sEMG-Based Torque Estimation for Robot-Assisted Lower Limb Rehabilitation

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***Abstract*—sEMG (surface electromyography) signals have been used as human-machine interface to control robots or prostheses in recent years. sEMG-based torque estimation is a widely research methodology to obtain human motion intention. Most researches focus on improving the accuracy of sEMG-torque models, which often makes them complicated and confined in the laboratory research. However, an accurate estimation of muscle torque could be unnecessary to perform the robot-assisted rehabilitation training. This paper proposes a practical method to estimate the net muscle torques of lower limbs using sEMG, which can be used to implement a real-time coordinated active training with *i*Leg−a horizontal exoskeleton for lower limb rehabilitation developed at our laboratory. Two three-layer back propagation (BP) neural networks are built to estimate the net muscle torques at hip and knee joints respectively. Experimental results show that the well-trained neural networks estimate the user's motion intention in real-time, and can assist the user to perform an active training with *i*Leg.**

I. Introduction

Robot-assisted devices aim to help users move their limbs and restore limb functionalities through rehabilitative processes [1]. The sEMG signals, resulting from motor neuron impulses that activate the muscle fibers, can be correlated with the force produced by muscles [2]. The sEMG signals are 30-100ms prior to body motion and therefore reflect motion intention in advance.

Recently, sEMG has been widely used as human-machine interface. A widely research methodology to obtain human motion intention is based on sEMG-torque model. [3], [4]. Many different approaches have been proposed to estimate joint torques, such as Hill-based models [5], [6], neural networks (black box models) [7] and regression methods [8].

Unfortunately, sEMG signals have the feature of changeability, which makes it very difficult to obtain the same sEMG signals because of time variation, muscle fatigue, sweating, electrode shifting or other changes. To produce an accurate and reliable model, time consuming and algorithm complexity are increased [9]. For these reasons, most estimation methods are confined in the laboratory research.

Additionally, sEMG is rarely used in torque estimation of lower limbs because the signals are weaker than the signals of upper limbs. Posture-varying and torque-varying are the most complicated conditions in sEMG-based torque estimation problems, which represent unconstrained motion. But the existing studies are often constrained to single-joint motion [10]. So these methods are not applicable to the multi-joint active training.

We recently achieved two single-joint active training strategies using sEMG and experiments were conducted with *i*Leg. We used the normalized sEMG difference between two muscles to control the extension and flexion of knee joint. However, the multi-joint coordinated active training is a complicated motion and the sEMG difference cannot reflect the complex relationship.

The aim of this study is to perform a real-time coordinated active training of lower limbs using sEMG-torque model. A rough estimate of muscle torques is enough to provide effective movement assistance to users, which ensures the stability of control system and also makes the model easy to use.

The remainder of the paper is organized as follows. Section II introduces dynamic parameter identification of robot system, experimental setup and data processing. Section III demonstrates the details of model development and shows the results. The last section comes up with the conclusion and discussion.

II. Methods

A. Dynamic Parameter Identification of Robot System

Fig. 1. Mechanical structure of *i*Leg for lower limb rehabilitation

In this study, the sEMG samples and joint information (actuating torques of hip and knee joints generated by robot, joint angles and angular velocities) were acquired with *i*Leg

[11], whose mechanical structure is shown in Fig. 1. It consists of two 3-DOF (degree of freedom) robotic legs. Joints 1, 2 and 3 correspond to the hip, knee and ankle joints of human limbs respectively. Only hip and knee joints are considered in this study, so the ankle joint is set to be a fixed angle. A torque sensor, an absolute encoder and a relative encoder are installed at each joint, so we can obtain the actuating torques generated by robot, joint angles and angular velocities of hip and knee joints through these components.

The dynamic parameter identification of robot system is aimed at obtaining the net muscle torques in human-robot hybrid system. [12], [13]. The dynamics of hybrid system is expressed as a linear equation with respect to the undetermined dynamic parameters ϕ, written as follows:

$$\boldsymbol{Y}(\boldsymbol{q}, \dot{\boldsymbol{q}}, \ddot{\boldsymbol{q}})\boldsymbol{\phi} = \boldsymbol{\tau_r} + \boldsymbol{\tau_h} \tag{1}$$

where $\boldsymbol{q}$ is the vector of joint angles; $\dot{\boldsymbol{q}}$ is the vector of joint angular velocities; $\ddot{\boldsymbol{q}}$ is the vector of joint angular accelerations; $\boldsymbol{\tau_r}$ is the vector of joint actuating torques generated by the robot; $\boldsymbol{\tau_h}$ is the vector of net muscle torques.

