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A Subject-Specific EMG-driven Musculoskeletal Model for the Estimation of Moments in Ankle Plantar-Dorsiflexion Movement

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Abstract. In traditional rehabilitation process, ankle movement ability is only qualitatively evaluated by its motion performance, however, its movement is actually achieved by the forces acting on the joints produced by muscles contraction. In this paper, the musculoskeletal model is introduced to provide a more physiologic method for quantitative muscle forces and muscle moments assessment during rehabilitation. This paper focuses on the modeling method of musculoskeletal model using EMG and angle signals for ankle plantar-dorsiflexion (P-DF) which is very important in gait rehabilitation and foot prosthesis control. Due to the skeletal morphology differences among people, a subject-specific geometry model is proposed to realize the evaluation of muscle length and muscle contraction force arm. Based on the principle of forward and inverse dynamics, difference evolutionary (DE) algorithm is used to adjust individual parameters of the whole model, realizing subject-specific parameters optimization. Results from five healthy subjects show the inverse dynamics joint moments are well predicted with an average correlation coefficient of 94.21% and the normalized RMSE of 12.17%. The proposed model provides a good way to estimate muscle moments during movement tasks.

Keywords: EMG signals, musculoskeletal model, ankle plantar-dorsiflexion, joint moment.

1 Introduction

With the development of society and technology, the aging problem has become more and more serious. At the same time, patients with limb disability are also increasing. There are nearly 1.4 million people losing their ability to live independently because of stroke in China each year [1]. Health care and rehabilitation for elderly and disabled people are increasing. The ankle joint plays an important role in human standing and walking but easy to be damaged [2]. It is important to assess the moment for ankle joint during its movement and rehabilitation. There are three degrees of freedom (DOFs) in the ankle joint: dorsiflexion/plantarflexion, adbuction/adduction, inversion/eversion. Plantar-dorsiflexion (P-DF) is the most important among them with great significance in gait rehabilitation [3] and foot prosthesis research [4].

The electromyography (EMG) signals are commonly used in rehabilitation to estimate the moments for the physiological significance. There are two main methods for muscle forces and moments assessment based on EMG signals: black-box method and musculoskeletal model [5]. Black-box method includes neural network, support vector regression and other fitting algorithms or related improved algorithms to build the relationship between EMG signals and muscle forces or moments. Predictive model can be built easily through part of the input and output data using black-box method. But this method cannot inform us of muscle changes during body movement and cannot provide good reference for rehabilitation analysis [6].

Musculoskeletal model is able to provide a better understanding in mechanical process of human motion. Hassani et al. estimated muscular activities detection by realistic musculoskeletal models of the muscles actuating the knee joint, realizing an active rehabilitation strategy following the wearer's intention [7]; Manal et al. built a musculoskeletal model for ankle P-DF and proposed an EMG-driven modeling approach and data processing framework that allowed them to predict Achilles tendon force in real-time [8]. Musculoskeletal model provides a better method for muscle forces and moments assessment with physiological significance, realizing quantitative assessment of physical exercise ability.

Many existing researches on ankle P-DF moment only focus on simple applications of mature models without musculoskeletal model optimization. Some researchers use sophisticated equipment such as nuclear magnetic resonance imaging (MRI) [9] or motion capture systems [10] to obtain actual model parameters, which is not suitable for practical applications. In this paper, EMG signals from four muscles related to ankle P-DF are collected along with angle signals. A subject-specific musculoskeletal geometry model is proposed to assess muscle length and muscle force arm length. Difference evolutionary (DE) algorithm is applied to adjust the parameters of the whole model in off-line condition. The rest of this paper is arranged as follows: Section 2 presents design details of the ankle P-DF musculoskeletal model. The experiment is carried out to verify performance of the model in Section 3. Section 4 draws conclusion of the paper.

