Creative Learning for Intelligent Robots

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ABSTRACT

This paper describes a methodology for creative learning that applies to man and machines. Creative learning is a general approach used to solve optimal control problems. The creative controller for intelligent machines integrates a dynamic database and a task control center into the adaptive critic learning model. The task control center can function as a command center to decompose tasks into sub-tasks with different dynamic models and criteria functions, while the dynamic database can act as an information system. To illustrate the theory of creative control, several experimental simulations for robot arm manipulators and mobile wheeled vehicles were included. The simulation results showed that the best performance was obtained by using adaptive critic controller among all other controllers. By changing the paths of the robot arm manipulator in the simulation, it was demonstrated that the learning component of the creative controller was adapted to a new set of criteria. The Bearcat Cub robot was another experimental example used for testing the creative control learning.

The significance of this research is to generalize the adaptive control theory in a direction toward highest level of human learning – imagination. In doing this it is hoped to better understand the adaptive learning theory and move forward to develop more human-intelligence-like components and capabilities into the intelligent robot. It is also hoped that a greater understanding of machine learning will motivate similar studies to improve human learning.

Key Words: Adaptive critic design, dynamic programming, creative learning, Neurocontrol, intelligent robots, artificial intelligence

1. INTRODUCTION

The purpose of this paper is to explore and develop an intelligent mobile robot using creative learning and to better understand human intelligence. Intelligence is the most outstanding human characteristic; however, it is still not totally understood and therefore has many varying definitions, implied meanings, and levels of sophistication. Current researchers are attempting to develop intelligent robots. Artificial intelligence, or AI, programs using heuristic methods have somewhat solved the problem of adapting, reasoning, and responding to changes in the robot's environment. Dynamic Programming (DP) is perhaps the most general approach for solving optimal control problems. Adaptive Critics Design (ACD) offer a unified approach to dealing with the controller’s nonlinearity, robustness, and reconfiguration for a system whose dynamics can be modeled by a general ordinary differential equation. Artificial Neural Network (ANN) and Backpropagation (BP) made it possible for ACD implementation. Werbos classified DP specified in ACDs into five disciplines, which are neural network engineering, control theory, computer science or artificial intelligence, operations research and fuzzy logic or control. Many researchers devoted their research to adaptive critic designs (learning) using various training methods in diversity of applications.

However, in order to develop “brain-like intelligent control”, it is not enough to just have the adaptive critic portion. Here we proposed a novel algorithm, called Creative Learning (CL). The structure of creative learning combines all of the components of adaptive critic learning. Furthermore, it is integrated in both decision-making and database theory. For instance, it selects the criteria or critics for the different sub-tasks and shows how to choose the criteria function or utility function, and how to memorize the experience as human-like memories. All are concerns of the creative learning techniques. In this paper, we proposed a creative learning structure with evolutionary learning strategies. The creative learning structure is to develop a generalization of adaptive critic learning called Creative Learning (CL) and explore the use of new learning methods that goes beyond the adaptive critic method for intelligent mobile robots in unstructured environments as shown in Figure 1.1.
2. ADAPTIVE CRITIC LEARNING

Werbos 42 summarized recent accomplishments in neurocontrol as a “brain-like” intelligent system. It should contain at least three major general-purpose adaptive components: (1) an Action or Motor system, (2) an “Emotional” or “Evaluation” system or “Critic” and (3) an “Expectations” or “System Identification” component.

“Critic” served as a model or emulator of the external environment or the plant to be controlled, solving optimal control problem over time classified as adaptive critic designs (ACD) 3. ACD is a large family of designs which learn to perform utility maximization over time. In dynamic programming, normally the user provides the function $U(X(t), u(t))$, an interest rate $r$, and a stochastic model. Then the analyst tries to solve for another function $J(X(t))$, so as to satisfy some form of Bellman equation, the equation (1) that underlies dynamic programming 43:

$$J(X(t)) = \max_{u(t)} \{U(X(t), u(t)) + J(X(t+1)) \}$$

(1)

where “<>” denotes expected value.

In principle, any problem in decision or control can be classified as an optimization problem. Many ACDs solve the problem by approximating the function $J$. The adaptive critic approach is a complex field of study with its own “ladder” of design from the simplest and most limited all the way up to the brain itself with five levels. The simplest level is the original Widrow design 44. He shaped the term “Critic. “Brain-like control”, represents levels 3 and above. Level 3 is to use heuristic dynamic programming (HDP) to adapt a Critic, and backpropagate through a Model to adapt the Action network. Levels 4 and 5 respectively use more powerful techniques to adapt the Critic – Dual Heuristic Programming (DHP) and Globalized DHP (GDHP). The specific discussion on HDP is followed in the next section 42.

