Experimental Studies on High Precision Tracking Control of Linear Motor Using Noncausal Filtering Based Iterative Learning Control [1]

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Abstract

In this paper, with a modest amount of modeling effort, a feedback-feedforward control structure is proposed for precision motion control of a permanent magnet linear motor (PMLM) for applications which are inherently repetitive in terms of the motion trajectories. An iterative learning controller (ILC) is applied as feedforward controller to the existing relay-tuned PID feedback controller to enhance the trajectory tracking performance by utilizing the experience gained from the repeated execution of the same operations. By using a simple zero-phase finite impulse response (FIR) filtering technique, the design task of the ILC can be reduced to tuning two parameters: length of the filter and the learning gain. Some practical considerations related to the parameter tuning are outlined. Experimental results are presented to demonstrate the practical appeal and effectiveness of the proposed scheme.

Key words: permanent magnetic linear motor; practical motion control; iterative learning control; zero phase filter.

1 Introduction

Permanent magnet linear motors (PMLM) are beginning to find widespread industrial applications, particularly in those requiring a high precision in positioning resolution such as stages for various key semiconductor fabrication and inspection processes as in step and repeat micro-lithography, wafer dicing, probing and scanning probe microscopy (SPM). The main benefits of a PMLM are the high force density achievable, low thermal losses and probably most importantly, the high positioning precision and accuracy associated with the mechanical simplicity of such systems. Unlike rotary machines, linear motors require no indirect coupling mechanisms as in gear boxes, chains, and screw coupling. This greatly reduces the effects of contact-types of nonlinearities and disturbances such as backlash and frictional forces [1].

The more predominant nonlinear effects underlying a linear motor system are the various friction components (Coulomb, viscous and stiction) and force ripples (detent and reluctance forces) arising from imperfections in the underlying components [2]. Due to the typical precision positioning requirements and low offset tolerance of their applications, the control of these systems is particularly challenging since conventional PID control usually does not suffice in these application domains. Some efforts have been made towards more advanced control of PMLM motion systems. In [2], a neural-network (NN) based feedforward assisted PID controller was proposed. A hybrid control strategy using a variable structure control (VSC) is suggested for submicron positioning control[3]. In these cases and more, the control framework can be described under a feedback-feedforward configuration.

In this paper, we are mainly concerned with the applications of the PMLM in operations involving repeated iterations of motion trajectories, such as pick and place assembly operations and many step and repeat process operations. In these typical tasks of PMLM, the time duration for the execution of an operational cycle is short. It is well-known that finite-time tracking control is difficult with conventional controllers like the PID controllers which are more suitable for set-point regulation. To achieve a better tracking performance, a feedforward controller is usually applied. In this paper, with *less* modeling work, a feedback-feedforward control structure is proposed for precision motion control of permanent magnet linear motor (PMLM) for applications which are inherently repetitive in terms of the motion trajectories.

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The remaining parts of this paper are organized as follows. In Sec. 2, the iterative learning controller via zero phase filtering is introduced and developed. In Sec. 3, the test bed system, control tasks and the ILC design are described. In Sec. 4, extensive experimental results are included to illustrate the effectiveness and practical appeal of the proposed intelligent control system for PMLM motion control.

2 Zero Phase Filtering Based Iterative Learning Control Scheme

The term 'Iterative Learning Control' (ILC) was coined by Arimoto and his associates' [4] for a better control of repetitive systems. It can be intuitively stated that *learning is a bridge between knowledge and experience. Knowledge* and *experience* in control language can be acquired by 'modeling' and by 'repetitions when applying some *learning* control laws'. Roughly speaking, the purpose of introducing the ILC is to utilize the system repetitions as *experience* to improve the system control performance even under incomplete *knowledge* of the system to be controlled.

