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Effects of Nerve Signal Transmission Delay in Somatosensory Reflex Modeling Based on Inverse Dynamics and Optimization

Akihiko Murai, Katsu Yamane, and Yoshihiko Nakamura

Abstract— **Human motion coordination is a long-standing research issue in biomechanics, and it should also have some implications for humanoid robot control. We have built a whole-body somatosensory reflex model based on our neuromusculoskeletal model and identified its parameters through non-invasive measurements and statistical analysis. Such models are crucial for analyzing and estimating signals in the nervous system. In this paper, we focus on signal transmission delay of the somatosensory reflex loop and investigate its relationship with the generalization capability of the reflex model. We obtain some sets of model parameters assuming different time delays using the data obtained from a stepping motion, and perform cross validations against stepping motions with different cycles as well as entirely different behaviors such as squat and jump. Interestingly, time delays close to the value expected from physiological properties show better cross-validation results than others. This result suggests that relatively simple reflex control can be generalized to multiple behaviors if the parameters are appropriate, and that robust control is possible even with large feedback delay.**

I. Introduction

Understanding the mechanism for generating and coordinating human motions is still an open research issue. Previous effort towards such problems have focused on either simplified macroscopic model of the musculoskeletal system [1] or microscopic models of the mechanical [2], [3] and sensory [4], [5] characteristics of the muscle. However, there is still a large gap between the two approaches. We have been building a whole-body neuromusculoskeletal system for somatosensory calculation [6], [7] to understand this mechanism utilizing many methods and knowledges from many different fields.

This mechanism has a hierarchical structure comprising the reflex behavior, the emotional behavior, and the rational behavior, in accordance with the hierarchical brain structure shown by MacLean [8]. A possible approach to understand the mechanism is to build and identify the model from the lower part of this hierarchical structure using anatomical, mathematical, and statistical knowledge, where the lower part includes the descending pathway from the spinal nerve rami to the muscles, and the ascending pathway from the proprioceptive sensory receptors on the muscles to the spinal nerve rami. Unlike the central nerve system, the peripheral nerve system including the somatic nerve system is investigated in the field of medicine and anatomy. For example, the function of proprioceptive sensory receptors [9], [10] and the physiological characteristics of muscles [2], [3] are experimentally verified, and modeled mathematically. The neuronal bindings between the spinal nerve rami and the muscles are also investigated in the anatomy field, and their functionality are partly verified in the field of the neurophysiology [11], [12].

In [6], [7], we presented our somatosensory reflex model that attempts to model a part of this system. This model has a three layered neural network that represents the relationship between the somatosensory information perceived by proprioceptive receptors (muscle spindle and Golgi tendon organ) and the muscle activity. The knowledge from many fields, e.g. anatomical knowledge about neuronal binding between spinal nerve ramus and muscle and physiological characteristics of proprioceptive receptors, are implemented in this model. Its weight parameters that represent the somatosensory feedback gains are identified using experimental human motion data and a back-propagation algorithm.

The time delay caused by the nerve signal transmission characterizes the timing and amplitude of somatosensory reflex signals. In this paper, we apply different time delays at the identification and cross-validation processes of the somatosensory reflex model. If this time delay is critical for the motion generation and coordination, an inappropriate time delay would have a negative impact on identification and cross-validation results. The experimental results show that the somatosensory reflex model with appropriate time delay yields better identification and cross-validation results than others, and can generalize to multiple motion patterns. This implies that human motion pattern is characterized by the geometric nerve structure and the anatomical properties, and the human nerve structure generates the whole-body motion pattern only from simple motion command signals.

The rest of this paper is organized as follows. In section II, we briefly describe our somatosensory reflex model and present the method to identify the model parameters using experimental human motion data. The identification and cross-validation results using different time delays are shown in section III, followed by the concluding remarks.

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Akihiko Murai was with Department of Mechano-Informatics, the University of Tokyo, 7-3-1, Hongo, Bunkyo-ku, Tokyo, 113-8656, JAPAN, murai@ynl.t.u-tokyo.ac.jp. He is now with Disney Research, Pittsburgh, amurai@disneyresearch.com.
Katsu Yamane is at Disney Research, Pittsburgh.
Yoshihiko Nakamura is with Department of Mechano-Informatics, the University of Tokyo.

II. Somatosensory Reflex Model

A. Modeling of Somatosensory Reflex Model [6], [7]

In the human body, the nerve network is composed of the following elements:

1) α motor neuron, γ motor neuron, and interneuron,
2) efferent pathway,
3) muscle,
4) muscle spindle,
5) Golgi tendon organ, and
6) afferent pathway.

