RESEARCH ARTICLE OPEN ACCESS

Evaluation of Frequency Domain Features for Myopathic EMG Signals in Mat Lab

Akash Kumar Bhoi[1], Devakishore Phurailatpam[2], Jitendra Singh Tamang[3]
[1]Department of AE&I Engg, Sikkim Manipal Institute of Technology (SMIT), Majitar
[2]Department of E&E Engg, National Institute of Technology, Manipur
[3]Department of E&C Engg, Sikkim Manipal Institute of Technology (SMIT), Majitar

Abstract: The proposed EMG signals analysis relies on the frequency domain where features of healthy EMG signal and myopathic EMG signals are analyzed and compared. Methodology described the relationship between the EMG signals and the properties of a contracting & myopathic muscle by analysing its power density spectrum. Periodogram Mean-Square Spectrum Estimate (PMSSE) of EMG Signal and the Power spectral Density is calculated with Welch's PSD estimate method by taking Hamming & Kaiser Window for both the healthy & myopathic signals. The analysis can provide important clues to design feature extraction methods and the resulting information can be used to determine the origin of the weakness.
Keywords: EMG Signal, Myopathic Signal, power density spectrum, Welch's PSD, PMSSE

I. Introduction

Clinical electromyography analyses the electromyogram (EMG) recorded from a contracting muscle using a needle electrode to diagnose neuromuscular disorders. EMG is composed of discrete waveforms called motor unit action potentials (MUAPs), which result from the repetitive discharges of groups of muscle fibers called motor units (MUs). The term MU refers collectively to one motoneuron and the group of muscle fibers it innervates and is the smallest unit of skeletal muscle that can be activated by volitional effort. MUAPs from different MUs tend to have distinct shapes, which remain almost the same for each discharge. The MUAPs can therefore be identified and tracked using pattern recognition techniques. The resulting information can be used to determine the origin of the weakness, i.e. neurogenic or myopathic diseases [1,3]. The changes brought about by a particular disease alter the properties of the muscle and nerve cells, causing characteristic changes in the MUAPs. Distinct MUAPs can be seen only during weak contractions when few motor units are active. When a patient maintains low level of muscle contraction, individual MUAPs can be easily recognised. As contraction intensity increases, more motor units are recruited. Different MUAPs will overlap, causing an interference pattern in which the neurophysiologist cannot detect individual MUAP shapes reliably. Usually, in clinical electromyography, neurophysiologists assess MUAPs from their shape using an oscilloscope and listening to their audio characteristics. Thus, an experienced electrophysiologist can detect abnormalities with reasonable accuracy. However, subjective MUAP assessment, although satisfactory for the detection of unequivocal abnormalities, may not be sufficient to delineate less obvious deviations or mixed patterns of abnormalities [4]. Therefore, for an effective automated MUAP assessment, a systematic handling of EMG signal must decompose the signal into MUAPs and classify each MUAP into different classes.

Although, a number of computer-based quantitative EMG analysis algorithms have been developed [5] practically none of them has gained wide acceptance for extensive clinical use. Most importantly, there are no uniform international criteria neither for pattern recognition of similar MUAPs or for MUAP feature extraction [8]. Out of the two assessment tasks (i.e. MUAP detection and classification) according to our knowledge only the first one has attracted attention. Buchthal et al. [9, 10] developed one of the earliest methods for quantitative EMG decomposition, where MUAPs were recorded photographically and then were selected for analysis. LeFever and DeLuca [11] used a special three channel recording electrode and a visual computer decomposition scheme based on template matching and firing statistics for MUAP identification. Stalberg et al. [8], in their original system used waveform template matching whereas more recently [12] they have used different shape parameters as input to a template matching technique. Andreassen [13] followed the manual method developed by Buchthal using template matching with four templates for the recognition of MUAP's recorded at threshold contraction. Stashuk and Qu [14] proposed a method to identify MUAPs based on power spectrum matching. Hassoun et al. [15] proposed a system called neural network extraction of repetitive vectors for electromyography (NNERVE) which uses the time domain waveform as input to a three layer

artificial neural network with a ‘‘pseudounsupervised’’ learning algorithm for classification. McGill et al. [16] used a method based on a combination of shape recognition of the MUAPs and statistical probability of occurrence. Fang et al. [17] developed a comprehensive technique to identify single motor unit (SMU) potentials based on one-channel EMG recordings measuring waveform similarity of SMU potentials in the wavelet domain.

