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Analysing MUAP of EMG Signal with Power Density Spectrum in Matlab

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***Abstract* – The lack of a proper description of the EMG signal is probably the greatest single factor which has hampered the development of electromyography into a precise discipline. Our proposed methodology described the relationship between the EMG signal and the properties of a contracting muscle by analysing its power density spectrum. We have also discussed the basic concepts on Motor Unit Action potential and analyzed the spectral density of a healthy person EMG signal. The Power spectral Density is calculated with Welch's PSD estimate method by taking Hamming & Kaiser Window. This model can be useful for the study of gate analysis and control scheme of the peripheral nervous system.**

***Keywords* – EMG Signal, Power Density Spectrum, Welch's PSD, Gate Analysis, MUAP.**

I. Introduction to MUAP

Under normal conditions, an action potential propagating down a motoneuron activates all the branches of the motoneuron; these in turn activate all the muscle fibers of a motor unit. When the postsynaptic membrane of a muscle fiber is depolarized, the depolarization propagates in both directions along the fiber.

The membrane depolarization, accompanied by a movement of ions, generates an electromagnetic field in the vicinity of the muscle fibers. An electrode located in this field will detect the potential or voltage (with respect to ground), whose time excursion is known as an action potential. This action potential is known as Motor Unit Action Potential (MUAP). [1]

A. The Motor Unit Action Potential Trains

The electrical manifestation of a MUAP is accompanied by a twitch of the muscle fibers. In order to sustain a muscle contraction, the motor units must be repeatedly activated. The resulting sequence of MUAPs is called a motor unit action potential train (MUAPT). The waveform of the MUAPs within a MUAPT will remain constant if the geometric relationship between the electrode and the active muscle fibers remains constant, if the properties of the recording electrode do not change, and if there are no significant biochemical changes in the muscle tissue. Biochemical changes within the muscle could affect the conduction velocity of the muscle fiber and filtering properties of the muscle tissue. The muscle fibers of a motor unit are randomly distributed throughout a subsection of the normal muscle and are intermingled with fibers belonging to different motor units. Evidence for this anatomical arrangement in the rat and cat has been presented by Edstrom and Kugelberg (1968), Doyle and Mayer (1969) and Burke and Tsairis (1973). There is also indirect electromyographic evidence suggesting that a similar arrangement occurs in human muscle (Stalberg and Ekstedt, 1973; Stalberg et aI, 1976). The cross-sectional area of a motor unit territory ranges from 10 to 30 times the cross-sectional area of the muscle fibers of the motor unit (Buchthal et aI, 1959; Brandstater and Lambert, 1973). [3] This admixture implies that any portion of the muscle may contain fibers belonging to 20 to 50 motor units. Therefore, a single MUAPT is observed when the fibers of only one motor unit in the vicinity of the electrode are active. Such a situation occurs only during a very weak muscle contraction. As the force output of a muscle increases, motor units having fibers in the vicinity of the electrode become activated, and several MUAPTs will be detected simultaneously. This is the case even for highly selective electrodes which detect action potentials of single muscle fibers. As the number of simultaneously detected MUAPTs increases, it becomes more difficult to identify all the MUAPs of any particular MUAPT due to the increasing probability of overlap between MUAPs of different MUAPTs. [1][16][18]

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:

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

where $Su,(\omega)$ = the power density of the MU APT, $Ui(t)$; and $Suiuj(\omega)$ = 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] [7]

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. [7]

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

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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 $R(\tau)$:

$$Sx(f) = \int_{-\infty}^{+\infty} R(\tau).e^{-j2\pi ft} d\tau$$

Where the autocorrelation function

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

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:

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

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. [4] [7]

V. Results

The EMG is collected from PhysioBank ATM having 4000 samples of a healthy subject and the length of the recorded signal was 10 seconds. The simulation part is carried out in Matlab platform.

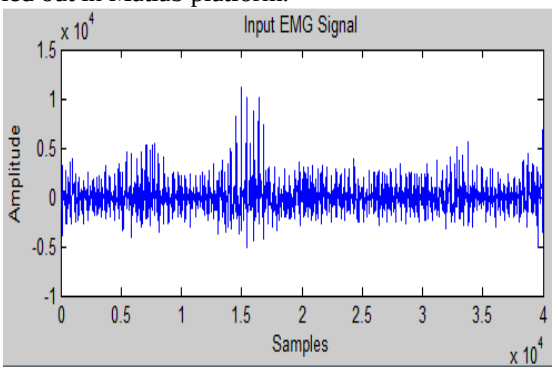

Fig.1. The input healthy/normal EMG signal

A. 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.

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

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.

