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An Iterative Learning Controller for Reduction of Repeatable Runout in Hard Disk Drives

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Abstract— **In this study we consider the iterative learning control (ILC) framework to design a reference signal that reduces the periodic component of disturbances in a feedback measurement containing both repeatable and non-repeatable components. Reduction of periodic disturbances is useful in alleviating undesirable repeatable tracking errors in applications such as the two-stage servo track writing process for disk drives. A general problem description is given for a linear discrete time system and convergence robustness results for the learning system are derived. A learning filter is designed with the use of an FIR model approximation for the inverse of the closed-loop sensitivity for fast nominal convergence while robustness to modeling errors and non-repeatable disturbances is achieved through additional filtering. The ILC algorithm is applied to a disk drive system where experimental results demonstrate the effectiveness of the design method in reducing periodic measurement disturbances.**

I. Introduction

In hard disk drive (HDD) servomechanisms disturbances that consist of both repeatable and non-repeatable nature appear in the position error signal (PES) of the head following a data track. The repeatable run-out (RRO) disturbance generally occurs at frequencies that are integer multiples of the frequency of rotation of the disk and is a considerable source position error with respect to the center of the data track [1]. Typically, control effort is focused at the frequencies of the periodic disturbances to improve the tracking performance of the system.

However, improved performance by the feedback system when the output measurement is perturbed by periodic disturbances leads to undesirable repeatable tracking errors. As an example, progress in HDD servo track writers has led to a two stage servo track writing process where a master servo disk, created in stage one, is used as a reference from which the servo tracks on the remaining disks in the stack are written in stage two [2]. Repeatable run-out either written-in during the servo track writing process or resulting from mechanical disk assembly can be eliminated by considering them as sources of periodic measurement noise and canceling them via a modified reference signal. Thus the objective of the servomechanism is not to follow the RRO error, but to follow a virtual perfectly circular track thereby reducing AC-squeeze of data track following.

This paper considers the framework of iterative learning control (ILC) algorithms to develop a method for repeatable disturbance rejection. Based on the internal model principle, ILC schemes have been shown as the dual of repetitive control [3] and have demonstrated application in the reduction of periodic disturbances [4], [5]. A learning algorithm designed for periodic disturbance rejection has been outlined for disk drive systems by [6], however accurate knowledge of a nominal plant model and access to the control signal were required. The result was a reference signal designated the zero acceleration path (ZAP) that canceled the RRO allowing the read/write head of the disk drive to follow a virtual circular track with zero actuator acceleration. This paper considers the learning filter design and robust convergence condition of [7], whereby a set of models which is known to contain the real system is evaluated such that convergence in the presence of model uncertainty is guaranteed. An extension is developed such that the learning system is robust against non-repeatable disturbances.

The effects of non-repeatable noise, which exists in most practical applications, often leads to lower performance or even divergence of the learning system [8]. Additional filtering in the learning algorithm extends the region of stability for learning system at the expense of convergence rate and total error elimination [9]. The motivation for this study is to extend periodic disturbance reduction results of [7] for systems subject to disturbances with mixed periodic and non-periodic components. Based on uncertain closed-loop models, disturbance canceling reference signals (DCRS) are developed which provide cancellation with the periodic component of the measurement disturbance based.

Section II outlines the general problem formulation for this study, provides a brief review of some of the extensively studied theory on ILC and discusses a learning filter design methodology for satisfying convergence. Section IV describes the HDD application, the development of the learning filter and presents the results for the DCRS experiment applied to a disk drive servomechanism.

II. General Problem Formulation and ILC Configuration

A. System Description

A general block diagram description for a linear time invariant (LTI) discrete time system in which periodic disturbances occur is presented in Figure 1. Let $G_p(q)$ be the plant and $G_c(q)$ be the feedback compensator operating over a finite time interval t where $t = 1, ..., N$ and q is the shift operator. The reference $r(t)$ is periodic with period N. The disturbance $d_i(t)$ consist of both repeatable component $d(t)$

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and non-repeatable component $\tilde{d}_i(t)$

$$d_i(t) = d(t) + \tilde{d}_i(t), \tag{1}$$

where the subscript i indicates the ith period. Due to the periodic nature of the signals, the assumption is made that at the end of each finite time interval the initial conditions of the system are resent.

