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EMG-based determination of upper extremity virtual trajectory

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ABSTRACT

EMG-BASED DETERMINATION OF UPPER EXTREMITY VIRTUAL TRAJECTORY

by
Akshata Anand Korgaonkar

Movement and position of the limbs of the human body are controlled by the interaction between the muscle and the peripheral and central nervous system. This interaction is nothing but the neural signals. Neural signals are electrical in nature and referred as action potentials. An EMG is a summation of action potentials from the muscle fibers under the electrode placed on the skin. Thus it is easy to estimate the nature and timing of the movement from the firing of an EMG signal. Kai Chen in his dissertation has built the model to represent the arm movement with stiffness, damping, actual trajectory and Virtual Trajectory.

Virtual trajectory is the representation of the actual movement and thus its onset and offset timings are obtained on the basis of EMG. This study is the extension of the Chen study in order to automate the system by changing the subjective method of finding onset and offset timing of the VT to computational method by means of MATLAB.

EMG-BASED DETERMINATION OF UPPER EXTREMITY VIRTUAL TRAJECTORY

by
Akshata Anand Korgaonkar

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APPROVAL PAGE

EMG-BASED DETERMINATION OF UPPER EXTREMITY VIRTUAL TRAJECTORY

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Shree Gurudev Datta!!!

I would like to dedicate this thesis to my father “Mr. Anand Korgaonkar”, to my mother “Mrs.Smita Korgaonkar” and my sister “Sanyogita Korgaonkar”. There is no doubt in my mind that without their continued support and encouragement I could not have achieved this.

My strong belief and conviction in Almight GOD and HIS grace has made my dreams come true.

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CHAPTER 1

INTRODUCTION

1.1 Background

Many neuromotor studies suggest that human arm movement can be represented with the control parameters such as trajectories of dynamic equilibrium point in combination with specified damping and stiffness associated with each joint. Kai Chen, in his dissertation (Chen, 2010) has worked on such (Hinder Milner, 2003) motor control model which will be helpful in executing most of the human arm movement planning, not only for neurologically healthy subject but also for children with cerebral palsy. In this study he has built a model which takes inputs such as intrinsic damping, relative damping, stiffness, moment of inertia, θ (angle of movement in radian) and trajectories. Moment of inertia is been calculated using each subject's anthropometrics where as damping and stiffness are obtained by optimizing the model in order to get the good experimental match.

Feldman in his study (Feldman AG, 1986) was working on the mechanism by which the neural input to the muscle changes the movement of the limb. For this study he examined the elbow movement. When this elbow movement was displaced, muscle produced a monotonically increasing force with the characteristics that were similar to the non linear spring. Later it was examined that the CNS uses the time series of function that define a sequence of equilibrium states of the system based on the threshold (λ) of the tonic stretch reflexes of the participating muscle beyond which the muscle produces the force. Chen has followed this approach in which the gradually descending neuron

signal for a joint movement is a simple instantaneous difference between the arm's actual position and the equilibrium position specified by the neural activity which is nothing but the monotonic virtual trajectory. Chen has improved earlier model (Chen, 2009) with the addition of a feedback element which produces torque based on the difference between the actual joint and virtual trajectory velocities. To plot the VT he has visually assessed the timing and amplitude of EMG signal of agonist and antagonist muscle. A less subjective method is required to describe this VT.

1.1 Objective

Movement and position of the limbs of the human body are controlled by the interaction between the muscle and the peripheral and central nervous system. This interaction is nothing but the neural signals. Neural signals are electrical in nature and referred as action potentials. An EMG is a summation of action potentials from the muscle fibers under the electrode placed on the skin. Thus it is easy to estimate the nature and timing of the movement from the firing of an EMG signal. Since VT is the representation of the actual movement one can estimate the start time and end time from the EMG firing.

EMG signal is stochastic in nature and it always has the some amplitude ranging from -10 milivolts to 10 milivolts. When EMG signal is collected it also collects the motion artifacts and noise. Thus to estimate the start and end of the EMG, it is essential to process the data.

Kai Chen in his study has made use of EMG timings to obtain the virtual trajectory. He has done this manually, but due to EMG nature and its features data processing is essential; also manual estimation of these timings might not be accurate and

is not easy. Thus objective of this study is to process the data and obtain the start and end time of the VT using the MATLAB code.

CHAPTER 2

BASIC INFORMATION OF EMG

Movement and position of the limbs of the body are controlled by electrical signals traveling between the muscles and the peripheral and central nervous system. The path of conduction in the motor system consists of spinal cord, motor neurons, muscles and the neuromuscular junction. Electromyography (EMG) is a diagnostic measure used to record the electrical activity of the muscle to find abnormalities in muscle and motor system and interpret muscle action potential. It gives a voltage difference or difference in electrical potential (E=Ir) measured between recording electrodes. The signal's origins include electrical activity in various tissues like Potentials in motor units (muap) of muscle fibers.

2.1 Features of Raw EMG Signal

It is well established that the EMG signal is stochastic (random) in nature and is never zero in amplitude. The amplitude of the signal can range from 0 to 10 mV (peak-to-peak) or 0 to 1.5 mV (rms).The usable energy of the signal is limited to the 0 to 500 Hz frequency range, with the dominant energy being in the 250-500 Hz range. Usable signals are those with energy above the electrical noise level. An example of the frequency spectrum of the EMG signal is shown in Figure2.1.

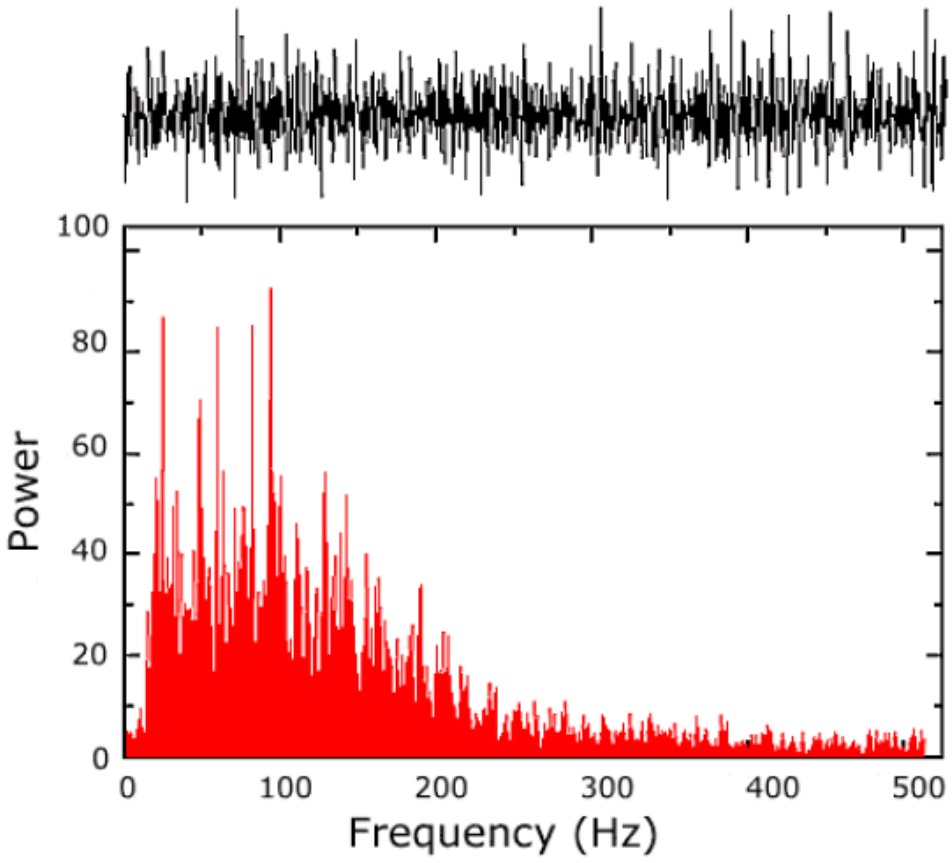

Figure 2.1 Frequency spectrum of the EMG signal detected from the Tibialis Anterior muscle during a constant force isometric contraction at 50% of voluntary maximum.(Source: Google image)

2.2 Application of the EMG Signal

Currently there are three common applications of the EMG signal. They are:

- To determine the activation timing of the muscle; that is, when the excitation to the muscle begins and ends.
- To estimate the force produced by the muscle.
- To obtain an index of the rate at which a muscle fatigues through the analysis of the frequency spectrum of the signal.

From the diagnostic EMG we could get the following information:

- Strength-duration curves to test nerve and muscle integrity

- Nerve conduction velocity to test for nerve damage / compression.
- Firing characteristics of motor neurons and motor units, including analysis of motor unit action potentials (muaps) to detect signs of pathology such as fibrillation potentials and positive sharp waves

2.3 Electrode Geometry

Throughout the history of electromyography, the shape and the layout of the detection surface of the electrode have not received much attention. Most likely past users of electromyography must have been interested only in the qualitative aspects of the EMG signal. The advent of new processing techniques for extracting quantitative information from the EMG signal requires greater focus on the configuration of the electrode. The major (but not all) points to consider are:

- The signal to noise ratio of the detected signal,
- The bandwidth of the signal,
- The muscle sample size, and
- The susceptibility to crosstalk.

2.3.1 Signal-to-Noise Ratio

The signal-to-noise ratio is a function of complicated interactions between the electrolytes in the skin and the metal of the detection surfaces of the electrode. This is an involved topic that is beyond the scope of this short treatise. Suffice it to say that there are several approaches for reducing the noise, such as using large surface areas for the detection surfaces, employing conductive electrolytes to improve the contact with the skin, and removing dead (less conductive) dermis from the surface of the skin.

