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A novel method for estimating continuous motion and time-varying stiffness of human elbow joint

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***Abstract*—This paper presents a method to estimate continuous motion and time-varying stiffness of the human elbow joint based on surface electromyography (sEMG). Firstly, based on the Hill-based muscle model (HMM), a continuous motion estimation model (CMEM) of elbow joint with sEMG signals as input and joint angle as output was established. And the genetic algorithm was used to optimize the unknown parameters in this model. Secondly, the joint kinetic equation expressed the relationship of skeletal muscle stiffness and the elbow joint stiffness. And the time-varying stiffness estimation model (TVSEM) of elbow joint based on sEMG signals was established. So that the TVSEM of the elbow joint based on sEMG signals was established. Finally, the accuracy and validity of the CMEM and the TVSEM of elbow joint were presented by the experimental platform.**

***Index Terms*—sEMG, HMM, Elbow joint movement, Muscle stiffness, Time-varying stiffness.**

I. Introduction

THE flexibility of body joints plays an important role in daily life, especially in the case of high-precision pose rapid switching, which can better reflect the superiority of joint flexibility. And the human body has natural and excellent motion flexibility, so how to apply the characteristics of human joint motion to the robot joint has become a hot topic in the field of flexible bionic robot[1].

Taking into account the flexibility of human joint is mainly reflected in the joint movement and joint stiffness. So, if the human body joint motion estimation results and joint stiffness estimation results apply to the robot joint, the robot joint can achieve humanoid joint effect [2]. The sEMG signals are the body's own resources. It contains abundant human motion information, and the acquisition technology is mature [3] [4]. Therefore, the human elbow joint motion estimation and joint stiffness estimation which are based on sEMG will be discussed in this paper.

There are many ways to estimate the continuous motion of human joints based on sEMG. Generally, they were based on muscle physiological mechanics to establish the joint dynamics model with sEMG as the input. Buchanan *et al*. [5] proposed a kinematic model of human elbow joint based on sEMG. Han *et al*. [6] used the EKF to improve the accuracy of the continuous motion estimation of the human elbow joint. Pau *et al.* [7] based on the HMM, proposed the muscle internal viscous force by studying the physiological structure of muscle, established the skeletal muscle model of human upper limb, and improved the elbow joint motion estimation.

Based on the HMM, this paper simplifies the model parameters, focus on skeletal muscle physiological structure, and proposes a new geometric model of human upper limb to estimate the continuous motion.

If only apply the estimated results of joint continuous motion to the robot control, the robot will not have the features of compliancy. Therefore, the researchers' study on the soft motion deeply, associated with the joint stiffness and other information estimation, which is based on motion recognition [2]. Mussa-Ivaldi *et al*. [8] used the perturbation method to estimate the stiffness of the man-made posture in the fixed case. Tsuji *et al*. [9] used the perturbation method with equilibrium point to estimate the joint stiffness of upper limb. Shin *et al.* [10] extracted muscle activity from sEMG to calculate muscle contraction force. The kinematic mapping model based on muscle activity to joint torque is established, and the joint stiffness is obtained by further differentiating the model; Kim *et al.* [11] estimated the human upper limb multi-joint stiffness by using sEMG and artificial neural network model.

In this paper, the time-varying stiffness estimation model (TVSEM) of human elbow joint based on sEMG is established, which is based on the continuous motion estimation model (CMEM) of human elbow joint. Firstly, the sEMG signals were collected to calculate the muscle activity, and the muscle force was calculated based on the HMM. Secondly, the kinematic equation of the elbow was used to estimate the angle of joint continuous motion and the genetic algorithm was used to adjust the model parameters. Finally, the TVSEM of skeletal muscle was established and we used the estimated joint angle to solve the joint stiffness. The calculation process is shown in Fig.1.

II. CMEM of Elbow Joint

The CMEM of elbow joint is a mathematical model with sEMG as input and joint angle as output. The modeling process is shown in the dashed box in Fig. 1. First, the sEMG signals of human body was extracted, and the muscle activity model was established; Then the muscle force was calculated based on the HMM; At last, the dynamic equation was used to solve the continuous motion of elbow joint.

