Optimal Control and Synergic Pattern Analysis of Upper Limb Reaching-Grasping Movements

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Abstract. A three-dimension, neuromusculoskeletal model of the human upper limb, consisting of 30 muscle–tendon systems, was combined with dynamic optimization theory to simulate reaching-grasping movements. The model was verified using experimental kinematics, muscle forces, and electromyographic(EMG) data from volunteer subjects performing reaching-grasping movements. Despite joint redundancy, the topological invariance was observed in the trajectories of different task performance, and the linear relationships between joints covariation were exhibited. Quantitative comparisons of the model predictions and muscle activations obtained from experiment show that the minimum torque-change criterion is a valid measure of reaching-grasping performance.

Keywords: Synergic Pattern, Optimal Control, Upper limb, Reaching to grasp movements.

1 Introduction

Prehension is a popular task for studying human sensorimotor control[1]. It involves reaching and grasping an object for a purpose such as manipulating it, transporting it or just feeling it. On the kinetic level, prehension entails applying forces during interaction with an object. On the kinematic level, prehension involves the orienting and posturing of the hand and fingers, with the appropriate transportation of the limb to the correct location in space. How the reaching and grasping to be well-coordinated? Experimental studies have been conducted to explore the processes and neural mechanisms that allow coordination of the prehensile act. With the exception of a few studies using the model prediction[2], most have examined prehension only using motion analysis system[3], and focusing on single-joint movements[4] within the last 15 years.

Quantitative analyses of muscle force synergies have not been reached, and the neural control mechanisms or muscle synergies (structural units) among the whole-arm involving in reaching-grasping remain unclear.

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In this paper, we will present a three-dimension, neuromusculoskeletal model of the human upper limb, and combined with dynamic optimization theory to simulate normal self-paced reaching-grasping movements. The model was partially verified using experimental kinematic, muscle forces, and electromyographic(EMG) data from volunteer subjects performing reaching-grasping movements. This verification lends credibility to the time-varying muscle force predictions and the synergic recruitment of muscles that contribute to both reaching and grasping manipulation.

Our specific aims are: (a) to present a physiologically supported, time-dependent, performance criterion for normal reaching-grasping; (b) to evaluate the model simulation results through comparisons with experimental data. (c) to decide whether a patterns of movement coordination and units of synergistic muscular group are involved into healthy people prehension.

2 Methods

2.1 Human Experiments

Five healthy male adults participated in this study. The average age, height, and mass of the subjects was 26 ± 3 years, 177 ± 3 cm, and 70.1 ± 7.8kg, respectively. Ethical approval from the Tsinghua University was granted for this study and all procedures were in accordance with ethical guidelines.

Subjects were instructed 'to grasp the glass and drink from the glass' using the right hand. No instructions about movement speed were given. As a warm-up, each subject had five practice trials prior to data collection in each condition,. The glass (height 11.8 cm and radius 5.8 cm) filled with water, and put on two heights (h_1 =710mm and $h_{2=}$=1100mm). Each subject was asked to perform four reaching-grasping tasks with different indices of difficulty (2 heights × 2 type of strap).

In the Task1 and Task4, Subjects were seated in a rigid-supported chair with their right shoulder strapped to the chair back with a wide belt. The trunk motion occurred in the condition had not the contribution to hand movement. Task1 was named as a "natural task", and Task 4 was named as a "difficult task".

The starting position and reach distances were standardized. At the beginning of each trial, the right arm of the subject was relaxed and rested on the chair, the hand being at the hip height. Seat height was adjusted to 100% of lower leg length as measured from the lateral knee joint line to the floor with the subject standing barefoot. Reach distances were standardized to 100% of arm length. Arm length was measured separately for each subject, and the length was defined as the distance from the shoulder marker to the most distal point of the hand, i.e. tip of the flexed middle finger around the glass for the grasp task.

Retroreflective marks (2.54 cm and 5.08 cm in diameter) were placed on the right arm and hand to measure the three-dimensional position of each segment. The joint coordinate system, as defined by Schimidt *et al.*[5], was used in this study. Subjects were video-taped from the right side as they reached for the object with their right hand. The video camera had a fixed sampling rate of 25 Hz and a shutter speed of 1/1000 s.

