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Continuous Prediction of Shoulder Joint Angle in Real-Time

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***Abstract*— Continuous prediction of dynamic joint angle from surface electromyography (sEMG) signal is one of the most important applications in rehabilitation area for stroke survivors as these can directly reflect the user motor intention. In this study, new shoulder joint angle prediction method in real-time based on the biosignal: sEMG is proposed. Firstly, sEMG to muscle activation model is built up to extract the user intention from contracted muscles and then feed into the extreme learning machine (ELM) to estimate the angle in real-time continuously. The estimated joint angle is then compare with the webcam captured joint angle to analyze the effectiveness of the proposed method. The result reveals that correlation coefficient between actual angle and estimated angle is as high as 0.96 in offline and 0.93 in online mode. In addition, the processing time for the estimation is less than 32ms in both cases which is within the semblance of human natural movements. Therefore, the proposed method is able to predict the user intended movement very well and naturally and hence, it is suitable for real-time applications.**

I. INTRODUCTION

Consequences of neuron impairment due to stroke, traumatic brain injury (TBI) or spinal cord injury (SCI) lead to severe physical disability either in one side of the body: *Hemiplegia* or both side of the body: *Quadriplegia* depends on which part of the brain is damaged. As a result, patients find it difficult to perform daily activities independently and this lead to low self-esteem and depression [1]. To recover from such impairment, rehabilitation is conducted in several phases such as in hospital, out-patient therapy and eventually in home-based program. In the context of rehabilitation, sEMG is a very useful and important tool to extract the intention of movement because the sEMG signal is able to indicate the intention of movement even before the actual movement has occurred [2]. Therefore, a lot of researchers have been making use of such benefit to develop sEMG based rehabilitation systems especially to predict the intention of movement. As far as prediction of movement by means of sEMG is concerned, various prediction models have been proposed [3]. Among the prediction methods, joint angle prediction is the most direct estimated output to drive the rehabilitation system or prosthesis. Therefore researchers are trying to predict the joint angles as accurate as possible so that rehabilitation system or prosthesis will mimic the natural movement of human arm. Such work can be found in Shrirao et al., [4] where sEMG signals were trained in several neural networks to predict the index finger joint angle and their results were reported with RMS errors ranged from 0.085±0.036 to 0.163±0.054 for both extension and flexion movements. In the study of Ngeo et al., [5], finger joint angles are estimation model were developed with parameterized electromechanical delay and artificial neural network for regression with the correlation as high as 0.85±0.07 for offline mode. In the work of Suncheol and K. Jung [6], shoulder and elbow joint angles were estimated from feedforward neural network with joint angular velocities and achieved less than 0.15 for normalized root mean square error while greater than 0.9 for correlation coefficient. Another prediction method of joint angles was proposed by Pan et.al.,[7]. In their method, the continuous joint angle prediction was done by linear discriminant analysis (LDA) classifier with 14 state-space models and average estimation performance of the joint angles was reported 0.843. However, there are very limited studies for online prediction with high accuracy between actual and estimated joint angle.

Therefore, in this paper, new prediction method of joint angle through sEMG signals alone is proposed for both offline and online prediction. Shoulder joint is chosen for prediction as this is the most important joint to rehabilitate in the context of upper limb. In proposed method, random movements of shoulder joint angle in abduction and adduction are mapped based on sEMG signals by well known machine learning regression technique with muscle activation model and performance is evaluated. The rest of the paper is organized as followed. Section II details the proposed method for prediction including hardware set-up, data collection and processing, and finally details the machine learning algorithm that employ in the proposed method. In Section III, experimental result and discussion are explained followed by conclusion and future work is described in Section IV.

II. METHODS

A. Hardware Set-up

In this paper, sEMG signals are utilized as a main input for the estimation of joint angle. The signals are extracted via FlexComp Infiniti data acquisition device from Thought

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Technology [8] with . Three pre-amplified sEMG sensors and electrodes are attached to three extrinsic muscles from upper arm namely anterior deltoid (AD), posterior deltoid (PD) and upper trapezius (UT) as shown in Fig.1 (red dot). These muscles are chosen as they are the most contributed muscles during shoulder articulation according to our previous study [9]. Two color markers are attached to shoulder joint and wrist joint to calculate the target joint angle via webcam as shown in Fig. 1 (yellow square). The signal processing is performed in Matlab 2012b platform and joint angle measurement is recorded with Adobe Flash Professional CS6. The recorded data are sent to Matlab for processing in real-time through user datagram protocol (UDP). Detail procedures of data collection and processing are explained in the following section.

