Sensorless Drive of Permanent Magnet Linear Motors Using Modified Kalman Filter

Yuan-Rui Chen
Electric Power College
South China University of Technology
Guangzhou 510640, China

Norbert C. Cheung
Department of Electrical Engineering
Hong Kong Polytechnic University
Hung Hom, KLN, Hong Kong, China

Jie Wu
Electric Power College
South China University of Technology
Guangzhou 510640, China

***Abstract*-This paper presents a novel method to eliminate the need for a position sensor in permanent magnet linear motor (PMLM) drives, by using modified Kalman filter estimation algorithm. Due to end effects, the PMLM must operate at large speed dynamics, and its lowest speed can go down to zero velocity. This problem is overcome by using sinusoidal open loop current control for speeds below 0.1m/s. The Kalman filter is engaged when the speed goes above 0.1 m/s. In the investigation, the control and estimation algorithm, together with the PMLM are simulated in MATLAB and SIMULINK. After that, the drive system is implemented in hardware with a DSP controller board. Results show that the Kalman filter is capable of estimating system states accurately and reliability without mechanical sensors. Together with the low-speed open-loop control, the PMLM can be operated under trajectory tracking mode without any position sensors.**

I. Introduction

With the emergence of high-performance power electronics and powerful digital signal processors (DSPs), permanent magnet linear motors (PMLMs) are increasingly utilized in industrial automation, transportation, and domestic appliances. The PMLMs are gradually substituting linear drive systems which use a combination of rotary motors and lead-screws. To achieve high dynamics and stable performance, linear position sensors are required for the servo loop feedback. However, linear position sensors account for a large proportion of the total system cost. Furthermore, most linear position sensors have problems of difficult installation, low reliability, and are sensitive to alien surroundings, such as vibration and moisture. In some applications, inadequate space to does not permit the mounting of a linear position sensor.

Due to the above disadvantages, the idea of eliminating mechanical sensors has attracted many research activities during the past decade. Many practical applications have been published [1-4]. Unfortunately, most of them are based on speed control of rotary motors only. There is still little in recent literature which concerns with sensorless control of PMLMs.

In this paper, we proposed to estimate the position and velocity of a PMLM using modified Kalman filter. The paper first describes the dynamic model of the PMLM. Then the modified Kalman filter algorithm is discussed in conjunction with the model. Numerical simulation is made and the estimation theory is verified. Finally, the algorithm is implemented onto hardware and the experimental results are presented.

II. Modelling of the PMLM

The PM linear motor, a linear guide and a linear encoder are mounted on an optic table. Fig. 1 shows the photograph of mechanical mounting. The mover and the scanning head of the encoder are in conjunction with the linear guide. The encoder gives the actual position with high precision.

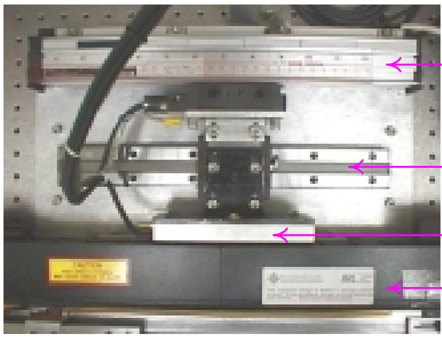


Fig.1 The photograph of mechanical mounting

The dynamic model of the PM linear motor can be described in state equations in a two-axes stationary reference frame (α,β).

$$\dot{x} = f(x) + Bu \quad \text{.....(1)}$$

$$y = h(x) \quad \text{.....(2)}$$

where $x = [i_\alpha\ i_\beta\ v\ d]^T$, is state vector, $u = [u_\alpha\ u_\beta]^T$, is control input vector, $y = [i_\alpha\ i_\beta]^T$, is measurement output, $h(x) = [i_\alpha\ i_\beta]^T$, $f(x)$ is a nonlinear system function, B is control input matrix.

