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13. ABSTRACT (Maximum 200 words)

The complexity of modern day aerospace, industrial, DoD, civil infrastructure, and vehicle systems is increasing, and performance requirements are becoming more stringent in terms of both accuracy and speed of response. Such systems are characterized by complex nonlinear dynamics and actuators with deadzones, backlash, and saturation. The control problems associated with such systems are not easy, as they do not satisfy most of the assumptions made in the controls literature. Military Leaders and JFACC require intelligent, dynamically reconfigurable wireless networks of distributed MEMS microsensors and deployable actuation units. This grant has three goals: We designed rigorous new nonlinear control schemes for a broad class of industrial and DoD systems based on direct approximate solution of the Hamilton-Jacobi-Bellman equation using neural networks. We developed new information content and controllers for wireless networked systems. Results were implemented on a mobile wireless network testbed built at ARRI. We built a prototype precision automated robotic microassembly system for future MEMS sensors and actuators for military networks. There were numerous publications and students, and significant leveraging funds were received.

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"Nearly Optimal Solution of HJB Equation using Neural Networks: Applications to Control of DoD Systems and MEMS Assembly"

PI: F. L. Lewis

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Scientific Progress and Accomplishments

Problem Statement: Background and Goals

The complexity of modern day aerospace, industrial, DoD, civil infrastructure, and vehicle systems is increasing, and performance requirements are becoming more stringent in terms of both accuracy and speed of response. Such systems are characterized by complex nonlinear dynamics and actuators with deadzones, backlash, and saturation. The control problems associated with such systems are not easy, as they do not satisfy most of the assumptions made in the controls literature.

Modern battlespace systems require increased speed and dynamical responsiveness, novel deployable sensor systems, greater information for Military Leaders and JFACC, and faster information assimilation connections for warfighters and weapons platforms. This requires intelligent, dynamically reconfigurable wireless networks of decision-making C&C centers, distributed sensors, and deployable actuation units. New information protocols and control architectures are needed for wireless networked systems that confront NP-complexity issues.

MEMS microsensors and possibly invasive microactuators will be incorporated for fully distributed and embedded battlefield network systems. However, microassembly techniques for MEMS are in an embryonic stage that does not allow mass production of micro embedded networks.

The goals of this grant were three. All have been accomplished.

Goal 1 designed rigorous new nonlinear control schemes based on **direct approximate solution of the Hamilton-Jacobi equations using neural networks (NN).** On-line NN control techniques were developed that stabilize the system based on NN weight learning to approximate the optimal value function. Computational complexity was confronted using specialized structured NN controllers to provide efficient numerical solution algorithms for nonlinear optimal controllers. Optimal constrained controls were designed that satisfy actuator saturation limitations.

Goal 2 proposed **new information content and controllers for wireless networked systems.** A new matrix-based discrete event controller was designed for wireless sensor networks with some mobile sentry nodes and some unattended ground sensors. The results were implemented on a mobile wireless sensor network testbed built at ARRI.

Goal 3 built a **prototype precision automated robotic microassembly system** for future MEMS sensors and actuators for military networks. Novel control schemes and user interfaces were provided for tele-operated vision-guided microassembly.

Neural Network Solution of HJB Equation for Nearly Optimal Controls

We have shown, in work with Abu-Khalaf, how to use neural networks to solve the Hamilton-Jacobi-Bellman (HJB) Equation for general nonlinear systems with constrained control inputs. This result provides a rigorous practical, computationally tractable algorithm to find nearly optimal saturated controls for a general class of practically useful nonlinear systems.

The solution of the optimal control problem for general nonlinear systems

$$\dot{x} = f(x) + g(x)u(x) \tag{1}$$

with quadratic cost function

$$V = \int_0^\infty \left(x^T Q x + u^T R u \right) dt \qquad (2)$$

is given by substituting into the generalized Hamilton-Jacobi-Bellman (HJB) equation

$$GHJB(V,u) \overset{\Delta}{=} \frac{\partial V}{\partial x}^T \left(f + gu \right) + Q + u^T R u = 0, \qquad V(0) = 0. \qquad (3)$$

the optimal control

$$u^*(x) = -\frac{1}{2} R^{-1} g^T(x) \frac{\partial V^*(x)}{\partial x}. \qquad (4)$$

This yields the well-known HJB equation

$$HJB(V^*) \overset{\Delta}{=} \frac{\partial V^*}{\partial x}^T f + Q - \frac{1}{4} \frac{\partial V^*}{\partial x}^T g R^{-1} g^T \frac{\partial V^*}{\partial x} = 0, \qquad V^*(0) = 0. \qquad (5)$$

The HJB is given in terms of the cost derivative or costate $\partial V / \partial x$.

Unfortunately, many cost functions are not of the quadratic form. To obtain bounded controls, and to factor into account the cost of *awareness*, design, maintenance, and other nonstandard performance measures, one needs nonquadratic costs. Moreover, and even worse, the HJB equation cannot be solved for practical complex nonlinear systems. Based on work by Werbos and others, there are recursive techniques for solving the HJB equation. If the costate is recursively computed, the result is an adaptive critic structure.

We have shown formally how to use nonlinear network structures to approximately solve the HJB equation for general cost functions to obtain nearly optimal controls. An off-line neural network learning scheme has been developed.

The GHJB is easier to solve than the HJB since it is linear in the costate. Saridis and Beard showed that if one begins with a stabilizing control and solves (3) and then (4) repeatedly, the result is a contraction map and converges to the solution for the HJB.

In our work, we select a general cost function of the form

$$V = \int_0^\infty \left[Q(x) + W(u) \right] dt \qquad (6)$$

with Q(x) positive definite and the control weighting given by

$$W(u) = 2 \int \left(\phi^{-1}(u) \right)^T R du.$$

This was first proposed by Lyshevski. This function is positive definite as long as $(\phi^{-1}(u))^T u > 0$. Then, the GHJB design equations (3), (4) are replaced with

$$\frac{\partial V}{\partial x}^T \left(f + g \cdot u \right) + Q + 2 \int \left(\phi^{-1}(u) \right)^T R du = 0, \qquad V(0) = 0 \qquad (7)$$

$$u(x) = -\phi \left(\frac{1}{2} R^{-1} g^T(x) \frac{\partial V(x)}{\partial x} \right). \qquad (8)$$

Note that, if $\phi(.)$ is selected as a bounded function, then equation (8) guarantees that $u(x)$ is bounded. That is, this guarantees the case of *saturated controls.* Most controls in industry and DoD systems are in practice saturated.

We have shown that if one begins with a stabilizing control (not necessarily saturated) and solves (7) and then (8) repeatedly, the result is a contraction map and converges to the solution for the HJB with the modified cost function. Moreover, if the control bound $\phi(\cdot)$ is monotonically non-decreasing and $V^{(i+1)}$ is the unique positive definite function satisfying the equation $GHJB(V^{(i+1)}, u^{(i+1)}) = 0$, with the boundary condition $V^{(i+1)}(0) = 0$, then $V^{(i+1)}(x) \le V^{(i)}(x) \;\; \forall x \in \Omega$. That is, the cost function decreases at each step. We also showed that the stability region increases at each step. Finally, one eventually converges to the optimal control and optimal cost.

Unfortunately, it is still generally impossible to solve the GHJB (7) at each step. Therefore, to successively solve (7), (8) for bounded controls, we approximate the cost $V^{(i)}(x)$ with a neural net

$$V_L^{(i)}(x) = \sum_{j=1}^{L} w_j^{(i)} \sigma_j(x) = W_L^{T(i)} \bar{\sigma}_L(x) \qquad (9)$$

where the activation functions $\sigma_j(x) : \Omega \to \Re$, are continuous. Substituting this into the GHJB and projecting onto the equation error using the method of weighted residuals yields the least-squares solution

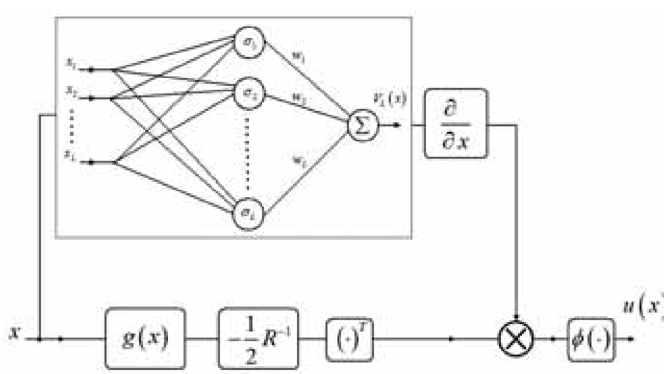
$$\left\langle \nabla \bar{\sigma}_L \left(f + gu \right), \nabla \bar{\sigma}_L \left(f + gu \right) \right\rangle w_L + \left\langle Q + 2\int \left(\phi^{-1}(u) \right)^T R du, \nabla \bar{\sigma}_L \left(f + gu \right) \right\rangle = 0 \qquad (10)$$

This is a linear equation that can be solved for the NN weights at each iteration. We showed that, on repeatedly solving (10) then (8), one converges to the optimal NN weights solving approximately the HJB.

