Combined $H_\infty$-feedback control and iterative learning control design with application to nanopositioning systems

Brian E. Helfrich
Chibum Lee
Douglas A. Bristow
Missouri University of Science and Technology, dbristow@mst.edu
Jingyan Dong
Srinivasa M. Salapaka

Follow this and additional works at: http://scholarsmine.mst.edu/faculty_work

Part of the Aerospace Engineering Commons, and the Mechanical Engineering Commons

Recommended Citation
Helfrich, Brian E.; Lee, Chibum; Bristow, Douglas A.; Dong, Jingyan; Salapaka, Srinivasa M.; Ferreira, Placid M.; Xiao, X. H.; and Alleyne, Andrew G., "Combined $H_\infty$-feedback control and iterative learning control design with application to nanopositioning systems" (2010). Faculty Research & Creative Works. Paper 1559.
http://scholarsmine.mst.edu/faculty_work/1559

This Article is brought to you for free and open access by Scholars' Mine. It has been accepted for inclusion in Faculty Research & Creative Works by an authorized administrator of Scholars' Mine. For more information, please contact weaverjr@mst.edu.
Combined $H_\infty$-Feedback Control and Iterative Learning Control Design With Application to Nanopositioning Systems

Brian E. Helfrich, Chibum Lee, Student Member, IEEE, Douglas A. Bristow, X. H. Xiao, Jingyan Dong, A. G. Alleyne, Srivivasa M Salapaka, Member, IEEE, and Placid M. Ferreira

Abstract—This paper examines a coordinated feedback and feedforward control design strategy for precision motion control (PMC) systems. It is assumed that the primary exogenous signals are repeated; including disturbances and references. Therefore, an iterative learning control (ILC) feedforward control strategy can be used. The introduction of additional non-repeating exogenous signals, including disturbances, noise, and reset errors, necessitates the proper coordination between feedback and feedforward controllers to achieve high performance. A novel ratio of repeated versus non-repeated signal power in the frequency domain is introduced and defined as the repetitive-to-non-repetitive (RNR) ratio. This frequency specific ratio allows for a new approach to delegating feedback and feedforward control efforts based on RNR value. A systematic procedure for control design is given whereby the feedback addresses the non-repeating exogenous signal content (RNR < 0 dB) and the feedforward ILC addresses the repeating signal content (RNR > 0 dB). To illustrate the design approach, two case studies using different nano-positioning devices are given.

Index Terms—Iterative learning control (ILC), nanopositioning, precision motion control (PMC).

I. INTRODUCTION

TECHNOCAL advancements in high precision manufacturing processes have produced a need for increased research in precision motion control (PMC) [1], [2] techniques. PMC systems can utilize feedback or feedforward control designs or a combination of both feedback and feedback in a two-degree-of-freedom approach. Effective feedback design tools for nanopositioning include $H_\infty$ robust [3], [4], state feedback [5], and double-integrator derivative [6] control to name a few. Additionally, for systems that repeat the same trajectory, as in the case of many manufacturing processes, iterative learning control (ILC) [7]–[10] is a good choice for feedforward control design. The goal of this article is to present a frequency-based design methodology to improve the overall system performance by delegating the roles of feedback and ILC controllers based on known classes of exogenous signals.

This investigation is motivated by physical phenomena. The class of physical systems under consideration consists of a structure, possibly multi-degree-of-freedom, which is forced by some type of actuation device. These could be small flexure-based structures with piezo actuators, as with atomic force microscope stages [11], or large inertia masses driven electromagnetically, such as wafer scanning stages [12]. By design, these systems tend to have well defined dynamics in the low frequency range, where “low” is relative to the 1st structural resonance. For the flexure-based systems, the dynamics are essentially a gain; for the inertia systems, the dynamics are essentially a double integrator. Above the first structural resonance, there are usually higher order structural modes that are lightly damped. Additionally, these modes can have very different frequency characteristics at different locations in the flexure stage’s work envelope. The high number of structural modes, and the fact that they vary with stage position, makes them difficult to compensate with feedback control. A clear identification of the known dynamics in the frequency domain suggests the use of modern robust control design tools such as $H_\infty$-feedback controllers. These tools are good for point to point regulation and lower frequency tracking.

For higher frequency tracking, it is advantageous to include a feedforward controller in the PMC system. The feedforward controller is usually an approximate inverse of the plant. For trajectories that repeat themselves, a very successful approach is to learn the feedforward signals for subsequent trials by iteratively updating them based on the error accumulated in previous trials. This approach has been formalized as ILC [7]–[10]. ILC has the benefit of not requiring a very accurate plant model yet still giving high performance tracking inputs. While an explicit plant model is not required, it can often be useful in the design of the ILC to minimize the number of iterations taken to converge to an appropriate feedforward input signal.

The primary assumptions for ILC systems include the fact that all exogenous signals, i.e., references and disturbances, are identical from trial to trial. Additionally, current ILC practice assumes that the initial conditions for the system are also identical at the start of each trial. As will be seen by experimental examples, those assumptions are violated in the current work necessitating a modification to current ILC practice. In particular,
this work examines the effect of non-repeating disturbances and imperfect resetting on ILC systems. Previous work [13]–[15] has examined the effects of imperfect resetting on ILC. ILC algorithms can be designed to converge stably to a finite level of error performance depending on the size and nature of the reset error. In contrast, this work has the ILC de-emphasize the reset errors, and any other nonrepetitive signals. The algorithm given here relies on an appropriately co-designed feedback controller to compensate for the nonrepetitive signals. As will be seen, frequency based delegation will be key to mitigating the effects of all exogenous signals on the output error.

In this work, two nanopositioning devices with multiple degrees of freedom are considered in an effort to show the generality of the design approach presented. The actuator layout is different for both systems. Serial kinematics is observed in one of the devices, whereas the other device has parallel kinematics. The serial kinematic device is used as a single input single output (SISO) system for simplifying the design approach presented here. Then, a more complex multiple-input multiple-output (MIMO) system is investigated, which is the parallel kinematic device.

The rest of this paper is organized as follows. Section II gives a brief background for the design of both $H_{\infty}$-feedback and ILC control schemes. This gives a common platform to describe coordination. Section III introduces an essential component to the controller design procedure, which is the exogenous signal analysis. Key to the coordination of feedback and feedforward algorithms is the knowledge of relative signal power between repeatable and nonrepeatable signals in the frequency spectrum. The overall design strategy employed to coordinate the two controller degrees of freedom is presented in Section IV. The two experimental systems are tested for tracking performance in Section V using the design procedure in Section IV. Concluding remarks are then made in Section VI.