The amplitude of the EMG signal is directly proportional to the distance between

the detection surfaces. Hence, this distance should be maximized. But, increasing this distance introduces undesirable characteristics to the electrode design. As the electrode becomes larger, it becomes unwieldy and cannot be used to detect EMG signals from relatively small (in width as well as in length) muscles such as those found in the hand, forearm and the leg. Thus, a compromise is necessary.

2.3.2 Muscle Sample Size

The muscle sample size need not be large because the muscle fibers of motor units are distributed throughout most of the muscle cross-section. Therefore, it is not necessary to cover a large portion of the muscle with the detection surface of the electrode to obtain a representative sample of the EMG signal for a particular set of active motor units.

2.3.3 Cross-talk Susceptibility

The susceptibility to cross-talk is an often overlooked design aspect of EMG electrodes. The greater the width and length of the detection surfaces and the greater the inter-detection surface distance the closer the electrode will be to adjacent muscles. Thus, larger electrodes are more susceptible to detecting signals from adjacent (lateral and below) muscles. In situations where this issue is of concern, it is advisable to reduce the size of the electrode.

2.4 EMG Electrode Placements

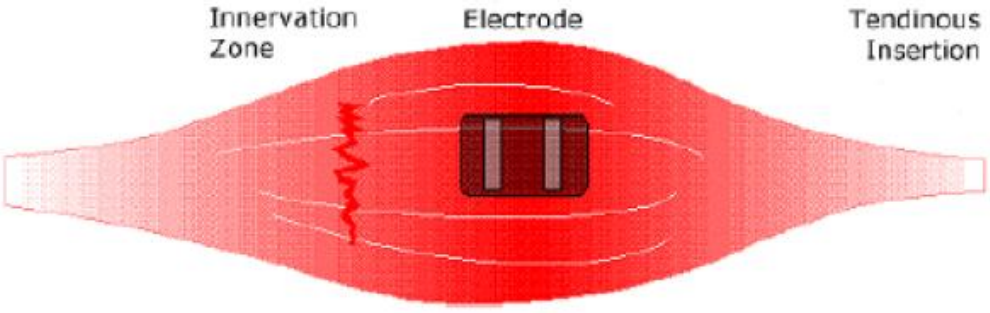

Figure 2.2 The preferred electrode location is between the motor point (innervations zone) and the tendinous insertion, with the detection surfaces arranged so that they intersect as many muscle fibers as possible. (Source: goggle image)

2.4.1 Location and Orientation of the Electrode

The electrode should be placed between a motor point and the tendon insertion or between two motor points, and along the longitudinal midline of the muscle. The longitudinal axis of the electrode (which passes through both detection surfaces) should be aligned parallel to the length of the muscle fibers. Figure 2.2 provides a schematic representation of the preferred electrode location.

2.4.2 NOT On or Near the Tendon of the Muscle

As the muscle fibers approach the fibers of the tendon, the muscle fibers become thinner and fewer in number, reducing the amplitude of the EMG signal. Also in this region the physical dimension of the muscle is considerably reduced rendering it difficult to properly locate the electrode, and making the detection of the signal susceptible to crosstalk because of the likely proximity of agonistic muscles.

2.4.3 NOT on the Motor Point

During the past one-half century it has been thought that for the purpose of detecting a surface EMG signal the electrode should be located on a motor point of the muscle. The motor point is that point on the muscle where the introduction of minimal electrical current causes a perceptible twitch of the surface muscle fibers. This point usually, but not always, corresponds to that part of the innervations zone in the muscle having the greatest neural density, depending on the anisotropy of the muscle in this region. Presumably, the motor points have been used as landmarks because they were identifiable and provided a fixed anatomical landmark. Unfortunately from the point of view of signal stability, a motor point provides the worst location for detecting an EMG signal. In the region of a motor point, the action potentials travel caudally and rostrally along the muscle fibers, thus the positive and negative phases of the action potentials (detected by the differential configuration) will add and subtract with minor phase differences causing the resulting EMG signal to have higher frequency components. In the time domain, the signal appears as more jagged and with more sharp peaks. The loss of stability occurs from the fact that a minor displacement (0.1 mm) will affect in an unpredictable fashion the amount of change in the frequency characteristics of the signal. A note of caution about the motor points and innervations zones, most muscles have multiple innervations zones throughout the muscle. They can be identified by applying electrical stimulation to the skin above the surface of the muscle or by other more technically complicated surface mapping techniques. If neither procedure is convenient, then place the electrode in the middle of the muscle between the origin and insertion point.

2.4.4 NOT at the Outside Edges of the Muscle

In this region, the electrode is susceptible to detecting crosstalk signals from adjacent muscles. It is good practice to avoid this situation. For some applications, crosstalk signals may be undesirable.

2.5 Orientation of the Electrode with Respect to the Muscle Fibers

The longitudinal axis of the electrode (which passes through both detection surfaces) should be aligned parallel to the length of the muscle fibers. When so arranged, both detection surfaces will intersect most of the same muscle fibers. Hence, the spectral characteristics of the EMG signal will reflect the properties of a fixed set of muscle fibers in the region of the electrode. Also, the frequency spectrum of the EMG signal will be independent of any trigonometric factor that would provide an erroneous estimate of the conduction velocity. The resultant value of the conduction velocity affects the EMG signal by altering the temporal characteristics of the EMG signal, and consequently its frequency spectrum.

2.6 Reference Electrode

The reference electrode (at times called the ground electrode) is necessary for providing a common reference to the differential input of the preamplifier in the electrode. For this purpose, the reference electrode should be placed as far away as possible and on electrically neutral tissue (say over a bony prominence).Often this arrangement is inconvenient because the separation of the detecting electrode and reference electrode

leads requires two wires between the electrodes and the amplifier. It is imperative that the reference electrode make very good electrical contact with the skin. For this reason, the electrode should be large (2 cm x 2 cm). If smaller, the material must be highly conductive and should have strong adhesive properties that will secure it to the skin with considerable mechanical stability. Electrically conductive gels are particularly good for this purpose. Often, power line interference noise may be reduced and eliminated by judicious placement of the ground electrode.

2.7 Causative Factors that Affect the Quality of EMG Obtained

The causative factors are those which have a basic or elemental effect on the signal. These are divided into two groups: extrinsic and intrinsic. The extrinsic causative factors are those associated with the electrode structure and its placement on the surface of the skin above the muscle. They include:

- The electrode configuration which describes:
  - the area and shape of the electrode detection surfaces which determine the number of active motor units that are detected by virtue of the number of muscle fibers in their vicinity;
  - the distance between the electrode detection surfaces which determines the bandwidth of the differential electrode configuration;

- The location of the electrode with respect to the motor points in the muscle and the myotendonous junction which influences the amplitude and frequency characteristics of the detected signal.

- The location of the electrode on the surface of the muscle with respect to the lateral edge of the muscle which determines the possible amount of crosstalk that may be detected by the electrode; and

- The orientation of the detection surfaces with respect to the muscle fibers which affects the value of the measured conduction velocity of the action potentials and, consequently, the amplitude and frequency content of the signal.

The intrinsic causative factors are the physiological, anatomical and biochemical characteristics of the muscle. Unlike the extrinsic factors, they cannot be controlled due to limitations of current knowledge and technology. They include:

- The number of active motor units at any particular time of the contraction which contributes to the amplitude of the detected signal;
- The fiber type composition of the muscle which determines the change in the pH of the muscle interstitial fluid during a contraction;
- The blood flow in the muscle which determines the rate at which metabolites are removed during the contraction;
- The fiber diameter which influences the amplitude and conduction velocity of the action potentials that constitutes the signal;
- The depth and location of the active fibers within the muscle with respect to the electrode detection surfaces -- this relationship determines the spatial filtering, and consequently the amplitude and frequency characteristics, of the detected signal;
- The amount of tissue between the surface of the muscle and the electrode which affects the spatial filtering of the signal; and

The length of the depolarization zone and ionic fluxes across the membrane, etc are factors that are yet to be identified. In this category, the firing characteristics of the motor units (which include the behavior of the firing rates of the motor units and any interaction among the firing rates, such as synchronization of motor unit firings) and the motor unit twitch are also included. These latter causative factors are presented in a dashed-line box because although they are causative, they are also deterministic in that they affect the EMG signal directly. The intermediate factors represent physical and physiological phenomena which are influenced by one or more of the causative factors, and in turn influence the deterministic factors. These include:

- The band-pass filtering aspects of the electrode which is an inherent characteristic

of a differential electrode configuration;

- The detection volume of the electrode which determines the number and weight of the motor unit action potentials that compose the signal;
- Superposition of action potentials in the detected EMG signal which influences the characteristics of the amplitude and frequency of the signal;
- Crosstalk from nearby muscles which contaminates the signal and may mislead the interpretation of the information in the signal;
- The conduction velocity of the action potentials that propagate along the muscle fiber membrane; the conduction velocity affects the amplitude and frequency characteristics of the signal; and
- The spatial filtering effect due to the relative position of the electrode and the active muscle fibers.

