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13. ABSTRACT *(Maximum 200 Words)*
This is the final report for research supported under AFOSR Grant F49620-95-1-0095 during the period December 15, 1994 through August 31, 1998. The research focused broadening class of solvable robust control problems and on developing a firm information theoretic foundation for incorporating the real-time effects of evolving experimental data in adaptive robust control system designs. Robust control concerns the problem of engineering control systems capable of robustly maintaining performance to within prescribed tolerances in the face of large-but-bounded modeling uncertainties and nonlinearities. Significant advances were achieved in developing *Bilinear Matrix Inequality* (BMI) robust control design methods. The BMI significantly expands the class controller design constraints that can be accommodated to include reduced order control, decentralized control, multi-model control, gain-scheduling, mixed H_2/H_∞ control and so forth. In a separate development, a theory of *unfalsified control* has emerged as a precise tool for characterization and optimal utilization of the evolving information flows in adaptive control processes. This theory has also been demonstrated to lead to faster, more reliable adaptive control designs. The results are expected to be useful in advanced aerospace control applications where robust performance is prerequisite.

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Final Report:
ROBUST CONTROL METHODS
AFOSR Grant F49620-95-1-0095

December 15, 1994 – August 31, 1998

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October 31, 1998

Contents

1 Research Objective

Research efforts supported by AFOSR Grant F49620-95-1-0095 have centered on development a cohesive theory for the design of systems for precision control of uncertain, highly nonlinear systems including, but not limited to, high performance military aircraft flight control, laser-based tracking and targeting sensors, missile autopilots, and so forth. While such applications form the context of the research, the aim has been to develop the mathematical concepts and theory needed to formulate, analyze and solve such problems in an engineering setting. Specifically, the focus has been on the development of flexible analytical tools for use in the design of design of feedback control systems which perform reliably in the face of imprecise knowledge regarding the differential equations representing the systems under consideration. The question of evolving information about uncertainties has emerged as critical for robust control theory and, towards the end of the grant period, the research emphasis shifted slightly in order to address this issue.

2 Accomplishments

Fifty publications supported under AFOSR Grant F49620-95-1-0095 have either appeared, been submitted or are currently pending publication [1]–[50]. Areas of significant progress represented by these AFOSR supported publications include the following:

- Real Multivariable Stability Margin (MSM) Analysis [5, 15, 17, 29, 43, 44]
- Theory for Reliable Numerical Computation of H_∞ Controllers [3]
- Beyond H_∞ Control [3, 7, 9, 24, 25, 26, 27, 33, 34]
- Bilinear Matrix Inequality (BMI) robust control synthesis [1, 4, 7, 9, 16, 19, 20, 22, 24, 25, 27, 33, 35, 46, 47, 48]
- Unfalsified-Control, Learning, Adaptation & Controller Identification [6, 10, 11, 12, 13, 14, 18, 21, 23, 28, 32, 34, 35, 36, 37, 38, 39, 41, 42, 45, 49, 50]
- H_∞ Control Design Applications [2, 8, 37, 36, 42, 43]

Generally, the theoretical developments embodied in the above listed recent AFOSR publications have been accompanied by software implementation and test case studies. The BMI theory plays a critical role in extending and generalizing the H_∞ robust controller design theory that has already proven its value in aircraft flight control applications [51, 52, 53]. It allows greater flexibility in handling structured uncertainties, controller complexity constraints and gain-scheduling requirements. The generalized Popov multiplier robustness analysis and synthesis techniques [2, 26, 27] developed in have led directly to improved approaches for the design of active vibration damping systems for flexible space structures [8]. The effective and rapid transition from theory to practice has been facilitated by my on-going non-AFOSR-supported involvement with Dr. R. Y. Chiang in upgrading the MATLAB ROBUST CONTROL TOOLBOX, a robust control design software product published by The MathWorks and in widespread use by government, university and aerospace engineering company labs [54]. But perhaps the most significant new results pertain to our recent development of ***unfalsified control theory.*** This new theory is a precise, experiment-based approach to adaptive controller synthesis based on evolving measurements of plant response. Unlike traditional control design methods where controller choices generally depend heavily of prior knowledge of plant models and error-bounds, the unfalsified control theory gives primary emphasis to the precise analysis of the implications of experimental measurement data. A plant model, though useful, is not required.

