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REAL-TIME CONTROLLING OF WHEELCHAIR BY BIO EMG

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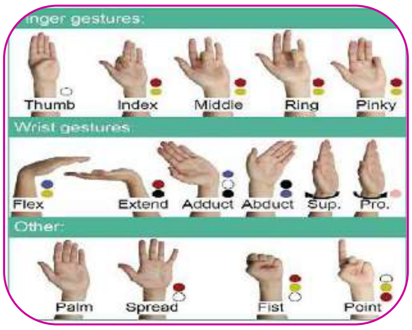
ABSTRACT



This paper shows the real time controlling of wheelchair by Bio signals ($sEMG$). Of late, the aged population & the patient of disablity in leg has increased substantially. The people who can not walk on their own use a conventional wheelchair which can be controlled by hands is used by the user with leg impairment only. It can also be controlled with the help of user interface by the user having severe impairment(arms & legs). The patient targated for this project are are Spinal cord injury(SCI) with major contractures of major joints, Cerebrum Vascular Accident(CVA) or stroke patient & Neurodegenerative spinal cord. An Automatic Wheelchair is made which work on the movement of hand i.e. forward, backward, left & right. EMG signals are taken from the hand muscle that is Flexor carpi radialis muscle. Surface Electromyography (EMG) signals are biomedical signals produced by the movement of muscles.The $sEMG$ signals are acquired by Myware muscle sensor through Arduino $MEGA$ 2560 and are processed using the $LabVIEW$. The processing consists of feature extraction, classification and pattern recognization along with data logging of different subjects. The project includes designing a system that is capable of classifying EMG signals for movement of different hand gestures. The classified output is used to control a wheelchair by acquiring the data from 10 subjects with different age groups and sex. The acquired EMG signals are used to train the system so that Automatic wheelchair can be made more reliable, accurate and efficient for its movements.

KEYWORDS: *Classification EMG, Feature Extraction, Flexor carpi radialis muscle, Real time classification & Pattern Recognization, SCI, SVM.*

1. INTRODUCTION

Biosignals[1] are the electrical signals that are generated due to the physiological activities of various tissues and organs in human body[2]. Surface EMG signals are biomedical signals produced by the movement of muscles[3]. EMG signals exhibit specific patterns for different activities and hence correct recognition of these patterns can be used for the control of assistive devices. EMG are signals that are generated by skeletal muscles during movement. Surface EMG is obtained using surface electrodes. EMG makes a diagnosis by measuring and recording electrical activities of muscles. These electrical signals of active muscles are easily obtained with electrodes which are placed on surface of the skin to identify the patterns. The patient who is injured is not able to move his body in surrounding environment without external help. So to make them independent for moving around an automatic wheelchair is made which work on the movement of Flexor carpi radialis muscle present on hand. So, signals are acquired from the Flexor carpi radialis muscle with the movement of hand in different gestures [4]. The features value for these different hand gestures are different that can be analyzed by further processing of the aforesaid signals. So, initially these signals are acquired by a Myoware muscle sensor through Arduino $MEGA$ 2560. The Acquired signals can be seen in the $LabVIEW$ where further processing takes place. The processing do not includes Filtering because Myoware muscle sensor's primary output is not a raw EMG but rather an amplified, rectified & integrated signal i.e.EMG's envelope that will work better. After acquiring the $sEMG$, feature extraction [5][6] & then with the help of machine learning [7],[8],[9] classification & pattern recognition[10] is also done. The paper is divided into several sections. In the first section related works and a brief introduction is presented. Section two presents the methodology. Section three explains the data acquisition. Section four explains about the data set. Section five contains the feature extraction in different domains. Section six explains the classification (SVM) Training & Deployment. Section seven explains Real time pattern recognition. Section eight consists of conclusion & Result.

2. METHODOLOGY

The basic steps include EMG acquisition, signal processing, feature extraction, classification, real time pattern recognition & hence, controlling the wheelchair. The steps followed in project are shown in figure 1. The Flexor carpi radialis muscle is used to acquire the signals with the help of Myoware sensor. It is placed on Flexor carpi radialis muscle with the help of Disposable Electrode. The input from sensors is provided to the the Arduino $MEGA$ 2560 which act as interface between Sensor & $LabVIEW$. The Acquired EMG signals are provided to $LabVIEW$ where further processing take place. First feature extraction is done.The features extracted are written in comma delimited (CSV) format which can be further read for classification. After feature extraction classification is done[10][11]. Classification consists of two parts Training & Deployment. The classification Techniques used is SVM[12][13].

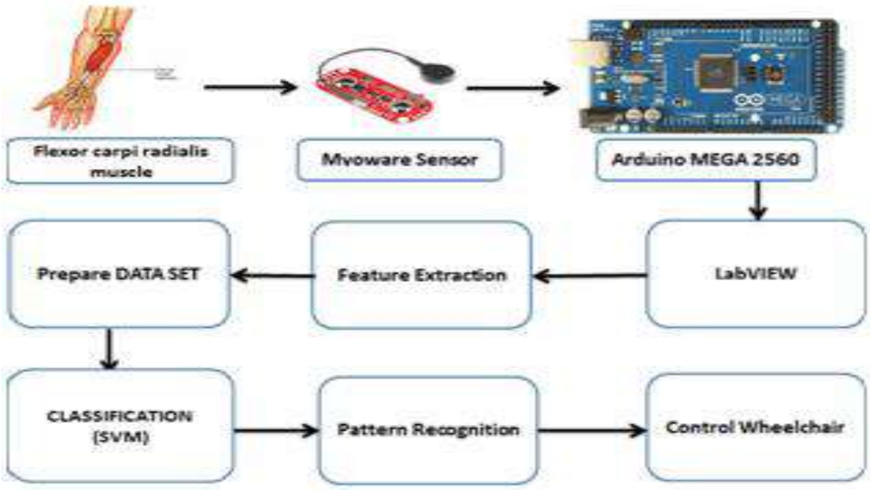


Figure 1: Methodology of Project

By deploying the classification model testing is done. At last, Real time classification & pattern recognition is also done with which wheelchair is controlled in the four directions (forward, backward, left & right) & rest command.

