NEURAL CONTROL SYSTEMS

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Contents

Mathematical Representation

Thorough this article, the following notation has been adopted to differentiate among scalars, vectors, and matrices:

x is a scalar

$\bar{x}$ is a vector

$\underline{x}$ is a matrix

Summary

A framework for intelligent control using neural networks is presented. Neural networks make use of a universal approximation property that allows them to be used in feedback control of unknown systems without a requirement for linearity in the system parameters.

This article shows that neural networks provide model-free learning controllers for a class of nonlinear systems, in the sense that not even a structural or parametrized model of the system dynamics is needed. Another remarkable issue in the use of neural networks is the reusability of the low-level controller, since the system dynamics are completely unknown to the controller. The same controller works even if the behavior or structure of the system changes. Several feedback control topologies and weight tuning that guarantee closed-loop stability and bounded weights are given. Applications to robot manipulator control, active vehicle suspension, and industrial system control are set out.

1. Introduction

Intelligent control has received a great deal of interest in the past years due to the desire to emulate the functioning of the human body, particularly the brain's learning process and the execution of bodily actions. The closer that any designed system's behavior conforms to human learning/adaptation capabilities the more efficient that system will become, and the less human operator intervention will be needed. Neural networks are among the structures used in this approach to achieving "intelligence" in systems.

Neural networks (NN) have achieved great success in classification, pattern recognition, and other open-loop applications in digital signal processing and elsewhere. There has been plenty of research into the use of neural networks for control applications, and they are considered 'universal model-free controllers' in the sense that a mathematical model of the controlled plant is not required. Neural networks try to mimic the functions of biological processes, in order to learn about their environment and account for it to improve overall performance.

We must distinguish between two main classes of neural network for control applications: *open-loop identification* and *closed-loop feedback control*. The former class resembles signal processing and classification, so most of the techniques and algorithms appropriate to these fields will still apply. On the contrary, in the feedback control applications, the NN reside inside the control loop, which requires special care to ensure the tracking error and NN weights remain bounded in the closed-loop system. This article concentrates on the latter class.

There is a considerable literature on NN for feedback control of unknown systems. However, it was not until the 1990s that repeatable design algorithms and stability proofs became available, thus guaranteeing performance. Most of the initial approaches required some off-learning phase (that is, training off-line) to tune the NN weights, using measurements of the system inputs and outputs, in order to guaranteed stability. This represented a problem for industrial and mechanical systems that usually required immediate control, besides the fact that "untrained" perturbation in the system was likely to affect handling performance and capability. Furthermore, in the early application stages of direct control back-propagation weight tuning was completely dependent on the unknown system, and/or satisfied its own differential equations, making them very difficult to compute.

In this article we present a comprehensive approach to the design and analysis of neural network controllers. The control structures discussed are multiloop controllers with outer tracking proportional-derivative (PD) loops, containing NN in some of the loops. The algorithms presented are of repeatable design, and guarantee the system performance by including small tracking errors and bounded NN weights. It is shown that the NN controllers require additional structures as uncertainty about the controlled system itself increases.

The NN controllers are adaptive learning systems but do not rely on the usual assumptions made in adaptive control theory, such as linearity in their parameters and availability of a known regression matrix. This is primarily due to the NN universal function approximation property. NN controllers may be called 'nonparametric controllers' in that they are not parametrized in terms of system parameters. When designed correctly, the NN controller does not call for assumptions about persistence of excitation or certainty equivalence.

The article begins by discussing multilayer nonlinear and linear in networks of parameters. Tracking controllers for robot manipulators are presented for networks with tuning algorithms that guarantee closed-loop stability and for those with bounded weights. Some extensions are also discussed, including NN force control, actuator dynamics nonlinearity compensation, and output-feedback control.

2. Neural Network Structures and Properties

Neural networks (NN) can be used in two classes of applications in system theory: signal processing/classification and control. There are two classes of control applications: open-loop identification and closed-loop feedback control. Identification applications resemble signal processing/classification, so the same open-loop algorithms may often be used. On the other hand, in closed-loop feedback applications the NN is inside the control loop, so special steps must be taken to ensure that the NN weights remain bounded during the control run.

