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# A Novel Method for Elbow Joint Continuous Prediction using EMG and Musculoskeletal Model

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***Abstract*— As a representation of muscle activation dynamics, electromyograms (EMG) signals can reflect muscle contraction status. The status has some relationship with body movements under certain circumstance. This paper is aimed at upper limb elbow joint continuous prediction using EMG signals. Unlike the conventional pattern recognition method, a more quantitative relationship between EMG signals and joint angles has been developed using the Hill-based musculoskeletal model. The EMG signals are recorded from biceps muscle and its antagonist muscle, triceps brachii muscle. The movements of upper limb are voluntary elbow flexion and extension in vertical plane and horizontal plane. The computational time consuming of the proposed method is little and it can be implemented in real-time easily. Five subjects participated in the experiment to evaluate the efficiency of this method.**

## I. INTRODUCTION

SINCE the discovery of electromyograms signal in 1666, it has been implemented in many kinds of fields, such as biorobots control[1]-[7], human body motion recognition[8]-[10], rehabilitation[12]-[13] and so on. Comparing with the other signals detected from conventional sensors, such as force sensor and acceleration sensor, EMG signals can reflect the intention of human motion and the electrode which is used to detect EMG signals is relevant small. But EMG signals are affected more strongly by the electrodes which are used, condition of surface skin or the tissue above the target muscle of subject, and even the temperature. It directly results in the low signal to noise ratio of EMG signals. Furthermore the differences between individuals and between the same subjects in different days make it much harder for the implementation of this biological electrical signal.

Given the unstable characteristic of EMG signals, many researchers implemented pattern recognition methods. M. Okamoto et al developed an automatically classification method using probabilistic neural networks based on boosting approach[14]. Tang et al [15] used two developed methods to extract features of EMG and designed a novel cascaded-structure classifier to achieve hand pattern recognition. And in our previous study[16], a neural network-based classification method using Autoregressive method is designed to recognize the multi-motion of upper limb.

One of the disadvantages of pattern recognition methods is the un-smoothness for controlling. It is more like a "switch" method and lacks quantitative analysis between EMG signals and motions. In fact, EMG directly reflects muscle activation dynamics and muscle activation dynamics can be transferred into musculotendon force[17]. And the joint movement is the sum of these musculotendon forces. Nevertheless, it is very hard to get the accuracy musculotendon force and even harder to calculate all the forces associated with the joint. But these associations provide us some potential to develop the relationship between the EMG signals and joint movement. E. Cavallaro et al[18] used the Hill-based model to calculate the forces/torque around upper limb. There are three parameters in his functions: muscle activation level $a_i$, muscle length changes and muscle velocity changes. The author used genetic algorithms to get optimal parameters tuning. In the Hill-based muscular model, there are at least five kinds of parameters and some of them are hard to record. And it is not very necessary to get estimation of all these parameters for implementation.

In this paper, a novel elbow joint continuous prediction method is presented. Only EMG signals are used as input in the proposed method. The motions of upper limb are elbow voluntary flexion and extension in vertical plane and horizontal plane. The Hill-based muscular model is used to calculate the musculotendon forces and two simplicities are assumed in calculation. Curve fitting method is implemented for developing relationship between musculotendon forces and joint motions. Five subjects participated in the experiment to evaluate the efficiency of this method.

## II. DESIGN OF ELBOW JOINT CONTINUOUS PREDICTION METHOD

### *A. Muscular Skeleton Model*

Figure 1 (a and b) shows side view and top view of muscular skeleton model in vertical plane and horizontal plane respectively. The distance between the attach point of tendon to skeleton and joint is l ($l_1$ and $l_2$ for biceps and triceps respectively). And according to the conclusion in [20], the tendon can regard as high stiff in upper limb which means the deformation of tendon is zero. And the deformation which results in the elbow motion is from the muscle contraction. The angle θ is the one to be predicted. L is the distance between the forearm centroid and elbow joint. In vertical

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plane, the main work for biceps muscle is to pull the forearm against the force of gravity and triceps muscle keeps almost un-activated. No obvious EMG signals can be recorded during elbow flexion and extension in vertical plane from triceps muscle. In horizontal plane the triceps pulls the forearm in order to extend the elbow.

