International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 07 Issue: 08 | Aug 2020 www.irjet.net p-ISSN: 2395-0072

A COMPARATIVE ANALYSIS ON EMG SIGNAL CLASSIFICATION APPROCHES

Priyanka Priyadarsani Pradhan[1], Miss. Karmila Soren[2]

[1]*I & E department, College of Engineering and Technology, Bhubaneswar, India*
[2]*Assistant Professors, College of Engineering and Technology, Bhubaneswar, India*

ABSTRACT – *EMG (Electro-myograpgy signal) signal, that is used in a fundamental component of modern prostheses in an individual's muscle myoelectric control system to regulate the movement of the prostheses. Used EMG signal to record the 10 different finger movements (i.e. individual and combined finger movements) was categorized using function (i.e. SVM and KNN approaches) by statistical methods. In the current system two separate function extractors are assimilated, namely Principal Component Analysis (PCA) and Linear Discriminate Analysis (LDA). The experimental result demonstrates that the LDA with SVM classifier is more acceptable as compared to other combinatory approaches with better accuracy 84.72%.*

Key Words*: *Myoelectric control, Principal Component Analysis, Linear Discriminate Analysis, K-Nearest Neighbor, Support Vector Machine

1. INTRODUCTION

EMG- it means recording electromyography signal of the electrical activity produced by the muscle. It measures the electrical currents produced during their contraction in muscles. It was done using an instrument of electromyography to produce a record called an electromyogram.

People have tried to create robots with the advent of technology which can do the same thing they want to do. Often people use other robots rather than missing limbs; sometimes they switch remotely operated robotic arms. Nowadays, EMG signal is used to direct more robots [1]. Biological signal work provided an overview of EMG signals and new hand phase classification models and methods [4].

The loss of the human forearm is a severe impairment that greatly limits the everyday capacities and upper-limb amputation relationship of a individual (Kuiken et al; 2009). The ability to interact with the physical world can be restored by myoelectric regulation (Englehart & Hudgins, 2003; Hudgins, Parker & Scott, 1993), in which the human muscle's electromyogram (EMG) is used to derive power commands for regulated upper-limb prostheses. For example, Peleg, Braiman, Yom-Tov, and Inbar (2000) used surface EMG signals to determine when a finger is turned on and the finger triggered using only two electrodes on the forearm [2].

In this paper we proposed a specific and integrated finger movement recognition device based on EMG, which uses only two EMG electrodes mounted on the human forearm. The block diagram for the proposed scheme appears in Fig.1.

EMG signal obtained during reconstructed from patients suffering from spinal cord injury. This is somewhat different from normal healthy people with same movements' EMG signal. But some of the muscle responses in this case are very weak and difficult to detect. The solutions suggested in this research are therefore useful not only for recovery after spinal cord injury, but also for other general processing tasks on different biological signals.

Thus, in this research, the LDA (Linear Discriminative Analysis) and PCA (Principal Component Analysis) are used to compress the signal to extract features, and classification is carried out using the classifier KNN (K-Nearest Neighbor) and SVM (Support Vector Machine).

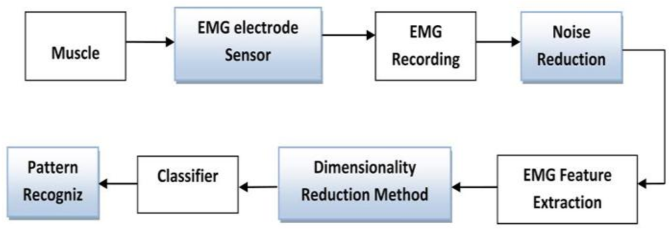


Fig.1. Block diagram of the EMG pattern recognition process in experimental calculation

2. RELATED WORK

With the improvement of innovation, individuals have attempted to create robots that can do something very similar that they need to do. Here and there individuals utilizes there robots as opposed to missing appendages. Once in a while they move robots arms controller. Nowadays more robots are driving using EMG signals. The amplitude of the EMG signals displaying a stochastic and characterized by Gaussian transport function ranges from 0 to 1.5mv (rms) everywhere. EMG signals provide data on muscle development, such as clinical conclusion, electrical stimulation in regions.

