CWT dominant frequency analysis forElectromyographical (EMG) Signals

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Abstract:

Electromyographical Signals are random in nature. The traditional signal analysis techniques such as time and frequency domain that we apply for stationary signal analysis are not providing good results of analysis. This paper aim to investigate new techniques from time-frequency domain analysis to extract prominent features for further analysis. This paper has investigated Wavelet analysis and its transforms (Discrete Wavelet transform(DWT) and Continuous Wavelet transform(CWT)). Literature survey is performed for comparison CWT and DWT analysis specifically for Electromyographical Signals. Comparison of these two transform is performed and CWT is selected over the threat of signal degradation because of down sampling (up to level 4) the signal at every level and acquired Surface Electromyographical signal has sampling frequency of 960 samples/second. CWT analysis requires large number computations at each scale value. Therefore, the new method CWT analysis at single dominant frequency is introduced and investigated over the traditional time and frequency domain analysis techniques. CWT analysis at dominant 7, 8 and 10 Hz of frequency leads to increase in accuracy by 17% reaching to95.33% for classification Healthy and Diseased person. Further, this analysis technique can be used for non-stationary/random signal analysis to extract better features leading to good accuracy.

Introduction:

In many applications of random signals, such as EEG and EMG, a time and frequency domain analysis alone is insufficient to reach a conclusion. Performance of time frequency domain analysis is required. More relevant features that cannot be visualised in time and frequency domain signals are required to be visualised using time-frequency domain analysis. Frequency domain alone cannot forecast the instances of occurrence of frequency. Time domain cannot view the frequencies of the entire signal. The first solution is to cut the signal in short time intervals (windows) as shown in Figure1, and perform the frequency domain analysis for the said time interval to observe the frequency contribution with in the specific time interval.This type of analysis is called as Short-Time Fourier Transform(STFT). Itpredict time interval of frequency band and is used to analyse the spectral components at a specific time interval. The selection of window size is crucial for STFT analysis. The time domain signal inside each window must be stationary. Stationarity analysis is required to be performed by selecting various window sizes to fix window size. Finding time intervals where a specific band of the signal is present is tough to find if signal is non-stationary. There is an issue with resolution. The frequency resolution of a small window is low, whereas the time resolution of a wide window is bad. As a result, the decision was made to transition from STFT to Wavelet Transform (WT).

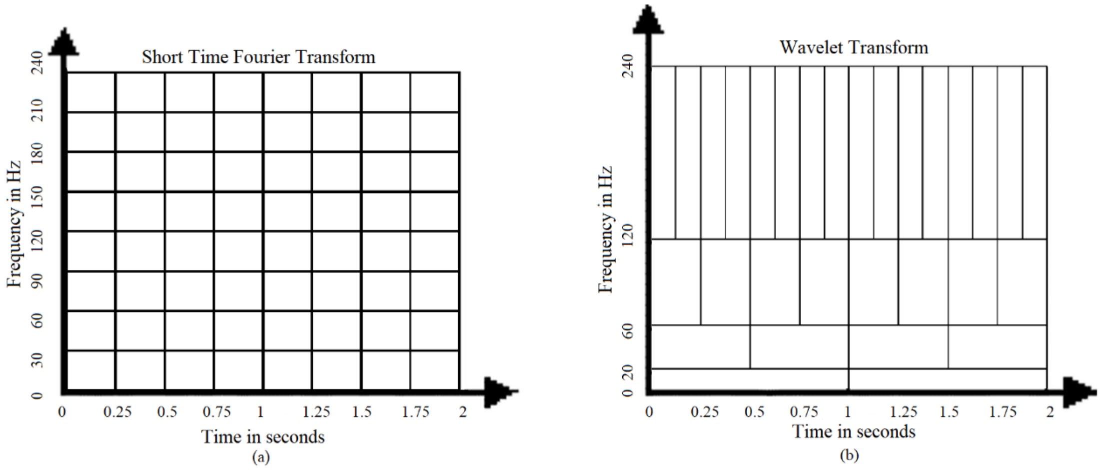

Figure 1: Time-frequency resolutiona)STFT: equal size of boxes b) Wavelet Transform: equal area of boxes

