



FEATURE EXTRACTION IN ELECTROMYOGRAPHY BY DIGITAL SIGNAL PROCESSING TECHNIQUES

Dr. Ahmed Ali Sadik
University of Technology

ABSTRACT

Myoelectric signals are the electrical manifestation associated with the movements exerted by the muscular system in the mammal beings (including the human). Examination of these signals should reveal the status of the muscles as well as the driving nervous system, This is important in diagnosis as well as prosthesis for the health of mankind and aids for handicapped . This would not be possible unless powerful digital processing techniques are available. In this paper, several techniques are investigated so as to extract the features of the ME signals both in time and frequency domains. The extracted features are subsequently employed in an automatic diagnostic classification system to decide whether or not they correspond to a normal muscle

الخلاصة

اشارات المخطط العضلي عبارة عن تغيرات كهربائية ملازمة لحركة العضلات في الثدييات (ومنها الانسان) فحص هذه الاشارات تعطي حالة العضلات و الاعصاب المسيطرة عليها و هذا الامر مهم جدا في التشخيص الطبي للحالة الصحية. ان استخدام معالجة الاشارة الرقمية في الهندسة الطبية يسهل هذه المهمة . ورقة البحث قدمت عدة تقنيات لاستخراج و تحليل الاشارة العضلية الكهربائية في البعدين الزمني و الترددي . ان الاستخراج لشكل و طبيعة هذه الاشارة الكهربائية بشكل العنصر الاساسي في التشخيص الطبي .

KEY WORD

Application of digital signal processing in biomedical Engineering .

INTRODUCTION

To determine the characteristic features of the ME signals nonparametric and parametric processing approaches can be applied. Nonparametric techniques are applied to ME signal without paying attention to its decomposition as a source and auto-regressive (AR) filter to determine a set of characteristics. Among these techniques are the evaluation of the probability density function (pdf), mean, variance with their relations to the muscle force, autocorrelation function (ACF) and spectral domain techniques (FFT) [A.S.88]. Parametric techniques are applied starting from decomposing the signal and separating source parameters from filter related parameters and yield parametric characterization for the filter and the source. Section 2 is devoted to the nonparametric characterization of the ME signal , mainly through the:- FFT and histogram determination. In section 3, signal decomposition is considered and a parametric model for the shaping filter is determined, Moreover, the source characteristics are evaluated. Section 4 considers the problem of automatic diagnosis for voluntary muscular system disorders.

ME SIGNAL DESCRIPTION (NONPARAMETRIC)

The nonparametric description of the myoelectric signal essentially directed, here, towards finding its spectrum and its probability density function.

a- Frequency domain description using FFT

Several processing techniques [A.V.75], [S.K.981] can be used to find the ME signal spectrum, of which the FFT (nonparametric) and the maximum entropy (parametric) methods are discussed in this work.

In this section, the spectral properties of the ME signal are obtained using FFT algorithm.

The available 5-second data records were segmented into consecutive 512 ms segments and processed. To reduce the abrupt changes at the beginning and at the end of the segment, a hanging window is applied to each segment. Then the spectrum of each segment was calculated by using the FFT routine. The spectrum of such a segment on a linear scale is shown in **Fig. (1a)** which emphasizes individual spectral peaks rather than the general spectral envelope, such as that obtained when using the logarithmic scale **Fig. (1b)**. From these figures we find that:

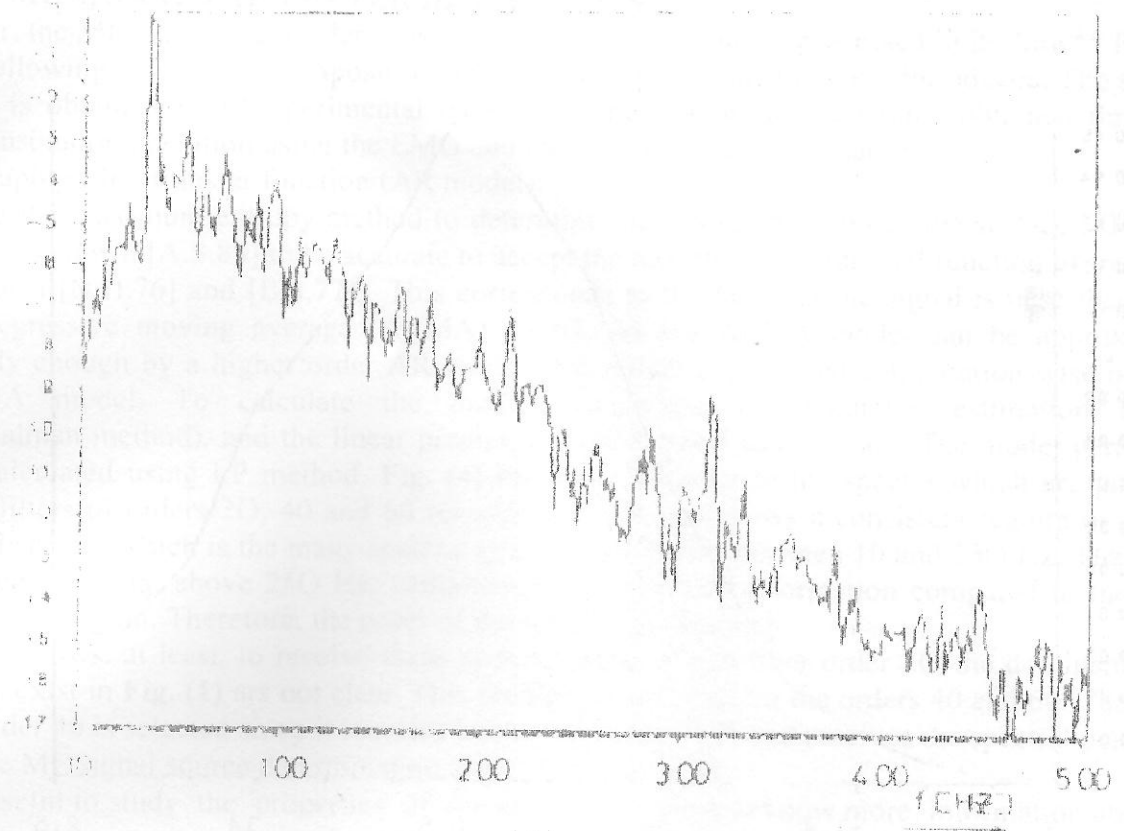
- 1- The spectrum consists of spikes mostly below 250 Hz, with an additional distribution of energy between 250 and 375 Hz. This conclusion was also attained in [G.F.84] and [B.H.86].
- 2- A clear peak in the frequency region below 50 Hz is exhibited by all records. This peak is caused by the signal potential which is indicative of the firing rate of MU's [Boxtel.83].

b-Time domain description

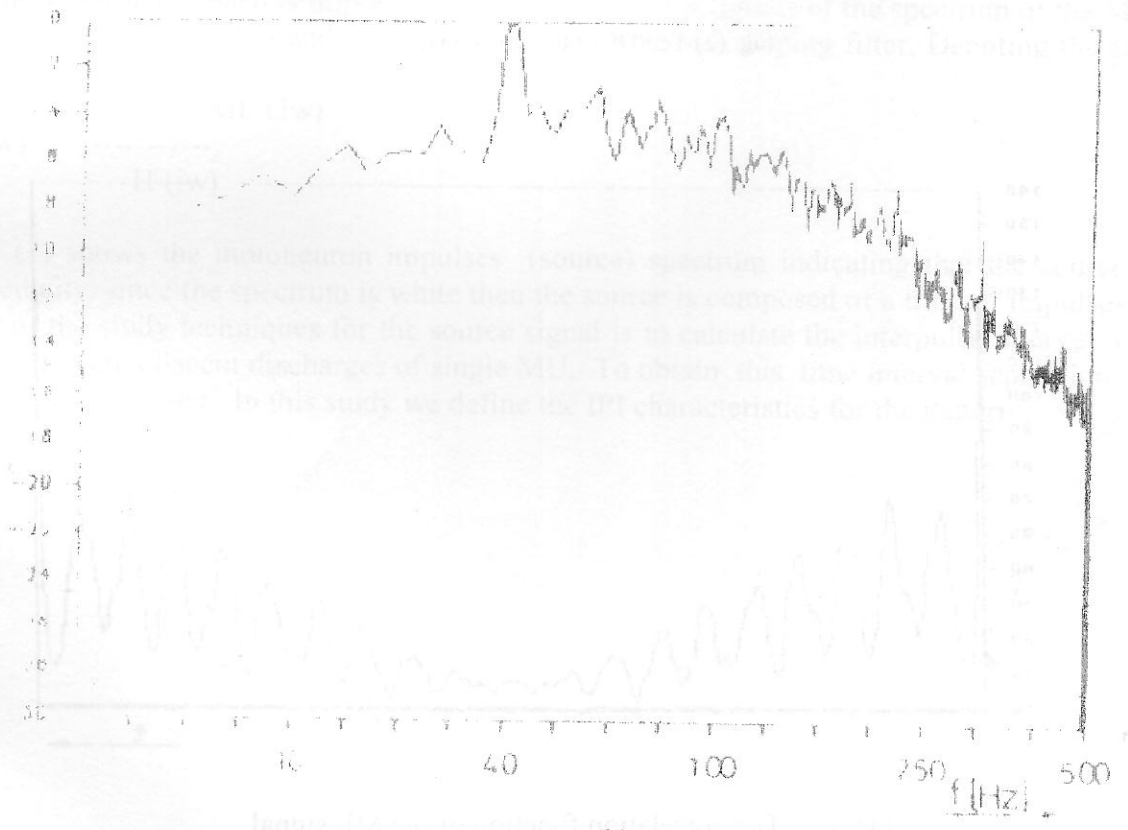
As a random process, the ME signal can be described by a Joint probability density function, from which a set of statistical parameters are computable. In the following, we are going to estimate the probability density function as well as the time autocorrelation function.

