Precision Speed Control of PMSM Using Neural Network Disturbance Observer on Forced Nominal Plant

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Abstract

This paper presents a neural network (NN) torque observer that is used to deadbeat load torque observer and regulation of the compensation gain by parameter estimator. Therefore, the response of permanent magnet synchronous motor (PMSM) follows that of the nominal plant. The load torque compensation method is composed of a neural deadbeat observer. To reduce of the noise effect, the post-filter, which is implemented by moving average (MA) process, is proposed. The parameter compensator with recursive least square method (RLSM) parameter estimator is suggested to increase the performance of the load torque observer and main controller. The proposed estimator is combined with a high performance neural torque observer to resolve the problems. As a result, the proposed control system becomes a robust and precise system against the load torque and the parameter variation. A stability and usefulness, through the verified computer simulation and experiment, are shown in this paper.

1. Introduction

Recently, precision position control become more and more important in chip mount machines, semiconductor production machines, precision milling machines, high resolution CNC machines, precision assembly robots, high speed hard disk drivers and so on. Also one of a merging technology is a nanotechnology. This part almost works in nano-fabrication but now spreads to bio-engineering, optical equipment, and so on. It is also very important for direct drive systems. A PMSM has replaced many DC motors since the industry applications require more powerful actuators in small sizes. The PMSM has low inertia, large power-to-volume ratio, and low noise as compared to a permanent magnet DC servomotor having the same output rating [1][2]. However, the disadvantages of this machine are the high cost and the need for a more complex controller because of the nonlinear characteristic.

The proportional-integral (PI) controller usually used in PMSM control is simple to realize but makes it difficult to obtain sufficiently high performance in the tracking application. A new systematic approach was done in state space using digital position information in BLDC motor system [3]. However, the machine flux linkage is not exactly known for a load torque observer that creates problems of uncertainty. The cogging effect, some damage on permanent magnet, over current can affect the value of k_t. This caused small position or speed errors and increased the chattering effect, which should be reduced as much as possible. It also makes miss-estimated load torque in deadbeat observer system. In this paper the NN torque observer and parameter compensator with RLSM parameter estimator is suggested to increase the performance of the load torque observer and main controller. This compensator makes real system as if it works in nominal system parameter. Therefore the deadbeat load torque observer has a good performance as if there is no parameter variation. Finally, this controller can be used in vestibular system which is one of the simulators. That system need the exact sinusoidal speed control even though unbalanced load is injected. Other production equipment also can take this controller to increase the production quality.

2. Modeling of PMSM

Under condition of vector control, the system equations of a PMSM model can be described as

$$\dot{\omega} = \frac{3}{2}\frac{1}{J}\left(\frac{p}{2}\right)^2 \lambda_m i_{qs} - \frac{B}{J}\omega - \frac{p}{2J}T_L \quad (1)$$

$$T_e = \frac{3}{2}\frac{p}{2}\lambda_m i_{qs}. \quad (2)$$

where

p : number of poles

λ_m : flux linkage of permanent magnet

ω : angular velocity of rotor

J :inertia moment of rotor

B :viscous friction coefficient.

3. Control algorithm

3.1 Speed controller

A new state is defined for the tracking controller as Eqn. (3). Where ω_r is the rotor speed reference [2]. The control input becomes Eqn. (4).

$$\dot{z} = \omega - \omega_r \quad (3)$$

$$u = -kx - k_1 z. \quad (4)$$

The augmented system for the speed control of a PMSM is expressed as follows:

$$\begin{pmatrix}\dot{\omega}\\ \dot{z}\end{pmatrix} = \begin{pmatrix}-\frac{B}{J} & 0\\ 1 & 0\end{pmatrix}\begin{pmatrix}\omega\\ z\end{pmatrix} + \begin{pmatrix}k_t\frac{p}{2}\frac{1}{J}\\ 0\end{pmatrix} i_{qs} - \begin{pmatrix}\frac{P}{2J}\\ 0\end{pmatrix} T_L - \begin{pmatrix}0\\ 1\end{pmatrix}\omega_r \quad (5)$$

$$y = \begin{pmatrix}1 & 0\end{pmatrix}\begin{pmatrix}\omega\\ z\end{pmatrix}. \quad (6)$$

If the load torque T_L is known, an equivalent current command i_{qc2} can be expressed as

$$i_{qc2} = \frac{1}{k_t}T_L. \quad (7)$$

Then, the feeding forward an equivalent q axis current command to the output controller can compensates load torque effect. However, disturbances are unknown or inaccessible in the real system.

