Acquisition of Automatic Activity Through Practice: Changes in Sensory Input*

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Abstract

This paper will present computer models of three robotic motion planning and learning systems which use a multi-sensory learning strategy for learning and control. In these systems machine vision input is used to plan and execute movements utilizing an algorithmic controller while at the same time neural networks learn the control of those motions using feedback provided by position and velocity sensors in the actuators. A specific advantage of this approach is that, in addition to the system learning a more automatic behavior, it employs a computationally less costly sensory system more tightly coupled from perception to action.

Introduction

There has been considerable discussion in the AI and robotics literature in recent years on the acquisition of planning and control behaviors which directly couple input to output, thereby avoiding unbounded search in planning and high computational costs for control (Brooks, 1989; Mitchell, 1990; Handelman et. al., 1990, 1992). The term "reactive behavior" is predominantly used in the planning domain and "reflexive behavior" is similarly used in the control domain for these direct responses. The more general term used in the psychology literature to denote the acquisition of stimulus-response behavior in the sensory-motor as well as other more cognitive domains is "automaticity" (Schneider & Fisk, 1983). We use the term automaticity here because planning and control functions both become automatic in the simulations below.

There are numerous examples of robotic systems which have been trained with a single sensory modality, e.g., vision, force or position feedback (Mitchell, 1987; Mel, 1989; Handelman et. al., 1990,1992). In this paper we present simulations of the acquisition of automatic behavior in systems which initially use vision to perform a task and then learn to perform the same task using proprioceptive sensory input. This mutli-sensory approach allows the system to switch from a global planning and control algorithm to simple control laws learned in restricted parts of state space. In addition, the automatic behavior utilizes a computationally less costly and more direct sensory input for the execution of the task.

Humans possess an ability to use multiple sensory modalities for both learning and control (Smyth, 1984). Typically they initially rely upon visual information for motor control, and then, with practice, switch to the proprioceptive control of motion (Notterman & Weitzman, 1981; Posner et. al., 1976; Fleishman & Schneider, 1985). This ability is particularly useful because vision is so important for monitoring the environment and planning motion. For example, in sports, a novice must devote a great deal of visual attention to the control of his or her limbs and the execution of those tasks necessary for play. On the other hand, an expert has learned, through practice, motor programs which rely for their execution predominantly upon kinesthetic input from limbs and muscles -- leaving the visual sense free to attend to other aspects of the game (Fischman & Schneider, 1985).

In this paper we present simulations for three examples of hybrid approaches to robotic systems. In the first, visual information is initially used to plan and control the motion of an arm, avoiding an obstacle. Then a neural net is trained to learn a chained response using angle feedback from the joints which generates the same trajectory. In the second task, a robotic arm dribbles a ball while using visual information to sense the position of the ball, arm, and obstacles. As the ball is dribbled, a neural network learns the proper responses for dribbling the ball through kinesthetic joint information. In this case the neural network learns the control law for the arm as it interacts dynamically with an external object. In the final task, an anthropomorphic planar manipulator uses vision to learn proprioceptive compensations to calibration errors in joint angle, velocity, and length perception for a repetitive reaching task.

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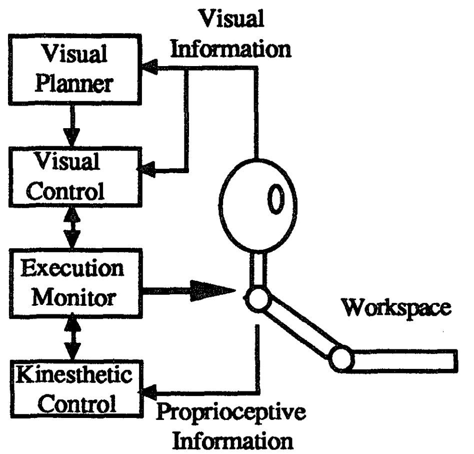

Figure 1. A schematic diagram of a hybrid learning and control system. This system plans and executes the motion of an arm using visual input and trains the arm to perform the task using feedback from position sensors in the actuators.

