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Human Joint Motion Estimation for Electromyography (EMG)-Based Dynamic Motion Control

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***Abstract*— This study aims to investigate a joint motion estimation method from Electromyography (EMG) signals during dynamic movement. In most EMG-based humanoid or prosthetics control systems, EMG features were directly or indirectly used to trigger intended motions. However, both physiological and nonphysiological factors can influence EMG characteristics during dynamic movements, resulting in subject-specific, non-stationary and crosstalk problems. Particularly, when motion velocity and/or joint torque are not constrained, joint motion estimation from EMG signals are more challenging. In this paper, we propose a joint motion estimation method based on muscle activation recorded from a pair of agonist and antagonist muscles of the joint. A linear state-space model with multi input single output is proposed to map the muscle activity to joint motion. An adaptive estimation method is proposed to train the model. The estimation performance is evaluated in performing a single elbow flexion-extension movement in two subjects. All the results in two subjects at two load levels indicate the feasibility and suitability of the proposed method in joint motion estimation. The estimation root-mean-square error is within 8.3% $\sim$ 10.6%, which is lower than that being reported in several previous studies. Moreover, this method is able to overcome subject-specific problem and compensate non-stationary EMG properties.**

I. INTRODUCTION

In advanced humanoid and prosthetic systems, joint motions are preferred to be inspired by human mind, such as Electroencephalography (EEG), Electromyography (EMG) and Electroneurography (ENG), in order to realize human-like natural movements. Wherein, surface EMG has attracted much attention since it provides noninvasive and reliable measurement of muscle activity. Under isometric muscle contraction, various EMG amplitude and frequency features were applied to investigate the muscle recruitment strategy [1] and torque estimation [2][3][4].

In comparison, under dynamic condition, most literature focused on the fundamental research with various kinematic or dynamic constraints due to the structural and functional heterogeneity of muscles and the inherent stochastic nature of EMG signals [5]. In other works, although EMG has been used to estimate joint motion in either a dynamic [6] or static manner, most of them focused on motion recognition in a static way, that is, several predefined motions were classified from EMG signals after sufficient data training [7] [8] [9]. For example, a time-delayed artificial neural network (TDANN) method was proposed to predict three shoulder motions and one elbow motion (flexion-extension) from six muscles, resulting in 20.2% root-mean-square (RMS) error during single elbow joint flexion-extension [7]. By assuming quasi-stationary EMG property during short-term dynamic movements, an EMG-based elbow joint angle estimation method was proposed with more than 20% prediction error in a 6-s elbow flexion-extension movement [10]. However, the control strategy based on such pattern recognition technique is different from the natural neuromuscular control strategy where the human's intention (represented for example by EMG) was consecutively mapped to the joint motion. Moreover, as reported in [11] and [12], EMG characteristics could be influenced by both physiological and nonphysiological factors during dynamic movements, resulting in subject-specific, non-stationary and crosstalk problems. Thus, it was difficult to find consistent patterns among subjects regarding the motor control strategies [11]. Even for single subject, since the concentric and eccentric muscle contractions adopted different motor control strategies, the joint angle had different effects on related EMG signals [13]. As a result, the EMG-based joint motion estimation was complicated by such phenomena.

This work proposes an alternative method to consecutively estimate joint dynamic motion from EMG signals which allows to cover subject-specific and time-variant problems in EMG-based motion control. The method is evaluated in a single elbow dynamic movement considering the importance of elbow flexion-extension function in performing daily activities.

II. METHOD

A. Model structure

In order to describe the muscle electromechnical dynamic system, it is difficult and unsuitable to choose a physiological model structure. In this study, the muscle mechanical behavior is mapped from the muscle electrical behavior by a multi input-single output autoregressive structure with exogenous input (ARX) model [2][3]:

$$A(z)y(k) = \mathbf{B}(z)\mathbf{u}(k) + w(k) \tag{1}$$

where y(k) and $\mathbf{u}(k)$ are respectively model output and input matrix, w(k) is zero mean and Gaussian white noise. The multiple model inputs and corresponding coefficient matrices were defined as:

$$\begin{aligned}\mathbf{u}(k) &= \begin{bmatrix} u_1(k) & u_2(k) & \cdots & u_n(k)\end{bmatrix}^T \\ \mathbf{B}(z) &= \begin{bmatrix} B_1(z) & B_2(z) & \cdots & B_n(z)\end{bmatrix}\end{aligned} \tag{2}$$