Heuristic Dynamic Programming (HDP)

HDP and its ACD form have a critic network that estimates the function $J$ (cost-to-go or strategic utility function) in the Bellman equation of dynamic programming, presented as follows 21, 45:

$$J(x(t)) = \sum_{k=0}^{\infty} \gamma^{k} U(x(t+k))$$

(2)

where $\gamma$ is a discount factor for finite horizon problems ($0<\gamma<1$), and $U(.)$ is the utility function or local cost. The critic network tries to minimize the following error measure over time:

$$\| E_{1} \| = \sum_{t} E_{1}^{2}(t)$$

(3)

$$E_{1}(t) = J[Y(t)] - \gamma J[Y(t+1)] - U(t)$$

(4)

Where $Y(t)$ stands for either a vector $R(t)$ of observables of the plant or a concatenation of $R(t)$ and a control (action) vector $A(t)$. The configuration for training the critic according to Equation (4) is shown Figure 2.1 (a). This is the same critic network shown in two consecutive moments in time. The critic’s output $J(t+1)$ is necessary in order to obtain the training signal $\gamma J(t+1) + U(t)$, which the target value for $J(t)$. It should be noted that, although both $J[Y(t)]$ and $J[Y(t+1)]$ depend on weights $W_{c}$ of the critic, we do not take into account the dependence of $J[Y(t+1)]$ on weight $W_{c}$ while minimizing in the least mean squares (LMS). The expression for the weights’ update for the critic is as follows:

$$\Delta W_{c} = -\eta \{ J[Y(t)] - \gamma J[Y(t+1)] - U(t) \} \frac{\partial J[Y(t)]}{\partial W_{c}}$$

(5)
Where \( \eta \) is a positive learning rate.

The objective here is to maximize or minimize the strategic function \( J \) in the immediate future, thereby optimizing the overall cost expressed as of all \( U(t) \) over the horizon of the problem. This is obtained by training the action network with an error signal \( \partial J / \partial A \). The gradient of the cost function \( J \) with respect to the action’s weights, is achieved by backpropagating \( \partial J / \partial \hat{J} \) (i.e. the constant 1) through the critic network and then through the model to the action network as shown in Figure 2.1 (b). This training gives us \( \partial J / \partial A \) and \( \partial J / \partial W_A \) for all the outputs of the action network and all the action network’s weights \( W_A \), respectively. Therefore, the weights updates for the action network can be expressed as follows (applying for the LMS):

\[
\Delta W_A = -\alpha \frac{\partial A(t)}{\partial W_A} \frac{\partial J(t)}{\partial A(t)}
\]

Where \( \alpha \) is a positive learning rate.

![Diagram](image-url) Fig. 2.1  Critic and action Adaptation in HDP

3. CREATIVE LEARNING

“Creative Learning” is the main contribution of this paper. It provides an architecture to deal with nonlinear dynamic systems with multiple criteria and multiple models. Creative learning is a general approach used to solve optimal control problems, in which the criteria changes in time. The theory contains all the components and techniques of the adaptive critic learning family but also has an architecture that permits creative learning when it is appropriate. The creative controller for intelligent machines integrates a dynamic database and a task control center into the adaptive critic learning model. The task control center can function as a command center to decompose tasks into sub-tasks with different dynamic model and criteria functions, while the dynamic database can act as an information system.

3.1 Creative Learning Architecture

As it is well-known, adaptive critic learning is a way to solve dynamic programming in a general nonlinear plant. It takes an approach to approximate the control processes or estimate the cost-to-go function \( J \) but does not relate to decision-making theory. For instance, what are the criteria or critics for the different sub-tasks, how does one choose the criteria function or utility function? All of these are concerns of novel learning techniques. In this paper, we proposed a creative learning structure with evolutionary learning strategies. Adaptive critic learning method is a part of the creative learning algorithm, however, creative learning with decision-making capabilities is beyond the adaptive critic learning.