A common problem in signal and image processing is in the rejection of signal noise components and the increase of the signal-to-noise ratio. This process involves the correct selection of signal sampling frequency, frequency regions of desired signal components and cut-off frequencies for their extraction. In most cases the low-pass filter is applied at first to reject signal noise and to reduce the auto-aliasing effect followed by the high-pass filter to remove signal trend components. The EMG signal is nonstationary as its statistical properties change over time. In most cases its sampling rate is greater than 1 kHz affecting possibilities of noise reduction. The MUAPa are transients that exist for a short period of time, which is not identical in all cases. For that reason, time-frequency methods are now being used to characterize the localized frequency content of each MUAP [1]. Most often and even in our case, wavelet transform is used.

II. Properties of the Power Density Spectrum for EMG Signal

The power density spectrum of the EMG signal may be formed by summing all the auto and cross-spectra of the individual MUAPTs, as indicated in this expression:

$$\sum_{i=1}^{p} \mathrm{S\mu i}(\omega) + \sum_{\substack{i,j=1 \\ i\neq j}}^{q} Suiuj(\omega)$$

Where, *Su, (* ω*)* = the power density of the MU APT, *Ui (t);* and *Suiuj(*ω*)* = the cross-power density spectrum of MUAPTs *Ui(t)* and *u;(t).* This spectrum will be nonzero if the firing rates of any two active motor units are correlated. Finally, *p* = the total number of MUAPTs that comprise the signal; *q* = the number of MUAPTs with correlated discharges. For details of this mathematical approach, refer to De Luca and van Dyk (1975). De Luca et al (1982b) have shown that many of the concurrently active motor units have, during an isometric muscle contraction, firing rates which are greatly correlated. It is not yet possible to state that all concurrently active motor units are correlated. Therefore, *q* is not necessarily equal to *p,* which represents the total number of MUAPTs in the EMG signal. The above equation may be expanded to consider the following facts:

1. During a sustained contraction, the characteristics of the MUAP shape may change as a function of time (r). For example, De Luca and Forrest (1973a), Broman (1973, 1977), Kranz et al (1983), and Mills (1982) have all reported an increase in the time duration of the MUAP. [4][6]
2. The number of MUAPTs present in the EMG signal will be dependent on the force of the contraction *(F).*
3. The detected EMG signal will be filtered by the electrode before it can be observed. This electrode filtering function will be represented by *R(w, d),* where *d* is the distance between the detection surfaces of a bipolar electrode.

Note that the recruitment of motor units as a function of time during a constant force has not been considered; however, the required modification to the equation is trivial, and the concept may easily be accommodated. The concept of "motor unit rotation" during a constant force contraction (i.e., newly recruited motor units replacing previously active motor units) which has, at times, been speculated to exist, has also not been included. No account may be found in the literature which has provided evidence of this phenomenon by definitively excluding the likelihood that the indwelling electrode has moved relative to the active muscle fibers and, in fact, records from a new motor unit territory in the muscle. [1][8][10]

$$Sm(\omega,t,F) = R(\omega,d)[\sum_{i=1}^{p(F)} Sui(\omega,t) + \sum_{\substack{i,j=1 \\ i\neq j}}^{q(F)} Suiuj(\omega,t)$$

Where, MUAPT power density function $Sm(\omega,t,F)$

There are three eventualities that may influence its time dependency: (1) the characteristics of the shape of the MUAP *Ui(t)* and *Uj(t)* change as a function of time; (2) the number of MUAPTs which are correlated varies as a function of time; (3) the degree of cross-correlation among the correlated MUAPTs varies. A change in the shape of the MUAP of *Ui(t)* and *Uj(t)* would not only cause an alteration in the cross-power density term but also would cause a more pronounced modification in the respective auto power density spectra. Hence, the *power density spectrum of the EMG signal* would be altered regardless of the modifications of the individual cross-power density spectra of the MUAPTs. There is to date no direct evidence to support the other two points. In fact, De Luca et al *(1982a* and *b)* have presented data which indicate that the cross-correlation of the firing rates of the concurrently active motor units does not appear to depend on either time during, or force of a contraction. [1][4] This apparent lack of time-dependent cross-correlation of the firing rates is not inconsistent with previously mentioned observations, indicating that the synchronization of the motor unit discharges tends to increase with contraction time. These two properties can be unrelated. Up to this point, the

modeling approach has provided an explanation of the following aspects and behavior of the power density spectrum:

1. The amplitude increases with additionally recruited MUAPTs.
2. The IPI firing statistics influence the shape of the spectrum below 40 Hz, although this effect is not necessarily consistent, and is less evident at higher force when an increasing number of motor units are active.
3. The tendency for motor units to "synchronize" will affect the spectral characteristics but will be limited to the low frequency components.
4. Modification in the waveform of MUAPs within the duration of a train will affect most of the spectrum of the EMG signal. This is particularly worrisome in signals that are obtained during contractions that are anisometric, because in such cases the waveform of the MUAP may change in response to the modification of the relative distance between the active muscle fibers and the detection electrode.

The above associations do not fully explain the now well-documented property of the EMG signal, which manifests itself as a shift towards the low frequency end of the frequency spectrum during sustained contractions. It is apparent that modifications in the total spectral representation of the MUAPs can only result from a modification in the characteristics of the shape of the MUAP. During attempted isometric contraction, such modifications have their root cause in events that occur locally within the muscle. Broman (1973) and De Luca and Forrest (1973a) were the first to present evidence that the MUAP increases in time duration during a sustained contraction. [5] More recently, Kranz et al (1981) and Mills (1982) have provided further support. [6]

III. Spectral Analysis of EMG Signal

Spectrum analysis is also applied to EMG studies. Various feature extraction methods based on the spectral analysis are experimented. By using of information contained in frequency domain could lead to a better solution for encoding the EMG signal. Time-frequency analysis based on short-time Fourier transform is a form of local Fourier analysis that treats time and frequency simultaneously and systematically. The characters of EMG signals in frequency domain are explored and demonstrated in this chapter. The short time variability of spectrum, which is an essential fact for using time-frequency methods in EMG feature extraction, is also discussed in this chapter. The analysis can provide important clues to design feature extraction methods. Wavelets approach is another powerful technique for time-frequency analysis.

IV. Power Spectral Density (PSD) of EMG Signal

EMG Signals cannot be described by a well-defined formula. The distributions for the various grasp types can be however described with the probability laws. EMG signal is a random process whose value at each time is a random variable. [7] The Fourier transform we used in the previous section views non random signals as weighted integral of sinusoidal functions. Since a sample function of random process can be viewed as being selected from an ensemble of allowable time functions, the weighting function for a random process must refer in some way to the average rate of change of the ensemble of allowable time functions. The power spectral density (PSD) of a wide sense stationary random process $X(t)$ is computed from the Fourier transform of the autocorrelation function $R(\tau)$:

$$\mathrm{Sx(f)} = \int_{-\infty}^{+\infty} \mathrm{R}(\tau).\, \mathrm{e}^{-\mathrm{j}2\pi\mathrm{ft}}\, \mathrm{d}\tau$$

Where the autocorrelation function

$$\mathrm{R}(\tau) = \mathrm{E}[\mathrm{X}(\mathrm{t}+\tau)\mathrm{X}(\mathrm{t})$$

The nonparametric methods are methods in which the estimate of PSD is made directly from a signal itself. One type of such methods is called periodogram. The periodogram estimate for PSD for discrete time sequence x_1, x_2, x_3 …. x_k is defined as square magnitude of the Fourier transform of data:

$$S(\%f) = \frac{1}{k}.|\sum_{\mathrm{m}=1}^{\mathrm{m}=\mathrm{k}} \mathrm{Xm}\,.\,\mathrm{e}^{-\mathrm{j}\Pi\mathrm{fm}}\,|^2$$

An improved nonparametric estimator of the PSD is proposed by Welch P.D. The method consists of dividing the time series data into (possibly overlapping) segments, computing a modified (windowed) periodogram of each segment, and then averaging the PSD estimates. The result is Welch's PSD estimate. The multitaper method (MTM) is also a nonparametric PSD estimation technique which uses multiple orthogonal windows.

The first step toward the computation of spectral variables is the estimation of the PSD function of the signal. When the voluntary myoelectric signal is processed (albeit the raw periodogram is an asymptotically unbiased but inconsistent spectral estimator), both spectral variables (MNF and MOF) are computed adding the amplitudes of many spectral lines, thus dramatically reducing the effect of the in determination of the power content of the individual spectral lines.

