A Novel Motion Estimate Method of Human Joint with EMG-driven Model

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***Abstract*—Electromyography (EMG) has been widely used as control commands for prosthesis, powered exoskeletons and rehabilitative robots. In this paper, an EMG-driven state-space model is developed to estimate joint angular velocities and angles throughout elbow flexion/extension. The state equation of the model combines the Hill-based muscle model with the forward dynamics of joint movement, and expresses the kinematic variables as a function of neural activation levels. Then, EMG features including integral of absolute value and waveform length are extracted, and two quadratic equations which associate the kinematic variables with EMG features are fitted to represent the measurement equation. Based on the proposed model, the joint angular velocities and angles are estimated just using the EMG signals with the Extended Kalman Filter (EKF), and the estimation results are used to control a manipulator. The experimental results demonstrate the efficiency of EMG-based motion control with the proposed model.**

Keywords-EMG; state space; Hill-based muscle model; EKF

I. INTRODUCTION

Using EMG as control signals to realize human-robot interface is popular in designing wearable robots. Many researchers study on classifying EMG to map different motions and construct pattern-recognition-based myoelectric control systems [1-4]. The reliability of these systems depends largely on the classification accuracy. To improve the classification accuracy, extracting various feature sets from EMG, along with developing multiple classification methods to discriminate feature sets for different motions, has already been investigated. Some commonly utilized EMG feature sets include EMG amplitude, autoregressive coefficients, waveform length, integral of EMG, cepstrum coefficients, and the wavelet packet transform. Certain feature sets, such as the wavelet packet transform, must be used in conjunction with dimensionality reduce such as principal components analysis (PCA) [1] or linear discriminant analysis (LDA) [2] to yield proper signal representation. For selected feature sets, the classification performance has been studied by various classifiers such as genetic algorithms [2], artificial neural networks [3], and Gaussian mixture models [4].

Based on pattern classification, some myoelectric control systems have been successfully designed. However, these systems only map EMG signals to finite motions, and can not accomplish smooth motion like human limb. To achieve smooth motion control, muscle physiological models have been investigated to quantitatively decode limb motion from EMG signals. The Hill-based muscle model is the most frequently utilized in previous researches [5, 6]. In [5], an EMG-based forward dynamics model has been presented, which includes muscle activation dynamics, Hill-based muscle contraction dynamics, musculoskeletal geometry, and joint forward dynamics. The model is complex, and has too many unknown physiological parameters. In [6], a simplified model for controlling lower extremity exoskeleton is developed, and a step calibration process is constructed to optimize the less unknown parameters. The studies mentioned above mainly investigate torque control for power assisting. The exoskeletons' movement, which is determined from the estimated joint torque, will be easily inconsistent with the movement of human limb. Thus, a model, which can estimate limb motion directly from EMG signals, is significant for motion matching between human and robots.

In this paper, a state-space model, which directly maps the muscle activations of the biceps brachii to the elbow joint motion, is developed. The state equation of the model fuses the Hill-based muscle model and joint forward dynamics, and the measurement equation associates the joint motion with EMG features in the form of quadratic equations. Based on the proposed model, the joint angular velocities and angles are estimated by using the EKF throughout elbow flexion/extension, and the estimation results are inputted to control a manipulator in real time. The experimental results suggest the model is feasible to estimate human limb motion just using EMG signals.

The rest of this paper is organized as follows. Section II describes the muscle physiological basis and the modeling process. The motion estimation and experiments will be presented in Section III. Section IV draws a conclusion.

II. EMG-TO-MOTION MODEL

Our EMG-driven model derives from Hill-based muscle model and joint forward dynamics. The model directly builds the relationship between the joint motion and EMG signals. Three sub-models are involved in the model: (a) EMG signal to muscle activation, (b) muscle activation to joint motion, and (c) joint motion to EMG features. The model's structure, including its application to estimate the joint motion by using EKF, is shown in Fig. 1.

