Webology (ISSN: 1735-188X)
Volume 19, Number 2, 2022

Analysis Of Muscle Function For Postural Correction Using Surface EMG Signals

Suma K V[1] , Lakshmi Shrinivasan[1] , Varun C R[1] , Nagendra B N[2]

[1]Department of Electronics and Communication, Ramaiah Institute of Technology, Bengaluru, India

[2] Ramaiah Indic Specialty Ayurvedic Hospital, Bengaluru, India

---

Abstract— When the muscle cells are activated electrically or neurologically, a kind of electric potential will be developed which is detected by a device named electromyography (EMG)**.** The analysis of EMG signals can be utilized by Yoga therapists and physiotherapists who provide corrective therapy to the patients suffering from muscle related weakness and ailments. In this work, hardware module has been designed and developed to acquire EMG signals from healthy controls and subjects in need of posture correction. Four muscles namely right trapezius, left trapezius, right sternocleidomastoid muscle (SCM) and left SCM are identified for EMG signal acquisition. The features of EMG signals like root mean square value, signal power, signal frequency, motor unit potential and simple square integral are computed. Statistical measures like maximum, minimum, mean and standard deviation of these features are compared and are found to be significantly useful in analyzing the muscle activity. Support Vector Machine and Random Forest Decision Tree (RFDT) are used for classifying the signals. Classification is carried out on individual muscle signals and the accuracy is found to be highest for Right Trapezium and lowest for Right SCM. Further, classification based on combined features of all the four muscles is found to give accuracy of 88% and 81% for SVM and RFDT respectively. Based on accuracy results obtained using SVM and RFDT, the combination of features of all four muscles has been found to be satisfactory and comparative performance metrics are presented. This novel work can be helpful for treating the subjects with posture related muscular disorders.

Keywords— EMG, Random Forest Decision Tree, Muscle Function, Support Vector Machine, Postural Correction

1. INTRODUCTION

Posture is the ability to maintain an upright symmetrical position of the spine (head, neck, pelvis and limbs) during static positions such as sitting and standing as well as during movement. In current times, where most of the professions require sitting in front of the computer for long hours, our sitting postures are being affected severely. School children also face postural issues as they carry heavy bags on their shoulders. This may lead to degradation of muscle activity and lead to different forms of physical inconveniences in neck, back etc. People have identified this fact and have started looking at correcting their sitting postures. The most commonly found postural correction issues are Forward Head Posture, Anterior Pelvic Tilt and Internally Rotated Shoulders.

Physical Therapists can help with postural exercises to strengthen core, shoulder, and back muscles. Yoga asanas tailored to individual's need can greatly reduce the discomfort and correct the damage caused to the muscles.

Yoga, an ancient Indian discipline, is understood to have mental as well as physical health benefits. It consists of a set of physical poses and deep breathing that is known to increase flexibility and muscle strength and also improve the respiratory system. The body movements of yoga practitioner must be smooth such that they can attain the required postures and in turn, activate the muscles influenced by the asana. Muscle activation patterns can yield information about the kinematics of the body during Yoga asanas. [2]

The asanas prescribed to the subjects participating in our study are: Dandasana, paschimottanasana, ardha uttanasana, vrikshasana, parshva konasana, vakrasana, bhujangasana, surya namaskar and vajrasana. The lower trapezius muscle is activated maximally in all of these poses to help stabilize the shoulder blades during overhead movements. Deep breathing in any of the above postures has to be maintained as proper breathing makes use of upper lobes of lungs which in turn creates movement in the muscles in and around the neck and trapezius region.

Electromyography (EMG) is used to record and evaluate the electrical activity produced by muscles of a human body, and with further medical investigation of the signal and its unique features, medical practitioners can assess the performance of the muscle from which the signal is recorded from, and suitable diagnosis can be prescribed. Two main kinds of EMG namely surface EMG and intramuscular EMG. In Surface EMG the muscle activities are acquired as signals from the surface of the muscle above the skin. The activity of the muscle is assessed only a limited manner in surface electrodes. It uses a pair or more complex array of multiple electrodes to perform these signal acquisition. It is essential to have more than one electrode to display the results as it uses potential difference. The pitfall of this technique is that it is restricted to superficial muscles and also influenced by the depth of tissue levels which in turn depends on the weight of a subject and highly variable as it cannot differentiate signals between the adjacent muscles.

In this study, a high accuracy intelligent system comprising of Multi-Channel Surface Electromyogram Acquisition hardware with firmware providing Statistical Analysis designed and machine learning based classification SVM and RFDT algorithms have been implemented. This can acquire EMG signals at four muscles simultaneously, store the signals, extract parameters for analysis and further interpretation. The work has been collaborated with Ramaiah Indic Specialty Ayurvedic (RISA) Hospital to efficiently identify anomalies in muscles during the prescribed progressive yoga course for rectifying body postures, specifically in sitting position (elaborate). The comparative study of classification accuracies, specificity and sensitivity has been presented in the work.

