A Computer Simulation Test of Feedback Error Learning-Based FES Controller for Controlling Random and Cyclic Movements

Takashi Watanabe and Naoya Akaike

Abstract

Feedback control of movements by functional electrical stimulation (FES) can be useful for restoring motor function of paralyzed subjects. However, it has not been used practically. Some of possible reasons were considered to be in designing a feedback FES controller and its parameter determination, and nonlinear characteristics with large time delay in muscle response to electrical stimulation, which are different between subjects. This study focused on the hybrid controller that consists of artificial neural network (ANN) and fuzzy feedback controller. ANN was trained by feedback error learning (FEL) to realize a feedforward controller. Although FEL can realize feedforward FES controller, target movement patterns are limited to those similar to patterns used in the training. In this paper, FEL-FES controller was tested in learning both random and cyclic movements through computer simulation of knee joint angle control with 4 different training data sets: (1) sinusoidal patterns, (2) patterns generated by low pass filtered random values, (3) using both the sinusoidal and the LPF random patterns alternatively and (4) patterns that consisted of 3 random sinusoidal components. Trained ANNs were evaluated in feedforward control of sinusoidal and random angle patterns. Training with data set (1) caused delay in controlling random patterns, and training with data set (2) caused delay in controlling sinusoidal patterns. Training with data set (3) showed intermediate performance between those with data set (1) and (2). Training with data set (4) could control adequately both random and sinusoidal patterns. These results suggested that generating movement patterns using sinusoidal components would be effective for various movement control by FEL-FES controller.

Keywords

FES • Feedback error learning • Ankle Tracking control

1 Introduction

Functional electrical stimulation (FES) can be useful for restoring or assisting paralyzed motor function due to a spinal cord injury or a cerebrovascular disease [1, 2]. However, feedback FES control has not been used practically, although it can be effective for restoring paralyzed movements, while a method of using pre-determined stimulation data were practical [3]. Some of possible reasons are considered to be in difficulties of designing a feedback FES controller and its parameter determination because the musculoskeletal system has nonlinear, time-variant characteristics with large time delay in muscle response to electrical stimulation, which are different between subjects, and redundancy in stimulation intensity determination.

In our previous work, a multichannel proportional- integral- derivative (PID) controller was developed to control the redundant musculoskeletal system that involves an ill-posed problem in stimulus intensity determination [4, 5] and the PID controller was applied to Feedback Error Learning (FEL) controller [6–10]. In the FEL controller for FES (FEL-FES controller), an artificial neural network (ANN) was trained by the FEL to develop the inverse dynamics model (IDM) of electrically stimulated musculoskeletal system, which can be used as a feedforward controller. Although FEL can realize feedforward FES controller for each subject, target movement patterns are limited to those similar to patterns used in the training such as sinusoidal angle patterns or randomly generated angle patterns of two-point reaching movement. In addition, there are few studies on FES control of movements of nonlinear musculoskeletal system [11–13]. Therefore, an FES control

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of various movements for paralyzed subjects has been desired.

In this study, FEL-FES controller was developed using fuzzy feedback controller. Fuzzy controller is considered to be useful to realize a practical feedback FES controller. The FEL-FES controller was tested in learning both random and cyclic movements through computer simulation of knee joint angle control with 4 different training data sets.

2 Methods

2.1 Outline of FEL-FES Controller

The block diagram of the FEL-FES controller used in this study is shown in Fig. 1, which is composed of a fuzzy feedback controller and ANN. The ANN was trained to realize the inverse dynamics model (IDM) of electrically stimulated musculoskeletal system, which can be used as a feedforward controller. The fuzzy controller consisted of 2 sub-fuzzy controllers. One calculates change of stimulation intensity from error and the other calculates stimulation intensity proportional to the error. Stimulation intensity u_{fb} is the sum of the previous stimulation intensity and the calculated intensities. The sum of stimulation outputs from the ANN and the fuzzy controller is applied to a muscle.