A Hybrid Learning and Control System

A schematic diagram of the system that was used in the first two simulations reported here is shown in Fig. 1. A robot manipulator is shown performing a task with a machine vision system initially determining the appropriate trajectory of the manipulator based on relevant information about the work space. This visual information is fed to the modules marked kinematic control and visual control. The visual control module utilizes visual feedback of the position of the arm to execute movement along the planned path. During the execution of this visually guided motion, sensors provide information about the arm's position to a CMAC neural network. (Albus, 1975) This network is trained to provide the proper control outputs to cause the arm to move in the same path as under visual system control.

The process described above is supervised by an execution monitor responsible for monitoring the performance of the kinesthetic control system relative to the visually controlled system and for switching control between the two systems. The execution monitor also monitors the gross performance of the system. If problems are encountered such as an unexpected collision, control may be switched back to the visual system, which allows for more comprehensive diagnostic and planning activity.

Learning Control of Arm Motion in the Presence of an Obstacle

In this demonstration, we use a visual system to locate an object in two dimensional space and to control the motion of the two link manipulator. The CMAC neural network, introduced by Albus, is particularly well suited as a function approximator for the performance of this control task (Albus, 1975; Lane et. al., 1992). The CMAC was trained to control the position of the manipulator as a function of joint angle. During the training passes, the RMS distance from the visually controlled manipulator position to the position suggested by the CMAC is monitored and determines when the CMAC has adequately learned the desired trajectory. When the CMAC is sufficiently trained, the execution monitor then switches from the visual controller to the kinesthetic controller.

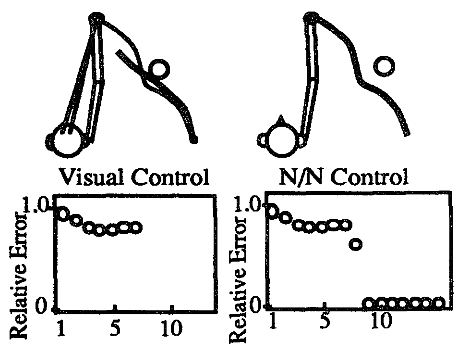

Figure 2a-2b. Diagram of a robotic arm under visual control training a CMAC neural network to execute the same trajectory using joint angle feedback. The graph at the bottom of each figure depicts the RMS difference between the visual and CMAC control as discussed in the text. In Fig. 2b control of the arm has been transferred to the CMAC.

Referring to Fig. 2, we see a two link manipulator constrained to a horizontal plane. The arrangement of the manipulator, the object, and the visual system are shown. For the sake of this demonstration we used a simple binocular visual system which locates the object in space using the angles from the object to the sensors. The path was calculated by first determining a point of closest approach to the obstacle based on the size of the end effector. This point and the given initial and final end effector positions were used to compute a spline function to represent the desired path. The visual system monitors the position of the end effector as the motion is controlled by torques calculated by the inverse dynamics of the arm. As arm moves along the path, the CMAC is given as input, the current joint angles and joint velocities, and the desired joint angles at the end of the segment. The CMAC is trained to output the required torques at each of the two joints to produce the desired end effector trajectory. The training consists of comparing the torque output of the inverse dynamic controller with that of the CMAC and training the weights by the standard CMAC learning algorithm (Albus, 1975; Lane et. al., 1992). When the error reaches a predetermined threshold, control is switched to the CMAC.

The results of this demonstration are shown in Figs. 2a-2b. These figures depict the behavior of the system after the indicated number of runs. Each training run consists of a complete sweep of the trajectory from the initial position to the final position. In each figure, we use a thin line to indicate the actual trajectory of the end effector as controlled by the visual input controller. The heavy lines are the motion that would result from commands from the CMAC controller. At the bottom of each figure, we show the RMS differences of the joint angles plotted against the number of training runs. In Fig. 2a, the dotted lines from the robot's binocular visual sensors to the end effector indicate that the system is under visual control. We can see that the output of the CMAC begins to approximate the desired path. The RMS difference becomes smaller and the trajectories depicted by the light and heavy lines become coincident. In Fig. 2b, we show the final performance of the system after control has been transferred to the CMAC.