2.1 EMG Acquisition

EMG are signals that are generated by skeletal muscles during movement. Surface EMG is obtained using surface electrodes. EMG signals are acquired by Myoware Muscle sensor. It is used for measuring muscle activation via electric potential. When the muscle is relaxed, the noise-free EMG baseline can be seen. Strong superposition spike will produce when two or more motor unit fire at the same time and the location between the motor unit and the electrodes is near. We get the EMG signal whenever there is any contraction in the muscle otherwise we get a baseline. The EMG signals acquired are fed to Arduino $MEGA$ 2560 which are further given to the $LabVIEW$. For interfacing Arduino with $LabVIEW$, $LIFA\_Base$

is uploaded in Arduino & hence the $LabVIEW$ is Interfaced with Arduino. After selecting the right port & Board the Arduino can be controlled from the $LabVIEW$. The $LabVIEW$ VI that is used for acquiring EMG signals is shown in figure 2.

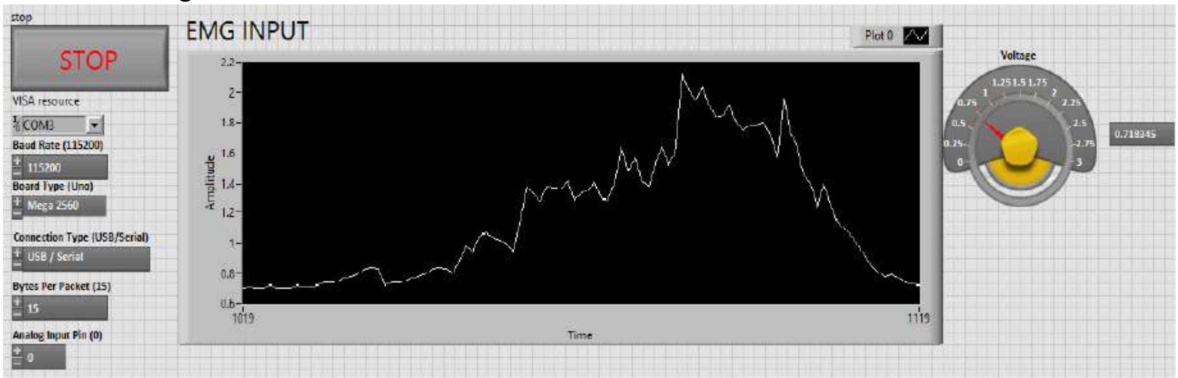


Figure 2: Acquisition of EMG Through Arduino in $LabVIEW$

In this program, the EMG signal is acquiered in the terms of voltage & the EMG signal of 30 seconds is writen in $TDMS$ format & hence a Data set is made. The waveforms of Acquired EMG is shown on the front panel in figure 3. The primary output of Myoware muscle sensor is not a raw EMG but rather an amplified, rectified & integrated signal i.e. EMG's envelope that will work better. The Front Panel also consists of $VISA$ Resource, Baud Rate, Board type, connection type (USB/serial), Bytes Per Packet & Analog input pin which can be selected as per requirement. The EMG signals are acquired for 5 different hand gestures which are defferentiated for different 5 classes for different directional command. These command are Forward, Backward, left, Right & Rest. These five hand gestures along with defined direction are Shown below in figure 3.

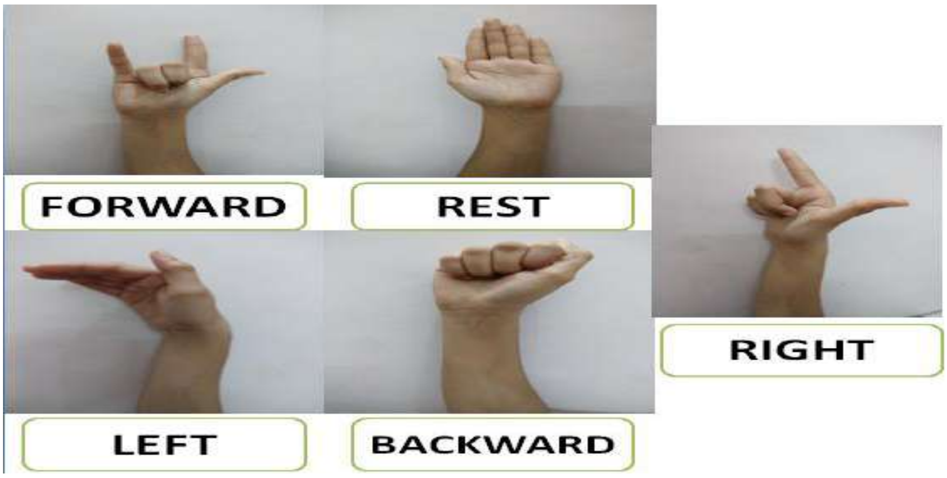


Figure 3: Hand gestures with asigned direction

2.2 Data Set

The VI shown in figure 2 is used for acquiring EMG as well as for making a data set. The data set is made for 5 classes for the five different movements(hand gestures). Signals are acquired from 10 Subjects (30 seconds each). The data set can be made in different formats like Test (LVM), Binary ($TDMS$), Binary with XML Header(TDM) & Microsoft excel($xlsx$) but I prefer Binary ($TDMS$) because it takes less time in Data logging.

