EMG-Based Muscle Torque Estimation for FES Control System Design

Bo-Ra Hyun[1], Tong-Jin Song[1], Sun-Hee Hwang[1], Gon Khang[1], Gwang-Moon Eom[2], Moon-Suk Lee[3], Bum-Suk Lee[3]

[1]*Department of Biomedical Engineering, Kyung Hee University, Yongin-si, Korea*
[2]*School of Biomedical Engineering, Konkuk University, Chungju-si, Korea*
[3]*National Rehabilitation Hospital, Seoul, Korea*

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Abstract

This study was designed to investigate the feasibility to utilize the electromyogram (EMG) for estimating the muscle torque. The muscle torque estimation plays an important role in functional electrical stimulation because electrical stimulation causes muscles to fatigue much faster than voluntary contraction, and the stimulation intensity should then be modified to keep the muscle torque within the desired range. We employed the neural network method which was trained using the major EMG parameters and the corresponding knee extensor torque measured and extracted during isometric contractions. The experimental results suggested that (1) our neural network algorithm and protocol was feasible to be adopted in a real-time feedback control of the stimulation intensity, (2) the training data needed to cover the entire range of the measured value, (3) different amplitudes and frequencies made little difference to the estimation quality, and (4) a single input to the neural network led to a better estimation rather than a combination of two or three. Since this study was done under a limited contraction condition, the results need more experiments under many different contraction conditions, such as during walking, for justification.

Key words : EMG, muscle torque estimation, functional electrical stimulation, neural network

I. INTRODUCTION

Functional Electrical Stimulation (FES) has been used as a useful means to cause contraction of paralyzed muscles for functional mobility such as walking, grasping and so forth. However, many problems should be solved before FES can be easily applied to daily lives of the plegic patients. There is no doubt that one of the major problems is the fact that electrical stimulation causes muscles to fatigue much faster than voluntary contraction. Consequently, in order to prolong and/or stabilize FES-induced mobility, muscle fatigue, i.e. the muscle force (or torque), needs to be monitored in real time to adjust the stimulation intensity.

We believe that the electromyogram (EMG) can be utilized to estimate muscle torque according to many reports [1, 2] stating that the muscle force may be somehow correlated with EMG. The major reason for using EMG to estimate the muscle torque is that there are few sensors available to measure muscle force directly and that, if any, they cannot be used for FES-induced movements such as walking. Erfanian et al. [1] developed a torque predictor for an electrically stimulated muscle in the isometric contraction. Each of the evoked EMG (EEMG) and electrical stimulation signal was used as the input to the predictive model for muscle torque estimates. They could obtain more accurate prediction of stimulated muscle torque with EEMG-to-torque models than with stimulation-to-torque models. Moreover, Tepavac et al. [2] suggested EMG parameters - root mean squared (RMS) value, integrated rectified EMG (IEMG), mean frequency and median frequency (MDF) - should be correlated with the muscle torque for FES-induced fatigue. However, their work was limited to finding the onset of muscle fatigue. This study was designed to adjust the stimulation intensities applied to paralyzed muscles by estimating the muscle torque during sustained contractions.

The neural network method was applied to the major EMG parameters for muscle torque estimation [3-5]. The neural network method has been already adopted in some studies since the EMG-torque relationship showed nonlinearity and nonstationarity as well. Kent et al. [3] used the neural network

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Corresponding Author : Gon Khang, Ph.D.
Department of Biomedical Engineering
College of Electronics and Information, Kyung Hee University, 1 Seocheon-dong, Giheung-gu, Yongin-si, Gyeonggi-do 446-701, Republic of Korea
Tel : +82-31-201-2998 / Fax : +82-31-206-8226
E-mail : gkhang@khu.ac.kr

