Fitts' Law and Human Control of an Electromyographic Signal from the Biceps Brachii Muscle Group

by

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SUBMITTED TO THE DEPARTMENT OF MECHANICAL ENGINEERING IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF BACHELOR OF SCIENCE

AT THE MASSACHUSETTS INSTITUTE OF TECHNOLOGY JUNE 2007

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Submitted to the Department of Mechanical Engineering
On May 21, 2007 in partial fulfillment of the
requirements for the Degree of Bachelor of Science in Engineering
as recommended by the Department of Mechanical Engineering

ABSTRACT

Six human subjects performed a modified Fitts' test by moving an electromyographic signal between two targets on a computer screen. For five out of six subjects, the results were consistent with Fitts' Law with correlation coefficients ranging between 29% and 72%. The low correlation of the sixth subject (0.6%) may have been due to electrode misplacement and the adoption of a “strategy” in how she performed the task.

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I. Introduction

Electromyography (EMG) has become a popular solution to the problem of controlling of multi-axis prosthetic devices. Many users are limited by the number of muscles which can be utilized for control. The limitation might be mitigated by partitioning a single EMG signal into multiple amplitude regions, each with its own function. Fitts' Law would provide a useful model for relating the widths, range and response times associated with the division of a single, uni-dimensional signal. The applicability of Fitts' Law to user control of an EMG signal was tested by measuring the time needed for users to move their EMG signal between two targets on a computer screen. The response times were plotted as a function of task difficulty as defined by Fitts' Law (see section IID), and a linear model was fit to the data points.

The results of the experiment are consistent with Fitts' Law for five out of the six human subjects who participated in the tests. Specifically, the data for the five subjects agreed with Fitts' linear model with correlation coefficients ranging between 29% and 72%. In the case of the sixth subject, however, there was essentially no relationship between the average movement time and Fitts' index of difficulty. One explanation for why the results of the sixth subject did not obey Fitts' Law might be that she adopted a special "strategy" in how she performed the experimental task. Future testing should include more extensive training in order to avoid the use of such strategies and, in general, variability in the results might be reduced through better experimental controls.
II. Background

A. History of Prostheses

The history of prosthesis technology is extensive and colorful. Archeologists have unearthed an artificial foot from an ancient Egyptian burial site which dates back to at least 600 B.C.. The foot, now stored at the British Museum in London, is one of the earliest examples of prosthesis technology. Until the 17th century, designs of prosthetic limbs were extremely simple and provided minimal or no functionality. Finally, in 1696, a Dutch doctor named Pieter Verduyn presented the first non-locking, below-knee prosthetic leg. His invention began a new trend in advanced prosthesis design, encouraging doctors and engineers to use scientific principles to design artificial limbs that allow users to move more naturally. Medical advancements made during the American Civil War concerning material properties and joint physiology helped to further improved contemporary designs.

The addition of joints on prosthetic limbs presented a new problem: how to control the movement of the limbs? One promising solution which presented itself during the second World War was the use of electrical activity during muscle contraction called myoelectric potentials. The first myoelectrically controlled prosthesis appeared in the early 1940’s in Germany. However, the idea did not become popular until the development of the “Russian Hand”, which was developed in Russia almost ten years later. It was the first to be used clinically, and was produced in Montreal, Canada during the 1960’s. The idea became more popular as engineers and doctors began to realize that electromyographic (EMG) potentials could solve the issue of controlling prostheses with multiple-axis mechanisms. Older prosthetic limb models relied on the movement of the residual limb for control, thus limiting the number of degrees of motion that the limb
could achieve. However, an artificial limb that more closely resembles a natural one may have even more modes of movement. The control of such a system is problematic not only because of the limited number of muscles that can be utilized for control, but also because of the intense concentration that such artificial control would require. However, control of multiple-axis systems became easier and more natural as the prosthetic system gained the ability to monitor the activity of individual muscle groups.

Many methods have been developed to simplify the relationship between the user's EMG signals and the movement of an artificial limb. In 1978, researchers at Southampton College introduced a new approach that used sensors in the prosthetic hand to choose the type of grasp to use on an object, thus freeing the user from controlling the minute details of the hand's movements. In 1982, researchers at the Illinois Institute of Technology proposed the use of time-based pattern recognition control instead of direct, proportional control of myoelectric signals. The pattern-recognition approach consolidated many complex movements into a single "word" which a user could create with contraction patterns instead of detailed muscle control. This approach was especially advantageous in situations in which an amputee could control only very few muscles at one time. In 1993, research conducted at the University of New Brunswick proved the usefulness of an artificial neural network to obtain more inputs from a myoelectric signal. In 2005, researchers at Northwestern University were able to preserve the nerves of an amputated limb and carefully re-implant the nerves in another part of the patient's body. The novel process, called targeted muscle re-innervation, allowed the user to control the artificial limb through electrodes placed on the re-innervated muscles. The advantage of this process was the preservation of each of the nerve endings related to each part of the amputated limb, thus giving the amputee a greater number of distinct output control points with which to control a prosthesis.

Each of the approaches to prosthesis control described above depends on the quality and rate of the information provided by the user's myoelectric signal. On the one hand, prosthesis engineers must devise ways to maximize the amount of information that can be gathered from the user's myoelectric signal. On the other hand, engineers must recognize the limitations of myoelectric control, and design their system to circumvent such restrictions. In the latter case, it is imperative that engineers understand exactly the
rate at which a user can communicate information to their prosthesis through a given system.

**B. Electromyography (EMG)**

It is important to understand the physiological basis of myoelectric signals in order to understand how to harness such signals for human-prosthesis communication. For instance, the origins of the electrical activity of the muscle cells are relevant to the interpretation of the signal. In most cases, the Hodgkin-Huxley model (HHM) of nerve cell excitation, first proposed in 1952, is also used to model the behavior of muscle cells. The HHM describes the electrical activity of a cell in terms of the behavior of three main ion channels in the membrane of each cell: potassium, calcium and chlorine. As neurotransmitter ions cause the voltage across the membrane to change, the conductance of other ion channels begin to change. After the membrane voltage crosses a threshold level, an action potential occurs as ions both inside and outside the cell rush through the opened ion channels. Other electrical characteristics, such as the refractory period, can also be explained by the physical limitations of ion movement across the cellular membrane. The refractory period persists until the level of each ion has returned to its initial state.

