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Rotor Displacement Estimation for MB Sensorless Control

***Abstract**. Abstract. This paper presents an on-line recursive least squares support vector machine(O-RLS-SVM)-based displacement estimator for magnetic bearings (MBs). The basic premise of the method is that an O-RLS-SVM forms an efficient mapping structure for a nonlinear MB. Through the measurement of phase flux linkages and currents, the O-RLS-SVM is able to estimate the rotor displacement; thereby it facilitates the elimination of the rotor displacement sensor. Simulation results show that the estimator has high estimation precision and favourable operation efficiency.*

***Streszczenie.** W artykule przedstawiono system estymacji położenia wirniku w maszynach z poduszką magnetyczną. System nie wymaga czujników – miarą położenia wirnika są przesunięcia fazowe prądu i strumienia magnetycznego. (**Estymacja położenia wirnika w maszynach z poduszką magnetyczną**).*

Keywords: active magnetic bearing; least squares support vector machine; displacement estimation; sensorless control
Słowa kluczowe: aktywne unoszenie magnetyczne, maszyny elektryczne, wirnik.

Introduction

magnetic bearings (MBs) with the advantages of no friction, no wear, no lubrication, longevity, high efficient, fail safe, makes it suitable for running at high speed and super-high speed applications like flywheels [1], [2]. The key to controlling MB is being able to measure or estimate the rotor displacement. Traditionally, displacement measurements for MB are made using proximity transducer systems. These systems are accurate and relatively simple to use but are a significant part of the overall system cost and size, proximity probes and bearings are practically impossible to collocate or place together and flexible modes of the supported shaft give rise to very difficult rotor dynamic control problems. Hence, engineers have been examining the potential of sensorless control.

Studies of the research literatures reveal that *linear* observers and *nonlinear* estimators have been applied to sensorless control of MB [3], [4]. It can be observed that observers are based on nonlinear model and the estimation quality depends on the model precision. Due to the nature nonlinear and parameter uncertainty of MB, these estimators are difficult to obtain a better estimation effect.

As a kind of intelligent control method, artificial neural network (ANN) can get rid of the dependence of control object and obtain a batter treatable and robustness in dealing with the problem of nonlinear and uncertainty [5]. However, ANN needs a great amount of training sample in training, the selection of network topology and the determination of initial weighted value is mainly according to experience, existence of local minimum and over-fitting problems, these shortcomings are always the difficult problems of ANN in application. Least squares support vector machines (LS-SVM), as a new machine learning method proposed by Vapnik and Suykens [6], [7], has been widely used in nonlinear modelling and control areas in recent years [8], [9]. Compared to ANN, the training process of LS-SVM follows structural risk minimization principle and small sample study has strong generalization ability. Its structure and parameters are formed automatically in the training process by the samples. LS-SVM defines a cost function which is different from classical SVM and changes its inequation restriction to equation restriction, which greatly accelerates the solution speed and there is no local minimum question. Therefore the LS-SVM can successfully overcome the defects of ANN, and have batter performance and wider application. Generally LS-SVM regression training algorithms mostly are off-line, which could not express the dynamic behaviour of plant real-time. Online LS-SVM algorithm is more useful when the system to be identified is time-variant, because this kind of algorithms can automatically track changes of system with time-varying and time-lagging characteristics.

The engineering problem addressed by this work is the estimation of air gap dimension in industrial MB. The contribution of this paper is to describe an online recursive LS-SVM (O-RLS-SVM) algorithm and the authors believe the work presented here is the first nonlinear estimation model of rotor displacement based on O-RLS-SVM for the MB application. Other types of nonlinear estimation model have been examined also, the results shows that the proposed method appears to be especially simple and suited for this problem.