During the motion of elbow flexion and extension in vertical plane, the following equation can be obtained:

$$F_B sin\theta l = I\ddot{\theta} + mgsin\theta L \tag{1}$$

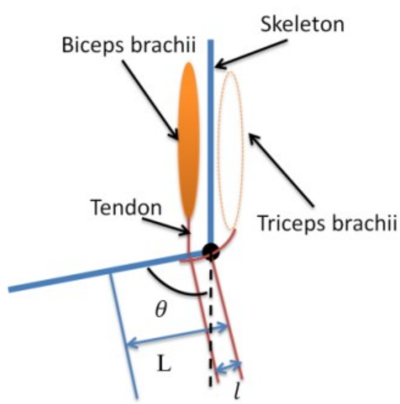
where $F_B$ is the musclotendon force exerted from biceps. The mass and inertia of forearm are m and I respectively. In horizontal plane the term of mgsinθL can be ignored and $F_B$ should be replaced by $F_T$ which means the force exerted from triceps in the motion of elbow extension. Equation 1 can be transformed into (2) by divided $\sin\theta l$ on both side:

$$F_B = \frac{I\ddot{\theta} + mgsin\theta L}{sin\theta l} \tag{2}$$

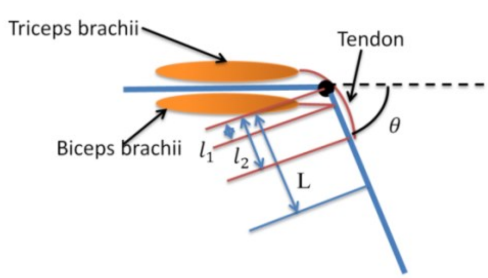
It is hard to get an accuracy estimation of m and I. The term on the right side of (2) can be considered as a function of θ(elbow joint angle): f(θ) and (2) can be transformed into the following:

$$\theta = f^{-1}(F_B) \text{ or } \theta = F(F_B) \tag{3}$$

where function of F is the inverse function of f. In this study we assume that the function of F is invariant under certain circumstance individually because of the control of central nervous system.




a). Side view of muscular skeleton model in vertical plane




b). Top view of muscular skeleton model in horizontal plane
Fig.1. Proposed muscular skeleton model.

*B. Hill-based Muscular Model*

In order to calculate the force generated from muscle, a conventional Hill-based muscular model is implemented. The schematic of this model is depicted in Figure 2. It contains a pair of elements arranged in series: the passive serial element (SE) and the active contractile element (CE); and a passive element (PE) arranged in parallel to the previous two. The equations [18]-[19] used to calculate the force based on this model are shown as follows:

$$F_{PE,SE} = \left[F_{\max} / e^S - 1\right]\left[e^{((S/\Delta L_{\max})\Delta L)} - 1\right] \tag{4}$$

$$\begin{cases} F_{CE} = u \cdot f_l \cdot f_v \\ f_l = \exp\left(-0.5\left(\left(\Delta L_{CE} / L_{CE_0} - 0.05\right)/0.19\right)\right) \\ f_v = 0.1433\left(0.1074 + \exp\left(-1.3\sinh\left(2.8\dfrac{V_{CE}}{V_{CE_0}} + 1.64\right)\right)\right)^{-1} \\ V_{CE_0} = 0.5(u+1)V_{CE_{\max}} \end{cases} \tag{5}$$

$$F_T = F_{CE} + F_{PE} \tag{6}$$

$$a(u) = \left(e^{u(t)R^{-1}} - 1\right) / \left(e^A - 1\right) \tag{7}$$

where ΔL is the change in length of the element with respect to the slack length, $f_l$ is the factor of force introduced by the changes of muscle length and $f_v$ is another factor of force introduced by changes of muscle change velocity. $S$ is a shape parameter, $F_{max}$ is the maximum force exerted by the element for the maximum change in length $\Delta L_{max}$, and $F_{PE,SE}$ is the passive force generated by the PE or the SE element depending on the set of parameters used. $F_T$ is the total force exerted by the muscle. $a(u)$ is the activation level of a muscle.

