Expert Systems with Applications 40 (2013) 975–983

Contents lists available at SciVerse ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

Active control of friction self-excited vibration using neuro-fuzzy and data mining techniques

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ARTICLE INFO

Keywords:
Data mining
Neuro-fuzzy systems
Active control
Friction
Self-excited vibration

ABSTRACT

Vibration caused by friction, termed as friction-induced self-excited vibration (FSV), is harmful to engineering systems. Understanding this physical phenomenon and developing some strategies to effectively control the vibration have both theoretical and practical significance. This paper proposes a self-tuning active control scheme for controlling FSV in a class of mechanical systems. Our main technical contributions include: setup of a data mining based neuro-fuzzy system for modeling friction; learning algorithm for tuning the neuro-fuzzy system friction model using Lyapunov stability theory, which is associated with a compensation control scheme and guaranteed closed-loop system performance. A typical mechanical system with friction is employed in simulation studies. Results show that our proposed modeling and control techniques are effective to eliminate both the limit cycle and the steady-state error.

1. Introduction

Friction-induced self-excited vibration (FSV) is a complex and nonlinear physical phenomenon with some uncertainties. Friction and vibration are almost ubiquitous in real life. Sometimes they can be beneficial to us under special circumstances. Such as, friction can be utilized in automotive brakes and vibration can be applied in nuclear magnetic resonance. However, friction usually causes degradation of system performances in most of the mechanical systems. In the case that the friction term critically impacts on mechanical dynamics, its presence may induce limit cycles, steady-state errors and other undesirable effects. In general, vibration generates additional dynamic loads to degrade the system performances. Thus, it is significant to reduce or eliminate vibration caused by friction force for performance improvement. From engineering viewpoints, it is meaningful to understand the FSV mechanism and develop effective control algorithms (Chatterjee, 2007; Das & Mallik, 2006; Sinou & Dereure, 2006). Recently, active control techniques have received considerable attention from mechanical and control engineers. These active control schemes have been widely applied for precision instrumentation, aerospace, transportation systems and mechanical engineering. In vibration control, active control schemes use sensors to measure the feedback signals, and generate control actions using some special control strategies for driving the actuator to reduce or eliminate vibration.

To eliminate or inhibit the FSV, it is necessary to introduce a friction compensation term in controller design. Therefore, effective modeling of the friction force play a key role to control the FSV in mechanical systems. It has been experimentally verified that the friction force is a nonlinear function of both the velocity and the direction of rotation or motion. Readers may refer to empirical models reported in the literature (Armstrong & Canudas De Wit, 1994; Bender, Lampaert, & Swevers, 2005; Canudas De Wit, Ollson, Astrom, & Lischinsky, 1995; Dupont, Hayward, Armstrong, & Altpeter, 2004; Kim & Ha, 2004; Rizos & Fassois, 2009; Swevers, Al-Bender, Ganseman, & Prajogo, 2000). From an analysis of these exiting friction models, we can see that the mathematical approach has difficulty in dealing with the problem of universal friction modeling due to the nonlinearity, uncertainty and time-varying nature of friction. Thus, it is useful to explore data-driven approaches for modeling the friction force with an adaptation mechanism.

Recently, fuzzy systems and neural network systems have been successfully applied to complex systems (Jiang, Zhang, & Zhang, 2011; Rana, 2011; Selmic & Lewis, 2002; Wang, 1993; Wang, Wang, & Chai, 2009; Wu, Lin, & Lee, 2011), where traditional approaches can rarely achieve satisfactory results due to the nonlinearity, uncertainty and lack of sufficient domain knowledge. Neuro-fuzzy systems have attracted considerable attention in the past due to their universal approximation power to nonlinear maps, learning capability, domain knowledge embedability and

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http://dx.doi.org/10.1016/j.eswa.2012.08.005

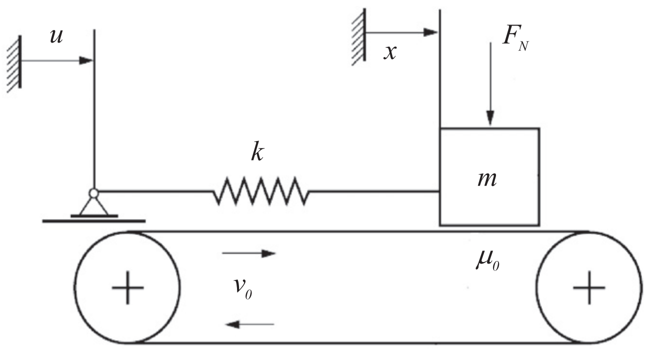

Fig. 1. Mass on a moving belt system.

result interpretation ability (Figueiredo & Gomide, 1999; Jang, 1992). The main merit of neuro-fuzzy systems for engineering modeling is that we can naturally integrate both numerical data and domain knowledge in a unified framework. The key step in building neuro-fuzzy system is to determine the architecture of a system, which can be done by data mining techniques. Notice that the data-mining-based neuro-fuzzy inference system (DNFIS) are not constructed in an optimal fashion in terms of parameter setting. Therefore, it is important to develop learning algorithms for tuning the parameters (weights) of neuro-fuzzy inference system (ANFIS). Traditional learning techniques for learner models, such as the well-known error back- propagation algorithm and its variations, are derived from various numerical optimization techniques. Although some theoretical results on adaptive neural control can be read in literature, it is rare to find reports that associate the learning algorithm with control system's performances.