The nearly optimal control is given by

$$u = -\phi\left(\frac{1}{2} R^{-1} g^T(x) \nabla \bar{\sigma}_L{}^T w_{L,\Delta} \right)$$

which is a NN controller as shown in the figure.



Neural-network-based nearly optimal saturated control law.

To solve (10), one may obtain a square coefficient matrix by using the collocation method to introducing a mesh in R^n. One requires at least L points x_i, with L the number of hidden layer units in the approximating NN. Defining

$$X = \left\lfloor \nabla \bar{\sigma}_L \left(f + gu \right)\Big|_{x1} \cdots\cdots \nabla \bar{\sigma}_L \left(f + gu \right)\Big|_{x_p} \right\rfloor$$

$$Y = \left[Q + 2\int \left(\phi^{-1}(u)\right)^T R du\Big|_{x1} \cdots\cdots Q + 2\int \left(\phi^{-1}(u)\right)^T R du\Big|_{x_p} \right]$$

one has that

$$Xw_L = Y$$

which can be solved by least-squares techniques. If the introduced mesh has points selected by random Montecarlo techniques, NP-complexity problems can be avoided, as can the worst-case lower error bound of Barron.

The main result is given by

Lemma 4.4: ***Consequences of Uniform Convergence of GHJB***

1. There exists a unique differentiable solution to the equation $GHJB(\hat{V}, u) = 0$ on Ω.

2. $\hat{V}(x) = \sum_{j=1}^{\infty} \hat{w}_j \, \sigma_j(x)$, is a Lyapunov function for the system $\left(f, g, u\right)$ on Ω.

3. $\sup_{x\in\Omega} \left|GHJB\left(V_{L,\Delta}; u\right)(x)\right| \to 0$ as $L \to \infty, \Delta \to 0$.

4. $\left\|w_{L,\Delta} - \alpha_L\right\| \to 0$ as $L \to \infty$, $\Delta \to 0$,

5. $\left\|V_{L,\Delta} - V\right\|_{L_2(\Omega)} \to 0$ as $L \to \infty$, $\Delta \to 0$,

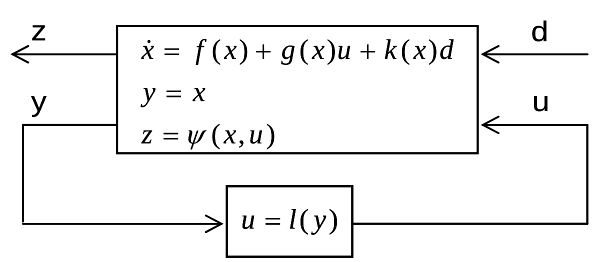
6. $\left\|u_{L,\Delta}\left(x\right) - \hat{u}(x)\right\|_R \to 0$ uniformly on Ω as $L \to \infty$, $\Delta \to 0$.

This can be used to show that the NN approximated cost technique converges to a nearly optimal control, and that the cost and stability region also converge uniformly.

Bounded L_2 Gain Solution for Input-Constrained Systems

The H-infinity problem for systems with constrained inputs had not been rigorously solved yet prior to our work. In the system

$$\dot{x} = f(x) + g(x)u + k(x)d$$
$$y = x$$
$$z = \psi(x,u)$$



where $\|z\|^2 = h^T h + \|u\|^2$, one desires to find a control *u(t)* such that, under the worst disturbance *d(t)*, one has

$$\frac{\int_0^\infty \|z(t)\|^2 dt}{\int_0^\infty \|d(t)\|^2 dt} = \frac{\int_0^\infty (h^T h + \|u\|^2) dt}{\int_0^\infty \|d(t)\|^2 dt} \le \gamma^2,$$

i.e. L_2-gain less than or equal to a prescribed γ.

The optimal control and the worst case disturbance are given by considering the Hamiltonian function

$$H(x, V_x, u, d) \equiv \frac{\partial V}{\partial x}^T \left(f + gu + kd\right) + h^T h + \|u\|^2 - \gamma^2 \|d\|^2$$

where *V(t)* is the value function. The necessary conditions for optimality are given as

$$0 = \frac{\partial H}{\partial u}, \quad 0 = \frac{\partial H}{\partial d}$$

Define the norm $\|d\|^2 = d^T d$. To make sure the control *u(t)* is constrained with prescribed saturation function *ϕ(.)*, one may select the quasi-norm

$$\|u\|_q^{\ 2} = 2\int_0^u \phi^{-T}(v) dv .$$

A quasi-norm is weaker than a norm in that the homogeneity property is replaced by the weaker symmetry property $\|x\|_q = \|-x\|_q$. Now one has the Hamiltonian

$$H(x, V_x, u, d) \equiv \frac{\partial V}{\partial x}^T \left(f + gu + kd\right) + h^T h + 2\int_0^u \phi^{-T}(v) dv - \gamma^2 d^T d$$

and the stationarity conditions

$$0 = \frac{\partial H}{\partial u} = g^T V_x + 2\phi^{-1}(u)$$

$$0 = \frac{\partial H}{\partial d} = k^T V_x - 2\gamma^2 d$$

so the optimal inputs are

$$u^* = -\tfrac{1}{2}\phi\left(g^T(x) V_x\right)$$

$$d^* = \frac{1}{2\gamma^2} k^T(x) V_x .$$

Note that the control is guaranteed to be saturated with saturation function *ϕ(.)*.

One can show that

$$H(x, p, u, d) = H(x, p, u^*, d^*) - \gamma^2 \|d - d^*\|^2 + 2\left\{\int_{u^*}^u \phi^{-T}(v) dv - \phi^{-T}(u^*)(u - u^*)\right\}^2$$

where the last term is positive definite. Therefore,

$$H(x_0, u^*, d) \le H(x_0, u^*, d^*) \le H(x_0, u, d^*)$$

which guarantees a unique solution to the bounded L_2-gain problem in a zero-sum differential game theoretic sense.

Since the system and performance integrand do not depend explicitly on time, one has that the optimal Hamiltonian is equal to zero. Substituting the optimal control and disturbance into the Hamiltonian, one obtains the Hamilton-Jacobi-Isaacs (HJI) equation

$$\frac{dV}{dx}^T \left(f + gu^* + kd^* \right) + h^T h + 2\int_0^{u^*} \phi^{-1}(v)dv - \gamma^2 \left\| d^* \right\|^2 = 0.$$

which can be rewritten as

$$\frac{dV}{dx}^T \left(f - g\cdot\phi\left(\frac{1}{2}g^T \frac{dV}{dx}\right)\right) + h^T h + 2\int_0^{-\phi\left(\frac{1}{2}g^T \frac{dV}{dx}\right)} \phi^{-1}(v)dv + \frac{1}{4\gamma^2}\frac{dV}{dx}^T kk^T \frac{dV}{dx} = 0.$$

It can be shown that the solution to the HJI is a Lyapunov function for the system.

The solution of the HJI equation provides the optimal control *u*(t)* solving the bounded L_2-gain problem for the worst case disturbance *d*(t)*.

Successive Solution Technique for the HJI Equation

Unfortunately the HJI cannot be solved for most nonlinear systems. Therefore, we provide a successive solution technique as shown.

Let γ be prescribed and fixed.

Successive Solution- Algorithm 1:

u_0 *a stabilizing control with region of asymptotic stability* Ω_0

1. Outer loop- update control

Initial disturbance $d^0 = 0$

2. Inner loop- update disturbance

Solve GHJI

$$\frac{\partial (V^i{}_j)}{\partial x}^T \left(f + gu_j + kd \right) + h^T h + 2\int_0^{u_j} \phi^{-T}(v)dv - \gamma^2 (d^i)^T d^i = 0$$

Inner loop update $d^{i+1} = \frac{1}{2\gamma^2} k^T(x) \frac{\partial V^i{}_j}{\partial x}$

go to 2.

