Mobile Robotics, Moving Intelligence

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1. Introduction

After proving to be an efficient tool for improving quality, productivity, and competitiveness of manufacturing organizations, robots now expand to service organizations, offices, and even homes. Global competition and the tendency to reduce production cost and increase efficiency creates new applications for robots that stationary robots can't perform. These new applications require the robots to move and perform certain activities at the same time. The availability and low cost of faster processors, better programming, and the use of new hardware allow robot designers to build more accurate, faster, and even safer robots. For example, Egemin Automation has been selling mobile robots for a number of years, available as a specialized unit that delivers mail within a large building to warehouse automation systems. Currently, mobile robots are expanding outside the confines of buildings and into rugged terrain, as well as familiar environments like schools and city streets (Wong, 2005).

The problem addressed in this paper is to describe the theory and architecture of robust learning for mobile robots and to illustrate the theory for designing intelligent mobile robots for a wide variety of applications anywhere in the world including complex and uncertain 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 is derived from the automatic changing of modes based on internal measurements of error at appropriate locations in the controller.

2. Types of Mobile Robots

Many different types of mobile robots had been developed depending on the kind of application, velocity, and the type of environment whether its water, space, terrain with fixed or moving obstacles. Four major categories had been identified (Dudek & Jenkin, 2000):

Terrestrial or ground-contact robots: The most common ones are the wheeled robots; others are the tracked vehicles and Limbed vehicles.

Aquatic robots: Those operate in water surface or underwater. Most use water jets or propellers.

Airborne robots: Flying robots like Robotic helicopters, fixed-wing aircraft, robotically controlled parachutes, and dirigibles.

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Space robots: Those are designed to operate in the microgravity of outer space and are typically envisioned for space station maintenance. Space robots either move by climbing or are independently propelled.

2.1 Terrestrial or Ground-contact Robots

There are three main types of ground-contact robots: wheeled robots, tracked vehicles, and limbed vehicles. Wheeled robots exploit friction or ground contact to enable the robot to move. Different kinds of wheeled robots exist: the differential drive robot, synchronous drive robot, steered wheels robots and Ackerman steering (car drive) robots, the tricycle, bogey, and bicycle drive robots, and robots with complex or compound or omnidirectional wheels. Army Research Labs with NIST support demonstrated defence robot vehicles, called Experimental Unmanned Vehicles (XUV) that developed at a cost of approximately $50 million over four years. It used technology from leading robotics laboratories in the US and Germany. XUV performed autonomous scout missions in difficult off-road terrain and run with general goal points and mission profiles given by Army scouts. XUV navigates through woods and fields to find and report enemy targets. In a demonstration, the XUVs drove autonomously over difficult terrain including dirt roads, trails, tall grass, weeds, brush, and woods. Using on board sensors, the XUVs were able to detect and avoid both positive and negative obstacles. The Demo III XUVs have repeatedly navigated kilometres of difficult off-road terrain with only high-level mission commands provided by an operator from a remote location. Figure 1 shows the XUV in action at Ft. Indiantown Gap (Alhaj Ali, 2003, Greenhouse & Norris, 2002). Another example is Bearcat III which was developed in the University of Cincinnati Robotics Center and is shown in Fig. 2. It has two driven wheels and a caster wheel. The driven wheels are of a fixed-wheel type.

Fig. 1. Experimental Unmanned Vehicle in action at Ft. Indiantown Gap. Photo courtesy of the Army Research Labs (Greenhouse & Norris, 2002).

Fig. 2. University of Cincinnati Bearcat III.

For more information on the construction, kinematic, and dynamic models of wheeled mobile robots, refer to Alhaj Ali (2003), de Wit, et al. (1996), and Dudek & Jenkin, (2000).

Tracked vehicles are robust to any terrain environment, their construction are similar to the differential drive robot but the two differential wheels are extended into treads which provide a large contact area and enable the robot to navigate through a wide range of terrain.

Limbed vehicles are suitable in rough terrains such as those found in forests, near natural or man-made disasters, or in planetary exploration, where ground contact support is not available for the entire path of motion. Limbed vehicles are characterized by the design and the number of legs, the minimum number of legs needed for a robot to move is one, to be supported a robot need at least three legs, and four legs are needed for a statically stable robot, six, eight, and twelve legs robots exists. For example of a limbed robot, ASIMO which is a humanoid two legs walking robot developed by Honda and features the ability to pursue key tasks in a real-life environment such as an office, ASIMO has an advanced level of physical capabilities. The new ASIMO model is shown in Fig. 3 (Honda, 2006).