2.3 Feature Extraction

After making the data set, next process is to calaculate the different features for the EMG data set.Time domain features are prefer if working with EMG. Different features which are calculated are **Arithmetic** Mean, Median, Mode, Standard Deviation, Variance, RMS, Kurtosis, Skewness & Summation.

2.3.1 Root mean square(RMS)

Root mean square is defined as the square root of the mean square (the arithmetic mean of the squares of a set of numbers) & is also known as the quadratic mean and is a particular case of the generalized mean with exponent 2. RMS is one of the most popular features in analysis of the EMG signal. It is modeled as amplitude modulated Gaussian random process that is related to constant force and non-fatiguing contraction. It is similar to standard deviation method. The mathematical definition [14] of RMS feature can be expressed as

$$\mathrm{RMS} = \sqrt{\frac{1}{N}\sum_{i=0}^{N-1} x_i^2} \tag{1}$$

where N is the number of elements in x.

2.3.2 Variance

Variance is a measurement of the spread between numbers in a data set. The variance measures how far each number in the set is from the mean. Variance is calculated by taking the differences between each number in the set and the mean, squaring the differences (to make them positive) and dividing the sum of the squares by the number of values in the set.

$$\sigma^2 = \sum_{i=0}^{n-1} \frac{(x_j - \mu)^2}{w} \tag{2}$$

where σ^2 is **variance**, μ is **mean**, and w is n when **Weighting** is set to Population and $(n - 1)$ when **Weighting** is set to Sample[15].

2.3.3 Arithmetic Mean

The mean is the average of the numbers or a calculated "central" value of a set of numbers. The VI calculates **mean** using the following equation.

$$\mu = \frac{1}{n}\sum_{i=0}^{n-1} \frac{x_j}{n} \tag{3}$$

where μ is **mean** and n is the number of elements in x[16].

2.3.4 Standard Deviation

The standard deviation is a statistic that measures the dispersion of a dataset relative to its mean and is calculated as the square root of the variance. It is calculated as the square root of variance by determining the variation between each data point relative to the mean. If the data points are further from the mean, there is higher deviation within the data set; thus, the more spread out the data, the higher the standard deviation. **Standard deviation** is the standard deviation calculated from the values in the input sequence X.

$$\sigma = \sqrt{\sum_{i=0}^{n-1} \frac{(x_j - \mu)^2}{w}} \tag{4}$$

where σ is **standard deviation**, μ is **mean**, and w is n when **Weighting** is set to Population and $(n - 1)$ when **Weighting** is set to Samples[17].

2.3.5 Median

The median is a simple measure of central tendency. To find the median, we arrange the observations in order from smallest to largest value. If there are odd numbers of observations, the median is the middle value. If there is an even number of observations, the median is the average of the two middle values [18].

2.3.6 Mode

The mode is a statistical term that refers to the most frequently occurring number found in a set of numbers. The mode is found by collecting and organizing data in order to count the frequency of each result. The result with the highest number of occurrences is the mode of the set [19].

2.3.7 Kurtosis

Kurtosis is defined as the measure of thickness or heaviness of the given distribution for the random variable along its tail. In other words, it can be defined as the measure of "tailedness" of the distribution. Hence, it is clear that it is considered as a common measure of shape. The outliers in the given data have more effect on this measure. it does not have any unit.

$$\text{Kurtosis} = \frac{\frac{1}{n}\sum_{i=0}^{n-1}(X_t(i)-\mu)^4}{\sigma^4} \tag{5}$$

where *n* is the number of samples of the input time series Xt, m is the arithmetic mean value of Xt, and s is the standard deviation of Xt. Kurtosis is a peakedness measurement of the time series distribution. Kurtosis values close to 3 indicate normal-peak distribution. Kurtosis values less than 3 indicate a flatter distribution than normal distribution. Kurtosis values greater than 3 indicate a sharper distribution than normal distribution[20].

2.3.8 Skewness

Skewness is a measure of the asymmetry of the probability distribution of a real-valued random variable about its mean. The skewness value can be positive or negative, or undefined.

$$\text{Skewness} = \frac{\frac{1}{n}\sum_{i=0}^{n-1}(X_t(i)-\mu)^3}{\sigma^3} \tag{6}$$

where *n* is the number of samples of the input time series X_t, m is the arithmetic mean of Xt, and s is the standard deviation of Xt. Skewness is a symmetry measurement of the time series distribution. Negative values indicate left skewness. Positive values indicate right skewness [21].

2.3.9 Summation

Summation is the addition of a sequence of numbers; the result is their *sum* or total. If numbers are added sequentially from left to right, any intermediate result is a partial *sum* or running total of the *summation* [22].

The VI made for feature extraction is shown below in figure 4. Left side contains controlling part such as index, label, size & write option (Enable/ Disable). The "Size" controls the length of the signal which will be processed or of which features will be calculated. Here index is used to choose/cut the EMG signal precisely.Label is used for writing the class of the signal. First, we choose the signal with the help of index then, write it by choosing the enable option. The calculated features are written in order to make the Data set along with class label that are five in this project for different hand gestures.