On-line recursive least squares support vector machine

Least squares support vector machine

Consider a given set of training samples $\{\boldsymbol{x}_k, y_k\}_{k=1,2,\cdots,N}$, where $\boldsymbol{x}_k$ is the input vector and y_k is the corresponding target value for sample k. With a LS-SVM, the relation underlying the data set is represented as a function of the following form:

$$\hat{y}(x) = w^{\mathrm{T}}\varphi(x) + b. \tag{1}$$

Where φ is a mapping of the vector $\boldsymbol{x}$ to some (probably high-dimensional) feature space, b is the bias and w is a weight vector of the same dimension as the feature space. For the LS-SVM regression, we introduce error variables for the fitting problem as follows:

$$e_k = w^{\mathrm{T}}\varphi(x) + b - y_k. \tag{2}$$

and for the given data we search for those weights that give the smallest summed quadratic error of the training samples in case of LS-SVM. Because this can easily lead to over-fitting, ridge regression (a form of regularization) is used to smoothen the approximation. The minimization of the error together with the regularization is given as

$$\min J(\boldsymbol{w}, e) = \frac{1}{2}\boldsymbol{w}^{\mathrm{T}}\boldsymbol{w} + \frac{\gamma}{2}\sum_{k=1}^{N} e_k^2 \tag{3}$$

$$\text{s.t. } y_k = w^{\mathrm{T}}\varphi(\boldsymbol{x}_k) + b + e_k,\ k = 1,2,\cdots,L. \tag{4}$$

where γ is the regularization parameter.

This problem can be solved using optimization theory. Instead of minimizing the primary objective (3), a dual objective, the so-called Lagrangian, can be formed of which the saddle point is the optimum. The Lagrangian for this problem is given as:

$$L(\boldsymbol{w}, a, b, e) = J + \sum_{k=1}^{L} a_k[y_k - \boldsymbol{w}^{\mathrm{T}}\varphi(x_k) - b - e_k]. \tag{5}$$

Where a_k is called the Lagrangian multiplier.

With Karush-Kuhn-Tucker conditions, the solution is given by the following set of linear equations:

$$\begin{bmatrix} 0 & \boldsymbol{1}^{\mathrm{T}} \\ \boldsymbol{1} & \boldsymbol{K}+\gamma^{-1}\boldsymbol{I} \end{bmatrix}\begin{bmatrix} b_t \\ \boldsymbol{\alpha} \end{bmatrix}=\begin{bmatrix} 0 \\ \boldsymbol{y} \end{bmatrix}. \tag{6}$$

Where $\boldsymbol{\alpha}$ is the L-vector $\boldsymbol{\alpha}=[\alpha_1,\cdots,\alpha_L]^{\mathrm{T}}$, $\boldsymbol{y}$ is the corresponding vector of y_k-values $\boldsymbol{y}=[y_1,\cdots,y_L]^{\mathrm{T}}$, $\boldsymbol{1}$ is the unity L-vector, and $\boldsymbol{K}$ is the $L\times L$ `Kernel matrix', The elements of matrix $\boldsymbol{K}$ equal $\boldsymbol{K_{ij}}=\varphi(\boldsymbol{x}_i)^{\mathrm{T}}\varphi(\boldsymbol{x}_j)=K(\boldsymbol{x}_i, \boldsymbol{x}_j)$, $i, j=1,2,\cdots, L$。$K(\boldsymbol{x}_i, \boldsymbol{x}_j)$ is symmetric function which satisfies Mercer condition. Kernel function is often used result in an approximation by radial basis function (RBF), by polynomial functions, or by splines. In this paper we focus on the RBF kernel:

$$K(x_i, x_j)=\exp[-|x_i-x_j|^2/(2\sigma^2)]. \tag{7}$$

The solution of the set of equations (6) results in a vector of Lagrangian multipliers $\boldsymbol{\alpha}$ and a bias b. The output of the approximator can be calculated for new input values of $\boldsymbol{x}$, with $\boldsymbol{\alpha}$ and b. The output is given as

$$\hat{y}(\boldsymbol{x})=\sum_{k=1}^{L}\alpha_k K(x_k,\boldsymbol{x})+b. \tag{8}$$

