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Computationally Fast Estimation of Muscle Tension for Realtime Bio-feedback

Akihiko Murai, Kosuke Kurosaki, Katsu Yamane and Yoshihiko Nakamura

Abstract— **In this paper, we propose a method for realtime estimation of whole-body muscle tensions. The main problem of muscle tension estimation is that there are infinite number of solutions to realize a particular joint torque due to the actuation redundancy. Numerical optimization techniques, e.g. quadratic programming, are often employed to obtain a unique solution, but they are usually computationally expensive. For example, our implementation of quadratic programming takes about 0.17 sec per frame on the musculoskeletal model with 274 elements, which is far from realtime computation. Here, we propose to reduce the computational cost by using EMG data and by reducing the number of unknowns in the optimization. First, we compute the tensions of muscles with surface EMG data based on a biological muscle data, which is a very efficient process. We also assume that their synergists have the same activity levels and compute their tensions with the same model. Tensions of the remaining muscles are then computed using quadratic programming, but the number of unknowns is significantly reduced by assuming that the muscles in the same heteronymous group have the same activity level. The proposed method realizes realtime estimation and visualization of the whole-body muscle tensions that can be applied to sports training and rehabilitation.**

Keywords: Estimation of Muscle Tension, Hill-Stroeve's Muscle Model, Quadratic Programming, Heteronymous Grouping.

I. INTRODUCTION

Bio-feedback is a training technique often used in sports and rehabilitation where people are taught to improve their health and performance by using signals from their own bodies as feedback. Giving the feedback as fast as possible, or ideally in realtime, is important for effective training. The objective of this work is to provide the muscle tension information in realtime for bio-feedback applications.

A number of algorithms have been proposed for estimating muscle tensions and joint loads using musculoskeletal models [1], [2], [3], [4]. The main problem of muscle tension estimation is that there are infinite number of solution to realize a particular joint torque due to the actuation redundancy (much more muscles than necessary to drive the skeleton). It is therefore impossible to obtain precise muscle tension information only from motion data. One of the solution is to use inverse dynamics algorithms developed in robotics to obtain the joint torques of the skeleton and then run numerical optimization to compute the muscle tensions [2], [4]. This approach does not require EMG data, and also physically correct at least if the skeleton model parameters, which are easier to identify than muscle model parameters, are correct. However, a problem is that the result relies entirely on the optimization criteria that may not reflex the real muscle tension pattern. And all of these algorithms are too computationally expensive.

We proposed the new algorithm to speed-up the computation for the whole-body muscle tension estimation [5]. First, the tension of some muscles is computed directly by measuring muscle activation by electromyogram (EMG) and using empirical muscle models to convert the activations to tensions [6], [7]. It is very fast because we only need to run the muscle model. The method can, however, only estimate the tensions of muscles with EMG information, which are strictly limited by the number of available EMG channels. For the remaining muscles, their tensions are computed using the inverse dynamics computation and the singularity-robust inverse (SR-inverse). However, the method does not consider the inequality constraint that muscles can only pull.

In this paper, we propose to reduce the computational cost by using EMG data and by reducing the number of unknowns in the optimization. First, we compute the tensions of muscles with surface EMG data based on a biological muscle data, which is a very efficient process. We also assume that their synergists have the same activity levels and compute their tensions with the same model. Tensions of the remaining muscles are then computed using quadratic programming, but the number of unknowns is significantly reduced by assuming that the muscles in the same heteronymous group have the same activity level. The proposed method realizes realtime estimation and visualization of the whole-body muscle tensions that can be applied to sports training and rehabilitation.

This paper is organized as follows. In Section II, the existing method to estimate the muscle tension using the inverse dynamics computation and optimization is shown. The heteronymous grouping of muscle is shown in Section III, and used to estimate the appropriate muscle tensions in high speed. We finally conclude the paper in section IV.

