Prediction of Human Elbow Joint Torque Based on Improved BP Neural Network

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Abstract

Pathological tremor brings too much inconvenience to patients in life and work. For better tremor suppression, a suitable biomechanical model must be established. Based on the Hill skeleton-muscle model, quantitative relations between EMG and static torque of elbow joint can be identified with improved neural network. The weights of improved neural network are adjusted according to the need, and muscle activation grade is confirmed. Through this method, a biomechanical model is established. Using OpenSim software we can simulate the drive of skeleton model by EMG signals and the validity of the model is tested by experiment.

Keywords: skeleton-muscle model, EMG(Electromyographic signal) , joint torque, improved neural network(NN)

Introduction

Pathological tremor is common in middle and old ages and gives patients too much inconvenience in life and work. Now there are no effective methods in medical field. FES(Functional electrical stimulation) method is good for physiological control of human body and is in deeper research now. Biomechanical model is helpful to solve questions such as the actions of a series of relevant muscles, control mode of FES and effectiveness. All these provide basis for tremor suppression.

Biomechanical model is the hotspot now and many institutions are in deep work. Modeling methods mainly include model or non-model methods. Typical model methods are Hill model with phenomena presentation and Huxley model with physiological presentation. Pennestri E.et al established virtual skeleton muscle model of upper limb which is fit for the movement description of skeletons simply. Muscle activation grade is also calculated. Zhang D.G studied on the effectiveness of tremor suppression by wearable exo-skeleton and FES. They presented physical model aimed to muscle electrical stimulation first and creatively leaded in muscle damper character, electrical stimulation, and activation when muscles are in contraction.

Non-model method mainly establish non-linear mapping by artificial neural network or polynomial fitting. There are many ways to establish the relations of muscle activation and joint dynamics using NN. Jer-JunnLuh estimated relation model between EMG and static moment of elbow joint using 3-layer feedforward adaptive NN. Sepulveda F. got the relations of force and EMG signals by extracting EMG eigenvalue using time domain. Freriks extracted EMG eigenvalue using RMS and meso-position MF to gain the amplitude and spectral characteristics of bicipital muscle of arm.

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Muscle activation grade is the conceptual expression of muscle stimulation and skeleton-muscle model is driven by it. In this paper using non-linear system identification ability of NN to calculate muscle activation grade, proper activation grade is got to reflex muscle excitement status. Using activation grade as input, with the comparison of the realistic moment and calculated moment generated in joints, the activation grade is verified and the valid model is then obtained.

Materials

Control action of EMG and joint moment is expressed in figure 1, which includes multiple complex transmission. Usually NN algorithm is used to identify the non-linear relations. Thinking about Hill's research in the expression of module 2 and 3 in mathematical formula, only muscle activation dynamics model(module 1) is not clear in math, so we think the module 1 as a blackbox and identify it using NN. For the activation grade is not measured directly and joint moment M can be measured, EMG and moment error training sets which are measured can train to setup NN (Fig.2).

