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INTELLIGENT CONTROL OF ROBOTIC ARM/HAND SYSTEMS FOR THE NASA EVA RETRIEVER USING NEURAL NETWORKS

Final Report

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Prepared by:	Robert A. McLauchlan, Ph.D.,P.E.
Academic Rank:	Associate Professor
University & Department:	Texas A & I University Civil & Mechanical Engineering Department Kingsville, Texas 78363

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JSC Colleague:	Cliff Hess
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ABSTRACT

Adaptive/general learning algorithms using varying neural network models are considered for the intelligent control of robotic arm plus dextrous hand/manipulator systems. Results are summarized and discussed for the use of the Barto/Sutton/Anderson neuronlike, unsupervised learning controller as applied to the stabilization of an inverted pendulum on a cart system. Recommendations are made for the application of the controller and a kinematic analysis for trajectory planning to simple object retrieval (chase/approach and capture/grasp) scenarios in two dimensions.

INTRODUCTION

Overview

The research work reported herein is important to the future development of the NASA/JSC EVA Retriever. This highly autonomous, free-flying robot or robotic system is comprised of MMU, arm and smart hands. It is being developed to aid crewmen in the performance of EVA tasks including the chase, capture and return capability required for adrift crewmen or station equipment. The ultimate goal of the work in developing this system is to enhance the effectiveness of EVA crewmen [1, 23].

The intelligent control of robotic arm/hand systems using neural network learning controllers is very relevant to EVA Retriever development. This follows because of the need for autonomous, adaptive behavior in both planned and unplanned contexts in the space environment. Neural networks and related advanced learning controllers offer such capabilities [23].

The work reported herein is concerned with the investigation and development of neural networks or other types of advanced learning controllers as:

(a) Supervised controllers with training which because of their connective, associative memory structure can develop significant controller generalization capability. Such generalization can lead to similar performance of the retriever arm/hand controller in different but analogous physical system situations and in stochastically related loading/excitation environments.

(b) Unsupervised controllers which can self train/adapt to new learning situations and also exhibit significant generalization capability. As learning develops, and unfamiliar situations become familiar ones, these neural networks should provide feedforward compensation with less compensation via the feedback path [7, 11, 15, 26].

Neural Networks for Intelligent Control

Neural networks are massively parallel, distributed processing systems. They have the ability to continuously improve their performance via dynamic learning [7, 9, 15-18, 36]. As used in this report, neural networks refers to "artificial", i.e., programmable systems of processing elements. As such they form a research area of intense interest in artificial intelligence.

Initial neural network research concentrated on the computationally intensive areas of adaptive signal processing, as, e.g., pattern recognition, real-time speech recognition and image interpretation. Recently there has been a resurgence of interest in neural networks because of (a) Advances in training algorithms for networks, and (b) Availability of extremely fast, relatively inexpensive computers for implementing these algorithms. These developments have lead to the consideration of neural networks for the real-time identification and control of large flexible/articulated aerospace and robotic systems [7, 27, 28].

Neural networks can provide mechanisms for (a) Associative memory, (b) Pattern recognition, and (c) Abstraction. These are emergent properties of networks of neuronlike units with adaptive synaptic connections [10, 14, 22, 29, 32]. These mechanisms arise from the neural network being a system of interconnected "neuron-like" elements modeled after the human brain. This system operates on input data in an "all at once" mode rather than in a conventional computer's "step by step" algorithmic approach [7, 9, 29]. Different learning architectures can be used in training for intelligent control. This is done to provide appropriate inputs to the system so that the desired responses are obtained. Uncertainty and noise can be handled by a neural network via the Hebbian type of associative learning arising from adaptively modified connection strengths [21, 29]. Kawato el al [15-18] indicate that a neural network model can be used to control voluntary movement with applications to robotics. Implemented as a multilayered, hierarchically intelligent control system, neural networks can be implemented to effect the following:

(a) Pattern recognition/ condition matching
(b) Trajectory and approach, grasping, etc. opertation
(c) "Point of view" transformations - as, e.g., visual to sensor/end effector to object, etc.
(d) System (robot, object, etc.) state observer or model synthesis and simulation behavior
(e) Generation of motion/actuator commands.

