2009 IEEE 11th International Conference on Rehabilitation Robotics
Kyoto International Conference Center, Japan, June 23-26, 2009

Motor Task Planning for Neuromuscular Function Tests using an Individual Muscle Control Technique

Jun Ueda, Moiz Hyderabadwala, Vijaya Krishnamoorthy, and Minoru Shinohara

***Abstract*— A functionality test at the level of individual muscles may be effective for neuromuscular function tests. This paper proposes a novel computational method for neuromuscular function test planning using an individual muscle-force control technique assisted by a rehabilitation robot. The algorithm will systematically compute an adequate amount and direction of force that a subject needs to exert, e.g., by his/her hand, to induce a desired muscle activation pattern of target muscle forces. A wearable robot with actuators (an exoskeleton robot, or a power-assisting device) is utilized to assist/resist the subject's joint torques. This paper presents a basic concept and preliminary simulation results. The simulation results justify the use of the wearable actuators in terms of the accuracy of muscle-level control during planned motor tasks.**

I. INTRODUCTION

Healthy individuals modulate muscle activation patterns according to intended movement and environment. Neurological patients with movement disorders (e.g., stroke and spinal cord injury), however, have problems in movement control due primarily to their inability to modulate their muscle activation pattern in an appropriate manner [1], [2]. Investigation into the association between neurological impairment and a muscle-activation pattern is critical for future diagnosis and treatment since the modulated muscle-activation pattern is expected to be associated with the type and degree of impairment. The most efficient way to find a difference in the modulation of muscle-activation pattern is to apply a unique load combination that induces a predictable modulation in the muscle-activation pattern in healthy adults while the modulation in patients is expected to be different [3]. A functionality test at the level of individual muscles may be effective, because the tests investigate the activity of a muscle of interest on various motor tasks. The functionality test would provide muscle-level information on, e.g., fatigue, impairment, and function recovery.

In the past two decades, a number of muscle-force prediction methods have been presented based on the Principle of Optimality [4], [5] that represent performance criteria on which the neuromuscular system optimizes the activation of muscle forces. Static optimization methods, dealing with isometric and relatively slow motions, predict redundant muscle forces by minimizing a cost function, comprising the sum of muscular stress or force raised to a power, subject to force/torque constraints associated with a given task. The biggest advantage is that the muscle force prediction is mathematically formulated and can be numerically solved, enabling a prediction for relatively complex tasks involving multiple joints such as walking and running. There are still arguments and criticism on the neurological background of this optimization; however, the effectiveness of this approach for predicting stereotyped motor performances has been reported in many papers [6], [7], [8].

To the authors' knowledge, there is no systematic method proposed to plan motor tasks for neuromuscular function tests to obtain favorable muscle activation patterns while the research on computational methods for muscle force prediction has been actively studied. Due to the presence of muscle redundancy [9], joint-torques and muscle-forces are intricately coupled. This makes the planning of muscle-level function tests difficult and greatly limits the variety of function tests. Single-joint tasks, i.e., asking subjects to exert a certain joint torque, are widely performed in neuromuscular science in order to investigate the activity of a single muscle of interest around the joint (e.g., [10]). Unfortunately, however, the number of one-to-one correspondences between a joint toque and muscle force that can be found in the human body is very limited due to the presence of biarticular muscles. Even multiple-joint tasks (e.g., [11]), such as a reaching motion in the horizontal plane, are performed by adding restraints to the trunk as well as to other body parts to minimize the degrees of freedom involved and to avoid the ambiguity in the joint torque-muscle force relationship. The body restraints prevent motion; however, they do not necessarily prevent muscle activities due to reaction forces at the restrained body parts.

The planning of a functionality test at the level of individual muscles will be accomplished by applying the individual force control technique [12], [13] using wearable actuators. For upper-limb tasks, a subject needs an adequate amount and direction of force to exert by his/her hand to induce a desired muscle activity pattern, which will be computed in a systematic manner. A wearable robot with actuators (an exoskeleton robot) is utilized to assist/resist the subject's joint torques if the exertion of a force by subject is not sufficient, and therefore, additional torque control is required.

This paper presents a computational method for motor-task planning for neuromuscular function tests by applying the individual muscle-force control technique [12], [13]. Simulation results justify the use of the wearable actuators in terms of the accuracy of the muscle-level force modification.

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II. Individual muscle-force control using a wearable robotic device

Although exoskeleton-type robots have been developed for industry, military, and biomedical areas [14], [15], [16], [17], the main focus was for joint-level torque assistance or arm/foot trajectory adjustment. Ueda et al. have presented the concept for a more sophisticated application of exoskeleton robots [12], [13]. The key idea of this concept is to adjust the load of a selected group of human muscles (target muscles) by applying torques via multiple physical interfaces of a wearable robot (an exoskeleton, or a power-assisting device) to multiple human joints that are involved in a task. Figure 1 shows the concept of individual muscle-force control.

