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EMG-based Continuous Prediction of the Upper Limb Elbow Joint Angle Using GRNN

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***Abstract* –Electromyography (EMG) signal is one of the important applied biological signals generated by human muscles which represents the human motor intention. In this paper, we proposed a prediction model of the elbow joint angle in the sagittal plane only using the EMG signal. After the signal acquisition and the pre-processing, the root mean square (RMS) feature of EMG signal was extracted as the input set of the General Regression Neural Network (GRNN) which has a high performance in the nonlinear fitting. Furthermore, three general regression neural networks were set up to predict the elbow angle in raising step, holding step and falling step, respectively. To evaluated the efficiency of the method, the subjects were asked to flex, hold and extend their forearm continuously in every 3 seconds. Meanwhile, the real angle and the predicted angle were compared in the experiment. The experimental results indicated the proposed method can predict the elbow angle in the sagittal plane with the best error rate no more than 5%.**

Index Terms –Electromyography, Upper limb elbow joint, motion intention prediction

I. INTRODUCTION

Stroke is a common reason for incapacitated people because it can break the blood vessels of the brain so that loss the partial brain function [1]. Nowadays, with millions of people all over the world suffering from motor cortex injuries, this phenomenon indicates the huge demand for professional and efficient disability rehabilitation training [2]. However, disability rehabilitation training always takes the long recovery cycle which causes a shortage of medical resources. In order to solve this problem, the concept that using the robots to replace the therapists to achieve equal efficiency rehabilitation training has been put forward. In recent years, more and more researchers have shown their high interest in this field and many efficient methods of rehabilitation robot systems have been given out. Furthermore, plenty of clinical studies have verified the recovery effect of post-stroke rehabilitation by robotic devices towards hemiparetic arm function [3]-[9]. Among the rehabilitation robots, the surface electromyographic (sEMG) signals-based rehabilitation robots are significant due to the sEMG signals which include the important information of muscles [10]-[11]. Combining the sEMG signals and the rehabilitation robots together can benefit to restore process by adding a reference to evaluate the patients' muscles state. Another typical system is the bilateral rehabilitation robot which can lead to activation of the damaged hemisphere by bilateral symmetrical movement practice. Song et al. [12]- [15] presented an upper extremity motion function rehabilitation system which has the ability to be manipulated by patients by a tactile device and an inertia sensor to perform a tracking task in a virtual-reality environment. Zhang and Liu et al. [16]- [19] proposed a novel rehabilitation system can provide the variable stiffness of elbow joint to the patients with different degrees of injury. In recent years, in order to realize the better rehabilitation effect, the human motion intention prediction which allows the patients and the robot to complete a shared task and preserves the safety of the rehabilitation has attracted a lot of researchers' eyes [20]-[21]. Pang et al. [22]-[23] presented an upper limb motion intention predict method which can recognize the sEMG signals to predict the muscle force and the elbow angle of the patients by the polynomial fitting method. Bu et al [24] proposed a classification method to predict the elbow angle in 4 settled angles such us 0 degrees, 30 degrees, 60 degrees, and 90 degrees. There are two kinds of problems in these researches. Above all, some of these angle prediction methods are based on the approximative model including some uncertain parameters which might influence the accuracy of prediction. Secondly, some of these methods are the discontinuous predict which has huge deviation and difficult to operate. In this regard, a more direct and more accuracy angle prediction method should be proposed to predict the angle.

In this paper, a continuous upper limb elbow joint angle prediction method is proposed. The sEMG signals generated by the biceps and the triceps were detected by dry electrodes attached on the subject's skin. After the noise signal was removed by a digital filter, the filtered signals should be preprocessed by a digital signal filter to get the most frequency power of sEMG signals from 10Hz to 150Hz. The time-domain features, root mean square (RMS), was applied as the sEMG signals feature extraction method. Then use a digital signal filter to get the filtered RMS signal as the input of the general regression neural network (GRNN). The general regression neural network is a variation to radial basis neural networks which have good performance in regression, prediction, and classification. It notes that the good ability of

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GRNN to fitting the nonlinear relationship between the input set and the target sat. Eventually, the effect of the prediction by GRNN based on RMS feature is evaluated by comparing the real angle and the predicted angle which is the output of GRNN.