The creative learning algorithm is presented as in Fig. 3.1. In this diagram, there are six important components: task control center, dynamic knowledge database, critic network, action network, model-based action and utility function. Both the critic network and action network can be constructed by using any artificial neural networks with sigmoidal function or radial basis function (RBF). Furthermore, the model is also used to construct a model-based action in the framework of adaptive critic-action approach. In this algorithm, dynamic databases are built to generalize the critic network and its training process and provide environmental information for decision-making purpose. For an example, it is especially critical when the operation of mobile robots is in an unstructured environments. Furthermore,
the dynamic databases can also be used to store environmental parameters such as Global Position System (GPS) weight points, map information, etc. Another component in the diagram is the utility function for a tracking problem (error measurement). In the diagram, \( X_k, X_{kd}, X_{kd+1} \) are input and \( Y \) is the output and \( J(t), J(t+1) \) is the critic function at the time, which is defined by the Hamilton-Jacobi-Bellman equation and represents the core of dynamic programming:

\[
J(t) = \sum_{k=0}^{\infty} \gamma^k U(t+k)
\]

where \( \gamma \) is the discount factor (0 < \( \gamma \) < 1), and \( U(t) \) is the primary utility function or local cost. Heuristic dynamic programming (HDP) is the most straightforward method of adaptive critic design in which the critic block is trained in time to minimize error measure as follows:

\[
J(t) = U(t) + J(t+1)
\]

Critic network output:

\[
r_c(t) = J(t) - \gamma J(t+1) - U(t)
\]

Action network output:

\[
Y_d = NN_d(x)
\]

Model based-action is considered as a plant identifier.

\[
Y_m = NN_m(x)
\]

The simulated results are presented in next sections on two-link robot manipulators tracking problem.

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**Fig. 3.1 Proposed CL Algorithm Architecture**

3.2 Dynamic Knowledge Database (DKD)

Dynamic knowledge database serves as a “coupler” between a task control center and a nonlinear system or plant that is to be controlled or directed. The purpose of the coupler is to provide the criteria functions for the adaptive critic learning system and filter the task strategies commanded by the task control center. The proposed dynamic database contains a copy of the model (or identification). Action and critic networks are utilized to control the plant under nominal operation, as well as make copies of a set of HDP or DHP parameters (or scenario) previously adapted to deal with a plant in a known dynamic environment. It also stores copies of all the partial derivatives required when updating the neural networks using backpropagation through time.\(^{16, 27}\)
The data stored in the dynamic database can be uploaded to support offline or online training of the dynamic plant and provide a model for identification of nonlinear dynamic environment with its modeling function. Another function module of the database management is designed to analyze the data stored in the database including the sub-task optima, pre-existing models of the network and newly added models. The task program module is used to communicate with the task control center. The functional structure of the proposed database is shown in Figure 3.2.

![Fig. 3.2 Functional structure of dynamic database](image)

### 3.3 Task Control Center (TCC)

The task control center (TCC) can build task-level control systems for the creative learning system. By “task-level”, we mean the integration and coordination of perception, planning and real-time control to achieve a given set of goals (tasks). TCC provides a general task control framework, and it is intended to be used to control a wide variety of tasks and permit responsive actions based on mission commands, interactions with other robots. Although TCC has no built-in control functions for particular tasks (such as robot path planning algorithms), it provides control functions, such as task decomposition, monitoring, and resource management, that are common to many applications. The particular task built-in rules or criteria or learning J functions are managed by the dynamic database controlled with TCC to handle the allocation of resources. The dynamic database matches the constraints on a particular control schemes or sub-tasks or environment allocated by TCC.

The task control center acts as a decision-making system. It integrates domain knowledge or criteria into the database of the adaptive learning system. According to R. Simmons 51, task control architecture for mobile robots provides a variety of control constructs that are commonly needed in mobile robot applications, and other autonomous mobile systems. Integrating TCC with adaptive critic learning system and interacting with the dynamic database, the creative learning system could provide both task-level and real-time control or learning within a single architectural framework as shown in Figure 3.3.