2.2 Computer Simulation Method

The FEL-FES controller was tested in computer simulation of knee joint angle control by stimulating the rectus femoris. A three-layered ANN was used as a feedforward controller. The inputs of the ANN were time series of angles, angular velocities and angular accelerations of target movements at continuous 6 times, from n to $n + 5$ (sampling frequency of 30 Hz). The numbers of neurons were 18, 18 and 1 for the input, hidden and output layers, respectively.

The ANN was trained by the FEL under 4 different training data sets. Learning of the ANN was performed after a single control trial. In each control trial, movement was controlled for 24 s, and the first 4 s was not used for the learning. The 4 training data sets were as follows:

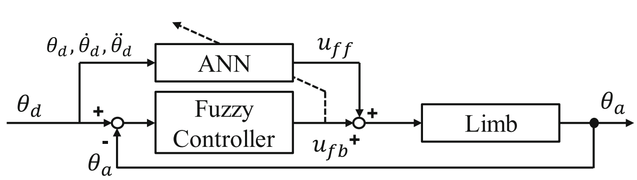

Fig. 1 Block diagram of the FEL controller for FES. θ_d and θ_a represent the desired and the measured joint angles. The ANN learns with the outputs of the fuzzy controller while controlling limbs

(1) sinusoidal patterns
(2) patterns generated by low pass filtered random values
(3) using both the sinusoidal and the LPF random patterns alternatively
(4) patterns consisted of 3 random sinusoidal components.

For the data set (1), sinusoidal pattern was determined for each control trial, in which cycle period and amplitude was selected randomly from 2, 3, 4, 5, and 6 s of cycle period and 2, 4, 6, 8, and 10° of amplitude with an offset of 5°. For the data set (2), random value between 0 and 1 was generated for 24 s data and the data was low pass filtered with cut off frequency of 0.2 Hz. Angle of the LPF random pattern was adjusted to be between 5 and 25°. Pattern of data set (4) was generated by the following for each control trial:

$$f(n\Delta t) = \sin\frac{2\pi}{T_1}n\Delta t + \sin\frac{2\pi}{T_2}n\Delta t + \sin\frac{2\pi}{T_3}n\Delta t \quad (1)$$

Here, Δt shows sampling interval and n is the sample number. Cycle period T_1, T_2 and T_3 were determined randomly in order to satisfy the following relation:

$$1.8 < T_1 < 3.2 < T_2 < 4.6 < T_3 < 6.0 \quad (2)$$

Amplitude was adjusted to be between 5 and 25°.

ANN learning was performed more than 10000 control trials, and stopped as mean error ME converged.

$$ME = \frac{1}{N}\sum_{n=1}^{N}|e(n\Delta t)| \quad (3)$$

where N is the total number of sampled data used for learning in a single control trial. The 4 ANNs trained with all data sets were tested in feedforward control of 3 sinusoidal angle patterns (cycle period of 2 s with amplitude of 10°, cycle period of 4 s with amplitude of 8° and cycle period of 6 s with amplitude of 6°). The 3 ANNs trained with data set (1), (2) and (3) were tested in feedforward control of LPF-random patterns and the ANN trained with data set (4) was tested in controlling random sinusoidal component patterns.

The model of electrically stimulated muscle was represented by a second order system with time delay. Gain of the model was determined by a cubic polynomial approximation of measured input-output characteristics of the rectus femoris of a healthy subject.

3 Results and Discussions

Examples of feedforward control by trained ANNs are shown in Figs. 2 and 3. ANN trained with sinusoidal patterns (data set (1)) could control properly all 3 sinusoidal patterns.

