Laguerre Based Adaptive Control of Piezoelectric Actuator for Nanopositioning

Yigang Wang, Kevin C. Chu, Herrick L. Chang and Tsu-Chin Tsao*

***Abstract*— This paper considers the Laguerre based adaptive control of piezoelectric actuator for nanopositioning. Laguerre-based adaptive filters provide an attractive alternative to adaptive FIR filters in the sense that they provide better approximation of system with a long impulse response with a restricted order. Laguerre also keeps many of the advantages of adaptive FIR filter, such as unique global minimum and guaranteed stability. In this paper, the Laguerre based model matching problem is studied. A better optimal solution can be achieved by proper chosen pole location of all-pass filter in Laguerre filter. The Least-Mean-Square (LMS) algorithm based on Laguerre structure is then discussed. The results show that with same step size constraint, the Laguerre based LMS algorithm introduces less excessive mean-square-error. The Laguerre-based LMS algorithm is then applied to the adaptive control for reference tracking. Due to the model mismatch, the traditional adaptive feed-forward structure is modified to the adaptive inverse control structure for better tracking performance. The proposed approach is implemented in FPGA with 100kHz sampling rate and applied to piezoelectric actuator for nanopositioning. Experimental results show effectiveness of the proposed approach.**

I. INTRODUCTION

Nanoscience and nanotechnology has had drawn much attention in the past two and a half decades [1], [2]. An important branch of research in nanotechnology involves precision control and manipulation of devices at a nanoscale level, i.e., nanopositioning. Nanopositioners are precision mechatronic systems designed to move objects with a nanoscale resolution. The desired attributes of a nanopositioner are stability, fast response and extremely high resolution and precision.

Typically, the nanopositioning stage is actuated by piezoelectric actuators. Piezoelectric actuators have many advantages for nanopositioning, such as, being able to provide repeatable sub-nanometer motion, no backlash, fast responses and the ability to generate large forces [2]. However, their application is hindered by a number of non-ideal characteristics, such as hysteresis, creep and mechanical resonance [2], [3]. As a result of these problems, control has been introduced to provide satisfactory performance of piezoelectric actuators.

Both feedback and feed-forward control are important in achieving precision positioning [4], [5], [6]. Feed-forward control is commonly applied to improve system performance if accurate plant model is obtained. LTI feed-forward controller suffer from lacking of robustness to plant dynamics uncertainty [7]. In this paper, adaptive algorithm will be applied. Although IIR filters have superior system modeling abilities provided by the infinite impulse response nature, it is not easy to apply adaptive IIR filters due to some practical obstacles. The obstacles include the possibility of local minima in the performance surface, the potential for unstable behavior during the adaptation process, and the relatively slow initial convergence [8]. In many applications, adaptive algorithms based on FIR filters are used [9], [10], [11].

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Increasing the operating speed of nanopositioner can significantly impact the throughput of a wide range of emerging nanoscience and nanotechnology. In order to achieve high speed, fast sampling rate is necessary. For example, It is suggested that 4-10 times faster than the rising time of system for reasonable control performance [12]. However, system zeros and poles approach to unit disk as sampling rate increases [13]. With fast sampling rate, FIR filters with long filter length have to be applied to model the desired system. It results in high computational costs when adaptive algorithms are applied.

Laguerre filter [14], [15] is a compromise between FIR and general IIR models. It shares the same structure with FIR filter except replacing unit delay block with identical first order all-pass filters as well as adding a initial normalization filter. If the pole of all-pass filter is at origin, Laguerre filter becomes conventional FIR filter. Hence we may consider the Laguerre filter to be a generalization of FIR filter. The main advantage of the Laguerre filter compared with FIR filter is that Laguerre filter is IIR filter with single adjustable repeating pole [16]. As we will show in this paper, it could dramatically improve the performance with proper chosen pole.

Using the Laguerre model in system modeling, the design problem is to optimally select the free parameter pole location to minimize the modeling error. Offline [17], [18] and online [19] algorithms have been developed to minimize the mean square energy in the error. Many adaptive algorithms based on Laguerre filters have been studied [20], [21], [22]. Applications of adaptive Laguerre filter include echo cancellation [23] and [24].