At the highest level of organization, all voluntary muscle movement is controlled by the cerebral cortex, whose signals are conveyed to the individual skeletal muscle groups through the central motor system (CMS). Signals from the CMS are received by each motor unit (MU) which consists of a motorneuron, its axon and the muscle fibers that it innervates. Each muscle contains between 100 and 1000 MUs each. There are three general types of MU: (1) fast-twitch fatigable, (2) fast-twitch fatigue-resistant, and (3) slow-twitch. As indicated by the names, each muscle exhibits different contractile properties. Fast-twitch muscles exhibit high contraction speeds, higher peak forces and higher sensitivity to fatigue whereas the slow-twitch muscles exhibit low contraction speeds, low peak forces and low sensitivity to fatigue. Every skeletal muscle group contains varying amounts of all three MU types, but the amount of each type of MU is dependent on the function of the particular muscle group. For example, it has been
shown that anti-gravity muscles tend to contain mainly slow-twitch MUs whereas muscles for rapid movement contain similar amounts of both fast and slow twitch MUs.\textsuperscript{13} 

The force created by a muscle group is a function of both the number of MUs recruited and the frequency of MU activation by the CMS. Since the electrical activity in a muscle group is determined by the number of MUs involved and the discharge frequency of their excitation, EMG activity tends to increase as a function of the force generated by the muscular contraction.\textsuperscript{14} In general, the amplitude of the EMG signal changes as a function of the number of MUs involved and the MU firing frequency, while the mean frequency of the power spectrum may depend on the "recruitment of superficial high threshold MUs that most likely possess large and sharp spikes".\textsuperscript{15} It has been shown that larger MUs tend to be located near the surface of a muscle bundle.\textsuperscript{16} It has also been shown that the measured amplitude of an action potential depends on the distance of the electrode from the motor unit. The relationship between the distance and measured amplitude varies according to the design of the electrodes, the connection between the skin and electrode, the consistency of the skin at that point, etc.\textsuperscript{17} It has also been shown that during high EMG readings, high-threshold MUs are recruited more often.\textsuperscript{18} The significant spikes caused by the large, high-threshold MUs become apparent at higher force levels, and tend to affect the frequency and amplitude of the EMG recordings in unpredictable ways. It should be noted that these spikes make EMG control at higher amplitudes very difficult.

The focus of this study will be limited to voluntary muscular contractions in the Biceps Brachii muscle group, a large skeletal muscle group located in the human upper arm. It is large and well-defined even in non-athletes, and therefore is easy to find and to connect to EMG sensors. It is also a fairly easy muscle for test users to control without prior training. The muscle is actually composed of two bundles, the long head and the short head. Both heads have a common connection at the elbow. The short head attaches to the scapula and the long head attaches to the head of the humerus bone in the upper arm. The placement of the muscle across three joints allows it to control two movements: the flexion of the elbow and the supination of the forearm. The dual-motion capability of the biceps muscle group may complicate the task of controlling a single EMG signal since two motions may be triggered by the same signal.
Surface-mounted electrodes were used in this study, as opposed to intramuscular electrodes, in order to measure muscle activity. Merletti and Parker (2004) have suggested that intramuscular electrodes are helpful primarily in studies of the physiological characteristics of MUs and the pathologies associated with them. Surface electrodes, in contrast, are more useful in studies of “various aspects of behavior, temporal pattern of activity, or fatigue of muscles as a whole or of muscle groups”. Based on the statements of Merletti and Parker, surface-mounted electrodes are more suitable for this study than intramuscular ones. Regardless, new surface-mounted electrodes feature a wide enough range of capabilities that they can now be used even in studies which traditionally utilized intramuscular electrodes. These new surface-mounted electrodes can even take measurements of cell conduction velocity and locations of innervated areas, thus allowing scientists to study cell physiology without sacrifice to user comfort.

In general, the effects of electrode size, distance, location and attachment methods continue to pose great challenges to the researchers both studying and using them. This confusion led to the creation of the Surface ElectroMyoGraphy for the Non-Invasive Assessment of Muscles (SENIAM). It is a European concerted action in the Biomedical Health and Research Program (BIOMED II) of the European Union. Its sole purpose is to study the problems surrounding the use of surface electrodes for EMG signals, and generate recommendations for researchers.

The most basic model of an EMG electrode is a voltmeter and amplifier. It is often incorrectly assumed that the electrode is infinitely small (measures a signal at a single point), the voltmeter has infinite impedance, and all measurements are taken with respect to a reference point infinitely far away with zero electric potential. However, in reality, the electrode has physical dimensions that are large (relative to the size of the nerve cells which generate the measured electrical activity), the skin-electrode interface has a finite and complex impedance, and the reference source is never exactly zero. Because the electrode has finite size, it is possible that the area that it covers may not have uniform voltage potential. Merletti and Parker have shown that the detected voltage will then be the average of all of the individual potentials underneath the electrode.

While attempting to determine an electrode size appropriate for a particular study, it is
important to note that noise tends to decrease as the size of the contact area increases. However, most modern EMG electrode systems feature negligible amounts of noise in the electrode as compared to the noise created at the contact point between the electrode and skin. There are several methods to improve the impedance of the skin-electrode interface, and thereby reduce the major source of noise in the EMG signal. The procedure most commonly used by practitioners is to shave, clean, briefly rub the skin surface with an abrasive material and apply a conducting electrode gel. Other options currently include capacitive electrodes, "dry" electrodes, and ceramic electrodes.

The materials used to make the electrode itself also play an important role in its ability to faithfully measure an EMG signal. Because the metal which forms the contact points of the electrodes are highly conductive metal, and because the tissue between the electrode and muscle normally is moderately conductive, the interface between the electrode and tissue will be "intrinsically noisy". Due to the nature of highly conductive materials, the metal at the skin-electrode interface will influence the surrounding skin to become equipotential, thus modifying the voltage potential near it. Furthermore, the skin-electrode interface features a capacitance effect that stores some amount of charge. As a result, the EMG measurement will feature a DC voltage offset.