Iterate i until convergence

Outer loop update $u_{j+1} = -\tfrac{1}{2}\phi\left(g^T(x) \frac{\partial V^i{}_j}{\partial x} \right)$

Go to 1.

Iterate j until convergence

The following results have been proven for this algorithm.

Let $\Omega^i{}_j$ be the region of asymptotic stability at iteration (i,j).

Let V* be the solution of the HJI and $\Omega *$ be the associated RAS.

Let u*, d* be the optimal control and disturbance.

Theorems

The algorithm converges to the HJI solution V*, u*, d*

For every iteration on the disturbance d^i one has

$V^i{}_j \leq V^{i+1}{}_j$ the value function increases

$\Omega^i{}_j \supseteq \Omega^{i+1}{}_j$ the RAS decreases

For every iteration on the control u_j one has

$V^i{}_j \geq V^i{}_{j+1}$ the value function decreases

$\Omega^i{}_j \subseteq \Omega^i{}_{j+1}$ the RAS does not decrease

□

H-Infinity Control for Constrained Systems

For H-infinity control, one desires to find the smallest γ for which there is a solution to the bounded L_2-gain problem. Call this value γ*. The nonlinear H-infinity control problem has certain technical issues not present in the linear case and its solution is challenging. The H-infinity norm is technically not defined for nonlinear systems, and an anomalous behavior occurs that involves the shrinking of the region of asymptotic stability. A modified well-posed problem must be formulated.

Nonetheless, we have provided a rigorous solution technique for H-infinity control for constrained nonlinear systems.

Successive algorithm to solve H-infinity problem

Select large enough γ_0

Perform Algorithm 1

If there is a solution, decrease γ and repeat.

The notion of 'large enough γ_0' was made rigorous. The following results were also shown. Let $\gamma_1 \geq \gamma_2 \geq \gamma *$. Then

$$\Omega^*_{\gamma_1} \supseteq \Omega^*_{\gamma_2}$$

$$V^*_{\gamma_1} \leq V^*_{\gamma_2}$$

Neural Network Solution of the Constrained H-infinity Control Problem

To provide a computationally attractive means of solving the HJI, we approximated the value function by a neural network as

$$V_L^{(i)}(x) = \sum_{j=1}^{L} w_j^{(i)} \sigma_j(x) = W_L^{T(i)} \bar{\sigma}_L(x)$$

where the activation functions $\sigma_j(x) : \Omega \to \Re$, are continuous and L is the number of hidden-layer neurons. Substituting this into the GHJI and projecting using the method of weighted residuals yields the least-squares solution

$$\left\langle \nabla\bar{\sigma}_L\left(f+kd\right), \nabla\bar{\sigma}_L\left(f+kd\right)\right\rangle W_L + \left\langle h^T(x)h(x) - \gamma^2 d^T d, \nabla\bar{\sigma}_L\left(f+kd\right)\right\rangle = 0$$

It can be shown that, if the set $\left\{\sigma_j\right\}_1^L$ is linearly independent and $f+kd$ is asymptotically stable, then the set $\left\{\nabla\sigma_j^{\ T}(f+kd)\right\}_1^L$ is linearly independent. Therefore, one may solve for the NN weights at iteration (i,j) using

$$W_L = -\left\langle \nabla\bar{\sigma}_L\left(f+kd\right), \nabla\bar{\sigma}_L\left(f+kd\right)\right\rangle^{-1} \left\langle h^T(x)h(x) - \gamma^2 d^T d, \nabla\bar{\sigma}_L\left(f+kd\right)\right\rangle.$$

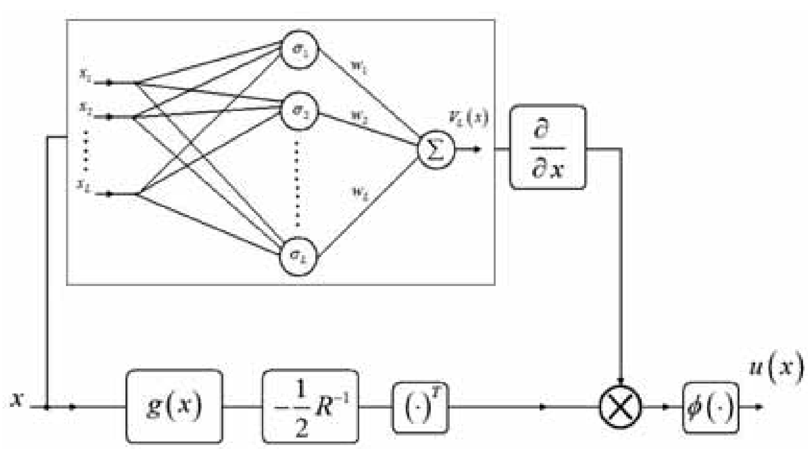
Having solved for the neural net weights, the updated disturbance is given by

$$d = \frac{1}{2} k^T(x) \nabla\bar{\sigma}_L^{\ T} W_L.$$

and the updated control by

$$u = -\tfrac{1}{2} R^{-1} g^T(x) \nabla\bar{\sigma}_L^{\ T} W_L$$

When the algorithm converges this yields a NN feedback controller as shown in the figure.



Neural-network-based nearly optimal saturated control law.

Neural Network H-infinity Output Feedback Control

Practical DoD and industrial systems always have restricted measurement information, with only certain outputs being available, not the full state information. Conditions for OPFB H-infinity control are well known in the literature. Most work has been done for dynamic OPFB. Unfortunately, design of static OPFB requires the solution of coupled partial differential equations, for which proven solution techniques do not yet exist. In the linear case the OPFB solution depends on solving three coupled matrix design equations or on solving Linear Matrix Inequalities. Therefore, in this work, we provided simplified computational solutions based on neural networks for the static output feedback H-infinity problem.

For linear systems

$$\dot{x} = Ax + Bu + Dd$$

$$y = Cx$$

one desires to find a constant output feedback (OPFB)

$$u = -Ky = -KCx$$

such that , for a prescribed γ, when $x(0)= 0$ and for all disturbances $d(t) \in L_2$ one has

$$\frac{\int_0^\infty \|z(t)\|^2 dt}{\int_0^\infty \|d(t)\|^2 dt} = \frac{\int_0^\infty (h^T h + \|u\|^2) dt}{\int_0^\infty \|d(t)\|^2 dt} \le \gamma^2,$$

i.e. L_2-gain less than or equal to γ.

We have shown that the problem has a solution if there exists a matrix L and a solution $P>0$ to the HJI equation, or Riccati equation for H-infinity control,

$$PA + A^T P + Q + \frac{1}{\gamma^2} PDD^T P - PBR^{-1} B^T P + L^T R^{-1} L = 0$$

with the OPFB gain and worst case disturbance satisfying

$$KC = R^{-1}(B^T P + L)$$

$$d^* = \frac{1}{\gamma^2} D^T Px$$

The first two of these equations are coupled and must be solved simultaneously. There may not be a solution. Parameter matrix L can be chosen to try to make a solution exist.

Unfortunately, even if there exists an OPFB H-infinity controller, it may not yield a well-defined saddle point in the game theoretic sense. It was shown that if these equations hold with L= 0, then a well-defined saddle point does indeed exist.

Nonlinear Filtering Problem

For nonlinear systems, one often uses the Extended Kalman Filter to extract information from the available measurements. Unfortunately, the EKF has performance problems in many practical applications, e.g. flight control. Therefore, we are studying nonlinear H-infinity filtering to develop neural network filters with guaranteed performance properties.

