

SVM Regression 을 이용한 PMSM 의 속도 추정

Speed Estimation of PMSM Using Support Vector Regression

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Abstract : We present a novel speed estimation of a Permanent Magnet Synchronous Motor(PMSM) based on Support Vector Regression(SVR). The proposed method can estimate wide speed range, including 0.33Hz with full load, accurately in the steady and transient states where motor parameters variations are known without parameter estimator. Moreover, the method does not need off-line training previously but is trained on-line. The training starts with the PMSM operation simultaneously and estimates the speed in real time. The experimental results shows the validity and the usefulness of the proposed algorithm for the 0.4Kw PMSM DSP(TMS320VC33) drive system.

Keywords : permanent magnet synchronous motor, speed estimation, support vector regression.

I. INTRODUCTION

Permanent magnet AC synchronous machines are widely used due to the development of power electronics and powerful signal processing microprocessors. The vector control of a permanent magnet synchronous motor is usually implemented through measuring the speed and position of the rotor. However, speed and position sensors require additional mounting space, reduce the reliability in harsh environments and increase the cost of a motor control system. Various control algorithms have been proposed for the elimination of speed and position sensors: estimators using state equations, Luenberger[1,2] or Kalman-filter observers[3,4] artificial intelligence[5-7]. These methods demonstrate excellent performance in middle and high speed applications. Nevertheless, in a more or less important degree depending on the characteristics of the particular observer, problems related to low and standstill operation, knowledge of motor parameters, influence of measurement disturbances and the computational charge of these methods still remain. Recently, new approaches to rotor position detection have been presented: saliency effects[8], and injection of proper test signal[9,10]. These methods offer a solution for both standstill and low speed operation, but they require high precision in the measurement. Moreover, the additional voltage to inject the test signal decreases the operating range at high speed.

In this paper, a novel estimation of a PMSM using Support Vector Regression(SVR) based on statistical learning theory is presented. Recently, a novel neural network algorithm, called Support Vector Machine(SVM), was developed by Vapnik and his co-workers[11,12]. Unlike most of the traditional neural network models which implement the empirical risk minimization principle, SVM implements the structural risk minimization principle which seeks to minimize an upper bound of the generalization error rather than the training error. This induction principle is based on the fact that the

generalization error is bounded by the sum of the training error and a confidence interval term that depends on the Vapnik-Chervonenkis (VC) dimension. Based on this principle, SVM achieves an optimum network structure by striking a right balance between the empirical error and the VC-confidence interval. This eventually results in better generalization performance than other neural network models. Another merit of SVM lies in the training of SVM equivalent to solving a linearly constrained quadratic programming.

Stationary voltage model is necessary to estimate the speed of a PMSM. The proposed method can estimate high speed and low speed range, including 0.33Hz with full load, accurately in the steady states and transient where motor parameters variations are known. Also, the method does not need off-line training previously but is trained on-line. The training starts with the PMSM operation simultaneously and estimates the speed in real time. The validity and the usefulness of proposed algorithm are thoroughly verified through numerical simulation and experiment on the 0.4Kw PMSM drive system.

II. MATHEMATICAL MODELING OF PMSM

Voltage models of stator and rotor, torque, and dynamic equation of PMSM are shown in this chapter.

The proposed SVR Speed estimation algorithm uses the stationary reference frame fixed to the stator voltage model for the voltage estimation. From the stator voltage equations in the real d_s^s -axis, and q_s^s -axis voltage equations in the stationary reference frame fixed to the stator can be expressed as

$$v_{ds}^s = R_s i_{ds}^s + L_s \frac{di_{ds}^s}{dt} - K_e \omega_r \sin(\theta_r) \quad (1)$$

$$v_{qs}^s = R_s i_{qs}^s + L_s \frac{di_{qs}^s}{dt} + K_e \omega_r \cos(\theta_r) \quad (2)$$

$$e_{ds}^s = -K_e \omega_r \sin(\theta_r) \quad (3)$$

$$e_{qs}^s = K_e \omega_r \cos(\theta_r) \quad (4)$$

where $v_{dq_s}^s$ is stator voltage, $i_{dq_s}^s$ is stator current, R_s is stator resistance, L_s is stator inductance, θ_r is the angle of rotor and K_e , $e_{dq_s}^s$ is the back-EMF constant, back-EMF respectively.

