Optically Driven Learning Control for Industrial Manipulators

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ABSTRACT: Dynamic interactions between the robot manipulator and its environment introduce control complications, whereas unmodeled dynamics and flexibilities in the manipulator itself introduce additional uncertainties. This paper presents an optically based learning controller that can utilize past experience and sensory information about the current state to overcome these difficulties. An inexpensive, single-function optical sensor uses a light-emitting diode and eight detectors to provide information on the distance normal to the surface of a workpiece. The method is implemented on an GE-P50 robot and can be used to track the unknown surface of the workpiece.

Introduction

Automation of manufacturing processes often involves integration of some type of robotic manipulator. Automatic brushing, painting, deburring, welding, and seam tracking are examples of tasks that manipulators should be able to perform accurately and autonomously. One special feature of an autonomous machine is learning capability. Human learning is usually achieved by means of observations and experiences. It is the human memory that provides a knowledge base for integrating present and past observations to perform recognition. Experience is accumulated by exposure to similar past environments, and that exposure could result from repeating the same action. For example, training is a form of learning where experience is gained by repeating a task. When more training is done, and there are more variations in the training, a person becomes more competent in the subject matter.

Several features that make the human learning process unusual are (1) memory size, (2) memory access time, (3) extremely fast data processing, (4) forgetting unimportant information, and (5) attention, or focusing on important information. These same special features are topics of current research. Currently, microprocessor technology is working to achieve larger memory size and faster memory access time. The recent research in neural networks attempts to achieve extremely fast data processing, similar to humans. Research in cognitive science explores how the human-brain utilizes its massive store of information in an effective manner.

Recently, the idea of learning by repetitive motions has been studied and applied to robotic manipulators [1]-[4]. The learning schemes are based on deterministic control theory and used to update driving inputs to manipulator joints. Simulation results have been reported [1]-[3]. This paper presents an extension of the learning controller proposed by Togai and Yamano [4] and shows implementation results on an industrial robot using a fiber-optic infrared distance sensor. In addition to the improved learning scheme, development and integration of the sensor output have formed a new automatic, non-contact technique for object recognition and construction of a three-dimensional image of an unknown surface. These results have many applications in manufacturing processes.

Because vision systems are usually expensive and have relatively long processing time, single-function, inexpensive optical sensors are often more attractive. Single-function optical sensors require little digital processing and can have a high rate of data transmission. In the study reported in this paper, a fiber-optic infrared distance sensor is used.

The information about an object is transferred first to the central processing unit and then used for the two areas of knowledge and control. Specifically, these areas are (1) formulation of experience (knowledge base) and (2) creation of appropriate control signals for direct command of the machine actuators (motion control). In the first area (i.e., gaining experience), knowledge representation schemes play an important role. Frames with attributes corresponding to the possible environments of the machine are defined. The knowledge is classified in terms of those frames and attributes.

The main focus of this paper is on the formatting of data for the second area [i.e., development of command inputs (controls) for machine actuators]. In particular, the emphasis is on the use of learning by repetition to enhance machine performance. The approach is detailed in the following sections by describing how the needed sensory information is acquired, explaining how the learning scheme is formulated, and presenting the implementation on an industrial manipulator.

Optical Sensor

Increasing the intelligence of an automated system demands improvements in the ability to perceive the surrounding environment. Perception in the sensory domain can be divided into coarse sensing and fine sensing. A coarse sensor, such as a camera vision system, examines a large portion of the field of view at low resolution. In such a system, resolution can be increased by increasing magnification, but only at the cost of decreasing the effective field of view. Furthermore, increasing magnification can result in partial blockage of the field of view when the camera is located at some distance from the workpiece. Alternatively, positioning an optical sensor on the end-effector itself can provide high-resolution information over a small area where it is most needed. Seam tracking and brushing of unknown surfaces are examples of situations that would benefit from a sensor on the end-effector.

With appropriate optical design, a simple sensor, based on detection of the reflected light intensity from a surface, can provide distance measurements. Some sensors of this type are dependent on surface reflectivity and tilt, and their operating range is extremely restrictive. However, an optical distance sensor based on light reflectance that is relatively insensitive to target object surface characteristics was designed at Purdue University [5]. This design introduces two light detection paths that receive light reflected from the surface in a slightly different manner than the typical single-detector design. The signals from two detectors are used to compute a relative signal, which is the nor-
malized differential of the two detector outputs, and this allows the calculation of distance information based only on geometric considerations.