Consider the system

$$\dot{x} = f(x) + g_1(x)d$$
$$y = h_2(x) + k_2(x)d$$
$$z = h_1(x) - h_1(\hat{x})$$

with $x(t) \in R^n$ the state, $d(t) \in R^r$ an unknown disturbance, $y(t) \in R^p$ the measurements, and $z(t) \in R^s$ a performance output. The initial condition is *x(0)= x0.*

It is desired to find a filter *l(y(t))* of the form

$$\dot{\hat{x}} = f(\hat{x}) + G(\hat{x})\left[y(t) - h_2(\hat{x})\right], \quad \hat{x}(0) = \hat{x}_0$$

such that, for a prescribed γ and *T*, and a prescribed $\hat{x}(0) = \hat{x}_0$, one has bounded gain, e.g.,

$$\int_0^T \|z(t)\|^2 \ dt \le \gamma^2 \int_0^T \|d(t)\|^2 \ dt + \gamma^2 \|x_0 - \hat{x}_0\|^2$$

By using the theory of differential games, one can show that the optimal filter gain is found by solving the coupled nonlinear equations

$$H(X, V_X, G^*, d^*) \equiv V_x{}^T f(x) + V_{\hat{x}}{}^T f(\hat{x}) + z^T z + \frac{1}{4\gamma^2} V_x{}^T g_1 g_1{}^T V_x - \gamma^2 (h_2 - \hat{h}_2)^T R_2{}^{-1} (h_2 - \hat{h}_2) = 0$$

with boundary equation $V(X(0)) = V(x_0, \hat{x}_0) = \gamma^2 \|x_0 - \hat{x}_0\|^2$ and optimal gain given by

$$V_{\hat{x}}{}^T G^* = -2\gamma^2 (h_2 - \hat{h}_2)^T R_2{}^{-1}.$$

Note that these are two *coupled* nonlinear equations for V_X, G. They cannot be solved for most nonlinear systems.

We plan to confront the solution of these equations using our techniques based on approximating the solution using neural networks. This will result in practical design algorithms for nonlinear filters using neural networks. It will yield recursive neural network filters.

Characterization of All Stabilizing State-Feedback H-infinity Controllers

In many design problems of practical interest, including problems in aircraft control, robotics, and vehicle control, one wishes to seek the optimal state feedback controller but also to satisfy *additional design conditions or constraints*. This is conveniently accomplished by characterizing the class of *ALL stabilizing SVFB controls*, and then selecting the particular controller that best satisfies the extra conditions. Such results have usually been shown in terms of the polynomial approach, or of a related Hamiltonian matrix. We have shown the following result, which provides a novel simplified solution for this problem.

For linear systems

$$\dot{x} = Ax + Bu + Dd$$
$$y = Cx$$

one desires to find the class of ALL constant state variable feedbacks (SVFB)

$$u = -Kx$$

such that , for a prescribed γ, when *x(0)= 0* and for all disturbances $d(t) \in L_2$ one has

$$\frac{\int_0^\infty \|z(t)\|^2 dt}{\int_0^\infty \|d(t)\|^2 dt} = \frac{\int_0^\infty (h^T h + \|u\|^2) dt}{\int_0^\infty \|d(t)\|^2 dt} \le \gamma^2,$$

i.e. L_2-gain less than or equal to γ.

We have shown that the problem has a solution if and only if K has the form

$$K = R^{-1}(B^T P + L)$$

where matrix L and $P>0$ satisfy the HJI equation, or Riccati equation for H-infinity control,

$$PA + A^T P + Q + \frac{1}{\gamma^2} PDD^T P - PBR^{-1}B^T P + L^T R^{-1} L = 0.$$

Then the worst case disturbance satisfies

$$d^* = \frac{1}{\gamma^2} D^T P x$$

Parameter matrix L provides extra design freedom that can be used to select the specific gain K that satisfies additional design requirements.

Static Output Feedback H-Infinity Control: Solution Algorithms

Practical DoD and industrial systems always have restricted measurement information, with only certain outputs being available, not the full state information. Conditions for OPFB H-infinity control are well known in the literature and generally rely on coupled matrix design equations or solving Linear Matrix Ineaualities. A lot of work has been done for dynamic OPFB. Therefore, last year, we provided simplified design equations for the static output feedback H-infinity problem for linear systems.

In static OPFB control, it is desired to select the controller so that

$$u = -Ky = -KCx .$$

Now it is clear from the above results that OPFB is a special case of SVFB. Thus, there exists a static OPFB that solves the bounded L-2 gain problem if and only if there exists a K such that

$$KC = R^{-1}(B^T P + L)$$

where matrix L and $P>0$ satisfy the HJI equation,

$$PA + A^T P + Q + \frac{1}{\gamma^2} PDD^T P - PBR^{-1}B^T P + L^T R^{-1} L = 0.$$

Now, however, the solution is complicated since these two equations are *coupled design equations.* Note, however, that despite this, these equations provide simplified design equations for static OPFB, for recall that the previously known OPTIMAL OPFB control satisfies *three* coupled matrix equations, which are more difficult to solve.

We have shown how to solve these OPFB design equations. The following algorithms were provided. Both converge on all examples tried so far, if there does indeed exist an OPFB solution.

Algorithm 1

1. Initialize:

Set $n=0$, $L_0 = 0$, and select γ, Q and R.

2. *n-th* iteration:

solve for P_n in

$$P_n A + A^T P_n + Q + \frac{1}{\gamma^2} P_n DD^T P_n - P_n BR^{-1} B^T P_n + L_n{}^T R^{-1} L_n = 0$$

Evaluate gain and update L

$$K_{n+1} = R^{-1}(B^T P_n + L_n) C^T (CC^T)^{-1}$$

$$L_{n+1} = RK_{n+1} C - B^T P_n$$

If K_{n+1} and K_n are close enough to each other, go to 3 otherwise set $n = n+1$ and go to 2.

3. Terminate:

Set K= K_{n+1} ■

Algorithm 2

$L_0 = 0$, $K_0 =$ Initial stabilizing gain.

Solve for P

$$P_n (A - BK_n C) + (A - BK_n C)^T P_n + \frac{1}{\gamma^2} P_n DD^T P_n + Q + C^T K_n{}^T RK_n C = 0 . \quad (9)$$

Update K

$$K_{n+1} = R^{-1}(B^T P_n + L_n) C^+ . \quad (10)$$

Where $C^+ = C^T (CC^T)^{-1}$ is defined as the right inverse of C.

Update L

$$L_{n+1} = RK_{n+1} C - B^T P_n . \quad (11)$$

Check for convergence $\|P_n - P_{n-1}\| < \varepsilon$, at convergence define $K_\infty = K$, go to 1 if not converged.

■

Note that Algorithm 1 extends an algorithm of Geromel, while Algorithm 2 extends an algorithm by Kleinman for SVFB design. Algorithm 1 solves a Riccati equation and so *does not require an initial stabilizing OPFB gain*. On the other hand, Algorithm 2 solves a Lyapunov equation (relative to *u(t)*) and so does require an initial stabilizing OPFB gain. The following result has been shown for both algorithms.

Lemma: If the algorithm converges, it provides the solution to the coupled OPFB design equations.

These algorithms have allowed us to design structured OPFB controllers, e.g. for an F-16 aircraft autopilot (see accepted paper for J. Guidance and Control). Now we are focusing on proving that the algorithms converge if *and only if* the solution to the H-infinity static OPFB problems exists.

NN Solution of Fixed-Final Time Optimal Control Problem

Systems such as nonholonomic dynamics, which describe vehicles and mobile autonomous robots, and others do not have continuous time-invariant feedback gain solutions. Therefore, one is motivated to study problems such as fixed-final-time optimal control, which results in time-varying feedback gains. We recently achieved the following results.

For the system $\dot{x} = f(x) + g(x)u(t)$ one prescribes the performance index

$$V(x(t_0),t_0) = \phi(x(T),T) + \int_0^T \left[Q(x) + W(u)\right]dt$$

with final time T fixed and finite. The optimal solution is a time-varying SVFB of the form

$$u^*(x) = -\frac{1}{2}R^{-1}g^T \frac{dV^*}{dx}$$

where the optimal value function satisfies the time-varying Hamilton-Jacobi-Bellman equation

$$HJB(V^*) = \frac{\partial V^*}{\partial t} + \frac{\partial V^*}{\partial x} f + Q - \frac{1}{4}\frac{\partial V^{*T}}{\partial x} gR^{-1}g^T \frac{\partial V^*}{\partial x} = 0$$

with final condition $V(x(T),T) = \phi(x(T),T)$. The solution provides the optimal control for ANY system in the given form, but the time-varying HJB is a nonlinear partial differential equation that is generally impossible to solve.

A nearly optimal solution can be provided by approximating the value function by a neural network as

$$V_L(x) = \sum_{j=1}^{L} w_j(t)\sigma_j(x) = w_L^T(t)\sigma_L(x)$$

with $w_L(t)$ the NN weights and $\sigma_L(x)$ the NN activation functions, which are selected as an independent basis, e.g. the polynomials. Note that the NN weights are *time-varying* now, since the HJB is time-varying.

