Engineering Robust Intelligent Robots

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ABSTRACT

The purpose of this paper is to discuss the challenge of engineering robust intelligent robots. Robust intelligent robots may be considered as ones that not only work in one environment but rather in all types of situations and conditions. Our past work has described sensors for intelligent robots that permit adaptation to changes in the environment. We have also described the combination of these sensors with a "creative controller" that permits adaptive critic, neural network learning, and a dynamic database that permits task selection and criteria adjustment. However, the emphasis of this paper is on engineering solutions which are designed for robust operations and worst case situations such as day night cameras or rain and snow solutions. This ideal model may be compared to various approaches that have been implemented on "production vehicles and equipment" using Ethernet, CAN Bus and JAUS architectures and to modern, embedded, mobile computing architectures. Many prototype intelligent robots have been developed and demonstrated in terms of scientific feasibility but few have reached the stage of a robust engineering solution. Continual innovation and improvement are still required. The significance of this comparison is that it provides some insights that may be useful in designing future robots for various manufacturing, medical, and defense applications where robust and reliable performance is essential.

Keywords: Intelligent robots, robust, engineering, eclecticism, creative control, reinforcement learning, adaptive critic

1. INTRODUCTION

For more than 25 years, the concepts and applications of intelligent robots have been explored in the SPIE Intelligent Robots and Computer Vision Conferences. These intelligent robots are often modeled by what we see when we look into a mirror or what we as humans can perform. Early work was motivated by Claude Shannon's pioneering work with information theory and his examples of chess end game solutions, maze solving mouse and balancing robots. Over the years a variety of intelligent robots have been described from game playing robots to novel industrial robots to mobile sensor guided robots. These intelligent robots are remarkable combinations of mechanisms, sensors, computer controls and power sources as shown in Figure 1. Each component, as well as the proper interfaces among and between the components is essential to a successful robust intelligent robot.

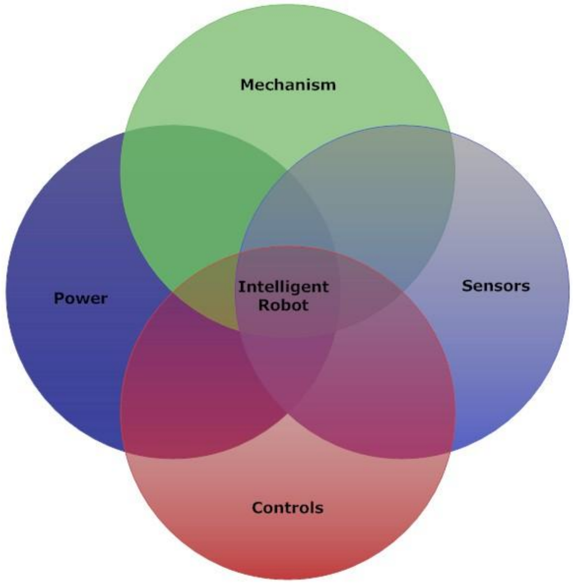


Figure 1. Intelligent robot components.

In a previous paper, the concept of eclecticism for the design, development, simulation and implementation of a real time controller for an intelligent, vision guided robots was introduced.[1] The use of an eclectic perceptual, creative controller that can select its own tasks and perform autonomous operations was illustrated. This eclectic controller is a new paradigm for robot controllers and is an attempt to simplify the application of intelligent machines in general and robots in particular. The idea is to use a task control center and dynamic programming approach with learning and multi criteria optimization.

The purpose of this paper is to examine the theory of robust learning for intelligent machines and their application to explore if a major paradigm shift can be accomplished that could result in more reliable and useful machines.

A review of some important theoretical concepts of dynamic programming will be described in Section 2. The creative control is described in Section 3. Some examples robust control scenarios are described in Section 4. Finally, some conclusions and recommendations for future work are given in Section 5.

2. THEORETICAL FOUNDATION

Dynamic Programming

The architecture of an intelligent robot can be considered to be modeled as a problem in dynamic programming and optimal control as defined by Bertsekas[2]. The robust intelligent robot in this paper is defined as a decision maker for a dynamic system that may make decisions in discrete stages or over a time horizon. The outcome of each decision may not be fully predictable but may be anticipated or estimated to some extent before the next decision is made. Furthermore, an objective or cost function can be defined for the decision. There may also be natural constraints. In fact, the solution may not be feasible. Generally, the goal is to minimize this cost function over some decision space subject to the constraints.