A. EMG Signal to Muscle Activation

Raw EMG signals are postprocessed with high-pass filtering, full-wave rectification, normalizing by peak rectified EMG value, and low-pass filtering. A recursive filter is then used to calculate neural activation, $u(t)$, from the postprocessed EMG value, $e(t)$. This process can be represented in the following discrete form [5, 7]:

$$u(t) = \alpha \cdot e(t-d) - \beta_1 \cdot u(t-1) - \beta_2 \cdot u(t-2) \qquad (1)$$

where d is the electromechanical delay, α, β_1, and β_2

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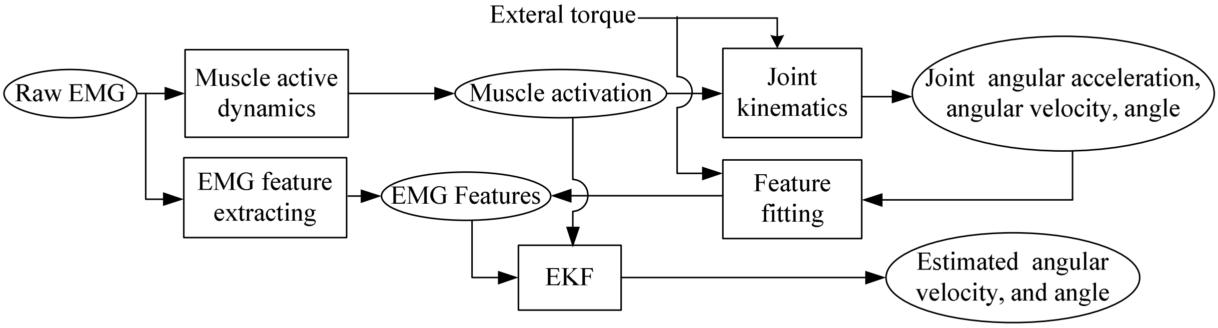

Figure 1. The model's structure and the process of motion estimation.

are coefficients that define the second-order dynamics. To realize a positive stable solution, a set of constraints is employed, i.e.

$$\beta_1 = \gamma_1 + \gamma_2, \ \beta_2 = \gamma_1 \cdot \gamma_2, \ \alpha - \beta_1 - \beta_2 = 1 \tag{2}$$

where $|\gamma_1| < 1$, $|\gamma_2| < 1$.

There exists nonlinear relationship between neural activation $u(t)$ and muscle activation $a(t)$ for some muscles, especially at lower level of EMG. To account for this, a simple transformation is proposed in [8], as follows:

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

where A is the nonlinear shape factor allowed to vary between -3 and 0.

B. Muscle Activation to Joint Motion

Once having obtained muscle activation, we compute the joint angular acceleration, by integrating Hill-based muscle model and joint forward dynamics into a single equation. Hill-based muscle model consists of two elements: a contractile element producing the active muscle force F_A^m, and a parallel elastic element producing the passive force F_P^m [6]. As shown in Fig. 2, l^m is the muscle fiber length, l^t is the total length of the tendons, and ϕ is the pennation angle. Thus, the musculotendon length l^{mt}, can be expressed through

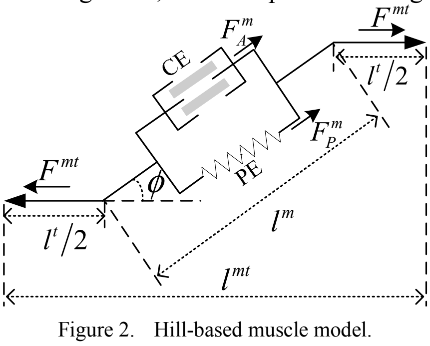

Figure 2. Hill-based muscle model.

$$l^{mt} = l^t + l^m \cdot \cos(\phi) \tag{4}$$

The muscle-tendon force (F^{mt}) is calculated as

$$F^{mt} = \left(f_A(l) \cdot f_V(v) \cdot a(t) + f_P(l)\right) \cdot F_0^m \cdot \cos(\phi) \tag{5}$$

where $l = l^m / l_0^m$, $v = v^m / v_0^m$. $a(t)$ is the muscle activation. F_0^m is maximum isometric muscle force, l_0^m represents the optimal fiber length, and v_0^m is the maximum muscle contraction velocity. l is the normalized muscle fiber length, and v is the normalized muscle fiber velocity. $f_A(l)$, $f_V(v)$, and $f_P(l)$ define the normalized active force-length relationship, force-velocity relationship, and the normalized passive elastic force-length relationship, respectively.