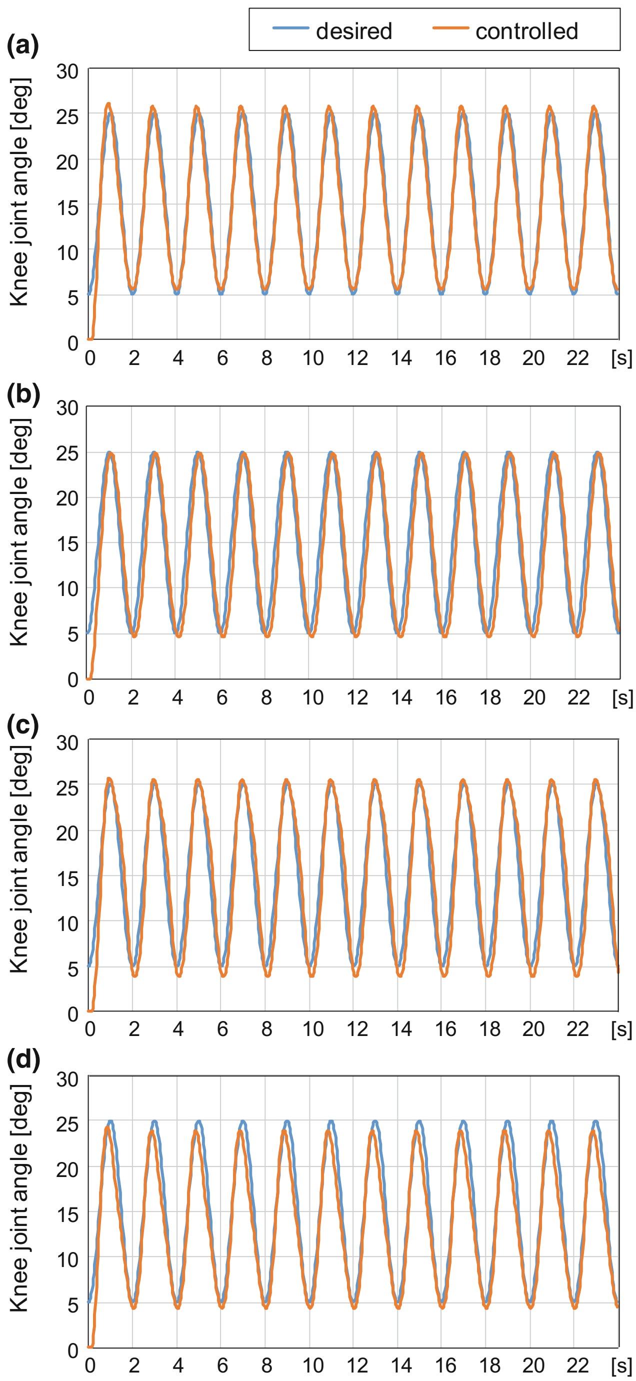

Fig. 2 Examples of feedforward control of sinusoidal angle trajectories by trained ANNs (cycle period of 2 s with amplitude of 10°). From the top, results of ANN trained with data set (**a**), (**b**), (**c**) and (**d**) are shown