On-line recursive least squares support vector machine

LS-SVM algorithm as an extension of standard SVM, the calculation speed has been improved, but it still not fully meet the requirements of on-line learning and Estimation for time-varying system. For time-varying system, the input and output dates generate continuously, and if we want the Estimation model response current system characteristics accurately, LS-SVM should be fitted by the new dates, meanwhile neglecting the old ones. That is the learning samples of LS-SVM should updated ceaselessly (adding the newest sample and eliminating the oldest one at the same time). In this case, LS-SVM training process becomes to solve time-varying linear equations, in which inverse matrix needs to calculate repeatedly, resulting in the computation tasks still greater. Therefore, combine the thought of the recursive calculation to improve the LS-SVM algorithm, Named online recursive LS-SVM (O-RLS-SVM). Principle of O-RLS-SVM as follows:

Set the online training samples window's width N. the sample window makes the sample to renew along with time t unceasingly, not increasing. Namely when a newest sample comes, the oldest one should be discarded simultaneously, so as to maintain the total number of training sample invariable. This may not only use the newest samples to reflect real-time performance of dynamic system effectively, but also solve problem of samples oversized influence online training speed. So the training samples at t can be written as $\{\boldsymbol{X}(t),\boldsymbol{Y}(t)\}$,where $\boldsymbol{X}(t)=[\boldsymbol{x}_{t-N+1},\cdots,\boldsymbol{x}_{t-1},\boldsymbol{x}_t]$,$\boldsymbol{Y}(t)=[y_{t-N+1},\cdots,y_{t-1},y_t]$, here $\boldsymbol{x}_t\in R^n$ is the input vector and $y_t\in R$ is the corresponding target value at time t. So the kernel function matrix $\boldsymbol{K}$, Lagrangian multiplier $\boldsymbol{\alpha}$ and the bias b are all the function about t: $\boldsymbol{K}_{ij}(t)=K(\boldsymbol{x}_{t-i+1},\boldsymbol{x}_{t-j+1}),(i,j=1,2,\cdots,N)$, $\boldsymbol{\alpha}(t)=[\alpha_{t-N+1},\cdots,\alpha_{t-1},\alpha_t]^{\mathrm{T}}$, $b(t)=b_t$.

Set $\boldsymbol{P}_t=\boldsymbol{K}(t)+\gamma^{-1}\boldsymbol{I}$, The solution of the set of equations (6) results in a vector of Lagrangian multipliers $\boldsymbol{\alpha}(t)$ and $b(t)$:

$$b_t=[\boldsymbol{1}^{\mathrm{T}}\boldsymbol{P}_t^{-1}\boldsymbol{Y}(t)]/(\boldsymbol{1}^{\mathrm{T}}\boldsymbol{P}_t^{-1}\boldsymbol{1}) \tag{9}$$

$$\boldsymbol{\alpha}(t)=\boldsymbol{P}_t^{-1}\{\boldsymbol{Y}(t)-[\boldsymbol{1}\boldsymbol{1}^{\mathrm{T}}\boldsymbol{P}_t^{-1}\boldsymbol{Y}(t)]/(\boldsymbol{1}^{\mathrm{T}}\boldsymbol{P}_t^{-1}\boldsymbol{1})\} \tag{10}$$

So the output of O-RLS-SVM is given as:

$$\hat{y}(t)=\sum_{k=t-N+1}^{t}\alpha_k(t)K(x_k,\boldsymbol{x})+b_t. \tag{11}$$

From formula (9) and (10), the solution of $\boldsymbol{\alpha}(t)$ and b_t involves a complex matrix inverse computation, it is not a favor for online training of LS-SVM. Here RLS algorithm is introduced..

Define regression parameter $\boldsymbol{\theta}=[b_t,\boldsymbol{\alpha}(t)]^{\mathrm{T}}=[b_t,\alpha_{t-N+1},\cdots,\alpha_t]^{\mathrm{T}}$, $\boldsymbol{H}_k=[1,K(\boldsymbol{x}_{t-N+1}, \boldsymbol{x}_k),\cdots,K(\boldsymbol{x}_t, \boldsymbol{x}_k)]^{\mathrm{T}}$, $k=t-N+1,t-N+2,\cdots,t$. Set the Test samples window's width equal N too. The training steps of O-RLS-SVM by RLS algorithm as follows:

(I) Initialization $\boldsymbol{\theta}(0)=\boldsymbol{0}$, $\boldsymbol{S}(0)=\delta^{-1}\boldsymbol{I}$, where δ is a Small positive number 10^{-6}, $\boldsymbol{0}$ is a zero vector, $\boldsymbol{I}$ is a unity matrix.