The latter two factors are emphatically important because they dramatically affect the characteristics of the signal. As the distance between the active fibers and the electrode detection surfaces varies, two important concerns arise. Firstly, the spatial filtering characteristics of the detection arrangement change, thus altering the amplitude and frequency characteristics of the motor unit action potentials (MUAPs) which are within the detection volume of the electrode. Secondly, the relative movement of the electrode and the active fibers may be sufficient to place a new set of active motor units within the detection volume of the electrode and to remove some of the motor units from the detection volume. This consideration requires that if the muscle fibers change length during a contraction, then the electrode position must change similarly. With current detection techniques, it is difficult to satisfy this requirement because the electrode is affixed to the surface of the skin which does not change length in concert with the muscle fibers during a contraction. Thus, for practical reasons, signal stability can only be approached if the contraction remains isometric. If signal stability is not a consideration

for the analysis being performed, such as determining the activation time, then the limitation of the isometric contraction need not be a concern. The deterministic factors are those which have a direct bearing on the information in the EMG signal and the recorded force. These include:

- The number of active motor units,
- The motor unit force-twitch,
- The mechanical interaction between muscle fibers,
- The motor unit firing rate,
- The number of detected motor units,
- The amplitude, duration and shape of the MUAPs, and
- The recruitment stability of motor units.

When one studies the rich and convoluted interaction between the many factors that influence the information content of the EMG signal, it is reasonable to ask if there is any hope of using the EMG signal in a constructive fashion to describe the state of the muscle. The answer is a confident "yes" for some applications and a guarded "maybe" for other applications. For example, we can have confidence in measurements where an electrode, which does not detect significant crosstalk from adjacent muscles, is placed on the surface of the muscle between the innervations zone and the myotendonous junction for the purpose of:

- Determining, in a particular subject, when the muscle turns "on and off" or
- Describing if the muscle is increasing or decreasing its force output over a period of time when the fatigue processes of the muscle do not significantly affect the characteristics of the signal. If, however, the circumstances change from this specific condition, the interpretation becomes complicated and caution is required.

2.8 Correlation of EMG with Virtual Trajectory Timings

As mentioned earlier EMG is an indication of muscle fiber depolarization and is therefore describing the activity of muscle.

$$I\ddot{\theta} + B(\dot{\theta} - \dot{\theta}_{vt}) + K(\theta - \theta_{vt}) + B_i(\theta) = 0 \qquad (2.1)$$

Equation (2.1) shows that activation and braking of joint action is described by active viscous damping (B) stiffness (K) and is $B_i(\theta)$ passive damping which is due to the muscle property. i.e. EMG results from $B(\dot{\theta} - \dot{\theta}_{vt})$ and $K(\theta - \theta_{vt})$. Hence EMG can be present only when $(\dot{\theta} - \dot{\theta}_{vt})$ and/ or $(\theta - \theta_{vt})$ are non zero.

Assuming that prior to movement ($\theta \cong \theta_{vt}$), EMG in both agonist and antagonist muscle groups is minimum. A change in EMG amplitude relative to the minimum resting EMG thickness indicates a non- zero ($\dot{\theta} - \dot{\theta}_{vt}$), and/or ($\theta - \theta_{vt}$). Observations of the this experimental data showing joint trajectories and agonist EMG shows onset of the EMG burst prior to the onset of movement. This is referred to as the physiologically well established neuromuscular delay (Chen, 2010). A gradually descending signal must have arrived at this muscle to initiate the change in EMG. Following this EPH model put forth by Chen, this onset time of the Agonist indicates the latest time at where VT can begin.

Just before VT starts, ($\theta - \theta_{vt}$) and ($\dot{\theta} - \dot{\theta}_{vt}$) is equal to zero and as soon as VT starts this becomes greater than zero. For this term to become non zero the slopes of theta and VT must either be different (different velocity) or theta and VT must be separated.

Also as VT further approaches $\dot{\theta}_{vt}$ becomes zero and $\dot{\theta}$ is maximum this is nothing but the point at which velocity peak and experiment peak shows that at this point antagonist EMG reaches to its maximum amplitude which is taken as the offset of the EMG.

Agonist and antagonist EMG roughly refers to the torque pattern as sinusoidal waveform. However, due to co-contraction, we say that agonist and antagonist bursts are not exclusively on and off. This constitutes the overlap. Hence onset of antagonist EMG cannot be used to determine the VT.

CHAPTER 3

RESEARCH DESIGN, HARDWARE AND METHODS

This study is extension of the Chen study. In order to obtain the accurate VT and to compare it with Chen's result after obtaining manually, same data is processed in this study. Chen has collected data from neurologically intact college students. All of them were healthy right handed subjects. They were informed about the experiment and were allowed to do five practice sessions in order to get the exact idea of the movement and speed.

3.1 Research Design

In his design subject was asked to sit in to the chair comfortably, facing to the table. An adjustable arm support was attached on the table top and subject was supposed to rest arm on it. Movement positions were marked on the table as shown in figure. Buzzer was used to indicate the start of the movement.

Two computers were used in the experiment, one was for controlling and initializing the haptic master and other was for data collection and EMG amplification. EMG from two muscles, position and force was recorded during each trial for all subjects. Both the computers were synchronized and kept ready before each trial. Few practice trials were carried before collecting the data to check the subjects comfort. To track the position and orientation of each segment trackstar sensor was mounted on haptic master cylindrical handle.

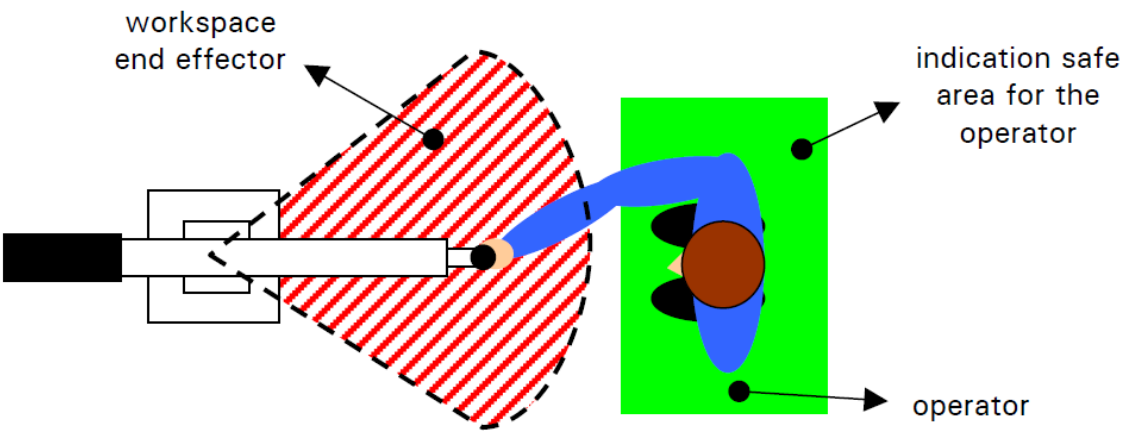

Figure 3.1 Experimental Design (Cited from Chen, 2010).

3.2 Electrode Placement

In order to collect proper EMG signal it's highly important where we place the electrodes. Four electrodes were used for collecting EMG signal in Chen study. Two electrodes were placed on biceps, with 3cm distance in between and other two on triceps again with 3 cm distance. One electrode was used as ground/reference electrode and was placed on shoulder. Ground /reference electrode is necessary for providing a common reference to the differential input of the preamplifier in the electrode.

Bellies of the biceps and triceps were cleaned with alcohol swabs before placing the electrodes, to ensure the better signal to noise ratio there by reducing the skin resistance. Pre-gelled general purpose electrocardiographic adhesive electrodes were used.

3.3 Hardware

For above mentioned design, following instruments were used in Chen study.

- EMG system
- Trackstar position measurement system
- Haptic Master (HM)

3.3.1 EMG System

A Grass Technologies® Model 15LT Bipolar Physiodata Amplifier System was used in the study. The Model 15A54 and 15A94 Quad Neuro-amplifiers, in the long line of high performance amplifiers from Grass are designed specifically for neuro-physiological measurements. The 15A54 has extended high frequency response to 6 kHz. The 15A94 has high frequency response to 100 Hz, suitable for clinical applications in EEG and PSG. This EMG system was used to collect the EMG from four electrodes and to amplify it.

3.3.2 Trackstar Position Measurement system

Figure 3.2 shows the Trackstar position measurement system. This system uses a sensor to track the arm movement. Sensor was attached to the handle of the HM. Sensor and transmitter has to align in proper direction before collecting the data. The data collection program was used with this system. Programming was done in MATLAB by Kai Chen. With the data obtained from trackstar, time vs. radian plot can be obtained and is used to find the θ . θ is the difference between starting angle and the angle at the end of the arm

movement in radian. θ is also used as one of the input in the model. Also upper threshold

Figure 3.2 TrakSTAR Device Introductions from Ascension Technology.

value is estimated from this system which is used to optimize the experimental result in model.

3.3.3 Haptic Master (HM)

The Haptic MASTER is 6 degrees of freedom, force-controlled haptic interface. It provides the user with a crisp haptic sensation and the power to closely simulate the weight and force found in a wide variety of human tasks. The programmable robot arm utilizes the admittance control (force control) paradigm, giving the device unique haptic specifications.

The workspace of the Haptic MASTER is depicted in Figure 3.3. The kinematic chain from the bottom up yields: base rotation, arm up/down, arm in/out, illustrated in Figure 3.3. This makes 4 degrees of freedoms at the end effectors, which spans a volumetric workspace.

