Intelligent Robot Control using an Adaptive Critic with a Task Control Center and Dynamic Database

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ABSTRACT

The purpose of this paper is to describe the design, development and simulation of a real time controller for an intelligent, vision guided robot. The use of a creative controller that can select its own tasks is demonstrated. This creative controller uses a task control center and dynamic database. The dynamic database stores both global environmental information and local information including the kinematic and dynamic models of the intelligent robot. The kinematic model is very useful for position control and simulations. However, models of the dynamics of the manipulators are needed for tracking control of the robot's motions. Such models are also necessary for sizing the actuators, tuning the controller, and achieving superior performance. Simulations of various control designs are shown. Also, much of the model has also been used for the actual prototype Bearcat Cub mobile robot. This vision guided robot was designed for the Intelligent Ground Vehicle Contest. A novel feature of the proposed approach is that the method is applicable to both robot arm manipulators and robot bases such as wheeled mobile robots. This generality should encourage the development of more mobile robots with manipulator capability since both models can be easily stored in the dynamic database. The multi task controller also permits wide applications. The use of manipulators and mobile bases with a high-level control are potentially useful for space exploration, certain rescue robots, defense robots, and medical robotics aids.

Keywords: Intelligent robots, adaptive control, creative control, reinforcement learning, adaptive critic

1. INTRODUCTION

The purpose of this paper is to describe a theory of robust learning for intelligent machines and propose its application to the design of intelligent systems in uncertain complex environments. The proposed architecture for machine learning is also based on the 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 will be derived from the automatic changing of modes based on internal measurements of error at appropriate locations in the controller.

The creative controller method is designed for complex environments. Creative learning architectures integrate a Task Control Center (TCC) and a dynamic database (DD) and adaptive critic learning algorithms to permit these solutions. Determining the task 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 describe a theory of learning that can be used for developing control architectures for intelligent machines. 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 were developed and the main emphasis was 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 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 will be 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 that illustrates the use for mobile robots.

Dynamic Programming

The 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. Generally, the goal is to minimize this cost function over some decision space subject to the constraints. With this definition, the intelligent robot can be considered as a set of problems in dynamic programming and optimal control as defined by Bertsekas[1].

Dynamic programming (DP) is the only approach for sequential optimization applicable to general nonlinear, stochastic environments. However, DP needs efficient approximate methods to overcome its dimensionality problems. It is only with the presence of artificial neural network (ANN) and the invention of back propagation that such a powerful and universal approximate method has become a reality.

The essence of dynamic programming is Bellman's *Principle of Optimality*.[2]

> *"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 decision"[2] (p.83).*

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

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

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.

The user provides a utility function, U, and a stochastic model of the plant, R, to be controlled. The expert system then tries to solve the Bellman equation for the chosen model and utility function to achieve the optimum value of J by picking the action vector u(t). If an optimum J cannot be determined, an approximate or estimate value of the J function is used to obtain an approximate optimal solution.

Regarding the finite horizon problems, which we normally try to cope with, one can use Eq (2):

$$J(R(t)) = \max_{u(t)}(U(R(t),u(t)) + < J(R(t+1)) >)/(1+r) \qquad (2)$$

Dynamic programming gives the exact solution to 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 <U(R(t))>, 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]

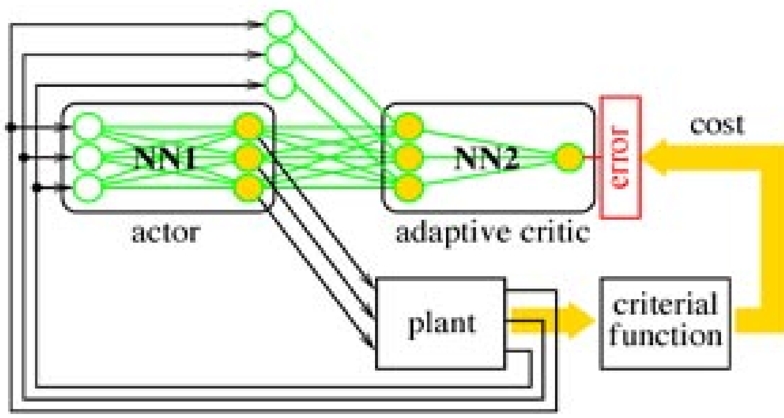
If the weights **W** are adapted or iteratively solved for, in real time learning or offline iteration, we call the Critic an Adaptive Critic[6].

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.

2. ADAPTIVE CRITIC AND CREATIVE CONTROL

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 1. 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 1 Structure of the adaptive critic controller [7]

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 2 [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.