This paper has been divided into four parts. The section I gives a brief overview of the rehabilitation system. Section II begins by laying out the theoretical dimensions of the research and the principle of GRNN-based elbow angle prediction model only by processed sEMG signals. Section III sets up the experiment, analyses the results gathered and evaluates the effect of this method. Section IV draws together the key results and gives our conclusion.

II. ANGLE PREDICTION METHOD

A. *The Muscle-kinematics model*

The elbow joint rotation is driven by two upper limb muscles that are biceps and triceps. The kinematic model converts a human arm motion into kinematic chains of rigid body parts [25]. When the forearm flexes, this flexion action needs the biceps to contract and the triceps relax. On the contrary, when the forearm extends, the extension action needs the triceps to contract and the biceps relax. We can see the structure of the upper limb clearly in the sagittal plane as shown as the Fig.1. When our forearm acting the extension motion or the flexion motion, the most important influence factor that should be taken into account is the force of gravity. In addition, if we want to set up the torque equation, the arm length must be defined in advance. The distance between the elbow joint and the muscle tendon is defined as l which is the arm length of muscles. On the other aspect, the distance between the elbow joint and the forearm centroid is L which is the lever arm of the gravity [26]-[27].

According to the previous research of our laboratory, based on the condition that no significant changes of EMG signal from the triceps muscle can be observed during the elbow flexion and extension in the sagittal plane which means the triceps brachii effect can be ignored. Therefore, the torque equation can be set up as follow:

$$F_B = mgLl^{-1} + Il^{-1}\ddot{\theta}\sin\theta \tag{1}$$

where F_B represents the force of the biceps brachii muscle. The quality and inertia of the forearm are m and I. The angle needs to predict is θ. Furthermore, the F_B can be represented by the root mean square (RMS) of the biceps sEMG signals [24].

Based on this muscle-kinematics model formula, we can see the relationship between the sEMG and the elbow angle. It seems like the elbow angle can be predicted to follow this formula. But there is a serious fact must be considered is that the sEMG signal is an extremely unstable and random time signal. In addition, the accurate representation of the human upper limb is challenging. The significant features of the sEMG signal are the individual difference. Hence the other more effective method to predict the elbow angle should be used.

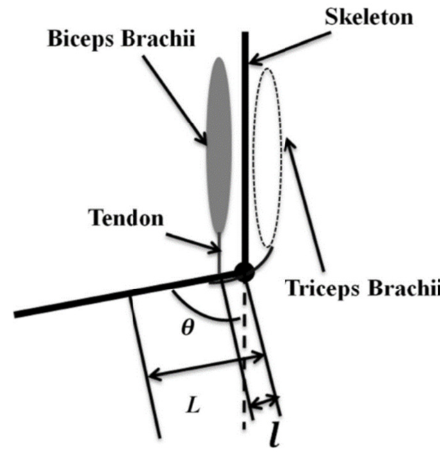

Fig. 1. Side view of the Muscle-kinematic model

B. *Raw sEMG signals process*

As we mentioned before, EMG signals is an extremely unstable complicated signal. It is necessary to preprocess the signals so that to get the most valuable information. Usually, raw sEMG signals processing has two steps. The first one is to remove the noise caused by the environment and the device. The second one is the feature extraction that the target is to get useful information. All processing flow chart has been shown in Fig.2. At first, before the program to record the signals, the noise such as power frequency noise and low-frequency noise should be removed. An efficient method to solve this problem is the Butterworth filter which has the ability to change the frequency response as flat as possible in the passband. Because of the most frequency power of sEMG signals is from 10Hz to 150Hz, so a fourth-order Butterworth high-pass filter with cut-off frequency of 10Hz is applicated in the system. The raw sEMG signals and the filtered signals by the Butterworth filter is shown as Fig.3.