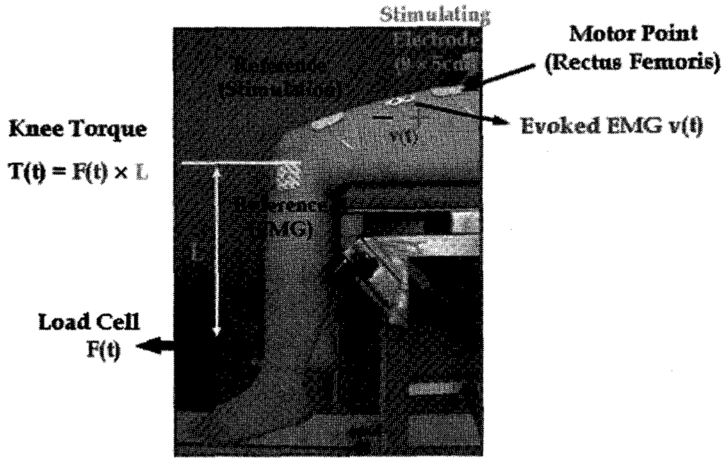

Fig. 1. Knee extensor torque measurement and electrode positions.

to find out the EMG-torque relationship in the ankle joint under isometric contraction. They measured EMG from six different muscle sites and trained the network. The prediction of the muscle torque was successful and the study showed the feasibility of the neural network. Winslow et al. [4] suggested the feasibility of the neural network using surface EMG to maintain muscle force and the joint angle to compensate for muscle fatigue during FES. Liu et al. [5] adopted the neural network method to predict and validate dynamic muscle force across subjects based on the measured EMG signals, reporting that the dynamic force predictions were excellent at some speeds with a little, but specific training input rather than a great deal of non-specific training input. However, we assumed in this study that the neural network is different from person to person, implying that each network should be trained using his/her own EMG/torque data and that the neural network should not be applied to anyone else.

The ultimate goal of this study is to keep the muscle torque within the desired range utilizing the mixed EMG, i.e. the EMG resulting from voluntary contraction and electrical stimulation simultaneously, measured from partially paralyzed muscles. The examples include incomplete spinal cord injury (SCI), stroke, etc. This paper describes how to estimate the muscle torque from the voluntary EMG (VEMG) and EEMG separately, assuming that the mixed EMG can be dissociated into two components (VEMG and EEMG).

II. METHODS

A. Subjects

Three male incomplete SCI patients participated in the experiment at the National Rehabilitation Hospital, Seoul, Korea. Their injury level was ASIA D, which means that they could walk with the aid of some orthotic devices. Assuming that the injury characteristics and the muscle contractile characteristics are not bilaterally symmetric, we collected the EMG/torque data separately from each leg. The left leg of one patient, however, was excluded because it showed a serious atrophy so that voluntary contraction was almost impossible. All of the patients were given detailed explanation about the experiment, and all the experiments were performed based on their written consent.

B. Measurements

EMG and the knee extensor torque were measured using the chair developed in our laboratory. As shown in Fig. 1, the stimulation electrodes were surface rectangular electrodes (5x9cm, Axelgaard Manufacturing Co., USA) positioned at the motor point of the quadriceps which was manually found at the beginning of each experiment. EMG was recorded, both for the VEMG and the EEMG, through surface Ag/AgCl dual electrodes (2cm in diameter, Noraxon, Arizona, USA). The EMG electrodes were placed on the rectus femoris 2cm distal to the stimulating electrode. An Ag/AgCl electrode (4x4cm, ALCARE Co., Tokyo, Japan) was used as the reference electrode placed near the patellar. The knee extensor torque was computed by multiplying the moment arm to the force measured using a load cell (SBL-100L, CAS Co., Seoul, Korea). The upper extremities of the subjects were kept at the upright position and the knee angle was fixed at 90 to avoid the gravitational effect.

The pulse waveform and three stimulus parameters (pulse width, pulse amplitude and frequency) were programmed in the LabVIEW (National Instrument Co., Austin, Texas, USA).