**II. CONTROLLER DESIGN BACKGROUND**

The PMC system layout used in this work is seen in Fig. 1. The block components in the diagram represent the plant model, $G(z)$, feedback controller, $K(z)$, and the feedforward ILC. Signals identified in the figure include: the reference, $r(z)$, error, $e_j(z)$, noise, $n_j(z)$, output, $y_j(z)$, repeating disturbance, $d(z)$, non-repeating disturbance, $d_j(z)$, learning control, $u_j(z)$, and the feedback control signal, $v_j(z)$. The argument $\arg(z)$ denotes that the analysis was done in discrete time. A subscript “$j$” represents the iteration for a signal that changes from trial to trial. For example, the iteration delay block takes the error or input at iteration $j$, $(e_j, u_j)$ and maps it to error and iteration in the subsequent $j-1$ iteration $(e_{j-1}, u_{j-1})$. For a more detailed explanation, the interested reader is referred to [10]. The system in Fig. 1 will be referred to throughout this work.

General assumptions were made to simplify the design and analysis, which are listed as follows.

A1) All signals are assumed to be infinite in time for frequency domain analysis.

A2) The expected value, or mean, of $n_j(z)$ and $d_j(z)$ is assumed to be zero.

Assumption A1 is used to allow a frequency domain representation of the signals and systems used in this work. Since all practical trajectories are finite, the ILC designs and results given here may be more conservative than possible under a lifted framework. However, the benefit is the ability to utilize frequency domain tools for codesign of feedforward and feedback algorithms.

A. Stand-Alone $H_{\infty}$-Feedback Control Design

A number of advanced feedback control designs are available [1], but one of the most prevalent strategies used in PMC systems is the $H_{\infty}$-feedback controller [11], [17]. Design goals for the $H_{\infty}$-feedback controller include maintaining stability while delivering adequate performance (i.e., bandwidth and high resolution, i.e., $(d_j(z), d(z)$, and $n_j(z)$ attenuation) under the influence of uncertainties in the operating environment. Classical control design approaches, such as proportional–integral–derivative (PID) or lead-lag control, require an ineffective search across the space of controller parameters that meet performance and resolution requirements. An advantage of the $H_{\infty}$-feedback control design approach is that the specifications set for performance, resolution, and robustness to model uncertainty can be directly considered in the frequency domain via appropriate weighting functions. Then a mathematical optimization framework [18] can be utilized to effectively search for a design.

Common closed-loop transfer functions used for $H_{\infty}$-feedback control design, $S(z)$, $T(z)$, and $KS(z)$ are defined as

$$S(z) = \frac{y_j(z)}{d_j(z)} = \frac{y_j(z)}{d(z)} = (I + G(z)K(z))^{-1} \quad (1)$$

$$T(z) = \frac{y_j(z)}{r(z)} = (I + G(z)K(z))^{-1} G(z)K(z) \quad (2)$$

$$KS(z) = \frac{v_j(z)}{r(z)} = K(z)(I + G(z)K(z))^{-1} \quad (3)$$

For a stand-alone $H_{\infty}$-feedback controller design, we assume $u_j(z) = 0$, and thus, $e_j(z)$ is given by

$$e_j(z) = r(z) - y_j(z) - n_j(z)$$

$$= S(z)r(z) - S(z)d_j(z) - S(z)d_j(z) - T(z)n_j(z). \quad (4)$$

From (4), we see that a sufficient condition to minimize the error is both $S(z)$ and $T(z)$ should be small. That is, the sensitivity function, $S(z)$, must be small to mitigate the effects of $r(z)$, $d_j(z)$, and $d_j(z)$. The complimentary sensitivity function, $T(z)$, should be minimized to decrease the presence of $n_j(z)$ in the error signal. It is not possible to design both $S(z)$ and $T(z)$ small for all frequencies due to the relationship

$$S(z) + T(z) = 1. \quad (5)$$
This is a key tradeoff in linear feedback controller design, and it stems from the well known Bode’s integral [19]–[21] defined as

$$\int_{-\pi}^{\pi} \log|S(z)| \, dz = 0. \quad (6)$$

Thus, if $|S(z)|$ needs to be small at low frequency for small tracking error, this will create large magnitude in $S(z)$ at a different frequency region. The result of increasing $S(z)$ in a specific frequency range is a decrease in the system’s closed loop bandwidth, where the bandwidth is defined at the crossover frequency or $|S(z)| = -3$ dB [3]. This phenomenon is known as the “waterbed” effect [3], and it serves to illustrate that there is always a fundamental tradeoff and limitation among bandwidth, robustness, and tracking error.

The controller transfer function, $K(z)$, is obtained through an iterative design of weighting functions to minimize

$$\gamma = \left\| \begin{array}{cc} W_S(z)S(z) & W_T(z)T(z) \\ W_T(z)T(z) & W_V(z)K(z) \end{array} \right\|_\infty \quad (7)$$

where $|X(z)|_\infty = \max_{\omega \in [-\pi, \pi]} |X(e^{j\omega})|$. The weighting functions $\{W_S(z), W_T(z), W_V(z)\}$, which can be seen in Fig. 2, penalize the error, output, and the controller output, respectively; these functions achieve the design objective by shaping the controller. Solutions to this minimization problem are well known [18], and iterative numerical techniques are widely available, e.g., in MATLAB software [22]. In the following, we summarize standard guidelines for the solution of $W_S(z)$, $W_T(z)$, and $W_V(z)$. The interested reader is referred to [3] and [4] for a more detailed discussion.

The transfer function $W_S(z)$ is typically chosen to have high gains at low frequencies and low gains at high frequencies. This scaling ensures that the optimal feedback law is such that $S(z)$ is small at low frequencies, thereby guaranteeing good tracking at the frequencies of interest. The weighting function $W_T(z)$ is often chosen such that it has high gains at high frequencies and low gains at low frequencies. This is done to shape $T(z)$ such that it “rolls off” at high frequencies for noise attenuation. The weighting function for the control $W_V(z)$ is chosen to ensure that the control signals remain within saturation limits. The Bode diagram in Fig. 3 shows general shapes for $W_S(z)$, $W_T(z)$, and $W_V(z)$.