A common design for surface electrodes is to use two electrodes in a differential configuration in order to filter some noise. However, this configuration cannot always filter the DC voltage due to the skin-electrode capacitance because the resulting DC voltage is not always uniform across the skin surface. In some cases, this DC voltage can reach up to the hundreds of millivolts. This effect can be reduced by rubbing the skin with an abrasive material before taking measurements.

Kumar and Mital have suggested that a pure, unfiltered, un-amplified signal would be useful for studying the force of contraction as related to electrical activity in cells. However, the signal must be carefully normalized and calibrated according to the particular conditions of the measurement: thickness and consistency of the skin, oiliness of the skin surface, hair, differences in electrode gel composition, and differences in electrode shape. Because such calibration is almost impossible, EMG signals are usually filtered.
Several methods of signal analysis are used, and the suitability of one method over the other depends heavily on the application. Common processing methods include integrated rectification, averaged rectification, root mean squared signal (RMS) and smoothed rectification (rectified with a low-pass filter). According to Kumar and Mital (1996), Basmajian and DeLuca (1985) have proposed that the RMS value of the EMG signal provides the most useful measure for researchers.\textsuperscript{27}

After the raw EMG signal is converted into a more useful measure using one or more of the signal processing methods described above, the signal is analyzed in order to extract information about the user’s intentions and to create control instructions for prosthesis. Especially for single-channel EMG readings, the signal-to-noise ratio may be extremely high. Therefore, care must be taken to filter as much noise as possible from the reading. In general, a decrease in noise will lead to an increase in prosthesis performance but a decrease in control range.\textsuperscript{28}

\textbf{C. Prosthesis Control Methods}

The single channel/single output function (SCSF) is the most popular commercial prosthesis control method currently used by prosthesis manufacturers such as Otto Bock. By this method, each movement is controlled by two complimentary muscles (one for each direction), and only one movement is allowed at a time. The advantages of such a method include a more natural method of motion selection (the muscle with the greatest electrical activity over a threshold initiates a movement). However, the main disadvantage is that it requires many control muscles, which is unreasonable for high-level amputees.\textsuperscript{29} In addition to SCSF, some commercial prostheses use proportional control, which sets the speed of motion of the prosthesis proportionally to the amplitude of the EMG signal. Other commercial prostheses have developed a method whereby the initial rate of increase of the EMG signal is used to select a function, thus expanding the functionality of the prosthesis without requiring more channels. Other methods of switching between functions include a mechanical switch arrangement (Boston Arm), or
a rapid contraction of a combination of muscles (Utah Arm). More elaborate switching mechanisms have proven to be less popular because of the amount of training required, and the resulting movements that remain unnatural and imprecise. A promising new method of control involves EMG pattern recognition, which allows users to relay commands to their prostheses using pre-determined sequences of EMG amplitude variation. Also, Parker, Englehard and Hudgins describe naturally occurring, involuntary EMG patterns which consistently coincide with the initiation of particular limb movements. These patterns would allow a prosthesis to identify the user's intention without special training. Pattern-recognition based control systems have achieved up to 96% success rate in discriminating between six motions while using four channels attached to various arm muscles.

**D. Fitts' Law**

Ultimately, all of the prosthesis control methods just described depend on the users' abilities to control their EMG signals, and to direct their signals with enough accuracy so that they can consistently place the EMG level in pre-determined amplitude regions.

Fitts' Law states that, in a one-dimensional task in which the subject must manually move back and forth between two regions as fast as possible, a linear relationship exists between the movement time and the index of difficulty ($I_d$) of the task. The index of difficulty is defined as:

$$I_d = \log_2(2A/B),$$

where $A$ is the distance between the center of the two targets, and $B$ is the width of the targets. According to Fitts' law, the movement time is:

$$t = a + b I_d,$$

where $t$ is the time to move between the two targets, $I_d$ is the index of difficulty as described in equation 1, and $a$ and $b$ are constants that vary with the subject and the
conditions of the test. Sheridan mentions that equation 2 describes the experimental
data gathered by Fitts "remarkably well". In Fitts’ tests, subjects were asked to perform
data gathered by Fitts “remarkably well". In Fitts’ tests, subjects were asked to perform
three simple tasks: (1) move a peg from one hole to another, (2) move a washer from one
peg to another, (3) tap two targets with a stylus. In 1969, Kuttan and Robinson showed
that the completion time for a task with three independent variables could be expressed as
a simple summation of each variable’s linear equation. In their test, subjects were
required to move a dial to a certain position within a certain tolerance. The three
independent variables were: (1) uncertainty about the required response, $I_r$, (2) movement
of the arm to the dial within a tolerance, $I_{d1}$, (3) movement of dial to within a tolerance,
$I_{d2}$. The relationship between the time to complete the task and the difficulty of each
subtask was found to be:

$$t = K_1 + K_2 I_r + K_3 I_{d1} + K_4 I_{d2}$$

where $K_1$, $K_2$, $K_3$ and $K_4$ are constants specific to the test and the subject.

It is remarkable that the time for a complex task can be found by calculating the
weighted sum of the index of difficulty of each subtask. It seems reasonable that a
similar relationship would apply to an EMG signal and ultimately to an EMG-controlled
device like a prosthetic arm.

Indeed, several studies have already been performed involving EMG-controlled
machinery and Fitts’ Law. In 2002, researchers compared the results of the Fitts’ test to a
different test involving the movement of a mouse using six pairs of electrodes attached to
distinct muscle groups. The results of the experiment suggested that the task when
performed using EMG-control was comparable in many ways to the same task when
performed by hand. Also, researchers in London compared the performance of a
normal computer mouse and a pointer controlled by two EMG channels attached to two
distinct muscle groups. These researchers used Fitts’ Law to quantify the quality of the
performance of both devices.
III. Methods

In this study, human subjects controlled the output of a processed EMG signal on a computer display in a modified Fitts' task by controlling the output of a processed EMG signal on a computer display. The processed EMG signal was calculated by computing the root mean squared value of the raw EMG output and, henceforth, the processed signal will simply be referred to as the EMG signal. The experimental task involved moving the output level back and forth between two regions on the display as quickly as possible. Unlike earlier EMG studies mentioned in the previous section, this study tested a subject's ability to control the amplitude and accuracy of a single EMG channel, which was attached to a muscle commonly used by upper-level amputees. The author served as the experimenter in all of the tests.