Dynamic programming (DP) is the only formulation that closely models the sequential optimization applicable to general nonlinear, stochastic environments. However, DP needs efficient approximate methods to overcome its dimensionality problems. The optimum solution for chess still has not been discovered. The application of artificial neural networks (ANNs) does provide a powerful and universal approximate method for approximate solutions.

The essence of dynamic programming is Bellman's *Principle of Optimality*:

> *"An optimal policy has the property that whatever the initial state and initial decision are, the remaining decisions must constitute an optimal policy with regard to the state resulting from the first decisi[3].*

The original Bellman equation of dynamic programming for an adaptive critic algorithm may be written as shown in Eq (1):

$$J(R(t)) = \max_{U(t)}(U\big(R(t), u(t)\big) + \frac{<J(R(t+1)>}{(1+r)} - U_0 \tag{1}$$

where *R(t)* is the model of reality or state form, *U(R(t),u(t))* is the utility function or local cost, *u(t)* is the action vector, *J(R(t))* is the criteria or cost-to-go function at time t, r and U_0 are constants that are used only in infinite-time-horizon problems and then only sometimes, and where the angle brackets refer to expected value.

We have found that in many modern problems the criteria function, *J*, changes along the trajectory to the goal requiring a solution more of the form shown in Eq (2):

$$J\big(R(t)\big) = \sum_{i=1}^{N} J_i(R(t)) \tag{2}$$

Where J_i is the criteria over segment i of the trajectory for the total problem. This permits the solution of a problem that consists of both decision problems and estimation problems.

Eclecticism may be defined as " a conceptual approach that does not hold rigidly to a single paradigm or set of assumptions, but instead draws upon multiple theories, styles, or ideas to gain complementary insights into a subject, or applies different theories in particular cases."
http://en.wikipedia.org/wiki/Eclecticism

A scientific paradigm had been defined by Kuhn (http://en.wikipedia.org/wiki/Thomas_Kuhn) as "answers the following key questions:

- what is to be observed and scrutinized,
- what kind of questions should be asked and probed for answers in relation to this subject,
- how are these questions to be structured,
- how should the results of scientific investigations be interpreted.
- how is an experiment to be conducted, and what equipment is available to conduct the experiment.
-

"Thus, within normal science, the paradigm is the set of exemplary experiments that are likely to be copied or emulated. The prevailing paradigm often represents a more specific way of viewing reality, or limitations on acceptable programs for future research, than the much more general scientific method."

In the eclectic control, some answers to the key questions are:

- *The performance of the intelligent machine will be observed*
- *Actual or simulated behaviors will lead to questions of normal or useful responses*
- *Questions should be structured to permit answers from queries of the database*
- *Objectively by anyone in the world*

- *Simulations are much more cost effective than actual performance tests*

The need for performance proofs by demonstration was anticipated Kuhn and elaborated in his questions. That is, we are not just building robots to “play around” but rather it is the scientific method required for a new paradigm. This fact accounts for chess tournaments and many of the grand challenges. The proof is in the doing.

The proposed theory for eclectic learning is also based on the previous perceptual creative controller for an intelligent robot that uses a multi- modal adaptive critic for performing learning in an unsupervised situation but can also be trained for tasks in another mode and then is permitted to operate autonomously. The robust nature is derived from the automatic changing of task modes based on a dynamic data base and internal measurements of error at appropriate locations in the controller.

The eclectic controller method is designed for complex real world environments. However, analysis and simulation is needed to clarify the decision processes and reduce the danger in real world operations.

The eclectic controller uses a perceptual creative learning architecture to integrate a Task Control Center (TCC) and a dynamic database (DD) with adaptive critic learning algorithms to permit these solutions. Determining the tasks to be performed and the data base to be updated are the two key elements of the design. These new decision processes encompass both decision and estimation theory and can be modeled by neural networks and implemented with multi-threaded computers.

