

# Adaptive Inverse Control of the Knee Joint Position In Paraplegic Subject Using Recurrent Neural Network

Ali-Reza Mirizarandi, Abbas Erfanian, and Hamid-Reza Kobravi

Dept of Biomed. Eng., Iran University of Science and Technology, Tehran, IRAN  
erfanian@iust.ac.ir

## Abstract

*In this paper, we employed an adaptive inverse controller for control of the knee-joint position in paraplegic subject with quadriceps stimulation. The control scheme includes two parts: a model plant and a controller. The controller is adapted online without pretraining phase by using information from the plant model. We used recurrent neural network that uses real-time recurrent learning algorithm for both identifying and controlling the plant. The control strategy was evaluated both on a physiological model simulator representing the knee-joint dynamics and on one paraplegic subject. The simulation studies indicate that the adaptive inverse controller provides excellent control and disturbance canceling and could perfectly track the time-varying properties of the plant simulator. The preliminary results on the human subject demonstrate the ability of the controller to track sinusoidal and quasi-trapezoidal trajectories.*

## 1. INTRODUCTION

Improved performance of the motor neuroprostheses can, in principle, be obtained through feedback control. Many feedback control strategies have been developed and reported in the literature. In [1], an adaptive feedforward controller utilizing neural network was developed and its performance was evaluated on spinal cord injured subjects to stimulate the quadriceps muscles to produce a cyclic movement of the lower leg under isotonic contractions. In [2], an adaptive control based upon a direct and an inverse model of the muscle-joint dynamics was developed. The main feature of the proposed scheme is that the model is closely based on the physiological processes underlying excitation and activation of human muscles. As the authors mentioned, the main disadvantage was the off-line identification of the muscle-joint dynamics. To identify the patient-specific parameters, a set of experiments

including isometric conditions, passive pendulum tests, and quasistatic passive movements of the knee should be performed. In [3], a feedforward neuro-control system was designed to control the knee-joint. The controller consists of a fixed parameter proportional-integral-derivative (PID) and a time-invariant feedforward neural network. The network was trained off-line as an inverse model of quadriceps muscle-joint dynamics of a paraplegic subject. In this work, we used an adaptive inverse control of knee-joint angle using dynamic neural network.

## 2. METHODS

### 2.1. Adaptive Inverse Control

Fig. 1 shows the general framework of the adaptive inverse control [4]. To control the plant, we first generate a plant model  $\hat{P}$  using adaptive system-identification techniques. Second, the dynamic response of the system is controlled using  $C$ , which is adapted using information from  $\hat{P}$ . Therefore, the tracking control performance relies on the accuracy of the plant model. In this work, we used a dynamic neural network called Nonlinear AutoRegressive Exogenous input (NARX) network [4] for on-line plant identification and adaptive feedforward control.

### 2.2. Recurrent NARX Neural Network

A popular mathematical modeling formalism for discrete-time nonlinear dynamical system is the AutoRegressive Exogenous input (NARX) model as  $y_t = f[x_{t-1}, x_{t-2}, \dots, x_{t-n}, y_{t-1}, y_{t-2}, \dots, y_{t-m}]$ , where  $[x_t, y_t]$  represents the input-output pair of the system at time  $t$  and  $f$  is a nonlinear function. The output at time  $t$  depends both on its past  $m$  values as well as the past  $n$  values of the input. When the function  $f$  is approximated by a neural network, the resulting model is called NARX network. We have chosen to use RTRL in this work to adapt the model plant and feedforward control. To adapt the controller, the series

combination of  $C$  and  $\hat{P}$  is regarded as a single nonlinear filter. Then, we can use the desired response,  $d_k$  (Fig. 1), to update the weights in  $C$ . The detail of algorithm can be found in [4].

