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Adaptive control of a nonlinear dc motor drive using recurrent neural networks

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Abstract

A model-following adaptive control structure is proposed for the speed control of a nonlinear motor drive system and the compensation of the nonlinearities. A recurrent artificial neural network is used for the online modeling and control of the nonlinear motor drive system with high static and Coulomb friction. The neural network is first trained off-line to learn the inverse dynamics of the motor drive system using a modified form of the decoupled extended Kalman filter algorithm. It is shown that the recurrent neural network structure combined with the inverse model control approach allows an effective direct adaptive control of the motor drive system. The performance of this method is validated experimentally on a dc motor drive system using a standard personal computer. The results obtained confirm the excellent disturbance rejection and tracking performance properties of the system.

Keywords: Recurrent neural network; Nonlinear system; Motor drive; Kalman filter; Inverse model

1. Introduction

High performance motor drive systems have become the preferred choice in many industrial applications and there is a strong interest to develop new control tools to further enhance their performance and their intelligence. In lieu of the recent advances in power electronics and microprocessors, digital control of motor drives has become increasingly popular. Micro-computer-based control systems with digital control strategies for dc/ac motors have gained the widest acceptance in high performance adjustable speed drives. However, conventional control schemes (e.g. proportional-integral controller) have certain limitations and cannot achieve a good speed response when the system parameters vary. Many other difficulties could be also encountered when dealing with highly nonlinear plants. To overcome these drawbacks, the control scheme should include an additional compensation scheme to eliminate the variations in the load disturbance and/or system parameters. New control algorithms such as adaptive, variable structure, and robust controllers, are therefore introduced. This however leads to an increasingly more complicated control algorithm requiring a complex design procedure and extensive computations for real-time implementation.

Recently, substantial research efforts were devoted to artificial neural networks and their application to control systems to deal with the problems of non-linearity and system parameters uncertainty [1–9]. Artificial neural networks (ANN) have proved to be very successful in different areas of engineering sciences. The fundamental characteristics of neural networks are their ability to produce good models of nonlinear systems; their highly distributed and paralleled structure, their simple implementation by software or hardware; and their ability to learn and adapt themselves to the behavior of any real process. ANN can also be trained using data taken from the system or when directly connected to the system, and require less processing time because of their parallel structure.

The design of an ANN starts by defining the structure of the graph, the synaptic coefficients and the activation function. The architecture of the network and the activation function can be fixed according to the task that should be realized; the synaptic coefficients are calculated during the learning phase. MultiLayers Perceptrons (MLP) are one of the most popular

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artificial neural net structures. If the network has feedback connections, the obtained graph is called a recurrent network. The standard and most popular procedure used to design an ANN is to have a feed-forward neural network structure trained with the back-propagation algorithm [10–12]. A limiting characteristic however of the feed-forward neural network is the absence of internal or hidden state, so that the processing of input patterns does not depend upon the order in which these patterns are represented during training or recall. Thus, the representation and processing of sequential or temporal information is not an intrinsic capability of feed-forward neural networks, although tapped-delay lines can be used to encode explicitly a finite number of past events [13–15].

Today, interest has been also increasing in the use of multiplayer neural networks as elements in dynamical systems [16–19]. This has been motivated by two considerations. Since all physical systems involve dynamics, modeling a physical system as a ''natural'' neural network should realistically include dynamical elements. Furthermore, from a control point of view, dynamical elements have to be included to have well-posed problems.

The use of recurrent neural networks (RNN) as system identification networks and feedback controllers offers a number of potential advantages over the use of static layered networks. RNN provide a means for encoding and representing internal or hidden states, albeit in a potentially distributed fashion, which leads to capabilities that are similar to those of an observer in modern control theory. RNN provide increasing flexibility for filtering noisy inputs. RNN feedback controllers may be less sensitive and more robust than static feed-forward controllers to changes in plant dynamics and parameters [20–24].

In this paper, a new robust adaptive control scheme using only one recurrent neural network is proposed for the identification and adaptive control of nonlinear dc motor drives. The RNN is designed and trained first off-line to learn the inverse dynamic model of the considered system from the observation of the input–output data. After the training process is completed, the proposed adaptive control structure is applied to control the speed and suppress the disturbances dues to nonlinearities in the system. Such development is sought to address the control problem for systems with nonlinear dynamics, the problem of disturbance suppression and offset-free control in the presence of such disturbances, which is of high priority in motion control systems [13,14,25].

The different sections of this paper are organized as follows: in Section 2 we present the dynamic model of the considered motor drive system. The description of the recurrent neural network used for identification and adaptive control is presented in Section 3. Section 4 presents the proposed version of a parameter-based decoupled extended Kalman filter algorithm (DEKF) used for adapting the weights of the RNN. The discrete time models of the considered system and the neural identification of the inverse model are presented in Section 5. Section 6 provides the proposed adaptive neuro-control structure and the detailed computation process. Experimental results of the identification and control system are illustrated in Section 7, and a conclusion is drawn in Section 8.

2. Dynamic model of the nonlinear motor drive system

The system considered for our analysis is a dc motor drive system composed of a dc motor connected to a mechanical load through a gear and flexible couplings. The complete system can be represented by the schematic diagram shown in Fig. 1.

The design of a high performance motion control system requires an accurate knowledge of the electro-mechanical system dynamics including the linear and nonlinear transmission attributes of the system. Friction on the other hand is an inevitable characteristic of mechanical systems and is undesirable by control system designers. Its presence is often responsible for performance degradation and closed-loop bandwidth limitation, and should be therefore taken into consideration in the modeling and control design phases.

The nonlinear dynamic equations of the system can be derived using a permanent magnet dc motor model with a two mass model equivalent system:

$$v_a = R_a i_a + L_a \frac{di_a}{dt} + K_b \omega_m, \qquad \tau_m = K_t i_a \tag{1}$$

$$J_m \frac{d\omega_m}{dt} + B_m \omega_m + \tau_f + \frac{h(\theta)}{N} = \tau_m \tag{2}$$

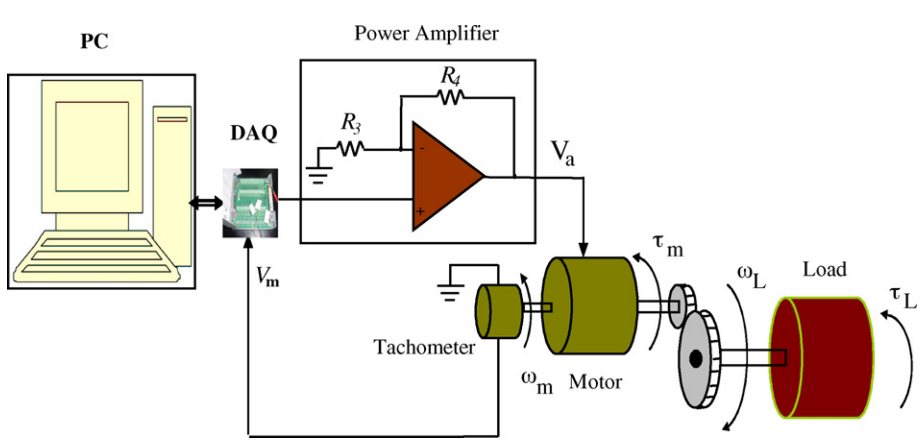

Fig. 1. Motor drive system.