The design of a hemiplegic upper limb rehabilitation training system based on surface EMG signals

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Abstract

In this paper, we designed a hemiplegic upper limb rehabilitation training system, which allowed both single degree of freedom and composite degrees of freedom for the training of shoulder and elbow. The system contained an upper limb rehabilitation robot, a pattern recognition system and a motion control system. Firstly, we designed a novel upper limb rehabilitation robot with three degrees of freedom, with the motor and reducer innovatively placed centrally in the shoulder of the mechanical limb arm. The movement is more stable because the inertia of each joint movement is reduced. The design makes simultaneously training both the left and right arm possible. In the control system design, the movement coupling problem is solved through the inverse operation of the target action. Lastly, to further enrich information of the single feature vector, a method integrating the AR model coefficients and wavelet coefficients was proposed. A method combining the Particle Swarm Optimization Algorithm and Levenberg-Marquardt (LM) was used to optimize the BP networks, addressing the problems associated with lower convergence speed and local minimum of standard BP networks. The experiments showed that the convergence speed of the network and the recognition rate of the target action were effectively improved, which demonstrated the effectiveness of the training system.

Keywords : BP network, Surface EMG signals, Hemiplegic upper limb rehabilitation training system, Recognition mode, Rehabilitation robot

1. Introduction

According to statistics, there are about 16.9 million people in the world suffering from apoplexy every year. So far there are 33 million survivors in total (Feigin et al., 2014; Langhorne et al., 2011). 80% of them are suffering from hemiplegia and are incapable of looking after themselves (Langhorne et al., 2009). Rehabilitation solutions for patients with hemiplegia become more and more urgent. The traditional methods for treating hemiplegia typically depend on the physiotherapists or some traditional physiotherapy devices, but the rehabilitation is often ineffective due to inefficiency of the devices or the patients' lack of motivation.

Over the past decades, researchers have developed several rehabilitation robots for upper limbs rehabilitation. Among them, the kind of rehabilitation robots can be divided into two parts, end-effector type and wearable type. The MIT-Manus (Hogan et al., 1992), which is a workstation for teaching and therapy and MIME (Lum et al., 2004), which is a robot manipulator that applies forces to the affected forearm, belongs to the end-effector type. While RUPERT (Sugar et al., 2007), which is a device for robotic upper extremity repetitive therapy, and L-Exos (Frisoli et al., 2009), which is a force-feedback exoskeleton in virtual reality, are wearable. In addition, the interaction between patient and

robot is so critical that several ways including force control (Vertechy et al., 2009), computed torque control (Rahman et al., 2014) and algorithms using EMG signals (Song et al., 2013), are proposed to solve this problem. A hemiplegic upper limb rehabilitation training system based on surface EMG signals (Hudgins et al., 1993; Zecca et al., 2002) is a training system that uses muscle electrical signals as the control signals and trains the hemiplegic patients through recognizing and performing the predetermined motions. Compared with the traditional training systems, the proposed system has two advantages: (1) Based on individual demands, the training intensity can be controlled by the patients themselves; (2) The training does not require manual repetitive operation, which is important for the training success. Existing upper limb sEMG-based rehabilitation training systems typically can only accomplish single degree of freedom training for the shoulder or elbow. This is due to the fact that the complex movements of the shoulder and elbow share several common muscles, which result in interferences between the sEMG signals. This increases the difficulty to select the appropriate muscle signals and design the classifier with a higher recognition rate. Some rehabilitation training periods need combined movements of the shoulder and elbow, so it is crucial to design a rehabilitation training system which can accomplish both single degree of freedom and composite degrees of freedom for the training of the shoulder and elbow. Therefore, a hemiplegic upper limb rehabilitation training system based on surface EMG signals was designed to achieve this purpose.