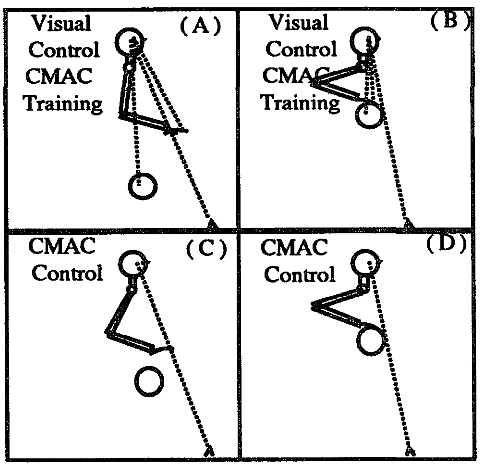

Figure 3a-3d. Diagrams of the simulated basketball dribbler described in text. In Figs. 3a-3b the vision system is responsible for both the control of the arm and for sensing of the obstacle position. In Figs. 3c-3d the arm is under CMAC neural network control using joint angle feedback and the sensing of the obstacle is under visual control.

Learning The Dynamics of the Interactions Between a Manipulator and an External Object

In this demonstration the arms of a simulated robot are depicted dribbling a ball using visual feedback while a CMAC is trained with kinesthetic feedback as its input. This dribbler is modeled in two dimensions and is shown in Figs. 3a-3d. The task involves dribbling a ball in the presence of an obstacle moving at a constant velocity from left to right. Initially, the planner uses the visual location of the ball to determine where and when to catch the ball and push it back towards the floor so as to avoid the obstacle. This is accomplished by visually observing the position and velocity of the ball, the position of the obstacle, and the position of the end effector. While this visually controlled dribbling is going on, the CMAC is trained with kinesthetic feedback from the joint angles of the manipulator.

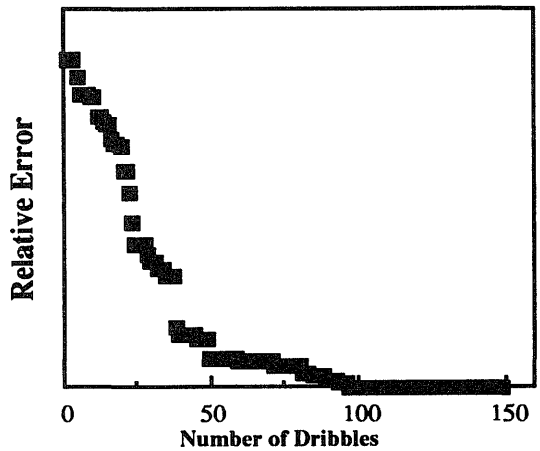

Figure 4. A graph of the relative RMS positional difference between the visually controlled end effector position and the suggested CMAC end effector position during the training of the dribbler. In this example, control of the arm was switched to the CMAC after the 125th dribble.

During dribbling, the momentum of the ball interacts with the impedance of the arm. When the ball strikes the hand, its momentum will cause the arm to fold upward, absorbing the impact. The final position of the arm can therefore be used to compute the velocity vector of the ball as it impacted the hand. The inputs to the CMAC are the position at which the ball makes contact with the hand, the total consequent deflection, and the obstacle's current position. The CMAC is then trained to output the position at which the end effector should stop in its downward motion in order to release the ball to continue towards the floor. For the sake of simplicity in this model, the manipulator arm moves in a straight path from the point of maximum deflection to the point of release. When the output of the CMAC is sufficiently close to the visually controlled output, the program switches control from the visual system to the CMAC. The performance of the model is shown in Fig. 4.

