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Continuous Estimation of Finger Joint Angles using Muscle Activation Inputs from Surface EMG Signals

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***Abstract*— Prediction of dynamic hand finger movements has many clinical and engineering applications in the control of human interface devices such as those used in virtual reality control, robot prosthesis and rehabilitation aids. Surface electromyography (sEMG) signals have often been used in the mentioned applications because these reflect the motor intention of users very well. In this study, we present a method to estimate the finger joint angles of a hand from sEMG signals that considers electromechanical delay (EMD), which is inherent when EMG signals are captured alongside motion data. We use the muscle activation obtained from the sEMG signals as input to a neural network. In this muscle activation model, the EMD is parameterized and automatically obtained through optimization. With this method, we can predict the finger joint angles with sEMG signals in both periodic and nonperiodic free movements of the flexion and extension movement of the fingers. Our results show correlation as high as 0.92 between the actual and predicted metacarpophalangeal (MCP) joint angles for periodic finger flexion movements, and as high as 0.85 for nonperiodic movements, which are more dynamic and natural.**

I. INTRODUCTION

In the coming years, human assistive and tele-manipulation technologies are expected to play a significant role in improving the lives and well-being of the ageing community and as well as the handicapped and injured. This predicted growth in assistive technology will be driven by the need to enhance functional independence and support among them. One specific area would be in the development of assistive devices and applications, such as exoskeletons, that would aid in hand rehabilitation. Tele-operated devices controlled by neural signals can give unconstrained and precise movement control in different environments [1].

Surface electromyogram (sEMG) signals are often used in prosthesis controls and rehabilitation support applications, because these reflect the motor intention of a user prior to the actual movements [2]. sEMG signals provide little delay when used in human interfaces and have been shown to represent muscle tension and joint positions very well.

Discrete classification of hand gestures have been successful, reaching a decoding accuracy of above 95% and classifying to up to more than 20 gestures [3]. However, natural hand movement is not limited to discrete gestures but are continuous and coordinated. As an initial step, our research aims to predict continuous finger joint-angle from muscle activation input.

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Studies have shown that it is possible to extract fine finger movement information contained in sEMG signals. Afshar and Matsuoka [1] were able to estimate index finger joint angles from EMG embedded inside seven muscles that specifically control the index finger. Shrirao et al. [4] were able to decode one index finger joint angle of a periodic flexion-extension motion at three different frequencies of movement. Their study evaluated different types of neural networks to predict the joint angles. Smith et al. [5] was able to asynchronously decode individual metacarpophalangeal (MCP) joint angles of all five fingers while moving one finger at a time. Their study used general placement of electrodes in muscle areas available to transradial amputees and extracted sEMG time-domain features used as input to also a neural network to predict MCP joint angles.

However in the previous studies [4][5], a time delay between the onset of the sEMG signal and exerted movement was present and observed. This time delay is called hysteresis or electromechanical delay (EMD). It is often compensated by introducing a time-delay line or manually realigning the EMG to the joint angle data before training is done. This delay can vary depending on many different factors such as muscle shortening velocity, type of muscle fiber, and fatigue [6]. In our method, we introduce this delay as a parameter, by using an EMG-to-Muscle Activation Model, which is determined along with other parameters through optimization. Here, we investigate the use of muscle activation as input in predicting both periodic and nonperiodic flexion and extension movement of all five finger joint angles. We try to predict the angular position of each finger joint, namely, the metacarpophalangeal (MCP), proximal interphalangael (PIP) and the distal interphalangeal (DIP) joints.