In the wavelet transform, the height of the box is shorter for low frequencies, indicating good frequency resolution, whereas the width of the box is larger, indicating poor temporal resolution. Box width reduces and height increases at higher frequencies, resulting in good temporal resolution but poor frequency resolution. At lower and higher frequencies, the height and width of the box changes; however, the area of each box remains constant, representing an equal segment of the time-frequency plane although with variable sizes of time and frequency.Wavelet handles high frequencies for a short time periodand low frequencies for a longer time period. The wavelet transform also has another important feature; we can select a mother wavelet corresponding to our application. Each mother wavelet has different shape, area and properties, and it concurrently delivers the time and frequency components of the data. The most difficult part of the wavelet transform is choosing the right mother wavelet. A literature review is conducted in order to validatethe use of wavelet transform to find time-domain features, as well as to determine the best suitable mother wavelet for the study. It resulted with Coiflet, Daubechies(db), Haar and Symlet as mother waveletssuitable for EMG analysis.

Nazmi et al., [1] examined various types of analysis for electromyographical analysis in various domains (Time, Frequency and Time-Frequency). They recommended Wavelet (Continuous and Discrete) transform. Gulshan Thukral and Singh [2] evaluated variousbiomedical-signal investigationapproachesand emphasised the use of Wavelet Transform for EMG signal analysis with db2, db6, and db8 as mother wavelets.Burhan et al. [3] investigated numerous electromyographic feature extraction approaches in the various domains. They recommended Continuous Wavelet Transform analysisthroughmother waveletdb7. Ghofrani J. et al. [4] investigated EMG analysis with wavelet transform and concluded that; CWT is a complex stillefficient methodthan DWT. The literature survey has suggested the use of wavelet transform for EMG analysis using mother wavelet such as: db, symlet, coiflet, and biorthogonal.

We reviewed literature specific to mother wavelet selection in order to choose one from these recommendations. For surface EMG data, Phinyomark et al. [5] found that employing the seventh order of Daubechies wavelet at fourth-level ofdecomposition improved classification accuracy in the relevant area. Zhang et al. [6] recommends the use of mother wavelet db4 at the 5thlevel of decomposition for analysis of EMG signals.Wang et al. [7] successfully classified arm movements using SEMG analysis utilising the Coiflet wavelet of order 5. Hussain and Mamun [8] has assessed EMG signal during fatigue analysis, suggested use of db45 mother wavelet. K. Mahaphonchaikul et al.

[9] shown that wavelet transform using mother wavelet Daubechies and selected feature as RMS improved the interpretation of forearm muscle movements.
The studied literature suggests the use of wavelet transform (Continuous and Discrete) for EMG analysis. Most of the researchers have recommended db7 mother wavelet for CWT as well as DWT analysis to get better features and classification accuracy.

Methodology:

One hundred and fifty Surface EMG samples are collected from the seventy diseased and eighty healthy subject by taking proper consent from the subjects. Samples containseighty sevenmales and sixty threefemales with average BMI of 20.40. The 2 channel RMS Salus EMG machine is utilised for acquisition of the Surface Electromyographical signal. A non-invasive Surface EMG technique using AgCl electrodes are used for acquisition. The aim of this paper is to identify diseased person by using suitable time frequency domain analysis technique and investigate easy to use, accuratetechnique for surface EMG analysis. Various time and frequency domain techniques are analysed in research papers [10,11,12] stating limitations of time and frequency domain analysis. Referring to the literature studied in introduction sectionlead towards the time-frequency domain analysis. Further literature survey confirms the use of wavelet analysis. Wavelet analysis is performed usingCWTand DWT. But, DWT downsamples the signal at each level of decomposition. For surface EMG analysis it is needed to down sample the signal up to three or four levels of decomposition to get required results. Acquired Surface EMG signals contain 960 samples per signal.Ifdown sampling Surface EMG signal is performed up to three or four levels,only 120/60 samples will be available for further processing.Considering the down sampling and results from literature instead of DWT; CWT analysis technique is selected for the further analysis. Referring to the literature; db7 is chosenas the mother wavelet.Limitations of CWTare; it more difficult to perform and requires more number of computations. CWT analysis is required to be performed at each scale/frequency.

