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An sEMG-driven Musculoskeletal Model of Shoulder and Elbow Based on Neural Networks

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***Abstract*— In this paper, an sEMG-driven musculoskeletal model of human shoulder and elbow joints is built based on time delay neural network (TDNN). Six principal muscles of the upper arm and forearm are included, and the experiment was conducted under isometric contractions with the aid of a planar haptic interface. Both force amplitude and direction were regulated continuously, and the experiment results proved the effectiveness and performance of this modeling method. The model was proved to have less overfitting risk than the most-used basic multilayer forward netwokrs, and the isometric model was proved to be still effective in estimation of slow movement cases.**

I. Introduction

HUMAN musculoskeletal system is highly nonlinear and subject dependent, and many researches have been conducted to investigate the relationship between neural commands and voluntary efforts. The increasing popularity of human machine interface (HMI) calls for more effective and simple human musculoskeletal model [1], [2].

Electromyography (EMG) reflects the electrical activities produced by skeletal muscles, and can be easily acquired from the skin surface (surface EMG, sEMG) or within the muscle using different electrodes and sensors. EMG is promising to be used as an effective HMI input which reflects the subject's motion intention for the high correlation and electromechanical delay characteristics between EMG and muscle force [3].

As shown in Fig. 1, EMG signals can be simply seen as the motor commands from CNS (central nervous system), and map to the movements through muscle activation dynamics, muscle contraction dynamics, joint geometry, and joint dynamics [4], where joint geometry represents the corresponding moment arm of each muscle. Meanwhile, muscle contraction dynamics is influenced by joint angles and joint angular velocities through the force-length (F-L) and force-velocity (F-V) relationships, and muscle moment arms also depend on joint angles [5].

Two kinds of models could be found in literature: Hill-type models [4], [6], [7] and black-box models like ANN etc [8], [9], [10]. Compared with the Hill-type models, where all the dynamic processes of each muscle are built one by one [5], ANN treats the musculoskeletal system as a whole system with EMG as the input and voluntary efforts or limb motions

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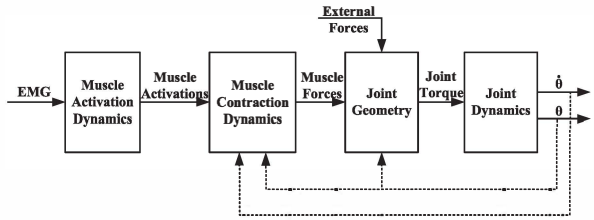

Fig. 1. Schematic diagram of the neuromusculoskeleton model (θ is joint angle, and $\dot{\theta}$ is joint angular velocity).

as the output. Therefore, ANN model is more appropriative for applications like HMIs, which doesn't need to investigate the physiological characteristics of each muscle.

As the human voluntary efforts under dynamic conditions are difficult to obtain in vivo, most previous studies focused on isometric [11] or isokinetic contractions [12]. Besides, as the structure of the human shoulder is very complex, complete upper limb model was difficult to build and used. Therefore, most previous studies focused on the elbow joint [13] or 2-dimensional movements of the shoulder and forearm [14].

In this paper, we built an sEMG-driven musculoskeletal model of the should and elbow joints based on ANN under isometric contractions in horizontal plane. Unlike in the previous studies where subjects contracted their muscles with different loads in hand [14], in this study the subjects' voluntary efforts were regulated continuously with the aid of an haptic interface which was designed for post-stoke rehabilitation.

Besides, in order to model the dynamics in musculoskeletal system, time-delay neural network (TDNN) was used, in stead of the most-used multilayer feedforward neural networks (MFNN) [8], [15]. MFNN model could fit the samples well, but it's a static model, and could not represent the dynamic processes in the musculoskeletal model, and MFNN model was proved to have larger risk of overfitting than TDNN model in the experiment.

Though the model was built under isometric conditions, in this sudy the model was proved to be also effective to estimate the human voluntary efforts in slow movement conditions. Therefore, this model could be used for static muscle force evaluation, and also can be used for neuromuscular interface in slow rehabilitation training [16] or exoskeleton robot manipulation [6].

The rest of this paper is organized as follows: Section II demonstrates the experiment procedure, which includes experiment setup, signal acquisition and preprocessing. Sec-

tion III presents the ANN model development procedures in detail, and the results are presented in Section IV. Finally, Section V contains some discussions and concludes this paper.

II. Experiment

Three healthy volunteers participated in this study, and informed consent was obtained from all individual participants. All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional research committee.