Before the identification, lower limbs are carried by the robot to perform the motion of exciting trajectory [12] while the subject is required not to generate any active effort, i.e. $\boldsymbol{\tau_h} = \mathbf{0}$. Then the least square estimation method is employed to identify the parameters ϕ, given by

$$\boldsymbol{\phi} = (\boldsymbol{Y}^T\boldsymbol{Y})^{-1}\boldsymbol{Y}^T\boldsymbol{\tau_r} \tag{2}$$

Therefore, the net muscle torques can be obtained by

$$\boldsymbol{\tau_h} = \boldsymbol{Y}(\boldsymbol{q}, \dot{\boldsymbol{q}}, \ddot{\boldsymbol{q}})\boldsymbol{\phi} - \boldsymbol{\tau_r} \tag{3}$$

The identification experiment was conducted on one healthy subject (male, 27 years old). The result shown in Fig. 2 indicates the parameters ϕ can be used to calculate the net muscle torques.

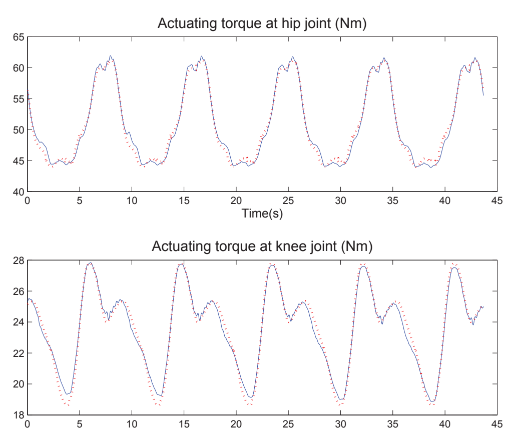

Fig. 2. Joint actuating torque estimation using identified parameters. The blue solid line shows the measurement torques and the red dash line represents the estimation torques. The root-mean-square error is 0.67 Nm for hip torque estimation and 0.37 Nm for knee torque estimation.

B. Experimental Setup

It is well-known that each muscle can act on more than one joint, and several agonist and antagonist muscle groups are needed to power each joint. In this study, sEMG samples are acquired from eight muscles after a careful selection of relevant muscles coherently with the intended motion shown in Fig. 3, which are gluteus maximus (GM), iliopsoas (IL), rectus femoris (RF), vastus lateralis (VL), vastus medialis (VM), biceps femoris (BF), semitendinosus (SE) and gastrocnemius (GA). *i*Leg has integrated an eight-channel sEMG acquisition device self-made at our laboratory, so we can obtain sEMG samples and joint information at the same time.

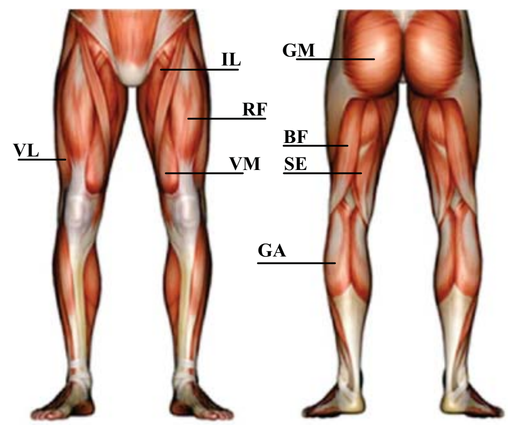

Fig. 3. Muscles used to acquire sEMG signals.

Most previous researches did a preparation work before placing electrodes, such as shaving and cleaning the skin surface, to reduce the input resistance and the external disturbance [14]. Although this preparation work is beneficial to data acquisition, it confines the practicability of the estimation method. So in this study, the electrodes were adhered to muscle surface directly without any disposal. Eight pairs of Ag/Agcl electrodes were employed to measure the analog sEMG signals. At each recording site, the electrodes were arranged in a differential configuration over the muscle belly and separated from each other by 2cm [15].

Before acquisition of data, the subject was asked to perform the motion of exciting trajectory [12] to identify the subject's dynamic parameters ϕ. Then, the subject would take an active motion to acquire sEMG samples and joint information at the same time. Cycling is employed in this case as it is the most commonly used exercises for rehabilitation.