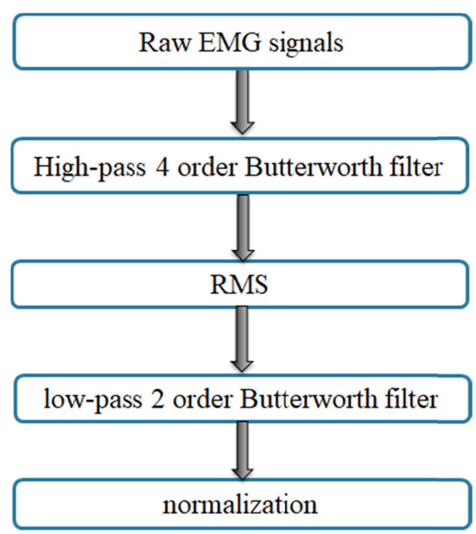

Fig. 2 EMG signal process flow chart

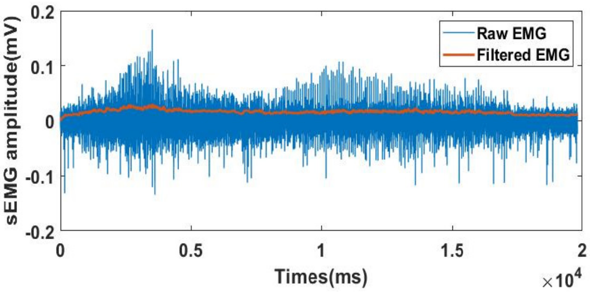

Fig. 3. sEMG signals filtered by Butterworth

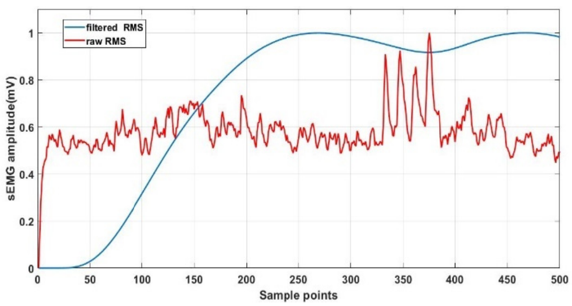

Fig. 4. RMS sEMG filtered by Butterworth

In the second part, features of the signal should be extracted. There are many ways to analyze the signal in the time-domain, frequency-domain, and time-frequency domain [28]-[29]. The Root Mean Square (RMS) has been proofed that it can reflect the muscle activation state both in the human motion period. On the other hand, RMS usually represents the mean power of the signal which indicates has the relationship with the muscle force. That is also identified with the muscle-kinematics model. General, the RMS method is defined follow this formula:

$$RMS = \sqrt{\frac{\sum_{i=1}^{n} x_i^2}{n}} \tag{2}$$

where the n is the total numbers of sample points, x_i is the value of the number i element's voltage. According to the project, the EMG signal should be calculated to get this time-domain feature with 25 data point (0.25ms) moving window.

After the RMS value of EMG has been getting, it is necessary to set a low-pass Butterworth filter in order to get the smooth RMS signal as the Fig.4 shown. The relationship between the smooth RMS signal and the filtered signal indicated the smooth RMS feature is impartable due to the unstable property of sEMG signals.

