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Neuromuscular Strategies for Dynamic Finger Movements: A Robotic Approach

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Abstract— **Human hand control mechanisms are extremely complex and currently there is no solution to restore full function to a paralyzed hand. The optimal solution is to use either cortical signals or desired joint angles/torques to stimulate existing muscles. One of the limiting factors in achieving this goal is a poor understanding of the relationship between the input (i.e. neural signals to muscles) and the output (i.e. joint movements) in the system (i.e. hand). There are infinitely many sets of muscle forces that generate any given set of joint torques because of redundancy and the ability to co-contract antagonist muscles. In this paper, we describe a methodology to estimate and compare biological and robotic solutions for the muscle forces for a given set of dynamic joint movements. Our preliminary results indicate that the robotic solution obtained by finding the minimum forces resembles the biological solution. This methodology may allow us to identify the neuromuscular control strategies used during dynamic finger movements.**

Keywords—**Dynamic movements, EMG, Force, Hand, Neural control**

I. Introduction

Human hand control mechanisms separate humans from other species. Despite the disproportionately large section of the human brain used to control hand movements, we understand little about the neural control of the hand. This lack of knowledge hinders the development of clinical interventions to resolve hand injuries and paralysis, leaving over 100,000 people in the United States every year with unusable hands [1,2].

One way to restore function to paralyzed hands is to find the relationship between the cortical signals and the joint movements [3] and to use an exoskeleton robotic system to control the joints. While exoskeleton devices are improving [4], this is a clumsy solution in the long term. The optimal solution is to stimulate existing muscles using either cortical signals or desired joint angles/torques. One of the limiting factors in this approach is a poor understanding of the relationship between the input (i.e. neural input signals) and output (i.e. joint movements) to the system (i.e. the hand).

There are infinitely many different sets of muscle contraction forces that result in the same joint torques [5]. The index finger has four degrees of freedom (the metacarpophalangeal joint (MCP) has both flexion/extension and abduction/adduction degrees of freedom) and seven muscles. Thus, to specify a set of four joint torques for the index finger, seven muscle forces must be identified. Because of this redundancy and the ability to co-contract antagonist muscles to achieve the same torques, the potential muscle forces reside in a seven dimensional space bounded by the minimum and maximum muscle forces. We are interested in finding and comparing the biological and engineering solutions for picking the appropriate set of forces for a given task. This comparison will generate hypotheses of how the central nervous system may be optimizing neuromuscular control for dynamic finger movements.

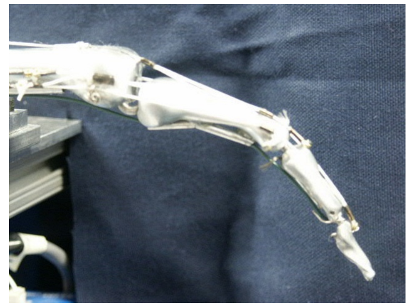

Fig. 1. Anatomically Correct Testbed (ACT) Index Finger. All components including bones, joints, tendons, sensors, and muscles that affect either the static or dynamic performance of the human hand are mimicked.

In this paper, we first describe an anatomically correct testbed (ACT) of a human index finger and how to determine the engineering solutions for the muscles' forces to produce a movement on this robotic finger. Then, we describe how to use electromyography (EMG) from the index finger muscles to determine the biological solution used for exactly the same movement.