Fig. 3. The new ASIMO model (Honda, 2006).

2.2 Aquatic Robots

Aquatic vehicles support propulsion by utilizing the surrounding water. There are two common structures (Dudek & Jenkin, 2000): torpedo-like structures (Feruson & Pope, 1995, Kloske et al., 1993) where a single propeller provides forward, and reverse thrust while the navigation direction is controlled by the control surfaces, the buoyancy of the vessel controls the depth. The disadvantage of this type is poor manoeuvrability.

Twin-burger (Fuji et al., 1939) and URV vehicles (Choi, 1993, Choi et al., 1995) robots which uses a collection of thrusters that are distributed over the vessel, more manoeuvrable are attained by controlling sets of the thrusters to change the vehicle orientation and position independently, however, the URV comes with the expense of operational speed. An example of an aquatic robot is shown in Fig. 4.a.

2.3 Flying Robots

Fixed-wing autonomous vehicles: This utilizes control systems very similar to the ones found in commercial autopilots. Ground station can provide remote commands if needed, and with the help of the Global Positioning System (GPS) the location of the vehicle can be determined (Dudek & Jenkin, 2000).
Automated helicopters (Baker et al., 1992, Lewis et al., 1993): These use onboard computation and sensing and ground control, their control is very difficult compared to the fixed-wing autonomous vehicles.
Buoyant (aerobots, aerovehicles, or blimps) vehicles: These vehicles can float and are characterized by having high energy efficiency ration, long-range travel and duty cycle, vertical mobility, and they usually has no disastrous results in case of failure (Dudek & Jenkin, 2000).
Unpowered autonomous flying vehicles: These vehicles reach their desired destination by utilizing gravity, GPS, and other sensors (Dudek & Jenkin, 2000). An example of a flying robot is shown in Fig. 4.b.

a. Aquatic Vehicle b. Flying Vehicle

Fig. 4. Aquatic and Flying vehicle (SSC San Diego, 2002).

2.4 Space Robots

These are needed for applications related to space stations like construction, repair, and maintenance. Free-flying systems have been proposed where the spacecraft is equipped with thrusters with one or more manipulators, the thrusters are utilized to modify the robot trajectory. For more information on the construction and kinematic models of mobile robots please refer to (Dudek & Jenkin, 2000).

3. Navigation

Navigation is the major challenge in the autonomous mobile robots; a navigation system is the method for guiding a vehicle. Several capabilities are needed for autonomous navigation (Alhaj Ali, 2003):

- The ability to execute elementary goal achieving actions such as going to a given location or following a leader;
- The ability to react to unexpected events in real time such as avoiding a suddenly appearing obstacle;

- The ability to formulate a map of the environment;
- The ability to learn which might include noting the location of an obstacle and of a three-dimensional nature of the terrain and adapt the drive torque to the inclination of hills (Golnazarian & Hall, 2000).

During the last fifteen years, a great deal of research has been done on the interpretation of motion fields as the information they contain about the 3-D world. In general, the problem is compounded by the fact that the information that can be derived from the sequence of images is not the exact projection of the 3D-motion field, but rather information about the movement of light patterns and optical flow (Golnazarian & Hall, 2000, Alhaj Ali, 2003).

3.1 Systems and Methods for Mobile Robot Navigation

Odometry and other dead-reckoning methods: These methods use encoders to measure wheel rotation and/or steering orientation (Alhaj Ali, 2003).

Vision based navigation: Computer vision and image sequence techniques were proposed for obstacle detection and avoidance for autonomous land vehicles that can navigate in an outdoor road environment. The object shape boundary is first extracted from the image, after the translation from the vehicle location in the current cycle to that in the next cycle, the position of the object shape in the image of the next cycle is predicted, then it is matched with the extracted shape of the object in the image of the next cycle to decide whether the object is an obstacle (Alhaj Ali, 2003, Chen & Tsai, 2000).

Sensor based navigation: Sensor based navigation systems that rely on sonar or laser scanners that provide one dimensional distance profiles have been used for collision and obstacle avoidance. A general adaptable control structure is also required. The mobile robot must make decisions on its navigation tactics; decide which information to use to modify its position, which path to follow around obstacles, when stopping is the safest alternative, and which direction to proceed when no path is given. In addition, sensors information can be used for constructing maps of the environment for short term reactive planning and long-term environmental learning (Alhaj Ali, 2003).