(II) For $k=t-N+1, t-N+2,\cdots, t$, refresh $\boldsymbol{\theta}$:

$$\begin{cases} \boldsymbol{M}_{i+1}=\boldsymbol{S}_i\boldsymbol{H}_k/(\lambda+\boldsymbol{H}_k^{\mathrm{T}}\boldsymbol{S}_i\boldsymbol{H}_k) \\ \boldsymbol{S}_{i+1}=\lambda^{-1}(\boldsymbol{S}_i-\boldsymbol{M}_i\boldsymbol{H}_k^{\mathrm{T}}\boldsymbol{S}_i) \\ \boldsymbol{\theta}_{i+1}=\boldsymbol{\theta}_i+\boldsymbol{S}_{i+1}(y_k-\boldsymbol{H}_k^{\mathrm{T}}\boldsymbol{\theta}_i)\boldsymbol{H}_k \\ i=i+1 \end{cases} \tag{12}$$

Where $\boldsymbol{S}_i$ is a covariance matrix, $\boldsymbol{M}_i$ is a gain vector, $\boldsymbol{\theta}_i$ is regression parameter vector to be identified, λ is called forgotten factor, it is to reduce the impact of old data and increased the role of the new data, $0.95\le\lambda\le 0.98$ in general, here $\lambda=0.98$。

(III) if $i\le t$, back to step (II), otherwise, stop training. $\boldsymbol{\theta}_i$ is the optimum regression parameter.

From above training steps, The process of training includes simple arithmetic but not involves complicated matrix inverse computation, the computation tasks is reduced and avoids the solution unstable question which causes as a result of the coefficient matrix morbid state. And it suits to be realized in the microprocessor, so the algorithm practical performance is enhanced.

Displacement Estimation using O-RLS-SVM

Rotor displacement estimation model

O-RLS-SVM above mentioned not only takes advantages of LS-SVM in small-sample learning, strong approximate and nonlinear mapping property, but also has a strong ability of adaptive, self-learning and generalization. It can affect the characteristics of current time-varying system through the on-line training accurately. So it can be used to realize the rotor potion real-time estimation. Fig.1 shows x-direction potion estimation model structure using O-RLS-SVM for a radial MB system. In this structure, x-and y-direction equivalent currents (i_x, i_y) and equivalent flux linkages (ψ_x, ψ_y) are the inputs and x-direction displacement $\hat{x}$ is the output.

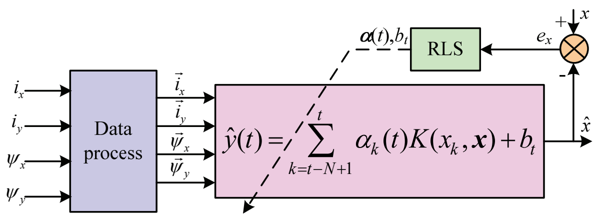


Fig.1. Displacement estimation model structure using O-RLS-SVM

Data process includes two steps: sample-hold and data renew. The function of sample-hold includes data acquisition, storage and detention, The function of data renew is to form a N-length data buffer area, namely time window mentioned before, and let N-length data according to the time sequence fill the time window, the time window makes the training sample renewing unceasingly along with the time, when a newest sample is added in, the oldest one is rejected out simultaneously, so as to maintain the sample length invariable. Through the data process, the inputs data are transformed to the training samples which are needed in the model online training. The Estimation model based on O-RLS-SVM is trained and adjusted online by RLS with error of estimated value $\hat{x}$ and actual value x. through the online training and online adjusting, the estimated value of the estimation model can match the actual value of object. y-direction displacement estimation model structure is similar to x-direction displacement estimation model structure.