2.1. Static Feedforward Neural Networks

A feedforward NN is shown in Figure 1.

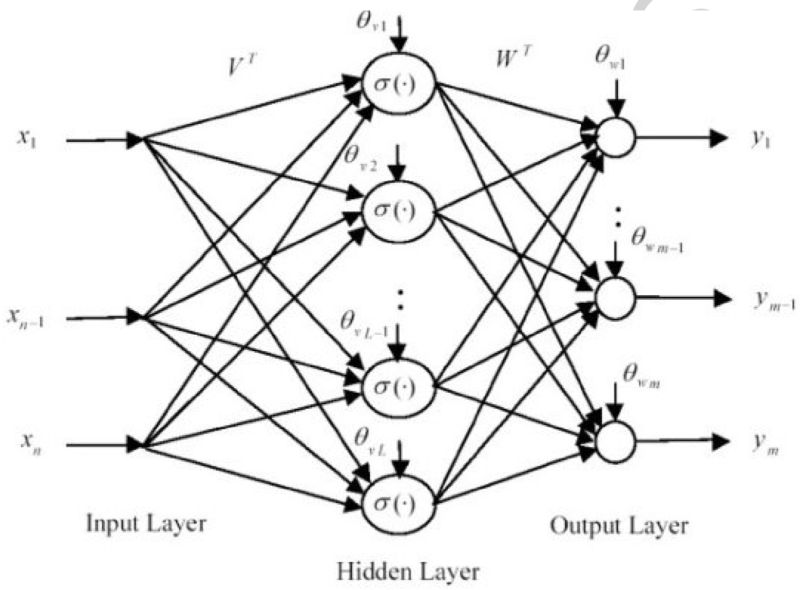


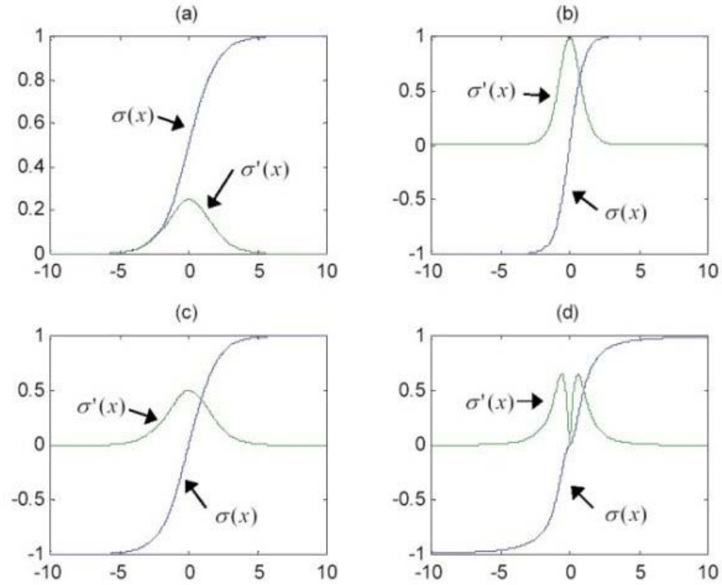
Figure 1. Two-layer feedforward neural network

This NN has two layers of adjustable weights, and is here termed a *two-layer net*. The NN output $\bar{y}$ is a vector with m components that are determined in terms of the n components of the input vector $\bar{x}$ by the formula

$$y_i = \sum_{j=1}^{L}\left[w_{ij}\sigma\left(\sum_{k=1}^{n} v_{jk}x_k + \theta_{vj}\right) + \theta_{wi}\right];\ i = 1,\ldots,m \qquad (1)$$

where $\sigma(\cdot)$ are the activation functions and L is the number of hidden-layer neurons. The first- to second-layer interconnection weights are denoted by v_{jk}, and the second- to third-layer interconnection weights by w_{ij}. The threshold offsets are denoted by θ_{vj}, θ_{wi}.