2. LITERATURE SURVEY

From research studies, it is understood that machine learning algorithms in pattern recognition is as near to perfect learning of the pattern in computing systems. There can be two ways from here, supervised and unsupervised learning. The clear distinction is the nature of data. If the researchers can afford large volumes of labelled multi- channel EMG training data, then it becomes easier to learn patterns, if there is unavailability of sufficient training data for analysis, then a finely tuned, computationally expensive unsupervised algorithm has to be designed. For the chosen problem statement, a binary classifier is designed to distinguish EMG parameters collected during a session of gait cycle for both heathy subjects and medically proven to have osteoarthritis [12]. A Support Vector Classifier is implemented to classify healthy and osteoarthritis patients based on gait EMG signals from the ready dataset. SVC was selected for the reason that it will be easier to migrate from the supervised domain to unsupervised domain. [11] rightly proposes an unsupervised algorithm to analyze EMG features, employing a particle adaptive learning strategy and least square support vector classifier. Another classifying algorithm Random Forest Decision Tree (RFDT) has been implemented. RFDT [14] will use multiple decision tree rather than a single decision tree for classification. The random forest ensemble learning algorithm is to create a forest of decision trees. Each decision tree provides one vote, and the final prediction is determined on the basis of all votes [15]. To obtain less correlated decision trees, different sets of features are randomly selected and used with multiple samples from the ready dataset to train each tree. The classification yielded positive results when trained on new data and gives confidence to us to expand on this problem statement of studying the muscle function in people requiring postural correction.

3. MATERIALS AND METHODS

In this study, healthy controls and subjects in need of postural correction during sitting are considered. After numerous consultations with doctors and instructors from RISA and Ramaiah Medical College, four muscles which are frequently affected due to bad sitting posture, are selected for this pilot study. The four muscle points are, as shown in Figure 1, near the neck and shoulder called sternocleidomastoid muscle SCM (one on the front side of the neck-left and right) and Trapezius, one each on both sides, near the posterior of the neck- shoulder region [3].

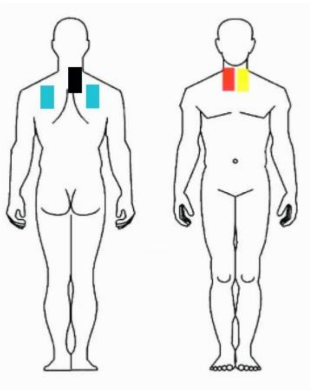

Fig 1. Muscle Activation Points

Blue (2)- Trapezius, Black – Ground/ Reference, Red- SCM(right), Yellow-SCM(left)

A four-channel EMG acquisition system is designed and EMG signals are acquired. These signals were analyzed in time domain by extracting certain parameters. Classification into healthy and that requiring postural correction is done based on these extracted parameters, using machine learning algorithms.

3.1 EMG acquisition hardware:

Hardware Design as shown in Figure 2, involved the following steps:

- Selection of EMG sensor - We tested both differential amplifier setup and instrumentation amplifier setup and concluded that instrumentation amplifiers were better for low noise and easy gain adjustment, so we chose an IC called AD620.

- Design of filter - The strongest EMG signals lie in the range of 150Hz on the frequency spectrum and a bandwidth of 50 to 500Hz, hence we designed a RC band pass filter for the same range.

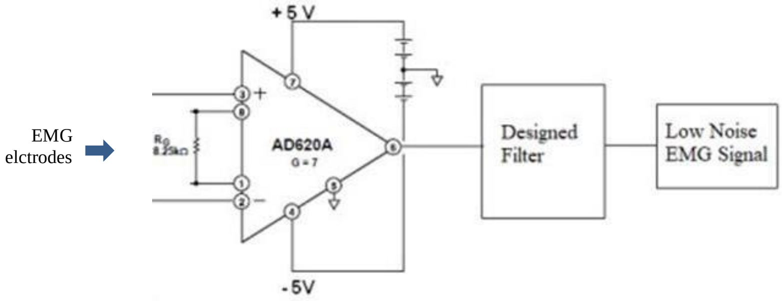

Fig 2. Overview of hardware

prototyping a Surface EMG Acquisition Device with a Low pass filter of 50Hz Cutoff. Many factors like Power, noise reduction, amplitude adjustment, frequency analysis of signal and noise baseline adjustment were simulated and analyzed on NI Multisim and Audacity.