Since the early eighties, increasing attention has been drawn from the control community for ILC research. Most of the existing work focused on the *analysis* issue of ILC schemes while the obtained convergence condition is clearly not sufficient for actual ILC applications. Therefore, in recent years, increasing efforts have been made on the *design* issue of ILC. These can be observed from the latest book [7]. Detailed literature review on ILC research can be found in [5]. A recent survey on the ILC *design* issue [8] documented various practically tested design schemes mainly for robotics applications. Other efforts in ILC design include using modern techniques like H^{∞} [6], frequency domain LFT (linear fractional transformation) [9], local ARMA (auto-regressive moving average) model approximation [10] etc. However, to draw the attention from the industry, the above mentioned design techniques are still not sufficient as compared to the successful use of PID (proportional-integral-derivative) controllers in industries. It is interesting to note the noncausal filtering [8], especially zero phase filtering [11] technique may provide a way for such a rudimentary design task as discussed above. This paper puts some efforts in this direction to provide a PID-autotuning type ILC design procedure.

ILC, originally proposed as an open-loop control [4], has been considered as a feedforward control in addition to an existing feedback controller. While most of the '*analysis*' results have been obtained in the continuous-time domain, e.g.,[12], discrete-time analysis, e.g., [13], is more important since the realization of ILC algorithm is memory based. The feedforward-feedback configuration of ILC algorithms has already been a standard consideration in either '*analysis*' or '*design*' [8] work on ILC. A block-diagram is shown in Fig. 1 where **FBC** stands for "feedback controller" and y_d is the given desired output trajectory to be tracked. After the i-th iteration (repetitive operation), the feedforward control signal u^i_{ff} and the feedback control signal u^i_{fb} are to be stored in the memory bank for constructing the feedforward control signal at the next iteration, i.e., u^{i+1}_{ff}. The stored feedback control signal u^i_{fb} are to be filtered by a zero phase filter operator h'_M* multiplied by a learning gain γ.

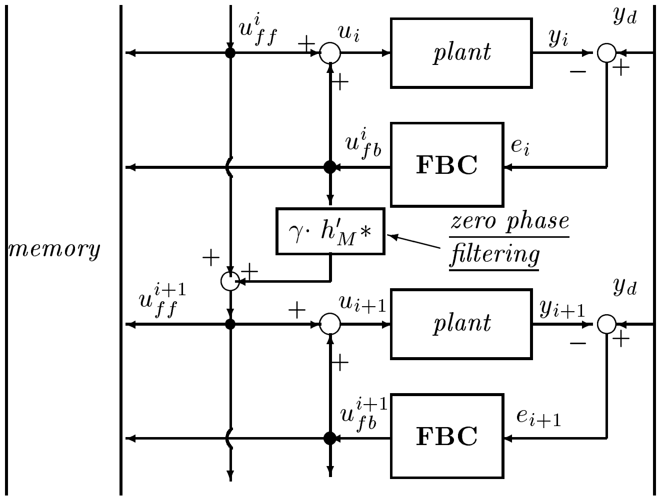

Figure 1: Block diagram of zero phase filter based iterative learning control

The learning updating law is hence given by

$$u^{i+1}_{ff}(k) = u^i_{ff}(k) + \gamma h'_M * u^i_{fb}(k) \quad (1)$$

while the overall control is simply that

$$u_{i+1}(k) = u^{i+1}_{ff}(k) + u^{i+1}_{fb}(k) \quad (2)$$

as shown in Fig. 1 where two parameters - γ the learning gain and M the length index of the zero phase filter, are to be designed and specified.

The simplest form of (1) [11] is

$$u^{i+1}_{ff}(k) = u^i_{ff}(k) + \frac{\gamma}{2M+1} \sum_{j=-M}^{M} u^i_{fb}(k+j) \quad (3)$$

where h'_M is simply an algebraic averager.

The convergence of the proposed learning controller is in the sense that u^i_{ff} approaches u^R_d, the repeatable part of u_{fb}, as i increases. Detailed theoretical analysis can be found in [15]. The convergence property [15] implies that the iterative learning controller is essentially applied for the *extraction* of the repeatable part of the system dynamics u^R_d while the nonrepeatable part is taken care of by the feedback controller. When the zero phase filter based ILC scheme (1), shown in Fig. 1, is used, there always exists a choice of learning gain γ which is a function of the length index of the filter such that the learning process converges.

3 Test-bed System, Control Tasks and ILC Design

3.1 The Testbed System

In the experimental studies, an Anorad laboratory test-bed system shown in Fig. 2 is used. The functional block-diagram is shown in Fig 3.