Learning to Compensate for Perceptual Calibration Errors

In this demonstration, we use a visual system to learn compensations for calibration errors in the proprioception of a six-link planar manipulator. Feedback error learning was used to train a CMAC to dynamically compensate for misperception of the vector distance from the endpoint of the manipulator to the desired target (Miyamoto, 1988). Feedback error learning occurs when a neural net is trained using the output of a feedback controller operating in parallel with the neural net. The output of Berkinblit's kinematic algorithm was filtered to generate desired joint angular positions, velocities and accelerations, which in turn were implemented by a hybrid dynamic controller composed of a PD controller and an adaptive Splinet trained using feedback error learning (Berkinblit, 1986, Lane et. al., 1991, 1990). This system is described in full detail in (Gelfand, et. al., 1992).

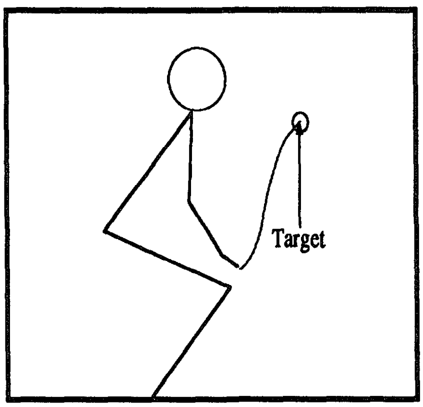

Figure 5. A diagram of the movement of REACHER as it moves from the original to the final posture. The heavy lines indicate the starting posture of the manipulator. The curved line indicates the path generated by the Berkinblit algorithm for the manipulator.

Fig. 5 shows the six link planar manipulator in the initial position with the end effector trajectory to the target. In this experiment we perturbed the perception of joint angles and velocities randomly with a maximum amplitude of ±.05 rad. and ±.02 rad./s respectively. In addition, we perturbed the lengths of the links by up to ±1cm. For comparison, the robot stands approximately 1m high. We began with a system with no sensor errors and then perturbed the calibrations and joint lengths twice, once after 5 sweeps and once after 30 sweeps. Fig. 6 displays the contribution of the vision system to the endpoint correction. When this contribution becomes sufficiently small, the visual system may be dedicated to another task without a significant change in performance.

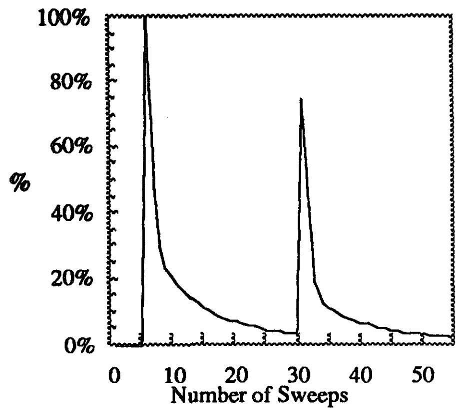

Figure 6. Percent contribution of vision to endpoint correction in response to two perturbations in the calibration of proprioceptive sensors and link lengths.

Discussion

The results described in this paper illustrate a powerful behavioral strategy used by intelligent biological systems to cope with a myriad of sensory input and control responsibilities. The functionality of present day machine vision systems is near the limit of their ability to contribute to the complex analysis of the robotic environment. Strategies which offload sensory responsibilities to other sensor systems make it possible to utilize vision systems for those tasks for which they are more qualified.

Finally, we should be aware that we learn multiple cues for the execution of learned tasks, some of which may not be apparent when we start. These cues include information from our auditory system, somatosensory system and other senses in addition to sight and kinesthesis. Intelligent robotic control systems of the kind described here should really measure the correlations among sensory inputs and pick those which provide the maximum sensitivity for the control of learned actions. As Mitchell points out, this is becoming "increasingly perceptive." (Mitchell, 1990; Tan, 1990.)

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