Estimated probability density function: The probability density function (pdf) of the ME signal **Fig. (2)** is estimated through histogram determination. **Fig. (2)** shows that the shape of the pdf of the HE signal approximates a truncated Gaussian distribution with a mean of 0.5 V and a standard deviation of 0.85 V. This shape of the pdf has been observed by many Investigators (e.g. [G.F.84] and [N.J.76]). It is to be noted that the filtering action exerted by the electrodes and muscle tissues manifests its control on the shape of the pdf.

- c- The Correlation function of the ME signal: The correlation function (cf) of the ME signal is computed by obtaining the inverse FFT of the squared magnitude spectrum. The obtained correlation function is shown in **Fig. (3)**. This correlation function has the form of a decayed periodic function and thus illustrates the inherent periodicity of the HE signal. The periodic nature is due to the periodicity of the input Impulses and the decay is due to the influence of the transmission medium (electrode effect, distance effected.).



(a)



(b)

Fig.(1) FFT spectrum of surface ME signal
a) linear scale b) logarithmic scale

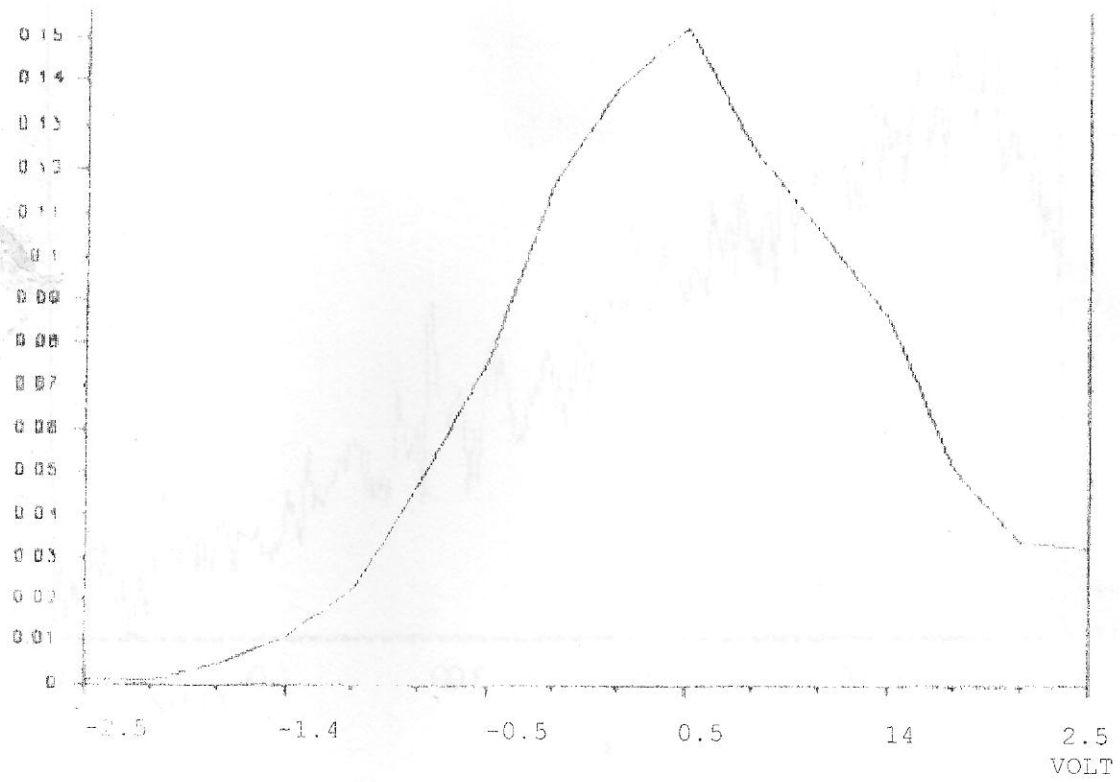


Fig (2) Te PDF of the ME signal

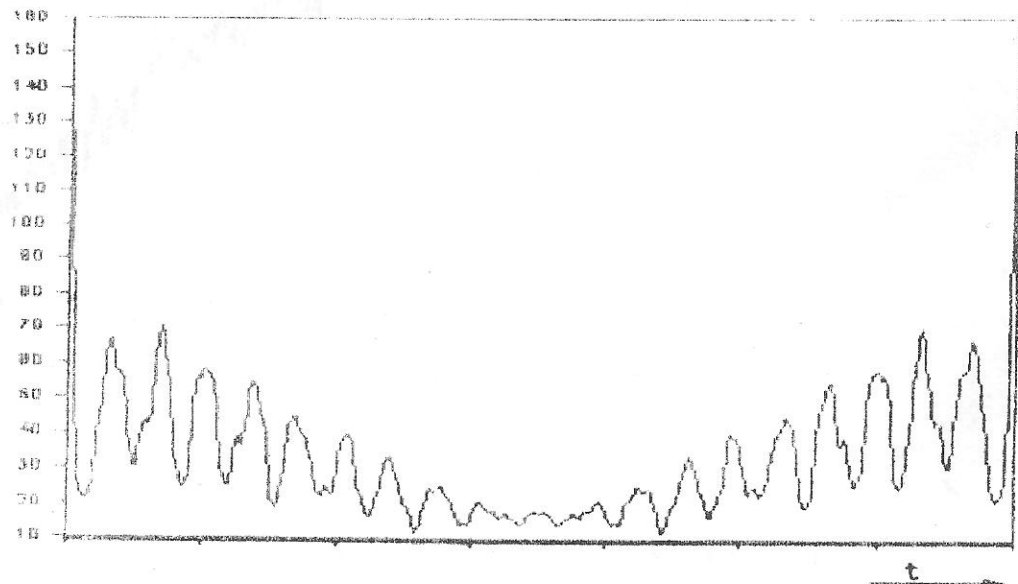


Fig. (3). The correlation function of the ME signal

THE ME SIGNAL PARAMETER DESCRIPTION

So far, the ME signal is considered as a composite process and is processed in its "raw**" form. In the following, a simple decomposition into its source filter constituents is introduced. The shaping filter is obtained from experimental data, Then the source can be simply obtained through a deconvolution operation using the EMG and the shaping filter combination.

a- Shaping filter transfer function (AR model):