Figure 2: Setup of the laboratory testbed

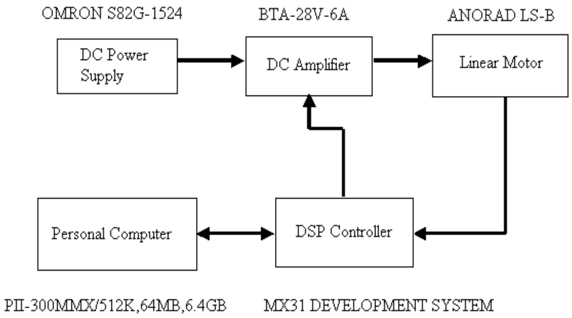

Figure 3: Block-diagram of the laboratory testbed

In Fig. 3, the control algorithms are implemented on an MX-31 DSP development system from Integrated Motions, Inc. (IMI), which utilizes a Texas Instruments TMS320c31 32-bit floating point processor with 60 ns single-cycle instruction execution time. Control programs are written in C, compiled on an IBM personal computer (PC) which can be downloaded into the MX-31 through a serial communication link. The position encoder is the only transducer available and the measurements can be transmitted to the PC through the same serial communication link. In our experiments, the encoder resolution is 1 μm. All data stored in MX-31 can be uploaded to the PC for post-analysis in a Matlab environment.

3.2 The Control Task

The particular PMLM considered in this work is a brushed DC PMLM LS-B series LS1-24 manufactured by Anorad Corp. [14]. The maximum effective travel length is 609.6 mm and the maximum velocity is 0.5 m/sec.

The major targeted applications of the PMLM, in this work, are for precision motion tracking and positioning necessary for dedicated stages such as those used in the various key semiconductor fabrication and inspection processes as in step and repeat micro-lithography, wafer dicing, probing and scanning probe microscopy (SPM).

The desired tracking trajectories are specified as

$$
\begin{aligned}
x_d(\tau) &= x_b + (x_b - x_f)(15\tau^4 - 6\tau^5 - 10\tau^3) \quad (4)\\
v_d(\tau) &= \dot{x}_d(\tau)\\
&= (x_b - x_f)(60\tau^3 - 30\tau^4 - 30\tau^2) \quad (5)
\end{aligned}
$$

where $\tau = t/(t_f - t_0) = t/T \in [0, 1]$. The velocity profile is in a bell form. Fig. 4 shows $x_d(t)$ and $\dot{x}_d(t)$ which correspond to the minimum and maximum velocities of 0.1 m/sec. and 0.5 m/sec. respectively (refer to [14]).

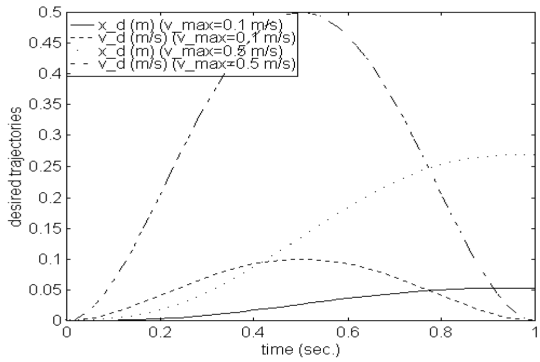

Figure 4: The Desired Trajectories

The control task is to track the given desired trajectories (5) as close as possible in a finite fixed time duration as the operation repeats from cycle to cycle.

3.3 Iterative Learning Feedforward Controller Design

It has been shown that the design task of ILC can be reduced to tuning two parameters: length index M of the filter h'_M* and the learning gain γ. In this paper, h'_M* is given directly in the discrete time domain with its normalized coefficients given by $h'(k)(k = -M, \cdots, M)$. The basic intuition in choosing an M is that M cannot be too large, and yet it cannot be too small. Small M will bring in more high frequency signal components stored in the memory bank. This is the *key* reason of the divergence for some ILC schemes which may be convergent at the initial iterations but as ILC runs, divergence can be observed in practical applications [8]. Meanwhile, an unnecessarily large M deteriorates the signal's low frequency components while smoothing out the high frequency components. How to design a suitable γ depends on what kind of knowledge is assumed about the plant to be controlled. In most engineering practice, it is quite common that the frequency response of the system is *partially* available and at certain range of frequencies concerned, it is always possible to approximate the practical system by a linear system. Since the system considered is controlled by a feedback controller, the closed-loop transfer function $G_c(j\omega)$ at the the cut-off frequency, ω_c, is assumed to be available.