2. The controlling strategy

The controlling strategy of the hemiplegic upper limb rehabilitation training system was firstly to extract EMG signals from the healthy upper limb signals muscle of the hemiplegic patients. Then we used the pattern recognition system to train the pre-defined actions. The trained model was used to identify the upper limb actions of the healthy side, and the recognition results were applied to the rehabilitation robot to drive the hemiplegia upper limb movement and complete the rehabilitation training. The principle is shown in Fig.1. This process is also called testing. However, we should train the robot to recognize the pre-defined actions firstly. We extracted EMG signals from the subjects of healthy upper limb muscles. And a label which was pre-defined corresponds to a set of data. Then we extracted the features from the data and used the PSO-LM optimized BP network to classify the labeled actions. After we achieved a good classification accuracy, we used the trained model to recognize the action by the data extracted from the healthy upper limb signals muscle. After a long-time training, we got a targeted accuracy and the training process was finished. Then the robot has learned to recognize the actions from the EMG signals. After that, when we get the EMG signals of the healthy side, the robot can recognize the motion pattern based on the data and the trained model before. Then the robot can finish the rehabilitation of the hemiplegic side.

The control system is a servo system which must use the arm of the signal source muscles from the healthy side as a control source. The amplitude of EMG signals is proportional to the velocity and power of the actions. Thus, the signal source of the hemiplegic limb is easily obscured by noise and the weak signals cannot meet the requirements of control accuracy. This is why we do not directly use the muscles of hemiplegia side arm as a source of control. It is obvious that our system must be used in patients with single-handed hemiplegia, while hemiplegia with both hands cannot use the system to achieve self-rehabilitation training. The number of patients with single-handed hemiplegia is much greater than that of patients with both-handed hemiplegia. Thus, the rehabilitation training system is effective for the vast majority of hemiplegic patients.

In this paper, the number of the target actions is 14 including 6 single degrees of freedom actions and 8 composite degrees of freedom actions. The designed shoulder, elbow and shoulder and elbow compound actions make the rehabilitation training actions more close to the natural movements of the arm. This natural training reduces the tedious training of rehabilitation training, and apparently also can speed up the rehabilitation process of hemiplegic patients. However, the number of signal source muscles will increase, leading to the increase in the number of pasted electrodes. To make patients more comfortable to wear, we set the EMG wireless transmission as the next research goal. In the pattern recognition algorithm, the PSO-LM optimized BP network is used as the classifier, and the AR model coefficients and wavelet coefficients are integrated as the eigenvalues. The purpose of it is to improve the accuracy of the identification of the target actions, which is described in detail in Section 5. The mechanical body is a three degrees of freedom rehabilitation arm, which can simultaneously achieve the left and right hand of the alternate training. The use of synchronous belt transmission can increase the flexibility of the system action. The electromyographic control system of the upper limb rehabilitation robot is shown in Fig.1. The control strategy of the control system is shown in

Fig.2.

Fig. 1. The electromyographic control system of upper limb rehabilitation robot

Fig. 2. The control strategy of the control system

3. The upper limb rehabilitation robot

3.1 The structure design of upper limb rehabilitation robot

Fig. 3. The upper limb rehabilitation robot

Legend: 1- weight plate; 2- column; 3- horizontal tube; 4- shaft base; 5- servo motor; 6- servo motor; 7- servo motor; 8- curved arm; 9- support pole; 10-upper arm; 11- forearm; 12-moving column of lifting column; 13- fixed column of lifting

column; 14- backplane.

Fig. 4 Mechanism transmission schematic of upper limb rehabilitation robot

The mechanical body of the upper limb rehabilitation robot is a three degrees of freedom rehabilitation arm, which not only can achieve the 14 target actions, but also has the following advantages. The reducer and drive motor placed on the beam 3, reduces the weight of the forearm. Thus, when using the synchronous belt to increase the flexibility of the system, it also can reduce the weight caused by the amplitude of the arm tremor. The design of column 2 can adjust the height of the robot arm to meet the needs of rehabilitation training for patients with different heights. 5-11 are designed on the beam 9, and the beam achieves two positions through the hinge flipping 180 degrees, which meet the different needs of left hand or right hand for the hemiplegic patients. The same pattern recognition algorithm is used for hemiplegic patients with left hand or right hand, but the outcome of target action is clearly different, that is, the implement of the drive system is different, which is easily achieved in the program.

3.2 Analysis of robot drive

To achieve the target action, the transmission part has the following 4 transmission lines:

(1) Elbow extension and flexion: Servo motor M1-reducer J1-timing pulley 1-timing pulley 2-spur gear 3-spur gear 4- bevel gear 5-bevel gear 6-timing pulley 7-timing pulley 8-timing pulley 9-timing pulley 10-forearm A.