The SE element presents the force generated by the deformation of tendon. As mentioned above, the tendon can be considered as stiff and the SE element is ignored in this study. For the voluntary elbow flexion and extension, PE element can also be ignored. Thus the force can be calculated from (5) to (7).

As mentioned above, accurate estimation of parameters

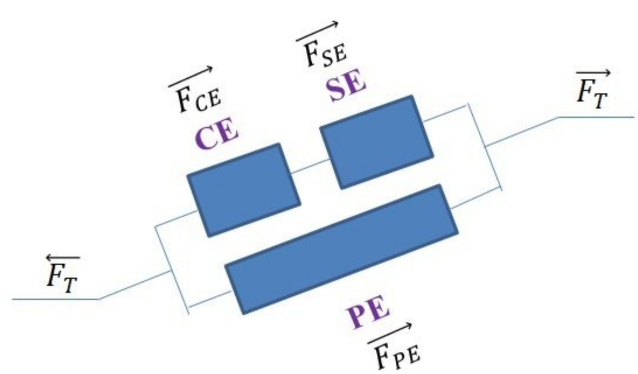



Fig. 2. Schematic of Hill-model with CE, SE and PE elements[11]

$\Delta L_{CE}$ and $V_{CE}$ is not easy. According to the muscular skeleton model build in part A and the assumption that tendon is stiff enough, $\Delta L_{CE}$ can be defined as:

$$\Delta L_{CE} = lcos\theta = \alpha Lcos\theta = \alpha L_{CE_0}cos\theta \quad (8)$$

where $\alpha$ is a ratio of $l$ to $L$.

$V_{CE}$ can be defined as:

$$V_{CE} = \frac{dlcos\theta}{dt} = -\dot{\theta}lsin\theta \quad (9)$$

According to the research of [17], $V_{CE}$ can be regarded as $10L_{CE_0}$ per second for the upper limb muscles for most of the cases. Given this condition, the following equation can be got:

$$\frac{V_{CE}}{V_{CE_0}} = -\frac{\dot{\theta}\alpha L_{CE_0}sin\theta}{10L_{CE_0}} = -\frac{\alpha}{10}\dot{\theta}sin\theta \quad (10)$$

In (8) and (10), there are two terms ($cos\theta$ and $sin\theta$) about the joint angle which is going to be predicted. For simplicity, these two terms are assumed to be proportional to muscle activation level $a(u)$. And this assumption was evaluated in the experiment which will be mentioned below. Another term which associates with (10) is $\dot{\theta}$. For simplicity, the subjects who participated in the experiments were asked to keep a constant rotation speed which is around 0.52rad/s. Given (5), (7), (8), (10) and the assumption, a function of musculotendon force F with the input of $a(u)$ can be built.

### *C. Muscle Activation Level*

The EMG signals can directly reflect the muscle activation level ( $a(u)$ ). And the muscle activation dynamics is uncoupled with musculotendon contraction dynamics. Usually, the raw EMG signals should be passed by a high-pass filter firstly to remove any DC offsets or low frequency noise. Then the signals should be rectified. Sometimes these rectified signals are directly transformed into muscle activation by dividing them by the peak rectified EMG value obtained during a maximum voluntary contraction (MVC) test. Some researchers also suggested that a more detailed model of muscle activation dynamics is warranted in order to characterize the time varying features of the EMG signal. In this study, a discretized recursive filter with a continuous form of a second-order differential equation shown as following is implemented:

$$u(t) = M\frac{de^2(t)}{dt^2} + B\frac{de(t)}{dt} + Ke(t) \quad (11)$$

where M, B and K are the constants that define the dynamics of (11) and $e(t)$ is the processed EMG signal. This equation can be presented as a discrete form using backward differences:

$$u(t) = \alpha e(t-d) - \beta_1 u(t-1) - \beta_2 u(t-2) \quad (12)$$

where $d$ is the electromechanical delay and $\alpha$, $\beta_1$ and $\beta_2$ are the coefficients that define the second-order dynamics. Selection of the values for $\alpha$, $\beta_1$ and $\beta_2$ should follow the following restrictions:

$$\beta_1 = \gamma_1 + \gamma_2 \quad (13)$$

$$\beta_2 = \gamma_1 \times \gamma_2 \quad (14)$$

$$|\gamma_1| < 1 \quad (15)$$

$$|\gamma_2| < 1 \quad (16)$$

$$\alpha - \beta_1 - \beta_2 = 1 \quad (17)$$

in order to guarantee the stableness of the equation and the neural activation does not exceed 1.

