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COMPARISON OF PREDICTED AND PREFERRED ARM CONFIGURATIONS IN A STATIC AND A DYNAMIC TASK

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INTRODUCTION

The seemingly effortless task of moving one's fingertip from one location to another is actually quite complex when one considers the underlying mechanisms that actuate the movements of the shoulder, elbow, and wrist. Though the relation between cell activity in the motor cortex and resulting limb endpoint movement is becoming quite well established (Georgopoulos *et al.*, 1986; 1988; Kettner *et al.*, 1988; Schwartz *et al.*, 1988; Schwartz, 1992), less is known about the intermediate actions elicited by the central nervous system and musculoskeletal system to create these movements. Once the cells of the motor cortex begin firing to signal a change in desired endpoint velocity, the CNS presumably must decide on a course of action, factor in the current limb configuration, its rate of change, and the state of muscular activations, transmit control actions to change these activations, and monitor the results -- all in the period of about 120 msec.

So how does the CNS accomplish this so effortlessly? In this study, we examined whether a specific strategy -- minimization of muscular effort -- seemed to be in evidence and also whether arm movements could be controlled by specifying endpoint positions or velocities. Specifically, we examined this by comparing joint trajectories obtained from animal experimentation and computational modeling under three conditions: [i] placement of the hand in the central location with zero joint (angular) velocities; [ii] placement of the hand in a central location with zero endpoint (linear) velocity; [iii] movement of the hand from the central location with the endpoint velocity specified.

REVIEW AND THEORY

An even more basic problem must be solved even before the aspect of movement is addressed. What is the strategy by which the arm configuration is chosen to hold the limb endpoint *statically* at the *starting* position? Preparing for the anticipated movement is as important as the movement itself, because the initial mass configuration of the limb directly determines how the endpoint will accelerate given the action of each individual musculotendon force (Zajac and Gordon, 1989).

In this study, we present a new model of a monkey upper extremity obtained through dissection and digitization of the muscle-tendon pathways. We then present a novel way to determine the initial static limb configuration via the pseudoinverse dynamic optimal control procedure (Yamaguchi *et al.*, 1995). In doing so, we hypothesize that the preferred initial limb configuration to hold the limb endpoint statically in a single location is chosen via a strategy of minimal effort. Finally, we present one movement trial where the monkey moves its hand upward and leftward to a secondary target.

PROCEDURES

The torsos of two male rhesus monkeys were dissected and digitized to obtain bone surface and musculotendon path geometries accurate to +/- 0.1 mm (Optotrak, Northern Digital, Inc., Waterloo, Ontario). SIMM software (Musculographics, Inc., Chicago, IL) and a computer graphic workstation was used to display the surface geometry and to further define the musculotendon pathways. The equations of motion for the matching seven degree-of-freedom dynamic musculoskeletal model was developed and coded in FORTRAN using Kane's method. Separate rigid bodies for the radius and ulna were used so that realistic pronation and supination could be achieved in the modeled forelimb.

In the experimental procedure, infrared diode markers (IREDs) were taped on the skin surface of a third rhesus monkey of similar size and weight. Marker locations were chosen to minimize underlying soft tissue and to maximize visibility to the

Optotrak cameras. The monkey was positioned in a primate holding chair in front of a computer graphics display screen. It viewed the screen via stereographic glasses (CrystalEyes, Stereographics Corporation) so that the virtual targets (light shaded spheres) appeared as full 3-D images (Fig. 1). Feedback regarding its hand (right index metacarpal-phalangeal joint) position was provided by displaying a second virtual sphere.

The monkey was trained to first match its hand position to a central location in its workspace by bringing the "hand" sphere to the initial "target" sphere. Once the two were held approximately concentric for a short time interval, the initial "target" sphere was instantaneously moved to the second location upward and leftward of the starting position. The monkey then moved its hand without constraint to match the virtual spheres in the new location.