II. Robotic Approach

A. Anatomically Correct Testbed

We created an anatomically correct testbed (ACT) of an index finger shown in Fig. 1. Our approach in building an ACT hand is to duplicate all of the features and properties of a human hand that affect both its static and dynamic performance. Much of our effort has gone into developing a working model of the extensor mechanism. The extensor mechanism is the complex web of tendons located on the dorsal side of each finger. Our robotic extensor mechanism is fabricated from a composite of woven nylon (that matches the tendon stress-strain characteristics), and duplicates the geometry and functionality of the human extensor

A B

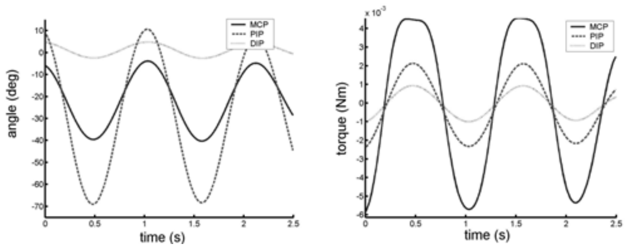

Fig. 2. A: Joint angles of the index finger recorded during a flexion-extension task. Negative joint angles indicate flexion and positive joint angles extension. B: Joint torques calculated using the recursive Newton-Euler technique.

mechanism [6]. We have demonstrated that this extensor mechanism gives independent control of the MCP joint and acts not only as an extensor but also as a flexor, abductor, adductor, or rotator depending on the finger's posture.

In addition to mimicking the extensor mechanism, we constructed the bones and the joints of the ACT finger to have human-like size, shape, strength, and mass [7]. The exact contours of the bones were replicated to accommodate the dynamically changing tendon paths and moment arms of muscles at each joint. The joint was designed to have the same degrees of freedom, range of motion, and relationships between the various axes, internal friction, and elastic properties as its human counterpart. The size of the entire finger is the same size as the human finger so that realistic object manipulation can be realized.

Although the actuators were mounted off the board, the insertion points and force vectors were kept consistent with human anatomy. Moreover, each muscle actuator has the passive properties matching the appropriate muscles [8]. The actuators have both tension and position sensors to mimic Golgi tendon organs and muscle spindles. Skin has not been implemented yet to date.

B. Determining Robotic Muscle Forces

The inputs required to control the ACT robotic finger are the motor commands that simulate the muscle forces. To provide this information to the robot for a given desired dynamic set of movements, an engineered solution must be sought from the set of possible muscle forces.

Our goal is to have the robotic finger follow a prescribed set of dynamic movements recorded from a human index finger. Using a Cyberglove™ (Immersion Technologies, Inc.), the index finger joint angles (MCP, proximal interphalangeal (PIP), and distal interphalangeal (DIP)) were measured. The Cyberglove™ was carefully calibrated by finding the relationship between the raw sensor output values and the joint angles measured by a goniometer, for each of the joints through the entire range of flexion and extension postures. Five pairs of data points per joint were measured and fit with linear regression. The correlation coefficient was greater than 0.96 for all joints.

Simple 1 Hz flexion and extension movements were recorded 100 times while the Cyberglove™ recorded at a rate of 315Hz. All data analysis was performed off line. The Cyberglove™ raw output values were converted to joint angles using the calibration equation. The joint angles were filtered with a 4^{th} order low pass Butterworth filter with a 5Hz cutoff frequency (Fig. 2A). Numerical differentiation was performed to obtain angular velocity and angular acceleration. These signals, together with the finger dimensions, were used to compute the joint torques using the recursive Newton-Euler method (Fig. 2B).

The relationship between the joint torques and muscle forces depends on the muscle moment arms as follows,

$$\tau_j(t) = \sum_m F_m(t) \cdot r_{m,j} \tag{1}$$

where τ is the joint torque, F is the muscle force, m and j are indices over the muscles and joints, and r is a matrix containing the moment arms of muscle m about joint j.

Because the index finger has more muscles than joints, there are infinitely many force solutions for a given set of torques. These solutions can be characterized by,

$$F_m = F_m^{\ *} + null(r_{m,j}) \cdot \mathbf{x} \tag{2}$$

where $null(r_{m,j})$ is a 7x4 matrix containing the null space of the moment arm matrix, F^*_m is any one solution of (2), and $\mathbf{x}$ is an arbitrary 4x1 vector. For simplicity, r was taken to be constant across all joint angles and equal to the average moment arms for each muscle according to [9]. In order to find the muscle force appropriate for robotic control, $\mathbf{x}$ was calculated to minimize the following function,

$$G = \sum_m^7 F_m^2 \tag{3}$$

subject to the constraint that F is positive (since muscles can undergo contraction only).