$$f(x) = \begin{bmatrix} -\frac{R}{L} i_\alpha + \frac{\lambda}{L}\frac{\pi}{\tau} v \sin\left(\frac{\pi}{\tau} d\right) \\ -\frac{R}{L} i_\beta - \frac{\lambda}{L}\frac{\pi}{\tau} v \cos\left(\frac{\pi}{\tau} d\right) \\ \frac{3p}{2m}\frac{\pi}{\tau}\lambda\left(i_\beta \cos\left(\frac{\pi}{\tau} d\right) - i_\alpha \sin\left(\frac{\pi}{\tau} d\right)\right) - \frac{B_v}{m} v - \frac{F_L}{m} \\ v \end{bmatrix}$$

.....(3)

$$B=\begin{bmatrix}\frac{1}{L} & 0\\ 0 & \frac{1}{L}\\ 0 & 0\\ 0 & 0\end{bmatrix} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(4)$$

where R is the motor phase resistance, L is the phase synchronous inductance, λ is the permanent magnet flux linkage, τ is the pitch of the magnet poles, p is the pole pair number, m is the total mass of moving parts, B_v is the viscous damping coefficient, and F_L is the load in unit of N.

III. The Modified Kalman Filter Algorithm

The Kalman filter is an optimal state estimator in the least-square or minimum variance sense for dynamic nonlinear systems [4]. To apply Kalman filter to this system, we need to rewrite the motor state equations as follows:

$$\dot{x}(t)=f(x(t))+Bu(t)+q_1(t) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(5)$$

$$y(t)=h(x(t))+q_2(t)\,. \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(6)$$

where $q_1(t)$ and $q_2(t)$ are zero-mean white Gausian noises with covariance $Q_1(t)$ and $Q_2(t)$, respectively.

The Jacobian matrices of the system are defined as $F(t)$ and $H(t)$:

$$F(t)=\frac{\partial f}{\partial x}=\begin{bmatrix}-\frac{R}{L} & 0 & \frac{\lambda}{L}\frac{\pi}{\tau}\sin\left(\frac{\pi}{\tau}d\right) & \frac{\lambda}{L}\frac{\pi^2}{\tau^2}v\cos\left(\frac{\pi}{\tau}d\right)\\ 0 & -\frac{R}{L} & -\frac{\lambda}{L}\frac{\pi}{\tau}\cos\left(\frac{\pi}{\tau}d\right) & \frac{\lambda}{L}\frac{\pi^2}{\tau^2}v\sin\left(\frac{\pi}{\tau}d\right)\\ -\frac{3p}{2m}\frac{\pi}{\tau}\lambda\cos\left(\frac{\pi}{\tau}d\right) & -\frac{3p}{2m}\frac{\pi}{\tau}\lambda\sin\left(\frac{\pi}{\tau}d\right) & -\frac{B_v}{m} & 0\\ 0 & 0 & 0 & 1\end{bmatrix} \quad \ldots(7)$$

$$H(t)=\frac{\partial h}{\partial t}=\begin{bmatrix}1 & 0 & 0 & 0\\ 0 & 1 & 0 & 0\end{bmatrix} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(8)$$

In order to perform digital simulations and experiments with DSP, the continuous differential state equations must be transformed into discrete difference equations with sampling interval T_s.

$$x(k+1)=\Phi(k)x(k)+G(k)u(k)+Q_{1d} \quad \ldots\ldots\ldots\ldots\ldots(9)$$

$$y(k)=H(k)x(k)+Q_{2d}\,. \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(10)$$

where $\Phi(k)$ is the state transition matrix, $\Phi(k) = I + F(k)\cdot T_s$, $G(k) = B\cdot T_s$, $H(k) = H(t)$, Q_{1d} and Q_{2d} are the discrete covariance matrices, respectively.

