35th Annual International Conference of the IEEE EMBS
Osaka, Japan, 3 - 7 July, 2013

Muscle synergy control model-tuned EMG driven torque estimation system with a musculo-skeletal model

Kyuengbo MIN, Duk Shin, Jongho Lee and Shinji Kakei

***Abstract*— Muscle activity is the final signal for motion control from the brain. Based on this biological characteristic, Electromyogram (EMG) signals have been applied to various systems that interface human with external environments such as external devices. In order to use EMG signals as input control signal for this kind of system, the current EMG driven torque estimation models generally employ the mathematical model that estimates the nonlinear transformation function between the input signal and the output torque. However, these models need to estimate too many parameters and this process cause its estimation versatility in various conditions to be poor. Moreover, as these models are designed to estimate the joint torque, the input EMG signals are tuned out of consideration for the physiological synergetic contributions of multiple muscles for motion control. To overcome these problems of the current models, we proposed a new tuning model based on the synergy control mechanism between multiple muscles in the cortico-spinal tract. With this synergetic tuning model, the estimated contribution of multiple muscles for the motion control is applied to tune the EMG signals. Thus, this cortico-spinal control mechanism-based process improves the precision of torque estimation. This system is basically a forward dynamics model that transforms EMG signals into the joint torque. It should be emphasized that this forward dynamics model uses a musculo-skeletal model as a constraint. The musculo-skeletal model is designed with precise musculo-skeletal data, such as origins and insertions of individual muscles or maximum muscle force. Compared with the mathematical model, the proposed model can be a versatile model for the torque estimation in the various conditions and estimates the torque with improved accuracy. In this paper, we also show some preliminary experimental results for the discussion about the proposed model.**

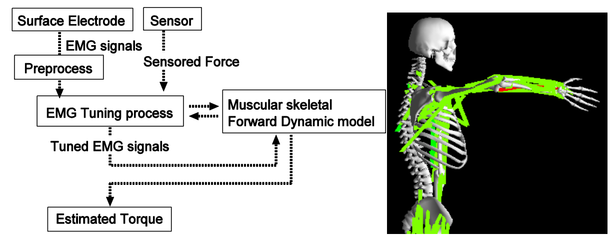
I. INTRODUCTION

As Electromyogram (EMG) signal represents the signal generated from the brain for the control of muscle activities, EMG can be applied to analyze the motion control process of brain. Moreover, this characteristic may be applied to make the device which can communicate between human and external environments such as external device. It will be possible for this system to be transferred for rehabilitation or for an EMG-controlled machine interface [1]. To do these, the EMG-driven torque estimation system needs to be modeled. The current EMG-driven torque estimation has three main limitations. First, EMG signal has a lot of noises from the real measurement environment. Second, the real condition may be different from the simulated computational condition in the EMG-driven torque estimation system. Third, the normalization of EMG is important to analyze the motion process but its estimation is impossible. Taking these issues into account, the system operates the optimization process to tune EMG as the input signal for the estimation of joint torque. Due to these problems, even though the EMG signal is pre-processed for normalizing its raw signal, this signal has serious problem to be applied as input control signal to the simulation system for the EMG-driven torque estimation. For this problem, the current EMG driven torque estimation model [2],[3] generally employed the mathematical model which estimates the nonlinear transformation function between the input signal and the output torque. These models need to estimate many parameters for estimating the joint torque because they need to estimate the musculo-skeletal forward dynamics process. These estimation models need the high cost to estimate the joint torque and their versatility for the different condition is poor. Moreover, as these models are focused to be designed to estimate the joint torque, the input EMG signals are tuned out of consideration for their synergetic contributions of the motion control. The normalization process of EMG is very important to analyze the contribution between muscles for motion control. We think that problems for current EMG tuning model are originated from this concept for just torque estimation, which is caused by unreliability for the precision of EMG signal due to three limitations of EMG introduced above.

Kyuengbo MIN is with the Department of Sensory Motor System, Tokyo Metropolitan Institute of Medical Science, 2-1-6, Kamikitazawa, Setagaya-ku, Tokyo 156-8506, Japan (corresponding author to provide e-mail: min-kb@igakuken.or.jp).

Duk Shin was with the Precision and Intelligence Laboratory, Tokyo Institute of Technology, 4259 Nagatsuta-cho, Midori-ku, Yokohama, Kanagawa 226-8503, Japan (e-mail: shinduk@cns.pi.titech.ac.jp).