Optimization Procedures. Two optimization procedures were tested. The first was used to zero the *angular* velocities of the modeled limbs while holding the endpoint in the initial static position (condition [i]). For this we used the pseudoinverse algorithm which superposes and integrates joint angular accelerations created by unit stress contractions of single muscles to achieve the desired joint velocities while simultaneously minimizing the criterion function of Crowninshield and Brand (1981). Because there were an infinite number of static limb configurations which could deliver the proper endpoint location, thousands of possible joint angle combinations were generated and tested to find the configuration which had the minimum cost related to maximizing the endurance time of the task, C ,

$$C = \sqrt{\sum_{j=1}^m \sigma_j^2}$$

where m is the number of muscles, and σ_j is the stress in muscle j ($j=1, \dots, m=36$). Once the configuration of the model delivering a small cost was identified, slight perturbations of each angle were introduced to compute the change in C resulting from the perturbations for $i=1, \dots, n=7$. If one or more of the gradients $\partial C / \partial \theta_i$ were negative, the process was repeated until all of the gradients were positive.

The second optimization procedure involved a modification of the first procedure to control the *linear* velocities of the hand during both the static task and a movement from the initial position to the new target location (conditions [ii] and [iii]). The endpoint velocities obtained from the animal experiments were defined as inputs to the model. The model attempted to match these by

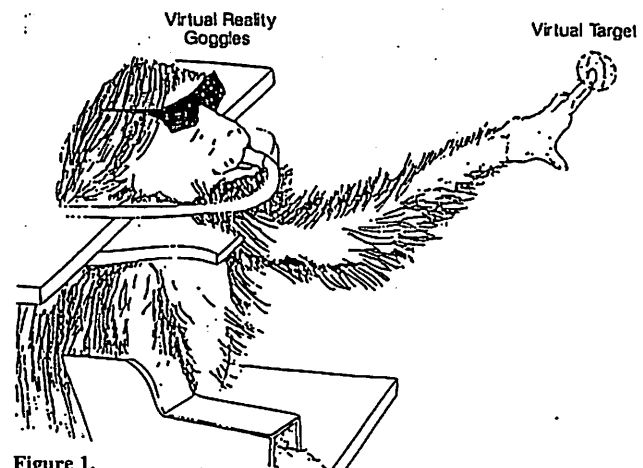


Figure 1.

superposing and integrating the endpoint accelerations created by unit stress contractions of each of the 36 muscles using a pseudoinverse procedure. The outputs from the numerical procedure were the joint trajectories, which were compared to the experimental results.

RESULTS

Utilizing the first optimization method resulted in a good prediction for the joint angles preferred by the monkey for the initial static configuration (Fig. 2), except for angle θ_7 (wrist ab/adduction). When the second optimization method was used to zero limb endpoint linear accelerations in the initial static configuration, the pseudoinverse algorithm delivered solutions that had lower cost but allowed the joints to move even though the endpoint remained fixed in space.

Using the experimentally measured joint angles as an initial configuration for the point-to-point movement, the second optimization procedure delivered limb endpoints that were within 2 mm of the desired positions. Again, the joint angles were not constrained in any way, yet the solution compared favorably in five out of the seven angles. Angles θ_1 (shoulder ab/adduction) and θ_7 from the simulation did not match the joint trajectories utilized by the experimental animal (Fig. 3).

DISCUSSION

The first optimization method appears to predict the preferred static configuration of the limbs very well. From these results it would appear that a strategy of minimizing muscle energy expenditure (the converse of maximizing the endurance time of the task) is in evidence for the static problem. On the other hand, the second optimization method did not predict either static or dynamic joint configurations very well. This is not surprising because the first method requires all seven joint velocities to be specified in time, while the second method requires as inputs only the three components of the endpoint velocity. What is rather surprising is that the second method actually delivers reasonable solutions for five out of the seven angles, even though reasonable solutions might be expected for only three. In succeeding work we will examine the consequences of adding additional input information.

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Figure 3. Error between experimental and numerical joint angles. The tick mark on the left indicates an error of 10 deg.

