DESIGN AND TESTING OF EMG MEASUREMENT SYSTEM

BY

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Abstract

Monitoring electromyography signals (EMG) leads to a greater understanding of muscle properties, gives insight into how muscles work together to coordinate tasks, and yields information about neuromuscular disorders. In this project we developed a PC based EMG data acquisition and analysis system to record and analysis EMG signals. We tested this system by recording EMG signals from the biceps brachii of a single normal subject. The acquired data was analyzed in both time and frequency domains to determine the behavior of the EMG signal during different experiment conditions. Fast Fourier Transform (FFT) and Short Time Fourier Transform (STFT) were applied during digital signal processing. The FFT only provides the information in frequency domain. STFT is a modification of the Fourier transform in an attempt to retain both time and frequency information during signal analysis. The STFT produces a two dimensional function with time and frequency as variables. Thus the STFT gives information about when in time a given frequency component occurs. The extracted features of EMG are RMS value, mean absolute value, mean power frequency, and median power frequency. The raw EMG signal is collected for 10 seconds. The sampling rate is set to 1000 Hz. The emphases of this project were software development, data collection, and simple signal analysis.

Acknowledgements

I would like to thank Dr. H. de Bruin for his assistance and support throughout the development of this thesis. His enthusiasm was contagious and contributed to making my experience at McMaster an enjoyable one. I would also like to express an appreciation for the advice of Dr. Ian Bruce. Special recognition should be given to Cheryl Gies for her friendly assistance with all administrative matters.

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CHAPTER 1 INTRODUCTION

1.1 Background

Feature extraction is the key in processing and analyzing biomedical signals. Signal

analysis is now widely applied in the field of clinical health for diagnosing health

related problems and monitoring rehabilitation. Today computers and software have

become more and more powerful, so people can use complex algorithms for large data

sets at high computation speeds. Software packages such as Labview and Matlab are

well known for their use in both data acquisition and mathematical processing.

This report describes a data acquisition and analysis system that can acquire and

process EMG signals. Test results are also presented; they show the system can

extract various features of the signal. These are the mean and median frequency of the

power spectrum and the RMS value of EMG. The following sections discuss the

background of muscle physiology, and EMG signals.

1.2 Basic Physiology of EMG Signal Generation

EMG stands for electromyography; it is the study of muscle electrical signals. EMG is

sometimes referred to as myoelectric activity. EMG is measured using similar

techniques to that used for measuring the electrocardiogram (ECG or EKG),

electroencephalogram (EEG) or other electrophysiological signals. [1]

According to their function and location, the muscle cells can be classified as cardiac

muscle, skeletal muscle, and smooth muscle. Skeletal muscle and cardiac muscle fibers show a pattern of cross banding under the microscope, so it is also called striated muscle. Since smooth muscle does not have this pattern, it is also called non-striated muscle. Cardiac muscle makes up the wall of the heart. It is regulated by the sinoatrial node or the heart's pacemaker and its signal is called ECG, or the electrocardiogram. Smooth muscle is found in the walls of all the hollow organs of the body (except the heart). Smooth muscle contractions are involuntary; they are controlled by the autonomic nervous system. Its contraction reduces the size of these structures. Skeletal muscle, as its name implies, is the muscle attached to the skeleton. The contraction of skeletal muscle is under voluntary control. Skeletal muscle contraction maintains posture and produces movement. For example when a person wants to move a limb, neural inputs from the brain travel down the spinal cord, and project from the spinal cord along efferent nerve fibers, then synapse onto target muscle fibers responsible for controlling the limb. Therefore when the muscle contracts, the tendon pulls on the bone and movement occurs. The electrical activity of skeletal muscle can be measured as EMG, or the electromyogram. The structure of the skeletal muscle fibers is shown in Figure 1.1

Skeletal muscle is made up of muscle fibers, each fiber being a single cell. The contraction of a fiber is achieved by the motor proteins actin and myosin. When action potentials travel deep into the muscle fiber by the transverse tubule system, calcium ions are released from the sarcoplasmic reticulum. Actin sites are normally

closed, and with calcium these sites are open. When actin sites are open the myosin head can insert in the actin site. Then the myosin filament contracts to pull the actin site closer.

SKELETAL MUSCLE

A — Muscle

B — Muscle fasciculus

C — Muscle fiber

H band   Z disc   A band   I band — D
Sarcomere   Myofibril

E — Myofilaments

G-Actin molecules — J

F-Actin filament — K

Myosin filament — L

Myosin molecule — M

Light meromyosin   Heavy meromyosin — N
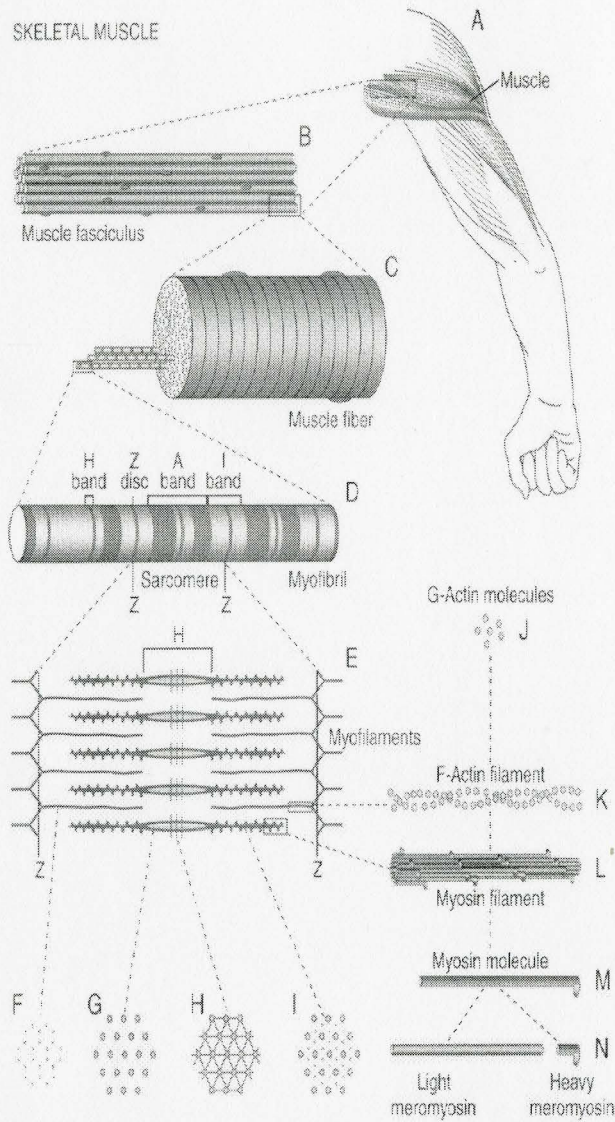
FIGURE 6-1

Organization of skeletal muscle, from the gross to the molecular level. *F, G, H,* and *I* are cross sections at the levels indicated. (Drawing by Sylvia Colard Keene. Modified from Fawcett DW: Bloom and Fawcett: A Textbook of Histology. Philadelphia: WB Saunders Co, 1986.)

Figure 1.1 Diagram of the Organization of the Skeletal Muscle from the Gross to the

Molecular Level.

Sourced from Arthur C. Guyton& John E. Hall: *Textbook of Medical Physiology* (10th

Edition)

Skeletal muscle consists of groups of motor units. A motor unit consists of a α motor neuron whose cell body is in the spinal cord, and the muscle fibers it innervates. Nerve impulses passing down a single α motor neuron axon will thus trigger contraction in all the muscle fibers on which the branches of that neuron terminate. All α motor neurons have axon branches, each of which terminates in a neuromuscular junction with a single muscle fiber. The neuromuscular junction is usually located near the longitudinal midpoint of the muscle fiber. When a nerve impulse arrives at the presynaptic terminal, the neuron fiber immediately releases acetycholine (Ach), a neurotransmitter, into the synaptic cleft. As Ach is released, it travels across the neuromuscular junction and causes Ach-gated receptors on the muscle fiber to open. This leads to sodium ions flowing into the cell, and creating an excitatory postsynaptic potential, depolarizing the muscular fiber membrane. The neurotransmitter does not bind to the receptor forever, it is rapidly broken down by enzymes, and therefore ion channels are closed. A muscle can have few or many motor units associated with it. A muscle with many motor units is capable of more precise movement than a muscle with fewer motor units for the same total number of muscle fibers [2].

Figure 1.2 shows the structure of the neuromuscular junction. Figure 1.2 (a) gives the configuration of one portion of the junction. Figure 1.2 (b) shows the general position of endings of the motor axon on the muscle fiber, and figure 1.2 (c) provides the schematic drawing from electron micrographs of a longitudinal section through the

muscle fiber.
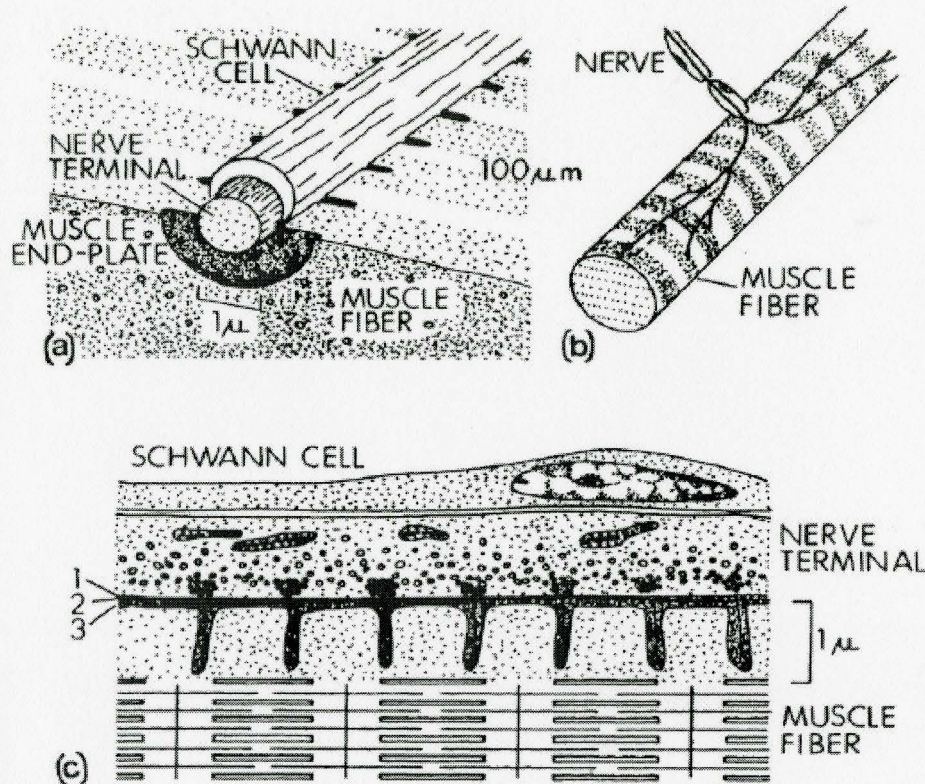
Figure 1.2 Structure of Neuromuscular Junction.

Sourced from Bernard Katz: *Nerve, Muscle, and Synapse*, McGraw-Hill, New York,

1966

Muscle fiber contractions are initiated by action potentials traveling the length of the

fibers from the synapses. These potentials are in the millivolt range at the fiber

surface and rapidly attenuate with distance. The EMG signal is a representation of the

electric potential field generated by the depolarization of the muscle fiber membranes.

The more fibers that are stimulated, the stronger the muscle contracts, and a greater

force is produced. This EMG signal can be measured by surface electrodes on the skin overlying the muscle, or by invasive electrodes directly in the muscle. The tissue separating the sources and the recording electrodes acts as a volume conductor. The features of the detected signals are largely depending on the volume conductor properties.

The surface electrodes collect the signal which is a composite of all the muscle fiber action potentials occurring in the muscle underlying the skin. The surface EMG is extremely valuable data in timing, force and fatigue analysis. It has already been widely used in clinical diagnosis. The invasive electrodes collect electrical signals composed of one or a few motor unit action potentials (MUAP). This gives important data for analysis of individual motor units, such as firing pattern analysis [3].

In our project, surface electrodes are chosen, since we want a signal from a large fraction of the muscle and are not specifically interested in MUAP variables such as amplitudes [4]. Further, EMG features such as the median and mean features are more applicable to the surface recorded signal. Surface electrodes are also non-invasive, so it is easier to operate and less painful compared to invasive electrodes.

CHAPTER 2 DIGITAL SIGNAL PROCESSING

2.1 Introduction

This chapter covers the principles of some digital signal processing methods, the Fast

Fourier Transform (FFT), and the Short Time Fourier Transform (STFT).

2.2 Data Acquisition

In the real world, EMG signal is an analog and continuous time signal. To be analyzed

by a computer system, the EMG signal should be converted to a digital and discrete

time signal. Let x(t) be a analog EMG signal, pick its values at certain time points. In

particular, if the sampling points are nT, T is called the sampling interval. The value

$$fs \quad =1/T$$

is called the sampling frequency. The sampled EMG function is then

$$x[n]=x(nT)$$

In figure 2.1 a typical analog EMG signal or a sampled Motor Unit Action Potential

(MUAP) was obtained with Delsys Inc. DE-2.1 surface electrode [5]. Its digital form

was obtained by recording data at 2 kHz sampling frequency.
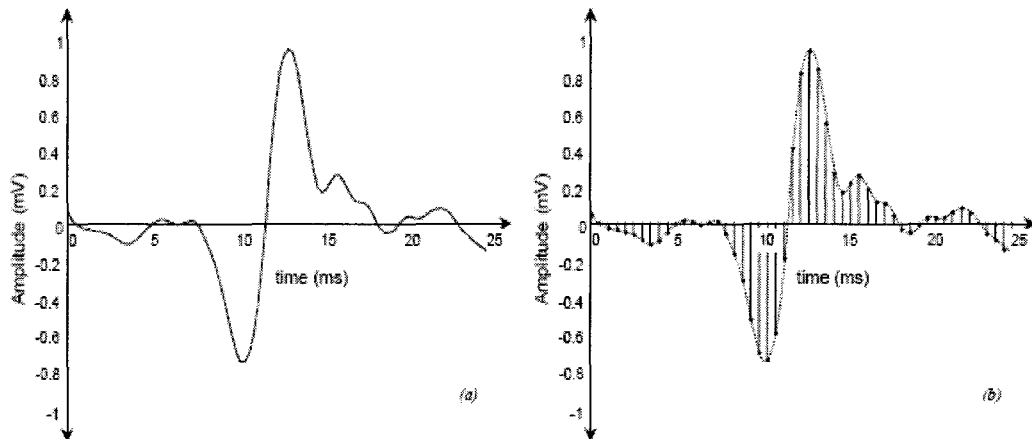
Figure 2.1: (a) A typical analog EMG signal detected by the DE-2.1 electrode. (b) The

digital sequence resulting from sampling the signal in (a), at 2 kHz.

