A Practical EMG-Driven Musculoskeletal Model for Dynamic Torque Estimation of Knee Joint

Long Peng, Zeng-Guang Hou, Liang Peng and Wei-Qun Wang

Abstract— **Multichannel electromyography (EMG) signals have been used as human-machine interface (HMI) to control robot systems and prostheses in recent years. EMG-based torque estimation is a widely research method to obtain motion intent. However, the existing torque models usually have the disadvantage of complexity for modeling or time consuming for model tuning. This paper presents a practical EMG-driven musculoskeletal model for the knee joint, which can estimate muscle force and active torque from EMG signals. The EMG-driven model consists of a muscle tendon model and a proposed musculoskeletal model. The muscle tendon model is used to calculate muscle force for each muscle group first. Then the forces are input to the musculoskeletal model to estimate the active joint torque. The dual population genetic algorithm (DPGA) is applied to optimize the model parameters. This tuning process takes only a few minutes and can reduce risk of fallen into local minimum. The ability to accurately predict the active torque of knee joint with relatively low root-mean-square error (RMSE) demonstrates the proposed EMG-driven model has potential applications towards the development of HMI.**

I. INTRODUCTION

Abnormal movement patterns are associated with disability following stroke [1]. Robot-assisted rehabilitation devices aim to help users move their limbs and restore limb functionalities through rehabilitative processes [2]. The EMG signals, resulting from motor neuron impulses that activate the muscle fibers, can be correlated with the force produced by muscles [3]. EMG has been recently used as human-machine interface (HMI), which achieves a user-friendly interface allowing easy control of these electromechanical systems.

EMG-based torque estimation is a widely research method to enable robots or assistive devices to be controlled using EMG signals. Many different approaches have been proposed in recent years, which can generally be divided into two common methods.

In the first method, a pattern recognition model is built using a machine learning algorithm, such as neural networks [4] and regression methods [3]. These approaches focus on model accuracy without considering the relationship between the EMG signals and internal muscle forces. However, knowledge of internal forces and torques during movements can be used to understand the body status and rehabilitation progress of the patients.

To overcome this deficiency, a musculoskeletal model is built in the second method. The Hill-based model is frequently employed to establish the musculoskeletal model, which applies contractile, series, and parallel elements to approximate the mechanical behavior of muscles [5]. Unfortunately, muscle parameters vary among individuals, and are typically difficult to obtain. To achieve an accurate model, complex nonlinear relationships involving muscle activation dynamics, muscle contraction dynamics, and musculoskeletal geometry need to be estimated and too many related parameters need to be optimized. This process is time consuming and causes its estimation performance in variou conditions to be poor.

An alternative approach is to use a simplified representation of the musculoskeletal system to simulate joint movements. Pau *et al.* [6] presented an EMG-driven model for the elbow joint to predict joint angle from EMG signals. Subject trials yielded an average root-mean-square error (RMSE) of $6.53°$ and $22.4°$ for a single cycle and random cycles of elbow joint movement, respectively. Their study demonstrated the feasibility of using a flexible, physiological model towards the development of HMI. However, the parameter optimization method in their study was run four times for each trial to reduce risk of fallen into local minimum and could take up to an hour each time.

The aim of this study is to establish a practical musculoskeletal model to estimate muscle force and active torque of knee joint using EMG signals. The dual population genetic algorithm (DPGA) [7] is applied to optimize the model parameters. This tuning process takes only a few minutes and can reduce risk of fallen into local minimum.

The remainder of this paper is organized as follows. In section II, the methods for torque estimation are illustrated, including establishment of the EMG-driven model, experimental setup, data processing, and model tuning. Section III shows the result. The last section raises some discussions and possible future improvements.

II. METHODS

A. Establishment of the EMG-Driven Model

The EMG-driven model developed in this study consists of two main modules: a muscle tendon model for each muscle group, and a proposed musculoskeletal model. The muscle tendon model uses muscle contraction dynamics to compute the muscle force of each muscle group. The proposed musculoskeletal model considers the muscle and

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bone structures around the knee joint. The muscle tendon model is used to calculate muscle force for each muscle group first. Then the forces are input to the musculoskeletal model to estimate the active joint torque.