Huangetal Likure recognize seven hand developments that use the EMG signal MLP from 3 channel surface with a normal 96.25 percent -98.75 percent precision. In addition, Ajiboye and Weir conducted Fuzzy logic application of EMG design recognition for multifunctional prostheses regulation. The achievement was achieved somewhere in the range between 94 percent and 99 percent in all arrangements. EMG signals from lower arm muscles of on innate in capacity and seven solid members for constant order were obtained in further examinations regarding this matter Momenetal. Every member's 2-minute information was grouped with 92.7 percent + 3.2 percent accuracy using fuzzy means.

Khushaba et al. are responsible for the eight prosthesis finger leaders using two surface EMG signal channels. SVM (Supporting Vector Machine) using the LIBSVM and KNN technique were used as classifiers in their study and Bayes' hybrid approach uses a larger portion voting method as a post-planning approach. In both classifier strategies, the proposed Bayesian combination method against MV has been proving increasingly effective. The standard CA using the Bayesian post-processing fusion classifier LIBSVM was 92 percent. The information used in the analysis is also depicted in the trail arrangement area, in this report. Separate highlights of PCA and LDA highlights are grounded on KNN and SVM. The most elevated CA with LDA is 98.94 percent natural.

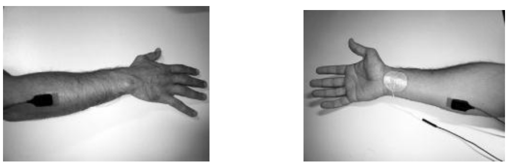
3. METHODS

3.1Information Set and Definition

The data set used for this analysis was taken from http:/www.rami-khushba.com/electromyogram-emg-repsitory.html, or obtained from it. This is an open access website which is free. Khushaba et al. describe the EMG signal obtained from eight healthy individual, i.e. 6 males and 2 females between the ages of 20 and 35, to better distinguish the individual and combined finger movements in their study.

No muscle or neurological disorders naturally limbed the participants. The EMG data were acquired by the Bagnoli Desktop EMG network for Delsys Inc. through two EMG channels of "Delsys DE 2.x series EMG sensors".

At the right forearm, 2-slot adhesive electrodes are deployed. Dermatrode Reference Electrode that is applied to each subject's wrist. So, such electrode positions are shown in Fig.2. The electrodes are obtained using a Delsys. Bagnoli-3 amplifier, with EMG signals from the muscle cell being amplified to a minimum gain of 1000. The signal data is sampled by analog-to-digital converter at 4000Hz. Then, this signal data was acquired through Delsys EMG-work Acquisition Software.



(A) 1st electrode position (B) 2nd electrode position

Fig.2.Electrode use in the right forearm

Here, 10finger groups have been introduced i.e. individual finger movements Thumb (T), Index (I), Middle (M), Ring (R), Little (L) and Thumb-Index (T-I), Thumb-Middle (T-M), Thumb-Ring (T-R), Thumb-Little (T-L), and finally Hand-Close (HC), all of those movements are the combined finger movements as shown in Fig.3.

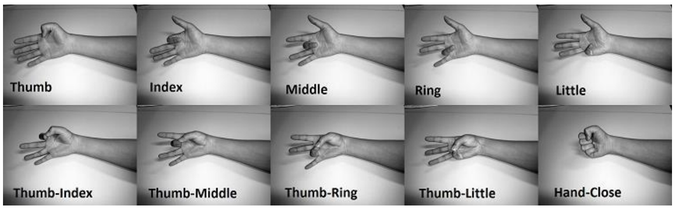


Fig.3.Ten different types of finger movements

Each movement was recorded in total for 6trials from each class within the resting period of 3-5secs each. From the collected dataset half of split in to training and other half is split in to testing. For all classes there are equal no of trails within the training and testing data set.
About any information regarding data set please refer to [2]. In general, direct assessment of the neural functions in the spinal cord is almost intolerable. On the other hand, if the motor neurons in spinal cord are activated, they send the potential for action down to the specific muscles and activate the muscle fibers. So, EMG is a function of the electrical activity around the fibers of the muscles. So, the EMG signal can therefore be used to infer motor neuron activity in the spinal cord. The EMG signal method of neuromuscular condition diagnosis is to decompose the EMG signal into its possible continuous motor unit (MUPS).