In this paper, Laguerre based LMS algorithm on a fixed-point architecture is used in the adaptive control of piezoelectric actuator. The remainder of this paper is organized as follows: Section 2 formulates the feed-forward tracking control as model matching problem. Section 3 presents the solution of model matching problem using Laguerre filters. Section 4 discusses the LMS algorithm based on Laguerre filters. Section 5 discusses different adaptive control structures for reference tracking. Section 6 shows the experimental results, and concluding remarks are discussed in section 6.

II. Problem Formulation

Let $G \in \mathbb{RH}_\infty$ be a stabilized plant, and $r(k)$ be the reference signal. The control input is applied to make the plant output $y(k)$ follow the desired output $d(k) = M(q^{-1})r(k)$, where $M \in \mathbb{RH}_\infty$ is a desired I/O map. The tracking problem can be formulated as model matching problem, as shown in Figure 1: the distance between a specified tracking reference model and the achievable tracking performance by feedforward compensation is minimized [25], [26]. The model tracking error e is

$$e = (M - GF)r = Er \tag{1}$$

The goal of this paper is to minimize the $\mathbb{H}_2$ norm of E

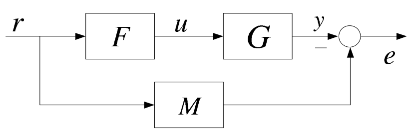


Fig. 1. Model Matching Problem

with reference signal $r(t)$, i.e.,

$$J_2^{opt} = \inf_{F \in \mathbb{RH}_\infty} \|M - GF\|_2 \tag{2}$$

If the infimum can be attained by a certain F, then $F = F^{opt}$ is called the optimal tracking controller.

III. Model Matching with Laguerre Filter

Figure 2 shows the structure of Laguerre filter with order n, where $a \in \mathbb{R}$ with $|a| < 1$.

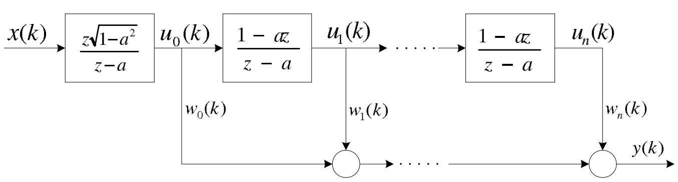


Fig. 2. Laguerre Filter Structure

Let

$$L_0(z) = \frac{z\sqrt{1-|a|^2}}{z-a} \tag{3}$$

$$L(z) = \frac{1-az}{z-a} \tag{4}$$

$$F_k(z) = L_0 L^k \tag{5}$$

Lemma 1: [27] Assume F_k is defined in Equation (5). $\{F_k\}_{k=0}^{\infty}$ forms a complete orthonormal basis of $\mathbb{H}_2$ space.

Note that if $a = 0$, $F_k(z) = z^{-k}$, that is, the traditional FIR filter. So, the Laguerre filter can be treated as the generalization of FIR filter. $\{F_k\}_{k=0}^{\infty}$ is also called the *Laguerre basis* of $\mathbb{H}_2$ space.

For any $G(z) \in \mathbb{H}_2$, it has the following Laguerre-Fourier series representation

$$G(z) = \sum_{k=0}^{\infty} c_k F_k(z) \tag{6}$$

where $c_k =< G(z), F_k(z) >$ is called *Laguerre-Fourier series coefficient*. Let the n-th order approximation of $G(z)$ be

$$\widehat{G}(z) = \sum_{k=0}^{n} c_k F_k(z) \tag{7}$$

Laguerre-Fourier series representation does not always guarantee superior performance compared with same order FIR filter. However, if $G(z)$ has slow impulse response, FIR filter approximation does not have satisfactory performance.

Lemma 2: Suppose $G(z) \in \mathbb{H}_2$ has the following partial fraction expansion:

$$G(z) = \sum_{k=1}^{n_0} \frac{b_k}{z - p_k} \tag{8}$$

where all poles satisfy $1 - \epsilon < |p_k| < 1$ and $0 < \epsilon_1 \ll 1$. Let $\hat{G}^{FIR}(z)$ and $\hat{G}^{Lag}(z)$ be FIR and Laguerre filter approximation with order n respectively, then there exists $a \neq 0$ such that

$$\|G - \hat{G}^{Lag}(z)\|_2 < \|G - \hat{G}^{FIR}(z)\|_2 \tag{9}$$

Proof: According to the result from [15], the modeling error is

$$G - \hat{G}^{FIR} = \sum_{k=0}^{n_0} x_k(z) = \sum_{k=0}^{n_0} \frac{b_k p_k^n}{z - p_k} z^{-n} \tag{10}$$