The CWT transform is a inner product of function f(t) which is test signal and basis function$\varphi_{\tau,s}(t)$.

$$CWT(\tau,s) = \int x(t).\varphi^*_{\tau,s}(t)\,dt \quad\text{...}(1)$$

where, $$\Psi s,\tau(t) = \frac{1}{\sqrt{s}}\Psi\left(\frac{t-\tau}{s}\right) \quad\text{..}(2)$$

Where τ:Translational parameter
s:Scale Parameter
$x(t)$: SEMG signal
$\varphi_{\tau,s}(t)$: Mother wavelet
* : Multiplying operator

The Surface EMG signal's time component is multiplied by the mother wavelet after it has been shifted by one sample period to determine the CWT coefficients. The factor $1/\sqrt{s}$ is a normalising factor that assures energy of the basis function remains constant. The mother wavelet get compressed for small scale factor and stretched forgreater scale factor.A stretched wavelet captures gradually shifting changes in the signal, whereas a compressed wavelet captures rapid changesof the signal. As recommended by the literature, the mother wavelet Daubechies (db) of order seven is selectedfor signal analysis, as illustrated in Figure 2.

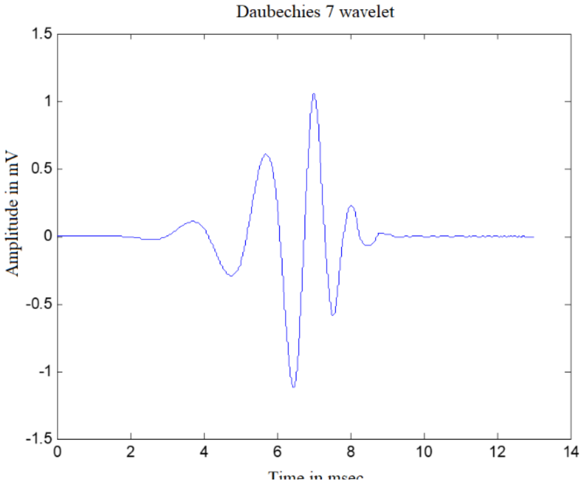

Figure 2: Daubechies 7 mother wavelet

Wavelet is a type of wave that consists of quickly decaying zero mean oscillations, also known as little vanishing waves that last for a finite amount of time.Mother wavelet is the basis function$\varphi_{\tau,s}(t)$. In this investigation, the mother wavelet is Daubechies (db) wave of order seven (see Figure 2).

Further, to investigate CWT for reduction in complexity and computations literature study is performed. Eric D. Ryan et al. [13] have used STFT and CWT to examine EMG signal. Theystated relation between wavelet scale and its centre frequency as: $Fa = \frac{Fc}{s}$. They transformed scale valuesto Fa with a 10Hz increment in central frequency ranging from 10 to 500 Hz. Wavelet analysis for Surface EMG signals is also examined by Dinesh Kant Kumar et al. [14] to detect muscular exhaustion.They have used Sym4 and Sym5 mother wavelet to highlight the alterationamong fatigue and non-fatigue muscle conditions. The difference inthe feature values for fatigue and non-fatigue conditions varies with the scale value, although it is noticeable at scale values 8 and 9. CWT analysis at specific scale index is performed by Kilby J. et al. [15] to retrieve important properties of the dominating frequencies by looking at muscle activation over a certain time period. They have observed that; CWT boosts Surface EMG characteristics more efficiently at specified scale values for dominant frequencies than traditional analysis approachreferred as the 'pseudo-frequency' of the scale.