**B. ILC Design**

ILC [7]–[10] is used to improve the performance of systems that repeat the same operation many times. ILC uses the tracking errors from previous iterations of the repeated motion to generate a feedforward control signal for subsequent iterations. Convergence of the learning process results in a feedforward control signal that is customized for the repeated motion, yielding very low tracking error. For the purposes of the ILC design, we assume that the feedback controller is given, and therefore $S(z)$ is fixed.

The ILC structure considered in this work is a plant inversion type [10], which is used for fast convergence of the feedforward control signal. In this structure, the error signal is filtered through a learning function $L(z)$ and a Q-filter $Q(z)$. $L(z)$ is a stable inversion of $P(z)$ up to a given frequency, which maps the error signal to the control signal. The use of a plant inversion approach is dependent on an accurate plant model. If such a model does not exist, a PD type learning law may be appropriate. $Q(z)$ is a robustness filter that can be designed to compensate for, among other things, uncertainty in the plant model $P(z)$. Additionally, $Q(z)$ is used to limit the frequency range of the learning for stability and noise attenuation. ILC holds previous control signals in memory and generates a control based on this error stored in memory (8)

$$u_j(z) = Q(z) (u_{j-1}(z) + L(z) e_{j-1}(z)). \quad (8)$$

This control signal is dependent on $e_{j-1}(z)$, which is derived from Fig. 1 and shown as follows:

$$e_{j-1}(z) = -G(z)S(z)u_{j-1}(z) + S(z)(r(z) - d(z) - d_{j-1}(z)) + T(z)u_{j-1}(z). \quad (9)$$

One of ILC’s fundamental limitations is its inability to compensate for non-repeating error or disturbances, $d_j(z)$. This will be demonstrated in the experimental results of this work. The well-known frequency domain ILC stability condition is

$$\|Q(z)(I - L(z)P(z))\|_\infty < 1. \quad (10)$$
For fast convergence [10], we select \( L(z) = S^{-1}(z)G^{-1}(z) \), which is the ILC plant inversion technique previously mentioned. Note that when \( S(z)G(z) \) is strictly proper, \( L(z) \) is improper. An improper learning function can be implemented by appropriately shifting the error signal during the learning process [10]. When \( S(z)G(z) \) is non-minimum phase, then \( L(z) \) is unstable, which can lead to large control signals. In this case, the learning function can be separated into stable and unstable components. Then, these two components are stably filtered in the forward time with the stable component and then in negative time with the unstable component [23]. Other references for stable-inversion for non-minimum phase systems can be found in [24].

Typically, there will be frequencies for which the system model is inaccurate. Equation (10) illustrates that for large uncertainties in some frequency range (e.g., gain uncertainty larger than 100%) we must have \( |Q(z)| \ll 1 \) in that frequency range for robust stability of the ILC.

The performance of the ILC at convergence is measured by the power spectrum of \( e_{\infty}(z) \triangleq \lim_{\tau \to \infty} e_j(z) \). In the following the “z” transfer function argument is dropped for compactness. We multiply (8) by \( G \)

\[
GSt_j = QGS_{t_j-1} + QGSLe_j-1. \tag{11}
\]

Next, substituting (9) for \( GSt_j \) and \( GSt_{j-1} \) results in

\[
e_j = Q(1 - GSL)e_{j-1} + (1 - Q)S(r - d) - S(d_j + Qd_{j-1}) + T(n_j - Qn_{j-1}). \tag{12}
\]

Since \( L = S^{-1}G^{-1} \), the \( e_j \) term conditionally depends on \( Q \) as

\[
e_j = \begin{cases} -S(d_j - d_{j-1}) + T(n_j - n_{j-1}), & \text{for } Q = 1 \\ S(r - d) - Sd_j + Tn_j, & \text{for } Q = 0 \end{cases}. \tag{13}
\]

The interested reader is referred to [25] for further analysis. The typical Q-filter design is a low pass filter [26]. This is because the system is usually well known at low frequencies, and non-repeating disturbances are minimized by the feedback controller at low frequencies. A tradeoff exists between minimizing repeatable error and amplifying noise when designing the Q-filter. When \( Q = 1 \), the repeatable error is eliminated, but the noise is amplified. Alternatively, \( Q = 0 \) has no effect on the noise or repeatable signal. Therefore, we want to vary the value of \( Q \) with respect to frequency. We should set \( Q = 1 \) in frequency regions where the repeatable component, \( S(r - d) \), is dominant, and set \( Q = 0 \) where the nonrepeatable component, \( Sd_j + Tn_j \) is dominant. The Section III will give a detailed procedure on how to determine the repeating and non-repeating content in the error signal \( e_j(z) \).

### III. Signal Analysis

When tracking repeating reference signals, ILC can be used to mitigate error that is repeated from trial to trial. If non-repeating error enters the learning function, the ILC signal does not converge effectively and can cause an increase in the tracking error. On the other hand, feedback control does not differentiate between repeating or non-repeating error; therefore, we can assign \( K(z) \) to reduce non-repeating error and ILC to mitigate the repetitive error. But first, it is imperative that we identify repeating and non-repeating error seen in the PMC system, which is discussed in the following paragraphs.

We need to define the repeating and non-repeating error elements in terms of the components in Fig. 1. The complete error signal has already been determined in (4), so the only requirement is to identify which exogenous signals are repeating or non-repeating. The components appearing in the repeating error would be \( r(z) \) and \( d(z) \). The non-repeating error would be compiled from \( d_j(z) \) and \( n_j(z) \). For this analysis, and throughout the remainder of this paper, we assume the noise, \( n_j(z) \), occurs at high frequencies and can be eliminated by appropriate filter design. Equations (14) and (15) respectively derive the repeating and non-repeating error in the discrete z-domain and frequency domain

\[
\bar{e}(z) \triangleq S(z)(r(z) - d(z)) \rightarrow R(\omega) = \|\text{FFT}[\bar{e}(z)]\|^2, \tag{14}
\]

\[
\hat{e}_j(z) \triangleq -S(z)d_j(z) \rightarrow \text{NR}(\omega) = \sum_{j=1}^{N} |\text{FFT}[\hat{e}_j(z)]|^2. \tag{15}
\]

A useful measure that can be used to directly compare the \( R(\omega) \) and \( \text{NR}(\omega) \) signal content is by the repeatable-to-non-repeatable ratio (RNR) of signal power. The RNR was introduced in [27] and is defined in the following manner (16):

\[
\text{RNR}(\omega) \triangleq 20\log_{10} \left( \frac{R(\omega)}{\text{NR}(\omega)} \right) = 20\log_{10} \left( \frac{\|\text{FFT}[S(z)(r(z) - d(z))]\|^2}{\sum_{j=1}^{N} |\text{FFT}[S(z)d_j(z)]|^2} \right). \tag{16}
\]

