Available online at www.sciencedirect.com
ScienceDirect
Engineering Applications of Artificial Intelligence 21 (2008) 1153–1163
Engineering Applications of
ARTIFICIAL INTELLIGENCE
www.elsevier.com/locate/engappai

Adaptive growing-and-pruning neural network control for a linear piezoelectric ceramic motor

Chun-Fei Hsu

Department of Electrical Engineering, Chung Hua University, Hsinchu 300, Taiwan, ROC

Received 6 August 2007; received in revised form 27 November 2007; accepted 4 December 2007
Available online 4 March 2008

Abstract

In this paper, an adaptive growing-and-pruning neural network control (AGPNNC) system is developed for a linear piezoelectric ceramic motor. The AGPNNC system is composed of a neural controller and a robust controller. The neural controller uses a self-constructing neural network (SCNN) to mimic an ideal computation controller, and the robust controller is designed to achieve L_2 tracking performance with desired attenuation level. If the approximation performance of the SCNN is inadequate, the SCNN can create new hidden neurons to increase learning ability. If the hidden neuron of the SCNN is insignificant, it should be removed to reduce computation loading; otherwise, if the hidden neuron of the SCNN is significant, it should be retained. Moreover, the adaptive laws of controller parameters are derived in the sense of Lyapunov function and Barbalat's lemma; so the system stability can be guaranteed. Finally, experimental results show that a perfect tracking response can be achieved using the self-constructing network mechanism and the on-line parameter-learning algorithm.

Keywords: Adaptive control; Neural network control; Self-constructing; Linear piezoelectric ceramic motor

1. Introduction

Modern mechanical systems, such as machine tools and automatic inspection machines, often require high-speed high-accuracy linear motions. These linear motions are usually realized using the rotary motors with a mechanical transmission, such as reduction gears and lead screw. These mechanical transmissions not only significantly reduce the linear motion speed and dynamic response, but also introduce backlash and large friction. To tackle this problem, a linear piezoelectric ceramic motor (LPCM) is introduced to apply the linear motion without using any mechanical transmission (Sashida and Kenjo, 1993). The LPCM has many advantages, such as high precision, fast control dynamics, large driving force, smaller dimension, high holding force, silence and more minimum step size than the class electromagnetic motors, so it can be used in many different applications (Sashida and Kenjo, 1993; Lin et al., 2001b). However, the driving principle of the LPCM is based on the ultrasonic vibration force of piezoelectric ceramic elements and mechanical frictional force. Therefore, its mathematical model is complex, and the motor parameters are time-varying because of increasing temperature and changes in motor drive operating conditions (Lin et al., 2001b). From the controller design viewpoint, the conventional control technologies are always based on a good understanding of the control system dynamics, so the conventional control scheme for LPCM cannot achieve satisfy control-tracking performance.

If the exact model of the controlled system is well known, there exists an ideal computation controller to achieve favorable control performance by possibly canceling all the system uncertainties (Slotine and Li, 1991). Since the LPCM system dynamics cannot be exactly known, the ideal computation controller for LPCM cannot be implemented. Recently, several neural-network-based intelligent control approaches have been addressed for the LPCM control without knowledge of the process dynamics (Lin et al., 2001b; Peng and Lin, 2007; Wai et al., 2002. 2004). The key success element is the approximation theory of neural network, where the parameterized neural network can estimate the unknown system dynamics or the ideal

E-mail address: fei@chu.edu.tw

0952-1976/$ - see front matter © 2008 Elsevier Ltd. All rights reserved.
doi:10.1016/j.engappai.2007.12.003

computation controller after learning. Some of these learning algorithms are based on the backpropagation algorithm (Lin et al., 2001b). However, these approaches are difficult to guarantee the stability and robustness of closed-loop system. Some of the learning algorithms are based on the Lyapunov stability theorem. The tuning laws of the neural network have been design to guarantee the system stability in the Lyapunov sense (Peng and Lin, 2007; Wai et al., 2002, 2004).

Though the tracking performances of LPCM are acceptable in Lin et al. (2001b), Peng and Lin (2007), and Wai et al. (2002, 2004), the learning algorithms only consider the parameter learning of the neural network, but do not consider the structure learning of the neural network. If the number of hidden neurons is too large, the computation loading is heavy so that they are unsuitable for practical applications. If the number of hidden neurons is too small, the learning performance may not be good enough to achieve the desired control performance. It is a trade off between the approximation performance of neural network and the number of hidden neurons. To tackle this problem, several self-constructing neural networks (SCNN), consisting of structure and parameter-learning phases, have been proposed (Huang et al., 2005; Juang and Lin, 1998; Lee and Ouyang, 2003; Lin et al., 2005). These learning algorithms not only decide the structure of neural network but also adjust the parameters of neural network.