Sourced from De Luca, G., Fundamental Concepts in EMG Signal Acquisition,

Delsys Inc, 2003

The sampling frequency is a very important parameter to accurately represent the

sampled signal. It is critical to know the minimum acceptable sampling frequency of a

signal should be in order to correctly reproduce the original analog information. If the

maximum bandwidth of the original signal is F, then the lowest sampling rate

$$fs \geq 2*F$$

This is called the Nyquist rate, given by the Nyquist sampling theorem. The Nyquist

sampling theorem states that perfect reconstruction of a signal is possible when the

sampling frequency is greater than twice the maximum frequency of the signal being

sampled. If lower sampling rates are used, the original signal's information can not be

completely recovered from the sampled signal, and aliasing of its frequency content

occurs.

In figure 2.2, a 1V, 1Hz sinusoid signal is sampling at 4/3 Hz. Since the sampling

frequency is smaller than the Nyquist rate, it must result in aliasing in the recovered

signal. The frequency of the recovered signal is 1/3 Hz.
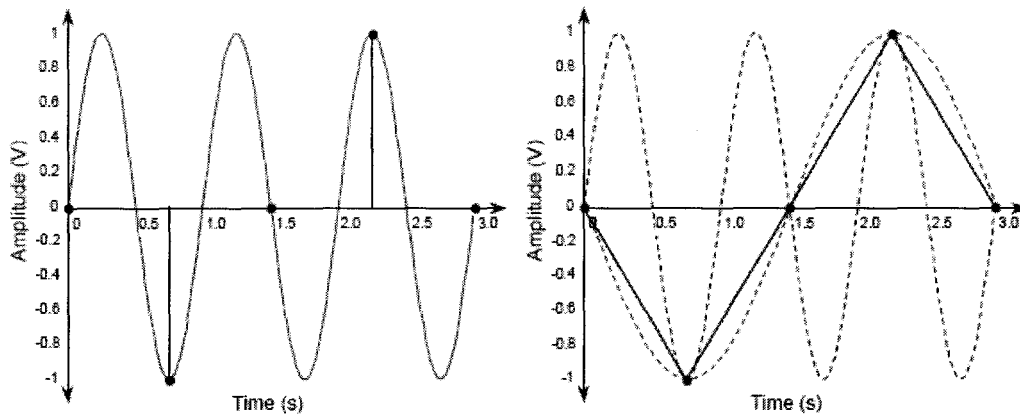
Figure 2.2: (a) Sampling a 1V, 1Hz sinusoid at 4/3 Hz. (b) Recreating the sinusoid

sampled at 4/3 Hz yields the red signal at 1/3 Hz. The original 1Hz signal is

undersampled.

Sourced from De Luca, G., Fundamental Concepts in EMG Signal Acquisition, Delsys

Inc, 2003

2.3 Fourier Transform Analysis

Fourier analysis is a mathematical technique for transforming a signal from the time

domain to the frequency domain by breaking down a signal into its constituent

sinusoids of different frequencies and phases. Fourier transform is a generalization of

the Fourier series where a periodic signal is represented by the sum of sines and cosines. Let x(t) be a continuous time signal, its values can be real or complex. The Continuous Time Fourier Transform (CTFT) of the signal is

$$X(\omega) = \int_{-\infty}^{\infty} x(t) * \exp(-\omega j t) dt$$

$X(\omega)$ is the output of the system, where w is called angular frequency and measured in radians per second (rad/s). The sufficient condition for the existence of the Fourier transform is $\int_{-\infty}^{\infty} |x(t)| dt < \infty$. For computers, only discrete time signals or sinusoids can be used, the Discrete Time Fourier Transform (DTFT)

$$X(\omega) = \sum_{n=-\infty}^{\infty} x[n] * \exp(-j\omega n)$$

Therefore by applying the Fourier transform, the original signal can be connected from the time domain to the frequency domain.

2.4 Fast Fourier Transform

The Fast Fourier Transform (FFT) using the Cooley-Tukey algorithm dramatically reduces calculation time. It is a divide and conquer algorithm that recursively breaks down the Discrete Fourier Transform (DFT, the transform that gives discrete Fourier coefficients for discrete time-sampled data) of any composite size N=N1*N2 into many smaller DFTs of sized N1 and N2. By setting $W_N = \exp(-2\pi j / N)$, the FFT is given as:

$$X(k) = \sum_{n=0}^{N-1} x(n) * W_N^{kn} \qquad k=0...N-1$$

$$= \sum_{n=even} x(n) * W_N^{kn} + \sum_{n=odd} x(n) * W_N^{kn}$$

$$= G_{N/2}(k) + W_N^{K} * H_{N/2}(k)$$

where $G_{N/2}(k)$ and $H_{N/2}(k)$ are the N/2 point DFT's involving x(n) with even and

odd n respectively. Fig 2.3 shows when total data number is 8, they are separated by

even and odd index into 2 groups. Applying DFT to both groups and then the final

result is linear combination of each element. Any N point DFT with even N can be

computed via two N/2-point DFT's. In turn, if N/2 is even then each of these

N/2-point DFT's can be computed via two N/4-point DFT's and so on. Figure 2.4

gives how the algorithm works recursively. The total complexity of FFT is $N \log_2 N$,

and for DFT is N^2 . The calculation speed is significantly improved by FFT. [6]
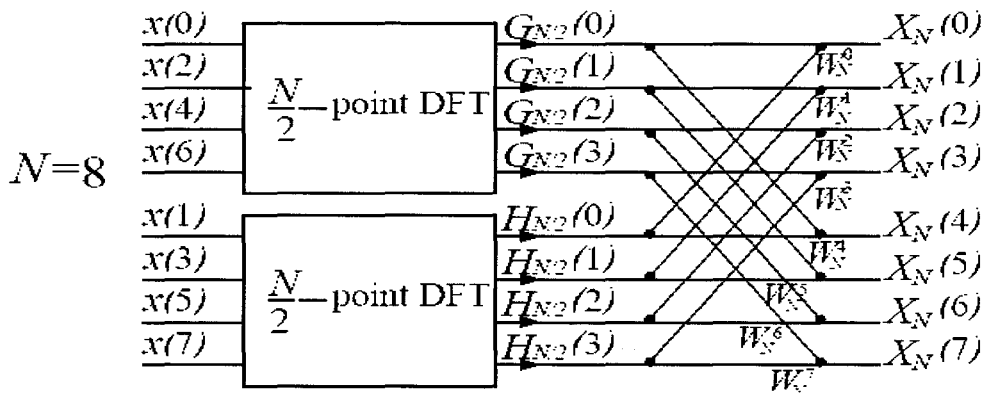
Figure 2.3:   Fast Fourier Transform algorithm

Sourced from A.V. Oppenheim and R. W. Schafer, *Discrete-Time Signal Processing*

(2nd Edition), Prentice-Hall, 1999
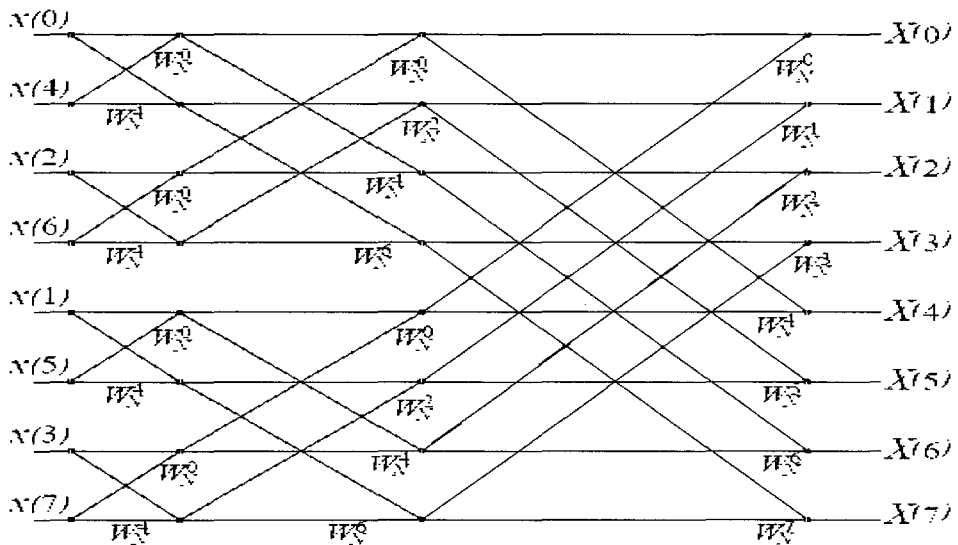
Figure 2.4:   Fast Fourier Transform algorithm.

Sourced from A.V. Oppenheim and R. W. Schafer, *Discrete-Time Signal Processing*

(2nd Edition), Prentice-Hall, 1999

2.5 Short Time Fourier Transform

The Short Time Fourier Transform (STFT) is a modification of the Fourier transform

in an attempt to retain both time and frequency information during signal analysis.

The STFT produces a two dimensional function with time and frequency as variables.

Thus the STFT gives information about when in time a given frequency component

occurs. However the precision of this information is limited and in effect a

compromise between time and frequency information exists. The STFT of the

resulting signal is taken as the window slides along the time axis. For a signal in the

continuous time domain STFT is given as:

$$X(\tau,\omega)= \int_{-\infty}^{\infty} x(t)*w(t-\tau)*\exp(-j\omega t)dt$$

Where $\omega(t)$ is the window function, and x(t) is the input signal. For a signal in the

discrete time domain the STFT is given as:

$$X(m,\omega)= \sum_{n=-\infty}^{\infty} x[n]*w[n-m]*\exp(-j\omega n)$$

The application of STFT is limited by the window function. The drawback of that is

once a particular size for the time window is selected, that window is the same for all

frequencies. According to the Heisenberg uncertainty principle, the accuracy of the

relationship between time and frequency domains can not be obtained. Figure 2.5

gives the accuracy relationship between time and frequency domain. If we choose

shorter window lengths, it would be good for time resolution, but poor for frequency

resolution. If we choose longer window lengths, it would be good for frequency

resolution, but poor for time resolution.
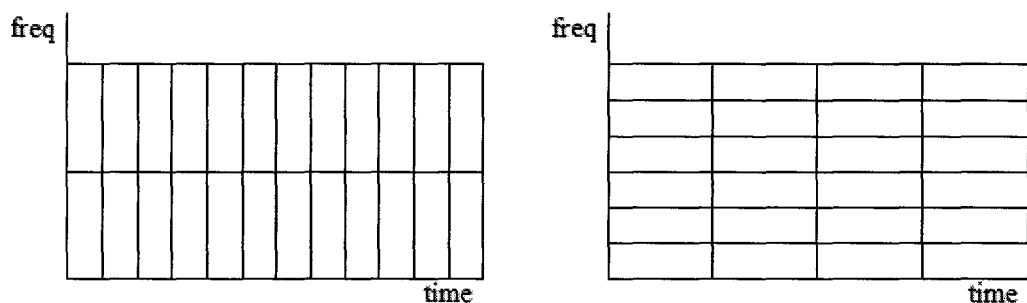
Figure 2.5 (a) Narrow window, good time resolution   (b) Wide window,

good frequency resolution

CHAPTER 3 PATIENT SETUP AND HARDWARE USED

3.1 Introduction

This chapter describes the system development and it is tested using one subject's EMG. The main hardware components are electrodes, an amplifier, a National Instruments data acquisition board with A/D and D/A capabilities and a personal computer. A program was written in the virtual instrument language Labview 8.0 to acquire and process the data. The analog EMG signal was first collected by electrodes, then amplified and filtered. Figure 3.1 describes the hardware connections between the computer and electrodes. This brief chapter describes the hardware and experiment used to test the developed system.
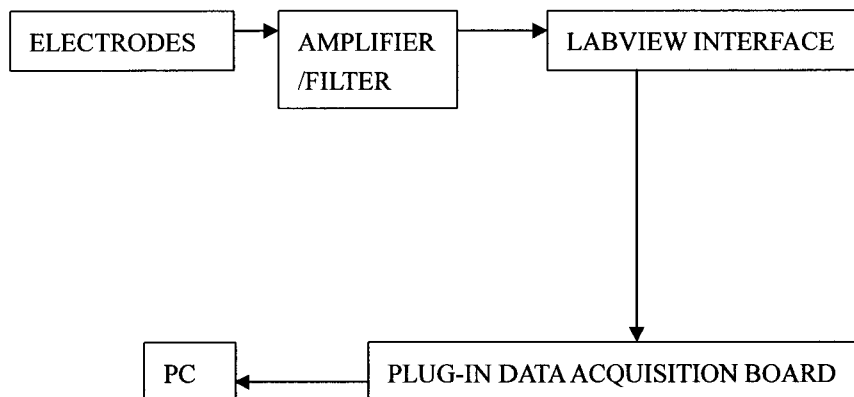
Figure 3.1 Data Acquisition System

3.2 Subject Set-Up

A subject with no previous history of musculoskeletal injury was selected for this test. The subject was seated comfortably and was required to perform a static, i.e. constant isometric, muscle effort. The subject held weights of 2.5, 5, 7.5, 10, 12.5, 15, 17.5, 20, 22.5, 25, 27.5 pounds each time in one hand while maintaining that arm in a constant forward flexion position at the elbow of 90 degrees. To avoid any motion, the subject was asked to not move his elbow and keep his upper arm held tightly against his trunk. Since the electrodes need to have good contact with the skin in order to get a high quality recording, the surface of the subject's skin was cleaned with alcohol prior to electrode attachment. For the best recordings, it is best to mildly abrade the surface skin with pumice or equivalent to minimize contact resistance by removing the outer dry skin layer. To avoid AC power line noise (60 Hz), the subject was kept away from electrical devices and power cords.