Before describing the details of (5), three assumptions are presented to simplifying the Hill-based muscle model.

- Suppose l^t is constant. According to [10], the tendon is rather stiff: the strain is only about 3% of the tendon length for maximum muscle force and can be neglected here.
- Suppose the pennation angle of the biceps brachii is constant throughout elbow flexion/extension. For muscles with a small pennation angle, the pennation angle will have little effect on the force in the musculotendonous unit [5]. According to [11], The pennation angle of the biceps brachii is 0°, so its change can be neglected.
- Suppose $f_V(v) = 1$. Since the movement considered in this paper is rather slow, and the maximum muscle velocity that is used for normalization of the muscle velocity is reported to be very large (about $10 l_0^m / s$) [5, 6], the force-velocity relationship of the biceps brachii can be omitted here.

Therefore, to describe (5), we only need to know the expressions of $f_A(l)$ and $f_P(l)$. A second-order polynomial is used to model $f_A(l)$ [5]

$$f_A(l) = \begin{cases} -2.06 + 6.16 \cdot l - 3.13 \cdot l^2, & 0.5 \le l \le 1.5 \\ 0, & otherwise \end{cases} \tag{6}$$

The passive muscle force function is given by

$$f_P(l) = e^{10 \cdot l - 15} \tag{7}$$

As is discussed above, once the length l^m or l^{mt}, and the constant physiological parameters (F_0^m, l^t, l_0^m and ϕ) are known, the muscle force can be calculated. Besides, if the muscle moment arm is acquired, then the muscle's contribution to joint moment can be computed. To compute the length and the moment arm for a musculotendonous unit, a musculoskeletal model accounting for their change as a function of joint angle is required [5]. The musculoskeletal model can be expressed by polynomials [5, 12]. In this study, we only consider the biceps brachii, and its corresponding joint is elbow. Thus, a first-order polynomial is given to express the musculotendonous length of the biceps brachii as a function of the elbow joint angle.

$$l^{mt} = b_0 + b_1 \cdot \theta \tag{8}$$

where θ is the elbow joint angle, and b_0, b_1 are constants.

Then we can compute the moment arm using the tendon displacement method described in [10]

$$r = \frac{\partial l^{mt}(\theta)}{\partial \theta} = b_1 \tag{9}$$

Thus, the biceps' contribution to the elbow joint moment is

$$\tau = F^{mt} \cdot r \tag{10}$$

where τ is the elbow joint moment.

During the elbow doing flexion/extension, the upper arm keeps stationary and parallel to body, as described in Fig. 3. Using the joint forward dynamics, we can compute the angular acceleration of the elbow joint.

$$\ddot{\theta} = \frac{1}{I} \cdot (\tau - \tau_{ex}) \tag{11}$$

where I is the elbow's inertia, which is assumed to be constant here. τ_{ex} includes the external torque and the forearm gravity torque. Here the gravity and length of the forearm are known, so τ_{ex} can be computed.

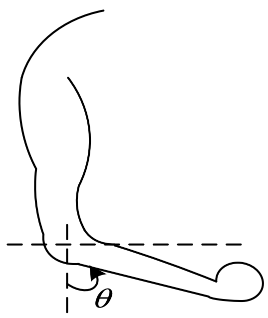

Figure 3. The movement of the elbow joint.

Combining the modified Hill-based with the joint forward dynamics, i.e. substituting (4)-(10) into (11), and simplifying the formula, we have

$$\ddot{\theta} = \left(s_0 + s_1 \cdot \theta + s_2 \cdot \theta^2\right) \cdot a(t) + s_3 \cdot e^{s_4 \cdot \theta} - s_5 \cdot \tau_{ex} \tag{12}$$

Noting that for simplifying the formula, we represent the products of the unknown constants mentioned above with some new symbols, i.e. $s_i, i = 0,1,\cdots,5$.