A. Experiment Setup

As shown in Fig. 2, the experiment was conducted with the aid of a planar 2-DOF (degree of freedom) robot, which features high stiffness and low inertial and friction. The force exerted to the subject at the handle can be regulated by controlling the motor torques, and the maximal force output of the robot is higher than 30 N with in the 500 mm×418 mm workspace.

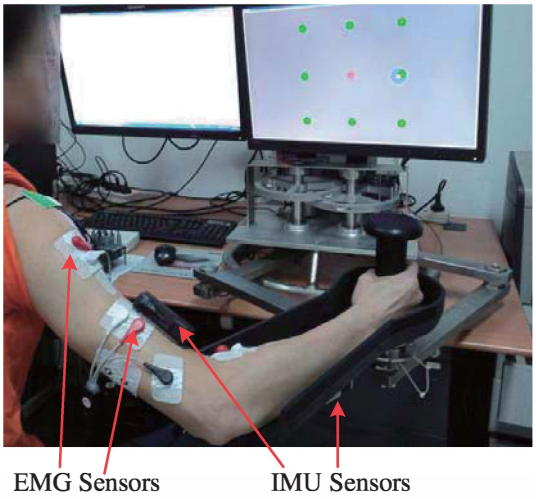

Fig. 2. Experiment setup, where sEMG sensors were used for EMG acquisition, and IMU sensors recorded the postures of the forearm and upper arm.

As the muscle contraction dynamics and muscle moment arms are effected by joint angles, sEMG signals were acquired at nine different positions within the workspace, which represented different configurations of the upper limb.

In order to obtain samples which can represent the overall characteristics of the related muscles, the robot regulated the the amplitude and direction of the force output continuously in the manner of Archimedes spiral (shown in Fig. 3) as:

$$r = a + b\theta \tag{1}$$

where r and θ are the amplitude and direction of the force, respectively, and real numbers a and b control the shape of the spiral. In this study, $a = 0$, and $b = 1/2\pi$, hence the distance between successive turnings was $2\pi b = 1$ N.

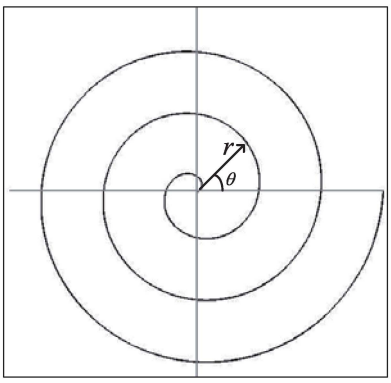

Fig. 3. Illustration of Archimedes spiral, where r and θ are the amplitude and direction of the force respectively.

The direction of the force varied with a constant speed $\frac{\pi}{2}$ rad/s:

$$\theta = \frac{\pi}{2}t \tag{2}$$

As a result, the amplitude of the force also varied linearly with time:

$$\begin{aligned} r &= a + b\theta \\ &= \tfrac{1}{2\pi} \times \tfrac{\pi}{2}t \\ &= \tfrac{1}{4}t \end{aligned} \tag{3}$$

In the experiment, the maximum force amplitude was 15 N. According to (3), the robot force regulation lasted for 60 s at each position.

The force outputs were displayed on the screen, and the subjects were required to contract their muscles to resist the robot and stay still, and the voluntary force of the subject at the handle was:

$$F_h = -F_r = -\begin{bmatrix} F_x \\ F_y \end{bmatrix} = -\begin{bmatrix} r\cos\theta \\ r\sin\theta \end{bmatrix} \tag{4}$$

where F_r is the robot's force output, and F_h is the human reactive force.

B. Slow Movement Experiment

Besides the isometric conditions at a static position, we also acquired some experiment samples under slow movement conditions. The robot were controlled to move along a circle (diameter: 160 mm) with a small velocity of $10°/s$.

The robot's position was controlled in the Cartesian space with a PD (proportional plus derivative) controller:

$$\mathbf{F}_r = \mathbf{K}_p(\mathbf{x}_r(t) - \mathbf{x}(t)) + \mathbf{K}_d(\dot{\mathbf{x}}_r(t) - \dot{\mathbf{x}}(t)) \tag{5}$$

where $\mathbf{K}_p$ and $\mathbf{K}_d$ are the proportional and derivative factor matrix respectively, and $\mathbf{x}_r$ and $\dot{\mathbf{x}}_r$ are the reference trajectory and velocity vector, which are defined as:

$$\mathbf{K}_p = \begin{bmatrix} 2000 & 0 \\ 0 & 2000 \end{bmatrix} \tag{6}$$

$$\mathbf{K}_d = \begin{bmatrix} 20 & 0 \\ 0 & 20 \end{bmatrix} \tag{7}$$

and

$$\mathbf{x}(t) = 0.16 * \begin{bmatrix} \cos(\frac{10\pi}{180}t) \\ \sin(\frac{10\pi}{180}t) \end{bmatrix} \quad (8)$$

The static experiment data were used to train the neural network model, while the slow movement data were used to test if the isometric model could be used to estimate the force of slow movement case.