Jongho Lee and Shinji Kakei is with the Department of Sensory Motor System, Tokyo Metropolitan Institute of Medical Science, 2-1-6, Kamikitazawa, Setagaya-ku, Tokyo 156-8506, Japan (e-mail: lee-jg@igakuken.or.jp, kakei-sj@igakuken.or.jp).



(a) (b)

Fig. 1. System: (a) System structure, (b) Muscular skeletal model.

To overcome the problem of the current models, we used the forward dynamic model based on the musculo-skeletal model. To tune the EMG signals as input control signal for the proposed torque estimation model, we proposed the new tuning model that does not only tune the EMG signals for torque estimation or its' motion trace but also re-estimates the EMG signals as the control signal of multiple muscles from brain. To do this, we focus on the tuning of EMG with the synergy mechanism between multiple muscles contributing to the motion control. To evaluate the proposed model, we show the some preliminary experimental results.

II. METHOD

A. System structure

The proposed system structure is shown in Fig.1(a). The EMG signals measured with the surface electrode are tuned with the EMG tuning process. The EMG tuning process is the optimization process for estimating the joint torque with the EMG signal tuning in the musculo-skeletal model-based forward dynamic model. The goal of the optimization process is the joint torque estimated with the force-input Jacobian transformation [4]. The force is measured with a sensor. As shown in Fig.1(b), the musculo-skeletal model [5] is designed with the precise musculo-skeletal data [6][7], such as origins and insertions of individual muscles or maximum muscle force. Moreover, to take the individuality of a subject into consideration, the human anthropometry [8] is applied to this model. The dynamic of muscle contraction is simulated with the parameter-normalized model [9] based on Hill model [10]. The forward dynamic process of the proposed system is estimated with Newton Euler model [5].

B. EMG tuning model

The system operates the optimization process to tune EMG as the input signal for the estimation of joint torque. The EMG tuning model is based on the optimization process which estimates the optimal tuning weight of EMG signals to maximize the similarity between the sensed torque and the estimated torque. Furthermore, to maximize the tuning effect of EMG, the contribution of unmeasured muscle taking part in the motion control is applied to the EMG tuning process. To apply the synergetic control contribution between multiple muscles to the EMG tuning, the proposed model is based on the synergy mechanism between multiple muscles. This model is introduced in the next subsection.

■ Synergetic EMG tuning

As shown in Fig.2, the multiple muscles are activated for the control of arm motion. These muscles are controlled with the signal from the cortico-motoneuron (CM) in primary motor cortex (M1). The proposed synergetic control mechanism is based on the activity of CM. Asanuma [11] showed that individual CM triggers one particular muscle. Based on this experimental data, Shinoda [12] found the experimental data for the new control mechanism of some CMs, which govern multiple muscles. Based on these experimental data, the new EMG tuning model is proposed. The proposed model is that

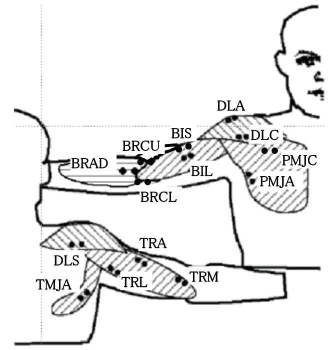


Fig. 2. Acting muscles for control of arm.

multiple muscles for the contribution of motion are controlled with the synergy mechanism between two kinds of control policy which are Group control policy and Individual control policy. Based on this mechanism, the input EMG signals $\mathbf{Emg}_t$ for the system are tuned as:

$$\begin{aligned} &\mathbf{Emg}_t = \mathbf{Emg}_t^{\mathrm{Diag}} \cdot \mathbf{w}, \\ &\mathbf{w} = \mathbf{w}^{\mathrm{I}} + \mathbf{w}^{\mathrm{G}} \end{aligned} \qquad (1)$$

where $\mathbf{w}$ is the weight vector for tuning $\mathbf{Emg}_t^{\mathrm{Diag}}$ at time **t**. $\mathbf{Emg}_t^{\mathrm{Diag}}$ is the diagonal matrix of normalized EMG signals. $\mathbf{w}^{\mathrm{I}}$ is the weight vector of the individual control policy and $\mathbf{w}^{\mathrm{G}}$ is the weight vector of the group control policy. The output tuning weight vector $\mathbf{w}$ estimated as the summation of $\mathbf{w}^{\mathrm{I}}$ and $\mathbf{w}^{\mathrm{G}}$ in (1). This $\mathbf{w}$ is optimized to the optimal tuning weight $\mathbf{w}^*$ with:

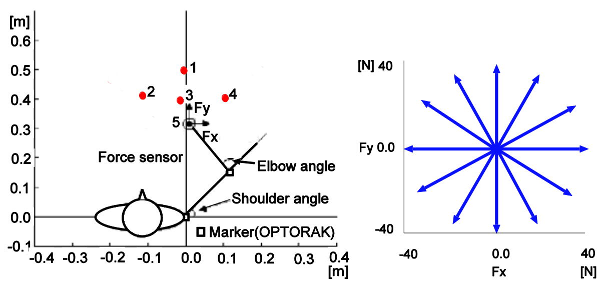
$$\begin{aligned} &\text{Object Function}: \mathbf{w}^* = \arg_{\mathbf{w}} \min \sum_{t=0}^{\mathrm{N}^{\mathrm{time}}} \left\| \boldsymbol{\tau}_t^{\mathrm{sns}} - \boldsymbol{\tau}_t^{\mathrm{sim}} \right\|, \\ &\boldsymbol{\tau}_t^{sim} = \mathrm{fd}(\mathbf{Emg}_{t-\Delta t^{\mathrm{Delay}}}), \\ &\mathbf{w} = (w_0, w_1, \ldots, w_m, \ldots, w_{\mathrm{N}^{\mathrm{dof}}}), \boldsymbol{\tau}_t = (\tau_t^{\,0}, \tau_t^{\,1}, \ldots, \tau_t^{\,m}, \ldots, \tau_t^{\,\mathrm{N}^{\mathrm{dof}}}), \\ &\text{Constraint}: 0.01 \le w_m \le 1.0, \quad 0.01 \le w_m^{\mathrm{I}} \le 1.0, \\ &\qquad\qquad 0.01 \le w_m^{\mathrm{G}} \le 1.0 \end{aligned} \qquad (2)$$

where $\boldsymbol{\tau}_t^{\mathrm{sns}}$ is the sensed torque and $\boldsymbol{\tau}_t^{\mathrm{sim}}$ is the torque estimated with the muscular skeletal forward dynamic model $\mathrm{fd}()$. As shown in (2), during the total time sequence $\mathrm{N}^{\mathrm{time}}$, $\mathbf{w}^*$ is optimally estimated with the object function, which makes $\boldsymbol{\tau}_t^{\mathrm{sim}}$ approximate $\boldsymbol{\tau}_t^{\mathrm{sns}}$ with optimizing $\mathbf{w}$. $\mathbf{w}$ is the vector consisting of the weight w^m for individual mucle *m*. $\boldsymbol{\tau}_t$ is also the vector consisting of the torque $\tau_t^{\,m}$ for individual muscle *m* at every time **t.** $\mathrm{N}^{\mathrm{dof}}$ is total degrees of freedom of the articulated skeletal model. This process is constrained with the constraint condition in (2). The process stated above is applied with the muscle grouping as table.1. Based on this table, the classification for $\mathbf{w}^G$ is processed. TMAJ, PMJC and PMJA excluded from grouping list are individually tuned with $\mathbf{w}^I$.

TABLE I
MUSCLES GROUPING

Group name	Muscle name
Shoulder Extensor	DLS,DLA
Elbow Flexor	BIL, BRCU, BRAD
Elbow Extensor	TRL, TRA, TRM

III. Measurement condition of EMG signal



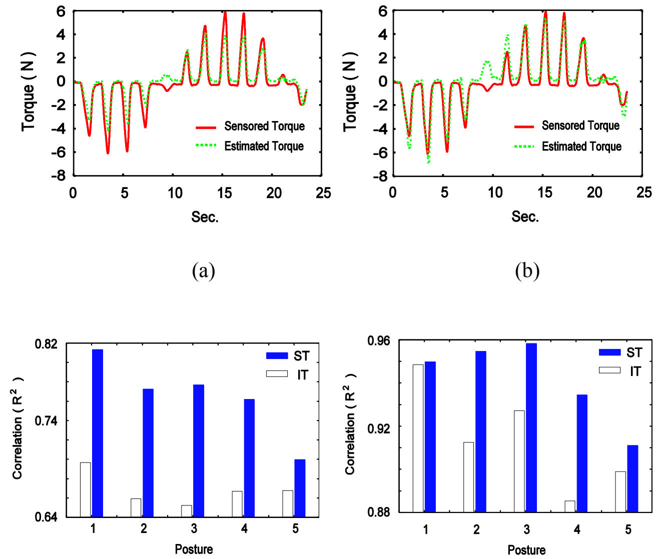
(a) (b)

Fig.3 Measurement condition of EMG signals and joint torque:
(a) Measurement postures: numbered locations mean the positions of hand, (b) Force directions exerted with the hand griping the stick on the every numbering position.