The influence of forces/torques applied from an exoskeleton on each individual muscle force is predicted using a human musculoskeletal model. By hypothesizing the Principle of Optimality in human muscle force generation, this prediction problem can be formulated as a standard constrained optimization problem introducing a cost criterion function comprising the subject's muscular stress or force raised to a power. The cost function is minimized by a numerical optimization technique subject to the constraints associated with the force and torque requirements to perform a specific task [4], [5].

Inversely, the predicted results are utilized to calculate the external forces/torques from a wearable robot such that desired muscle forces are obtained, thus enabling muscle force grading at the level of individual muscles. Assume that the above prediction holds when external loads are applied to a subject from a wearable robotic device. The key idea is to treat the above-mentioned mathematical formulation for muscle-force prediction in the opposite way; a task that induces a desired change of target muscle force is calculated. This muscle force control can be regarded as a problem to determine equality constraints for the Optimality criterion such that the desired muscle forces are obtained as a result of cost function minimization. Note that some of the equality constraints directly correspond to a subject's joint toques. These joint torques can be modulated by a subject's voluntary exertion of force, i.e., motor-task planning. However, the sole change of a subject's voluntary force may be insufficient in terms of the number of control degrees of freedom (DOF) for explicitly inducing specific muscle activities. If the exertion of a force by a subject is not sufficient to create adequate equality constraints regarding joint torques, a wearable robotic device (exoskeleton) generates external torques to assist/resist joint torques, improving the control of muscle forces.

III. Computational method of motor task planning for neuromuscular function tests

The overall system consists of a wearable actuator device, a handle, a muscle force control problem solver, a musculoskeletal human model, and a user-friendly graphical interface. The handle to which a subject experts a force is equipped with a force transducer and securely attached on a table. The planning and test procedure are as follows:

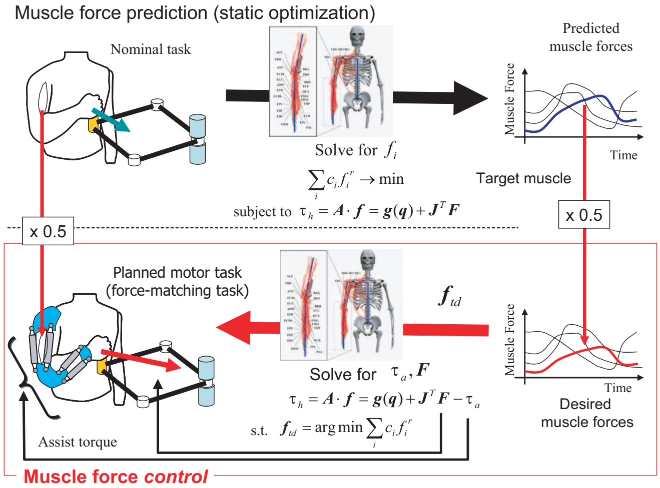


Fig. 1. Motor-task planning for neuromuscular function tests using an individual muscle control technique: Concept

Step1-Nominal muscle force prediction: Determine the body posture and nominal task. The musculoskeletal model calculates nominal muscle forces by Static Optimization.
Step2-Designation of muscle forces: Using the graphical user interface, designate target muscle(s) and determine the change rates of forces based on the nominal muscle forces.
Step 3-Motor task planning: The muscle force control solver checks the feasibility of the designated muscle forces in terms of the Principle of Optimality. The force that the subject needs to exert to the handle is calculated. Control commands to the wearable robot are calculated if needed.
Step4-Execution: The wearable robot applies joint torques. An instruction monitor displays the computed force using an arrow and the current force using another arrow. Subjects perform force-matching tasks to match the hand-force with the instructed force.

IV. Muscle-force control system

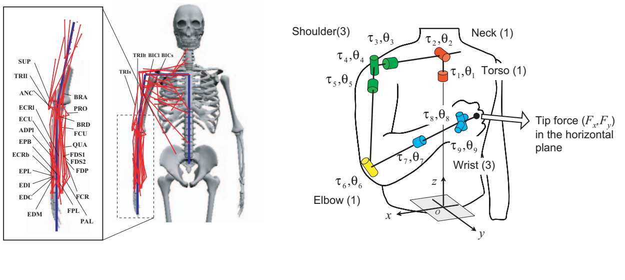
Currently the component-level development is completed and the integration of the system is in progress.