C. Data Acquisition

During the experiment, sEMG signals of six principal muscles (pectoralis major, deltoid, infraspinatus, biceps brachii, triceps brachii, brachioradialis) relevant to the should-elbow motions were acquired.

A self-designed 6-channel sEMG amplifier (gain: 1000, built-in filter: 20-500 Hz) was used for sEMG acquisition, and two MEMS inertial measurement units (IMU) were used to record the posture of the upper arm and forearm respectively. The filtered sEMG signals were saved in the computer using a 16-bit DAQ card (USB6211 by NI, USA) at a sample rate of 2 kHz, and the IMU outputs were sent to the computer via bluetooth at an update rate of 40 Hz.

A representative data acquisition result is shown in Fig. 4.

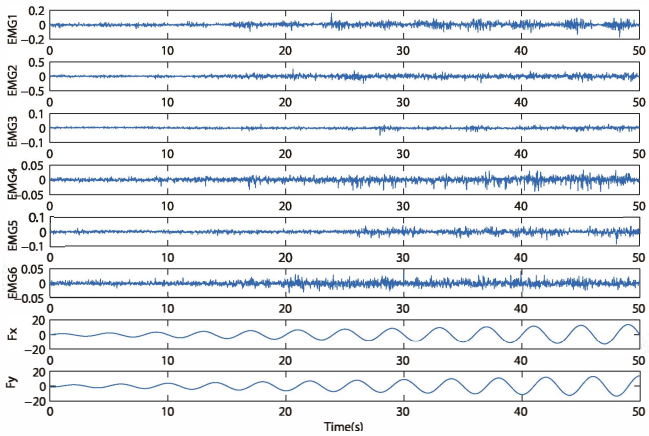

Fig. 4. Representative recordings of sEMG of six muscles and forces exerted by the robot at the handle.

D. Data Preprocessing

The complete flowchart of sEMG preprocessing is shown in Fig. 5.

In order to obtain smooth EMG amplitude signals, the raw sEMG outputs were full-wave rectified and passed a low-pass fourth-order Butterworth filter with a cutoff frequency of 3 Hz. The joint angles of the shoulder and elbow were calculated based on the IMU outputs. Then both the EMG amplitude signals and joint angles were averaged over 50 ms moving windows, and the EMG amplitude signals were normalized to the maximal isometric activations.

III. ANN Model Development

The development processes of the ANN model were conducted based on MATLAB Neural Network Toolbox (Version 8.0, The MathWorks, Inc., USA).

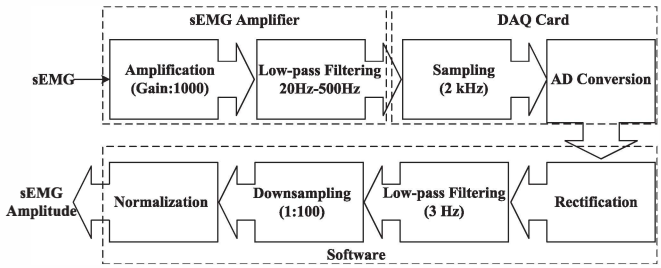

Fig. 5. Preprocessing flowchart of sEMG.

A. ANN Model Structure

As we have mentioned before, musculoskeletal system has very complicated nonlinear dynamics. In this study, we built a time-delay neural network (shown in Fig. 6) to represent this dynamic relationship.

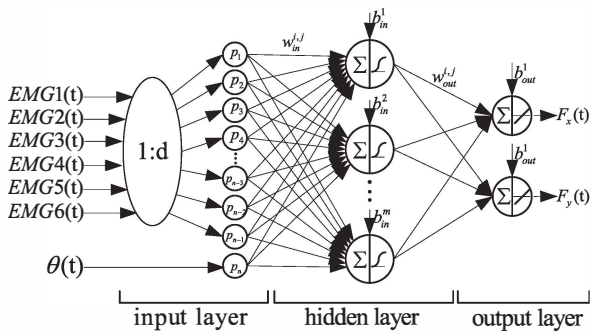

Fig. 6. Structure of the TDNN model used in this study with time delay d. n is the number of the input features, m is the number of the hidden layer, w is the weight, and b is the bias.