II. OPTIMIZATION-BASED MUSCLE TENSION ESTIMATION

In this section, we review the basic equations of optimization-based methods for muscle tension estimation and show that they are too slow for realtime applications. In general, the relationship between muscle tensions $\boldsymbol{f}$ and equivalent joint torques $\boldsymbol{\tau}_G$ is described by the following

Akihiko Murai and Kosuke Kurosaki are with Department of Mechano-Informatics, the University of Tokyo, 7-3-1, Hongo, bukyo-ku, Tokyo, 113-8656, JAPAN, murai@ynl.t.u-tokyo.ac.jp

Katsu Yamane was with Department of Mechano-Informatics, the University of Tokyo. He is currently at Disney Research, Pittsburgh.

Yoshihiko Nakamura is with Department of Mechano-Informatics, the University of Tokyo.

equation [4]:

$$\boldsymbol{\tau}_G = \boldsymbol{J}^T \boldsymbol{f} \quad (1)$$

where $\boldsymbol{J}$ is the posture-dependent Jacobian matrix of muscle lengths with respect to joint angles. If we know the joint angles, velocities, and accelerations, we can compute the joint torques $\boldsymbol{\tau}_G$ by applying inverse dynamics algorithms such as [8] and subtracting the effect of external forces including ground contact forces. Estimating muscle tensions then becomes the problem of finding a solution of linear equation (1). Unfortunately, we cannot solve Eq. (1) directly because of two reasons: 1) the equation is usually under-constrained, meaning that there may be infinite number of solutions, and 2) muscles can only pull, which imposes the inequality constraint $\boldsymbol{f} \leq 0$. An approach used in some papers is to form an optimization problem where the cost function can be linear [2], [4], [9], or quadratic [4]. Here we implement the quadratic version of [4] and measured its computation time for two models. The cost function:

$$Z = \frac{1}{2}|\boldsymbol{\tau}_G - \boldsymbol{J}^T \boldsymbol{f}|^2 + \frac{k}{2}|\boldsymbol{f} - \boldsymbol{f}^*|^2 \quad (2)$$

is to be minimized subject to the following constraint:

$$\boldsymbol{f} \leq 0 \quad (3)$$

where $k > 0$ is a constant weight and $\boldsymbol{f}^*$ is a reference muscle tension, which can simply be set to zero to obtain least-square solution [4] or determined from EMG data [9]. We applied this algorithm to two models and measured the computation time. The first model is built for detailed analysis and comprises almost 1000 muscles including the trunk part. The second model is a simplified version focused on the limb movements, although it still contains 274 muscles. They share the same skeleton model with 155 degrees of freedom (DOF). The typical computation time for estimating the muscle tensions were around 1.7 s and 0.17 s for the first and second models respectively using a workstation with an Intel Xeon 3.33GHz processor. The frame rate would be under 6 fps even with the simplified model and excluding the rendering time, which is far too slow for realtime visualization.

III. Heteronymous Muscle Grouping for Optimization

We proposed an algorithm to speed up the estimation of muscle tension for realtime applications [5]. The algorithm comprises the following two steps:

1) The tensions of muscles whose EMG are directly measured ($\mathcal{M}_{EMG}$) are computed using an empirical muscle model [6], [7].
2) The tensions of remaining muscles are computed using the inverse dynamics computation and the singularity-robust inverse. First, the inverse dynamics computes the joint torque $\boldsymbol{\tau}_G$. We also compute the joint torque $\boldsymbol{\tau}_{EMG}$ equivalent to the tensions obtained in step 1). The residual torque $\boldsymbol{\tau}'_G = \boldsymbol{\tau}_G - \boldsymbol{\tau}_{EMG}$ is the torque that should be realized by the remaining muscles. We apply the SR-inverse to compute the tensions of remaining muscles.

This method does not consider the inequality constraint (Eq. (3)). Complete optimization considering the inequality constraints is computationally expensive as shown in Section II.

The computational cost of quadratic programming is proportional to the square of number of unknowns. Therefore, the reduction of the number of unknowns would be effective for reducing the computational cost. In this paper, we propose a method of reducing the number of unknowns by grouping the remaining muscles into the heteronymous muscle groups.