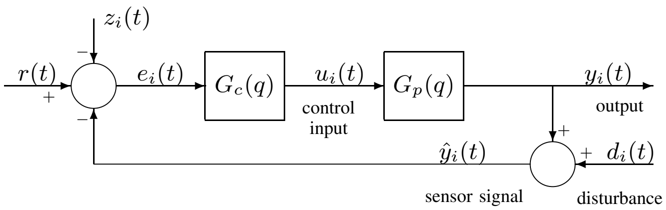

Fig. 1. Block diagram of the feedback control system with periodic components in the measurement disturbance $d_i(t)$.

The periodic component of the measurement disturbance $d(t)$ is canceled by subtracting its value as the adjunct reference signal $z(t)$. The effect of the periodic disturbance on the feedback error is given by

$$e(t) = S(q)d(t) \ , \quad S(q) = \frac{1}{1 + G_p(q)G_c(q)}$$

where $S(q)$ denotes the discrete time sensitivity function. Intuitively, with $r(t) = 0$, the $z(t)$ that directly cancels the periodic disturbance would be given by the error signal $e(t)$ filtered by the inverse of the sensitivity function $S^{-1}(q)$. In practice however, perfect models for the closed-loop sensitivity function are not available and the effectiveness of $z(t)$ for canceling periodic disturbances depends upon the accuracy of the model $\hat{S}^{-1}(q)$. Furthermore, in servomechanisms where the plant contains an integrator for steady state tracking, a stable model for the sensitivity function generally lends to an unstable inverse making the signal $z(t)$ unbounded. Fortunately, ILC methods have been shown to implicitly find through iteration the stable approximation to the inverse of the system [10] which would result in a modified reference signal that cancels with the periodic disturbance.

B. Iterative Learning for Periodic Disturbance Reduction

Iterative learning control methods applied to systems have primarily focused on compensating for periodic disturbances, thus first consider the case where $\tilde{d}_i(t) = 0$ for all i. This restricts attention to purely periodic disturbances and relaxation of this assumption is handled with additional filtering for robust convergence in Section III. The ILC structure most commonly studied in the literature considers feedforward redesign of the control signal added to the system input [11], [12], however modification of the reference signal can also achieve improved control performance for systems where it is undesirable to reconfigure the control signal. The iterative modification of reference signals has been referred to as *cascaded* ILC [13]. A block diagram representation for ILC with the cascaded structure is shown in Figure 2. Here $z_i(t)$, $\hat{r}_i(t)$, $\hat{y}_i(t)$ and $e_i(t)$ denote the adjunct reference signal, modified reference signal, system output measurement, and error signal respectively and let the subscript i indicate the ith iteration. The disturbance is assumed periodic such that $d_i(t) = d(t)$ for all i. The blocks labeled MEM denote memory arrays [13] that store signals of the current iteration for use in the next learning iteration.

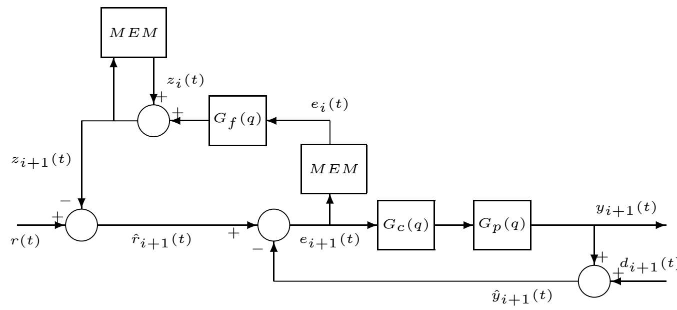

Fig. 2. Illustration of Cascade ILC System

Notice from Figure 2 that the ILC scheme is added outside the existing control loop through a modified reference signal, $\hat{r}_i(t) = r(t) - z_i(t)$. The ILC update law is classified under previous cycle learning (PCL) whereby the current iteration of the adjunct reference signal $z_{i+1}(t)$ is some form of signals from previous iterations:

$$\begin{aligned} z_{i+1}(t) &= z_i(t) + G_f(q)e_i(t) \\ z_0(t) &= 0, \quad t \in [1, N] \end{aligned} \tag{2}$$