(2) Shoulder extension and flexion: Servo motor M2-reducer J2-spur gear 12-bevel gear 13-bevel gear 14-timing pulley 15-synchronous pulley 16-upper arm B.

(3) Shoulder abduction and adduction: Servo motor M3-reducer J3-spur gear 17-spur gear 18-bending arm C.

(4) Compound action: When (2) and (1) or (3) and (1) is complex, it can complete shoulder and elbow joint 8 compound actions. From the Fig. 4, the motion diagram of the mechanism, it can be found that there is a coupling relationship between the three drive motors when the 14 target actions are carried out. The decoupling operation of each target action needs to be done, and the joint angle of each target action is decoupled into three servo motors.

3.3 Solver of the target motion

Inverse kinematics calculations of the target action are performed due to the coupling relationship existing in the designed manipulator structure. The aim is to calculate the correspondence that exists between the target motion and the three servo motors. When the upper limb rehabilitation robot carries out the shoulder flexion motion, this motion does not influence the shoulder abduction and shoulder adduction motion. However, it does influence the elbow flexion and elbow extension motion. At this time, (1) Curved arm C is equivalent to a frame; (2) Pulley 10 (planetary gear), forearm (planet carrier) and Pulley 9 (Center gear) constitute a planetary gear system; (3) Pulley 1, pulley 2, spur gear 3, spur gear 4, bevel gear 5, bevel gear 6, pulley 7 and pulley 8 constitute a fixed axis gear system; (4) Spur gear 11, spur gear 12, bevel gear 13, bevel gear 14, pulley 15 and pulley 16 constitute a fixed axis gear system too. Joint angles of the 14 target motions are shown in Tab.1. The target movement angles here refer to the motion range of the rehabilitation robot, which is determined by the actual angle of rotation of the corresponding human arm.

The initial position and ending positions of fourteen target actions are shown in Tab.2, in which 'a' represents the positive movement of the elbow joint, 'b' and 'c' respectively show the positive movement of the shoulder flexion or extension and abduction or adduction.

Inverse kinematics calculations of the other target motions are the same as the shoulder flexion motion. We set the servo motor 10000 pulses in one revolution and combine with the corresponding joint angle of each target action in Tab.1 and the completion time. The pulse frequency, the number of pulses and decoupling of the motor are based on the principle of relative motion. In other words, to get the motor rotation speed and motor pulses required to achieve a certain target action in the planetary, we set the opposite motor rotation speed and motor pulses for the motors that are not need. The results of the final solution are shown in Tab. 3. The number of pulses and the pulse frequency in Tab. 3 are calculated on the basis of the joint angle corresponding to the 14 target actions in Tab. 1 and 1s for completing each target action.

Table 1 Joint angle of the target motion

Action Name	Joint angle (degree)	Action Name	Joint angle (degree)
Elbow flexion	elbow: 45	Shoulder flexion and elbow extension	shoulder: 90 elbow: -90
Elbow extension	elbow: -90	Shoulder extension and elbow flexion	shoulder: -30 elbow: 45
Shoulder flexion	shoulder: 90	Shoulder and elbow extension	shoulder: -30 elbow: -90
Shoulder extension	shoulder: -30	Shoulder abduction and elbow flexion	shoulder: 60 elbow: 45
Shoulder abduction	shoulder: 60	Shoulder abduction and elbow extension	shoulder: 60 elbow: -90
Shoulder adduction	shoulder: -30	Shoulder abduction and elbow flexion	shoulder: -30 elbow: 45
Shoulder and elbow flexion	shoulder: 90 elbow: 45	Shoulder abduction and elbow extension	shoulder: -30 elbow: -90

Table 2 Target action initial and ending positions

Initial position	Ending positions of 14 action						
	Elbow flexion	elbow extension	shoulder flexion	Shoulder extension	Shoulder abduction	Shoulder adduction	shoulder and elbow flexion

	shoulder flexion and elbow extension	shoulder extension and elbow flexion	shoulder and elbow extension	shoulder abduction and elbow flexion	shoulder abduction and elbow extension	shoulder adduction and elbow flexion	shoulder adduction and elbow extension