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d_r^r -axis, and q_r^r -axis voltage equations in the rotor reference frame fixed to the stator can be expressed as

$$v_{dr}^r = R_s i_{dr}^r + L_s \frac{di_{dr}^r}{dt} - \omega_r L_s i_{qr}^r \quad (5)$$

$$v_{qr}^r = R_s i_{qr}^r + L_s \frac{di_{qr}^r}{dt} + \omega_r L_s i_{dr}^r + \omega_r K_e \quad (6)$$

where v_{dqr}^r is rotor voltage, i_{dqr}^r is rotor current.

The electromagnetic torque in the rotor reference frame may be expressed as

$$T_e = K_T i_{qr}^r \quad (7)$$

where K_T is torque constant

The mechanical equation of a PMSM may be expressed as

$$T_e = J_m \frac{d\omega_{rm}}{dt} + B_m \omega_{rm} + T_L \quad (8)$$

where J_m is the inertia coefficient and B_m is the friction coefficient, ω_{rm} is the mechanical speed of the rotor, and T_L is the load torque.

III. SUPPORT VECTOR MACHINE REGRESSION

A regression method is an algorithm that estimates an unknown mapping between a system's input and outputs, from the available data or training data. Once such a dependency has been accurately estimated, it can be used for prediction of system outputs from the input values. The goal of regression is to select a function which approximates best the system's response. A function approximation problem can be formulated to obtain a function f from a set of observations, $(y_1, x_1), \dots, (y_N, x_N)$ with $x \in R^m$ and $y \in R$, where N is the number of training data, x is the input vector, and y is the output data. The function in SVR has the form of

$$f(x, \omega) = \omega^T K(x) + b \quad (9)$$

where $K(\cdot)$ is a mapping from R^m to so-called higher dimensional feature space F , $\omega \in F$ is a weight vector to be identified in the function, and b is a bias term. To calculate the parameter vector ω , the following cost function should be minimized[13,14]

$$\text{Min } \frac{1}{2} \|\omega\|^2 + C \sum_{i=1}^N (\xi_i + \xi_i^*)$$

subject to

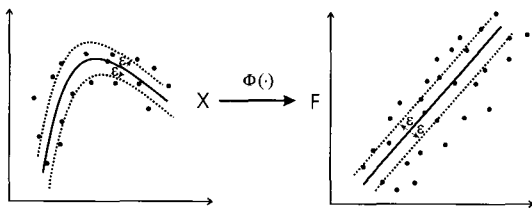


Fig. 1. A feature map from input space to higher dimensional feature space.

$$y_i - \alpha x_i - b \leq \varepsilon + \xi_i \quad (10)$$

$$\alpha x_i + b - y_i \leq \varepsilon + \xi_i^*$$

$$\xi_i, \xi_i^* \geq 0, C \neq 0, i = 1, \dots, N$$

where C is a pre-specified value that controls the cost incurred by training errors and the slack variables, ξ_i, ξ_i^* are introduced to accommodate error on the input training set. With many reasonable choice of loss function, ξ , the solution will be characterized as the minimum of a convex function. The constraints also include a term, ε , which allows a margin of error without incurring any cost. The value of ε can affect the number of support vectors used to construct the regression function. The bigger ε is, the fewer support vectors are selected. Hence, ε -values affect model complexity.

Our goal is to find function $f(x, \omega)$ that has at most ε deviation from the actually obtained targets y_i for all the training data, and at the same time, is as flat as possible for good generalization. In other words, we do not care about errors as long as they are less than ε , but will not accept any deviations larger than ε . This is equivalent to minimizing an upper bound on the generalization error, rather than minimizing training error.