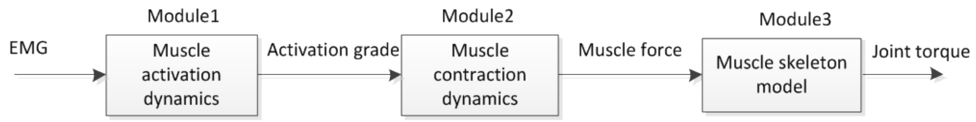


Fig.1 Control relationship of EMG and joint torque

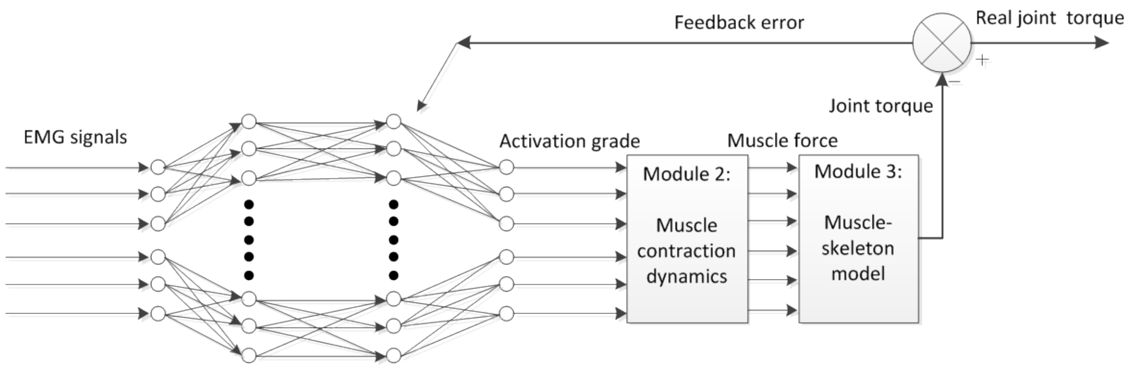


Fig.2 activation dynamics of NN with the error training of joint torque

When choosing BP NN to predict joint moment, the prediction error of joint moment can be used to prediction error of muscle activation grade(Fig.1). It is that when the prediction error of joint moment is ΔM, the muscle I is Δa_i

$$\Delta M = \frac{\partial M}{\partial a_1}\Delta a_1 + \frac{\partial M}{\partial a_2}\Delta a_2 + \cdots + \frac{\partial M}{\partial a_s}\Delta a_s = \sum_{i=1}^{s}\frac{\partial M}{\partial a_i}\Delta a_i \tag{1}$$

In which a_i represents the activation grade of muscle I, s represents the number of muscles which participates contribution of torque, M represents output joint moment. ΔM represents variable quantity of joint moment after the change of activation grade of muscle.

In description of Hill muscle model, joint moment is the function of ai(the activation grade of muscle) and θ (joint angle). The function can be expressed in formula 2

$$M = M\left(a_1, a_2, \ldots, a_s, \theta\right) \tag{2}$$

Joint moment M has the partial derivative $\partial M / \partial a_i$ of the activation grade of muscle, which can expressed in the main part of the first order of Taylor expansion as formula 3:

$$\delta M = M\left(a_1, a_2, ..., a_s, \theta\right) - M\left(a_1, a_2, ..._i\left(a_i + \delta a_i\right) ..., a_s, \theta\right)$$
$$\frac{\partial M}{\partial a_i} \approx \frac{\delta M}{\delta a_i} \tag{3}$$

In which δa_i is a very small variable at point a_i , δM is a variable of joint moment M which is derived when a δa_i increased in a_i while others parameters is fixed. Though joint moment prediction error ΔM and $\partial M / \partial a_i$ can be got during the course of prediction, it is not enough to equate $\Delta a_1, \Delta a_2, ..., \Delta a_6$ of the prediction error from equation 1. So we need to gain prediction error further by network weights management.

According to the method of counter propagation algorithm, when a network layer has no direct error signals, the signals can be derived from the next network layer. It is similar to the course of using NN to identify EMG and the activation grade of muscle. So the output layer of NN can be seen as a hidden layer and the muscle-skeleton model as an output layer. The weights of the hidden layer are adjusted as:

$$\Delta w_{ji} = -\eta \frac{\partial \xi(n)}{\partial \varpi_{ji}} = \eta \delta_j(n) y_i(n) \tag{4}$$

$$\delta_j(n) = -\frac{\partial \xi(n)}{\partial y_j(n)} \frac{\partial y_i(n)}{\partial v_j(n)} = -\frac{\partial \xi(n)}{\partial y_i(n)} \psi_j'(v_j(n)) \tag{5}$$

The key point of weights adjustment is to calculate the $\partial \xi(n) / \partial y_i(n)$

The NN signals' output is joint moment after muscle-skeleton model. The error of mean square of the sample is defined as:

$$\xi(n) = \frac{1}{2}\left(M_{measured} - M_{output}\right)^2; \quad y_i(n) = a_j(n) \tag{6}$$