A. Experimental Arrangement

The experimental set-up was as follows (see Figure 1). The subject was seated comfortably in a chair with armrests, and was positioned directly in front of the computer screen. A single electrode was attached to the Biceps Brachii muscle on the subject’s dominant arm. The electrode was firmly attached using double-sided tape and electrode gel. The subject was also instructed to hold a ground pin, also coated with electrode gel. The EMG signal was then amplified by the EMG Delsys Bagnoli System (Delsys Inc., Boston, Massachusetts). The unprocessed signal was then sent to a National Instruments PCI-MIO-16E-4 data acquisition card inside the computer via a BNC-2110 connector block.
The experimental Fitts' task, including the EMG signal, was displayed to the human subject using software that was developed for the experiment in Labview (National Instruments). The experiment program processed and filtered the EMG signal from the data acquisition card, displayed the EMG signal to the subject, provided test conditions for the subject to follow, and recorded the subject's responses.

Figure 2 presents the computer display viewed by the subject during a test. The primary feature of the display was the central graph which plots the EMG signal
amplitude (vertical axis) as a function of time (horizontal axis) in real time like a strip chart recorder. The EMG signal was the faint white line at the bottom of the graph in the example shown. The other horizontal lines on the graph defined the target regions of the experimental task.

Figure 2: Test Display. The horizontal lines on the graph indicate the EMG signal of the subject, as well as the target regions of the task. From top to bottom, the lines on the graph are red, yellow, green and white.

The lower, green line indicated the relax threshold, and formed the upper bound of the lower target. The yellow, middle line indicated the tensing threshold and formed
the lower bound of the upper target. The red, top line indicated the upper bound of the upper target.

Three circular lights were placed near the top of the chart in order to assist the subject with completing the tests. The large light on the far left labeled “Start” glowed green only during active testing. When the “Start” light was not on, the subject was told that no data was being recorded and that the subject could relax or practice as they felt necessary. The middle, circular light labeled “Target Reached” glowed green when the subject’s EMG signal was inside the upper target (i.e. above the yellow middle line). The light to the right labeled “Over Shoot” glowed red when the subject’s EMG signal surpassed the red topmost line, thereby indicating that the subject had overshot the upper target. The “Over Shoot” light only stopped glowing once the current trial had ended.

B. Subjects

Permission to use human subjects in this study was granted by the MIT Committee On the Use of Humans as Experimental Subjects (COUHES). Six human test subjects, including the author of this paper, gave informed consent prior to taking part in the experiments. The group consisted of two males and four females, who ranged in age from 20 to 52 years. The group included one person with a dominant left hand, and whose electrode was attached to the left arm. All other subjects were right-handed, and the electrodes were attached to the right arm. All subjects were healthy and capable of understanding and following the instructions given by the experimenter.

C. Procedure

The procedure of the tests was as follows. After the subjects were informed of their rights and they signed the consent form, a brief description of the study and the test was given. Then, each subject was asked to hold the ground pin and the surface electrodes were attached to his or her dominant arm near the Biceps Brachii muscle. The electrode was not fully attached until an adequate location was found on each subject.
arm for sensing electrical activity associated with muscle contraction. An adequate location was defined as a location in which a noticeable difference could be seen between a baseline relaxed EMG signal and a contracted muscle EMG signal. The electrodes were also coated in electrode gel in order to decrease the noise in the signal.

At the beginning of each test, the subjects were asked to raise their EMG signals as high as possible. The maximum signal achieved was then used as the maximum voluntary contraction (MVC) for the entire test. The buttons to the far right of the test display (see Figure 2) allowed the experimenter to change the amplitude (height of center of upper target with respect to the green, relax boundary) and the tolerances (the widths) of the two targets. Both the tolerances and amplitudes were controlled as a percentage of the MVC of the subject.

After the instructions were given, the subjects were encouraged to practice contracting their Biceps muscle. While the subjects were practicing, the amplitude scale on the graph was adjusted to approximately match the subject’s MVC. The subject was then informed of the two targets, and of the purposes of the relax (green), tense (yellow) and overshoot (red) lines on the chart, as well as the three lights above the chart. The subjects were told that the amplitudes and tolerances of the targets would change throughout the test, and that they must move their EMG signal successfully between the two targets five times as quickly as possible.

Specifically, during the test, the subjects were given a series of trials with different amplitudes and tolerances, the parameters being constant throughout any given trial. Twenty-two separate trials were performed in each test with the tolerance levels ranging from 20% MVC to 50% MVC, and the amplitude levels ranging from 20% MVC to 90% MVC. Each subject performed two tests when possible. During the first test, the tolerances and amplitudes were presented in descending or ascending order. During the second test, they were presented in a random order.

During each trial, the subjects were asked to move their EMG signal back and forth between the two targets five times as quickly as possible. A trial was considered successful only if the subject performed the five task movements successfully. A task movement was judged to be successful if the subject moved the EMG signal between the targets without going over the red topmost line. If the subjects’ EMG signal passed the
red topmost line, the trial was abandoned and the trial conditions were then repeated three more times (at most) or until the subjects performed five successful task movements.
The subjects were also informed that, although the trials needed to occur during an active testing period, the timing of the trials began only when their processed EMG level passed above the relax (green) line for the first time, and ended only when their processed EMG level passed below the relax (green) line at the end of the fifth movement. In this way, the test avoided the effects of reaction time.

**D. Data Analysis**

The information recorded for each test included the time in tenths of seconds, the subject’s RMS EMG signal sampled at 10 kHz, the subject’s MVC level, the start and end times and the levels of the relax (green), tense (yellow) and overshoot (red) lines. After the completion of the tests, the resulting data was analyzed using Matlab (MathWorks) software. The analysis program anal.m, which was written specifically for this project, is included in Appendix A. The inputs for the analysis program were the seven measurements recorded during the test.

The anal.m program filtered out unsuccessful tests (tests which did not contain five successful trials), and recorded the amplitude, tolerances and duration of the successful tests. The program then calculated the average movement time by dividing the total duration of each test by five. The analysis program also calculated the index of difficulty for each test using equation (1) presented in section IID.