$$\begin{aligned} G - \hat{G}^{Lag} &= \sum_{k=0}^{n_0} y_k(z) \\ &= \sum_{k=0}^{n_0} \frac{b_k}{z - p_k} \left(\frac{p_k - a}{1 - ap_k} \cdot \frac{1 - az}{z - a} \right)^n \end{aligned} \tag{11}$$

for any $k \in \{0, 1, \cdots, n_0\}$,

$$\begin{aligned} \left\| \frac{y_k}{x_k} \right\|_2 &= \left\| \left(\frac{p_k - a}{p_k(1 - ap_k)} \right)^n z^n \left(\frac{1 - az}{z - a} \right)^n \right\|_2 \\ &\leq \left| \left(\frac{p_k - a}{p_k(1 - ap_k)} \right)^n \right| \end{aligned} \tag{12}$$

We assume p_k takes the form $(1 - \epsilon_1)e^{j\theta}$, where $0 < \epsilon < \epsilon_1 \ll 1$. Equation (12) reduces to

$$a(\epsilon^2 - 2\epsilon)(a + (\epsilon - 1)\cos(\theta)) > 0 \tag{13}$$

if $a > 0$ then (13) reduces down to

$$0 < a < (1 - \epsilon)\cos(\theta) \tag{14}$$

So, if Equation (14) holds, we have

$$\|G - \hat{G}^{Lag}(z)\|_2 < \|G - \hat{G}^{FIR}(z)\|_2$$

∎

From Lemma 2, we know that the modeling error decreases with ratio $|\frac{p_k-a}{1-ap_k}|$ as $n \rightarrow \infty$. Then, the offline selection of a can be formulated as the following min-max problem:

$$a^{opt} = \arg\min_a \max_k \left|\frac{p_k-a}{1-ap_k}\right| \quad (15)$$

But intuitively, a should be selected to close to the slowest pole of plant. For general case, i.e., $G(z)$ has poles both close to unit disc and origin, for which will Lemma 2 not hold.

Before we go to model matching problem with Laguerre filter, it is necessary to review the result of $\mathbb{H}_2$ norm optimization with general IIR filter:

Lemma 3: [28] Suppose $M, G, F \in \mathbb{RH}_\infty$, then,

$$\begin{aligned} J_2^{opt} &= \|(G_i^* M)_-\|_2 &(16)\\ F^{opt} &= G_o^{-1}(G_i^* M)_+ &(17)\end{aligned}$$

where $G = G_i G_o$, where G_i and G_o represents the non-minimum and minimum phase portions of the system respectively. $(G_i^* M)_+$ and $(G_i^* M)_-$ are the causal and anti-causal parts of system, respectively.

Applying Lemma 3, we have

$$\begin{aligned}\|M - GF\|_2 &= \|(G_i^* M)_+ + (G_i^* M)_- - G_o F\|_2 \\ &= \|(G_i^* M)_-\|_2 + \|G_o(G_o^{-1}(G_i^* M)_+ - F)\|_2\end{aligned}$$

For simplification, let $H = G_o^{-1}(G_i^* M)_+$. Looking at the norm $\|G_o(H - F)\|_2^2$, we know that each transfer function as a Laguerre series expansion,i.e.,

$$G_o = \sum_{k=0}^{\infty} g_k F_k, \;\; H = \sum_{k=0}^{\infty} h_k F_k, \;\; F = \sum_{k=0}^{n} f_k F_k$$

Since all basis are orthogonal, we know $q_k = h_k$ for $k \leq n$, making it

$$\begin{aligned}&\left\|\sum_{k=0}^{\infty} g_k F_k \sum_{l=n+1}^{\infty} h_l F_l\right\|^2 \\ &= \sum_{k=0}^{\infty}\sum_{j=n+1}^{\infty} g_k^2 h_l^2 \frac{1}{2\pi j}\oint F_k F_l \left(F_k F_l\right)^* \frac{dz}{z} = \sum_{k=n+1}^{\infty} g_k^2 h_k^2 \quad (18)\end{aligned}$$

From Lemma 2, if H has a dominant pole near the unit disk, then we know that the mismatch $\sum_{k=n+1}^{\infty} h_k^2$ is smaller. In general M can be used to ensure Lemma 2 holds. If a similar argument can be made for $G_0(z)$, the model matching problem using Laguerre Filter will be guaranteed to perform better that FIR with same order.