Positive Real Synthesis and Singular H_∞ Control

One of the topics on which our research has touched has been positive-real feed back synthesis, a topic closely related to H_∞ robust control theory. Motivated by problems in active vibration control in flexible space structures, control engineers have long been interested in how to synthesize feedback controllers which make a mechanical structure appear to be energy dissipative to potential sources of vibrational disturbances. Linear time-invariant dissipative systems are called positive real, because their impedance are have positive real parts at each frequency. The design of feedback controllers which will make a system seem positive real also has uses in decentralized robust control synthesis, since interconnections of several independently designed energy dissipative systems remain energy dissipative and, hence, robustly stable.

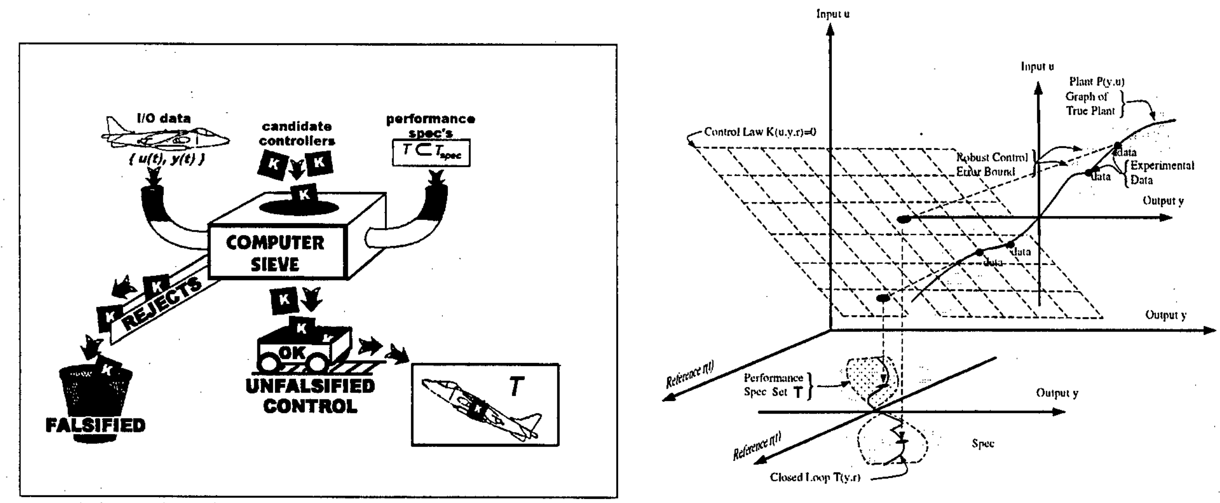
While methods for solving positive real problems have long been available [55, 56], we have recently been able to simplify the theory somewhat with alternate derivations based on the positive-real Parrott theorem and linear matrix inequality (LMI) control synthesis theory [7, 9, 25, 26, 27]. We have also developed extensions of the theory in which unstable "generalized Popov multipliers" promise to provide a more direct and numerically reliable LMI solution to real/complex mu-synthesis [27, 48]. Also, we have developed an LMI solution to the more general conic-sector synthesis problem; this generalization includes H_∞ and positive-real control synthesis problems as special cases [33].

In an unrelated development, we have obtained a result that enlarges the class of problems for which optimal H_∞ controllers may be reliably computed. Singular H_∞ problems having $j\omega$-axis zeros and infinite zeros could not be solve using standard "two-Riccati" H_∞ control algorithms. In [3], we reported results which make it possible to handle these singular cases.

