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Improvement of Tracking Accuracy of Positioning Systems with Iron Core Linear DC Motors

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ABSTRACT

Higher productivity requires high-speed motion of machine tool axes. The iron core linear DC motor (LDM) is widely accepted as a viable candidate for high-speed machine tool feed unit. LDM, however, has two inherent disturbance force components, namely cogging and thrust force ripple. These disturbance forces directly affect the tracking accuracy of the feeding system and must be eliminated or reduced. In order to reduce motor ripple, this research adapted the feedforward compensation method and neural network control. Experiments carried out with the linear motor test setup show that these control methods are effective in reducing motor ripple.

Key Words : Linear DC motor (LDM), Tracking control, Feedforward compensation, Neural network, Cogging force

1. Introduction

High-speed machining systems conventionally employ indirect feeding systems with rotary motors and ball screws, which have limitations to increasing speed and acceleration. On the other hand, the direct drive method with linear motors has become more popular, and it is no longer rare to see machine tools using linear motors at various international exhibitions like the EMO. The recent popularity of the direct drive method is due to the following merits.

- There is no backlash and only small friction
- There is no limit for acceleration and velocity; velocity is restricted only by the bandwidth of the encoders and electric power circuits.
- It shows high reliability and high frame stiffness because of its mechanical simplicity.

Among the various types of linear motors, the linear DC motor (LDM) is frequently used as a feed unit for machine tools. There are two types of LDM, the iron core type and the non-iron core type. Because of having a high thrust force, the iron core LDM is more often adapted in machine tool applications. Instead of having a high thrust force, however, the iron core LDM experiences a motor ripple that disturbs the feeding system including the LDM itself. This motor ripple decreases the moving accuracy of the feeding system.

There are two types of motor ripple: cogging and force ripple. Cogging is a disturbance caused by a magnetic force, while force ripple is a disturbance caused by an electro-magnetic effect.

The iron cores in the moving parts of the LDM are magnetically attracted by the permanent magnets arranged on the yoke. Therefore the moving part is forced to move into a magnetically stable position. The force is the cogging. The magnitude of the cogging is only dependent on the relative position of iron cores to the permanent magnets and is not dependent on the motor current. Force ripple, however, is concerned with motor current. When the current flows through a coil wound on iron cores, a magnetic field is induced. This magnetic field and the permanent magnet jointly generate the force ripple, as explained by Fleming's rule. Force ripple also exists in non-iron core linear motors too.

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Force ripple is generated only when the motor current is not equal to zero and its absolute value is dependent on magnitude of the required force and on the relative position of the moving parts. This motor ripple causes velocity fluctuation and the fluctuation leads to tracking errors in moving systems [1-6]. In this study, a method is suggested to improve the tracking accuracy of iron core LDM feeding systems by reducing motor ripple. Feedforward compensation and neural network control are used in this method to reduce the motor ripple.

First, characteristics of the motor ripple in iron core LDM were studied and the results of feedforward compensation utilizing these characteristics as pre-filter were shown. Then it was suggested that the results of neural network control were better than those of feedforward compensation, even though no cogging measurement was needed for neural networks.

To verify the usefulness of the suggested method, a test setup of the iron core LDM feeding system was built and experiments were carried out. The results of the experiments showed that the tracking accuracy of the feeding system was improved.

2. Feedforward compensation

2.1 Test setup

In order to test on improving traceability, an iron core LDM test setup was built as shown in Fig. 1. It was composed of a Samick LMS linear motor and a linear motion guide (THK HSR55R) with a linear scale of 1μm resolution (Renishaw RGH-22). The Samick LMS LDM has iron cores wound around three-phase coils. Its maximum thrust force is 12,000 N and its continuous thrust force is 6,000 N.