1) Muscle Tendon Model: The aim of the muscle tendon model is to calculate muscle force from EMG signals. The muscle force is the sum of active contractile force, passive elastic force, and passive viscous force in each muscle tendon unit [6]. It should be noted that only the active contractile force is selected in this study to estimate the active torque of knee joint. That is, passive muscle properties do not affect the active motions.

The active contractile force of each muscle group is calculated based on the work by R. Riener and T. Fuhr [8], which is given by

$$\boldsymbol{F} = A_{act} \cdot F_{max} \cdot f_{fl} \cdot f_{fv} \tag{1}$$

where A_{act} is the normalized level of EMG signals, which is described in the section entitled “Data Processing”; F_{max} is the maximum isometric force of corresponding muscle; f_{fl} and f_{fv} describe the force-length and force-velocity relations, respectively. The model details and model parameters can be found in [8].

2) Musculoskeletal Model: The musculoskeletal model simulates the knee joint with a union of simplified muscle and bone structures, which is shown in Fig. 1. The motions of knee joint can be attributed to three main muscle groups: the quadriceps femoris (Qf) muscle, which causes knee extension; the hamstrings (Ha) and gastrocnemius (Ga) muscles, which cause knee flexion.

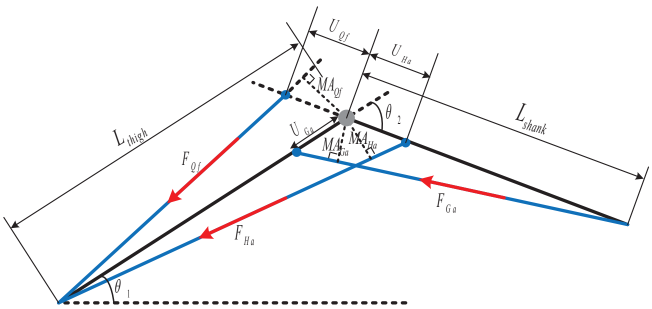

Fig. 1. Musculoskeletal model of the leg in the sagittal plane, where L_{thigh} and L_{shank} are the lengths of the thigh and shank respectively, θ_1 and θ_2 represent the joint angles of hip and knee.

The femur and combined tibia and fibula of the leg are indicated by black solid lines, and the three muscle groups are indicated by blue solid lines. One sides of the Qf and Ha muscles are jointly attached to a point (on the femur) nearing the hip joint, and the other sides are attached to bilateral position of the center of rotation at distances of U_{Qf} and U_{Ha} respectively. Similarly, one side of the Ga muscle is attached to a point (on the tibia) nearing the ankle joint, and the other side is attached to a point (on the femur) nearing the center of rotation at a distance of U_{Ga}. The red arrows show the main forces generated by the three muscle groups, which are represented as F_{Qf}, F_{Ha}, and F_{Ga} respectively. The moment arms for torque calculation are labeled as MA_{Qf}, MA_{Ha}, and MA_{Ga}.

Considering knee flexion as the positive direction, the active torque of knee joint is given by

$$\begin{aligned}\boldsymbol{T}_{act} = K_{Ha} \cdot F_{Ha} \cdot MA_{Ha} + K_{Ga} \cdot F_{Ga} \cdot MA_{Ga} \\ - K_{Qf} \cdot F_{Qf} \cdot MA_{Qf} + \Phi(\theta_1, \theta_2)\end{aligned} \tag{2}$$

where K_{Ha}, K_{Ga}, and K_{Qf} are correction constants due to the simplification of model. Φ is an correction function which account for the changes in joint angles. It is aware that the torque caused by gravity acting on the shank is a function of θ_1 and θ_2, which is substituted for the correction function Φ in this study. The combined weights of shank and foot are approximated to act at the midpoint of the shank.