V. Results

The EMG is collected from Physio Bank ATM having 4000 samples of a healthy & Myopathic subject where the length of the recorded signal was 10 seconds. The simulation part is carried out in Mat lab platform.

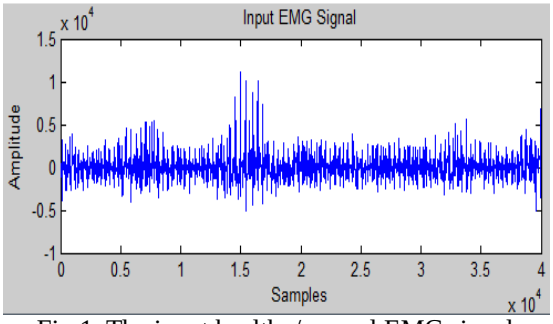

Fig 1. The input healthy/normal EMG signal

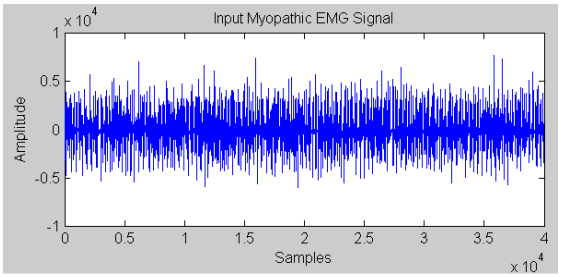

Fig 2. The input Myopathic EMG signal

1.1. Hamming window

The hamming window, w = hamming(L) returns an L-point symmetric Hamming window in the column vector w. L should be a positive integer. The coefficients of a Hamming window are computed from the following equation.

$\omega(n)=0.54-0.46\cos(2\pi\frac{n}{N}), 0 \leq n \leq N$

The window length is L=N+1

w = hamming (L,'sflag') returns an L-point Hamming window using the window sampling specified by 'sflag', which can be either 'periodic' or 'symmetric' (the default). The 'periodic' flag is useful for DFT/FFT purposes, such as in spectral analysis. The DFT/FFT contains an implicit periodic extension and the periodic flag enables a signal windowed with a periodic window to have perfect periodic extension. When 'periodic' is specified, hamming computes a length L+1 window and returns the first L points. When using windows for filter design, the 'symmetric' flag should be used.

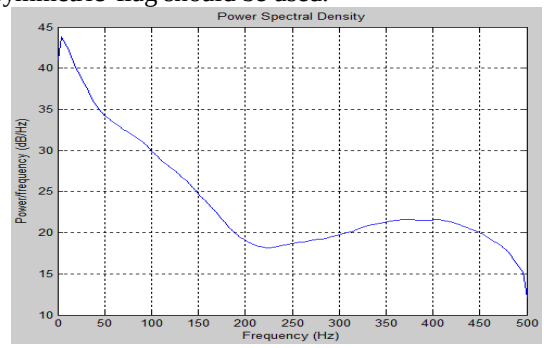

Fig 3. Power Spectral Density of Normal EMG Signal with Hamming window

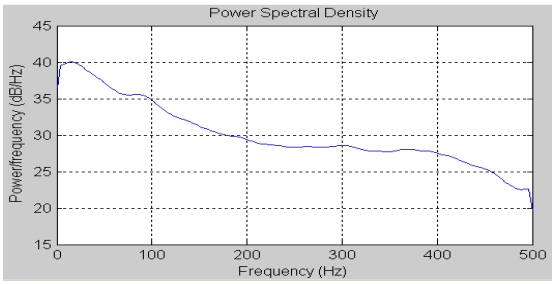

Fig 4. Power Spectral Density of Myopathic EMG Signal with Hamming window

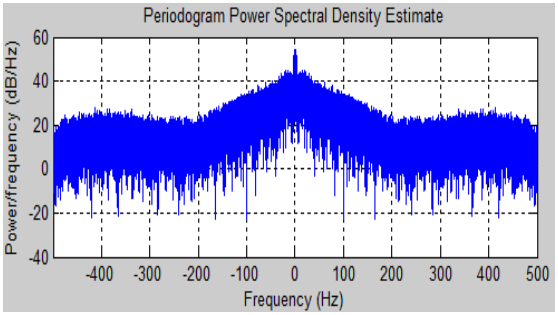

Fig 5. Periodogram Power Spectral Density Estimate of Normal EMG Signal with Hamming Window