When joint torques calculated from Cyberglove™ measurements are used to determine the muscle forces, positive solutions of (3) may not always be found because the average moment arms from [9] are not exactly those of the subject. It has been previously reported in [10] that the force calculation is sensitive to the moment arms. Since there was no direct way to measure the moment arms, (1) was turned into a soft constraint and included in our modified optimization equation,

$$G' = \sum_m^7 F_m^2 + \lambda \cdot \sum_j^3 \left(\sum_m^7 r_{m,j} F_m - \tau_j \right)^2 \tag{4}$$

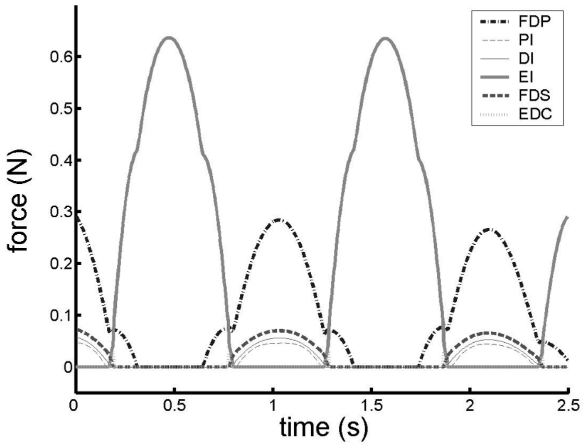

Fig. 3. Muscle forces calculated from the dynamic joint movements in Fig. 2B using (4). The lumbrical muscle was excluded from this data. These forces can be used to control the ACT index finger.

where λ is a large scalar that multiplies the error between the predicted and calculated torque. Fig. 3 shows the muscle forces calculated by minimizing (4), and which can be used to control the robotic finger.

III. Biological Approach

While using a minimum force strategy allows us to control the robotic finger, there are many other solutions that produce the same dynamic movements. Ideally, we want to identify where in the 7-dimensional force space the human force solution lies, understand the human control strategy (given a specific task), and control the robot with this strategy. To do this, we developed a methodology outlined in Fig. 4 to derive muscle forces from EMG signals.

EMG signals were recorded from all the muscles controlling the index finger while the finger joint angles were recorded using the Cyberglove™. A fine wire recording technique was employed from [11] and the signal was filtered with a 4th order Butterworth filter and normalized with the minimum and maximum contraction forces.

The neural activation, *n(t)*, was recursively calculated from the EMG using the following equation

$$n(t) = \kappa \cdot EMG(t) + \beta \cdot n(t-1) + \gamma \cdot n(t-2) \qquad (5)$$

from [12] where κ, β, and γ are optimized scalars (described below). While the relationship between *n(t)* and muscle activation, α*(t)*, are known to be nonlinear at low muscle forces [13], we assume they were equivalent in order to reduce the number of parameters of the model. This assumption is shown to be an acceptable approximation of muscle activation by [13].

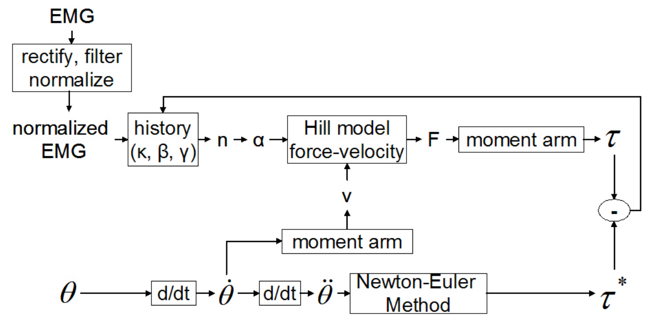

Fig. 4. The methodology we designed to derive muscle forces from the EMG signals. The normalized EMG signal is converted to neural activation, *n,* using Equation (5). Neural activation is assumed to be equivalent to muscle activation, α. Hill's force-velocity model is used to calculate muscle force, *F*, from α and muscle contraction velocity, *v*. *F* is then converted to a torque-estimate, τ*, using the muscles' moment arms. In parallel, the measured joint angles are used in the Newton-Euler method to calculate another estimate of the torque, τ. The squared difference in torque predictions is used to optimize κ, β, and γ.