II. METHOD

A. Experimental Set-up

The system is composed of a surface electromyograph and an optical motion capture device. Surface EMG signals are extracted from 8 extrinsic muscles of the hand that are known to contribute to wrist and finger movements . These muscles are the Abductor Pollicis Longus (APL), Flexor Carpi Radialis (FCR), Flexor Digitorum Superficialis (FDS), Flexor Digitorum Profundus (FDP), Extensor Digitorium (ED), Extensor Indices (EI), Extensor Carpi Ulnaris (ECU), and Extensor Carpi Radialis (ECR). Twenty markers for motion capture are attached on one hand, with each marker located on each finger joint. The sEMG signals are measured using a compact BA1104 electromyograph with active-type (Ag/AgCl) electrodes and interelectrode distance of 20 mm,

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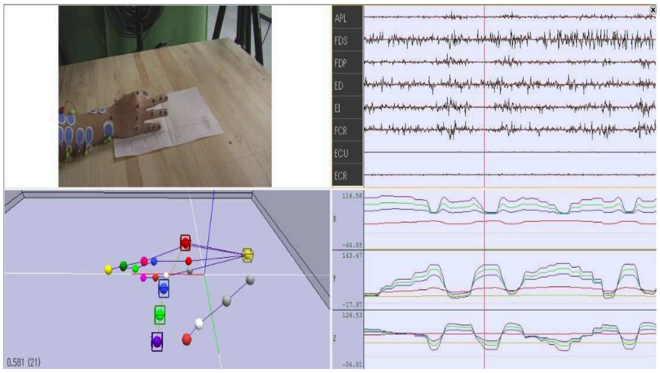

Fig. 1. The experimental setup. SEMG electrodes and motion markers attached on the subject's forearm and finger joints, respectively.

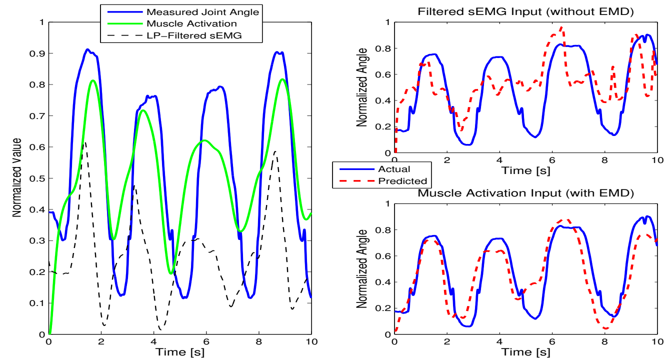

Fig. 2. The left figure shows a measured joint angle, alongside with a filtered sEMG signal and its muscle activation transformation. While the right side shows two prediction results, one with EMD, and one without.

and a telemetry unit TU-4. Both devices are from the Digitex Laboratory Co. Ltd. The hardware provided a high-pass filter with cut-off frequency of 1 kHz during the EMG data acquisition process. While finger movements are made, the motion is recorded using a MAC3D motion capture system (Motion Analysis Corp.). The sEMG signals are sampled at 2 kHz, and are input to the A/D converter, while, the finger motions are sampled at 200 Hz with measurement units in millimeter, having a precision of 0.5 mm. With the x, y, z positions of each marker continuously recorded, the angular position of each finger joint, namely, the MCP, PIP and DIP angles are calculated.

B. Data Collection

A healthy male subject (age 25), with no known physical impairments, was seated with his elbow positioned on a flat surface in a comfortable position. For the first part of the experiment, the subject was tasked to move one finger at a time, while the other fingers including the rest of the arm remained in neutral position. The subject was told to periodically move the finger in the flexion and extension plane, reaching maximum flexion and extension of the finger at least once. Ten trials were done for each finger, with each trial lasting 20 seconds. All in all, 5 sets of EMG and motion data were obtained from individual finger movements. For the second part of the experiment, the subject was tasked to randomly and freely move his finger, following no constant periodicity. Ten trials were also done in this free-form movement. All trials were sequentially done and the subject was allowed to rest anytime during the experiment.

C. Data Preprocessing

The raw sEMG signals were first preprocessed into a form, that after further manipulation, can be used to estimate muscle activation [6]. The sEMG signals are rectified and normalized by the maximum voluntary contraction (MVC), obtained from each muscle throughout the entire duration of the experiment. The signals are then filtered using a 2nd-order low-pass filter with cut-off frequency of 4 Hz. This is done prior to obtaining the muscle activations, which are highly related to muscle force found in low frequencies. The filtered sEMG signals were then downsampled to 200 Hz to match that of the motion data. With the exception of the thumb, which we considered only two joints of interest, the remaining fingers produced all three angles of interest. Thus, a total of 14 joint angles were obtained. A low-pass filter with cut-off frequency of 10 Hz was also applied on the motion data, to remove noise and jitters in the signal.