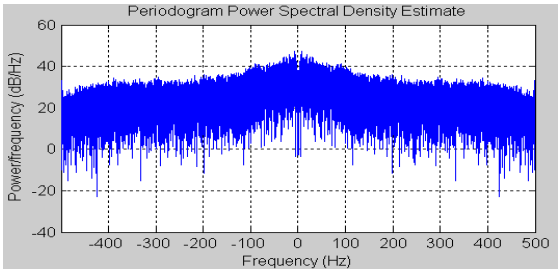

Fig 6. Periodogram Power Spectral Density Estimate of Myopathic EMG Signal with Hamming Window

The power spectral density of the input Normal EMG signal (fig-5) can be estimated by its periodogram where the frequency range is from -500 to 500 Hz and the Power per frequency is -20 to +25 db/Hz in the both side-lobe of the spectrum but the mid portion the Power per frequency (frequency -200 to +200 Hz) is about 0 to +40 db/Hz for Hamming Window method.

Whereas the power spectral density of the Myopathic EMG signal (fig-6) can be estimated by its periodogram and the frequency range is from -500 to 500 Hz and the Power per frequency is -10 to +30 db/Hz in the both side-lobe of the spectrum but the mid portion the Power per frequency (frequency -100 to +100 Hz) is about +10 to +40 db/Hz for Hamming Window method.

1.2. Kaiser window

The Kaiser Window, w = Kaiser (L, beta) returns an L-point Kaiser window in the column vector w. beta is the Kaiser window β parameter that affects the sidelobe attenuation of the Fourier transform of the window. The default value for beta is 0.5.To obtain a Kaiser window that designs an FIR

filter with sidelobe attenuation of α dB, use the following β.

$$\beta = \begin{cases} 0.1102(\alpha - 21), & \alpha > 50 \\ 0.5842(\alpha - 21)^{0.4} + 0.07886(\alpha - 21), & 50 \geq \alpha \geq 21 \\ 0, & \alpha < 21 \end{cases}$$

Increasing beta widens the main lobe and decreases the amplitude of the sidelobes (i.e., increases the attenuation).

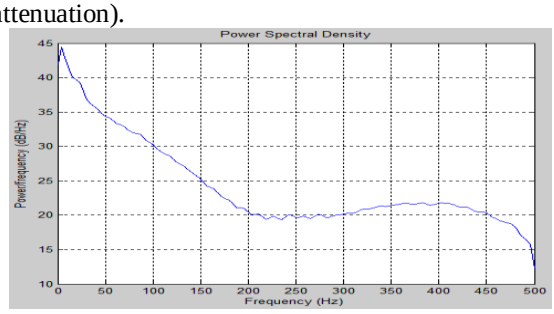

Fig 7. Power Spectral Density of Normal EMG Signal with Kaiser Window

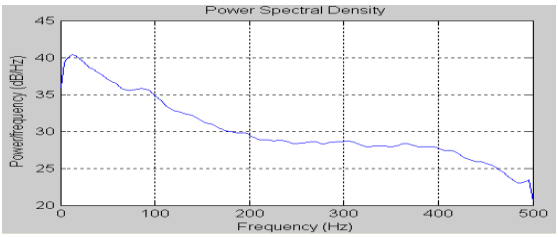

Fig 8. Power Spectral Density of Myopathic EMG Signal with Kaiser Window

The Power Spectral Density of Normal EMG Signal is found to be higher than that of myopathic signal. In case of Hamming Window the max PSD is 44dB/Hz for normal signal and 40 dB/Hz for Myopathic signal whereas for Kaiser Window it is 45dB/Hz for normal signal & 41dB/Hz for myopathic signal.

