CHAPTER 1

INTRODUCTION

1.1 PREAMBLE

In the world of health care, application of innovations and advances in the various fields of Engineering and Technology to the medical field, has given rise to betterment of human life. The modern Technology developed for diagnosis and therapy have resulted in pinpointing the defect and giving accurate treatment which has made life easy and comfortable for many affected persons.

The advances in Signal Processing have provided a definite edge to bio-potential signal analysis and its applications. These developments have led to plenty of scope for orthotic and prosthetic systems development making use of physiological signals. The Bio-medical signals require specialized sensors and methodologies of signal conditioning because these signals are weak and generally immersed in noise. Some physiological parameters are deterministic and some are random.

This work deals with some modern techniques of handling electromyographic signals which, in its raw form, are random and noisy. The work explores the possibility of using the signals for orthotic and prosthetic device control. More attention is paid to the requirements of paralyzed people who have lost control over their voluntary movements of limbs. Unfortunately the available drugs are incapable of curing the paralyzed patients. With the result, the victims of traffic, diving or other accidents as well as polio patients, often continue their lives as partially or totally paralyzed. Amputees of all kinds are only a small part
of the total number of such handicapped persons. Many others are suffering, from neuromuscular diseases (Bernard, K 1966).

Several mechanical devices have been in use for the rehabilitation of patients suffering from neuromuscular insufficiencies (Granit et al. 1957, Ruch, T.C et al. 1965, Mann et al 1979). These assistive devices are either passive or active. Passive devices are braces attached to the body to reproduce the desired mechanical trajectories and support. The active devices aid the paralyzed patients to perform certain simple movements, for example, the hydro-pneumatic control system which helps to walk. In the case of totally disabled people, these orthotic splints are often powered by an external power source, such as an electric motor or a compressed gas system. The size, weight and overall complexity of these devices, for very few degrees of freedom, have seriously impeded the design of more comprehensive orthotic aids. For simple and limited movements these devices consume tremendous amount of energy. Moreover, none of the presently available orthotic devices aid the patients with long-term rehabilitation. Due to these many disadvantages, research activities for development of devices which would probably make use of the available energy resources of the body and modern electronic technology are picking up momentum.

Functional Electrical Stimulation (FES) refers to Electrical Stimulation of paralyzed muscles of a person for functional movement of his/her movements. Controlled FES aims to provide a fully paralyzed person, a support device to regain controlled movement of his limbs for basic requirements (Kralj A et al. 1977, Kralj A et al. 1980).

The concept of Electrical Stimulation of paralyzed muscles evolved from Galvani's discovery in the late 18th century that neurologically isolated muscles of a frog's leg can be made to contract by applying an electrical potential between its ends through the electrodes. When a proper electrical stimulus is applied to the skin overlying the general area of a muscle, the muscle will contract. There is one particular point on the skin (Vodovnik 1964) above each superficial muscle which,
when stimulated, will produce a greater contraction than at any other point over
the muscle. This point is defined as the motor point of the muscle. The speed of
this contraction is roughly proportional to the amplitude if the stimulus applied to
the motor point. The magnitude of the stimulus must be above the threshold value
and a delay time must elapse before any movement of the joint takes place
(Vodovnik et al. 1965). This threshold value is reported to be about 20 volts on
an average, which varies from individual to individual.

As is explained clearly in the next chapter, if there is a disruption in the
Neurological System, paralysis occurs. These disconnections are classified into two
groups:

1. Upper motor neuron lesion; when the disconnection occurs in the
spinal cord.
2. Lower motor neuron lesion; when the disconnection occurs in the
peripheral nerve between the spinal cord and muscle.

In group one, the contractibility of the muscle is preserved for years after
injury. But due to disuse of muscle, it weakens considerably. In the second group,
the contractibility of the muscle is also maintained, but for a shorter length of time
and the muscle gradually wastes away.

It is possible to make these paralyzed muscles contract by external electrical
stimulation of appropriate parameters through suitable electrodes for functional
movement of the limbs (Vodovnik et al. 1967).