Surface electromyography (EMG) electrodes (Meditrace™, 11 mm, self-adhesive, silver-silver chloride) were placed over five muscles on the right arm: biceps brachii (BIC), triceps brachii (TRI), anterior deltoid (DEL), flexor digitorum superficials(FDS), and extensor pollicis longus(EPL). The electrodes were placed in a bipolar arrangement over the muscles in the recommended locations.

The right shoulder of subject was in the plane of the glass which was parallel to the subject's sagittal plane. We are going to refer to this plane as ``movement plane'' in the following statement since endpoint movements as well as wrist and elbow rotations occurred mostly in this plane.

2.2 Mathematical Model of the Upper Limb

We developed a three-dimensional neuromusculoskeletal model of the human upper limb, the model allows elbow flexion/extension, forearm pronation/supination, wrist flexion/extension and radial/ulnar deviation.

The skeleton of the upper arm was articulated by joints and moved by the actions of muscles actuators. Each actuator was modeled as a 3-element, Hill-type muscle in series with an elastic tendon . Altogether, 30 muscle-tendon systems, having effect on the motion of the forearm, palm and fingers, are included. Parameters determining the nominal properties of each actuator were based on data reported by Delp. Following Chao et al.[6], additional tendons are introduced to model the extensor systems of the fingers. Values of the musculotendon parameters assumed for each actuator in the model are given in Ph.D. theses 0f Yang Yi-yong [7].

The corresponding dynamical equations for the upper limb model can be written as follows:

(a) skeletal dynamics

$$A(q)\ddot{q} = B(q)\dot{q}^2 + G(q) + M(q)P^T + T(q,\dot{q}) \tag{1}$$

where $A(q)$ is 3×7 system mass matrix; $B(q)\dot{q}^2$ is a 3×1 vector describing both Coriolis and centrifugal effects; $G(q)$ is a 3×1 vector containing only gravitational terms; $M(q)$ is a 3×30 the moment arm of musculotendon force; P^T is an 30×1 vector of musculotendon actuator forces; $T(q,\dot{q})$ is the passive movements at each joint; q $\dot{q}$ $\ddot{q}$ are 7×1 vectors of upper limb segmental displacements, velocities, and accelerations.

(b) musculotetendon dynamics,

$$\dot{P}^T = f(q,\dot{q},P^T,a_i(t)); i = 1,30 \tag{2}$$

where $a_i(t)$ is the level of activation in the *i*th muscle.

(c) muscle excitation-contraction dynamics

$$\dot{a}_i(t) = (1/\tau_r)(1-a_i(t))u_i(t) + (1/\tau_f)(1-a_i(t))(1-u_i(t)) \quad (3)$$

where $u_i(t)$is the input excitation given to the ith muscle in the model; τ_r and τ_f are the rise and decay times for muscle activation, respectively.

(d) parameterized optimal control theory and solution

The optimal control problem can be stated as follows: minimize the performance criterion subject to the dynamical equations of the model (Eqs.(1)-(3)), and the constraints imposed at the beginning and end of the simulated reaching-grasping movement cycle.

Examined some performance criteria (e. g. energy, torque, movement time etc.), we hypothesized that the motor patterns that typify normal grasping movement are the result of a minimization in torque-change model.

The objective function of the criterion is expressed as

$$C^T = \frac{1}{2}\int_0^{tf}\sum_{i=1}^{n}(\frac{dz_i}{dt})^2 dt \quad (4)$$

Here, t_f indicates the motion duration. N is the number of joints, and Z_i shows the commanded torque generated in joint i.

Presuming that the objective function must be related to the dynamics, we proposed the following measure of a performance index: sum of square of the rate of change of torque integrated over the entire movement. Here, let us call this model "minimum torque-change model".

The model described above was implemented with commercially available software, Automatic Dynamic Analysis of Mechanical Systems (ADAMS^R) analyzed and solves the motions and forces of three-dimensional mechanical systems. The user enters the body parts, joints, and imposed forces or motions and the software produces and solves over time the equations of motion of the mechanical system using Lagrangian equations and predictor-corrector methods of numerical integration.