The frequency and the pulse width were fixed at 20Hz and 500s, respectively, in this study, and we employed the unbalanced biphasic waveform which generally produced more force and less fatigue than the other three typical waveforms [6]. The stimulation intensity was controlled by adjusting the pulse amplitude, and assumed to be 1 at or higher than the maximum amplitude and 0 at or lower than the threshold level of the amplitude. Three different stimulation intensity patterns were selected, as shown in Fig. 2, to obtain the EMG/torque data necessary for training and validating the neural network. All of them were sinusoidal with different amplitudes and periods. The LabVIEW transmitted the stimulation intensity patterns to the stimulator, which generated the corresponding pulse train. For the VEMG/torque, three different activation intensity patterns similar to Fig. 2 were selected. First, each patient was told to maximally activate the knee extensors, which was regarded as the peak intensity 1. The patients were asked and trained to change the activation level according to those shown in Fig. 2. One stimulation/activation intensity pattern per day was applied to each subject. The patient took a rest for at least 2-3 min to avoid any effect from the previous stimulation(or voluntary activation).

The EMG and the knee extensor torque were measured simultaneously using a 12-bit ADC DAQ device (NI 6070E, National Instruments Co., Austin, Texas, USA) with the sampling rate of 4,000Hz. The on-off blanking signals were applied to EMG in order to erase the large-magnitude stimulating current. The EMG signals were filtered and amplified in the LabVIEW. The Butterworth filter was employed with the bandwidth of 24-400Hz. The EMG parameters obtained from the filtered signal was smoothed because of its rapid fluctuation.

C. Neural Networks

As inputs of the neural network to predict the muscle torque, EMG parameters can be used instead of EMG itself. Hwang et al. [7] selected three EMG parameters that could be used for representing the muscle torque. They were RMS, PTP and median frequency. They reported that RMS alone could be employed for real-time estimation of the muscle torque. We used RMS and PTP for electrical stimulation, while RMS and IEMG for voluntary contraction. Hwang et al. [7] also suggested the radial basis function network (RBF) algorithm to monitor muscle fatigue during electrical stimulation. They compared the estimation error resulting from three nonlinear algorithms, RBF algorithm, error back-propagation (Levenberg-Marquardt algorithm) and error back-propagation (Scaled Conjugate Gradient algorithm). Since the RBF algorithm showed the least error, we employed the RBF algorithm to estimate muscle torque from EEMG and VEMG.

We applied three different analysis protocols for torque estimation. First, we investigated how the number of training data affected the quality of the network output. Since three different EMG-torque data sets were obtained from the three different stimulation intensity patterns described earlier, the number of training data set could be one, two, or three. Second, our interest lied in effects of the amplitude and the frequency of the training data on the estimation quality. We therefore applied the larger-amplitude and/or the larger-frequency training data with the other data for validation and vice versa. Third, we employed different input parameters for the neural network. In this study, RMS, PTP and the combination of RMS and PTP were selected for stimulation-induced contraction, while RMS, IEMG and the combination of RMS

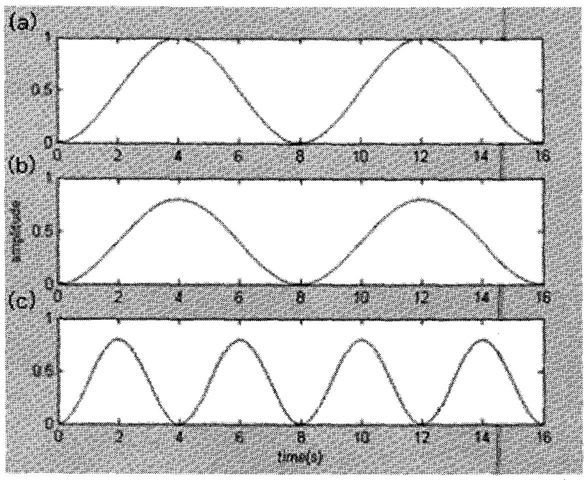

Fig. 2. Three stimulation/activation intensity patterns: the peak intensity and the period were (a) 1 and 8 seconds, (b) 0.8 and 8 seconds, and (c) 0.8 and 4 seconds, respectively.