As early as 1960s (Liberson et al., Long et al, and Lyons) researchers had
started work in this field. Since early days of FES, the control of the stimulation
was made through hand or finger switches, manipulated by fingers. These were
special walker assisted devices enabling a paraplegic to make few steps. But here
the use of his hands while using the walker was limited. Moreover, the patient had
to concentrate on his finger switches, where as he had to have equal concentration
on his posture. These two requirements could not be met with simultaneously as the patient is already dependant. So there were all chances that he would lose his overall control balance and fall. Hence it was obvious that we basically needed some kind of control over the FES which did not need patient's constant manipulations.

Even for a totally paralyzed person, it has been found that the trapezius (left and right) muscles or the shoulder muscles are under voluntary control. Particularly for a paraplegic, if the shoulder muscle could operate an external stimulator, the patients fingers could be used for other necessary functions and his concentration also could be spared for posture balance.

Figure 1.1 illustrates the mechanism of conscious movements in a simplified way for a two axis motion in the X-Y plane (Vodovnik et al. 1965). After a person has decided to perform a complex motion, say, from X1 to X2, the command is passed to a cerebral centre C which commands the spinal motor neuron pool(SMNP). These centres send neural impulses to the appropriate muscles. The eye observes the movement and serves as the measuring device in the physiological feedback loop. In addition, proprioceptive signals from muscle tendon and joint sensors are sent to the central nervous system. If lesion L1 and L2 occur in the afferent and efferent pathways, the extremity becomes paralyzed. Let us now assume that other muscles still remain normally innervated and that these muscles (AM1 - AM4) are not used in the essential activities. If by means of learning, the cerebral pathways could be transferred from C to AC and if external bi-pass connections EB1 - EB4 could be established, the patient would regain control over his paralyzed muscles.

Therefore, work on available musculature EMG to be used as control signal, was thought of.

Parallel to using EMG signals for FES control, attempts have been made to make use of available EMG for control of artificial limbs also (Jacobson et al.
FIGURE 1.1 MECHANISM OF CONSCIOUS MOVEMENTS
1973, Lawrence et al., 1973, D. Graupe et al. 1975). In both the applications what is required is a way to extract some sort of EMG signature, which exhibits a discernible discrimination that could be attained using the available musculature.

### 1.2 THE EMG SPECTRUM

Electromyography (EMG) is the art of describing myo-electric signals. These signals are electric manifestations of the excitation process preceding the mechanical contraction in striated muscles. The signal observed with surface electrodes is composed of the action potentials originating from the individual muscle fibers. At low, moderate or higher levels of muscle contractions, so many motor units are active that the observed surface EMG has the characteristics of random noise (Carlo J. De Luca et al. 1975). However, there is considerable amount of information in the myo-electric signal. The noisy appearance of the signal suggests methods of random signal analysis for extraction of this information. Figure 1.2 shows the power spectrum of the myo-electric signal (Lars H. Lindstrom et al. 1977) from the biceps muscles obtained with bipolar surface electrodes. It is seen that information exists in the EMG up to frequencies 1 kHz.

### 1.3 PREVIOUS APPROACHES TO EMG SIGNAL PROCESSING

Initially EMG signal processing was started for using it as control signal for prosthesis. The usual approach was to assume that total force is proportional to the power in the EMG signal (S.C. Jacobson et al. 1973). The estimation procedure for this approach involved two basic steps, rectification and smoothing. A zero-memory rectifier was used to demodulate the observed EMG signal. Some type of smoothing was then done on the demodulated signal to generate the force estimate.
FIGURE 1.2  POWER SPECTRUM OF MYOELECTRIC SIGNAL FROM THE BICEPS BRANCHII MUSCLE OBTAINED WITH A BIPOLAR SURFACE ELECTRODE OF PLATE SEPARATION = 4cm
The same approach to EMG signal was used for controlling an external stimulator and also for EMG feedback (Sushama Kumari et al. 1977). Figure 1.3 gives the block diagram of the system. Here, the average EMG signal was used for controlling an external electrical pulse generator. DC rectangular pulses of duration 0.2 milliseconds were used for stimulation (Vodovnik 1964). This method did not pick up much momentum because the average EMG values did not exhibit much variation across the maximum and minimum muscle exertion levels.

