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# Adaptive Robust Control: Theory and Applications to Integrated Design of Intelligent and Precision Mechatronic Systems

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***Abstract*— The rapid advances in microelectronics and microprocessor technologies during the past decades have made the physical integration of mechanical systems, various sensors, and computer based control implementation platform rather affordable and a standard choice for any modern precision machines. Such a hardware configuration enables the control of the overall system to be constructed in the same way as what a human brain normally does - seamless integration of the fast reaction (or instantaneous feedback reaction) to immediate feedback information and the slow learning utilizing large amount of stored past information that is available in the computer based control systems. The theoretically solid nonlinear adaptive robust control (ARC) theory that has been developed recently well reflects such an intuitive integrated design philosophy of human brains, and has been experimentally demonstrated achieving better control performance than existing nonlinear robust controls (e.g., sliding mode controls) or nonlinear adaptive controls in a number of control applications. This paper is to introduce researchers and practicing engineers to the essences of such an advanced nonlinear control design methodology, and its applications to the integrated design of intelligent and precision mechatronic systems. The control of a high-speed/acceleration linear motor driven precision electro-mechanical system, and the energy-saving control of electrohydraulic systems using novel programmable valves are used as application examples to illustrate the effectiveness of the presented ARC approach in the integrated design of intelligent and precision mechatronic systems.**

## I. INTRODUCTION

Recently, a new approach, adaptive robust control (ARC) [1], [2], [3], [4], has been developed to preserve the advantages of both adaptive control [5], [6] and DRC [7] while overcoming their practical performance limitations for a reasonably large class of nonlinear systems. Specifically, the following categories of ARC controllers have been developed: (i) the smooth projection based full state feedback ARC designs [2], (ii) the discontinuous projection based full state feedback ARC design [1], [8] that has a more stable parameter adaptation process for a better performance in implementation, (iii) the desired compensation ARC controllers [9] that reduce the effect of measurement noise and have a faster adaptation rate in implementation to improve overall tracking performance, (iv) the saturated adaptive robust controller (SARC) [10] developed for uncertain nonlinear systems in the "chain-of-integrator" form in the presence of practical constraint of control input saturation, (v) the partial state feedback ARC scheme [11] that incorporates a nonlinear observer to recover the unmeasured states associated with the dynamic uncertainties for better performance, (vi) the output feedback ARC schemes [12], [13] that need the output measurement sensor only, (vii) the indirect adaptive robust control (IARC) designs [14] that, in addition to good control performance, achieve the secondary goal of having as accurate parameter estimates as possible, (viii) the integrated direct/indirect adaptive robust control (DIARC) [15] that achieves the dual objectives of having excellent control performance as well as accurate parameter estimates for secondary purposes such as machine health monitoring and prognostic, (ix) the neural network adaptive robust controls [16], [17] that incorporates the universal approximation capability of neural networks in learning general nonlinearities into the ARC designs to enlarge the applicable systems of the proposed ARC theory, and (x) the adaptive robust repetitive controls [18] that utilizes repetitive learning for applications having repetitive tasks.

The proposed ARC approach has also been applied to the control of precision mechanical systems driven by rotary [19] or linear electro-magnetic motors with different physical characteristics [20], [21], [22], [23], and the electro-hydraulic systems [24], [25], [26], [27], [28], [29] in various specific applications. Extensive comparative experimental results have been obtained to verify the effectiveness of the proposed ARC approach and the significant improvement in the tracking accuracy of motion over the existing methods.

The theoretical breakthrough and the significant performance improvement of the proposed ARC in various implementations make the approach an ideal choice for industrial applications demanding stringent performance. At the same time, the by-product of the approach – accurate parameter and nonlinearity estimations – makes adding intelligent features such as prognostic to the system possible. It is thus beneficial for control engineers to get exposed to such an advanced nonlinear control design methodology and to master how the method can be used to build intelligent and yet precision mechatronic systems, which is the main objective of the paper.