The main thrust of this paper is to present the robust theory of learning that can be used for developing control architectures for robust intelligent machines. Emphasis will be placed on the missing key element, the dynamic data base, since the control architectures for neural network control of vehicles in which the kinematic and dynamic models are known but one or more parameters must be estimated is a simple task that has been demonstrated.

The mathematical models for the kinematics and dynamics are necessary and have been developed so that the main emphasis can be to explore the use of neural network control and demonstrate the advantages of these learning methods. The results indicate the method of solution and its potential application to a large number of currently unsolved problems in complex environments. The adaptive critic neural network control is an important starting point for future learning theories that are applicable to robust control and learning situations.

The general goal of this research is to further develop a robust theory of learning that is based on human learning but applicable to machine learning and to demonstrate its application in the design of robust intelligent systems. To obtain broadly applicable results, a generalization of adaptive critic learning called Creative Control (CC) for intelligent robots in complex, unstructured environments has been used. The creative control learning architecture integrates a Task Control Center (TCC) and a Dynamic Knowledge Database (DKD) with adaptive critic learning algorithms.

Recently learning theories such as the adaptive critic have been proposed in which a critic provides a grade to the controller of an action module such as a robot. The creative control process is used that is “beyond the adaptive critic.” A mathematical model of the creative control process is presented in the next section.

3. ADAPTIVE CRITIC AND CREATIVE CONTROL

Dynamic programming gives the exact formulation for the problem of how to maximize a utility function U(R(t), u(t)) over the future times, t, in a nonlinear stochastic environment. Dynamic programming converts a difficult long-term problem in optimization over time $\langle U(R(t))\rangle$, the expected value of U(R(t)) over all the future times, into a much more straightforward problem in simple, short-term function maximization – after we know the function J. Thus, all of the approximate dynamic programming methods discussed here are forced to use some kind of general-purpose nonlinear approximation to the J function, the value function in the Bellman equation, or something closely related to J[3].

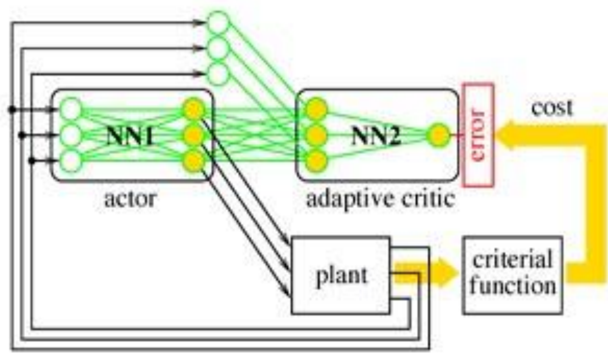
In most forms of adaptive critic design, we approximate J by using a neural network. Therefore, we approximate J(R) by some function $\hat{J}(R,W)$, where W is a set of weights or parameters, $\hat{J}$ is called a Critic network [4,5]

If the weights **W** are adapted or iteratively solved for, in real time learning or offline iteration, we call the Critic an Adaptive Critic[6,7].

An adaptive critic design (ACD) is any system which includes an adapted critic component; a critic, in turn, is a neural net or other nonlinear function approximation which is trained to converge to the function **J(X).**

In adaptive critic learning or designs, the critic network learns to approximate the cost-to-go or strategic utility function J and uses the output of an action network as one of its' inputs, directly or indirectly. When the critic network learns, back propagation of error signals is possible along its input feedback to the action network. To the back propagation algorithm, this input feedback looks like another synaptic connection that needs weights adjustment. Thus, no desired control action information or trajectory is needed as supervised learning.

Most advanced methods in neurocontrol are based on adaptive critic learning techniques consisting of an action network, adaptive critic network, and model or identification network as show in Figure 2. These methods are able to control processes in such a way, which is approximately optimal with respect to any given criteria taking into consideration of particular nonlinear environment. For instance, when searching for an optimal trajectory to the target position, the distance of the robot from this target position can be used as a criteria function. The algorithm will compute the proper steering, acceleration signals for control of vehicle, and the resulting trajectory of the vehicle will be close to optimal. During trials (the number depends on the problem and the algorithm used) the system will improve performance and the resulting trajectory will be close to optimal. The freedom of choice of the criteria function makes the method applicable to a variety of problems. The ability to derive a control strategy only from trial/error experience makes the system capable of semantic closure. These are very strong advantages of this method.