As mentioned above, U_{Qf}, U_{Ha}, and U_{Ga} are the distances between the attachment points of three muscle groups and the center of rotation, respectively. Therefore, the three moment arms can be calculated using trigonometry and are given by

$$\begin{aligned} MA_{Qf} &= \frac{L_{thigh} \cdot U_{Qf} \cdot \sin\theta_2}{\sqrt{L_{thigh}^2 + U_{Qf}^2 - 2L_{thigh} \cdot U_{Qf} \cdot \cos\theta_2}} \\ MA_{Ha} &= \frac{L_{thigh} \cdot U_{Ha} \cdot \sin\theta_2}{\sqrt{L_{thigh}^2 + U_{Ha}^2 + 2L_{thigh} \cdot U_{Ha} \cdot \cos\theta_2}} \\ MA_{Ga} &= \frac{L_{shank} \cdot U_{Ga} \cdot \sin\theta_2}{\sqrt{L_{shank}^2 + U_{Ga}^2 + 2L_{shank} \cdot U_{Ga} \cdot \cos\theta_2}} \end{aligned} \tag{3}$$

Consequently, the musculoskeletal model has 6 parameters totally to be further optimized, which are K_{Ha}, K_{Ga}, K_{Qf}, U_{Ha}, U_{Ga}, and U_{Qf}. Other components, such as L_{thigh}, L_{shank}, MA_{Qf}, MA_{Ha}, and MA_{Ga}, can be measured from the subject or calculated using trigonometry from the estimated geometry parameters.

DPGA is employed to optimize these 6 model parameters, which will be described later.

B. Experimental Setup

1) EMG Signal Acquisition: An 8-channel EMG acquisition device has been developed at our laboratory, whose structure is indicated in Fig. 2. It consists of an amplifier, a linear isolation circuit and an analog/digital (A/D) converter. The amplifier employs differential-mode input with differential-mode amplification of 1000. The linear isolation circuit is used to achieve electrical isolation between the amplifier and the A/D converter. The analog EMG signals are sampled at 2048Hz and digitized with 12-bit conversion resolution using the A/D converter. After converted to digital signals, the raw EMG signals are transmitted to a PC for the following signal processing. In this study, EMG signals were acquired from three muscle groups mentioned above, which are Qf, Ha, and Ga.

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 [9], [10]. Although this preparation work is beneficial to data acquisition, it confines the practicability of the estimation method. So in this study, the electrodes

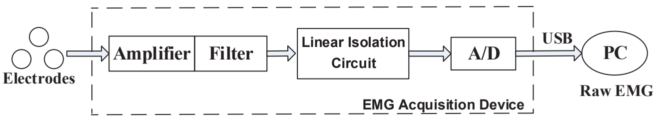

Fig. 2. Structure of EMG Acquisition Device.

were adhered to muscle surface directly without any disposal. Three pairs of Ag/AgCl electrodes were employed to measure the analog EMG signals. At each recording site, the electrodes were arranged in a differential configuration over the muscle belly and separated from each other by 2 cm [11].

2) Motion Data Acquisition: The active torque of knee joint and joint angles were acquired with *i*Leg−a horizontal exoskeleton for lower limb rehabilitation developed at our laboratory, whose mechanical structure is shown in Fig. 3. Joints 1, 2 and 3 correspond to the hip, knee, and ankle joints of human limbs respectively. A torque sensor, an absolute encoder, and a relative encoder are installed at each joint. *i*Leg has integrated the EMG acquisition device so we can obtain EMG signals and motion data simultaneously.

Fig. 3. Mechanical structure of *i*Leg for lower limb rehabilitation.

One healthy subject (male; 27 yrs) participated in the experiment. He was required to perform cycling movements with his own effort. The experimental procedure and the details of obtaining the active torque have been illustrated in [12], which is omitted here. The maximum voluntary contraction (MVC) and resting state of three muscle groups were recorded at last.

C. Data Processing

As EMG signals are difficult to be precisely measured due to its unstable measurement circumstance, the EMG signals need to be processed prior to use.

The effective frequency band of EMG signals is distributed within 10-500 Hz, mostly within the range of 50-150 Hz. Therefore, the EMG acquisition device has designed with a 50 Hz notch filter and a 20-200 Hz band-pass filter in hardware. The digital EMG samples are filtered first. A fourth-order Butterworth filter with cutoff at 2 Hz is employed for the envelope processing because this provides an appropriate compromise between the smoothness of the signals and time delays [14].