![Fig. 3.3 The structure of the task control center](image)

A planning and execution module will be developed to perform dynamic route planning of mobile robot in unstructured environments. This module takes inputs including mission objectives and derived constraints, the health status from subsystem health monitors, and the vehicle state, and provides a task list of command instructions (e.g., modes, commands, parameters) to the subsystem tasks. The subsystem tasks provide guidance, control, communications, payload management and other state monitoring and control corresponding to the mobility of the mobile vehicle. In order to make the solution of complex problems tractable, they are often decomposed into simpler, decoupled sub-problems that can be solved (nearly) independently. If the decomposition is formulated with proper coordination across the processes generating the solutions to the sub-problems, then the set of solutions for the sub-problems can be combined into a near-optimal, complete solution for the original, more complex problem.
3.4 Intelligent Robot Creative Controller

Creative learning is used to explore the unpredictable environment, permit the discovery of unknown problems, ones that are not yet recognized but may be critical to survival or success. By learning the domain knowledge, the system should be able to obtain the global optima and escape local optima. As an ANN robot controller, the block diagram of the creative controller can be presented in Figure 3.4. Experience with the guidance of a mobile robot has motivated this study to progress from simple line following to the more complex navigation and control in an unstructured environment.

![Fig. 3.4 Creative controller structure](image)

4.5 Creative Control Mobile Robot Scenarios

One scenario for intelligent machines can be an autonomous mobile robot in an unstructured environment. Suppose a mobile robot is used for urban rescue as shown in Fig. 3.5. It waits at a start location until a call is received from a command center. Then it must go rescue a person. Since it is in an urban environment, it must use the established roadways. Along the roadways, it can follow pathways. However, at intersections, it can choose various paths to go to the next block. Therefore, it must use different criteria at the corners. The overall goal is to arrive at the rescue site with minimum distance or time. To clarify the situations consider the following steps.

1. Start location – the robot waits at this location until it receives a task command to go to a certain location.
2. Along the path, the robot follows a road marked by lanes. It can use a minimum mean square error between its location and the lane location during this travel.
3. 
4. At intersections, the lanes disappear but a database gives a GPS waypoint and the location of the rescue goal.

![Fig. 3.5 Simple urban rescue sites](image)

In an unstructured environment as shown in Fig. 3.5, it is assumed that information collected about different potions of the environment could be available to the mobile robot, improving its overall knowledge. As any robot
moving autonomously in this environment must have some mechanism for identifying the terrain and estimating the safety of the movement between regions (blocks), it is appropriate for a coordination system to assume that both local obstacle avoidance and a map-building module are available for the robot which is to be controlled. The most important module in this system is the adaptive system to learn about the environment and direct robot action, and then it has the necessary capabilities to allow good behaviors.

Using Global Position System (GPS) to measure the robot position and the distance from the current site to the destination and provide part of information for the controller to make decision on what to do at next move. GPS system also provides the coordinates of the obstacles for the learning module to learn the map, and then try to avoid the obstacles when navigating through the intersections A, B or G, D to destination T. This example requires the use of both continuous and discrete tracking, a database of known information and multiple criteria optimization. It is necessary to add a large number of real-world issues including position estimation, perception, obstacles avoidance, communication, etc.

4. CASE STUDY WITH ROBOT ARM MANIPULATORS

As discussed in previous sections, the concept of creative control is very broad and complicated. The implementation of each component of creative controller is important. In order to simplify this research topic, two-link robot arm manipulators as shown in Fig. 4.1 are used to implement the adaptive critic learning control, which is a critical learning component of creative control system. The purpose of this two-link robot arm manipulator simulation is to show that the creative control permits the robot to more closely approximate its desired output in an ideal situation. The simulation results of two-link robot manipulators using different control methods such as digital control, adaptive control, neurocontrol, adaptive critic control are addressed in the following sections.

![Two-link robot arm manipulator](image)

**4.1 Robot Manipulators and Nonlinear Dynamics**

Robot manipulators have complex nonlinear dynamics that might make accurate and robust control difficult. In this study, a framework for the tracking control problem based on approximation of unknown nonlinear functions provided by Lewis is employed on a broad family of controllers including adaptive, robust and adaptive critic learning controllers. As experimental studies, two-link robot arm manipulators are used to compare the tracking errors with different types of controllers. The simulation starts with PD controller in an ideal condition followed by digital control, adaptive control, and neurocontrol. Furthermore, as the most important component of creative control system, adaptive critic learning system is proposed and implemented in this paper and its results are compared with other controllers.