D. EMG-to-Muscle Activation Model

For any intended motor action, it is known that there occurs a time delay, which is known as the electromechanical delay (EMD), between the onset of the sEMG signals and the exerting tension in the muscles. EMD has been observed by previous studies in the leg and as well as in the arm [4][6]. EMD has been reported to range from 10 ms to about 100 ms, but varies differently depending on the intended tasks [2]. Thus, EMD cannot be ignored in sEMG studies involving motor actions, and must be considered accordingly.

To learn a suitable filtered signal which automatically considers EMD, we introduce the use of a so called EMG-to-Muscle Activation model. EMG is a measure of electrical activity that spreads across muscles, which causes the muscles to activate. This results to the production of force, to which the model used transforms the sEMG signals to a suitable force representation. Zajac modeled this muscle activation dynamics using a first-order recursive filter [7]. While Buchanan et al. created a second-order model filter that models the relationship between EMG and muscle activation [6]. In this study, we make use of their filter:

$$u_j(t) = \alpha e_j(t-d) - \beta_1 u_j(t-1) - \beta_2 u_j(t-2) \tag{1}$$

where $e_j(t)$ is the preprocessed EMG of muscle j at time t, In this model, α, β_1, β_2 are recursive coefficients and d is the EMD. Filter stability is guaranteed by putting constraint conditions on α, β_1, and β_2.

$$\beta_1 = \gamma_1 + \gamma_2 \tag{2}$$

$$\beta_2 = \gamma_1 \cdot \gamma_2 \tag{3}$$

$$|\gamma_1| < 1, |\gamma_2| < 1 \tag{4}$$

$$\alpha - \beta_1 - \beta_2 = 1 \tag{5}$$

The transformation to muscle activation v_j is given by:

$$v_j = \frac{e^{A_j u_j(t)} - 1}{e^{A_j} - 1} \tag{6}$$

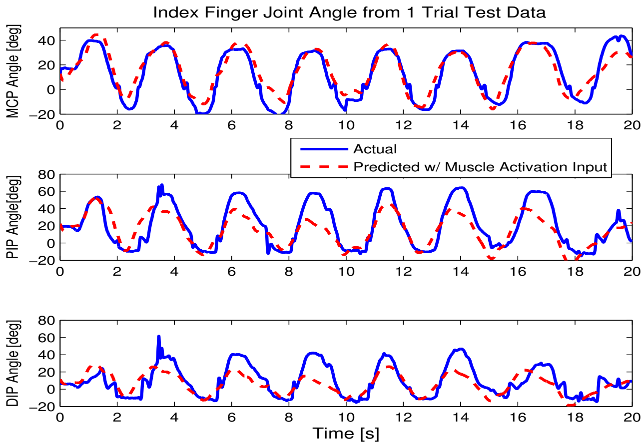

Fig. 3. Index finger joint angle prediction for 1 test trial of periodic motion. The correlation coefficient between the predicted and measured MCP, PIP, and DIP angles are 0.92, 0.82, and 0.75 respectively. While the parameters obtained are $d = 40ms$, $\gamma_1 = \gamma_2 = -0.9748$, and $A_j = -1.26$.