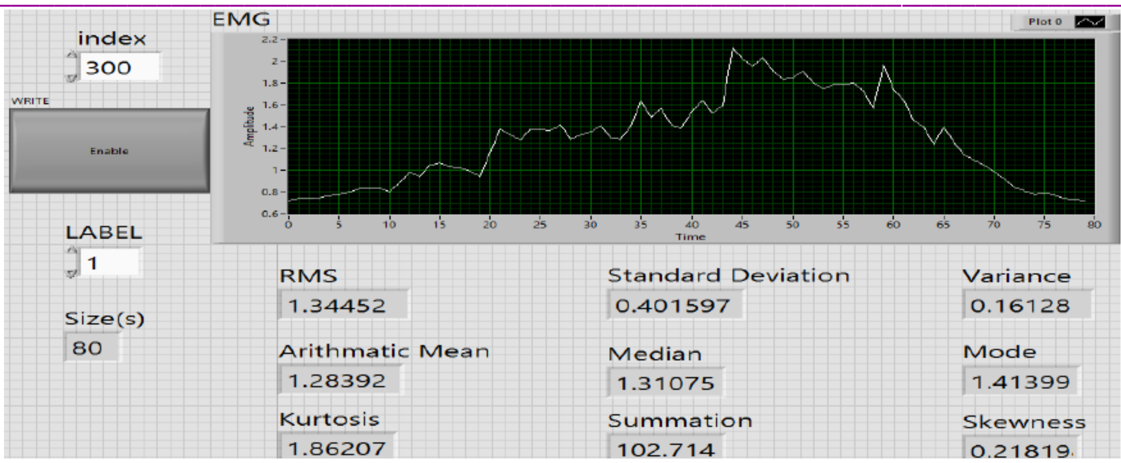


Figure 4: Feature Extraction VI

2.4. Classification

The classifier is supposed to classify between the different classes of signals which are acquired by different hand gestures. Classification includes two parts: Training & Deployment. The classification process is done by SVM. SVM is a technique derived from statistical learning theory & it is the most promising technique for data classification and regression and function estimation [23-28].

2.4.1 Classification Training

Initially, Training is done with the help of Data set that was prepared in the CSV format which is provided as input to the Classifier in the Left side of front panel. The lebel setting is also given which will allow us to feed the numbers of labels.

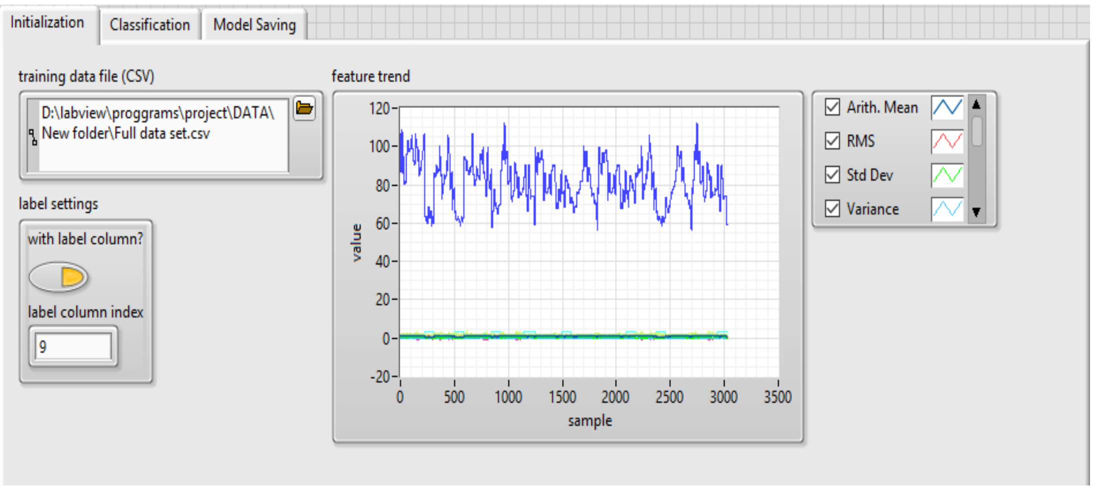


Figure 5: Input(data set of features) provided to Classifier

The number of labels are equal to the $(n-1)$ where n are equal to the number of coloumns. Different features are also shown in figure 5 on the Front panel. In this project, the classification techniques are used which is SVM(Polynomial).The paramenters of these Classifer are selected so that maximum accuracy can be acieved. SVM classifer is shown in figure 6 with the different paramentes along with the accuracy achieved. The accuracy for SVM is 98.87, respectively.

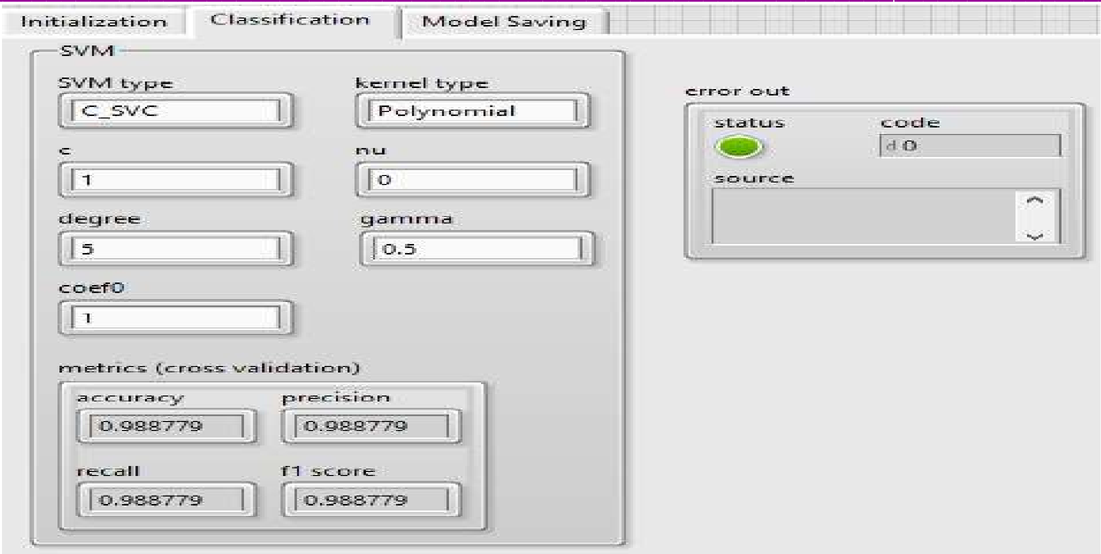


Figure 6: Different Paramenters, Classification Pattern & Accuracy

In the last part of classification training, the model file which is made by classifier in the process of classification is saved in $JSON$ format. Here, the controls for 2 purpose are given which can be seen in figure 7. One gives the address of this file & second gives the type of clasifier in which it will be saved. Since we are working on SVM so it will be choosen by default.