Rotor displacement online estimation

To estimate MB rotor displacement online using O-RLS-SVM including the following several steps:

(I) Acquire the training samples. In MBs, the winding current can be measured by the current sensor in the power amplifier, but flux linkage must be estimated. According to the bearing electrical dynamics, the magnetic flux can be determined from the following relationship:

$$\psi = \int (v - ri)dt \tag{13}$$

Where v is the applied terminal voltage, i is the winding current, r is the winding resistance, and ψ is the magnetic flux linkage of the winding.

(II) Optimize the RBF kernel function parameter σ^2 and the regularization parameter γ. To enhance the estimation precision of O-RLS-SVM and obtain an optimal combination of (γ, σ^2), a two-step grid search technique with leave-one-out cross validation is employed. The ranges of γ and σ^2 are set using experience and previous researches. Grid search tries values of each parameter across the specified search range using geometric steps. The first step grid search is a crude search with a large step size and the second step is the specified search with a small step size. After the process of grid search, the optimal combination of (γ, σ^2) would be achieved.

(III) Train O-RLS-SVM by the training samples obtained as initial estimation model.

(IV) Verify whether the estimation precision meets the requirement, if the estimates results are valid, turn to (VI), else, adjust parameters $\alpha(t)$ and b_t of estimation model by RLS. Evaluation model using RMS error:

$$E_{\mathrm{RMS}} = \sqrt{\frac{1}{N}\sum_{i=0}^{N-1}(\hat{y}_{t-i} - y_{t-i})^2}, \quad i = 0,1,\cdots N-1. \tag{14}$$

where $\hat{y}_{t-k}$ is the estimated value, y_{t-k} is the actual value.

(V) Acquire the inputs and outputs data at t+1 sample time and fill them to the time window, meanwhile eliminate the data at t-N+1 sample time from the time window. Then, set t =t+1, return to (IV).

MB Sensorless Control

Take 3-phase AC active MB as an example of radial magnetic suspending system [10], [11], [12]. Fig.2 shows the schematic representation of the 3-phase MB. It is observed from the figure that it has three U type electromagnet shifted by 120^0. I_0 is the direct current in the bias winding, 3-phase current $\{i_A, i_B, i_C\}$ are control current supplied by 3-phase power converter.

Consider the rotor radial x- and y-direction displacements are respectively x and y, the radial suspending force respectively are F_x and F_y in the two-phase static coordinates. When the rotor is in the center position, according to the principle of magnetic circuit imitation, the suspending force equations are as follows:

$$\begin{bmatrix} F_x \\ F_y \end{bmatrix} = \frac{\mu_0 S N^2 I_0}{4\delta_0^2}\begin{bmatrix} i_x \\ i_y \end{bmatrix} + \frac{3\mu_0 S N^2 I_0^2}{8\delta_0^2}\begin{bmatrix} x \\ y \end{bmatrix} \tag{15}$$

where μ_0 is the permeability of air, δ_0 is the nominal air gap, S is the cross-sectional area of the pole face for each air gap, N is the turns of each winding, i_x and i_y are respectively x- and y-direction equivalent control currents, which can be interconvert with 3-phase alternating current i_A, i_B and i_C by $C_{3/2}$ and $C_{2/3}$:

$$\begin{bmatrix} i_x \\ i_y \end{bmatrix} = C_{3/2}\begin{bmatrix} i_A \\ i_B \\ i_C \end{bmatrix}, \quad C_{3/2} = \begin{bmatrix} 1 & -1/2 & -1/2 \\ 0 & \sqrt{3}/2 & -\sqrt{3}/2 \end{bmatrix}. \tag{16}$$

$$\begin{bmatrix} i_A \\ i_B \\ i_C \end{bmatrix} = C_{2/3}\begin{bmatrix} i_x \\ i_y \end{bmatrix}, \quad C_{2/3} = \begin{bmatrix} 1 & 0 \\ -1/2 & \sqrt{3}/2 \\ -1/2 & -\sqrt{3}/2 \end{bmatrix}. \tag{17}$$