In which Mmeasured is the measured joint moment, Moutput is the calculated joint moment using activation grade of muscle in NN. aj(n) is the activation grade of muscle j , which is also the output of the output layer of NN. So the calculation formula for the weights of output layer is as follows:

$$\frac{\partial \xi(n)}{\partial y_j(n)} = -(M_{measure} - M_{output}) \frac{\partial M_{\text{output}}}{\partial a_j} \tag{7}$$

$$\delta_j(n) = (M_{measure} - M_{output}) \frac{\partial M_{\text{output}}}{\partial a_j} \varphi_j'(v_j(n)) \tag{8}$$

$$\Delta w_{ji} = \eta \delta_j(n) y_i(n) = \eta (M_{measure} - M_{output}) \frac{\partial M_{\text{output}}}{\partial a_j} \varphi_j'(v_j(n)) y_i(n) \tag{9}$$

Up to now, the weight adjustment of the NN output is clear. Using traditional formula we can calculate the former layer weights.

Experiment

Experimental platform

A single freedom experimental platform is designed. During the course of the test, motion of the joints of shoulder and upper arm of the testers is restrained. In the meantime the motion of the wrist is limited in the horizontal plant to avoid the effect of gravity torque. Device structure is as figure 3 which includes rotated stick, fixed stick and a set of pulley. The pulley is to transmit vertical load to horizontal load. Joint angle is measured by subjacent fixed angle encoder and joint torque is measured by 6-D force sensor which is installed between the rotated stick and fixed stick. The force sensor is SI-80-4 made by ATI Corp.. Data acquisition program of force sensor is compiled with VC++ and acquisition frequency is 256Hz.

Using multiple channel EMG recorder and one-time Ag/AgCl electrode, main muscles including biceps, brachioradialis and triceps are measured from the muscle group of elbow joint. Electrodes are pasted on the tester's arm, and the position of fossa cubitalia and olecranon is the reference to paste electrode (fig. 4). The use of electrodes refers to Freriks's presentation .

Experimental procedure

4 male testers in average age of 25 are selected and they are all healthy with no nervous system or motion disorder. In the rotation course, rotation axis of elbow joint is coaxial with rotation axis of experiment table. So the measured angle of angle sensor is the direct position of elbow angle. Shoulder joint is fixed in 90 degree's position and motion range of elbow's joint is limited during 0 and 130 degree in the level.

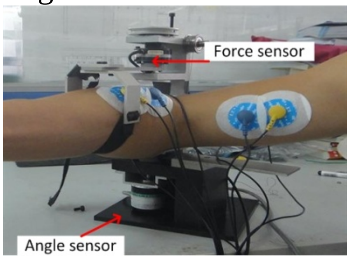


Fig.3 Single freedom platform

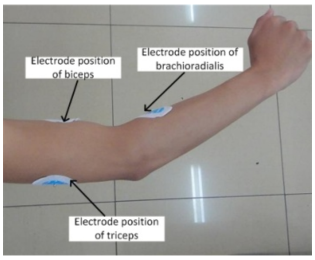


Fig.4 Electrode position

Main steps are as follows:

1. Each tester will finish isometric contraction of elbow joint in 120°, 90°, 60° separately, and EMG signals and joint moments are measured.
2. Each tester will finish stretching and curving motions during 3 cycles separately in each degree.
3. Recording EMG signal values in the max isometric contraction to normalize processing of EMG.
4. Choosing No.1 tester to simulate tremor for NN to predict tremor moment.

Results and discussion

Testers finished experiments in three joint degrees. Using established 0 output network as the original training network, first NN's training is gained by joint angle 120° . With measured EMG signals and corresponding joint moment, after 16000 times training, joint moment after the output of muscle-skeleton model is in figure 5.