Structure of the adaptive critic controller based on artifical neural networks.

Figure 2 Structure of the adaptive critic controller [8]

Creative Learning Structure

It is assumed that we can use a kinematic model of a mobile robot to provide a simulated experience to construct a value function in the critic network and to design a kinematic based controller for the action network. A proposed diagram of creative learning algorithm is shown in Figure 3 [7-11]. In this proposed diagram, there are six important components: the task control center, the dynamic knowledge database, the critic network, the action network, the model-based action and the utility funtion. 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 kinematic 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 evironmental information for decision making. It is especially critical when the operation of mobile robots is in an unstructured environments. Furthermore, the dynamic databases can also used to store environmental parameters such as Global Position System (GPS) way 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 inputs and Y is the ouput and J(t), J(t+1) is the critic function at the time.

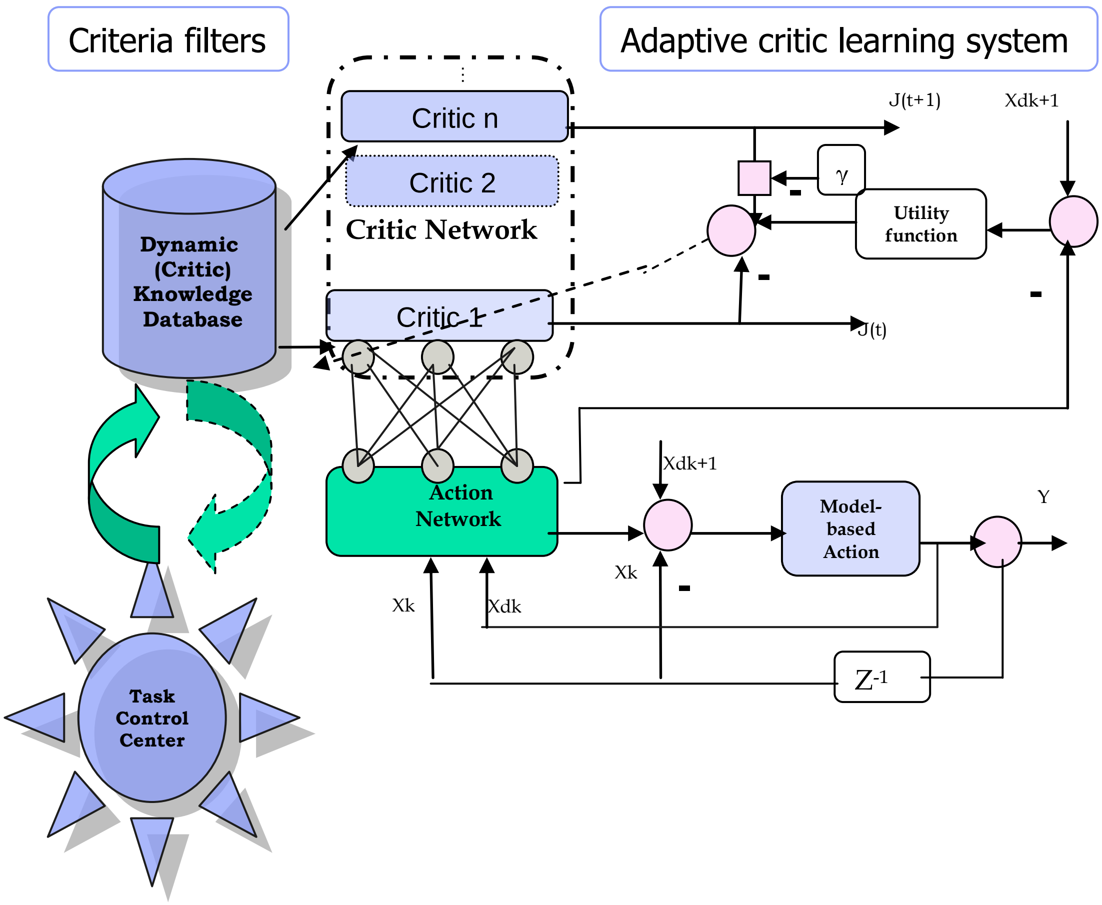


Figure 3 Proposed Creative Learning Algorithm Structure

Dynamic Knowledge Database (DKD)

The dynamic databases contain domain knowledge and can be modified to permit adaptation to a changing environment. Dynamic knowledge databases may be called a "neurointerface" [12] in a dynamic filtering system based on neural networks (NNs) and 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 parameters (or scenario) previously adapted to deal with a plant in a known dynamic environment. The database also stores copies of all the partial derivatives required when updating the neural networks using backpropagation through time[13] . The dynamic database can be expanded to meet the requirements of complex and unstructured environments.