3.2Extraction Function

(a) Principal Analysis of the Component (PCA)

A commonly used technique is called PCA to minimize noise or dimensionality in a dataset, by identifying patterns within it while maintain the most variance. PCA has been used in facial recognition, gene analysis and in several other fields as well.
First, in a Vector Mn the mean is determined from the individual dimensions of traces Ti.

$$M_n = \frac{\sum_{i=1}^{I} T_{in}}{n}$$

For particular trace Ti construct the covariance matrix, this mean Mn has to be extracted from each entity of dimensions n.
A matrix called the covariance matrix, whose (i, j) th element was the covariance of each trace between the ith and the jth dimension. Matrix will be an m*m matrix where m is equal to the number of samples (dimensions) of the power traces. The calculation time in that equation increased quadratically in relation to the number of samples. This is also PCA's

principal drawback. The covariance is denoted as follows for two dimensions Z and Y:

$$\operatorname{cov}(X,Y) = \frac{\sum_{t=1}^{n}(X_t - X)(Y_t - Y)}{n-1}$$

The covariance matrix was described as follow using the formula for the covariance:

$$\Sigma^{n\times n} = c_{ij}, c_{ij} = \operatorname{cov}(Dim_i, Dim_j)$$

Where, the Dimx dimension is xth
Calculate the covariance matrix's eigenvectors and values then:

$$\Sigma = U \times \Lambda \times U^{-1}$$

We must find the transformed data set X. This is the original data chosen principal components.

$$Y = U^T \times X^T = (X \times U)^T$$
$$\hat{X} = Y^T = ((X \times U)^T)^T = X \times$$

(b) Linear Discriminative Analysis (LDA)

For supervised classification problem LDA method was commonly used. It is also a dimensionality reduction technique. For separating two or more classes LDA was used i.e. for modeling difference in group. When we change the coordinate from higher dimensions space to lower dimensions space LDA was used to project the features.

Calculate Between-Class Variance (Sb)
The total sample no (N) shall be calculated as follows

$$N = \sum_{i=1}^{3} n_i$$

To measure the difference between classes (Sb), the distance of separation between different classes denoted by (mi-m) is determined as follows:

$$(m_i - m)^2 = (W^T\mu_i - W^T\mu)^2 = W^T(\mu_i - \mu)(\mu_i - i)^T W$$

$$\mu_j = \frac{1}{n_j}\sum_{x_i \in w_j} x_i$$

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i = \sum_{i=1}^{C}\frac{n_i}{N}\mu_i$$

$$(m_i - m)^2 = W^T S_{B_i} W$$

Calculate Variance by Class (Sw)
The variance of each class within class (Swj)is calculated as in equation:

$$\sum_{x_i \in w_j}(W^T x_i - m_j)^T = \sum_{x_i \in w_{j,j=1,2..}}(W^T x_i - m_j)^2$$

The total variance inside class represents the sum of all matrices within class of all classes, and can be calculated as in equation:

$$S_W = \sum_{x_i \in w_{i=1}}^{C}(x_i - \mu_i)(x_i - \mu_i)^T$$

For Dimensional Space Measure
Unless we calculate all class variance (Sb) within class variance (Sw), after which the LDA technique's transformation matrix (W) can be measured, this called the Fisher criterion. The equation formulated for this is:

$$\operatorname{argmax} \frac{W^T S_B W}{W^T S_W W}$$

$$S_W W = \lambda S_B W$$

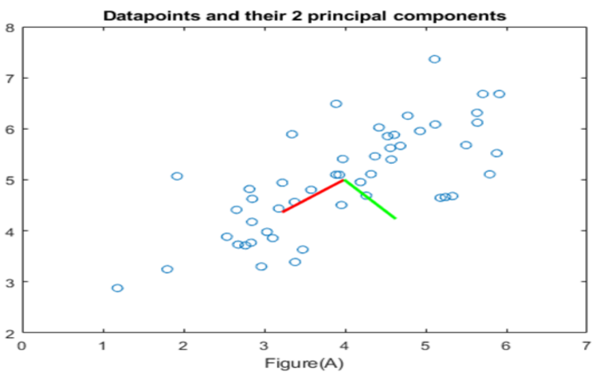
(c) K-Nearest Neighbor (KNN)

It is a non-parametric lazy learning algorithm. This is done to the full in the real world. Much of the realistic data does not adhere to the standard theoretical assumption made i.e. Gaussian mixtures, linearly separable etc. Thus KNN is very useful in such cases. It is primitive type of algorithm that can store a huge content identified by using the metric functions of distances. It is an unbiased algorithm and has no assumption regarding the data being considered. Its simplicity and ease of implementation plus effectiveness make it very popular.

(d) Vector Machine Support (SVM)

It is a linear classifier of the non-probabilistic binary. It is a discriminative classifier that is described via a separate hyperplane. It is a supervised learning algorithm and regression. But it's used for classification problems in machine learning.

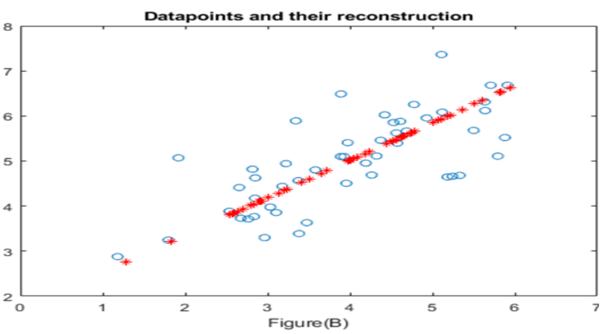
4. RESULT



X axis=Principal Component

Y axis=Random Data Points

Fig.4.Principal Component of Random data points



X axis=Original Data Points

Y axis= Reconstructed Data Points

Fig.5.Reconstructed data points and Original data points

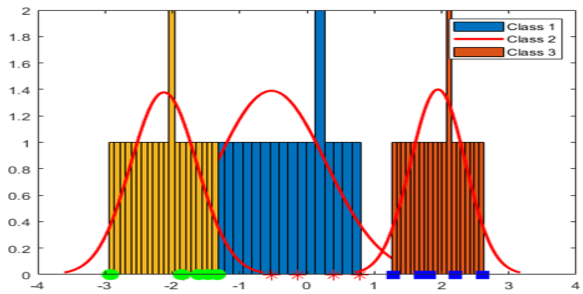


Fig.6. Example of LDA for three class data (randomly generated with different mean and variance)

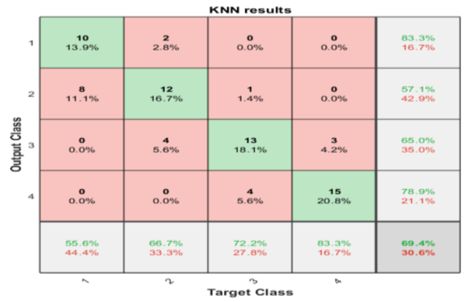


Fig.7.EMG classification for PCA feature extractor with KNN classifier using Confusion Matrix

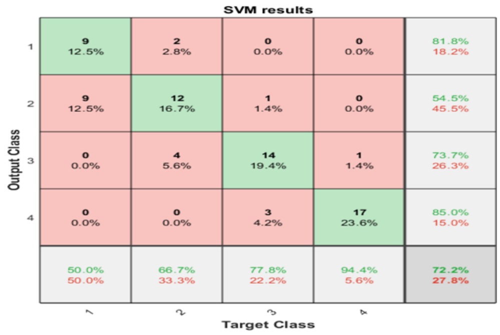


Fig.8. EMG classification for PCA feature extractor with SVM classifier using Confusion Matrix