3.3 Electrodes

The recording electrodes were made from disposable self adhesive ECG electrodes (Product No: 30807732, Tyco Healthcare Group, Mansfield, MA). The recording electrode was constructed by cutting the 12mm by 23mm electrode longitudinally. Two electrodes were attached about one inch apart above the belly of the biceps; one electrode was attached to the bony part of the elbow to use as the ground electrode. The EMG leads were clipped to the electrodes. To avoid noise resulting from

movement artifacts, medical tape was used to secure the cables so they would not move during the experiments. Figure 3.2 shows where and how the electrodes were attached on the subject.
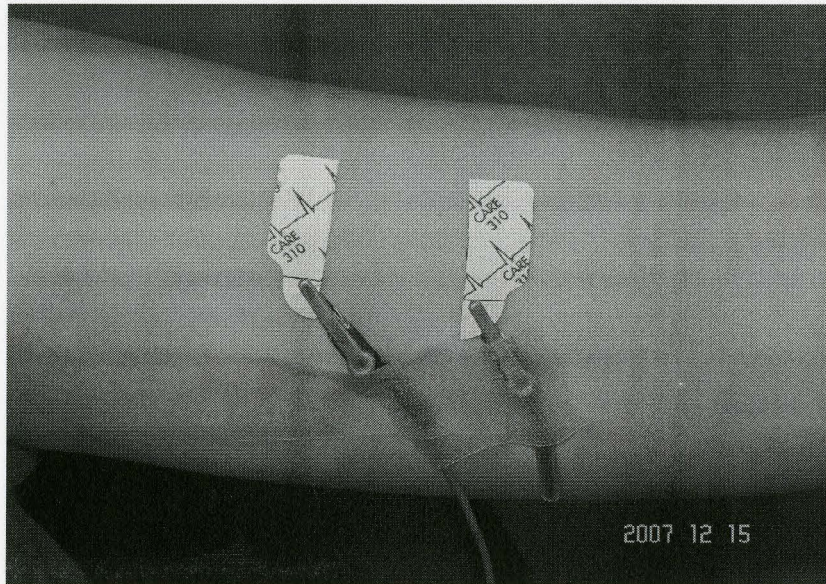
Figure 3.2 Location of Electrodes Set Up

3.4 EMG Amplifier

The raw surface EMG signal is quite small, with a range between +/- 2000 microvolts. We therefore need an amplifier here. All recorded signals were amplified and band-passed filtered using an A-M System 1700 differential amplifier (A-M Systems, Sequim, WA) with high pass and low pass settings at 10 Hz and 500 Hz respectively. The gain of the amplifier was typically set at 1000 for data collections. To avoid amplifier saturation before recording, maximal contractions were tested. If there existed an amplifier saturation, the gain of the amplifier was reduced.
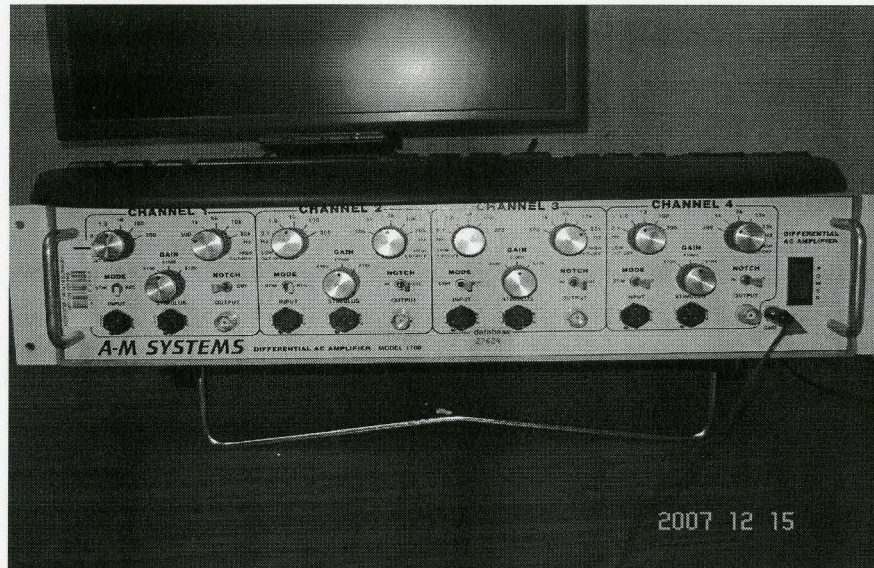
Figure 3.3 EMG Amplifier

3.5 SOFTWARE DEVELOPMENT

The data acquisition (DAQ) and analysis software was developed using Labview 8.0

Full Development System (National Instruments, Austin, Texas, United States).

Labview (Laboratory Virtual Instrumentation Engineering Workbench) is a graphical

programming environment developed by National Instruments (NI). Programs written

in Labview, known as virtual instruments (VIs), can control hardware devices that

acquire output electrical signals. VIs also display the acquired data using the PC

display screen. Analog electrical signals output from measuring devices, and sensors

are interfaced to a computer via a DAQ board and acquired by Labview programs. Labview provides data acquisition, analysis, and visualization features well suited for digital signal processing (DSP) system-level design. Thoughtful programming in Labview will minimize common sources of measurement error and ensure accurate, valid, and reliable data. It is widely used in the clinical research area.

CHAPTER 4 SIGNAL PROCESSING AND FEATURE EXTRACTION

4.1 Introduction

The EMG signal recorded during isometric constant force contractions can be considered a wide-sense stationary (WSS) process, i.e., when both the mean and autocorrelation of a discrete time stochastic process are invariant to time shifts. Processing programs were written in Labview 8.0 and Matlab 7.0. Linear Envelop Analysis, Fast Fourier Transform (FFT) and Short Time Fourier Transform (STFT) were used for data processing. The signal conditioning steps and feature extractions are shown for both the FFT and STFT approaches in Figure 4.1 to Figure 4.4. The user can select data of interest either by segment selection or cursor selection. Several features of EMG were extracted, and their relationships with force were studied. The results show that there is an approximately linear relationship between muscle force output and EMG activity during isometric contractions. In the case of fatigue, the spectrum shifts downwards in frequency and the median power frequency decreases.

Figure 4.1 Labview Signal Conditioning and Feature Extraction, Including Spectral

Estimation Using FFT
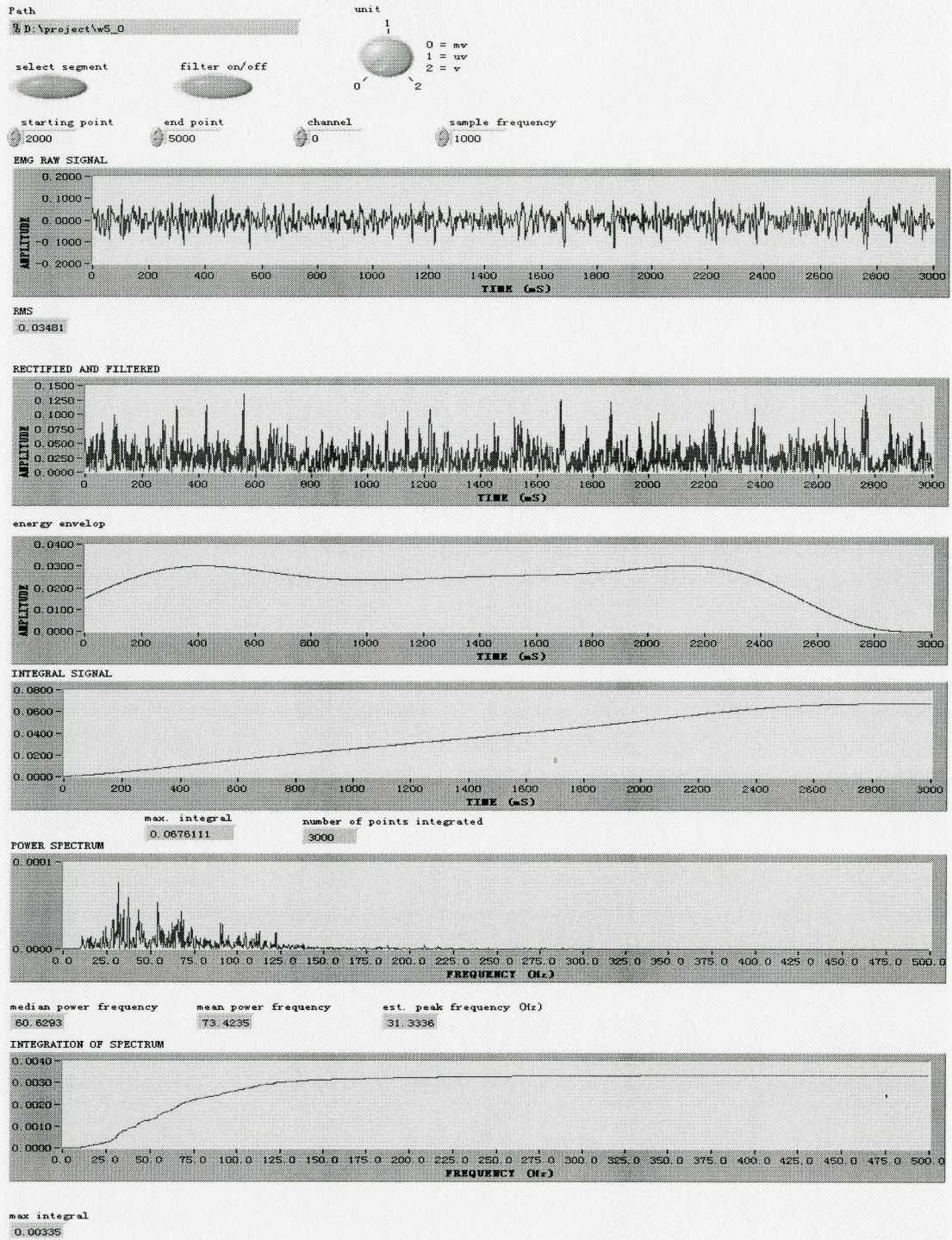
Figure 4.2 User Interface and Displays for the Processing Steps of Figure 4.1

```
┌─────────────────────────┐
│   Load Raw EMG Data     │
└─────────────────────────┘
            │
            ▼
┌─────────────────────────────┐
│ Unit Selection by SubVI 'units' │
│    ( 0= mv, 1= uv, 2= v)    │
└─────────────────────────────┘
            │
            ▼
┌─────────────────────────────┐          ┌──────────────────────┐
│  Interested Interval Selection │          │ Show  Raw  EMG       │
│     3.   Cursor Selection   │─────────▶│ Signal of Interested │
│     4.   Segment Selection  │          │ Interval             │
└─────────────────────────────┘          └──────────────────────┘
            │
            ▼
┌─────────────────────────────────────┐
│ Remove DC Bias by SubVI 'DC_OFF'    │
└─────────────────────────────────────┘
            │
            ▼
┌─────────────────────────────────────────────────────┐
│ Filter by 4th Order Bandpass Butterworth Filter by SubVI 'filters' │
│ User can set:   low cutoff frequency                │
│                 high cutoff frequency               │
│                 sample rate                         │
└─────────────────────────────────────────────────────┘
       │                    │
       ▼                    │
┌─────────────────────┐     │          ┌──────────────────────┐
│ Rectify EMG Signal by │────┼────────▶│ Show   Rectified  and │
│ Taking Absolute Value │    │          │ Filtered EMG Signal   │
└─────────────────────┘     │          └──────────────────────┘
                            ▼
          ┌─────────────────────────────────┐
          │ Get STFT Spectrum by SubVI 'STFT │
          │ spectrograms'                   │          ┌──────────────────────┐
          │ User can set:   window type     │─────────▶│ Show STFT Spectrum   │
          │                 window length   │          └──────────────────────┘
          │                 time increment  │
          └─────────────────────────────────┘
```
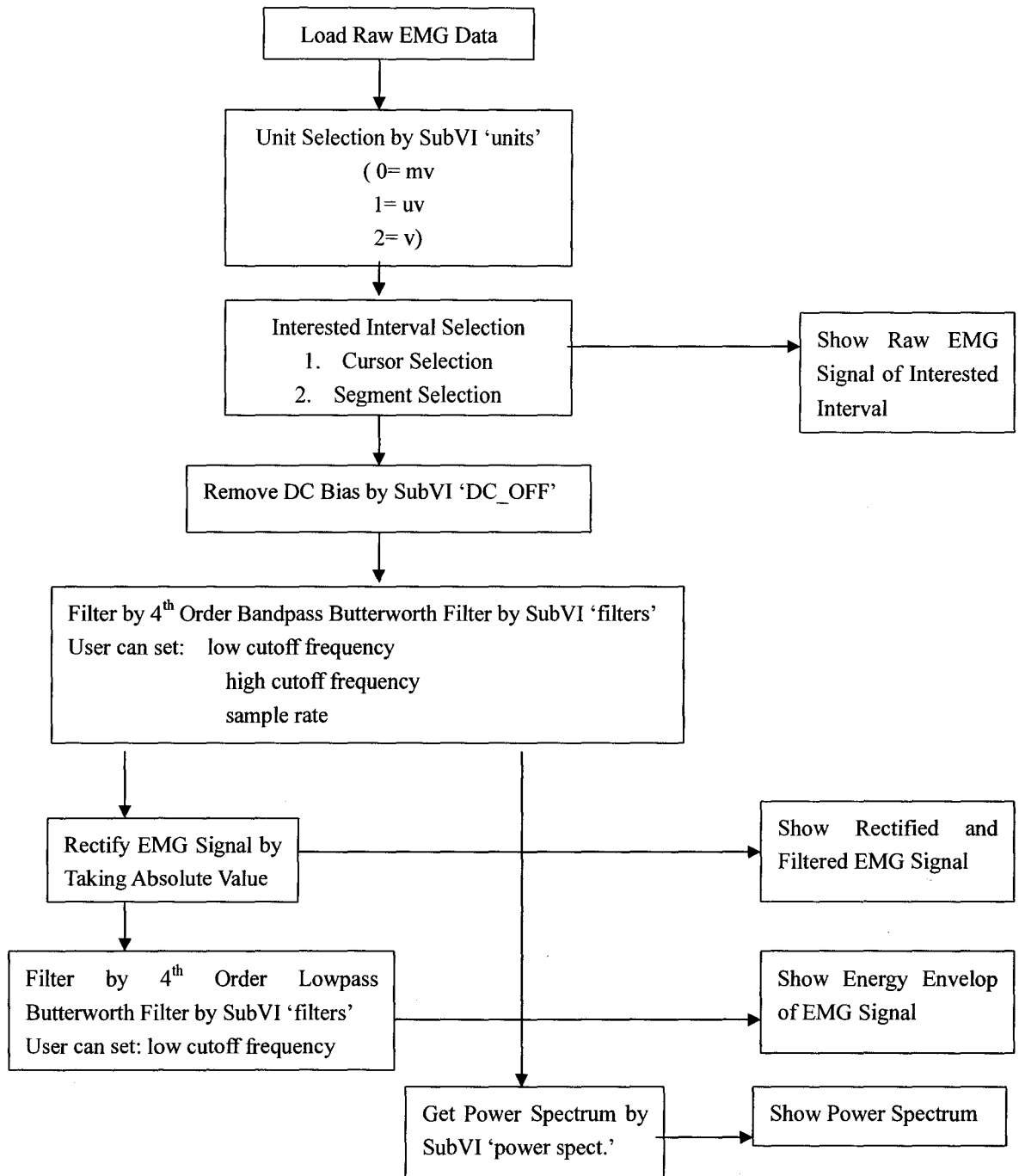
Figure 4.3 Labview Signal Conditioning and Feature Extraction Including Spectral