Using the sliding square approach, M.H. Pope et al. [16] equated the ability of viewers to check the reaction time of the spine response. They have allowed user to select the desired scale from the available options. The results showed that the wavelet domain was more accessible and accurate in determining the spine muscle reaction time than the original signal representation. The relationamong the mean frequency and signal amplitude of the SEMG signal is verified by Stefan Karlsson and Bjorn Gerdle [17]. In the study of localised muscle fatigue, Pascal Coorevits et al. [18] discovered a link between CWT and STFT spectral characteristics. They used all of the frequency-related scale values. John Sadowsky [19] used CWT analysis to analyse random signals and supplied source code for producing CWT for number of octaves using scales. The performance of CWT analysis utilising EEG signals was tested by Real et al. [20]. They generated logarithmically spaced scales between 1Hz and 32Hz using five steps per octave.In terms of sensitivity and specificity, it outperforms a range of other methods. The literature review provides the usage of scale values in accordance with the application's requirements, as well asdetermines the optimum CWT analysis approach with scale values.

In the study of EMG signals, CWT is very important. Many studies have proposed using multi-scale analysis by varying scale at octave, logarithmic, values, while others have recommended using single-frequency analysis at a certain frequency.By observing these studies; dominant frequency CWT analysis technique is selected.Dominant Frequencies are converted into scale using equation 4.

$$S = \frac{Fc}{Fa.\Delta} \quad \ldots\ldots(4)$$

Where Fa: Dominant frequency
Fc: Mother wavelet center frequency
S: Scale value
Δ: Sampling Period

Traditional methods of CWT analysis uses all scale values for the analysis leading towards complexity in computations. As an alternative propose research proposes single frequency CWT analysis of the signal only for dominant frequencies.

This paper has proposed EMG analysis method based on frequency domain analysis to detect dominant frequency range succeeded by CWT analysis at identified dominating frequencies. Fast Fourier Transform(FFT) is used to identify dominant frequencies andequation 4 has converted dominant frequency into scale value. Further; mother wavelet is built at the identifiedscale. The raw EMG signal shown in Figure 3is considered for CWT calculations. The corresponding scaled wavelet is shifted in time along the whole length of the raw SEMG signal (along x-axis), as shown in Figure 4 and inner product is calculated to calculate the continuous wavelet transform coefficients. As illustrated in Figures 5, greater resemblancebetween raw EMG and mother wavelet results in higher CWT coefficient values, whereas less resemblanceresults in a small CWT coefficient.This single frequency CWT analysis approachcombine spectrum analysis with FFT (to pick the frequencies) and time-frequency domain analysis with CWT (to determine the scale values corresponding to the dominating frequencies)usingdb7 mother wavelet.

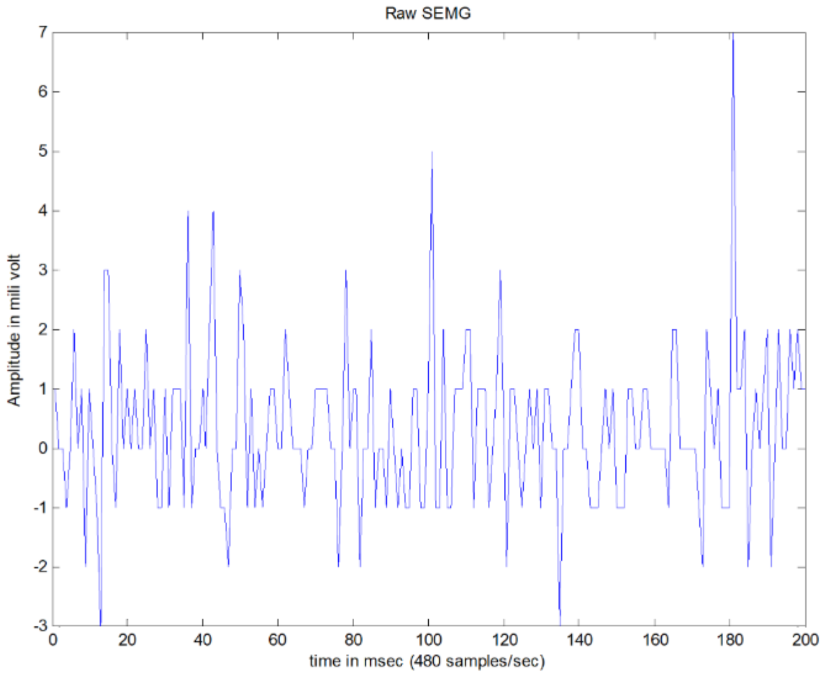

Figure3: Raw Surface Electromyographical signal.