The data stored in the dynamic database[14] 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 management system (DBMS) is shown in Figure 4. The DBMS can be customized from an object-relational database.

In existing models the database is considered to be static. The content of the data base may be considered as information. However, our experience with the World Wide Web is that the "information" is dynamic and constantly changing and often wrong.

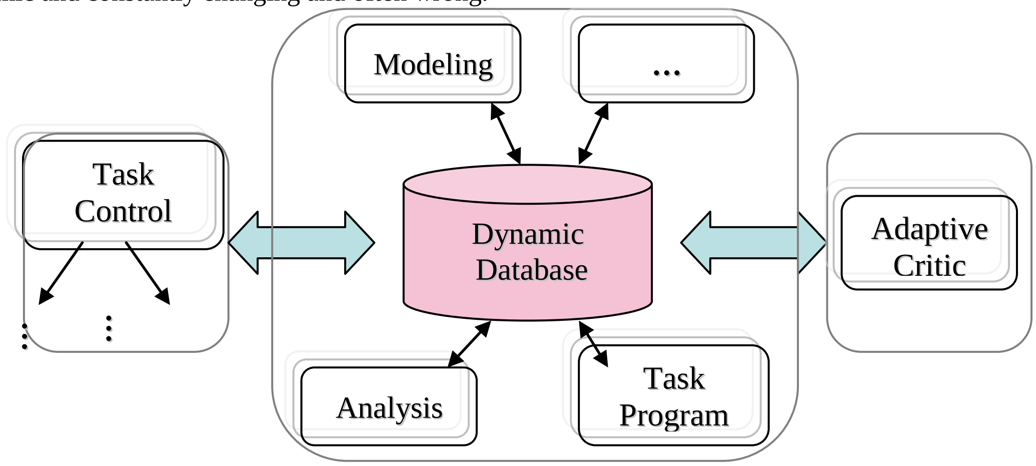


Figure 4 Functional structure of dynamic database

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)[15]. TCC provides a general task control framework, and it is to be used to control a wide variety of tasks. Although the 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 scheme 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 Simmons[15], the 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. The goal of the architecture is to enable autonomous mobile robot systems to easily specify hierarchical task-decomposition strategies, such as how to navigate to a particular location, or how to collect a desired sample, or how to follow a track in an unstructured environment. This can include temporal constraints between sub-goals, leading to a variety of sequential or concurrent behaviors. TCC schedules the execution of planned behaviors, based on those temporal constraints acting as a decision-making control center.

Integrating the TCC with the adaptive critic learning system and interacting with the dynamic database, the creative learning system provides both task-level and real-time control or learning within a single architectural framework. Through interaction with human beings to attain the input information for the system, the TCC could decompose the task strategies to match the dynamic database for the rules of sub-tasks by constructing a distributed system with flexible mechanisms, which automatically provide the right data at the right time. The TCC also provides orderly access to the resources of the dynamic database with built-in learning mechanisms according to a queue mechanism. This is the inter-process communication capability between the task control center and the dynamic database. The algorithm on how to link the task control center and the dynamic database is currently done by the human designers .

Creative learning controller for intelligent robot control

Creative learning may be used to permit exploration of complex and unpredictable environments, and even 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. The method attempts to generalizes the highest level of human learning –

imagination. As a ANN robot controller, the block diagram of the creative controller can be presented in Figure 5.

Experience with the guidance of a mobile robot has motivated this study and has progressed from simple line following to the more complex navigation and control in an unstructured environment. The purpose of this system is to better understand the adaptive critic learning theory and move forward to develop more human-intelligence-like components into the intelligent robot controller. Moreover, it should extend to other applications. Eventually, integrating a criteria knowledge database into the action module will develop a powerful adaptive critic learning module.