The state estimation steps are done in the following sequence [5]:

1) Prediction step presents the initial values of state $x(k|k-1)$ and error covariance matrix $P(k|k-1)$.

$$\hat{x}(k\,|\,k-1)=\hat{x}(k-1\,|\,k-1)+[f(\hat{x}(k-1\,|\,k-1))+Bu(k-1)]\cdot T_s \quad \ldots\ldots(11)$$

$$P(k\,|\,k-1)=[\Phi(k-1)P(k-1\,|\,k-1)\Phi^T(k-1)]\cdot T_s+Q_{1d} \quad \ldots(12)$$

2) Computation of Kalman filter gain matrix is derived by the following equation:

$$K(k)=P(k\,|\,k-1)H^T(k)[H(k)P(k\,|\,k-1)H^T(k)+Q_{2d}]^{-1}\,. \quad \ldots\ldots(13)$$

3) Correction (innovation) step gives the final estimation of state $x(k|k)$ and error covariance matrix $P(k|k)$ during the period t_{k-1} to t_k.

$$\hat{x}(k\,|\,k)=\hat{x}(k\,|\,k-1)+K(k)[y(k)-H(k)\hat{x}(k\,|\,k-1)] \quad \ldots\ldots(14)$$

where $y(k)$ is the actual value of the measurement output.

IV. Results of Simulation and Hardware Implementation

The proposed scheme was verified by both numerical simulation and experiment with a PC computer and a DSP control card from dSPACE. Fig. 2 shows the wiring block diagram of our sensorless control system. The overall experimental system setup is shown in Fig. 3. An incremental linear encoder LS176 is used to measure the actual position of the moving part as a reference. An integrated IGBT circuit CPV363M4K serves as the power drive module. An IC

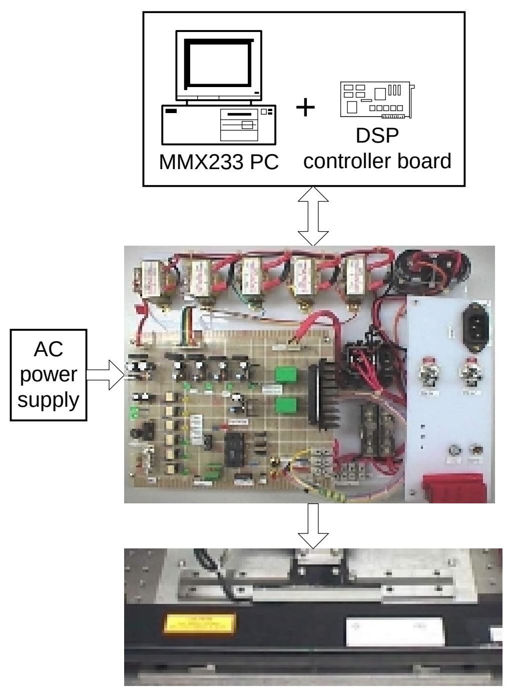


Fig.2 The sensorless control system

IR2132 is used to drive the gates of the IGBT. The main circuit is isolated from the controller board by opto-couplers. Since it is a direct digital control method, the system hardware is simple and straightforward. Fig.4 shows the schematic diagram of the proposed drive system.