Estimation Using STFT

Figure 4.4 User Interface and Display for the Processing Steps of Figure 4.3
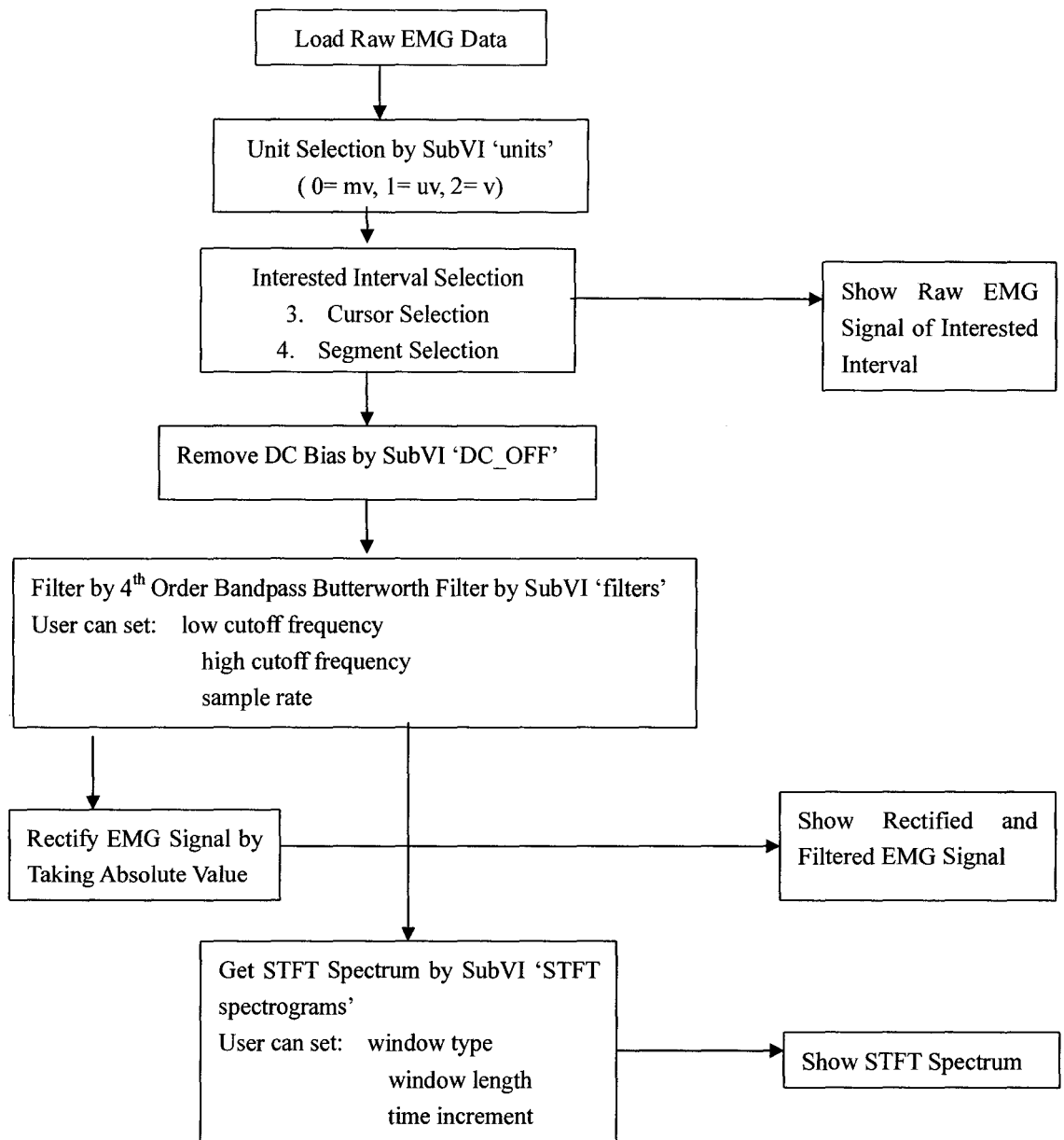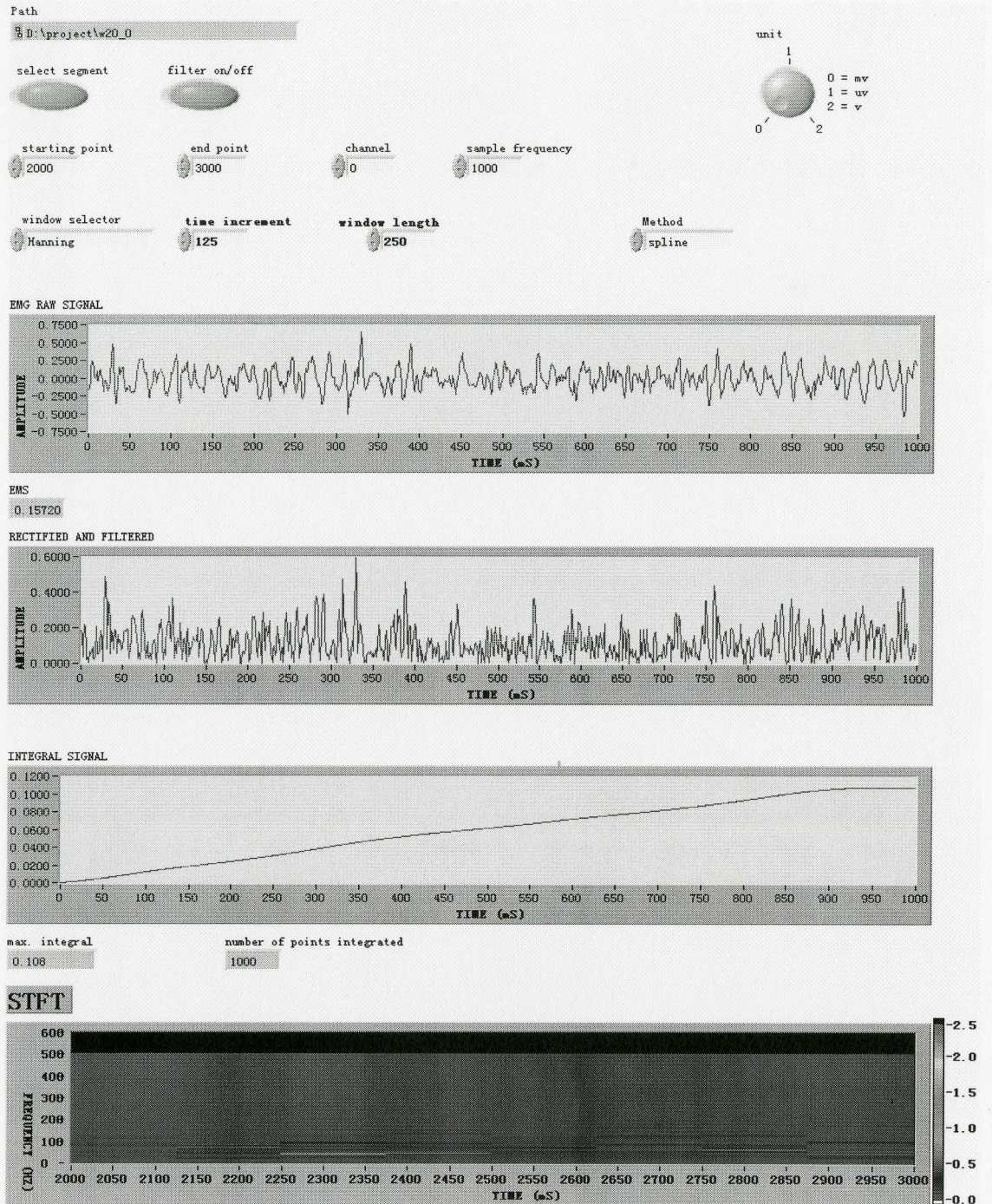
4.2 EMG Signal Processing

After acquiring or loading sample EMG signal, the data window for processing was selected either by segment selection or cursor selection. By using segment selection the user enters the start and end points, and only analyzes the interval between these two points. By using cursor selection the user can move the cursors along the x-axis in displayed EMG graph until the interval is determined. Figure 4.5 shows how cursor selection works. Figure 4.6 gives the front panel of segment selection. For both cases the sampling frequency was set to 1000 Hz and the analysis part was chosen from 2010 ms to 2996 ms. Both of methods provide the same answer.

In case there was a DC bias in the selected signal, a subVI called "DC_OFF" is utilized here. It calculates the mean value of the signal and subtracts the mean from the signal. EMG signals should be zero mean and any DC bias must result from instrumentation offsets.

A subVI named "filters" was implemented to filter the raw EMG signal. Users can set filter type, low frequency cut off, high frequency cut off, sampling rate used, and filter order as required. For the tests, the filter type was chosen as band-pass, with the low cutoff set at 10 Hz, and the high frequency cutoff assigned to 500 Hz, a sampling rate of 1000 Hz, and the filter order chosen as 4. Since the high frequency cut off is 500 Hz, according to Nyquist sampling theorem the sampling rate should be greater than or equal to 1000 Hz. Therefore the sampling rate of 1000 Hz should be sufficient. In subVI "filters", 2 Butterworth filters are separated by a *Reverse 1D Array* function.

Since digital filtering causes a phase shift, this can be corrected by reversing the

sample sequence of the signal and passing it through the filter again.
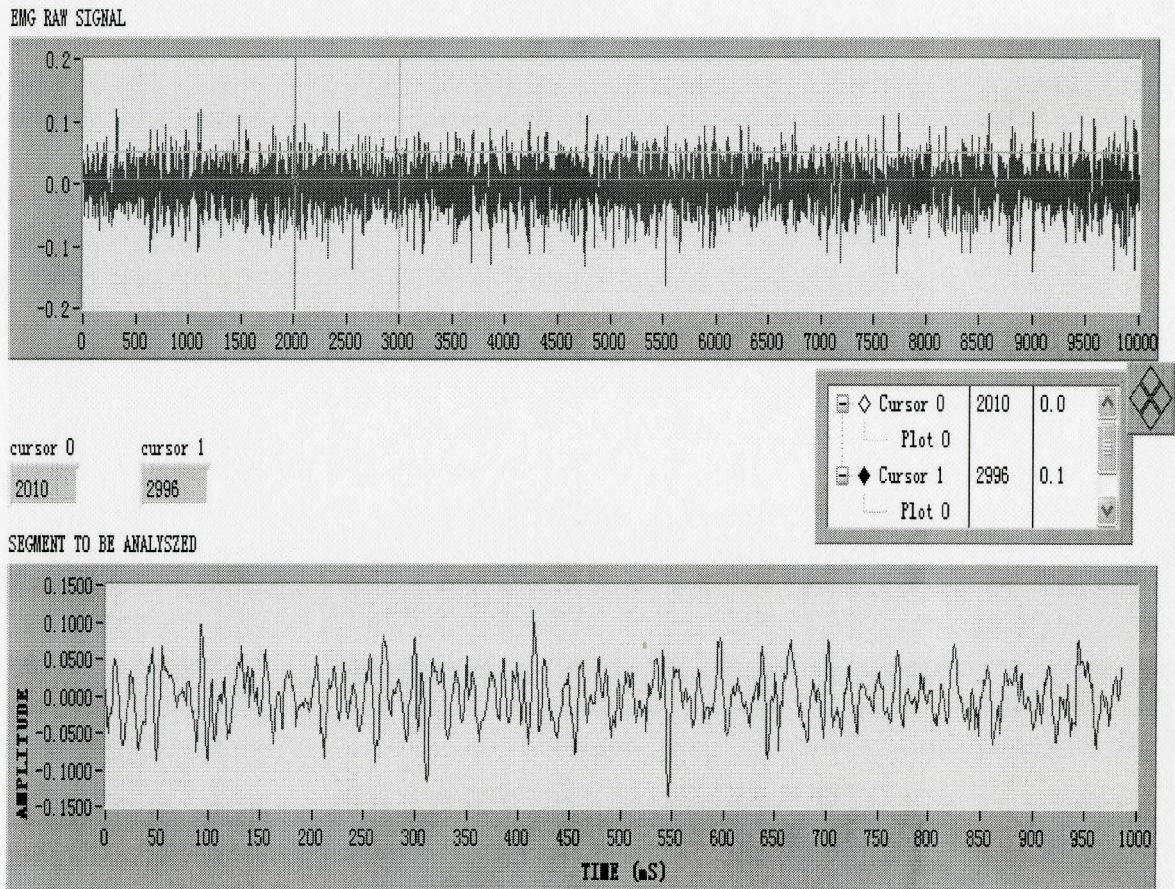
Figure 4.5 Window Selection by Cursors Selection
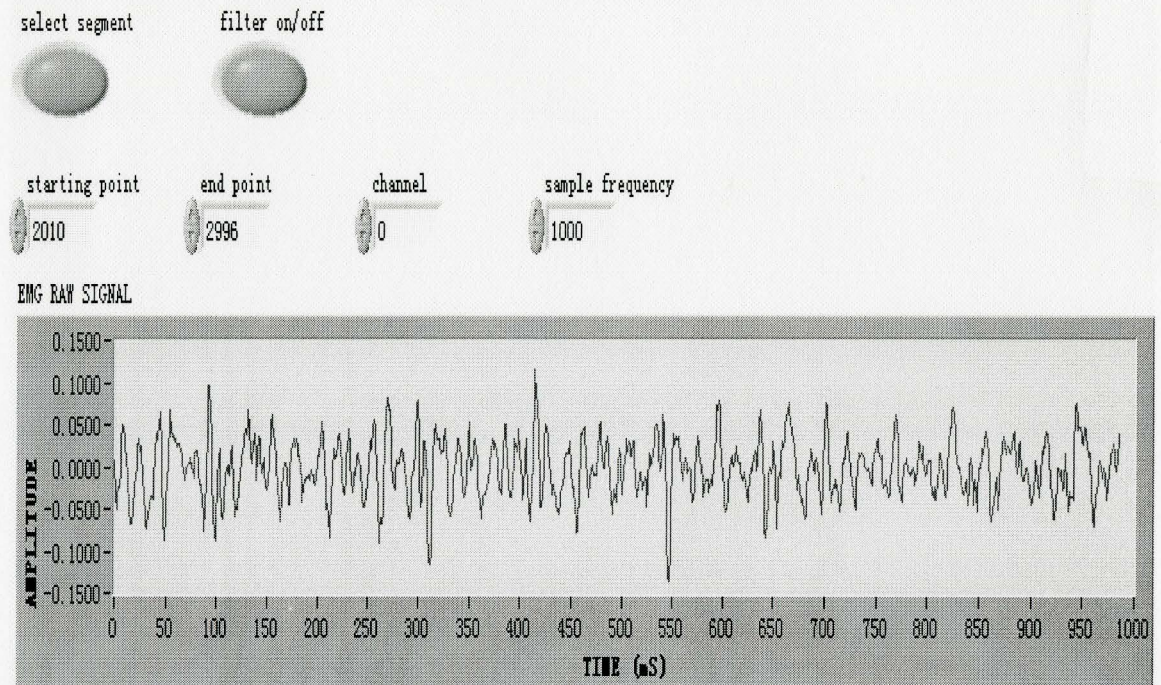
Figure 4.6 Window Selection by Segment Selection

The raw EMG signal is a bi-polar signal; it has positive and negative phases. To extract the linear envelop, full-wave rectification is first applied. Since the total energy of EMG signal is due to both positive and negative parts, the absolute value should be taken for the negative part. After rectification the EMG signal can be passed through a low-pass filter to give the linear envelop. The cutoff frequency can be set from 1 to 5 Hz. Figure 4.7 shows the linear envelop of the example EMG signal. The raw EMG signal was collected while asking the subject to hold a 7.5 pound dumbbell for 10 seconds.