Using the maximum entropy method to determine the power spectrum of the surface ME signal has been shown [A.S.88] to be accurate to accept the modeling by a rational function of frequency (see also [N.H.76] and [E.S.77]). This corresponds to the fact that the signal is described by an autoregressive moving average (ARMA) model. As the ARMA model can be approximated closely enough by a higher order AR model, AR model is preferred computation-wise over the ARMA model. To calculate the model parameters, the recursive estimation method (or Kalman method), and the linear prediction (LP) method can be used. The model parameters are calculated using LP method. **Fig. (4)-Fig. (6)**. demonstrate the spectra which are predicted with filters of orders 20, 40 and 60 respectively. **Fig. (1)** shows a consistent feature of the HE signal spectra which is the many spectral peaks in the region between 10 and 250 Hz. The higher frequency region, above 250 Hz, contains minor amplitude information compared to the lower frequency region. Therefore, the order of the filter is chosen such

that it allows, at least, to resolve these spectral peaks. For a filter order 20, the dominant peaks which exist in **Fig. (1)** are not clear. This problem is resolved for the orders 40 and 60. Therefore, the order 40 is selected since it requires less computation time and resolves the spectral peaks,

b- The ME signal source determination and characterization:

It is useful to study the properties of the anterior impulses to know more information about the nervous system. To find the ME signal source the deconvolution approach is used, The deconvolution approach is implemented through the calculations of the spectrum of the ME signal using the FFT algorithm and the transfer function of the shaping filter. Denoting the source by $U(j\omega)$ then:

$$U(j\omega) = \frac{ME(j\omega)}{H(j\omega)} \quad (1)$$

Fig. (7) shows the motoneuron impulses (source) spectrum indicating that the source has a periodicity, since the spectrum is white then the source is composed of a train of impulses. One of the study techniques for the source signal is to calculate the interpulse interval (IPI), the time between adjacent discharges of single MU. To obtain this time interval separation of single MUAPT is required. In this study we define the IPI characteristics for the pattern