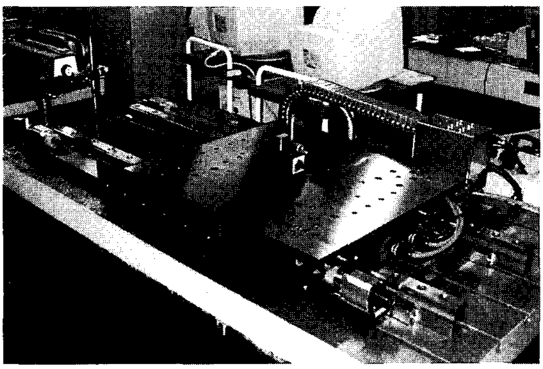

Fig. 1 Experimental setup for linear DC motor feeding system

2.2 DSP controller

A DSP control board is used to control the experimental setup. The DSP board used was the M44 of Innovative Integration Co., with a TMS320C44 DSP chip of TI. This chip is capable of a 32-bit float point calculation with a speed of 60 MHz. The M44 board has a 'MOT' optional board that is exclusively used for motor control. This optional board enables simultaneous control of all 4 axes. A CodeWrite editor was used to write a target program that was downloaded on the DSP board, and the host program was coded by Visual C++ to adjust the positioning distance, speed, acceleration, PID gain and amp on/off. In this study, the encoder signal was sampled at a 1 kHz sampling speed.

2.3 Cogging measurement

To measure the cogging of a linear motor, a measurement setup was built with a load cell and laser interferometer, as shown in Fig. 2. Turning the screw behind the load cell moved the carriage and its position was read by laser interferometer. At each interval of 1 mm moving position, the force on the carriage was measured by the load cell.

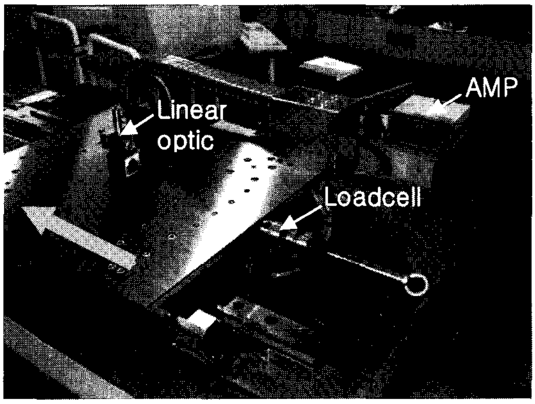

Fig. 2 Experimental setup for cogging measurement in linear motor feeding system

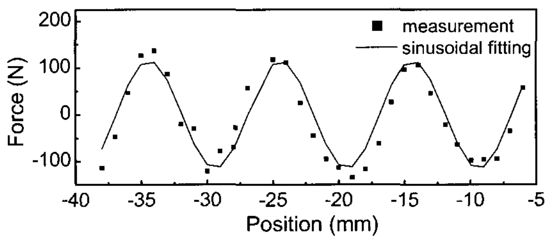

Fig. 3 Cogging force measured from setup in Fig.1

In Fig. 3, measured cogging value and its sinusoidal fitted value are plotted. It is assumed that each permanent magnet on the yoke has identical features, so the measuring process is performed at only one pitch section of the yoke.

In Fig. 3, it is found that the cogging period is 10 mm and this period is equal to 1/3 of the pitch between magnets (in Fig. 4, 30 mm). This phenomenon occurs because the motor current has three phases. The fitted sinusoidal cogging function is expressed in terms of position in Equation (1):

$$F = 116.6\sin\{2\pi\frac{x-3.18}{9.99}\}\ N \tag{1}$$

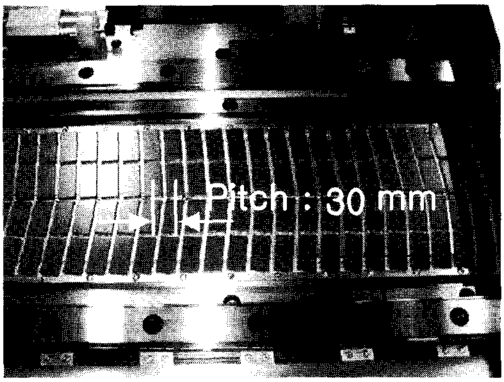

Fig. 4 Photography of magnet placement

Unwanted thrust force corresponding to the cogging measured at a certain position is generated at the position, so it is necessary to find the corresponding voltage of the cogging force to compensate unwanted thrust force. Thus, the thrust force and voltage relationship of the linear motor must be determined to calculate the voltage of cogging. A measured voltage-force relationship is shown in Fig. 5. Although saturation is shown above 4 V, linearity existed below 4 V. In general, 4 V is sufficient to control the linear motor.