The calculation results should be processed by a low-pass filter (with a cut-off frequency of 3-10 Hz) because the muscle naturally acts as a filter and the force changing frequency is much lower than EMG.

### *D. Schematic of Designed Elbow Joint Continuous Prediction Method*

Figure 3 depicts the schematic of proposed method. Raw EMG signals pass a high-pass 4th order Butterworth filter with a cut-off frequency of 10Hz firstly and then are processed with (12). After processed with a low-pass filter, results ($u$) are used as the input of (7). The outputs of this step are the muscle activation level ($a$). Then the musculotendon force $F$ can be calculated using the modified Hill-based muscular model with the input of $a$. The $F$ is used as the input of a Polynomial which is generated off-line by curving fitting method(input is the musculotendon force and output is the elbow joint angle). The polynomial is developed individually and is different from biceps and triceps muscles.

## III. EXPERIMENTS AND EXPERIMENTAL RESULTS

### *A. Muscle Activation Level*

sEMG signals were collected using bipolar surface electrodes which is 12mm long and located 18mm apart (as shown in Figure.4). The sampling rate was 1000Hz with differentially amplified (gain 1000) and common mode rejection (104dB). The used 4th order Butterworth filter was implemented in the software which was programmed using C++. The user interface was programmed using Visual C++ 2010 ( Microsoft Co. USA ) which can collect A/D data from the AD board through the application programming interface and process the data with MATLAB ( MathWorks Co. USA ) via a communication from the custom interface to the commercial software running on a person computer with a 2.8GHz quad-core processor ( Intel Core i7 860 ) and 4GB RAM. A MTx sensor (Xsens Technologies B.V. USA) was attached on subject's forearm to record the elbow joint angle. And the recorded data were used for off-line polynomial generation.

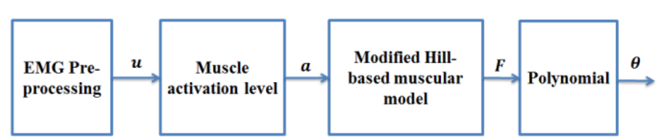
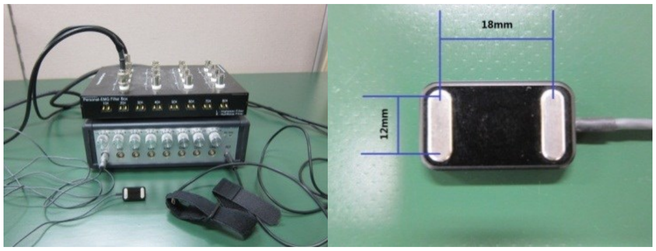



Fig. 3. Schematic of proposed method




a). sEMG Filter box b). Electrode

Fig. 4. sEMG recording devices

Five healthy volunteers (age: 24.60±1.67, height: 1.70±0.07(m), weight: 67.66±9.54(kg), all male, one left-handed and four right-handed) participated in the experiments. Before placing the electrodes which were aligned parallel to the muscle fibres over the belly of the muscle, the skin was shaved and cleaned with alcohol in order to reduce the skin impedance. In order to keep the rotation speed and generalize the upper limb movement of the volunteers, their motions were restricted as requirement by practices before the experiments.

In the experiment of upper limb flexion and extension in vertical plane, the volunteers were asked to sit on a chair started with upper limbs relaxed vertically and then flexed their upper forearms by 90 degree. After a short stop keeping forearms to the horizontal position (3 seconds), the volunteers were asked to extend forearms to the initial vertical position. In the experiment of upper limb flexion and extension in horizontal plane, the volunteers put their upper limb horizontally and repeat the same motions as in the vertical experiments.

Furthermore, a step experiment was implemented to estimate the proposed method. In the step experiment, volunteers were asked to move their upper limb by step with stepping angle of 30 degree, 20 degree and 10 degree respectively and kept for 5 seconds for every step. In the step experiment, the $V_{CE}$ was considered as 0 rad/s.