and IEMG for voluntary contraction. RMS, PTP, and IEMG were defined and calculated as:

$$\mathrm{RMS} = \sqrt{\frac{1}{N}\sum_{n=1}^{N} v^2(n)}$$

$$\mathrm{PTP} = |v_{\max} - v_{\min}|$$

$$\mathrm{IEMG} = d\sum_{n=1}^{N} |v(n)|$$

($v(n)$: n-th EMG value, N : number of data, d:sampling interval)

Evaluation of the torque prediction from EMG was performed by comparing the RMS error (%) and the correlation coefficient between the target torque and the estimated torque. The RMS error was defined and computed as:

$$\text{RMS error (\%)} = \sqrt{\frac{1}{N}\sum_{n=1}^{N}\left(\frac{t(n)-y(n)}{t(n)}\times 100\right)^2}$$

Here t is the target torque, y is the estimated torque, and N is the number of data. The correlation coefficient was also computed since it showed similarity of the two graphs, whereas the RMS error represented only the difference between the two data sets. Their values ranged from -1 to 1 and two shapes were regarded similar if the correlation coefficient value was higher than 0.95.

III. RESULTS AND DISCUSSION

The muscle torque estimation was accurate as shown in Fig. 3, and the involved computation time was negligibly short. We therefore believe that the proposed method can be adopted for a real-time feedback control in FES. In some cases, however, the RMS values exceeded the normal range, which was presumably due to a change in the skin impedance, so that unallowable errors were obtained between the estimated torque and the target value. Effort was made to keep the skin impedance within a given range by caring the skin before every experiment.

Liu et al. [5] used the neural network to predict the muscle torque with EMG (with and without considering the ankle angle and the angular velocity) at four different speeds. They trained the neural network with EMG/torque data at three of the four speeds, so that the torque prediction was performed using the data obtained at the fourth speed. In their experiment, the torque predictions with EMG plus kinematics showed lower errors and higher correlation coefficients than with EMG without kinematics. This result implied that the additional information to EMG could play an important role in the torque predictions. Unallowable errors caused by skin impedance changes in this study can be reduced if the additional information such as the stimulation intensity is used as another input to the neural network.

In the RBF algorithm, the choice of the centers and the variances of the nonlinear function is very important for the estimation quality [8]. Especially, if the variance is too small, their selectivity is good but the resulting data is too noisy. On the other hand, the estimated quality can be deteriorated if the variance is too large. Therefore, we should consider modifying the RBF algorithm to find the proper centers and variances, which is one of the continuing subjects in our laboratory. Although the RBF algorithm was employed in this study as the learning was very fast and accurate, other algorithms can be also used for muscle torque estimation. One example can be the error back-propagation (EBP) algorithm which has been also widely used in many researches [5,9,10]. The EBP algorithm has an advantage over the RBF algorithm in that the estimation error is fed back to the training unit of the neural network, implying that the training is performed based on the error at each time instant. Another important aspect related to the neural network is to find the optimal number of the hidden

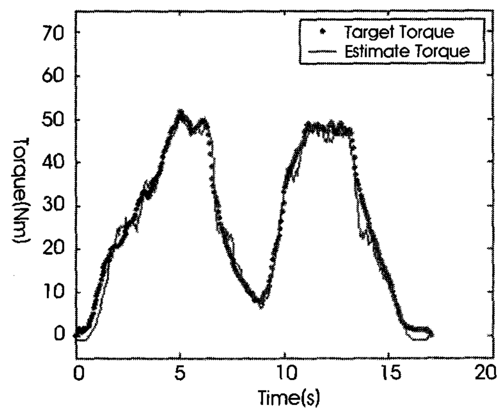

Fig. 3. Torque estimation based on the RMS values of VEMG: the RMS error and the correlation coefficient were 12.1% and 0.9890, respectively.