Adaptive control is useful for systems which perform over the large ranges of uncertainties which result from large variations in physical and operating parameter values, environmental conditions, and signal inputs. However, adaptive control as such (i.e., without unsupervised learning/unanticipated problem solving features) has difficulty with the following generic problems in designing controllers:

* Sensor data overload - arising from (a) Data redundancy

per se, and (b) Specialized, rarely required data
* Multi-spectral, multi-sensor data fusion and mapping/use in the proper feedback control law
* Need for system robustness to handle large parameter excursions
* Required high-speed, real-time control degradation resulting from time consuming artificial intelligence calculations
* Unsolved sensor choice and placement problems for robotic/large control systems.

It should be noted that human intervention is used in traditional control systems operating with large uncertainty. Such intervention is unacceptable in many real-time applications. This is especially true for the hostile space environment in which the NASA EVA Retriever is to operate [1, 23]. It means that automatic techniques for handling uncertainty must be developed. Neural networks show great promise for the intelligent, unsupervised control of the multiple arm plus dextrous robotic hands of the Retriever. The next section of the report describes the author's research work with the Barto et al intelligent controller which is a special kind of neural network with associative search and associative critic neuronlike elements.

ACE/ASE NEURONLIKE LEARNING CONTROLLER

The Barto/Sutton/Anderson adaptive learning controller is composed of two types of neuronlike elements with significant unsupervised problem-solving capacities. These elements are the associative search element (ASE) and adaptive critic element (ACE). Barto et al 1983 used a single element of each type. Their ASE element exhibits a learning strategy which is similar to the earlier "BOXES" adaptive problem solving system of Michie and Chambers [24, 25]. The ASE/ACE elements embody refinements discussed in the literature by Barto and colleagues [2-6, 30-31]. They evolved from the heterostatic brain function and adaptive systems work of Klopf [19, 20]. Adding a single ACE element improves the learning performance over that of a single ASE alone. This can be clearly shown by comparing the problem-solving capabilities of BOXES with those of a single ASE/single ACE learning system and solving the control problem of balancing an inverted pendulum on a cart. It is interesting to note that strong analogies exist between the behaviorial interpretations of the ASE, ACE adaptive elements and animal behavior in instrumental learning. There are also strong parallels with the "bootstrap adaption" systems work of Widrow et al [33-35]. This work considered the (a) punish/reward critical learning and (b) pattern recognizing control problems. Relevant artificial (i.e., programmable) neural networks the ASE, ACE neuronlike elements are significant. This follows because they indicate that if adaptive elements are to learn effectively as network components, then they are constrained to have adaptive capabilities at least as robust as these Barto et al learning controller elements [2].

Figure 1 depicts the inverted pendulum on a cart system which is

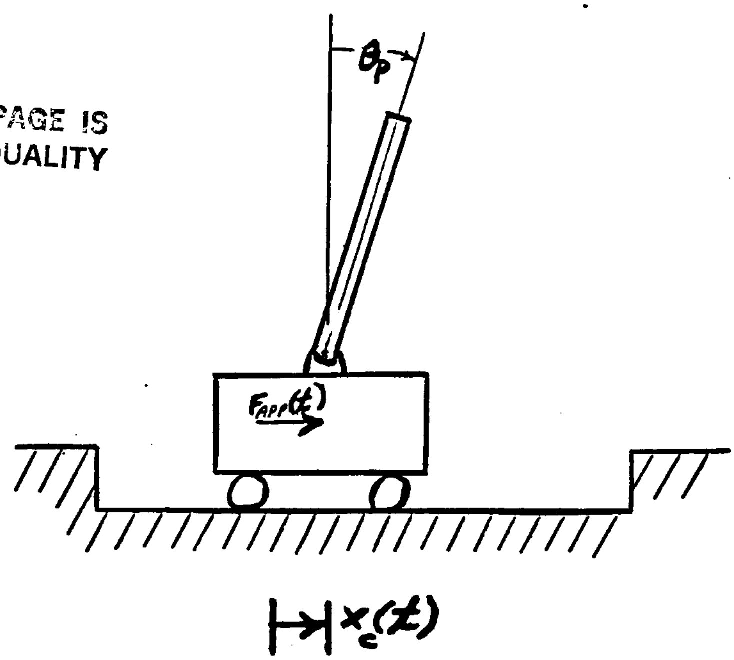

Figure 1. Representative Model for Cart and Inverted Pendulum System.