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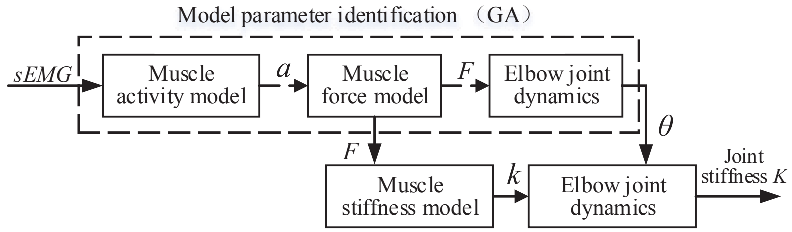

Fig. 1. Overview of model to estimate continuous motion and time-varying stiffness of human elbow joint based on sEMG.

A. Muscle Activity Model

Muscle activity represents the level of muscle excitability, and reflects the level of muscle force. In order to extract muscle activity, we need to extract the features of sEMG signals, and the flow chart of sEMG signals pretreatment is shown in Fig. 2.

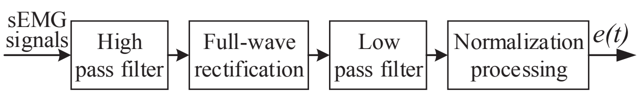

Fig. 2. Flow chart of sEMG signals pretreatment.

We used a recursive filter to deal with the preprocessed sEMG signals, and we could get the neuromuscular activation [5], [12]. i.e.,

$$\begin{cases} u(t) = \alpha \cdot e(t - d/T) - \beta_1 \cdot u(t-1) - \beta_2 \cdot u(t-2) \\ \alpha - \beta_1 - \beta_2 = 1 \\ \beta_1 = \gamma_1 + \gamma_2,\ \beta_2 = \gamma_1 \cdot \gamma_2,\ |\gamma_1| < 1,\ |\gamma_2| < 1 \end{cases} \quad (1)$$

Where $e(t)$ represents the preprocessed sEMG signal at time t; $u(t)$ is the level of neuromuscular activation at time t; T is the sampling time; d is the signal delay time, usually in the range of 10-100ms[13], this paper takes 40ms; α, γ_1, γ_2, β_1, β_2 are the correlation coefficients in this filter.

The mathematical relationship between the neuromuscular activation $u(t)$ and muscle activation $a(t)$, we could use (2) to express [14]:

$$a(t) = \frac{e^{A \cdot u(t)} - 1}{e^{A} - 1} \quad (2)$$

Where, A is a nonlinear shape factor from -3 to 0.

B. Muscle Force Model

At present, most of the researches on muscle biomechanics are based on HMM. HMM can be shown in Fig. 3:

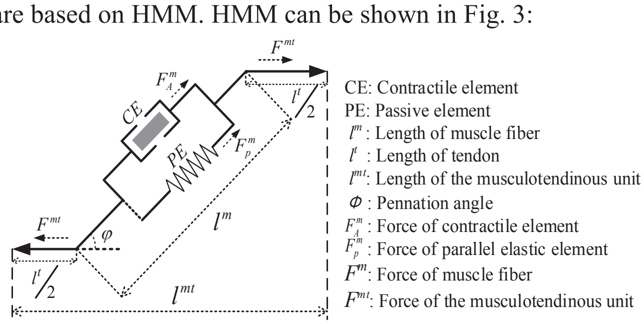

Fig. 3 HMM

The muscle belly can be seen as the main unit of the skeletal muscle, which is composed of contraction unit and passive unit. So the muscle force F is the combined effect of muscle contraction force and muscle passive force [5]. i.e.,

$$F = (F_C + F_P)\cos\varphi \quad (3)$$

Where F_c is muscle contraction force, F_p is muscle passive force, φ is the pennation angle.

Usually in the accessory muscles of the elbow, the pennation angles of biceps and triceps are almost equal to zero. The optimal pennation angles are no more than 10° [15]. It can be regarded as $\varphi=0$, that is $\cos\varphi \approx 1$ [1].