As shown in Fig. 6, the EMG amplitude samples of recent several steps and joint angles were used as the input, and the voluntary efforts at the hand were the output. As a result, the TDNN model worked as an NMA (nonlinear moving average) poster filter of the EMG signals.

In this study, the activation functions of input and output neurons were linear, and the activation function of the hidden layer were sigmoid, which are defined as below:

$$F = f_{out}(W_{out} f_{in}(W_{in} P + b_{in}) + b_{out}) \quad (9)$$

$$f_{in}(x) = \frac{1}{1+e^{-x}} \quad (10)$$

where W is the weight and f is the activation function.

The time delay d in TDNN was set to 3 in this study, which means all the sEMG samples of last 150 ms were used in ANN building. As a result, the TDNN model has 26 inputs (EMG: 4 steps×6 channels, joint angles: 2) and 2 outputs (F_x, F_y).

B. ANN Training

The experimental samples were divided into 3 subsets randomly: the training subset (70%), the validation subset (15%), and the test subset (15%). The network was adjusted

according to the training set errors, and the validation error measured the network generalization during the training process, and halted the training process when the network generalization stopped to improve. The test subset had no effect on the training but provided an independent measure of network performance during and after training [17].

The network performance function was mean square error (MSE, the average squared error between the network outputs and the target outputs):

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(e_i)^2 = \frac{1}{N}\sum_{i=1}^{N}(t_i - a_i)^2 \qquad (11)$$

where a is the network output and t is the target output. The training method was Levenberg-Marquardt backpropagation:

$$x_{k+1} = x_k - [J^T J + \mu I]^{-1} J^T e \qquad (12)$$

where J is the Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases, e is a vector of network errors, I is the identity matrix, and μ is a non-negative damping factor which is adjusted at each iteration [17].

Besides the experiment samples, we generated some additional zero-EMG training samples, where the EMG features of each muscle were zero, and the shoulder and elbow joint angles averagely spanned the joint angle space (shoulder joint: 50 values among 0-80°, elbow: 50 values among 0-130°). As the EMG features were zero, the force samples were zero, too. These samples were used with the experiment samples for ANN training, and worked as the zero boundary condition.

IV. Results

In this section, training result and estimation performance of the TDNN model are presented. Besides, the performance of MFNN model and TDNN model are compared, and slow movement samples are used to test TDNN model's generalization ability.

A. Training Result

Based on the TDNN structure, the complexity of the network increased with the increase of the number of hidden neurons. The MSEs of the training samples and test samples changed by adjusting the number of hidden neurons. In this experiment, the network was trained 5 times with different random initial conditions, and the training MSEs had no obvious decreases after the number of hidden neurons was above 25. Since there was a risk of overfitting when the network was set more complicated, the scale of the hidden layer was set 25.

Besides the number of hidden neurons, the number of training iterations was also a factor that affected the result. Fig. 7 shows the relationship between the number of iteration and the MSEs of the training, validation, and test samples. As shown in Fig. 7, the validation error decreased during the initial phase of training, as did the training set error. However, when the network began to overfit the sample, the MSE of the validation set began to rise. In order to avoid overfitting, a method named early stopping supported by MATLAB was used. When the MSE of validation set increased for a specified number of iterations (default: 6), the training process was stopped, and the weights and biases at the minimum of the validation error were returned [17].

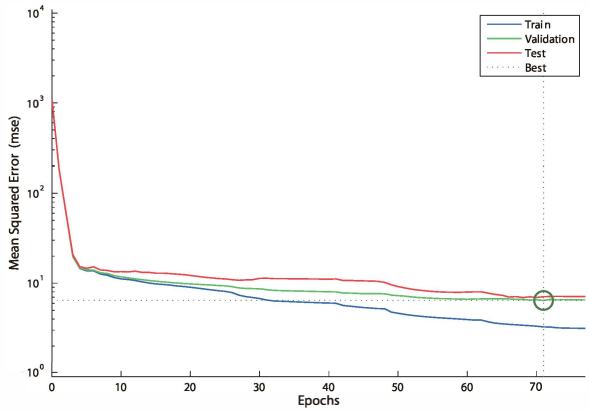

Fig. 7. Typical MSEs changes of the TDNN model with training iterations.