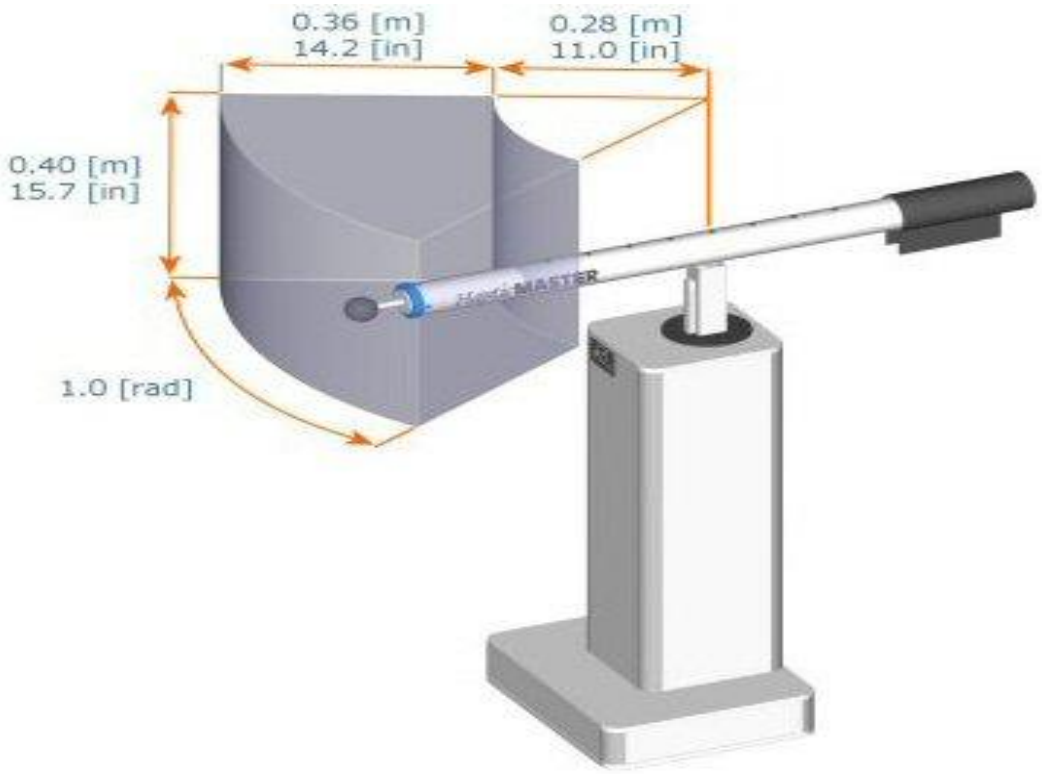

Figure 3.3 Haptic MASTER Workspace (cited from H3D, 2010).

Table 3.1 Specification of the Haptic Master (cited from H3D, 2010).

Position resolution	$4x10^{-6}$ - $12x10^{-6}$ [m]	1.6 X 10^{-4} [in]
Stiffness	$10x10^{3}$ - $50x10^{3}$ [N/m]	285.5 [lbf/in]
Nominal/max force	100/250 [N]	22.5/56.2 [lbf]
Minimal tip inertia	2 [kg]	4.4 [lb]
Maximum velocity	1.0 [m/s]	39.4 [in/s]
Maximum deceleration	50 [m/s^2]	39.4 [in/s^2]
Force sensitivity	0.01 [N]	$2.25x10^{-3}$ [lbf]

Source:http://www.h3dapi.org/modules/mediawiki/index.php/MOOG_FCS_HapticMASTER

The Haptic MASTER measures the Cartesian forces exerted by the subject, measured close to the human hand, with a sensitive force sensor. An internal model then calculates the Cartesian Position, Velocity, and Acceleration (PVA), for which a (virtual) object touched in space would behavior as a result of this force. The PVA-vector is commanded to the robot, which then makes the movement by means of a conventional control law. The general control algorithm is illustrated in Figure 3.4. The internal model typically contains a certain mass, to avoid commanding infinite accelerations. The inner servo loop cancels the real mass and friction of the mechanical device.

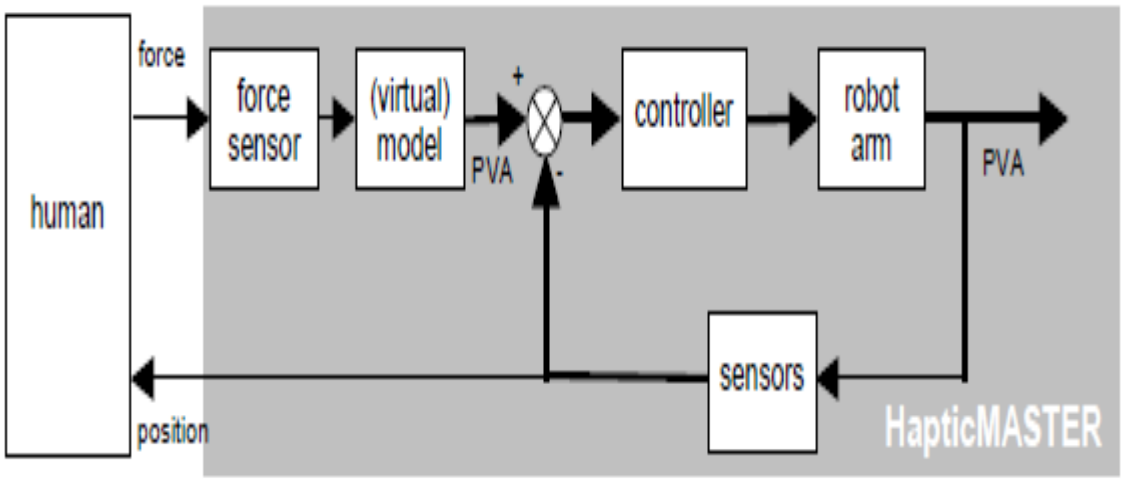

Figure 3.4 The General Control Scheme of the Haptic MASTER Comprises an Outer Control Loop, and an in Inner Servo Loop. A (virtual) model converts the force sensor signal to a Position/Velocity/Acceleration set point vector. The inner servo loop controls the robot to the PVA set point values (Vander Linde, 2002).

The Cartesian velocity, position and forces of the robot's endpoint are measured 1000 HZ are available as output via the Haptic MASTER Application Programming Interface (API). The API allows one to program the robot to produce haptic effects, such as spring, damper and constant force and to create haptic objects like blocks, cylinders and spheres as well as walls, floors, ramps and complex surfaces. These effects can be used to provide a haptic interface with realistic haptic sensation that closely simulates the forces found in upper extremity tasks (Adamovich et al., 2009).

An important goal for the utilization of the Haptic Master was to take advantage of its multi-planar, 3-D workspace. To accomplish this goal and to accommodate subjects with both normal subject and the subject with a variety of impairments it was necessary to design several mechanical attachments to interface the upper extremity with the Haptic Master robotic arm (Adamovich et al., 2009). The Haptic MASTER can be fitted with any customized end effectors, facilitating different applications. Any self-made end effectors below 3 kg can be mounted at the end of the Haptic MASTER robot arm. Two different sized forearm supports were fabricated for different arm shape and one universal articulating arm support was purchased to support the forearm effectively, counteracting gravity. Subjects with arm function simply grasp a stationary 1.2 inch diameter, 6 inch height cylinder connected to the Haptic Master. The HM was programmed by Chen using a set of MATLAB functions (written by Ramirez) that implemented the HM's C++ functions.

3.4 Methods

In Chen study, he collected data from 10 subjects in four methods.

- Unobstructed Fast Elbow Movement without Haptic Master
- Unobstructed Fast Elbow Movement with Haptic Master
- Unexpected Perturbed Movement
- Arrested Arm Movement

During these methods he collected raw EMG from biceps and triceps muscle, force, angular displacement in radians, HM force and position. Using this data he built the model for unobstructed fast elbow movement with HM. In the model (figure 3.5) he has entered all anthropometric data, starting time of the movement (estimated from the actual virtual trajectory, fig 3.6), saturation of the actual trajectory (estimated from the trackstar position plot) and to obtain VT plot, slope was calculated using the difference of starting and end point and dividing it to the saturation (manually estimated from the EMG). The main goal

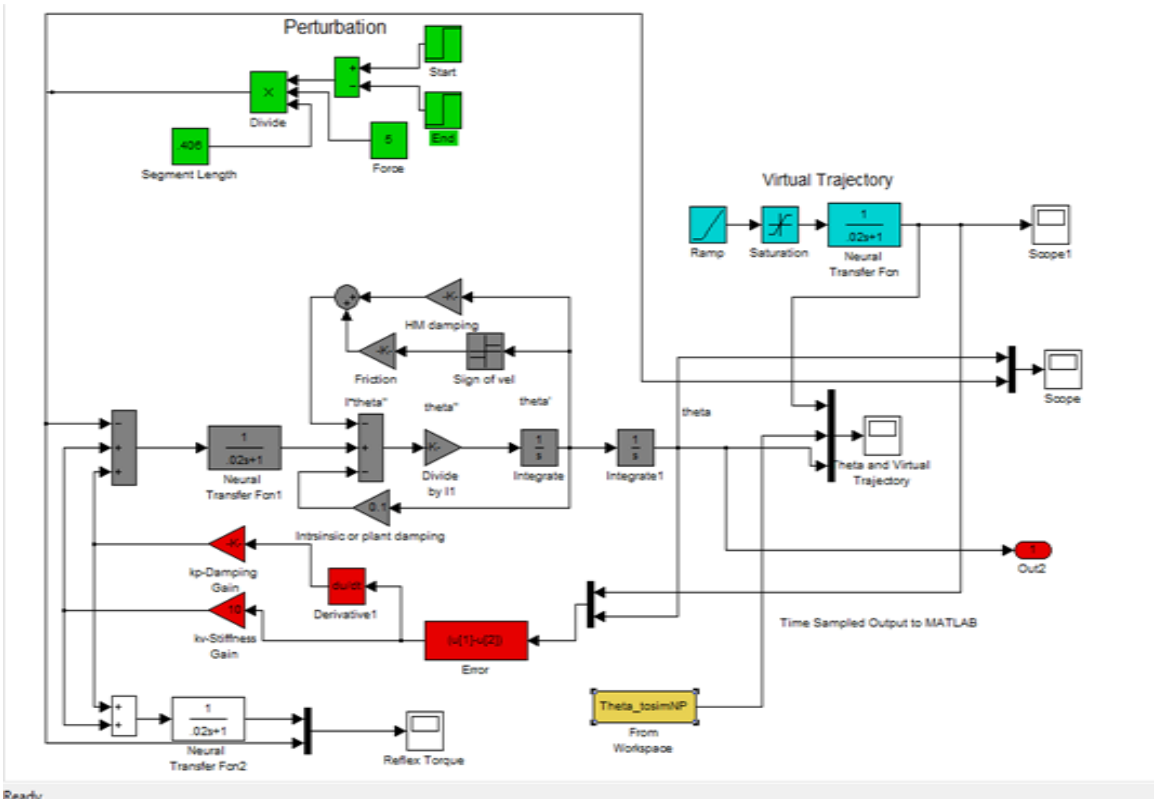

Figure 3.5 Simulink Model.