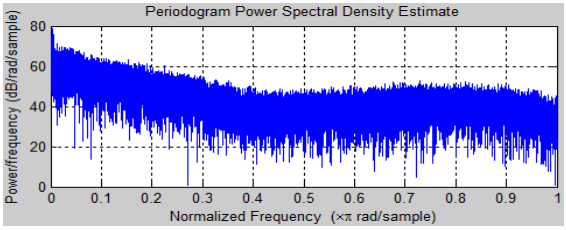

Fig 9. Periodogram Power Spectral Density Estimate of normal EMG Signal with Kaiser Window

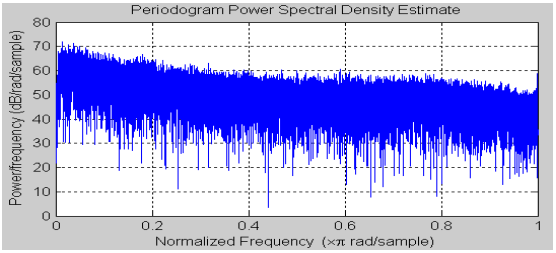

Fig 10. Periodogram Power Spectral Density Estimate of Myopathic EMG Signal with Kaiser Window

The Periodogram Power Spectral Density Estimate of Normal EMG Signal with Kaiser Window is being shown in Fig-9 where the Power per frequency is decreasing from initial 80 dB/rad sample to nearby 20 dB/rad sample gradually with respect to its normalized frequency.

Whereas the Periodogram Power Spectral Density Estimate of Myopathic EMG Signal with Kaiser Window is being shown in Fig-10 and the Power per frequency is decreasing from initial 70 dB/rad sample to nearby 20 dB/rad sample gradually with respect to its normalized frequency

The Periodogarm Mean-Square Spectrum estimate for the Normal EMG signal (fig-12) and its frequency limits in the interval of -100 to 100 Hz and the myopathic signal spectrum spreads over the frequency range of -400 to 400 Hz.

During a sustained isometric contraction the surface EMG signal becomes "slower", the power spectral density is compressed toward lower frequencies and spectral variables (MNF, MDF) decrease. The decrease of these variables reflects a decrease of muscle fiber conduction velocity and changes of other variables (such as active motor unit pool, degree of synchronization, etc).

$$fm = \int_0^\infty f\,P(f)df \Big/ \int_0^\infty P(f)d$$

$$\int_0^{fmed} P(f)df = \int_{fmed}^\infty P(f)df = \frac{1}{2}\int_0^\infty P(f)df$$

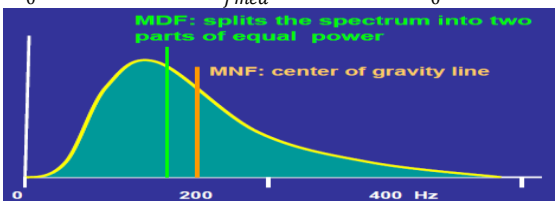

Fig11. Mean and median spectral frequencies of the EMG signal (MNF and MDF)

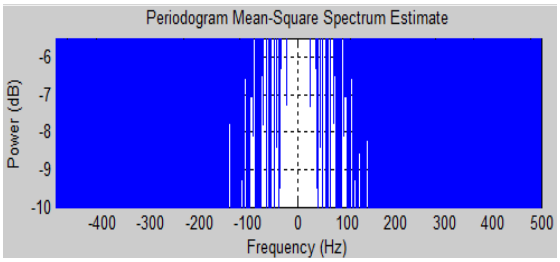

Fig12. Periodogram Mean-Square Spectrum Estimate of Normal EMG Signal

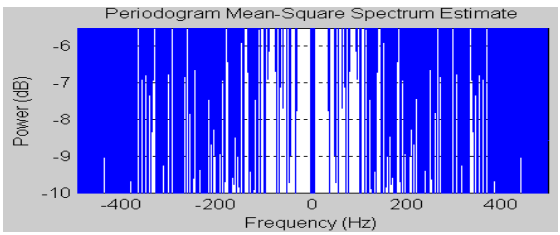

Fig13. Periodogram Mean-Square Spectrum Estimate of Myopathic EMG Signal

The PSD shown above summarizes the frequency components for the entire length of the EMG data. Another important part of spectral analysis relies on studying how the frequency components vary with time. Qualitative assessments can be made by calculating the PSD for each segment of data and comparing them.

VI. Conclusion

It has been shown that the mean and median frequencies of the EMG signal decrease with time during a task that induces fatigue. The result essentially gives an evaluation of what contribution each frequency has to the original signal. In order to gain meaningful information from this type of calculation, the segment of data being studied must be stationary, meaning that the statistics of the signal do not change with time. The most important application of spectral analysis in our study was to make differentiate between normal and myopathic EMG signals and the spectral behaviour. Our analysis leads to better investigation of myopathic diseases and the origin of such diseases. Future research involves the neuromuscular signal analysis and disease findings.