## II. ADAPTIVE ROBUST CONTROL (ARC) THEORY

To avoid getting bugged down to the technical design complexity, in this section, the tracking control of a simple

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first order nonlinear systems with uncertainties will be used to illustrate the advantages and limitations of different types of adaptive robust controls. The system is described by

$$\dot{x} = f(x,t) + u, \qquad f = \varphi^T(x)\theta + \Delta(x,t) \tag{1}$$

where $x, u \in R$, and $f$ is an unknown nonlinear function. In general, $f$ can be approximated by a group of known basis functions $\varphi(x) \in R^p$ with unknown weights $\theta \in R^p$, and the approximation error is denoted by the unknown nonlinear function $\Delta(x,t)$. The objective is to let $x$ track its desired trajectory $x_d(t)$ as closely as possible. The following reasonable and practical assumption is made, which is satisfied by most applications:

**A1** . The extent of parametric uncertainties and uncertain nonlinearities is known, i.e.,

$$\begin{array}{rcl} \theta & \in & \Omega_\theta \triangleq \{\theta: \ \ \theta_{min} < \theta < \theta_{max}\ \} \\ \Delta & \in & \Omega_\Delta \triangleq \{\Delta: \ \ \|\Delta(x,t)\| \leq \delta(x,t)\ \} \end{array} \tag{2}$$

where $\theta_{min},\ \theta_{max}$ and $\delta(x,t)$ are known. $\diamondsuit$

### A. Direct Adaptive Robust Control (DARC)

The simplest ARC design is the direct ARC (DARC) designs presented in [4], [1], in which learning laws such as parameter adaptations are synthesized along with the control law to achieve the sole purpose of reducing output tracking error. Specifically, for (1), the parameter estimate $\hat{\theta}$ is updated through a parameter adaptation law having the form given by

$$\dot{\hat{\theta}} = Proj_{\hat{\theta}}(\Gamma\tau) \tag{3}$$

where $\Gamma$ is any symmetric positive definite (s.p.d.) adaptation rate matrix, $\tau$ is an adaptation function to be specified later, and $Proj_{\hat{\theta}}(\bullet)$ is the standard projection mapping used in the adaptive control area [1]. The ARC control law consists of two parts given by

$$\begin{array}{ll} u = u_f + u_s, & u_f = \dot{x}_d(t) - \varphi^T\hat{\theta} \\ & u_s = u_{s1} + u_{s2}, \quad u_{s1} = -kz \end{array} \tag{4}$$

where $z = x - x_d$ is the tracking error. In (4), $u_f$ is the adjustable model compensation needed for achieving perfect tracking, and $u_s$ is the robust control law consisting of two parts: $u_{s1}$ is used to stabilize the nominal system, which is a simple proportional feedback in this case; and $u_{s2}$ is a nonlinear robust feedback used to attenuate the effect of model uncertainties, which is synthesized to satisfy the following two constraints

$$\begin{array}{ll} \text{i} & z[-\varphi^T\tilde{\theta} + \Delta(x,t) + u_{s2}] \leq \varepsilon \\ \text{ii} & zu_{s2} \leq 0 \end{array} \tag{5}$$

where $\varepsilon$ is a positive design parameter representing the attenuation level of the model uncertainties that one would like to have. In (5), condition i is used to represent the fact that $u_{s2}$ is synthesized to dominate the model uncertainties coming from both the parametric uncertainties and uncertain nonlinearities to achieve a guaranteed level of attenuation $\varepsilon$, and the passive-like constraint ii is imposed to make sure that introducing $u_{s2}$ does not interfere with the nominal identification process of parameter adaptation. The specific forms of $u_{s2}$ satisfying constraints like (5) can be found in ARC designs in [3], [2], [1].

*Theorem 1:* [1] If the adaptation function is chosen as

$$\tau = \varphi(x)z \tag{6}$$

then, the ARC law (4) with the parameter adaptation law (3) guarantees that

A. In general, all signals are bounded and the tracking error is bounded by

$$|z|^2 \leq exp(-2kt)|z(0)|^2 + \frac{\varepsilon}{k}[1 - exp(-2kt)] \tag{7}$$

i.e., the tracking error exponentially decays to a ball. The exponential converging rate $2k$ and the size of the final tracking error ($|z(\infty)| \leq \sqrt{\frac{\varepsilon}{k}}$) can be freely adjusted by the controller parameters $\varepsilon$ and $k$ in a *known* form.