Inertial navigation: This method uses gyroscopes and sometimes accelerometers to measure the rate of rotation and acceleration.

Active beacon navigation systems: This method computes the absolute position of the robot from measuring the direction of incidence of three or more actively transmitted beacons. The transmitters, usually using light or radio frequencies must be located at known sites in the environment (Janet, 1997, Premvuti & Wang, 1996, Alhaj Ali, 2003).

Landmark navigation: In this method distinctive artificial landmarks are placed at known locations in the environment to be detected even under adverse environmental conditions (Alhaj Ali, 2003).

Map-based positioning: In this method information acquired from the robot's onboard sensors is compared to a map or world model of the environment. The vehicle's absolute location can be estimated if features from the sensor-based map and the world model map match (Alhaj Ali, 2003).

Biological navigation: biologically-inspired approaches were utilized in the development of intelligent adaptive systems; biomimetic systems provide a real world test of biological navigation behaviours besides making new navigation mechanisms available for indoor robots (Alhaj Ali, 2003).

Global positioning system (GPS): This system provides specially coded satellite signals that can be processed in a GPS receiver, enabling it to compute position, velocity, and time (Alhaj Ali, 2003).

4. Mobile Robots and Artificial Intelligence

While robotics research has mainly been concerned with vision (eyes) and tactile, some problems regarding adapting, reasoning, and responding to changed environment have been solved with the help of artificial intelligence using heuristic methods such as ANN. Neural computers have been suggested to provide a higher level of intelligence that allows the robot to plan its action in a normal environment as well as to perform non-programmed tasks (Golnazarian & Hall, 2000, Alhaj Ali, 2003).
A well established field in the discipline of control systems is the intelligent control, which represents a generalization of the concept of control, to include autonomous anthropomorphic interactions of a machine with the environment (Alhaj Ali, 2003, Meystel & Albus, 2002). Meystel and Albus (2002) defined intelligence as "the ability of a system to act appropriately in an uncertain environment, where an appropriate action is that which increases the probability of success, and success is the achievement of the behavioural sub goals that support the system's ultimate goal". The intelligent systems act so as to maximize this probability. Both goals and success criteria are generated in the environment external to the intelligent system. At a minimum, the intelligent system had to be able to sense the environment which can be achieved by the use of sensors, then perceive and interpret the situation in order to make decisions by the use of analyzers, and finally implements the proper control actions by using actuators or drives. Higher levels of intelligence require the abilities to: recognize objects and events store and use knowledge about the world, learn, and to reason about and plan for the future. Advanced forms of intelligence have the ability to perceive and analyze, to plan and scheme, to choose wisely, and plan successfully in a complex, competitive, and hostile world (Alhaj Ali, 2003).
Intelligent behaviour is crucial to mobile robots; it could be supported by connecting perception to action (Kortenkamp et al., 1998). In the following a brief review for the literature in the use of artificial intelligence in mobile robots will be presented (Alhaj Ali, 2003).

4.1 Use of Artificial Neural Networks (ANN)

ANN has been applied to mobile robot navigation. It had been considered for applications that focus on recognition and classification of path features during navigation. Kurd and Oguchi (1997) propose the use of neural network controller that was trained using supervised learning as an indirect-controller to obtain the best control parameters for the main controller in use with respect to the position of the AGV. A method that uses incremental learning and classification based on a self-organizing ANN is described by Vercelli and Morasso (1998). Xue and Cheung (1996) proposed a neural network control scheme for controlling active suspension. The presented controller used a multi-layer neural network and a prediction-correction method for adjusting learning parameters. Dracopoulos (1998) present the application of multi-layer perceptrons to the robot path planning problem and in particular to the task of maze navigation. Zhu, et al. (1998) present results of integrating omni-directional view image analysis and a set of adaptive networks to understand the outdoor road scene by a mobile robot (Alhaj Ali, 2003).
To navigate and recognize where it is, a mobile robot must be able to identify its current location. The more the robot knows about its environment, the more efficiently it can operate (Cicirelli, 1998). Grudic and Lawrence (1998) used a nonparametric learning algorithm to build a robust

mapping between an image obtained from a mobile robot's on-board camera, and the robot's current position. It used the learning data obtained from these raw pixel values to automatically choose a structure for the mapping without human intervention, or any prior assumptions about what type of image features should be used (Alhaj Ali, 2003).

