Combined Feedforward/Feedback Control for Tape Head Track-Following Servo Systems

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Abstract: In order to remain competitive with other data storage technologies, the tape industry is planning to significantly increase track densities on tape. Higher track densities require narrower track pitch and more precise positioning of the read/write heads. Hence, improved track-following servo systems for the head assembly are needed. Longitudinal transport of the tape along the tape path is subject to lateral disturbances that cause displacement between the head and the desired track and hence increase position error. This paper proposes a combined feedforward/feedback control scheme to improve the track-following performance of the tape head positioning system in the presence of lateral tape motion (LTM). In this architecture, the feedback controller is designed to guarantee system stability and take into account the lower frequency components in the disturbances. The feedforward controller requires as its input a prediction of the lateral tape motion displacement (LTMD) at the head assembly. We propose a least squares based algorithm to predict the LTMD at the head from a history of upstream and downstream LTMD measurements. Compared to using feedback-only control, the combined feedforward/feedback controller enables the head assembly to be positioned more accurately over the desired track.

Keywords: Feedforward control; Mechatronics; Tape storage systems.

1. INTRODUCTION

Tape storage is currently the least expensive solution for backing up large amounts of data. Furthermore, it consumes less energy than hard disk drive technologies. To retain a competitive storage capacity compared with other data storage technologies, the tape industry is planning to increase areal storage capacity and data transfer rates. Increasing track density on tape has been identified as a critical step to achieve higher areal densities. Track density is the number of data tracks per inch (TPI) laterally across the width of the tape. The current track densities in contemporary half-inch wide tape are about 3000 TPI. An industry roadmap [INSIC Roadmap (2008)] projects that tape track densities must reach 24 KTPI by 2018. As the TPI increases, the track pitch becomes narrower, and more precise positioning of the read/write heads is needed. This requires further reduction of the position error between the head assembly and the desired track.

When the tape transports, it tends to vibrate in the lateral direction (perpendicular to the transport direction). Lateral tape motion (LTM) can misalign the head and the desired track and increase position error. A review of measurements and sources of LTM is given in [Raeymaekers and Talke (2009)]. The typical peak-to-peak amplitude of measured LTM in an operating tape drive is about 10 μm [Kartik (2006)].

There are two approaches to reduce position error arising from lateral tape motion. The first approach tries to reduce the LTM from the source by applying more advanced guiding in the tape path. The use of externally-pressurized porous air bearing guides and friction guiding are discussed in [Kartik (2006)]. In [Xia and Messner (2010)], the authors describe an active steering system that compensates the lateral tape motion by tilting the guides. These approaches require installation of additional hardware in the tape drive and often change the tape transport path.

The second approach aims to reduce the effects of the LTM on the position error by improving the track-following performance of the head servo mechanism. Existing tape head positioning servo systems typically use proportional-integral-derivative (PID) feedback controllers, and the higher-frequency components in the LTM are beyond the bandwidth of typical closed-loop systems. A robust estimation and adaptive controller tuning (REACT) compensator that increases the bandwidth of the closed-loop tape head positioning servo system is developed in [de Callafon and Kinney (2010)]. In the REACT controller, the basic PID controller is augmented with an additional feedback loop that is tuned to minimize the output error.

This paper proposes to apply a feedforward controller in combination with the REACT feedback controller to further reduce the position error caused by the LTM. In this architecture (Fig. 1), the feedback controller is designed to guarantee system stability and address lower frequency components in the position error. The feedforward controller requires a prediction of the lateral tape motion displacement (LTMD) at the head in order to generate a feedforward input \( u_{ff} \) to the tape head that ideally would cancel the position error caused by the LTM. The main contributions of this paper include a) the development of a LTMD predictor that provides predicted LTMD to the feedforward controller; and b) the comparison of different feedforward controllers developed for this application.

The rest of this paper is organized as follows. In Section 2, we first introduce the model of a typical tape head track-following

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Fig. 1. Combined feedforward/feedback control structure for tape head positioning system.