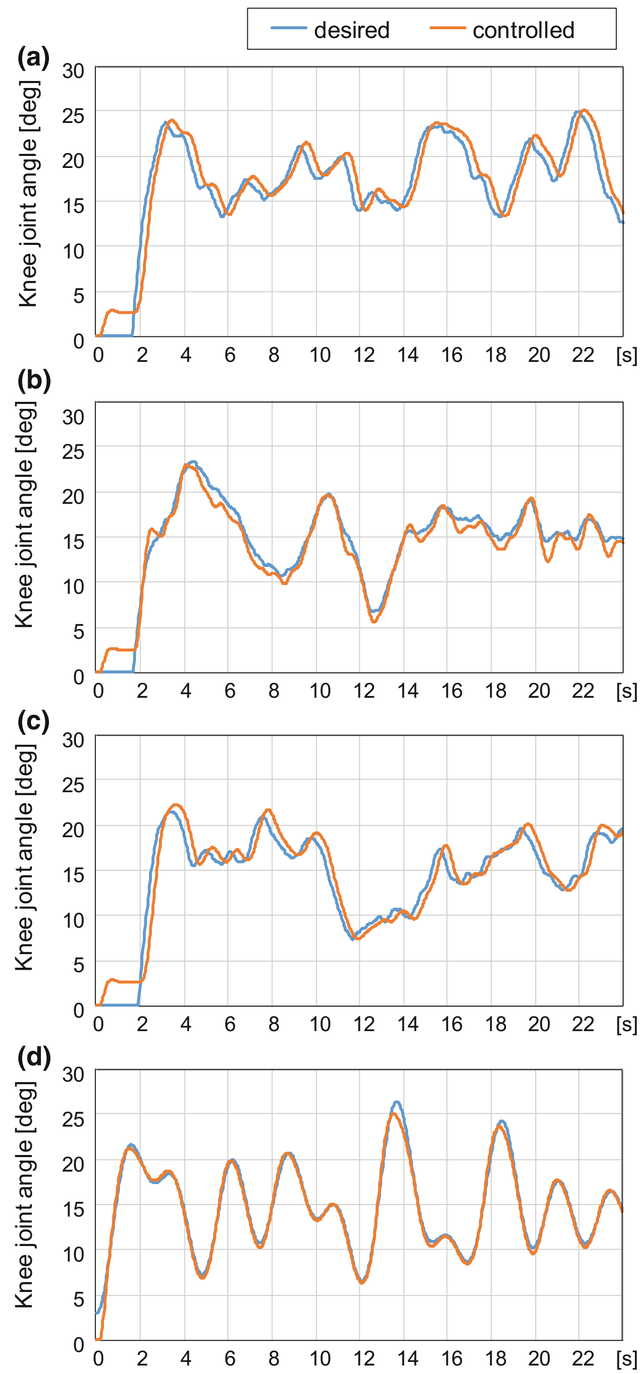

Fig. 3 Examples of feedforward control of unlearned random angle trajectories by trained ANNs. From the top, results of ANN trained with data set (**a**), (**b**), (**c**) and (**d**) are shown

However, time delay was caused in controlling LPF-random patterns. On the other hand, ANN trained with LPF-random patterns (data set (2)) could control LPF-random patterns well, while it caused larger time delay in controlling sinusoidal patterns than ANNs trained with other data sets. ANN trained with data set (3) showed intermediate results between those by the ANN trained with data set (1) and those with data set (2). The ANN trained with random sinusoidal component patterns (data set (4)) could control adequately both sinusoidal and random sinusoidal component patterns.

Table 1 Average *ME* of feedforward control of 3 sinusoidal angle patterns and 3 unlearned random angle patterns by trained ANNs using ANN connection weights after 10000 learnings

Data set	Sinusoidal	Random
(1)	0.52 ± 0.34	1.16 ± 0.08
(2)	1.23 ± 0.94	0.72 ± 0.12
(3)	0.91 ± 0.82	0.90 ± 0.07
(4)	0.68 ± 0.79	0.37 ± 0.04

Table 1 shows average mean error (*ME*) for 3 sinusoidal patterns and 3 random patterns. Values of *ME* were calculated for 20 s of each control trial from 4 s after the beginning of control. The error for tracking of sinusoidal angle patterns was smallest by the ANN trained with data set (1), although the ANN trained with data set (4) also showed small error. Training with data set (3) sometimes caused increase of error after decrease as the learning progresses. The ANN trained with the data set (4) showed small error for both patterns. Especially, 2 sinusoidal patterns with larger cycling periods and smaller amplitudes were controlled with better performance than the ANN trained with sinusoidal patterns (data set (1)).

The computer simulation tests suggested that generating movement patterns using sinusoidal components would be effective for various movement control by FEL-FES controller. As shown in our previous study [10], it is considered that using various target positions and movement velocities rather than repeated training with same target would be effective, even if training data is used only one time.

The model of electrically stimulated musculoskeletal system used in this study was a simple second order system although it included time delay and nonlinear gain. Therefore, data sets (1) and (2), which were basically effective for angle patterns similar to those used in ANN training, are considered not to be suitable for FES application. Using both patterns alternatively could not improve significantly the ANN learning. Although the computer simulation tests suggested that random sinusoidal component patterns (data set (4)) could be effective for learning various movement patterns for FES, target angle trajectories used in this paper did not include constant angle as used in moving between 2 points [10]. Random patterns for evaluation of data set (4) were different from others. It is necessary to test the trained ANN with various angle patterns including keeping constant angles.

The ANN used in this study was a 3-layered network with the fixed numbers of neurons. Learning coefficients were determined by a trial and error manner. Therefore, further examinations to determine parameters of ANN would be required.