IV. Laguerre Based LMS algorithm

Let $\mathbf{d}$ be a zero-mean scalar-valued random variable with variance $\sigma_d^2 = \mathsf{E}(|\mathbf{d}|^2)$, $\mathbf{u}^*$ be a zero-mean $M \times 1$ random variable with a positive-definite covariance matrix, $R_u = \mathsf{E}(\mathbf{u}^*\mathbf{u}) > 0$. The $M \times 1$ cross-covariance vector of $\mathbf{d}$ and $\mathbf{u}$ is denoted by $R_{du} = \mathsf{E}(\mathbf{d}\mathbf{u}^*)$. For Laguerre filter shown in Figure 2, define

$$\mathbf{u}_k = [u_0(k)\; u_1(k)\; \cdots\; u_n(k)] \quad (19)$$

with

$$\begin{aligned} u_0(k) &= L_0(q^{-1})x(k) &(20)\\ u_i(k) &= L^i(q^{-1})u_0(k) &(21)\end{aligned}$$

Note again that if $a = 0$, Equation (19) becomes

$$\mathbf{u}_k = [x(k)\; x(k-1)\; \cdots\; x(k-M+1)] \quad (22)$$

which is same as the traditional FIR regressor.

The autocorrelation matrix is defined as

$$R_u = \begin{bmatrix} r_{u_0,u_0}(0) & r_{u_0,u_1}(0) & \cdots & r_{u_0,u_{M-1}}(0) \\ r_{u_1,u_0}(0) & r_{u_1,u_1}(0) & \cdots & r_{u_1,u_{M-1}}(0) \\ \cdots & \cdots & \cdots & \cdots \\ r_{u_{M-1},u_0}(0) & r_{u_{M-1},u_1}(0) & \cdots & r_{u_{M-1},u_{M-1}}(0)\end{bmatrix} \quad (23)$$

where $r_{u_i,u_j}(m) = \mathsf{E}(u_i(k)u_j^*(k+m))$

Lemma 4: Consider the Laguerre filter shown in Figure 2. Assume $x(k)$ is zero mean white Gaussian noise with variance σ_x^2, then

$$R_u = \begin{bmatrix} 1 & -a & \cdots & (-a)^{M-1} \\ -a & 1 & \cdots & (-a)^{M-2} \\ \cdots & \cdots & \cdots & \cdots \\ (-a)^{M-1} & (-a)^{M-2} & \cdots & 1\end{bmatrix}\sigma_x^2 \quad (24)$$

Proof: Let $X(z)$, $U_i(z)$, $R_x(z)$ and $R_{u_i,u_j}(z)$ be z-transform of $x(k)$,$u_i(k)$,$r_x(k)$ and $r_{u_i,u_j}(k)$, respectively. without loss of generality, assume $i \geq j$

$$\begin{aligned} R_{u_i,u_j}(z) &= [L_0(z)L^i(z)][L_0(z)L^j(z)]^* R_x(z) \\ &= L^{i-j}(z)R_x(z)\end{aligned}$$

Then take inverse z-transform

$$\begin{aligned} r_{u_i,u_j}(0) &= \frac{1}{2\pi j}\oint\left(\frac{1-az}{z-a}\right)^{i-j}\sigma_x^2\frac{dz}{z} \\ &= \sigma_x^2\sum_p \mathtt{Res}\left[\left(\frac{1-az}{z-a}\right)^{i-j} z^{-1} \;\mathtt{at\ pole}\; z_p\right] \\ &= \sigma_x^2\left[\left(-\frac{1}{a}\right)^{i-j} + (-a)^{i-j} - \left(-\frac{1}{a}\right)^{i-j}\right] \\ &= (-a)^{i-j}\sigma_x^2 \quad (25)\end{aligned}$$

Here the proof is finished. ■

There are some observations about this result:

1) If $a = 0$, $R_u = \sigma_x^2 I$, which is again the FIR case.
2) If $|a| \rightarrow 1$, the eigenvalues of R_u separate from σ_x^2.
3) $\mathtt{tr}(R_u) = M\sigma_x^2$, which does not change with a.