The optimization problem in (6) can be transformed into the dual problem[13,14], and its solution is given by

$$f(x) = \sum_{i=1}^N (\alpha_i - \alpha_i^*) K(x_i) \cdot K(x) + b$$

$$\text{s.t. } 0 \leq \alpha_i^* \leq C, 0 \leq \alpha_i \leq C \quad (11)$$

In (7), the inner product $(K(x_i) \cdot K(x))$ in the feature space is usually considered as a kernel function $K(x_i, x)$. Several choices for the kernel are possible to reflect special properties of approximating functions:

Linear kernel: $K(x_i, x) = x_i^T x$

RBF kernel: $K(x_i, x) = \exp(-\|x - x_i\|^2 / \sigma^2)$ (12)

The input data are projected to a higher dimensional feature space by mapping $K(\cdot)$. A linear regression is made in this higher dimensional feature space, responding to a nonlinear regression in the original input space of interest as shown in Fig. 1.

IV. SPEED ESTIMATION USING SVR

The speed estimator is derived by estimating the voltage where the measured voltage, v_{dqs}^s , and the sum of the terms with motor parameters in controller of eq. (1) and (2) are compatible. Since the speed is estimated based on the estimated voltage, robust estimation can be performed without compensating for parameter variation of motor. Equations (1) and (2) can be transformed to equations (13) and (14).

$$(v_{ds}^s)^2 + (v_{qs}^s)^2 = ((i_{ds}^s)^2 + (i_{qs}^s)^2) + (K_e \omega_r)^2 (\cos(\theta_r))^2 + \sin(\theta_r)^2 = R^2 ((i_{ds}^s)^2 + (i_{qs}^s)^2) + K_e^2 \omega_r^2 \quad (13)$$

$$K_e^2 \omega_r^2 = (v_{ds}^s)^2 + (v_{qs}^s)^2 - R^2 ((i_{ds}^s)^2 + (i_{qs}^s)^2)$$

$$\therefore \omega_r = \frac{1}{K_e} \sqrt{(v_{ds}^s)^2 + (v_{qs}^s)^2 - R^2((i_{ds}^s)^2 + (i_{qs}^s)^2)} \bullet \text{sign}(\omega_r^{\text{ref}}) \quad (14)$$

where, $\text{sign}(\omega_r^{\text{ref}}) = \begin{cases} +1(\omega_r^{\text{ref}} \geq 0), \text{ Clock wide} \\ -1(\omega_r^{\text{ref}} \leq 0), \text{ Counter clock wide} \end{cases}$

In equation (13) and (14), $L_s \frac{di_{qs}^s}{dt}$ is not contained, under the assumption that estimation of stator current is not changed in a period of sampling time. The voltage and current are measured, while resistor, inductance and Back-emf are known parameters. SVR Speed estimation algorithm needs target and training data for training. Target data and training data are defined as $(v_{ds}^s)^2 + (v_{qs}^s)^2$, and $((i_{ds}^s)^2 + (i_{qs}^s)^2)$ respectively. The basic idea is to minimize error between measured voltage and calculated voltage in the controller. Hence, Robust speed estimation under parameter R_s, L_s variation circumstance is achieved. The speed estimation model is expressed as

$$y = (v_{ds}^s)^2 + (v_{qs}^s)^2 \quad (15)$$

$$x = (i_{ds}^s)^2 + (i_{qs}^s)^2 \quad (16)$$

$$b = (K_e \omega_r)^2 \quad (17)$$

Using quadratic loss function, one has to find Lagrange multipliers $\alpha_i, \alpha_i^*, i = 1, \dots, N$, that minimize the quadratic form

$$W(\alpha_i, \alpha_i^*) = \frac{1}{2} \sum_{i,j=1}^N (\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*) K(\mathbf{x}_i, \mathbf{x}_j) - \sum_{i=1}^N y_i (\alpha_i - \alpha_i^*) + \frac{1}{2C} \sum_{i=1}^N (\alpha_i^2 - \alpha_i^{*2}) \quad (18)$$

The regression function is given by

$$\omega^T \mathbf{x} = \sum_{i=1}^N (\alpha_i - \alpha_i^*) K(\mathbf{x}_i, \mathbf{x}) \quad (19)$$

$$b = \text{mean} \left(\sum_{i=1}^N \{ y_i - (\alpha_i - \alpha_i^*) K(\mathbf{x}_i, \mathbf{x}) \} \right) \quad (20)$$

In order to solve this problem, one has to choose C and ϵ . Parameters C and ϵ usually are selected by users based on a prior knowledge of expert users. It is well-known that the value of ϵ should be proportional to the input noise level that is difficult to estimate from data and the value of ϵ can effect the number of support vectors used to construct the regression function. In other words, SVR performance depends on C and ϵ . Unfortunately, SVR framework does not provide clear guidelines on how to select the value of C and ϵ .