The program then produced four plots for each run. The first plot was a scatter plot of the average movement time versus index of difficulty for all of the successful tests. An example is shown in figure 3.
Figure 3: Sample of data taken from one test of one subject, showing the movement time vs. Fitts’ index of difficulty. Each data point represents an individual trial in the test. The equation of the best-fit line and the correlation coefficient $r^2$ are printed at top left.

The best-fit line in the figure is calculated by minimizing the sum of the squares of the offsets, also known as least squares fitting. The correlation coefficient, which is a measure of the goodness of fit, is calculated by:

$$r^2 = 1 - \frac{\text{norm}^2}{(n-1)s^2}$$

where $r^2$ is the correlation coefficient, $n$ is the number of data points, $s$ is the standard deviation which is calculated by:
where $\bar{y}$ is the average of all of the points in the $y$ direction and $y_i$ is the value of each point $i$ in the $y$-direction. The norm is also known as the norm of the residuals and is calculated by:

$$s = \sqrt{\frac{\sum (y_i - \bar{y})^2}{n-1}}$$

(4)

where $d_i$ is the vertical distance between a data point $i$ and the best-fit line. The correlation coefficient $r^2$ indicates the fraction of the variance in the data points that is explained by the best-fit line. In other words, it quantifies the ability of the line to explain the differences in the values of the points. If the best-fit line plots the data points perfectly, then the line has described perfectly the distribution of the data points and the correlation coefficient is one. If the best-fit line has no relation to the data, then the correlation coefficient is zero.

The second plot generated by the analysis program anal.m plots the tolerances versus average movement times, and the amplitudes versus average movement times for each run. This plot is useful for seeing a trend, or the lack of a trend, in the movement time as the tolerance and amplitude change.
Figure 4: A sample of data taken from one test of one subject showing average movement time vs. tolerance and amplitude. Each tolerance or amplitude data point represents a single trial in the test.

The third and fourth plots generated by the analysis program show the average movement times as a function of the index of difficulty, like the first plot. However, in the latter plots, the data points are differentiated according to tolerance in the third plot, and according to the amplitude in the fourth plot. These plots facilitate the identification of trends in average trial times according to either amplitude or tolerance. A sample is shown in Figure 5.
Figure 5: A sample of data taken from one test of one subject showing the average movement times vs. index of difficulty differentiated by amplitude (left) and tolerance (right).

IV. Results

The data collected from the six subjects were analyzed as described in the previous section. A summary of the results on the relationship between average movement time and the index of difficulty (see Figure 3 in Section III) is presented for all of the tests in Table 1. The full set of results for every subject has been included in the Appendix B.
Table 1. Summary of Results.

<table>
<thead>
<tr>
<th>Subject</th>
<th>Test</th>
<th>Order of Target Conditions</th>
<th>Best-fit Line Equation</th>
<th>Correlation Coefficient ($r^2$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>1</td>
<td>Ascending</td>
<td>$y = 1x + 0.73$</td>
<td>40%</td>
</tr>
<tr>
<td>A</td>
<td>2</td>
<td>Random</td>
<td>$y = 1.1x + 0.36$</td>
<td>71%</td>
</tr>
<tr>
<td>B</td>
<td>1</td>
<td>Descending</td>
<td>$y = 0.63x + 0.055$</td>
<td>60%</td>
</tr>
<tr>
<td>B</td>
<td>2</td>
<td>Random</td>
<td>$y = 0.7x + 0.036$</td>
<td>72%</td>
</tr>
<tr>
<td>C</td>
<td>1</td>
<td>Descending</td>
<td>$y = 0.52x + 0.14$</td>
<td>67%</td>
</tr>
<tr>
<td>D</td>
<td>1</td>
<td>Descending</td>
<td>$y = 0.35x + 0.74$</td>
<td>29%</td>
</tr>
<tr>
<td>D</td>
<td>2</td>
<td>Random</td>
<td>$y = 0.67x + 0.26$</td>
<td>52%</td>
</tr>
<tr>
<td>E</td>
<td>1</td>
<td>Ascending</td>
<td>$y = -0.021x + 0.81$</td>
<td>0.6%</td>
</tr>
<tr>
<td>F</td>
<td>1</td>
<td>Descending</td>
<td>$y = 0.12x + 0.56$</td>
<td>34%</td>
</tr>
<tr>
<td>F</td>
<td>2</td>
<td>random</td>
<td>$y = 0.11x + 0.56$</td>
<td>50%</td>
</tr>
</tbody>
</table>

Table 1. Summary of Results. The equations in the third column describe the best-fit lines corresponding to Fitts' Law (see Figure 3 in section III). The fourth column is the correlation coefficient of the best-fit line to the data.

It can be seen from Table 1 that, with the exception of Subject E, the results are consistent with Fitts' Law, although the performances of the subjects varied widely. If one neglects Subject E, whose results show essentially no relationship between the average movement time and the index of difficulty (indeed, the slope of the line is slightly negative), all of the subjects had at least one test for which the correlation coefficient was greater than or equal to 50%. Of the four subjects who completed two tests (A, B, D, and F), the best-fit equations for three of the subjects showed noticeable similarities between the best-fit equations of their two tests. In contrast, the slope of the best-fit line for Subject D almost doubled between her first and second tests. The observed consistency across different tests occurred regardless of the trial order.
V. Discussion

The experimenter recorded the following observations, many of which impact the interpretation of the results summarized in Table 1.

Subject C was the author of this paper. She had the most experience with the EMG system, and was very familiar with the test. She may have also been biased toward a certain conclusion although the nature of the test would have minimized the effects of such bias.

Subject F was the author’s advisor. He had some experience with the EMG system, and was also familiar with the test. During the first run, the experimenter noticed that he sometimes did not go below the relax (green) line between trials and reminded him that he had to do so in order to make a successful trial. Afterwards, the duration of his tests were noticeably longer as he had to concentrate on relaxing his muscle in order to go below the relax threshold.

Subject B, like the previous two subjects, was instructed that the maximum voluntary contraction (MVC) was the maximum level that he could comfortably reach by contracting his biceps muscle. After experiencing fatigue during the first run, he decreased his MVC by almost 20% for the second run. The reduction in MVC would make it easier for him to reach targets with higher amplitudes, and also would allow him to avoid the initiation of high threshold, spiking motor units as described earlier in section IIB. One explanation for the improvement in correlation may be the decrease in MVC.