After having computed the angular acceleration, we can acquire the angular velocity and the angle by integrating (12). Write the equations in discrete form

$$\begin{cases} \ddot{\theta}(k+1) = \left(s_0 + s_1 \cdot \theta(k) + s_2 \cdot \theta(k)^2\right) \cdot a(k) \\ \qquad + s_3 \cdot e^{s_4 \cdot \theta(k)} - s_5 \cdot \tau_{ex}(k) \\ \dot{\theta}(k+1) = \dot{\theta}(k) + \ddot{\theta}(k) \cdot T \\ \theta(k+1) = \theta(k) + \dot{\theta}(k) \cdot T \end{cases} \tag{13}$$

where T is time-step. $\dot{\theta}$ and θ are the joint angular velocity and angle, respectively.

C. Joint Motion to EMG Features

If knowing the muscle activation $a(k)$ and the external torque $\tau_{ex}(k)$, we can determine the joint movement using (13). But (13) is an open-loop system, its estimation result is easily divergent. A measurement equation, which can correct the estimation result in real time, is introduced in our study. Two reasons motivate us to acquire the reasonable measurement equation.

- EMG signals contain many features, such as EMG amplitude, waveform length, and cepstrum coefficients, but only muscle activation $a(k)$ is involved in (13). Other useful information of EMG signals will be lost.
- In actual motion controlling, the frequency of sending control commands is far less than the sampling frequency of EMG signals. Thus, we can extract certain EMG features in a time window as the adjustment information to correct the motion estimation.

The chosen EMG features are integral of absolute value and waveform length. Let ξ_i be the *i*th sample of EMG signals, and *N* be the time window size.

Integral of Absolute Value (*IAV*): *IAV* is an estimate of the summation of the absolute value of the EMG signals.

$$IAV = \frac{1}{N} \cdot \sum_{i=1}^{N} |\xi_i| \tag{14}$$

Waveform Length (*WL*): *WL* is a cumulative variation of the EMG that can indicate the degree of variation about the EMG signals.

$$WL = \sum_{i=1}^{N-1} |\xi_{i+1} - \xi_i| \tag{15}$$

To relate the EMG features with the joint movement, we use two second-order polynomials to represent the relationship between them. Because angular acceleration is fluctuant frequently in actual movement, only angular velocity and angle are involved in the equation

$$\begin{aligned} y^i(k) &= c_0^i \cdot \tau_{ex}(k) + c_1^i \cdot \dot{\theta}(k) + c_2^i \cdot \theta(k) \\ &+ c_3^i \cdot \dot{\theta}(k)^2 + c_4^i \cdot \theta(k)^2 + c_5^i \cdot \dot{\theta}(k) \cdot \theta(k) \end{aligned} \tag{16}$$

where $i = 1,2$, y^1 and y^2 represent the *IAV* and *WL* of EMG signals. Combining (13) and (16), we acquire the state space model, which relates EMG signals with the joint movement.

III. Motion Estimation

In this section, we will study the motion estimation with the proposed model.

A. Estimation Algorithm

For the state estimation of a state-space model, Kalman Filter (KF) is the most commonly used estimator. Because the state equation and the measurement equation are nonlinear in our model, an extended Kalman Filter is applied to estimate the elbow joint motion. The EKF gives an approximation of the optimal estimate. The nonlinear equations are linearized around the last state estimate by using Taylor series expansion.

Then the consecutive prediction-update cycle of the KF is used to propagate the minimum mean-square-error estimate. Refer [9] for more details of the EKF.

B. Data Acquisition

An active surface electrode is placed on the biceps brachii to sample the EMG signals. The EMG signals are amplified by using a self-designed circuit module, and then digitized by using an A/D converter board (PCL-818HD). The sampling frequency is 1024Hz. At the same time, an inertial measurement unit (IMU, Vn100) is used to record the real angular velocities and angles of the elbow joint at the frequency of 20Hz, as shown in Fig. 4.