Muscle contraction force and muscle passive force can be expressed by equation (4) [5] [6]:

$$\begin{cases} F_c = f_A(l) \cdot f_V(v) \cdot a(k) \cdot F_{\max} \\ F_p = f_P(l) \cdot F_{\max} \end{cases} \quad (4)$$

Where $a(k)$ is muscle activation; F_{max} is maximum isometric muscle force; $f_A(l)$, $f_V(v)$ and $f_p(l)$ are the muscle force–length relationship, muscle force–velocity relationship and the passive elastic force–length relationship, respectively. In this paper, we take $f_V(v)$=1 [6][16]. l is the normalized muscle fiber length, which is equal to the current muscle fiber length l^m divided by the optimal muscle fiber length l_0^m, the calculation equation is shown in equation (5):

$$l = \frac{l^m}{l_0^m} \quad (5)$$

The muscle force–length relationship $f_A(l)$ can be simplified as a second-order polynomial, and Vilimek [17] expressed it in his paper as follows:

$$f_A(l) = \begin{cases} 1 - (\frac{l-1}{0.5})^2, 0.5 < l < 1.5 \\ 0, \qquad otherwise \end{cases} \quad (6)$$

Suhutte *et al.* [18] used the exponential relationship to express muscle passive force, i.e.,

$$f_p(l) = e^{10 \cdot l - 15} \quad (7)$$

In order to obtain the parameters of the muscle force model, we need to get the normalized muscle fiber length l. According to Fig. 3, the length of skeletal muscle unit can be calculated as follows:

$$l^{mt} = l^t + l^m \cdot \cos\phi \tag{8}$$

From this equation we can get the current length of muscle fiber l^m; l^t is the length of tendon, which can be regarded as a constant; l^{mt} is the length of skeletal muscle, which can be get through the geometric model of human upper limb (See Fig.4). The biceps and triceps skeletal muscle length as follow:

$$l_b^{mt} = \sqrt{l_{OK}^2 + l_{OC}^2 - 2l_{OK} \cdot l_{OC} \cdot \cos(\pi - \theta - \arctan(\frac{l_{AC}}{l_{AO}}))} \tag{9}$$

$$l_t^{mt} = \sqrt{l_{OB}^2 + l_{OJ}^2 - 2l_{OB} \cdot l_{OJ} \cdot \cos\theta} \tag{10}$$

So, when determining the constants F_{max}, l^t and l_0^m, we could calculate l^m by (8), l by (5), muscle force F by (3).

C. Joint Dynamics Model

The elbow joint movement of the human body is flexion and extension. Studies have shown that the elbow joint movement is mainly related to the biceps, triceps and radials groups. The force of radials has little effect, so it can be ignored [5]. Through the study of the physiological structure of human upper limbs, this paper established the geometric model of human upper limb to solve the elbow joint dynamics model (See Fig.4). In this figure, F_{bi}, F_{tr} represent biceps and triceps muscle force, respectively; *AO* represents humerus; *JC* represents humeral condyle; *BOE* represents ulna and radius, and the triceps group is connected to the point *B* of ulnar end. The point *B* and the joint point *O* and the forearm end *E* are not in the same straight line.

When the upper limb is only around the elbow joint to do the rotation, it can be regarded as the fixed axis rotation of the forearm. In this course, the total torque equation can be expressed as (11):

$$T = F_{bi} \cdot l_{OH} - F_{tr} \cdot l_{OI} - M_F - M_G \tag{11}$$

Where M_G is the gravitational moment of forearm and hand on the elbow joint; M_F is the external moment on the elbow joint; L_{OH}, L_{OI} are the arms of biceps and triceps force.

Assuming that the moment of inertia of the forearm is J, the following equation can be obtained from the kinetic equation $J{\cdot}\alpha{=}T$ (α is the angular acceleration), i.e.,

$$J \cdot \ddot{\theta}_k = T_k \tag{12}$$

Through the elbow joint dynamics analysis, we can get the elbow joint dynamics model in discrete time, i.e.,

$$\begin{cases} \dot{\theta}_{k+1} = \dot{\theta}_k + \ddot{\theta}_k \cdot \Delta t \\ \theta_{k+1} = \theta_k + \dot{\theta}_k \cdot \Delta t + \frac{1}{2} \cdot \ddot{\theta}_k \cdot \Delta t^2 \end{cases} \tag{13}$$

The dynamic model of elbow joint can be solved by simultaneous equations (11) (12) (13), which is based on biceps and triceps muscle force as input, elbow angle as output.