Table 3 Inverse operation outputs of the target motion

Action name	Configuration of servo M1		Configuration of servo M2		Configuration of servo M3	
	Rotating speed (r/min)	Pulse number (Times)	Rotating speed (r/min)	Pulse number (Times)	Rotating speed (r/min)	Pulse number (Times)
Elbow flexion	50	8334	0	0	0	0
Elbow extension	-100	16667	0	0	0	0
Shoulder flexion	100	16667	100	16667	0	0
Shoulder extension	-34	5556	-34	5556	0	0
Shoulder abduction	-10	1667	-10	16666	50	8334
Shoulder adduction	5	834	5	834	-25	4167
Shoulder and elbow flexion	150	25001	100	16667	0	0
Shoulder flexion and elbow extension	0	0	100	16667	0	0
Shoulder extension and elbow flexion	17	2778	-34	5556	0	0
Shoulder and elbow extension	-136	22224	-34	5556	0	0
Shoulder abduction and elbow flexion	-150	25000	-100	16667	500	83334
Shoulder abduction and elbow extension	0	0	-100	16667	500	83334
Shoulder abduction and elbow flexion	0	0	50	8334	-250	41667
Shoulder abduction and elbow extension	200	33334	50	83334	-250	41667

4. Hardware design of rehabilitation training system

4.1 The design of EMG signal acquisition system

The designed EMG acquisition system is shown in Fig.5, where the acquisition electrodes extract sEMG signals. The front-end acquisition circuit amplifies the weak signal before the A/D converter. The data acquisition card converts the sEMG analog signal into digital signal and stores it in the computer. Fig.6 is the physical setup of the EMG acquisition system.

Fig. 5 The composition of EMG signal acquisition system

Fig. 6 The EMG signal acquisition system

4.2 The design of motion control system

As is shown in Fig.7, the motion control system identifies the target motion and then transfers it to the motion control card through the PC. The motion control card delivers the instruction to the server driver and the server driver drives the motor.

Fig. 7. Control method of the motion control system

5. Design of the pattern recognition algorithm

5.1 Feature extraction

The feature extraction methods of sEMG signals include time domain method, frequency domain method, time-frequency domain method and model parameters method (Oskoei and Hu, 2007; Sharma et al., 2012), etc. To further enrich information of the single feature vector, we proposed a method integrating the AR model coefficients and wavelet coefficients. We only chose the energy value and the max value of the low-frequency part in the last layer wavelet decomposition to merge with the AR model coefficients. The reason why we chose the low-frequency part in the last layer wavelet decomposition was that it represented the main features of the signal (Sharma et al., 2013). The following parameters need to be determined:

(1)The AR model order: The Levinson-Durbin recursive algorithm (Farmer et al., 2014; Al-Angari et al., 2016) and the empirical value can be used to solve the AR model coefficients. Previous research showed that when the order was 3~5 (Gokgoz and Subasi, 2014; Napoli et al., 2015), the AR model can represent the feature of the sEMG signal perfectly. Here 4th order was chosen for the AR model.

(2)The selection of wavelet function and wavelet decomposition level: Sym4 was chosen as the wavelet function because of its frequency domain characteristics and higher resolution of time series that the Sym4 has when compared with other wavelet functions (Arjunan and Kumar, 2010). The number of layers was usually chosen as 3~5. In this paper, 3 layers were chosen to improve the real time capability of the EMG control system.

5.2 Classifier design

The pattern classifier classifying the target motion includes neural networks, linear classifier and probability method (Boostani and Moradi, 2003; Asghari Oskoei and Hu, 2007; Kumar et al., 2003) etc. In this paper, the BP network was chosen as the pattern classifier because the BP network allowed nonlinear mapping, fault-tolerance, generalization and easy implementation (Hahne et al., 2014). The principle of the BP network can be described in Fig.8, and the input vector is transferred to the output layer through each layer. When the actual output of the network does not meet the expected output, the mean square error is propagated backwards. The expected output is the output layer of the network, generally based on the number of target actions. By constantly correcting the weight of each layer, the mean square error finally satisfies the set value, and the learning algorithm is gradient descent method. The model used the features extracted from the EMG signals data to classify the different motions. However, this result need long time to learn. During training, the model tried to recognized the motion. If the prediction did not match the actual label, it would calculate the gradients to decrease the loss which was the mean square error. This process was called propagation. Then, we got new weights to perform the matrix multiplication. After the calculation of hidden layers, the model would get the relationships between the data and label. After many steps, the loss can reach a low level and we can get a good classification accuracy. The commonly used structure of BP network is a single hidden layer of the three-layer structure, in which $X = (x_1, \dots, x_i, \dots, x_n)$ is the input vector, $O = (o_1, \dots, o_i, \dots, o_m)$ is the output vector and V and W are the weight vectors for each layer.