Fig. 1 shows our neuromuscular network model. The model is constructed as a six-layered neural network. The part enclosed by the dashed rectangle represents the somatosensory reflex network model. In this part, each layer represents:

1) $\mathrm{N}_{\mathrm{NJ},i}(i = 1, \ldots, n_m)$ (filled circle): This layer represents the neuromuscular junctions on the muscles. Here, n_m represents the number of muscles included in this musculoskeletal model. This layer receives and integrates the motion command signal from the α motor neuron in the spinal nerve ramus. The integrated signal activates the muscle, which produces tension.
2) $\mathrm{N}_{\mathrm{MS},i}(i = 1, \ldots, n_m)$ (filled square): This layer represents the muscle spindles that measure the muscle length and its velocity. In our model, these values are computed by forward or inverse kinematics computation using the musculoskeletal model.
3) $\mathrm{N}_{\mathrm{GT},i}(i = 1, \ldots, n_m)$ (filled triangle): This layer represents the Golgi tendon organs that measure the muscle tensions. These values can be computed from the muscle activity (the motion command signal) using the Hill-Stroeve muscle model [2], [3] or from the inverse kinematics and dynamics computation using the musculoskeletal model.

These layers are connected to each other as follows:

1) From N_{NJ} to N_{MS} and N_{GT} (solid line): $\mathrm{N}_{\mathrm{NJ},i}$ is connected to $\mathrm{N}_{\mathrm{MS},i}$ and $\mathrm{N}_{\mathrm{GT},i}(i = 1, \ldots, n_m)$. The descending connections between these layers represent the conversion from the motion command signal to the muscle tension through the muscle dynamics model, and this tension is perceived by N_{GT}. This tension changes the posture of musculoskeletal model subject to the dynamics of the musculoskeletal model. This posture determines the muscle length and its velocity, which are perceived by N_{MS}.
2) From N_{MS} and N_{GT} to N_{MS} (dashed line): These ascending connections represent the reflex arc between proprioceptive receptor and muscle via the interneurons and α motor neurons in the spinal nerve rami. These connections are the main part of this model and modeled in detail following the anatomical nerve structure. The neuronal bindings between the spinal nerve rami and the muscles are also investigated in the anatomy field [11], [12].

The weight parameters of the somatosensory reflex model are identified using experimental human motion data. The muscle length, velocity and tension are computed using the inverse kinematics and dynamics computations [13], and the muscle activity is computed using the physiological muscle model [2], [3]. We train this network model so that it outputs the computed muscle activity at N_{NJ} when the somatosensory information is fed back to N_{MS} and N_{GT}.

TABLE I
Neural Transmission Speed of Each Nerve Fiber [15], [16].

type of fiber	transmission speed [m/sec]
α motor fiber	100
Ia fiber	75
Ib fiber	75
II fiber	55

B. Time Delay by the Nerve Signal Transmission

One of the critical characteristics of the somatosensory reflex is the time delay caused by the nerve signal transmission. The reflex arc consists of the proprioceptive sensory receptors, the Ia and II nerve fibers, the interneurons and α motor neuron, and the α motor fiber. The total time delay in somatosensory reflex therefore consists of:

1) The signal transmission by the Ia/II fiber and the α motor fiber.
2) Time between the beginning of muscle extension to the beginning of muscle spindle actual potential discharge.
3) The synaptic transmission from the Ia/II fiber to the α motor neuron or interneuron.
4) The signal transmission from the end plate to the muscle fiber.
5) The diffusion of action potential along the muscle fiver.
6) The induction of muscle contraction by the action potential (excitation-contraction coupling).

The time delay for a particular muscle can be estimated from physiological properties. The delay 1) (δT) can be estimated by dividing the length of the fiber between a spinal nerve ramus and muscle [14] by the neural signal transmission speed shown in Table I [15], [16]. The delays 2)–6) (δt) have been investigated experimentally. In Quadriceps, for example, the time delay caused by 1) is 16 msec[1], and the time delay caused by 2)–6) is 9–14 msec. So the total time delay of monosynaptic extension reflex of Quadriceps is therefore 25–30 msec[2].

In this paper, we consider the time delay as a parameter that represents the geometrical nerve structure of human body. Based on the hypothesis that the mechanism for generating and coordinating whole-body motion optimizes its parameters for the body through the evolution or growth process, the time delay of somatosensory reflex that is decided by the anatomical and physiological structure is assumed to have some advantages in the motion control. We identify and cross validate the somatosensory reflex network with some different time-delay condition $\delta T' = \delta T + \delta t$ ($\delta t =$

[1]The distance between Quadriceps and spinal nerve ramus is 800 mm
[2]This delay is often observed as the latency of knee-jerk reflex.