Hogan (1976) had taken a different approach to muscle force estimation. He assumed that the observed scalar EMG signal $y(t)$ is a zero mean Gaussian process with variance parameter $\sigma(t)$. In turn, $\sigma(t)$ is related to the force $F(t)$ via $\sigma^2(t) = g(F(t))$, where $g(.)$ is an invertible non-linear function determined by experiment. Since the frequency content of $F(t)$ is much lower than for $y(t)$, the spectrum of EMG signal $y(t)$ may be written in the form $S_y(w) = H_n^2(w) * g(F(t))$ where $H_n(w)$ is shaping filter specifying the high frequency behaviour of $y(t)$.

He then obtained the force estimate by maximum likelihood estimation of $g(.)$ and inversion of $g(.)$ to obtain the estimate of $F(t)$. The muscle force estimate must be combined into actuator control signals in some manner for prosthesis. Generally, for multi-function prosthesis, multiple EMG channels have been required (D.R.Taylor et al. 1974).

Other mechano-physiological approaches have also been used. For example, Jacobson et al. (1973) have used biomechanical kinematics of the upper arm and shoulder to derive constraints relating shoulder kinematic variables to upper arm kinematic variables. Then, using the EMG derived estimates of shoulder muscle forces, they were able to compute what values the upper arm kinematic variables must take.

EMG signal processing through parametric modelling for orthosis picked up momentum from the pioneering work of D. Graupe et al. (1975).
FIGURE 1.3 THE FES AND EMG FEEDBACK
In his work on EMG prosthesis control, Graupe has taken advantage of spectral properties of EMG signal and showed that these properties changed when conditioned on different limb functions. From a single EMG lead, he reported the ability to control five limb functions in real time. He defined the spectra of his limb function classes by an Autoregressive (AR) model. Thus for each limb function \( m \), \( 1 \ldots m \ldots M \), he assumed a scalar model of the form

\[
\begin{align*}
y_m(k) &= \sum_{j=1}^{p} a_{mj} y_m(k-j) + e_m(k) \quad (1.1)
\end{align*}
\]

where \( y_m(k) \) is the \( m \)th limb function signal at time \( k \), \( a_{mj} \) is the \( j \)th regression coefficient for the \( m \)th limb function, \( e_m(k) \) is the one-step-ahead prediction error for the \( m \)th limb function at time \( k \), and \( p \) is the order of the Autoregressive model. This set of \( m \) models is derived in an off-line calculation made by a least squares procedure that minimizes the set of cost functions

\[
J_m = \sum_{i=p+1}^{N} e_m^2(i) \quad (1.2)
\]

where \( N \) was 200 and the sampling rate was 5kHz. Then he computed the second order statistics for the one-step-ahead prediction errors.

\[
\overline{S}_m = \frac{1}{N-p-1} \sum_{i=p+1}^{N} [y_m(i) - \sum_{j=1}^{p} a_{mj} y_m(i-j)]^2; \quad (1.3)
\]

\[ m = 1, 2, \ldots, M \]

He has generally used \( p=3 \) or \( p=4 \).

In the on-line operation mode, Graupe determined which limb function gives the best fit to the current data. This was done by calculating the sample second order
statistics for the one-step-ahead prediction errors using the mth limb function model on the data windows of specified length say $N_1$. For data upto and including $y(t)$ he computed

$$S_m(i) = \sum_{k=i-N_1+1}^{i} [y(k) - \sum_{j=1}^{p} a_{m,j} y(k-j)]^2, \quad i > N_1+p$$  \hspace{1cm} (1.4)

In addition, signal energy

$$E(i) = \sum_{k=i-N_2+1}^{i} y^2(k)$$  \hspace{1cm} (1.5)

is calculated over a signal length $N_2$. The controller activates a limb function $E(i) \geq E_{\text{min}}$, where $E_{\text{min}}$ is set minimum energy. If a limb is to be activated, that function was chosen which satisfies

$$S_m < \rho_m S_m$$

for a set of $M$ parameters $\rho_1, \rho_2, \ldots, \rho_M$.

Peter C. Doerchute et al. (1983) treated EMG as vector valued stochastic process and viewed EMG discrimination problem as a statistical decision problem. They assumed that models are linear and time-invariant and may be modelled as vector AR process. Thus he assumed a set of models

$$y(k) = \sum_{j=i}^{p} A_{m,j} y(k-j) + e_m(k); \quad m = 1, \ldots, M$$  \hspace{1cm} (1.6)

where $y(k)$ is the observed L*1 vector EMG signal, $(A_{m,1}, \ldots, A_{m,p})$ are L*L coefficient matrices, $e_m(k)$ is the one-step-ahead prediction error vector, subscript $m$ refers to the limb function being modelled, $M$ is the number of limb functions, and $L$ is the number of electrodes.
In off-line, the values of $A_{ij}$ and $S_i$ were determined for each limb function by fitting them to actual EMG data recorded during the execution of the particular limb function of interest. The parameters were computed from serial Autocorrelations using an efficient technique due to Levinson (Kailath 1974).