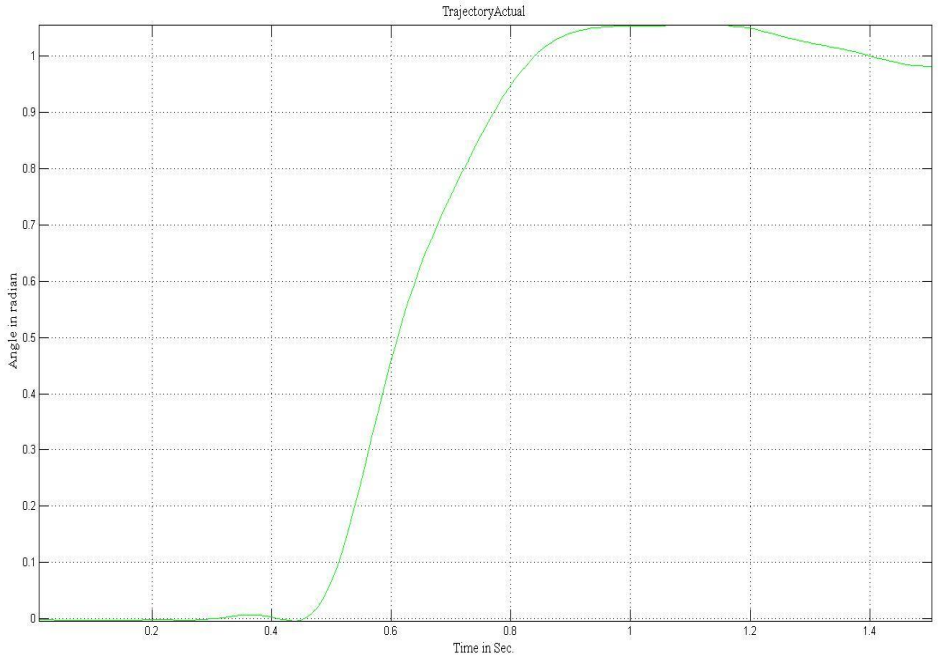

Figure 3.6 Actual Trajectory.

of the model was to replicate the actual trajectory in order to prove the efficiency of the model in planning the arm movement.

CHAPTER 4

DATA PROCESSING AND MATLAB PROGRAMMING

4.1 Data Processing

In order to obtain reliable data, the calibration of the system was necessarily done in Chen study. He ran the system calibrations before the data collection, with procedures including calibrations of EMG, trakSTAR, HM and device synchronization hardware and programs. The typical calibration results are shown in the Figure 4.1.

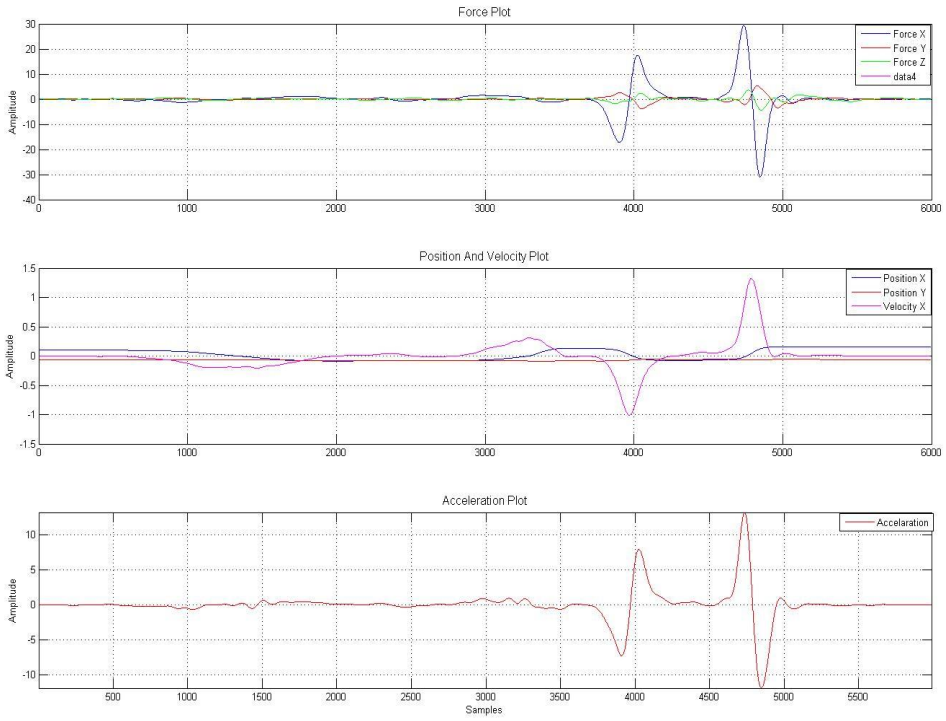

Figure 4.1 The Calibration of HM Forces, trakSTAR Positions and System Synchronization (cited from Kai 2010).

4.2 Trouble Shooting in Data Collection System

In the data obtained by the Chen, (Figure 4.2) the noise of EMG was found to be much higher than the expected. It seems that the strength of signal was weaker than the noise,so the signal had been covered by the noise. The source of noise has been concluded to be from the transmitter of trackStar. After investigation, moving the trackStar transmitter to its 1 meter expired range can lead to inaccurate data, although it significantly reduced the EMG noise.

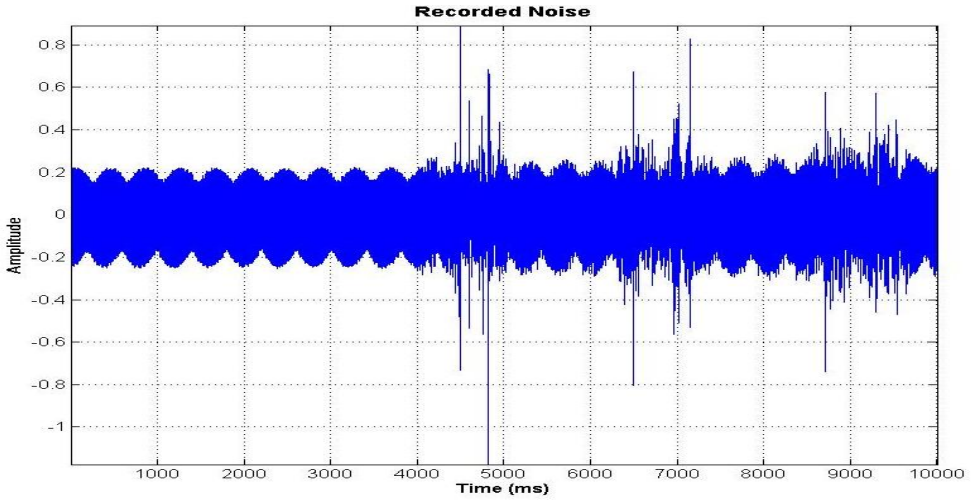

Figure 4.2 the Recorded Environmental Noise.

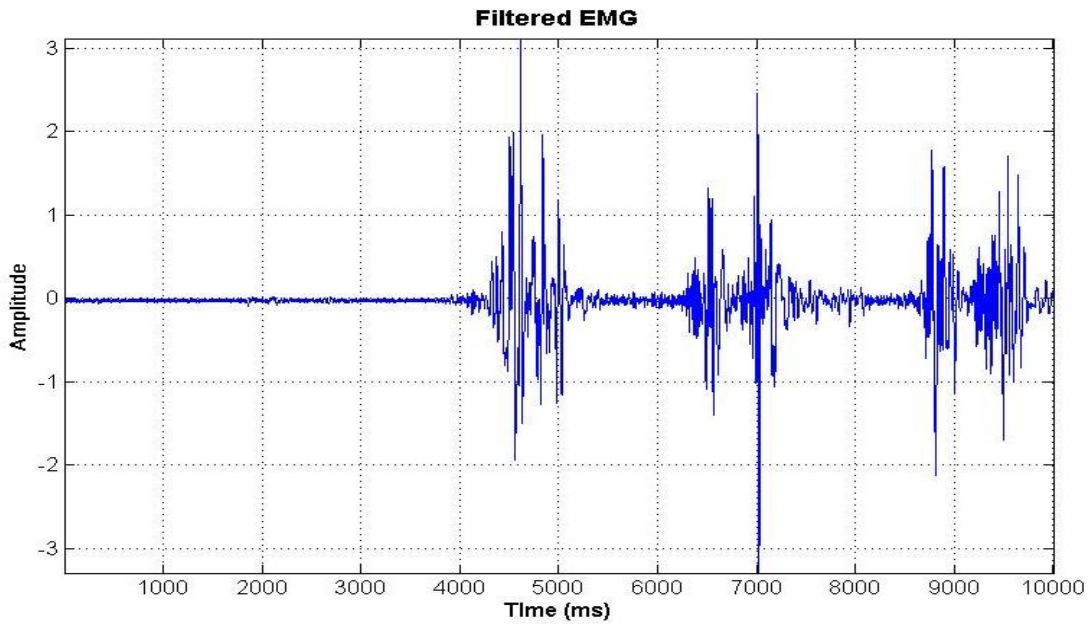

Figure 4.3 the Filtered EMG Signal.