RECTIFIED AND FILTERED
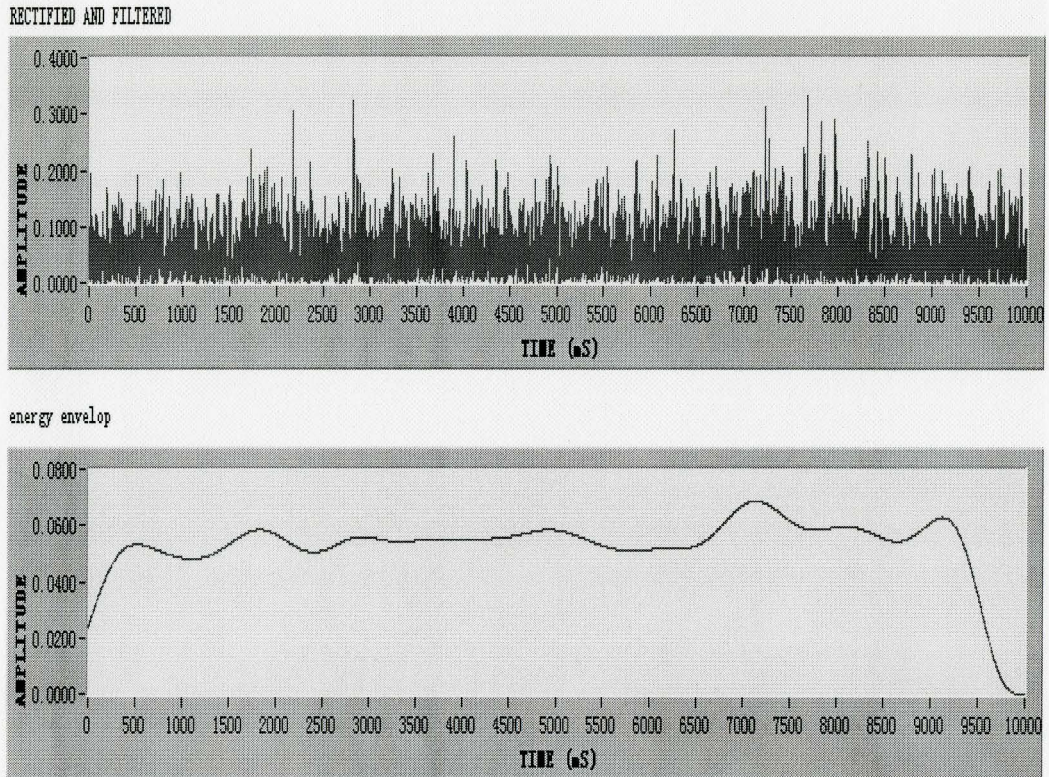
energy envelop

Figure 4.7 Energy Envelop of EMG

4.2.1 Fast Fourier Transform (FFT)

The subVI called "power spect." uses a Fast Fourier Transform procedure to convert the time domain EMG signal into the frequency domain. A Hanning window is used in processing the power spectrum to obtain smoothness of the output spectrum avoiding spectral leakages. The power spectrum can be presented in linear or logarithm scales. Here linear scales were chosen and the power spectrum was measured in volts rms squared per hertz (V_{rms}^2/Hz). The power spectrum of the total

signal reveals the component of the individual motor unit action potentials [7]. The area under the power spectral curve equals the signal power. A sample EMG obtained from isometric contraction of biceps sampled at 1000 Hz is shown in Figure 4.8. The subject was asked to hold a 5.0 pound dumbbell for 10 seconds. The power spectrum calculated by the FFT is shown in Figure 4.9. The median power frequency is 65.3415 Hz, the mean power frequency is 77.3864 Hz, and the estimated peak frequency is 67.2322 Hz. It can be seen that the signal is random in nature with significant spectral components between 10-50 Hz. However, there is no information describing when each of the frequency components dominates the signal.
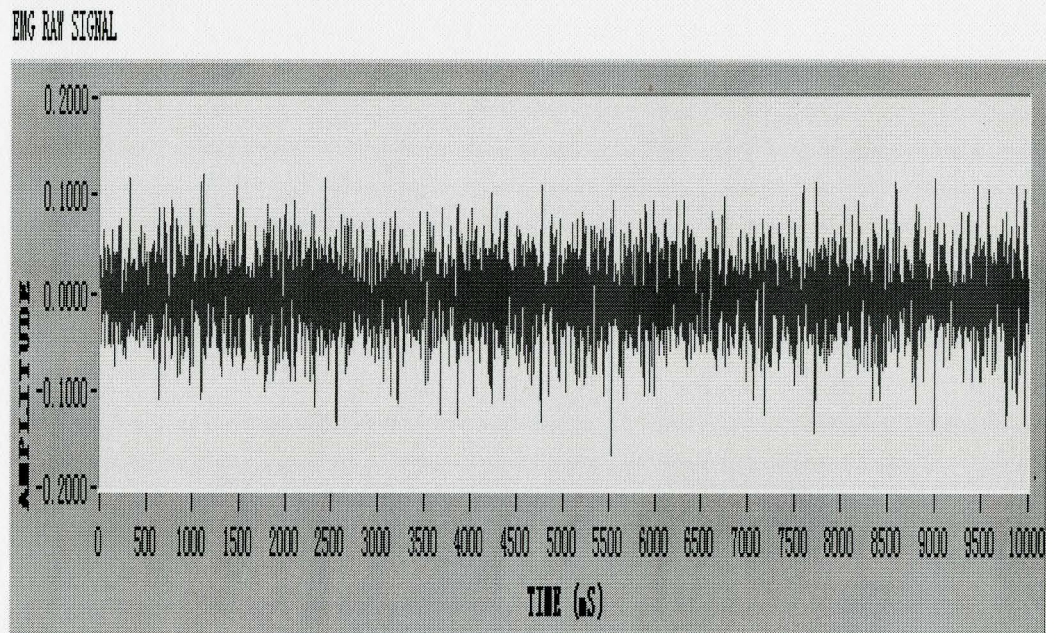
Figure 4.8 Raw EMG Signal
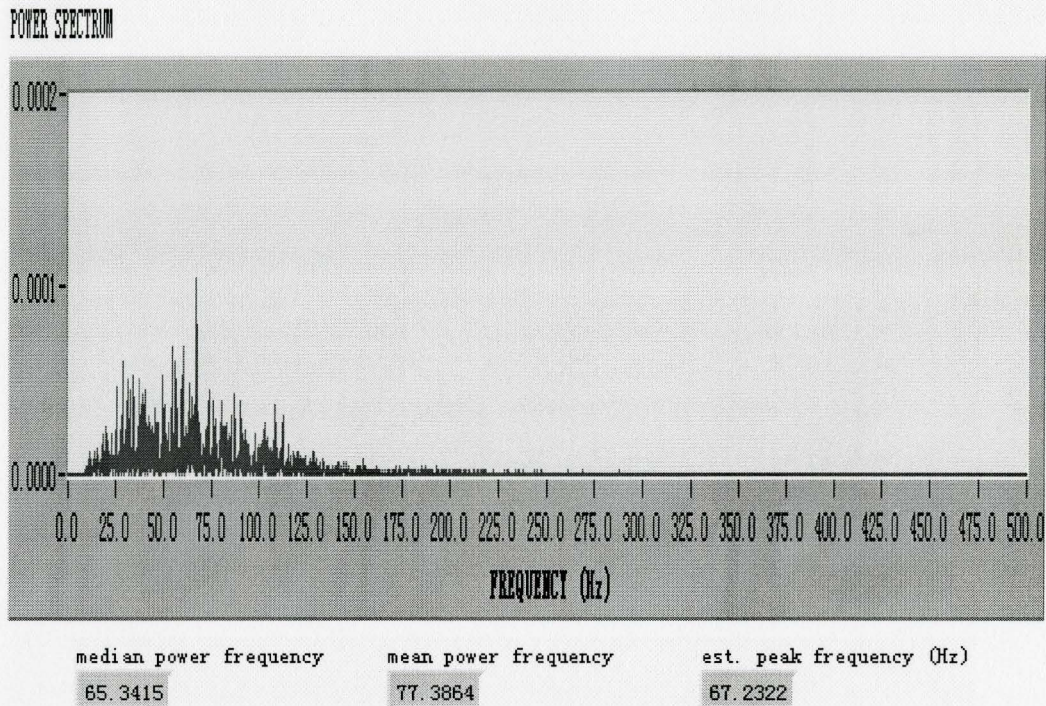
POWER SPECTRUM

Figure 4.9 Power Spectrum of EMG

median power frequency	mean power frequency	est. peak frequency (Hz)
65.3415	77.3864	67.2322

4.2.2 Short Time Fourier Transform (STFT)

The Short Time Fourier Transform (STFT) maps a signal into a two dimensional function of time and frequency. The STFT provides some information relating to when different frequency components occurring. It is done simply by multiplying the time domain signal with an analysis window and then computing the Fourier transform. In this test, a Hanning window was chosen for the analysis window. Window length was set as 500 ms, and the shift increment was set at 250 ms. The raw EMG was acquired at 1000 Hz.

If a user wants to resample data at different frequency, for example 1024 or 2048 samples/sec, the subVI "Interpolate 1D" is applied here. This VI accepts tabulated dependent and independent variable values Y and X and provides interpolated values Y_i corresponding to each X_i location. There are 5 interpolation methods that can be chosen: nearest, linear, spline, cubic Hermite, and Lagrange. In this project the linear method was chosen.   A sample EMG obtained from isometric contraction of biceps is shown in Figure 4.10. The raw EMG signal was recorded while asking the subject to hold a 25 pound dumbbell for 10 seconds, and the analysis window was chosen from 4000 ms to 5000 ms. The spectrogram of STFT is shown in Figure 4.11. The sampling frequency was set at 1024 Hz, and the window length was chosen as 512 ms with 50% overlap. The brighter lines in the spectrogram represent the amplitude of the frequencies that dominate within the window length. With this windowing we can clearly see the times when each frequency component occurs.
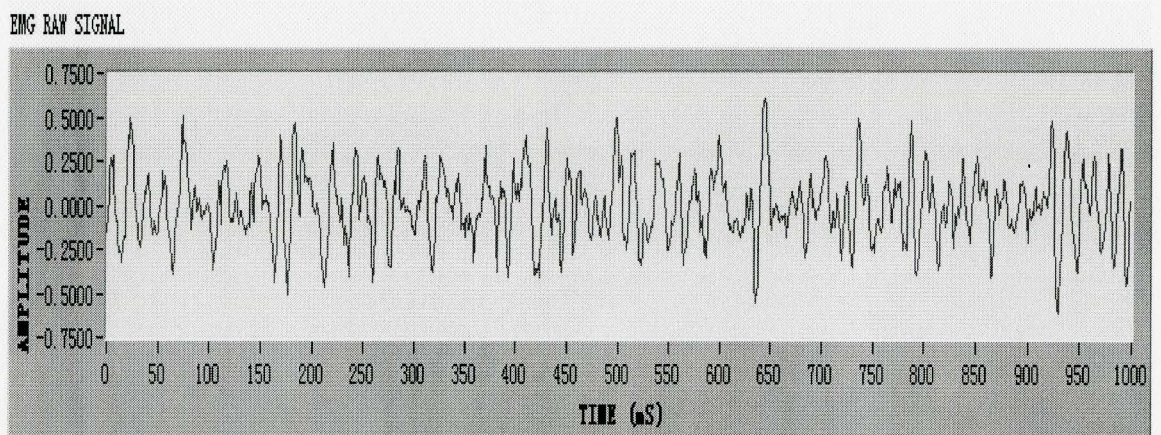
Figure 4.10 Raw EMG Signal
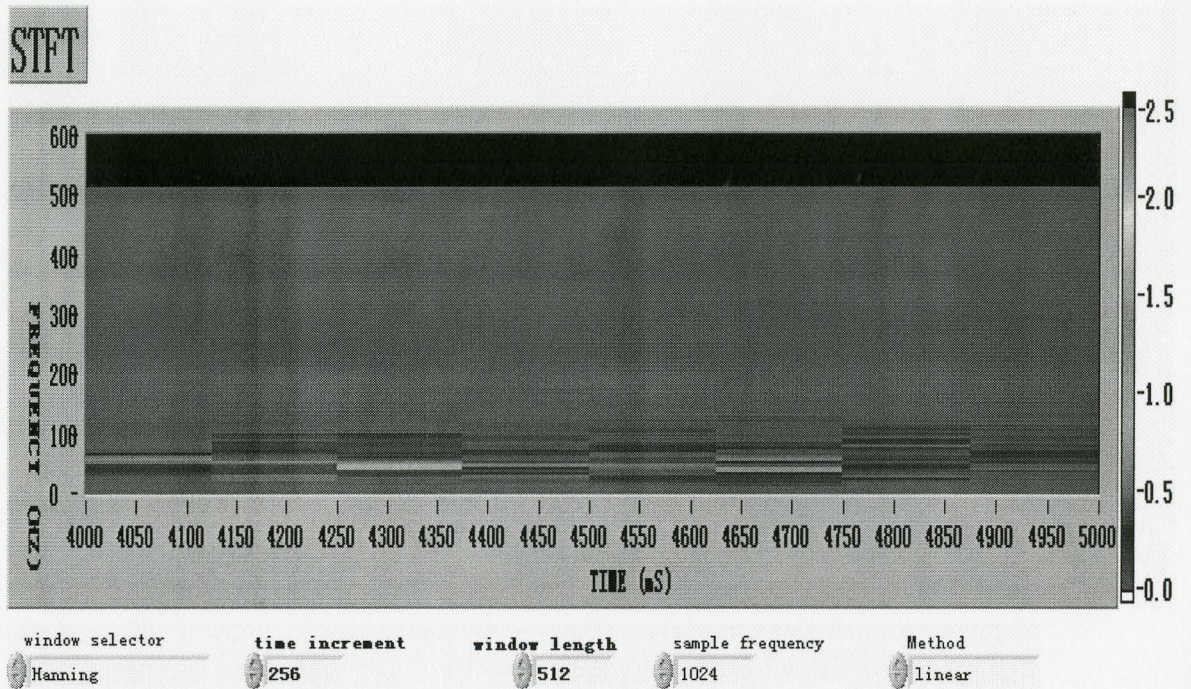
Figure 4.11 Short Time Fourier Transform