Bilinear Matrix Inequality (BMI) Robust Control Synthesis

Traditionally, robust control theory has been concerned with the control of systems under the assumption of precise prior knowledge of modeling uncertainty — i.e., traditional robust control theories apply to situations where the uncertainty bounds are themselves completely certain. For these cases, the H_∞ and the more general μ/K_m-synthesis theories are now fairly well developed tools for solving robust control problems. In terms of simplicity of mathematical representation, the Bilinear Matrix Inequality (BMI) formulation of μ/K_m-synthesis theory provides an especially flexible formulation [57, 4]

A suboptimal solution to the right problem is more likely to be useful than an 'optimal' solution to a crude approximation to the problem. The BMI mathematically represents the 'right' problems — problems which fully and accurately reflect diverse types of plant uncertainty information and controller structure/order constraints. These include: (1) mixed H_2/H_∞ performance criteria, (2) robustness against real/complex uncertainties, (3) controller order and complexity constraints, (4) decentralized and hierarchical control, (5) multi-objective control (pole placement, robustness), and (6) multi-plant control (one robust controller for multiple nominal plants). Despite the fact that globally optimal BMI solutions in general may be difficult to obtain (e.g., [58, 22]). suboptimal solutions to BMI feasibility problems are routinely computed via alternating LMI methods. This has made fully automated, albeit possibly suboptimal, BMI μ/K_m-synthesis both practical and, apparently, reliable (e.g., [59, 60, 8]) albeit computationally demanding.



(a) Unfalsified control provides a sieve. (b) Consistency of controller, data and goal.

Figure 1: Unfalsified control sifts controllers for consistency with experimental data and control performance goals. A control law K is unfalsified (i.e., consistent with data and control goals) if the projection under K of the data point (u, y) onto the (r, y)-plane produces a point (r, y) in the performance specification set $\mathbf{T}$.

Mathematically, the BMI is defined as follows:

Definition 2.1 (BMI Feasibility Problem) *Given real Hermitian matrices $F_{i,j} = F_{i,j}^T \in \mathcal{R}^{m\times m}$, for $i \in \{1, \ldots n_x\}$, $j \in \{1, \ldots n_y\}$. Define the matrix-valued bilinear function $F : \mathcal{R}^{n_x} \times \mathcal{R}^{n_y} \to \mathcal{R}^{m\times m}$:*

$$F(x, y) \triangleq \sum_{i=1}^{n_x} \sum_{j=1}^{n_y} x_i y_j F_{i,j} \tag{2.0}$$

Find, if they exist, real vectors $x = [x_1, \ldots, x_n]^T \in \mathcal{R}^{n_x}$ and $y = [y_1, \ldots, y_n]^T \in \mathcal{R}^{n_y}$ such that $F(x, y)$ is positive definite. This is called the **bilinear matrix inequality feasibility problem.**

The global solution of such BMI's would resolve many of the major limitations the existing μ/K_m-synthesis theory for robust control design.

For example, as shown in [4], BMI's provide a natural formulation for the problem of optimal reduced-order H_∞ control synthesis introduced by [63, 64]. The BMI formulation seems to us rather simpler than the nonlinearly coupled LMI's proposed in [65, 66]. When this research project begin, BMI's and nonlinearly coupled LMI's had so far defied attempts to develop globally convergent solution algorithms, except for several special cases (e.g., [67]). However, we now have several globally convergent algorithms [1], though in general they may be very slow for problems where n_x and n_y are large. This is as expected, since the BMI problem is known to be non-convex and NP-complete, which means that polynomial-time algorithms are not possible. And, the class of special cases that can be reduced to more tractable LMI problems has been expanded to include a certain subset of positive real feedback synthesis problems of that arise adaptive control theory [9].

Likewise, while the controller structure constraints required in the synthesis of decentralized controllers have so far defied attempts to embed them in the LMI framework, these constraints are readily embedded within the BMI framework. Even more importantly, the BMI framework naturally handles the μ/K_m-synthesis with fixed-order generalized Popov multipliers [4].