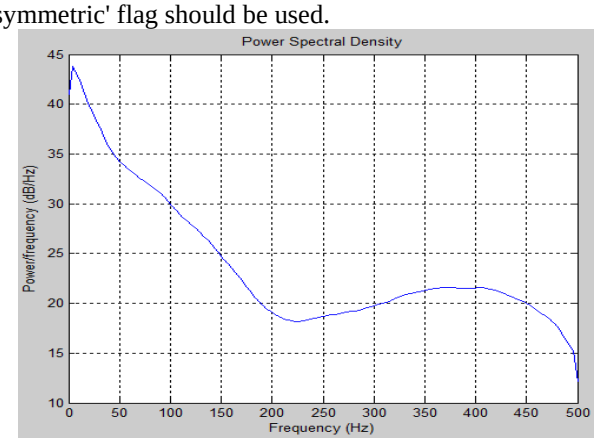

Fig.2. Power Spectral Density of EMG Signal with Hamming window

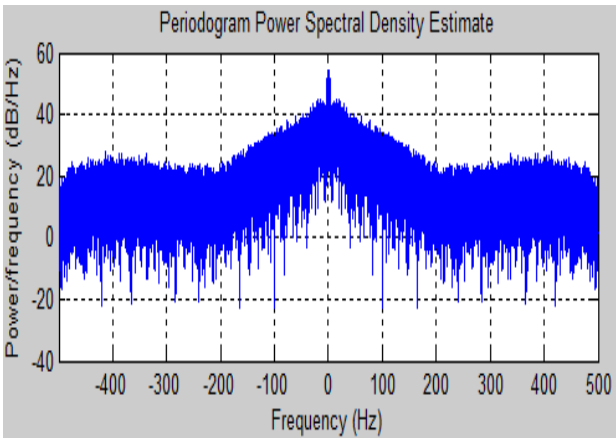

Fig.3. Periodogram Power Spectral Density Estimate of EMG Signal with Hamming Window

The power spectral density of the input EMG signal (fig-3) 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 +20 to +40 db/Hz for Hamming Window method.

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B. 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).

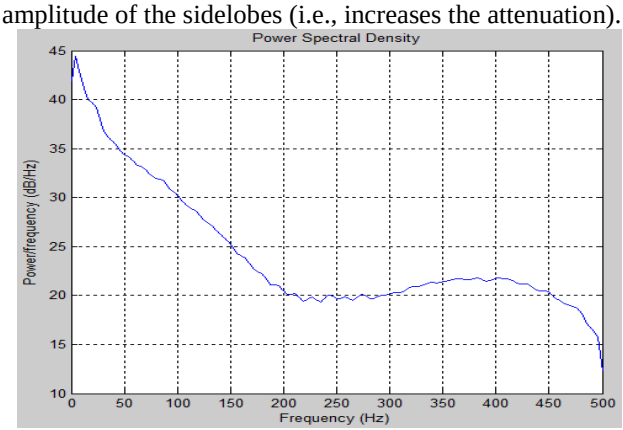

Fig.4. Power Spectral Density of EMG Signal with Kaiser Window

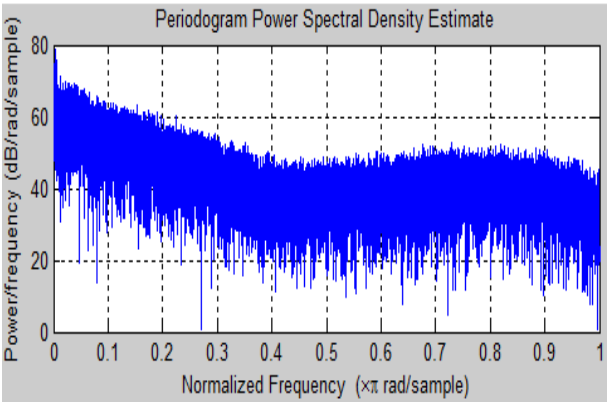

Fig.5. Periodogram Power Spectral Density Estimate of EMG Signal with Kaiser Window

The Periodogram Power Spectral Density Estimate of EMG Signal with Kaiser Window is being shown in Fig-5 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.

Below fig-7 represents the periodogarm Mean-Square Spectrum estimate for the given input EMG signal and its frequency limit in the interval of -100 to 100 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).

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

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

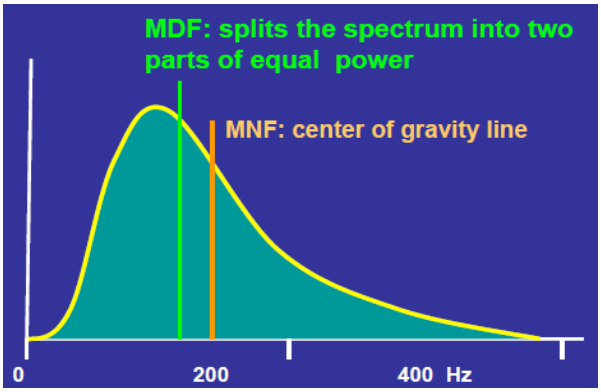

Fig.6. Mean and median spectral frequencies of the EMG signal (MNF and MDF)