To find the best weights in a least-squares sense, set the projection $\left\langle \frac{de_L(x)}{d\dot{w}_L}, e_L(x) \right\rangle = 0$, with

$$e_L(x) = -\dot{w}_L(t)^T \sigma(x) - w_L(t)^T \sigma'(x) f(x) + \frac{1}{4} w_L(t)^T \sigma'(x) g(x) R^{-1} g^T(x) (\sigma'(x))^T w_L(t) - Q(x)$$

the residual equation error after substituting the NN approximation into the HJB, and the inner product defined in space L-2. Then, using the collocation method one solves for the NN weight derivative $\dot{w}_L$, so that a Runge-Kutta method yields the time-varying LS weights by integrating backwards given the prescribed final conditions.

The result is the nearly optimal controller

$$u_L(t) = -\frac{1}{2} R^{-1} g^T(x) \sigma'^T(x) w_L(t)$$

with prime denoting the jacobian.

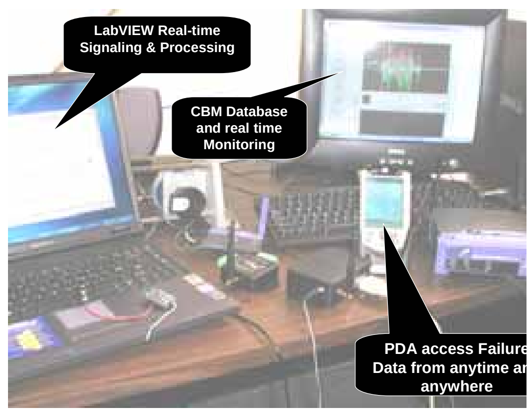
Full conditions for convergence have been derived and the journal paper is in preparation. The procedure gives a very effective design method for time-varying optimal controllers for a large class of interesting systems. Applications to mobile autonomous vehicles are now being investigated, including the fixed-final-point (e.g. parking maneuvering) problem.

Wireless Networked Sensor Systems

We developed under ARO sponsorship two wireless network testbeds at ARRI: WSN for condition-based machinery monitoring, and mobile WSN for Secure Area monitoring and assurance.

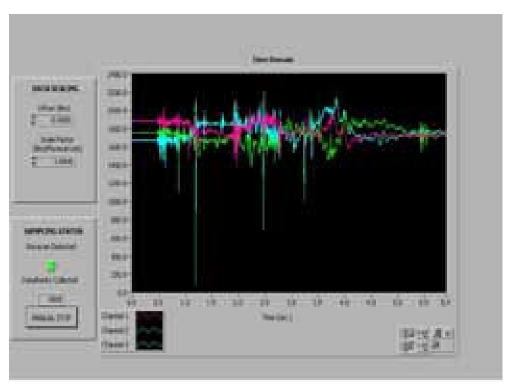
Wireless Sensor Net for Machinery Condition-Based Monitoring

With G. Vachtsevanos (Ga Tech) we are working on automated machine maintenance, condition-based maintenance (CBM) and prognostics & health management (PHM). We developed dynamical models for rotating machinery that include gears, bearings, and other mechanical subsystems. We are able to simulate tooth wear and other faults, as well as failures.



User Interfaces for ARRI Wireless Sensor Networks

We purchased wireless nodes from Microstrain, Inc. including accelerometers, and incorporated sensors for machinery monitoring. We built a wireless sensor net for CBM that can be installed in ½ hour on machinery systems using magnetic sensors. This has been installed on the ARRI CBM Testbed- an HVAC room with pumps, compressors, fan motors, piping, etc. A laptop PC was programmed to quickly configure and sample the sensors and compute the operating condition of each machine. Code is being added to allow internet-based monitoring and to send alarms on any out-of-range status.



GUI Display for CBM Wireless Sensor Net

We are working with National Instruments, and have an agreement to obtain LabVIEW software free. NI has developed LabVIEW software that can run on a PDA. Leveraging funds of $25K were received from NI for this project.

Wireless Sensor Net Testbed for Secure Area Personnel Monitoring

We developed a discrete event supervisory controller for distributed wireless networks that performs battlefield decision-making and dynamic resource management for complex systems with heterogeneous agents and sensors. We implemented the DE controller using a mobile wireless sensor network (WSN) testbed. This has ramifications in battlefield multi-platform and remote-site wireless sensor network control.

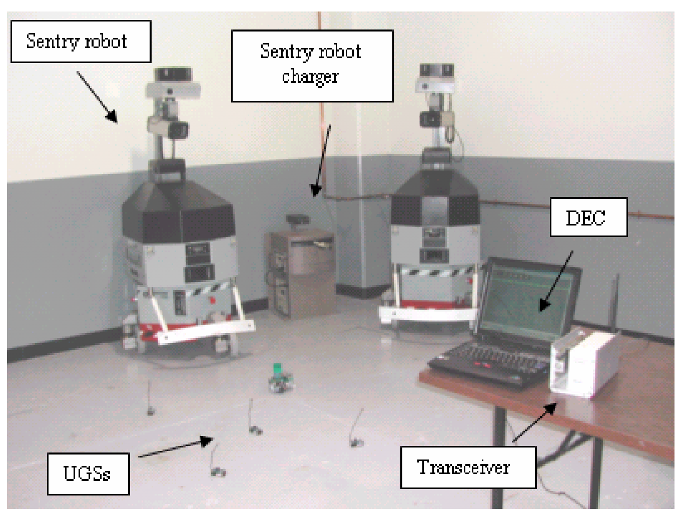
We built the ARRI Secure Area Assurance Testbed, which is a mobile WSN consisting of mobile sentry robots, Unattended Ground Sensors, a wireless network, and a centralized coordination system running on a portable laptop.

Mobile Sentry Robots. We modified two CyberGuard SR2/ESP Robots to communicate over WiFi internet. These robots are 6 ft tall, weigh 590 lbs and can carry a payload of 255 lbs. Drive system has 3 wheels and turning radius of zero ft. The robots can patrol a building, and navigate using a stored map in Autocad enhanced by dead reckoning, and motion and position sensors for localization. They carry a high-speed B&W camera with pan/tilt and wireless communications. They have an extensive sensor suite including ultrasonic intrusion, optical flame detector, dual passive IR, microwave intrusion, smoke sensors, temperature, humidity, and light sensors, and gas sensors including oxygen, NO_x, and CO.

CyberGuard Mobile Sentry Robot (6 ft tall)

The NI PXI embedded controller was installed on the robots and they communicate to a PC over wireless serial port for centralized coordination, programming, and control. The user can program behaviours into the sentries such as wall-following, go-through-door, locate prescribed feature in a stored map, proceed to prescribed navigational point, and so on. He can then sequence the behaviours using a Behaviour Control Palette of special architecture to produce a planned motion sequence.

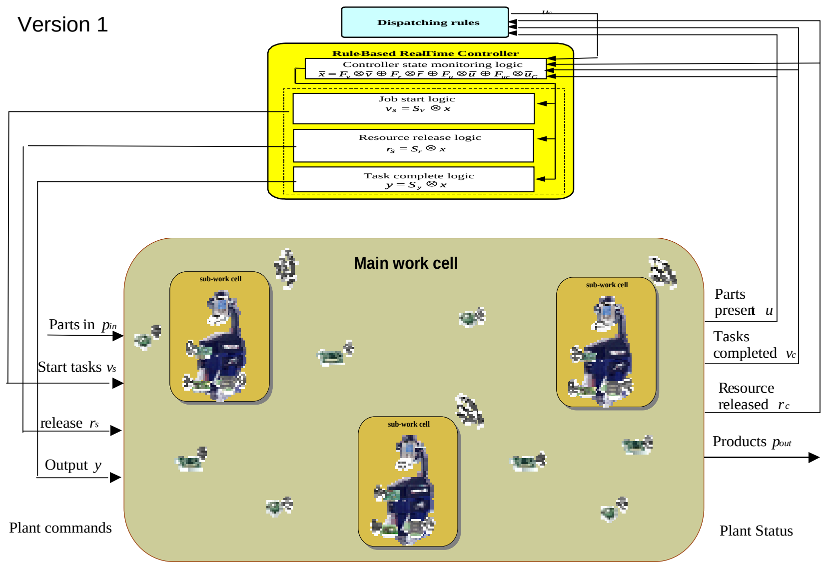
Unattended Ground Sensors (UGS). A set of Berkeley Xbow sensors has been incorporated into the Secure Area Testbed at ARRI. These wireless sensors communicate with a wireless central node and each has 5 sensors: light, sound, magnetic, accelerometer, and temperature. These UGS are deployed in a prescribed coverage area and transmit information back to the base station, where decisions can be made based on the reading of all sensors and information provided by the mobile sentry robots. The Tiny OS operating system supports some signal processing at the nodes, which were employed in this project.