C. General Regression Neural Network

General regression neural network (GRNN) is the is a variation to Radial Basis Function neural network (RBF). Compared with the RBF, GRNN has a better performance in curve fitting, especially in nonlinear relationship fitting. It noted that GRNN can map the numerical function between the input and the desired target. According to the muscle-kinematics model formula (1), the relationship

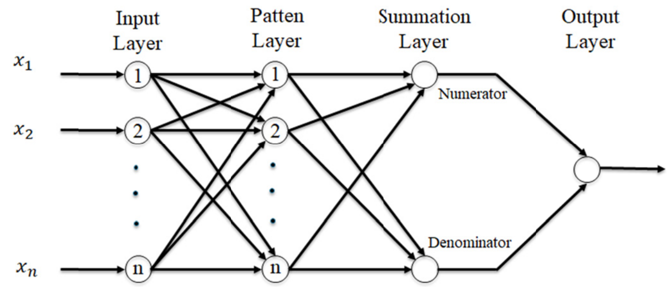

Fig. 5. General Regression Neural Network structure

between the RMS signal which represents the muscle force and the elbow joint angle should be a nonlinear mapping. That is the reason that the GRNN was applicated to set up the prediction model. The working principle of GRNN can be described as the following formula:

$$y(x_0) = \frac{\sum_{i=1}^{n} y^i e^{-\frac{C_i}{\sigma}}}{\sum_{i=1}^{n} e^{-\frac{C_i}{\sigma}}} \tag{3}$$

where

$$C_i = \sum_{j=1}^{p} \left| x_j - x_j^i \right| \tag{4}$$

where the n is the number of sample observations and p is the dimension of the vector variable x [30]. If we change the value of σ, the fitting performance will fluctuate. If the σ is too large, the fitting curve will be smooth but the error will be large at the same time. On the contrary, if the σ is too small, the fitting curve will through every point but will be unsmooth. This phenomenon is regarded as the overfitting. Both of these two kinds of the condition should be avoided. It is important to find the appropriate σ so that the good performance can be get. The GRNN structure which can be represented by (3) is different from the normal neural network for the other more unit in the Hidden unit.

The Fig.5 has shown the GRNN structure clearly. The first unit is the Pattern Unit of which Gaussian function is used as the basis function. The second unit is the Summation Units. Especially, in the Summation Units, there are two kinds of neurons named molecular neurons and the denominator neurons respectively. The molecular and the denominator are corresponding to the formula (3). The Output unit needs to calculate the ratio of these two kinds of neurons. In our method, the input was the RMS value of the EMG signal and the target was the real angle. Meanwhile, the value of σ was settled as 0.5 to train the GRNN.

D. Angel Prediction Model

In our project, the angle prediction is required to estimate both in the flexion motion and the extension motion. Based on this principle, the experiment was settled by the process as follow. In the beginning, the forearm was at zero degrees with the whole arm was straight line state. Then the forearm raising from zero degrees to the 90 degree when the forearm was vertical to the upper limb. Finally, the forearm comes back to the original position zero degrees. All the motion was carried by constant speed velocity in the 3s period.

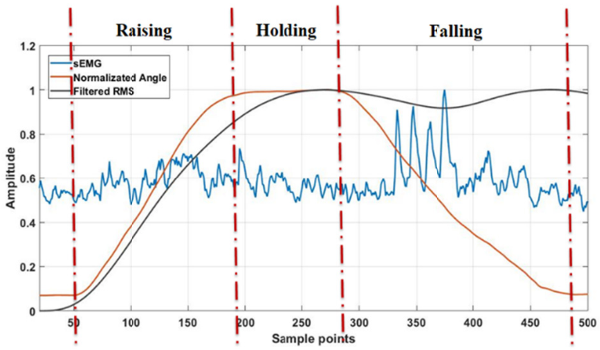

Fig.6 Separated data into the Raising period, the Holding period, and the Falling period

The angle prediction cannot be set up by fitting the RMS and the angle together directly. Because this relationship is not a one-to-one single mapping. As the Fig.6 shown, we solved this problem by separating the whole motion data into a 3-period step, the Raising period, the Holding period, and the Falling period, respectively. In each motion period, we set up a GRNN in MATLAB and trained the neural network by the data. All the data should be processed in normalization for the standard data to train the GRNN. As the normalization process, in the GRNN test period, all the data also should be mapped back to the original state, especially the real angle and the predicted angle.