Hence, under our approach, we propose to choose quadratic loss function with zero ϵ -value ($\epsilon = 0$). For selection of C directly from the training data, we propose to use the following prescription for regularization parameter.

A. Selection of parameter C

Parameter C determines the trade off between the model complexity (flatness) and the degree to which deviations larger than ϵ are tolerated in optimization formulation.

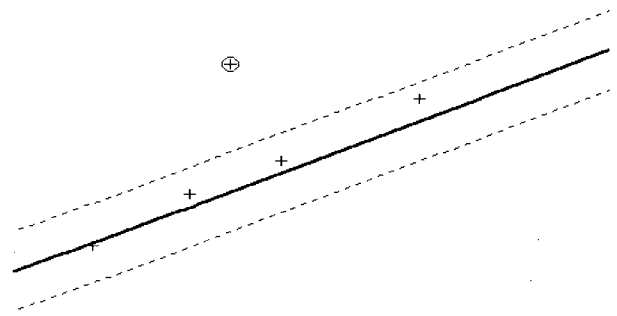


Fig. 2. Insensitive band for a one dimensional regression with small parameter C .

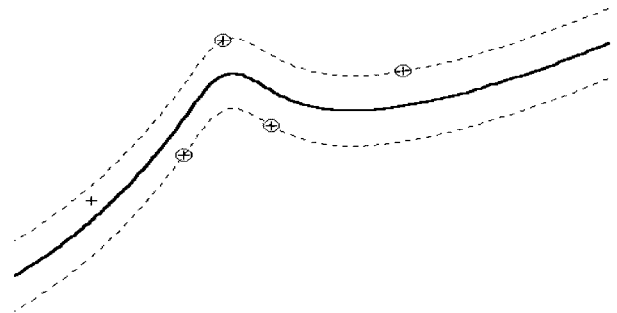


Fig. 3. Insensitive band for a one dimensional regression with large parameter C .

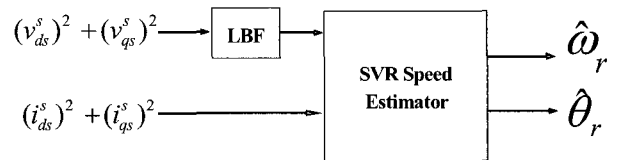


Fig. 4. Structure of the speed estimator using SVR.

The smaller C is less sensitive to the noisy data or outliers as shown in Fig. 2. The larger C gives less training error with more of the noisy data included as shown in Fig. 3 and this increases the model complexity. At boundary, there are some bound support vectors whose Lagrange multipliers equal the C parameter. In this study, parameter C is selected as maximum voltage value.

Combining (15), (16), and (17), the estimated voltage is given by

$$\hat{v}_{dqs}^s = \sum_{i=1}^N (\alpha_i - \alpha_i^*) K(\mathbf{x}_i, \mathbf{x}) = \sum_{i=1}^N x_i \cdot \beta_i \quad (21)$$

where β_i is some real value and its maximum equals.

Equation (14) can be expressed as

$$\therefore \hat{\omega}_r = \frac{1}{K_e} \sqrt{(\hat{v}_{ds}^s)^2 + (\hat{v}_{qs}^s)^2 - \omega^T((i_{ds}^s)^2 + (i_{qs}^s)^2)} \bullet \text{sign}(\omega_r^{\text{ref}}) \quad (22)$$

VI. EXPERIMENTS

The experiment has been performed for the verification of the speed estimation algorithm. The experiment conditions are as follows

Table 1. Motor specifications.