The EMG samples are sub-sampled from 2560 Hz to 50 Hz through a sliding window first. Then the EMG samples are normalized by:

$$\bar{x}(t) = \frac{|x(t) - x_r|}{x_m - x_r} \tag{4}$$

where x_r and x_m represent the resting state value and MVC of EMG; $x(t)$ is the value of EMG samples at time t; $\bar{x}(t)$ is the normalized value of EMG samples at time t.

The processed EMG signals and active torque of knee joint are shown in Fig. 4. The envelope of EMG signal indicates normalized level produced by each muscle, which is called A_{act} in this study.

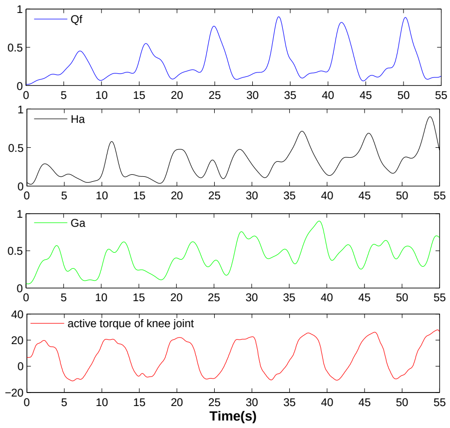

Fig. 4. EMG signals and active torque after data processing acquired from one trial.

D. Model Tuning

Since the musculoskeletal model of knee joint has 6 parameters totally to be further optimized, they are tuned by genetic algorithm (GA) first. The cost function is RMSE between the predicted torque and the actual torque of the knee joint.

It was found that the traditional GA is easily fallen into local minima in optimal searching. DPGA is therefore applied to reduce risk of fallen into local minimum. Fig. 5 shows the main steps of the DPGA for parameter optimization. The evolution of two sub-populations takes the different strategies. In more specific terms, the first sub-population has a larger crossover and mutation probabilities, which is used to keep higher search efficiency and avoid premature convergence; the second sub-population has a smaller crossover and mutation probabilities, which is used to find a current optimal chromosome for local scope and keep it.

Two sub-populations evolve independently except the "migration" step. The operation of "migration" can be described as follows: The two sub-populations exchange the current optimal chromosome together with N randomly selected chromosomes with each other, whereas the current optimal chromosome in each sub-population cannot be replaced. As

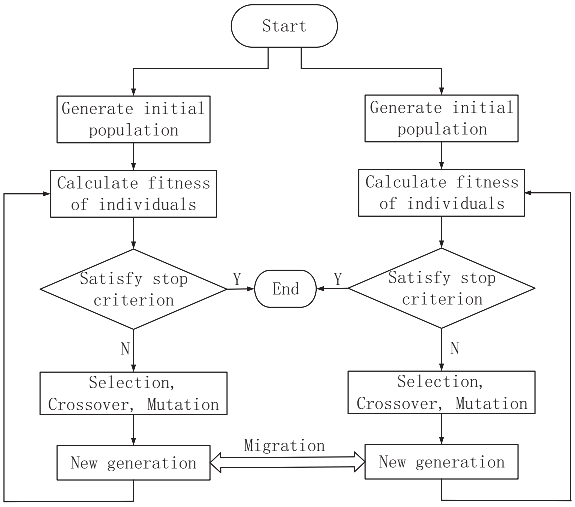

Fig. 5. Flowchart of the DPGA for parameter optimization.

a consequence, the current optimal chromosome and N-1 novel chromosomes are spread to the other sub-population in each evolution. The "migration" increases the diversity of each population and reduces the risk of local minima while maintaining higher search speed.

The change of average costs in population during the tuning process is illustrated in Fig. 6. It can be determined that DPGA improves the search performance.

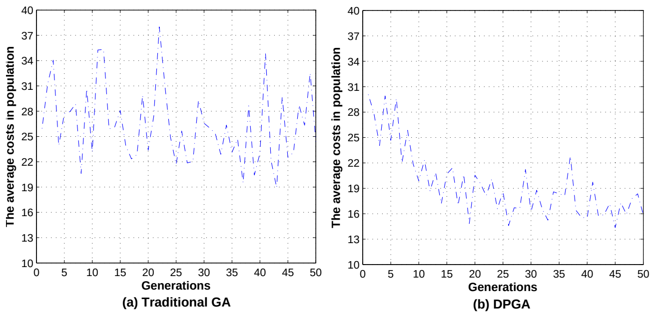

Fig. 6. The change of average costs in population during the tuning process.