The learning convergence condition is derived by observing the feedback error evolution from one iteration to the next. The current iteration feedback error is given by:

$$\begin{aligned} e_{i+1}(t) &= \hat{r}_{i+1}(t) - \hat{y}_{i+1}(t) \\ e_{i+1}(t) &= [1 - S(q)G_f(q)]e_i(t) \end{aligned} \tag{3}$$

The desired convergence $\lim_{k\to\infty} e_k(t) = 0$ is obtained by designing the operator $G_f(q)$ such that

$$\|1 - S(e^{j\omega})G_f(e^{j\omega})\|_\infty \leq \rho < 1 \tag{4}$$

where $\|G(\cdot)\|_\infty$ denotes the infinity norm of the discrete time transfer function G. Designing $G_f(q)$ such that condition (4) is satisfied, is a sufficient condition for reducing the amplitudes of all frequency components of the error monotonically with each iteration [8]. Methods exist for designing G_f such that (4) is minimized, however most are computationally intensive algorithms. Simplification of the filter design can be achieved by minimizing with respect to a nominal filter at the frequencies of the periodic disturbance and including robustness via additional filtering.

C. Nominal Learning Filter $G_f(q)$ Design

Little information about the closed-loop system is required to satisfy learning convergence conditions, however, it is intuitive that knowledge of the sensitivity function $S(q)$ is beneficial when designing the learning filter $G_f(q)$ in order to satisfy (4). Observe the error propagation given by (3) written as a function of the error prior to the first iteration of the learning algorithm, $e_0(t)$.

$$e_{i+1}(t) = [1 - S(q)G_f(q)]^{i+1} e_0(t) \tag{5}$$

Equation (5) indicates that fast convergence in the iteration domain is achieved for all frequencies up to the Nyquist frequency ω_N when the upper bound ρ from (4) is close to zero. Individual frequency components of the error signal can exhibit different convergence rates which depend upon $|1-S(e^{j\omega})G_f(e^{j\omega})|$ evaluated at those frequencies [8]. Over the entire frequency range fast convergence is achieved with a learning filter designed as an approximation to the inverse sensitivity function, $G_f(q) = \hat{S}^{-1}(q) = 1 + \hat{G}_p(q)\hat{G}_c(q)$. In [6] a design was presented that assumed knowledge of a nominal plant model $G_n(q)$ as well as access to the control signal $u(t)$ in order to construct the approximation $\hat{S}^{-1}(q)$. However this method requires access to open-loop nominal plant models $\hat{G}_n(q)$ as well as additional filtering of signals to maintain stability of the learning system. For servomechanisms in general, a stable model describing the sensitivity function is not guaranteed to be stably invertible. However, there are several methods for determining a stable approximation to the system inverse, one of which uses standard identification methods to fit a model to the inverse of the frequency response [14]. To address stability in modeling the inverse of $S(q)$ first recognize that the system only deals with periodic disturbances.

The periodic disturbance $d(t)$ acts only at frequencies $\omega_k \in \Omega$, where

$$\begin{aligned}\Omega \;=\; & \Big\{\omega_k \mid \omega_k = \frac{k}{N} 2\pi f_s,\ k = 1, ..., \frac{N}{2}\ (for\ N\ even) \\ & or\ k = 1, ..., \frac{N-1}{2}\ (for\ N\ odd)\Big\}\end{aligned} \tag{6}$$

are integer multiples of the first harmonic frequency up to ω_N of the discrete time system with sampling frequency f_s. The learning convergence condition (4) can be rewritten as

$$|1 - S(e^{j\omega_k})G_f(e^{j\omega_k})| < 1 \tag{7}$$

since there is no disturbance effect between the frequencies ω_k. This provides the following conditions for the design of the learning filter

(i) $G_f(e^{j\omega_k}, \theta) \approx S^{-1}(e^{j\omega_k})$ s.t. (7) holds
(ii) $G_f(q, \theta) \in \mathcal{RH}_\infty$

where θ describes the parameter vector of the learning filter. The approximation in (i) must be done such that condition (7) holds. Furthermore, the rate at which the individual frequency components of the error converge in the iteration domain depends upon $|1-S(e^{j\omega_k})G_f(e^{j\omega_k})|$ evaluated at the frequencies ω_k. The smaller the value over all frequencies the faster the convergence of the learning algorithm.