One frequently used zero phase filter is considered as a rectangular one, denoted by $h'_M(t)$, for illustrating the design consideration, which is just an algebraic averager described in (3). The Fourier transform of $h'_M(t)$ is denoted by $H'_M(\omega)$.

$$H'_M(\omega) \quad = \quad \frac{\sin(\omega M T_s)}{\omega M T_s}. \qquad (6)$$

A practical design procedure can be as follows. At the first iteration, only the feedback controller is commissioned. At the end of the first iteration, performing a discrete Fourier transform (DFT) of the feedback signal $u^0_{fb}(t)$ gives the spectrum of the feedback signal. Therefore, the cut-off frequency ω_c of the filter can be obtained. ω_c should be chosen a little bit higher than the frequency corresponding to the magnitude peak in the amplitude-frequency plot of $u^0_{fb}(t)$. Using ω_c and setting and the sampling period of T_s (0.001 sec. in this study), M can be estimated as [15]

$$M \approx \frac{1.392}{\omega_c T_s}. \qquad (7)$$

And the γ can be obtained as [15]

$$\mid 1 - \gamma H'(\omega) G_c(j\omega) \mid < 1, \quad \forall \omega \leq \omega_c. \qquad (8)$$

Since $H'(\omega)$ is known as shown in (6), γ can be obtained from the knowledge of $G_c(j\omega)$. A plot of $\gamma(\omega)$ can be available from (8). This plot is useful in selecting a suitable γ when different frequencies of interest are to be considered. Usually, with the only information of $G_c(\omega_c)$, one can still determine a suitable γ.

In this work, the system bandwidth is desired to be around 20 Hz. The PID controller is designed so that the closed loop transfer function is a first order one with a time constant set to be 0.008 sec. Applying (7), one obtains

$$M \geq \frac{1.392}{2\pi * 20 * 0.001} \approx 11$$

while using

$$\mid 1 - \gamma \frac{1}{j2\pi * 20 * 0.008 + 1} \mid = \mid 1 - \gamma * (0.4974 - 0.5000j) \mid < 1$$

one obtaines that (note: when M is small, $H'(2\pi * 20) = \sin(2 * \pi * 20 * M * .001)/(2 * \pi * 20 * M * .001) \approx 1$)

$$0 < \gamma < 2.$$

For an effective implementation of the ILC, in the PID feedback controller, the velocity is estimated using

$$\tilde{\dot{x}}(t) = (x(t) - x(t - N))/(N t_s) \qquad (9)$$

where a practical choice of N is $N = 3$. It has been validated in many robotic applications that the simple scheme (9) is equivalent to many advanced and complex smoothing or filtering schemes.

4 Experimental Results

4.1 Fixed γ with Different M.

A cautious γ is chosen to be 0.1. Different filter lengths were used to test the ILC convergence. As shown in Fig. 5, when $M = 0$, it is not convergent because according to Shannon's sampling theorem, $\frac{2\pi}{\omega_c T_s}$ should be larger than 2, that means M should not be less than 2. However, the ILC convergence at several initial iterations can be observed. The similar situation happened when $M = 1, 2, 3$. When $M > 4$, the ILC exhibits good convergence property. When M increases to 20, no further significant improvement can be obtained. This verifies the ILC design formula (7).

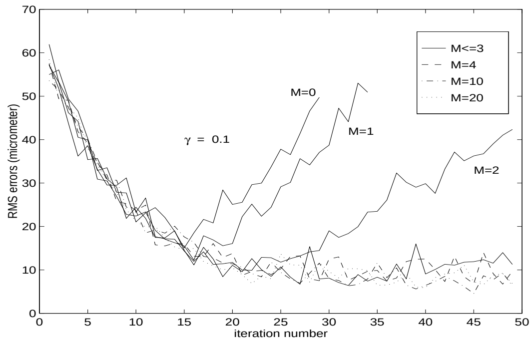

Figure 5: Learning convergence comparison, fixed $\gamma = 0.1$ with different M

4.2 Fixed M with Different γ.

As verified in Fig. 5, a suitable M ($M = 10$) is chosen and fixed. Contrary to Sec. 4.1, different learning gains were used here to test the ILC convergence. As shown in Fig. 6, when γ increases, ILC converges faster. However, sustainable ILC convergence (or long term stability of ILC [8]) will not be guaranteed as γ increases from 0.3 and beyond.