By combining the above three models (*part A, B and C*), we can get the CMEM of the elbow joint, which is based on sEMG signals as input, elbow rotation angle as output.

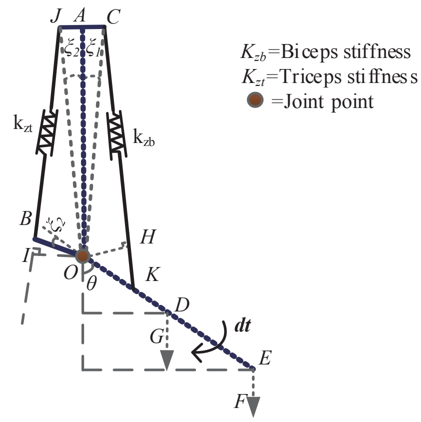

Fig. 4. Geometric model of upper limb based on physiological structure.

D. Model Parameter Identification

There are many undetermined parameters in the CMEM of elbow joint, and it is difficult to be measured directly, for example, γ_1, γ_2, A, F_{max}, l^t, m, I, L_{AO}, L_{AC}, L_{OE}, L_{OK}, etc. For different individuals, due to individual differences, the model parameters of elbow joint are different. Therefore, it is necessary to identify the relevant parameters for the model before the model applied to the specific object.

The goal of model parameter identification is to find a set of optimal parameters finally through adjusting the parameters of the CMEM, so that the joint angles θ obtained by the model will be close as much as possible to the real values. In this paper we used the algorithm of parameter optimization to achieve this goal. The genetic algorithm is used to optimize the parameters which have great influence on the output. The optimization objective function is as follow:

$$\min \sum_1^n (\theta_c - \theta_m)^2 \tag{14}$$

θ_c represents the actual measured angle, and θ_m represents the angle of model estimation.

Through the model parameter identification, we can get a set of optimal model parameter values, which are closest to the actual joint angles. Then, the values of joint angles and muscle force obtained by the model are used as the input of the next part, which also improve the output accuracy of the TVSEM.

III. TVSEM OF ELBOW JOINT

The human joints are flexible because the joints are driven by skeletal muscles with the characteristics of variable stiffness [19], so we first estimate the skeletal muscle stiffness which is associated with the elbow joint.

In general, skeletal muscle stiffness can be described as the initial response of muscle length caused by external perturbations, before the changes in activation mediated through reflexive and voluntary mechanisms [20].

The skeletal muscle stiffness model can be described as Fig. 5, and the stiffness of a complete skeletal muscle can be considered as a result of a serial linkage between muscle stiffness unit and tendon stiffness unit [20] [21], as shown in (15):

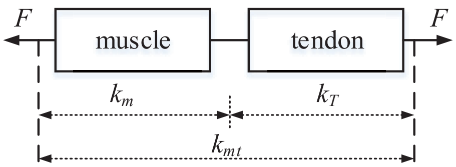

Fig. 5. The model of skeletal muscle stiffness.

$$k_{mt} = \frac{k_m \cdot k_T}{k_m + k_T} \tag{15}$$

The short-range stiffness (SRS) of muscle was used for muscle stiffness estimation, which is considered to be proportional to muscle force F and inversely proportional to the optimal muscle fiber length l_0^m [20][22], i.e.,

$$k_m = \frac{\tau \cdot F}{l_0^m} \tag{16}$$

Where τ is a dimensionless proportional constant, this paper takes τ=24.1 [20] [23], and F can be obtained by (3).

We use the linear model proposed by Zajac [15] to describe the tendon stiffness, i.e.,

$$\tilde{k}_T = k_T \cdot \frac{l_0^m}{F_{\max}} \tag{17}$$

Where $\tilde{k}_T$ is the normalized dimensionless tendon stiffness, Zajac [15] used the slope of the linear model to represent it as follow:

$$\tilde{k}_T = \frac{30}{\tilde{l}^t} \tag{18}$$

Where $\tilde{l}^t$ is the normalized dimensionless tendon length, which can be expressed as follow:

$$\tilde{l}^t = \frac{l^t}{l_0^m} \tag{19}$$

When the tendon length l^t, the optimal fiber length l_0^m and the optimal muscle strength F_{max} are known, we can obtain the tendon stiffness k_T. Then, we can calculate the complete skeletal muscle stiffness by Eq. (15).