Recently, several SCNN-based adaptive control schemes have been applied to control the unknown nonlinear systems (Gao and Er, 2003; Lin et al., 2001a; Lin and Lin, 2004; Park et al., 2005; Hsu, 2007). Gao and Er (2003) proposed an error reduction ratio with QR decomposition to prune the hidden neurons; however, the design procedure is too complex. In Lin et al. (2001a), Lin and Lin (2004) and Hsu (2007), the structure-learning algorithm is based on the partitioning the input space and the parameter learning is based on the supervised gradient decent method; however, as the number of input variables is too large, heavy computation loading of similarity checking will occur. Park et al. (2005) proposed a neural network with online variation of the number of hidden neurons. However, the developed condition only considers the growing algorithm of the neural network. The proposed approach cannot avoid the structure of neural network growing in an unbound manner.

The motivation of this paper is to design an adaptive growing-and-pruning neural network control (AGPNNC) system for the LPCM system without any knowledge of the LPCM system dynamics. The developed AGPNNC system is composed of a neural controller and a robust controller. The neural controller uses an SCNN to estimate an ideal computation controller, and the robust controller is designed to achieve L_2 tracking performance with attenuation of disturbances including approximation errors and external uncertainties. The learning phase of AGPNNC includes the structure learning and the parameter-learning phases. In the structure-learning phase, the SCNN not only can create the new hidden neurons on-line if the approximation performance is inappropriate, but can also prune the insignificant hidden neurons on-line if the hidden neuron is inappropriate. In the parameter-learning phase, the controller parameters are on-line tuned based on the Lyapunov function and Barbalat's lemma, so the stability of the closed-loop system can be guaranteed. Finally, the computer control experimental system for the LPCM system is setup. The experimental results show the AGPNNC system can achieve the perfect tracking response after the SCNN is sufficiently trained.

This study is organized as follows. Section 2 briefly describes an LPCM system. In Section 3.1, a novel SCNN with online variation of the number of hidden neurons according to the proposed condition is described. In Section 3.2, an AGPNNC system is designed for an LPCM system to track a reference command. The design procedures and qualitative analysis are described in detail. Some experimental results are provided to show the effectiveness of the proposed AGPNNC method in Section 4. Conclusions are drawn in Section 5.

2. Linear piezoelectric ceramic motor

The structure of the LPCM is a large face of a relatively thin rectangular piezoelectric ceramic device. The driving principles of the LPCM are based on the ultrasonic vibration force of piezoelectric ceramic element and mechanical frictional force. Fig. 1(a) shows the principal structure of the LPCM (Sashida and Kenjo, 1993; Peng and Lin, 2007). Four electrodes (A, A′, B and B′) are

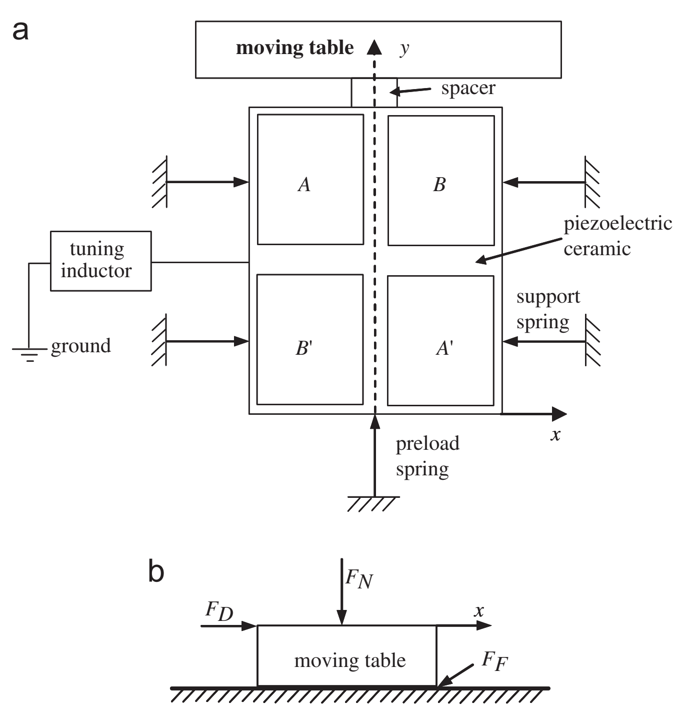

Fig. 1. (a) Structure of LPCM and (b) friction drive system.