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Soft sensing of magnetic bearing system based on support vector regression and extended Kalman filter

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ABSTRACT

The rotor displacement measurement plays an important role in an active bearing system, however, in practice this measurement might be quite noisy, so that the control performance might be seriously degraded. In this paper, a soft sensing method for magnetic bearing-rotor system based on Support Vector Regression (SVR) and Extended Kalman Filter (EKF) is proposed. In the proposed method, SVR technique is applied to model the acceleration of the rotor, which is regarded as a nonlinear function of rotor displacement, rotor velocity and bearing currents; then this SVR model is used to construct an EKF estimator of rotor displacement. In the proposed method the bearing current is incorporated to the estimation of displacement, so that displacement can be precisely estimated even if very large observation noise is present. A series of experiments are performed and the results verify the validity of the proposed displacement soft sensing method.

1. Introduction

Compared with conventional bearings, active magnetic bearings (AMBs) [1,2] possess several attractive advantages, such as no friction, no need of lubrication, and the ability of long-term high speed running. An AMB system includes the following parts: a rotor, bearings, sensors, a power amplifier and a controller. The sensors measure the rotor displacement real-timely, based on this measurement, the controller computes the control signal, the power amplifier transforms this signal to control current and feeds the current to the bearings, and the bearing generate magnetic force to hold the rotor in the suspension position.

In an AMB system, the lateral displacement of the rotor can be measured by the displacement sensors, this measurement plays an important role in the control loop and significantly affects the control performance. Nevertheless, in practice the displacement signal may be quite noisy, especially when high power motors or invertors are nearby. The noisy signal may result in poor suspension stability and terrible acoustic noise. The main idea of this paper is that the noise in measurement can be eliminated based on a precise rotor-bearing model, in other words, this paper offers a model-based soft sensing method of rotor displacement in an AMB system. More precisely, we notice that if a precise model of rotor displacement-bearing current is available, the displacement measurement can be significantly improved in that the bearing current is involved into measurement and this additional information will help to eliminate the noise of the displacement measurement.

Soft sensing [3–5] is an approach to estimate hard-to-measure variables of a dynamic system from easy-to-measure variables. The soft sensing technique can also be applied to improve the measurement quality of some variables by incorporating information from various sources. However, to our best knowledge no achievement of soft sensing of magnetic bearing systems is reported. The model of plant is the most important part of a soft sensing method. The characteristics of an AMB system can be modeled theoretically and it is usually approximated by linearized models, however, they are inherently nonlinear. The most important source of nonlinearity is the force-current relationship of the bearing [6,7], due to magnetic hysteresis, machining error, eddy effect and the inaccurate and inconsistent magnetic property of iron core, in practice the theoretical model and the linearized model of bearings are sometimes not precise enough. The rotor model, namely the force-displacement relationship, is normally regarded as linear as well and can be calculated by finite element method and other numerical methods [8], but a practical rotor is usually quite complex, it may compose of many different parts, these parts may join together by screw thread, shrink-fitting and other connections, all these will lead to nonlinearity and inaccuracy of the rotor model. Moreover, the magnetic bearings introduce the so-called "negative

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stiffness", namely the current-displacement relationship of the bearing-rotor system is open-loop unstable. Thus a linear-model-based soft sensing method for AMB system highly relies on the observations and will be negatively affected by the observation noise.

Some researches on the nonlinear modeling of magnetic bearing systems are reported [7,9–11], all these works are based on parametrical regression technique, namely some mechanism and/or empirical models are utilized in modeling. Unlike these methods, in this paper a nonparametric modeling method is applied to establish a static model, and this static model is utilized to make dynamical estimation of the rotor-displacement. On the other hand, many achievements of soft sensing based on Neural Network (NN) are published [12–16], however, in this paper we apply Support Vector Regression (SVR) technique [17,18] as a modeling method, since according to the statistical learning theory [19] it outperforms NN in generalization performance.

For a rotating rotor, suppose an impulse tachometer is mounted and signals can be divided into periods according to the tachometer pulses. Then the proposed method includes the following steps: (1) The velocity and acceleration of the rotor is estimated from the displacements in the recent periods. Considering the response is periodic, this estimation can be precise enough even if the displacement data is very noisy. (2) The rotor acceleration-bearing current relationship is established by SVR. (3) The Extended Kalman Filter (EKF) [20] method is applied to make rotor displacement estimation by incorporating the displacement measurement and the estimated acceleration together. These steps can be performed online to realize real-time displacement sensing.

An experimental system with a five degrees-of-freedom (DOF) suspended rotor (about 3.5 m long and 630 kg heavy) is utilized to perform a series of experiments and validate the proposed method. The experimental results show the validity of the proposed method.