Unfalsified Control Theory

Unfalsified control is a type of direct adaptive control based on a precise analysis of the control-goal-relevant information in measurement data. Inspired by the "unfalsified model" concepts used in model validation (e.g., [68, 69, 70, 71, 72, 73, 74]), but disappointed by their relative complexity and inherent conservativeness when used for control-oriented identification in conjunction with state-of-the-art robust control methods, a more direct "unfalsified control" approach was introduced by us in [6, 13, 21, 75] — see also [76, 77, 78, 79, 80].

The unfalsified control concept is a "model-free" approach to the problem of deciding which control law to use. The theory works directly with input-output measurement data. The only model required is that of a parameterized class of candidate hypotheses as to control laws to be considered. The central idea in unfalsified control approach is that controller hypotheses can be "validated" against performance specifications directly from plant input-data without any need to identify or validate models of the plant itself. Furthermore, the computations required for direct "controller validation" are really no more difficult than those required for plant model validation of the type in [70, 69, 72, 74, 73, 81]. The theory is non-conservative in that it provides a precise set-theoretic characterization of the controller relevant information in experimental data. The result is an efficient sure-footed algorithm for identifying controllers consistent with performance goals. A salient feature of the theory is that data acquired with one controller in the loop can often be used to falsify other as-yet-untried controllers before they are ever physically connected to the plant.

At the conceptual level, unfalsified control is closely related to the *candidate elimination algorithm* of machine learning theory [82]. It works by successive elimination of hypotheses that are found to be inconsistent with goals and evolving observational evidence. In the case of unfalsified control, the evidence consists of measurements of plant input-output signals, the hypotheses are candidate control laws, and the goals are closed-loop performance functionals. The theory allows one to sift through candidate control laws in real-time, eliminating those inconsistent with performance goals — cf. Fig. 1(a).

The essence of the unfalsified control concept is depicted abstractly in Figure 1(b). The three axes represent the three (infinite dimensional) function spaces of which the signals r, y, u are members. The three signals r, y, u are, respectively, commands $r(t)$, plant output $y(t)$ and control signal $u(t)$. In this context, a plant is a collection of input-output signal pairs (u, y). A control design specification is a constraint on the signal pairs (r, y) — i.e., a set, say $\mathbf{T}$, in which the pair (r, y) must lie. A control law, say K, is a constraint on the triple (r, y, u), i.e., a subset of the set of triples (r, y, u). In Figure 1(b) the plane $K(u, y, r) = 0$ represents a particular linear control law. The key observation is that one may test consistency of the control law $K(u, y, r) = 0$ with the specification $\mathbf{T}$ and the past plant data (u, y) by checking that the image of the pair (u, y) under the constraint $K(u, y, r) = 0$ is a pair (r, y) in $\mathbf{T}$. Moreover, this controller consistency test may be performed even if the plant data (u, y) has been generated by another control law — or even if is has been generated open-loop with no control law at all. A control law K which fails to be consistent with the performance specification and the past plant input-output data is invalidated, i.e., *falsified*; those control laws which are not falsified are said to be *unfalsified.*

Instead of attempting to enforce a somewhat artificial separation between modeling and control design, the unfalsified control concept can, if so desired, dispense with plant models and uncertainty models altogether, focusing instead directly on the controller model and the implications of the available plant data regarding its capability to meet performance specifications. It replaces the conventional indirect two-step approach of (a) finding unfalsified plant models and (b) designing robust controllers. The unfalsified control concept takes one directly from plant input-output data to control designs without the necessity of plant or uncertainty modeling. This is possible since all needed information about the plant is already in the plant input-output data — and this information turns out to be sufficient to validate control laws.

This simple idea is the essence of the *unfalsified control concept.* But, simple though it may be, it is a revolutionary concept. It makes no explicit use of plant models other than the data itself, so in this sense it is a "model-free" approach to control. Because it requires no unverifiable assumptions and works only with data and specifications, it provides a direct, nonconservative approach to control design, as illustrated by the examples and design studies in [21, 36, 42, 12].

Thus, unfalsified control is beginning to emerge as a practical theory for real-time robust control suitable for use when prior knowledge of plant models is very limited. The "ACC Benchmark" robust control design problem solved by us using unfalsified control techniques in [13, 80] established not only the conceptual feasibility of the unfalsified control approach, but also that it can actually lead to superior designs.