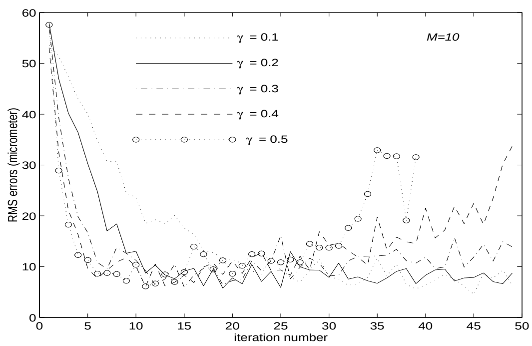

Figure 6: Learning convergence comparison, fixed $M = 10$ with different γ

4.3 Rule-Based Setting of γ

A rule-based scheme could be used to further improve the ILC convergence performance to achieve long term stability as well as fast convergent speed. In this experiment, γ is set to 1 at the first ILC update. Afterwards, γ is set to 0.1. A comparison of ILC convergence is shown in Fig.7. The ILC convergence rate is increased significantly when a rule-based γ is used. It speeds up at the beginning and maintains a good long term stability as the case with a fixed $\gamma = 0.1$. Fig.7 presents an impressive improvement of ILC convergence rate which may become a standard technique in implementing ILC applications.

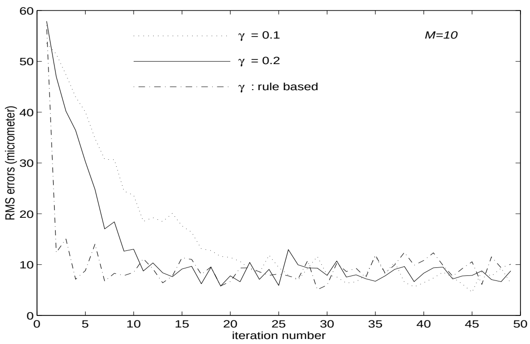

Figure 7: Learning convergence comparison, fixed $M = 10$ with a rule-based γ

To have a clear understanding about the proposed ILC scheme, a series of plots for feedforward and feedback control signals at several ILC iterations are shown in Fig. 8 and Fig. 9. As shown in Fig. 8, the feedforward control signal converges from 0 to the repeatable part of the feedback control signal . On the other hand, the feedback control signal, as shown in Fig. 9, reduces as ILC converges. It is true that the feedback control signal at the 50-th iteration is almost a zero mean random signal. Collectively from Fig. 8 and Fig. 9, it can be observed that through iterative learning u_{ff}^i tends to relieve the burden of feedback controller. This implies, critical or optimal design of a feedback controller may not be necessary.

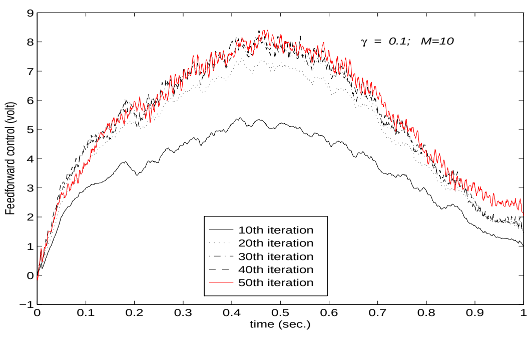

Figure 8: Feedforward control signals during iterative learning process, fixed $M = 10$ $\gamma = 0.1$