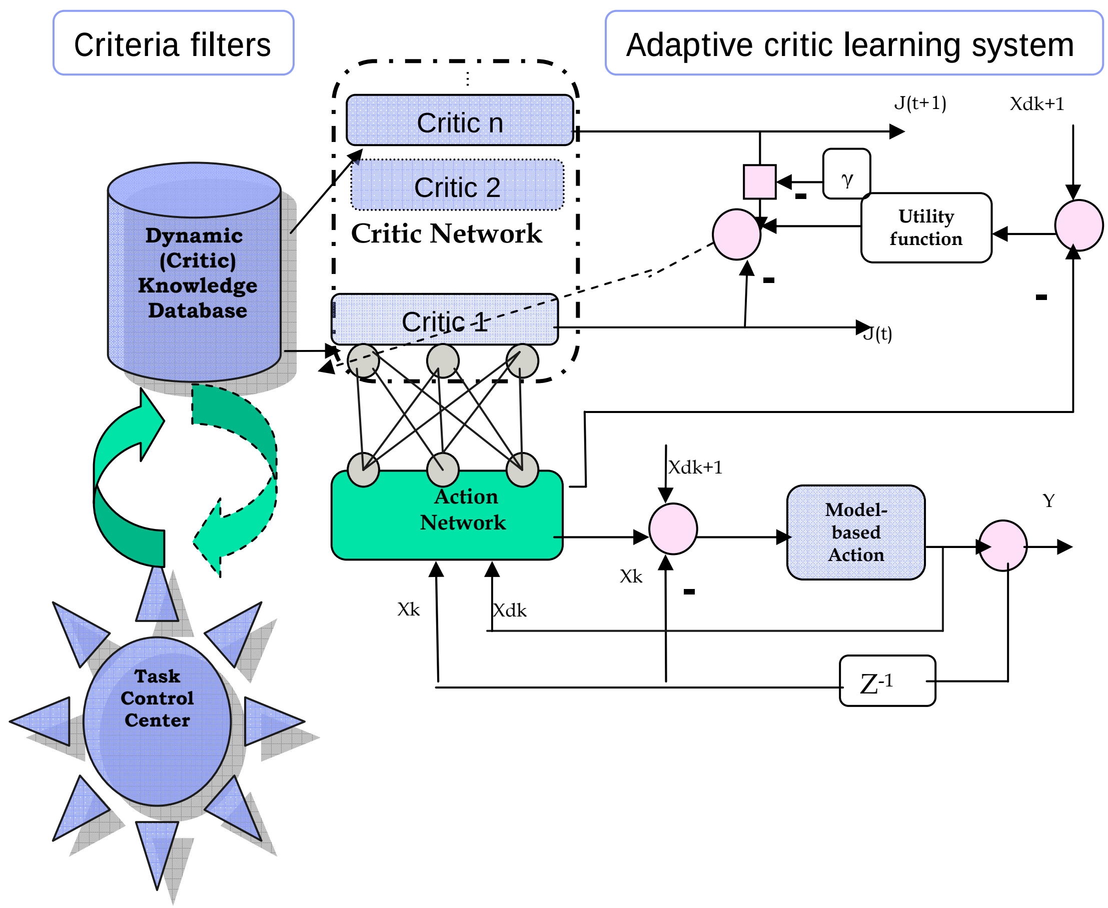


Figure 2 Proposed Creative Learning Algorithm Structure

Dynamic Knowledge Database (DKD)

The dynamic databases contain domain knowledge and can be modified to permit adaption 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 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 3. The DBMS can be customized from an object-relational database.