Though there remain some questions regarding what, if any, is the appropriate role for modeling assumptions and noise in unfalsified control theory, it has become increasingly clear that stochastic noise is not as great an issue as had been believed. In fact, the emerging theory of unfalsified control is providing a sharper picture of the fundamental nature of learning and adaptation than has previously been possible precisely because it does not rely upon prior knowledge of noise statistics and plant models in formulating control objectives or evaluating consistency of controller hypotheses with data and goals. This is so because, unlike traditional control theory which is essentially based on an introspective analysis of mathematical models, unfalsified control theory is a precise characterization of the raw implications of open-eyed observation — observation of past data which may not always conform to the predictions of models, but which *a posteriori* is always deterministic. And, even though it may sometimes be convenient to express control design goals in terms of unseen internal plant signals that are tied to experimental observations via stochastic noise models, the probabilistic character of such performance criteria inevitably evaporates when these criteria are evaluated *a posteriori*, as would normally be the case in unfalsified control applications. Thus, even when performance criteria are given implicitly in terms of stochastic models, the corresponding unfalsified control problem generally has an equivalent deterministic interpretation.

Looking beyond control theory, we see unfalsified control as a key to beginning the important task of building a solid common foundation for robust, adaptive and intelligent systems — a foundation sufficiently broad to be embraced not only by control theorists but by the artificial intelligence (AI) community as well. Along the latter line, we note that the AI community where falsification concepts are already widely embraced as an integral part of machine learning theory for example, in the *candidate elimination algorithm* [82].

Control System Design Studies

The unfalsified control theory has enjoyed further successes in design studies involving an adaptive missile flight control system [42] and a nonlinear robot arm controller [36, 12]. Figure 2 depicts the results of the missile control design study. Here, time domain inequalities specified the acceptable response shape for a bang-bang stepping command signal. The controller had a PID structure, with adaptive time-varying gains. The unfalsified control theory sifted through candidate PID gains "on the fly," allowing it to automatically discover the right gains without any prior knowledge of the missile dynamics. The unfalsified control algorithm was able to eliminate most of the candidate gains based on data collected early in the flight while other as yet unfalsified controllers were in the loop, so that after only a very few controller gain switches, the algorithm was able to discover

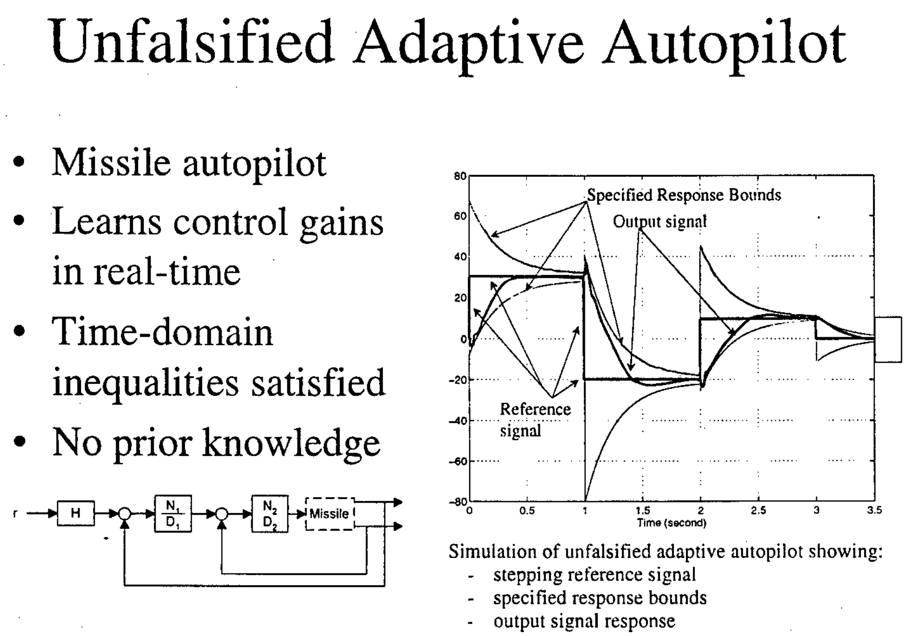
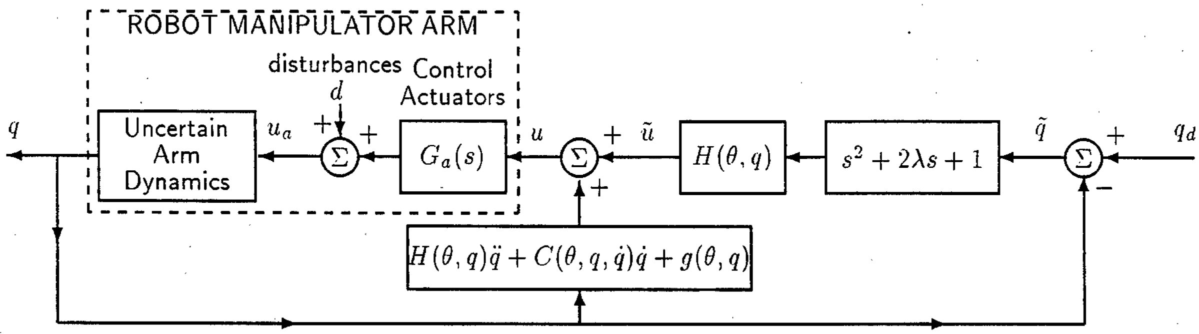