Many different activation functions $\sigma(\cdot)$ are in common use. In this work, it is required that $\sigma(\cdot)$ is sufficiently smooth that at least its first derivative exists: suitable choices are shown in Figure 2.



$$(a) \quad \sigma(x) = \frac{1}{1+e^{-x}} \qquad (b) \quad \sigma(x) = \tanh(x) = \frac{e^{x}-e^{-x}}{e^{x}+e^{-x}}$$

$$(c) \quad \sigma(x) = \frac{1-e^{-x}}{1+e^{-x}} \qquad (b) \quad \sigma(x) = \frac{x^2}{1+x^2}\mathrm{sgn}(x)$$

Figure 2. Common neural network activation functions and derivatives

By collecting all the NN weights v_{jk}, w_{ij} into matrices of weights $\underline{V}^T, \underline{W}^T$, we can write the NN equation in terms of vectors as

$$\bar{y} = \underline{W}^T \bar{\sigma}(\underline{V}^T \bar{x}). \qquad (2)$$

The thresholds are included as the first columns of the weight matrices. Any tuning of $\underline{V}$ and $\underline{W}$ then includes tuning of the thresholds as well. To accomplish this, the vectors $\bar{x}$ and $\bar{\sigma}(\underline{V}^T \bar{x})$ need to be augmented by placing a '1' as their first element (e.g., $\bar{x} \equiv [1 \quad x_1 \quad x_2 \quad \cdots \quad x_n]^T$). In this equation, in order to represent Eq. (1) we have sufficient generality if $\sigma(\cdot)$ is taken as diagonal function from $\Re^L$ to $\Re^L$: that is, $\bar{\sigma}(\bar{z}) = diag\{\bar{\sigma}(z_i)\}$ for a vector $\bar{z} = [z_1 \quad z_2 \quad \cdots \quad z_L]^T \in \Re^L$.

2.2. Universal Function Approximation Property

Neural networks (NN) satisfy many important properties. A major concern for feedback control purposes is the universal function approximation property. Let $\bar{f}(\bar{x})$ be a general smooth function from $\Re^n$ to $\Re^m$. From this it can be shown—as long as $\bar{x}$ is restricted to a compact set $S \in \Re^n$—that weights and thresholds exist, such that

$$\bar{f}(\bar{x}) = \underline{W}^T \bar{\sigma}(\underline{V}^T \bar{x}) + \bar{\varepsilon} \tag{3}$$

for a number of hidden layer neurons L. This holds for a large class of activation functions. This equation indicates that a NN can approximate any smooth function on a compact set. The value $\bar{\varepsilon}$ is called the *NN functional approximation error*, and generally decreases as the net size L increases. In fact, for any choice of a positive number ε_N we can find a feedforward NN such that $\|\bar{\varepsilon}\| < \varepsilon_N$ for all $x \in S$. This means that a NN can be selected to approximate $\bar{f}(\bar{x})$ to any desired accuracy ε_N.

The ideal NN weights in matrices $\underline{V}, \underline{W}$ that are needed to best approximate a given nonlinear function $\bar{f}(\bar{x})$ are difficult to determine. In fact, they may not even be unique. However, all that must be known for control purposes is that some ideal approximate NN weights exist for a specified value for ε_N. Then, an estimate of $\bar{f}(\bar{x})$ can be given by

$$\hat{\bar{f}}(\bar{x}) = \hat{\underline{W}}^T \bar{\sigma}(\hat{\underline{V}}^T \bar{x}) \tag{4}$$

where $\hat{\underline{W}}$ and $\hat{\underline{V}}$ are estimates of the ideal NN weights that are provided by certain on-line weight-tuning algorithms, which will be detailed subsequently.

The assumption that there exist ideal weights, such that the approximation property holds, resembles various similar assumptions in adaptive control, including Erzberger's assumptions and parameter linearity (see *Adaptive Control*). The very important difference in the case of NN is that the approximation property always holds: in adaptive control such assumptions often do not hold in practice, and so they imply restrictions on the form of the systems that can be controlled.