B. Estimation Performance

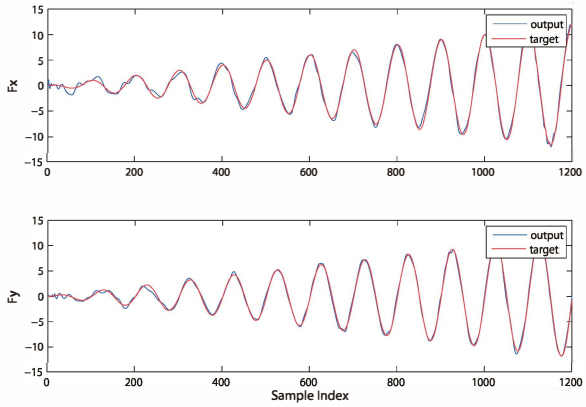

Fig. 8. Comparison of the force estimation and the actual force samples.

Fig. 8 presents a typical estimation result of the TDNN model we have built, where the output of the model could fit the targets well most of the time, except at small-value samples. We can see from Fig. 4 that sEMG of these samples were weak, and the existing noise might cause larger estimation errors than at other samples.

Table I shows the RMSE (root mean square error), and the relative estimation error between the estimation value and the target value of the model of each subject. The estimation results of both the training set and test set are given, and the average estimation error of the training set across three subjects was 0.72 ± 0.18 N.

C. TDNN vs. MFNN

Basic multilayer forward neural networks are the most-used networks in isometric contractions. However, MFNN is

TABLE I

ESTIMATION PERFORMANCE OF THE TDNN MODEL ACROSS ALL SUBJECTS.

Subject	Force range N	Training set RMSE N	Training set Relative error	Test set RMSE N	Test set Relative error
A	0-15	0.70	4.7%	1.30	8.7%
B	0-15	0.91	6.1%	1.02	6.8%
C	0-15	0.55	3.7%	0.90	6.0%
Mean	0-15	0.72	4.8%	0.99	7.2%
Standard deviation	0	0.18	1.2%	0.31	1.4%

RMSE=$\sqrt{\text{MSE}}$; Relative error = RMSE/Force range.

a kind of static network, while the musculoskeletal system has complicated dynamics, even in isometric conditions, and electromechanical delay is a well-known result of musculoskeletal dynamics. In order to compare these two types of neural networks, we built a basic MFNN model (shown in Fig. 9), and then trained with the same experimental samples and zero-EMG samples.

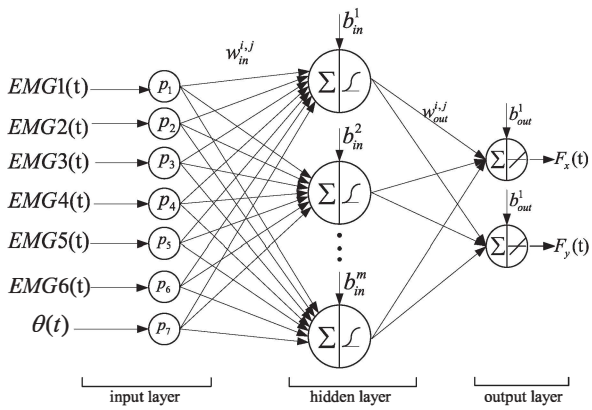

Fig. 9. Structure of the MFNN model used in this study. m is the number of the hidden layer, w is the weight, and b is the bias.

After training, the MFNN model could achieve a estimation precision of 0.66 N, which was comparable with that of TDNN model. In order to test their generalization performance, we calculated the error autocorrelation function of MFNN and TDNN model respectively. For a perfect estimation model, there should only be one nonzero value at zero lag (this is the MSE), which means the estimation errors were completely uncorrelated with each other (white noise) [17].

As shown in Fig. 10(a), there were significant correlations within 0-3 lag (0-150 ms), which means the MFNN model we built could not represent this dynamic process well, and had large risk of overfitting.

On the contrary, as shown in Fig. 10(b), the error autocorrelation function of the TDNN model was small except at 0 and 1 lag. Compared with the case of MFNN model, the TDNN model had less overfitting risk. On the other hand, the error autocorrelation had no more improvement if the time delay was set above 3.