A. Musculoskeletal model

A musculoskeletal model of the human upper-right limb shown in Fig. 2(a) was developed [13] to calculate moment-arms to attached bones for each of the muscles. This model consists of 5 rigid links with 12 joints corresponding to the waist, neck, shoulder, elbow, and wrist. Massless wires model a total 51 muscles of the upper-right limb according to [8] [6]. In this paper, a total of 9 joints from the torso to wrist will be considered as shown in Fig. 2(b). By applying the Static Optimization method (e.g., Crowninshield's method, see Appendix), the redundant muscle forces can be predicted by minimizing a cost function for static tasks or relatively slow (i.e., quasi-static) motions.

B. Wearable robot

A wearable robotic device using pneumatic actuators shown in Fig. 3 has been developed to control the muscle



(a) Muscles in the Upper-right limb

(b) Joint configuration

Fig. 2. Human musculoskeletal model

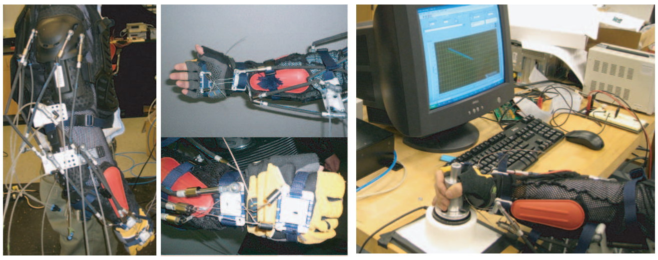


Fig. 3. Wearable robot with actuators to control joint torques

forces of the human upper-right limb. This device applies 4 degrees of freedom of torques (DOFs) of the right arm: 1 DOF of the elbow joint and 3 DOF of the wrist joint, by a total of 10 actuators. The shoulder mechanism will be added in the near future. Both ends of each actuator are attached to plastic frames which are then attached to the body by Velcro tape. Unlike other exoskeleton mechanisms, this device does not have any rigid frames, but FESTO's flexible actuators for safety reasons.

C. Muscle-force control solver and graphical user-interface

An operator designates target muscles and determines rates of change using a graphical user-interface. The muscle-force control solver described later computes an adequate amount and direction of force that a subject needs to exert, e.g., by his/her hand, to induce the desired muscle forces of the target muscle forces. The solver also computes joint torques that the wearable robot applies to the subject's joints if the exertion of force by the subject is not sufficient, and therefore additional torque control is required.

V. Problem Formulation and Solution

A. Static equation

In this paper, muscle-force control for static tasks is considered; we assume that a subject does not change his/her posture during a task and all muscle contractions are isometric. The dynamics of the body and wearable robot is neglected. Consider a human musculoskeletal model that has M joints and N muscles. The static equation of this musculoskeletal system (e.g., see Fig. 2(b)) is given by

$$\begin{aligned} \boldsymbol{\tau}_h &= \boldsymbol{g}(\boldsymbol{\theta}) + \boldsymbol{J}(\boldsymbol{\theta})^T \boldsymbol{F} - \boldsymbol{\tau}_a = \boldsymbol{A}(\boldsymbol{\theta})\boldsymbol{f} \\ &= \begin{bmatrix} a_{11} & \cdots & a_{1N} \\ \vdots & \ddots & \vdots \\ a_{M1} & \cdots & a_{MN} \end{bmatrix} \begin{bmatrix} f_1 \\ \vdots \\ f_N \end{bmatrix}. \end{aligned} \tag{1}$$

where $\boldsymbol{\tau}_h \in \Re^M$ is the human joint torque vector, $\boldsymbol{\theta} = [\theta_1, \cdots, \theta_M]^T \in \Re^M$ is the joint angle vector, $\boldsymbol{F} = [F_x, F_y, F_z]^T$ is the translational force at the tip, $\boldsymbol{J}(\boldsymbol{\theta})$ is the Jacobian between the tip-force and joint torques, $\boldsymbol{g}(\boldsymbol{\theta})$ is the gravity force, $\boldsymbol{\tau}_a \in \Re^M$ is the joint torque generated by the wearable robot, $\boldsymbol{A} \in \Re^{M\times N}$ is the moment-arm matrix of the muscles, and $\boldsymbol{f} = [f_1, \cdots, f_N]^T \in \Re^N$ is the human muscle force vector. The element a_{ij} of $\boldsymbol{A}$ denotes the moment arm of muscle j for joint i. $a_{ij} = 0$ is given if f_j does not affect on joint i. Note $f_j \geq 0$ $(j = 1, \cdots, N)$ because of muscle contraction. $\boldsymbol{g}(\boldsymbol{\theta})$, $\boldsymbol{J}(\boldsymbol{\theta})$, and $\boldsymbol{A}(\boldsymbol{\theta})$ for a given posture $\boldsymbol{\theta}$ can be calculated by the musculoskeletal model in Fig. 2(a). To simplify the problem, we assume that the robot can produce joint torques without any mechanical limitations.