The weight vector w that solves

$$\min_w \mathsf{E}(|\mathbf{d} - \mathbf{u}w|^2) \quad (26)$$

is given by

$$w^o = R_u^{-1}R_{du} \quad (27)$$

and the minimum mean-square error is

$$\mathtt{m.m.s.e} = J_{2,Lag}^{opt} = \sigma_d^2 - R_{ud}R_u^{-1}R_{du} \quad (28)$$

The LMS algorithm with Laguerre structure is

$$w_i = w_{i-1} + \mu u_i^*[d(i) - u_i w_{i-1}], \quad i \geq 0 \quad (29)$$

The steepest-decent method suggests the step size μ is bounded by

$$2/\lambda_{\max} > \mu > 0 \tag{30}$$

From the previous observations, the admissible step size of Laguerre filter is smaller than FIR filter. Equation (30) turns out the sufficient for convergence of the weight vector in the mean, but not sufficient for convergence of the variance of the weight vector. A stronger condition for convergence of mean and variance is needed, namely,

$$2/\mathtt{tr}(R_u) > \mu > 0 \tag{31}$$

From observation 3), the step size bound for convergence of mean and variance is same for both Laguerre filter and FIR filter.

Let $\mathbf{v}(i)$ denote the estimation error, i.e.,

$$\mathbf{v}(i) = \mathbf{d}(i) - \mathbf{u}_i w^o \tag{32}$$

The variance of $\mathbf{v}(i)$ is equal to the minimum cost, i.e.,

$$J_{2,Lag}^{opt} = \sigma_v^2 = \mathsf{E}(|\mathbf{v}(i)|^2) \tag{33}$$

Assume the sequence $\{\mathbf{v}(i)\}$ is i.i.d. and independent of all $\{\mathbf{u}_j\}$, then, the excess-mean-square error (EMSE) is

$$\mathtt{EMSE} = \frac{\mu\sigma_v^2 \mathtt{tr}(R_u)}{2} \tag{34}$$

for sufficiently small μ. The total steady state mean-square error (MSE) is

$$\mathtt{MSE} = \sigma_v^2 + \mathtt{EMSE} = \sigma_v^2 + \frac{\mu\sigma_v^2 \mathtt{tr}(R_u)}{2} \tag{35}$$

According to the previous session, if $J_{2,Lag}^{opt} < J_{2,FIR}^{opt}$, the steady state mean-square error (MSE) with Laguerre based LMS algorithm is smaller than FIR structure.

V. Adaptive Control for Reference Tracking

A. Adaptive Feed-forward Control Structure

Figure 3(a) shows the structure of adaptive feed-forward control for periodic reference tracking, where $\hat{G}(z)$ is the model of plant. In Figure 3(a), the adaptive filter training loop is trying to minimize $\|M - \hat{G}F\|_2$. However, the feed-forward control channel is evaluating $\|M - FG\|_2$. Thus, the reference tracking performance is determined by the accuracy of model. In order to further improve the tracking performance, feedback effect need to be introduced.

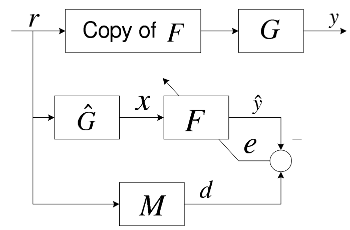
B. Adaptive Inverse Control Structure

Figure 3(b) shows the structure of adaptive inverse control for reference tracking.

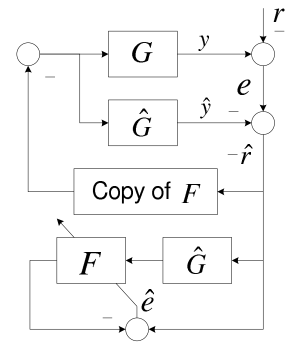
The relationship between disturbance r and output error e can be shown to be,

$$e = \frac{-(1 - F\hat{G})}{1 + F(G - \hat{G})} r \tag{36}$$

Using the small gain theorem [29], if $\hat{G}$ accurately represents the true closed-loop system G, then the system shown in Figure 3(b) is guaranteed to be stable with any stable



(a) Adaptive Feed-forward Control



(b) Adaptive Inverse Control

Fig. 3. Adaptive Control Structures for Reference Tracking

controller F. If $G = \hat{G}$, then Equation (36) reduces down to

$$e = -(1 - F\hat{G})r \tag{37}$$

Comparing with previous structure, the training loop and reference tracking channel are both based on $\hat{G}$, instead of G. Hence, the adaptive inverse control structure is supposed to have better performance compared with adaptive feed-forward control.