B. Data Collection

One healthy able-bodied subject with the age of 31 who gave informed consent to participate in the experiment was recruited for this study. Data were collected at one of the laboratory rooms in Faculty of Engineering and Information Technology, University of Technology Sydney. The subject was requested to sit in front of the desktop that attached to the webcam at comfortable height with shoulder 0˚ abduction, 0˚ extension and 0˚ external rotation. After the hardware preparations were completed, both sEMG signals and joint angles were collected. There were two sessions for data collection. In the first session, the data were collected for training and testing in offline mode. After that, the collected data were fed into extreme learning machine (ELM) for angle estimation. In second session, online estimation was performed to estimate the shoulder joint angle in abduction/adduction based on the trained result. During all sessions, subject was asked to move his shoulder joint from 0˚ to 170˚ randomly in abduction/adduction for 10 cycles for 10 trials. The subject was allowed to rest anytime between the trials. Among the recorded data, 8 trials were used for training in ELM and 2 trials for testing.

C. Data Processing

The overall block diagram of proposed prediction system is depicted in Fig. 2. The raw signals from data acquisition device are first preprocess (block #1) by band-pass filtering (20Hz – 500Hz) to remove both low and high frequency noise followed by rectification and normalization by maximum voluntary contraction (MVC). The normalized data are then down samples to match the joint angle data. The processed data are send to muscle activation model with EMD (block #2) to convert from EMG to muscle activation level. There is an EMD between EMG signals and exerted tension in the muscles in which the values are generally between 30ms and 100ms. Therefore, EMD cannot be ignored in prediction process to estimate the muscle activation at the current time. The neural activation values in terms of EMD can be approximated by (1):

$$n_k(t) = \lambda\, emg_k(t-d) - \mu_1 n_k(t-1) - \mu_2 n_k(t-2) \quad (1)$$

where $emg_k\ (t - d)$ is processed sEMG signal of muscle k at time t, d is electromechanical delay and λ, $\mu1$, and $\mu2$ are the recursive coefficients with constraint as follows:

$$\mu_1 = \gamma_1 + \gamma_2 \quad (2)$$

$$\mu_2 = \gamma_1 \cdot \gamma_2 \quad (3)$$

$$|\mu_1| < 1,\ |\mu_2| < 1 \quad (4)$$

$$\lambda - \mu1 - \mu2 = 1 \quad (5)$$

Then the muscle activation a_i is given in (6):

$$a_i(t) = \frac{(e^{A_i \cdot n_i(t)} - 1)}{(e^{A_i} - 1)} \quad (6)$$

where $a_i(t)$ is muscle activation for muscle "i" at time "t" and the A_i coefficient is a shaping factor specific to muscle "i". The example of signal processing for 2 cycles of shoulder abduction/adduction is shown in Fig. 3. The resultant data are then feed into block #3, regression ELM for should joint angle prediction.

D. Proposed Joint Angle Prediction Method

In this paper, shoulder joint angle prediction is proposed in both offline and online (real-time) by making use of sEMG signals. The signal is first preprocessed: rectified, normalized and filtered, and then fed into muscle activation model which converts neural activities into muscle activities by considering electromechanical delay (EMD). The parameters of the EMD are optimized using the Optimization Toolbox from Matlab 2012b. The joint angle of the shoulder is recorded from subject upper limb motion via webcam,

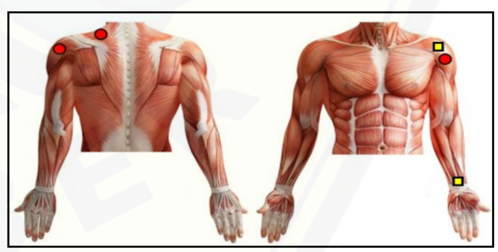

Figure 1. Locations of sEMG electrodes (red dot) and color markers (yellow square)