Thus after getting raw data from Chen, each trail was analyzed and was filtered using 6th order Butterworth filter. As mentioned earlier for each subject 5 to 6 trials were recorded out of these trials good trials were selected for father processing.

4.3 Synchronization Details

Chen in his study optimized the onset and offset timings after synchronizing the data with trackstar position data. Thus in this study after obtaining the timings from the program, synchronization delay was added to it to get the correct start and end time. To calculate the synchronization delay timing of the start of the data collection for HM was checked. Then using this factor, matrix was obtained in which EMG starting time and HM data collection time was represented. First value of this particular matrix was the synchronization delay. Hence it was added to the time estimated by the program.

4.4 Programming Detail

Filtfilt command is used in the program for filtering the raw EMG. Filtfilt performs zero-phase digital filtering by processing the input data, both the forward and reverse directions. The result has the following characteristics:

- Zero-phase distortion
- A filter transfer function, which equals the squared magnitude of the original filter transfer function
- A filter order that is double the order of the filter specified by b and a.

Filtfilt minimizes start-up and ending transients by matching initial conditions, and can be used for both real and complex inputs. Cut of frequencies used for low pass filter and high pass filter are 10Hz and 500 Hz respectively.

4.4.1 Starting Point

The majorities of studies evaluating the EMG do not report the methods used for the identification of EMG onset (Belenkii et al, 1967). In studies where the EMG onset determination method is described is usually performed by the visual evaluation of the EMG trace, generally without reporting the criteria on which this visually determined decision is made. Several studies reports criteria such as the earliest detectable rise in EMG activity above the steady state (Bowrsset and Zottarer, 1981) or the point where the signal first deviates, more than 1.5 to 2 Standard Deviation from the level recorded during the steady state. Some of the studies have also estimated it by using baseline of the EMG signal and multiplying it by some factor and then compared it to get the rise (Studenski et al, 1991).

Primarily looking at the previous study majority of them has dealt with the initial signal just before the actual movement as a basic element to estimate the major change in the amplitude of the EMG. Thus from the history of obtaining the onset and from the nature of EMG obtained from the subjects, the onset of EMG is nothing but the earliest detectable rise. As stated in the chapter 2, EMG amplitude is never zero to obtained the exactact rise in amplitude of EMG following algorithm is been used in this study.

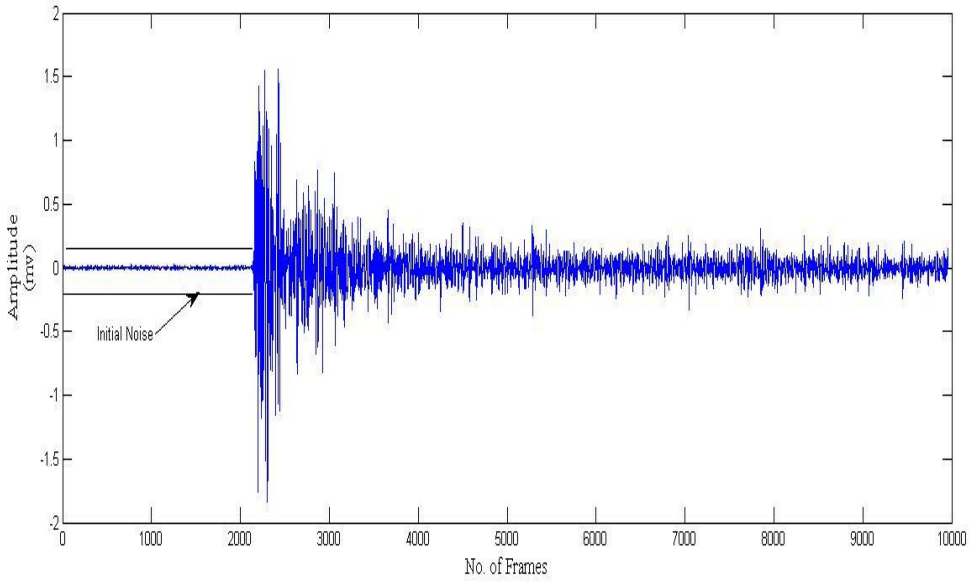

Figure 4.4 Standard deviation of the low amplitude EMG.

- After filtering the EMG data, standard deviation of the initial low amplitude EMG (signal obtained during resting arm) was obtained (fig.4.4).
- MATLAB function std was used to calculate the standard deviations and saved as a. Later this result was multiplied by 2.
- Then each point of the EMG signal was compared with (2*a) to check the deviation of the signal amplitude from this factor and all results were saved.
- Matrix was made of this results using temp (t).
- Finally the first value of this matrix which is nothing but the deviation of the signal from the resting signal was divided by 1000 to get the actual time and

displayed as the start point of the EMG. It was divided by 1000 because during data collection sampling frequency was 1000 Hz.

- The first value of t_emg matrix (synchronization delay) was then added in the final result obtained from the temp (1) and the starting point was displayed.

MATLAB Code

```
%%Starting Point of EMG

clc

clear all

%%Loading the EMG data saved in text format

data1=load('mar51.txt');

%% Filetering the data using butterworth filter

[Bh Ah]=butter(6,2*10/1000,'high');

[Bl Al]=butter(6,2*500/1000,'low');

dh=filtfilt(Bh,Ah,data1);

dl=filtfilt(Bl,Al,dh);

plot (dl)

%% Obtaining the standard deviation of initial points

a=dl(1:2000);

b=std(a,1);

c=size(dl);

t=1;

%%Comapring each point of EMG with the 2*b

for i=1:c
```

```
        if dl(i) >(b*2);
        temp(t)=i;
        t=t+1;
    end
end
%Synchronization
%%sync function is made to calculate the t_emg matrix for synchronization
starting_point =(temp(1)+(t_emg(1)))/1000;
display(starting_point)
```

4.4.2 End Point

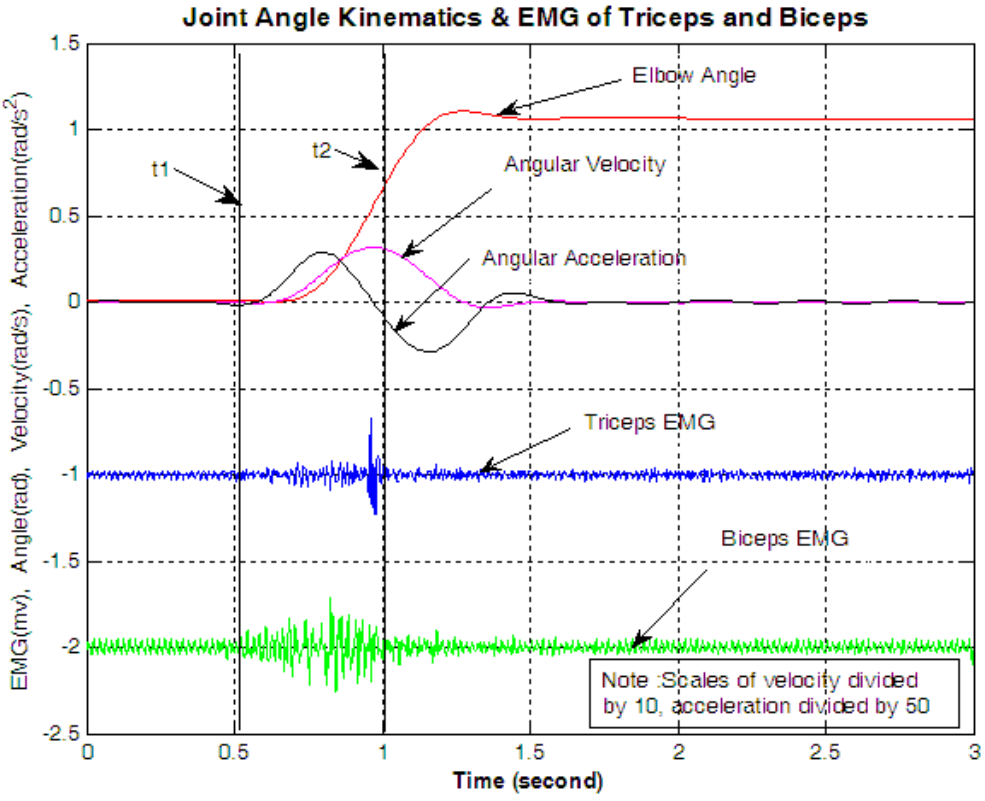

Figure 4.5 Joints angle kinematics and EMG of Triceps and Biceps with start time and end time of VT (Cited from Chen, 2010).