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where n is the number of model input. $A(z)$ in (1) and $B_i(z)$ $(i = 1 \sim n)$ in (2) are polynomials in the backward shift operator, z^{-1}, given by:

$$A(z) = 1 + a_1 z^{-1} + a_2 z^{-2} + \cdots + a_l z^{-l}$$
$$B_i(z) = b_{1i} z^{-1} + b_{2i} z^{-2} + \cdots + b_{mi} z^{-mi} \quad (i = 1 \sim n)$$

In state-space form, the state vector consists of $q = max(l, m1, m2, \cdots, mn)$ variables. The previous state $\mathbf{x}(k-1)$ is transferred to the current state $\mathbf{x}(k)$ by a transfer matrix $\mathbf{A}(k) \in \mathbb{R}^{q \times q}$, such that

$$\mathbf{x}(k) = \mathbf{A}(k)\mathbf{x}(k-1) + \mathbf{B}(k)\mathbf{u}(k-1) + \mathbf{w}(k) \quad (3)$$

where $\mathbf{u}(k-1) \in \mathbb{R}^{n \times 1}$ contains the previous model inputs which are known at each current step. Matrix $\mathbf{B}(k) \in \mathbb{R}^{q \times n}$ relates the previous model input $\mathbf{u}(k-1)$ to the current state $\mathbf{x}(k)$. The measurement model relies on the state element $\mathbf{x}(k)$ by

$$y(k) = \mathbf{C}(k)\mathbf{x}(k) + v(k) \quad (4)$$

The $\mathbf{w}(k)$ in (3) and v(k) in (4) are respectively Gaussian white noise of the system model and the measurement sensor. All the model coefficients contained in $\mathbf{A}(k)$ and $\mathbf{B}(k)$ are combined into coefficient vector $\theta(k)$ and identified later.

B. Estimation method

As the muscle electromechanical dynamics are usually non-stationary, an adaptive estimator is required to catch the time-variant system characteristics. The model states in $\mathbf{x}(k)$ and the coefficients in $\theta(k)$ were combined into an augmented state vector $\mathbf{\Theta}(k) = \begin{bmatrix}\mathbf{x}(k)^T & \theta(k)^T\end{bmatrix}^T$. Correspondingly, the original process and measurement model in (3) and (4) were rewritten as following:

$$\mathbf{\Theta}(k) = \mathbf{F}(\mathbf{\Theta}(k-1), \mathbf{u}(k-1), \mathbf{w}(k))$$
$$y(k) = \mathbf{G}(\mathbf{\Theta}(k), v(k))$$

In order to identify the time-variant system, a Kalman filter with fading factor was previously proposed to adaptively identify joint torque from EMG during isometric muscle contraction [2]. This method is applied in this study to estimate the joint angle from EMG during dynamic movement. The recursive algorithm of KF consists of two phases, prediction and correction.

In the prediction phase, the system is assumed to be stationary, the *a priori* state estimate at instant k, $\hat{\mathbf{\Theta}}^-(k)$, is calculated from the *a posteriori* state at previous instant k-1, $\hat{\mathbf{\Theta}}(k-1)$, according to (5). The estimate error covariance $\mathbf{P}(k)$ is propagated according to (6).

$$\hat{\mathbf{\Theta}}^-(k) = \mathbf{F}(\hat{\mathbf{\Theta}}(k-1), \mathbf{u}(k-1), 0) \quad (5)$$
$$\mathbf{P}^-(k) = \mathbf{D}(k)\mathbf{P}(k-1)\mathbf{D}^T(k)/\lambda \quad (6)$$

where $\mathbf{D}(k)$ is the Jacobian matrix of partial derivations of process transfer function $\mathbf{F}$ with respect to the variables involved in $\mathbf{\Theta}$.