There are the facilitatory and inhibitory nerve connections between muscles. If the muscles are connected facilitatory they work as synergist, and if inhibitory work as antagonist. The muscle group of the former is called the heteronymous muscle group, and the functional significances of the muscles in this group are similar. The relationship between activations of muscle in such group can be assumed to follow some rule [10], [11], [12]. For example, the muscle activation pattern has been suggested to be determined so as to minimize the sum of the muscle force, squared, or cubed [13], [14], [15], [16]. Based on this knowledge, we can predefine some constraints between the activities of muscle in heteronymous muscle group, and this will reduce the number of unknowns of the musculoskeletal model. In the subsequent paragraphs, we show a method for grouping the whole-body muscles into the heteronymous groups, and using them to speed up the estimation of muscle tensions with optimization.

In this paper, we follow the method shown in [5], and propose the optimization method instead of using the SR-inverse. First, the whole-body 274 muscles are divided into 36 heteronymous muscle groups by considering the limb and trunk motion and rotation axes for each side. Members of each group, $\mathcal{M}_i (i = 1, 2, \ldots, 36)$, are further divided into the following three sets:

1) $\mathcal{M}_{iEMG}$: The representative muscle of the group, whose EMG signal is measured. Not all the group has this representative muscle because there are restraint of the EMG channel number.
2) $\mathcal{M}_{ihigh}$: The muscles that should have the same activation as the representative muscle of the group (Only if i-th group has the representative muscle). Here, only the muscles whose original and end points are same as the representative muscle are included in this set to consider the problem of multi-joint and single-joint muscle problem.
3) $\mathcal{M}_{ilow}$: The muscles that are included in non of the above 2 sets. They may be further divided into subsets ($\mathcal{M}_{i,1low}, \ldots \mathcal{M}_{i,n_i low}$) depending on the pair of bone they connect, where n_i represents the number of heteronymous groups in $\mathcal{M}_i$.

We also define new sets of muscles $\mathcal{M}_{EMG}$, $\mathcal{M}_{high}$, and $\mathcal{M}_{low}$ by $\mathcal{M}_{EMG} = \mathcal{M}_{1EMG} \cup \mathcal{M}_{2EMG} \cup \ldots \cup \mathcal{M}_{36EMG}$ and so forth. The number of muscles included in each group is shown in Table I, and the detail of the groups of leg muscles is shown in Table II. In the groups with representative muscle, the first row in each group is $\mathcal{M}_{high}$, other rows are $\mathcal{M}_{low}$.

The algorithm for the speed-up of the whole-body muscle tension estimation comprises the following two steps:

1) Compute the tensions of muscles in $\mathcal{M}_{EMG}$ and $\mathcal{M}_{high}$ using the EMG data of the representative muscles and a physiological muscle model [6], [7].
2) Estimate the tensions of remaining muscles ($\mathcal{M}_{low}$) using inverse dynamics and an efficient optimization algorithm.

The following paragraphs describe the second step in detail.

TABLE I
NUMBER OF MUSCLES IN EACH MUSCLE GROUP.

group	number
$\mathcal{M}_{EMG}$	16
$\mathcal{M}_{high}$	20
$\mathcal{M}_{low}$	238
total elements	274

The relation between the joint torque and the muscle tensions are written as follows:

$$\boldsymbol{\tau}_G = \left[\boldsymbol{J}^T_{EMG}\boldsymbol{J}^T_{high}\boldsymbol{J}^T_{low}\right]\begin{bmatrix}\boldsymbol{f}_{EMG}\\ \boldsymbol{f}_{high}\\ \boldsymbol{f}_{low}\end{bmatrix} \tag{4}$$