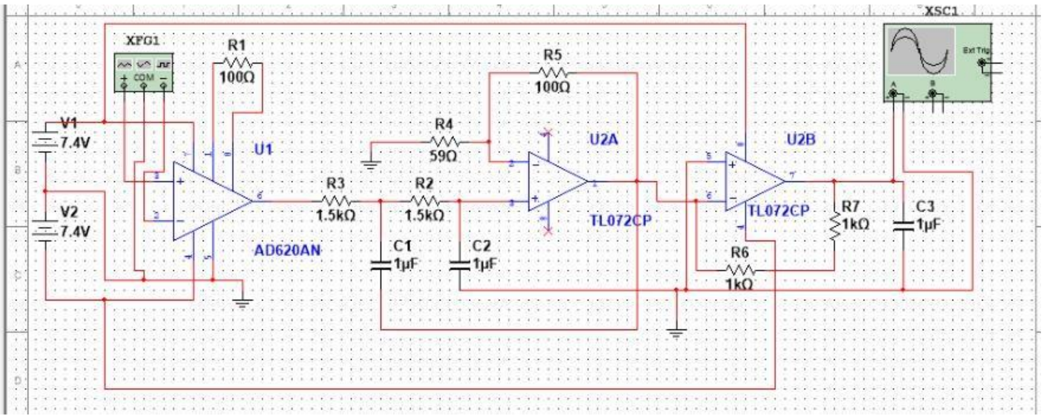

Fig 3. Circuit Design on NI Multisim

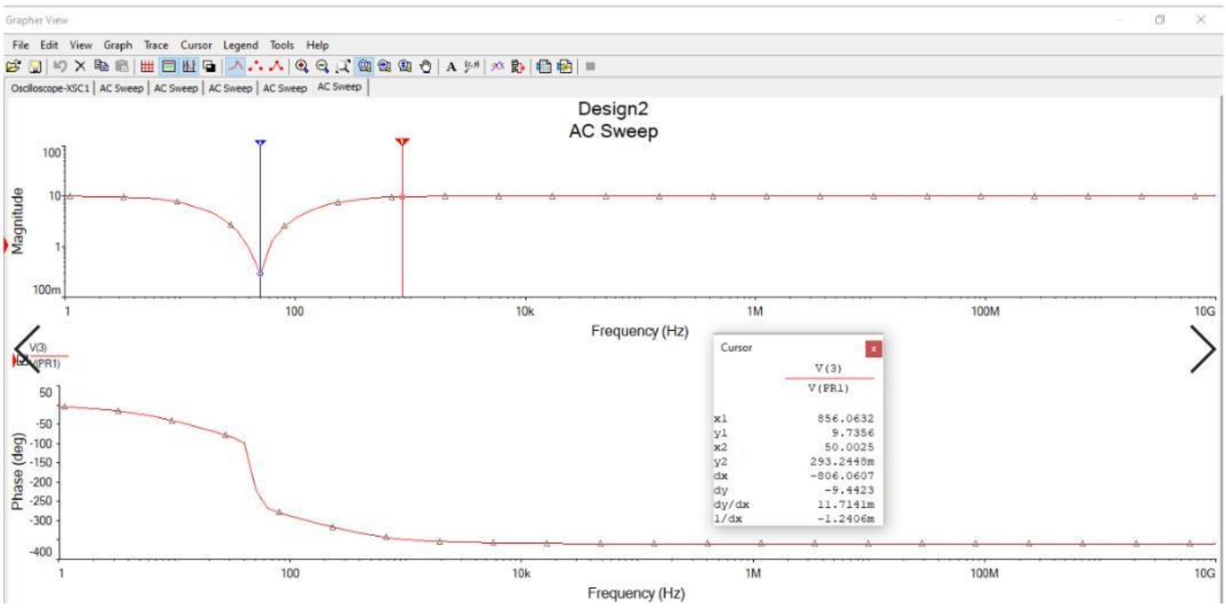

Fig 4. Frequency Response plot for notch filter design

For eliminating the 50Hz AC noise we designed a notch filter (passive) and simulated the same using an AC sweep. The simulation results are shown in figures 3 and 4. It can be seen that the notch filter is performing well in removing the 50Hz signal. But when built practically we did not see significant improvement in the EMG signals. So, we tried out the Band pass filter instead. The simulation of this modified circuit and its frequency response are shown in figures 5 & 6. The cutoff frequency was designed for 50 Hz and when implemented practically, the circuit response was satisfactory.