In this study, the authors describe an algorithm for predicting the LTMD data used in the study, simulation results of applying the predictor on both synthesized and actual LTMD data, demonstrating the effectiveness of the predictor. Discussions on the feasibility of implementing the predictor on an actual tape drive are also included in Section 3. Section 4 outlines the overall combined feedforward/feedback control scheme and presents initial simulation results of different feedforward controller algorithms. Finally, Section 5 provides conclusions and a discussion of future work.

2. TAPE HEAD TRACK FOLLOWING SYSTEM

An example of a reel-to-reel tape system is shown in Fig. 2. This schematic is modified from the graphical user interface of a LTMSim tool (LTMSim) [Wickert and Brake (2007)].

Fig. 2. Schematic of tape head track-following system.

The tape winds longitudinally between the source reel and the take-up reel. It passes over the head, where data is read or written to the tape. Data is stored on the tape in tracks parallel to the longitudinal motion of the tape and data track spans the entire length of the tape. Contemporary tape is 0.5 inches wide and there are typically over a thousand tracks across the width of the tape. A voice coil actuator moves the head assembly in the lateral direction to position the head on the desired track.

When tape transports longitudinally between the two reels, it can exhibit lateral motion. One primary purpose of the head positioning servo system is to follow the desired data track as accurately as possible during read/write operations in spite of disturbances such as the lateral tape motion. Both the tape and the head can also have out-of-plane motion. This study focuses only on the in-plane motion of the tape and the head.

2.1 System Model

A voice coil actuator moves the head assembly laterally with respect to the tape. The motion of the head is restrained by flex circuits that provide signals from the head to the read/write channel. This coupling can be simply modeled as a spring-mass-damping system with a couple of resonances. Ignoring the out-of-plane motion, a typical tape head track-following system has one resonance usually in the 10-100s Hz range and another one in the 1-10 KHz range. Hence, a transfer function model from the voice coil motor current to the head position is

\[ G(s) = \frac{K \omega_1^2 \omega_2^2}{(s^2 + 2 \zeta_1 \omega_1 s + \omega_1^2)(s^2 + 2 \zeta_2 \omega_2 s + \omega_2^2)} \]

where \( \omega_i \) (\( i = 1, 2 \)) are the two resonances and \( K \) is a gain. In this study, \( \omega_1 \) is chosen to be 100 Hz and \( \omega_2 \) is set to 1 KHz. The damping ratios are \( \zeta_1 = 0.0796 \) and \( \zeta_2 = 0.05 \) and the gain \( K = 2000 \). The system is modeled in the discrete-time domain assuming the use of a zero-order-hold (ZOH) on all inputs as in [Franklin et al. (1998)]. When the sampling rate is 10 KHz, the discrete-time transfer function is

\[ G(z) = \frac{0.12633(z + 9.52)(z + 0.9853)(z + 0.102)}{(z^2 - 1.986z + 0.99)(z^2 - 1.569z + 0.9391)} \]

The non-minimum phase (NMP) zero at \(-9.52\) is due to the fast sampling rate [Åström et al. (1984)]. The Bode plot of the discrete-time model is depicted in Fig. 3.

Fig. 3. Bode plot of the tape head track-following model at a sampling frequency of 10 KHz.

2.2 Lateral Tape Motion

Sources that excite LTM include the radial runout of reels/rollers and the impacts between the tape and the flanges of the reels/rollers. If LTM is not addressed, it generates position error between the head and the desired track, as shown in Fig. 4.