where $\boldsymbol{J}_{EMG}$, $\boldsymbol{J}_{high}$, and $\boldsymbol{J}_{low}$ respectively represents the Jacobian matrix of the length of muscles in $\mathcal{M}_{EMG}$, $\mathcal{M}_{high}$, and $\mathcal{M}_{low}$ with respect to the joint angles, and $\boldsymbol{f}_{EMG}$, $\boldsymbol{f}_{high}$, and $\boldsymbol{f}_{low}$ are the tensions of muscles in each set. Since we have already computed $\boldsymbol{f}_{EMG}$ and $\boldsymbol{f}_{high}$, we can move them to the left-hand side as

$$\boldsymbol{\tau}'_G = \boldsymbol{J}^T_{low}\boldsymbol{f}_{low} \tag{5}$$

In order to reduce the number of unknowns, we assume that the muscles in the same heteronymous group have the same activity level. The muscles connected facilitatory work as synergist, so the activities of these muscles will follow a function $E_{i,m\to n}$ that represents the relationship of muscle activities between the m-th and n-th muscle in $\mathcal{M}_{i,jlow}$. This function determines the variability of muscle tensions among the synergist group. One of the methods to determine this function is to measure the EMG of all the muscles in the synergist group, but this is impossible because of the number of electrodes required for the electromyograph. Another approach is to apply optimization techniques [13], [15], [16]. In our implementation, we use a simple identity mapping called the muscle equivalent model [17]:

$$E_{i,j\to k}(a_{i,j}) = e_{i,j\to k}(l_k,\dot{l}_k)a_{i,j}. \tag{6}$$

The empirical muscle model proposed by [6], [7] can be written in the following equation:

$$\begin{aligned} f^*_k &= -E_{i,j\to k}(a_{i,j})F_l(l_k)F_v(\dot{l}_k)F_{\max k}\\ &= -e_{i,j\to k}(l_k,\dot{l}_k)a_{i,j}F_l(l_k)F_v(\dot{l}_k)F_{\max k}. \end{aligned} \tag{7}$$

In Eq. (7), $F_l(l_k)$, $F_v(\dot{l}_k)$, and $F_{\max k}$ are computed by the inverse kinematics computation with the musculoskeletal model, so we can divide the constant term and the variable term for the muscle k as follows:

$$\begin{aligned} \boldsymbol{J}^T_k f_k &= \left[-e_{i,j\to k}(l_k,\dot{l}_k)F_l(l_k)F_v(\dot{l}_k)F_{\max k}\boldsymbol{J}^T_k\right]a_{i,j}\\ &= \boldsymbol{H}^T_k a_{i,j} \end{aligned} \tag{8}$$

Eq. (5) can be deformed as follows:

$$\begin{aligned} \boldsymbol{\tau}'_G &= \left[\sum_{k\in\mathcal{M}_{1,1low}}\boldsymbol{H}^T_k \cdots \sum_{k\in\mathcal{M}_{n_g,n_{n_g}low}}\boldsymbol{H}^T_k\right]\begin{bmatrix}a_{1,1}\\ \vdots\\ a_{n_g,n_{n_g}}\end{bmatrix}\\ &= \boldsymbol{H}^T\boldsymbol{A}. \end{aligned} \tag{9}$$

The cost function of the optimization (Eq. (2)) can be written as follows:

$$Z = \frac{1}{2}|\boldsymbol{\tau}'_G - \boldsymbol{H}^T\boldsymbol{A}|^2 + \frac{k}{2}|\boldsymbol{A}-\boldsymbol{A}^*|^2. \tag{10}$$

Because $F_l(*) \geq 0$, $F_v(*) \geq 0$, and $F_{\max} \geq 0$, the inequality constraint of Eq. (3) can be written as:

$$\boldsymbol{A} \leq 0. \tag{11}$$

By setting the number of groups a little bigger than the DOF of the skeleton model, Eq. (10) can be minimized subject to the inequality constraint Eq. (11) using quadratic programming. The heteronymous grouping in this paper divide the whole-body muscles into 56 groups, and the DOF of musculoskeletal model is 54. The proposed method is capable of estimating the tensions of whole-body 274 muscles from motion capture and 16-channel EMG data in only 16 msec per frame, though the existing method takes 170 msec.