B. Static optimization

The human body has a redundant number of muscles than the number of joints, i.e., $N >> M$. This fact makes the prediction of muscle forces $\boldsymbol{f}$ by knowing joint torques $\boldsymbol{\tau}_h$ an ill-posed problem. Various optimization approaches have been proposed to model the Principle of Optimality [4], [5] and to solve this problem by minimizing a cost function. The main difference among the approaches is the structure of cost functions that represent performance criteria on which the neuromuscular system optimizes the activation of muscle forces. In much literature that deals with isometric or relatively slow motions, the cost functions have a general form comprising the sum of muscular stress or force raised to a power. The static optimization method can be formulated as follows.

$$\text{Minimize} \quad u(\boldsymbol{f}) = \sum_{j=1}^{N} c_j f_j^r \tag{2}$$

$$\text{subject to} \begin{cases} \boldsymbol{\tau}_h = \boldsymbol{A}\boldsymbol{f} \\ 0 \leq f_j \leq f\mathrm{max}_j (j = 1, \cdots, N) \end{cases}$$

where $u(\boldsymbol{f})$ is a cost function, c_j's are weighting factors, and r is an integer number. It should be noted that arguments still exist on the choice of the weighting factors c_j and the integer r of the power [4], [5]. This research will treat this general form of cost functions "as is" since it provides a sufficient form for mathematical analysis. The different choice of parameters can be treated easily in numerical calculation. Therefore, the muscle force control technique is expected to be applicable for any static optimization criteria.

C. Muscle force control

Excluding direct stimulation of individual muscles, muscle forces are indirectly controlled through the modification of joint torques. Technically speaking, even if the wearable robot device assists the modification of joint torques by applying external torques, the total number of joints (i.e., control inputs) is much fewer than the number of muscles (i.e., control outputs). Since we hypothesize that human muscle forces obey the Principle of Optimality, a distribution of muscle forces against the principle can never be realized.As described earlier, the wearable device merely modifies the human joint torques, which is equivalent to the modification of the equality condition of the cost minimization in (2). In other words, the proposed pinpointed muscle force control is an indirect control of muscle forces by an appropriate modification of the equality condition for cost function optimization.

Let $\boldsymbol{f}_0$ be the nominal muscle forces obtained in Step 1 in Section III. Based on the nominal muscle forces, the N muscles are classified into two groups: active muscles and inactive muscles. The active muscles correspond to the elements having nonzero values in $\boldsymbol{f}_0$, and the inactive muscles correspond to zero elements. Let $\tilde{N} \leq N$ be the number of the active muscles, and $N - \tilde{N}$ be the number of the inactive muscles. In the muscle-force control, the inactive muscles' forces are kept inactive. The active muscles are further divided into two portions: **target muscles** $\boldsymbol{f}_t \in \Re^{N_t}$ and **non-target muscles** $\boldsymbol{f}_n \in \Re^{N_n}$ where $N_t + N_n = \tilde{N}$. Without the loss of generality, the order of the N muscles may be permutated according to these three groups for the simplicity of description:

$$\boldsymbol{f} \triangleq \left[\begin{array}{c} \boldsymbol{f}_t \\ \boldsymbol{f}_n \\ \hline \mathbf{0} \end{array} \right] . \begin{array}{l} \cdots \text{target muscles} \\ \cdots \text{non-target muscles} \\ \cdots \text{inactive muscles} \end{array} \tag{3}$$

The desired muscle forces $\boldsymbol{f}_{td}$ are given as follows by explicitly specifying the change rate for each of the target muscles:

$$\boldsymbol{f}_{td} = \mathrm{diag}[\gamma_1, \gamma_2, \cdots, \gamma_{N_t}]\boldsymbol{f}_{t0} \tag{4}$$

where γ_j is the change rate of the j-th target muscle. Hereafter the subscript d denotes the desired muscle forces, and 0 denotes the nominal muscle forces. The above permutation for $\boldsymbol{f}$ is also applied to the moment-arm matrix $\boldsymbol{A}$ accordingly:

$$\boldsymbol{A}^T = \left[\begin{array}{c} \boldsymbol{A}_t \\ \boldsymbol{A}_n \\ \hline \boldsymbol{A}_v \end{array} \right] . \begin{array}{l} \cdots \text{target muscles} \\ \cdots \text{non-target muscles} \\ \cdots \text{inactive muscles} \end{array} \tag{5}$$

Hereafter these permutated vectors and matrices will be used.