Knowing skeletal muscle stiffness we can calculate the elbow stiffness by joint dynamics. The relationship between skeletal muscle stiffness and elbow stiffness can be shown in Fig. 4.

Assuming an instantaneously external torque dt make the elbow joint engender the rotational angle is $d\theta$, this time the biceps and triceps will be deformed, the deformation is as follows:

$$dx_1 = \frac{l_{OK} \cdot l_{OC} \cdot \sin(\theta + \arctan\frac{l_{AC}}{l_{OA}})}{\sqrt{l_{OK}^2 + l_{OC}^2 + 2 \cdot l_{OK} \cdot l_{OC} \cdot \cos(\theta + \arctan\frac{l_{AC}}{l_{OA}})}} \cdot d\theta \tag{20}$$

$$dx_2 = \frac{l_{OB} \cdot l_{OJ} \cdot \sin\theta}{\sqrt{l_{OB}^2 + l_{OJ}^2 - 2 \cdot l_{OJ} \cdot l_{OB} \cdot \cos\theta}} \cdot d\theta \tag{21}$$

Therefore, according to the dynamic moment balance equation can be obtained elbow stiffness, i.e.,

$$K = \frac{K_{zb} \cdot dx_1 \cdot l_{OH} - K_{zt} \cdot dx_2 \cdot l_{OI}}{d\theta} \tag{22}$$

Where K_{zb} is the biceps muscle stiffness, K_{zt} is the triceps muscle stiffness.

The input in equation (22) contains the muscle activity $a(t)$ and the elbow angle θ, which can be determined by muscle activity model and CMEM, previously. So, from the view of theory we built the TVSEM of human elbow joint based on sEMG.

IV. EXPERIMENT AND RESULTS

A. *Experiment for CMEM Verification*

In order to make the experiment more persuasive, we selected five subjects with an average age of 25 years, holding 1.25kg and 2.5kg load to do continuous joint motion experiments, respectively.

Before the application of sEMG electrodes, the skin surface was cleared by rubbing with alcohol to remove dirt. In the course of the experiment, the subject was asked to: The upper limb relaxed as much as possible, and the upper arm stayed vertical with the ground; Elbow joint rotated from 0 -90 degrees, and the rotation speed should be smooth and required to be a continuous (See Fig. 6(a) and (b)).

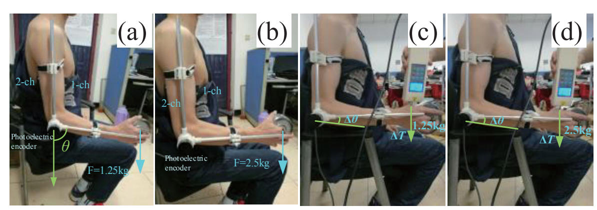

Fig. 6 Experimental environment.

Using Delsys wireless acquisition module to collect sEMG signals, the sampling frequency was set to 2000Hz; Elbow joint angle measurement using incremental photoelectric encoder sensor, using the STM32F4 development board for angle capture, capture frequency was set to 400Hz.

The original sEMG signals collected from the experiment are shown in Fig.7 that (a) and (b) show the original sEMG signals of the biceps and triceps with 1.25 kg load; (c) and (d) show the original sEMG signals of the biceps and triceps with 2.5 kg load. We can see from (a) and (c), in this course of elbow rotation, the triceps force is very small, because the resulting of sEMG signals is almost equal to zero, so in the actual simulation we can ignore the triceps force.