The dark line shows the data track position variation due to lateral motion and the grey line is the controlled head position without addressing LTM. The displacement caused by lateral tape motion is one of the most critical factors limiting track densities on tape. Here, we assume that the data tracks on the tape are perfectly parallel with the edges of the tape. This is usually not true in a real tape cartridge because a) the edge of the tape is not perfectly straight due to manufacturing constraints; and b) tracks on the tape contain written-in error. However, the majority of the position error caused by the misalignment between the edges and the track is in a lower frequency range that can be addressed by the feedback controller.
3. PREDICTION ALGORITHM

A good prediction of the LTMD at the head can help the servo system to align the head assembly with the desired track in the presence of LTM. We propose an algorithm to predict the LTMD \( w_h \) at the head from a history of the upstream \( w_u \) and downstream \( w_d \) LTMDs near the head. In practice, edge sensors may be placed at both upstream and downstream locations of the head to measure \( w_u \) and \( w_d \), as shown in Fig. 4. Since tape winds in both forward and reverse directions, the sensors should be placed at locations symmetric to the head.

Define the vector of a sequence of \( k_p \) past upstream LTMD measurements at time step \( k \) as \( k_p w_u, k \) and the vector of past downstream LTMD measurements as \( k_p w_d, k \).

\[
\begin{align*}
  k_p w_u, k &= [w_{u, k-1}, w_{u, k-2}, \ldots, w_{u, k-k_p}] \\
  k_p w_d, k &= [w_{d, k-1}, w_{d, k-2}, \ldots, w_{d, k-k_p}].
\end{align*}
\]

The prediction of \( w_h \) at \( N \) \((N \geq 0)\) samples in advance can be computed from the history of the upstream and downstream LTMD measurements as

\[
\hat{w}_{h, k+N} = \Phi_{udh} (k_p w_u, k, k_p w_d, k).
\]

The correlation between successive LTMDs is incorporated into the predicting function \( \Phi_{udh}(\cdot) \). We initially assume \( \Phi_{udh}(\cdot) \) to be a linear function. In future work, more complex nonlinear functions will be investigated for \( \Phi_{udh}(\cdot) \).

3.1 Least Squares Algorithm

To determine the linear predicting function \( \Phi_{udh}(\cdot) \) that correlates \( w_u, w_d \), and \( w_h \), Equation (2), a least squares based algorithm is developed. Define the coefficient vectors

\[
\begin{align*}
  a_u &= [a_{u1}, a_{u2}, \ldots, a_{u_{k_p}}]^T \\
  a_d &= [a_{d1}, a_{d2}, \ldots, a_{d_{k_p}}]^T,
\end{align*}
\]

where \([\cdot]^T\) denotes the transpose of \([\cdot]\). The predicted LTMD at the head then is

\[
\hat{w}_{h, k+N} = k_p w_u, k \cdot k_p w_d, k \cdot [a_u \ a_d]^T.
\]

Letting \( k_p w_{ud, k} = k_p w_u, k \cdot k_p w_d, k \) and \( a_{ud} = [a_u^T \ a_d^T]^T \), Equation (3) becomes

\[
\hat{w}_{h, k+N} = k_p w_{ud, k} \cdot a_{ud}.
\]

The optimal value \( a_{ud}^* \) of the coefficient vector is computed offline by

\[
a_{ud}^* = \arg \min_{a_{ud}} \sum_{i=0}^{M-1} \left[ w_{h, k+N+i} - \hat{w}_{h, k+N+i} \right]^2 \]

\[
= \arg \min_{a_{ud}} \sum_{i=0}^{M-1} \left[ w_{h, k+N+i} - k_p w_{ud, k+i} a_{ud} \right]^2. \quad (4)
\]

Here, the LTMD data is measured synchronously. \( M \) is the total number of LTMD samples used for optimization. The least squares method minimizes the difference between the measured and predicted LTMD at the head, \( w_h \) and \( \hat{w}_h \), respectively.