In order to force Subject D to avoid the strategy of Subject B, the experimenter described the MVC as the maximum level possible, regardless of comfort. During the test, the subject had noticeable difficulty reaching even medium (60%) amplitudes and thus adopted a “twitching” strategy. Her strategy was to flex quickly, increasing the amplitude of each “twitch” until she reached the upper target. In this way, she was able to avoid fatigue, but she also often overshot or undershot the upper target. Her strategy caused the average times to become less dependent on her ability and more dependent on
chance, thus providing an explanation for why the slope of her best-fit line almost doubled between the first and second test.

Subject E was present during the testing of subject D, and therefore heard the same instructions and observed the “twitching” strategy. Subject E decided to adopt the same “twitching” strategy after Subject D advised her that the strategy would make the test easier. The experimenter also noticed that Subject E moved her arm excessively in an attempt to control her arm contraction, leading to the displacement of the electrodes. The electrodes were re-attached as soon as the experimenter noticed the problem, but the data may have been affected. Given the difficulty with electrode attachment and the subject’s use of the “twitching” strategy, it is understandable that her data does not agree with Fitts’ Law.

In order to avoid the twitching strategy adopted by Subjects D and E, Subject A was advised to make her transitions between the targets as smooth and fast as possible. She was also told that the MVC was the maximum EMG level that could be attained. During the tests, she made a noticeable effort to move smoothly between the two targets to the point that the experimenter assumed the subject could have moved much faster. Indeed, her average movement times were much slower than those of any other subject.

Some of the differences between the correlation coefficients of the first and second tests of each subject may also be explained by a learning curve. The correlation coefficients for all of the subjects improved noticeably during their second run. This may be attributed to better familiarity with EMG control and the testing system. Also, several subjects, such as Subject B, reset their MVC values to a lower level during the first test in order to make the test easier. Better correlation with lower MVC values (and at lower amplitudes in general) may indicate that subjects performed significantly better at lower amplitudes.

There are some observable trends according to tolerance and amplitude. As can be seen in plot 2 of average movement time of trial vs. tolerance and amplitude (see Appendix A), many subjects showed an observable increase in average movement time as the tolerance decreased. The trend makes sense considering that they would need to increase their EMG levels more slowly in order to reach smaller targets without overshooting the upper (red) boundary of the high target. There is also a weak but
perceptible trend according to amplitude, as the average movement time tends to increase as the amplitude increases. The trend makes sense considering that targets at higher amplitudes require more effort to reach, and thus more time may be required to create the necessary level of muscular contraction.

The fourth plot produced by the analysis program, which plots the average movement time as a function of index of difficulty according to the tolerance levels. This plot facilitates the observation of trends according to specific tolerance levels. Using this plot, it is observed that the 20% tolerance in particular tends to yield more erratic results than the others. During testing, the experimenter noticed that many subjects had great difficulty reaching the 20% tolerance targets, and often overshot the upper boundary of the higher target. Therefore, the average movement time of the tests at that tolerance tended to correlate much more poorly with the linear model than at lower tolerances. In general, if this tolerance level is removed from the data group for each run, the correlation of the fit of the data to a line improves. This would suggest that Fitts' Law may be relevant only within certain boundaries of tolerance and amplitude.

The results of this study show that Fitts' Law appears to apply to EMG signals in some circumstances. Further studies may include the conduction of more tests per subject in order to describe specific trends within one user's responses. More comprehensive testing may also study the effect of practice by including a longer training period.
References

11 Merletti and Parker (2004), 17.
12 Merletti and Parker (2004), 27
22 Merletti and Parker (2004), 110.
23 Merletti and Parker (2004), 110.
28 Merletti and Parker (2004), 460.
29 Merletti and Parker (2004), 460.
30 Merletti and Parker (2004), 463.
32 Merletti and Parker (2004), 467.
Appendix A

Complete Subject Data
Subject D, Test #1

\[ y = 0.35x + 0.74 \]
\[ r^2 = 0.29 \]

Subject D, Test #1

Normalized Tolerance and Amplitude (x1/MVC)

Subject D, Test #1

Index of Difficulty

Subject D, Test #1

Tolerance
Amplitude

Subject D, Test #1

Index of Difficulty

Subject D, Test #1

Tolerance = 20%
Tolerance = 30%
Tolerance = 40%
Tolerance = 50%
Tolerance = 60%
Tolerance = 70%
Tolerance = 80%
data
Appendix B

Data Analysis Program:
anal.m
This function takes in a twelve column matrix:

1) Time from Labview
2) Maximum Voluntary Contraction
3) Time from DAQ
4) EMG (RMS) signal
5) Time from Labview
6) Relax Threshold
7) Time from Labview
8) Upper Tense Threshold
9) Time from Labview
10) Lower Tense Threshold
11) Time from Labview
12) Test On Indicator

This code is meant to work with 12-input data txt such as Kim_0425.txt

function [result, stdev, test_num] = anal(data, win)

% extract data and assign to variables
mvc = data(:,2); % maximum voluntary contraction
t = data(:,3); % time vector
d = data(:,4); % EMG signal vector
relax = data(:,6); % relax threshold, also tolerance
hi_tense = data(:,8); % upper limit for tense target
\lo_tense = data(:,10); % lower limit for tense target
amp = \lo_tense - relax; % amplitude
onoff = data(:,12); % signal beginning and end of a trial

% plot signal with legend
figure(1);
hold off;
plot(t, emg, '-r');
hold on;
plot(t, relax, '-g');
plot(t, hi_tense, '-b');
plot(t, \lo_tense, '-c');
plot(t, onoff, 'y');
grid on;
title('EMG Test Data');
xlabel('Time (seconds)');
ylabel('Test signals and User EMG Response (Volts)');
legend('User EMG RMS Value', 'Relax Threshold', 'Tense Higher Thresholds', 'Tense Lower Threshold');
figure(1)