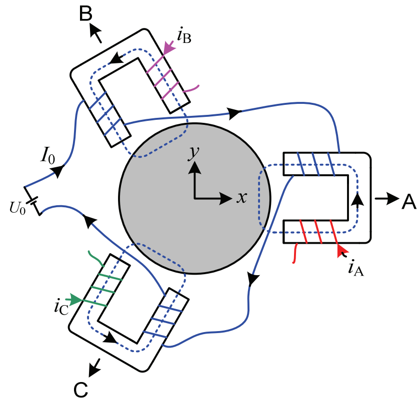


Fig.2. Structure sketch of a 3-phase AC active MB

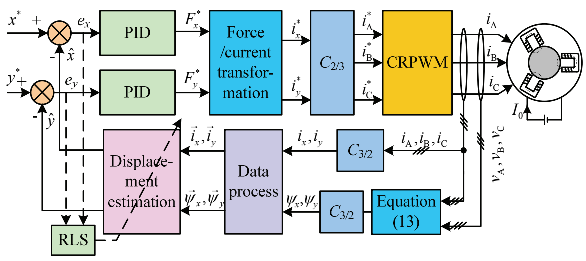


Fig.3. Sensorless control system for 3-phase AC active MB

Fig.3 shows the Sensorless control system diagram for MB. The equation (15) provides the accurate force/current transformation. The 3-phase winding currents $\{i_A, i_B, i_C\}$ and terminal voltages $\{v_A, v_B, v_C\}$ can be measured by current sensors. Then through the $C_{3/2}$ transformation and equation (15), i_x, i_y and ψ_x, ψ_y can be obtained. With inputs $\{i_x, i_y, \psi_x, \psi_y\}$, the displacement estimation model estimates the rotor displacement in the x- and y-direction$\{\hat{x}, \hat{y}\}$. x^* and y^* are the displacement values given by command in the x- and y-direction, respectively (x^*=0, y^*=0), the errors generated by the given value and the estimated feedback value can generate the command values of radial forces$\{F_x^*, F_y^*\}$ through displacement controllers, the current command values$\{i_x^*, i_y^*\}$in the two-phase x-y fixed coordinates can be obtained after transformation of force/current in equation (15), then after $C_{3/2}$ transformation, 3-phase current command values of suspension windings $\{i_A^*, i_B^*, i_C^*\}$ can be obtained. Finally, 3-phase currents $\{i_A, i_B, i_C\}$ of suspension force windings can be obtained through the 3-phase CRPWM inverter, and then loop control of radial suspending displacements can be realized for 3-phase AC active MB.

Simulation and analysis

According to the rotor displacement Estimation method proposed, the displacement sensorless control for the MB is conducted in Matlab/Simulink. The system block diagram used in the simulation is shown in Fig.2. The model parameters used in the simulation are from the Jiangsu University Electrical and Information Engineering small MB test bed and are listed in Table I. Results of the computer simulation study are presented here.

Table I. Magnetic bearing model parameters

N	Number of turns in a winding	150
S	Cross-sectional area of pole face, m2	7×10^{-4}
I_0	the bias winding direct current, A	1
m	Payload mass, Kg	1
r	Winding resistance, Ω	10
δ_0	Nominal air gap, m	5×10^{-4}
μ_0	Permeability of free space, H/A	$4\pi\times10^{-7}$