As shown in Fig.1(a), EMG signal and joint torque estimation are simultaneously measured. For the subject's postures shown in Fig.3(a), the EMG signals of 11 including muscles in table1 are measured and the joint torques of both elbow and shoulder are simultaneously sensed. The torque is estimated with exerting force for fixed stick in 12 directions shown in Fig.3(b). With the same condition as this setting, the measurements for 5 different postures were operated as shown in Fig.3(a).

IV. Results

The proposed synergetic tuning (ST) model was compared with the Individual tuning (IT) model for evaluating the function of torque estimation. The estimation process of tuning weight in (1) is proceeded for only one posture, which is posture 5 in Fig.3(a). Fig.4(a) shows the IT-estimated elbow joint torque for the posture 5 and Fig.4(b) shows the ST-estimated elbow joint torque for the posture 5. The red line means the measured torque and the green dots line means the estimated torque. These results show that ST estimates the



(a) (b)

(c) (d)

Fig.4 Joint torque estimation with tuning process: (a) Elbow joint torque estimated with Individual tuning (IT), (b) Elbow joint torque estimated with Synergetic tuning (ST), (c) Correlation (R^2) between the measured torque and the estimated torque for elbow joint, (d) Correlation (R^2) between the measured torque and the estimated torque for shoulder joint.

torque with more improved accuracy than IT. The tuning weight estimated for posture 5 is applied to the all postures for tuning their EMG signals. Fig.4(c) and Fig.4(d) are the results from this process. Fig.4(c) show the correlation between the measured torque and the estimated torque for elbow joint and Fig.4(d) show the correlation between the measured torque and the estimated torque for shoulder joint. In these two figures, the blue box means the result of ST and white box means the result of IT. These results show the superiority of ST to the IT in torque estimation. The square of correlation coefficient R^2 shows that ST-torque estimation is better than IT-torque estimation for both the elbow joint and the shoulder joint in all postures. These results show the robust versatility of the proposed model for various postures.

These results are caused by the difference of tuning policy between ST and IT as explained in (1). Fig.5 shows the EMG signals estimated with the different two tuning models. Fig.5(a) shows the input original EMG signals and its individuality is expressed with coloring. Fig.5(b) shows the EMG signals tuned with IT and Fig.5(c) shows the EMG signals tuned with ST. Compared the ST estimated result with the IT estimated result, the muscles activity in Fig.5(c) is more synergetically controlled than the muscles activity in Fig.5(b). Fig.5(b) show that the activity of Brachioradialis (BRAD) is singularly tuned to the high level over maximum activity 1.0 with keeping the others' activity depressed. This result showed that the muscle activity tuned with IT is transformed out of normal activity of muscles. Moreover, the EMG signals tuned with ST in Fig.5(c) are synergetically activated like the original EMG signals in Fig.5(a). These results show that the

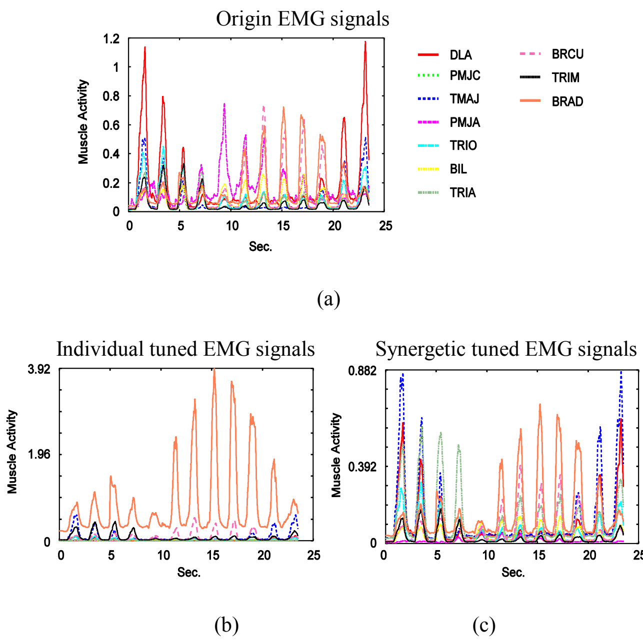


Fig.5 Comparsion of original EMG signals and tuned EMG signals: (a) Origin EMG signals, (b) Individual tuned EMG signal, (c) Synergetic tuned EMG signals.

proposed tuning model can not only estimate the joint torque but also estimate the muscle activity.