In the correction phase, $\mathbf{K}(k)$ in (7) is called as KF gain that minimizes the *a posteriori* error covariance,

$$\mathbf{K}(k) = \mathbf{P}^-(k)\mathbf{H}^T(k)(\mathbf{H}(k)\mathbf{P}^-(k)\mathbf{H}^T(k) + \lambda)^{-1} \quad (7)$$

where λ is a fading factor allowing to neglect some old measurements for enhancing the identification performance. The choice of λ must consider a tradeoff between tracking smoothness and accuracy. Generally, it is within [0.9,1]. $\mathbf{H}(k)$ is the Jacobian matrix of partial derivations of sensor transfer function $\mathbf{G}$ with respect to $\mathbf{\Theta}$.

When actual measurement $y(k)$ is available, an *a posteriori* state estimate is generated by incorporating measurement as in (8). An *a posteriori* error covariance estimate is obtained via equation (9).

$$\hat{\mathbf{\Theta}}(k) = \hat{\mathbf{\Theta}}^-(k) + \mathbf{K}(k)(y(k) - \mathbf{G}(\hat{\mathbf{\Theta}}^-(k), 0)) \quad (8)$$
$$\mathbf{P}(k) = (\mathbf{I} - \mathbf{K}(k)\mathbf{H}(k))\mathbf{P}^-(k) \quad (9)$$

C. Data collection and processing

Experimental data were collected from two able-bodied subjects to evaluate the proposed model and estimation method. The subjects stood upright with a barbell in their right hand. They were asked to perform elbow flexion-extension movement in a natural way periodically as performing exercise. In order to have a large range of elbow angle, the joint was flexed and extended to the maximum position. To assess the estimation method performance at different motor recruitment levels, two barbell weight levels were tested for each subject.

Two channels of wireless EMG (Myon320, Prophysics, Zurich, Switzerland) were placed respectively on the Biceps and lateral Triceps muscles. The EMG signals were amplified (gain 1000) and sampled at 1000 Hz. An inertial sensor (IMU Pocket U2) was located on the forearm proximate to the wrist joint. The y axis of the inertial sensor was adjusted parallel to the elbow joint flexion axis with z axis of IMU pointing towards the elbow joint. The inertial sensor records nine variables including three coordinate motions, three angular velocity variables and three displacement variables with respect to its axes. The inertial sensor recording was sampled at 100 Hz and synchronized with the EMG recording by a customized approach. An example of the raw EMG and inertial data is plotted in Fig. 1. A time delay between EMG and joint motion is clear, which is around 1.5 s for subject S1 and 3.6 s for subject S2 in this study.

Both the EMG and inertial data recordings were saved in a computer and treated off-line in Matlab. The EMG signals were first low-pass filtered (Butterworth, 6th order, cutoff frequency 300 Hz), and then two EMG time-domain features, peak-to-peak (PTP) and variance (VAR), were calculated every 10 ms with analysis window length of 15 ms. PTP is a measurement from the negative peak value to the positive peak value within an analysis window. VAR measures the power of signals x_i and was calculated as $VAR = \frac{1}{n-1}\sum_{i=1}^{n} x_i^2$.

The elbow joint angle was computed from the angular velocity along y axis. As the pure numerical integration of angular velocity tends to generate unwanted linear trend of error, resulting in inaccurate angle derivation, a least square-based method was used to eliminate the drift to obtain accurate joint angle in this work. The calculation

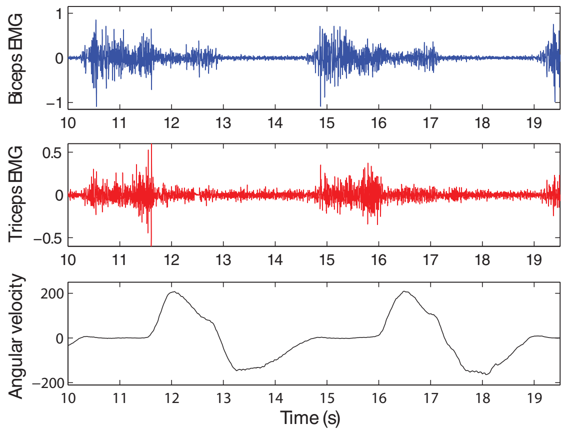

Fig. 1. Raw EMG signals recorded from Biceps (Top) and Triceps (Middle). Bottom: Raw elbow angular velocity signals recorded by an inertial sensor. There is a clear time delay between EMG and joint motion.