For the computation of $G_f(e^{j\omega_k}, \theta)$ consider the frequency response $\hat{S}(e^{j\omega})$ of a model of the actual sensitivity function. The model $\hat{S}(q)$ can be parameterized as an approximation of the sensitivity function over the entire frequency range or just at frequencies ω_k such that $\hat{S}(e^{j\omega_k}) \approx S(e^{j\omega_k})$. Although a model structure for $G_f(q, \theta)$ that satisfies conditions (i) and (ii) is not unique, consider the ILC update algorithm (2) with the following finite impulse response (FIR) filter design.

$$G_f(q, \theta) = \sum_{k=0}^{N-1} \theta_k q^{-k} \quad \text{s.t.} \quad \sum_{k=0}^{N-1} \theta_k = 0 \tag{8}$$

The condition on the sum of the parameters equating to zero guarantees that the filter $G_f(q, \theta)$ has a DC gain of zero, since no compensation for DC components is required. In order to make $G_f(e^{j\omega_k}, \theta) = \hat{S}^{-1}(e^{j\omega_k})$ the parameters θ_k in the FIR filter of $G_f(q, \theta)$ given by (8) can be computed as follows

$$\overline{\theta}_k = \mathcal{F}^{-1}\left\{\hat{S}^{-1}(e^{j\omega_k})\right\}, \quad \theta_k = \overline{\theta}_k - \frac{1}{N}\sum_{k=0}^{N-1} \overline{\theta}_k \tag{9}$$

where $\mathcal{F}^{-1}\{\cdot\}$ denotes the inverse discrete Fourier transform (IDFT). The parameters θ_k are the N coefficients of a FIR model that exactly matches the frequency response of $\hat{S}^{-1}(e^{j\omega_k})$ at frequencies $\omega_k \in \Omega$. FIR models are by definition stable therefore condition (ii) is satisfied trivially. The FIR model structure provides an additional implementation advantage since the ILC update law (2) is linear in the parameters θ and the error signal $e(t)$

$$\begin{aligned} z_{i+1}(t) = z_i(t) \quad &+ \quad \theta_0 e_i(t) + ... \\ &+ \quad \theta_{N-1} e_i(t - N - 1) \end{aligned} \tag{10}$$

where (10) only requires multiplication and addition computations of the shifted error signal that can be implemented efficiently in a digital signal processor (DSP) environment.

D. Robustness to Model Uncertainties

A robust convergence criteria can be used to guarantee convergence of the ILC algorithm in the presence of uncertainties that arise from the learning filter designed from either a nominal model $\hat{S}(e^{j\omega})$ or frequency response measurements $S(e^{j\omega})$. Different approaches have been considered for adding robustness to ILC update algorithms with respect to modeling uncertainties, see e.g. [15], [16]. Following [7] the learning filter can be designed such that the convergence condition (7) is robustly satisfied. Consider uncertainty on the measurements $S(e^{j\omega_k})$ be characterized by $\mathcal{S}(e^{j\omega_k})$,

$$\begin{aligned}\mathcal{S}(e^{j\omega_k}) = \Big\{ & S(e^{j\omega_k}) \mid \hat{S}(e^{j\omega_k}) - \underline{\beta}_k < |S(e^{j\omega_k})| < \\ & \hat{S}(e^{j\omega_k}) + \overline{\beta}_k; \quad \angle\hat{S}(e^{j\omega_k}) - \underline{\varphi}_k < \angle S(e^{j\omega_k}) < \\ & \angle\hat{S}(e^{j\omega_k}) + \overline{\varphi}_k; \quad \forall\omega_k \in \Omega \Big\}\end{aligned} \tag{11}$$

where $\underline{\beta}_k$, $\overline{\beta}_k$ and $\underline{\varphi}_k$, $\overline{\varphi}_k$ are frequency dependent parameters that overbound the uncertainty in magnitude and phase respectively. Then the ILC convergence criteria (7) for periodic disturbances converges robustly provided

$$\max_{S \in \mathcal{S}} |1 - S(e^{j\omega_k})G_f(e^{j\omega_k})| < 1, \quad \forall\omega_k \in \Omega. \tag{12}$$