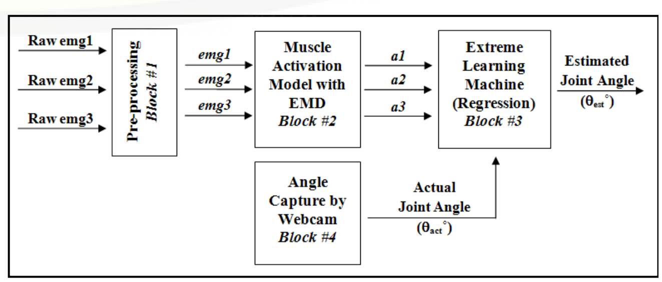

Figure 2. Block diagram of proposed prediction system

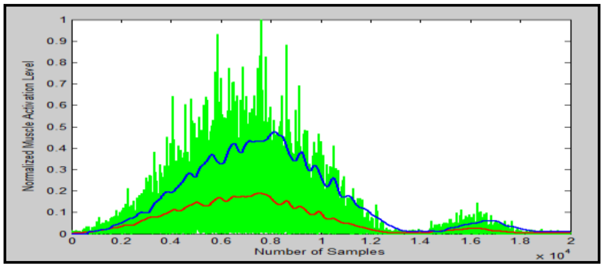

Figure 3. sEMG signal processing for two cycle of abduction motion: rectified sEMG signal (Green), low pass filtered sEMG (Red) and muscle activation with EMD (Blue)

processed and input to ELM as target data. Together with the resultant data from muscle activation model and target data, *ELM* regression algorithm trains and predicts the shoulder joint angle. The block diagram of the proposed joint angle prediction method is presented in Fig 2.

E. Arm Motion Recording

The motion of the arm is recorded with Logitech QuickCam E3560 which attached to the same PC as data processing. The markers that attached on the subject shoulder joint and wrist joint are registered via webcam to track the current position of the subject arm. The processing of the joint angle calculation is performed in Flash Professional CS6. The marker at shoulder joint is calibrated as an origin position to calculate arm length and horizontal distance between shoulder marker and wrist marker. The captured parameters are used to calculate the abduction/adduction joint angle by trigonometry. Tracking of the markers are refreshed in every frame to update the current position of markers and therefore update the joint angle calculation in every frame as real-time joint angle data. The calculated angles are sent to Matlab platform in real-time via UDP to serve as training and testing data for ELM in offline mode and as target data to evaluate the prediction performance in online mode.

F. Regression Extreme Learning Machine Model

ELM is a generalization of single-hidden layer feedforward networks (SLFNs) which hidden layer's nodes implement a random computational process and does not required to be tuned [10]. The algorithm has proven that it has higher scalability and less computational complexity, hence, it becomes the most attractive for nonlinear modeling. In this work, muscle activation data as input to the regression ELM model and estimated the joint angle with non-kernel based output function as follows [11]:

$$f(x) = h(x)\beta \tag{7}$$

$$\beta = H^{+}T \tag{8}$$

$$H^{+} = H^{T}\left(\frac{1}{C} + HH^{T}\right)^{-1} \tag{9}$$

where $h(x) = [h_1(x), \ldots, h_L(x)]$ is the output vector of the hidden layers of L nodes with respect to input x. $h(x)$ and $\beta = [\beta 1, \ldots, \beta L]^T$ is the vector of the output weights between hidden layer and output node. H^{+} is the Moore-Penrose generalized inverse of matrix H which is the hidden layer output matrix and C is a user specified parameter. The activation function of the ELM is employed sigmoid function as (10) due to its better prediction result compared to other activation functions such as hard-limit, Gaussian and multiquadric.

$$G(a,b,x) = \frac{1}{1+\exp\{-(a.x+b)\}} \tag{10}$$

where $G(a, b, x)$ is a nonlinear piecewise continuous function for universal approximation capability theorems [12]. In offline mode, 8 out of 10 trials data are trained and the rest are used for testing. In online mode, the trained result from the offline is utilized for real-time prediction. The results from both offline and online testing are discussed in the following section.

III. Experimental Result and Discussion

Prediction of the joint angle is experimented in both offline and online mode. Before the experiment was conducted, the objective of the experiment was explained to the subject and few sessions of training were also given. Afterward, subject was asked to move his shoulder joint with random degree such as 45˚, 90˚, 135˚ and 170˚ in abduction/adduction motion. During the process of motion, sEMG and arm motion data were recorded via data acquisition device and webcam. After getting the sEMG data, preprocessing of the signals were performed followed by computing the optimized parameters for the EMD with optimization toolbox in Matlab. The best parameters of the EMD were given as $\gamma 1 = \gamma 2 = -0.9612$ and d = 60ms. Then, the angle data from recorded motion were computed via webcam and together with muscle activation data (block #2 and block #4), sent for ELM training and testing. The outcome of the offline result in one test trial is presented in Fig. 4. The results are validated with 5-fold cross validation and average correlation is as high as 0.9613 with processing time of less than 32ms. This result proved that proposed method for joint angle estimation is quite accurate with very fast processing time than other aforementioned approaches. With this motivated result from offline mode, online or real-time estimation was performed based on the trained offline results from ELM. Fig. 5 shows the 5-fold cross validation result of real-time testing. The average correlation of the real-time result achieved 0.9371 with the processing time of less than 32ms which is same as offline testing. This shows that the proposed prediction method is able to reflect well for the joint angle even in real-time. Although offline and online testing that presented in this paper focus on one degree of freedom at joint angle at shoulder joint, multiple degree of freedom of upper limb are currently under study and positive results will report in near future.