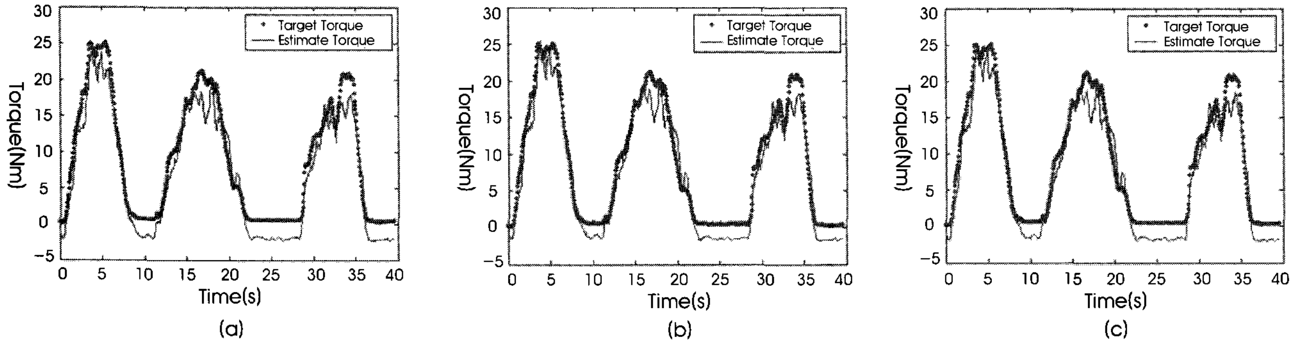

Fig. 4. Torque estimation with (a) one training set (RMS error: 17.2%, correlation coefficient: 0.9823), (b) two training sets (RMS error: 15.9%, correlation coefficient: 0.9825), and (c) three training sets (RMS error: 16.1%, correlation coefficient: 0.9821).

layers [8]. This should be another problem solved before the neural network can be easily used for the muscle torque prediction not only in the laboratory but in the users' daily life. It should be emphasized, however, that one needs to modify the selected neural network algorithm according to the intrinsic characteristics of the EMG/torque data.

Increasing the number of the training data did not help enhance the accuracy of the estimation. We found no differences when we changed the number of the training data sets as shown in Fig 4.

The experimental results suggested that the neural network could lead to a better estimation when the training data covered the entire range of the VEMG and/or EEMG values than when they did not. Fig. 5 shows one example where (a) and (c) were obtained with the training data covering the whole amplitude range as in Fig. 1(a), and their estimation quality was better than (b) and (d) based on the training data set covering 80% of the whole amplitude range as in Fig. 1(b).