III. RESULT

The experimental data is divided into two subsets, the training subset and the validation subset. After the model parameters have been optimized by the training subset, the model is used to estimate the knee torque using the validation subset on which it is not tuned. RMSE and correlation coefficient (CC) are used as the main criteria to show the performance of EMG-driven model, which are produced by averaging across the 3-fold cross-validation results. If $\hat{\tau}$ is the estimate for the actual torque τ, RMSE and CC are defined as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{k=1}^{N}(\tau_k - \hat{\tau}_k)^2} \quad (5)$$

$$CC = \frac{\sum_{k=1}^{N}(\tau_k - \bar{\tau})(\hat{\tau}_k - \bar{\hat{\tau}})}{\sqrt{\sum_{k=1}^{N}(\tau_k - \bar{\tau})^2 \sum_{k=1}^{N}(\hat{\tau}_k - \bar{\hat{\tau}})^2}} \quad (6)$$

where $\bar{\tau}$ and $\bar{\hat{\tau}}$ represent the mean of the actual torque τ and estimated torque $\hat{\tau}$ across N testing samples, respectively.

Fig. 7 shows one trial of the active torque estimation result. The active torque of knee joint is time-varying because the subject exerts his effort randomly. It can be found that the tuned model can predict the active torque in real time. The whole process including model tuning and prediction takes only a few minutes.

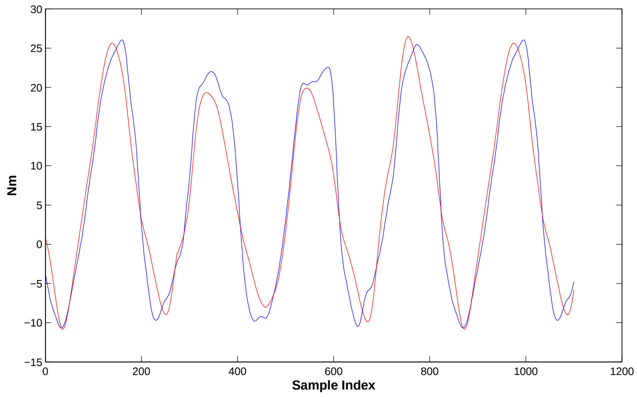

Fig. 7. The active torque estimation of knee joint using the EMG-driven model. The blue solid line shows the actual torque and the red solid line represents the predicted result. $RMSE = 3.81$ Nm, $CC = 0.95$.

IV. DISCUSSIONS

It is interesting that the predicted torque curve (red) is slightly ahead of the actual torque curve (blue) shown in Fig. 7. The values of those two criteria improve to $RMSE = 3.65$ Nm and $CC = 0.96$, when the predicted torque curve is delayed for 100 ms. This may be due to the unique nature of the EMG signals, which is 10-100 ms prior to body motion [15] and therefore reflects motion intent in advance. In summary, the performance of the EMG-driven model is superior to torque sensor in two counts: reflect degree of activity in specific muscle and reflect motion intent in advance. These characteristics make it promising as HMI to make devices react pre-actively rather than re-actively to motion intent.

In this paper, a practical EMG-driven model is proposed to estimate muscle force and active torque of knee joint from EMG signals. The estimation of muscle activity is very important to estimate the contribution of individual muscle for the motion control. This could be useful to make better planning during patient's rehabilitation process. In the tuning process, DPGA is applied to optimize the model parameters. It has been demonstrated that DPGA reduces the optimization time of the algorithm and risk of fallen into local minimum greatly.

This preliminary experiment shows the feasibility of the EMG-driven model used in dynamic torque estimation of knee joint. The next step is to consider the model robustness. The accomplishment of a single-joint active rehabilitation training based on *i*Leg is expected to verify the effectiveness of EMG-driven model proposed in this study. Further more, the approach proposed in this study will be expanded to other joints and a robust interface is expected to be employed in a multitude of applications.

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