B. If after a finite time, there exist parametric uncertainties only (i.e., $\Delta(x,t) = 0,\ \forall t \geq t_0$), then, in addition to the results in A, asymptotic tracking or zero final tracking error is achieved, i.e, $z \longrightarrow 0$ as $t \longrightarrow \infty$. Furthermore, if the desired trajectory satisfies the following persistent excitation (PE) condition

$$\int_t^{t+T} \varphi(x_d(\nu))\varphi^T(x_d(\nu))d\nu \geq \varepsilon_p I_p \qquad \forall t \geq t_0 \tag{8}$$

where $T, t_0$ and $\varepsilon_p$ are some positive scalars, then, the parameter estimates $\hat{\theta}$ converge to their true values as well (i.e., $\tilde{\theta} \longrightarrow 0$ when $t \longrightarrow \infty$). $\triangle$

*Remark 1:* In the absence of parameter adaptation (i.e., $\Gamma = 0$), the proposed ARC law reduces to a deterministic robust control (DRC) law and Result A of Theorem 1 still holds. Therefore, the adaptation loop can be switched off at any time without affecting the stability and the guaranteed output tracking transient performance. However, such a control law does not discriminate the difference between parametric uncertainties and uncertain nonlinearities and results in a conservative design since Result B of Theorem 1 is lost. As for adaptive control [5], the proposed ARC uses certain coordination mechanisms (e.g., the discontinuous projection mapping used in (3)) and nonlinear robust feedback control $u_s$ to achieve a guaranteed output tracking transient performance even in the presence of uncertain nonlinearities (A of Theorem 1) while without losing its nominal performance (B of Theorem 1). $\triangle$

### B. Indirect Adaptive Robust Control (IARC)

For the applications that need accurate parameter estimates for other secondary purposes in addition to the good output tracking performance, the indirect adaptive robust control design (IARC) presented in [14] can be used, which completely separates the construction of parameter estimation law from the design of underline robust control law as illustrated as follows.

One of the key elements of the ARC design [4], [2] is to use the practical available prior process information to construct projection type adaptation law for a controlled learning process even in the presence of disturbances. In the DARC designs in the previous section, the discontinuous projection mapping [1] is used for its simplicity to ease implementation. However, theoretically, such a discontinuous projection mapping is valid only for diagonal adaptation rate matrix $\Gamma$, which is not a problem for the direct ARC designs that use gradient type adaptation laws only. For the indirect ARC introduced below, as the least square type adaptation law will be used to achieve better convergency of parameter estimations, the adaptation rate matrix will be time-varying and non-diagonal. As such, the standard projection mapping $Proj_{\hat{\theta}}(\bullet)$ in the adaptive control [30], [5] should be used to keep the parameter estimates within the known bounded set $\bar{\Omega}_\theta$, the closure of the set $\Omega_\theta$. The expression of $Proj_{\hat{\theta}}(\Gamma\tau)$ is

$$\begin{cases} \Gamma\tau, & \text{if } \hat{\theta} \in \mathring{\Omega}_\theta \text{ or } n_{\hat{\theta}}^T \Gamma\tau \leq 0 \\ \left(I - \Gamma \frac{n_{\hat{\theta}} n_{\hat{\theta}}^T}{n_{\hat{\theta}}^T \Gamma n_{\hat{\theta}}}\right)\Gamma\tau & \hat{\theta} \in \partial\Omega_\theta \text{ and } n_{\hat{\theta}}^T\Gamma\tau > 0 \end{cases} \tag{9}$$

where $\Gamma(t)$ can be any time-varying positive definite symmetric matrix. In (9), $\mathring{\Omega}_\theta$ and $\partial\Omega_\theta$ denote the interior and the boundary of $\Omega_\theta$ respectively, and $n_{\hat{\theta}}$ represents the outward unit normal vector at $\hat{\theta} \in \partial\Omega_\theta$. Such a projection mapping has the same nice properties as the discontinuous one in [1].