A circular path is displayed on a computer screen, and the subject was required to drive the robotic leg to run an approximately circular track with his effort. The subject was asked to accomplish 6 cycles at each trial with no time limit, and repeated 6 trials with no rest to contain muscle fatigue information. The maximum voluntary contraction (MVC) and resting state of eight muscles were recorded at last.

C. Data Processing

The sEMG acquisition device has designed with a 50 Hz notch filter and a 20-200 Hz band-pass filter in hardware, so as to remove most of the signal artifacts while retaining the information within the signals. The raw sEMG samples were full-wave rectified and filtered first. The fourth-order Butterworth filter with cutoff at 2 Hz was selected for the envelope processing because this provides a appropriate compromise between the smoothness of the signals and time delays [16].

Since the sEMG samples were sampled at 2560 Hz, while the joint information (actuating torques generated by robot, joint angles and angular velocities) were sampled at 50 Hz, the sEMG samples were sub-sampled to 50 Hz through a sliding window. Then the signals divided MVC of corresponding muscles for normalization. After data processing, several typical sEMG signals and net muscle torques at hip and knee joints (calculated through equation (3)) are shown in Fig. 4.

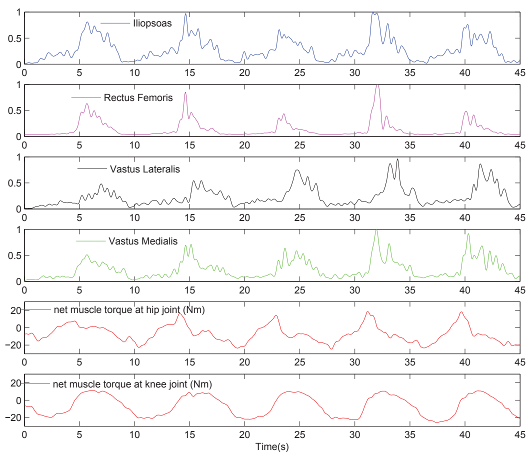

Fig. 4. Some typical sEMG signals and net muscle torques at hip and knee joints after data processing acquired from one trial.

III. MODEL DEVELOPMENT AND RESULTS

A. BP neural network for net muscle torque estimation

The process of model development was conducted based on Neural Network Toolbox of MATLAB.

Two BP neural networks are used to estimate the net muscle torques at hip and knee joints respectively. sEMG signals from five muscles (GM, IL, RF, BF and SE) were employed to estimate net muscle torque at hip joint as they generate the extension or flexion of hip. Similarly, sEMG signals from six muscles (RF, VL, VM, BF, SE and GA) were employed to estimate net muscle torque at knee joint. Both agonist and antagonist muscles were included in two models to account for co-contraction (particularly at higher contraction levels). Meanwhile, joint angle and angular velocity can influence muscle contraction dynamics [17], so they also served as the inputs of two neural networks.

Previous study showed that the sEMG-torque model is a dynamic mapping relationship, adding sEMG samples of recent several times as inputs can improve the estimated accuracy. However, the sEMG information was sufficient in this study, and adding previous samples increased the complexity of neural network largely while the improvement of accuracy was limited. To build a practical and reliable model, we only used the current sEMG samples. The number of neurons in the hidden layer was selected as 2n+1 (n is the length of input vector) on the basis of empirical law.

Therefore, the neural network for estimation of net muscle torque at hip joint has 7 input nodes and 15 neurons in the hidden layer, whose structure is shown in Fig. 5. The neural network for estimation of net muscle torque at knee joint has 8 input nodes and 17 neurons in the hidden layer, which is similar to that shown in Fig. 5. The performance of BP neural network is very sensitive to the selection of learning rate. As a consequence, the variable learning rate BP with momentum algorithm was used in our research, nonlinear tansig function and linear purelin function were selected as the transmission functions in the hidden layer and output layer respectively.

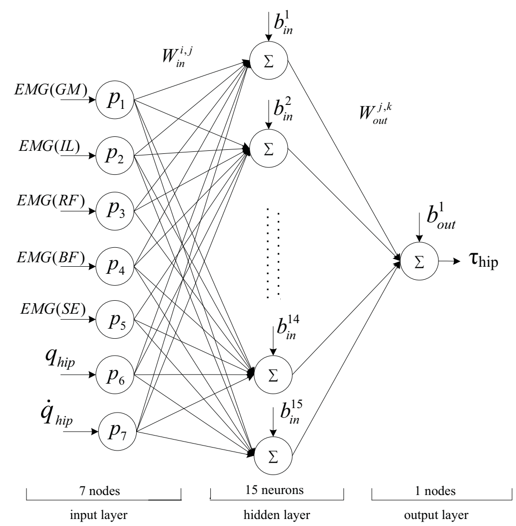

Fig. 5. Structure of the BP neural network used in the estimation of net muscle torque at hip joint.