The muscle-force control is to obtain the tip-force $\boldsymbol{F}$ that a subject exerts against the handle and the external torques $\boldsymbol{\tau}_a$ that the wearable robot generates. Define the total external torque vector as the sum of the torque due to the reaction force of $\boldsymbol{F}$ and $\boldsymbol{\tau}_a$:

$$\boldsymbol{\tau}_{ex} = \boldsymbol{J}^T\boldsymbol{F} - \boldsymbol{\tau}_a \tag{6}$$

The mathematical formulation of the muscle-force control is given as follows.

$$\boldsymbol{f}_{td} = \underset{\boldsymbol{\tau}_{ex}}{\mathrm{argmin}} \sum_{j=1}^{N} c_j f_j^r. \tag{7}$$

Note that there exists a certain freedom for determining $\boldsymbol{F}$ and $\boldsymbol{\tau}_a$ at the level of joint torque. The simulation section will solve this problem from a practical point of view.

D. Solution of muscle-force control

The solution of the above-mentioned muscle-force control is not straightforward while many numerical optimization packages are applicable for muscle force prediction. Applying optimality conditions for constrained optimization problems such as those given in the Karush-Kuhn-Tucker (KKT) conditions [18] can analytically solve the problem.

Since the number of control inputs (i.e., the number of the elements of $\boldsymbol{\tau}_{ex}$) is limited, the priority-based approach is applied. The first priority is to exactly realize the desired forces $\boldsymbol{f}_{td}$ of the target muscles. The second priority is to minimize the changes of the non-target muscles since the non-target muscle forces will be influenced by the first-priority muscle control due to the physical coupling among the muscles.

Theorem: The external torque $\boldsymbol{\tau}_{ex}$ as the solution of (7) is given by

$$\boldsymbol{\tau}_{ex} = \left[\begin{array}{c} \boldsymbol{A}_t \\ \boldsymbol{A}_n \end{array} \right]^+ w^{-1}\left(\left[\begin{array}{c} \boldsymbol{A}_t \\ \boldsymbol{A}_n \end{array} \right] \boldsymbol{\alpha} \right) \tag{8}$$

where $w(*)$ is a function that converts the muscle force vector $\boldsymbol{f}$ to a new vector $\boldsymbol{q}$ as $\boldsymbol{q} = w(\boldsymbol{f})$ where the j-th elements of $\boldsymbol{f}$ and $\boldsymbol{q}$ have the following relationship:

$$q_j \triangleq \frac{\partial u(\boldsymbol{f})}{\partial f_j} = r c_j {f_j}^{r-1}, (j = 1, \cdots, N). \tag{9}$$

$\boldsymbol{f} = w^{-1}(\boldsymbol{q})$ is the inverse function of $w(*)$. Also, $\boldsymbol{\alpha}$ is given as $\boldsymbol{\alpha} = \boldsymbol{A}_t^+ [w(\boldsymbol{f}_{td}) - w(\boldsymbol{f}_{t0})] + (\boldsymbol{I} - \boldsymbol{A}_t^+\boldsymbol{A}_t)\boldsymbol{\beta}$, where $\boldsymbol{I}$ is the identity matrix, and $\boldsymbol{\beta}$ is a free parameter that represents the remaining redundancy for controlling the non-target muscles as the second priority. To minimize the influence on the non-target muscles in terms of the root-mean-square (RMS) change, $\boldsymbol{\beta}$ is given as $\boldsymbol{\beta} = \left[-\boldsymbol{A}_n(\boldsymbol{I} - \boldsymbol{A}_t^+\boldsymbol{A}_t) \right]^+ \boldsymbol{A}_n\boldsymbol{A}_t^+ [w(\boldsymbol{f}_{td}) - w(\boldsymbol{f}_{t0})]$.
Proof: Omitted.

E. Feasibility conditions

The existence of $\boldsymbol{\alpha}$ for given $\boldsymbol{f}_{td}$ can be checked by the following three conditions.

1) $\boldsymbol{f}_{td}$ for the target muscles is completely realized if $\mathrm{rank}(\ \boldsymbol{A}_t\ ) = \mathrm{rank}(\ [\boldsymbol{A}_t \quad w(\boldsymbol{f}_{td}) - w(\boldsymbol{f}_{t0})]\ )$.
2) The inactive muscles keep inactive if $-\boldsymbol{A}_v \left[\begin{array}{c} \boldsymbol{A}_t \\ \boldsymbol{A}_n \end{array} \right]^+ \left[\begin{array}{c} \boldsymbol{q}_{t0} \\ \boldsymbol{q}_{n0} \end{array} \right] - \boldsymbol{A}_v\boldsymbol{\alpha} > 0$.
3) The resultant muscle forces of the non-target muscles remain positive if $\boldsymbol{A}_n\boldsymbol{\alpha} + w(\boldsymbol{f}_{t0}) > 0$.