ARRI Mobile Wireless Sensor Networks Testbed

Matrix-Based Discrete Event Controller

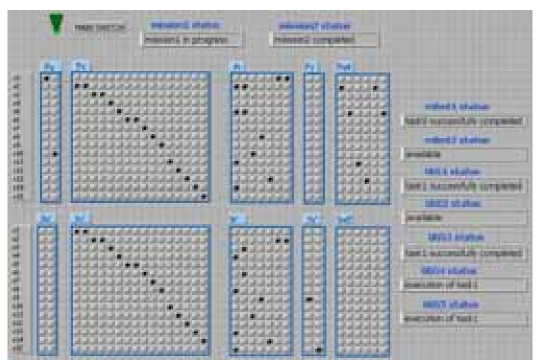
We have developed a discrete event supervisory controller for distributed networks that performs battlefield decision-making and dynamic resource management for complex systems with heterogeneous agents and sensors. The figure shows the structure of the discrete event supervisory controller, which is based on a patent received under ARO support. It is based on *matrices*, which allow fast programming of decision-making capabilities based on mission objectives from mission commanders, and resource availability information from field commanders.



Discrete event controller for Mobile Wireless Sensor Network

We implemented the DE controller on the ARRI wireless sensor network testbed. The DEC shown in the figure allows for coordination of the mobile sentries and the UGS to perform Missions, which are easily programmed into the WSN after deployment using our matrix-based formulation.

We focused on efficient methods for specifying Missions for a mobile WSN. We showed how to quickly deploy and program a WSN. Methods were developed for dynamic resource assignment that avoid blocking phenomena and deadlock. Papers have been submitted. The depicted LabVIEW interface shows the graphical User Interface for fast programming of missions into the DEC based on matrices. A US patent was received for this matrix form DEC under ARO support.



LabVIEW Interface for Specifying the DEC matrices

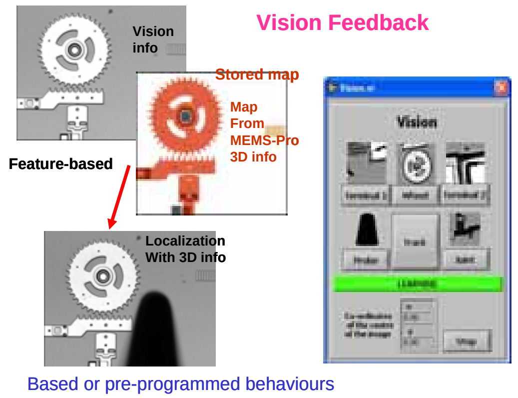
MEMS Microassembly Station

We have built a MEMS microassembly station with teleoperation and vision-guided motion capabilities using ARO DURIP funding, UTA Centennial funding, and Texas State matching LERR funds. The microassembly probe station is shown in the figure. It consists of a Karl Suss PM-5 probe station, a high resolution 2000x FS-70 Mitutoyo microscope with 100x objective, two 1 micron resolution PH150/50 micropositioners, two 0.5 resolution 0PH150/100 micropositioners, and a STC-

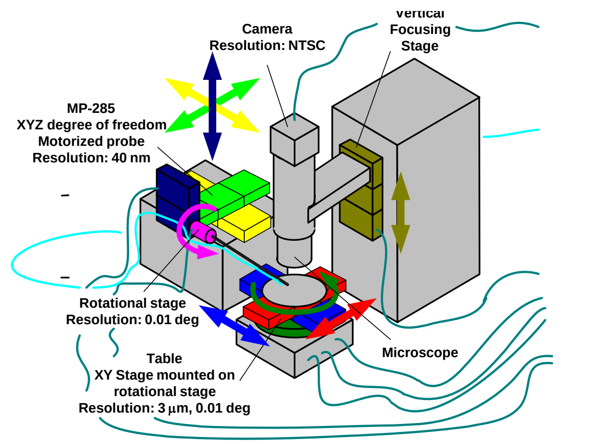
ARRI Probe Station for MEMS Testing

630CT color video DSP camera with microscope adapter and 20” monitor.

We purchased an automated Sutter MP285 3-DOF XYZ probe with controller that has repeatability and accuracy to 40 nm. For data acquisition, analysis, vision feedback and DSP, LabVIEW and MATLAB are used. We closed a feedback loop around the nanopositioner stage using vision feedback based on the LabVIEW IMAQ library. We developed a suite of vision-processing software that allows one to manipulate the nanoprobe using vision-guided inputs from the operator. Fine motions are performed automatically, while desired trajectory commands are specified by the user. Feature recognition allows us to impose on the MEMS wafer the 3-D design map stored in MEMS-PRO. We use Open GL to produce a Virtual Reality 3-D scene for manipulation control. This allows us to achieve precise map-based 3-D micropositioning on the wafer.



Feature-Based Vision System with 3-D depth information from stored CAD model



Concept design for extra motion stages needed for 3-D MEMS assembly station

Leveraging Funding Received

1. F.L. Lewis, “Nonlinear Network Structures for Dynamic System Control,” NSF, $200,000 for 3 years, 2002.

   This is a related grant for nonlinear control by neural networks with applications to high-level decision-making and awareness.
2. L. Holder, I. Ahmad, S. Das, F.L. Lewis, F. Lu, NSF MRI- “Acquisition of Instrumentation for Engineering Research in Advanced Security Detection Systems,” $250K, Sept. 2004, 3 years.
3. F.L. Lewis, “LabVIEW Applications for Wireless Sensor Networks,” National Instruments, Inc., Lead User Program, $25,000, May 2005.
4. F.L. Lewis, “Wireless Sensor Network Development System for Security, BDA, and Biochemical Monitoring,” Army Research Office DURIP equipment grant, $78,741, March 2005.
5. F.L. Lewis, G. Guo, and S.S. Ge, “Intelligent Control for Hard Disk Drives,” Data Storage Institute, A-Star, National Univ. Singapore campus, $25,000 for 3 months, August 2005.

List of Publications

Copies of publications are forwarded under separate cover through standard channels.

Books in Progress

1. Jie Huang, F.L. Lewis, and M. Abu-Khalaf, *Nonlinear Control Using Neural Networks*

2. G. Vachtsevanos and F.L. Lewis, *Machinery Condition-Based Maintenance*

Book Chapters

[1] J. Campos and F.L. Lewis, “Neural Control Systems,” Encyclopedia of Life Support Systems, ed. H. Unbehauen, chapter 6.43.24, EOLSS Publishers, Oxford, UK, 2003.

[2] J. Mireles and F.L. Lewis, “Blocking Phenomena Analysis for Discrete Event Systems with Failures or Preventive Maintenance Schedules,” in *Advances in Automatic Control*, pp. 225-238, ed. Mihail Voicu, Kluwer, Boston, 2003.

[3] J. Mireles, F.L. Lewis, A. Gurel, and S. Bogdan, “Deadlock Avoidance Algorithms and Implementation, a Matrix-Based Approach,” in *Deadlock Resolution in Computer-Integrated Systems*, chapter 7, ed. Mengchu Zhou, Marcel Dekker, New York, 2004.

[4] F.L. Lewis, “Wireless Sensor Networks,” in *Smart Environments: Technologies, Protocols, Applications*, ed. D.J. Cook and S.K. Das, Wiley, New York, 2004.

[5] M. Abu-Khalaf and F.L. Lewis, “A Neural Network Approach for Nearly Optimal Control of Constrained Nonlinear Systems,” in *Intelligent Systems Using Soft Computing Methodologies*, ed. A. Ruano, IEE Press, Stevenage, UK, 2005.

[6] F.L. Lewis and S.S. Ge, “Neural Networks in Feedback Control Systems,” in *Mechanical Engineer’s Handbook*, John Wiley, New York, 2005, to appear.