As can be seen from (16), the RNR is scaled in the numerator and denominator by the sensitivity function \( S(z) \). \( S(z) \) can then be cancelled, so this RNR calculation is not affected by a change in the \( S(z) \) or, in other words, not affected by the \( K(z) \) design. These theoretical equations work well for analysis, but \( d(z) \) and \( d_j(z) \) can not be directly measured from an experimental system. We will approximate \( \bar{e}(z) \) and \( \hat{e}_j(z) \) from experimental data in the following manner:

\[
\bar{e}(z) \approx \sum_{j=1}^{N} e_j(z) \text{for } N \gg 1 \tag{17}
\]

\[
\hat{e}_j(z) \approx e_j(z) - \bar{e}(z). \tag{18}
\]

A standalone feedback controller is used to stabilize the closed-loop system in order to record multiple iterations of tracking error signals. Repetitive error, \( \bar{e}(z) \), is found by averaging the tracking error signals in the time domain (17). Non-repeating error, \( \hat{e}_j(z) \), is approximated by subtracting \( \bar{e}(z) \) from each trial’s tracking error (18). A conversion of these two signals from the time domain to the frequency domain via the Fast Fourier Transform is performed, because the controller design is based in the frequency domain. Equations (17) and (18)
are used to calculate the repeating, $R(\omega)$, and non-repeating error, $NR(\omega)$, respectively.

The RNR is then calculated using (16). This RNR function leads to the design of the combined controller. The design process is discussed in Section IV.

IV. COMBINED CONTROLLER DESIGN

This section presents a heuristic design procedure that utilizes a priori knowledge of the error signal content in the design of the feedback and ILC controllers. A flowchart of the procedure is depicted in Fig. 4. Within the blocks of Fig. 4 are some of the key control elements introduced in Fig. 1.

The first step is the development of a model for the particular system of interest by means of system identification. Two common techniques for system identification are by the use of a swept sine input for frequency domain identification or using a pseudo random binary sequence (PRBS) input to identify the model in the time domain [28]. The former is used in Section V-A and the latter in Section V-B. For both cases, a discrete linear time invariant (LTI) model was estimated using the System Identification Toolbox in MATLAB [29].

Once a model has been identified, a stabilizing controller can be designed to track the desired reference signal. Experimental tracking data for several iterations is collected and then used to differentiate repeating and non-repeating error content. By using the process in Section III, the $R(\omega)$, $NR(\omega)$, and $RNR(\omega)$ signals can be estimated.

Frequency regions where $RNR > 0$ dB signify that the repeating content is dominant, and ILC should allow the stabilizing signal to enter the learning update. Therefore $Q(z)$ should be set to a value of 1 at frequencies where $RNR > 0$ dB, but should be close to zero at frequencies where $RNR < 0$ dB. For the $K(z)$ design, frequencies with $RNR < 0$ dB should be targeted to minimize the dominant non-repeating error. This is done by designing the weighting functions, $W_S$ and $W_T$, such that the magnitude of $S(z) < 0$ dB at these particular frequencies, which indicates that the error is effectively mitigated. The second design component of ILC is the learning function, $L(z)$. From the discussion of plant inversion ILC in Section II-B, we know that any change in the feedback controller causes a change in $L(z)$. Therefore, $L(z)$ should be designed after $K(z)$.

Experimental testing of the system tracking is then required to evaluate the performance of the combined controller design as in step 4 of Fig. 4. If the tracking objectives were not achieved, then an iterative approach is suggested to redesign the combined controller. The error signal obtained after ILC convergence is used in another iteration starting at step 2 whereby a new RNR is determined. This analysis provides valuable insight into how the repeating and non-repeating error content has reduced in comparison to the original signal analysis. Then, feedback and feedforward controllers can be redesigned if necessary. Sections IV-A–IV-D discuss this design approach on several scenarios with different exogenous signal content.

A. Scenario #1

The first scenario can be seen in Fig. 5(a) and (b). Large non-repeating error content appears at $\omega_{\text{LOW}}$, and large repeating content exists around $\omega_{\text{LOW}}$. From the RNR plot 5b, we clearly notice that the non-repeating content dominates the repeating content at $\omega_{\text{LOW}}$, whereas the relationship is switched around $\omega_{\text{HIGH}}$. ILC will be effective if it learns exclusively at $\omega_{\text{LOW}}$. Therefore, our combined controller design consists of a $H_\infty$ feedback controller with low frequency error mitigation, and an ILC controller design with a band pass Q-filter. The general shapes of the band pass Q-filter and $H_\infty$ weighting functions are shown in Fig. 5(b) and (d).

B. Scenario #2

The next scenario in Fig. 6 has large non-repeating exogenous signal content at $\omega_{\text{LOW}}$, but the RNR remains above 0 dB at low and mid frequencies. Due to the RNR having a value greater than 0 dB up to $\omega_{\text{HIGH}}$, ILC should be allowed to learn all of the
low to mid-frequency error content. A low pass Q-filter would then be designed for ILC. As for $K(z)$, the non-repeating error dominates between $\omega_{\text{mid}}$ and $\omega_{\text{high}}$ as indicated by the $\text{RNR} < 0$ dB. To minimize these effects, $K(z)$ should be designed to have high bandwidth in attempt to reduce this error. The suggested design uses a low pass Q-filter and a high bandwidth $H_\infty$-feedback controller. This suggested controller design may have inadequate performance, because of the large magnitude of non-repeating error that exists at $\omega_{\text{low}}$, which was not clearly identified by the RNR. Following experimental tests, the error data could be used to iterate on the first design.

C. Scenario #3

The plots for the last scenario in Fig. 7 illustrate an RNR curve that is similar to that of Section IV-A. With this RNR contour, the Q-filter should be a band pass type as discussed previously. The $H_\infty$-feedback controller should be focused on minimizing the error in the frequency band where the RNR < 0 dB, which is in the $\omega_{\text{low}}$ region. The combined controller design would be a band pass type Q-filter and a $K(z)$ that reduces low-frequency error content. Again, the combined controller design suggested here may need to be iterated upon due to the existence of non-repeating content near $\omega_{\text{mid}}$. The $K(z)$ design was intended to mitigate error near $\omega_{\text{low}}$, so it would not effectively reduce the large amount of non-repeating content.