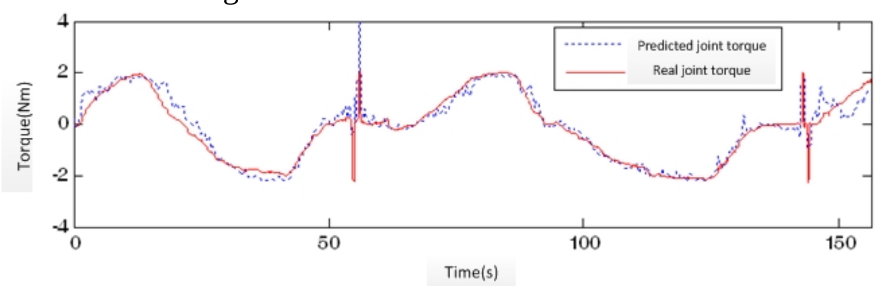


Fig.5 Result of No.1 tester's NN training in joint angle 120°

During the training of NN, the change of all samples' error sum of squares of output moment is in figure 6. The figure reflects the good study performance of NN. Figure 7 is the correspondence between real moment and prediction value. The muscle activation grade of NN calculation is in figure 8.

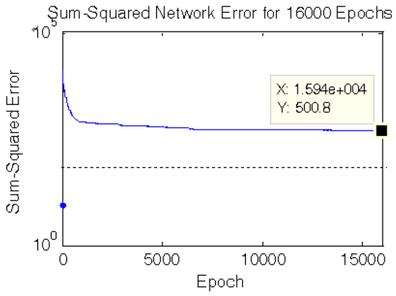


Fig.6 Error during the torque training

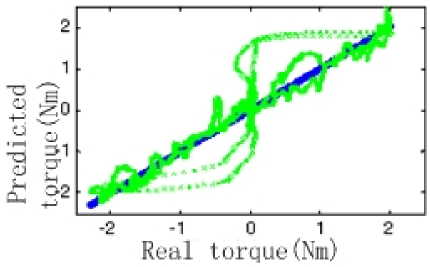


Fig.7 Relationship between real and predict value of torque

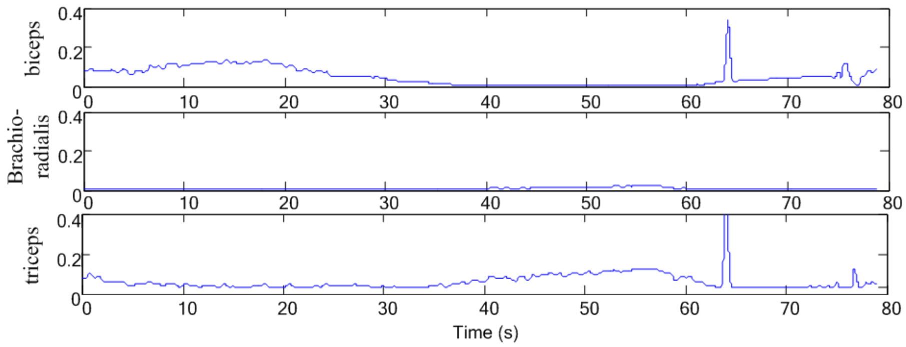


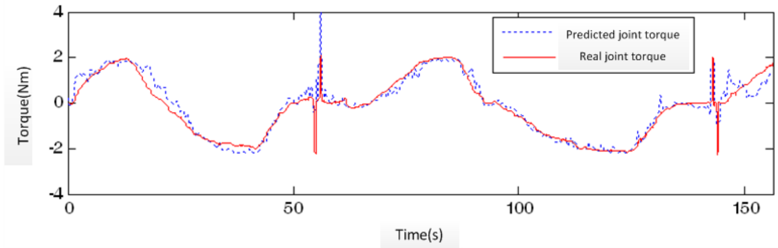
Fig.8 Activation grade of NN's calculation result

After the training network of 120° ,the network is trained using experimental data of 90° and 60° separately. The average error after training is in table 1.