With the use of the projection type adaptation law structure (9), the parameter estimates are bounded within known bounds, regardless of the estimation function $\tau$ to be used. As a result, the same adaptive robust control law as in the direct ARC designs (i.e., (4) and (5)) can be used to achieve a guaranteed output tracking transient and final accuracy, independent of the specific identifier to be used later. Thus, the reminder of the IARC design is to construct suitable estimation functions $\tau$ so that an improved final tracking accuracy– zero final tracking error in the presence of parametric uncertainties only–can be obtained with an emphasis on good parameter estimation process as well. For this purpose, it is assumed that the system is absence of uncertain nonlinearities, i.e., $\Delta = 0$ in (1). Using any filters with a stable transfer function $H_f(s)$ having relative degree no less than 1, the filtered system dynamics is obtained as

$$\dot{x}_f = \varphi_f^T \theta + u_f \tag{10}$$

where $x_f = H_f[x]$, $\varphi_f = H_f[\varphi(x)]$, and $u_f = H_f[u]$ are the filter output, regressor, and input respectively. Define the estimation output and its estimate as

$$y = \dot{x}_f - u_f, \qquad \hat{y} = \varphi_f^T \hat{\theta} \tag{11}$$

With the calculable prediction error defined as $\epsilon = \hat{y} - y$, the resulting static prediction error model is linearly parameterized in terms of parameter estimation error $\tilde{\theta}$ as

$$\epsilon = \varphi_f^T \tilde{\theta} \tag{12}$$

Various estimation algorithms can then be used to identify unknown parameters [14]. For example, when the least squares type estimation algorithm with co-variance resetting [31] and exponential forgetting [6] is used, the resulting adaptation law is given by (9), in which $\Gamma(t)$ is updated by

$$\dot{\Gamma} = \alpha\Gamma - \Gamma \frac{\varphi_f \varphi_f^T}{1 + \nu\varphi_f^T \Gamma \varphi_f}\Gamma, \quad \Gamma(t_r^+) = \rho_0 I, \quad \nu \geq 0 \tag{13}$$

where $\nu = 0$ leads to the unnormalized algorithm, and $\tau$ is defined as

$$\tau = -\frac{\varphi_f \epsilon}{1 + \nu\varphi_f^T \Gamma \varphi_f} \tag{14}$$

In (13), $\alpha$ is the forgetting factor, $t_r$ is the covariance resetting time, i.e., the time when $\lambda_{min}(\Gamma(t)) = \rho_1$ where $\rho_1$ is a pre-set lower limit for $\Gamma(t)$ satisfying $0 < \rho_1 < \rho_0$.

With the above estimator and the adaptive robust control law, it is shown in [14] that the same theoretical output tracing performance results as in DARC in Theorem 1 are achieved.

### *C. Integrated Direct/Indirect ARC (DIARC)*

As shown in the comparative experimental results [32], though the proposed IARC design has a much better accuracy of parameter estimates than the direct ARC, the output tracking performances of IARC are not as good as those of DARC, especially during the transient periods. A more detailed thorough analysis reveals that the poorer tracking performance of IARC is caused by the loss of dynamic compensation type fast adaptation that is inherited in the DARC designs. To overcome this loss of tracking performance problem of IARC, an integrated direct/indirect ARC (DIARC) design framework is developed in [15]. The design not only uses the same adaptation process as in the IARC design [14] for accurate estimation of physical parameters, but also introduces dynamic compensation type fast adaptation to achieve a better transient performance as illustrated below.

For (1), the resulting DIARC law is:

$$\begin{aligned} u = u_a + u_s, \quad u_a &= u_{a1} + u_{a2}, \quad u_s = u_{s1} + u_{s2}, \\ u_{a1} &= -\varphi^T\hat{\theta} + \dot{x}_d(t), \quad u_{a2} = -\hat{d}_c \\ u_{s1} &= -k_{s1} z, \quad u_{s2} = -k_{s2}(x,t) z \end{aligned} \tag{15}$$

In (15), $u_{a1}$ represents the usual model compensation with the physical parameter estimates $\hat{\theta}(t)$ updated using the same indirect parameter estimator as in the above IARC design, $u_{a2}$ is a model compensation term similar to the fast dynamic compensation type model compensation used in the DARC design, in which $\hat{d}_c$ can be thought as the estimate of the low frequency component of the lumped model uncertainties defined later. From (1) and (15), the error equation is obtained as

$$\dot{z} = u_s + u_{a2} - \varphi^T\tilde{\theta} + \Delta \tag{16}$$

Define a constant $d_c$ and time varying $\Delta^*(t)$ such that

$$d_c + \Delta^*(t) = -\varphi^T\tilde{\theta} + \Delta \tag{17}$$

Conceptually, (17) lumps the disturbances and the model uncertainties due to physical parameter estimation error together and divides it into the static component (or low frequency component in reality) $d_c$ and the high frequency components $\Delta^*(t)$, so that the low frequency component $d_c$ can be compensated through fast adaptation similar to those in the above direct ARC design as follows.