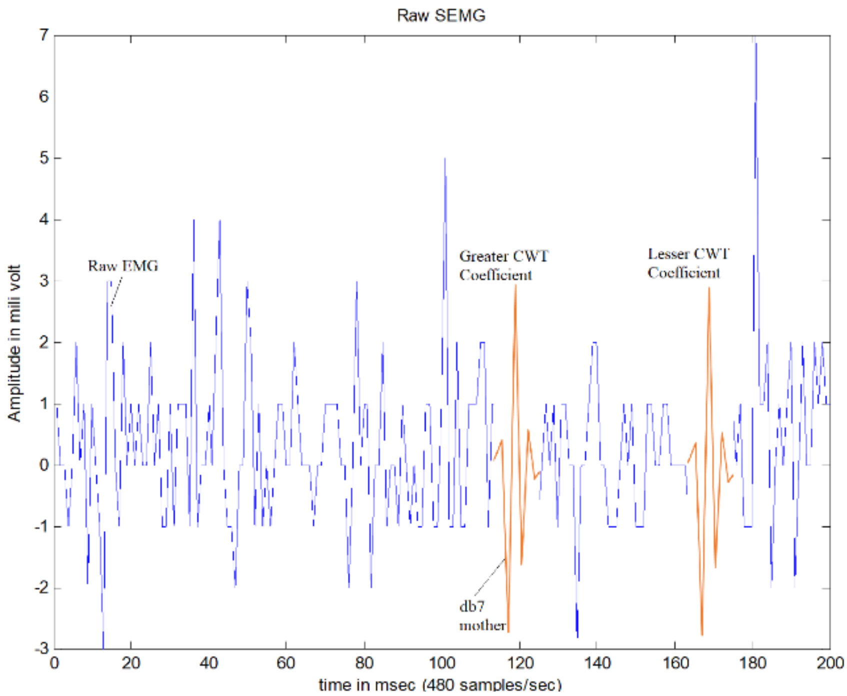

Figure 4: Raw Surface Electromyographical signal shown in bluecolour and overlapping mother wavelet db7 shown in orange colourat regions of overlap.