4.2 Use of Fuzzy Logic

Fuzzy logic and fuzzy languages have also been used in navigation algorithms for mobile robots as described in (Wijesoma et al., 1999, Mora and Sanchez, 1998). Lin and Wang (1997) propose a fuzzy logic approach to guide an AGV from a starting point toward the target without colliding with any static obstacle as well as moving obstacles; they also study other issues as sensor modelling and trap recovery. Kim and Hyung (1998) used fuzzy multi-attribute decision-making in deciding which via-point the robot should proceed to at each step. The via-point is a local target point for the robot's movement at each decision step. A set of candidate via-points is constructed at various headings and velocities. Watanabe, et al. (1998) described a method using a fuzzy logic model for the control of a time varying rotational angle in which multiple linear models are obtained by utilizing the original non-linear model at some representative angles (Alhaj Ali, 2003).

4.3 Use of Neural Integrated Fuzzy Controller

A neural integrated fuzzy controller (NiF-T) that integrates the fuzzy logic representation of human knowledge with the learning capability of neural networks has been developed for nonlinear dynamic control problems (Alhaj Ali, 2003). Daxwanger and Schmidt (1998) presented their neuro-fuzzy approach for visual guidance of a mobile robot vehicle.

5. Navigation in Unstructured Environments

Some research has been conducted regarding robotics in unstructured environment. Alhaj Ali (2003) presented the development of an autonomous navigation and obstacle avoidance system for a wheeled mobile robot operating in unstructured outdoor environments. The algorithm presented produces the robot's path positioned within the road boundaries and avoids any fixed obstacles along the path. The navigation algorithm was developed from a feedforward multilayer neural network. The network used a quasi-Newton backpropagation algorithm for training. Computed-torque, digital, and adaptive controllers were developed to select suitable control torques for the motors, which cause the robot to follow the desired path from the navigation algorithm.

Martínez and Torras (2001) presented visual procedures especially tailored to the constraints and requirements of a legged robot that works with an un-calibrated camera, with pan and zoom, freely moving towards a stationary target in an unstructured environment that may contain independently-moving objects.

Kurazume and Hirose (2000) proposed a new method called Cooperative Positioning System (CPS). The main concept of CPS is to divide the robots into two groups, A and B, where group A remains stationary and acts as a landmark while group B moves. Then group B stops and acts as a landmark for group A. This process is repeated until the target position is reached. Their application was a floor-cleaning robot system. Torras (1995) reviewed neural learning techniques for making robots well adapted to their surroundings.

Yahja et al. (2000) propose an on-line path planner for outdoor mobile robots using a framed-quadtrees data structure and an optimal algorithm to incrementally re-plan optimal paths. They showed that the use of framed-quadtrees leads to paths that are shorter and more direct compared to the other representations; however, their results indicate that starting with partial information is better than starting with no information at all. Baratoff et al. (2000) designed a space-variant image transformation, called the polar sector map, which is ideally suited to the navigational tasks.
Yu et al. (2001) presented a hybrid evolutionary motion planning simulation system for mobile robots operating in unstructured environments, based on a new obstacle representation method named cross-line, a follow boundary repair approach, and a hybrid evolutionary motion planning algorithm. Yan et al. (1997) presents an attempt to devise and develop a domain-independent reasoning system scheme for handling dynamic threats, and uses the scheme for automated route planning of defence vehicles in an unstructured environment (Alhaj Ali, 2003).
Computer vision and image sequence techniques were proposed for obstacle detection and avoidance for autonomous land vehicles that can navigate in an outdoor road environment. Jarvis (1996) report some preliminary work regarding an autonomous outdoor robotic vehicle navigation using flux gate compass, DGPS and range sensing, and distance transform based path planning. An adaptive navigation method suited for the complex natural environments had been proposed based on a multi-purpose perception system that manages different terrain representations, the method focuses on the functions that deal with the navigation planning and the robot self-localization which have been integrated within the robot control system (Devy, 1995).
Krishna and Kalra (2001) proposed incorporating cognition and remembrance capabilities in a sensor-based real-time navigation algorithm, they stated that these features enhance the robots performance by providing a memory-based reasoning whereby the robot's forthcoming decisions are also affected by its previous experiences during the navigation, which is apart from the current range inputs, the suggested robot navigates in a concave maze-like unstructured altered environment which has been modelled by classifying temporal sequences of special sensory patterns.
Marco et al. (1996) developed a hybrid controller for semi-autonomous and autonomous underwater vehicles in which the missions imply multiple task robot behaviour. They proposed the use of Prolog as a computer language for the specification of the discrete event system (DES) aspects of the mission control, and made the connections between a Prolog specification and the more common Petri Net graphical representation of a DES (Alhaj Ali, 2003).