4.3 Feature Extraction

Root Mean Squared (RMS)

The RMS value provides a measure of the square root of the average power in EMG signal. The RMS of raw EMG can be viewed as the standard deviation of the recorded signal. The EMG signal is first squared and then the average value of the squared waveform is calculated. Finally the square root of that value is calculated yielding the RMS.

$$\text{RMS} = \sqrt{(1/n) * \sum_{i=0}^{n-1} x[i]^2}$$

Mean Absolutely Value

After the signal is rectified, the mean value can be calculated. This provides a measurement of the amplitude of EMG in the time domain, and is also an approximation of the linear envelop. There is an approximate linear relationship between muscle force output and EMG activity during isometric contraction.

$$\text{Mean Absolutely Value} = (1/n)* \sum_{i=0}^{n-1} |x[i]|$$

Mean and Median Frequencies of Power spectrum

These are very important parameters in power spectral analysis. The mean frequency is the average of all frequencies from the power spectrum. The median frequency is the frequency that has 50% of the frequency distribution on each side. The median frequency appears to be less sensitive to noise than the mean frequency [8]. They are useful in fatigue analysis: the mean and median power frequency would be expected to shift downwards in frequency.

$$\int_{0}^{MedianPowerFrequency} P(\omega)d\omega = \int_{MedianPowerFrequency}^{\infty} P(\omega)d\omega$$

$$\text{Mean Power Frequency} = \frac{\int_{0}^{\infty} \omega * P(\omega)d\omega}{\int_{0}^{\infty} P(\omega)d\omega}$$

CHAPTER 5 RESULT AND DISCUSSION

5.1 Introduction

There are two methods the body uses to recruit muscle force. These methods are temporal and spatial summation. Temporal summation is effected by increasing the firing frequencies of the active motor units (MU), thus increases the force output of the muscle. Spatial summation occurs when more motor units are recruited in parallel, causing greater contractile force than the contraction of a single motor unit. The subject was asked to perform several isometric contraction trials. The relation between the force production requirements of a whole muscle and the EMG signals during muscle activity has been studied. There was an approximate linear relationship between muscle force out put and EMG activity during isometric contractions. In the fatigue trial, the subject was asked to hold the dumbbell for as long as possible. The mean and median power frequencies were found to decrease as time passed. The weights of the dumbbells for each trial are listed in Table 5.1. The unit for first row is pounds and for the second is kilograms.

Pound	2.5	5.0	7.5	10	12.5	15	17.5	20	22.5	25	27.5
KG	1.14	2.27	3.41	4.55	5.68	6.82	7.95	9.09	10.23	11.36	12.50

Table 5.1 Weights of Dumbbell in Each Trail

5.2 Load and EMG Activity

In general for voluntary contractions, force is modulated by a combination of MU recruitment and changes in MU activation frequency. As more motor units are recruited, the total force produced by the muscle increases. Therefore the increased magnitude of the EMG signal, i.e., the peak to peak amplitude increases, is an indicator of the increased muscle recruitment, and an indicator of increased force. In signal processing, RMS values and the mean values of rectified EMG data were calculated.

Figure 5.1 shows the relationship between the mean absolute value and weight of the dumbbell. It shows that as the load increases, the corresponding value of mean absolute value also increases. The force output of a muscle is related to the amplitude of the recorded EMG signal. For lighter loads, fewer MUs are recruited, and the EMG signal is relatively small. However for heavy loads, spatial summation is used to recruit more MUs, and consequently the EMG signal is larger. Figure 5.2 gives the relationship between RMS and weight of dumbbell. It also illustrates that the RMS value is proportional to the weight of dumbbell. As the load for each trial increased, more output power of the muscle was needed. Since the RMS value provides a descriptor of the average power in EMG signal, it should increase corresponding to each trial. It is interesting to note that Figure 5.1 and Figure 5.2 are very similar and RMS and mean absolute values are equally sensitive to the muscle force.
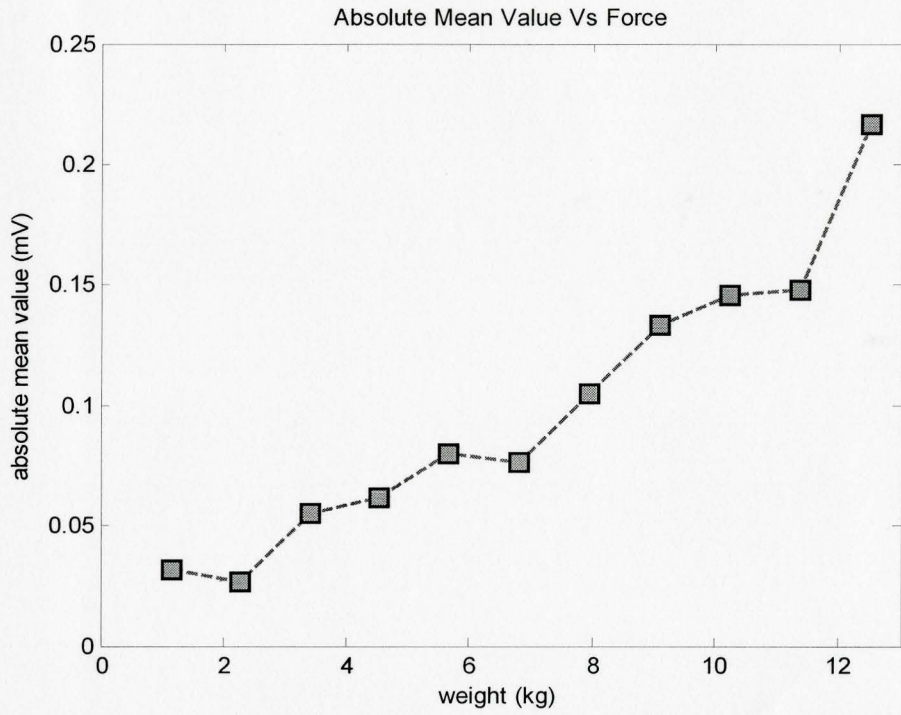
Figure 5.1 Mean Absolute Value of EMG Vs Load
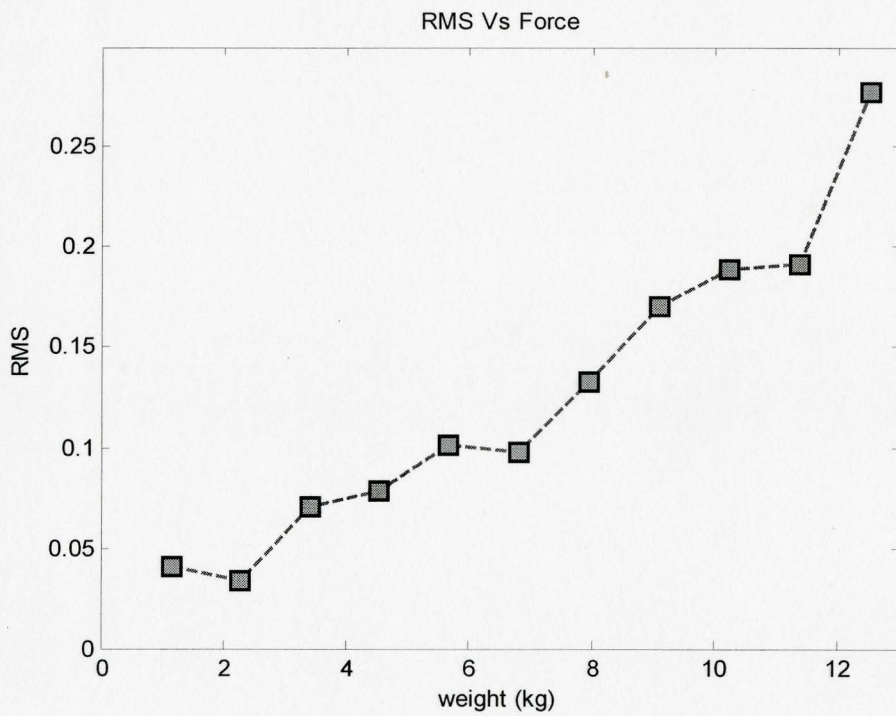
Figure 5.2 RMS of EMG Vs Load

Power spectra were calculated for every 2 seconds of data with an overlap of 50%. With an overlap of 50%, it created a total of nine 2-second intervals. The average power spectrum was formed from these 2-second intervals by averaging all of the spectra lying within the 10 second data read. This method was used to reduce the variance in the spectral estimates and create an estimate of the power distribution. From this average spectrum, the median frequencies were calculated.

Figure 5.3 shows the values of MPF corresponding to each trial. This graph seems to indicate that the median frequency decreases with increasing muscle force from 72 to 58 Hz. This could be due to larger units with larger duration MUAPs being recruited for higher forces. This would tend to increase the lower frequency content of the signal.
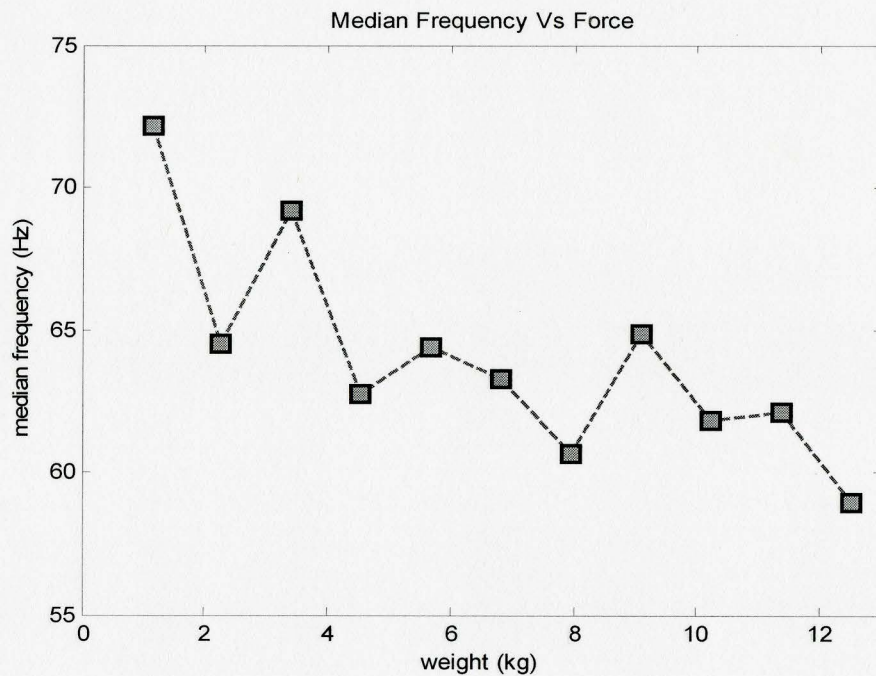
Figure 5.3 MPF of EMG Vs Load

5.3 Fatigue Analysis

Fatigue refers to the decline of maximal force during voluntary activity. The MU firing rates have an influence on the low frequency region of the EMG power spectrum. The higher frequency components (and middle frequency as well) are determined by the average duration of the MUAPs. During a fatiguing contraction the amplitude of EMG gradually increased while the EMG spectrum was compressed toward lower frequencies. The frequency shift is mainly related to motor unit action potential conduction velocity decrease and hence longer MUAPs. The increase in amplitude could be due to MU synchronization and/or more MUs being recruited. For the fatigue analysis, the subject was asked to a hold 27.5 pound dumbbell and 50 seconds of data were recorded. Power spectra were calculated for every 2-second interval with an overlap of 50%.

Figure 5.4 shows that the median power frequency gradually decreases in 50 seconds. It proves that there is fatigue during strong sustained isometric contractions. Figure 5.5 shows that the values of RMS increase during muscle fatigue period.