After all the angle had been processed to normalization, the GRNN can be trained by these data. The input set of the GRNN was the RMS data, and the target set was the real angle data. The output set represented the fitting curve which was also the predicted angle we needed.

III. Experiments and Results

A. Experimental Setup

Five healthy male volunteers (average age: 24.4 years; average weight: 69.1 kg; average height: 177.6 cm) participated in the experiments. The potentiometer MTx sensor (Xsens Technologies B.V., USA) of which sampling rate was 200 Hz) was placed on the forearm of the subjects. When placing the electrode which was placed in the direction of the muscle fibers on the midline of the muscle belly, not only the skin should be ensured that has been shaved and cleaned by the alcohol to reduce the environmental disturb and the skin impedance. The EMG signal sampling rate was settled at 1000 Hz with differential amplification (gain: 1000) and common mode rejection (104 dB). The real-time data of EMG was recorded through an analog/digital (A/D) converter and processed by MATLAB (The MathWorks Co., USA).

A continuous uniform velocity motion of the upper limb elbow flexion and extension movement experiment had been carried out in the condition that all the subjects were not had any disable problem and the muscle fatigue. All the subjects were asked to obey the experimental protocol as follows. Forearm flexion motion was acted from 0 degrees to 90 degrees during no more than about 3 seconds.

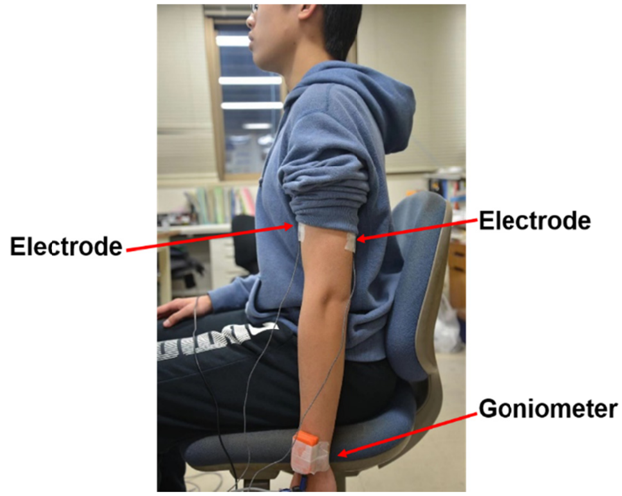

Fig. 7. Experimental process of the proposed system

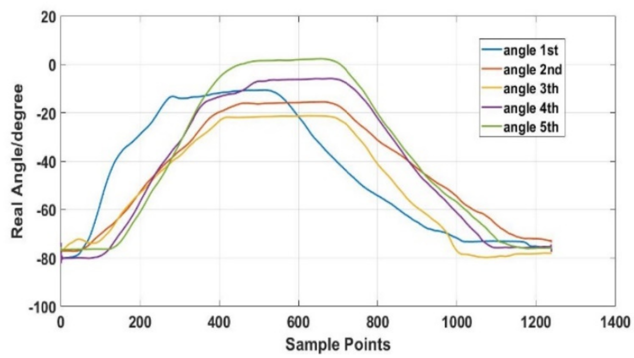

Fig. 8. 5 times real angle data compare

When the Forearm place was arriving the 90 degrees, the forearm was asked to hold at 90 degrees for about 3 seconds. Finally, the forearm extension motion was operated during about 3 seconds. The experiment process and details were shown in Fig.7. During the whole experiment, the biceps muscle EMG signals and the sagittal elbow joint angle was collected. The experiment was operated for 5 times with the time interval for 1 minute in order to avoid muscle fatigue and 5 times per person. The 5 times real angle data was display in Fig.8. Although the subjects tried their best to flex or extend their forearm in a uniform velocity, there was also some human operation error which could influence the accuracy of the prediction model (such like the 1st time operation in the raising period and the falling period, the 4th time operation in the holding period). In the other hand, considering the individual difference of the EMG signal, every angle prediction model should be set up after using the RMS signal data as the input set and using the corresponding real angle data as the target set to train each time GRNN.