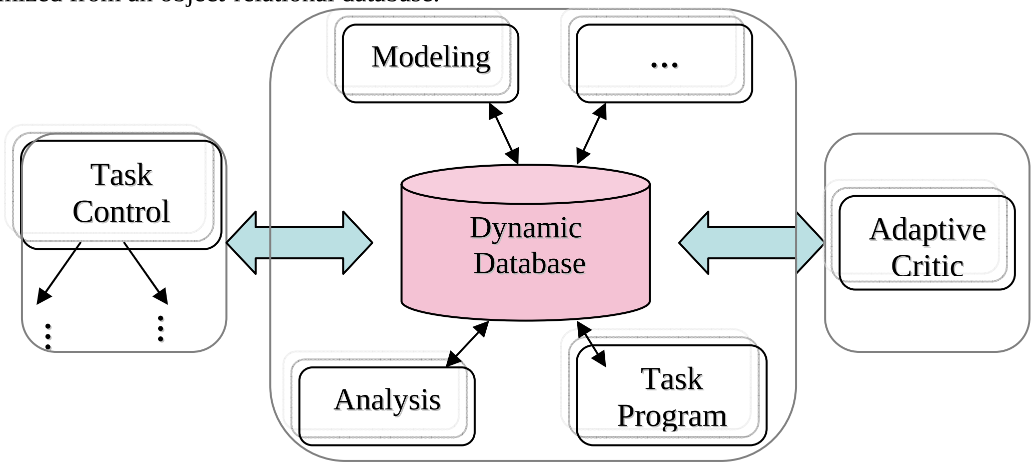


Figure 3 Functional structure of dynamic database

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[14], 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 4.

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.

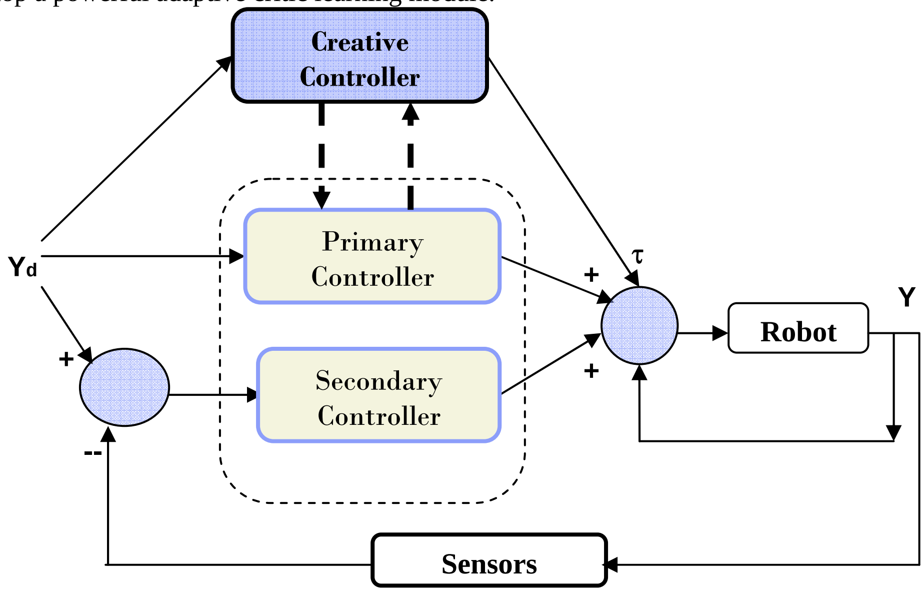


Figure 4 Block diagram of creative controller

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

$$\dot{x} = f[x(t), u(t)]$$
$$y = g[x(t), u(t)] \qquad (8)$$

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.

3 SOME. CREATIVE CONTROL MOBILE ROBOT SCENEARIOS

Urban Rescue Scenarios

Suppose a mobile robot is used for urban rescue as shown in Figure 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 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.

