Neural Networks Identification of Electrical Stimulation Model Based on Hammerstein

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Abstract

We developed a wrist model using neural networks based on Hammerstein cascade. The model can predict the wrist angle while stimulating by different pulse widths of the stimulation. It consists of neural networks to represent the muscle recruitment properties, and a linear dynamical system to represent the time variation. Simulation results on actual measurements were compared with the output from the wrist model.

Introduce

Identification of the dynamic of electrically stimulated muscle is essential for developing stable adaptive controllers in Functional Electrical Stimulation (FES), but it is a difficult to get a general forms[1][2][3][4]. The muscle is strongly nonlinear and time-varying, as the behavior of the muscles under excitation varies with many parameters. The Hammerstein cascade[5], using in muscle model, is an important way to model nonlinear biological system. In this structure, high-order nonlinear muscle system can be represented accurately using relatively few parameters.

Neural networks is used in the identification of model[7], because it can map arbitrarily complicated nonlinear input/output relationships from given training data set[6]. They have been applied in FES also because neural networks are based on biological systems and have potential application for motor control. An example is[3], who present a special networks structure based on Hammerstein model to model an knee.

In our system, we developed a wrist model using neural networks, The model structure composed two parts: the static nonlinear and the dynamic linear. And its core is a Hammerstein model, which has been successful in the identification of isometric contraction. Finally, we demonstrated that it can describe the wrist's characteristics in stimulation.

Methods

2.1. Model Structure

The model structure is shown in Fig. 1. It composed a static nonlinear part using artificial networks and a dynamic-linear part expressing the second order dynamics. The static nonlinearity is thought to represent the recruitment curve of the muscle. The linear part stands for the oscillation movement, which may be caused by time variation (like the fatigue or operating environment).The model input is electrical stimulus which is represented by stimulating pulse-width, and the model output is the wrist angle during electrical stimulating. Moreover, the internal variable is the static response by the wrist.

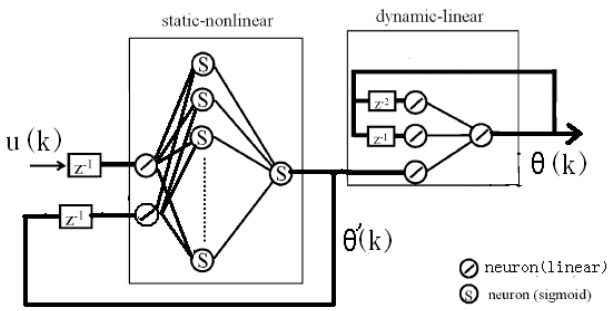

Fig.1 model structure

The static part is a basic layer networks, two types of neurons were included in the network. The first kind neurons of which output function was the

sigmoid function given by:

$$f(x) = \frac{1-e^{-x}}{1+e^{-x}}. \qquad (1)$$

And the other had a linear output function:

$$f(x) = x \qquad (2)$$

The output angle $\theta(k)$ can be written as (3):

$$\theta(k) = b_0 f\left(u(k-1), \dot{\theta}(k-1)\right) + a_1\theta(k-1) + a_2\theta(k-2) \qquad (3)$$

There are four parts to be identified: function f and parameters b_0, a_1, a_2. Function f reflects the muscle's static response which represents essentially the recruitment curve of the muscles, and the latter stands for the position depending oscillation movements.

The thick line of the structure shown in Fig.1 is unique, and the thin line is adjusted by error back-propagation algorithm, which is to reduce total error (E) in the network outputs by gradient descent method

$$\Delta\omega_i = -\varepsilon \bullet \frac{\partial E_i}{\partial \omega_i} \qquad (4)$$

2.2. Training of the model

The training of the model is in two steps: learning of the static model and learning of the second-order dynamics. Actually, the signals, obtained from unimpaired subjects, contain two parts: static part reflecting the recruitment of the wrist and dynamics reflecting the variation (like the fatigue or operating environment). So, the training of the model is to divide the two parts of the signals properly.

The signals, training for the first static part, consisted of the stimulus intensity $u(k)$ and the wrist angle $\theta'(k)$. This $\theta'(k)$ is the response to a given stimulating intensity in the initial state as shown in Fig.2. And the signals for training the second part were response of the wrist under continuous stimulation, as shown in Fig.3 and Fig.4

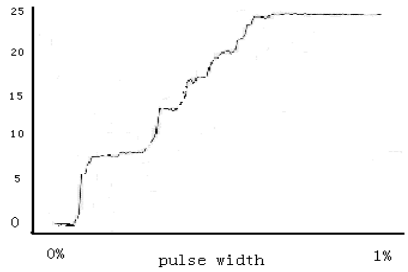

Fig.2 recruitment curve

The experiment

All measurements were obtained from healthy able bodied subjects. During the experiment the subject had with his forearm and hand relaxed. The wrist could extend from horizontal position to upward. The wrist angle was measured with a goniometer, and the data was recorded at a stimulating frequency of 30Hz. In order to vary the stimulating intensity, only the pulse width was varied from 0ms to 1ms in our system.