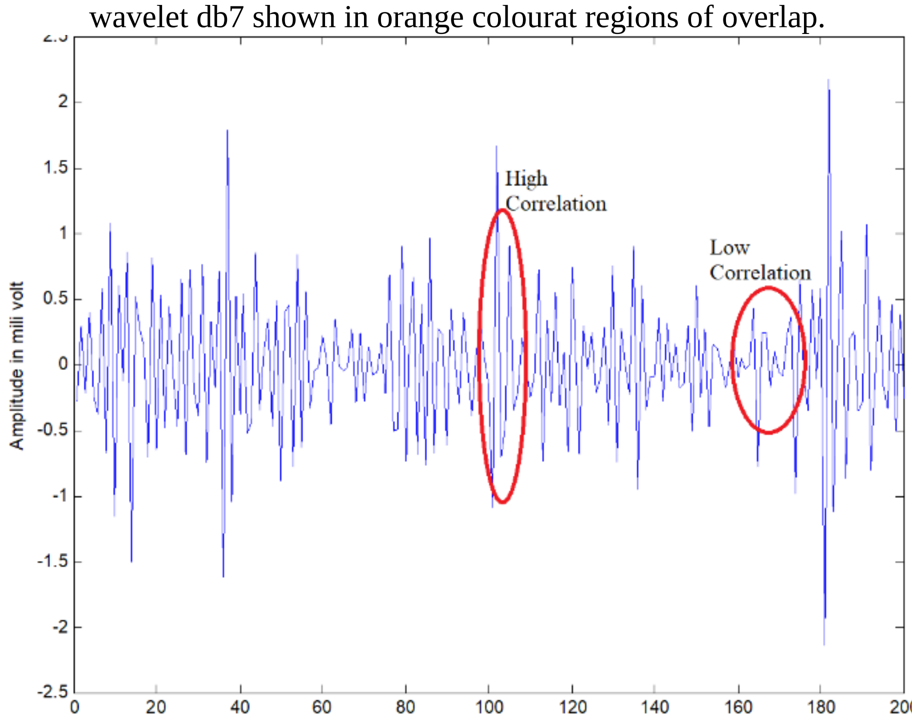

Figure 5: CWT coefficients of Raw Surface Electromyographical signalshowing higher correlation and lower correlation.

The raw EMG signal has transformed using Fast Fourier Transform to identify dominant frequencies as shown in Figure 6. It can be clearly identified that; the dominant frequencies range is 0 to 10Hz.

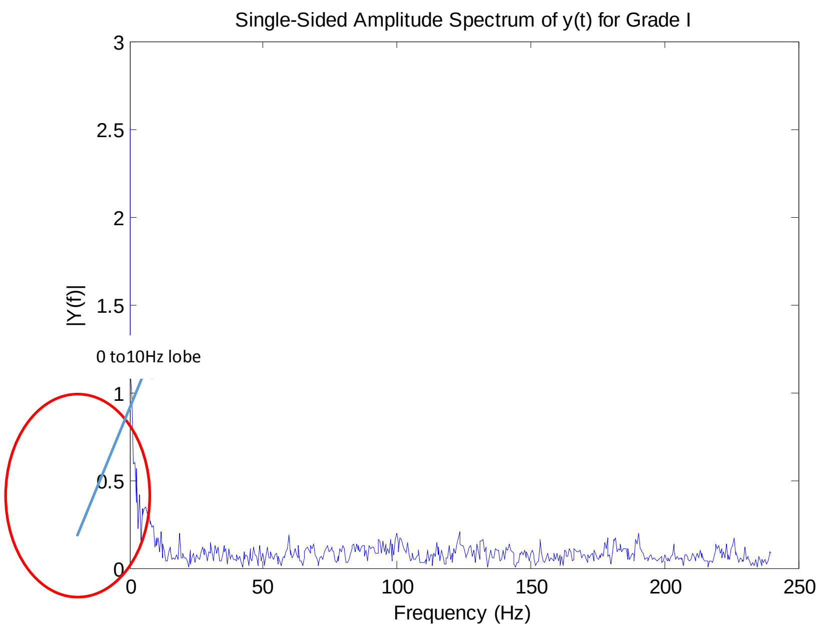

Figure 6: Results of Fast Fourier Transform showing dominating frequencies of the Surface Electromyographical signal.

Single-sided amplitude spectrum can be observed from figure 6showing range of dominant frequencies up to 10Hz.CWT analysis is performed at dominating frequencies to uncover the features that contribute towards EMG signal classification between healthy and diseased person. For all the healthy and diseased subject, the spectrum of SEMG signals has been investigated to find dominant frequencies for single frequency CWT analysis that will lead to classification of Surface EMG signals. Dominant frequencies are majorly accumulated between 0 to 10Hz of frequency range. Therefore, this paper has opted to undertake cwt analysis between 0-10Hz of frequencies. Scale values are identified using equation 4. Following Table 1shows the calculated scale values for the identified dominant frequency.

Table 1: Frequencies and its conversion to scale values at 960 of sampling frequency

Frequency	**Scale**
1 Hz	662.4
2 Hz	331.2
3 Hz	220.8
4 Hz	165.6
5 Hz	132.48
6 Hz	110.4
7 Hz	94.63
8 Hz	82.8
9 Hz	73.6
10 Hz	66.24

From Table 1 it can be observed that; with increase in frequency, scale value decreases. They are inversely proportional to each other.