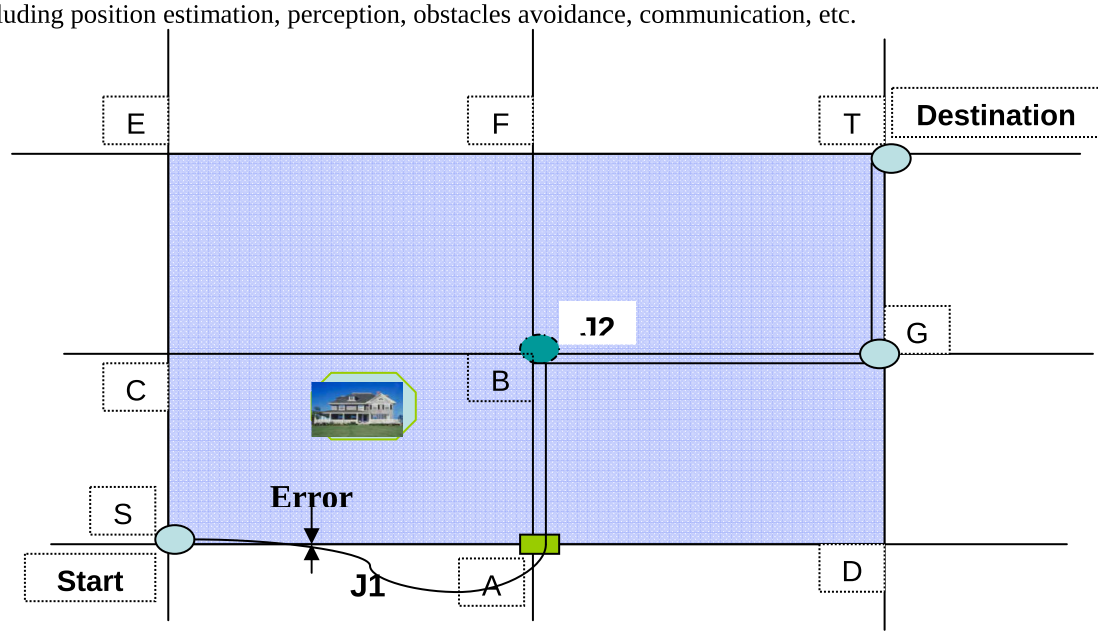


Figure 5 Simple urban rescue site

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.[18]

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 6. 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.

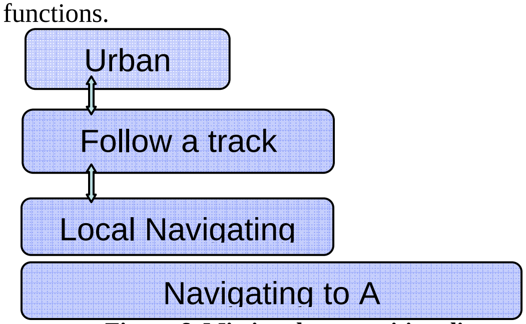


Figure 6 Mission decomposition diagram

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 7. 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 7 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.

Another Demonstration – Urban Challenge Scenarios

The Cincinnati Bearcat Urban Challenge Team (www.darpa.mil/grandchallenge) is a merger of the UC Robot Team and the Bearcat Motor Sports Teams. The UC Robot Team will exploit its many years of autonomous ground vehicle research experience to demonstrate its capabilities for designing and fabricating a smart vehicle control for tactical unmanned systems operation as shown in Figures 8 and 9. The Bearcat Team also builds on many years of experience in the SAE Motor Sports competitions with respect to structural design, analysis, and fabrication, testing and model validation as shown in Figure 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. This new Creative Control has been developed over the past several years and has been the subject of many UC dissertations and papers. The 20 vehicle tasks listed in the requirements of the Urban Challenge are a perfect test for this multiple criteria and multi task approach.

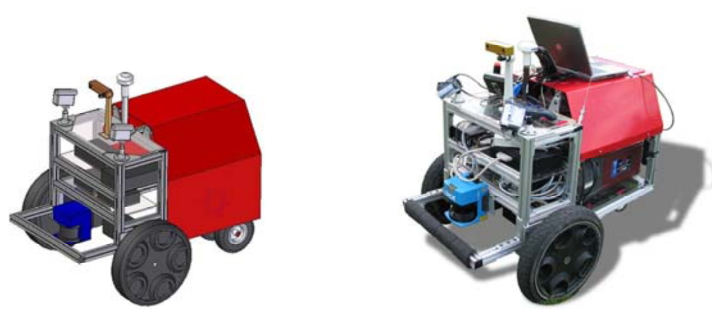


Figure 8 Bearcat Cub intelligent vehicle designed for IGVC

Figure 9 NAC Jeep prototype at UC

Figure 10 UC GMC Truck and Racing Trailer

Our primary objective for the Urban Challenge is to use Creative Control to demonstrate safe, effective autonomous ground vehicle navigation over a 60-mile, 6-hour mission in urban traffic, while conforming to California state traffic laws and established traffic conventions.

The selected Cincinnati vehicle is a GMC Sierra Denali with Quadrasteer.

The contest objectives can be divided into solvable objectives, requirements, primary sensors and constraints as shown in Table 1 for the first 5 of the 20 missions.

Table 1 Mission objectives for 5 missions of 20, requirements, primary sensors and constraints