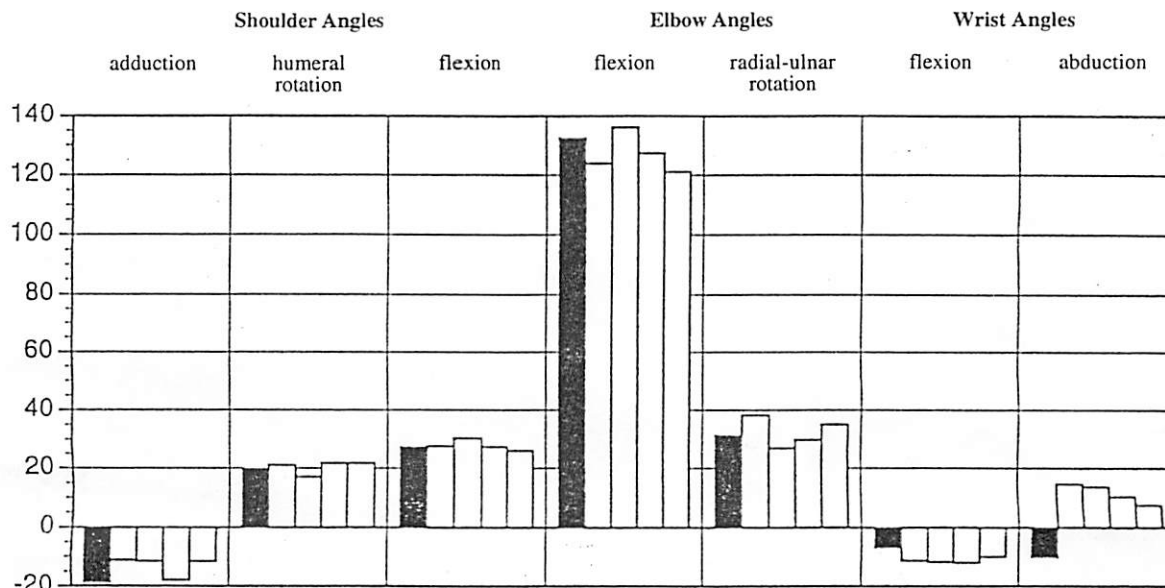
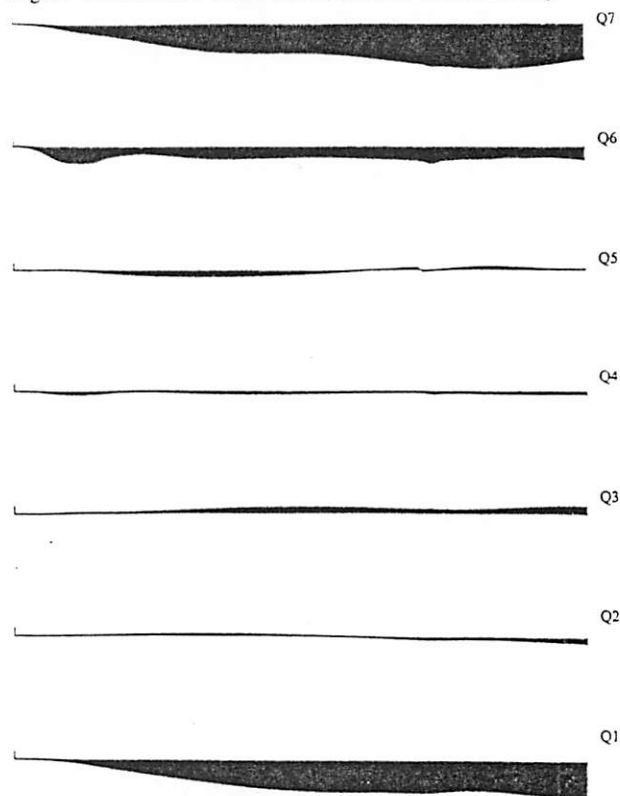


Figure 2. Histogram showing the preferred static arm configuration predicted by the model (black) as compared to four experimental trials with a live monkey (white). Angles are listed in order from θ_1 (leftmost) to θ_7 (rightmost).