B. Experimental Result

As mentioned before, in order to get the best performance of the prediction model, the most smooth data was selected to set up the GRNN. To evaluate the performance of the angle prediction model, the other data was put into this trained GRNN

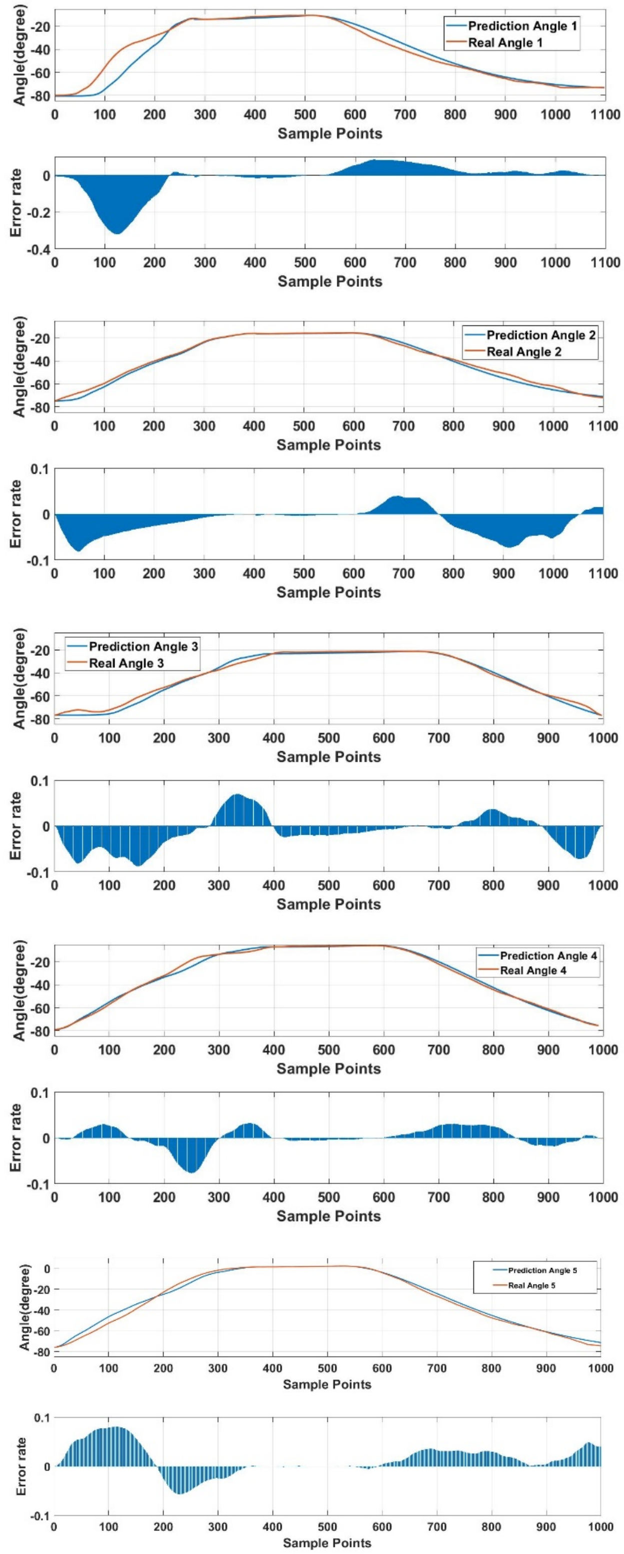

Fig. 9. 5 times representation results with the proposed method from five subjects