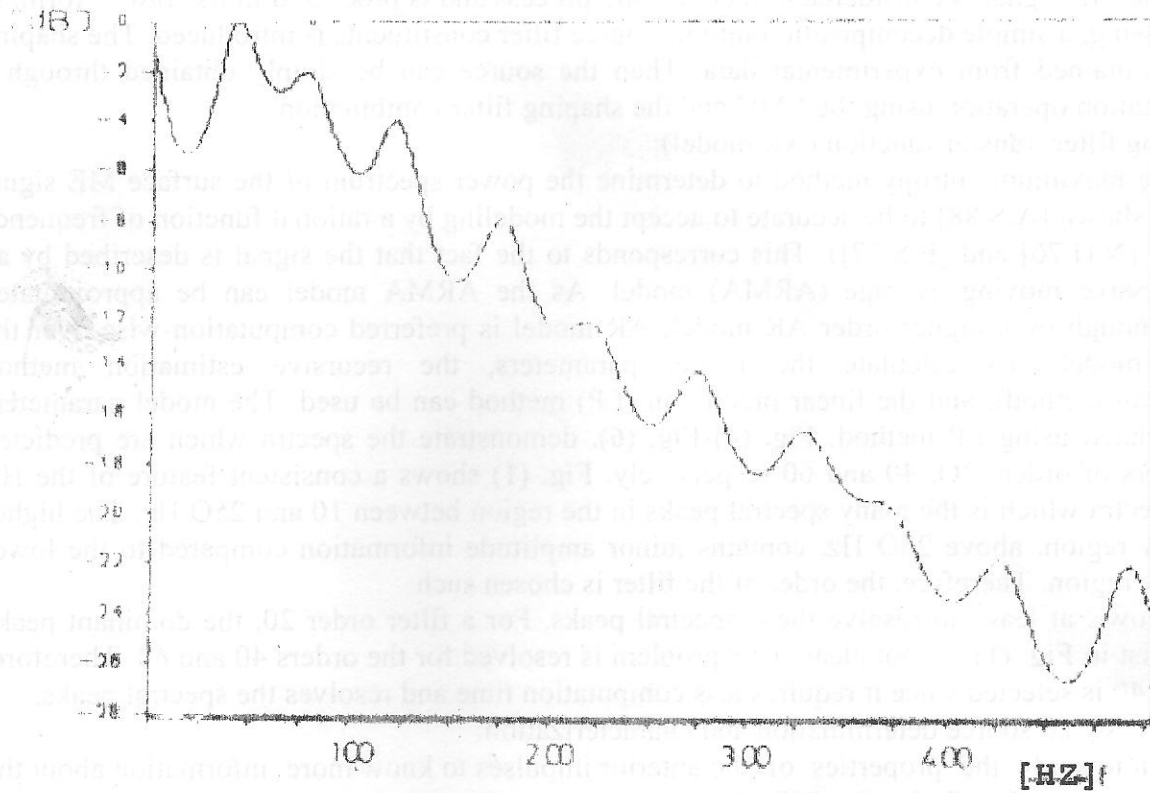


Fig (4). all- pole spectrum with order 20

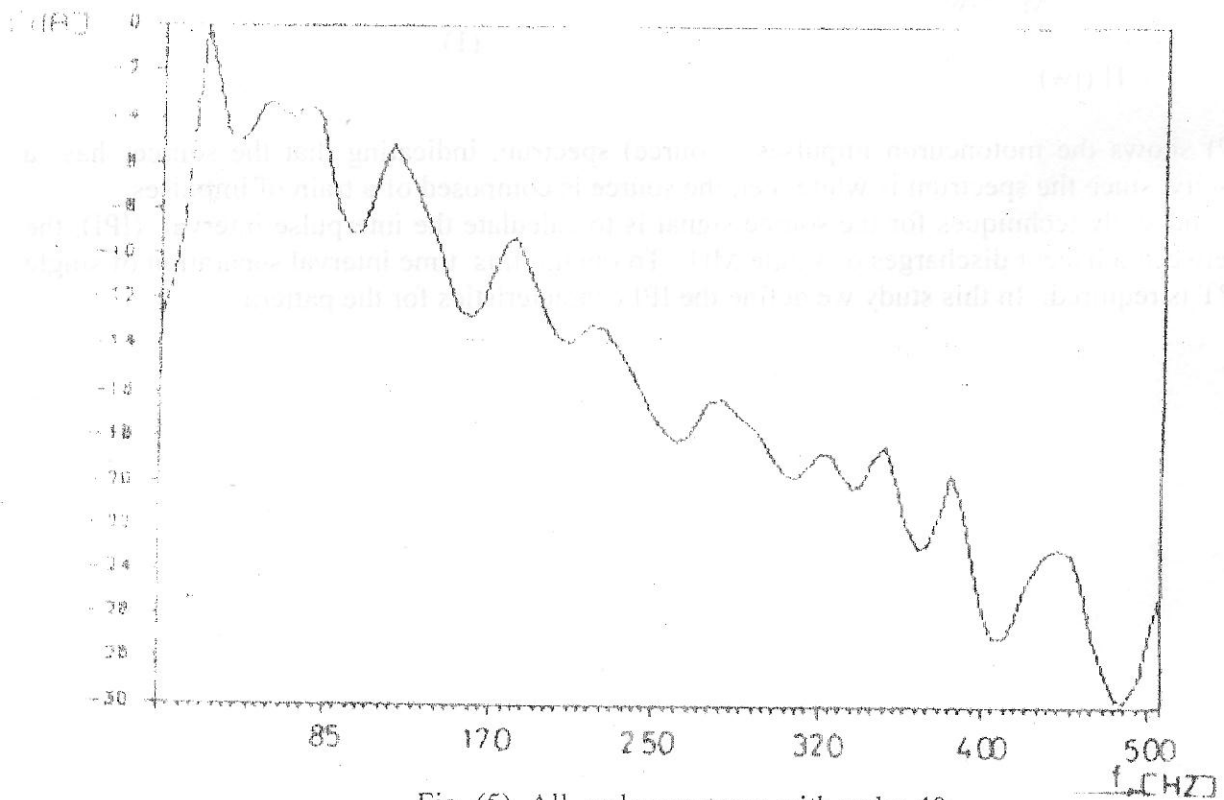