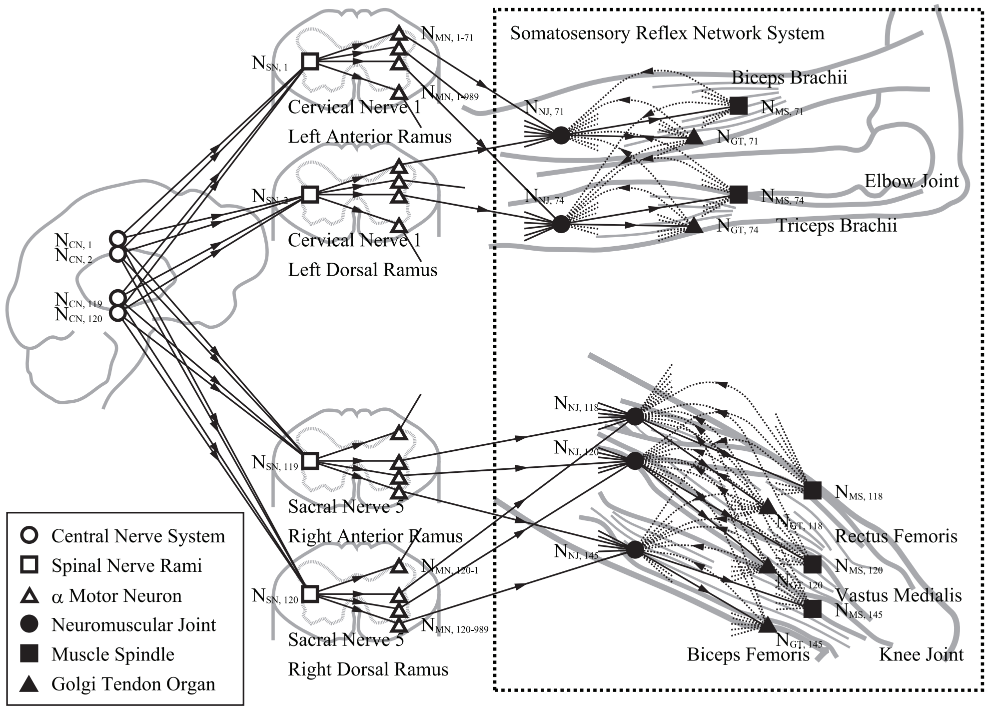

Fig. 1. The neuromuscular network modeled with 6 layered neural network. Each layer represents central nerve system, spinal nerve rami, α motor neuron, neuromuscular joint, muscle spindle and Golgi tendon organ. The part enclosed by dashed rectangle represents the somatosensory reflex network model.

$0, 5, 10, 15, 30, 60$msec) to confirm this. If this parameter is critical for the mechanism of generating and coordinating whole-body motion, the results of identification and cross validation will be better with the physiologically appropriate time delay.

C. Identification of Somatosensory Reflex Model with Time Delay

The identification proceeds as follows. We first analyze a whole-body motion with T frames measured using an optical motion capture system with 35 markers (improved version of Helen Hayes Hospital marker set). The inverse kinematics computation based on a $n_{DOF}(=143)$-DOF skeleton model calculates the joint angle data $\boldsymbol{\theta} \in \mathcal{R}^{n_{DOF}\times T}$, and the lengths of $n_m(=989)$ muscles and their velocities $\boldsymbol{l}, \dot{\boldsymbol{l}} \in \mathcal{R}^{n_m\times T}$. Then an inverse dynamics calculation is carried out to obtain the generalized force data $\boldsymbol{\tau}_G \in \mathcal{R}^{n_{DOF}\times T}$ and we estimate the muscle tensions $\boldsymbol{f} \in \mathcal{R}^{n_m\times T}$ using a biological muscle model and mathematical optimization. Finally the muscle activity $\boldsymbol{a} \in \mathcal{R}^{n_m\times T}$ is computed based on the biological muscle model that represents the relationship between muscle tension, activity, length, and its velocity [2], [3].

We then estimate the sensor activities from those physical quantities. The somatosensory information of the i-th muscle associated with the somatosensory reflex are $\boldsymbol{m}_i$, the activity of muscle spindle, and $\boldsymbol{g}_i$, the activity of Golgi tendon organ. The former feeds back the information of muscle length and its velocity, and the latter feeds back the muscle tension as follows:

$$m_i(t) = 4.3\dot{l}_i(t)^{0.6} + 2l_i(t) + \delta m_i \ (t = 1, \ldots, T) \tag{1}$$

$$g_i(t) = f_i(t). \tag{2}$$

Eq. (1) represents muscle spindle model proposed by Prochazka and Gorassini [17] that considers the discharge rate of the Ia nerve fiber. Here each value $\boldsymbol{a}_i$, $\boldsymbol{m}_i$, $\boldsymbol{g}_i \in \mathcal{R}^T (i = 1, \ldots, n_m)$ is normalized to $[0-1]$.

Then we identify the parameters of the somatosensory reflex model. First, the somatosensory information fed back by the proprioceptive sensory receptors, $\boldsymbol{m}_{ref}, \boldsymbol{g}_{ref} \in \mathcal{R}^{n_{SN}n_m^2}$, are computed considering the time delay of nerve signal transmission. The reflex arc between muscles goes through one or more spinal rami, and we consider them separately. If the i-th muscle and j-th muscle are connected via the k-th spinal nerve ramus:

$$\begin{aligned} m_{ref}(n_{SN}n_m(i-1) + n_{SN}(k-1) + j)(t) \\ = m_j(t - \delta T'_{i,j,k}) \end{aligned} \tag{3}$$

$$\begin{aligned} g_{ref}(n_{SN}n_m(i-1) + n_{SN}(k-1) + j)(t) \\ = g_j(t - \delta T'_{i,j,k}) \end{aligned} \tag{4}$$

where $\delta T'_{i,j,k}$ is the time delay caused by the nerve signal transmission from i-th muscle to j-th muscle via k-th spinal nerve ramus computed from the nerve length and neural transmission speed. Then we use the simple back propagation to obtain the weight parameters $\boldsymbol{W}_{ref,m}$ and $\boldsymbol{W}_{ref,g} (\in \mathcal{R}^{n_m \times n_{SN} n_m^2})$ that satisfy:

$$\boldsymbol{a}(t) = \sigma(\boldsymbol{W}_{ref,m}\boldsymbol{m}_{ref}(t) + \boldsymbol{W}_{ref,g}\boldsymbol{g}_{ref}(t)) \tag{5}$$

where $\sigma(*)$ is the sigmoid function:

$$\sigma(x) = 2\left(\frac{1}{1+e^{-x}} - \frac{1}{2}\right). \tag{6}$$

Here we consider the anatomical neuronal binding between the spinal nerve ramus and the muscles [18], [19] as the constraints of these weight matrices. If the i-th muscle and j-th muscle are not anatomically connected via the k-th spinal nerve rams, $(i, n_{SN}n_m(i-1) + n_{SN}(k-1) + j)$-th elements of $\boldsymbol{W}_{ref,m}$ and $\boldsymbol{W}_{ref,g}$ are constrained to be 0. The convergence calculation continues until the residue at the muscle activity:

$$\delta\boldsymbol{a}(t) = \boldsymbol{a}(t) - \sigma(\boldsymbol{W}_{ref,m}\boldsymbol{m}_{ref}(t) + \boldsymbol{W}_{ref,g}\boldsymbol{g}_{ref}(t)) \tag{7}$$

becomes sufficiently small.

III. Experimental Results

A. Measurements

We use experimental human motion data for the identification and evaluation of the neuromuscular network. The motion data is measured by a commercial optical motion capture system composed of 10 cameras with the resolution of 1280x1024 pixels and the frame rate of 200 frame/sec. The contact forces between the human and the floor are measured by two force plates. Each plate measures the center of pressure, three-axial force, and moment around the vertical axis. The muscle activity is measured by a wireless electromyograph (EMG) system with 16 electrodes. Contact force and EMG data are measured at 1000 Hz and synchronized with the motion data. The subject wears 35 markers based on an improved version of Helen Hayes Hospital marker set and 16 EMG electrodes on the muscle as shown in Table II. The muscles to attach the EMG electrode are selected to cover at least one single- and multi-joint muscle for flexion and extension of each of hip, knee, and foot joints.

The following three types of motions are measured for the analysis:

1) Step motion in 100 step/min by Subject A (DATA_{100}).
2) Step motion in 170 step/min by Subject A (DATA_{170}).
3) Step motion with its speed change gradually from 120 step/min to 150 step/min in 6 sec by Subject A ($\mathrm{DATA}_{120-150}$).
4) Jump motion by Subject B ($\mathrm{DATA}_{\mathrm{jump}}$).
5) Squat motion by Subject B ($\mathrm{DATA}_{\mathrm{squat}}$).

The speed of stepping is controlled with a metronome.

B. Result of Identification of Somatosensory Reflex

First, we train the model with seven different time delays using the motion data $\mathrm{DATA}_{120-150}$. Fig. 2 shows the result of identification of the somatosensory reflex network model. The standard back-propagation algorithm [20] is carried out for the training where the learning rate is 0.01, forgetting rate is 0.001, and the number of iteration is 1000. The horizontal axis represents time [sec] and vertical axis represents the normalized activity of right Vastus Lateralis. The top and bottom graph show the first and last 2.5 seconds of $\mathrm{DATA}_{120-150}$ respectively. The black dashed line represents the muscle activity computed using the musculoskeletal model, and the solid lines represent the reconstructed activity using the identified somatosensory reflex networks with different time delays as shown in the figure. Table III represents the average and variance of the error between computed and reconstructed muscle activities.

TABLE II

MAPPING BETWEEN EMG ELECTRODE AND MUSCLE.

# of channel	name of muscle
ch01 / 09	Right / Left Rectus Femoris
ch02 / 10	Right / Left Vastus Lateralis
ch03 / 11	Right / Left Tibialis Anterior
ch04 / 12	Right / Left Gluteus Maximus Os
ch05 / 13	Right / Left Biceps Femoris Caput Longum
ch06 / 14	Right / Left Biceps Femoris Caput Breve
ch07 / 15	Right / Left Gastrocnemius
ch08 / 16	Right / Left Soleus

TABLE III

AVERAGE AND VARIANCE OF ERROR IN THE IDENTIFICATION RESULT. ($\mathrm{DATA}_{120-150}$)

time delay	average	variance
$\delta\boldsymbol{T}+0$msec	2.60e-002	1.60e-002
$\delta\boldsymbol{T}+5$msec	2.59e-002	1.42e-002
$\delta\boldsymbol{T}+10$msec	2.40e-002	1.18e-002
$\delta\boldsymbol{T}+15$msec	2.47e-002	1.21e-002
$\delta\boldsymbol{T}+30$msec	2.57e-002	1.20e-002
$\delta\boldsymbol{T}+60$msec	3.97e-002	2.29e-002
$\delta\boldsymbol{T}+120$msec	3.63e-002	1.55e-002

Then we apply these somatosensory reflex network models to the other motion data DATA_{100}, DATA_{170}, $\mathrm{DATA}_{\mathrm{jump}}$, and $\mathrm{DATA}_{\mathrm{squat}}$ for cross validation. The cross validation is performed for each of the seven time delays and the resulting errors are evaluated.