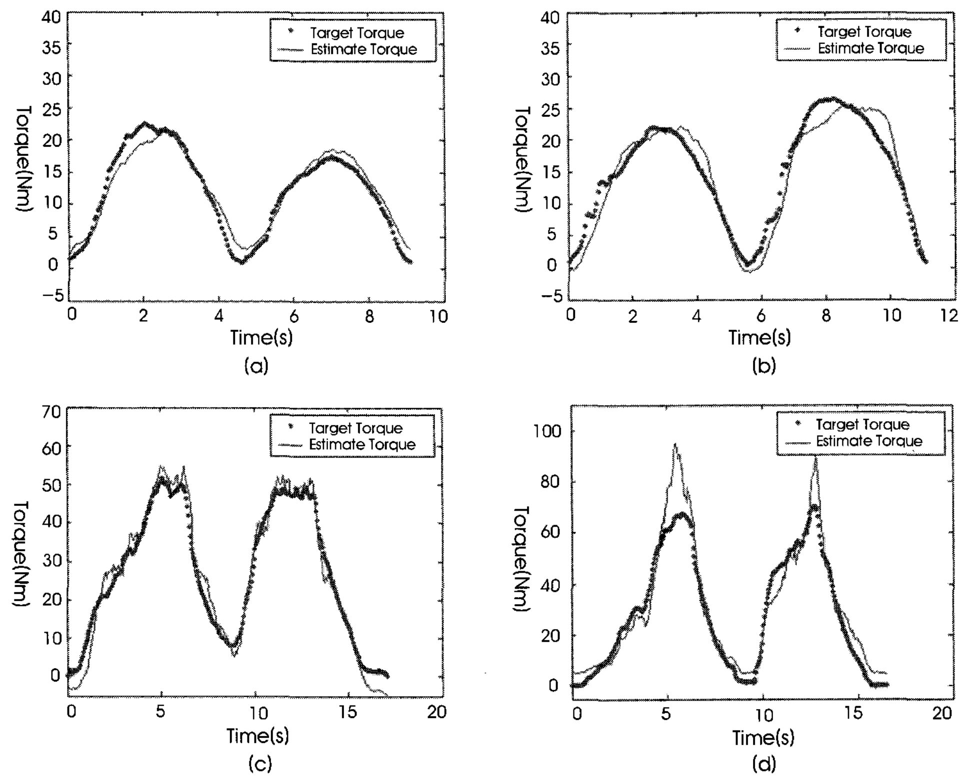

Fig. 5. Estimation of the stimulation-induced torque ((a) and (b)) and volitional torque ((c) and (d)): in (a) and (c) the EMG value range was larger in the training data than in the validation data, (b) and (d) being the opposite case. The RMS errors and the correlation coefficients were (a) 14.2%, 0.9791, (b) 17.8%, 0.9639, (c) 14.7%, 0.9872, and (d) 18.0%, 0.9620, respectively.

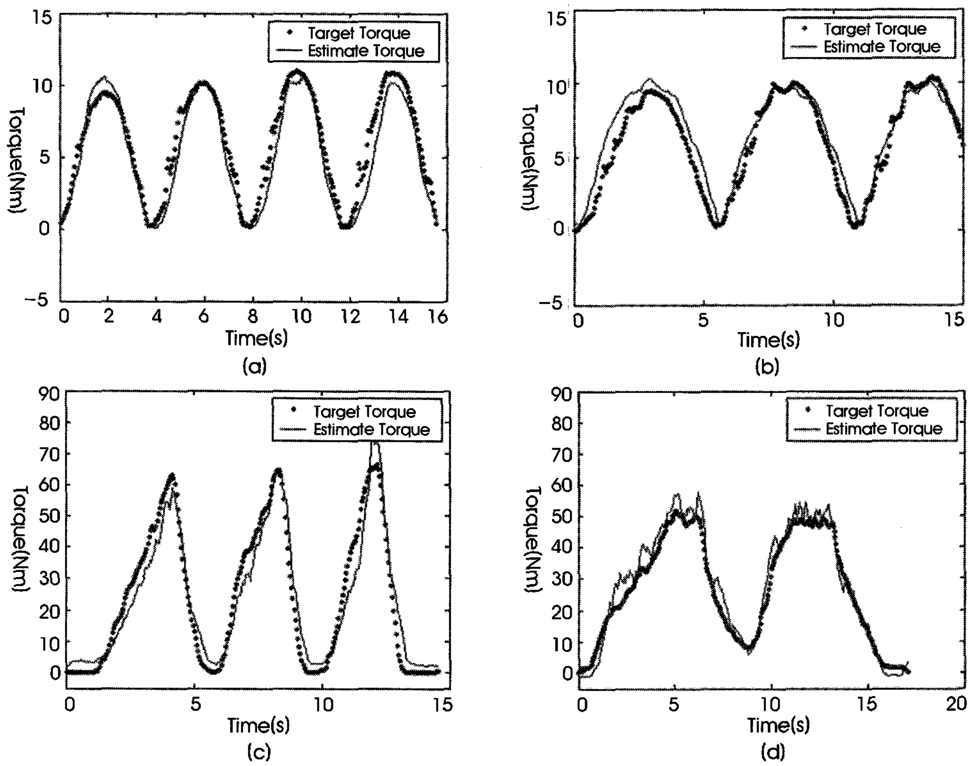

Fig. 6. Torque estimation at different frequencies: (a) and (b) were obtained from stimulation-induced contractions, and (c) and (d) were from voluntary contractions. The RMS errors and the correlation coefficients were (a) 22.6%, 0.9721, (b) 26.4%, 0.9719, (c) 18.5%, 0.9715, and (d) 16.8%, 0.9856, respectively.