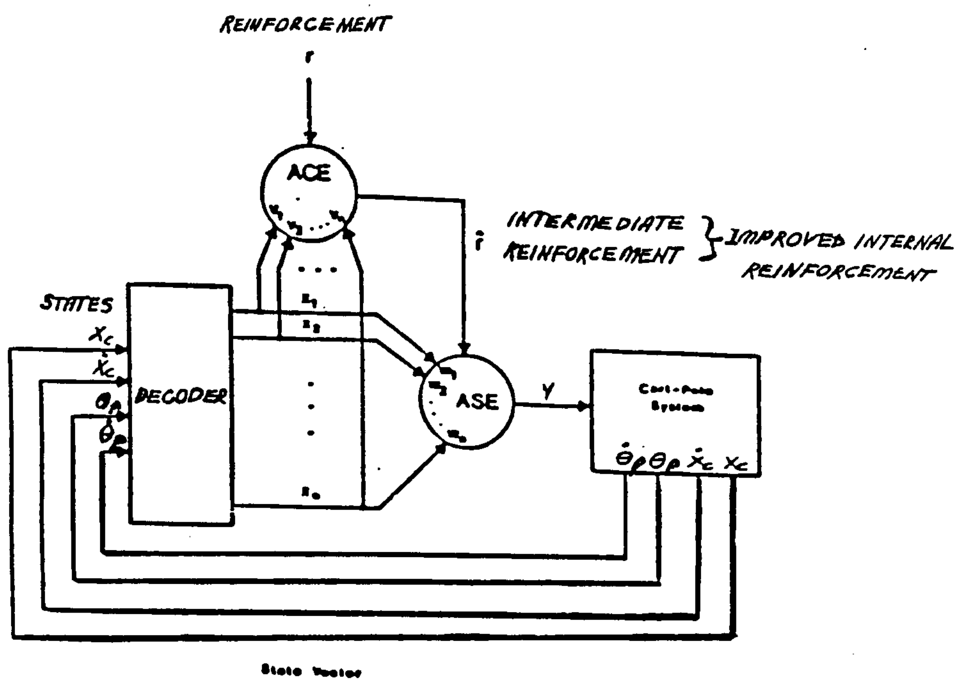

Figure 2. ASE and ACE Controller for Cart Plus Inverted Pendulum System

to be controlled. Here the cart can move within the bounds indicated on a one-dimensional track. The pendulum can move only in the vertical plane of the cart and the track. The applied force $F_{APP}(t)$ results from the output of the learning controller. It is applied in a bang-bang (+/-) manner and acts with a fixed magnitude to the left or right at discrete time intervals. The pendulum-cart system is described by a four state variable model in the time domain [8]. The four state variables are as follows: (a) x_c - the position of the cart on the track, (b) θ_p - the angle of the pendulum with the vertical, (c) $\dot{x}_c$ - the cart velocity, and (d) $\dot{\theta}_p$ - the rate of change of the pendulum angular displacement. The state variable model for this system can be written as

$$\begin{bmatrix} \dot{x}_c = V_c \\ \dot{\theta}_p = \omega_p \end{bmatrix}$$

$$\begin{bmatrix} \dot{V}_c \\ \dot{\theta}_p \end{bmatrix} = \begin{bmatrix} [Mc + Mp] & [Mp*L_p*Cos(\theta_p)] \\ [Mp*L_p^2*cos(\theta_p)] & [Jp + Mp*L_p^2] \end{bmatrix}^{-1} \begin{bmatrix} [Mp*L_p*sin(\theta_p)*\omega_p^2 - \mu_c*sgn(V_c) + Fapp(t)] \\ [-Mp*g*L_p*sin(\theta_p) - \mu_p*\omega_p] \end{bmatrix} \qquad (1)$$

Physical parameters in the above equations specify pendulum length and mass, cart mass, the coefficients of friction between the cart and the track and at the pin connection between the pendulum and the cart, the applied control force, the force due to gravity, and time. Table 1 defines the notation used in equation 1.