Fig.3 The overall experimental system

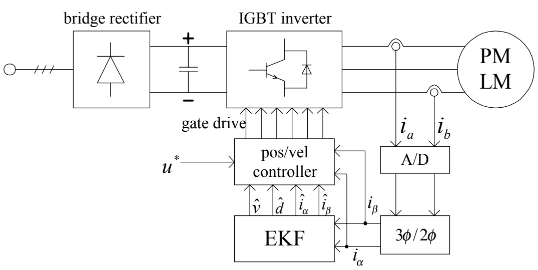


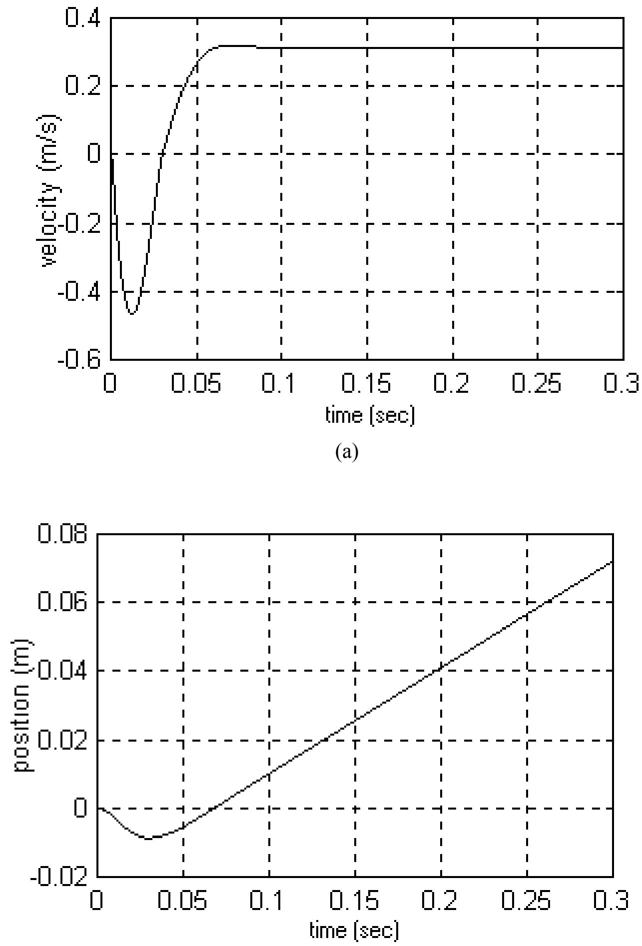
Fig.4 The schematic diagram of the drive system

A. Simulation results

The open loop step velocity response of the system starting from rest is investigated with MATLAB. The frequency of voltage exerting the windings is set to 5Hz, so the steady velocity is 0.31m/s, which is equal to the synchronous speed (See appendix for the other parameters). Fig.5(a) and (b) show the simulation results of velocity and position. Fig.5(a) shows that the system arrives at the steady state within 0.1 second, i.e., in half of a signal period. Note that there is also a negative velocity pulse at the beginning of the motion. This is because the initial position of the moving part is unknown during startup. The final steady velocity is fixed at 0.31m/s.

B. Experimental results

Both open loop and closed loop experiments have been implemented through the hardware setup and dSPACE's ControlDesk software combined with SIMULINK. In the open loop experiment, the motor is fed with voltage-source PWM inverter. The signal frequency is still 5Hz, while the PWM switching frequency is 20kHz. The experimental results of velocity and position are shown in Fig.6(a) and (b), respectively. From Fig.6, we can see that the estimated velocity and position are very close to the actual results. So



(a)

(b)

Fig.5 Simulation results of velocity and position (f = 5Hz)
(a) velocity; (b) position.

we can use the estimated results to construct a closed loop control system. The simulation and experiment results of current waveforms are shown in Fig.7 and Fig.8, respectively.

In the closed loop experiment, a dual loop dual rate control scheme is employed. The current loop is considered as an inner loop, which has fast time constant. While the velocity loop serves as the outer loop, which has a relatively slow response. The sampling rate of the inner loop is set to 10KHz while the outer loop, 500Hz. The current loop uses a proportional controller, which has fast tracking performance. In the velocity loop, a PI control law is applied to make the whole system error free at steady state. Both the controllers of the two loops are simple and effective, so the DSP has enough time to execute the estimation algorithm. Fig.9, Fig.10 and Fig.11 show the experimental results of velocity, position and current waveform of i_a, respectively, where the velocity command is set to 0.9 m/s.

Both the simulation results and the experimental results show that the maximum error between estimation and actual value occurs at the starting up period. It is because the initial state is unknown and some model parameters have been ignored. Therefore, for the actual trajectory control of the PMLM open loop control is used for zero to the low speed; the Kalman filter is used for speeds above 0.1m/s.