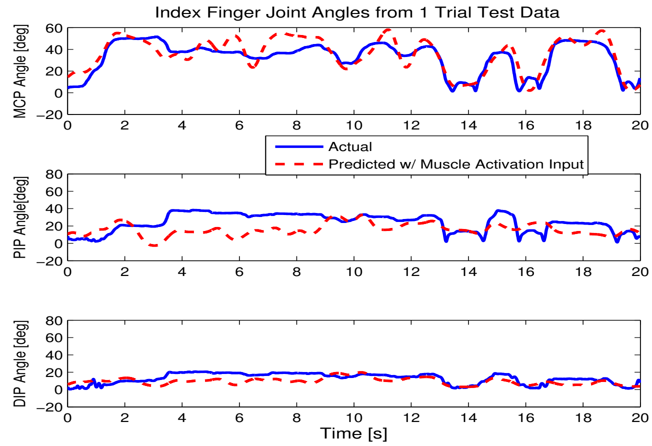

Fig. 4. Index finger joint angle prediction for 1 test trial of free random motion. The correlation coefficient between the predicted and measured MCP, PIP, and DIP angles are 0.88, 0.52, and 0.60 respectively. While the parameters obtained are $d = 50ms$, $\gamma_1 = \gamma_2 = -0.9618$, and $A_j = -1$.

where A_j is a parameter that introduces the nonlinearity between EMG and muscle activation, and is constrained between -3 (highly exponential) and 0 (linear).

This model not only solves the EMD of the muscle, but also requires only a few parameters. The parameters of this filter, γ_1, γ_2, d, and A are obtained by using constrained nonlinear programming in Matlab's Optimization Toolbox to minimize a cost function:

$$\sum_t (\theta_{est} - \theta_{target})^2 \tag{7}$$

where θ_{est} and θ_{target} are the estimated and measured finger joint angles, respectively. If we only want to map the EMG signals to a single finger's joint angles and if the training time needs to be fast, then a linear estimation of the joint angles to obtain θ_{est} would suffice. However, the complex relationship between the muscle activation, and the corresponding joint angles are known to be nonlinear. Hence, we resort to using an artificial neural network as our nonlinear estimator.

E. Artificial Neural Network for Regression

In general, neural networks are considered to be attractive for nonlinear modelling because of their ability to approximate any arbitrary functions [10]. We use the muscle activation, which is related to muscle force, as input to an artificial neural network. In our study, a simple feed forward network was used. The network is made up of 3 layers: an input layer, a single hidden layer with a tan-sigmoidal activation function, and a single linear output layer. The input layer had 8 nodes coming from the muscle activation of the each muscle, while the output has 14 nodes consisting of the finger joint angles. To train the network, we input a set of training data to the neural network and minimize a mean square error function. We evaluated the network's performance with various number of neurons in the hidden layer, ranging from 5 to 250. To avoid overfitting, total data set was divided into a training and a validation set and apply an early stopping method during training iterations [11].

In all of the six tasks of the experiment, 8 out of 10 trials were used for training while the remaining 2 were used for testing. All the data in each task were concatenated together to form a larger training and test dataset.

III. Results and Discussion

With the neural network trained, we now estimated all finger joint angles simultaneously. Figure 3 shows the result of the index finger joint angles in one test trial involving that of a periodic motion. Correlation as high as 0.92 was obtained for the MCP angle estimation. While the prediction of the PIP and DIP joint angles were consistent, which were about 0.8 and 0.7 correlation, respectively. Processing the sEMG into its muscle activation dynamics was straightforward. For this trial, the EMD obtained was 40 ms, suitably aligning the sEMG onset to the motion data. This model works very well for motion with constant velocity where EMD is approximately the same in a trial.

Similarly, figure 4 shows the result of the predicted index finger joint angles but in a test trial involving free and random movement of the fingers. The predictor is able to predict the index finger joint angles rather well, but not as accurate as when movement was limited to constant frequency. In this trial task, EMD varied differently, depending on the movement. The optimization step chooses the best possible values for EMD from the training data, but does not account for the EMD changes resulting from different velocities. Also in the previous task with the periodic motion, the two lesser angles followed movements similar to the MCP angles, but for random motions, they may totally differ. The muscle activation input that we use does not give an explicit feature that relates the angles from one another.