In order to record the static response of the wrist in the initial state, the subject was stimulated by a continuous fixed pulse width with the rest interval 1s in every 200 data (1 set of data is a continuous stimulating for 2s). Fifty stimulations with different stimulating intensity were produced by random and applied to the subject to record the wrist response during stimulation. This measured data were used as the training signals for the forward dynamics model. Another fifty random stimulations were used as the testing signals for the validation of the forward model.

Results

The applied stimulation signals for training the static part are shown in Fig. 2. The Fig.3 and Fig.4 are the validation signals for the model.

After training static part, we got an approximation of the input nonlinearity, as shown in Fig.5. And the validation is shown in Fig.6 using the testing data set. The solid lines show the experimental data and dashed lines show the simulation from the model. The wrist angle was ranged from 0 to 25 degree. The graph showed that the model tracks relatively well. The dynamics can be modeled with the mean error 3.2 degree and the standard deviation was 0.7.

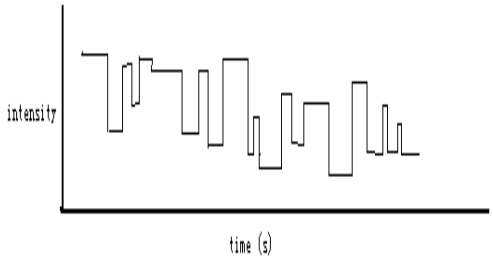

Fig.3 validation of input signals

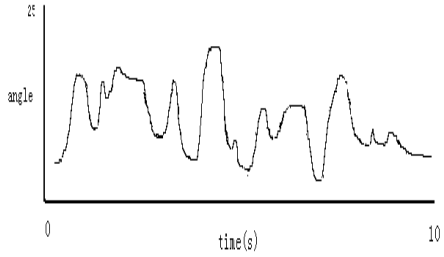

Fig.4 validation of output angle

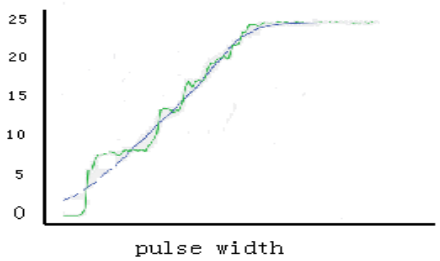

Fig.5 identification of recruitment curve

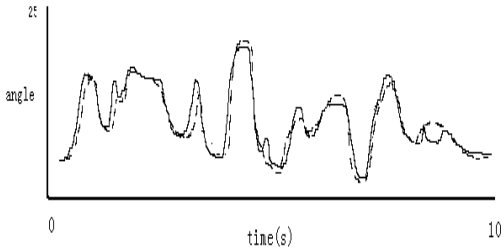

Fig.6simulation with validation data

Conclusions

The wrist model using neural networks based on Hammerstein cascade showed a good performance and has the potential could be applied in FES control.

Acknowledgement

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Reference

[1] Howard J. Chizeck, Seokjoo Chang, Richar B. Stein, Avram Scheiner, and Donald C. Ferencz. Identification of electrically stimulated quadriceps muscles inparalegic subjects. IEEE Trans. Biomed. Eng., vol. 46, no.1, pp. 51-61, 1999.

[2] Kenneth J. Hunt, Marko Munih, Nick de N. Donaldson, and Fiona M> D. Barr. Investigation of the Hammerstein hypothesis in the modeling of electrically stimulated muscle. IEEE Trans. Biomed. Eng., vol. 45, no. 8, pp. 998-1009, 1998.

[3] J. Schultheiss and L. del Re. Neural networks identification of muscular response using extended Hammerstein models. Proc. Annu. Int. Conf. IEEE. Biomed. Eng., pages 2566-2569, 1998.

[4] Waleed F. and Hugh H. A method for Identification of Electrically Stimulated Muscle. Proc. Annu. Int. Conf. IEEE. Biomed. Eng., pages 6225-6228, 2005.

[5] I. W. Hunter and M. J. Korenberg. The identification of nonlinear biological system: Wiener and Hammerstein cascade models. Biol. Cybern, vol. 55, pp. 135-144, 1986.

[6] K. S. Narendra and K. Parthasarathy, Identification and control of dynamical systems using neural networks. IEEE Trans Neural Networks. vol. 1, no. 1, pp. 4-27, 1990

[7] Kenji Kurosawa, Ryoko Futami and Takashi Watanabe, et al. Joint Angle Control by FES Using a Feedback Error Learning Controlle. IEEE Trans Neural System and Rehab. Eng, vol.13, no. 3, pp.359-371, 2005