2.3. Weight-Tuning Algorithms

In order for the NN to learn and adapt to its environment, the weights should be continuously updated on-line. Many types of NN weight-tuning algorithm are used, usually based on some sort of gradient algorithm. Tuning algorithms may be given either in continuous time or in discrete time, where the weights are updated only at discrete time points. Discrete-time tuning is useful in digital control applications of NNs. A common weight-tuning algorithm is the gradient algorithm based on the propagation error, where the NN is trained to match specified exemplar pairs $(\bar{x}_d, \bar{y}_d)$, with $\bar{x}_d$ the ideal NN input that yields the desired NN output $\bar{y}_d$. The discrete-time version of the backpropagation algorithm for the two-layer NN is given by

$$\hat{\underline{W}}_{k+1} = \hat{\underline{W}}_k + \underline{F} \cdot \bar{\sigma}\left(\hat{\underline{V}}_k^T \bar{x}_d\right) \bar{E}_k^T \tag{5}$$

$$\hat{\underline{V}}_{k+1} = \hat{\underline{V}}_k + \underline{G} \cdot \bar{x}_d \left(\hat{\underline{\sigma}}_k^{'\,T} \hat{\underline{W}}_k \bar{E}_k\right)^T$$

where k is the discrete-time index and $\underline{F}$, $\underline{G}$ are positive, definite-design parameter matrices governing the speed of convergence of the algorithm. The hidden-layer output gradient or Jacobian may be explicitly computed: for the sigmoid activation functions, for instance, it is

$$\underline{\hat{\sigma}}' = diag\left\{\underline{\hat{V}}^T \bar{x}_d\right\} \cdot \left[\underline{I} - diag\left\{\bar{\sigma}\left(\underline{\hat{V}}^T \bar{x}_d\right)\right\}\right] \quad (6)$$

where $diag\{\bar{v}\}$ denotes a diagonal matrix whose diagonal elements are the components of the vector $\bar{v}$. The error $\overline{E}_k$ that is backpropagated is selected as the desired NN output minus the actual NN output $\overline{E}_k = \bar{y}_d - \bar{y}_k$. Backpropagation tuning is accomplished off-line and requires specified training data pairs $(\bar{x}_d, \bar{y}_d)$; thus it amounts to a supervised training scheme.

The continuous-time version of the backpropagation algorithm for the two-layer NN is given by

$$\dot{\underline{\hat{W}}} = \underline{F} \cdot \bar{\sigma}\left(\underline{\hat{V}}^T \bar{x}_d\right)\overline{E}^T \quad (7)$$

$$\dot{\underline{\hat{V}}} = \underline{G}\bar{x}_d\left(\underline{\hat{\sigma}}'^T \underline{\hat{W}}\overline{E}\right)^T$$

The Hebbian algorithm is a simplified NN weight-tuning scheme, a continuous-time version of which is

$$\dot{\underline{\hat{W}}} = \underline{F} \cdot \bar{\sigma}\left(\underline{\hat{V}}^T \bar{x}\right)\overline{E}^T \quad (8)$$

$$\dot{\underline{\hat{V}}} = \underline{G} \cdot \bar{x}\left(\bar{\sigma}(\underline{\hat{V}})^T \bar{x}\right)^T$$

Thus, in Hebbian tuning, no Jacobian needs to be computed. Instead the weights in each layer are updated on the basis of the outer product of the input and output signals of that layer.

2.4. Functional-Link Basis Neural Network

The NN can be considered with the first layer of weights $\underline{V}$ and thresholds fixed, and with only the second-layer weights $\underline{W}$ tuned.