Let $d_{cM}$ be any pre-set bound and use this bound to construct the following projection type adaptation law for $\hat{d}_c(t)$

$$\dot{\hat{d}}_c = \begin{cases} 0 & \text{if } |\hat{d}_c| = d_{cM} \text{ and } \hat{d}_c z > 0 \\ \gamma_d z & \text{else} \end{cases} \tag{18}$$

with $\gamma_d > 0$ and $|\hat{d}_c(0)| \leq d_{cM}$. Such an adaptation law guarantees that $|\hat{d}_c(t)| \leq d_{cM}, \forall t$. Substituting (17) into

(16) and noting (15),

$$\begin{aligned}\dot{z} &= u_s + u_{a2} + d_c + \Delta^*(t) \\ &= u_{s1} + \left[u_{s2} - \tilde{d}_c + \Delta^*(t)\right]\end{aligned} \tag{19}$$

Due to the use of projection type adaptation law, all estimation errors are bounded within known bounds. As such, the same as in the DARC, it can be shown that, as long as the nonlinear feedback gain $k_{s2}$ is chosen large enough, the same robust performance condition as (5) can be satisfied

$$z\left[u_{s2} - \tilde{d}_c + \Delta^*\right] \le \varepsilon_c \tag{20}$$

With the above estimator and the adaptive robust control law, it can be shown [15] that theoretically the same output tracing performance results as in DARC in Theorem 1 are achieved.

## III. Essences of Adaptive Robust Control

In addition to the mathematically rigorous designs presented in the previous section, in this section, some intuitive explanations and the link to the traditional fundamental control design philosophy for linear systems will be presented to reveal the essences of the proposed ARC approach – knowing the essences will significantly help a control engineer in correctly applying the proposed ARC approach in practice without getting bugged down to the technical design complexity necessary for theoretical rigorousness.

The salient feature of the proposed ARC lies in the **seamless integration** of (i) *proper controller structure that enables the use of local high-gain nonlinear robust feedback in attenuating the effect of various model uncertainties as much as possible,* and (ii) *controlled parameter adaptation (or learning in general) in reducing the extent of model uncertainties caused by repeatable unknown quantities (e.g., parametric uncertainties)* to maximize the achievable control performance with built-in intelligences. Such a design philosophy is well in-line with how human beings utilize feedback information: (a) routine workouts and training in combination with good physical body for faster immediate reaction capability – essential for survival and having consistent control performance in various uncertain situations, and (b) brain power of using large amount of stored past feedback information in figuring out the underline dynamics of the particular environment encountered (i.e., slow learning) to gain predication capability for even faster response time or smoother actions. As pointed out by the Bode Lecture awardee, Professor G. C. Goodwin, *"the core idea in control is that of inversion; the inversion can be conveniently achieved by the use of two key mechanisms: feedback and feedforward "* and *"high loop gain gives approximate inversion, which is the essence of control"* (page 36 in [33]). These fundamental control design philosophies are well reflected in the proposed adaptive robust control theory – the nonlinear model compensation with on-line parameter adaptation or other learning tools is an advanced version of feedforward design, and the emphasis of local high-gain feedback for good transient and steady-state performance touches the essence of feedback control. The reader is strongly advised to keep these fundamental design philosophy in mind when going through various specific design techniques presented to avoid getting bugged down in the complicated mathematics.

## IV. Applications to Integrated Design of Intelligent and Precision Mechatronic Systems

The seamless integration of fast feedback and robust slow learning of the proposed ARC approach makes it well suited for the integration design of intelligent and precision mechatronic systems, as demonstrated through various applications in [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29]. Some specific aspects of this integrated design framework are outlined below.