Fig (5) All- pole spectrum with order 40

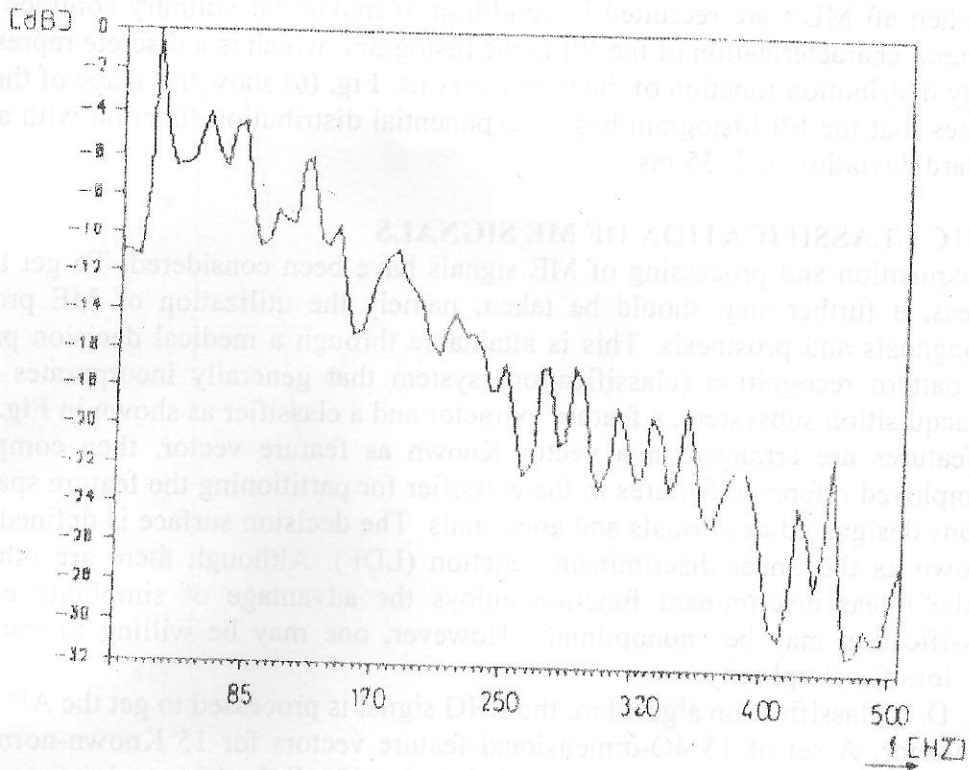


Fig. 6. All pole spectrum with order 60.