Fig. 3–5 show the results of the cross validation. In each graph, the horizontal axis represents time [sec] and vertical axis represents the normalized activity of right Rectus Femoris(Figs. 3 and 4) or right Vastus Intermedius (Fig. 5). The top graph shows the result of DATA_{100} and bottom graph shows the result of DATA_{170} in Fig. 3, and the top graph shows the result of $\mathrm{DATA}_{\mathrm{jump}}$ and bottom graph shows the result of $\mathrm{DATA}_{\mathrm{squat}}$ in Figs. 4 and 5. The line types and colors are same as in Fig. 2. Table IV represents the average and variance of error between computed and reconstructed muscle activity for cross validation. Fig. 6 summarizes the results in Table III and IV as a graph. The horizontal axis represents the offset of time delay, and the vertical axis represents the average error of the lower-body normalize muscle activity and its standard deviation. The

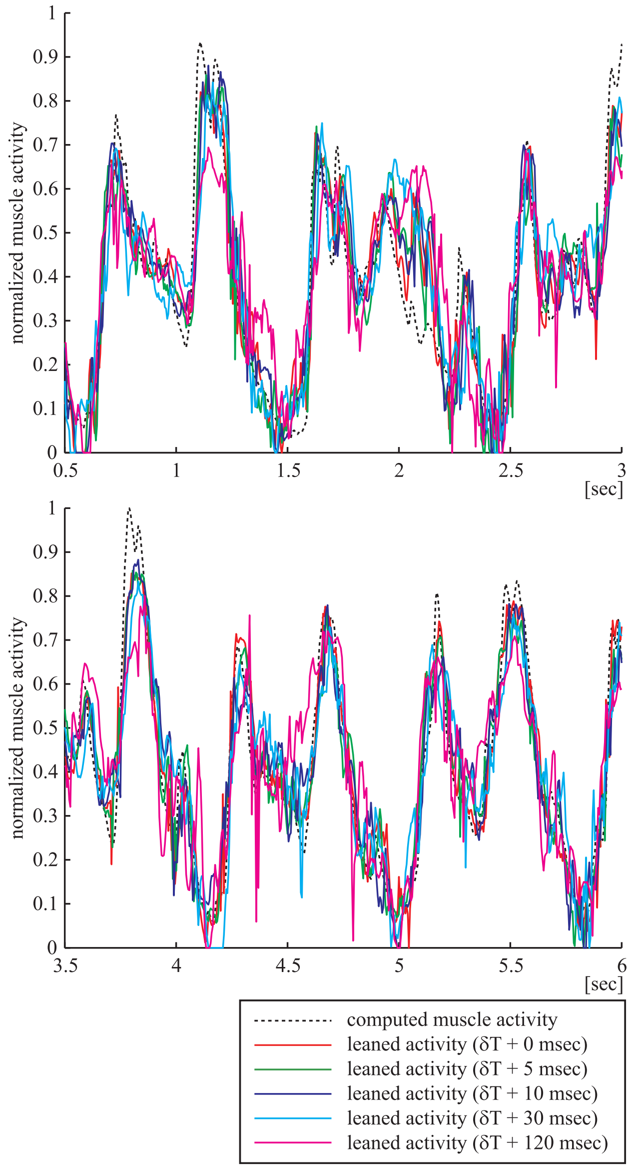

Fig. 2. The computed activity of right Vastus Lateralis and reconstructed data for $\mathrm{DATA}_{120-150}$ using the identified neuromusculoskeletal system model. Black dashed line: computed muscle activity, red solid line: reconstructed data by somatosensory reflex system whose time delay is $\delta\boldsymbol{T}+0$msec, green solid line: $\delta\boldsymbol{T}+5$msec, blue solid line: $\delta\boldsymbol{T}+10$msec, cyano solid line: $\delta\boldsymbol{T}+30$msec. magenta solid line: $\delta\boldsymbol{T}+120$msec. Top: first part of stepping motion, bottom: last part of stepping motion.

black dashed line is the result of $\mathrm{DATA}_{120-150}$, the red solid line is the result of DATA_{100}, the green solid line is the result of DATA_{170}, the blue solid line is the result of $\mathrm{DATA}_{\mathrm{jump}}$, and the cyano solid line is the result of $\mathrm{DATA}_{\mathrm{squat}}$.

C. Discussion

These experimental results suggest the following points:

1) The result of identification shows that the somatosensory reflex network models can learn the muscle activity pattern with only 2–4 % error. The difference of time-delay offset has little impact on the result of identification if the offset is less than 30 msec. If the time delay offset is greater than 60 msec, the wave shape of reconstructed muscle activity becomes inaccurate in both timing and amplitude.
2) The cross validations using DATA_{100} and DATA_{170} show that the identified somatosensory reflex network model can estimate the muscle activity with 2 % error when the time-delay offset is less than 10 msec. The difference due to the time-delay offset is more significant than at the identification. Both DATA_{100} and DATA_{170} show the minimum error when the time-delay offset is 10 msec. In particular, the simulated muscle activity with 10 msec offset is more accurate at the peaks of the wave form than the others. This time delay is within the range of measured delay of knee-jerk reflex (between $\delta T+9$ and $\delta T+14$ msec). The precision of the reconstruction is somewhat surprising because the novel stepping motions are much slower or faster than the learned motion, and the muscle usage, especially the co-contraction pattern, is likely to change depending on the speed. Our result suggests that humans apply similar control strategies for a wide range of instances of the same behavior.
3) The result of cross validations using the motion data $\mathrm{DATA}_{\mathrm{jump}}$, $\mathrm{DATA}_{\mathrm{squat}}$ show that the the identified somatosensory reflex network model can estimate the muscle activity with 5 % error when the time-delay offset is 5 msec. These motions are significantly different from stepping, so the usage of synergist and antagonist muscles and the pattern of co-contraction must be entirely different. For example, the co-contraction of the muscles around knee joint at the preparatory phase of jumping motion is not included in the normal stepping motion, and it can be computed only with the measured EMG. The reconstructed activities of Rectus Femoris and Vastus Intermedius have impulsive shapes that are same as those seen in the activities computed using the dynamics computation and optimization[3], if the offset of time delay is appropriately selected. The difference due to the time-delay offset is much more significant than the cross validations with DATA_{100} and DATA_{170}. The wave shape of estimated activity is significantly different especially in the Vastus Intermedius (Fig. 5), and 5 msec is more appropriate than others in terms of the muscle tension.
4) The comparison between the results of cross validation using DATA_{100}, DATA_{170}, and $\mathrm{DATA}_{\mathrm{jump}}$, $\mathrm{DATA}_{\mathrm{squat}}$ shows the interesting results about the offset of time delay. Fig. 6 shows that the error changes particularly in $\mathrm{DATA}_{\mathrm{jump}}$ and $\mathrm{DATA}_{\mathrm{squat}}$, though it does not change so much in DATA_{100} and DATA_{170}. From statistical point of view, the error does not change so much if the patterns of data used for the identification and cross validation are similar (e.g. between

[3]We use the measured EMG to estimate the activity of Rectus Femoris, so its co-contraction during the jump and squat motions appears in the computed activities.

TABLE IV

AVERAGE AND VARIANCE OF ERROR IN THE CROSS VALIDATION RESULT. (AVERAGE / VARIANCE)

delay	$DATA_{100}$	$DATA_{170}$
0msec	1.65E-02 / 2.60E-04	3.96E-02 / 8.49E-04
5msec	1.89E-02 / 7.46E-04	1.77E-02 / 4.37E-04
10msec	1.63E-02 / 7.10E-04	1.43E-02 / 3.82E-04
15msec	2.00E-02 / 1.09E-03	2.80E-02 / 1.91E-03
30msec	3.21E-02 / 2.34E-03	3.03E-02 / 2.20E-03
60msec	3.32E-02 / 2.54E-03	3.41E-02 / 2.17E-03
120msec	6.51E-02 / 4.53E-03	6.04E-02 / 5.17E-03
delay	$DATA_{jump}$	$DATA_{squat}$
0msec	1.22E-01 / 1.07E-02	6.76E-02 / 1.62E-03
5msec	5.56E-02 / 1.38E-03	4.54E-02 / 9.18E-04
10msec	8.17E-02 / 4.30E-03	5.70E-02 / 9.69E-04
15msec	7.04E-02 / 2.25E-03	7.59E-02 / 3.56E-03
30msec	8.46E-02 / 7.50E-03	7.51E-02 / 2.92E-03
60msec	1.85E-01 / 1.55E-02	1.55E-01 / 6.26E-03
120msec	2.96E-01 / 5.03E-02	3.17E-01 / 2.18E-02

$DATA_{120-150}$, $DATA_{100}$, and $DATA_{170}$), or there is no relationship between the somatosensory information and muscle activity. The phenomenon that the relation between the time-delay offset and the error of cross validation is not ever-increasing or -decreasing and has a minimum value suggests that the reflex system is optimized for a particular time delay. Furthermore, this length of time delay roughly matches the value estimated from the anatomical structure and geometry of the human body.

5) The result that the somatosensory reflex network model identified using the stepping motion can be generalized to jumping and squat motions suggests that there is a possibility that the human body can generate whole-body motions only from simple motion command signals. In this model, muscle activity patterns can be generated by giving the first few frames of muscle length, its velocity and tension. This information will work as the trigger for the somatosensory reflex network model to generate the muscle activity of the rest of motion.