Fig.8. The principle of the BP network

In Fig.8, we can get the formulation:

$$o_k = f\left(\sum_{j=1}^m w_{jk} y_j\right), k = 1, 2, L, s \quad (1)$$

$$y_i = f\left(\sum_{j=1}^n v_{ij} x_j\right), i = 1, 2, L, m \quad (2)$$

Because of the random initial weights and gradient descent algorithm, standard BP network suffers local extremum and low convergence speed. In this paper, a new method combining the Particle Swarm Optimization (PSO) algorithm and the Levenberg-Marquardt algorithm was proposed to optimize the BP network. LM algorithm is the most widely used non-linear least squares method with the advantages of Newton's French gradient descent method. The use of LM algorithm can speed up BP network convergence and prevent BP network into the local optimal. PSO algorithm is a new evolutionary algorithm, which starts from the random solution, and the optimal solution is obtained by iteration. Here the stochastic solution is used to optimize the weight of the BP network. We used the PSO algorithm to optimize the weight of the BP network to get close to the optimal weight, and the convergence speed of the BP network is accelerated. The BP network implementation process based on PSO-LM optimization is shown in Fig.9. The initial weights are first optimized with PSO algorithm (Silva et al., 2015; Subasi, 2013) and then corrected with LM algorithm. The guiding ideology of using PSO algorithm to optimize weight of the BP network particle is regarding the weight as

particle of PSO algorithm. Essence of the LM algorithm is the combination of gradient descent algorithm and Newton method.

Fig. 9. Process of the BP network weight optimized by the PSO algorithm

Next we will design the BP network optimized by PSO-LM algorithm:

(1)The design of Network architecture: ① Input layer design: The character dimension of method merging AR model coefficients and wavelet coefficients was 36 (Wang et al., 1998), so 36 was chosen as the input layer nodes; ② Output layer design: There were 14 target motions which were represented with 2^n . When n equals 4, the 14 target motions were represented by 0001, 0010, 0011,..., 1110. ③ Hidden layer design: Through iterations of testing it was determined that the training effect was best when the hidden layer node was 18.

(2)The determination of initial weights and learning factor: On the basis of the BP network architecture, PSO Algorithm was used to optimize the initial weights of the network. Meanwhile, in order to maintain the stability of the network, the learning factor value (η) was 0.01 (Ali et al., 2015; Manalo et al., 2016).

(3)The determination of transfer function: Considering the target action, category was expressed in 2^n . The transfer function of every layer in BP network used unipolar sigmoid function to avoid the negative number. The output O was determined through the following formula .

$$O = \begin{cases} 1, & 0.5 \leq O \leq 1 \\ 0, & 0 \leq O < 0.5 \end{cases}$$

The final training system is shown in Fig.10.

Fig. 10. The rehabilitation training prototype system

6. Experiments

We compared the classification results from standard BP network and BP network optimized by PSO-LM algorithm through experiments. We collected 60 sets root mean square feature data from the 6 signal source muscles (the biceps brachii, triceps brachii, anterior deltoid muscle, posterior deltoid muscle, side deltoid muscle and teres major. The choice of the signal source muscles is based on the relevance of the action.) for the 14 target motions in the domain features. (The root mean square feature data here can be simplified to RMS, $\text{RMS} = \sqrt{\frac{1}{N} \sum_{i=1}^N x^2(i)}$, $x(i)$ represents the amplitude of the i -th EMG signal sample point and N is the number of signal sample point. The channel configuration of sEMG signal acquisition system from 1~6 channel respectively acquire signals of biceps, triceps, deltoid(front) muscle, deltoid(side) muscle, deltoid(rear) muscle, teres major. Sampling rate is 1280HZ). The first 30 sets of data are used as training data, the last 30 sets of data are used for testing. The result is shown in Tab.4.