V. Conclusions

This paper describes a new method to drive a PMLM without any position sensors. The paper first investigates the dynamic model of the PMLM. Then, a modified Kalman filter algorithm is adapted to the PMLM to estimate its position and velocity. Numerical simulation and experiments have been conducted to verify the validity of the proposed scheme. The results show that modified Kalman filter is an efficient algorithm to estimate the states of the controlled plant, and as a result, the mechanical sensors can be eliminated from the drive system. Through the proposed estimation algorithm, cost-efficient sensorless drive systems can be constructed.

VI. Appendix

The motor parameters are listed below:
phase resistance R: 8.6 ohm;
phase synchronous inductance L: 6 mH;
permanent magnet flux linkage λ: 0.35 V·s;
pole pitch of the permanent magnets τ: 0.031 m;
pole pair number p: 1;
total mass of moving parts m: 1.635 kg;
viscous damping coefficient B_v: 0.1 N·s/m;
load F_L: 10 N;
maximum travelling distance: 0.18m.

Acknowledgment

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References

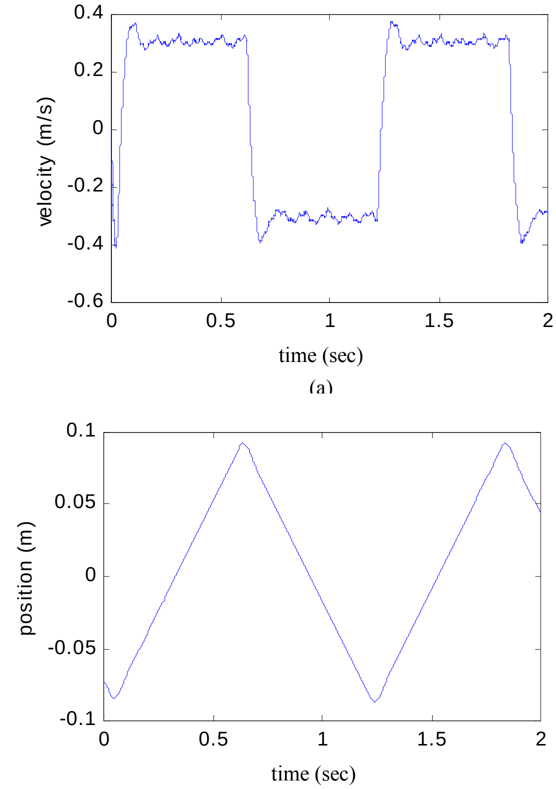
[1] M.J. Coreley and R.D. Lorenz, "Rotor Position and Velocity Estimation for a Salient-Pole Permanent Magnet Synchronous Machine at Standstill and High Speeds", *IEEE Trans. Indus. Appli.*, vol.34, no.4, pp.784-789, July/August 1998.

[2] N. Ertugrul and P.P. Acarnley, "Indirect Rotor Position Sensing in Real-Time for Brushless Permanent Magnet Motor Drives", *APEC'97, 12th Annual Applied Power Electronics Conference and Exposition*, vol.2, pp.736-742, 1997.

[3] N. Matsui and M. Shigyo, "Brushless dc motor control without position and speed sensors", *IEEE Trans. on Industry Applications*, Vol.28, No.1, pp.120-127, Jan./Feb., 1992.

[4] S. Bolognani, R. Oboe, and M. Zigliotto, "Sensorless Full-Digital PMSM Drive With EKF Estimation of Speed and Rotor Position", *IEEE Transactions on Industrial Electronics*, Vol.46, No.1, 1999, pp. 184-191.

[5] C.K. Chui and G. Chen, *Kalman Filtering with Real-Time Applications*, 2nd Ed., Springer-Verlag, 1991.



(b)

Fig.6 The open loop experiment results (f=5Hz)
(a) velocity; (b)position.