3 Results

3.1 Kinematics

Table1 shows the human movement time (HMT) affected by both height and strap condition. As *Index of difficulty* increased, there was a significant increase in HMT [Flinear(1, 5)=41.6, P=0.001]. The difficult grasp task took longer time to complete than the normal task at each trial [F(1, 5)=61.2, P=0.001]. The movement time measured for Task 1 of the subject and predicted by model subject to minimum torque-change criterion were 0.990 and 0.960 seconds, respectively, a 5% difference in the final times, which is very close to the optimal speed.

Fig. 1 shows the spatial trajectories of the hand in performing different tasks by the same subject in normalized time (for ease of comparison, each experimental and predicted results was normalized its respective final time to compare overall patterns). In the reaching phase (about 70% movement cycle), the hand was consistently moved in a relatively straight path to the object (even though the pattern of segmental motion and hence the amount of weight shift varied between conditions). In the grasping phase (about 30% movement cycle), it can be seen that the trajectories of the hand

Table 1. Means and standarded diviation of HMT for each task

Task	HMT (ms)	S.D.	Index of difficulty
Task 1	960	56	0.1
Task 2	1020	61	0.3
Task 3	1180	78	0.6
Task 4	1238	89	1.0
Model	990	0	0.0

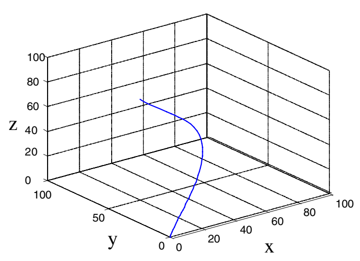

Fig. 1. Three dimension trajectories of prehension

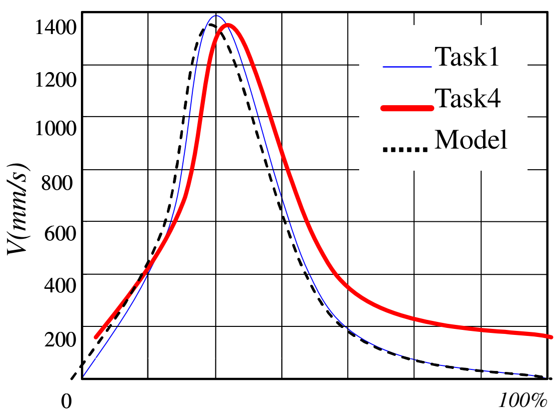

Fig. 2. The Velocity of the hand from a representative trial and model prediction

were not in straight lines (an arc).The figures also indicate that the movements in spite of different tasks have topological invariance in spatial trajectories.

Experimental (Task1, Task 4) and predicted velocity trajectories for a reaching and grasping movement are shown in figure 2. All curves were normalized with respect to its respective final time. The velocity profiles also indicate a good fit between the model's and the experiment's. The peak velocities for the Task1 are larger for the Task4. The peak occurs in task4 slightly later in the model (8%). Both velocity profiles of the subject and model showed a pattern indicating a bell-shaped profile. Also apparent in Fig. 2 is the final velocity of the hand (i.e. the velocity at contact