4 Conclusion

In this paper, FEL-FES controller was tested in learning both random and cyclic movements through computer simulation of knee joint angle control with 4 different training data sets. Trained ANNs were evaluated in feedforward control of sinusoidal and random angle patterns. The ANN trained with random sinusoidal component patterns could control both sinusoidal and random patterns appropriately, while training with sinusoidal patterns and using both patters alternatively caused delay in controlling random angle patterns, and training with the LPF-random patterns caused delay in controlling sinusoidal patterns. These suggested that generating movement patterns using sinusoidal components would be effective for various movement control by FEL-FES controller.

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References

1. Handa, Y.: Current Topics in Clinical Functional Electri-cal Stimulation in Japan. J. Electromyogr. Kinesiol. 7(4), 269–274 (1997).
2. Lyons, G. M., Sinkjær, T., Burridge, J. H. and Wilcox, D. J.: A Review of Portable FES-Based Neural Orthoses for the Correction of Drop Foot. IEEE Trans. Neural Sys. Rehabil. Eng., 10(4), 260–279 (2002).
3. Hoshimiya, N., Naito, A., Yajima, M., Handa, Y.: A multi-channel FES system for the restoration of motor functions in high spinal cord injury patients: a respiration-controlled system for multijoint upper extremity. IEEE Trans. Biomed. Eng., 36(7), 754–760 (1989).
4. Watanabe, T., Iibuchi, K., Kurosawa, K. and Hoshimiya, N.: Method of Multichannel PID Control of 2-Degree of Freedom of Wrist Joint Movements by Functional Electrical Stimulation. Systems and Computers in Japan, 34(5), 25–36 (2003).
5. Kurosawa, K., Watanabe, T., Futami, R., Hoshimiya, N. and Handa, Y.: Development of a closed-loop FES system using 3-D magnetic position and orientation measurement system. J. Automatic Control, 12(1), 23–30 (2002).
6. Kurosawa K, Futami R, Watanabe T, Hoshimiya N.: Joint angle control by FES using a feedback error learning controller. IEEE Trans Neural Syst Rehabil Eng. 13(3), 359–371 (2005).
7. Watanabe, T., Kurosawa, K. and Yoshizawa, M.: An Effective Method of Applying Feedback Error Learning Scheme to Functional Electrical Stimulation Controller. IEICE Transactions on Information and Systems, E92-D(2), 342–345 (2009).
8. Watanabe, T. and Sugi, Y.: Computer Simulation Tests of Feedback Error Learning Controller with IDM and ISM for Functional Electrical Stimulation in Wrist Joint Control., J. Robotics, 2010, 908132, https://doi.org/10.1155/2010/908132 (2010).
9. Watanabe, T and Fukushima K.: An approach to applying feedback error learning for functional electrical stimulation (FES) controller: Computer simulation tests of wrist joint control. Advances Artificial Neural Systems, 2010, 814702, https://doi.org/10.1155/2010/814702 (2010).

10. Watanabe, T., Fukushima, K.: A Study on Feedback Error Learning Controller for Functional Electrical Stimulation: Generation of Target Trajectories by Minimum Jerk Model. Artificial Organs, 35(3), 270–274 (2011).
11. Lynch, C.L., Popovic, M.R.: A comparison of closed-loop control algorithms forregulating electrically stimulated knee movements in individuals with spinal cord injury. IEEE Trans. Neural Syst. Rehabil. Eng., 20(4), 539–548 (2012).
12. Alibeji, N., Kirsch, N., Farrokhi, S., Sharma, N.: Further Results on Predictor-Based Control of Neuromuscular Elec-trical Stimulation. IEEE Trans. Neural Syst. Rehabil. Eng., 23(6), 1095–1105 (2015).
13. Oliveira, T.R., Costa, L.R., Catunda, J.M.Y., Pino, A.V., Barbosa, W., Souza, M.N.: Time-scaling based sliding mode control for Neuromuscular Electrical Stimulation under uncertain relative degrees. Med. Eng. Phys., 44, 53–62 (2017).