consists of two steps, numerical integration first and then trend of error removal. After the joint angle was derived through the numerical integration of angular velocity, we got dataset (t_i, s_i). Assuming the trend term can be fitted by a polynomial function:

$$f_m(t) = \sum_{k=0}^{m} p_k t^k$$

where p_k is the polynomial coefficient, m indicates the polynomial order. The next step is to find appropriate coefficient sequence p_k which minimizes the squared residuals I,

$$I = \sum_{i=0}^{n-1} (s_i - f_m(t_i))^2$$

This quadratic problem can be resolved by making $\partial I / \partial p_k = 0$. As only the first-order trend error exists in the integration process from angular velocity to angle, the real joint angle was calculated as $s_i - f_1(t)$.

The EMG features and joint angle were finally both normalized by their maximum value and served to train the joint motion estimation model shown in (1). The performance of trend error removal method for joint angle calculation from angular velocity was demonstrated in Fig. 2. The trend error-free joint angle (red) matches our intuitive motion tendency comparing with the purely integrated joint angle (blue).

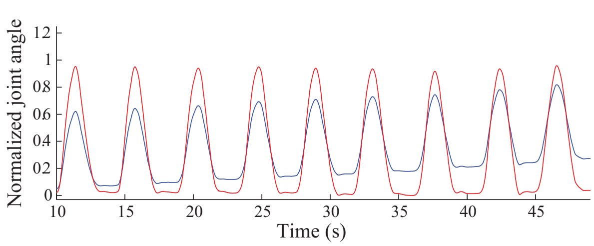

Fig. 2. The joint angle calculated by pure numerical integration of angular velocity has clear trend error over time (blue). Trend error-free joint angle was calculated by a least square trend error removal method (red).

III. Results

In order to evaluate the proposed muscle electromechanical model and estimation method, the experimental data were used to train the model firstly. Then the cross validation was conducted and the EMG-based joint angle estimate was compared with the measured joint angle. An ARX(2,2,2,2,2) model was applied to map EMG PTP and VAR features from both the Biceps and Triceps to the elbow joint angle. The evaluation process was conducted at two external load levels in each subject, in total four test sessions. The prediction performance was determined by RMS error defined by $RMS = \sqrt{\frac{1}{N}\sum_{k=1}^{N}(s_r - s)^2}$, where s_r is the joint angle calculated from the inertial sensor and s is the predicted joint angle based on EMG signals.

Fig. 3 reveals the joint angle estimation result in subject S1 at external load of 2.3 kg. The experimental data within the first 35 s were used to identify the model. The identified model was used to predict joint angle from two channel of EMG recordings. The RMS error of identification process and prediction process are respectively 4.5% and 8.3%. This performance is much better than the results reported in [7] and [10]. Fig. 4 shows the result in subject S1 at external load of 1.8 kg. Fewer data were used to validate the method here as some data were not correctly recorded. The possible reason is that the electrodes did not tightly contact with the skin during the dynamic movement. By identifying with 20-s data, the joint angle estimate error is still less than 10% only from EMG signals. Fig. 5 and Fig. 6 are the estimation results in subject S2. The average angle prediction error is around 10%. We can notice that the estimation accuracy in Fig. 3$\sim$ Fig. 6 does not decline over time, indicating that the method can be used longer than 50 s in such experimental condition. The similar results in two subjects at two load levels suggest that this method can be used for different subjects even when EMG signals have subject-specific properties. The relatively lower estimation quality in subject S2 probably comes from the involuntary nervous effects which were seen in this subject in the experiments.