Objective	*Requirement*	*Primary Sensors*	*Criteria*	*Constraints*
Complete mission 1	Defined by an ordered series of checkpoints in a complex route network	GPS and obstacle detectors	Minimum distance while avoiding obstacles	5 minutes to process a mission description
Complete mission 2	Interpret static lane markings (e.g., white and yellow lines)	Vision systems And obstacle avoidance	Detect lane markings while avoiding obstacles	Behave in accordance with applicable traffic laws and conventions.
Complete mission 3	Exhibit context-dependent speed control	Tachometers and obstacle avoidance	MSE between given and measured speeds	Adherence to speed limits
Complete mission 4	Exhibit safe-following behavior when approaching other vehicles from behind	Frontal laser scanner, MTI radar	MSE in distance from leader vehicle	Maintaining a safe-following distance
Complete mission 5	Exhibit safe check-and-go behavior when pulling around a stopped vehicle	Frontal long range distance measurement, MTI radar	Clear to pass	Locate left side objects
Mission outside the scope	Recognition of external traffic signals such as traffic lights and stop signs through the use of sensors. The Urban Challenge RND file will include information such as stop sign locations, nominal lane width, lane markings, and parking spot locations. Behaviors necessary for highway driving such has high speed passing or high speed merge at an onramp. Speed limits for the Urban Challenge will be 30 mph or less. Driving in difficult off-road terrain is outside the scope of the program.			
Mission within scope	Off-road navigation in an unpaved area, travel along roads with potholes, and travel along a dirt road are within scope.			

Design Approach – Cincinnati Bearcat Intelligent Vehicle

Computer Network

The vehicle computers will be connected in a Local Area Network using the new *GbE*, a version of Ethernet, which supports data transfer rates of 1 Gigabit (1,000 megabits) per second.

A modern teamware approach will be used to provide security, coordination of versions, testing and acceptance testing. A user friendly operator interface GUI will be developed to permit easy visualization of all sensor data, the dynamic data bases, and easy observation of the system diagnostics and track the vehicle decisions and movements and positions.

Sensor Description

A review of the sensors used on the previous DARPA Grand Challenge vehicles is shown in Table 2 that has been updated for the Urban Challenge. Sensor timing is critical and will greatly benefits from the high speed communications.

Table 2 Sensing review and projections

Urban Challenge Sensing Review Sensor Category	Grand Challenge 2004	Grand Challenge 2005	UC Existing	Urban Challenge Proposed 2007
Inertial Navigation/Gyro Includes measuring translational and rotational distance, velocity, and acceleration through conventional macroscopic systems, MEMs or laser gyros. Inertial nav provides immediate short range feedback on the movement of the vehicle and can fill in the gaps where GPS information is not available or accurate enough. Often inertial nav is integrated with GPS to offer a total solution. Manufacturers include: *Applanix (Trimble), XSens, Crossbow, Analog Devices*.	YES	YES		YES
Magnetic Compass Measurement of the earth's magnetic field to supplement other forms of directional measurement. Manufacturers include: *Crossbow, Honeywell*.	YES	YES	YES	YES
Global Positioning System (GPS) Includes conventional and differential GPS. Most teams used differential GPS where satellite information is compared to terrestrial fixed stations for more accurate positioning. GPS suppliers can also closely link GPS with Graphical Information Systems (GIS) to provide detailed terrain mapping. Manufacturers include: *Applanix (Trimble), Garmin, Navcom Starfire, OmniSTAR*.	YES	YES	YES	YES
Optical These include color cameras, stereo vision systems, 2D image analysis, 3D reconstruction, infrared, and low-light level sensing. Manufacturers include: *Point Grey (Bumblebee stereo vision), SAIC (stereo vision), Kenyon Labs (gyro stabilizers for cameras), Indigo Systems (FLIR)*;	YES	YES	YES	YES
Light Detecting And Ranging (LIDAR) or Laser Radar (LADAR) Lasers are used to scan surfaces, provide range information, and perform 3D reconstruction. Manufacturers include: SICK, Riegl.	YES	YES	YES	YES
Radio Detection And Ranging (RADAR) Can be used for long and short range obstacle detection or as a radar odometer. Phased array technology warns of potential hazards, such as stopped or slow-moving vehicles. Doppler radar can be used to measure the velocity of moving objects. Manufacturers include: *Dickey-John, Eaton*	YES	YES		YES

(VORAD).				
Ultrasonic Can use single or multiple elements to gauge distance or as a basic point proximity sensor. Manufacturers include: *Honeywell, EchoMaster, Polaroid, Massa*.	YES	YES	YES	YES
Novel Technologies and New Opportunities			YES	YES
http://www.roboticstrends.com/displayarticle389.html (updated)				

4. CONCLUSIONS AND RECOMMENDATIONS

The creative learning system is proposed and described as an adaptive critic learning system. The creative learning structure also includes a task control center and dynamic knowledge databases. The task control center is a decision-making command center for the intelligent creative learning system. The dynamic knowledge database integrates task control center and adaptive critic learning algorithm into one system. It also provides a knowledge domain for the task command center to perform decision-making. Furthermore, 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. It is a step toward generalizing the highest level of human learning – imagination.

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