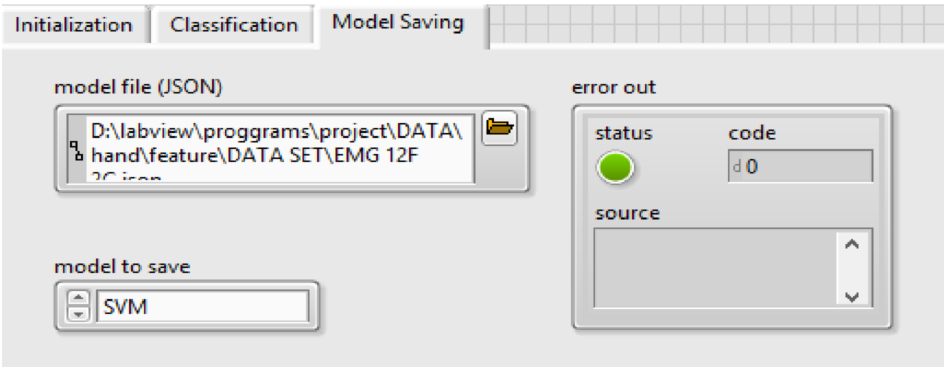


Figure 7: $JSON$ model file output from SVM classifier

2.4.2 Classification Deployment

The classification Deployment part is used for testing, it test whether classifier is able to classify between different classed or not. In this project we are working with five classes which will be tested in this VI. There will be two input to this VI, These are model file ($JSON$) & test data file(CSV). Label setting is also provided which must be assigned the same value which was fed to the classification training earlier. The featured trend & predicted result is also shown along with the Acuracy. The test file with difeerent classes can be tested here to find out the accuracy. If it gives us good accuracy with the different class after testing then we can further work with the data set.

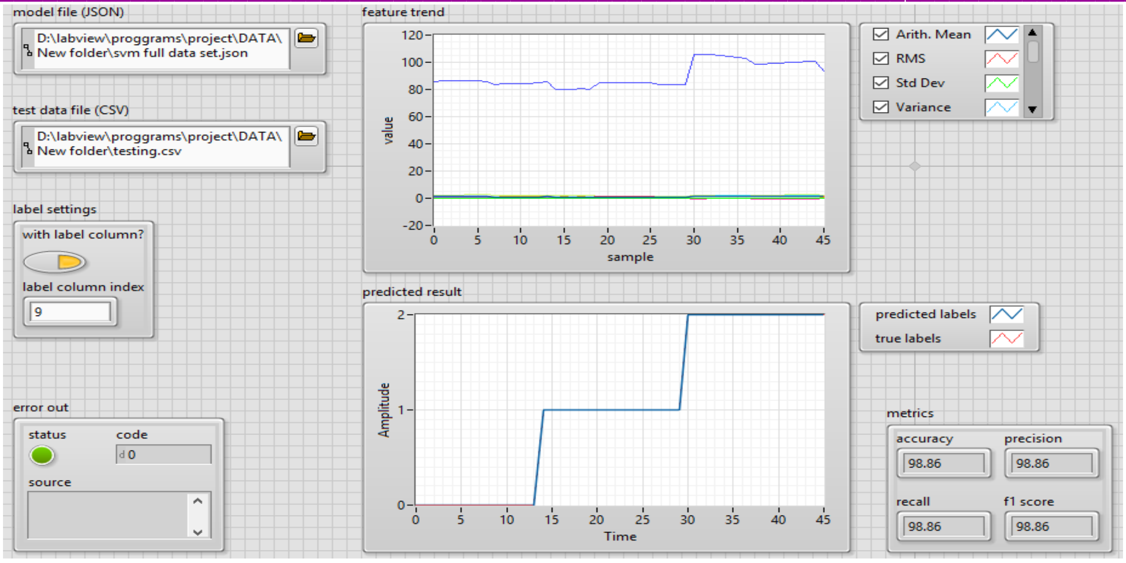


Figure 8: Classification Deployment/Testing

2.5. Real time classification of EMG

After testing the data with different classes, next step is to classify the different classes in real time. In this part not only real time classification of EMG for different classes is done but different predicted result for different hand gestures are also shown & are taken as output from the Arduino $MEGA$ 2560. The five different DC outputs are taken out which are further given to the wheelchair & hence wheelchair gets the different dc output from the Dc pins of the Arduino $MEGA$ 2560. All the controls for Arduino are given on the left side of the VI. These controls includes Analog input pin, Digital output pins, of $VISA$ Resource, Baud Rate, Board type, connection type (USB/serial) & Bytes Per Packet.The real time waveform, its value in voltage, size of waveform, its numerical value, size of array, real time values of features in array, predicted value & result output such as (Forward, Backward, Left, Right & Rest) are also shown on the Front panel.

3. RESULT & DISCUSSION

In this project, Acquisition of EMG, making data set, feature extraction, classification trainig is done. Once all these processes are completed offline then all are added in a single VI so that all these process can be implimented in real time except classification training & making data set. In real time, classification training is replaced by clasification deployment. So, this VI will be used to acquire EMG, feature extraction & classification in real time. As a result of this VI, the different classes of hand gestures will be classified & will give the respective direction as assigned to that hand gesture like forward, backward, left, right & rest. All possible result with output such as Forward, Backward, Left, Right & Rest are shown in figure 9 to figure 13 respectively.