On-line detection and identification of the limb functions were done using the multiple level Kalman filter. It was assumed that data upto $(k-1)$ were available and new data $y(k)$ had to be computed. Under the hypothesis that $i$th function is taking place, the predicted value of $y(k)$ was taken as

$$\hat{y}(k) = \sum_{j=1}^{p} A_{ij} y(k-j)$$  \hspace{1cm} (1.7)

The prediction error

$$e^i(k) = y(k) - \hat{y}^i(k)$$

was calculated. The probability $p_i(k)$ that limb function $i$ is taking place, given data upto and including $y(k)$, is found from Bayes' rule,

$$p_i(k) = \frac{P_i(y(k) | Y^{(k-1)})p_i(k-1)}{\sum_{i=1}^{M} P_i(y(k) | Y^{(k-1)})p_i(k-1)}$$  \hspace{1cm} (1.8)

where $Y^{(k-1)}=(y(1), y(2), ..., y(k-1))$ and $P_i(y(k) | Y^{(k-1)})$ is the probability of occurrences of $y(k)$, given $Y^{(k-1)}$ and limb function $i$. Assuming Gaussian data, $P_i(y(k)/Y^{(k-1)})$ is Gaussian with mean $\hat{y}_p^i(k)$ and covariance matrix $S_i$. Using equation (1.8) probabilities were calculated.

Graupe et al. (1985) has computed AR parameters $(a_1, ..., a_m)$ in terms of Autocorrelation functions with $R(i) = E[y(k)*y(k-i)]$.
Yitong et al. (1986) developed a method for estimation of the Intra-muscular EMG signal from surface EMG signal. They represented surface EMG signal as an Auto-regressive model with the delayed Intra-muscular(IM) EMG signal as input.

This model called “Tissue Filter” relates the IM EMG signal waveform to the surface EMG signal. Assuming that proto-type Intra-muscular and surface EMG were available, the parameters of the tissue filter including delay were estimated. Using the identified model, a Weiner filter was used to estimate IM EMG signal from surface EMG signal.

1.4 BRIEF OUTLINE OF THE THESIS

This work starts with describing the preliminary studies on EMG signals for its statistical properties. The signals have also been examined for its qualifications as candidate for being control signal for FES. Then, an off-line analysis of the signals have been made using four recursive algorithms namely 1. Recursive Least Squares 2. The Extended Recursive Least Squares 3. Fixed Memory Identification and 4. Modified Generalized Least Squares.

From the results obtained, the best suited algorithm has been identified. This algorithm has been implemented in real time mode on the fixed point DSP.
chip TMS 320 based processor and the inferences have been presented. The methodology of real time implementation of the identification algorithm, for the EMG signals has been described.

The parameters of the prototype FES model simulator developed, have been chosen based on the recommendations suggested by Graupe et al. (1983).

In the ensuing chapter a brief outline of the Neuromuscular System and mechanism of muscle contraction are described. Chapter 3 describes the analytical experiments conducted for study of EMG signals and the results obtained to its suitability as FES control signal. The mathematical modelling of surface EMG has been illustrated in Chapter 4. Then, the algorithms that have been used to model the EMG signal have been described in Chapter 5.

The signal analysis of EMG has been presented in two phases. In Phase-I, Chapter 6, an off-line analysis of the signal and its results are presented. Phase-II constitutes the on-line signal acquisition and TMS320C10 based EMG discrimination system, as described in Chapters 7 and 8. In Chapter 7, EMG acquisition using TMS320C10 DSP chip is dealt with. Chapter 8 describes the issues involved in implementation of EMG discrimination algorithm on the fixed point processor. A 4-step methodology has been evolved to address these issues which is described in detail. The results of the implementation are also presented. The last Chapter concludes highlighting the practicality of the total system developed and the future avenues for further research.