The system of first order equations has been solved using second order numerical intergration procedures which have been implemented in the FORTRAN computer program NRLNET. In implementing the learning controller algorithm the state space has been partitioned based on the following 252 quantization interval thresholds:

(1) Cart position x_c: +/- 0.8, +/- 2.4 m ,(4 quantization intervals including failed regions above and below 2.4 m)

(2) Pendulum angular displacement θ_p: 0,+/- 1, +/- 6, +/- 12 degrees, (7 quantization intervals including failed regions above and below 12 degrees)

(3) Cart velocity $\dot{x}_c$: +/- 0.5, +/-∞ m/s, (3 quantization intervals)

(4) Pendulum angular velocity $\dot{\theta}_p$: +/- 50, +/- ∞ degrees per second, (3 quantization intervals)

Figure 2 depicts the ASE plus ACE adaptive learning controller of Barto et al [2]. The neuronlike learning system can be described by the following equations:

<u>Element output y(t)</u> which is determined from the decoded state quantization interval vector input

$$y = f[(w(I,t) * x(I,t)) + n(t)] \qquad (2)$$

Here the noise $n(t)$ is a real random variable with probability function $p(x)$ and f is either a threshold, sigmoid, or identity transfer function. For the work reported herein, $p(x)$ is the zero mean Gaussian distribution with standard deviation σ, and f is the bang-bang type <u>threshold function</u>:

$$f(x) = \begin{cases} +1, & x \text{ .EG. } 0 \text{ (applied force action to the right)} \\ -1, & x \text{ .LT. } 0 \text{ (applied force action to the left)} \end{cases} \tag{3}$$

<u>ASE weights $w(I,t)$</u>, 1 .LT. I .LT. N which change over discrete time as follows:

$$w(I,t+1) = w(I,t) + ALPHA * r(t) * e(I,t) \tag{4}$$

In equation 4:

ALPHA = positive constant determining the rate of change in $w(I,t)$

$r(t)$ = real-valued reinforcement at time t

$e(I,t)$ = eligibility at time t via the input pathway I.

<u>Eligibility traces for the ASE weights</u> which exponentially decay with increasing time, given in equation 5 as:

$$e(I,t+1) = DELTA * e(I,t) + (1-DELTA) * y(t) * x(I,t) \tag{5}$$

in which,

DELTA = the eligibility decay rate.

<u>ACE weights $v(I,t)$</u>, 1 .LT. I .LT. N which change over discrete time as follows:

$$v(I,t+1) = v(I,t) + BETA * rhat(t) * xbar(I,t) \tag{6}$$

In equation 6,

BETA = positive constant defining the rate of change of $v(I,t)$

$rhat(t)$ = $r(t) + GAMMA * p(t) - p(t-1)$, the <u>improved internal reinforcement signal</u> for the critic element

$xbar(I,t)$ = $LAMBDA * xbar(I,t) + (1-LAMBDA) * x(I,t)$, the <u>eligibility traces for the ACE weights</u>

$p(t)$ = $\sum_I v(I,t) * x(I,t)$, the <u>prediction of eventual reinforcement</u>

GAMMA = reinforcement learning rate

LAMBDA = xbar(I,t) trace delay weight

Barto and Sutton [2, 5] explain the derivation of the ACE learning rule as used above. Additional discussion of the ASE, ACE adaptive learning controller can be found in references [30, 31].