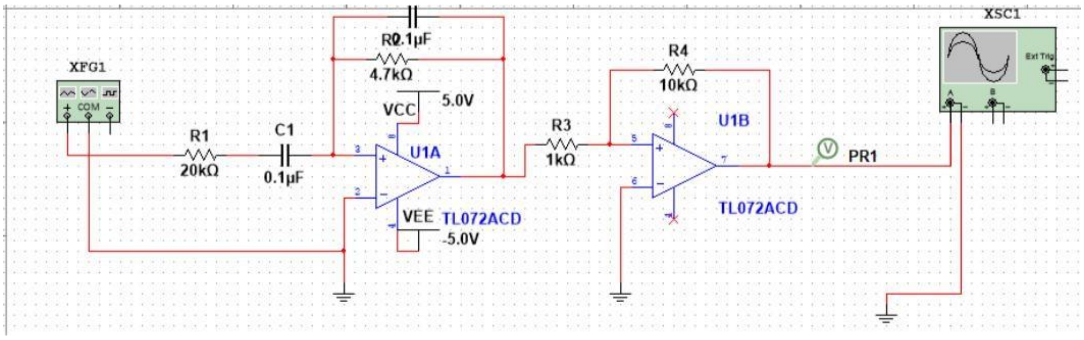

Fig 5. Finalized Design

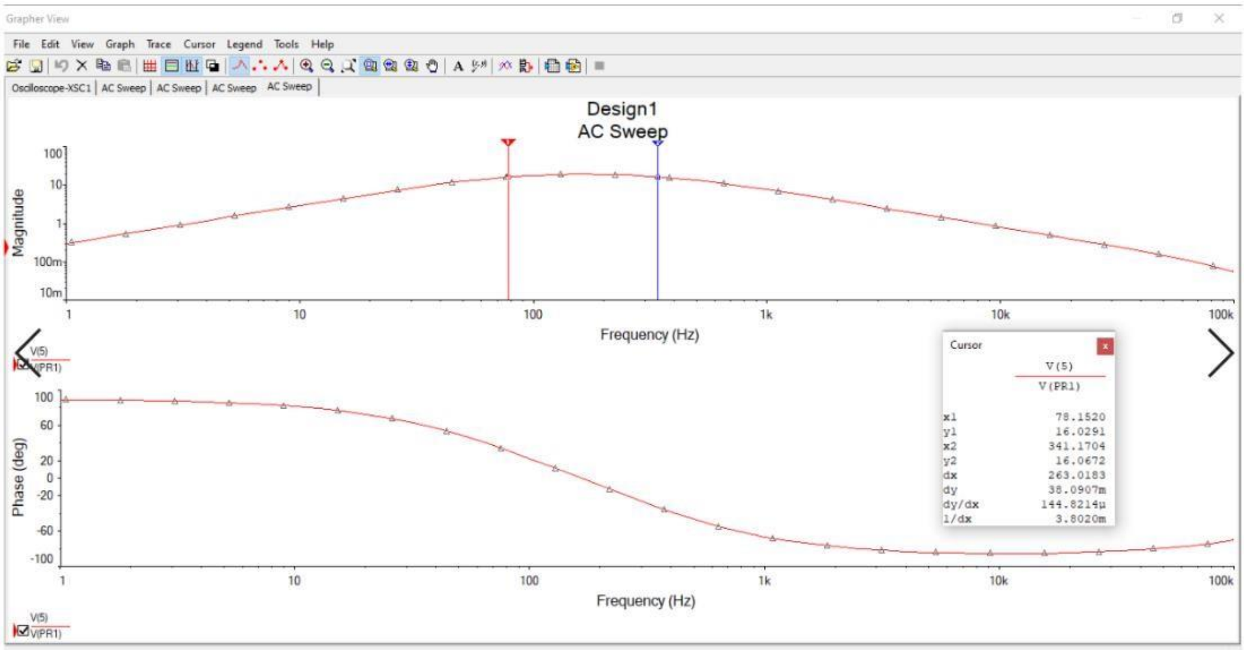

Fig 6. Frequency Response for bandpass filter design

Audacity software has been used throughout the course of project for recording and analyzing EMG Signals. It is a free and open- source audio recording software, available for Windows. It was selected as the recording software for initial recordings and preliminary analysis because it possesses features like noise reduction, audio pitch adjustment, adjusting audio speed, multitrack mixing for multi-channel modes with sampling rates up to 96 kHz with 32 bits per sample and also supported Free Lossless Audio Codec (FLAC). Figure 7 shows a sample signal displayed on the tool.

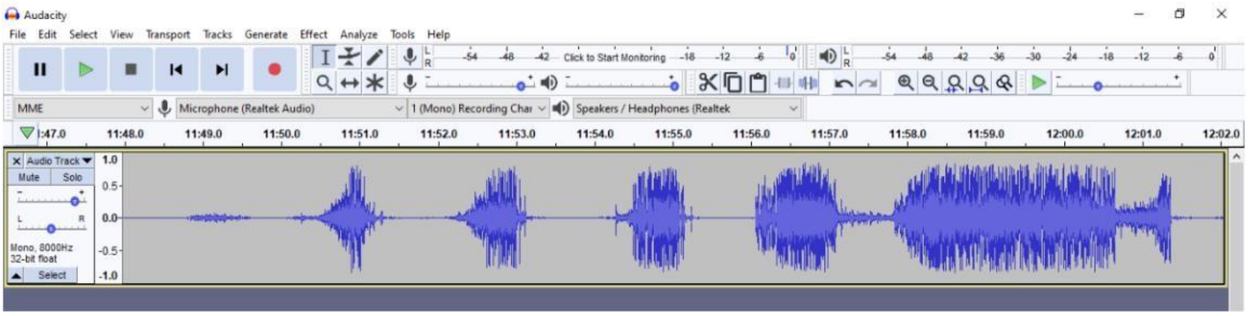

Fig 7. A snapshot of Signal Recording using Audacity Software

Figures 8 and 9 depict the signals acquired from the implemented hardware. A sample signal taken from a healthy control as well as a subject requiring postural correction is shown. The signals exhibit different patterns for the same activity and consequently the study of these muscle activity parameters can be beneficial in clinical practice.