2 Musculoskeletal Modelling Methods

The EMG-driven musculoskeletal model in ankle P-DF derives from Hill-based muscle model and joint forward/inverse dynamics. The model in this paper builds direct relationship between EMG signals and joint moments, which consists of three modules: muscle activation dynamics, Hill-type muscle-tendon model and subject-specific musculoskeletal geometry model, as shown in Fig. 1. Raw EMG signals collected from medial gastrocnemius (MG), lateral gastrocnemius (LG), soleus (SO) and tibialis anterior (TA) are pre-processed and then used as input to the muscle activation dynamics to get muscle activations. Angle signals are taken as input to the subject-specific musculoskeletal geometry model to get the muscle length and muscle force arm length. Hill-type muscle-tendon model is used to get muscle force of each muscle and finally get the whole moment output.

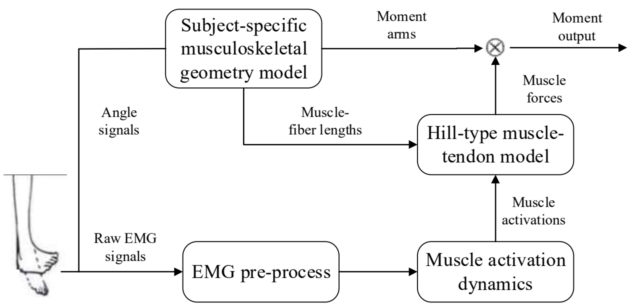

Fig. 1. EMG-driven musculoskeletal model

2.1 EMG Pre-process and Muscle Activation Dynamics

In ankle movement, raw EMG signals contain some low-frequency noise due to EMG acquisition device itself and environment impact. Therefore, EMG signals can be pre-processed by a band-pass filter with a cutoff frequency in the range of 5-30Hz and then be rectified and normalized. The processed EMG signals are expressed by $e(t)$. Neural activation $u(t)$ is related to its past magnitude and $e(t)$. A two order difference equation can be used to describe the dynamic relationship between them as follows:

$$u(t) = \gamma e(t-d) - \beta_1 u(t-1) - \beta_2 u(t-2) \tag{1}$$

where d is time delay. γ, β_1 and β_2 are the scaling coefficients. To realize a positive stable solution, they must satisfy the constraints as shown in equation (2).

$$\beta_1 = c_1 + c_2, \beta_2 = c_1 \cdot c_2, \gamma - \beta_1 - \beta_2 = 1 \tag{2}$$

where $|c_1| < 1, |c_2| < 1$. Since there is a nonlinear relationship between $u(t)$ and muscle activation $a(t)$, a simple transformation is needed as follows:

$$a(t) = \frac{e^{Au(t)} - 1}{e^{A} - 1} \tag{3}$$

where A represents nonlinear shape factor with values ranging from -3 to 0.

2.2 Hill-type Muscle-tendon Model

When muscles are activated, they will produce muscle contraction forces. This section focuses on the process of muscle contraction dynamics from muscle activations to contractile forces. Muscles are mainly composed of muscle fibers and tendons. The Hill model equates muscle fibers with a passive element CE in parallel with the shrink element PE and equates muscle tendon to a non-linear spring element shown in Fig. 2.

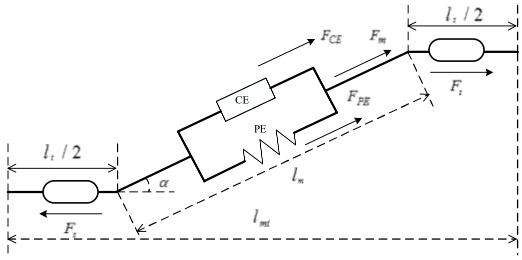

Fig .2. Schematic of Hill-type muscle-tendon model

The relationship between muscle unit l_{mt}, muscle fibers l_m and muscle tendon l_t can be described by equation (4), where α is pennation angle. Muscle fibers contraction force F_m is equal to the sum of the forces from the contraction element and the passive element, as shown in equation (5).

$$l_{mt} = l_m \cos\alpha + l_t \tag{4}$$

$$F_m = F_m^{\max}\left[F_A(l)\cdot F_V(v)\cdot a + F_P(l)\right] \tag{5}$$

where $F_m^{\max}$ is maximum isometric contraction force, a denotes muscle activation, $F_A(l)$ is active force-length relationship. $F_V(v)$ describes force-velocity relationship and $F_p(l)$ represents passive elastic force–length relationship. And $l = l_m / l_{mopt}$ is normalized muscle fiber length, $v = v_m / (0.5\cdot v_{\max}(a+1))$ represents the normalized muscle fiber contraction velocity, l_{mopt} is the muscle fiber length when maximum isometric force is produced and $v_{\max}$ is the maximum velocity.