ASE/ACE LEARNING CONTROLLER RESULTS

This section of the report discusses representative results obtained by the author with his FORTRAN computer program NRLNET131 implementing the Barto et al ASE/ACE neuronlike learning controller. This program is the result of several modifications by the author to incorporate general data file input and the file and printer plot output of the applied control force and the four state variables as functions of time. The original FORTRAN program NRLNET00 was the author's implementation of a PASCAL program written in 1988 by Doug Walker of GHG in support of the Special Projects Branch (EC5) in the Crew and Thermal Systems Division at NASA/JSC.

TABLE 1. SUMMARY OF PHYSICAL PARAMETER VALUES FOR CART PLUS INVERTED PENDULUM SYSTEM

Mc	= Cart Mass, 1.0 kg
Mp	= Pendulum Mass, 0.10 kg
Lp	= Pendulum Length, 0.50 m
MUc	= Cart Coefficient of Coulomb Friction, 0.005
MUp	= Pendulum/Cart Pin Coefficient of Friction, 0.00002 N m sec/rad
Fapp	= Magnitude of Force Applied to Cart in x Direction, (+/-) 10 N

TABLE 2. SUMMARY OF THE ASE/ACE NEURONLIKE LEARNING CONTROLLER PARAMETERS

ALPHA	= Rate Constant for ASE Weights, 1000.0
BETA	= Rate Constant for ACE Weights, 0.50
DELTA	= Decay Rate for ASE Eligibility Traces, 0.90
GAMMA	= Learning Rate for Improved Internal Reinforcement, 0.95
LAMBDA	= Decay Rate for ACE Eligibility Traces, 0.95
μ	= Mean Value for Gaussian Normal Distribution Used to Define ASE/ACE Output Noise Function, 0.00 and 0.10
σ	= Standard Deviation Value for Gaussian Normal Distribution Used to Define ASE/ACE Output Noise Function, 0.01, 0.05, 0.10, 0.15, 0.20, and 0.25

Table 1 gives the physical and control parameter values used in the simulation work with NRLNET131 for the cart plus inverted pendulum system depicted in Figure 1. Values used for the ASE/ACE neuronlike learning controller parameters are summarized in Table 2. These

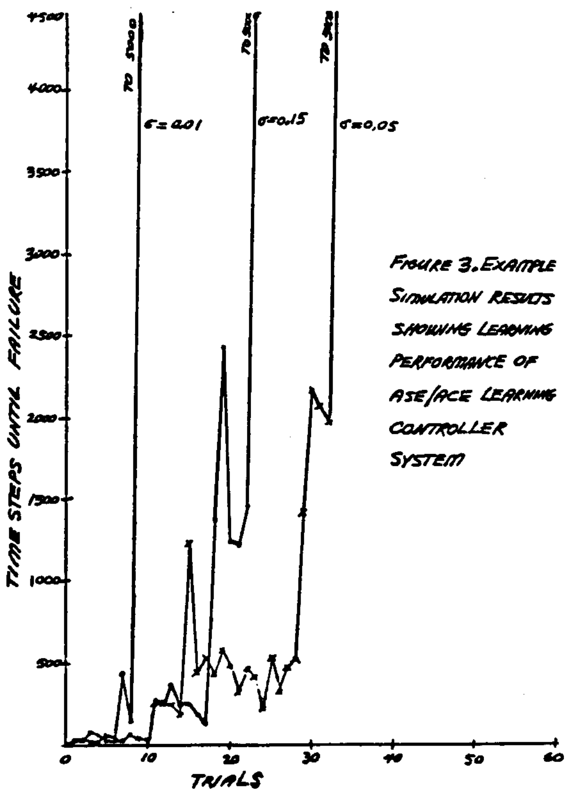

Figure 3. Example Simulation Results Showing Learning Performance of ASE/ACE Learning Controller System