3.2 Load torque observer and MA process

It is well known that observer is available when input is unknown and inaccessible. For simplicity, a 0-observer is selected [3]. The system equation can be expressed as

$$\begin{pmatrix}\dot{\hat{\omega}}\\ \dot{\hat{T}}_L\end{pmatrix} = \begin{pmatrix}-\frac{B}{J} & -\frac{p}{2}\frac{1}{J}\\ 0 & 0\end{pmatrix}\begin{pmatrix}\hat{\omega}\\ \hat{T}_L\end{pmatrix} + \begin{pmatrix}k_t\frac{p}{2}\frac{1}{J}\\ 0\end{pmatrix} i_{qs} + L\left(y - \begin{pmatrix}1 & 0\end{pmatrix}\begin{pmatrix}\hat{\omega}\\ \hat{T}_L\end{pmatrix}\right). \quad (8)$$

To reduce disadvantage of deadbeat observer that is too sensitive of noise, moving average (MA) filter is considered [5].

$$\tilde{T}_L(k) = \frac{1}{2}(\hat{T}_L(k) + \hat{T}_L(k-1)) \quad (9)$$

3.3 Parameter estimator and compensator

The discrete dynamic equation of PMSM can be written as

$$\omega(k+1) = \alpha\omega(k) + \beta i_{qs}(k) - \gamma T_L(k) \quad (10)$$

where $\alpha = e^{-\frac{B}{J}h}$, $\beta = -\frac{P}{2J}(-\frac{J}{B}e^{-\frac{B}{J}h} + \frac{J}{B})k_t, \gamma = \frac{\beta}{k_t}$.

Respectively, on the assumption that there is no effect of the load torque, a feed back gain and a feed forward gain are defined as C_1 and C_2 respectively [6][7]. Then a control input for a compensate parameter variation to make the system as a equivalent nominal system becomes as follow:

$$i^*_{qc}(k) = C_1(k)\cdot i_{qc}(k) + C_2(k)\cdot\omega(k) \quad (11)$$

Therefore resultant compensated system is equal to the nominal equivalent system.

$$\alpha\omega(k) + \beta(i_{qs}(k)\cdot C_1(k) + \omega(k)\cdot C_2(k)) = \alpha_n\omega(k) + \beta_n i_{qs}(k) \quad (12)$$

where α, β and α_n, β_n are actual parameters and nominal parameters, respectively. These values can be obtained easily with Eqn. (12) as $C_1(k) = \frac{\beta_n}{\beta}$, $C_2(k) = \frac{(\alpha_n - \alpha)}{\beta}$.

Parameter compensation requires real parameter estimation. Using a discrete system equation without disturbance Eqn. (13) we can separate a parameter and a measured parameter.

$$\omega(k+1) = \alpha\omega(k) + \beta i_{qs}(k) = \theta^T\phi(k) \quad (13)$$

where $\theta^T = [\alpha \quad \beta]$, $\phi(k)^T = [\omega(k) \quad i_{qs}(k)]$.

A RLSM can estimate real parameter. Resultant equations are as follows [8][9]:

$$\hat{\theta}(k+1) = \hat{\theta}(k) + F(k+1)\tilde{\phi}(k)E(k+1) \quad (14)$$

$$F(k+1) = F(k) - \frac{F(k)\tilde{\phi}(k)\tilde{\phi}(k)^T F(k)}{1+\tilde{\phi}(k)^T F(k)\tilde{\phi}(k)} \quad (15)$$

$$E(k+1) = y(k+1) - \hat{\theta}(k)^T\tilde{\phi}(k) \quad (16)$$

where $\hat{\theta}^T = [\hat{\alpha} \quad \hat{\beta}]$, $\tilde{\phi}(k)^T = \left[\omega(k) \quad i_{qs}(k) - \frac{\hat{T}_L}{k_t}\right]$,

$F(0) = \frac{1}{\delta}I \qquad (0 < \delta << 1)$.