The uncertainty set (11) encompasses various uncertainty descriptions, additive, multiplicative, etc., which can be represented as enclosed regions $\mathcal{S}(e^{j\omega_k})$ centered around the nominal frequency response $\hat{S}(e^{j\omega})$ in the complex plain [17]. The parameters $\underline{\beta}_k = \overline{\beta}_k$ and $\underline{\varphi}_k = \overline{\varphi}_k$ are then the magnitudes and phases of the uncertainty overbound evaluated at the frequencies $\omega_k \in \Omega$.

III. Including Robustness to Non-repeatable Disturbances

Consider the case where the disturbance $d_i(t)$ contains both periodic and non-periodic components $d_i(t) = d(t) + \tilde{d}_i(t)$. Without adding much to the complexity of the learning algorithm, robustness to non-periodic disturbances can be designed into the learning system by introducing an additional filter. The ILC update algorithm (2) becomes

$$z_{i+1}(t) = Q(q)\left[z_i(t) + G_f(q)e_i(t)\right] \tag{13}$$

where Q is a linear, possibly non-causal filter. The current iteration feedback error is then derived as follows:

$$\begin{aligned} e_{i+1}(t) &= \hat{r}_{i+1}(t) - \hat{y}_{i+1}(t) \\ &= S(q)[r(t) - d_{i+1}(t) - z_{i+1}(t)] \\ &= S(q)[r(t) - d_{i+1}(t) - \\ &\qquad Q(q)(z_i(t) + G_f(q)e_i(t))] \end{aligned}$$

add and subtract $S(q)Q(q)[r(t) + d_i(t)]$ to obtain

$$\begin{aligned} e_{i+1}(t) = Q(q)[1 - S(q)G_f(q)]e_i(t) + [1 - Q(q)]S(q)r(t) \\ + S(q)[Q(q)d_i(t) - d_{i+1}(t)]. \end{aligned} \tag{14}$$

The convergence condition is determined from the homogeneous part of the error propagation (14) where a sufficient condition for convergence is given by [9]

$$|1 - S(e^{j\omega})G_f(e^{j\omega})| < |Q^{-1}(e^{j\omega})| \quad \forall\ \omega. \tag{15}$$

A filter Q with gain less than one, in some frequency range, increases the region of stability for the learning control algorithm. However, the increased stability region comes with a price in that the error can no longer be completely eliminated. This can be seen directly from (14) or via asymptotic analysis of the learning algorithm [9]. Design of the learning filter according to (8) and (9), directly minimizes the left hand side of the argument in (15) at frequencies $\omega_k \in \Omega$. However for frequencies $\omega \notin \Omega$ the filter Q can be designed to provide stability of the learning algorithm is the presence of non-repeatable components in the disturbance.

IV. Experimental Results

A. Application to HDD

The servomechanism of disk drives operates by the feedback of PES perturbed by disturbances that are a combination of the repeatable and non-repeatable run-out. For certain HDD applications, such as two-stage servo track writing and read/write head testing, the objective is to follow a virtual perfect circle track. This is equivalent to assuming periodically perturbed measurements of the PES and providing reduction of the periodic disturbances via disturbance canceling reference signals.

The experimental system consists of a 2.5” magnetic disk drive with specifications presented in Table I. The disk drive servo processor is replaced by a DSP and host computer that allow access to the PES and have the capacity to input modified reference signals to the system.