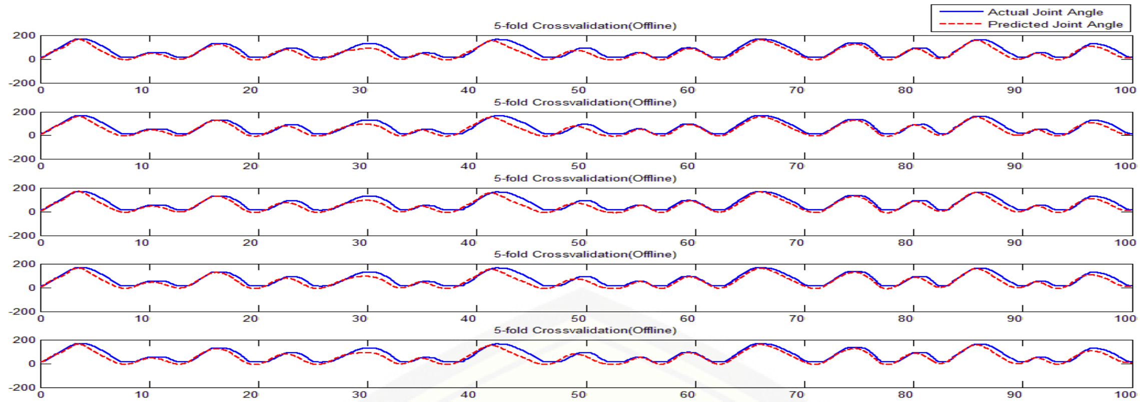

Figure 4. Result from offline testing with the correlation coefficient between actual and predicted angle is 0.9613. The label on x-axis correspond to time in sec and y-axis of the plot correspond to the abduction joint angle

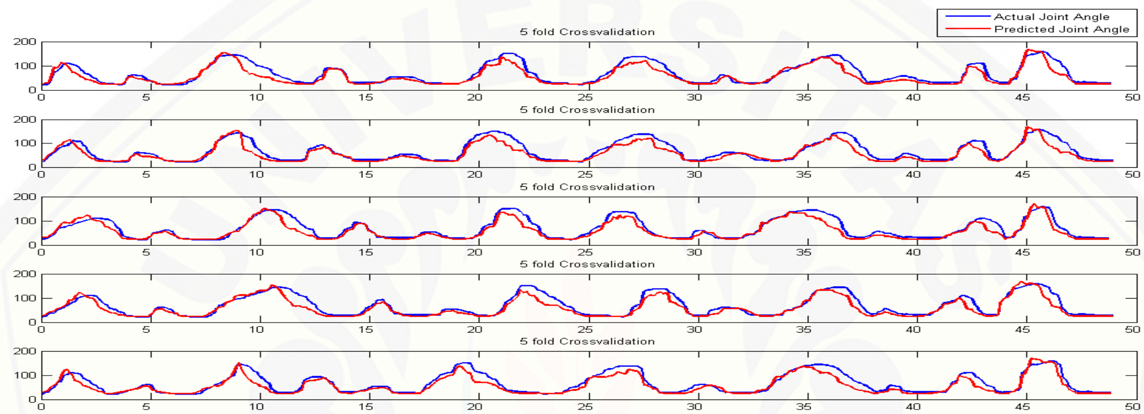

Figure 5. Result from online testing with the correlation coefficient between actual and predicted angle is 0.9371. The label on x-axis correspond to time in sec and y-axis of the plot correspond to the abduction joint angle

IV. Conclusion and Future Work

The fast and accurate joint angle prediction method is proposed in this paper. With the consideration of electromechanical delay in extracted sEMG signal along with less computational complexity extreme learning machine are employed as an angle estimator. The experiments were conducted in both offline and online mode to estimate shoulder abduction/adduction motion. The accuracy results are very encouraging with very fast processing time as a preliminary step for direct joint angle estimation from just sEMG signals. These positive results encourage for the next steps: more non-clinical and clinical trials, multiple joint angle predictions in random motion of upper limb which are currently under testing and results will be published in near future. As a whole picture, the proposed estimation method will be integrated with our previous work [9] to offer as an novel fast recovery upper limb rehabilitation system.

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