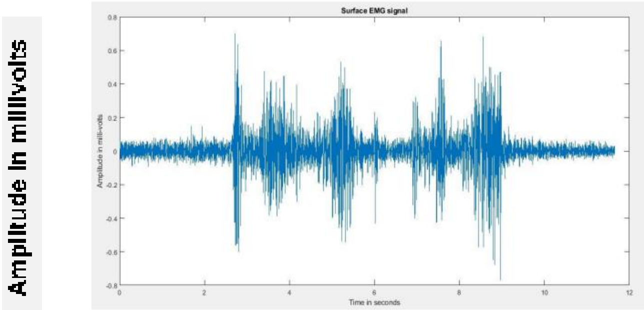

Fig 8. Signals recorded from a healthy control

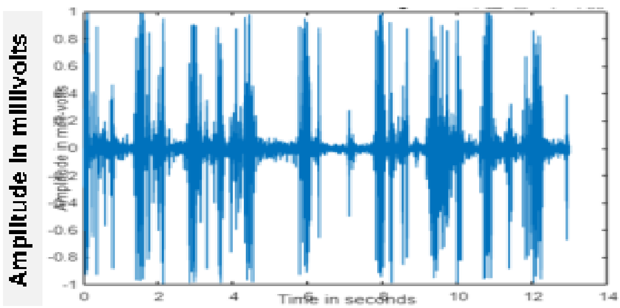

Fig 9. Signals recorded from a subject requiring sitting postural correction

3.2 Database generation:

The database of EMG signals of 20 healthy controls and 20 subjects requiring postural correction (PC) was generated. The age group considered was 30 to 60 years of age. 22 females and 18 males participated in the study. Based on the health condition of the subject, asanas were recommended and taught by the professionals at RISA. EMG signals from four muscles namely right trapezius, left trapezius, right SCM and left SCM are acquired from the subjects while they performed 4 actions namely neck twist left, neck twist right, relaxation of neck muscles with nasal breathing and shoulder lift. The signals were acquired twice from the same subject to check for muscle fatigue or better activation of muscle. The signals used in this study is currently restricted to the signals obtained prior to this yoga practice. These signals are compared with the signals from healthy controls having normal posture.

Number of signals acquired per person is as shown in equation (1):

[Resting + neck left turn + neck right turn + shoulders lifting] * [4 muscles] = 16 signals/person ……..(1)

In total, 640 EMG signals were collected from forty subjects.

3.3 Data preparation for signal processing in computer:

Following steps were followed to prepare data for processing and MATLAB™ was used as the tool.

- Extract Surface EMG Signal as .wav file.
- Import EMG Signal as .wav file using import data () and use audio info () functions to create a struct with critical fields namely compression method, sample rate, number of channels, number of samples, duration of the signal, bits per sample of the EMG Signal.
- Extract features by instancing the signal values (data) in the function.
- The features for the corresponding channel will be saved as a variable and later a feature vector constructed out of these variables.
- Export the feature vectors to Excel sheet as .xlsx or .csv file for further analysis.

3.4 EMG parameters:

Time-domain parametric analysis of EMG Signals is an analysis of physical signals, mathematical functions, or time series of economic or environmental data. EMG Parameters extracted for analysis are as follows: RMS is a feature that describes the muscle force and non-fatigue contraction, Signal power is best measured by the feature VAR, WA indicates the motor unit potential firing, ZC provides the information about frequency of EMG signal. Simple Square Integral, SSI provides the overall sum of EMG signal amplitude squares. These parameters are computed using equations (2) to (6).

Root Mean Square (RMS):

$$RMS = \left(\frac{1}{N} \sum_{n=1}^{N} Y_n^2 \right)^{1/2} \qquad \text{…….(2)}$$

where wavelet coefficient is represented by Yn and its length by N

Zero Crossing (ZC):

$$ZC = \sum_{n=1}^{N-1} f\left(Y_n\right) \qquad \text{……..(3)}$$

$f(Yn) = 1, if\ \{(Yn > 0\ \&\ Yn{+}1 < 0)|(Yn < 0\ \&\ Yn{+}1 > 0)\}\ \&\ |Yn - Yn{+}1| \geq T$

$f(Yn) = 0, otherwise$

where threshold is represented by T, wavelet coefficient by Yn and its length by N

Willison Amplitude (WA):

$$WA = \sum_{n=1}^{N-1} f\left(Y_n\right) \qquad \text{……..(4)}$$

$f(Yn) = 1, if\ |Yn - Yn{+}1| \geq T\ f$

$(Yn) = 0, otherwise$

where threshold is represented by T, wavelet coefficient by Yn and its length by N