% plot signal on four panels
figure(2);
\text{L_win} = \text{round}(\text{length(t)}/4) - 1;
hold off; subplot(4,1,1); plot(t(1:L_win), emg(1:L_win), 'r');
plot(t(1:L_win), relax(1:L_win), '-g');
plot(t(1:L_win), hi_tense(1:L_win), '-b');
plot(t(1:L_win), \lo_tense(1:L_win), '-c');
plot(t(1:L_win), onoff(1:L_win), 'y');
axis([0 t(L_win) 0 max(mvc)*1.5]);
hold off; subplot(4,1,2); plot(t(L_win:L_win*2), emg(L_win:L_win*2), 'r');
plot(t(L_win:L_win*2), relax(L_win:L_win*2), '-g');
plot(t(L_win:L_win*2), hi_tense(L_win:L_win*2), '-b');
plot(t(L_win:L_win*2), \lo_tense(L_win:L_win*2), '-c');
plot(t(L_win:L_win*2), onoff(L_win:L_win*2), 'y');
axis([t(L_win) t(L_win*2) 0 max(mvc)*1.5]);
hold off; subplot(4,1,3);
% plot(t(L_win*2:L_win*3),emg(L_win*2:L_win*3), 'r'); hold on;
% plot(t(L_win*2:L_win*3),relax(L_win*2:L_win*3), '-g');
% plot(t(L_win*2:L_win*3),hi_tense(L_win*2:L_win*3), '-b');
% plot(t(L_win*2:L_win*3),lo_tense(L_win*2:L_win*3), '-c');
% plot(t(L_win*2:L_win*3), onoff(L_win*2:L_win*3), 'y');
% axis([tt(L_win*2) tt(L_win*3) 0 max(mvc)*1.5])
% hold off; subplot(4,1,4); plot(t(L_win*3:t),emg(L_win*3:t), 'r'); hold on;
% plot(t(L_win*3:t),relax(L_win*3:t), '-g');
% plot(t(L_win*3:t),hi_tense(L_win*3:t), '-b');
% plot(t(L_win*3:t),lo_tense(L_win*3:t), '-c');
% plot(t(L_win*3:t), onoff(L_win*3:t), 'y');
% axis([tt(L_win*3) tt(L_win*4) 0 max(mvc)*1.5])
% figure(2)

% analyze each trial for meeting test conditions, and calculate time
n = 3;
amp = 0;
amp_calc = 0;
tol = 0;
tol_calc = 0;
success = 0;
start_test = 0;
end_test = 0;
time_test = 0;
time_trial = 0;
trial_num = 0;
over = 0;
target = 0;
test_num = 0;
trial_per = zeros(30,1);
avg_sum = zeros(20,1);
testoff = 0;
trial = 0;
target = 0;

while (n < length(t)),
    n = n+1;
    time = t(n);
    tol_calc = (hi_tense(n)-lo_tense(n))./mvc(n);
    amp_calc = (tol_calc/2) + (lo_tense(n) - relax(n))./mvc(n);
    if (onoff(n)<1 & & testoff == 0) % detect test period and no overshoot
        if (onoff(n-1)<1 & & onoff(n)>1) % detect START of test period
            test_num = test_num + 1;
            amp(test_num)= amp_calc;
            tol(test_num)= tol_calc;
            over(test_num) = 0;
            start_test(test_num) = 0;
            end_test(test_num) = 0;
            time_test(test_num) = 0;
            trial = 0;
            target = 0;
        end
        % detect starts of every trial
        if (emg(n)>= relax(n) & & emg(n-1)<relax(n-1))
            if (target >= trial) % only start new trial if last one reached target
                trial = trial + 1;
            end
            if (trial == 1)
                start_test(test_num) = t(n);
            end
        end
        % detect each trial passing lower tense threshold
    end
    end
end

Page 2
if (emg(n) >= lo_tense(n) && emg(n-1)< lo_tense(n-1))
    target = target + 1;
end
% if emg signal goes outside of tense target range, erase test
if (emg(n) >= hi_tense(n) && emg(n-1)< hi_tense(n-1))
    test_num = test_num - 1;
    testoff = 1;
end
if (emg(n) <= relax(n) && target >= 5)   % detect end of last trial
    if trial == 5
        end_test(test_num) = t(n);
        testoff = 1;
    end
elseif (onoff(n) == 0 && onoff(n-1)>0) % detect only end of test
    if (trial == 5)
        trial = 0;
        if testoff == 0
            test_num = test_num - 1;
        else
            trial = 0;
        end
    end
end
end
testoff = 0;
end

%display preliminary results in matrix form
result = zeros(test_num,7);
result(:,1) = 1:1:target;
result(:,2) = start_test(1:test_num);
result(:,3) = end_test(1:test_num);
time_test = end_test - start_test;
avg_test = time_test./5;
result(:,4) = avg_test(1:test_num);
AT = result(:,4);
result(:,5) = amp(1:test_num);
AMP = result(:,5);
result(:,6) = tol(1:test_num);
TOL = result(:,6);
Id = log2(AMP.*2./TOL);
result(:,7) = Id(1:test_num);
stddev = std(AT)
figure(win);
% plot a best fit line
subplot(2,2,1);
hold on
plot(Id, AT, '.b');
xlabel('Index of Difficulty')
ylabel('Average Time per Trial')
axis([0 3 0 5])

% plot raw results
subplot(2,2,2);
hold off;
plot(TOL, AT,'*b');
hold on;
plot(AMP, AT,'.r');
xlabel('tolerance and amplitude')
ylabel('average time of trial');
analprint.txt

legend('Tolerance','Amplitude');
% subplot(2,3,2);
% hold off;
% plot3(TOL,AMP,AT,',.b');
% xlabel('tolerance');
% ylabel('amplitude');
% zlabel('time');