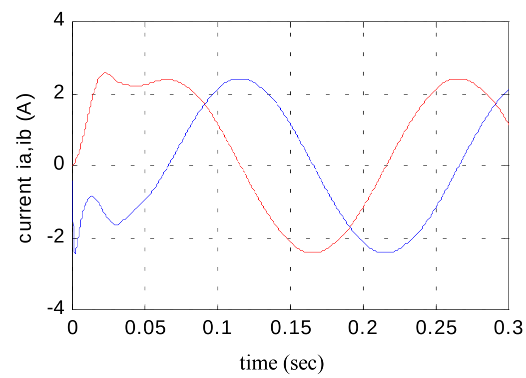


Fig.7 Simulation of current waveforms

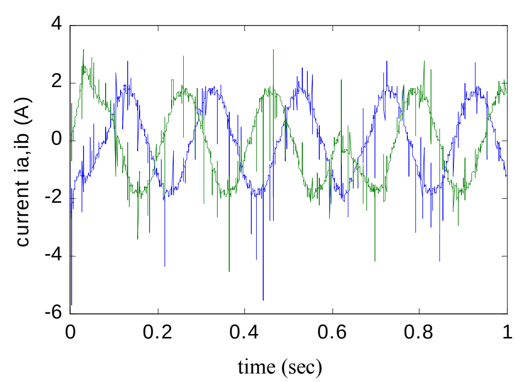


Fig.8 The actual current waveforms

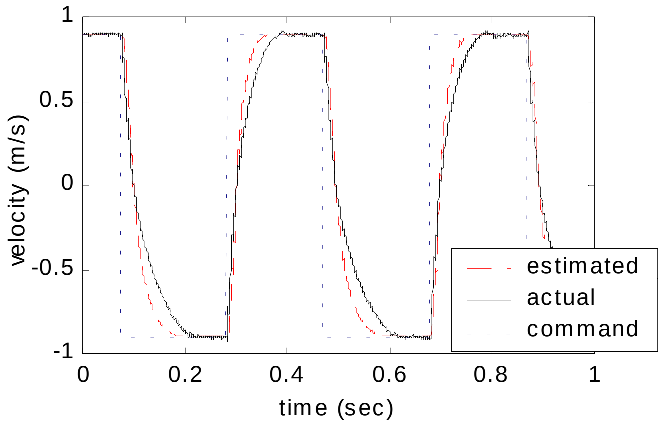


Fig.9 Step velocity response at 0.9m/s

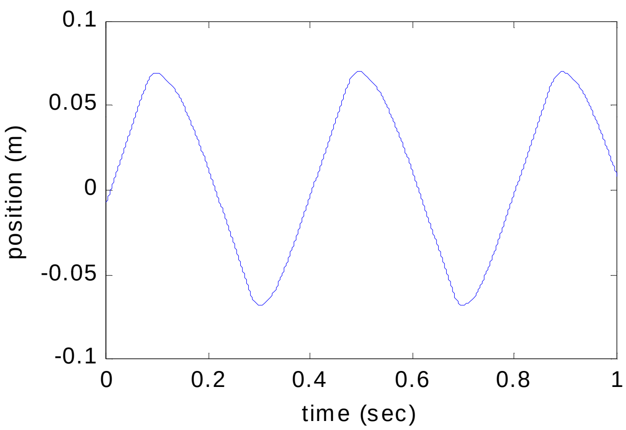


Fig.10 Position result at 0.9m/s

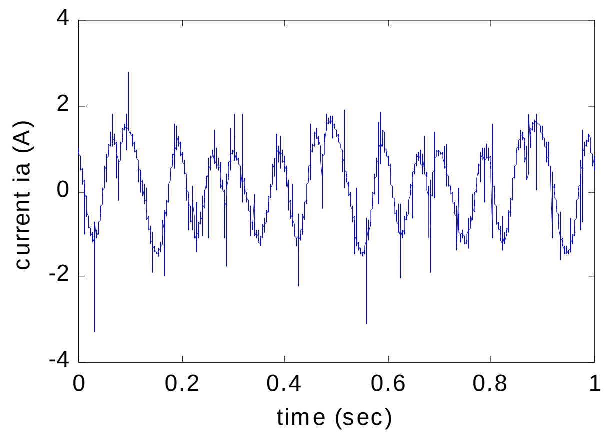


Fig.11 Current waveform of ia at 0.9m/s