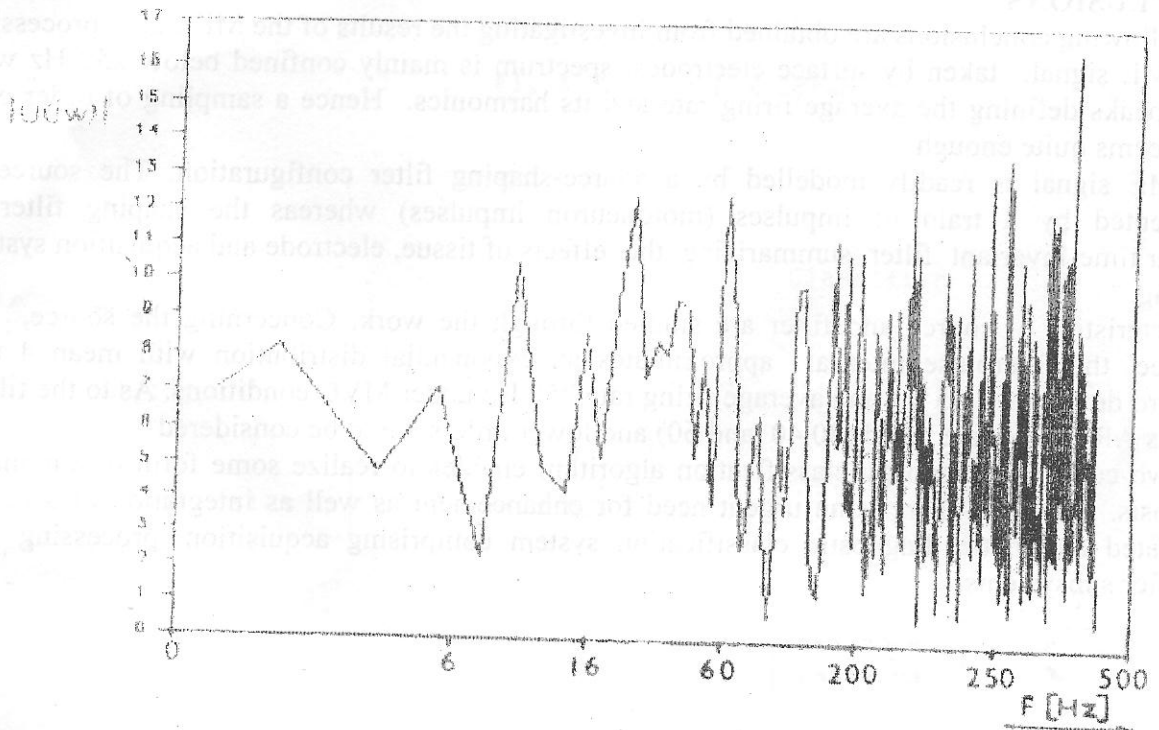


Fig. 7. The motoneuron impulses (source) spectrum.

generation when all MU's are recruited in condition of maximum voluntary contraction (MVC). The most general characterization of the IPI is the histogram, which is a discrete representation of the probability distribution function of the time intervals. **Fig. (6)** show the shape of the histogram which indicates that the IPI histogram has an exponential distribution function with a mean of 4 ms and standard deviation of 2.35 ms.

DIAGNOSTIC CLASSIFICATION OF ME SIGNALS

So far, the acquisition and processing of ME signals have been considered. To get the fruits of such a process, a further step should be taken; namely the utilization of ME properties for automated diagnosis and prosthesis. This is attainable through a medical decision procedure or formally by pattern recognition (classification) system that generally incorporates three basic subsystems: acquisition subsystem, a feature extractor and a classifier as shown in **Fig. (9)**.

ME signal features are arranged in a vector Known as feature vector, then compared to a previously employed reference features in the classifier for partitioning the feature space into two disjoint regions designated as normals and abnormal. The decision surface is defined by a scalar function Known as the linear discriminant function (LDF). Although there are other methods [G.D.75], the linear discriminant function enjoys the advantage of simplicity even though relevant classification may be nonoptimal. However, one may be willing to trade-off some performance loss for simplicity.

To test the L. D. F classification algorithm, the EHG signal is processed to get the AR coefficients as a feature vector. A set of 15 40-dimensional feature vectors for 15 Known-normal muscles was tested and the classification algorithm enabled to classify all the 15 muscles as normal.

CONCLUSIONS

The following conclusions are obtained from investigating the results of the ME signal processing. The ME signal, taken by surface electrodes, spectrum is mainly confined below 250 Hz with some peaks defining the average firing rate and its harmonics. Hence a sampling of order of 1 KHz seems quite enough.

The ME signal is readily modelled by a source-shaping filter configuration. The source is represented by a train of impulses (motoneuron impulses) whereas the shaping filter is a linear time-invariant filter summarizing the effects of tissue, electrode and acquisition system filtering.

Characteristics of source and filter are studied through the work. Concerning the source, for instance, the interpulse interval approximates an exponential distribution with mean 4 ms, standard deviation 2.35 ms and average firing rate 250 Hz under MVC conditions. As to the filter, various AR models are used (80,40 and 60) and lower orders are to be considered.

The two-category diagnostic classification algorithm enables to realize some form of automatic diagnosis. However, there is an urgent need for enhancement as well as integration of a more-elaborated automatic diagnostic classification system comprising acquisition, processing and classifier subsystems.