Proof: Omitted. Note that each of the conditions has a physiological meaning. If all of the conditions are not satisfied,

TABLE I

TARGET MUSCLES AND CHANGE RATES FOR TASKS A AND B

Task A		Task B	
Muscle name	Ratio	Muscle name	Ratio
Biceps long	x 1.3	Biceps long	x 1.5
Flexor Carpi Ulnaris	x 0.8	Flexor Carpi Ulnaris	x 0.5
Extensor Carpi Ulnaris	x 0.9	Deltoideus lateral	x 1.5

the control of the designated target muscles for given $\boldsymbol{f}_{td}$ is not physiologically realizable, i.e., the violation of the Principle of Optimality. Therefore, the change rates of the target muscle forces or the choice of the target muscles must be modified.

VI. SIMULATION

A. Task planning

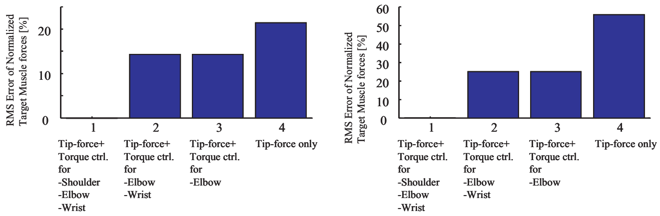
Consider a static posture shown in Fig. 4(a) for the musculoskeletal system in Figs 2(a) and 2(b) where $M = 9$ and $N = 51$. The Crowninshield's cost function (see Appendix) is applied for the Optimality criterion. A subject exerts a tip-force in the horizontal plane to a handle, i.e., $\boldsymbol{F} = [F_x, F_y, 0]^T = [10, 10, 0]^T$[N] as the nominal task as the nominal task as shown in Fig. 4. Tasks A and B in Table I are considered. Note that both the Tasks A and B satisfy the feasibility conditions (1)–(3). To investigate the relationship between the accuracy of the muscle-force control and the number of joints supported by the wearable robot, the following four types of actuator configurations are considered as shown in Fig. 5. In Type 1, the wearable robot applies torques to a total of 7 joints from the shoulder to the wrist. In Type 2, the wearable robot applies torques to a total of 4 joints from the elbow to the wrist. The current experimental device shown in Fig. 3 has the same actuator configuration. Type 3 applies torque to the elbow joint. In Type 4 wearable actuators are not used. The application of torques to the torso and the neck joints is considered difficult in terms of the mechanical design; therefore we excluded the type that controls all the 9 joints of the skeletal model.

B. Computation of tip-forces and joint-toques

The external torque $\boldsymbol{\tau}_{ex}$ that realizes the goal of each of Tasks A–D can be computed by (8). For Type 1, in which the torque control for both the torso and the neck joints is missing, a unique combination of $\boldsymbol{F}$ and $\boldsymbol{\tau}_a$ that realize $\boldsymbol{\tau}_{ex}$ in (6) can be obtained. Since

$$\boldsymbol{\tau}_{ex}^{9\times 1} = \boldsymbol{J}^T \begin{bmatrix} F_x \\ F_y \\ 0 \end{bmatrix} - \begin{bmatrix} 0 \\ 0 \\ \tau_3 \\ \vdots \\ \tau_9 \end{bmatrix}, \tag{10}$$

a total of 9 unknown parameters, $(F_x,\ F_y,\ \tau_3, \cdots, \tau_9)$, are uniquely determined for any 9 elements of $\boldsymbol{\tau}_{ex}$ if $\boldsymbol{J}$ is not singular. However, $\boldsymbol{F}$ and $\boldsymbol{\tau}_a$ for obtained $\boldsymbol{\tau}_{ex}$ may not be found for Types 2–4 due to the lack of the number of parameters. For these types, the tip-forces and joint-toques



(a) Task A

(b) Task B

Fig. 6. Simulation results for Task A and B

are computed so that $|\boldsymbol{\tau}_{ex} - \boldsymbol{J}^T\boldsymbol{F} + \boldsymbol{\tau}_a|$ is minimized. Note that for Types 2–4, the desired target muscle forces are not completely realized if $|\boldsymbol{\tau}_{ex} - \boldsymbol{J}^T\boldsymbol{F} + \boldsymbol{\tau}_a| \neq 0$.