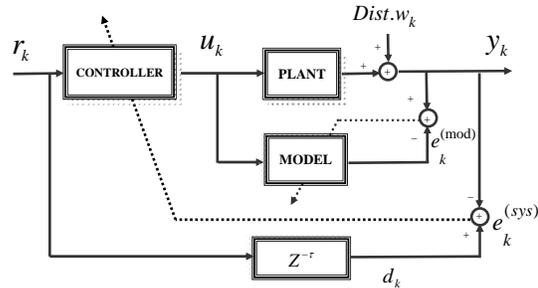


Fig. 1. Adaptive inverse control

### 3. RESULTS

#### 3.1. Simulation Results

In order to conduct preliminary investigation into the feasibility of adaptive inverse control, we chose to conduct our investigations using computer simulation on a musculoskeletal model based on [2], before proceeding with experimental evaluations on human subject. The desired trajectory is a sinusoidal wave with randomly-varied amplitude between  $110^0$  and  $160^0$  and randomly-varied frequency within the range of 0.13 to 0.4 Hz satisfying a uniform distribution.

The knee-joint angle trajectory using adaptive inverse control is shown in Fig. 2. It is observed that the controller is able to track well the desired trajectory from the beginning of the simulation. For all simulation studies, the networks have been adapted on-line without any off-line training phase.

#### Fatigue Compensation

To simulate the muscle fatigue, the scaling factor of the activation dynamics is decreased exponentially to 23% of its original value over 120 s simulation. The ability of the controller to continuously adjust the stimulation pattern to produce the desired knee-joint angle is shown in Fig. 3.

#### External Disturbance Rejection

To simulate the external mechanical disturbance, the knee-joint angle was decreased by  $25^0$  at  $t = 40$  s and increased by  $25^0$  at  $t = 80$  s. Fig. 4 shows the result of mechanical disturbance rejection. It is observed that the controller provides a perfect disturbance rejection.

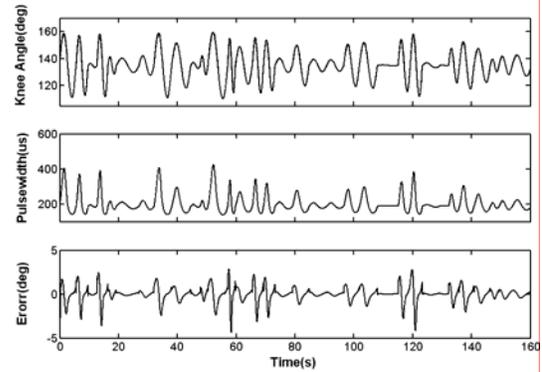


Fig. 2. Simulation results: desired joint angle trajectory (solid line), adaptive controller response (dotted line), pulsewidth values and error.

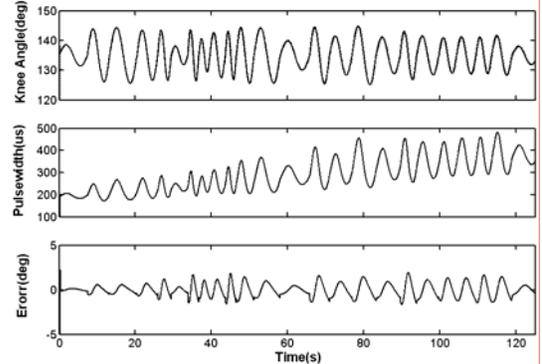


Fig. 3. Simulation results as muscle fatigues: desired joint angle trajectory (solid line), adaptive controller response (dotted line), pulsewidth values, and error.

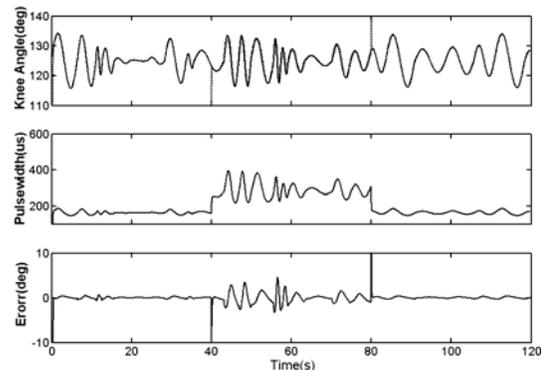


Fig. 4. Simulation result of external disturbance rejection using adaptive inverse control: desired trajectory (solid line), adaptive controller response (dotted line), pulsewidth values, and error.