IV. CONCLUSION

In this paper, we proposed a method to speed-up the whole-body muscle tension estimation by reducing the number of unknowns of musculoskeletal model. The key idea of the algorithm is to divide the muscles into heteronymous groups based on their neuronal binding and the kinematical original/end point, and decrease the number of unknowns of musculoskeletal model. The synchronized EMG onsets and patterns of elbow and shoulder flexor muscles (Posterior Deltoid, Intermediate Deltoid and Brachialis, Brachioradialis) were observed in [10], and our algorithm agrees with this observation in that it divides the elbow and shoulder flexor/extensor muscles into heteronymous groups and optimizes activities of muscles in same group to become equal. The proposed method realize the estimation and visualization of the whole-body muscle tensions in realtime. Figure 1 shows one result in which the rendered musculoskeletal model with muscle tension information estimated in realtime is overlaid on top of the image captured by a standard video camera. Possible applications include interface for assisting training and rehabilitation.

TABLE II

JOINT ROTATIONS AND ASSOCIATED MUSCLE GROUPS.

#	joint	rotation	representative muscle	muscles in group	# of muscles
10	hip knee	flexion extension	Rectus Femoris	Sartorius, Grachilis	3
				Iliacus, Pectineus, Adductor Longus, Adductor Brevis, Adductor Magnus, Tensor Fasciae Latae	7
				Vastus Lateralis, Vastus Medialis, Vastus Intermedius	3
11	hip knee	extension flexion	Biceps Femoris CaputLongum	Semitendinosus, Semimembranosus	3
				Gluteus Maximus Os Coccygis, Gluteus Maximus Crista Iliaca, Gluteus Maximus Os Sacrum, Gluteus Medius, Gluteus Minimus	7
				Biceps Femoris Caput Breve	1
12	hip	external rotation		Piriformis, Obturatorius Internus, Gemellus Superior, Gemellus Inferior, Quadratus Femoris, Obturatorius Externus	6
13	ankle	dorsal	Tibialis Anterior	Extensor Hallucis Longus, Peroneus Tertius	3
14	ankle	plantal	Gastrocnemius	Popliteus	2
				Soleus	1
				Plantaris	1
				Flexor Hallucis Longus, Tibialis Posterior, Peroneus Longus, Peroneus Brevis	4
15	foot	flexion		InterosseiDorsales	2
				Extensor Digitorum Brevis, Abductor Hallucis, Flexor Digitorum Brevis, Abductor Digiti Minimi, Lumbericales, Flexor Hallucis Brevis, Flexor Digiti Minimi Brevis, Interossei Plantares	13

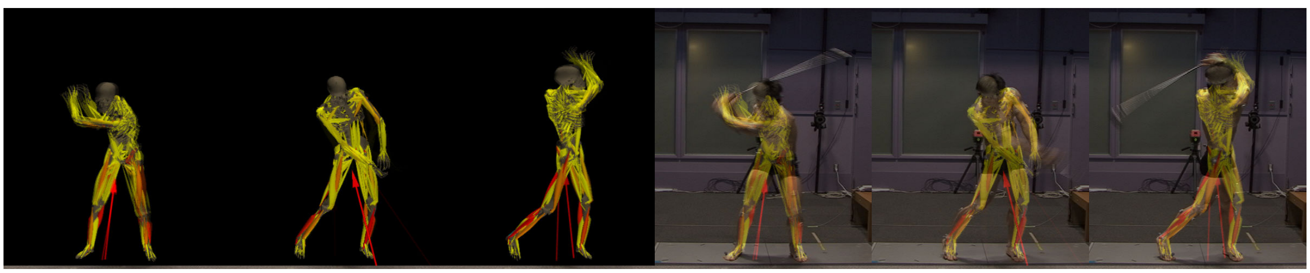

Fig. 1. Images of realtime estimation and visualization of the muscle tensions. The rendered musculoskeletal model with estimated muscle tension information is overlaid on top of the image captured by a standard video camera.

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