6. Controllers for Autonomous Mobile Robots

Robots and robots manipulators have complex nonlinear dynamics that make their accurate and robust control difficult. On the other hand, they fall in the class of Lagrangian dynamical systems, so that they have several extremely nice physical properties that make their control straight forwarded (Lewis et al., 1999). Different controllers had been developed for the motion of robot manipulators, however, not until recently where there has been an interest in moving the robot itself, not only its manipulators (Alhaj Ali, 2003).
Shim and Sung (2003) proposed a WMR asymptotic control with driftless constraints based on empirical practice using the WMR kinematic equations. They showed that with the appropriate selection of the control parameters, the numerical performance of the

asymptotic control could be effective. The trajectory control of a wheeled inverse pendulum type robot had been discussed by Yun-Su and Yuta (1998), their control algorithm consists of balance and velocity control, steering control, and straight line tracking control for navigation in a real indoor environments (Alhaj Ali, 2003).
Rajagopalan and Barakat (1997) developed a computed torque control scheme for Cartesian velocity control of WMRs. Their control structure can be used to control any mobile robot if its inverse dynamic model exists. A discontinuous stabilizing controller for WMRs with nonholonomic constraints where the state of the robot asymptotically converges to the target configuration with a smooth trajectory was presented by Zhang and Hirschorn (1997). A path tracking problem was formulated by Koh and Cho (1999) for a mobile robot to follow a virtual target vehicle that is moved exactly along the path with specified velocity. The driving velocity control law was designed based on bang-bang control considering the acceleration bounds of driving wheels and the robot dynamic constraints in order to avoid wheel slippage or mechanical damage during navigation. Zhang et al. (2003) employed a dynamic modelling to design a tracking controller for a differentially steered mobile robot that is subject to wheel slip and external loads (Alhaj Ali, 2003).
A sliding mode control was used to develop a trajectory tracking control in the presence of bounded uncertainties (Corradini & Orlando, 2001). A solution for the trajectory tracking problem for a WMR in the presence of disturbances that violate the nonholonomic constraint is proposed later by the same authors based on discrete-time sliding mode control (Corradini et al., 2002).
An electromagnetic approach for path guidance of a mobile-robot-based automatic transport service system with a PD control algorithm was investigated by Wu et al. (2001). Jiang, et al. (2001) developed a model-based control design strategy that deals with global stabilization and global tracking control for the kinematic model with a nonholonomic WMR in the presence of input saturations. An adaptive robust controller was proposed for the global tracking problem for the dynamic of the non-holonomic systems with unknown dynamics (Dong, 1999). However, real time adaptive controls are not common in practical applications due partly to stability problems (Werbos, 1999, Alhaj Ali, 2003).
A fuzzy logic controller had been tried for WMRs navigation. Montaner and Ramirez-Serrano (1998) developed a fuzzy logic controller that can deal with the sensors inputs uncertainty and ambiguity for direction and velocity manoeuvres. A locomotion control structure was developed based on the integration of an adaptive fuzzy-net torque controller with a kinematic controller to deal with unstructured unmodeled robot dynamics for a non-holonomic mobile robot cart (Topalov, 1998). Toda et al. (1999) employed a sonar-based mapping of crop rows and fuzzy logic control-based steering for the navigation of a WMR in an agricultural environment. They constructed a crop row map from the sonar readings and transferred it to the fuzzy logic control system, which steers the robot along the crop row. A local guidance control method for wheeled mobile robots using fuzzy logic for guidance, obstacle avoidance and docking was proposed by Vázquez and Garcia (1994), the method provide a smooth but not necessary optimal solution (Alhaj Ali, 2003).

7. Creative Control for Intelligent Mobile Robots

Since mobile robots must be able to select among many concurrent tasks, such as moving while sensing and reacting and learning, a new control structure is needed. The creative controller concept is excellent for complex environments since it permits a divide and conquer approach,

with one or more tasks at a time in a multi-threaded, distributed computing environment. 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 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 is appropriate and that it has 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.
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 that illustrates the use for mobile robots.

7.1 Dynamic Programming

The intelligent robot is defined as a decision maker for a dynamic system that may make decisions in discrete stages or over a continuous or discrete 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 (Liao, 2002).
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*. (Bellman 1957)

> *"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".*

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

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

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.
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):

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

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.
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, and $\hat{J}$ is called a Critic network. If the weights **W** are adapted or iteratively solved for, in real time learning or offline iteration, we call the Critic an Adaptive Critic.
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 it's 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.