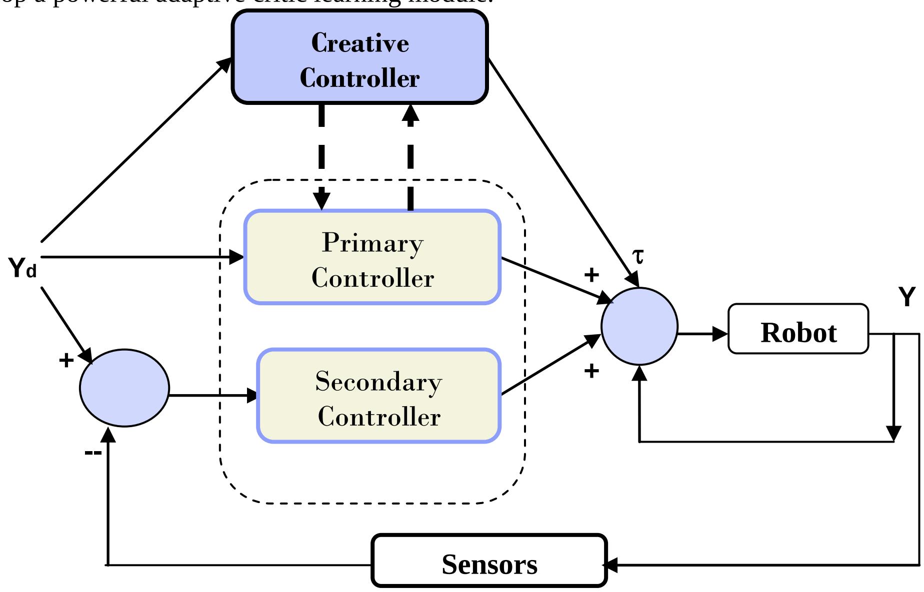


Figure 5 Block diagram of creative controller

A creative controller is designed to integrate domain knowledge or criteria database and the task control center into the adaptive critic neural network controller. It provides a needed and well-defined structure for autonomous mobile robot application. In effect, it replaces a human doing remote control. We have used the intelligent mobile robot as the test-bed for the creative controller.

The task control center of the creative learning system can be considered hierarchically as follows:

- Mission for robot – e.g. mobile robot
  - Task for robot to follow – J : task control
    - Track for robot to follow
      - Learn non-linear system model- model discovery
        - Learn unknown parameters

Adaptive Critic system Implementation

Adaptive Critic system and NN

In order to develop the creative learning algorithm addressed above, we have taken a bottom-up approach to implement adaptive critic controllers by first using neural network for on-line or off-line learning methods. [16] Then the proposed dynamic knowledge database and task control center are added with some to be realized in future research projects.

Tuning algorithm and stability analysis

For linear time invariant systems it is straightforward to examine stability by investigating the poles in the s-plane. However, stability of a nonlinear dynamic systems is much more complex, thus the stability criteria and tests are much more difficult to apply than those for linear time invariant systems[17-19]. For general nonlinear continuous time systems, the state space model is

$$\dot{x} = f[x(t), u(t)]$$
$$y = g[x(t), u(t)] \tag{3}$$

where the nonlinear differential equation is in state variable form, x(t) is the state vector and u(t) is the input and the second equation y(t) is the output of the system.

Creative controller and nonlinear dynamic system

For a creative controller, the task control center and the dynamic database are not time-variable systems; therefore, the adaptive critic learning component determines the stability of the creative controller. As it is discussed in the previous section, the adaptive critic learning is based on critic and action network designs, which are originated from artificial neural network (ANN), thus stability of the system is determined by the stability of the neural networks (NN) or convergence of the critic network and action network training procedure.

The creative controller is a nonlinear system. It is not realistic to explore all the possibilities of the nonlinear systems and prove that the controller is in a stable state. We have used both robot arm manipulators and mobile robot models to examine a large class of problems known as tracking in this study. The objective of tracking is to follow a reference trajectory as closely as possible. This may also be called optimal control since we optimize the tracking error over time.