D. Scenario Summary

The preceding sections developed several possible scenarios with varying exogenous signal content, and in each scenario a first iteration combining $H_\infty$-feedback and ILC design was suggested. The selection of $K(z)$ is not limited to a $H_\infty$ controller, but this type is investigated throughout this work due to the frequency domain design. In order to make the integration seamless, we advise that $K(z)$ be selected such that its design is done in the frequency domain.

A summary of the suggested controller designs has been produced in Table I. It should be noted that there is a large number of possibilities when it comes to scenarios of exogenous repeating and non-repeating signals. Therefore, the combined controller designs are in no way limited by the summary in the following table. Further discussion is included in [30].

V. EXPERIMENTAL RESULTS

The aforementioned design procedure was implemented on two different nanopositioning systems in order to properly illustrate this approach. These two nanopositioning devices are termed the NanoCube and the parallel kinematic mechanism (PKM). The former is actuated by piezo electric actuators in a serial architecture and is commercially available from Physik Instrumente as model P-611.3S. The PKM is also actuated by piezos, but in a parallel architecture. It was designed at the University of Illinois at Urbana-Champaign, and the interested reader is referred to [31] for a detailed discussion on its kinematics and design. Both systems use a dSPACE DS1104 DSP controller board for data acquisition and control at a sampling rate of 4 kHz.

These devices are considered MIMO systems, since each system has three actuators (inputs) and shows movement in the $x$, $y$, and $z$ spatial dimensions (outputs). An approximate range of motion for all of the piezos is 100 $\mu$m. For means of illustration and simplicity, this work treats the NanoCube...
as a SISO system, in which only the x-axis is used for precise positioning control. This was feasible due to the serial and decoupled kinematics of the NanoCube, where only one actuator caused movement in the x-direction. Following the SISO system discussion, we use the parallel actuator structure of the PKM as a testbed for controller design on a MIMO positioning system. The PKM system experiences a different set of exogenous signal content than the NanoCube system that complements the reasoning behind the proposed design procedure. Sections V-A and V-B, which discuss the results from the NanoCube and PKM, respectively.

### A. SISO Experimental System

Fig. 8 above shows the Physik Instrumente NanoCube and E-664 Controller (amplifier) system setup. Frequency domain system identification was performed on the x-axis by fitting a model to the frequency response curves seen in Fig. 9. The model fit was a 12th-order discrete LTI model (19). High frequency pole-zero pairs in the model cause model inaccuracy above 100 Hz. Therefore, controller designs had bandwidths below 100 Hz

\[
G(z) = \frac{0.025031 (z - 0.5323) \left( z^2 - 1.891z + 0.9723 \right) \left( z^2 - 1.733z + 0.9595 \right) \left( z^2 - 1.462z + 0.9289 \right)}{(z - 0.6193) (z - 0.9251) \left( z^2 - 1.294z + 0.5162 \right) \left( z^2 - 1.723z + 0.9719 \right) \left( z^2 - 1.589z + 0.9055 \right) \left( z^2 - 1.268z + 0.8754 \right) \left( z^2 - 0.502z + 0.8917 \right)}.
\]

As with many piezo actuated systems, the NanoCube shows hysteretic behavior. This nonlinear effect is common with typical voltage driven piezo systems and is difficult to eliminate. Custom-built charge amplifiers [32] can be used to significantly reduce this effect in hardware. Fig. 10 shows the open-loop hysteresis in this system. Nonlinear hysteresis models [32] typically include an internal state variable to capture the direction dependent characteristics. This internal state is dependent on the reset path in which the positioner has taken. If the positioner is not reset to its initial condition in exactly the same trajectory prior to tracking, the internal hysteresis state is altered. This causes the controller to output a different initial control effort from trial to trial in order to hold the positioner at the same initial condition. This change in the controller output is typically a dc offset, which explains why hysteresis is considered a low frequency phenomenon.

The reset command was designed to change the reset path prior to tracking each iteration in effort to induce a non-repeating hysteresis effect. This is typically a problematic scenario for ILC. Normally when ILC is used, all initial conditions and exogenous signals are assumed to be identical every iteration. It should be noted that ILC was not utilized for tracking the non-repeating reset path. The reference, \(r(z)\), is shown later in

![Fig. 8. NanoCube experimental setup.](image)

![Fig. 9. System identification model fit.](image)

![Fig. 10. Hysteresis plot from experimental open-loop response of NanoCube.](image)
Fig. 11. (a) Error periodogram for repeatable $d(z)$ and nonrepeatable, $d_j(z)$. (b) RNR of signal power.

Fig. 12. Bode plot of $H_\infty$ controller designs.

Fig. 13. The dominant signal content occurs at 20 Hz. There is a clear frequency separation, as in Fig. 5(a), between the low frequency non-repeating hysteresis content and the repeating content of $r(z)$.

A stabilizing $H_\infty$-feedback controller was designed to collect reference signal tracking data for signal analysis purposes. Signal analysis produced repeating and non-repeating content periodograms as seen in Fig. 11(a). The large low frequency non-repeating content represents the hysteresis effect in the piezo actuator. From the RNR plot in Fig. 11(b), the repetitive error appears to be dominant in the frequency range between 10–100 Hz. This leads to the design of a Q-filter for ILC that has a value of one for frequencies between 10 and 100 Hz, and a small value for all other frequencies. By definition this Q-filter design is a band pass filter. In the operating frequency range, i.e., 0–100 Hz, the RNR $< 0$ dB below 15 Hz, which suggests that $K(z)$ be designed to mitigate error in this low frequency region. Thus, the combined design then utilizes a $H_\infty$-feedback controller with low frequency disturbance rejection and a band pass Q-filter.

Due to constraints from (6), there is typically a tradeoff between system bandwidth and low frequency disturbance rejection when designing a robust $H_\infty$-feedback controller. In this

Fig. 14. RMS tracking error versus iteration.

|| Four Control Scenarios | ILC Q-filter Design |
|--------------------------|----------------------|
| $H_\infty$ Feedback Controller Designs | Low Bandwidth | High Bandwidth |
| Low Pass | Reduce low frequency effects | Typical Design |
| Band Pass | Approach presented here | Approach presented here |

TABLE II

**FOUR CONTROLLER SCENARIOS**
work, we have two $K(z)$ designs, in which this tradeoff is observed. The first design, $K_{LBW}$, has large gains at low frequency to mitigate low frequency error content as suggested by the RNR, but the closed-loop system bandwidth was only 15 Hz. The other controller, $K_{HBW}$, was designed as a standalone feedback controller with a bandwidth of 45 Hz. Their frequency responses are plotted in Fig. 12.