Number of Pole	8
Rs, Ls	1.49[Ω], 9.53e-3[H]
Back-emf constant	0.25
Nominal power	0.4Kw

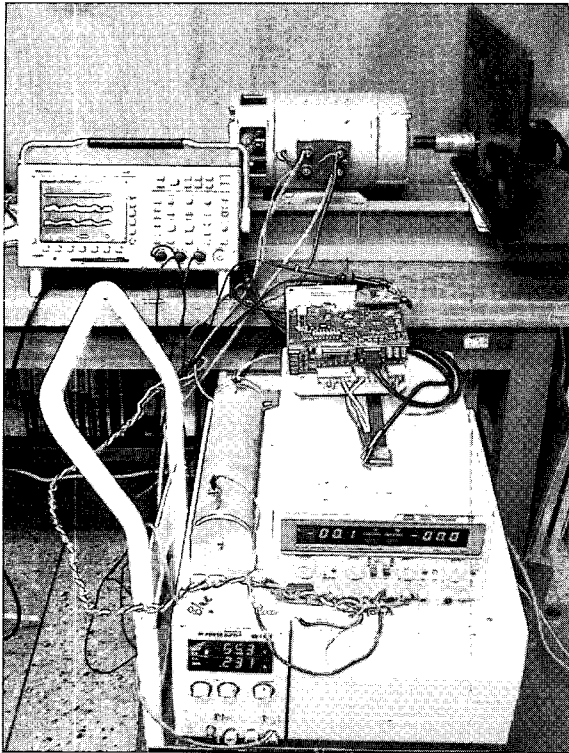


Fig. 5. The experimental apparatus.

In the experiment, the switching frequency of the inverter is 5Khz(200usec), control period is 10Khz(100usec), training input signal is lowpass filtered at bandwidth of 100Hz, and sampling period of SVR estimator is 10Khz(100usec). The DSP(TMS320VC33) system is used for the digital processing of the proposed algorithm. The experimental apparatus is shown in Fig. 5. Fig. 6 shows that rotor speeds for transient and steady state approach to measured values at low speed(Fig. 6(a)), medium speed (Fig. 6(b)), and high speed(Fig. 6(c)) without load. It is well known that speed estimation at low speed is difficult. Fig. 7 and Fig. 8 depict the speed estimation results with parametric variation of stator resistor R_s , and stator inductance L_s at both low and high speed with load. The speed characteristic with 130% variation of stator resistor is described in Fig. 7. At low speed as shown in Fig. 7(a), the speed estimation is robust to variation of resistor with negligible noise. Fig. 7(b) shows good speed estimation for both transient and steady state at 500 rpm. This paper proposes equation 22 without stator inductance L_s .

Speed estimation at transient and steady state with 120% variation of stator inductance L_s is depicted in Fig. 8. As shown in Fig. 8(a), we can get satisfactory result at steady state without any influence by stator inductance differently from transient state. Fig. 8(b) shows good characteristic of speed estimation regardless of variation of stator inductance L_s for both transient and steady state. The q-axis currents with full load are described in Fig. 9-12. In Figures 9(③)-11(③), q-

axis current is shown for low speed estimation with load as Fig. 7(a) and Fig. 8(a). The proposed algorithm shows good result at low speed though variation of q-axis current at low speed is bigger than that at high speed as shown in Fig. 12(③).