TABLE I

Experimental Disk Drive Specifications

Spindle motor speed	$4200rpm(70Hz)$
Number of data sectors, N	120
Servo sampling frequency, f_s	$8.4KHz$
Track pitch	$8\mu in$

The HDD system can be represented by the general LTI discrete time system described in Section II-A, where the finite time interval $t = 0, ..., N$ corresponds to the number of sectors on the disk. The learning system of Figure 2 generates the current iteration signal based on information from previous iterations. Under the assumptions of ILC, at the end of each finite time interval the initial conditions of the system are reset, with the exception of the non-repeatable disturbances. The periodic disturbance $d(t)$ includes RRO effects such as the written in eccentricity of the track that contribute to the PES, $e(t)$, and appear at integer multiples of the frequency of rotation of the disk. The non-periodic disturbance $\tilde{d}_i(t)$ includes effects such as windage and measurement noise which are generally zero-mean. Both repeatable and non-repeatable components for the disturbance can be seen in Figure 3 where 60 rotations of the disk are shown as well as the average leaving on the periodic disturbance effect on the PES.

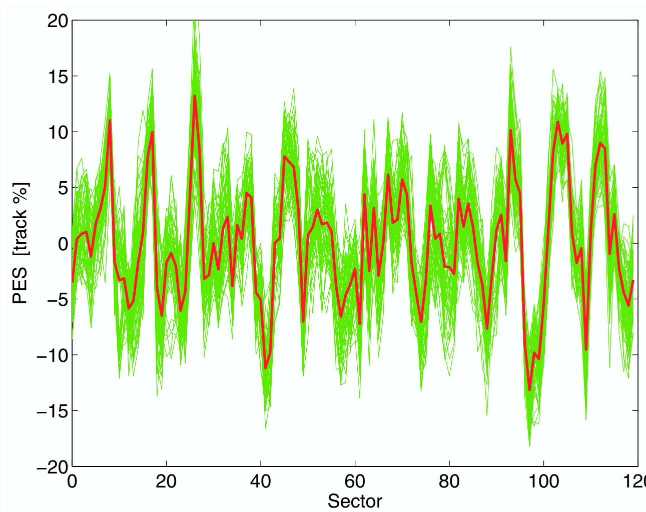

Fig. 3. Sector plot of the original PES (grey) and the averaged PES (dark).

Closed-loop disturbance rejection or amplification is determined by the sensitivity function. Measured closed-loop frequency response data along with a 5th order model for the sensitivity function, $\hat{S}(q)$, are presented in Figure 4 for the disk drive system.

For designing the nominal learning filter the disk drive sensitivity function model $\hat{S}(q)$ is not stably invertible and thus its inverse can not be used directly. Motivated by the procedure in Section II-C, the sensitivity model is used

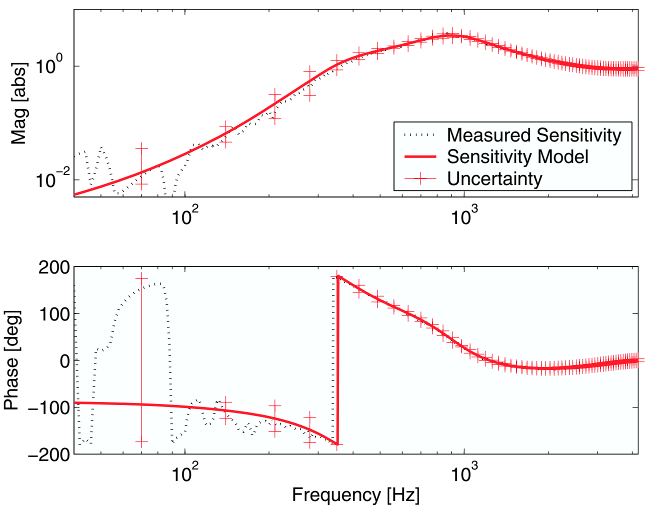

Fig. 4. Measured closed-loop sensitivity frequency response (dotted line) and 5th order model $\hat{S}(e^{j\omega})$ (solid line).

to generate closed-loop frequency response $\hat{S}(e^{j\omega})$ at the frequencies of the periodic disturbance ω_k, where $\omega_k = [70, 140, ..., 4200]Hz$ are the integer multiples of the frequency of rotation up to the Nyquist frequency. FIR model coefficients, θ_k, are generated from the inverse of the closed-loop frequency response of $\hat{S}^{-1}(e^{j\omega_k})$. The FIR model $G_f(q, \theta)$ describes a stable system that exactly intersects the frequency response of $\hat{S}^{-1}(e^{j\omega_k})$ at the frequencies ω_k, as shown in Figure 5.