The experimental data should be divided into two subsets, the training subset and the validation subset. As the subject did the circular-like motion with his own willingness, the data variation between different trials (even between different cycles of the same trial) could be observed. In this situation, cross validation method was used to verify the generalization ability of the networks, which is that every single trial's data were set as validation subset alternately while the other five trails' data were set as the training subset.

Since sEMG signals are 30-100ms prior to body motion, the sEMG signals were delayed for 60ms before inputting to the neural networks.

B. Experiment results

Fig. 6 shows one trial of net muscle torque estimation result. The subject's torques are time-varying because he exerts his effort randomly. It can be seen that the well-trained neural networks can estimate the subject's active motion intention in real time. Though the root-mean-square errors are relatively large, the estimation performance is enough to provide effective assistance to users and perform the active training.

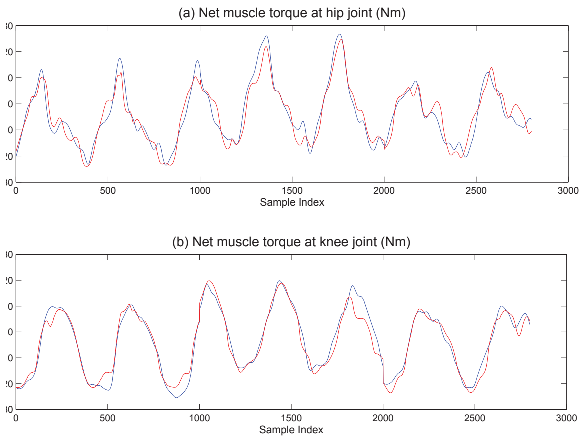

Fig. 6. Net muscle torque estimation using BP neural networks. The blue solid line shows the identification torques calculated through equation (3) and the red solid line represents the BP estimation torques. The root-mean-square error is 3.71 Nm for hip joint and 2.92 Nm for knee joint.

We introduced the neural networks to the control system of *i*Leg and the output torques of networks were used to drive the robotic leg. Fig. 7 illustrates the real-time motion trajectory of ankle joint when the subject performs active training.

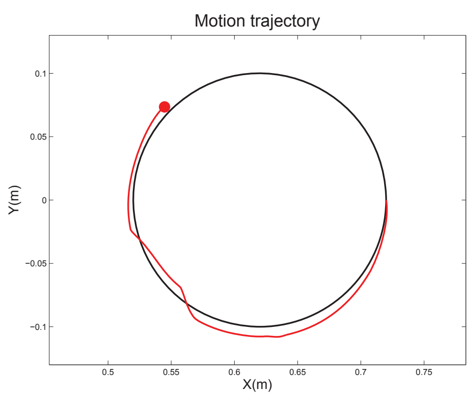

Fig. 7. Visual feedback from *i*Leg. This user interface can provide real-time motion trajectory of ankle joint in cartesian space. The black solid line represents the desired motion path and the red solid line shows the actual motion trajectory. The big red point displays the current motion point.

IV. Conclusion and Discussion

This paper presents a practical method to estimate the net muscle torques of lower limbs using sEMG, which can be used to perform a real-time coordinated active training with our rehabilitation robot. It can be seen from Figs. 6 and 7 that the outputs of network models are able to reflect the subject's active motion intention and assist the subject to perform active training. So a rough estimate of net muscle torques is enough when providing effective movement assistance. The proposed approach has been tested with a circular-like trajectory. We believe that it can be generalized to other forms of movement in accordance with the model development described above.

Compared with torque sensor data, the sEMG signals reflect degree of activity in specific muscle and can be detected ahead of movement without electromechanical delay. These characteristics make it promising as the human-machine interface to make devices react pre-actively rather than re-actively to user intent.

This preliminary experiment demonstrates the feasibility of a rough estimation model used in multi-joint coordinated active training based on sEMG. Future research will concentrate on the improvement of motion compliance and enhancing the robustness of sEMG-torque estimation model.

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