7. 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 5. 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.

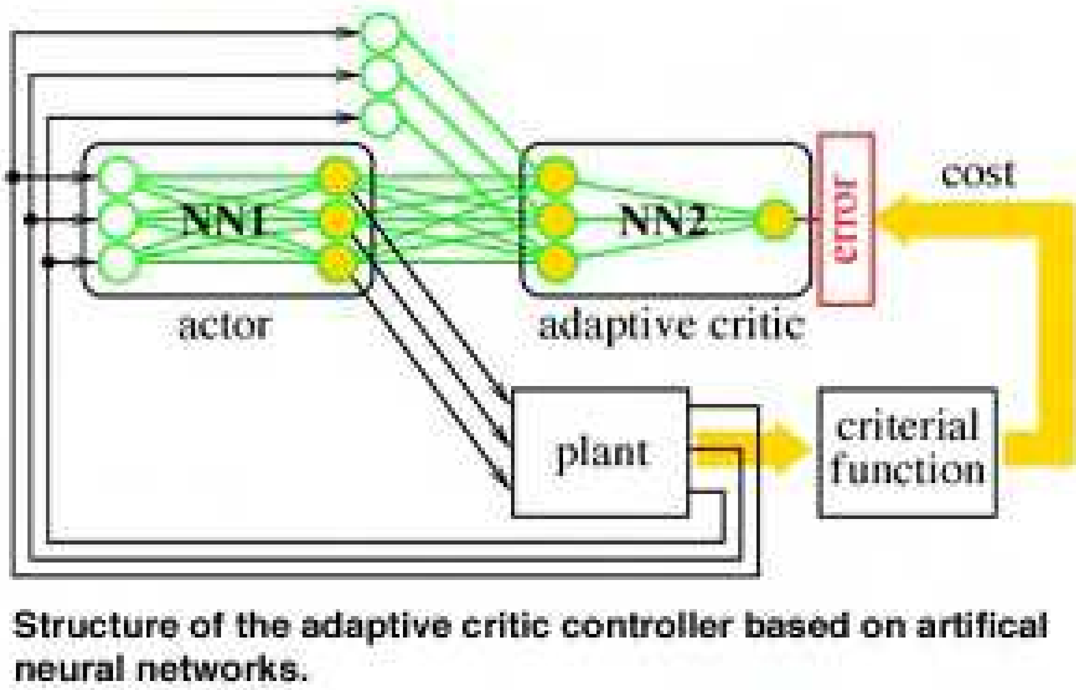

Fig. 5. Structure of the adaptive critic controller (Liao et al., 2003).

7.3 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 6. 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 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 with respect to time.