Select $\underline{V} = \underline{I}$ so that the NN output is

$$y_i = \sum_{j=1}^{L}\left[w_{ij}\sigma(\bar{x}) + \theta_{wi}\right]; i = 1, \ldots, m \quad (9)$$

or, in matrix form,

$$\bar{y}(\bar{x}) = \underline{W}^T \bar{\sigma}(\bar{x}) \tag{10}$$

Now, $\bar{\sigma}(\bar{x})$ is not diagonal but is a general function from $\Re^n$ to $\Re^L$, making it a *functional-link neural net* (FLNN). In this case, the NN approximation property does not generally hold. However, a one-layer NN can still approximate functions as long as the activation functions $\bar{\sigma}(\bar{x})$ are selected as a basis. This makes the NN linear in the parameters: this case has been treated for the radial basis functions, using a projection algorithm for weight tuning and for discrete-time systems. It is proven that linearity in the unknown parameters has the so-called 'best-approximation property': for a given function f, there always exists a parameter that approximates f better than all other possible choices.

Following this, to ensure suitable NN approximation properties some conditions must be satisfied by the activation function $\sigma(x)$.

Definition 1: Let S be a compact, simply connected set of $\Re^n$, and let $\varphi(x): S \to \Re^L$ be integrable and bounded. Then $\varphi(x)$ is said to provide a basis for $C^m(S)$ if:

- a constant function on S can be expressed as (10) for finite L, and
- the functional range of neural network (10) is dense in $C^m(S)$ for countable L.

It was shown by Barron that the neural network approximation error $\varepsilon(x)$ for one-layer NN is fundamentally bounded below by a term of the order $(1/n)^{2/d}$, where n is the number of fixed basis functions and d is the dimension of the input to the NN. This does not limit the tracking performance in our controller, because of the control system structure selected.

It is not straightforward to pick a basis $\varphi(x)$. CMAC, RBF, and other structured NN approaches allow one to choose a basis by partitioning the compact set S. This can be a tedious process, however. If one selects

$$\bar{y}(\bar{x}) = \underline{W}^T \bar{\sigma}(\underline{V}^T \bar{x}) \tag{11}$$

with $\bar{\sigma}(\bar{x}) = 1/(1+e^{\alpha \bar{x}})$, for example, as the sigmoid, then it can be shown that $\underline{\sigma}(\underline{V}^T \bar{x})$ is a basis if $\underline{V}$ is selected randomly. Once selected, $\underline{V}$ is fixed and only $\underline{W}$ is tuned. Then, the only design parameter in constructing the one-layer NN is the number of hidden layer neurons N_h. A larger N_h results in a smaller $\bar{\varepsilon}(\bar{x})$.

2.5. Gaussian or Radial Basis Function Networks

The selection of a suitable set of activation functions is considerably simplified in various kinds of structured nonlinear networks, including radial basis functions. A NN activation function is given as

$$\sigma(x) = e^{-(x-\mu)^2/2p} \qquad (12)$$

when x is a scalar with mean μ and variance p. These are called *Gaussian* or *radial basis functions* (RBF). A RBF NN can also be written as Eq. (2), but this function has an advantage over the usual sigmoid NN in that the n-dimensional Gaussian is well understood from probability theory, Kalman filtering, and elsewhere, so that n-dimensional RBFs are easy to conceptualize.

The j-th activation function can be written as

$$\sigma_j(\overline{x}) = e^{-\frac{1}{2}(\overline{x}-\overline{\mu}_j)^T \underline{P}_j^{-1}(\overline{x}-\overline{\mu}_j)} \qquad (13)$$

with $\overline{x}$, $\overline{\mu}_j \in \Re^n$. Let the vector of activation functions be defined as $\overline{\sigma}(\overline{x}) \equiv [\sigma_1(\overline{x}) \quad \sigma_2(\overline{x}) \quad \cdots \quad \sigma_L(\overline{x})]^T$. If the covariance matrix is diagonal so that $\underline{P}_j = diag\{p_{jk}\}$, then Eq. (13) becomes separable, and may be decomposed into its component parts as

$$\sigma_j(\overline{x}) = e^{-\frac{1}{2}\sum_{k=1}^{n} -(x_k-\mu_{jk})^2/p_{jk}} = \prod_{k=1}^{n} e^{-\frac{1}{2}(x_k-\mu_{jk})^2/p_{jk}} \qquad (14)$$

where x_k , μ_{jk} are the k-th components of $\overline{x}$, $\overline{\mu}_j$. Thus, the n-dimensional activation functions are the product of n scalar functions. This allows us to visualize the hidden-layer neurons as having n-dimensional activation functions, as in Figure 1.