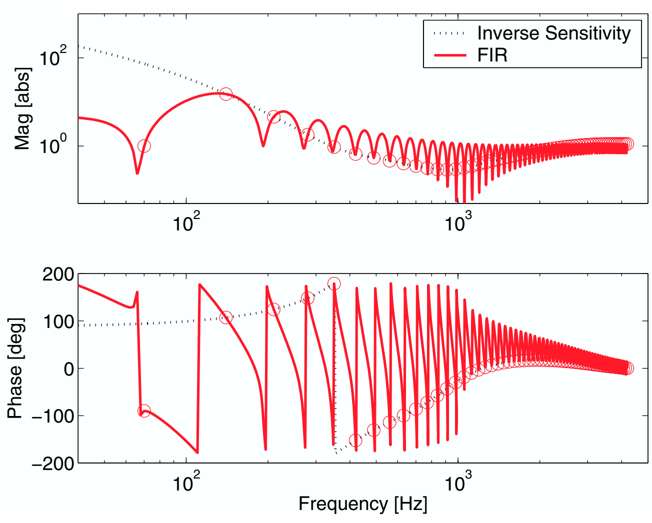

Fig. 5. Frequency response of FIR model $G_f(q, \theta)$ approximation (solid line) to $\hat{S}^{-1}(e^{j\omega})$ (dotted line) and the intersection of the FIR model with $\hat{S}^{-1}(e^{j\omega})$ at ω_k (circles).

In [7] the effects of non-repeatable disturbances are overcome by averaging over the sector interval the PES measurement taken over many disk rotations. It was shown that only a few iterations were required to reach sufficient level of periodic disturbance rejection, but at the cost of many overall rotations of the disk for averaging. Robustness to non-periodic disturbances can be provided through additional filtering of the ILC update algorithm (13). The Q-filter is chosen such that stability of the learning system is provided over all ω. The evaluation of Q is achieved as an over bound of the convergence condition magnitude (12), as shown in Figure 6, where the Q-filter is constructed from notch filter with lead compensation in order to maintain low computational complexity in the learning algorithm.

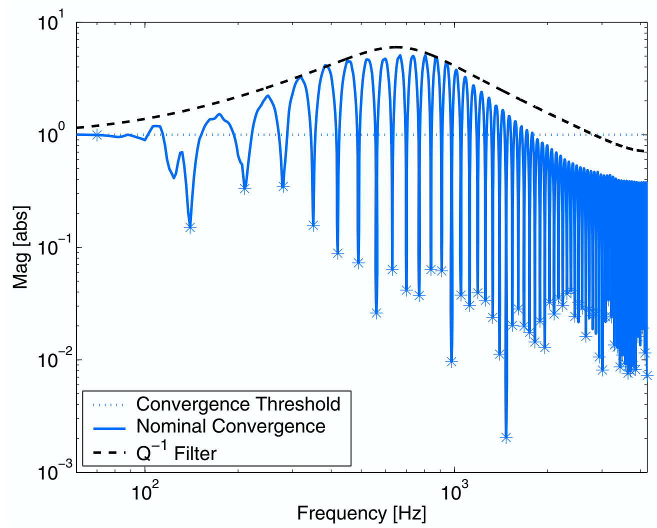

Fig. 6. Iterative learning control convergence condition (solid-line) and the inverse of filter Q (dashed-line) designed for robustness against non-periodic disturbances.

B. Application of the ILC Algorithm

For one rotation of the disk drive, distinguishing repeatable from non-repeatable disturbances is a difficult task. The experiment conducted used four rotations of the disk for every iteration of the ILC learning algorithm. Although with every rotation more is learned about the realization of the repeatable disturbance, with as few as four iterations there remains significant non-repeatable disturbances to effect the averaged PES measurement. Application of the robust learning algorithm given in (13) demonstrates that although more iterations are required convergence is robustly satisfied, see Figure 7.