3.4 Proposed neural network observer

The approximation of the multi-variable neural network can be done by Hornick function method. This neural network can compensate the system of parameter variation effects. Fig. 1 shows a controller with back-propagation neural network (BPNN) used base on augmented state feedback.

This BPNN use rotor speed, rotor speed reference, error of the speed, and equivalent q-phase current command of the torque observer as input nodes to learn optimal current command. The error between real controller out put and neural network propagate back to hidden layer under following bipolar activation function.

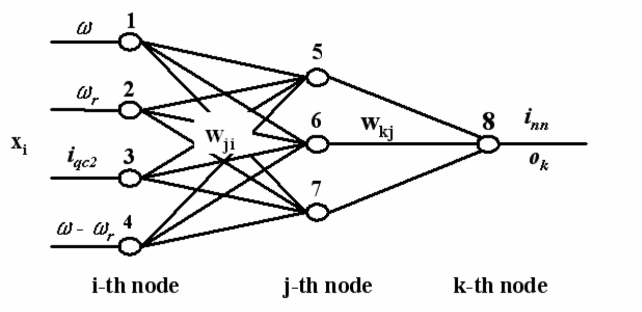


Fig. 1: Diagram of the neural network using error back-propagation

$$f(net_k) = \frac{2}{1+\exp(-\lambda net_k)} - 1 \quad (17)$$

$$net_k = \sum_j \omega_{kj} y_j \quad (18)$$

$$o_k = f(net_k) \quad (19)$$

The slop of the activation function is considered as 1 for simplicity and weight is changed by delta learning rule. Eqn. 19 means neural network output of the each node.

$$E = \frac{1}{2}\sum_{k=1}^{n}(d_k - o_k)^2 \quad (20)$$

$$\Delta\omega_{kj} = -\eta\frac{\partial E}{\partial\omega_{kj}} \quad (21)$$

where d_k is i_{qc}. A connection weight w_{kj} is a weight between j-th and k-th hidden layer is of NN. This delta rule can guarantee weight move to negative line of the error variation. The error signal is known as Eqn. 22 applying a chain rule. Therefore from Eqn. 17 and Eqn. 22 error signal can be obtain as Eqn. 23.

$$\delta_{ok} = -\frac{\partial E}{\partial net_k} = -\frac{\partial E}{\partial o_k}\frac{\partial o_k}{\partial net_k} \quad (22)$$

$$\delta_{ok} = \frac{1}{2}(d_k - o_k)(1 - o_k^{\,2}) \quad (23)$$

From these results, the weighting functions are adapted by delta learning rule as follows:

$$\omega_{kj}(k+1) = \omega_{kj}(k) + \eta \delta_{ok} y_j \tag{24}$$

Hidden layer weights are also changed as same method.

$$\delta_{yj} = \frac{1}{2}(1 - y_j^{\,2}) \sum_{k=1}^{n} \delta_{ok} \omega_{kj} \tag{25}$$

$$\omega_{ji}(k+1) = \omega_{ji}(k) + \eta \delta_{yj} x_i \tag{25}$$

The resultant block diagram of proposed controller is shown in Fig. 2.

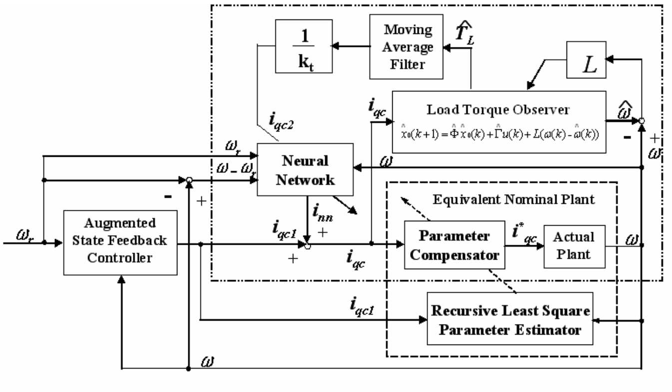


Fig. 2: Block diagram of the proposed algorithm.