% plot separate lines for each tolerance
% - assume tolerances limited to 20%,30%,40%,50%
% - assume amplitudes are limited to multiples of 10
% - produces four arrays for each tolerance: TOL_2,TOL_3,TOL_4,TOL_5
% - each array contains the (1) Id and the (2) AT

n = 1;
TOL_2 = [.,.];
TOL_3 = [.,.];
TOL_4 = [.,.];
TOL_5 = [.,.];
m2 = 0;
m3 = 0;
m4 = 0;
m5 = 0;
while (n <= test_num)
    if (TOL(n) <= 0.21)
        m2 = m2 + 1;
        TOL_2(m2, 1) = Id(n);
        TOL_2(m2,2) = AT(n);
    elseif (TOL(n) <= 0.31)
        m3 = m3 + 1;
        TOL_3(m3, 1) = Id(n);
        TOL_3(m3,2) = AT(n);
    elseif (TOL(n) <= 0.41)
        m4 = m4 + 1;
        TOL_4(m4, 1) = Id(n);
        TOL_4(m4,2) = AT(n);
    elseif (TOL(n) <= 0.51)
        m5 = m5 + 1;
        TOL_5(m5, 1) = Id(n);
        TOL_5(m5,2) = AT(n);
    end
    n = n + 1;
end
TOL_2 = sortrows(TOL_2,1);
TOL_3 = sortrows(TOL_3,1);
TOL_4 = sortrows(TOL_4,1);
TOL_5 = sortrows(TOL_5,1);

subplot(2,2,4);
plot(TOL_2(:,1),TOL_2(:,2),',.y');
hold on;
plot(TOL_3(:,1),TOL_3(:,2),',.g');
plot(TOL_4(:,1),TOL_4(:,2),',.r');
plot(TOL_5(:,1),TOL_5(:,2),',.b');
legend('Tolerance = 20%','Tolerance = 30%','Tolerance = 40%','Tolerance = 50%','Location','Northwest')
xlabel('Index of Difficulty');
ylabel('Average Time Per Trial');
grid on
% plot separate lines for each amplitude
% - assume tolerances limited to 20%, 30%, 40%, 50%
% - assume amplitudes are limited to multiples of 10
% - produces four arrays for each tolerance: TOL_2, TOL_3, TOL_4, TOL_5
% - each array contains the (1) Id and the (2) AT

n = 1;
AMP_2 = [ ,  ];
AMP_3 = [ ,  ];
AMP_4 = [ ,  ];
AMP_5 = [ ,  ];
AMP_6 = [ ,  ];
AMP_7 = [ ,  ];
AMP_8 = [ ,  ];
AMP_9 = [ ,  ];
a2 = 0;
a3 = 0;
a4 = 0;
a5 = 0;
a6 = 0;
a7 = 0;
a8 = 0;
a9 = 0;

while (n <= test_num)
    if (AMP(n) <= 0.21)
        a2 = a2 + 1;
        AMP_2(a2, 1) = Id(n);
        AMP_2(a2, 2) = AT(n);
    elseif (AMP(n) <= 0.31)
        a3 = a3 + 1;
        AMP_3(a3, 1) = Id(n);
        AMP_3(a3, 2) = AT(n);
    elseif (AMP(n) <= 0.41)
        a4 = a4 + 1;
        AMP_4(a4, 1) = Id(n);
        AMP_4(a4, 2) = AT(n);
    elseif (AMP(n) <= 0.51)
        a5 = a5 + 1;
        AMP_5(a5, 1) = Id(n);
        AMP_5(a5, 2) = AT(n);
    elseif (AMP(n) <= 0.61)
        a6 = a6 + 1;
        AMP_6(a6, 1) = Id(n);
        AMP_6(a6, 2) = AT(n);
    elseif (AMP(n) <= 0.71)
        a7 = a7 + 1;
        AMP_7(a7, 1) = Id(n);
        AMP_7(a7, 2) = AT(n);
    elseif (AMP(n) <= 0.81)
        a8 = a8 + 1;
        AMP_8(a8, 1) = Id(n);
        AMP_8(a8, 2) = AT(n);
    elseif (AMP(n) <= 0.91)
        a9 = a9 + 1;
        AMP_9(a9, 1) = Id(n);
        AMP_9(a9, 2) = AT(n);
    end
    n = n + 1;
end

AMP_2 = sortrows(AMP_2, 1);
AMP_3 = sortrows(AMP_3, 1);
AMP_4 = sortrows(AMP_4, 1);
AMP_5 = sortrows(AMP_5, 1);
AMP_6 = sortrows(AMP_6,1);
AMP_7 = sortrows(AMP_7,1);
if a8 > 0
    AMP_8 = sortrows(AMP_8,1);
end
if a9 > 0
    AMP_9 = sortrows(AMP_9,1);
end
subplot(2,2,3);
hold off;
plot(AMP_2(:,1),AMP_2(:,2),'.-r');
hold on;
plot(AMP_3(:,1),AMP_3(:,2),'.-', 'Color', [1 .6 .78]);
plot(AMP_4(:,1),AMP_4(:,2),'.-', 'Color', [.7 0.78 1]);
plot(AMP_5(:,1),AMP_5(:,2),'.-c');
plot(AMP_6(:,1),AMP_6(:,2),'.-q');
plot(AMP_7(:,1),AMP_7(:,2),'.-', 'Color', [1 .69 .39]);
if a9 > 0
    plot(AMP_8(:,1),AMP_8(:,2),'.-', 'Color', [.8 .9 .4]);
    plot(AMP_9(:,1),AMP_9(:,2),'.-y');
    legend('Amp = 20%', 'Amp = 30%', 'Amp = 40%', 'Amp = 50%', 'Amp = 60%', 'Amp = 70%', 'Amp = 80%', 'Amp = 90%', 'Location', 'NorthWest')
elseif a8 > 0
    plot(AMP_8(:,1),AMP_8(:,2),'.-', 'Color', [.8 .9 .4]);
    legend('Amp = 20%', 'Amp = 30%', 'Amp = 40%', 'Amp = 50%', 'Amp = 60%', 'Amp = 70%', 'Amp = 80%', 'Location', 'NorthWest')
else
    legend('Amp = 20%', 'Amp = 30%', 'Amp = 40%', 'Amp = 50%', 'Amp = 60%', 'Amp = 70%', 'Location', 'NorthWest')
end
grid on

% plot index of difficulty vs. average time
subplot(2,2,3);
hold on;
plot(Id, AT, 'ob');
xlabel('Index of Difficulty');
ylabel('Average Time per Trial');
hold on;

subplot(2,2,4);
hold on;
plot(Id, AT, 'ob');
xlabel('Index of Difficulty');
ylabel('Average Time per Trial');