Simple Square Integral (SSI):

$$SSI = \sum_{n=1}^{N} Y_n^2 \quad \text{……..(5)}$$

where wavelet coefficient is represented by Yn and its length by N

EMG signal Variance (VAR):

$$VAR = \frac{1}{N-1} \sum_{n=1}^{N} Y_n^2 \quad \text{…….(6)}$$

where wavelet coefficient is represented by Yn and its length by N

3.5 Muscle Function Analysis using Machine Learning Algorithm:

Binary classifiers are often used in biomedical parametric analysis to study the correlation between inter-patient data or intra-patient data. Of them, Support-vector classification and RFDT are often the popular binary classifiers. SVM's are supervised machine learning models for regression analysis, correlation and classification. RFDT uses the power of multiple decision trees, it basically does not rely only on feature importance from a single decision tree rather a collection of trees. SVM assigns one of the two labels to the test data so as to broaden the distance between the two categories to the extent possible. Later the test data is then classified according to which side of the gap they fall on. Non-Linear SVM is employed when data with a straight line cannot be separated, i.e., for complex non-linear data. In RFDT, the features are selected randomly during the training the process and combines multiple decision trees. This process of randomization makes it more accurate and yields good results.

The functions in SVM, also called kernels, that can be used for training are sigmoid, radial basis function (RBF), polynomial and linear. We use Radial Basis Function to train a C-support vector classification to train two classes of Surface EMG time domain parameters obtained. Radial Basis Function is a mathematical real-valued function with deterministic values based on the distance between the input point and a fixed point on a multi-dimensional plane. There are two distinct parameters that needs to be tuned to achieve the best throughput using SVM. The RFDT decision trees are built and training and test dataset have been split and various performance parameters have been obtained and analyzed.

The time domain surface EMG parameters are highly non-linear in nature, this leads to select the SVM and RFDT classification algorithms to analyze the various performance metrics of muscle performance.

4. RESULTS AND DISCUSSION

Tables 1 to 4 list the parameter values of EMG parameters, as listed in section 3.4, in the 4 muscles considered namely, Right Trapezius, Left Trapezius, Right SCM and Left SCM respectively. The statistical values namely Maximum, Minimum, Standard Deviation and Mean of each of the parameter are computed and tabulated. In the tabulation, comparison between the statistical values of the parameters is listed for both healthy and postural correction (PC) subjects side-by-side for comparison. All the values tabulated are the average values for the 20 subjects considered in each category.

Table 1: Parameters for assessment of functions for muscle on Right Trapezius

Parameter	**Right Trapezius**			
	Maximum	Minimum	Mean	Standard Deviation

	Healthy control	PC subject	Healthy control	PC subject	Healthy control	PC subject	Healthy control	PC subject
RMS	0.91324	0.82586	0.71255	0.62856	0.68324	0.75864	0.00034	0.00041
VAR	0.95244	0.85762	0.32529	0.2825	0.60128	0.48567	0.000298	0.00048
ZC	32	42	0	2	6	8	0	3
WA	9580	7896	841	598	4153	3586	359	438
SSI	16254	17859	7934	8535	11985	13964	303	418

As can be observed from Table 1, for the muscle Right Trapezius, the RMS values are lesser for the PC subject as compared to healthy controls. However, the signal power and WA have shown to decrease while ZC and SSI have increased.

Table 2: Parameters for assessment of functions for muscle on left Trapezius

Parameter	**Left Trapezium**							
	Maximum		Minimum		Mean		Standard Deviation	
	Healthy control	PC subject	Healthy control	PC subject	Healthy control	PC subject	Healthy control	PC subject
RMS	0.900613	0.790212	0.756921	0.52578	0.756924	0.73422	0.00021	0.00033
VAR	0.911141	0.891141	0.362878	0.25846	0.572955	0.46285	0.000379	0.00042
ZC	36	40	0	0	6	8	0	2
WA	10148	8024	841	624	4153	3860	379	402
SSI	17736	18906	7934	8324	12528	14586	303	388

The values for Left Trapezius as shown in Table 2, shows that RMS, VAR and WA are higher for PC subjects as compared to the healthy controls. Similar to the right trapezius muscle, left trapezius also showed decrease in the values of ZC and SSI of PC subjects in comparison with the other group.

Table 3: Parameters for assessment of functions for muscle on Right SCM

Parameter	**Right SCM**							
	Maximum		Minimum		Mean		Standard Deviation	
	Healthy control	PC subject	Healthy control	PC subject	Healthy control	PC subject	Healthy control	PC subject
RMS	0.72145	0.59648	0.56121	0.42589	0.63956	0.50211	0.00011	0.00019
VAR	0.65874	0.75412	0.32548	0.31145	0.42518	0.4831	0.000218	0.00034
ZC	28	33	0	2	4	6	0	2

WA	8258	6859	598	502	3688	4152	286	362
SSI	13859	14965	5954	6244	10145	11524	195	265

From Tables 3 and 4, it is clear that even in SCM muscles show similar pattern as the Trapezius muscles, with respect to all the parameters. However, the individual values of RMS or power or frequency are seen to be lesser in comparison with the Trapezius muscle parameter values.