In this paper, the motion of the rotor in a radial plane is considered. Two displacement sensors are utilized to measure the rotor's lateral displacements. The lateral displacements are denoted by x_1 and x_2, respectively. The velocities of the rotor (i.e. the derivative of x_1 and x_2) will be denoted as $\dot{x}_1$ and $\dot{x}_2$ and the accelerations of the rotor as $\ddot{x}_1$ and $\ddot{x}_2$. The notations i_{x_1+} and i_{x_1-} stand for the currents in the plus and minus coils of the magnetic bearing x_1. All involved signals are sampled at discrete time instants $\kappa = 1, 2, \ldots$. A signal (say x_1) at sampling instant κ is denoted by $x_1(\kappa)$. The rotational speed of the rotor is measured by an impulse tachometer in which each revolution of the rotor generates an electric pulse. Suppose the tachometer pulses occur at time instants $p_1, p_2, \ldots$. We define that the kth rotational period is started at time instant $(p_{k-1} + 1)$ and ended at p_k.

2. An introduction to support vector regression

Support vector regression (SVR) is a novel nonparametric modeling method. It can offer regression of real-valued functions based on observed samples. SVR is very popular in machine learning, pattern recognition, artificial intelligence and the related regions. However, it might be not so well-known for researchers in the range of mechatronics. Thus in this section we offer a brief introduction to SVR.

The SVR possesses the following attractive features: (1) A large class of modeling problems can be treated with SVR, since by SVR modeling the only mathematical assumption on the actual model is the Lipschitz continuity. (2) SVR is a nonparametric modeling method, that is, no prior model is needed in modeling. (3) The computational complexity of an SVR hardly depends on the dimension of the problem. (4) SVR is a distribution-free method, i.e. no prior-knowledge or assumptions on the distribution of the samples are needed other than that all samples are generated independently from the same distribution. (5) The generalization ability of SVR is ensured theoretically. The generalization ability is the precision (in the statistical sense) of a modeling method when only finite samples are available. Based on the statistical learning theory [19], the generalization ability of SVR can be estimated, that is, the boundary on modeling error of an SVR can be calculated in the statistical sense. With these features, SVR provides solutions to many complex modeling problems.

The ensured generalization ability is the most important and attractive feature of SVR, in contrast, the generalization performance of neural network methods may depend on the network structure and train algorithm and can hardly be controlled. As a result, applying NN methods requires more understanding of the problem and practical tricks in adjusting structure and parameters and hyper-parameters and the risk of overfitting can hardly be prevented. By applying SVR method these defects are much less serious.

SVR is a sample-based modeling method. When some input-output relationship have to be modeled, some training samples (input-output pairs (ξ, ζ)) should be observed first, then an SVR model can be established. The process of establishing the SVR model based on the training samples is usually called as "training" and the algorithm for training is called as "training algorithm". For a new input ξ', the SVR model predicts the corresponding output according to the relationship of the training samples and new sample ξ'. Mathematically, the collection of samples is usually assumed to be a subset of some topological space, however, in practice it is common to assume that the samples lie in the real vector space, namely $(\xi, \zeta) \in \mathcal{R}^n \times \mathcal{R}$, where n is called as "sample dimension".

SVR is a kernel method, that is, a kernel function is applied to evaluate the relationship between various samples. A kernel function $K : \mathcal{R}^n \times \mathcal{R}^n \mapsto \mathcal{R}$ is a bivariable real-valued function defined by user. For a sample ξ and a sample sets $\Theta = \{\boldsymbol{\theta}_1, \ldots, \boldsymbol{\theta}_m\}$, we use the following notation:

$$K(\xi, \Theta) = \mathbf{K}_{\xi,\Theta} = [K(\xi, \boldsymbol{\theta}_1) \ \cdots \ K(\xi, \boldsymbol{\theta}_m)] \tag{1}$$

Suppose the unknown actual model of some relationship is described as follows:

$$\hat{\zeta} = \phi(\xi) + \nu, \tag{2}$$

where $\hat{\zeta} \in \mathcal{R}$ is the observation of output of ϕ, $\xi \in \mathcal{R}^n$ is the n-dimensional input, $\phi : \mathcal{R}^n \mapsto \mathcal{R}$ is a real-valued continuous function and ν is the observation noise. Suppose m samples $\Xi = \{\xi_k, \zeta_k\}_{k=1}^m$ are obtained, the SVR model is in the following form:

$$\tilde{\zeta} = \rho + \sum_{k=1}^{m} \alpha_k K(\xi_k, \xi) = \rho + \mathbf{K}_{\xi,\Xi}\boldsymbol{\alpha}, \tag{3}$$

where α_k are coefficients, $\boldsymbol{\alpha} = [\alpha_1, \ldots, \alpha_m]^\top$ and ρ is the bias. The parameters α_k and ρ will be determined in the training procedure. If a ν-dimensional vector output $\boldsymbol{\zeta}$ is required, a direct way is to use ν scalar-valued SVR and to combine the results together. SVR with 2-dimensional output is involved in this paper. The SVR method makes a tradeoff between the model complexity (roughly speaking the smoothness of function (3)) and the estimation error, this feature ensures the boundedness of the generalization ability of SVR.

Nowadays there are many well-developed SVR training algorithms, so a user needs not care the details of training. The modeling procedure of SVR includes the following steps:

1. Establish the modeling problem, i.e. determine the input-output relationship to be modeled.
2. Measure training samples.