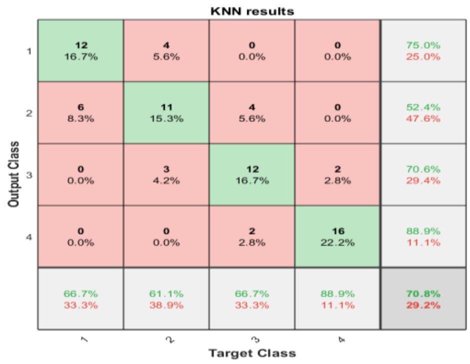


Fig.9.EMG classification for LDA feature extractor with KNN classifier using Confusion Matrix

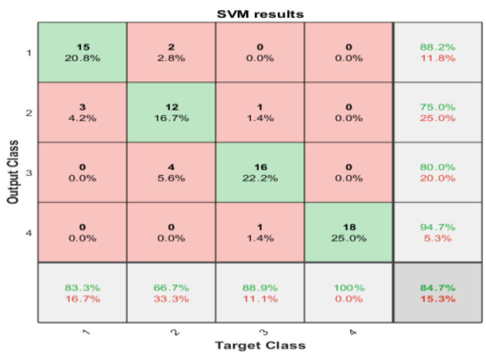


Fig.10.EMG classification foe LDA feature extractor with SVM classifier using Confusion Matrix

	PCA		LDA	
Class	KNN	SVM	KNN	SVM
1	55.56	50	66.67	83.33
2	66.67	66.67	61.11	66.67
3	72.22	77.78	66.67	88.89
4	83.33	94.44	88.89	100
Accuracy	69.44	72.22	70.83	84.72

Table.1. Comparison of the proposed approaches with class specific and overall accuracy

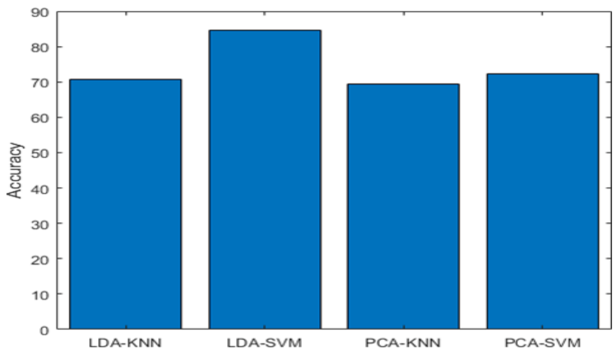


Fig.11.Comparision of the approaches with obtained accuracy

5. CONCLUSION

The EMG signal Employed as a kind of prostheses prospect sign very normal. Because of the way it best uncovers the individual muscular condition that embraces the message. Cause for this investigation is to structure appropriate classifier. EMG knowledge from different participants was employed in the most appropriate way to group the previously described finger development. So, the quick and most exactly outcomes acquired with the project LDA and SVM based strategy.