Median Frequency Vs Time
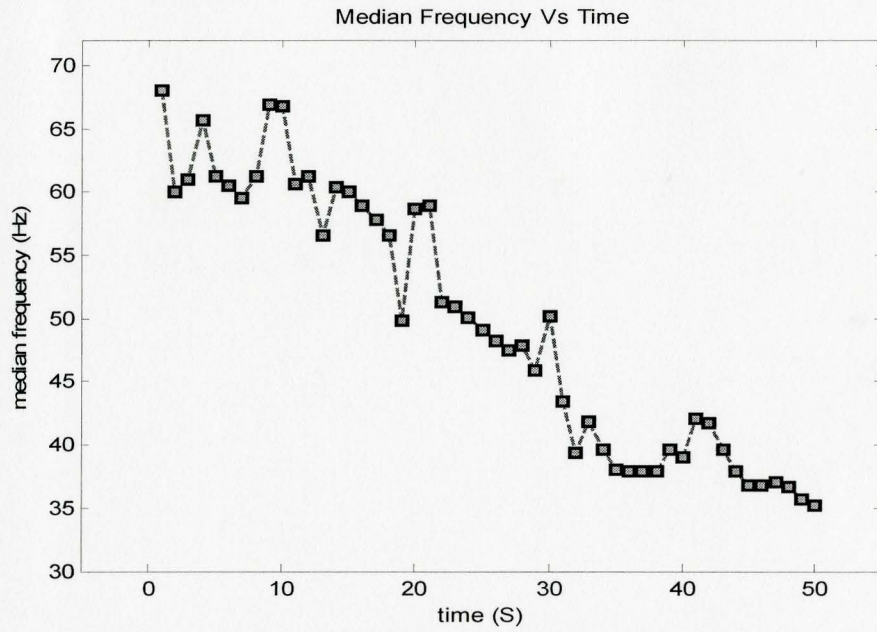
Figure 5.4 Fatigue Analysis: Median Power Frequency

RMS Vs Time
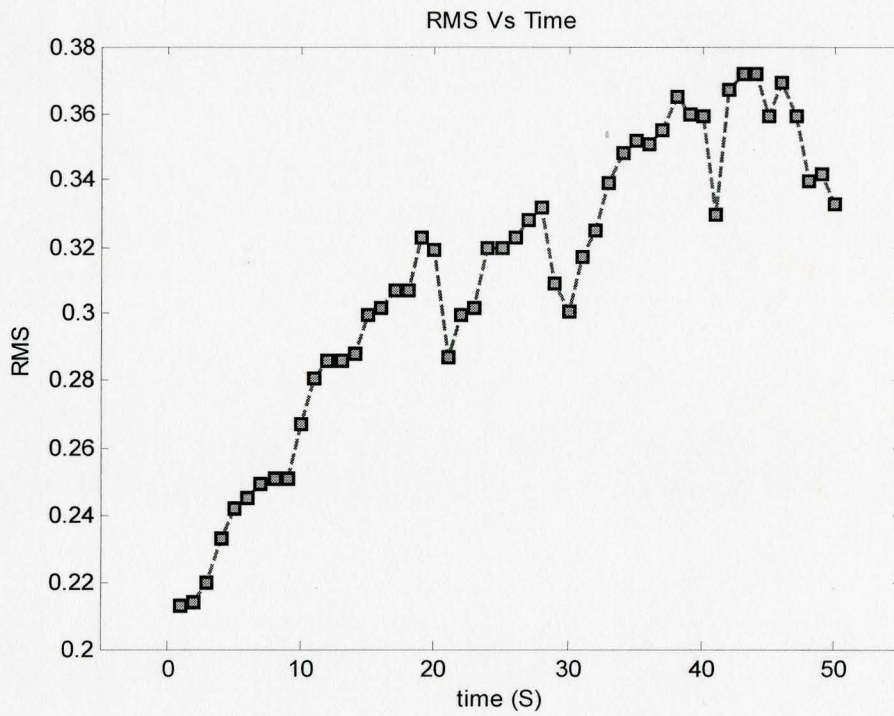
Figure 5.5 Fatigue Analysis: RMS

CHAPTER 6 CONCLUSIONS

In summary this project describes the development and testing of a multi-channel

EMG data acquisition and analysis system that is very flexible and easy to use with

excellent user interfaces. To test this system we investigated digital signal processing

using FFT and STFT for feature extraction of EMG signals. We showed that there was

an approximate linear relationship between muscle force output and EMG activity

during isometric contractions. In fatigue analysis the mean and median power

frequency were found to decrease with time. Labview and Matlab are used for

programming.

The area which had been covered in this project included:

-Understanding the EMG signals: how EMG relates to muscle force and fatigue.

-Learning the Labview language and implementing a virtual instrument

-Development which using different analysis schemes of FFT, STFT to extract

features.

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APPENDICES:

Appendix 1 Signal Processing by Fast Fourier Transform method 1 (cursor selection)

Path

% F:\project\project\New Folder\project\back up\15

filter on/off

sample frequency
1000

channel
0

EMG RAW SIGNAL

cursor 0	cursor 1	RMS
1497	3006	0.09757

◇ Cursor 0	1497	0.1	
Plot 0			
◆ Cursor 1	3006	0.0	
Plot 0			

SEGMENT TO BE ANALYSZED

RECTIFIED AND FILTERED

INTEGRAL SIGNAL

max. integral	number of points integrated
0.101221	1509

POWER SPECTRUM

median power frequency	mean power frequency	est. peak frequency (Hz)	est. peak power
62.3812	77.6662	51.7918	0.00066

INTEGRATION OF SPECTRUM

max integral
0.01444

Appendix 2 Signal Processing by Fast Fourier Transform method 2 (segment selection)

Path
F:\project\project\New Folder\project\w15_0

select segment   filter on/off

starting point   end point   channel   sample frequency
3000   8000   0   1000

EMG RAW SIGNAL

RMS
0.09627

RECTIFIED AND FILTERED

energy envelop

INTEGRAL SIGNAL

max. integral   number of points integrated
0.341451   5000

POWER SPECTRUM

median power frequency   mean power frequency   est. peak frequency (Hz)   est. peak power
61.0072   73.9126   60.0602   0.00045
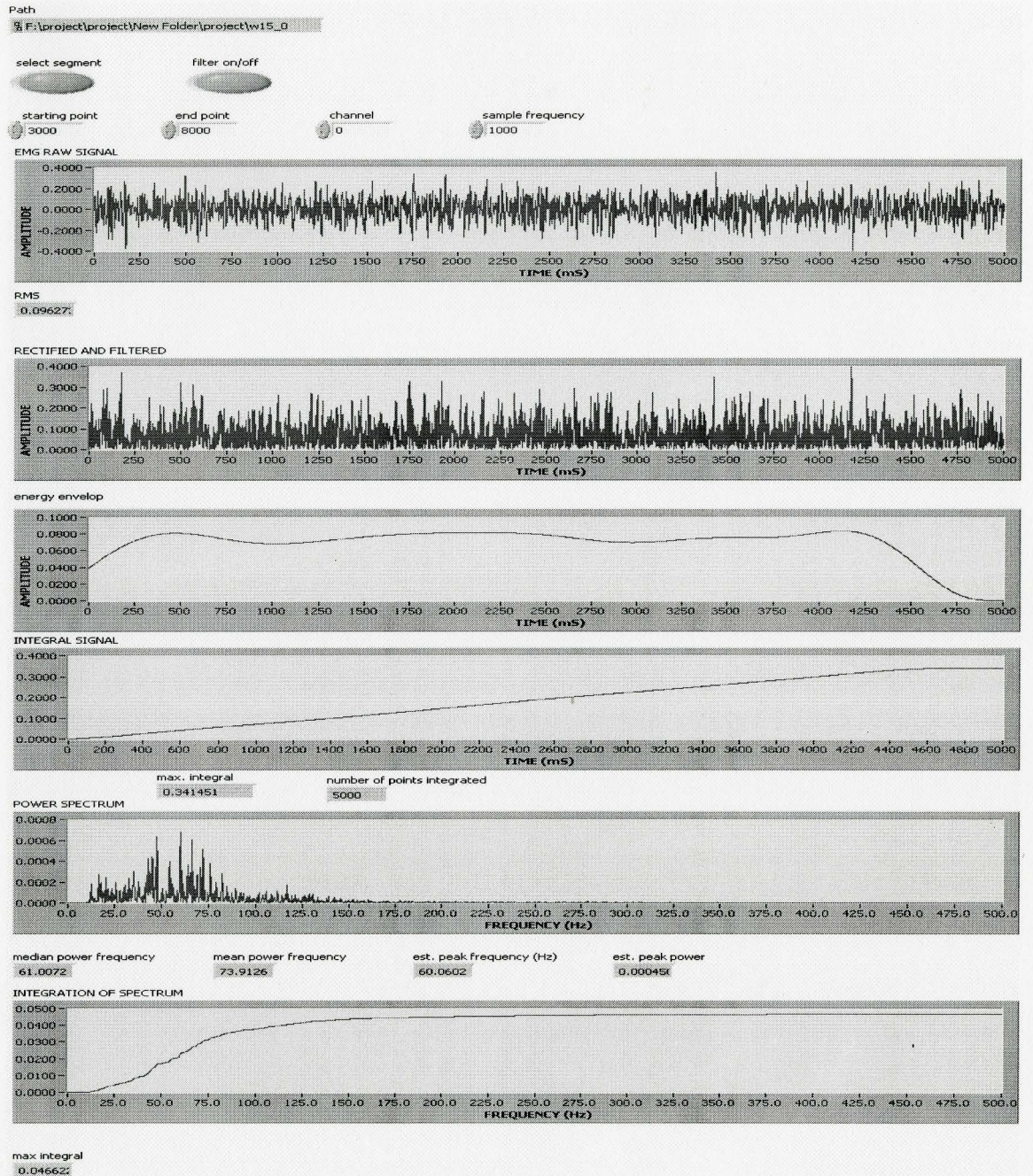
INTEGRATION OF SPECTRUM

max integral
0.04662

Appendix 3 Signal Processing by Short Time Fourier Transform method 1 (cursor selection)

Path
F:\project\project\New Folder\project\w25_0

filter on/off

sample frequency
1000

channel
0

window selector
Hanning

time increment
128

window length
256

Method
spline

EMG RAW SIGNAL

cursor 0
0

cursor 1
999

EMS
0.19168

◇ Cursor 0		0	-0.2
⋯ Plot 0			
◆ Cursor 1		999	0.4
Plot 0			

SEGMENT TO BE ANALYSZED

RECTIFIED AND FILTERED

INTEGRAL SIGNAL

max. integral
0.118196

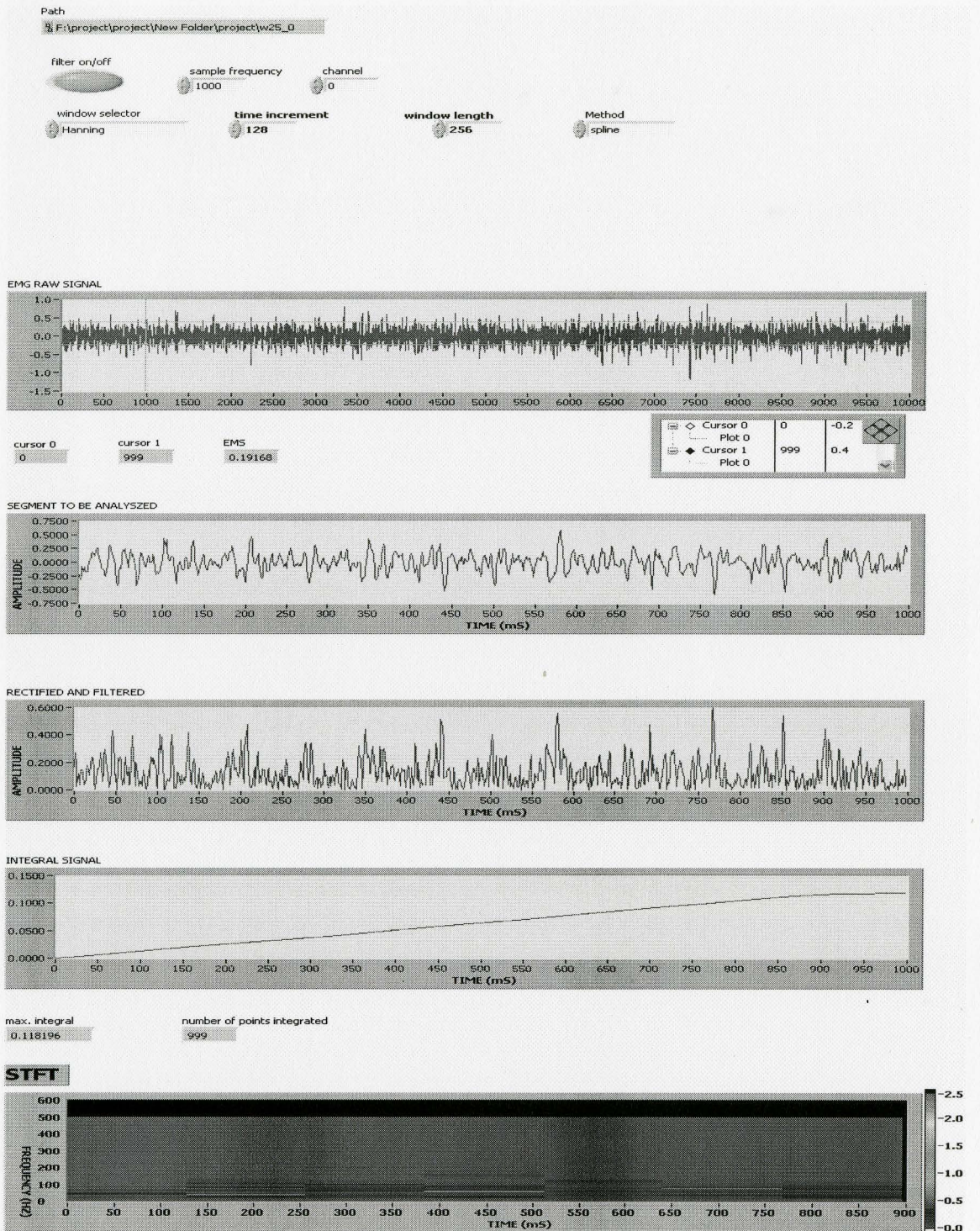number of points integrated
999

STFT
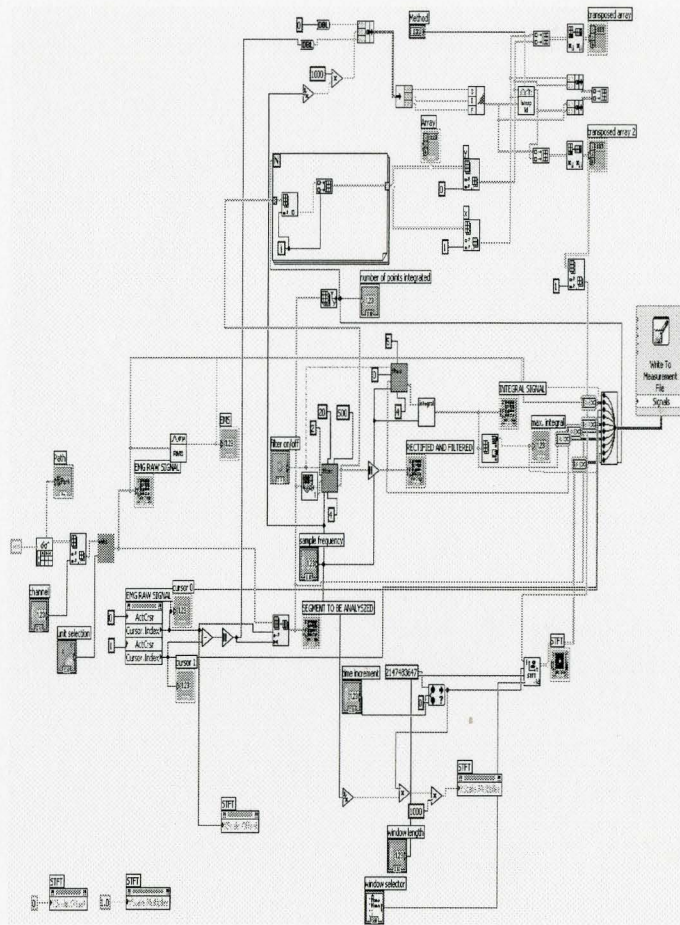
Appendix 4 Signal Processing by Short Time Fourier Transform method 2 (segment selection)