Critic and Action NN Weights Tuning Algorithm

In adaptive critic learning controller, both the critic network and action network use multilayer NN. Multilayer NN are nonlinear in the weights V and so weight tuning algorithms that yield guaranteed stability and bounded weights in closed-loop feedback systems have been difficult to discover until a few years ago.

4. EXAMPLE ROBUST SCENARIO

Urban Rescue Scenarios

Suppose a mobile robot is used for urban rescue as shown in Figure 6. 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 must choose between various paths to go to the next block. Therefore, it must use a different criteria at the corners than along the track. The overall goal is to arrive at the rescue site with minimum 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. At intersections, the lanes disappear but a database gives a GPS waypoint and the location of the rescue goal.

This example requires the use of both continuous and discrete tracking, a database of known information and multiple criteria optimization. It is possible to add a large number of real-world issues including position estimation, perception, obstacles avoidance, communication, etc.

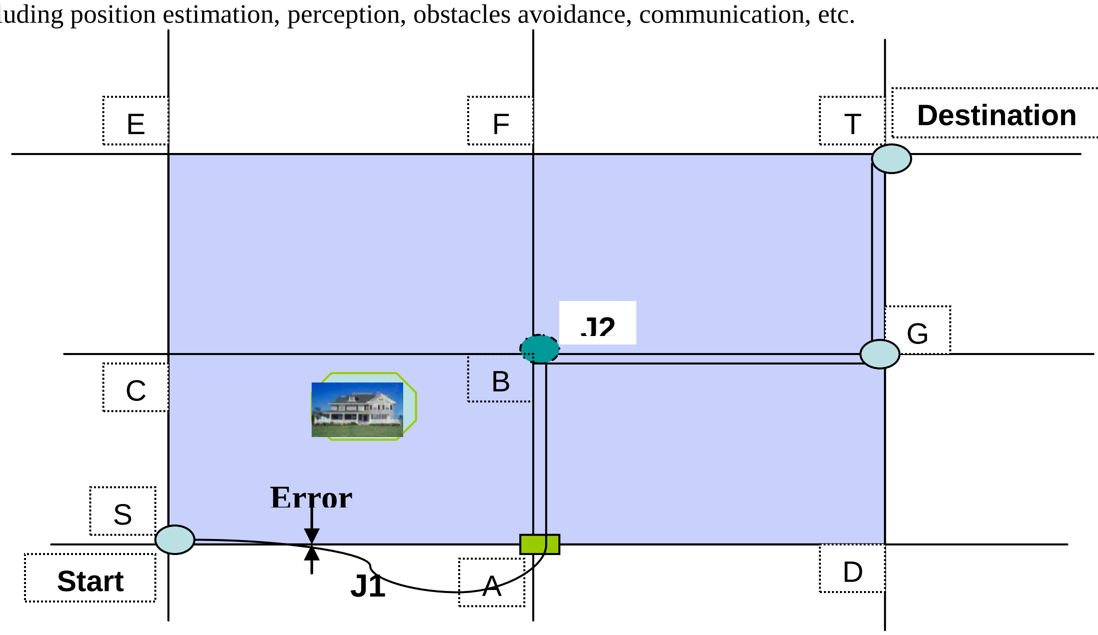


Figure 6 Simple urban rescue site

In an unstructured environment as shown in Figure 5, we assume 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 the robot action.[20]

A Global Position System (GPS) may be used to measure the robot position and the distance from the current site to the destination and provide this information to the controller to make its decision on what to do at next move. The GPS system or other sensors could also provides the coordinates of the obstacles for the learning module to learn the map, and then aid in avoiding the obstacles when navigating through the intersections A, B or G, D to destination T.

Task control center

The task control center (TCC) acts a decision-making command center. It takes environmental perception information from sensors and other inputs to the creative controller and derives the criteria functions. We can decompose the robot mission at the urban rescue site shown as Figure 5 into sub-tasks as shown in Figure 7. Moving the robot between the intersections, making decisions is based on control-center-specified criteria functions to minimize the cost of mission. It's appropriate to assume that J1 and J2 are the criteria functions that the task control center will transfer to the learning system at the beginning of the mission from the Start point to Destination (T). J1 is a function of t related to tracking error. J2 is to minimize the distance of the robot from A to T since the cost is directly related to the distance the robot travels.