Figure 2: Unfalsified controller for missile.

suitable control gains directly from real-time sensor and actuator data. The result, as seen in the figure, was a sure-footed control response capable of adapting rapidly to abrupt changes in missile dynamics. A more theoretical study of issues arising in the face of changing plant dynamics are addressed in [11], where an unfalsified control problem with a quadratic performance criterion and a parameterized infinite set of candidate controllers was shown to lead to a computationally tractable unfalsified control problem. This is important because early examples of unfalsified control applications had required the set of candidate controller gain values to be finite, which had proved somewhat restrictive. The ability of the unfalsified control design to maintain precise control in the face of evolving uncertainties enables it to better compensate for uncertain and time-varying effects such as battle damage, equipment failures and other changing circumstances.

Depicted in Fig. 3 is another recent application of unfalsified control theory to the design of an adaptive 'computed torque' controller for a nonlinear robot manipulator [12, 36]. The plot shows that the method yields significantly more precise and rapid parameter adjustments than a conventional adaptive controller. The unfalsified control theory allows sure-footed, precise control in the face of evolving uncertainty because it is a precise non-conservative technique that relies on data — not on possibly incorrect modeling assumptions and approximations. Unfalsified control optimally exploits *all* information in the data to robustly adapt controller gains.



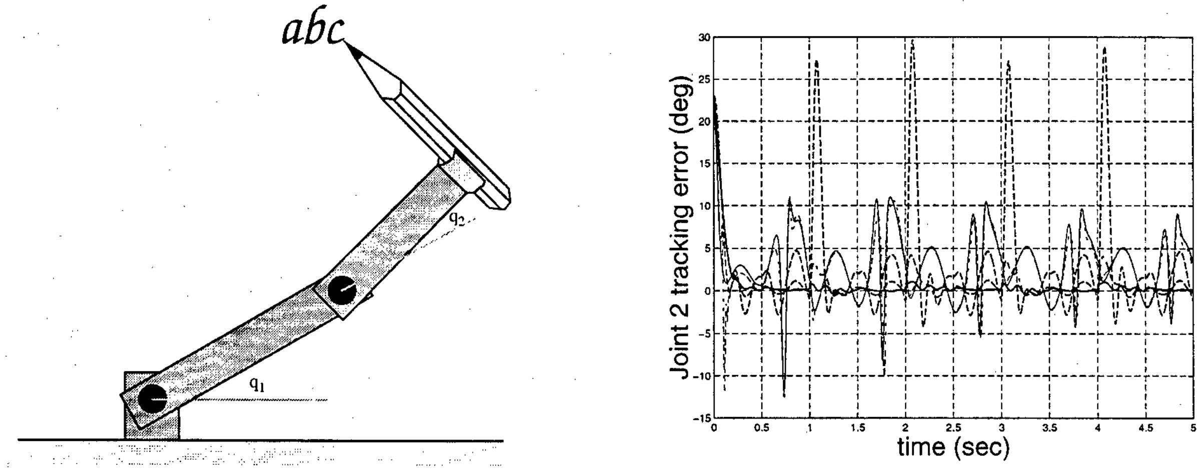


Figure 3: Unfalsified control produced superior results for a nonlinear two-link robot manipulator subject to uncertain dynamics, noisy disturbances and abrupt changes in load mass. The two sluggishly smooth traces large amplitude signals in the plot are with a conventional adaptive controller used to adjust control gain-vector $\theta(t)$, and the two very low amplitude traces are for the unfalsified controller. The unfalsified controller had a much quicker, sure-footed and precise response without increased control effort.

3 Conclusions

With support from AFOSR Grant F49620-95-1-0095, significant progress has been made to theory for reliable computation of robust controllers, to the field of robust BMI synthesis theory, and to the development of the unfalsified control theory formulation of adaptation and learning problems.

The *Bilinear Matrix Inequality* (BMI) formulation of the robust control synthesis problem has been found to be among the most flexible, allowing a broad spectrum of control design constraints to be embedded within the single simple mathematical framework afforded by the BMI. Constraints which can be readily embedded in this framework include controller complexity, decentralized control, uncertainty tolerance, bandwidth, noise attenuation, nonlinear gain-scheduling, energy dissipativeness, control precision, stability