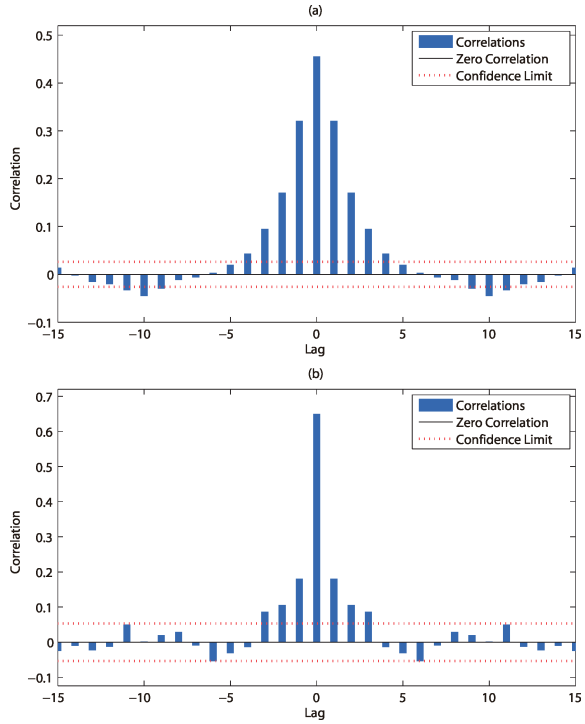

Fig. 10. Error autocorrelation function of (a) MFNN model and (b) TDNN model (95% confidence limits).

D. Test Result with Slow Movement Samples

As we had proved the effectiveness of TDNN model to estimate voluntary efforts in isometric contraction, we turned to test if this model can estimate voluntary efforts accurately in slow movement.

The EMG and joint angle samples acquired in slow circle movements were fed into the TDNN model we had built, and the network outputs were compared with the force samples to test the generalization performance of the model.

As shown in Fig. 11, though the estimation error was higher than training error of isometric contractions (MSE:19.4), the model could detect the variation trend of the force in both directions, and part of the error might attribute to the neglection of the inertial force of the robot and human limb.

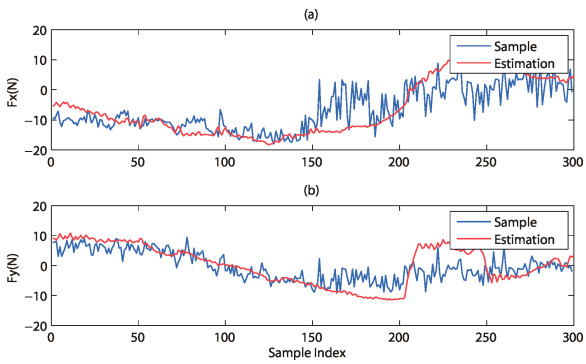

Fig. 11. Estimation result of the TDNN model, where (a) and (b) are the result of F_x and F_y respectively.

V. Discussions and Conclusions

In this study, an sEMG-driven musculoskeletal model of the shoulder and elbow joints under isometric contractions was developed based on TDNN. The sEMG and force samples were acquired with the aid of a 2-DOF robot with force feedback abilities, where both the magnitudes and directions of the force were regulated continuously. The TDNN model was shown to be able to fit the training samples well, and the average estimation error was 0.72 ± 0.18 N.

The TDNN model was shown to have less risk of overfitting than the commonly used MFNN model. Though in the isometric experiment, the subjects had no movements, the related muscles contracted to resist the force exerted by the robot. As shown in Fig.1, there are two dynamics between EMG and muscle contraction force: muscle activation dynamics and muscle contraction dynamics, and the electromechanial delay is a well known result of these dynamics.

Though MFNN model could fit the experiment samples well, it's an static networks, where the output only depends on the current EMG sample, and cannot represent the inherent complicated dynamics. The autocorrelation function in this study has proved that MFNN model had larger risk of overfitting. On the contrary, the TDNN model included several steps of EMG samples, and worked as a nonlinear moving average (NMA) filter, which was a nonlinear counterpart of the linear moving average filter.

Besides, the TDNN model we built in isometric conditions could be used to estimate voluntary efforts in slow movements. As we have mentioned before, the musculoskeletal model under dynamic conditions are difficult to built, as the voluntary efforts cannot be measured in vivo, and estimation methods are not accurate enough for some applications like robot control [18]. On the other hand, there are many applications where the muscles are in isometric contractions (like in muscle force evaluation) or in slow movements (like in rehabilitation training or exoskeletal robots).

Though the TDNN model in this study was built under isometric conditions, the experiment results have proved its power to be used in slow movement cases. Though the estimation error was higher than that of training samples, the model is accurate enough for motion intention detection and perform a closed-loop control, where the subject can regulate its EMG outputs to adapt to the numerical model [19].

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