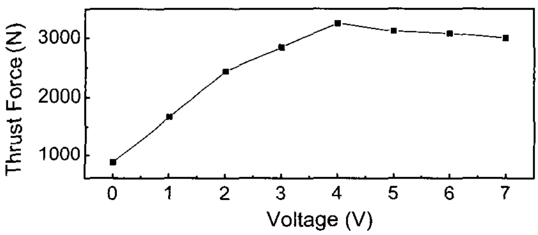

Fig. 5 Relationship between voltage and thrust force

By using the relationship as shown in Fig. 5, Equation (1) is replaced by Equation (2).

$$u = 213.6\sin\{2\pi\frac{x-3.18}{9.99}\}\ mV \tag{2}$$

Fig. 6 shows a control block diagram with a traditional PID control scheme and an additional feedforward pre-filter for reducing cogging.

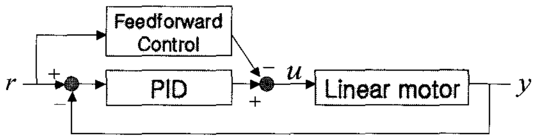

Fig. 6 Control method of feedforward control

Two experiments were performed. In the first, PID control was used without feedforward control. In the second, PID plus feedforward control were used. The two results are shown in Fig. 7. While PID control alone showed a tracking error of 150μm, the tracking error from PID with feedforward control was reduced to 75μm. Therefore, it is determined that the addition of feedforward compensation achieved a 50% improvement over PID control alone.

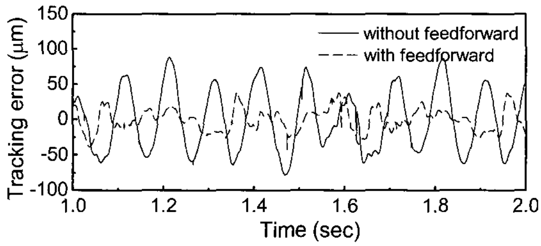

Fig. 7 Comparison between feedforward and non-feedforward control

3. Neural network control

3.1 Neural network algorithm

In the neural network algorithm, output follows input by a learning process. This algorithm is known as a very effective in controlling nonlinear systems because of its learning capability.

The learning process begins with setting up an object function. Then the learning process should find the weighting factors to minimize the object function. In the neural network algorithm, weighting factors are updated by using the back propagation algorithm.

In the back propagation algorithm, the weighting factors are updated by an error signal and the Jacobian matrix must be searched because the error signal comes through the system. However, it is very difficult to obtain a Jacobian matrix so, in this study, the object function was set up without the Jacobian matrix. This method, suggested by Kawato, sets object function not as a difference between input and output of system, but as an output voltage of the PID controller, as in Equation (3)[7]. That is to say, in the control block diagram of Fig. 8, if the error signal is set up as u_{pid} not as $r-y$, then finding the Jacobian matrix is unnecessary.

$$E=\frac{1}{2}u_{pid}{}^{2} \tag{3}$$

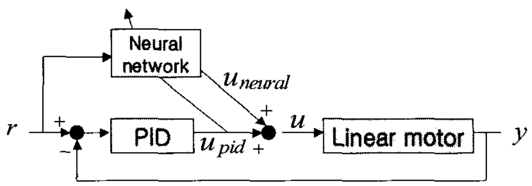

Fig. 8 Control method of neural network control

In the first stage of control, the system is controlled only by PID controller because the neural network has not learned yet. But as learning is achieved, the output of the PID controller, u_{pid}, becomes smaller while the output of the neural network, u_{neural}, becomes bigger. So, in the last stage of control, u_{neural} controls the total system. The system retains stability although sudden disturbance is inflicted on the system because PID feedback loop is continued after learning is completed. In this study, the neural network had 3 neurons as a hidden layer and its input was the reference position (r) and its output was the voltage of neural network output (u_{neural}), as shown in Fig. 9.

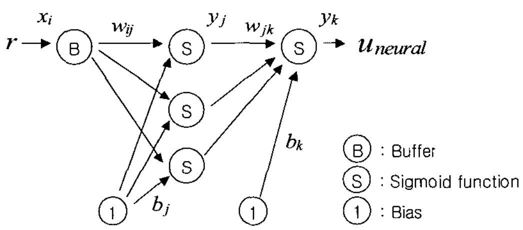

Fig. 9 Neural network

3.2 Experiment results

In neutral network control, the weighting factors are the same for each input. But in the case of position control problem, it exists a very efficient method for applying the weighting factors. If different weighting factors are set up in different positions, the effort of searching for the optimal weighting factors is only related to not all positions but one position. However, this method requires more memory for saving each weighting factor.