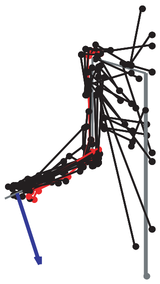
C. Results and discussion

Table II shows the computed tip-forces and assist-torques for all combinations between Tasks A, B and Device Types 1–4. Figure 6 shows the RMS errors between the resultant target muscle forces and desired forces normalized by the nominal muscle forces. As can be observed in the results, Type 1 has no error for all the tasks, indicating the muscle-force control of the target muscles is perfectly accomplished. Type 2 that lacks torque control of the shoulder joint exhibits control error for the target muscles, but the error is approximately less than 15%. The control errors tend to increase as the number of control DOF decreases toward Type 4. Type 4 particularly exhibits large errors. This implies that the sole exertion of a tip-force is insufficient to induce a desired muscle activation patterns, justifying the use of the wearable robot that generates joint torques for the muscle-level force control.

Recall the Extensor Carpi Ulnaris muscle controlled in the Tasks is known as a biarticular muscle, working on both the wrist and the elbow joints. The proposed method models the complex coupling between the joint-torques and muscle-forces including biarticular muscles and computes an adequate task. With the increased number of joints that are influenced by a motor task, the proposed approach becomes more effective, leading to obtaining a wider variety of muscle activity data.

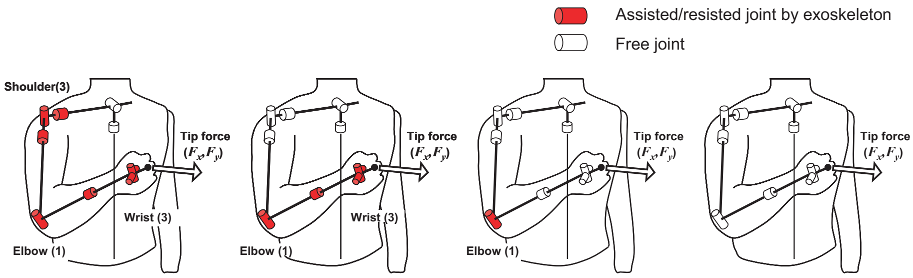
VII. CONCLUSION

This paper has presented a motor task planning method for neuromuscular function tests using the individual muscle force control technique. The proposed method would enable users, or therapists, to efficiently conduct neuromuscular function tests for target muscles by arbitrarily inducing muscle-activation patterns. The preliminary simulation results have confirmed the validity of the analytical solution as well as justified the use of the wearable robot in terms of the accuracy of muscle-level force modification. Experimental validations by recording surface/needle electromyographic signals (EMGs) will follow in our future paper. Future work will investigate the clinical aspects of this method such as applications for novel neurological diagnosis and treatment. This research was supported in part by the 2008-2009 GT/Emory Health Systems Institute Seed Grant Program.



$F_x, F_y = [10,10]$

Fig. 4. Nominal task and posture



(a) Type 1: Tip-force+ Torque control for the Shoulder, Elbow, and Wrist joints

(b) Type 2: Tip-force+ Torque control for the Elbow, and Wrist joints

(c) Type 3: Tip-force+ Torque control for the Elbow joint

(d) Type 4: Tip-force only

Fig. 5. Justification of the use of wearable actuators: 4 types of actuator configurations for comparison

TABLE II

COMPUTED TIP-FORCES AND ASSIST-TORQUES

		Shoulder			Elbow	Wrist			Tip-force	
Task	Type of exoskeleton	τ_3[N/m]	τ_4[N/m]	τ_5[N/m]	τ_6[N/m]	τ_7[N/m]	τ_8[N/m]	τ_9[N/m]	f_x[N]	f_y[N]
Task A	Type 1	0.179	0.515	0.180	0.157	0.024	0.031	0.087	9.606	10.108
	Type 2	–	–	–	0.157	0.024	0.031	0.052	10.556	9.305
	Type 3	–	–	–	0.157	–	–	–	10.560	9.296
	Type 4	–	–	–	–	–	–	–	10.560	9.296
Task B	Type 1	0.444	1.536	0.604	-0.117	-0.054	-0.221	-0.192	8.646	10.371
	Type 2	–	–	–	-0.117	-0.054	-0.221	-0.297	11.223	7.948
	Type 3	–	–	–	-0.117	–	–	–	11.196	8.001
	Type 4	–	–	–	–	–	–	–	11.196	8.001

APPENDIX

Crowninshield's method [4] predicts human muscle forces by minimizing a physiologically based criterion $u(\boldsymbol{f})$:

$$u(\boldsymbol{f}) = \sum_{j=1}^{N} \left(\frac{f_j}{\mathrm{PCSA}_j} \right)^r \to \min \tag{11}$$

$$\text{subject to} \quad \begin{cases} \boldsymbol{\tau}_h = \boldsymbol{A}\boldsymbol{f} \\ f_{\min j} \le f_j \le f_{\max j} (j = 1, \cdots, N) \end{cases},$$

where PCSA_j is the physiological cross sectional area (PCSA) and $f_{\max j} = \varepsilon \cdot \mathrm{PCSA}_j$ is the maximum muscle force of the j-th muscle. $\varepsilon = 0.7 \times 10^6 [\mathrm{N/m^2}]$ is found in [7]. PCSA_j's are given according to [19]. $f_{\min j} = 0, \forall j$ and $r = 2$ are used. See [4] for the choice of r.