Forward

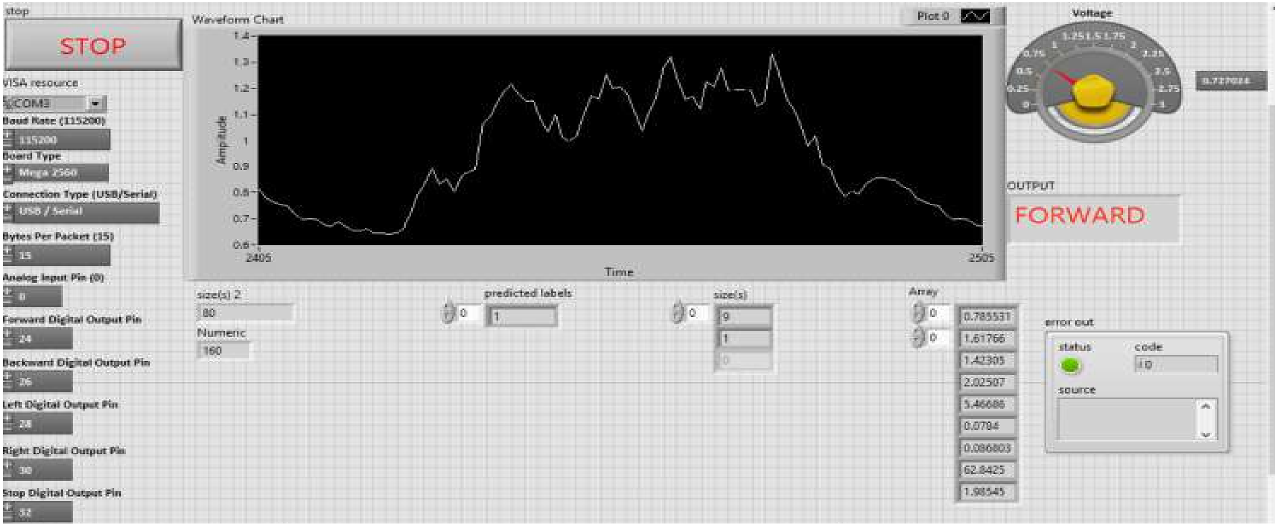


Figure 9: Classification For Forward Movement

Backward

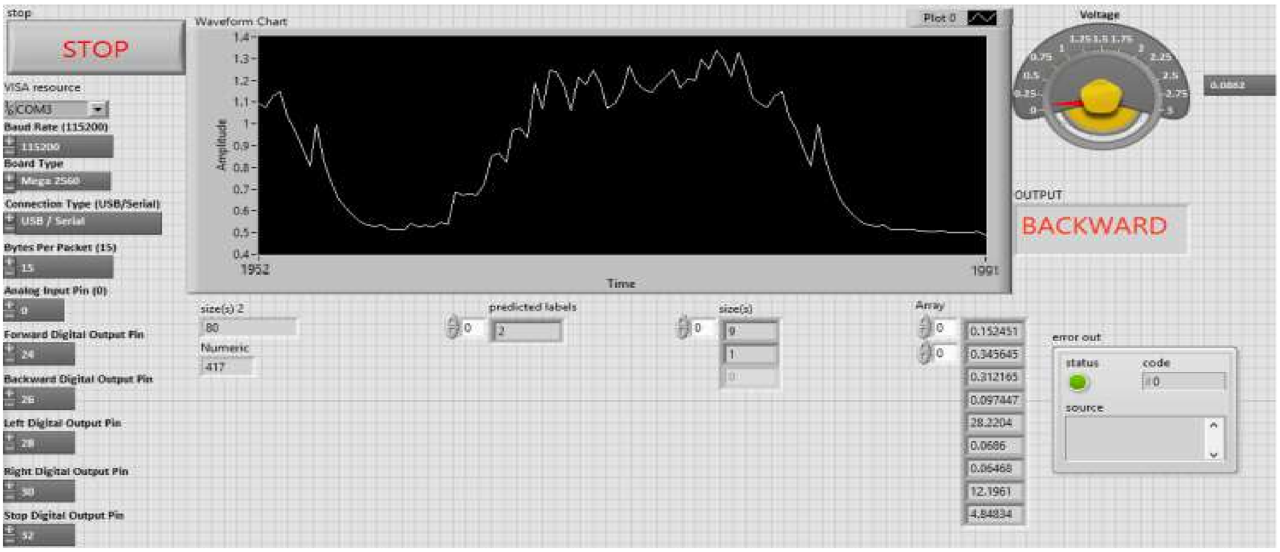


Figure 10: Classification For Backward Movement

Left

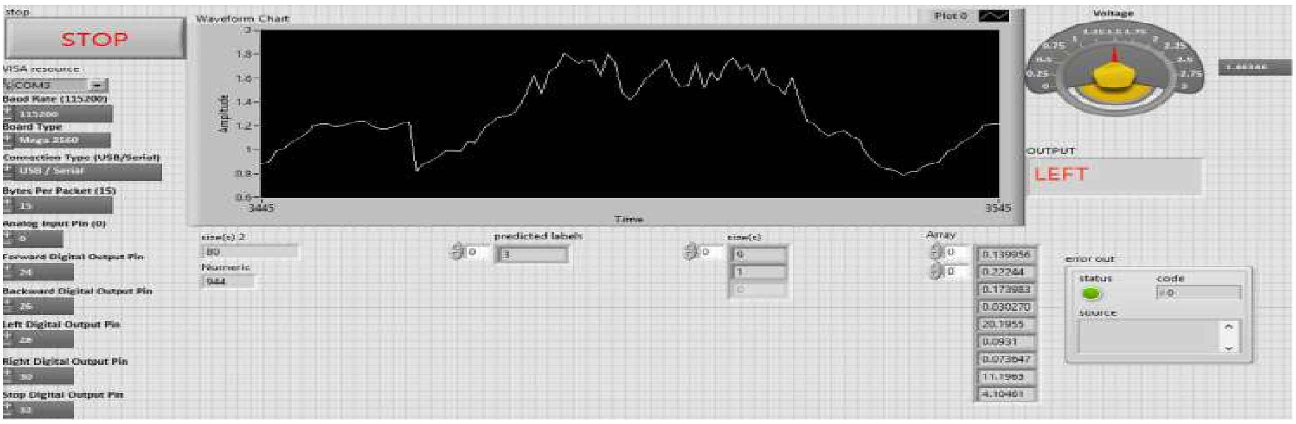


Figure 11: Classification For Left Movement

Right

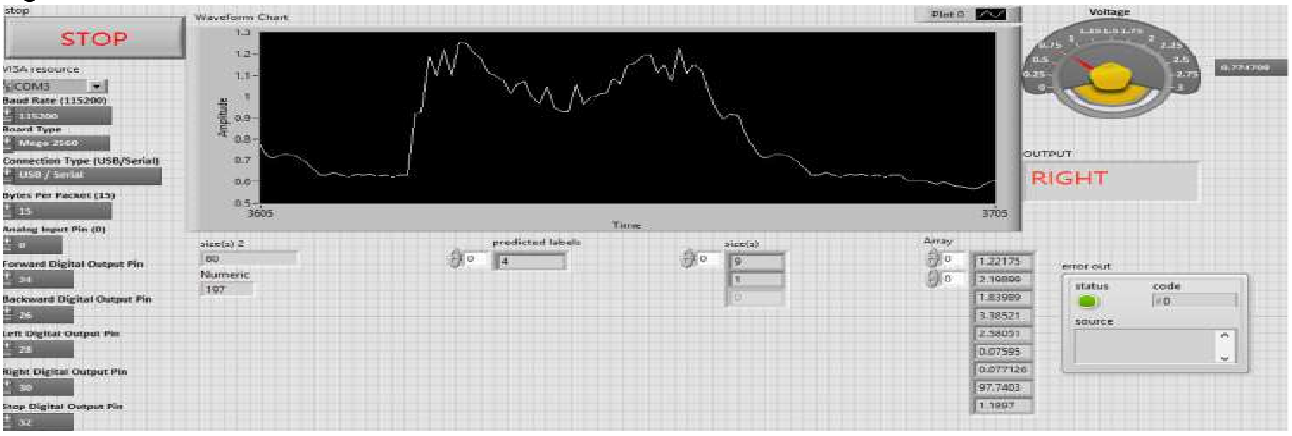


Figure 12: Classification For Right Movement

Rest

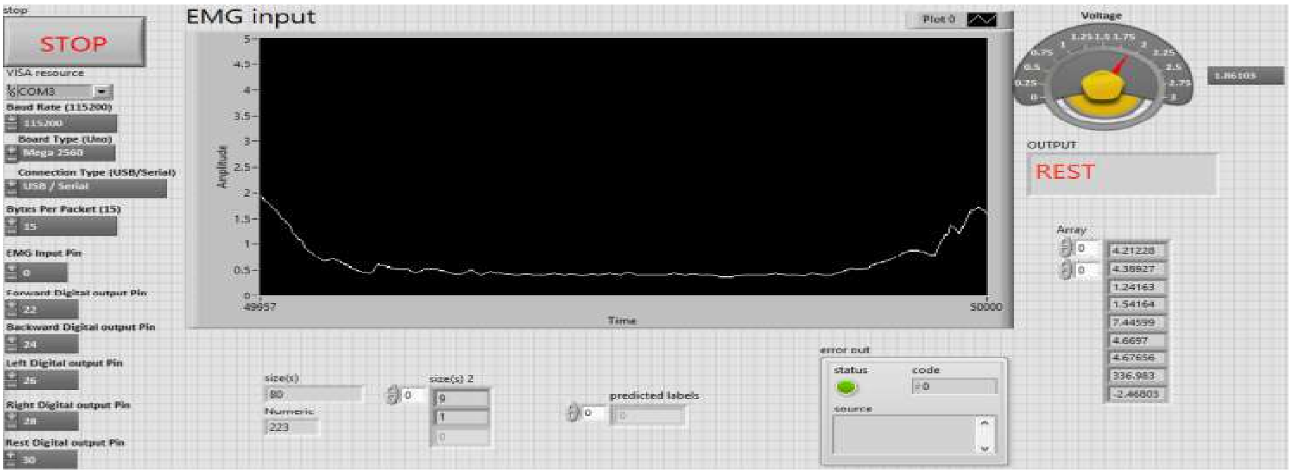


Figure 13: Classification For Rest

4. CONCLUSION

An EMG based Smart wheelchair has been designed that can be controlled by the user in four directions (forward, backward, left & right) & rest by respective hand gestures. This smart wheelchair will detect these different hand gestures by EMG signals acquired from Flexor carpi radialis muscle & make the user independent for movement in the surroundings. These signals are taken by Myoware muscle sensor through Arduino $MEGA$ 2560 which are further processed in $LabVIEW$ for classification. The processing in $LabVIEW$ consists of Signal Acquisition, feature Extraction, Classification includes Training & Deployment, Real time Pattern Recognition. Working in real time will give output for different hand gestures for respective movement i.e. Forward, Backwaard, Left, Right & Rest. These outputs are provided to the Wheelchair & as a result the wheelchair is controlled by EMG signals from different hand gestures in the different directions.