For real-time implementation, a 128ms moving window with a 64ms window increment is set to extract the EMG features. Thus, the estimation result is generated per 64ms. It satisfies the requirement of real-time control.

All processes, including data acquisition, model construction, motion estimation and motion control, are implemented in QNX real-time system environment.

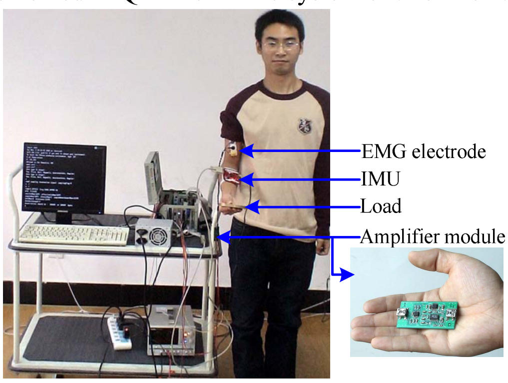

Figure 4. The data acquisition system.

C. Experiments and Experimental Results

Two phases are included in our experiments: the parameter-identification phase and the real-time operation phase. During the parameter-identification phase, the subject takes a 1.92kg external load, and flexes/extends his/her elbow with normal velocity to generate about 30s of data. We use these data to identify the unknown parameters in the state-space model, i.e. γ_1, γ_2, A, s_i and c_i, i=0,1,...5. The Levenberg-Marquardt algorithm is used to minimize a chosen merit function, i.e.

$$\min \sqrt{\sum \left(z(\chi) - z_{measured} \right)^2} \tag{17}$$

where χ is an unknown parameter vector, z is the estimated value, and $z_{measured}$ is the measurement value.

The unknown parameters in the state equation and the measurement equation are identified off-line independently, and the minimum errors computed from (17) are recorded to build the covariance matrices $\boldsymbol{Q}$ and $\boldsymbol{R}$, which will be used in the EKF.

After the identified parameters are substituted into our model, the real-time operation phase commences. The subject respectively takes 1.92kg and 3.23kg external load in two experiments. Raw EMG signals are collected, prepossessed, and then inputted into the EKF to estimate the angular velocities and angles of the elbow in real time.

Raw EMG signals, the muscle activation, EMG features and the estimated results are shown in Fig. 5 ~ Fig. 8.

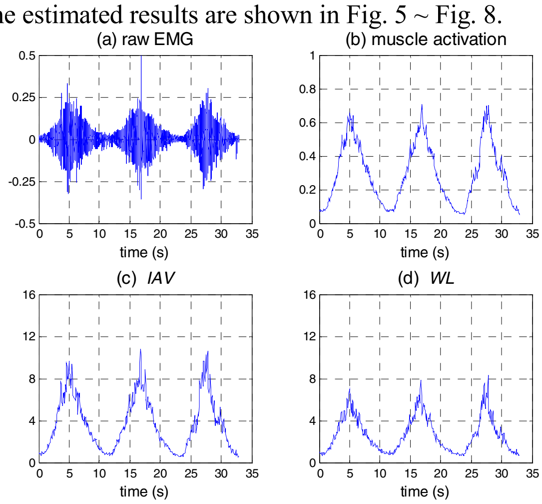

Figure 5. Raw EMG signals and the EMG features for taking 1.92kg load.

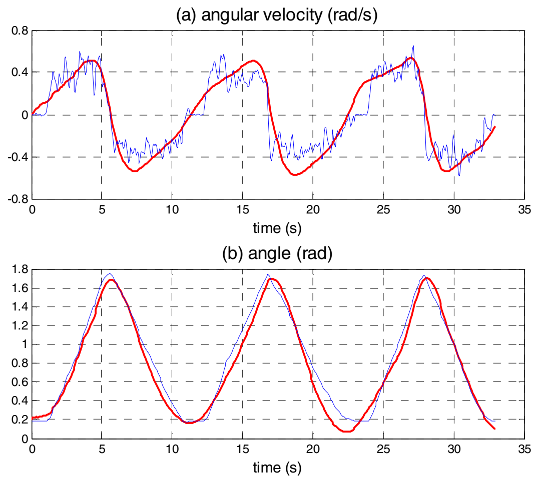

Figure 6. The movement of the elbow joint and the estimated motion for taking 1.92kg load. The thick red lines represent the estimated values, and the thin blue lines represent the real measurement values.