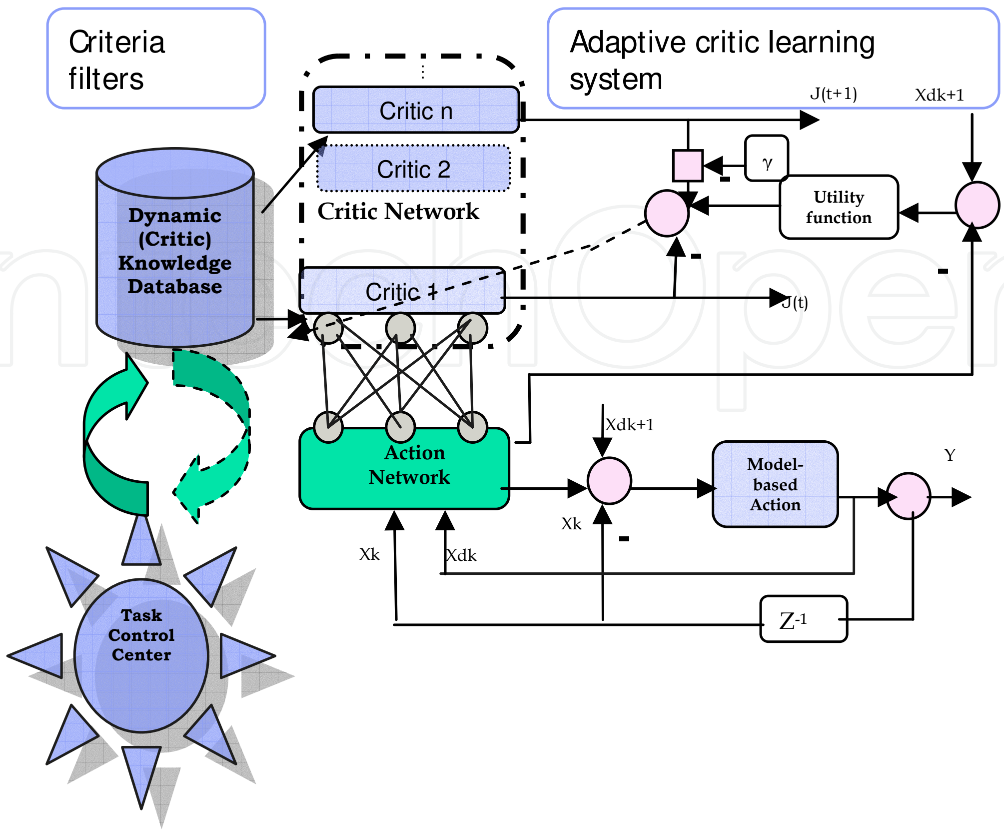

Fig. 6. Proposed creative learning algorithm structure.

7.4 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" 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 function 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 7. The DBMS can be customized from an object-relational database.

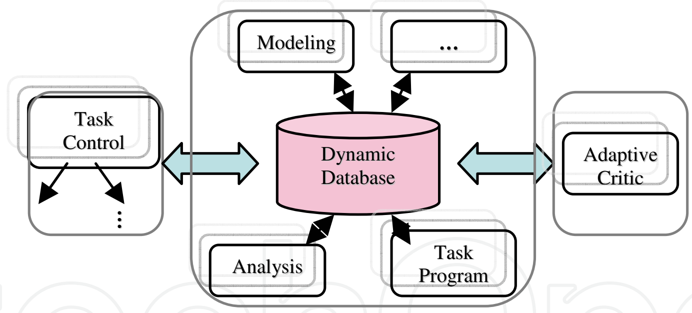

Fig. 7. Functional structure of dynamic database.

7.5 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 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, 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. 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.

7.6 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 generalize the highest level of human learning – imagination. As a ANN robot controller, the block diagram of the creative controller can be presented as shown in Figure 8.
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.

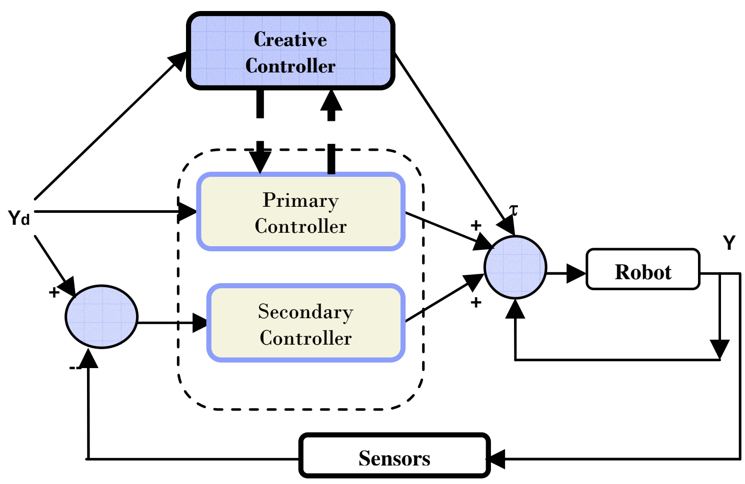

Fig. 8. Block diagram of creative controller.

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

7.7 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. (Campos and Lewis, 1999) 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 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 (Stubberud, A.R. and S.C. Stubberud, (2000)). For general nonlinear continuous time systems, the state space model is

$$\begin{aligned} \dot{x} &= f[x(t), u(t)] \\ y &= g[x(t), u(t)] \end{aligned} \tag{8}$$

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.

7.8 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 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.

7.9 Critic and Action NN Weights Tuning Algorithm

In adaptive critic learning controller, both the critic network and the 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.

7.10 Urban Rescue Scenarios

Suppose a mobile robot is used for urban rescue as shown in Figure 9. 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 different criteria at the corners than along the track. The overall goal is to arrive at the rescue site in minimum time. To clarify the situation 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.