- From Start (S) to intersection A: robot follow the track SA with the J1 as objective function
- From intersection A to B or D: which one will be the next intersection, the control center takes both J1 and J2 as objective functions.

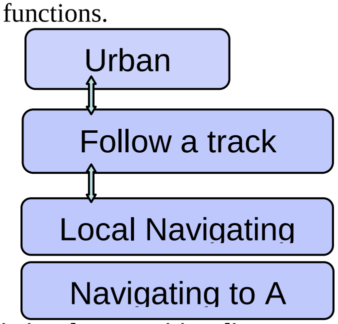


Figure 7 Mission decomposition diagrams

Dynamic databases

Dynamic databases would store task-oriented environment knowledge, adaptive critic learning parameters and other related information for accomplishing the mission. In this scenario, the robot is commanded to reach a dangerous site to conduct a rescue task. The dynamic databases saved a copy of the GPS weight points S, A, B, C, D, E, F, G and T. The map for direction and possible obstacle information is also stored in the dynamic databases. A copy of the model parameters can be saved in the dynamic database as shown in the simplified database Figure 8. The action model will be updated in the dynamic database if the current training results are significantly superior to the previous model stored in the database.

Database fields	
Field	**Description**
MODEL_ID	Action model ID
MODEL_NAME	Action model name
UTILITY_FUN	Utility function
CRITERIA_FUN	Criteria function
…	…
Adaptive Critic Training Parameters	

INPUT_CRITIC	Input to critic network
DELT_J	J(t+1)-J(t)
…	…

Figure 8 Semantic dynamic database structure.

Robot Learning Module

Initial plans such as road tracking and robot navigating based on known and assumed information, can be used to incrementally revise the plan as new information is discovered about the environment. The control center will create criteria functions according to the revised information of the world through the user interface. These criteria functions along with other model information of the environment will be input to the learning system. There is a data transfer module from the control center to the learning system as well as a module from the learning system to the dynamic database. New knowledge is used to explore and learn, training according to the knowledge database information and then decide which to store in the dynamic database and how to switch the criteria. The simplest style in the adaptive critic family is heuristic dynamic programming (HDP). This is NN on-line adaptive critic learning. There is one critic network, one action network and one model network in the learning structure. U(t) is the utility function. R is the critic signal as J (criteria function). The learning structure and the parameters are saved a copy in the dynamic database for the system model searching and updating.

Robust Module Through Demonstrations

The UC Robot Team is attempting to exploit its many years of autonomous ground vehicle research experience to demonstrate its capabilities for designing and fabricating a smart vehicle control for unmanned systems operation as shown in Figures 9 and 10. The purpose of this research is to perform a *proof by demonstration* through system design and integration of a new autonomous vehicle that would integrate advanced technologies in Creative Control with advanced autonomous robotic systems.

The main thrust of our effort is the intelligent control software which provides not only adaptation but also learning and prediction capabilities. However, since a proof by demonstration is needed, further efforts in simulation and implementation are necessary. This new robust control has been developed over the past several years and has been the subject of several UC dissertations and papers[21-24].

Figure 9 Bearcat Cub intelligent vehicle designed for IGVC

Figure 10 Eco hybrid jeep

5. CONCLUSIONS AND RECOMMENDATIONS

The robust intelligent robot control proposed in this paper may be described as a general perceptual, creative, adaptive critic, learning system with exceptional intelligence. The task control center is a decision-making command center for the intelligent creative learning system. However, the task controller needs to be able to determine a priori if a task is feasible for the system. If a task is not feasible then a request for assistance needs to be generated. The dynamic knowledge database integrates task control center and adaptive critic learning algorithm into one system and needs to be continually updated with fresh information. The data base also provides a knowledge domain for the task command center to perform decision-making. Furthermore, robust creative learning can be used to explore complex and unpredictable environments, and even permit the discovery of unknown problems. By learning the domain knowledge, the system should be able to obtain the global optima and escape local optima. The challenge is now in implementing such concepts in practical applications.

As indicated by Kuhn, the proof by demonstrations are required as the scientific method for new solutions that are breakthrough or new paradigms. Many new solutions are possible that can potentially, significantly improve the world.

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