All the motions were voluntary without any external force applied on the upper limb. Each volunteer repeated these three experiments ten times with a relaxation of one minute in every test.

### B. Experimental Results

Figure 5 depicts the muscle activation levels from biceps and triceps in the motion of elbow flexion and extension in vertical plane from one subject. The Y axes of subplot 1 and 2 are the normalization ratio with MVC test. The biceps muscle almost un-activates during this motion and only activation values calculated by the EMG from biceps are used for musculotendon force calculation during the motions in vertical plane.

Figure 6 depicts the muscle activation levels from biceps and triceps in the motion of elbow flexion and extension in horizontal plane. The triceps activates during the elbow extension. The activation levels of biceps are lower than they are in the vertical plane. One of the reasons is the gravity term which is described in (1). During the motion in horizontal plane, subject doesn't need to conquer the torque generated by gravity. And the activation levels are not very obvious during the motion from 0 to 40 degree which will bring some errors in the prediction.

In order to predict elbow joint only using EMG, a linear relation between muscle activation level and trigonometric terms in (5) is assumed. The compared results of musculotendon force calculated using both EMG and data recorded from MTx sensor with the results calculated using only EMG are shown in Figure 7. The correlation coefficient of these two results is 0.9885, which is high enough to guarantee that this assumption will not bring too much error.

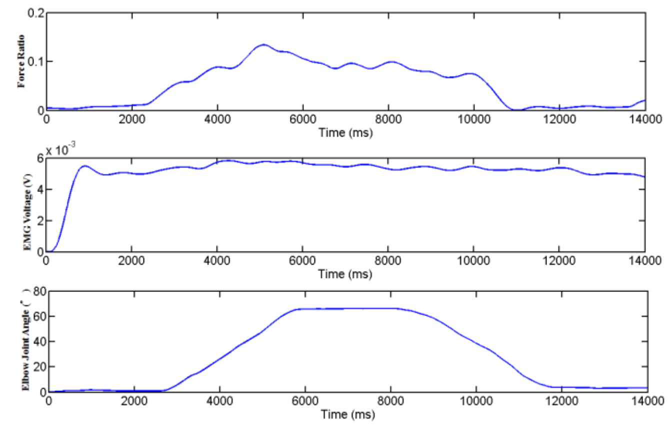



Fig. 5. Muscle activation levels from biceps and triceps in the motion of elbow flexion and extension in vertical plane

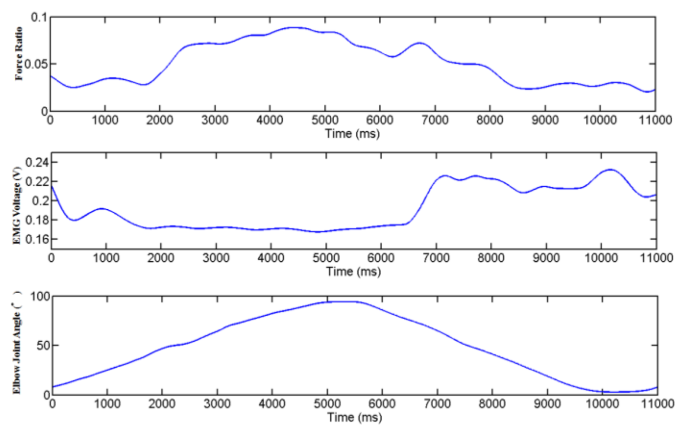



Fig. 6. Muscle activation levels from biceps and triceps in the motion of elbow flexion and extension in horizontal plane

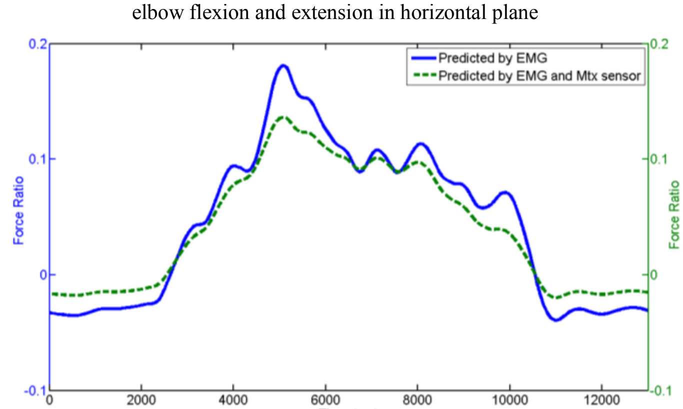



Fig. 7. Compare of prediction results only using EMG and using EMG together with data from MTx sensor