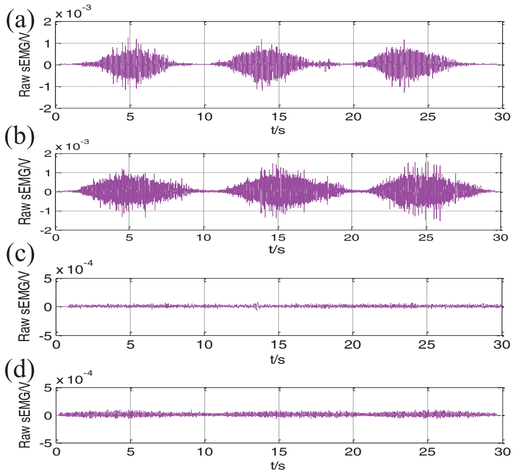

Fig. 7. The original sEMG signals

Since the sampling frequency of the joint angle is 400Hz, the frequency of muscle activity is the same as sEMG signals, which is 2000Hz. Therefore, in order to ensure that the measured joint angle and muscle activity have the same sample size, in the 5ms time window to take the muscle activity mean, i.e.,

$$a_k = \frac{1}{5}\sum_{j}^{5} v_{j,k} \tag{23}$$

Fig. 8 (a) shows the results of continuous motion estimation of elbow joint with 1.25 kg load. The joint angles of the model predicted are almost coincident with the actual measured joint angle. The angle errors are between -0.47rad and 0.30rad, as shown in Fig. 12(b), RMSE is 0.17rad. Fig. 12(c) shows the results of continuous motion estimation of elbow joint with 2.5kg load. The joint angles of the model predicted are also almost coincident with the actual measured joint angle. And the angle errors are between -0.41rad and 0.34rad, as shown in Fig. 12(d), RMSE is 0.18rad. The average value of RMSE for all tests was 0.185 rad.

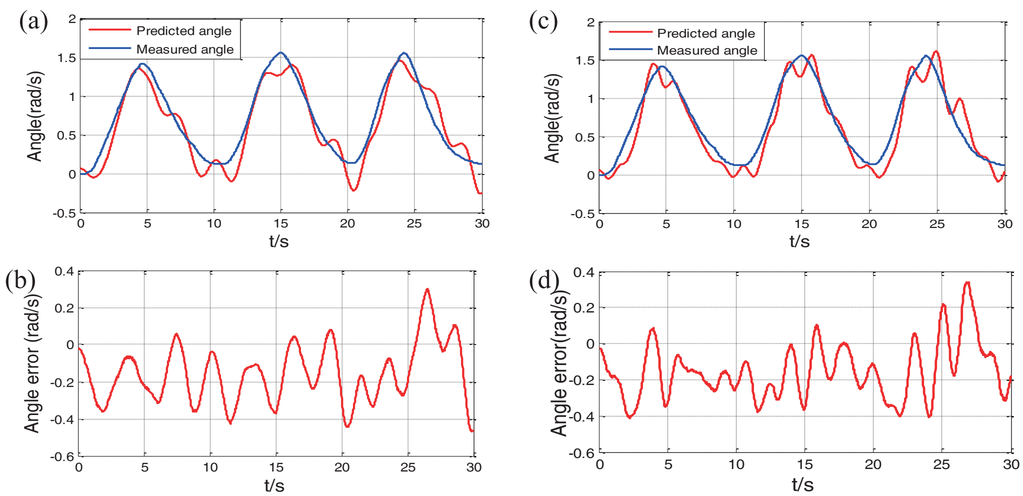

Fig. 8. The results of continuous motion estimation.

B. Experiment for TVSEM Verification

Fig. 9 (a) shows the stiffness curve of the skeletal muscle simulated by human elbow stiffness model presented in this paper. From which we can see: a) Under the same joint angle condition, the skeletal muscle stiffness with 2.5kg load is obviously larger than the skeletal muscle stiffness with 1.25kg load; b) Under the same load condition, the muscle activity a is close to zero when θ is close to 0°. That is, the skeletal muscle stiffness k_{mt} is minimal, close to 0 N/m, when the muscle force F is close to 0 N; When θ is close to 90°, the muscle activity a is the largest and the muscle force F is the largest, that is, k_{mt} is close to the peak value.

Therefore, we can think that in the normal movement of human body joints, when the muscles with larger activity that the muscles will have stronger stiffness.