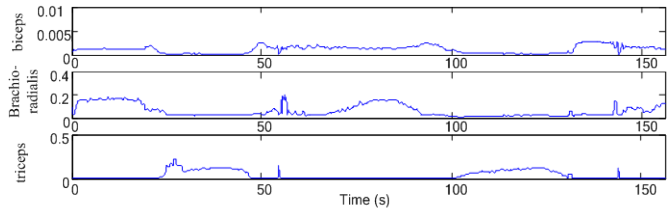
Table 1Average error of joint torque training

Joint angle(°)	60	90	120
Average error(Nm)	0.052	0.065	0.058

We use the trained network to predict joint moment and the prediction data is the RMS values of EMG when No.1 tester did twice stretch and bend motions. The prediction result of joint moment is in figure 9(a). The average error of prediction value and real value is 0.102. The activation grade of NN output is in figure 9(b), in which the activation grade of bicipital muscle of arm is smaller than brachioradialis'. That means that the NN predicts the power of elbow bending from the action of brachioradialis. It results from the multiple solutions of NN.



(a) Prediction result of elbow joint torque



(b) Prediction result of the muscle activation grade

Fig.9 NN identification for EMG and elbow joint torque

The results above illustrate that the prediction accuracy of the NN meets requirements and then we can use the NN to predict the joint moment of tremor. A set of EMG signals of elbow tremor is measured as figure 10 and the predicted joint moment through NN model calculation is in figure 11. The activation grade of NN calculation is in figure 12.

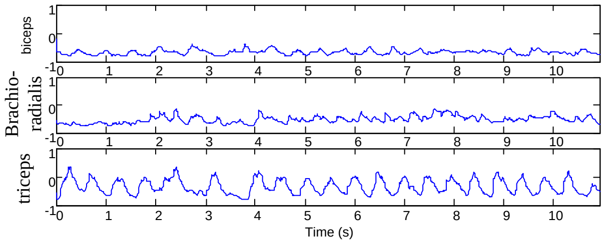


Fig.10 Normalized RMS value of EMG signal

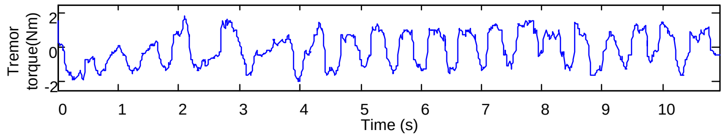


Fig.11 Prediction value of joint torque of tremor

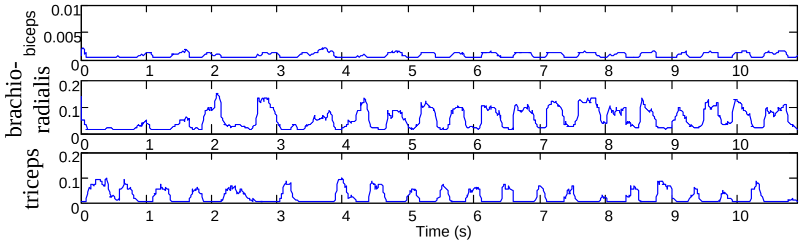


Fig.12 Activation grade of tremor motion

The activation grade of NN calculation controls the muscle-skeleton model in OpenSim software environment (fig. 13).The variable curve of each muscle force is in figure 14 during the course of calculating elbow joint tremor.

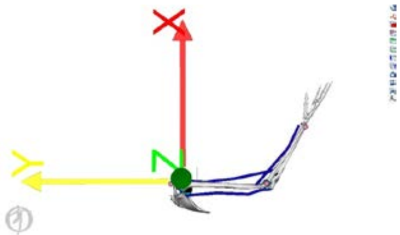


Fig.13 Model in OpenSim software

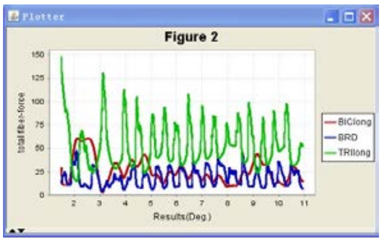


Fig.14 Calculated muscle forces

Conclusions

An improved neural network is developed to solve the problem of a blackbox of muscle activation dynamics. With the proper weight adjustment in hidden layer, muscle activation grade can be identified. And then using Hill skeleton-muscle model parameters we can get the relationship between the input of EMG signals and the output of joint torque. The experiment verified the valid model.

Acknowledgments

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