4. Configurations of overall systems

The total block diagram of the proposed controller is shown in Fig. 3. The C-Language program and a TMS320C31 DSP implement the digital control part. The MT method, which is realized by the FPGA, is used to reduce the quantization error.

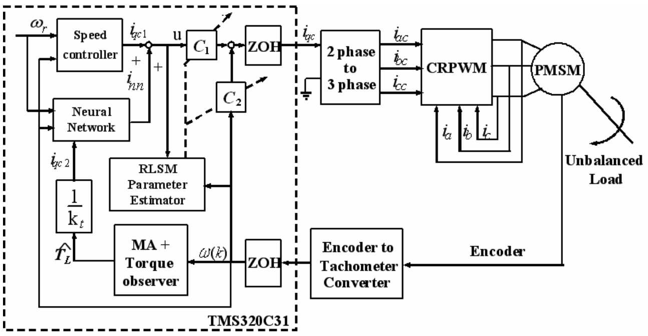
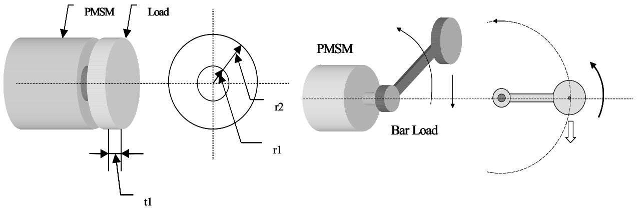


Fig. 3: Block diagram of the proposed control system.

Experimental load systems directly coupled to motor axis are depicted in Fig. 4. This system creates time varying load torque to show effectiveness of the proposed algorithm. Fig. 5 shows this experimental system.



(a) inertia load (b)bar load

Fig. 4: The figure of load for parameter and load variation

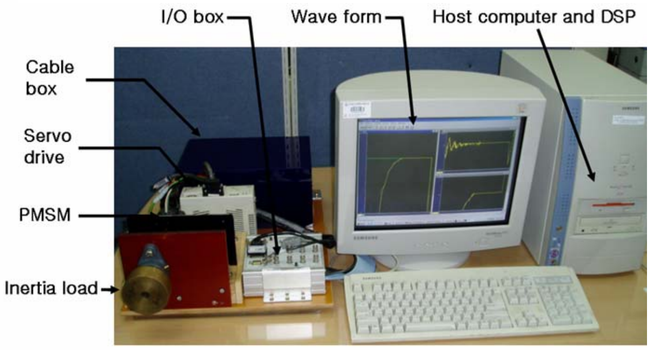


Fig. 5: The configuration of the experimental system

5. Simulation and experimental results

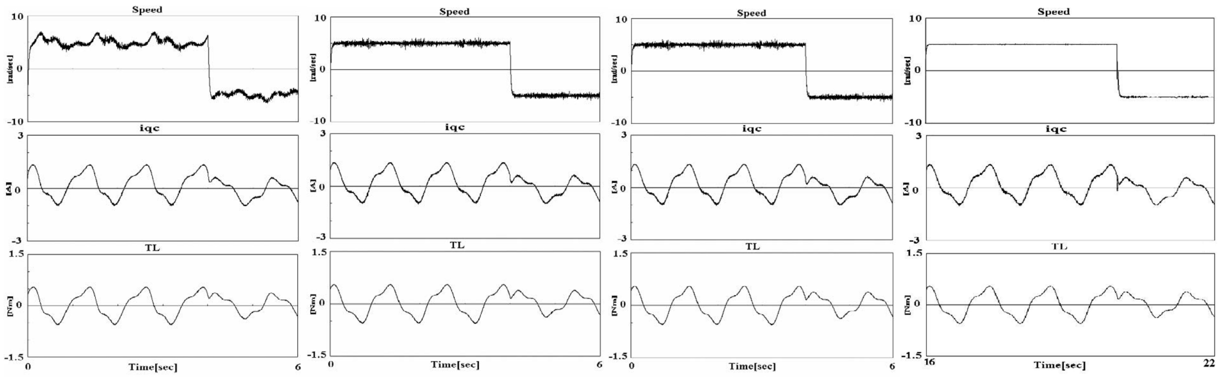
The parameters of a PMSM motor used in this simulation and this experiment will be given as Table 1. The hysteresis band gap is chosen as 0.01[A] and the sampling time h is determined as 0.2 [ms].