Muscle activation was used in a dynamic Hill-type model to predict the muscle forces [14]. The model uses the velocity of muscle contraction, *v,* and the muscle activation α to predict contraction force using,

$$F(t) = \alpha(t) \cdot \left[b \cdot \frac{F_{\max} + a}{v(t) + b} - a \right] \qquad \text{for } v(t) > 0 \quad (6a)$$

$$F(t) = \alpha(t) \cdot \left[\frac{F_{\max}}{F_{\max} \cdot v(t) - 1} + 1.75 F_{\max} \right] \quad \text{for } v(t) < 0 \quad (6b)$$

where F_{max} is the maximum force of contraction, and a and b are Hill constants [15]. The muscle velocity was estimated as the angular velocity for the joint multiplied by the moment arm for the muscle. If the muscle spanned more than one joint, the velocity was taken as the average velocity across all joints that it spanned.

Using this set of muscle forces, a set of joint torques was calculated using (1). The difference between these torques and those calculated from the Newton-Euler method described in Section II were used to optimize the neural activation parameters (κ, β, and γ) in (5).

Optimization yielded a torque error of less than 5% per joint. The muscle forces determined from the EMGs after the optimization are shown in Fig. 5.

IV. Discussion

A. Fidelity of the proposed methodology

The Hill force-velocity curve in (6a) and (6b) that was used to determine the muscle forces exploits the relationship between changes in muscle length and muscle contraction

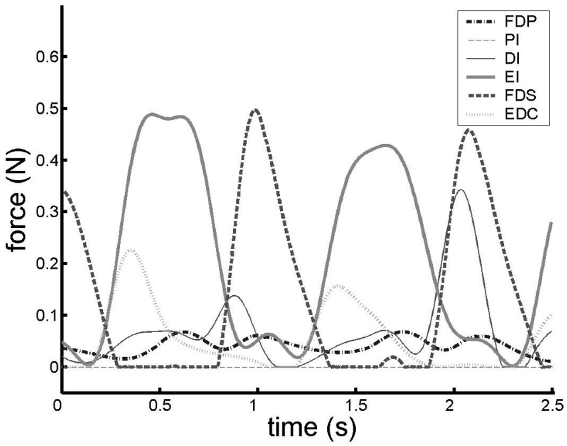

Fig. 5. Force predicted from the EMG signals. The EMG signals are rectified, normalized and filtered. A 3 parameter model is used to estimate muscle activation from the filtered EMG. A Hill-type force-velocity relationship is then used to determine muscle force from muscle activation and muscle contraction velocity.

force. Compared to this, canonical approaches to EMG processing often employ a static Hill-type model. When the more common, static Hill model was used, parameter selection in equation 4 yielded a torque error of over 70% compared to 5% for our method.

B. Comparison of Robotic and Human Muscle Forces

Controlling a robotic device in a physiological way involves calculating the muscle forces necessary to produce a given movement. We have determined the space of forces that correspond to a specified dynamic movement and found the minimum muscle force pattern. In addition, we have determined the force set selected by physiology to produce the same movement.

To generalize the physiological solution in the 7-dimensional force space, we match the forces found with an optimization criterion (e.g. minimum force in Fig. 3) and the forces derived from the EMG signal (Fig. 5). As we determine the optimization function that results in the physiological force pattern, we intend to use this methodology to find the general control strategy used in the central nervous system for a given task.

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