Path

F:\project\project\New Folder\project\w22_5

select segment   filter on/off

starting point   end point   channel   sample frequency
5000   6000   0   1000

window selector   time increment   window length   Method
Hanning   128   256   spline

EMG RAW SIGNAL

EMS
0.19794

RECTIFIED AND FILTERED

INTEGRAL SIGNAL

max. integral   number of points integrated
0.134393   1000

STFT
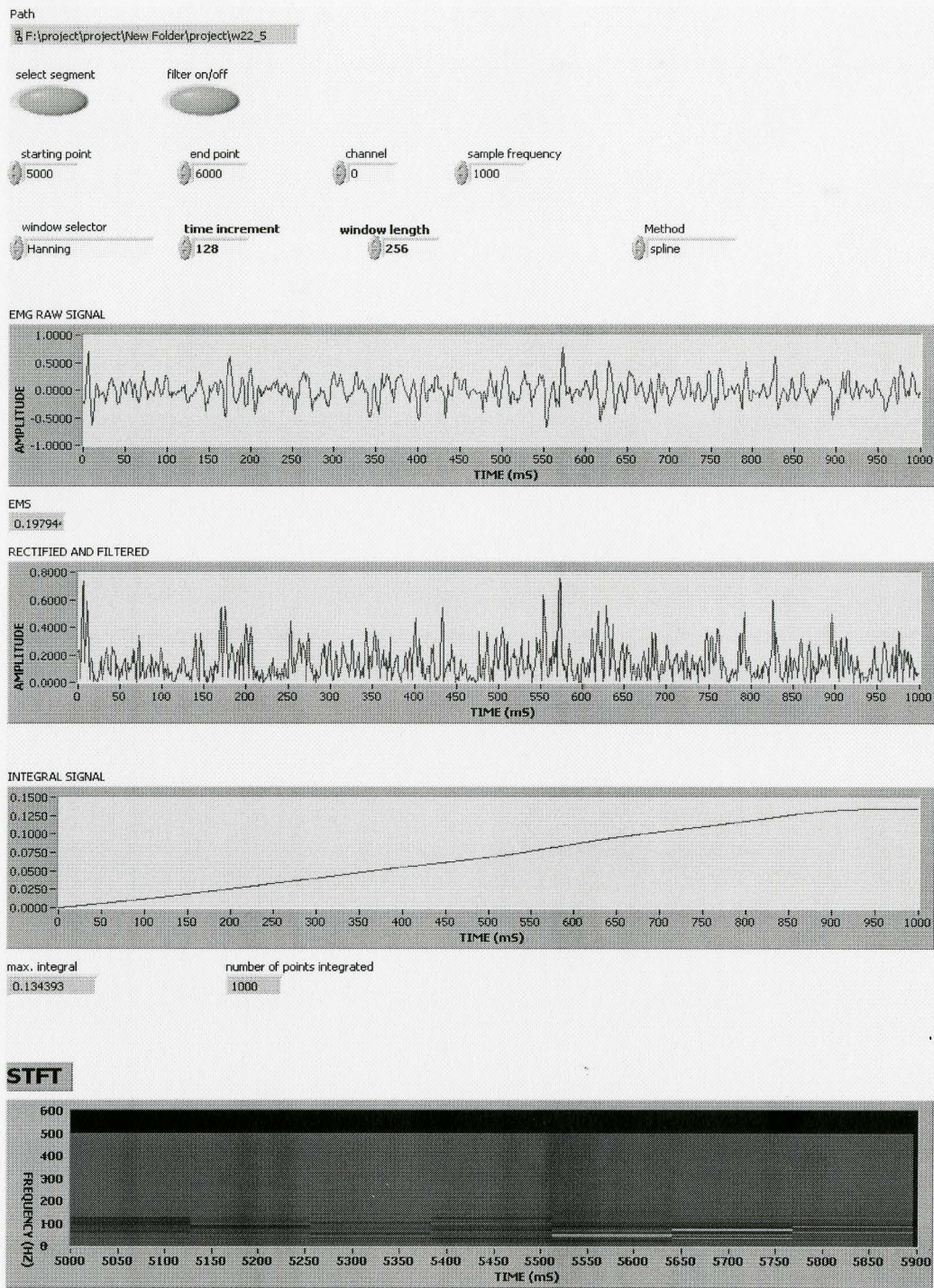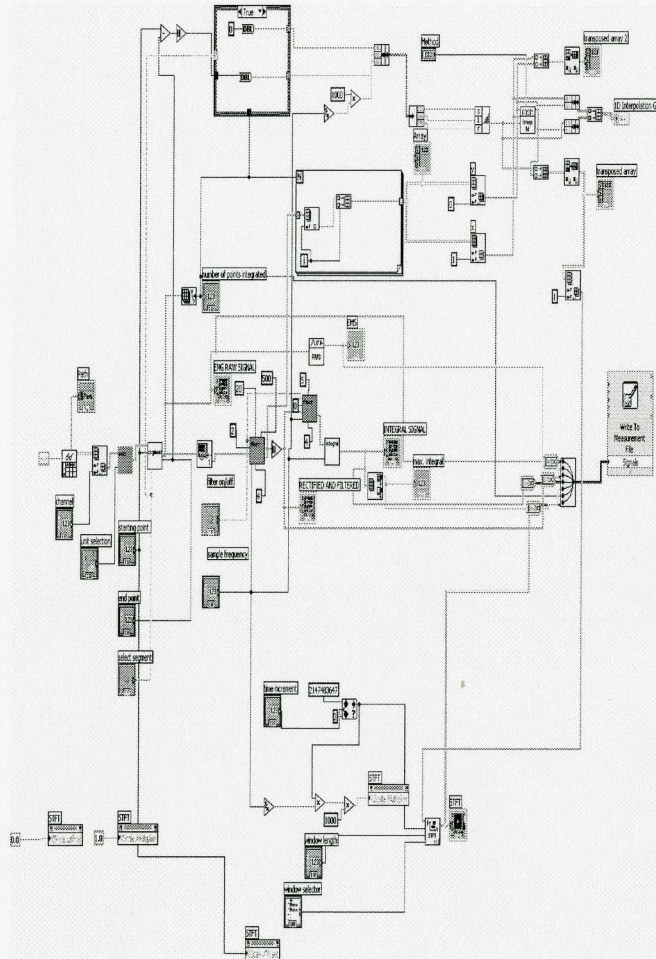
Appendix 5 Data Collection
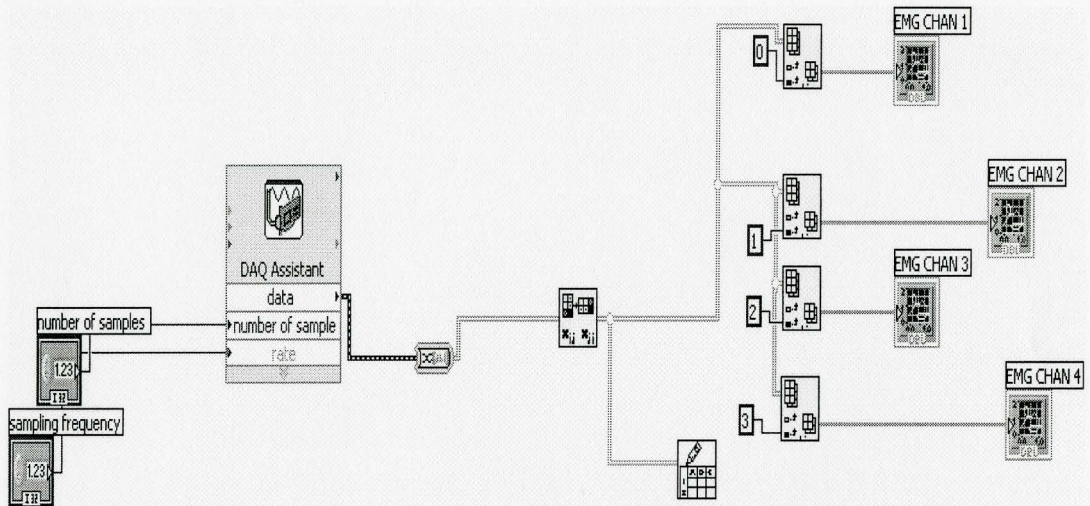
Appendix   6 Forces_Vs_absmean.m

```
clear all;
close all;
load f1;
data_1=f1(1,:);
abs_data_1=abs(data_1);
m(1)=mean(abs_data_1);


load f2;
data_2=f2(1,:);
abs_data_2=abs(data_2);
m(2)=mean(abs_data_2);

load f3;
data_3=f3(1,:);
abs_data_3=abs(data_3);
m(3)=mean(abs_data_3);

load f4;
data_4=f4(1,:);
abs_data_4=abs(data_4);
m(4)=mean(abs_data_4);

load f5;
data_5=f5(1,:);
abs_data_5=abs(data_5);
m(5)=mean(abs_data_5);

load f6;
data_6=f6(1,:);
abs_data_6=abs(data_6);
m(6)=mean(abs_data_6);

load f7;
data_7=f7(1,:);
abs_data_7=abs(data_7);
m(7)=mean(abs_data_7);
```

```
load f8;
data_8=f8(1,:);
abs_data_8=abs(data_8);
m(8)=mean(abs_data_8);


load f9;
data_9=f9(1,:);
abs_data_9=abs(data_9);
m(9)=mean(abs_data_9);


load f10;
data_10=f10(1,:);
abs_data_10=abs(data_10);
m(10)=mean(abs_data_10);


load f11;
data_11=f11(1,:);
abs_data_11=abs(data_11);
m(11)=mean(abs_data_11)


w=[1.14  2.27  3.41  4.55  5.68  6.82  7.95  9.09  10.23  11.36  12.50]


plot(w,m,'--rs','LineWidth',2,...
            'MarkerEdgeColor','k',...
            'MarkerFaceColor','g',...
            'MarkerSize',10)
xlabel('weight (kg)')
ylabel('absolute mean value (mV)')
xlim([0 13])
ylim([0 .25])
title('Force Vs absolute mean value')
```

Appendix 7 Forces_Vs_RMS.m

```
clear all;
close all;
load w2_5;
data_1=w2_5(:,1);
%abs_data_1=abs(data_1);
S_D(1)=std(data_1);

load w5_0;
data_2=w5_0(:,1);
%abs_data_2=abs(data_2);
S_D(2)=std(data_2);

load w7_5;
data_3=w7_5(:,1);
%abs_data_3=abs(data_3);
S_D(3)=std(data_3);

load w10_0;
data_4=w10_0(:,1);
%abs_data_4=abs(data_4);
S_D(4)=std(data_4);

load w12_5;
data_5=w12_5(:,1);
%abs_data_5=abs(data_5);
S_D(5)=std(data_5);

load w15_0;
data_6=w15_0(:,1);
%abs_data_6=abs(data_6);
S_D(6)=std(data_6);

load w17_5;
data_7=w17_5(:,1);
%abs_data_7=abs(data_7);
S_D(7)=std(data_7);
```

```
load w20_0;
data_8=w20_0(:,1);
%abs_data_8=abs(data_8);
S_D(8)=std(data_8);
load w22_5;
data_9=w22_5(:,1);
%abs_data_9=abs(data_9);
S_D(9)=std(data_9);


load w25_0;
data_10=w25_0(:,1);
%abs_data_10=abs(data_10);
S_D(10)=std(data_10);


load w27_5;
data_11=w27_5(:,1);
%abs_data_11=abs(data_11);
S_D(11)=std(data_11)


w=[1.14  2.27  3.41  4.55  5.68  6.82  7.95  9.09  10.23  11.36  12.50]


plot(w,S_D,'--rs','LineWidth',2,...
            'MarkerEdgeColor','k',...
            'MarkerFaceColor','g',...
            'MarkerSize',10)
xlabel('weight (kg)')
ylabel('standard deviation')
```

Appendix 8 Forces_Vs_MPF.m

```
clear all;
close all;


load MPF1;
data_1=MPF1(1,:);
med(1)=mean(data_1)

load MPF2;
data_2=MPF2(1,:);
med(2)=mean(data_2)

load MPF3;
data_3=MPF3(1,:);
med(3)=mean(data_3)

load MPF4;
data_4=MPF4(1,:);
med(4)=mean(data_4)


load MPF5;
data_5=MPF5(1,:);
med(5)=mean(data_5)

load MPF6;
data_6=MPF6(1,:);
med(6)=mean(data_6)

load MPF7;
data_7=MPF7(1,:);
med(7)=mean(data_7)

load MPF8;
data_8=MPF8(1,:);
med(8)=mean(data_8)
```

```
load MPF9;
data_9=MPF9(1,:);
med(9)=mean(data_9)
load MPF10;
data_10=MPF10(1,:);
med(10)=mean(data_10)

load MPF11;
data_11=MPF11(1,:);
med(11)=mean(data_11)
w=[1.14  2.27  3.41  4.55  5.68  6.82  7.95  9.09  10.23  11.36  12.50]

plot(w,med,'--rs','LineWidth',2,...
              'MarkerEdgeColor','k',...
              'MarkerFaceColor','g',...
              'MarkerSize',10)
xlabel('weight (kg)')
ylabel(' median frequency (Hz)')
xlim([0 13])
ylim([55 75])
title('Force Vs median frequency')
```

Appendix 9 Time_Vs_MPF.m

```
clear all;
close all;
load fati1;
data_1=fati1(1,:);

load fati2;
data_2=fati2(1,:);

load fati3;
data_3=fati3(1,:);

load fati4;
data_4=fati4(1,:);

load fati5;
data_5=fati5(1,:);
data=[data_1  data_2  data_3 data_4  data_5];
T=[1:50];
plot(T,data,'--rs','LineWidth',2,...
            'MarkerEdgeColor','k',...
            'MarkerFaceColor','g',...
            'MarkerSize',5)
xlabel('time (S)')
ylabel('median frequency (Hz)')
xlim([-5 55])
ylim([30 72])
title('Time Vs Median Frequency')
```

Appendix 10 Time_Vs_RMS

```
clear all;
close all;
load fatiRMS1;
data_1=fatiRMS1(1,:);

load fatiRMS2;
data_2=fatiRMS2(1,:);

load fatiRMS3;
data_3=fatiRMS3(1,:);

load fatiRMS4;
data_4=fatiRMS4(1,:);

load fatiRMS5;
data_5=fatiRMS5(1,:);
data=[data_1  data_2  data_3 data_4  data_5];
T=[1:50];
plot(T,data,'--rs','LineWidth',2,...
            'MarkerEdgeColor','k',...
            'MarkerFaceColor','g',...
            'MarkerSize',5)
xlabel('time (S)')
ylabel('RMS')
title('Time Vs RMS')
xlim([-5 55])
```