Table 4: Parameters for assessment of functions for muscle on left SCM

Parameter	**Left SCM**							
	Maximum		Minimum		Mean		Standard Deviation	
	Healthy control	PC subject	Healthy control	PC subject	Healthy control	PC subject	Healthy control	PC subject
RMS	0.73451	0.60157	0.54105	0.45126	0.63956	0.52475	0.00018	0.00021
VA	0.68142	0.7214	0.30145	0.32154	0.40518	0.4521	0.000198	0.00028
ZC	29	33	0	2	4	6	0	3
WA	8125	6541	578	533	3598	3215	301	352
SSI	13021	14235	5845	6168	11211	10586	211	322

From the tables 1 to 4, we can observe that the parameters listed show a significant change between the healthy control and subject requiring postural correction. It gives a good indication of what parameter values to expect once the correction course is followed by the subject. This is very helpful in quantifying the therapy for postural correction and gives a structured analysis for the treatment.

Table 5. Confusion matrices

a) Right Trapezius

SVM	Actual			**Random Forest**	Actual		
		True	False			True	False
Predicted	True	68	12	Predicted	True	58	22
	False	15	65		False	18	62

b) Left Trapezius

SVM	Actual			**Random Forest**	Actual		
		True	False			True	False
Predicted	True	51	29	Predicted	True	46	34
	False	24	56		False	27	53

c) Right SCM

SVM	Actual			**Random Forest**	Actual		
		True	False			True	False
Predicted	True	50	30	Predicted	True	44	36
	False	21	59		False	25	55

d) Left SCM

SVM	Actual			**Random Forest**	Actual		
		True	False			True	False
Predicted	True	63	17	Predicted	True	55	25
	False	29	61		False	22	58

e) Confusion matrix

	Actual		
Predicted		True	False
	True	**TP**	**FP**
	False	**FN**	**TN**

Support Vector Machine (SVM) and Random Forest Decision Tree (RFDT) are used for classification with 75% of the dataset being used for training, while 25% of the dataset was used for testing. Tables 5a to 5d show the classification results by employing two classifiers SVM and RFDT individually. The parameters computed for individual muscles are used for classification. The actual and predicted classification by each of the classifiers is shown side by side for comparison.

Table 5e is the format for confusion matrix, based on which, the parameters used to evaluate the performance of the models are computed as follows:

$$\text{Sensitivity} = \frac{\text{Number of true positive (TP) classification}}{\text{Number of all positive(TP+FP) classifications}} \quad \ldots\ldots\ldots(7)$$

$$\text{Specificity} = \frac{\text{number of true negative (TN) classification}}{\text{Number of all negative (TN+FN) classifications}} \quad \ldots\ldots\ldots(8)$$

$$\text{Accuracy} = \frac{\text{Number of correct classifications}}{\text{Number of true positive+number of true negative}} \quad \ldots\ldots\ldots(9)$$

Performance metrics namely sensitivity, specificity and classification accuracy are computed using equations (7), (8) and (9) respectively. Sensitivity is the ability of a test to correctly identify those patients with the disease. Specificity is the ability of a test to correctly identify those patients without the disease. Accuracy means that healthy controls and subjects requiring postural correction was classified appropriately.

The performance of classifiers is compared in Table 6. It is observed that for all the four muscles, the accuracy is higher for SVM as compared to RFDT. Similarly, SVM gives better sensitivity and specificity than RFDT.

Table 6 Comparison of Performance Metrics

Muscle Name	Accuracy (%)		Sensitivity (%)		Specificity (%)	
	SVM	**Random Forest**	**SVM**	**Random Forest**	**SVM**	**Random Forest**
Right Trapezium	83	75	85	72.5	81.25	77.5
Left Trapezium	66.8	61.8	63.75	57.5	70	66.25
Right SCM	60.5	61.8	62.5	55	73.7	68.7
Left SCM	77.5	70.6	78.75	68.7	76.25	72.5

Further experimentation involved combining the features obtained for all the four muscles, the training to testing ratio remained as in table 6 and all the five parameters namely RMS, VA, ZC, WA and SSI are considered.

Table 7 Performance of classifiers by using all the four muscle parameters

	Accuracy (%)	**Sensitivity (%)**	**Specificity (%)**
SVM	88	90	93
Random Forest	81	83	85

As shown in Table 7, the classification accuracy was found to be higher at 88%, while sensitivity was 90% and specificity was 93% when SVM was employed. Similarly, the accuracy was higher at 81%, sensitivity was 83% and specificity was 85% when RFDT was employed. On comparing the metrics of the two classifiers, it can be inferred that SVM gives a better performance.