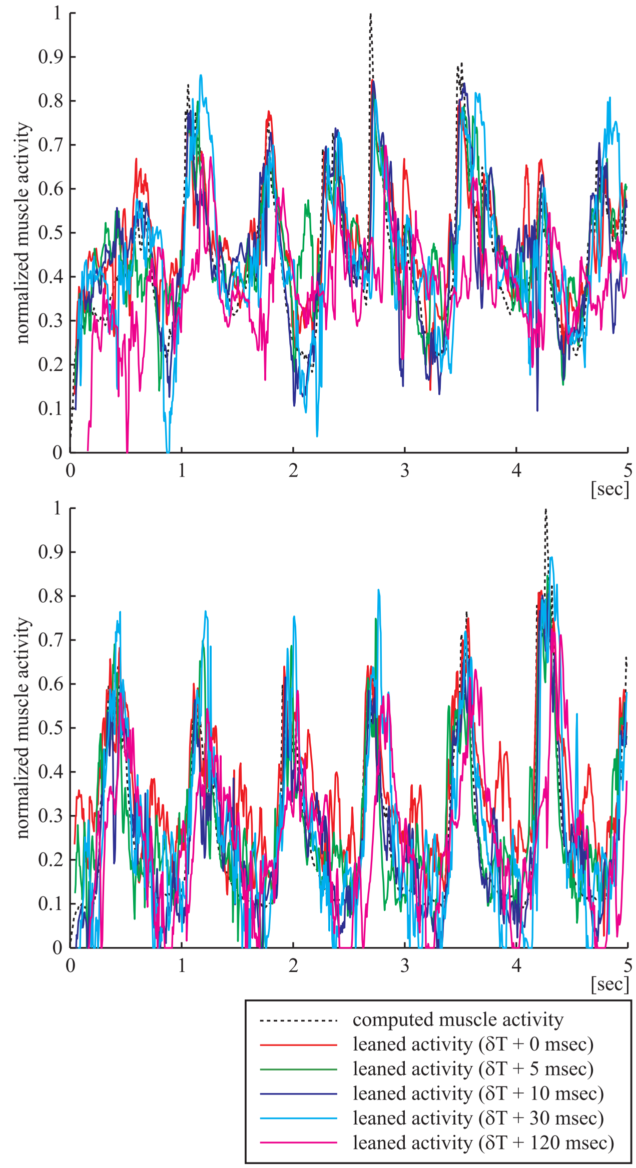

Fig. 3. The computed activity of right Rectus Femoris and reconstructed data for $DATA_{100}$ and $DATA_{170}$ using the identified neuromusculoskeletal system model. The parameter of somatosensory reflex is identified using $DATA_{120-150}$. The color of lines are same as in Fig. 2 Top: $DATA_{100}$, bottom: $DATA_{170}$.

IV. CONCLUSION

In this paper, we investigated the effect of the nerve signal transmission delay on the generalization capability of our human somatosensory reflex model. We first identified the parameters of the model assuming several different time delays, using the motion and muscle tension data obtained from a stepping motion with continuously changing speed. We then performed cross validations against slower and faster stepping motions as well as entirely different behaviors such as jump and squat. The results suggest the following two important points:

1) The model identified with physiologically appropriate time delay resulted in better identification and cross-validation results than others. This result suggests that the reflex parameters are optimized for the time delay determined by the geometric nerve structure of the human body.
2) The model identified with physiologically appropriate time delay had better generalization capability to different behaviors than others. This result suggests that the human nerve structure generates various whole-body motion patterns only from simple motion command signal.

These results indicates that the human nerve system generates muscle activities that realize balanced whole-body motions by a feedback system as slow as 10 Hz. In contrast, today's humanoid robots usually employ high-speed feedback control at around 1000 Hz, although their control

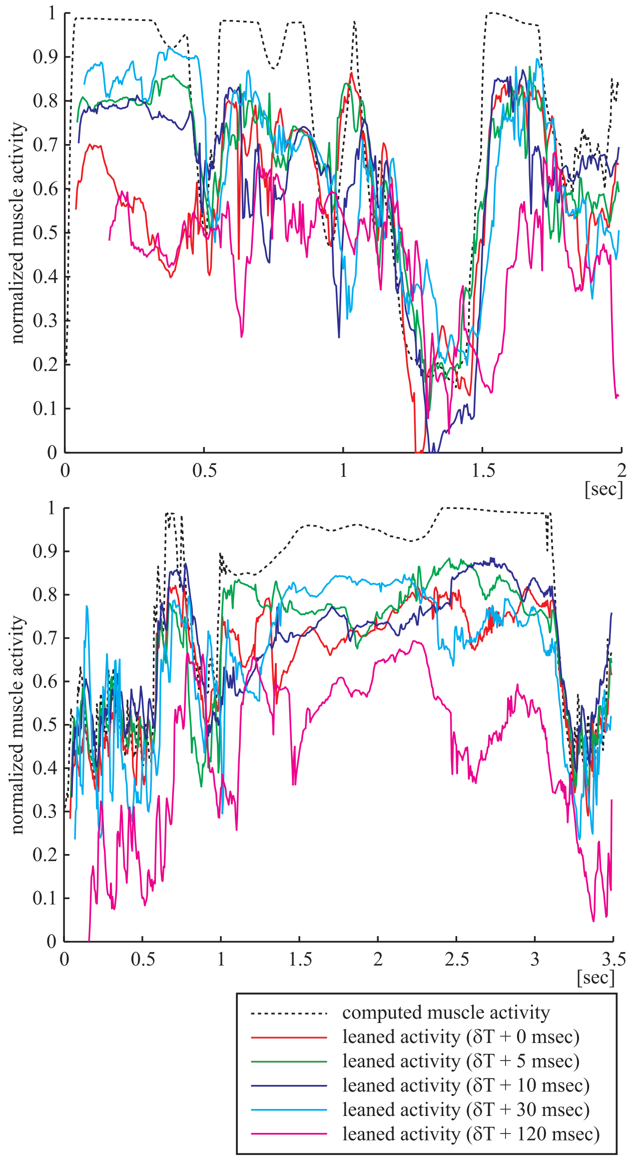

Fig. 4. The computed activity of right Rectus Femoris and reconstructed data for $\mathrm{DATA_{jump}}$ and $\mathrm{DATA_{squat}}$ using the identified neuromusculoskeletal system model. The parameter of somatosensory reflex is identified using $\mathrm{DATA_{120-150}}$. The color of lines are same as in Fig. 2 Top: $\mathrm{DATA_{jump}}$, bottom: $\mathrm{DATA_{squat}}$.