#### 3.2. Experimental Results

Experiments were conducted on a complete level T7 spinal cord injury paraplegic. The subject was seated on a bench with his hip flexed at  $90^0$ , while the shank was allowed to swing freely. The quadriceps muscle was stimulated using adhesive surface electrodes. Pulse amplitude modulation with balanced bipolar stimulation pulses, at a constant frequency (25 Hz) and constant pulse width was

used. An electrogoniometer is fixed on the knee-joint to measure the knee-joint position.

During each experiment day, different 40-s trials were conducted. First, a plant model is identified using a 40-s stimulation pattern. The stimulus pulses were generated by amplitude modulation of the sine wave whose amplitude was randomly chosen to vary according to a uniform distribution. Second, the knee-joint angle was controlled using  $C$ , which was adapted on-line using information from identified plant model.

Fig. 5 (a) shows the adaptive controller response when the desired trajectory was a sinusoidal wave with frequency 0.25 Hz. Fig. 5 (b) shows the measured knee joint angle for the second trial on the same experiment day using the identified parameters during the first trial. However, adaptation was allowed to continue to account the time-varying properties of the plant.

The adaptive controller response for a periodic quasi-trapezoidal trajectory is shown in Fig. 6. It is observed that the control strategy has the same performance for a different trajectory.

#### 4. DISCUSSION AND CONCLUSIONS

In this paper, we employed an adaptive inverse controller for on-line control of the knee-joint position in paraplegic subject. The simulation studies on a physiological model simulator indicate that the adaptive inverse controller provides excellent tracking during different conditions of operation including nonlinear perturbation and muscle fatigue. The preliminary results on the human subject demonstrate the feasibility and practicality of the approach. The experimental evaluation of the control scheme during perturbation, muscle fatigue, and different range of movements is under investigation.

#### References

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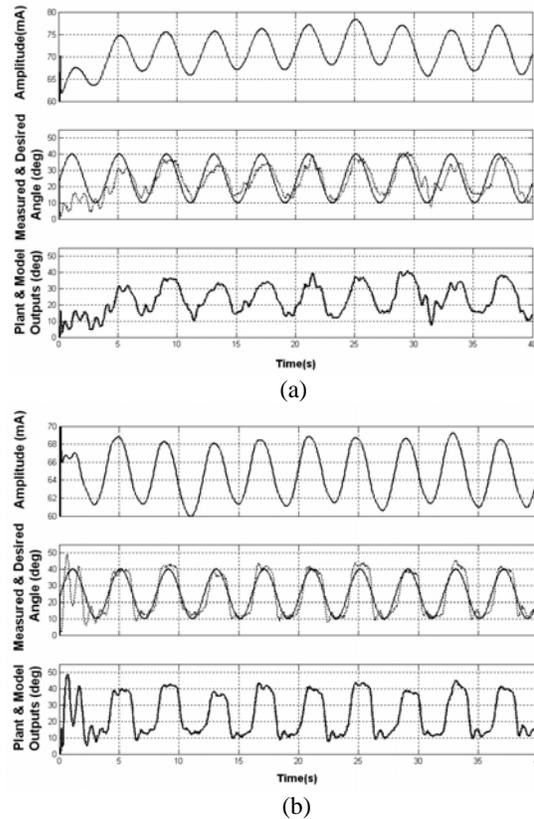


Fig. 5. Experimental results obtained by using adaptive inverse control for two trials (a)-(b): pulse amplitude values, desired (solid line) and measured knee joint-angle trajectory (dotted line).

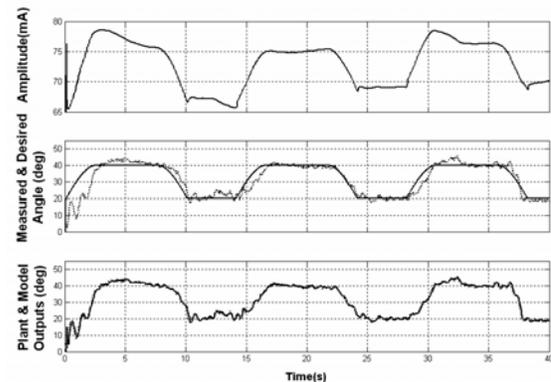


Fig. 6. Experimental results obtained by using adaptive inverse control for a periodic quasi-trapezoidal trajectory: pulse amplitude values, desired (solid line) and measured knee joint-angle trajectory (dotted line).