Fig. 10 shows the result of learning when all weighting factors are identical. Here, n is the number of learning. When the same weighting factor was applied, the number of learning was more than 15 but the tracking error results were not better than those acquired before learning; on the contrary, in fact, the tracking errors partially worsened. This means that the weighting factor was quite suitable at some positions but was unsuitable at other positions. In conclusion, then, learning was not yet completed.

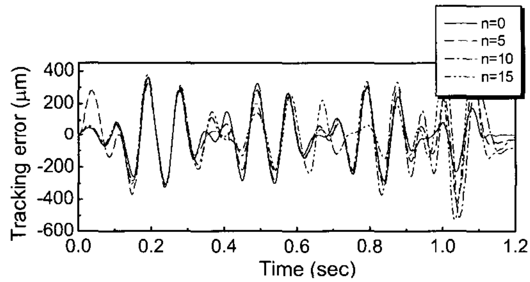

Fig. 10 Learning result where identical weighting factors were applied

Fig. 11 shows the result of different weighting factors at each position. As shown in the figure, learning proceeds and tracking errors decrease. After the 15th learning, the tracking error is 60μm; this value is 10 times better than that achieved before learning.

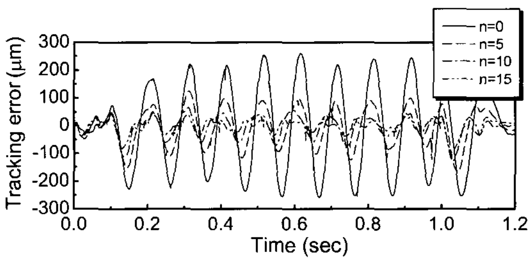

Fig. 11 Learning result where individual weighting factors were applied

In Fig. 12 and Fig. 13, the output voltage of the PID controller, u_{pid}, and the output voltage of the neural network, u_{neural}, are compared to find the characteristics of the neural network PID controller before and after learning. As shown in Fig. 12, u_{pid} exhibits sinusoidal shape, like a cogging graph, before learning but, as learning proceeds, u_{pid}, the object function, decreases to near zero. On the other hand, u_{neural} shows a meaningless form before learning, but after learning, it has a shape similar to u_{pid} before learning, as shown in Fig. 13. In the figure, it is found that the peak-to-valley value of u_{neural} is less than that of u_{pid}.

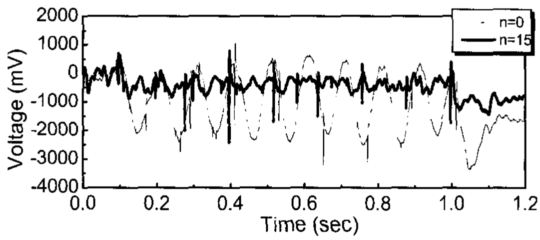

Fig. 12 Comparison of PID control voltage without (n=0) and with learning (n=15)

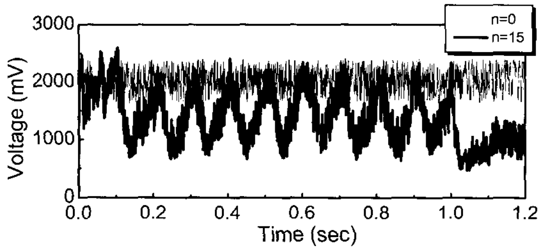

Fig. 13 Comparison of Neural network voltage without (n=0) and with learning (n=15)

4. Conclusion

The iron core linear DC motor has an inherent disturbance, so called motor ripple, which often becomes the principal source of tracking errors. This paper proposes a method for reducing motor ripple in iron core linear DC motor by employing a feedforward compensation with cogging measurement together with a neural network control algorithm. Through the experiments, the proposed method is proved effective to reduce the motor ripple in linear DC motor.

When we applied feedforward compensation, the tracking error was decreased by 50%.

When we applied neural network control and reached the 15th learning, the tracking accuracy was better than the results of the feedforward test. Furthermore, this method does not require cogging measurements.

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