*The first step in the integrated design is to figure out various practical ways in achieving fast feedback, which should put equal emphasis on both software and hardware design optimizations.* Software side, nonlinear local-high-gain-global-low-gain robust feedback structure instead of traditional linear high gain feedback should be used as illustrated in Fig.1, which enables the explicit consideration of the control input saturation while having enough flexibility in achieving a better trade-off in meeting various conflicting design objectives. Hardware side, innovative mechanical designs with product functionality in mind should be sought to make the resulting physical system capable of having fast response or conducive to high-gain feedback. Two such practical examples are the positioning systems driven by linear motors studied in [20], [21], [22], [23] and the novel energy-saving valves developed by the author in [34], [35], [36]. Specifically, for electro-mechanical positioning systems, the use of linear motor drive systems instead of rotary motors provides the hardware possibility of having fast reaction due to the rigid construction of linear motor based positioning systems [20]. For electro-hydraulic systems, the use of a unique combination of five independently controlled poppet type cheap cartridge valves completely bypasses the sandwiched deadband problem of traditional expensive proportional directional control valves when controlled properly, [36], which in return provides the hardware possibility of having fast reaction – sandwiched deadband physically limits the response speed of a control valve, regardless the type of advanced controls to be used.

*The next step in the integrated design is to look for practical ways to have good and robust learning capability.* These include (i) separation of estimation model from the controller design model [14], (ii) parameter estimation algorithms with better convergence properties, (iii) explicit on-line monitoring of persistence excitation level for accurate parameter estimates, and (iv) the use of available prior process knowledge such as the physical bounds of parameter variations to achieve a controlled learning process; this helps get rid off the destabilizing effect of on-line learning and enable a fast adaptation loop to be used in practice for better control performance.

*Finally, a system design perspective should be emphasized through out the integrated design process.* An impossible-to-solve hard control problem (e.g., the precision control of conventional rotary motor driven high-speed/acceleration positioning systems that may involve flexibility and backlash of drive mechanisms along with the unavoidable highly nonlinear Coulomb frictions) could be easily overcome through the seamless integration of software based complex control architectures (e.g., the presented adaptive robust control which is very effective in dealing with the highly-nonlinear Coulomb frictions) and the use of innovative hardware redesign (e.g., the rigid construction of linear motor driven positioning systems).

## V. Precision Motion Control of Linear Motor Drive Systems

All the proposed ARC designs have been applied to the precision motion control of a linear motor drive system [20]. The details on how the ARC control laws are implemented are given in [32]. This section only gives some typical experimental results for illustration purpose.

A typical high-speed/high-acceleration motion trajectory for the pick-and-place operations in industry is used in all experiments. The desired trajectory has a movement of $0.4m$ with a maximum speed of $1m/s$ and an acceleration of $12m/sec^2$. The experimental results in terms of the quantitative indexes defined in [20] are given in Table 1 with time history given in Figs.1-2.

TABLE I

| | without load | | | with load | | |
|---|---|---|---|---|---|---|
| controller | D | I | DI | D | I | DI |
| $e_M$ $(\mu m)$ | 10.4 | 13.0 | 10.7 | 18.4 | 14.9 | 10.7 |
| $e_F$ $(\mu m)$ | 10.4 | 12.7 | 9.2 | 10.8 | 12.7 | 9.3 |
| $L_2[e]$ $(\mu m)$ | 1.84 | 3.32 | 1.66 | 1.64 | 3.36 | 1.76 |
| $L_2[u]$ $(V)$ | 0.28 | 0.29 | 0.28 | 0.45 | 0.46 | 0.46 |
| $L_2[\Delta u]$ $(V)$ | 0.10 | 0.11 | 0.11 | 0.10 | 0.10 | 0.10 |
| $c_u$ | 0.34 | 0.38 | 0.39 | 0.21 | 0.23 | 0.22 |

As seen from these results, the tracking errors of all the controllers are very small, which are within $20\mu m$ over the entire run. For both no load and load cases, the parameter estimates of IARC and DIARC algorithms are better than that of DARC, especially the inertial load (not shown) and the friction estimates (Fig.2 and 3). However, the tracking performances of DARC and DIARC controllers are better than that of IARC as seen from Fig.1. Overall, DIARC achieves the best tracking performance while having more robust parameter estimation process and accurate parameter estimates than DARC.