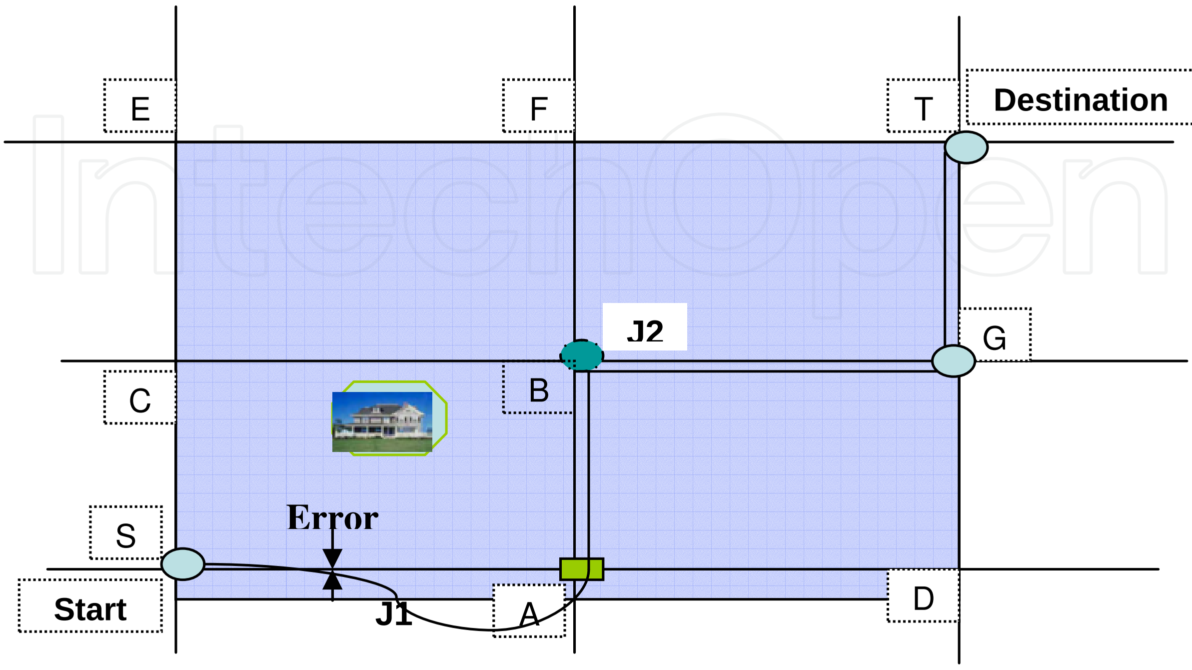

Fig. 9. Simple urban rescue site.

In an unstructured environment as shown in Figure 9, we assume that information collected about different positions 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.

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 9 into sub-tasks as shown in Figure 10. 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.

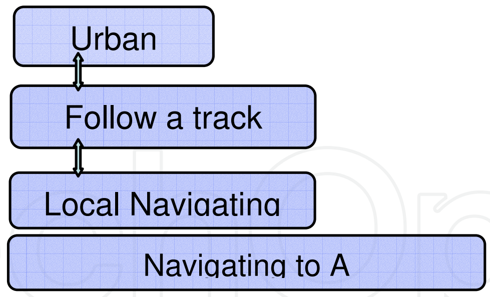

Fig. 10. Mission decomposition diagram.

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 11. 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)
…	…

Fig. 11. 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.

8. Conclusion

A new concept for mobile intelligence is presented in this paper. A series of experimental robots named the Bearcats, have been constructed at the University of Cincinnati over the past several years. This experience has evolved into our current, creative control design that is presented in this paper. Fortunately, our intelligent robots have been able to use our increasingly capable computer controls in which multi-threaded, distributed computing is now easily available.
The theory presented shows how to design intelligent robots that are capable of adapting, learning and predicting. This is a step toward understanding the semiotic closure exhibited by biological creatures and a further step toward appreciating the wonderful capabilities of human intelligence.

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This book covers many aspects of the exciting research in mobile robotics. It deals with different aspects of the control problem, especially also under uncertainty and faults. Mechanical design issues are discussed along with new sensor and actuator concepts. Games like soccer are a good example which comprise many of the aforementioned challenges in a single comprehensive and in the same time entertaining framework. Thus, the book comprises contributions dealing with aspects of the Robotcup competition. The reader will get a feel how the problems cover virtually all engineering disciplines ranging from theoretical research to very application specific work. In addition interesting problems for physics and mathematics arises out of such research. We hope this book will be an inspiring source of knowledge and ideas, stimulating further research in this exciting field. The promises and possible benefits of such efforts are manifold, they range from new transportation systems, intelligent cars to flexible assistants in factories and construction sites, over service robot which assist and support us in daily live, all the way to the possibility for efficient help for impaired and advances in prosthetics.