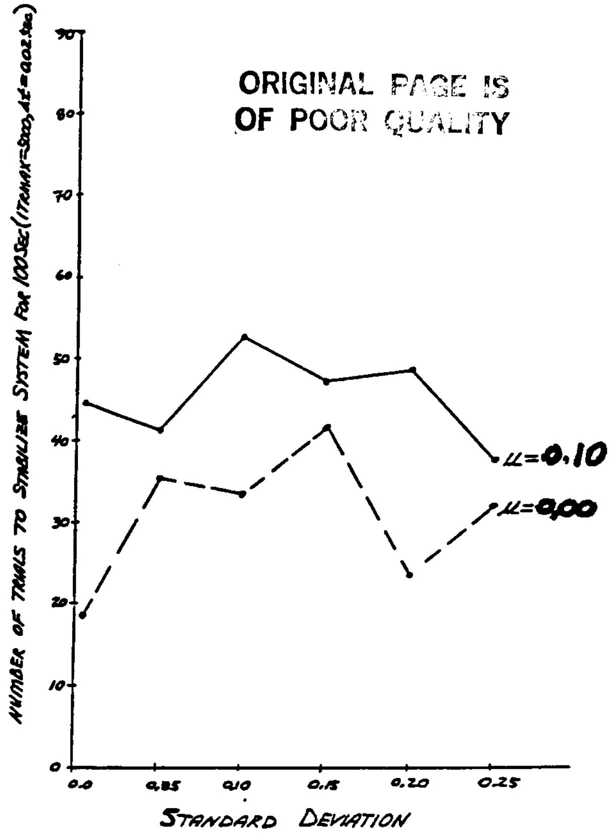

Figure 4. Average Number of Trials for Five Runs as a Function of Standard Deviation With Mean Value as Parameter