The prediction error \( w_{eh}, k \) is defined as

\[
w_{eh}, k = w_{h, k} - \hat{w}_{h, k} = w_{h, k} - k_p w_{ud, k-N} a_{ud}^* \quad (k > M+N).
\]

Denoting the maximum and minimum value of \( w_h \) as \( w_{h, \text{max}} \) and \( w_{h, \text{min}} \), respectively, the normalized root mean square (NRMS) of the error then is

\[
\text{NRMS} = \frac{\|w_{eh}\|_2}{\sqrt{P(w_{h, \text{max}} - w_{h, \text{min}})}}.
\]

Here, \( \| \cdot \|_2 \) denotes the 2-norm and \( P \) is the number of samples evaluated. The NRMS of the prediction error is a metric to evaluate the performance of the algorithms in this study.

It should be noted that this algorithm requires knowledge of \( M \) data samples of actual \( w_h \). In general, more data points of actual \( w_h \) (larger \( M \)) used to solve for \( a_{ud}^* \) and a longer history of the information vector \( k_p w_{ud, k} \) (larger \( k_p \)) lead to less prediction error. At the same time, larger \( M \) and \( k_p \) increases the computational complexity required to solve for the optimal value of the coefficient vector. Hence, there is a trade-off between the performance and cost of the algorithm.

3.2 Lateral Tape Motion Displacement Data

We first evaluate the prediction performance of the coefficients computed by the least squares method on an artificially synthesized lateral tape motion displacement (LTMD) data set and then on an actual LTMD data set measured from an industrial tape system testbed.

Synthesized LTMD Data. The artificial LTMD data is synthesized by a number of sinusoidal components [Brake (2007)],

\[
w(x, t) = \sum_{j=1}^{J} A_j \sin \left( \frac{2\pi}{\lambda_j}(x - vt) \right).
\]

Here, \( x \) is the distance between the starting point of the tape path and the location of interest. The full length of the tape path is from the tangential point of the source reel to that of the take-up reel. \( w(x, t) \) is the lateral tape motion displacement at location \( x \) and time \( t \). \( v \) is the tape longitudinal velocity, \( J \) is the total number of sinusoidal components, and \( A_j \) and \( \lambda_j \) are the magnitude and wavelength of each component, respectively.

Defining the distance between the head and the starting point of the tape path as \( x_h \), the LTMD at the head \( w_h(t) \) is then

\[
w_h(t) = \sum_{j=1}^{J} A_j \sin \left( \frac{2\pi}{\lambda_j}(x_h - vt) \right).
\]

The upstream LTMD \( w_u(t) \) and downstream LTMD \( w_d(t) \) can be determined in a similar way.
The synthesized LTMD data used in this study consists of a total of 20 different sinusoidal components, i.e., $J = 20$. The length of the tape path is 0.4 m, and the head is at the middle of the path, i.e., $x_h = 0.2$ m. The distance between the head and the upstream and downstream edge sensors is set to be 0.003 m, which is approximately the closest distance that photonic edge sensors can be placed next to the tape head. The tape longitudinal velocity $v$ is 5 m/sec. The frequencies of the components are randomly chosen between 5 Hz and 1 KHz and the magnitudes are randomly picked between 0.05 and 1.

The performance of the prediction algorithm (Equation (3)) depends on the values of $k_p$, $M$, and $N$. Fig. 5 illustrates the NRMS of the prediction error on synthesized LTMD data for different combinations of $k_p$ and $M$ values when $N = 10$.

![Fig. 5. The performance of the prediction algorithm depends on $M$ and $k_p$. In this simulation, $M = 500$ and $k_p = 10$ predicts $\bar{w}_h$ 10 samples ahead of time reasonably well.](image)

Generally speaking, larger $M$ and $k_p$ yield better prediction of the LTMD at the head. In this simulation, the NRMS of the prediction error is on the order of $10^{-7}$ when $M = 500$, $k_p = 10$, and $N = 10$.

**Actual LTMD Data.** The actual LTMD data set includes upstream and downstream LTMDs measured by photonic edge sensors placed near the head of an actual tape system. The purple line in the top plot of Fig. 6 is $w_u$ and the blue line in the bottom plot depicts the downstream LTMD $w_d$. The LTMD at the head, however, is not available for the tape drive under investigation because there is not enough room to place an edge sensor at the head. Due to the proprietary nature of the data, its magnitude is normalized so as not to divulge the actual LTMD measurements. Results of spectrum analysis on the LTMD data set show that $w_u$ and $w_d$ contain the same frequency components.