In this study, the focus is on the real-time motion control of the robot manipulators— the tracking problem of two-link robot manipulators. The purpose of tracking design problem is to make the robot manipulators follow a prescribed desired trajectory. Tracking error stability can be guaranteed by selecting a variety of specific controllers. The two-link robot arm manipulator dynamics is shown as Eq. 18.

\[ \dot{M}(\mathbf{q})\ddot{\mathbf{q}} + V(\mathbf{q}, \dot{\mathbf{q}})\dot{\mathbf{q}} + F(\dot{\mathbf{q}}) + \mathbf{G}(\mathbf{q}) + \tau_d = \tau \]  

(18)

with \( \mathbf{q} \) the joint variable n-vector and \( \tau \) the n-vector of generalized forces. \( M(\mathbf{q}) \) is the inertia matrix, \( V(\mathbf{q}, \dot{\mathbf{q}}) \) the Coriolis/centripetal vector, \( \mathbf{G}(\mathbf{q}) \) the gravity vector, a friction term \( F(\dot{\mathbf{q}}) \) and also added is a disturbance torque \( \tau_d \).
4.2 Simulation Results

There are two facts to be used as a standard to compare the simulation results. One fact is the estimated measure of tracking errors of two robot arm joints. The ideal tracking errors should converge to zero for both robot arm manipulator joints. Another fact is how fast the control system to achieve stability. In the following sections, simulation results show how fast the tracking error can reach stable state (settling time) and how much is the tracking steady state accuracy by using different control techniques including digital controller, adaptive controller, neurocontroller and adaptive critic controller. One of the most important conclusions that can be drawn from the experimental study is that one can achieve a significant improvement in performance when going from the simplest control to more advanced adaptive controller, neurocontroller and adaptive critic controller or creative controller. As discussed in the following, the adaptive critic control as a component of Creative Controller has the best simulation results among all the control methods 46.

4.2.1 PID CT Controller

The PID controller is obtained as follows 53:

\[
\tau = M(q)\ddot{q} + K_p \dot{e} + K_i \int e \, dt + K_d (\dot{e}) + N(q, \dot{q})
\]

Which has the tracking error dynamics

\[
\dot{e} = -K_p \dot{e} - K_i e.
\]

According to the characteristics of the PID (K = [K_p, K_i, K_d]) controller, the values of the matrices K_p, K_i, and K_d are chosen by using trial-and-error method K = [K_p = 100, K_i = 5, K_d = 5]; the actual trajectories and the desired ones match around the 2 second time units and the tracking errors reduced to zero shown in Figures 4.2, 4.3. The gain matrices need to be selected in order to obtain an optimal control performance.

Fig. 4.2 Joint tracking errors using PID CT controller (K_p=100, K_i=5, K_d=5)  
Fig. 4.3 Actual and desired angles using PID CT controller (K_p=100, K_i=5, K_d=5)

4.2.2 Adaptive Controller

One adaptive controller given by Lewis 53 is utilized in the following simulation. It has a multi-loop structure with an outer PD tracking loop and an inner nonlinear adaptive loop whose function is to estimate the nonlinear function required for feedback linearization of the robot arm. The response of the adaptive controller is given in Figs. 4.4-4.5, which is good even though the masses m_1, m_2 are unknown by the controller. The joint tracking errors become relatively stable around the 3rd time unit as shown in Fig. 4.4. In Fig. 4.5, it shows that the actual angles closely match the desired joint angles around 3 sec.

Fig. 4.4 Joint tracking errors using adaptive controller  
Fig. 4.5 Actual and desired angles using adaptive controller
4.2.3 Neural Network Controller (NN controller)

In this simulation, a NN is employed to approximate unknown nonlinear functions in the robot arm dynamics, thereby overcoming some limitations of adaptive control. For the NN controller, all the dynamics are unmodeled as the controller requires no knowledge of the system dynamics. No initial NN training or learning phase was needed. The NN weights were simply initialized at zero in this simulation.

The two-layer NN controller is developed by using augmented backprop tuning rules according to Lewis, et al\textsuperscript{53}. The simulation program is similar to the code in the adaptive controller in the previous section. To implement the two-layer NN controller, 10 hidden-layer neurons and sigmoid activation functions are selected \textsuperscript{53}. The simulation results of the NN controller is given in Figs. 4.6-4.7. The joint tracking errors become relatively stable around the 1\textsuperscript{st} time unit as shown in Fig. 4.6. In Fig. 4.7, it shows that the actual angles closely match the desired joint angles around 1 sec.