Table 1 PMSM parameter

Power	400 $watt$
Inertia	$0.363 \times 10^{-4}\, kgm^2$
Rated torque	1.3 Nm
Rated current	2.7 A
Stator resistance	$1.07\Omega / phase$
Time constant	0.5 ms

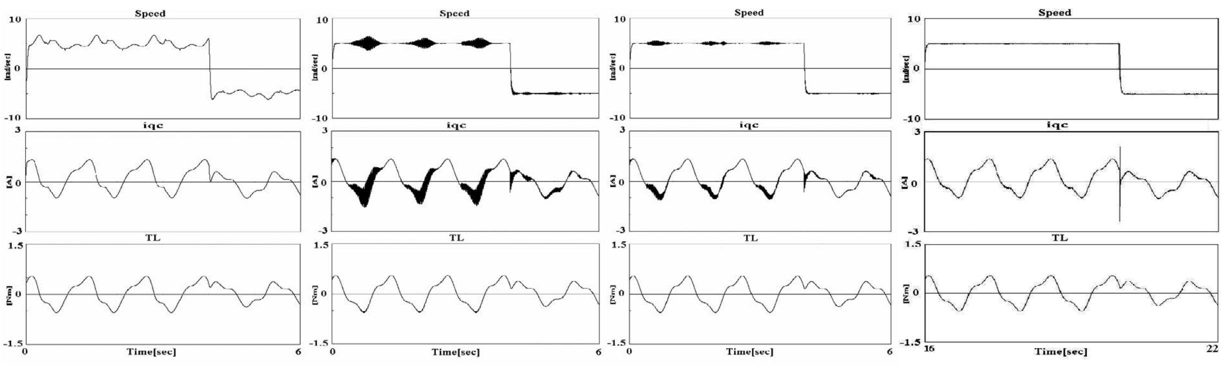
The weighting matrix is selected as $Q = diag[1 \quad 3000]$, R = 1 and optimal gain matrix becomes $k = [\,0.0763 \quad 6.1802]$. The deadbeat observer and the gain matrices are calculated from nominal values. The gain is obtained using the pole placement method at origin in z domain and becomes $L = [1.6703 \quad -0.0549]$. Learning rate is chosen as 0.55 after some trial end error, and learning is done 3 times at each sampling time. Timer interrupt is used in DSP board for sampling data.

The simulation results are shown in Fig. 6 and Fig. 7. Fig. 6(b) shows the speed response of the conventional controller. There is small speed ripple and small overshoot caused by a current ripple of hysteresis band gap, load, and parameter variation. Fig. 6(d) shows the result of a proposed algorithm that is the same speed command and a same disturbance condition as Fig. 6(a). We can see this load effects those are reduced by proposed algorithm of parameter compensation and learning effects. Fig. 7(b) and Fig. 7 (d) show that it is more effective in the inertial load case than bar load case.



(a) augmented state feedback (b) dead beat observer (c) parameter compensation (d) proposed algorithm