VI. Application to Piezoelectric Actuator for Nanopositioning

The Laguerre based LMS algorithm with AIC structure is applied to piezoelectric actuator for nanopositioning. The description of PZT actuator can be found in [30] and thus omitted here. The actuator displacement, measured by a capacitance probe is 16.5μm/V.The control system is implemented on a LabVIEW PXI-7833R FPGA board with 100kHz sampling rate. An external triangular wave reference signal of 1kHz is used.

A. System Identification of PZT actuator

Figure 4 shows the frequency response data of actual PZT actuator and the 6th order model obtained by frequency domain curve fitting. The poles of model are $0.9433 \pm 0.3150i,\ 0.8736 \pm 0.2047i, 0.9243 \pm 0.0645i$, which are very close to unit disc as we expect. It is also true for the zeros: $20.1475, 1.3004 \pm 0.4031i, 0.8895 \pm 0.4180i$.

B. Adaptive Filter Order Selection

From previous sections, higher filter order yield better model matching performance. However, since the Laguerre based LMS algorithm is implemented in FPGA, the system is limited in multipliers and memory. For periodic reference tracking, a low order adaptive filter can be sufficient for many applications. We wish to characterize required order for an arbitrary repeating signal $x(k)$ of length N can be represented by

$$x(k) = A + \sum_{l=0}^{N} \alpha_l \cos\left(\frac{2\pi l}{N}k + \phi_l\right) \tag{38}$$

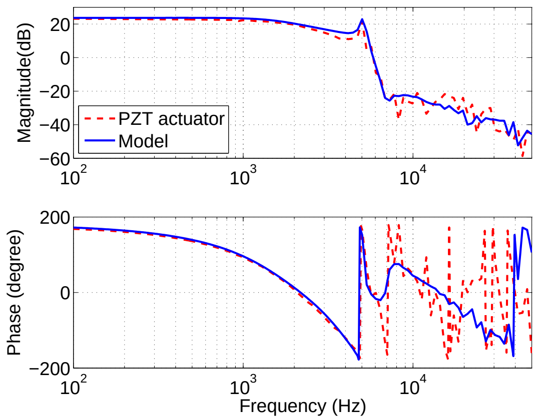


Fig. 4. Frequency Response of PZT actuator and Model

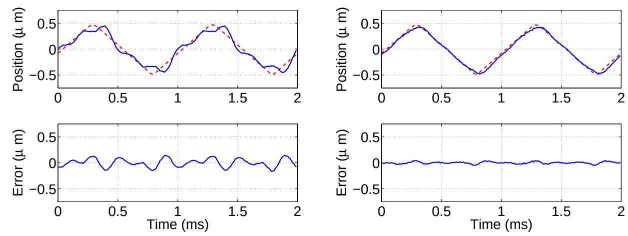
where α_l and ϕ_l are the magnitude and phase of each sinusoid. Thus for each harmonic, a two degrees of freedom are required. Adding another degree for the DC bias, a $(2N + 1)$th order filter is required for perfect periodic reference tracking. Due to model mismatch in the higher frequency regions, the performance of both structures can degrade and cause instabilities. To ensure robustness, we restrict the filter $M(z)$ so that the control emphasis no longer resides in the high frequency range.

C. Fixed-point Implementation Issues

The proposed algorithm is implemented in FPGA using fixed-point arithmetic. In the experimental setup, signed 16bit ADCs and DACs are used. 16bit integers are used to represent most signals unless stated otherwise. Because the magnitude of adaptive filter coefficients can not be easily predicted, to ensure high dynamic range and resolution, 32bit integers are used to represent coefficients. In order to implement the 1st order all-pass filter, a positive feedback loop is used. If a is very close to 1, this feedback loop behaves much like an integrator, which can easily overflow, so 64bit integers are used in the states of the all pass filters, which are later truncated back down to 16bit. Besides the different words lengths, different bit shifts are also used in different stages to get best trade-off between range and resolution.