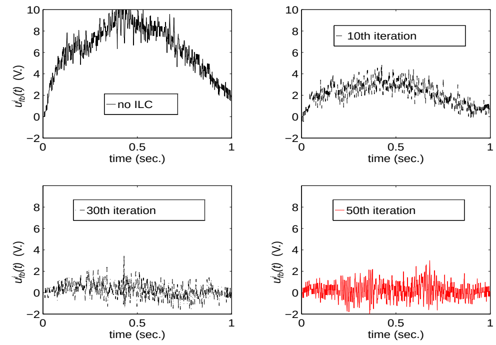

Figure 9: Feedback control signals during iterative learning process, fixed $M = 10$ $\gamma = 0.1$

4.4 Different x_f

In this case, fixed M and γ are to be used but with different x_f. This is to illustrate that a single fixed pair of M and γ will work satisfactorily in various cases with different task parameter x_f. In this section, M and γ are fixed to 10 and 0.1 respectively. Three tasks are considered, i.e., $x_f = 53.333$ mm (corresponding to the minimal velocity), $x_f = 200.000$ mm and $x_f = 266.660$ mm (corresponding to the maximal velocity). Fig. 10 shows the ILC convergence processes for the all experimental results. Satisfactory results can be observed from Fig. 10. However, it is reasonable to see that a larger x_f leads to a larger converged RMS because the nonrepeatable system dynamics may become more significant. The tracking errors at the 50-th ILC iteration are compared in Fig. 11 while the feedforward control signals in Fig. 12. It is interesting to see from Fig. 12 that the nonrepeatable parts differ at difference task parameters. This implies that the PMLM's dynamic varies significantly when performing different tasks. Therefore, conventional controller is not capable of achieving a high precision requirement. From Fig. 10, it can be observed that the ILC enhances the tracking precision by a factor of 3 to 7, with only a modest amount of modeling effort.

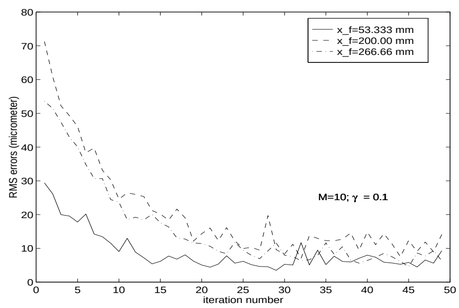

Figure 10: Learning convergence comparison, fixed $M = 10$ and $\gamma = 0.1$

5 Conclusions

It has been successfully shown in this paper that, with a modest amount of modeling, it is possible to achieve

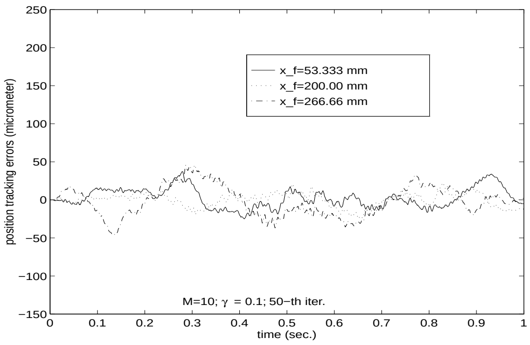

Figure 11: Tracking errors comparison at the 50-th iteration, fixed $M = 10$ and $\gamma = 0.1$

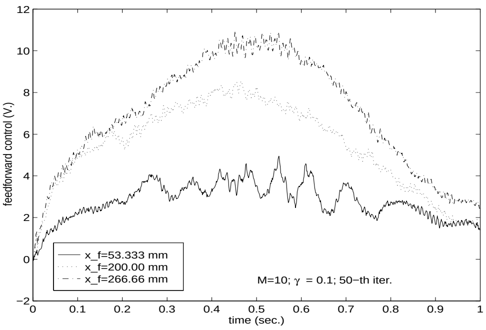

Figure 12: Feedforward control signals comparison at the 50-th iteration, fixed $M = 10$ and $\gamma = 0.1$

precision motion control of a permanent magnetic linear motor (PMLM). A feedback-feedforward control structure is proposed for applications which are inherently repetitive in terms of the motion trajectories. By using a simple zero-phase filtering technique, the design task of ILC is reduced to tuning two parameters: length of the filter and the learning gain. Convergence analysis and detailed design procedures are presented. Some practical considerations in the parameter tuning are outlined. Experimental results are presented to demonstrate the practical appeal and effectiveness of the proposed scheme. The clearly illustrated controller design procedures are also appealing for other applications.

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