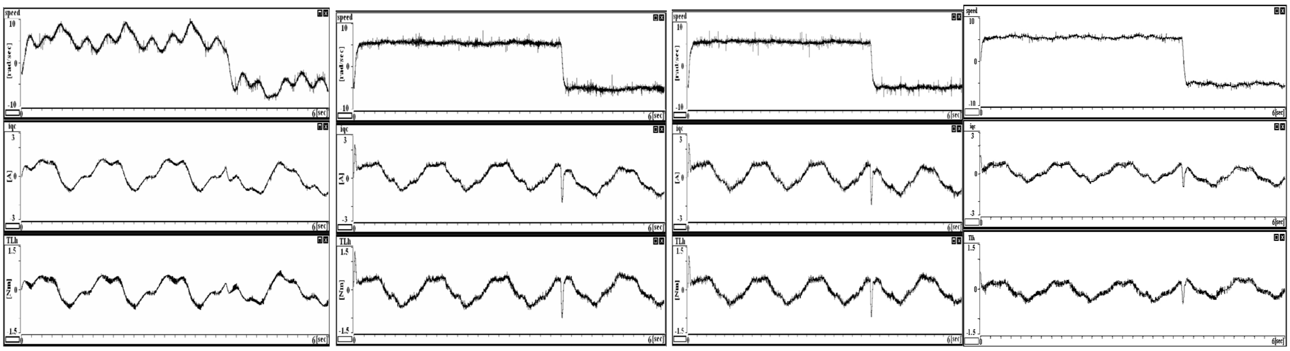
Fig. 6: Simulation results of bar load case



(a) augmented state feedback (b) dead beat observer (c) parameter compensation (d) proposed algorithm

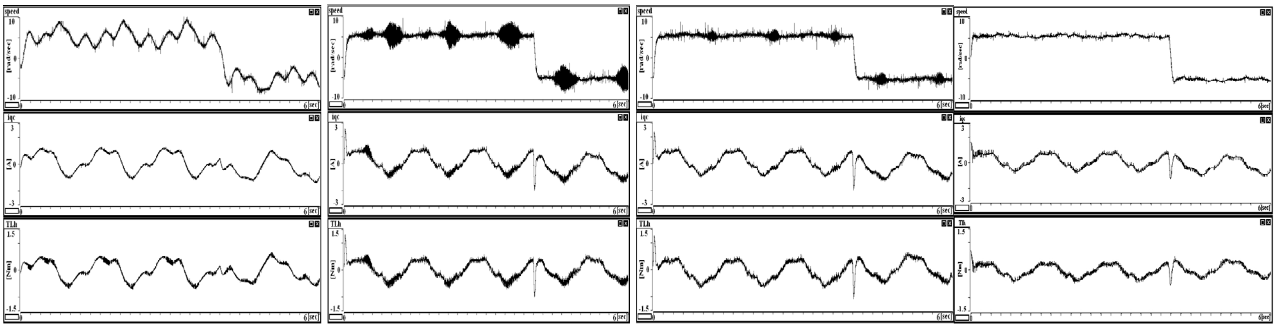
Fig. 7: Simulation results of the inertia load.

The proposed algorithm results the inertia load case give same shape of the position as bar load case as shown in Fig. 7 (d). In case of bar load, inertia variation is not so big. Therefore parameter algorithm does not work too large. On the other hand, if we introduce inertial load, the parameter compensation method shows good performance. The experimental results are in Fig. 8 and Fig. 9. The NN dead-beat observer has also quite good results with an unbalanced load as shown in Fig. 8 as same as simulation. Even if there are some noises of the speed detection in these results, the effectiveness of the proposed algorithm is clear as shown in simulation results.



(a) augmented state feedback (b) dead beat observer (c) parameter compensation (d) proposed algorithm

Fig. 8: Experiment results of the bar load case



(a) augmented state feedback (b) dead beat observer (c) parameter compensation (d) proposed algorithm

Fig. 9: Experiment results of the inertia load case

6. Conclusions

A new neural network load torque observer with a system parameter compensator is proposed to obtain better performance from the PMSM in a precision speed control system. This compensator makes real system work as in nominal parameter system. Therefore the NN load torque observer has a good performance as if there is no parameter variation. To reduce of the effect of the noise, the post-filter implemented by MA process, is adopted. The system response comparison between the deadbeat gain observer and the NN observer plus parameter compensated system with deadbeat observer has been done. Since parameter compensated system acts as there is no parameter, NN observer load torque well adapts to real system. It can be also used to cancel out the steady state and the transient position error due to the external disturbances, such as various friction, load torque and small chattering effect of deadbeat control. This algorithm can be used in precision control system also.

Acknowledgement

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