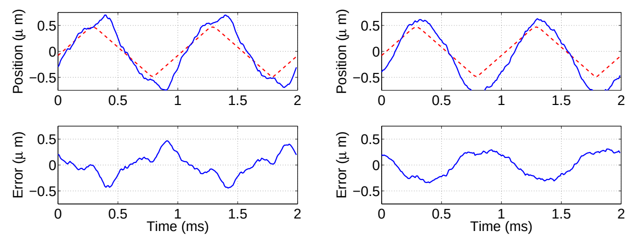
D. Experimental Results using Adaptive Feed-forward Control Structure

Figures 5(a) and Figure 5(b) show the error signal of adaptive filter training loop using FIR filter and Laguerre filter respectively. The error with Laguerre filter, has been dramatically decreased. The Root-Mean-Square (RMS) error has been improved from 0.0779 μm to 0.0196 μm. However, due to the modeling error in $\hat{G}$, the actual PZT displacement does not preserve the performance. As shown in Figure 6(a) and 6(b), the tracking performance in both cases are poor. The actual RMS tracking error are 0.2152μm and 0.2146μm, respectively.



(a) FIR, $a = 0$ (b) Laguerre, $a = 0.9375$

Fig. 5. Reference $r(k)$ (dashed) and predicted output $\hat{y}(k)$ (solid)

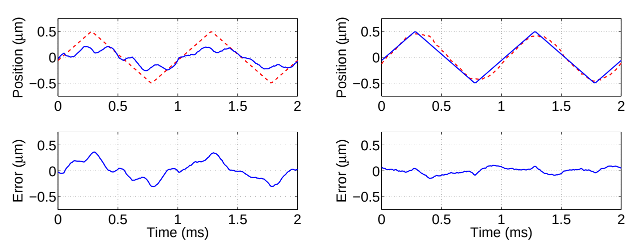


(a) FIR, $a = 0$ (b) Laguerre, $a = 0.9375$

Fig. 6. Reference $r(k)$ (dashed) and PZT output $y(k)$ (solid)

E. Experimental Results using Adaptive Inverse Control Structure

Figures 7(a) and 7(b) show the true tracking error with FIR and Laguerre filter, respectively using the structure seen in Figure 3(b). Compared with Figure 6(a) and 6(b), the adaptive inverse control structure shows better performance than adaptive feed-forward control structure. From Figure 7(a) and 7(b), the Laguerre based algorithm shows improved performance compared to its FIR counterpart. The RMS tracking error goes from 0.2675 μm to 0.0580 μm.



(a) FIR, $a = 0$ (b) Laguerre, $a = 0.9375$

Fig. 7. Reference $r(k)$ (dashed) and PZT output $y(k)$ (solid)

Figure 8 shows the coefficient updates of Laguerre Filter when LMS algorithm is applied. As can bee seen, the coefficients converges and steady state performance can be analyzed.

As we discussed before, the free-design parameter a will dramatically change the performance of Laguerre filter.

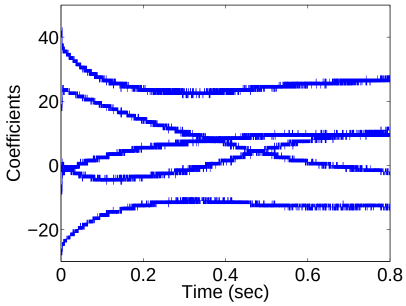


Fig. 8. Coefficients update of Laguerre filters using LMS algorithm

Figure 9 shows the RMS error with different selections of a. Since the PZT model has both poles and zeros close to the unit disc, the larger a will achieve better performance. The experimental data verifies the conclusions from previous sections.

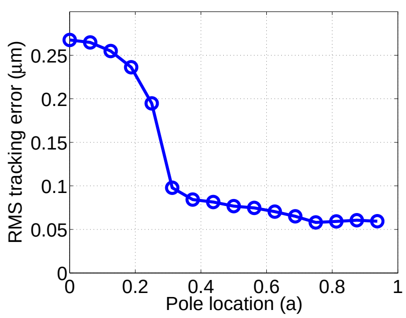


Fig. 9. Root-Mean-Square (RMS) error v.s. pole location a

VII. Conclusions

In this paper, Laguerre based adaptive control was introduced for reference tracking of piezoelectric actuator. It has been shown that:

1) The Laguerre structure achieves better model matching performance if the model G has a long impulse response.
2) The LMS algorithm based on Laguerre filters admit the same step size constraints as the FIR filter but introduce smaller EMES.
3) The performance adaptive feed-forward control is determined by the accuracy of model. However, the proposed adaptive inverse control structure can significantly reduce model sensitivity by introducing feedback in the loop.
4) With FPGA implementation, 100kHz sampling rate has been achieved. It assures satisfactory performance when 1kHz reference was tracked.

With this structure, an internal model could be introduced to further improve the performance of reference tracking.

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