In this paper, we try to make a link between the learning algorithm of neuro-fuzzy system and the stability performance of a closed-loop dynamical system. Concretely, we employ an improved data mining algorithm (Wang, Wang, & Chai, 2010) to extract a set of fuzzy rules. Based on these generated fuzzy rules, a neuro-fuzzy system is constructed for approximate the unknown friction force. Then, an active control scheme, the proportional-derivative (PD) controller with a friction compensation term, is applied to control the dynamical system. To eliminate the limit cycle and the steady-state error caused by frictions in the systems, a updating rule for the weights of the neuro-fuzzy system is derived from Lyapunov stability theory. It is shown that such a learning algorithm can guarantee the control performance.

The remainder of the paper is organized as follows: Section 2 gives some information on description of mechanical systems used in this study and some observations on numerical analysis of the FSV. Section 3 mainly describes a data-driven approach for modeling the friction force using neuro-fuzzy systems. Section 4 proposes an updating rule for tuning the weights of the neuro-fuzzy system according to the Lyapunov stability theory, which is associated with a PD control scheme with a friction compensation term. Section 5 reports simulation results on a one-dimensional motion dynamics of a mass which moves on a surface with friction to illustrate the effectiveness of our proposed neuro-fuzzy system modeling and active control techniques. Section 6 concludes this work.

2. Friction-induced self-excited vibration

The free body diagram of a block of mass m, placed on a moving belt and constrained by a spring of stiffness k, is shown in Fig. 1. The non-dimensional equation of motion of a single-degree-of-freedom undamped oscillator with the proposed control is governed by the following differential equation (Hinrichs, Oestreich, & Popp, 1998; Zjinjade & Mallik, 2007):

$$mx''(\tau) + kx(\tau) = F_f(v) + u_c, \tag{1}$$

where m is the mass of the block, x is the displacement of the mass, u_c is the control signal, $F_f(v)$ is the friction force, v is the relative velocity.

Let $t = \omega_0\tau,\ \omega_0 = \sqrt{\frac{k}{m}}$ and

$$\begin{cases} \dot{x} = dx/dt = x'/\omega_0, \\ \ddot{x} = d(\dot{x})/dt = x''/\omega_0^2. \end{cases} \tag{2}$$

System (1) can be rewritten as:

$$\ddot{x}(t) + x(t) = F(v) + u, \tag{3}$$

where $v = v_0 - \omega_0\dot{x}$, v_0 is the velocity of the belt, $F(v) = F_f(v)/k$, $u = u_c/k$.

Friction-induced vibration, a type of self-excited vibration, is a serious problem in many engineering systems. The friction force acting on the system provides the energy needed to maintain these vibrations. The nature of the friction force, dependent on the relative (slip) velocity, time, temperature, material properties, geometry and roughness of sliding surfaces, normal load etc., is really complex. Modeling of friction force and friction vibration has attracted the attention of both physicists and engineers. To understand the physical phenomenon of the friction vibration, some numerical simulations were carried out using two typical friction models, i.e., the Coulomb friction model and Stribeck friction model. The Coulomb friction model can be expressed as:

$$F(v) = F_c sgn(v), \tag{4}$$

where the friction force F_c is proportional to the normal load, i.e., $F_c = \mu F_N$. Notice that the model (4) is an ideal relay model. The Coulomb friction model does not specify the friction force for zero velocity.

The Stribeck friction model describes the steady-state friction behavior in sliding regime and hence are dependent on the sliding velocity v. This friction model incorporates Coulomb, viscous, and Stribeck friction:

$$F(v) = F_c + (F_s - F_c)e^{-|v/v_s|^{\delta_s}} + F_v v, \tag{5}$$

where v_s is called the Stribeck velocity and F_v is the viscous friction coefficient.

For $u = 0$ one has the case of pure self excitation in (3). In our simulations, Matlab command (ode45) was used to obtain numerical solutions corresponding to these friction models. The following parameters were used in the simulations: $m = 0.6$ [kg], $x_0 = (-0.02, 0.02)$, $F_N = 15.0$ [N], $v_0 = 0.3$ [m/s], $k = 763$ [N/m]. Fig. 2 depicts the Coulomb and the Stribeck friction-induced limit cycles with various parameters in (3)–(5).

These numerical results demonstrate the physical phenomena of the friction vibration. To eliminate or inhibit the friction-induced self-excited vibration, it is important to add a compensation term based on friction model in PD controller design. But the existing friction models are parameterized and will not be able to characterize accurately all types of friction under an unified framework. Therefore, it is very necessary to make efforts on developing data-driven-based intelligent approaches for modeling friction force and controlling the friction vibration.

3. Modeling friction force using neuro-fuzzy systems

Modeling friction force from a collection of sampling data can be implemented by various learner models. Usually, there are three key steps towards to a successful modeling: data collection and filtering; learner model identification and model parameter