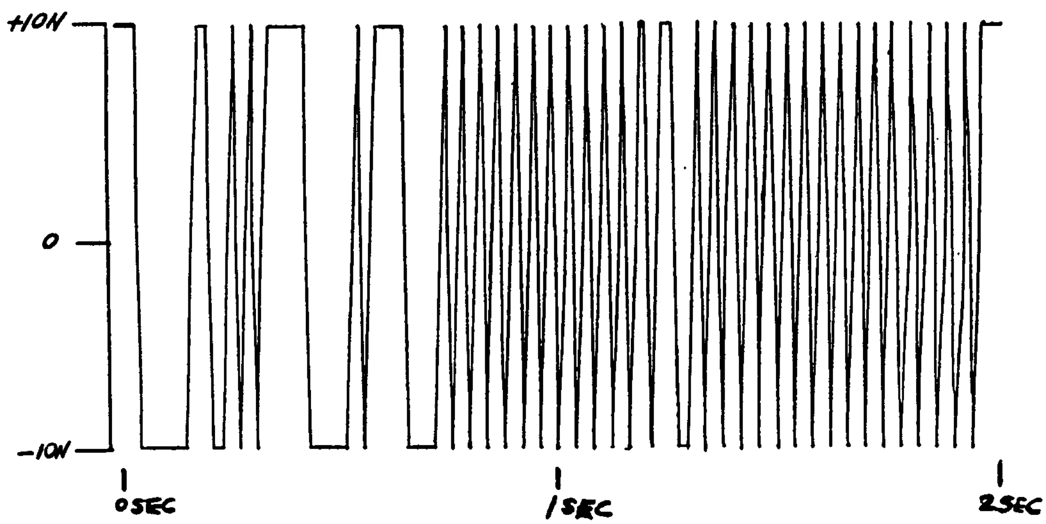

Figure 5. Applied Force Fapp(t), N

Figure 6. Cart Displacement $x_c(t)$, m

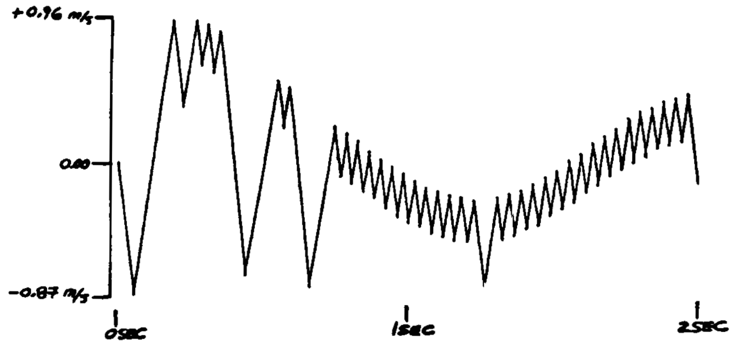

Figure 7. Cart Velocity $\dot{x}_c(t)$, m/sec

Figure 8. Pendulum Angular Displacement $\theta_p(t)$, rad

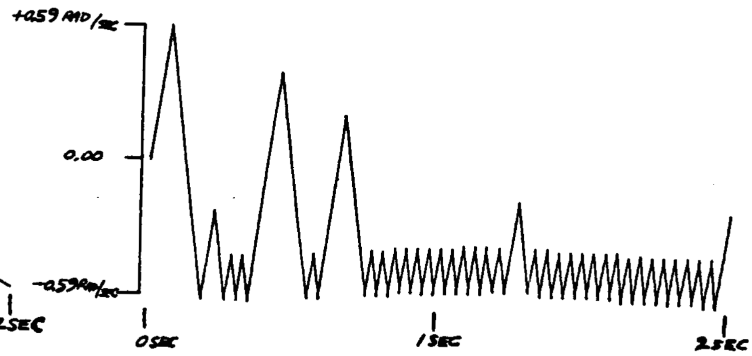

Figure 9. Pendulem Angular Velocity $\dot{\theta}_p(t)$, rad/sec

parameter values were used to generate the simulation performance results plotted in Figures 3 and 4. Figure 3 plots curves for the number of time steps until failure versus the trial number. These are typical curves for individual runs of the ASE/ACE learning controller system. Figure 4 gives plots of the average number of trials which are required to stabilize the cart plus pendulum system for 5000 time steps (100 seconds with Δt = 0.02 seconds). The average number of trials are given as a function of the standard deviation for the Gaussian normal random noise process with the mean for the process as parameter. The mean equal zero curve indicates a trend toward an increasing number of trials as the standard deviation is increased from 0.01 to 0.25. The other curve for the mean equal to 0.10 shows relative constancy over the same range in standard deviation. These runs were originally made to examine the sensitivity of the ASE/ACE learning controller performance to variation in the noise process used in generating its output function. An additional objective was to develop a base from which the generalization and robustness properties of the controller weights could be investigated. Five runs were used to generate each point plotted in Figure 4. The results shown in Figures 3 and 4 are in general agreement with those published by Barto et al [2]. However, the author has found that his NRLNET131 implementation of the ASE/ACE controller usually takes a lesser number of trials for successfully learning to stabilize the cart plus pendulum system for both the 5000 Δt (100 seconds) cases shown here and the 200,000 Δt (66.7 minutes) cases which the author ran to directly compare his results with those of Barto et al. Extensive runs were not made for the 200,000 Δt (66.7 minutes) stabilization period because of the excessively long elapsed time rerequired for the VAX system available to the author to return answers for a single run.

Figure 5 shows the controller output force which is applied to the cart in stabilizing the inverted pendulum. Here the applied force is plotted as a function as a function of time over the first 100 Δt intervals (2 seconds). Extensive runs have been made with the ASE/ACE controller system and all exhibit the characteristic +/- 10N on-off or bang-bang behavior with Δt = 0.02 sec. This value of the time increment should be adequate, based on physical system oscillation behavior, for the second order numerical integration scheme used.

Figures 6-9 plot the four state variables: cart displacement (x_c), cart velocity ($\dot{x}_c$), pendulum angular displacement (θ_p), and pendulum angular velocity ($\dot{\theta}_p$), respectively. They are also plotted as functions of time over the first 100 Δt intervals (2 seconds). Consideration of these and similar time domain results for the state variables and the applied force indicates that (a) significant inefficiencies can occur with respect to the input force and its impact on the actual state variable behavior of the cart plus pendulum system, (b) with Δt = 0.02 sec there may be some interaction between the numerical integration method used and the dynamics of the ASE/ACE learning controller. To investigate (b) above, additional runs were made in which Δt was reduced (Δt= 0.01, 0.005, 0.001 sec). These results although not included here did show significant reduction with decreasing Δt in the bang-bang nature of the input force and the higher frequency oscillations present in the state behavior over time (especially for the cart linear and the pendulum angular velocities).