[7] F. Hong, S.S. Ge, F.L. Lewis, and T.H. Lee, “Adaptive neural-fuzzy control of nonholonomic mobile robots, in *Autonomous Mobile Robots: Sensing, Control, Decision-Making, and Applications*, ed. S.S. Ge and F.L. Lewis, CRC Press, 2005, to appear.

[8] V. Giordano, F.L. Lewis, P. Ballal, and B. Turchiano, “Supervisory control for task assignment and resource dispatching in mobile wireless sensor networks,” in *Cutting Edge Robotics*, ed. V. Kordic, to appear, 2005.

[9] D.O. Popa and F.L. Lewis, “Algorithms for robotic deployment of WSN in adaptive sampling applications,” in *Wireless Sensor Networks and Applications*, ed. Y. Li, M. Thai, and W. Wu, Springer-Verlag, Berlin, 2005, to appear.

Journal Papers

[1] J. Gadewakir, M. Abu-Khalaf, and F.L. Lewis, “Necessary and sufficient conditions for H-infinity static output-feedback control,” J. Guidance, Control, and Dynamics, to appear, 2005.

[2] B. Borovic, A.Q. Liu, D. Popa, C. Hong, and F.L. Lewis, “Open-loop vs. closed-loop control of MEMS devices,” Journal of Micromechanics & Microengineering, to appear, 2005.

[3] O. Kuljaca, N. Swamy, F.L. Lewis, and C.M. Kwan, “Design and implementation of industrial neural network controller using backstepping,” IEEE Trans. Industrial Electronics, vol. 50, no. 1, pp. 193-201, 2003.

[4] J.-Q. Huang and F.L. Lewis, “Neural-network predictive control for nonlinear dynamic systems with time delay,” IEEE Trans. Neural Networks, vol. 14, no. 2, pp. 377-389, 2003.

[5] O. Kuljaca and F.L. Lewis, "Adaptive Critic design using nonlinear network structures," Int. J. Adaptive Control and Signal Proc., vol. 17, no. 6, pp. 431-445, June 2003.

[6] J. Campos and F.L. Lewis, "Backlash compensation with filtered prediction in discrete time nonlinear systems by dynamic inversion using neural networks," Asian J. Control, vol. 6, no. 3, Sept. 2004.

[7] M. Abu-Khalaf and F.L. Lewis, "Nearly optimal state feedback control of constrained nonlinear systems using a neural networks HJB approach," IFAC Annual Reviews in Control, vol. 28, pp. 239-251, 2004.

[8] M. Abu-Khalaf and F.L. Lewis, "Nearly optimal control laws for nonlinear systems with saturating actuators using a neural network HJB approach," Automatica, vol. 41, pp. 779-791, 2005.

Refereed and Published Conference Papers

[1] F.L. Lewis and M. Abu-Khalaf, "Nearly optimal state feedback control of constrained nonlinear systems using a neural network HJB approach," Proc. Int. Conf. on Intelligent Control Systems, Algarve, Portugal, April 2003, *invited plenary paper.*

[2] M. Abu-Khalaf and F.L. Lewis, "Nearly optimal control laws for nonlinear systems with saturating actuators using a neural network HJB approach," Proc. Mediterranean Conf. Control and Automation, Rhodes, June 2003.

[3] F.L. Lewis and M. Abu-Khalaf, "A Hamilton-Jacobi Setup for constrained neural network control," Proc. IEEE International Symp. Intelligent Control, paper Mon-PL, Houston, Oct., 2003, *invited plenary paper.*

[4] R.R. Selmic, V.V. Phoha, and F.L. Lewis, "Intelligent compensation of actuator nonlinearities," Proc. IEEE Conf. Decision and Control, pp. 4327-4332, Maui, Dec. 2003.

[5] M. Abu-Khalaf, F.L. Lewis, and J. Huang, "Computational techniques for constrained nonlinear state feedback H-infinity optimal control using neural networks," Proc. Mediterranean Conf. Control and Automation, paper 1141, Kusadasi, Turkey, June 2004.

[6] F.L. Lewis, M. Abu-Khalaf, and J. Huang, "Robust optimal control of constrained input systems using neural networks," Proc. Chinese Control Conf., Wuxi, China, Aug. 2004, *invited keynote paper.*

[7] F.L. Lewis and M. Abu-Khalaf, "Hamilton-Jacobi-Isaacs Formulation For Constrained Input Systems: Neural Network Solution," Proc. Symp. Systems Structure and Control, paper 323, Oaxaca, Mexico, Dec. 2004, *invited plenary paper.*

[8] O. Kuljaca and F.L. Lewis, "Neural Network Frequency Control for Thermal Power Systems," Proc. IEEE CDC, pp. 3509-3514, Bahamas, Dec. 2004.

[9] M. Abu-Khalaf, F.L. Lewis, and J. Huang, "Hamilton-Jacobi-Isaacs Formulation for Constrained Input Nonlinear Systems," Proc. IEEE CDC, pp. 5034-5040, Bahamas, Dec. 2004.

[10] J. Gadewadikar, F.L. Lewis, and M. Abu-Khalaf, "Necessary and sufficient conditions for H-infinity static output-feedback control," Proc. 16th IASTED Int. Conf. on Control & Applications, pp. 18-23, Cancun Mexico, May 2005.

[11] W. Gao, R.R. Selmic, and F.L. Lewis, "Robust composite saturation compensation for a single flexible link using neural networks," Proc. Mediterranean Conf. Control and Applications, pp. 280-285, Limassol, Cyprus, June 2005.

[12] M. Abu-Khalaf, F.L. Lewis, and J. Huang, "Neural network H-infinity state feedback control with actuator saturation: the nonlinear benchmark problem," Proc. Int. Conf. Control and Applics., pp. 1-9, Keynote paper, Budapest, June 2005.

[13] O. Kuljaca and F.L. Lewis, "Dynamic focusing of awareness in fuzzy control systems," Proc. Mediterranean Conf. Control and Automation, Paper T3-004, Rhodes, June 2003.

[14] O. Kuljaca and F.L. Lewis, "Adaptive elastic fuzzy logic controller," Proc. Mediterranean Conf. Control and Automation, Paper 1103, Kusadasi, Turkey, June 2004.

[15] A. Tiwari, F.L. Lewis, and S.S. Ge, "Wireless Sensor Networks for Machine Condition Based Monitoring," Proc. Int. Conf. Control, Automation, Robotics, and Vision, pp. 461-467, *invited paper*, Kunming, China, Dec 2004.

[16] V. Giordano, F.L. Lewis, J. Mireles, B. Turchiano, "Coordination control policy for mobile sensor networks with shared heterogeneous resources," Proc. Int. Conf. Control & Automation, pp. 191-196, Budapest, June, 2005.

[17] V. Giordano, F.L. Lewis, B. Turchaino, P. Ballal, V. Yeshala, "Matrix computational framework for discrete event control of wireless sensor networks with some mobile agents," Proc. Mediterranean Conf. Control & Automation, Limassol, Cyprus, June 2005. *This paper won an award at MED 05.*

[18] D.O. Popa, K. Sreenath, and F.L. Lewis, "Robotic deployment for environmental sampling applications," Proc. Int. Conf. Control and Applics., pp. 197-202, Budapest, June 2005.

[19] J. Mireles and F.L. Lewis, "Blocking phenomena analysis for discrete event systems with failures or preventive maintenance schedules," Proc. Mediterranean Conf. Control and Automation, paper T4-008, Rhodes, June 2003.

[20] J. Mireles, P. Dang, and F.L. Lewis, "Virtual places for the development and implementation of modified matrix-based discrete event controller," Proc. Mediterranean Conf. Control and Automation, paper 1106, Kusadasi, Turkey, June 2004.

[21] V. Giordano, F. Lewis, B. Turchiano, P. Ballal, and V. Yeshala, "Matrix computational framework for discrete event control of wireless sensor networks with some mobile agents," Proc. Mediterranean Conf. Control and Automation, pp. 176-181, Limassol, Cyprus, June 2005.

[22] B. Borovic, Hong Cai, Ai Qun Liu, Lihua Xie, F.L. Lewis, "Control of a MEMS Optical Switch," Proc. IEEE CDC, Bahamas, pp. 3039-3044, Dec. 2004.

[23] B. Borovic, A.Q. Liu, D. Popa, Z. Xuming, and F.L. Lewis, "Lateral motion control of electrostatic comb drive: new methods in modeling and sensing," Proc. 16th IASTED Int. Conf. on Modeling & Simulation, pp. 301-307, Cancun Mexico, May 2005.