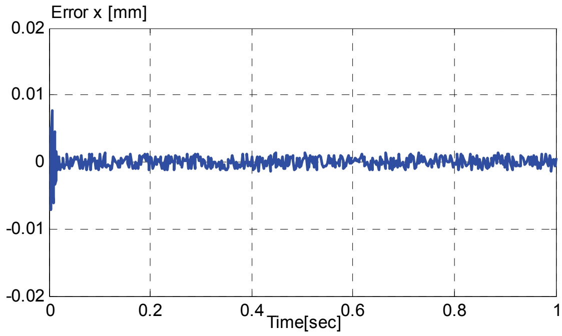


Fig.4. Displacement estimation error

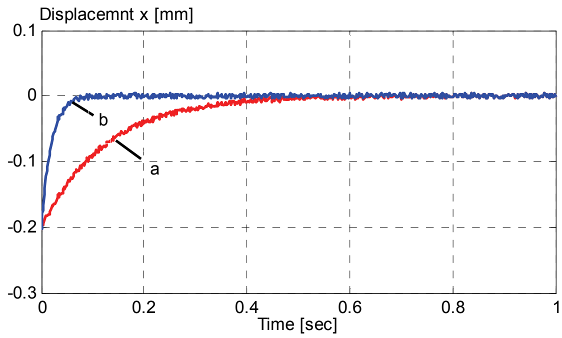
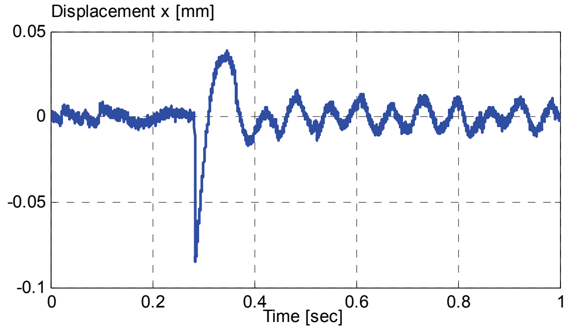


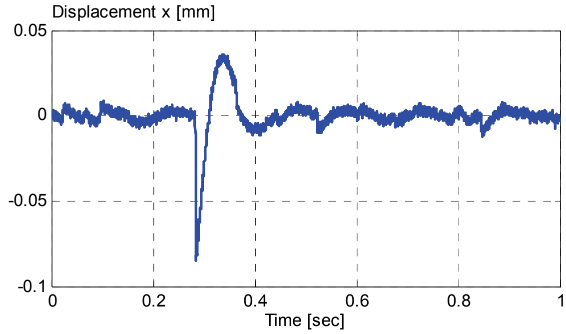
Fig.5.Displacement dynamic response when the rotor suspending up. (a) Response of LS-SVM estimator, (b) Response of O-RLS-SVM estimator

Shown in Fig.4 is the estimation error between the response of the displacement estimation model built by O-RLS-SVM and the actual displacement measured by conventional displacement sensor. From the error carve we can see that the error exist in a small area, and the max error is 0.08 mm, it is much less than the nominal air gap 0.5mm. So the displacement estimation model can achieve correct rotor displacement estimation, and thus the sensorless control of MB can be realized.

In Fig.5 is the displacement dynamic response comparison between estimation models built respectively by LS-SVM and O-RLS-SVM when the rotor start to suspending up. Both models converge to the correct rotor center position, but the response of O-RLS-SVM is faster. This is to be expected, since the O-RLS-SVM as an improvement of LS-SVM has a swifter convergence speed.



(a)LS-SVM estimator response under shock load



(b) O-RLS-SVM estimator response under shock load

Fig.6. Displacement response under shock load

In Fig.6 are the response plots for the case where a shock load change in reference position at time t=0.28s. Both estimation models exhibit sensitivity to this shock load. Note the oscillation exhibited by LS-SVM estimation model response. But the steady state of O-RLS-SVM estimation model is much less influenced. This is due to the fact that the O-RLS-SVM estimation model is based on the online training and has strong adaptive ability.

Conclusions

The work presented describes a rotor displacement real-time estimator for 3-phase AC active MB sensorless control. The approach is to use O-RLS-SVM to construct an efficient mapping structure which uses phase current and phase magnetic flux to estimate rotor displacement. Because the proposed displacement estimator is model independent, so it appears to be much less sensitive than linear observers that have been used. The simulation results are very encouraging, and the findings show that the O-RLS-SVM-based estimator has very high estimation precision, good responses, and it has better robustness against the shock load than LS-SVM-based estimator.

A recommendation for future work is to design an real-time flux linkage estimator that estimates the value of the magnetic flux linkage. The authors believe the estimation can be performed using measured current and knowledge of the control command, which is always known. This advance would further reduce the feedback requirement for sensorless control of industrial MB. The test hardware system would be designed in the near future.

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