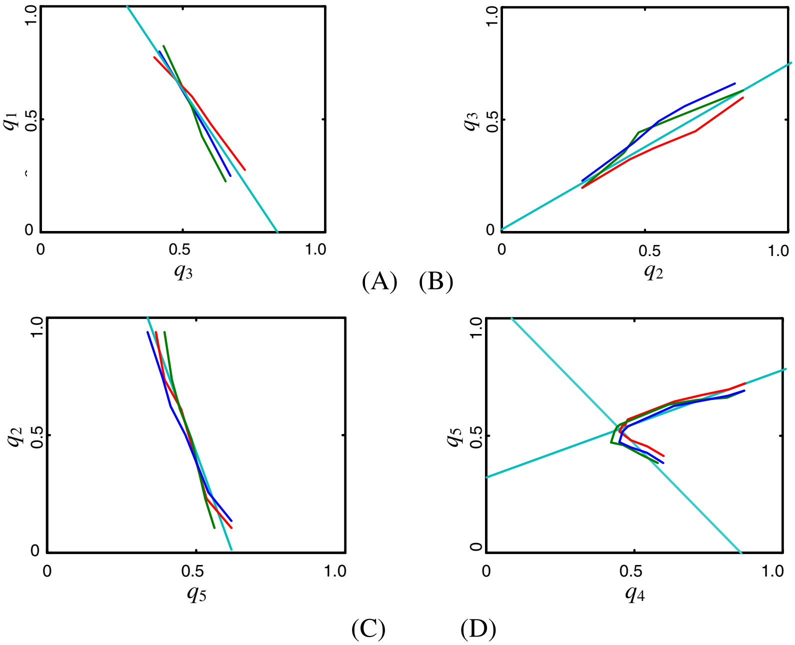

Fig. 3. The Angular covariations of prehension in normal condition (task1). q1=δ:Forearm rotation , q2=δ: Upper arm rotation ,q3=α: Upper arm azimuth, q4=β: forearm elevation, q5=ψ: Elbow flexion.

with the object). In Task4, final velocity was not zero, indicating that subjects used the object to stop the action. In contrast, in the Task1, which involved more accuracy, the hand slowed markedly as it approached the glass in order to prevent spillage.

This comparison indicates that the minimum torque-change kinemaitcs solution of the model for a hand reaching-grasping movement corresponds well with how the subject performed.

3.2 Angular Covariations

Fig.3 shows angular covariations for the normal condition (Task1). Here, q1=δ:Forearm rotation , q2=δ: Upper arm rotation , q3=α: Upper arm azimuth , q4=β: forearm elevation , q5=ψ: Elbow flexion. They (in Fig.6)are averaged values for 3 subjects.(shows single trials performed by subject 3 during the normal task). Regression lines were computed on averaged curves. The coefficients of regression were highly significant for all the single and averaged curves ($p < 0.0001$). This observation indicated the existence of a linear relationship between joint covarivation.

3.3 Muscle Excitation Patterns

The predicted muscle activations from the model's sub-optimal minimum performance criterion solution were compared to the experimental activations.

In general, the model predicted muscle excitation patterns similar to the processed EMGs, especially for the acceleration portion of the movement.

Results of the predicted musculotendon forces and activations indicate that it would be correct to assume that so called "synergistic muscles" at the upper limb produce similar time-varying forces and activations. Therefore, to lump these muscles together to reduce the system would be possible.

4 Discussion

Because the number of the freedom of the upper limb (DOF=7 when finger joints are neglected) exceeds those necessary to completely specify the location and orientation of an object in space (DOF=6). The mathematical relationship associating the coordinates of the object to grasp and the final posture of the arm (inverse mapping) is a priori indeterminate. Optimal control theory is potentially the most powerful method for determining redundancy muscle forces during movement.

The power of an optimal control approach derives from the scope of the modeling not only does optimal control theory allowing muscle dynamics to be included in the formulation of the problem, but also delivers a purely predictive result independent of experiment. Once an optimal control solution is found, there is a wealth of information available to compare with experimental data. Optimal control theory requires that a model of the system dynamics be formulated and that a performance criterion is specified as well.

In this paper, the model computational solutions were compared to the grasping experimental kinemaitcs and EMG data and matched well with each other. This comparison indicates that minimum torque-change kinematics solution of the model for upper limb reaching-grasping corresponds well with how the subject performed. This criterion has been proposed in a computational model of brain's activity during a reaching movement.

Several researchers measured the hand trajectories of skilled movements and found common invariant features. The integrated components for developing computational musculoskeletal models have been established for the human limbs through long time efforts[8]. The models of musculoskeletal systems have used optimal control strategies to solve the indeterminate problem using a variety of performance indices[7]. These attempts have yielded a better understanding the coordination of muscle forces.

During our trials, the joint covariations patterns were very stable, the individual variations o f the upper limb angles were systematically coupled with respect to the time (joint synergies). During the movement, joint angle variations are not controlled independently, but in a synergic way (temporal coupling). The movement trajectory observed, either in the task or joint space, results directly from this temporal coupling.

These results suggest that natural movements are mostly carried out in joint space by postural transitions.

5 Conclusion

The results show that the topological invariance was observed in the trajectories of different task performance, and the linear relationships between joints covariation were exhibited. Moreover, the different muscles were controlled and combined into units of synergistic muscular group necessary to reach and grasp the goal.

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