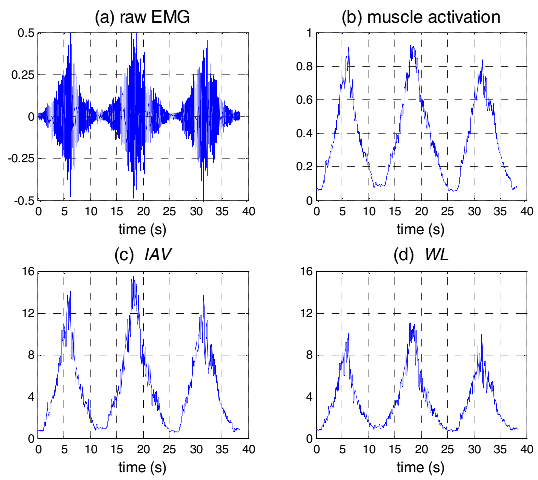

Figure 7. Raw EMG signals and the EMG features for taking 3.23kg load.

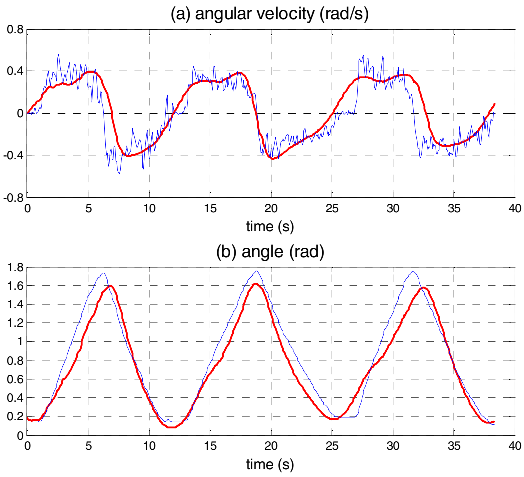

Figure 8. The movement of the elbow joint and the estimated motion for taking 3.23kg load. The thick red lines represent the estimated values, and the thin blue lines represent the real measurement values.

As can be seen from Fig. 6 and Fig. 8, the model is applicable for estimating the human limb motion with different external loads, and the estimated angular velocities and angles well fit the real measurement values from IMU. The estimated curves are smooth, and fit to motion control. In the next experiment, the estimated angles are used to control a manipulator to follow human limb's motion. The manipulator works in position control mode, and can real- timely track the elbow joint angles, as shown in Fig. 9

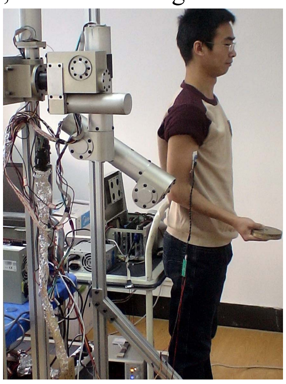

Figure 9. The EMG-based position control of a manipulator.

IV. CONCLUSION

In this paper, An EMG-driven state-space model for motion estimation is constructed. The state equation of the model, which combines the Hill-based muscle model with joint forward dynamics, directly maps muscle activations to the joint motion. To make full use of the EMG signals, the measurement equation extracts the integral of absolute value and waveform length of the EMG signals, and defines the extracted EMG features as functions of the joint motion. With the proposed closed-loop model, the angular velocities and angles of the elbow joint are estimated using the EKF in real time. The model estimations are fit to motion control. Because our model is developed based on the muscle physiology, it is useful to explore the EMG-based human-robot interface in designing wearable robots. In the future study, we will consider to build a multi-joint EMG-motion model.

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