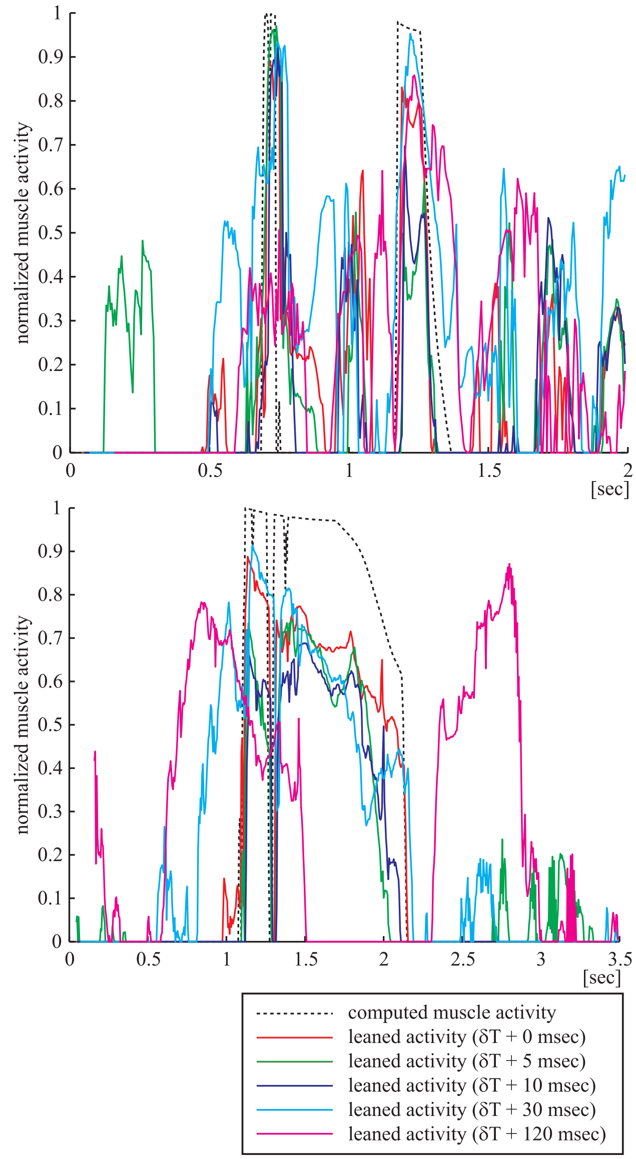

Fig. 5. The computed activity of right Vastus Intermedius and reconstructed data for $\mathrm{DATA_{jump}}$ and $\mathrm{DATA_{squat}}$ using the identified neuromusculoskeletal system model. The parameter of somatosensory reflex is identified using $\mathrm{DATA_{120-150}}$. The color of lines are same as in Fig. 2 Top: $\mathrm{DATA_{jump}}$, bottom: $\mathrm{DATA_{squat}}$.

is not as robust as human motor control. The somatosensory reflex model proposed in this paper does not consider the external forces including the ground contact forces that gives us the information of environment and our own status. We expect that including these data as the feedback signal will improve the accuracy and capability of the somatosensory reflex model, and give some insights about the generation and coordination of humanoid robot motions.

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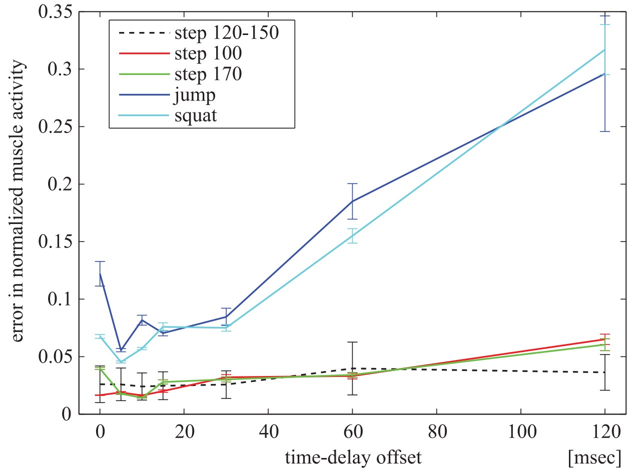

Fig. 6. Errors and their variances between computed and estimated muscle activities. Black dashed line: $\mathrm{DATA}_{120-150}$, Red solid line: DATA_{100}, green solid line: DATA_{170}, blue solid line: $\mathrm{DATA}_{\mathrm{jump}}$, cyano solid line: $\mathrm{DATA}_{\mathrm{squat}}$.

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