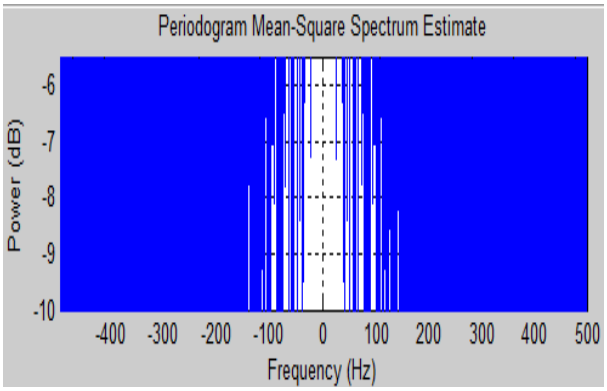

Fig.7. Periodogram Mean-Square Spectrum Estimate of EMG Signal

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. Quantitative assessments can be made by calculating the mean frequency or the median frequency of the PSD sequentially for epochs of EMG data. It has been shown that the mean and median frequencies of the EMG signal decrease with time during a task that induces fatigue.

VI. Conclusion

The previous two methods of analysis make use of the EMG signal in the time domain, as it was sampled in its original form. Our category of EMG signal analysis relies on the frequency domain. Any signal can actually be mathematically deconstructed into a collection of sine waves of different frequencies through an operation called a Fourier Transform. 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 is the study of muscle fatigue. Due to the characteristics of the PSD function of the electrically evoked myoelectric signal, the estimate of the spectral density is far more accurate than that obtained from voluntary signals. Median frequency of EMG signal can be used to identify the speed of walk of a normal human. There is need to identify the normal ranges of EMG variations of local population. Our further investigation involves the analysis of EMG MUAP of myopathy and neuropathy signals and the variation in density of the Spectral properties.

REFERENCES

[1] Basmajian, J. and De Luca, C. J., Muscles Alive, 5th ed., Williams & Wilkins, Baltimore, 1985.
[2] Gath, L. and Stalberg, E., On the volume conduction in human skeletal muscles: in situ measurements, EEG Clin. Neurophysiol., 43, 106, 1977.
[3] Buchthal, F., Guld, C., and Rosenfa1ck, P., Propagation velocity in electrically activated muscle fibers in man, Acta Physiol. Scand., 34,75, 1955.
[4] Brody, L., Pollock, M., Roy, S., De Luca, C., and Celli, B., pH induced effects on median frequency and conduction velocity of the myoelectric signal, J. Appl. Physiol., 71, 1878, 1991.
[5] Broman, H., Bilotto, G., and De Luca, C. J., A note on the non-invasive estimation of muscle fiber conduction velocity, IEEE Trans. BME, 32, 341, 1985.
[6] Kranz, H., Williams, A. M., Cassell, J., Caddy, D. J., and Silberstein, R. B., Factors determining the frequency content of the electromyogram, J. Appl. Physiol. Respir. Environ. Exercise Physiol., 55, 392, 1983.
[7] Mills, K. R., Power spectral analysis of EMG and compound muscle action potential during muscle fatigue and recovery, J. Physiol., 326, 401, 1982.
[8] Edwards, R., Chapman, S., Newman, D., and Jones, D., Practical analysis of variability of muscle function measurements in Duchenne muscular dystrophy, Muscle Nerve, 10,6, 1987.
[9] Elden, R. R., Biophysical Properties of the Skin, Vol. I, John Wiley & Sons, New York, 1971.
[10] Emley, M., Catani, F., Roy, S., and Knaflitz, M., Myoelectric crosstalk in antagonist muscles of the human thigh, Proc. IEEE-EMBS 9th Annu. Int. Conf., Boston, 1987.
[11] Etnyre, B. and Abraham, L. D., Comparison of wire and surface electrode recordings between antagonist pairs of muscles, Proc. 6th ISEK Congr., Tokyo, 1985.
[12] Fang, Z. and Mortimer, T., Selective activation of small motor axons by quasitrapezoidal current pulses, IEEE Trans. BME, 38, 168, 1991.
[13] Dimitrova, N., Influence of the length of depolarization in the extracellular potential field of a single unmyelinated nerve fibre, Electromyogr. Clin. Neurophysiol., 13,547, 1973.
[14] Duchateau, J. and Hainaut, K., Electrical and mechanical failures during sustained and intermittent contractions in humans, J. Appl. Physiol., 58, 942, 1985.
[15] Gracanin, F. and Trnkoczy, A., Optimal stimulus parameters for minimum pain in the chronic stimulation of innervated muscle, Arch. Phys. Med. Rehab., 56,243, 1975.
[16] Graupe, D. and Kohn, K. R., A critical review of EMG-controlled electrical stimulation in paraplegics, Crit. Rev. Biomed. Eng., 15, 187, 1988.
[17] Gruener, R., Stern, L., and Weisz, R., Conduction velocities in single fibers of diseased human muscle, Neurology, 29, 1293, 1979.
[18] Gydikov, A. and Kosarov, D., Influence of various factors on the length of the summated depolarized area of the muscle fibers in voluntary activating of motor units and in electrical stimulations, Electromyogr. Clin. Neurophysiol., 14,79, 1974.

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