According to Chen study t_1 is the start and t_2 is the end point of VT (figure 4.5). As mentioned in earlier chapter VT offset time occurs at the peak of the velocity of the actual trajectory (Ghafouri and Feldman, 2001).

Experimental result shows that peak velocity occurs at the peak of antagonist EMG. Hence in this study peak of the antagonist EMG is taken as the end point of the VT. Following algorithm is used in this study to find the respective end point.

- After filtering the EMG data envelope was obtained using Butterworth filter with cut off frequency 2 and order 6.envelope was obtained in order to get the linear plot of the signal.

- Each point of envelope was then compared with the next subsequent point until the peak point is obtained.
- This peak point was then divided by 1000 to get the actual end point. 1000 was selected since the sampling frequency during data collection was 1000 Hz.
- For synchronization first value of t_emg was added in to the peak point to get the actual end point.

MATLAB code

```
%%End Point

close all

clear all

%%Loading the data

data1= load ('nap22.txt');

%%Filtering using butterworth filter

[Bh Ah]=butter(6,10/1000,'high');

[Bl Al]=butter(6,2*500/1000,'low');

 dh=filtfilt(Bh,Ah,data1);

dl=filtfilt(Bl,Al,dh);

%%To plot the envelope

[Be Ae]=butter(6,2*2/1000);

de=filtfilt(Be,Ae,abs(dl));

figure

plot (dl)

hold on

plot(de,'r')
```

```
 a=size(d);
 t=1;
 %% Comapring each point of envelope to get the maximum point
for i=2:(i+1):a-1
  if de(tend)<=de(i)
     t=i;
  end
end
%% Synchronization using sync function
end_point =(tend+(t_emg(1)))/1000;
display(end_point)
```

After obtaining the t_1 and t_2 from the MATLAB program, they were compared with the manual data. Also virtual trajectory plot was plotted for two subjects to check the accuracy of the program. Detailed results are shown in later chapter.

CHAPTER 5

RESULT AND DISCUSSION

5.1 Results

After estimating the t_1 and t_2 from the MATLAB code for all the subjects they were compared with the manually obtained values. Table 5.1 shows the tabulated data of manually and automatically obtained values and the difference between both. Average of the absolute difference was taken and it was approximately 67 msec for t_1 and 28msec for t_2.

Table 5.1 Comparison of Hand and Automatically obtained t_1 and t_2.

Subject	t_1_Hand	t_1_Code	Diff in t_1	t_2_Hand	t_2_Code	diff in t_2
S1	0.97	1.01	0.04	1.67	1.66	0.01
S2	2.32	2.32	0	2.744	2.77	0.026
S3	2.32	2.34	0.02	2.81	2.808	0.002
S4	2.232	2.3	0.068	2.67	2.63	0.04
S5	0.96	1.09	0.13	1.642	1.61	0.032
S6	3.96	4.08	0.12	4.5	4.47	0.03
S7	3	3.1	0.1	3.68	3.7	0.02
S8	2.55	2.6	0.05	3.11	3.16	0.05
S9	1	1.06	0.06	1.5	1.54	0.04
S10	3.23	3.31	0.08	3.63	3.6	0.03

Later using MATLAB graphs are plotted to show the comparison of hand obtained and automatically obtained t_1 and t_2. Figure.5.1 and figure 5.2 shows the graph for t_1 and t_2 respectively. From graph it is clear that the difference between hand obtained and automatically obtained values is negligible.

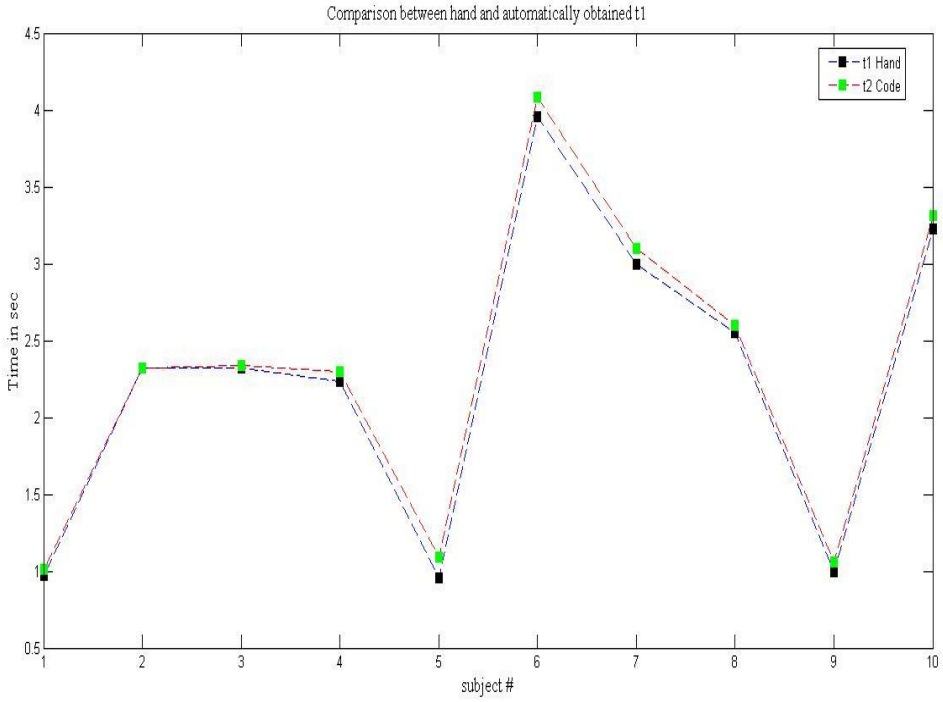

Figure 5.1 Comparison between hand and automatically obtained t_1.

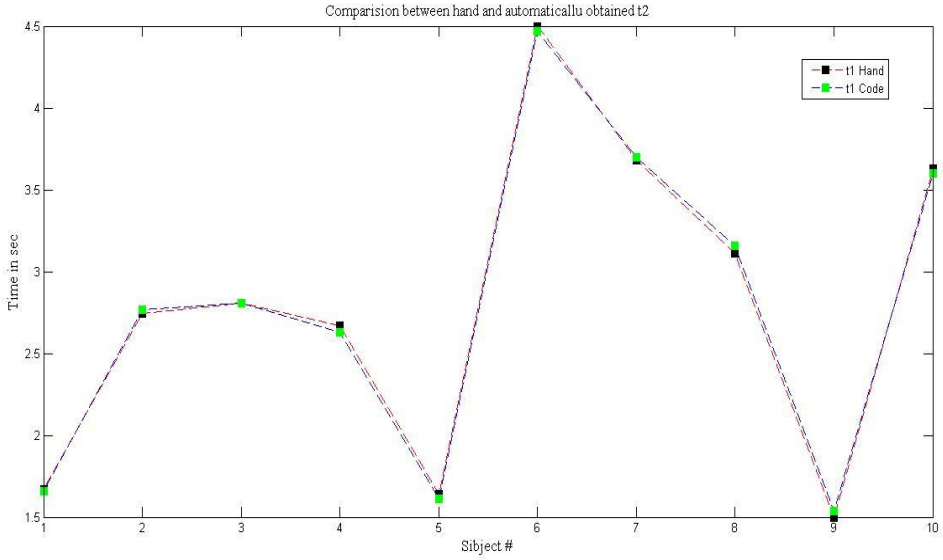

Figure 5.2 Comparison between hand and automatically obtained t_2.

Table 5.2 Paired T- test for t_1.

Paired T for t_1_Hand – t_1_code							
	N	Mean	STD	SE Mean			
t_1_Hand	10	2.253	1.023	0.323			
t_1_Code	10	2.321	1.032	0.326			
Difference	10	-0.0668	0.0419	0.0133			
95% CI for mean difference: (-0.0968, -0.0368)							
T-Test of mean difference = 0 (vs not = 0): T-Value = -5.04 P-Value =0.001							

Also paired T-Test was taken for the both the hand obtained and automatically obtained t_1 and t_2. Table 5.2 shows the result of the paired test. From the results it is clear that t_1 hand obtain values and automatically values are significantly values. Whereas for $t_{2,}$ (Table 5.3) there was no significant difference; also hand estimated t_1 values are little before the automatically obtained $t_{1.}$

Table 5.3 Paired T- test for t_2.

Paired T for t_2_Hand – t_2_code						
	N	Mean	STD	SE Mean		
t_2_Hand	10	2.795	0.988	0.312		
t_2_Code	10	2.796	0.983	0.311		
Difference	10	0.0008	0.0328	0.0104		
95% CI for mean difference: (-0.0227, 0.0243)						
T-Test of mean difference = 0 (vs not = 0): T-Value = 0.08 P-Value = 0.940						

Thus to check the accuracy of the MATLAB, VT was obtained from automatically obtained timings and it was plotted next to hand estimated VT. Figure 5.3 shows the comparison of both the VT. In the figure blue color line shows the hand estimation and red line shows the automatic estimation of VT. There was slight difference in the slopes, but the automatically obtained VT is more parallel to actual trajectory as compared to that of the hand estimated VT.