[24] S. Ramanathan, B. Borovic, A. Shacklock, and F.L. Lewis, "Behaviour-Based Vision-Guided Teleoperated MEMS Probestation," Proc. Mediterranean Conf. Control and Applications, pp. 1591-1596, Limassol, Cyprus, June 2005.

[25] B. Borovic, C. Hong, X.M. Zhang, A.Q. Liu, and F.L. Lewis, "Open vs. closed-loop control of the MEMS electrostatic comb drive," Proc. Mediterranean Conf. Control and Applications, pp. 976-982, Limassol, Cyprus, June 2005.

Manuscripts Submitted but not Published

N/A. They were all accepted.

Scientific Personnel Supported During the Grant and Awards

PhD Students

1. O. Kuljaca, Intelligent Neural Network and Fuzzy Logic Control of Industrial and Power Systems, May 2003.

   Kuljaca won the ARRI Best Paper Award, 2003.

2. N. Swamy, *Control Algorithms for Networked Control and Communication Systems*, May 2003.
3. M. Abu-Khalaf, Neural Network Control of Constrained Input Systems Using Hamilton Jacobi-Bellman Approximate Solutions, Aug. 2005.
4. B. Borovic, *Microelectromechanical Systems (MEMS) Design and Control,* in progress.
5. V. Giordano, *Decision-Making for Wireless Sensor Networks*, co-adviser with B. Turchiano, Tech. Inst. Bari, Italy, in progress.
6. J. Gadewadikar, *Neural Networks in High-Level Decision Making Systems*, in progress.
7. Asma Al-Tamimi, *Neural Network Control,* in progress.
8. Cheng Tao, *Neural Network Solution of Time-Varying HJ Equations,* in progress.
9. P. Ballal, *Wireless Sensor Networks,* in progress.
10. D. Vrabie, *Neural Networks for control*, in progress.

Masters Students

1. A. Tiwari, "Design and Implementation of Wireless Sensor Networks for Condition Based Maintenance," Master's Thesis, May 2004.
2. P. Dang, "Controller for swing-up and balance of single inverted pendulum using SDRE-based solution," MS Thesis, July 2004.
3. S. Ramanathan, "Behavior-based vision-guided MEMS probe station with implementation in LabVIEW," MS Thesis, Aug. 2004.
4. A. Bhilegaonkar, "Design and Implementation of Advanced Control Algorithms on an Electromechanical Plant for Trajectory Tracking," MS Thesis subst., May 2005.
5. P. Ballal, "Control Structure and Decisions in Wireless Sensor Networks," Aug. 2005.
6. N. Srianekkul, "Control with Nonlinearity Compensation for 2-D Flexible-Link Robot Arm," Master's Thesis Subst., Dec. 2003.

Undergraduate and K-12 Students

7. Tyson Henry, "Control of mobile robot," NSF REU Scholar, summer 2003.
8. Joshua Small, "MEMS design," NSF REU Scholar, summer 2003.

9. Andrew Dunn, "LabVIEW for control," 8th grade student, Oakridge School, summer 2003.
10. Keith Francis, "Wireless Sensor Networks," NSF REU Scholar, 2003.
11. Antonio Quevedo, NSF REU Scholar, 2003. His paper "Developing High Aspect Ratio MicroGrippers Using Electroplating Techniques for Robustness" was selected for presentation at the Society of Hispanic Professional Engineers Conference, Chicago, Jan. 2004.
12. Roma Ivanov, "Mobile robots," 8th grade student, Oakridge School, summer 2004.
13. Chris Lewis, "Mobile robots," 8th grade student, Oakridge School, summer 2004.

F. Lewis Awards

Ft. Worth Business Press, Who's Who in Manufacturing, Top 200 Leaders, annually 1999-pres.

Elected Guest Professor, Shanghai Jiao Tong University (SJTU), Shanghai, China, March 2003.

Elected as Consulting Professor, South China University of Technology, March 2004.

Elected as Charter Member of UTA Academy of Distinguished Scholars, March 2004.

Senior Fellow, Automation & Robotics Research Institute, 2005.

Marquis Who's Who in the World, Who's Who in America, Who's Who in the South and Southwest, Who's Who in Frontiers of Science and Technology, Who's Who of Emerging Leaders in America, Who's Who in Science and Engineering, Who's Who in American Education, Who's Who Among America's Teachers, Who's Who in Finance and Business.

Inventions

1. R. Selmic, F.L. Lewis, A.J. Calise, and M.B. McFarland, "Backlash Compensation Using Neural Network," U.S. Patent 6,611,823, Awarded 26 Aug. 2003.

This patent is based on work done in the previous ARO grant but finalized during this award.

Technology Transfer and Outreach

Tech. Transfer

1. US PATENT. This work developed a neural network apparatus and algorithm to compensate for industrial and DoD motion systems having backlash in the actuators by using a dynamic inversion approach. The work was performed with Tony Calise, Ga Tech.
2. TEXTBOOK: Writing a text book with Jie Huang on neural networks for HJ control.
3. TEXTBOOK. Tech transfer in machine monitoring- writing a book with Prof. G. Vachtsevanos at Ga Tech based on an industry workshop run at UTA.
4. Respironics Inc., InterMEMS Inc., UT Southwestern Medical Institute, Design of MEMS Optical Biosensors for Control of Critical Care Pulmonary Ventilators, funded by NSF.
5. Texas Instruments, organized TEXMEMS 03.
6. Univ. Autonoma de Ciudad Juarez, Mexico, and Mexico/US Foundation for Science, organizedWorkshops on US/Mexico MEMS Collaboration.

7. Georgia Tech, Texas Manufacturing Assistance Center, National Instruments, Lockheed-Martin, Workshop on Automated Machinery Maintenance, July 2003.
8. Univ. Texas at Dallas, US EPA, Russian Academy of Rocket & Artillery Sciences, UK QinetiQ, International Symposium on Homeland Security.
9. National Instruments, uses of LabVIEW in wireless sensor networks.
10. Working with scientists at Ft. Worth Health Science Center and UTA chemists to develop wireless MEMS biochemical warfare sensors.

Technology Transfer Workshop Series Organized

1. UTA/UNM Joint Workshop on Research and Academic Opportunities with Latin America, 1 April 2003
2. Texas MEMS Workshop, 6 May, 2003, at ARRI, UTA.
3. Workshop on US/Mexico MEMS Collaboration, 7 May, 2003, at ARRI, UTA.
4. ARRI/Georgia Tech Workshop on Automated Machinery Maintenance, 17 July, 2003, at ARRI, UTA.
5. International Symposium on Homeland Security, Developing Agile Enterprises to Overcome Vulnerability, 28-30 July, 2003, at ARRI, UTA.
6. Workshop on Wireless Sensor Networks and Condition-Based Maintenance, National Singapore University, Oct. 2003.

International Outreach Activities

1. General Chairman, Mediterranean Control Conference, Rhodes, June 2003.
2. General Chairman, IEEE Conference on Decision and Control, Hawaii, Dec. 2003.
3. Organized Plenary Panel on International Funding Thrusts and Mechanisms at CDC 2003.
4. We organized an international series of events with Singapore universities, Hong Kong universities, Mexico, and others.
5. International tech. transfer- Hosted visiting students for 2 months from Guadalajara CINVESTAV and Univ. de Ciudad Juarez for cross training in control systems and robotics.

Broader Impact Activities

1. Ran a Summer Program for K-12 students and undergraduate students, summer 2003, summer 2004.
2. Robotics Workshop for local High School Teachers, summer 2003.
3. Initiated a scholarship program for UNT Health Science Center students to do research at UTA. A top female minority student was the first awardee.
4. Started US/Mexico MEMS workshop series with J. Mireles, Univ. Autonoma de Ciudad Juarez. Two workshops have been organized so far, one at UTA and one in Puerto Vallarta.
5. Started a UTA/Mexico student exchange program for Mexico graduate and undergraduate students.
6. Obtained NSF REU supplement funding to support minority students, one of whom wrote a winning paper.

7. Started several Dallas/Ft Worth Metroplex-wide activities in MEMS, CBM, and Homeland Security with TCU, UTD, UNT Health Science Center, Lockheed-Martin. Ran a series of technology transfer workshops in these areas.