5. CONCLUSION

An EMG acquisition hardware was built and EMG signals were procured from healthy controls as well as subjects in need of postural correction. EMG signals were collected from four muscle points while the subjects performed four actions namely neck twist left, neck twist right, shoulder lift and relaxation of neck muscles. EMG parameters were computed for all the subjects. The RMS value, signal power value and unit motor potential were lesser in subjects requiring postural correction as compared to healthy controls. On the other hand, signal frequency and Simple Square Integral were lesser in healthy controls. Thus, these can quantify the muscle function analysis and hence can be used for therapeutic study of yoga therapy and treatment. Classifiers used were SVM and Random Forest Decision Tree. As seen from table 6, classification based on features from individual muscle indicated that Right Trapezius gives a good accuracy as compared to Right SCM. But, combining the features of all the four muscles produced more reliable classification. Also, SVM yielded a better classification accuracy of 88% as compared to RFDT which gave 81% accuracy. This analysis can be used for identifying the severity of postural correction as well as in therapeutic study.

REFERENCES

[1]. V, Ramesh AB, Alva KK, Debur VR, Omkar SN. A Mathematical Method for Electromyography Analysis of Muscle Functions during Yogasana. Int J Yoga. 2019 Sep-Dec;12(3):240-246.

[2]. Mrithunjay & Periyasamy, R. & Sharma, Dr & Sinha, Manisha & Sachin, Pandey & Trivedi, Soumitra. (2014). Electromyographical Analysis of the Effect of Yoga Posture On The Trunk Muscle Activities And Its Significance: A Pilot Study. Indian Journal of Clinical Anatomy and Physiology. 2. 74-80.

[3]. KK, Giannico K, Lesnett G, Romano A. A comparison of EMG output of four lower extremity muscles during selected yoga postures. J Bodyw Mov Ther. 2019 Apr;23(2):329-333.

[4]. Raez MB, Hussain MS, Mohd-Yasin F. Techniques of EMG signal analysis: detection, processing, classification and applications. Biol Proceed Online. 2006; 8: 11-35

[5]. Petrofsky, Jerrold & Cuneo, Maria & Dial, R. & Morris, A. (2005). Muscle Activity during Yoga Breathing Exercise Compared to Abdominal Crunches. Journal of Applied Research. 5. 501-507.

[6]. Baofeng Sun, Wanzhong Chen, Xin Zheng, The System Design for the Extraction and Pre-processing of Surface EMG, Physics Procedia, Volume 33, 2012, ISSN 1875-3892

[7]. Sadikoglu, Fahreddin, Cemal Kavalcioglu, and Berk Dagman. "Electromyogram (EMG) signal detection, classification of EMG signals and diagnosis of neuropathy muscle disease." Procedia computer science 120 (2017): 422-429.

[8]. Sharma, Sanjeev Kumar, Shiv Lal Yadav, U. Singh, and Sanjay Wadhwa. "Muscle activation profiles and co-activation of quadriceps and hamstring muscles around knee joint in Indian primary osteoarthritis knee patients." Journal of Clinical and Diagnostic Research: JCDR 11, no. 5 (2017): RC09.

[9]. Abdullaev, N.T., Pashaeva, K.S. Methods and Means of Evaluating Muscle Asymmetry by Analysis of Electromyographic Signals. Biomed Eng 55, 69–72 (2021).

[10]. Diana C. Toledo-Pérez, Support Vector Machine-Based EMG Signal Classification Techniques: A Review

[11]. Ling SM, “Electromyographic patterns suggest changes in motor unit physiology associated with early osteoarthritis of the knee” Published: Osteoarthritis Cartilage. 2007;15(10):1134-1140. doi: 10.1016/j.joca.2007.03.024

[12]. W. M. Bukhari, C. J. Yun , A. M. Kassim ,M. O. Tokhi, Study of K-Nearest Neighbour Classification Performance on Fatigue and Non-Fatigue EMG Signal Features, IJACSA) International Journal of Advanced Computer Science and Applications, Vol. 11, No. 8, 2020

[13]. Multi-Channel Muscle Armband Implementation: Electronic Circuit Validation and Considerations towards Medical Device Regulation Assessment Martha Rocio Gonzales Loli , Elsa Regina Vigo Ayasta, (IJACSA) International Journal of Advanced Computer Science and Applications, Vol. 11, No. 11, 2020

[14]. Z. E. Ashari and S. L. Broschat, t-Tree and t-Forest: Decision Tree and Random Forest Algorithms Including the Relevance Factor with Applications in Bioinformatics, 2019 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), 2019, pp. 2779-2783, doi: 10.1109/BIBM47256.2019.8983065

[15]. S. Bernard, L. Heutte and S. Adam, On the selection of decision trees in Random Forests, 2009 International Joint Conference on Neural Networks, 2009, pp. 302-307, doi: 10.1109/IJCNN.2009.5178693.