zhang, and Xinjun Sheng (2019), ‘Improving Myoelectric Control for Amputees through Transcranial Direct Current Stimulation’, IEEE Trans on Biomedical Engineering, Vol. 62, No.8, pp. 1927 – 1936.

[19]. Meena Abdel Maseeh, Tsu-Wei Chen and Daniel Stashuk (2017), ‘Extraction and Classification of Multichannel Electromyographic Activation Trajectories for Hand Movement Recognition’, IEEE Acess, Vol. 24, No. 6, pp. 662 - 673.

[20]. Omkar S. Powar , Krishnan Chemmangat and Sheron Figarado (2018), ‘A novel pre-processing procedure for enhanced feature extraction and characterization of electromyogram signals’, Biomedical Signal Processing and Control, Vol. 29, No. 5, pp. 277-286.

[21]. Patcharin Artameeyanant and Kosin Chamnongthai (2016), ‘An EMG- based feature extraction method using a normalized weight vertical visibility algorithm for myopathy and neuropathy detection’, Springer Plus , Vol. 23, pp. 2270–2273.

[22]. Pornchai Phukpattaranont, Sirinee Thongpanja, Khairul Anam, Adel Al- Jumaily and Chusak Limsakul (2018), ‘Evaluation of feature extraction techniques and classifiers for finger movement recognition using surface electromyography signal’, Medical & Biological Engineering & Computing, Springer, Vol. 56, No. 1– 2, pp.2259–2271.

[23]. Sibasankar Padhy (2020), ‘A Tensor-based Approach using Multilinear SVD for Hand Gesture Recognition from sEMG signals’, IEEE Sensors Journal, Vol. 21, No.5. 1, pp. 6634 – 6642.

[24]. Weidong Geng (2017), ‘Surface EMG-Based Inter-Session Gesture Recognition Enhanced by Deep Domain Adaptation’, Research Gate, Vol. 96, No. 4, pp. 1486– 1495.

[25]. Wan-Ting Shi ,Shih-Tsang Tang, Tsorng-Lin Chia and Chia-Yen Yang (2015), ‘Aggregate Features in Multisample Classification Problem’, Science Direct, Vol. 83, pp. 501 – 510.