Tendons are rather stiff and the strain is only about 3% of tendon length for maximum muscle force, which can be neglected [11]. Tendon changes during general ankle P-DF in OpenSim (Simtk, Stanford, USA) [12] also illustrate the tendon stiffness. Therefore, tendon slack length scale s_t can be introduced to adjust personalized tendon length l_t based on tendon slack length l_{tr}, as shown in equation (6). In this way, the muscle fiber length can be calculated indirectly by equation (4) when tendon length l_t and muscle length l_{mt} are obtained.

$$l_t = s_t \cdot l_{tr} \tag{6}$$

2.3 Subject-Specific Musculoskeletal Geometry Model

Muscle paths need to be determined first to build musculoskeletal geometry model, which can be done by medical device or by anatomical measurement on cadaveric samples. General musculoskeletal geometry model is built based on the mean of data from above methods, which is not suitable for different people. Muscles are attached to skeletons, whose paths are related to skeletal morphology. Muscle path assessment equations [13] are used to determine morphological parameters of the actual subjects, and the paths of main muscle group in ankle joint are obtained. For simplicity, muscles are assumed as straight lines. Suppose the body sitting on a chair with the knee staying 90 degrees, taking SO as an example, as shown in Fig. 3.

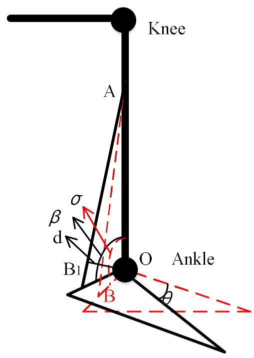

Fig. 3. Musculoskeletal geometry model of SO

A is the origin point, B is the insertion point and O represents the center of ankle joint. The dashed line indicates the foot is in the horizontal position and the solid line indicates the foot moves to a certain position. θ is the angle of ankle motion, l_{AB_1} represents the muscle length and d is arm length. The calculation equation is shown in equation (7).

$$\begin{cases} l_{AB_1} = \sqrt{l_{AO}^2 + l_{B_1O}^2 - 2l_{AO}l_{B_1O}\cos\beta} \\ d = l_{AO}l_{B_1O}\sin\beta / l_{AB_1} \end{cases} \tag{7}$$

2.4 Parameters Identification

There are many parameters with subject-specific differences and difficult to be measured directly in musculoskeletal model. To improve the prediction accuracy, subject-specific parameters should be selected for different subjects.

Since pennation angle α is usually small, it can be assumed as consistent, to reduce the complexity of parameters identification. Also, it can be assumed that all muscle activation parameters are the same, and $v_{\max}$ can be replaced by $10l_{mopt}$. Thus, the parameters needed to be identified are d , c_1 , c_2 and A in muscle activation model, $F_m^{\max}$, l_{mopt} and s_t in Hill-type muscle-tendon model. The original data for parameters identification are derived from the average data of autopsies [14]. The principle of parameters identification is shown in equation (8). The left side of the equation is the reference torque calculated according to the inverse dynamics and the right side is the predicted torque of the skeletal muscle model.

$$I\ddot{\theta} + Mgl\cos\theta = -F_{MG}d_{MG} - F_{LG}d_{LG} - F_{SO}d_{SO} + F_{TA}d_{TA} \tag{8}$$

where θ is the angle of ankle P-DF movement, I , M , g , l are the moment of inertia for the foot, the mass of the foot, the gravity acceleration and the gravity arm length of the foot, respectively, F and d represent muscle forces and arm lengths.

3 Experimental Results and Analysis

3.1 Experiment Setup

Five healthy subjects were recruited to collect the signals (right foot, 23.5±1.6 years old). Written informed consent was obtained from them. The subjects were asked to sit on a suitable table to conduct the ankle P-DF movement, with his/her knee joint staying 90 degrees and foot above the ground. Four electrodes were attached to the skin surface on muscle bellies center of MG, LG, SO and TA. Raw EMG signals were recorded by the EMG acquisition equipment (DataLOG MWX8, Biometrics Ltd. UK) and angle signals were recorded by the angle acquisition equipment(MPU6050, InvenSense. USA). To reduce the effects of muscle fatigue, subjects relaxed their ankle muscles for 10 min between every two experiment trials.