For comparison purposes, two ILC Q-filters were designed, which include a 3rd order Butterworth low pass (0–100 Hz) and band pass (10–100 Hz) filter labeled as $Q_{Lowpass}$ and $Q_{Bandpass}$, respectively. The two $Q(z)$ and $K(z)$ designs are listed in the Appendix A.1. The plant inverse learning

<table>
<thead>
<tr>
<th>Feedback</th>
<th>ILC Q-filter Design</th>
<th>Low Pass</th>
<th>Band Pass</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low Bandwidth</td>
<td>Mean</td>
<td>35.9 nm</td>
<td>35.4 nm</td>
</tr>
<tr>
<td>Standard Dev.</td>
<td>3.3 nm</td>
<td>2.8 nm</td>
<td></td>
</tr>
<tr>
<td>High Bandwidth</td>
<td>Mean</td>
<td>46.0 nm</td>
<td>41.1 nm</td>
</tr>
<tr>
<td>Standard Dev.</td>
<td>8.0 nm</td>
<td>3.6 nm</td>
<td></td>
</tr>
</tbody>
</table>

Fig. 15. Top view of PKM.

Fig. 16. (a) PKM reference signal. (b) Reference signal periodogram.

Fig. 17. Initial RNR for: (a) X-axis; (b) Y-axis; (c) Z-axis.
functions, \( L_{LBW} \) and \( L_{HBW} \), for the system with \( K_{LBW} \) and \( K_{HBW} \) are also shown in the Appendix A.1. A summary of the different controller scenarios is compiled in Table II. The low pass Q-filter and low bandwidth \( H_{\infty} \) control would focus primarily on minimizing the effect of low frequency exogenous signals (references and disturbances) on the system error. The low pass Q-filter and high bandwidth \( H_{\infty} \) control is typical of most feedforward/feedback designs in the literature.

The right column of Table II indicates novel approaches given here.

To illustrate the difference between the feedback controllers, tracking results are plotted in Fig. 13. The standalone controller, \( K_{HBW} \), clearly tracks the reference with less error than \( K_{LBW} \). This result is expected, because the 20 Hz operating frequency is within the bandwidth of the \( K_{HBW} \) system but not of the \( K_{LBW} \) system.
When ILC is added to the system, the results are less intuitive. First, we introduce the primary performance measure for this work, which is the root mean squared (RMS) error (20). For systems utilizing ILC, this is a common performance metric [10], and it should also be stated that a control system achieving lower RMS error is considered more desirable. When \( K_{LBW} \) and \( K_{HBW} \) controllers are used with ILC, large decreases in RMS error are recorded after ILC convergence, which occurs by the third iteration. Fig. 14 plots the RMS error per iteration, and the control scenario with the lower RMS error was \( K_{LBW} + Q_{BandPass} \). In typical ILC and feedback controller design, a \( K_{HBW} + Q_{LowPass} \) type of configuration would be considered the more suitable control scenario, because these two...
designs are thought of as being superior in their respective control areas. Statistical results from these experimental tests are summarized in Table III.

\[
e_{\text{RMS}} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} |e_i|^2}. \tag{20}
\]

We conclude from the experimental results that signal analysis provides valuable intuition, which leads to the appropriate combined design of feedback and ILC controllers. Better performance was obtained by using an atypical choice for \( K(z) \) and \( Q(z) \). The low frequency disturbance rejection of \( K_{\text{LIDW}} \) mitigates these effects better than \( K_{\text{HIDW}} \). This is supported by the results in Table III where \( K_{\text{LIDW}} \) has lower average RMS error than \( K_{\text{HIDW}} \). The RNR plot was the critical component of this design approach, because this plot identified frequency ranges with dominant repeating or non-repeating error. The results validate this RNR approach by pointing out that \( Q_{\text{BandPass}} \) provides better performance than \( Q_{\text{LowPass}} \).

### B. MIMO Experimental System

The PKM in Fig. 15 is actuated by the use of three piezo actuators and flexure linkages. Capacitance gages and the A/D of the dSPACE DS1104 were used to measure the position of the PKM with resolution of 2 nm. For the interested reader, additional control results using this testbed were explored in [33] and [34].

Time domain system identification was performed using a PRBS input on each actuator, producing three different responses. A single-input multiple-output (SIMO) discrete LTI model was estimated for each actuator, and then compiled into a final MIMO model. Each SIMO model was estimated by a discrete LTI model with 13 states based on the Hankel Singular Value decomposition. Combining three of these models resulted in a final discrete MIMO LTI model with 39 states. As seen in Fig. 22, the PKM model has large system resonances above 100 Hz, so the operating frequency range of this system will be below 100 Hz, similar to the NanoCube in Section V-A.

A 3-D reference signal was devised in the form of a raster scanning pattern, shown in Fig. 16(a). This tracking pattern had a constant velocity of 125 \( \mu \text{m/s} \), and the scanning frequency was approximately 20 Hz. The individual axes periodograms are plotted in Fig. 16(b), where it can be seen that the majority of signal content lies below 25 Hz. The periodograms did not plot above 200 Hz due to absence of significant error content.

Tracking data was collected for multiple iterations in order to conduct signal analysis, which is discussed here. The RNR plots for the \( x, y, \) and \( z \) axes are displayed in Fig. 17. These plots show a different scenario than that of the NanoCube in Section V-A. Here, \( \text{RNR} > 0 \text{ dB} \) at all frequencies below 100 Hz. This suggests that a low pass Q-filter be designed for the ILC. For the
$H_{\infty}$-feedback controller design, it is not clear as to what frequency range should be delegated to $K(z)$, because in the operating range the RNR $> 0$ dB. Thus, we disregard the signal analysis, and design a potential stand-alone $K(z)$. The Bode magnitude diagrams for the low pass $Q(z)$ and the standalone $K(z)$ designs can be found in Figs. 23 and 24, respectively.

Before presenting results from the combined controller, we need to design different $Q(z)$ and $K(z)$ functions to compare performance. The new combined controllers were developed using the iterative method in steps 5–7 of Fig. 4. Signal analysis was performed on tracking data obtained from testing the first controller design, and the RNR plots are shown in Fig. 18.