REFERENCES

1. The Journal of the American Medical Association, 301(6), 619–628. J. R. Cram, G. S. Kasman, J. Holtz, Introduction to Surface Electromyography. Aspen Publishers Inc., Gaithersburg, Maryland, 1998.
2. R. N. Khushaba, M. Takruri, S. Kodagoda, and G. Dissanayake, "Toward Improved Control of Prosthetic Fingers Using Surface Electromyogram (EMG) Signals", Expert Systems with Applications, vol 39, no. 12, pp. 10731–10738, 2012
3. K. Englehart, B. Hudgins, P.A. Parker, M. Stevenson, Classification of the myoelectric signal using time-frequency based representations, Elsevier Medical Engineering& Physics 21 (1999) 431-438p.
4. Y. Al-Assaf, 2006. "Surface Myoelectric Signal Analysis: Dynamic approaches for change Detection and Classification." IEEE Transactions on Biomedical 53 (11) 2248 – 2256p.
5. O.Aydemir, T.Kayikcioglu Decision tree structure based classification of EEG signals recorded during two-dimensional cursor movement imagery. J Neurosci Meth 2014; 229: 68-75.
6. C. C. Chang and C. J. Lin, “LIBSVM: A library for support vector machines”, Available Online: http://www.csie.ntu.edu.tw/ cjlin/libsvm/, 2001.
7. K., Englehart, B. Hudgins, A.D.C Chan, 2003. "Continuous multifunction myoelectric control using pattern recognition." Technology and Disability 15: 95-103.
8. D. Graupe, W. K. Cline., “Functional Separation of EMG Signals via ARMA Identification Methods for Prosthesis Control Purposes”, IEEE Tr. on Systems, Man, and Cybernetics SMC-5 (2), s: 252–259, (1975).
9. A. B., Ajiboye, R.F. Weir, “A Heuristic Fuzzy Logic Approach To EMG Pattern Recognition For Multifunctional Prosthesis Control”. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 13(3), 280-291s, 2005.
10. K. Momen, S.Krishnan, T. Chau, “Real-Time Classification of Forearm Electromyography Signals Corresponding to User-Selected Intentional Movements for Multifunction Prosthesis Control”. IEEE Transactions On Neural Systems And Rehabilitation, 15(4), 2007.
11. Scheme, E., Founger, A., Stavdahl, O., Chan, A. D. C., & Englehart, K. (2010). Examining the adverse effect of limb position on pattern recognition based myoelectric control. In Proceedings of the 32nd annual international conference of the IEEE EMBS (pp. 6337–6340).
12. Smith, R. J., Huberdeau, D., Tenore, F., & Thakor, N. V. (2009). Real-time myoelectric decoding of individual finger movements for a virtual target task. In: Proceedings of the 31st annual international conference of the IEEE EMBS (pp. 2376–2379).
13. Andrews, A., Morin, E., & Mclean, L. (2009). Optimal electrode-configurations for finger movement classification using EMG. In Proceedings of the 31st annual international conference of the IEEE EMBS (pp. 2987–2990).
14. Tenore, F., Ramos, A., Fahmy, A., Acharya, S., Etienne-Cummings, R., & Thakor, N. V. (2007). Toward the control of individual fingers of a prosthetic hand using surface EMG signals. In Proceedings of the 29th annual international conference of the IEEE EMBS (pp. 6146–6149).
15. Peleg, D., Braiman, E., Yom-Tov, E., & Inbar, G. F. (2002). Classification of finger activation for use in a robotic prostheses arm. IEEE Transactions on Biomedical Engineering, 10(4), 290–293.
16. Kuiken, T. A., Li, G., Lock, B. A., Lipschutz, R. D., Miller, L. A., Stubblefield, K. A., et al. (2009). Targeted muscle reinnervation for real-time myoelectric control of multifunction artificial arms.
17. Smith, R.J., Tenore, F., Huberdeau, D., Etienne-Cunnings, R., &Thakor, N. V. (2008). Continuous decoding of finger

position from surface EMG signals for the control of powered prostheses. In Proceedings of the 30th annual international conference of the IEEE EMBS (PP.197-200).

18. Amady, M.M., & Horwat, F. (1996). Evaluation of Hjorth parameters in forearm surface EMG analysis during an occupational repetitive task. Electroencephalography and Clinical Neurophysiology/Electromyography and Motor Control, 101(2), 181-183.
19. K. K. Mohanty, P. K. Barik, R. C. Barik and K. C. Bhuyan, “An Efficient Prediction of Diabetic from Retinopathy Using Machine Learning and Signal Processing Approach,” 2019 International Conference on Information Technology (ICIT), Bhubaneswar, India, 2019, pp. 103-108, doi: 10.1109/ICIT48102.2019.00025.
20. R. K. Sethi, K.K. Mohanty, “Optical Odia Character Classification using CNN and Transfer Learning: A Deep Learning Approach,” International Research Journal of Engineering and Technology (IRJET), vol.07, no.07, pp.3885-3890, 2020.