3.2 Experimental Results

Without loss of generality, two subjects (Sub.1 and Sub.4) are selected to analyze the results shown in Fig. 4. Both the value and trend of the estimated moment (the green and the red dashed line) are in good agreement with the reference moment (the blue solid line) calculated by inverse dynamics illustrated in the section of parameters identification, which shows the EMG-driven model can be used for ankle joint moment tracking with an acceptable accuracy. It can be seen that under the same test conditions, the subject-specific model (the green dashed line) is closer to the reference moment and better than the general model (the red dashed line), which demonstrates different people have different parameters and it is thus of great importance to build their own subject-specific musculoskeletal model.

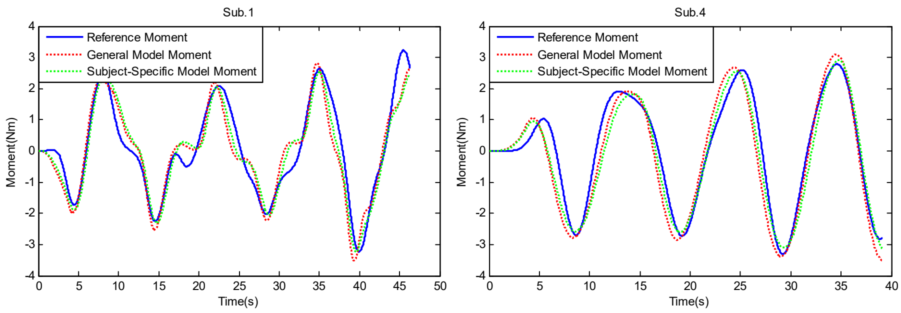

Fig. 4. Comparison of torque

The same experiments have been performed with five subjects. The normalized RMSE and correlation coefficient (CC) are used as the main criteria to show the performance of the model. A high level of CC and a low normalized RMSE have been obtained as presented in Table 1.

Table 1. Summary of prediction performance of the model

Subject	Model	Correlation Coefficient(%)	Normalized RMSE(%)
Sub.1	G	93.57	14.71
	S	95.08	11.78
Sub.2	G	92.62	13.62
	S	94.44	11.97
Sub.3	G	89.35	17.37
	S	91.16	14.29
Sub.4	G	96.02	12.48
	S	96.78	10.29
Sub.5	G	91.76	14.28
	S	93.57	12.53
Mean	G	92.66	14.49
	S	94.21	12.17

(Note: G and S stands for general model and subject-specific model, respectively.)

It is evident that the estimated moments in G and S are both in good agreement with the reference moment but the result in S is better than that in G. The mean of the correlation coefficient in S (94.21%) is greater than that in G (92.66%) and the mean of the normalized RMSE in S (12.17%) is smaller than that in G (14.49%). In addition, the correlation coefficients in S are greater and the normalized RMSEs in S are smaller across all subjects compared with that in G, indicating the proposed model is capable of providing better representations of the subjects involved in this study. Through the results of the experiment, it can be concluded that the performance of subject-specific model is superior to general model.

4 Conclusion

Researches on ankle P-DF musculoskeletal model are beneficial to evaluate muscle contraction force and moment from a more physiological point of view, and can thus improve the flexibility of human-computer interaction. In this paper, EMG signals and angle signals in ankle P-DF movement are used to assess the joint moment off-line through a subject-specific EMG-driven musculoskeletal model with an acceptable accuracy. The average correlation coefficient is high (94.21%) and the normalized RMSE is relatively small (12.17%), which shows the feasibility and effectiveness of the proposed model. Experimental results also show the importance of acquiring more accurate musculoskeletal geometry. Limitations of this paper include the fact that off-line musculoskeletal model is studied but without using it in real-time applications. Therefore, our future work is to verify the on-line effectiveness of EMG-driven model proposed in this study and consider the practical conditions. Further more, the approach proposed in this study will be expanded to other joints that can be employed in various applications.

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