The plots in Fig. 18 show that the low pass $Q(z)$ has allowed ILC to eliminate the repeating error dominance at frequencies below 50 Hz, because the RNR $< 0$ dB. The alternative $K(z)$ design should then mitigate the low frequency non-repeating error. In doing so, the tradeoff for low frequency error mitigation is a lower system bandwidth. This $K(z)$ design had $x$-, $y$-, and $z$-axes bandwidths of 10, 15, and 20 Hz due to constraints on the size of the controller. We will refer to this controller as $K_{\text{LBW}}$, because all axes have a lower bandwidth than the 30, 40, and 50 Hz bandwidths of the $x$-, $y$-, and $z$-axes of the first $K(z)$ design, which is labeled $K_{\text{HBW}}$. The performance of the $K_{\text{HBW}}$ controller is very similar to that given in [33], [34] since the design weightings were very similar. Therefore, $K_{\text{HBW}}$ can be thought of as the best feedback controller developed to date for this PKM system.

For comparison purposes, an additional $Q(z)$ design was produced, which was a band pass type filter (1–100 Hz). This alternate $Q(z)$ design is named $Q_{\text{Bandpass}}$, whereas the initial Q-filter is referred to as $Q_{\text{Lowpass}}$. Frequency response plots for the $K(z)$ and $Q(z)$ designs can be seen in Appendix B.2. The two $Q(z)$ discrete LTI functions can be found in [30] along with the two $K(z)$ and $L(z)$ functions used to produce these experimental results.

Comparing the tracking results of $K_{\text{LBW}}$ and $K_{\text{HBW}}$ without ILC in Figs. 19 and 20, it is apparent that $K_{\text{HBW}}$ has significantly less tracking error than $K_{\text{LBW}}$. This is an expected result. However, when ILC is added to the positioning system, the results are not as intuitive. Fig. 21 shows the converged RMS error reduction when using $K_{\text{LBW}} + Q_{\text{Lowpass}}$ or, the more typical, $K_{\text{HBW}} + Q_{\text{Lowpass}}$ design. Again, we observe that the atypical design, $K_{\text{LBW}} + Q_{\text{Lowpass}}$, has lower converged RMS error in the $x$, $y$, and $z$ directions. Results with $Q_{\text{Bandpass}}$ were poor due to the high RNR value in Fig. 17 for all frequencies up to 100 Hz, so these results were not plotted. From Fig. 19, it should be noted that the RMS values for the feedback controllers without feedforward were on the order of 0.2 $\mu$m for the $K_{\text{HBW}}$ case and 0.5–1.0 $\mu$m for the $K_{\text{LBW}}$ case. Therefore, the use of feedforward lowered the RMS tracking error by approximately an order of magnitude. Statistics for all feedback+feedback controller scenarios can be viewed in Appendix B.1.

In the piezo actuated PMC systems of this section, we expect to see significant quantities of non-repeating content at very
low frequencies due to the nonlinear hysteresis in the piezos. Both examples in this work used piezo actuators and showed this effect. The goal of the feedback controller design was relatively similar in both systems, in that the $K(z)$ was designed to minimize the low frequency error within the system. However, the Q-filter design in these examples provided different results due to the ratio of repeating to non-repeating content occurring at low frequencies, or as introduced here, the RNR. This design approach is applicable to different types of PMC systems utilizing ILC, not just piezo actuated PMC systems.

VI. CONCLUSION

The combined controller design process presented in this paper introduces a novel approach for frequency domain delegation between feedback and feedforward controller authority; specifically $H_\infty$ and ILC. The design approach incorporates the identification of different classes of error signals, i.e., repeatable and nonrepeatable, through a novel function: the RNR ratio. The RNR ratio determines the frequency range in which feedback or feedforward control should be employed. Through a combined controller design approach, appropriate frequency domain weighting functions for $H_\infty$-feedback and Q-filters have been discussed and proven to be effective from experimental results of two PMC systems. This design process is an improvement upon typical ILC, where the feedback controller design is decoupled from that of the ILC design.

TABLE IV

<table>
<thead>
<tr>
<th>RMS error (iterations 2-20)</th>
<th>ILC Q-filter Design</th>
</tr>
</thead>
<tbody>
<tr>
<td>X-Axis Feedback K\text{low}</td>
<td>Mean: 17.6 nm, 356 nm</td>
</tr>
<tr>
<td>Std. Dev.: 16.6 nm, 2.0 nm</td>
<td></td>
</tr>
<tr>
<td>Y-Axis Feedback K\text{low}</td>
<td>Mean: 18.3 nm, 124 nm</td>
</tr>
<tr>
<td>Std. Dev.: 1.4 nm, 0.4 nm</td>
<td></td>
</tr>
<tr>
<td>Z-Axis Feedback K\text{low}</td>
<td>Mean: 29.6 nm, 116 nm</td>
</tr>
<tr>
<td>Std. Dev.: 10.8 nm, 6.0 nm</td>
<td></td>
</tr>
<tr>
<td>X-Axis Feedback K\text{low}</td>
<td>Mean: 35.8 nm, 61.6 nm</td>
</tr>
<tr>
<td>Std. Dev.: 0.6 nm, 0.6 nm</td>
<td></td>
</tr>
<tr>
<td>Y-Axis Feedback K\text{low}</td>
<td>Mean: 31.3 nm, 48.5 nm</td>
</tr>
<tr>
<td>Std. Dev.: 2.4 nm, 1.4 nm</td>
<td></td>
</tr>
<tr>
<td>Z-Axis Feedback K\text{low}</td>
<td>Mean: 36.6 nm, 36.0 nm</td>
</tr>
<tr>
<td>Std. Dev.: 2.0 nm, 1.4 nm</td>
<td></td>
</tr>
</tbody>
</table>

APPENDIX A

NANOCUBE TRANSFER FUNCTIONS: See equations (A.1)–(A.6) at the top of the next page.

APPENDIX B

PKM PERFORMANCE STATISTICS: See Table IV.