![Fig. 4.6 Tracking error with two-layer NN (432)](image)

![Fig. 4.7 Actual and desired joint angles with two-layer NN (432)](image)

4.2.4 Adaptive Critic Control and Creative Learning

The creative controller is based on adaptive critic learning as discussed in previous sections. To implement adaptive critic controller, two-link robot arm manipulators are used to perform the simulation. In this study, Dual Heuristic Programming (DHP) adaptive critic design is used to explore creative control theory. The DHP nonlinear control system is comprised of a critic network and an action network that approximates the global control based on the nonlinear plant and its model. In this nonlinear control system, the minimizing control law is modeled by a neural network is referred to as an action network. A critic network evaluates the action network performance by approximating the derivative of the corresponding cost-to-go with respect to the state. It provides an indirect measure of performance that is used to formulate an optimality criterion with respect to the control law. On-line learning based on a DHP adaptive critic approach improves control response by accounting for differences between actual and assumed dynamic models. The simulation results generated by DHP proved to be the best performance among all the previous controllers such as PID control, adaptive control and neural network control (neurocontroller).

In Figures 4.8, and 4.9, the simulation is performed in 10 seconds time period. Comparing to the simulation results of the controller discussed in the previous sections, the tracking errors with the AC controller is the fastest to converge to zero as shown in Fig. 4.8. Although the tracking error in general is relatively small in magnitude, the AC controller generated smoother curve than the neurocontroller as shown in Fig. 4.9.

![Fig. 4.8 Tracking error with Adaptive Critic Controller (t=10sec)](image)

![Fig. 4.9 Actual and desired joint angles with Adaptive Critic Controller (t=10)](image)

To more effectively demonstrate improvement of the performance of the AC controller, the simulations are modified to perform in one second time unit shown in Figs. 4.10, 4.11. The actual angle of the joint 1 (robot arm manipulator joint 1) trained with the AC controller matches the desired angle at 0.5sec time respectively as shown in Fig.
4.11. The actual angle of joint 2 trained with AC controller reaches the desired angle at 0.1sec. When trained with AC controller, the tracking error measures of both joint 1 and joint 2 approximate to zero as shown in Fig. 4.10.

![Fig. 4.10 Tracking errors with Adaptive Critic Controller](image1)

![Fig. 4.11 Actual and desired joint angles with Adaptive Critic Controller (λ=10)](image2)

The simulation results are shown in Figs. 4.12, 4.13. The tracking errors are tuned to stable state quickly after the simulation starts as shown in Fig. 4.12. The actual trajectories match the desired trajectories right after the simulation starts as shown in Fig. 4.13. It is demonstrated that the adaptive critic controller can obtain ideal simulation results when the robot arm manipulators follow different robot arm paths.

![Fig. 4.12 Tracking error with AC](image3)

![Fig. 4.13 Actual and desired joint angles with AC](image4)

The experimental study initiates with the basic two-link robot arm manipulators simulation from CT PD control, CT PID control to CT digital control followed by adaptive controller and then neural network controller (neurocontrol) and adaptive critic control. The simulation is conducted by using a set of values of the controller parameters as presented. By comparing the response of the trajectory of joint angles and the tracking errors, one can attain a significant improvement in performance when going from digital control, adaptive control and neurocontrol to adaptive critic control. The adaptive critic controller training results demonstrate the important characteristics of adaptive critic control, which adaptive critic learning is a way to solve dynamic programming in a general nonlinear plant. The simulation is also studied by changing the desired trajectories of the robot arm manipulator. By changing the paths of the robot arm manipulator in the simulation, it is demonstrated that the learning component of the creative controller is adapted to a new set of criteria.

### 5. CONCLUSION

In this paper, the term Creative Learning was introduced. The scope of application of this method was wider than the adaptive critic control method, especially while the intelligent mobile robot is in unstructured environments. This method has a potential for massive parallel computation, resilience to failure of components and robustness in the presence of disturbances like noise, etc. Modeled and forecasted critic modules resulted in a faster training network.

In the experimental study, the simulation results on the robot arm manipulator showed that the adaptive critic controller obtained the best performance among all the other controllers including PD CT controller, PID CT controller, digital controller, adaptive controller and neurocontroller. In the second experimental study, which is not stated in detail in this paper, the kinematic and dynamic models were derived. The simulation was conducted by using the classic controllers but not using adaptive critic controller. The Bearcat Cub mobile robot is a good example to study the creative learning theory.

The creative learning algorithm still needs considerable effort to develop the entire system. However, it is a step towards the development of more human like intelligent machines. The broader impact of this research is to advance the development of human-like intelligent machines.
state of the art in learning systems. Creative learning could also lead to a new generation of intelligent systems that have more human-like creative behavior that would permit continuous improvement.

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