REFERENCES

[1] S. Nayak, et al., "Development of a simultaneous acquisition system for ECG, PCG and body temperature signals," in 2015 Annual IEEE India Conference (INDICON), 2015, pp. 1-6.

[2] S. Nayak, et al., "Development of a simultaneous acquisition system for ECG, PCG and body temperature signals," in 2015 Annual IEEE India Conference (INDICON), 2015, pp. 1-6.

[3] D. Carroll, A. Subbiah, "Recent Advances in Biosensors and Biosensing Protocols" Journal of Biosensors & Bioelectronics 2012.

[4] M. A. Oskoei, and H. Hu. "Myoelectric control systems-A survey." Biomedical Signal Processing and Control, vol. 2, no. 4, pp.275-294, 2007.
[5] M.T. Pham, K. Tachibana, E.M.S. Hitzer, T. Yoshikawa and T. Furuhashi. Classication and Clustering of Spatial Patterns with Geometric Algebra, AGACSE 2008 Leipzig, 2008.
[6] M.T. Pham, K. Tachibana, E.M.S. Hitzer, S. Buchholz, T. Yoshikawa and T. Furuhashi. Feature Extractions with Geometric Algebra for Classication of Objects, IEEE World Congress on Computational Intelligence / International Joint Conference on Neural Networks, Hong Kong, 2008.
[7] T. Nitta. An Extension of the back-propagation algorithm to complex numbers, Neural Netw. Vol. 10, No. 8, pp. 13911415, 1997.
[8] N. Matsui, T. Isokawa, H. Kusamichi, F. Peper and H. Nishimura. Quaternion neural network with geometrical operators, J. Intell. Fuzzy Syst. Vol. 15, No. 34, pp. 149164, 2004.
[9] A. Hirose. Complex-Valued Neural Networks: Theories and Applications, Series on Innovative Intelligence, Vol. 5, 2006.
[10] *Bishop, Christopher M. (2006).* Pattern Recognition and Machine Learning *(PDF). Springer. p. vii. Pattern recognition has its origins in engineering, whereas machine learning grew out of computer science. However, these activities can be viewed as two facets of the same field, and together they have undergone substantial development over the past ten years.*
[11] M.T. Pham, T. Yoshikawa, T. Furuhashi and K. Tachibana. Feature Extraction with Space Folding Model and its Application to Machine Learning. JACIII Vol. 15, No. 6, pp. 662-670, 2011.
[12] M. Volpi, D. Tuia, F. Bovolo, M. Kanevski and L. Bruzzone. Supervised change detection in VHR images using contextual information and support vector machines, International Journal of Applied E
[13] C.W. Hsu and C.J. Lin. A Comparison of Methods for Multiclass Support Vector Machines. IEEE Transactions on Neural Networks, 2002.
[14] S. Maji, A. C. Berg and J. Malik. Classification using intersection kernel support vector machines is efficient. In Proc. CVPR, 2008
[15] Graupe, D., & Cline, W. K. (1975). Functional separation of EMG signals via ARMA identification methods for prosthesis control purposes. IEEE Transactions on Systems, Man and Cybernetics, SMC-5(2), 252–259.
[16]A Dictionary of Physics (6 ed.). Oxford University Press. 2009. ISBN 9780199233991.
[17] J. Y. Lin, C. T. Cheng, and K. W. Chan, "Using support vector machines for long term discharge prediction," Hydrological Sciences Journal, vol. 51, no. 4, pp. 599–612, 2006.
[18] Park & Lee, 1998; Zardoshti-Kermani et al., 1995).
[19] *Jacobs, Harold R. (1994). Mathematics: A Human Endeavor (Third ed.).* W. H. Freeman*. p. 547.* ISBN 0-7167-2426-X*.*
[20] ^ Jump up to:[a] [b] *Medhi, Jyotiprasad (1992).* Statistical Methods: An Introductory Text*. New Age International. pp. 53–58.* ISBN 9788122404197*.*
[21] Page 19 in: *Stephen K. Bangert MA MB BChir MSc MBA FRCPath; William J. Marshall MA MSc MBBS FRCP FRCPath FRCPEdin FIBiol; Marshall, William Leonard (2008). Clinical biochemistry: metabolic and clinical aspects. Philadelphia: Churchill Livingstone/Elsevier.* ISBN 0-443-10186-8*.*
[22] Weisstein, Eric W. "Statistical Median". MathWorld*.*
[23] Damodar N. Gujarati f Econometrics. McGraw-Hill Irwin. 3rd edition, 2006: p. 110.probability distribution]]
[24]Westfall, PH. "Kurtosis as Peakedness, 1905 - 2014. R.I.P.". AmStat. 68:191195. doi:10.1080/00031305.2014.917055. PMC 4321753. PMID 25678714.] [25] "1.3.5.11. Measures of Skewness and Kurtosis". *NIST*. Retrieved 18 March 2012.
[26] Oxford English Dictionary, 2nd ed. - algebraic (esp. of a sum): taken with consideration of the sign (plus or minus) of each term.

[27] L. Y. Chuang, C. H. Yang, and L. C. Jin, “Classification for multiple cancer types using support vector machines and outliner detection methods,” Biomedical Engineering Applications, Basis & Communications, vol. 17, pp. 300–308, 2005.
[28] M. D. Ashanira, M. Z. Azlan, and S. Roselina, “Hybrid GRSVM for prediction of surface roughness in abrasive water jet machining,” Meccanica, vol. 48, no. 8, pp. 1937–1945, 2013.