It can be seen that Eq. (14) is of the form taken by the activation functions in Eq. (1), but with thresholds that are more general. The first-layer thresholds of the RBF NN are n-dimensional vectors corresponding to the mean values of the Gaussian functions, which serve to shift the functions in the $\Re^n$ plane. The first-layer weights in $\underline{V}^T$ are scaling factors that served to scale the width of variance of the Gaussians. These are both usually selected in designing the RBF NN and left fixed; only the output-layer weights $\underline{W}^T$ are generally tuned. Therefore, the RBF NN is a special sort of FLNN shown in Eq. (10).

Figure 3 shows separable Gaussians for the case $\overline{x} \in \Re^2$. In this figure, all the variances p_{jk} are identical, and the mean values μ_{jk} are chosen in a special way that spaces the activation functions at the node points of a 2D grid. To form an RBF NN that approximates functions over the region $\{-1 < x_1 \le 1, -1 < x_2 \le 1\}$, here we have selected $L = 5x5 = 25$ hidden-layer neurons, corresponding to five cells along x_1 and five along x_2. Nine of these neurons have 2D Gaussian activation functions, while those along the boundary require the illustrated ‘one-sided’ activation functions.

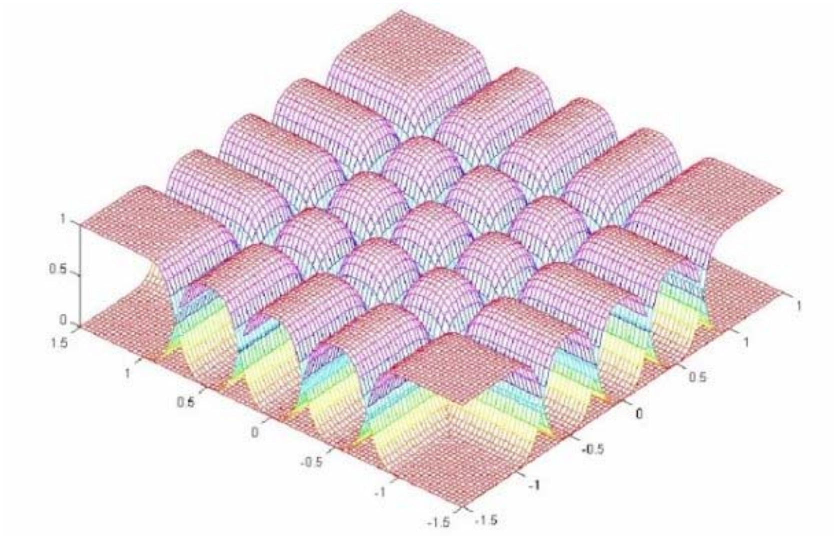


Figure 3. Two-dimensional separable Gaussian functions for an RBF NN

The importance of RBF NNs is that they show how to select the activation functions and the number of hidden-layer neurons for specific NN applications, including function approximation, while also providing insights on the information stored in the NN.

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Biographical Sketches

Dr. Javier Campos was born in Maracaibo, Venezuela in 1967. He received his bachelor's degree in electrical engineering from La Universidad del Zulia, Maracaibo, Venezuela in 1991. He received a M.S. degree from The University of Texas at Arlington (UTA), USA, in 1996. He received his Ph.D. degree from The University of Texas at Arlington in 2000. From 1991 to 1994 he worked for Maraven Sociedad Anonima (S.A.), an oil company subsidiary of Petroleos de Venezuela Sociedad Anonima (PDVSA), where he worked mainly as a software engineer in charge of the maintenance and improvement of the Supervisory Control and Data Acquisition System (SCADA) system for electrical power plants and substations. In 1992 he received the Antonio Jose de Sucre Award, a Venezuelan Government scholarship awarded to selected individuals throughout the country, to pursue graduate studies in the USA.