margins, and more. The mathematical and numerical properties of the BMI optimization problems have been comprehensively studied. Though in general, BMI problems are NP-complete and hence theoretically hard to solve, cases for which alternative closed-form solutions are known have been generally found to be reducible to simpler LMI (linear matrix inequality) problems for which reliable computation methods are available. Thus, it may be said that the BMI theory has unified and simplified robust control theory, bringing it to a fairly mature state.

As robust control theory has matured, a key remaining challenge to control theorists has been the need for a more flexible theory that provides a unified basis for representing and exploiting *evolving* information flows from models, noisy data, and more. The *unfalsified control theory* developed with AFOSR support gives sharp mathematical representation of the role of experimental data in identifying robust control laws and provides a practical technique for identifying robust controllers in real-time with little or no apriori information. The theory paves the way for important links between robust control, adaptive control and artificial intelligence. It is a conceptual breakthrough because it distills the mathematical essence of control-oriented learning by focusing sharply on what is, and is not, knowable from experimental data and by challenging both the need and the appropriateness of a number of common assumptions. The results of our unfalsified control research lay a firm theoretical foundation for the design of feedback control systems with the ability to efficiently exploit evolving real-time information flows as they unfold, thereby endowing control systems with the intelligence to adapt to unfamiliar environments and to more effectively compensate for the uncertain and time-varying effects battle damage, equipment failures and other changing circumstances.

Publications Supported by AFOSR Grant F49620-95-1-0095

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Coupling Activities

Talk: M. G. Safonov.
The unfalsified control concept: A direct path from experiment to controller.
Talk, Hughes Aircraft, El Segundo, CA, November 9, 1994.

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Focusing on the knowable: Controller invalidation and learning.
Talk, MIT Lab for Information and Decision Systems, Cambridge, MA, October 4, 1995.

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Direct identification of controllers via unfalsified control theory.
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Distinguished Lecture Series in Systems and Controls.

Talk: M. G. Safonov.
Multivariable stability margin analysis.
Talk, Hughes Aircraft, El Segundo, CA, May 27, 1997.

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Invited talk at workshop organized by R. E. Kalman.

Talk: M. G. Safonov.
Focusing on the knowable: Controller invalidation and learning.
Talk, Imperial College, London, England, June 23, 1997.

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