PKM FREQUENCY RESPONSE PLOTS: See Figs. 22–24.
\[
L_{\text{LBW}}(z) = \frac{1.067 (z+0.4935)(z-0.0925)(z-0.5294)(z^2-1.914z+0.910) (z^2-1.964z+0.965)(z^2-2.728z+0.9563)
}{(z-0.857z+0.2833)(z^2-1.782z+0.9648)(z^2-1.293z+0.9535)(z^2-1.716z+0.9615)}
\]
\[
L_{\text{HBW}}(z) = \frac{1.067 (z+0.4935)(z-0.0925)(z-0.5294)(z^2-1.914z+0.910) (z^2-1.964z+0.965)(z^2-2.728z+0.9563)
}{(z-0.857z+0.2833)(z^2-1.782z+0.9648)(z^2-1.293z+0.9535)(z^2-1.716z+0.9615)}
\]
\[
Q_{\text{Lowpass}}(z) = \frac{2.00841z^3+0.2571z^5}{(z-0.897z+0.2571z^5)}
\]
\[
Q_{\text{Bandpass}}(z) = \frac{2.00841z^3+0.2571z^5}{(z-0.897z+0.2571z^5)}
\]
\[
K_{\text{HBW}}(z) = \frac{1.067 (z+0.4935)(z-0.0925)(z-0.5294)(z^2-1.914z+0.910) (z^2-1.964z+0.965)(z^2-2.728z+0.9563)
}{(z-0.857z+0.2833)(z^2-1.782z+0.9648)(z^2-1.293z+0.9535)(z^2-1.716z+0.9615)}
\]
\[
K_{\text{LBW}}(z) = \frac{1.067 (z+0.4935)(z-0.0925)(z-0.5294)(z^2-1.914z+0.910) (z^2-1.964z+0.965)(z^2-2.728z+0.9563)
}{(z-0.857z+0.2833)(z^2-1.782z+0.9648)(z^2-1.293z+0.9535)(z^2-1.716z+0.9615)}
\]

ACKNOWLEDGMENT

The authors would like to thank Dr. J. Lewis for the use of the NanoCube.

REFERENCES


**Brian E. Helfrich** received the B.S. degree from Purdue University, West Lafayette, IN, in 2006 and the M.S. degree from the University of Illinois at Urbana-Champaign, in 2008, both in mechanical engineering.

He is currently a Systems Engineer with Sandia National Laboratories, Albuquerque, NM. While working towards the B.S. degree, he completed the cooperative education program with Toyota Motor Manufacturing Indiana as a Manufacturing Engineer, and during his pursuit of the M.S. degree, he was a Research Assistant with the Center for Nanoscale Chemical-Electrical-Mechanical Manufacturing Systems (Nano-CEMMS). His research focused on precision motion control utilizing combined efforts from H-infinity feedback control and iterative learning control.

**Chibum Lee** (S’08) was born in Seoul, Korea, in 1975. He received the B.S. and M.S degrees in mechanical design and production engineering from Seoul National University, Seoul, Korea, in 1998 and 2000, respectively. He is currently pursuing the Ph.D. degree in mechanical science and engineering, University of Illinois, Urbana-Champaign.

From 2000 to 2005, he was with Hyundai Mobis, Korea as a Dynamics and Control Engineer. His research is primarily focused on the application of control theory to nanoscale systems. He has worked on the development of control design for nanopositioning systems and the new mode for atomic force microscopes.

**Douglas A. Bristow** received the B.S. degree in mechanical engineering from the Missouri University of Science and Technology, Rolla, in 2001, and the M.S. and Ph.D. degrees in mechanical engineering from the University of Illinois at Urbana-Champaign, Urbana-Champaign, in 2003 and 2007, respectively.

From 2007 to 2008, he was a Postdoctoral Researcher with the Nano-CEMMS at the University of Illinois. In 2008, he joined the Department of Mechanical and Aerospace Engineering, Missouri University of Science and Technology, where he is an Assistant Professor. His research interests include precision motion control and nanopositioning systems.

**Jingyan Dong** received the B.S. degree in automatic control from the University of Science and Technology of China, Hefei, China, in 1998, the M.S. degree from the Institute of Automation, Chinese Academy of Sciences, Beijing, China, in 2001, and the Ph.D. degree in mechanical engineering from the University of Illinois at Urbana-Champaign, Urbana-Champaign, in 2006.

From 2006 to 2008, he was a Postdoctoral Research Associate with the Center for Nanoscale Chemical-Electrical-Mechanical Manufacturing Systems (Nano-CEMMS), the University of Illinois at Urbana-Champaign. Since 2008, he has been a faculty member with the Department of Industrial and Systems Engineering, North Carolina State University, Raleigh. His research interests include micro/nano manufacturing, multidimensional scale mechatronics and manufacturing systems, and their design, fabrication, sensing, control and application to micro/nano/macro manipulation and manufacturing.

**A. G. Alleyne** received the B.S.E. degree in mechanical and aerospace engineering from Princeton University, Princeton, NJ, in 1989 and the M.S. and Ph.D. degrees in mechanical engineering from The University of California at Berkeley, Berkeley, in 1992 and 1994, respectively.

He joined the University of Illinois, Urbana-Champaign, in 1994, where he currently holds the Ralph M. and Catherine V. Fisher Professorship in the College of Engineering. He was a Fulbright Fellow to the Netherlands where he held a Visiting Professorship in Vehicle Mechatronics at TU Delft. His research interests include a mix of theory and implementation with a broad application focus.

Dr. Alleyne was a recipient of the ASME Dynamics Systems and Control Division’s Outstanding Young Investigator Award and the 2008 ASME Gustus L. Larson Memorial Award. He is a Fellow of the ASME.

**Srinivasa M. Salapaka** (M’93) was born in Andhra Pradesh, India, in 1973. He received the B.Tech. degree in mechanical engineering from the Indian Institute of Technology, Chennai, India, in 1995 and the M.S. and Ph.D. degrees in mechanical engineering from the University of California, Santa Barbara, in 1997 and 2002, respectively.

From 2002 to 2004, he was a Postdoctoral Associate with the Laboratory for Information and Decision Systems, Massachusetts Institute of Technology, Cambridge. Since 2004, he has been a Faculty Member in mechanical science and engineering, University of Illinois, Urbana-Champaign. His current research interests include controls for nanotechnology, combinatorial resource allocation, and numerical analysis of integral equations.

Dr. Salapaka was a recipient of the National Science Foundation CAREER Award in 2005.

**Placid M. Ferreira** received the Ph.D. degree in industrial engineering from Purdue University, West Lafayette, IN, in 1987.

Currently, he is the Grayce Wicall Gauthier Professor of Mechanical Science and Engineering at the University of Illinois at Urbana-Champaign, Urbana-Champaign, where he directs the NSF-sponsored Center for Nanoscale Chemical-Electrical-Mechanical Manufacturing Systems (Nano-CEMMS). His research interests include precision engineering, automation and control of manufacturing systems, MEMS and nanoscale manufacturing.