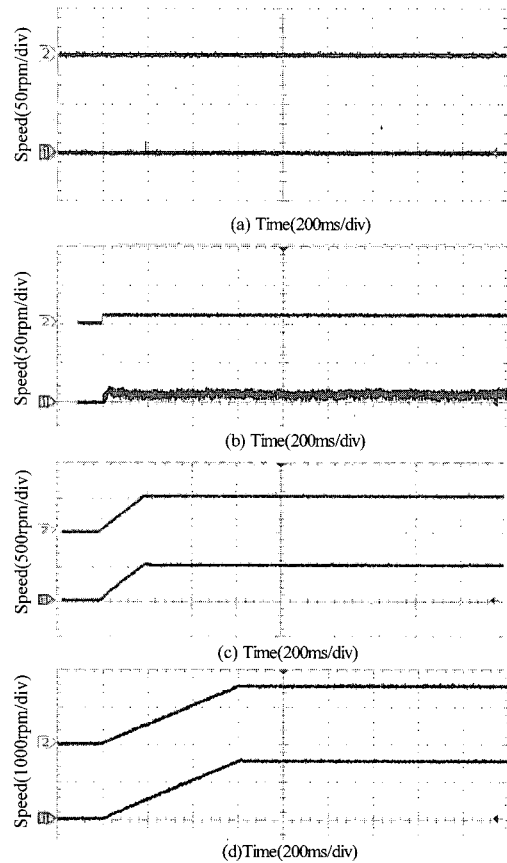


Fig. 6. Rotor speed response(②: estimated speed, ①: measured speed), at (a) 0 rpm, (b) 0-10 rpm, (c) 0-500 rpm, (d) 0-1500 rpm.

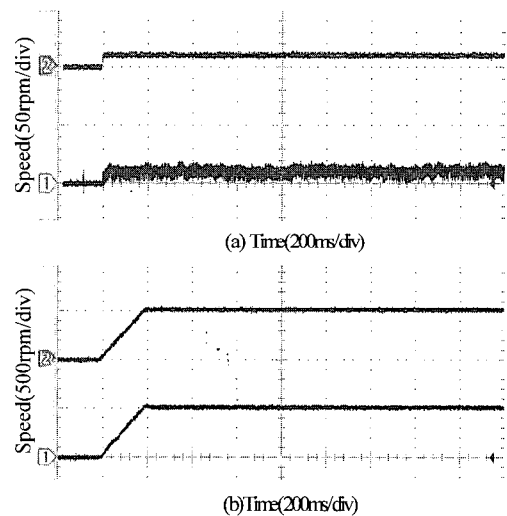


Fig. 7. Rotor speed step response(②: estimated speed, ①: measured speed) with parameter variation $\hat{R}_s = 1.3 \bullet R_s$ at (a) 0-10 rpm, (b) 0-500 rpm.

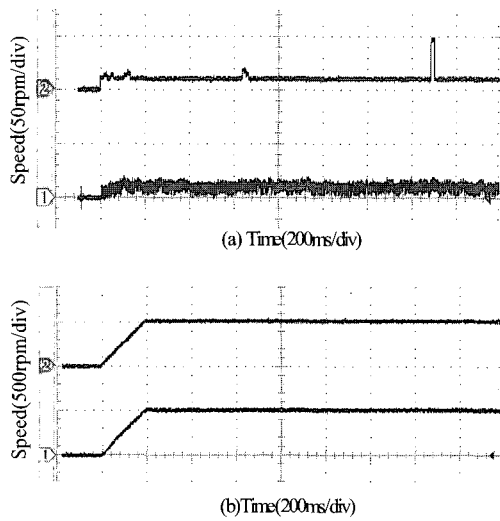


Fig. 8. Rotor speed step response(②: estimated speed, ①: measured speed) with parameter variation $\hat{L}_s = 1.2 \cdot L_s$ at (a) 0-10 rpm, (b) 0-500 rpm.

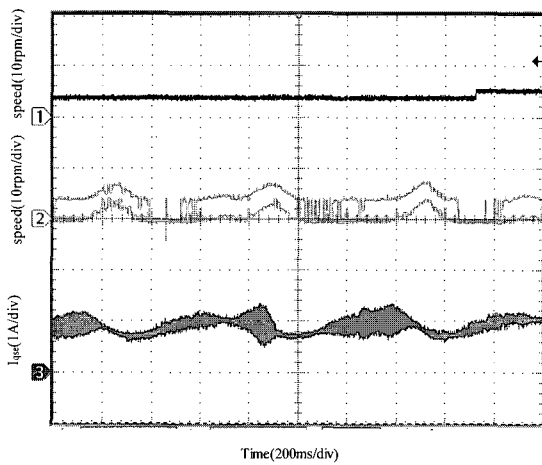


Fig. 9. Rotor speed response of 5 rpm with full load(①: estimated speed, ②: measured speed, ③: i_{qs}^e).