Since the LTMD at the head of the tape drive under investigation cannot be measured at this time, the $M$ samples of $w_h$ required to solve the coefficient vector $\mathbf{a}_u^*$ are not available. To demonstrate the performance of the prediction algorithm, we evaluate the algorithm on actual LTMD measurements by predicting the downstream LTMD $\bar{w}_d$ from the upstream LTMD $w_u$ data. $M$ samples of the available $w_u$ data is used to solve for the correlation function $\Phi_{u,d} (\cdot)$ for $\bar{w}_d$ in a similar way as discussed in Section 3.1, using $w_u$ only as the data vector. The prediction error $w_{ed}$ is then computed based on the differences between the estimated $\bar{w}_d$ and actual $w_d$ data.

![Fig. 6. Actual upstream and downstream LTMD measurements from a tape drive system. The magnitude is normalized due to intellectual property protection reasons.](image)

Fig. 7 depicts the NRMS prediction errors of predicting the downstream LTMD $\bar{w}_d$ 10 samples ahead of time from $w_u$, with different combinations of $M$ and $k_p$ values. The NRMS of the prediction error is on the order of $10^{-2}$. As seen before, larger $M$ and $k_p$ generally lead to better prediction. Considering computational efficiency, the combination of $M = 300$ and $k_p = 30$ yields a reasonably good predicted $\bar{w}_d$. When $N$ equals 10, the NRMS is about 0.056. Fixing the values of $M$ and $k_p$, the prediction error increases as $N$ increases (Fig. 8).

![Fig. 7. The NRMS of the prediction error $w_{ed}$ decreases when $M$ and $k_p$ increase.](image)

Note that the distance between the head and the upstream location is shorter than that between the upstream and downstream locations. Intuitively, $w_h$ and $w_u$ should be better correlated than $w_d$ and $w_u$. Thus, the prediction algorithm should yield at
least the same performance when predicting \( w_h \) from \( w_u \), if \( M \) samples of \( w_h \) are available to solve for the coefficient vector.

### 3.3 Implementation Feasibility

There are a few concerns when implementing this algorithm on a tape drive. First, before accurate track following can occur, the least squares algorithm requires a certain length of tape to allow training data to be collected and used to determine the correlation for predicting the LTMD at the head. For the example tape system used in this study in which the sampling frequency is 10 kHz and the tape longitudinal velocity is 5 m/sec, when \( M = 300 \), \( k_p = 30 \), and \( N = 10 \), the required length of tape to collect training data is about 0.15 m.

Second, after collecting the training data set, the least squares problem described in Equation (4) is solved for \( \mathbf{a}_{m,d}^* \) using batch processing. The total number of floating point operations needed to solve a least squares problem

\[
y^* = \arg\min_y \| Ay - b \|^2, \quad A \in \mathbb{R}^{m \times n} \quad (m > n)
\]

\[
flops = 2mn^2 + 2mn + n^2.
\]

The computational complexity to determine \( \mathbf{a}_{m,d}^* \) then is

\[
flops = 8Mk_p^2 + 4Mk_p + 4k_p^2.
\]

When \( M = 300 \) and \( k_p = 30 \), it is about 250,000 flops. Assuming the speed of the DSP board used in the tape drive is 250 MHz, an approximate estimate of the calculation time is about 1 ms. This requires an additional 0.005 m of tape.

Finally, the closer the edge sensors are placed to the head, the better correlated the successive LTMDs are. In practice, the distance between the head and the sensor is restricted by the physical size of the components. The optimal distance also depends on the online time the algorithms need to predict \( w_h \) from \( w_u \) and \( w_d \) measurements.