References

[1] N. S. Arikidis, A. Forster, and E. Abel. Interscale Wavelet Maximum - A Fine to Coarse Algorithm for Wawelet Analysis of the EMG Interference Pattern. IEEE Transaction on Biomedical Engineering, 49(4), April 2002.

[2] Krarup C. Pitfalls in electrodiagnosis. J Neurophysiol 1999; 81:1115—26.

[3] McGill KC. Optimal resolution of superimposed action potentials. IEEE Trans Biomed Eng 2002;49:640—50.

[4] Richfield EK, Cohen BA, Albers JW. Review of quantitative and automated needle electromyographic analyses. IEEE Trans Biomed Eng 1981;506—14.

[5] Gerber A. A new framework and computer program for quantitative EMG signal analysis. IEEE Trans Biomed Eng 1984;31:857—63.

[6] Loudon GH, Jones NB, Sehmi AS. New signal processing techniques for the decomposition of EMG signals. Med Biol Eng Comput 1992;30:591—9.

[7] Nandedkar SD, Barkhaus PE, Charles A. Multimotor action potential analysis (MMA). Muscle Nerve 1995;18:1155—66.

[8] Stalberg E, Andreassen S, Falck B, Lang H, Rosenfalck A, Trojaborg W. Quantitative analysis of individual motor unit potentials: a proposition for standardized technology and criteria for measurement. J Clin Neurophysiol 1986;3:313—48.

[9] Buchthal F, Guld C, Rosenfalck P. Action potential parameters in normal human muscle and their dependence on physical variables. Acta Physiol Scand 1954;32:200—15.

[10] Buchthal F. An introduction to electromyography. Copenhagen: Gyldendal; 1957.

[11] LeFever RS, DeLuca CJ. A procedure for decomposing the myoelectric signal into its constituent action potentials: part I, execution and test for accuracy. Technique, theory and implementation. IEEE Trans Biomed Eng 1982;29:149—57.

[12] Stalberg E, Falck B, Sonoo M, Stalberg S, Astrom M. Multi- MUP EMG analysis——a two year experience in daily clinical work. In: Electroencephalography and clinical neurophysiol. Amsterdam, The Netherlands: Elsevier Science; 1995 . pp. 145—154.

[13] Andreassen S. Methods for computer aided measurement of motor unit parameters. In: Ellington RJ, et al., editors. Proceedings of the London Symp., EEG suppl. 13—20. 1987.

[14] Stashuk DS, Qu H. Automatic decomposition of selective needle detected myoelectric signals. IEEE Trans Biomed Eng 1988;35:1—10.

[15] Hassoun MH, Wang C, Spitzer AR. NNERVE: neural network extraction of repetitive vectors for electromyography——part II: algorithm. IEEE Trans Biomed Eng 1994;41:1053—61.

[16] McGill K, Cummins K, Dorfman L. Automatic decomposition of the clinical electromyogram. IEEE Trans Biomed Eng 1985;32:470—6.

[17] Fang J, Agarwal GC, Shahani BT. Decomposition of multiunit electromyographic signals. IEEE Trans Biomed Eng 1999; 46:685—97.

[18] Wu S, Gong YX, Xue C, Zhi Z. Extraction of MUAP from NEMG signal using self-organization competing NN. Hefei 230026: Dept. of Electronic Science & Tech., Univ. of Science & Tech. of China; 2001.

[19] Chauvet E, Fokapu O, Hogrel JY, Gamet D, Duchene J. Automatic identification of motor unit action potential trains from electromyographic signals using fuzzy techniques. Med Biol Eng Comput 2003;41:646—53.

[20] DeLuca, C.J. and Forrest, W.H., An electrode for recording single motor unit activity during strong muscle contraction, IEEE Trans. Biomed. Eng., 19, 367, 1972.

[21] DeLuca CJ. Towards understanding the EMG signal, 4th ed., Baltimore: Williams & Wilkinson; 1978.

[22] De Luca CJ, LeFever RS, Stulen FB (1979) Pasteless electrode for clinical use. Med Bioi Eng Comput 17: 387-390