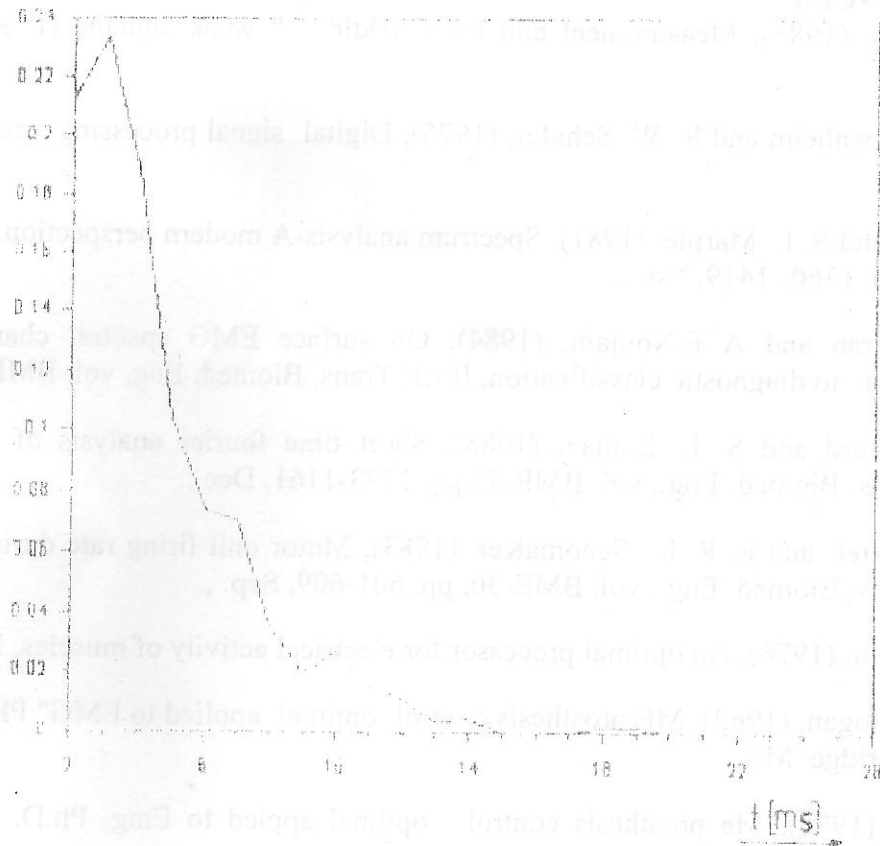


Fig. 8. The IPI histogram.

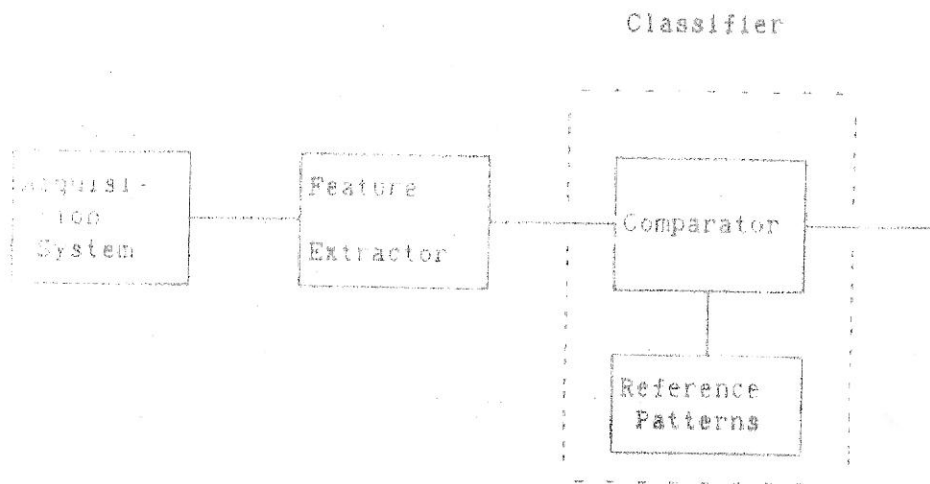


Fig (9) elements of pattern classification system

REFERENCES

- A.S.Ragab, (1988), Measurement and Identification of weak signals, H. Sc. Thesis, M, T. C, Cairo.
- A. V. Oppenheim and R. W. Schafer, (1975), Digital signal processing, prentic-hall Inc. , New Jersey.
- S.M.Kay and S. L. Marple, (1981), Spectrum analysis-A modern perspection, IEEE Proc. Vol. 69, No. 11. pp. 1360- 1419, Nov. .,
- G. F. Inbran and A E.Noujain, (1984), On surface EMG spectral characterization and its application to diagnostic classification, IEEE Trans. Biomed. Eng, vol. BME-Sep,
- B. Hannaford and S. L. Ehman, (1986), Short time fourier analysis of theelectromyogram", IEEE Trans. Biomed. Eng., vol. BME-33,pp. 1173-1161, Dec.,.
- A. V. Boxtel and L. R. b. SchomaKer, (1983), Motor unit firing rate during static contraction, IEEE Trans. Biomed. Eng., vol. BME-30, pp. 601-609, Sep. .,
- N. J. Hogan, (1976), An optimal processor for electrical activity of muscles, Philadelphia, PA, Sep., N. Hogan, (1962), ME prosthesis control: optimal applied to EMG" Ph.D. disersion, M. I. T. , Cambridge, MA,
- N.Hogan (1976). Me prosthesis control : optimal appled to Emg, Ph.D. disersion , M.I.T. , Cambridge, Ma.,
- E. SchwedyK and R. BalasKubramanian , (1977), An nonstationary model for the EMG, IEEE Trans. Biomed. ENG. vol. BME-24, pp. 417-484, .
- G. Daniel and K. C. William, (1975), Functional separation of EMG signals via ARMA identification methods, IEEE Trans. of systems, Vol. SMC-5, No. 2, March.,