The author has extended the single ASE/single ACE learning controller system to include two search and two critic elements. The elements in each pair work in parallel. Since the outputs are averaged in the 2 ASE/2 ACE learning controller system, it has -Fapp, 0, +Fapp as three possible outputs. This extension was implemented in the author's FORTRAN computer program NRLNET20. Initial runs indicate that the new controller as implemented has good performance up to a maximum learning point (maximum time for stability as a function of number of trials). Beyond this point the learning is severely degraded with increasing trials, or a form of limit cycle behavior occurs. These results indicate that the split-decision nature of the 2 ASE/2 ACE system as implemented in its averaging form may cause the observed behavior. In this case using a 3, 5, etc.(i.e., odd number of elements) in the ASE/ACE system may be warranted. These controllers would also have a "smoother" (i.e., less bang-bang) control action. Another alternative to improve performance is to more richly connect the elements both within and across the search element and the critic element layers. This would give the ASE/ACE neuronlike controller system a counter propagation/Grossberg layer plus Kohonen layer type of neural network structure [12, 13].

CONCLUSIONS

An examination has been made of the use of neural networks for the intelligent control of robotic arm plus hand/manipulator systems for the EVA Retriever. Based largely to the present time on a review of the literature and computer simulation work, this examination has indicated that a hierarchical, multi-layer neural network system can be used for intelligent control. Baseline feedforward control is used in conjunction with trajectory planning in these systems. Joint torque feedback provides the correction signal. These systems have the characteristic that as additional response behaviors are learned, much of the control action passes to the feedforward path.

Additional investigation into neural networks for intelligent control has focused on the use and extension of the Barto et al neuronlike ASE/ACE intelligent controller. A FORTRAN family of computer programs (NRLNETXX) were developed by the author as extensions of a previous Pascal language implementation of the controller at NASA/JSC. Work with these programs has concentrated on the following: (a) Verifying published results for convergence to stable solution (number of trials for a specified period of stability), (b) Developing graphics, etc. feedback tools to monitor system behavior (as, e.g., given by the applied control force and the four state variables as functions of time), (c) Investigate learning control behavior as a function of the number of unsupervised trials required to obtain stability and the random process parameters (Gaussian process mean and standard deviation), and (d) Basic extensions to the learning controller network incorporating two adaptive search elements (ASEs) and 2 adaptive critic elements (ACEs) in its structure.

RECOMMENDATIONS

This section of the report presents recommendations for the intelligent control of smart robotic arm plus hand systems using neural networks. These recommendations are based on the results presented above and on additional related work done by the author during Summer 1988. They are presented in the form of a research and development program plan. The R & D program plan gives activities that can continue the author's research begun during the 1988 summer program.

(1) Investigation of two dimensional graphics as a kinematic simulation tool for planning EVA object retrieval in terms of the approach to and grasping of objects using an articulated two-link arm/scissor hand system.

(2) Implementation of dynamics, sensing, and control models of the articulated two-link arm/scissor hand system. It is desired to mount this arm/hand system on a cart to represent the EVA Retriever in two dimensions.

(3) Examination of hierarchical neural networks with fuzzy logic reasoning as adaptive/general learning systems comprised of (a) Network architectures, (b) Transfer functions, and (c) Dynamic learning rules. These systems can employ joint torque and state vector feedback to control the arm/hand system(s) in object retrieval as discussed above.

(4) Investigation of extensions to the Barto/Anderson neuronlike learning system and counter propagation/back propagation type networks to the related problem of stabilizing/controlling the motion of simple and compound (articulated linkage) pendulums on a cart. Successful employment here can lead to similar use with the arm/hand retriever systems.

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