### 4. COMBINED FEEDFORWARD/FEEDBACK CONTROL

Once the prediction coefficients are determined, they are used to predict \( \hat{w}_h \) in the combined feedforward/feedback control architecture, as illustrated in Fig. 9.

Fig. 9. Block diagram of the combined feedforward/feedback control scheme for a tape head track-following system.

The plant \( G \) represents the dynamics of the tape head track-following system, as given in Equation (1). The saturation block limits the size of the input to the plant. The feedback controller \( C_{fb} \) is designed to guarantee system stability and address lower frequency components in the position error.

The disturbances consist of two components: a) the lateral tape displacement \( w_h \) at the head; and b) the sum of other noise disturbances \( N_u \). \( G_{cw} \) and \( G_{cen} \) are the transfer functions from the two disturbances to the position error. The noise disturbances \( N_u \) are highly uncorrelated and addressed by the feedback control input \( u_{fb} \) only. The feedforward controller \( C_{ff} \) generates a feedforward input \( u_{ff} \) that ideally would cancel the position error caused by the lateral tape motion disturbances. The input to \( C_{ff} \), \( \hat{w}_h \), is the prediction of the LTMD at the head.

### 4.1 Feedback Controller

The feedback controller used in the tape industry is usually a simple PID controller. In this study, we adopt the more advanced robust estimation and adaptive controller tuning (REACT) controller [de Callafon and Kinney (2010)] for \( C_{fb} \). The REACT controller \( C_R \) is obtained by augmenting the basic PID controller \( C_{PID} \) with an additional feedback loop that can be tuned to minimize the output error, as shown in Equation (5).

\[
C_R = \frac{C_{PID} + Q}{1 - GQ}.
\]

Here, \( \hat{G} \) is the model of the plant and \( Q \) is the tuning parameter. Theoretically, \( Q \) can be any stable transfer function. We assume the model is perfect (\( \hat{G} = G \)) and design the basic PID controller to have a closed-loop crossover frequency at 500 Hz:

\[
C_{PID} = \frac{0.019363 - 0.04843z^{-1} + 0.0467z^{-2} - 0.01701}{z^3 - 1.785z^2 + 1.449z - 0.4067}.
\]

The tuning parameter \( Q \) is chosen to be a 7th-order FIR filter that minimizes the system output \( e \). The obtained REACT controller is a 14th-order transfer function.

### 4.2 Feedforward Control

In the tape head track-following system (Fig. 9), the position error \( e \) is

\[
e = \frac{G_{cw}w_h - GC_{ff}\hat{w}_h}{1 - GC_{fb}} + \frac{G_{cw}N_u}{1 - GC_{fb}}.
\]

\( G_{cw} \) is assumed to be a 4th-order low-pass filter with a bandwidth at 1 kHz in this study. We aim to attenuate the position error caused by \( w_h \) by designing the feedforward controller \( C_{ff} \) to minimize the first term in Equation (6). Four different methods are investigated to develop \( C_{ff} \): the zero magnitude error tracking control (ZMETC) [Rigney (2008) and references therein], the zero phase error tracking control (ZPETC) [Tomizuka (1987)], the Taylor series approximation method [Oppenheim et al. (1996)], and the \( H_\infty \) model matching method [Reyes et al. (1992)].

The first three methods each develop a feedforward controller \( C_{ff} \) that includes an approximate inversion \( G_{cw}^{-1} \) of the system dynamics \( G \). The tape head actuator dynamics (Equation (1)) contains a NMP zero at -9.52 and directly inverting the NMP zero will yield an unstable \( C_{ff} \). The ZMETC approach reflects the unstable zero about the unit circle and converts it to a pole in the inverse system, thereby inverting the magnitude response due to the NMP zeros. The ZPETC approach reflects the unstable zero about the unit circle and converts it to a pole in the inverse system, thereby inverting the magnitude response due to the NMP zeros. In this application, the performance of these two algorithms is very similar, so only simulation results for the ZMETC algorithm are presented.