Fig. 9 (b) shows the simulation results of the TVSEM of elbow joint. From which we can see: a) Under the same joint angle condition, the elbow joint stiffness with 2.5kg load is obviously larger than the elbow joint stiffness with 1.25kg load; b) Under the same load condition, when θ is close to 0°, the muscle activity a is close to zero. At this time, F is close to 0 N, so k_{mt} is minimal, and K is also close to 0 Nm/rad; When θ close to 90 °, with the largest muscle activity a, so the muscle force F, skeletal muscle stiffness k_{mt}, and the joint stiffness K are also close to the peak. When the load is 1.25kg, the peak value is about 25 Nm/rad, and the peak value is about 30Nm/rad when the load is 2.5kg.

Therefore, we can also think that in the normal joint movement of the human body, the joint stiffness is stronger when the relevant muscles have larger activity.

In order to verify the correctness of the TVSEM of elbow joint, we selected the method that fixed position pose with representative joint angle for data fitting. Using digital thrust meter to produce disturbance torque, and the thrust meter can communicate with the computer by USB to Rs232. And we can observe the peak of disturbance force in the computer. The perturbation angles were measured by using a photoelectric encoder, the experimental environment is shown in Fig. 6 (c) and (d). During the experiment, the subjects were obscured eyes so that they could not produce voluntary resistance to overcome the disturbance through vision. And the disturbing force was randomly generated by another experimenter.

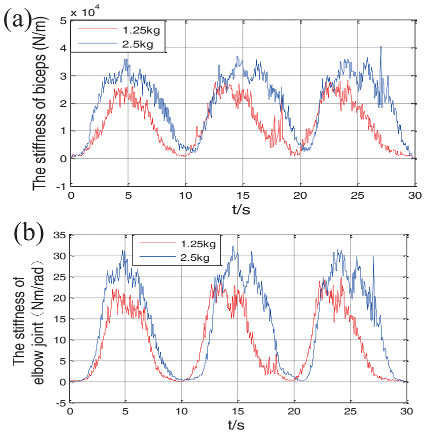

Fig. 9 (a)The characteristic curve of muscle stiffness; (b)The characteristic curve of elbow joint stiffness.

The experimental subjects in *experiment A* were pre-selected with θ=30°, 70° and 90° with 1.25 kg and 2.5 kg load, and subjected to multiple disturbances at each pre-selected angle. Because the actual joint angle was difficult to be controlled, we selected the nearest five sets of experimental data to the initial angle with recording and analysis. And in order to reduce the muscle fatigue, the subjects had a rest for five minutes between the different pre-selected angle experiments. We selected the disturbance angles ($\Delta\theta_1$, $\Delta\theta_2$, etc.) whose initial angles were the most frequently displayed in this group. Using the measured disturbance force we could calculate the disturbance torque ΔT.

The results between the real and estimated stiffness of elbow joint is shown in Fig. 10. It can be seen from Fig. 10 that the fitting curve of the measured joint stiffness and the curve of simulation results have the same trend.

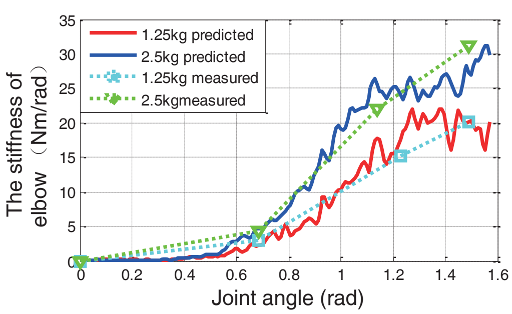

Fig. 10 The results between the real and estimated stiffness of elbow joint; (dotted) the thrust meter measurement; (solid) estimated value via TVSEM.

V. Conclusion

In this paper, the geometric model of elbow physiological structure was built, and based on it the joint forward dynamics was built for estimating continuous joint motion. GA was used to get optimal parameters of CMEM on different external loads. The SRS was used for muscle stiffness estimation, and the moment balance equation of elbow joint was built for estimating elbow joint stiffness. Extensive experiments, that are the comparisons between the model-based estimations and the photoelectric encoder measurements for CMEM, verified the effectiveness of the method. And extensive experiments, that are the comparisons between the model-based estimations and the thrust meter measurements, verified the effectiveness of the TVSEM.

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