Javier Campos currently works for Montavista Software, Inc. as a Linux consultant engineer, developing and supporting the Linux operating system for embedded systems with emphasis on the x86, powerpc, arm and mips processor architectures. During 1996–1999, he worked as a consultant for small companies, mainly under Army Small Business Innovative Research (SBIR) projects for development and implementation of intelligent control algorithms for flexible mode damping, inertia stabilization, active suspension control, and satellite tracking. His current research interests are in nonlinear and adaptive control, digital control, neural networks, fuzzy logic, and active suspension systems. He is reviewer for several Institute of Electrical and Electronics Engineers (IEEE) Conferences and Journals, including *Conference on Decision and Control* (CDC), *Transactions on Automatic Control*, *Transactions on Systems, Man, and Cybernetics*, and *Automatica*.

He received the second prize at the IEEE Fort Worth Section Graduate Paper Contest in 1999. He also received the Automation and Robotics Research Institute (ARRI) Best Student Paper Award in 1998, and the ARRI Invention Award in 2000. He is currently a member of the IEEE and an associate member of the Sigma Xi research society. He has a patent application pending for the project entitled "Backlash Compensation Using Neural Networks."

Dr. F.L. Lewis was born in Würzburg, Germany, subsequently studying in Chile and at Gordonstoun School in Scotland. He obtained a Bachelor's Degree in Physics/Electrical Engineering and a Master's in Electrical Engineering Degree at Rice University in 1971. He spent six years in the US Navy, serving as Navigator aboard the frigate USS Trippe (FF-1075), and Executive Officer and Acting Commanding Officer aboard USS Salinan (ATF-161). In 1977 he received the degree of Master of Science in Aeronautical Engineering from the University of West Florida. In 1981 he obtained his Ph.D. at the Georgia Institute of Technology in Atlanta, where he was employed as a professor from 1981 to 1990 and is currently an Adjunct Professor. He is a Professor of Electrical Engineering at The University of Texas at Arlington, where he was awarded the Moncrief-O'Donnell Endowed Chair in 1990 at the Automation and Robotics Research Institute.

Dr. Lewis has studied the geometric, analytic, and structural properties of dynamical systems and feedback control automation. His current interests include robotics, intelligent control, neural and fuzzy systems, nonlinear systems, and manufacturing process control. He is the author/co-author of two US patents, 124 journal papers, twenty book chapters and encyclopedia articles, 210 refereed conference papers, and eight books: *Optimal Control*, *Optimal Estimation*, *Applied Optimal Control and Estimation*, *Aircraft Control and Simulation*, *Control of Robot Manipulators*, *Neural Network Control*, *High-Level Feedback Control with Neural Networks* and the IEEE reprint volume *Robot Control*. Dr. Lewis is a registered Professional Engineer in the State of Texas and has been selected to the Editorial Boards of the *International Journal of Control*, *Neural Computing and Applications*, and *International Journal on Intelligent Control Systems*. He is the recipient of a National Science Foundation (NSF) Research Initiation Grant and has been continuously funded by NSF since 1982. Since 1991 he has received $1.8 million in funding from NSF and upwards of $1 million in SBIR/industry/state funding. He has received a Fulbright Research Award, the American Society of Engineering Education F.E. Terman Award, three Sigma Xi Research Awards, the UTA Halliburton Engineering Research Award, the UTA University-Wide Distinguished Research Award, the ARRI Patent Award, various Best Paper awards, the IEEE Control Systems Society Best Chapter Award (as Founding Chairman), and the National Sigma Xi Award for Outstanding Chapter (as President). He was selected as Engineer of the Year in 1994 by the Fort Worth IEEE Section, and is a Fellow of the IEEE. He was appointed to the National Academy of Engineering (NAE) Committee on Space Station in 1995 and to the IEEE Control Systems Society Board of Governors in 1996. In 1998 he was selected as an IEEE Control Systems Society Distinguished Lecturer. He is a Founding Member of the Board of Governors of the Mediterranean Control Association.