Figure 8 and figure 9 depict the joint angle prediction results using the proposed method in vertical plane and in horizontal plane respectively. There is a large error appeared at 7.1 second in the vertical plane where there is a decrease in force. This force decrease can also be indicated in Figure 7. In horizontal plane, a large error prediction can be indicated during the motion of elbow flexion and a discontinuous part can be indicated at the motion of elbow extension. The reason caused the discontinuous is that two polynomials were used to predict the motion of flexion and extension separately and these two polynomials are not continuous at the connection point.

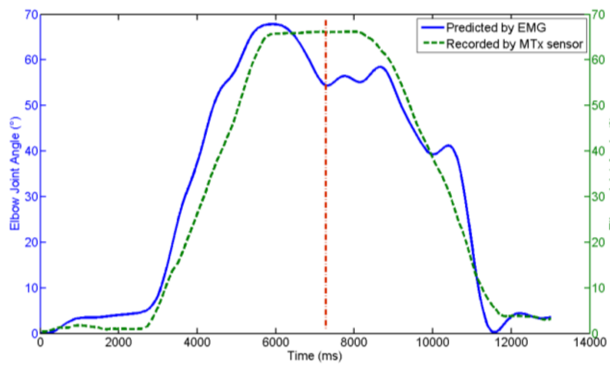



Fig. 8. Compare of elbow flexion and extension in vertical plane prediction results with data recorded by MTx sensor

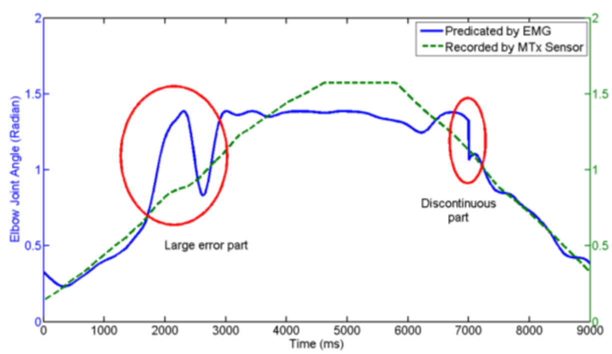
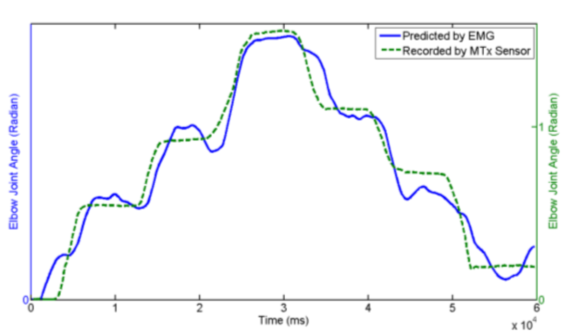
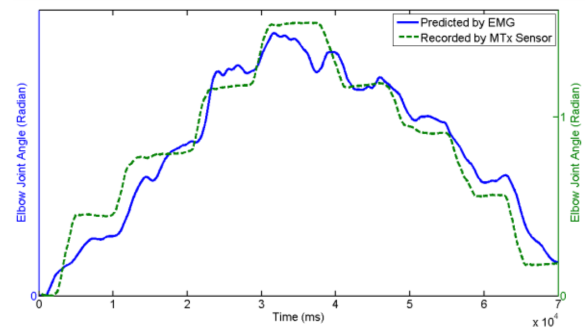



Fig. 9. Compare of elbow flexion and extension in horizontal plane prediction results with data recorded by MTx sensor