the angle prediction model based on GRNN has good prediction performance as Fig. 9 displayed. Each time prediction result is fitting the real angle well. Except for the 1st time, the other 4 times error of the angle prediction model was no more than the 10%. The reason why the 1st time prediction error is over 30% is that in the 1st time experiment, there was the variable speed motion during the flexion motion period which influences the prediction accuracy. The other significant result is that all the error is distributed on the raising period and the falling period. The first reason for this phenomenon is due to the not so perfect uniform velocity motion. And the other important reason is the mapping of the anti-normalization process. In our study, the max value and the min value were used for this linear anti-normalization mapping. The max value and the min value of the raising period and the falling period are much more than the holding period. Therefore, the error will be much larger through this process.

In order to evaluate the proposed angle prediction model performance and simulated effect, the root-mean-square error (RMSE), R^2, and the correlation coefficients r were used to calculate the performance parameters [30]. The RMSE was defined as the following formula:

$$RMSE = \sqrt{\frac{1}{n}\sum_{n=1}^{N}(\theta_p - \theta_r)^2} \quad (5)$$

Where θ_p is the predict angle, θ_r is the real angle, N is the numbers of sample points.

The correlation coefficient was defined as the following formula:

$$R^2 = \left(\frac{\sum\theta_p\,\theta_r - \frac{\sum\theta_p\,\theta_r}{N}}{\sqrt{\left(\sum\theta_p{}^2 - \frac{\left(\sum\theta_p\right)^2}{N}\right)\left(\sum\theta_r{}^2 - \frac{(\sum\theta_r)^2}{N}\right)}}\right)^2 \quad (6)$$

The performance parameters of each subject can be shown in Table I.

TABLE I
THE PARAMETERS OF THE PROPOSED PREDICTION METHOD

Subject		1	2	3	4	5
A	$RMSE$	5.9119	1.1023	1.1813	1.6641	1.7349
	R^2	0.9404	0.9970	0.9963	0.9953	0.9963
	SSE	38166	1368	1384	2731	3208
B	$RMSE$	0.9526	1.7721	4.3873	5.5169	1.8587
	R^2	0.9984	0.9930	0.9671	0.9496	0.9945
	SSE	614.3236	2157	12839	20301	2356
C	$RMSE$	1.8591	0.6250	2.3949	1.4021	3.3997
	R^2	0.9942	0.9994	0.9911	0.9972	0.9821
	SSE	2060	225.8142	3648	1154	6426
D	$RMSE$	2.4264	1.0554	3.3779	3.2981	5.7658
	R^2	0.9909	0.9984	0.9792	0.9832	0.9559
	SSE	3485	667.2	7782	6255	18783
E	$RMSE$	1.5791	3.5210	1.9615	1.0233	1.1164
	R^2	0.9976	0.9832	0.9919	0.9988	0.9986
	SSE	1561	7265	2409	603.1166	618.1588

As demonstrated by the Table we can see that the strong correlation relationship between the prediction angle and the real angle form the correlation coefficient R^2. And the best performance of the proposed method is no more than 5% error rate.

IV. Conclusions

In this paper, a novel elbow joint angle prediction method for rehabilitation recovery system based on GRNN which has the ability to improve the evaluation of training effect and the system performance was proposed. Compared with the sensor-based angle prediction method, sEMG signals generated from the relative muscle were applied in the proposed method to predict the angle of the elbow as well as evaluate the recovery. Besides, GRNN has been utilized to improve the fitting accuracy and prediction speed. Five subjects who have intact motion function are invited to participate in these experiment, the proposed angle prediction method has been proved effective.

In the future, this angle prediction method can be developed for the online prediction in real time and the rapidity and the stability of state between each period changing is also a difficult point to research. Furthermore, the post-stroke patients who still have a partial motor function are expected to participate in these experiments to retrieve more detailed and valid data for further research.

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