Because we were able to predict all finger joint angles accurately in some trials, a 5-fold cross validation was conducted to see the overall statistical performance of the predictor. Figure 5 and figure 6 show the average correlation coefficients and mean overall normalized root-mean-square

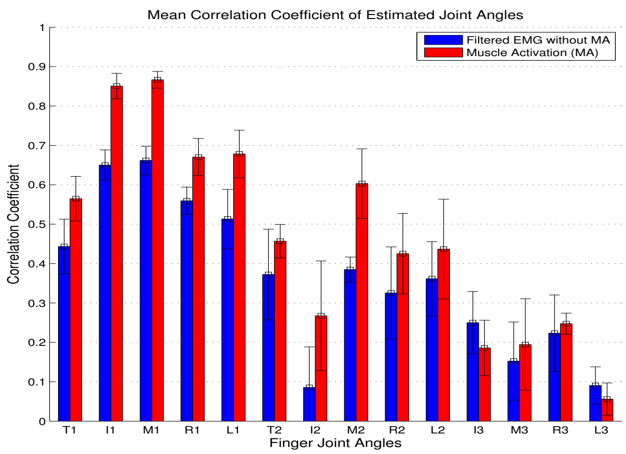

Fig. 5. The blue and red bar graph shows the mean correlation coefficient of the predicted and actual joint angle results, when the muscle activation model was not used and when it was used, respectively. T, I, M, R, and L x-axis label represent the thumb, index, middle, ring, and little finger, while the numbers 1,2, and 3, are the MCP, PIP, and DIP angles, respectively.

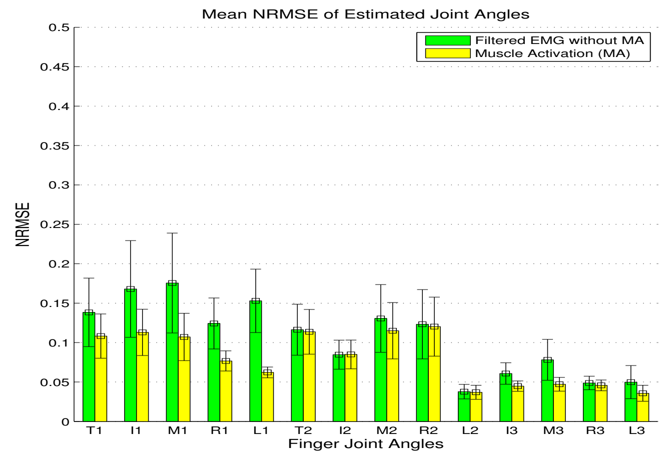

Fig. 6. The green and yellow bar graph shows the mean normalized root-mean-square error (NRMSE) of the predicted and actual joint angle results, when the muscle activation model was not used and when it was used, respectively. Like in figure 5, the x-label axis represent the same corresponding finger joint angles.

error (NRMSE) of the estimated and measured finger joint angles, respectively, of all the test data partition in the cross validation. Here, we compared the estimation performance of two cases, when the proposed biomechanical muscle activation model was used and when it was not used (using only the filtered sEMG as input). We can see that using the proposed model gave better prediction results and lesser mean errors (about 0.05 to 0.15). For MCP angles, correlation coefficients of above 0.8 were achievable. This is consistent and can even go as high as 0.9 when the movement condition is constrained (e.g. in predicting only individual finger as opposed to simultaneous movement, or in predicting only periodic movements as opposed to random finger movements).

Our current method captures the general trend of the finger movement. We have shown that we can use muscle activation features as input to a regressor to continuously predict finger joint angles. A reliable biomechanical model that relates the lesser angles (PIP and DIP) to the MCP angle would better improve the system and estimation, even for random motions. In this study, we have shown that by using muscle activation dynamics, parameters such as the EMD can be determined through optimization, which automatically synchronizes the muscle activation to the actual finger actuation, resulting to a smoother and accurate prediction of the joint angles.

IV. Conclusion

This paper presented an alternative method in predicting finger joint angles using a muscle activation model that parameterizes electromechanical delay (EMD), which has been observed by numerous investigators. Automatically determining this delay improves the synchronization of sEMG signal and the finger joint angle thus providing better estimation. We have shown that during testing, we were able to predict finger joint angles with reasonable accuracies for both periodic and random finger movement. Because fine hand movement is complex, future work would include investigating other factors such as finger force, and analyzing different muscle activation patterns in doing skillful activities that require the use of the fingers.

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