The non-causal Taylor series approximates the inverted unstable pole with a non-causal, stable, Taylor series expansion. The higher the order of the series approximation, the smaller the
approximation error. Balancing improvements in the approximation accuracy against the increased order of the resulting inverse filter, we choose a third-order approximation.

As an alternative to approximate model inversion, we also employ a $H_{\infty}$ model matching method that minimizes the $H_{\infty}$ norm of the transfer function from the LTM disturbance to the position error $e$. Assuming $\hat{w}_h = w_h$, the feedforward controller then is

$$C_{ff} = \arg \min_{C_{ff}} \| G_{ew} - GC_{ff} \|.$$  

The Matlab robust control toolbox is used to design the $H_{\infty}$ feedforward controller.

4.3 Simulation Results

We implement the combined feedforward/feedback control scheme on the synthesized LTMD data. With the REACT feedback controller only, the position error is on the order of $10^{-1}$. Simulation results of the feedforward controller designed using the ZMETC method is shown in Fig. 10. The feedforward controller further attenuates the position error to the order of $10^{-2}$. Here, the parameters in the predictor are $M = 500$, $k_p = 30$, and $N = 10$.

![Simulation Results](image)

Fig. 10. The ZMETC feedforward controller further attenuates the position error caused by LTM.

Feedforward controllers designed using the Taylor series approximation method and the $H_{\infty}$ model matching method demonstrate similar attenuation in the position error, as shown in Table 1. The complexity of $C_{ff}$ designed using these three different methods is comparable. Both ZMETC and Taylor series approximation methods yield non-causal feedforward controllers that require knowledge of the input signal ahead of time. Since the input $\hat{w}_h$ to $C_{ff}$ is a prediction of $w_h$, the non-causal feedforward controllers are implementable.

Table 1. Comparison of the performance of different feedforward controllers.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Position Error</th>
<th>$C_{ff}$ Order</th>
<th>$C_{ff}$ Causality</th>
</tr>
</thead>
<tbody>
<tr>
<td>ZMETC</td>
<td>5e-3</td>
<td>8</td>
<td>Non-causal</td>
</tr>
<tr>
<td>Taylor Series</td>
<td>1e-4</td>
<td>8</td>
<td>Non-causal</td>
</tr>
<tr>
<td>$H_{\infty}$ Model Matching</td>
<td>5e-3</td>
<td>10</td>
<td>Strictly proper</td>
</tr>
</tbody>
</table>

5. CONCLUSIONS, DISCUSSION, AND FUTURE WORK

A combined feedforward/feedback control scheme to attenuate the position error caused by lateral tape motion in tape head track-following systems has been demonstrated. The feedback loop consists of a robust estimation for automatic controller tuning compensator. The feedforward controller requires as its input a prediction of the lateral tape motion displacement at the head. A least squares based algorithm is implemented to predict the LTMD at the head from a history of LTMD measurements adjacent to the head. Simulations results on synthesized data demonstrate that the combined feedforward/feedback control further reduces the position error caused by lateral tape motion.

We are currently working with our industry collaborators to obtain actual LTMD data at the head so as to fully implement and evaluate the developed predictor using actual LTMD data. In practice, the LTMD measurements from edge sensors might not be accurate enough to yield a good prediction of $w_h$. Hence, the possibility of using existing heads in the tape drive to measure upstream and downstream LTMDs is also under investigation. Moreover, the correlation between successive LTMDs is likely to be a non-linear relationship. Better understanding of the equations of motion for lateral tape motion [Wickert and Brake (2007)] will help us to determine a more accurate correlation function to predict the LTMD at the head.

ACKNOWLEDGEMENTS

This work has been partially sponsored by the Information Storage Industry Consortium and the Richard and Joy Dorf Professorship. We are also grateful for support from Oracle and the guidance from Mark Watson and Dan Underkofler.

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