V. Conclusion

The proposed model is a EMG-driven torque estimation model. As EMG signals are difficult to be precisely measured due to its unstable measurement circumstance and the discrepancy between real and simulation conditions, the EMG signals need to be tuned for estimating the joint torque. Compared with the current mathematical torque estimation models, the proposed model can precisely estimate both torque and normalized muscle activity with the EMG signal tuning model. The estimation of muscle activity is very important to estimate the contribution of individual muscle for the motion control. The EMG signal tuning is based on the synergy mechanism between multiple muscles in the cortico-spinal tract. Due to this process, the muscle activity can be estimated much more similar to the real EMG signals than the general individual tuning models. The simulation of the proposed model makes use of the musculo-skeletal forward dynamic model. With this model, the torque estimation cost is lower than the mathematical model that needs to estimate a number of parameters for the musculo-skeletal forward dynamic. Moreover, this characteristic brings more robust versatility of torque estimation in various conditions than the mathematical models in Fig.4.

As muscle activities represent the final control signals from the brain, the proposed system may be applicable to the man-machine interface that controls the external device with EMG signals. For the future work, we will apply this system to a rehabilitation process for stroke patients and a device aiding people with a physical disability.

Acknowledgment

We thank Dr. Yasuharu Koike for his valuable advice on the optimization process for torque estimation. We also thank Dr. Masami Iwamoto for his discussion on the muscle synergy mechanism.

References

[1] K. Akazawa, H. Takizawa, Y. Hayashi, K. Fujii, “Development of control System and Myoelectric signal processor for bio-mimetic prosthetic,” Society of biomechanisms Japan, pp. 43-53, 1988.
[2] Y. Koike, M. Kawato, “Estimation of dynamic joint torques and trajectory formation from surface electromyography signals using a neural network model,” Biological Cybernetics, 73, pp. 291-300, 1995.
[3] D. Shin, J. Kim, Y. Koike, “A myokinetic arm model for estimating joint torque and stiffness from EMG signals during maintained posture,” Journal of Neurophysiology 101, pp. 387-411, 2009.
[4] J. J. Craig, Introduction to robotics: Mechanics and control 2ed. Addison-Wesley, 1989, pp. 211-214.
[5] K. Min, Y. Koike, “Human Arm model for forward dynamics simulation based on muscular skeleton data,” IEICE Technical report EID2002-36, 2002, pp. 30-34.(In Japanese)
[6] J. E. Wood, S.G. Meek And S.C. Jacobsen, “Quantitation of human shoulder anatomy for prosthetic arm control – I. Surface modeling,” Jounal of biomechanics 22-3, pp. 273-292, 1989.
[7] J. E. Wood, S.G. Meek And S.C. Jacobsen, “Quantitation of human shoulder anatomy for prosthetic arm control – II. Anatomy matrices,” Jounal of biomechanics 22-4, pp. 309-325, 1989.
[8] W. T. Dempster, WADC Technical Report, TR-55-159, Wright-Patterson Air Force Base, OH, 1955.
[9] F.E. Zajac, F.L. Toppand, P.J. Stevenson, “A Dimensionaless musculotendon model,” IEEE/Eight Annual Conference of the Eng. In Medicine and Biology Society, pp. 601-604, 1985.
[10] A.V. Hill, R.C. Sec, “The heat of shortening and the dynamic constants of muscle,” Proc Roy Soc (London)126B, pp. 136-195, 1938.
[11] H. Asanuma, H. Sakata, “Functional organization of a cortical efferent system examined with focal depth stimulation in cats,” Journal of Neurophysiology 30, pp. 35–54, 1967.
[12] Y. Shinoda, P. Zarzecki, H. Asanuma, “Spinal branching of pyramidal tract neurons in the monkey,” Experimental brain research 34, pp. 59-72, 1979.