Despite the larger number of iterations required by the robust ILC algorithm, the amount of disk rotations and thus the overall time required reach sufficient levels periodic disturbance rejection is greatly reduced. Note however, that using the robust ILC algorithm no longer allows arbitrary reduction of the repeatable disturbance.

V. Conclusions

In this paper iterative learning control for the design of reference signals has been developed for the reduction of periodic measurement disturbances in the presence of non-periodic measurement disturbances. The ILC method is illustrated with experimental results on a hard disk drive where issues of computational complexity and robust implementation have been addressed. The contributions of this paper

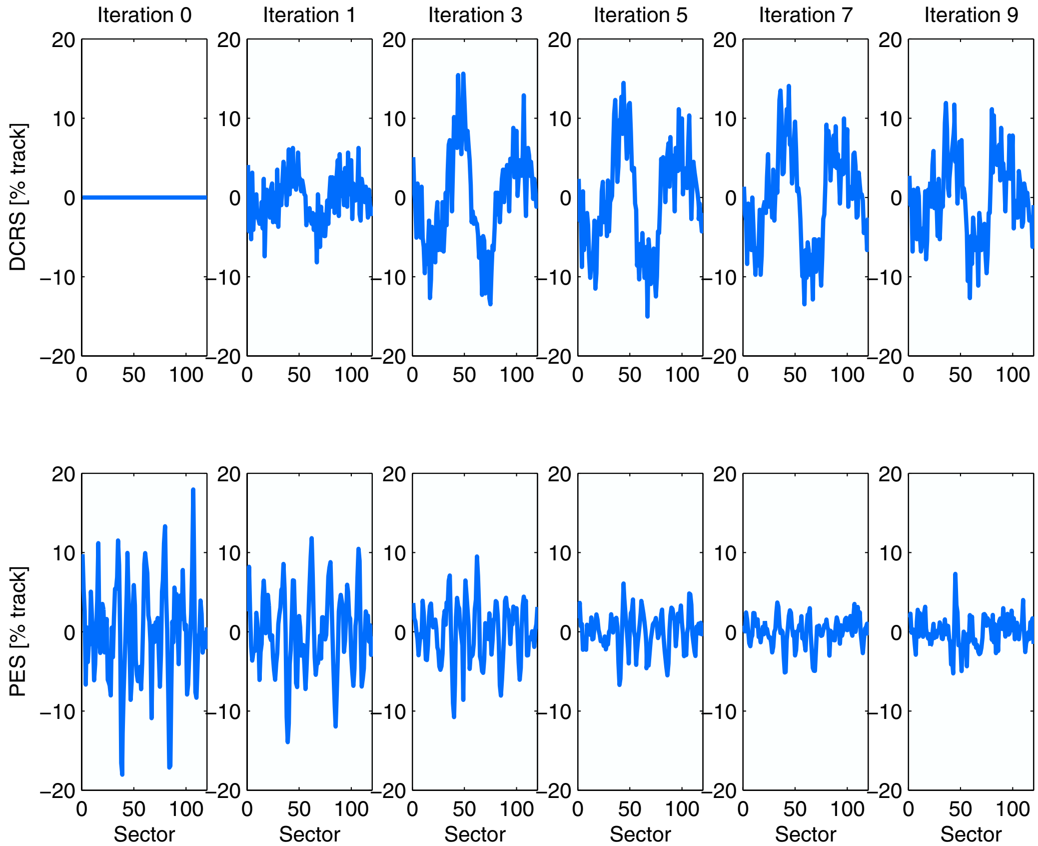

Fig. 7. Odd iterations 0 through 9 with DCRS $z_i(t)$ (top plot) and resulting PES $e_i(t)$ (bottom plot).

are to discuss the robustness of the nominal learning filter design and demonstrate experimentally the effectiveness of robust ILC reference design methods for improving control performance in the presence of non-repeatable disturbances. Convergence robustness provides the tradeoff between the number of averages versus the number of iterations required in effectively reducing repeatable disturbances.

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