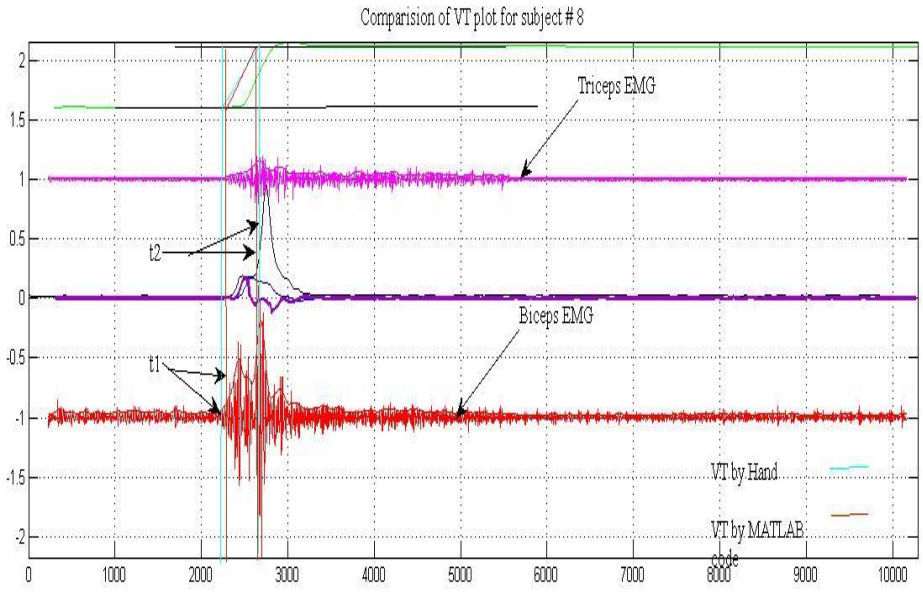

Figure 5.3 Comparison of VT plot using hand and automatically obtained values for subject # 8.

Further automatically obtained timings were put in to the model to see the model output. In the model, ramp block is used to input the slope for the VT. Slope is calculated by dividing the saturation time of actual trajectory by the difference of t_2 and t_1. Thus for subject # 4 calculated slope by hand determined values was 2.17 and that of values obtained by program was 2.31.

Table 5.4 Model Results for Subject #4.

	Before Optimization		After Optimization	
	Hand	Code	Hand	Code
SSE	0.36	0.3	0.33	0.29
Damping	6.5	6.5	7	6
Stiffness	16	16	22	19

Table 5.4 illustrates the result of the model before optimization and after optimization. For both the time SSE (sum square error for actual trajectory and modeled trajectory) with hand estimated timings were higher than the automatically obtained time. This indicates that the automatically obtained timings are more accurate than the manually estimated values. After optimization new damping (B) and stiffness (K) values were obtained. There was approximately 10% to 15 % change in the B and K values. Figure 5.4 shows the model result of both the inputs. The plots are almost similar to each other.

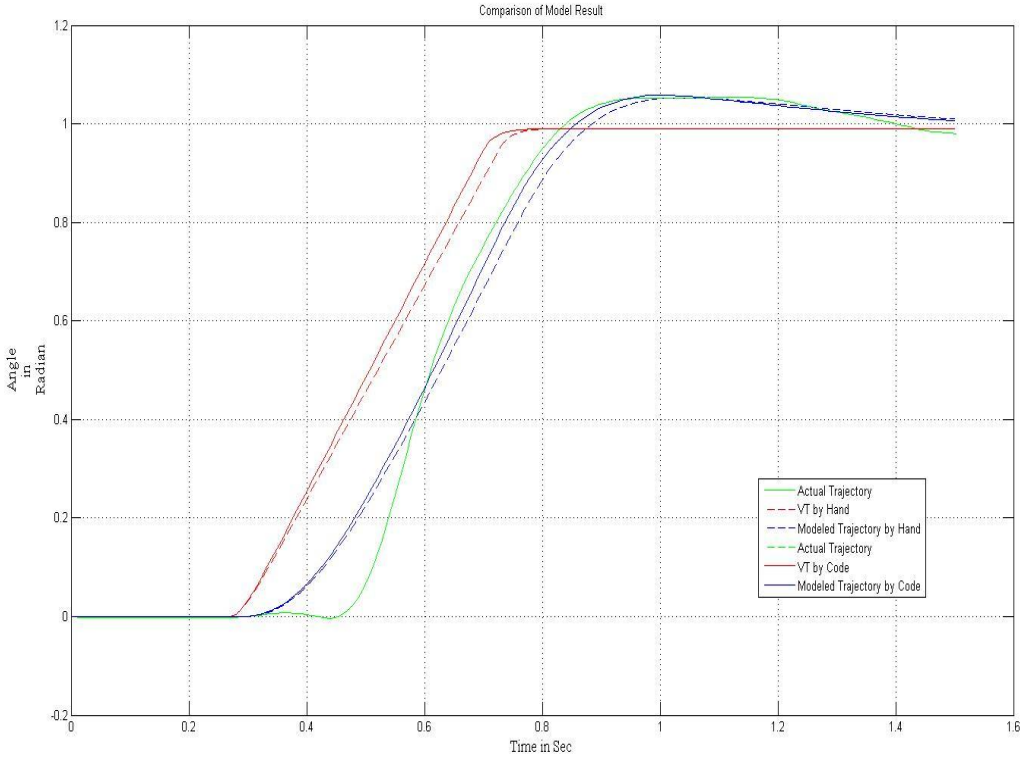

Figure 5.4 Model output.

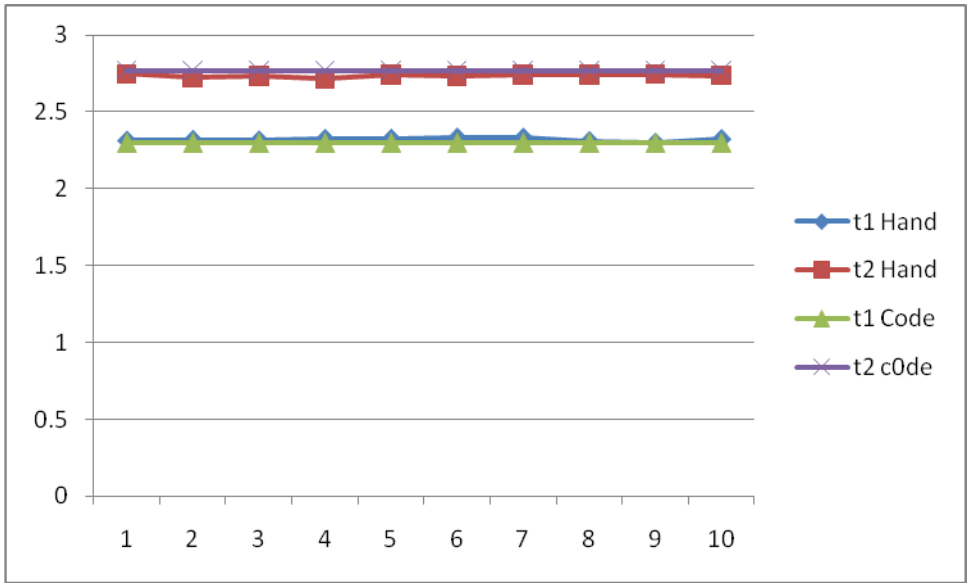

Figure 5.5 Hand estimated t_1 and t_2 for one subject done for several time to see the range.

Finally to check how close the automatically obtained timing to the hand estimated timing, 9 hand estimations were done and plotted. Result shows all of them were close to the automatically estimated timings (Automatically obtained t_1 = 2.300 sec and t_2=2.774 sec).

5.2 Discussion

Muscle co-contraction or co-activation is primary means by which the nervous system stabilizes the position of the limb. With this fact a relative damping model, for the planning of the limb movement was designed. As mentioned earlier stiffness, damping and trajectories plays an important role to replicate the movement of limb. In Chen 2010, he has enhanced this model with an EMG based determination of virtual trajectory and with physiologically realistic delays. In his study he used the perturbed and arresting movement to prove that the control parameters (VT, damping, stiffness) remains almost same even though kinematics and EMG changes.

In this study on set and off set time of VT is obtained automatically to improvise the model output and then analyzed to see if the automated system gives the same result. To verify this all subjects hand estimated and automatically obtained timings were compared; also the model result was analyzed to check the accuracy of the automated system. All the result shows that the automatically obtained timings are more accurate than hand estimations and are easy to obtain. Thus this timings can be use to obtain VT and this VT can be used in to the model to get the better result.

APPENDIX A

MATLAB FUNCTION FOR SYNCHRONIZATION

Sync function used for synchronization in the main program.

```
T_force=HMtest(:,[3 5 7]);

If_F=size(T_force,1);

F_fingdif=difnum(T_force,3,If_F,.001,1,1,1);

F_Tangvel=(sqrt(sum((F_fingdif.^2)')))';

F_Tangvel=procfilt(F_Tangvel,1000);

F_Tangvel=F_Tangvel';

t_hm=HMtest(:,1);

% Plot the HM resultant force and displacement

F_M = [t_hm'; F_Tangvel'/2000]; % make a matrix for data analysis

figure; plot(t_hm,F_Tangvel/2000,'k');

hold on

%% HMframe is used to identify the Matlab data collection from HMtest

% This is used to find where the Matlab star first simple data

flag = true;

k=1;

while ((flag) && (k<=100))

    if ((sum(HMforce(1,:)==HMtest(k,[3 5 7]))>=2) && ...

        (sum(HMposition(1,:)==HMtest(k,[2 4 6]))>=2))

     HMframe=k
```

```
      flag=false;
     end
    k=k+1;
end
% In
 the extrmely case, HMframe may not available, then HMframe is equal 10
if ~exist('HMframe','var') == 1
    HMframe = 10;
end
td_emg=HMtest(HMframe,1)+45+(ceil(td*100))*10-(ceil(min(timeemg)*100))*10;
t_emg=td_emg+round(timeemg*1000);
```

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