FES Adaptive Feedback Control using Neural networks with PID

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Abstract

FES control is difficult for musculoskeletal system’s time-variability and dynamic nonlinearity. It often needs good performance control models and complex control methods to get better tracking precision, also the high performance control model is hard to build. Neural network (NN) can learn complex nonlinear mappings so it can be used to identify control model on-line. At the mean while, PID control is a widely used feedback control method for its simplicity. However, its parameters need to be confirmed before it using in a control system. By using the NN identifying results, the self-adaptive PID feedback control strategy can be modified in real-time. This will improve the wrist tracking precision. Some testing experiments done on the able-bodied subject showed the control method was robust and stability.

1 Introduction

Functional electrical stimulation (FES) is applied to the paralyzed muscles for rebuilding or restoring the functions of paralyzed muscles [1]. Although the open-loop stimulations are still widely used in clinical practice [2], they are found poor robustness properties and unsatisfactory for accurate movement control [3]. Recently, an important goal of FES research is to develop neuroprostheses that are useful for grasping, standing and walking. Some of these functional activities require higher accuracy, different modeling strategies were in demand [4].

It has been evidenced by experiments that neuromuscular-skeletal systems are accompanied by the muscle fatigue, inherent time-variance, time-delay, and strong nonlinearities [5]. The linear closed-loop controllers can hardly provide good tracking of reference trajectories in the full range movement, although in some specific applications a linear controller can get acceptable tracking and robustness properties [6]. Nonlinear adaptive control strategies are obviously the most suitable candidates to tackle the FES control problem so that the use of nonlinear control methods is strongly advisable in FES control [7,8]. Previdi et al. [3] proposed a direct control design approach used the Virtual Reference Feedback Tuning (VRFT) strategy, which allowed the tuning of a feedback controller without resorting to a model of the plant. Adamczyk and Crago [5] gave a wrist movement dynamics model structure consisted of a static nonlinear part and a second-order dynamics part. These two models were suit for the wrist locomotion control. Recently, some controller-driven approaches have been presented. Ferrarin et al. [9] presented a mixed strategy based on a closed-loop PID controller and an open-loop nonlinear inverse model of the plant.

In the last decade, artificial neural networks (ANN) have been incorporated into the control schemes for learning complex nonlinear mappings [8,10]. Heller et al. [10] compared a rule base inductive learning and a NN learning technique to reconstruct muscle activation patterns from kinematic data measured during normal walking. The results showed that it was feasible to use both techniques based on the prediction results on the timing were accurate. Tong and Granat [11] used a three-layer structure ANN to successfully clone the paraplegic expertise to walk with FES. Kostov et al. [12] used Adaptive Logic Networks for real-time control of walking subjects with incomplete spinal cord injury that limited their ability to walk. The learning of rules was further improved by adding the history of the sensory data as suggested by Lan et al. [13]. Augmenting feedforward control with time-variation or closed-loop feedback has been only partially success in applications. There are lots of problems need to deal with either for using muscle model or not using muscle model on controlling the stimulation parameters.

This paper used a self-adaptive PID (SA-PID) control strategy for wrist movement control. Considering the inherent characteristics of neuromuscular-skeletal and the calculation complexity, the control strategy was simple and straightforward to implement. An ANN was adopted to identify the wrist movement system and feedback the identification results to PID controller. PID controller modified its parameters accordingly. The control strategy would perform better adaptability than the traditional fixed parameter PID (FP-PID) control method.
2 Control strategy

Fig. 1 shows the control strategy used in this paper. It contains a neural network identifier (NNI), an SA-PID controller and a training algorithm. The controller’s input is desired trajectory (desired angle), \( \theta(t) \). Variable, \( u(t) \), is the stimulation energy. And the wrist angle, \( y(t) \), is the system output. NNI is used to identify the I/O relationship of dynamical system (wrist movement system). Its input and output are \( u(t) \) and \( \hat{y}(t) \), respectively. PID controller can determine the stimulation level by the error of \( \theta(t) \) and \( y(t) \).

3 FES Experiment

3.1 Initial model identifying of NNI

Considering the patient bearing capacity in the clinic environment, the initial training should complete within 30s, which included the wrist model FES data acquisition and NNI training. At each stimulation level, we would keep the same stimulation intensity for 0.25s and record the max angle change when the wrist fully extended. Then, let the muscle relax for another 0.25s. This would make the experiment data more robust. The total data acquisition time needed about 22.5s. The acquisition data was shown in Fig. 2(a) and (b).

The data would be used to calculate the relationship about the stimulation levels and the wrist joint angle. The maximal iteration number was 500 and the identification results were shown in Fig. 2(c) and (d) when \( N \) (the number of hidden nodes in the middle layer) was 3, 6, 10 and 20 at the learning speed coefficient, 0.3. The convergence speed curves were given in Fig. 2(e) and (f) at different learning speed when \( N=6 \). From the identification experiments, we could see that the test results were same as the stimulation experiments. And NNI could work well in the real work environment either for convergence speed or identification precision. The identification errors were dropped down fast and the errors would be less than 0.25 at the first 150 iterations. It was good for on-line identifying. This could ensure the real-time in FES tracking control.

3.2 The tracking control results under the stochastic trajectory

Fig. 3 showed the control results in two situations: SA-PID control and FP-PID. Fig. 3(a) was the tracking result of FP-PID control. Apparently, FP-PID control could not generate satisfactory tracking result as SA-PID. It showed that the tracking error would not be improved in control process although the control parameter could be also accepted at the beginning if the control parameter. Once the FES working, the muscle could feel it and would change right away. Because \( P \) and \( I \) were fixed, the controller did catch up with this changing, and made the tracking performance getting worse. Fig. 3(b) showed its error (the total error of this time was 8.7%). The tracking error was increased gradually. That showed FP-PID could not be adaptive to the working condition of the muscle changed.

Fig. 3(c) was the tracking result of SA-PID method. To make these two experiments comparing more dis-
tinctly, we recorded the desired trajectory in FP-PID experiment and did SA-PID control experiment in the next day at the same environment. We could see that SA-PID could get better tracking result than FP-PID. For the first iteration, small output energy and large delay in response were observed. And as the number of iterations increased, the tracking error decreased gradually. It showed that the tracking error became small when the NNI provide an initial model to PID controller. Furthermore, Fig. 3(d) showed that the tracking error decreased in whole control process. The results demonstrated that the control performance improved because our control strategy included a NNI. It could apperceive the real muscle system changes and revise the control parameters. The total control error of Fig. 3(c) was 3.6%.

4 Conclusion

We proposed a neural network self-adaptive control strategy to realize tracking on FES wrist movement control. By a volunteer tracking control experiment, the results showed that the controller could learn within an acceptable iteration number and perform better tracking capability than fixed parameter PID controller.

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Reference