## VI. Conclusions

This paper focuses on the essence of the recently developed adaptive robust control strategy – seamless integration of (i) local-high-gain-global-low-gain nonlinear robust feedback for fast instantaneous reaction to maximize the attenuation level of various model uncertainties for a guaranteed robust performance, and (ii) controlled parameter adaptation and learning to achieve a fine tuned high performance. In addition, by-product of the learning process such as accurate parameter estimates can be used to add built-in machine intelligences such as prognostic capability. The applications of the approach to the integrated design of intelligent and precision mechatronic systems are illustrated through several practical examples.


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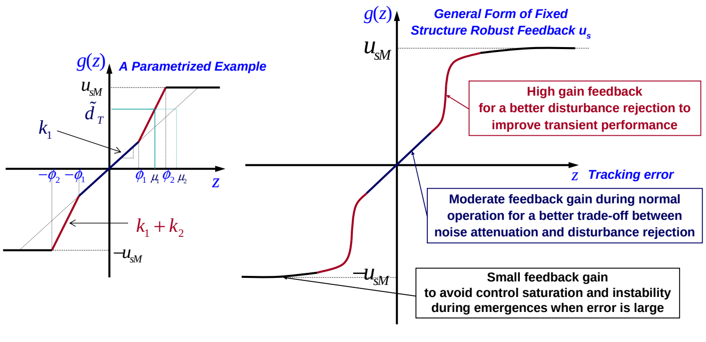


Fig. 1. Nonlinear Feedback for Improved Transient Performance and Better Trade-off in Meeting Various Needs

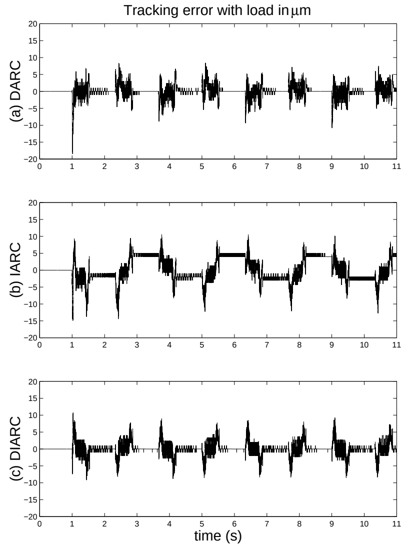


Fig. 2. Tracking error for (a)DARC, (b)IARC, (c)DIARC with load

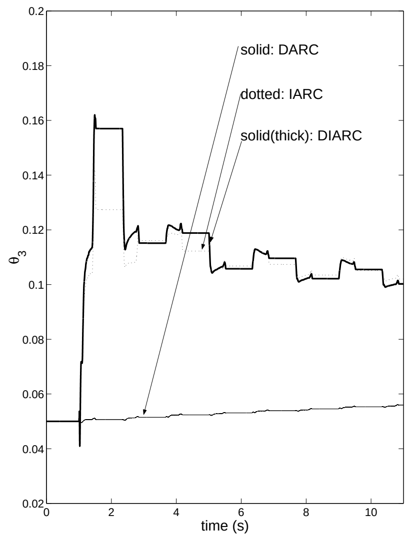


Fig. 3. $\hat{\theta}_3$ for (a)DARC, (b)IARC, (c)DIARC without load

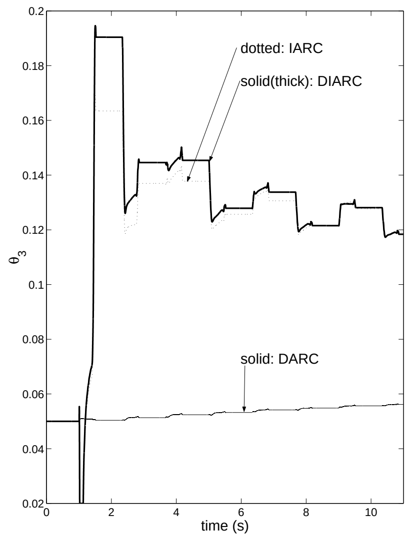


Fig. 4. $\hat{\theta}_3$ for (a)DARC, (b)IARC, (c)DIARC with load