REFERENCES

[1] P. Davies, *Steps to Follow: The Comprehensive Treatment of Patients with Hemiplegia*. Springer, 2000.

[2] V. Krishnamoorthy, J. Scholz, and M. Latash, "The use of flexible arm muscle synergies to perform an isometric stabilization task," *Clinical Neurophysiology*, vol. 118, no. 3, pp. 525–537, 2007.

[3] D. Reisman and J. Scholz, "Aspects of joint coordination are preserved during pointing in persons with post-stroke hemiparesis." *Brain*, vol. 126, no. 11, p. 2510, 2003.

[4] RD. Crowninshield, et al., "A physiologically based criterion of muscle force prediction in locomotion," *J. Biomechanics*, vol. 14, pp. 793–801, 1981.

[5] B. van Bolhuis and C. Gielen, "A comparison of models explaining muscle activation patterns for isometric contractions," *Biological Cybernetics*, vol. 81, no. 3, pp. 249–261, 1999.

[6] S. Delp, J. Loan, M. Hoy, F. Zajac, E. Topp, J. Rosen, V. Center, and P. Alto, "An interactive graphics-based model of the lower extremity to studyorthopaedic surgical procedures," *Biomedical Engineering, IEEE Transactions on*, vol. 37, no. 8, pp. 757–767, 1990.

[7] D. Karlsson and B. Peterson, "Towards a model for force predictions in the human shoulder," *Journal of biomechanics*, vol. 25, no. 2, pp. 189–199, 1992.

[8] W. Maurel and D. Thalmann, "A Case Study on Human Upper Limb Modelling for Dynamic Simulation," *Computer Methods in Biomechanics and Biomedical Engineering*, vol. 2, no. 1, pp. 65–82, 1999.

[9] F. Martini and E. Bartholomew, *Essentials of Anatomy & Physiology*. Prentice Hall, 2000.

[10] A. Hamilton, K. Jones, and D. Wolpert, "The scaling of motor noise with muscle strength and motor unit number in humans," *Exp Brain Res*, vol. 157, pp. 417–430, 2004.

[11] R. Osu, N. Kamimura, H. Iwasaki, E. Nakano, C. Harris, Y. Wada, and M. Kawato, "Optimal Impedance Control for Task Achievement in the Presence of Signal-Dependent Noise," *Journal of Neurophysiology*, vol. 92, no. 2, pp. 1199–1215, 2004.

[12] J. Ueda, M. Ding, M. Matsugashita, R. Oya, and T. Ogasawara, "Pinpointed control of muscles by using power-assisting device," in *Robotics and Automation, 2007 IEEE International Conference on*, 2007, pp. 3621–3626.

[13] J. Ueda, M. Matsugashita, and T. O. R. Oya and, "Control of muscle force during exercise using a musculoskeletal-exoskeletal integrated human model," in *10th International Symposium on Experimental Robotics(ISER2006)*, Rio de Janeiro, Brazil, July 6 to July 10, 2006.

[14] H. Kazerooni, J. Racine, L. Huang, and R. Steger, "On the Control of the Berkeley Lower Extremity Exoskeleton (BLEEX)," in *IEEE INTERNATIONAL CONFERENCE ON ROBOTICS AND AUTOMATION*, vol. 4. IEEE; 1999, 2005, p. 4353.

[15] H. Krebs, J. Celestino, D. Williams, M. Ferraro, B. Volpe, and N. Hogan, "A wrist extension for MIT-MANUS," *Lecture notes in control and information sciences*, pp. 377–390.

[16] S. Lee and Y. Sankai, "Power assist control for walking aid with HAL-3 based on EMG and impedance adjustment around knee joint," in *Intelligent Robots and System, 2002. IEEE/RSJ International Conference on*, vol. 2, 2002.

[17] A. Toth, G. Arz, G. Fazekas, D. Bratanov, and N. Zlatov, "Post stroke shoulder-elbow physiotherapy with industrial robots," *Lecture notes in control and information sciences*, pp. 391–411.

[18] D. Bertsekas, *Nonlinear programming*. Athena Scientific Belmont, Mass, 1999.

[19] MotCo Project, "http://motco.info/data/pcsa.html."