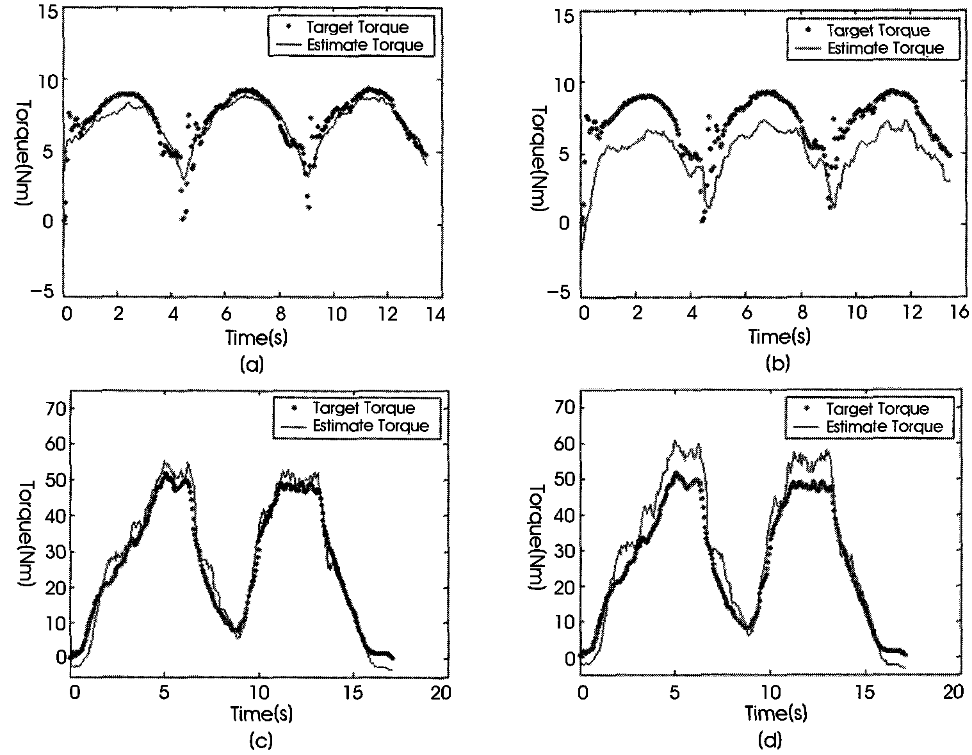

Fig. 7. Torque estimation with different input parameters: RMS was input to the neural network in (a) and (c), RMS+PTP in (b), and RMS+IEMG in (d). Note that (a) and (b) were from simulation-induced contractions, and (c) and (d) from voluntary contractions. The RMS errors and the correlation coefficients were (a) 11.1%, 0.8976, (b) 33.3%, 0.8046, (c) 15.2%, 0.9881, and (d) 22.1%, 0.9884, respectively.

Using different frequencies of the training data made no difference to the estimation quality. In Fig. 6, (a) and (c) show the estimation results when we used low-frequency training data (based on Fig. 2(b)) and high-frequency validation data (based in Fig. 2(c)), and (b) and (d) in the opposite case. All the correlation coefficients in Fig. 6 were higher than 0.96 and all the RMS errors were approximately 20%. It can be noted that the RMS error tended to increase near the peaks of the torque.

As far as the number of the inputs to the neural network is concerned, one parameter was preferred over a combination of two parameters. In Fig. 7, the torque estimation based on the RMS values was better than the torque estimation based on a combination of the RMS and PTP values in the stimulation- induced contraction. Also, one input (RMS) to the network resulted in a better or as good estimation than the RMS+IEMG input in the voluntary contraction. Though it is generally known that the neural network performance is affected by the number of the neurons, we found little difference in the esti- mation quality when the number of the neurons was varied. Also, this result was desirable in that the data processing time should be as short as possible for a real-time control of the muscle torque.

Ⅳ. CONCLUSION

The results suggested that we could adopt the neural network method and the experimental protocol described in this paper to estimate the muscle torque in real time based on the EMG parameters such as the RMS, PTP and IEMG values. However, the current results need more experiments in different conditions, e.g. during walking, for justification, which is one of our continuing studies.

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