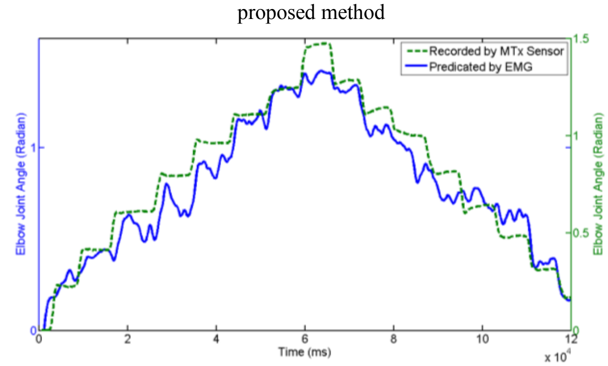
To evaluate the proposed method, a step experiment was also performed. The prediction results are shown in Figure 10. In the step experiment, the angular velocity was considered as 0 rad/s. The accuracy rate decreases with the decreasing of stepping angle.




a). Step experiments of 30 degree stepping angle prediction results using proposed method




b). Step experiments of 20 degree stepping angle prediction results using proposed method




c). Step experiments of 10 degree stepping angle prediction results using proposed method

Fig. 10. Step experiments prediction results

## IV. Discussion

According to the muscular skeleton model which is presented in (1), the angular acceleration or velocity of subject's forearm is one of the factors involved the proposed method. Subjects were asked to do practice before the experiment in order to guarantee that the motion dynamic was under a certain range. This motion dynamic is one of the reasons which result in the phenomenon of force decrease depicted in Figure 8. When subjects move their forearm at the target place and hold there, the term of $I\ddot{\theta}$ deceases to zero and the value of force exerted from biceps decreases. This force decrease results in the error of elbow joint angle prediction. Although a threshold may be set to restrict the peak muscle activation level or musculotendon force, the value of this threshold is hard to choose.

External force will also involve the proposed method. If there is an external force applied on forearm, there will be an extra term in (1) and biceps muscle will generate more force than voluntary situation at the same joint angle. One of this external force cases is the isometric contraction. In isometric contraction, the muscle activation level is the same or much stronger than in the voluntary flexion and extension case. The proposed method will lose its function because there is a prediction output but the real elbow joint angle stays unchanged.

The third factor involved the method is the unstable characteristic of EMG signal. The prediction function, which in this study is a polynomial, is developed by one set of experimental results off-line. But EMG signals may or in most of the cases drift a lot at the same elbow joint angle for one subject. In this case, the errors will be inevitable. One possible method to improve the prediction accuracy using EMG signal is to increase the order of degree of the polynomial, or implement other more complex functions. But it will reduce the robustness of the method. For example, the fitting accuracy will be much higher for a polynomial with 5th degree, but it will completely lost its function with the other set of EMG data. It will be suitable to set the degree around 2 or 3.

The biceps concerns not only the elbow flexion but forearm supination. In the motion of elbow flexion and extension, the subjects were asked to keep their forearms at natural relaxed position. The phenomenon of muscle activation level increasing was observed in all of the five subjects when they supinated their forearm during the motions. So the supination of forearm also involved the accuracy of the proposed method.

In horizontal plane, the error of prediction result is larger. Although the correlation coefficient is 0.918±0.027 (mean±SD) during the five subjects, the large error in one part and discontinuous connection (as shown in Figure 9) will bring some troubles for application, such as robot control. One possible way to solve the discontinuous is to set an offset. The value of the offset is the last prediction result using the former polynomial. For the large prediction error, maybe a smooth method should be implemented to make the prediction results more reasonable.

## V. Conclusion and Future Works

A novel elbow joint continuous prediction method using EMG and Hill-based musculoskeletal model is presented in this paper. Compared with the other methods, such as pattern recognition, the proposed method is based on a modified Hill-based musculoskeletal model and a quantitative relationship between EMG and elbow joint angle is developed. Compared with the conventional isometric motion, the proposed method can provide prediction of elbow joint angles in dynamic flexion and extension motion. This method can be implemented in human-machine interface easily, such as to control a robot arm or used in virtual-reality system. Contrasting with complicated pattern recognition method, only simple calibration test should be done instead of large amount of off-line data training. To evaluate the efficiency of the proposed method, stepping experiments were performed. Although many restrictions must be guaranteed, the proposed method can provide an acceptable prediction results.

Furthermore, this method will be used to control a rehabilitation exoskeleton device. And a compensation method will be developed to improve the accuracy of results.

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