IV. Conclusions and Perspectives

In comparison with physical sensor-based motion control, natural sensor-based motion control allows to trigger movement by human's intention. As electrical muscle activity occurs earlier than mechanical muscle response, it is feasible to use EMG-motion mapping information for motion control. In this study, we proposed an alternative method to consecutively estimate joint motion from EMG signals during dynamic movement. This method used two-channel EMG signals from a pair of agonist and antagonist muscles to estimate the intended joint motion (angle) for motion control. The proposed predictive model and estimation method were validated in two subjects at two load levels. The estimation results are comparable comparing with the previous studies. In addition, the experiments were conducted without any kinematic or dynamic constraints which suggests the method can be applied in a natural manner. Moreover, the proposed

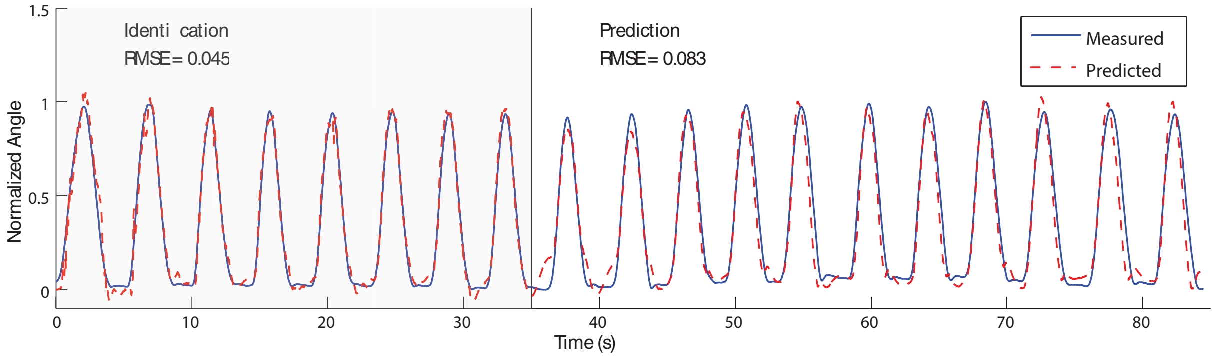

Fig. 3. Prediction result in subject S1 with 2.3 kg load. The first 35-s data were used for model training. The trained model was used to predict joint angle from EMG signals for the last 50 s.

method has advantages to cover time-variant and subject-specific variations which usually make trouble in EMG-based motion controls. In the future, this method would be applied for EMG-based humanoid or prosthetic arm control.

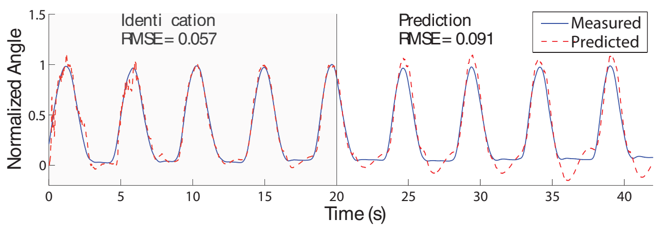

Fig. 4. Prediction result in subject S1 with 1.8 kg load.

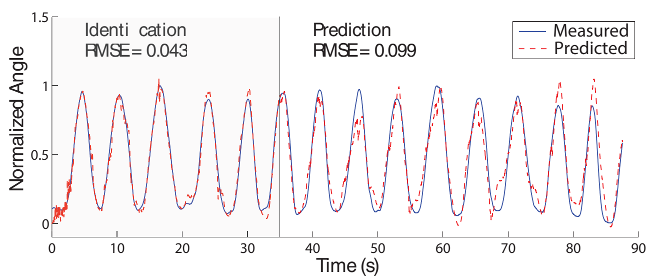

Fig. 5. Prediction result in subject S2 with 2.3 kg load.

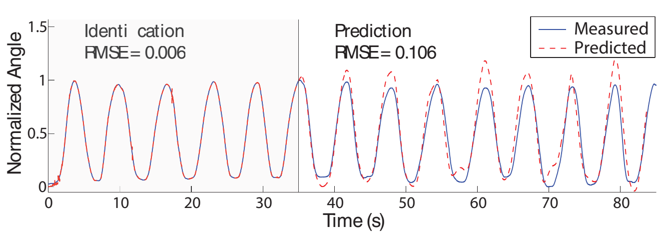

Fig. 6. Prediction result in subject S2 with 1.8 kg load.

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