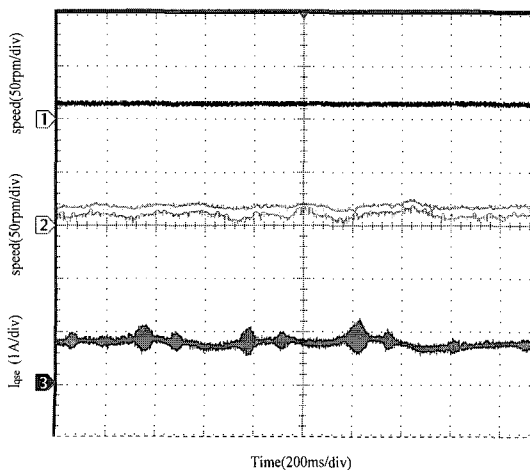


Fig. 10. Rotor speed response of 15 rpm with full load(①: estimated speed, ②: measured speed, ③: i_{qs}^e).

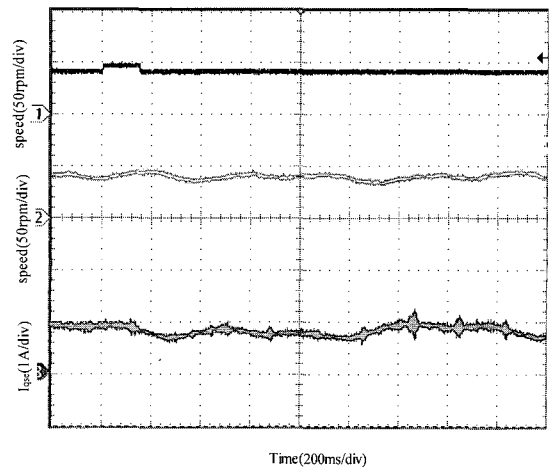


Fig. 11. Rotor speed response of 40 rpm with full load(①: estimated speed, ②: measured speed, ③: i_{qs}^e).

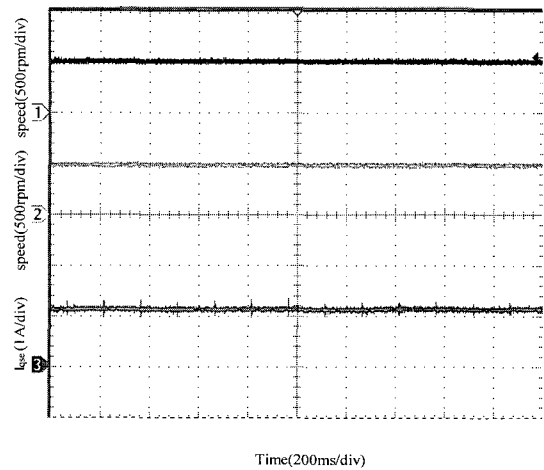


Fig. 12. Rotor speed response of 500 rpm with full load(①: estimated speed, ②: measured speed, ③: i_{qs}^e).

VI. CONCLUSIONS

The SVR method is an algorithm that estimates an unknown mapping between a system's input and outputs, from the available data or training data. Stationary voltage model is necessary to estimate the speed of a PMSM. The proposed method can estimate wide speed range, including 0.33Hz with full load, accurately in the steady states and transient where motor parameters variations are known without compensation for parameter variation of motor. Also, the method does not need off-line training previously but is trained on-line. The training starts with the PMSM operation simultaneously and estimate the speed in real time. The simulation and experimental result show the validity and the usefulness of proposed algorithm.

Based on the experimental results for estimation of parameters, an effective control algorithm is under research in our lab.

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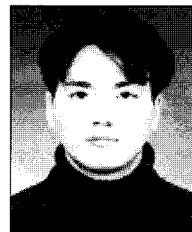
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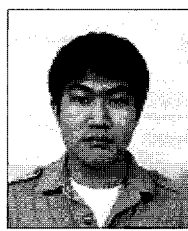


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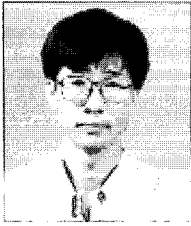
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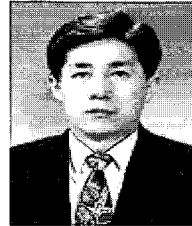


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