Table 4 The outputs of the BP network optimized by PSO-LM algorithm

Classifier name	Training time[s]	Iterations number	Mean square error	The average recognition rate
Standard BP network	55	519	3.43×10^{-25}	83.7%
BP network optimized by PSO-LM	47	431	2.89×10^{-25}	84.9%

When comparing BP network based on PSO-LM algorithm with the standard BP network, the training time was reduced by 8s and the average recognition rate increased by 1.2%.

We extracted 60 sets of data from 5 healthy subjects and 12 sets from each subject. The data came from 6 signal source muscles. We used the wavelet coefficients of 60 sets of data to fuse the fourth order AR model coefficients as the input data and training model of BP network based on POS-LM optimization. And then we used the trained model to identify the 14 target actions of the 6 subjects. Each action was identified 5 times for each person. The total recognition rate was calculated and the average recognition rate was calculated. In this paper, limited by the experimental conditions, five subjects were selected. As for the patients are hemiplegic or not, the experimental results do not have any effect because the signal source is provided by the healthy side arm muscles. In future applications, it is necessary to establish a database of each target action so that the trained model is universal, or to further study the online learning algorithm. (channel configuration and adoption rate are the same). The experimental results are shown in Tab.4. The recognition rates for the 14 target motions were compared when using 4 different coefficients in the PSO-LM algorithm including only AR model coefficients, the maximum value of wavelet coefficients, the energy values of wavelet coefficients and AR model coefficients merging wavelet coefficients to optimize the BP. The results are shown in Tab.5.

Table 5 The outputs of the BP network optimized by PSO-LM algorithm

		AR coefficient	Max value of wavelet	Energy value of wavelet	AR+ wavelet
TARGET MOTION	Elbow flexion	96.7	96.7	93.3	100
	Elbow extension	93.3	86.7	83.3	80
	Shoulder flexion	96.7	100	100	100
	Shoulder extension	70	93.3	80	90
	Shoulder abduction	70	96.7	76.7	100
	Shoulder adduction	93.3	66.7	83.3	80
	Shoulder and elbow flexion	86.7	96.7	90	100
	Shoulder flexion and elbow extension	93.3	100	96.7	96.7
	Shoulder extension and elbow flexion	83.3	86.7	93.3	93.3
	Shoulder and elbow extension	86.7	96.7	100	93.3
	Shoulder abduction and elbow flexion	100	96.7	96.7	100

	Shoulder abduction and elbow extension	70	100	100	86.7
	Shoulder adduction and elbow flexion	93.3	73.3	83.3	83.3
	Shoulder adduction and elbow extension	100	66.7	83.3	100
Average recognition rate (%)		88.1	89.8	90	93.1
Average response time(s)		0.154	0.207	0.233	0.243

When the BP network was optimized based on PSO-LM algorithm, using the maximum value of wavelet coefficients can increase the average recognition rate of 5% compared with AR model coefficients and using the energy value of wavelet coefficients can increase the average recognition rate of 3.3%, while using the method combined with AR model coefficient and wavelet coefficients increased the average rate of 3.1% compared with AR model coefficients. At present, the average recognition rate is still the most commonly used indicator to determine the validity of the model. This paper studied a new evaluation standard, the recognition rate of each action was weighted according to the frequency of normal use. However, a database of the usage frequency of each action has not been established. The response speed of the target action is also an important index to consider the effectiveness of the system. From the experimental results, the average response time of the recovery robot is less than 0.3s, which indicated that the response speed of the upper limb rehabilitation training system is fast. Based on these findings, it is concluded that the training is effective.

7. Conclusions

In this paper, a hemiplegic upper limb rehabilitation training system based on surface EMG signals was designed, which mainly included an EMG acquisition system, motion recognition system and motion control system. An innovative feature was that the motor and reducer are centrally placed in the shoulder of the machine arm. The movement was stable because the inertia of each joint movement was reduced. Input vectors used for optimizing BP network merge the AR model coefficients and wavelet coefficients which can effectively identify the operation mode including elbow flexion, elbow extension, shoulder flexion, shoulder extension, shoulder abduction, shoulder adduction and other 8 motions. The average recognition rate can reach up to 93.1% which demonstrated the effectiveness of the system.

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