Results:

To beginthe research with, traditional features in the time and frequency domains are examined [10,11,12] and extractedif they have passedstatistical t-test(t= 1.6593) with 95% of confidence interval. If the calculated ‘t’ value of the particular feature is largercritical ‘t’ value; the corresponding feature is selected for classification. Many extracted features has failed to cross 't' value, only limited (12 features) havecrossed the 't' crucial. These features are selected and forwarded to the classifier.True Positive, False Positive, and accuracy are calculated for classification between Healthy and diseased subject. Classification results are not satisfactoryshowing accuracy of 78%. In this paper dominant frequency CWT analysis is performed to extract features like variance, a number of peaks, entropy, and peak to peak amplitude and added to the prior feature set (Time and Frequency domain). The classification is performed, results are compared using with and without inclusion of dominant frequency CWTanalysis. The results of COPD grade categorization with and without the use of CWT features are shown in Table 2.

Table 2: True Positive, False Positive and Precision values for diseased and Healthy subject classification

Analysis method and corresponding frequencies	**Diseased and Healthy Classification Accuracy**
Time and Frequency domain	78.00
CWT at 1 Hz	86.00
CWT at 2 Hz	85.33
CWT at 3 Hz	80.00
CWT at 4 Hz	83.00
CWT at 5 Hz	84.67
CWT at 6 Hz	83.33
CWT at 7 Hz	89.33
CWT at 8 Hz	92.00
CWT at 9 Hz	87.33
CWT at 10 Hz	88.67

Healthy and diseased subject are categorised usingfeatures extracted inTime and Frequency domain to achieve 78%of accuracy. Single frequency CWT analysishas improved the accuracy by 14% leaded to 92%. CWT analysis at 8Hz frequency and corresponding extracted features has contributed towards increase in accuracy to 92%. When time domain features and dominant frequency CWT analysis features are combined together accuracy has increased up to 95.33percent. Therefore, it can be concluded that; suggested dominant frequency CWT analysis has contributed torise in classification accuracy from 78 percent to 95.33 percent. The resultsvalidates the importance of dominant frequency CWT analysis.Results are represented using confusion matrix as shown in table 3 and 4. True

Positive, False Positive, False Negative, and True Negative are identified and used for calculations of sensitivity, specificity and precision.

Table 3: Confusion matrix representation for the Diseased and healthy subject classification.

	Healthy	**Diseased**
Healthy	78	2
Diseased	5	65

Table 4: Diseased and healthy classification results in terms of sensitivity, specificity, and precision.

Measure	**Value**
Sensitivity	0.9398
Specificity	0.9701
Precision	0.9750
Accuracy	0.9533

From table 4, it can be concluded that; the analysis method is specific towards disease identification but with lesser sensitivity. Features acquired using dominant frequency CWT analysis at 7, 8, and 10 Hz of frequency has increased the classification accuracy by 17.30% (from 78% to 95.33%).

Conclusion:

The presented paper is an effort to identify technique to analyse the Surface Electromyographical Signals for classification into healthy and diseased person's signal. Numerous time and Frequency domain features are studied and selected using feature selection algorithm. Selected features are provided for classification of signals into diseased and healthy subject. But these features are found to be insufficient for classification leading to very less accuracy of 78%. Detail study of time-frequency domain analysis is executed to identify dominant frequency CWT analysis technique. The developed dominant frequency CWT analysis has improved performance to 95.33%. Selected features are applied toSVM classification algorithm,diseased and healthy subjects are classified with an accuracy of 95.33%. It is concluded that dominant frequency CWT analysis at dominant frequencies of surface EMG signal is leading towards greater classification accuracy. A simple, rapid, non-invasive, and effort independent diseased and healthy subject classification techniqueis developed.The research is contributing towards health of the society by developing more accurate way of surface EMG analysis technique.

Future Scope: The Surface EMG analysis technique using dominant frequency CWT analysis can be effectively standardized to support medical fraternity in identifying the muscle conditions. This technique can also help physiotherapists in developing and recommending exercises.

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