This concept was extended further to the optical sensor used in this research and implemented on the industrial manipulator, as shown in Fig. 1. The combined hardware and software for this sensor provide distance information independent of sensor angle within a range of ±25 deg off the normal axis to a surface. Eight infrared detectors and one light-emitting diode are employed in the optical sensor, as shown in Fig. 2. All are in an electrically shielded box remote from the end-effector. The emitter is connected to a cylindrical GRIN (gradient index) lens at the center of the sensor head using a fiber-optic cable. Detector lenses are arranged in two groups of four spaced 90 deg apart around the emitter lens. Voltage outputs of the inner and outer detector rings ($V_i$ and $V_o$) are used in Eq. (1) to calculate an index ($I_{\text{out}}$) that is proportional to the distance between the sensor head and the surface.

$$I_{\text{out}} = \left( \frac{\sum_{i=1}^{4} V_I - \sum_{j=1}^{4} V_O}{\sum_{j=1}^{4} (V_I + V_O)} \right)$$

The summation of the inner and outer sensor voltages is implemented using the Detector Summing Circuit (Fig. 3). An analog-to-digital (A/D) converter is used to read the output of the inner and outer sensor summing circuits. Control of the emitter output is achieved by the Emitter Drive Circuit (Fig. 4) coupled to a digital-to-analog (D/A) converter. The A/D and D/A converters reside in a microcomputer, which controls the emitter and computes sensor distance.

Room lighting can affect the output of the optical sensor. A DC offset and 120-Hz AC ripple were observed in early tests. To reduce these effects, the emitter was modulated and the detector output was high-pass filtered and demodulated. This scheme is currently implemented in software. The

Fig. 1. Robot and sensor system diagram.

Fig. 2. Sensor head design (dimensions in millimeters).
emitter is turned on by a positive voltage from the D/A converter. The computer waits for the detectors to settle and then reads the detector output using an A/D converter. The emitter is then turned OFF, and, after the sensors have settled, the sensor voltages are read again. The sensor ON and OFF voltages are sent to a finite-impulse-response high-pass filter implemented in the software. The difference between the filtered ON and OFF sensor voltages is then used to solve Eq. (1).

The settling time of the detectors (Darlington phototransistors) determines the rate at which the emitter can be modulated. Detector rise and fall times are dependent on incident light intensity. This implies that, as the sensor head moves away from a reflective surface, incident light intensity will decrease, and sensor rise and fall times will increase. Thus, the sensor response time will be faster when it is close to a surface and slower when it is far from a surface. The modulation frequency was chosen to match sensor response time at its maximum range of operation. At a distance of 4 cm, the sensor has a response time of approximately 500 μsec. With the sensor head flush against a normal surface, the sensor response time was measured at 150 μsec. The entire cycle time for making a distance measurement, including modulation and filtering, is 1.5 msec.

In addition to incident light, other factors were found to affect sensor response. As shown in Fig. 3, the photodarlington detectors are coupled to the optical head using plastic fiber-optic cables and GRIN lenses. The quality of the junctions among detector, cable, and lens directly influences sensor response both in time and magnitude. Variations in sensor output magnitude caused by optical junction nonuniformity are corrected by resistors R1, R2, R3, and R4 in the Detector Summing Circuit.

The plastic fiber-optic cable is very flexible, but is less effective than glass fiber in terms of transmitting light to the detectors. The emitter and detector are designed for peak operation at a wavelength of 820 nm. However, a plot of the spectral transmissivity of the plastic fiber-optic cable shows only 40 percent of the 820-nm infrared light being transmitted over a 1-m distance. This limits the length of the fiber that can be employed due to the strong dependence of detector response time noted earlier.

The photodarlington detectors are connected to an operational amplifier, which presents a low-impedance load to the sensor, thus reducing the time constant of the circuit. This helps to achieve the sensor's rated dynamic characteristics. The detector outputs are routed through switches, enabling them to be switched in or out for balancing. Balancing is achieved using potentiometers R1, R2, R3, and R4. Circuit gain is controlled by resistor R6 and potentiometer R5. A potentiometer is used so that the inner and outer sensor summations can be balanced. Output from this circuit is read by an A/D converter on the host computer. The Emitter Drive Circuit controls the amount of current through the infrared-emitting diode. Resistor R7 limits the current, and resistor R8 determines the gain. Input to the circuit is via a D/A converter on the host computer.

Learning Control Scheme

The control scheme is composed of several subroutines, with each assigned to a specified task. For general operation of the manipulator, the following seven tasks should be performed: (1) path planning, (2)
trajectory generation, (3) calibration, (4) learning system parameters, (5) learning about environmental dynamic interactions, (6) commanding movements of different joints, and (7) mapping of sensory information onto usable feedback-control signals.

Whereas the research has dealt with all seven of these aspects, only the portion related to the learning task is presented in this paper. Details of other schemes are presented in [6]. More specifically, assume that the path planning and trajectory generation in \( x, y \) are done, and the objective is to keep a constant \( z \) distance normal to the surface of an object. Therefore, if an unknown surface is to be tracked, the robot would move in a planned \( x, y \) motion while keeping a constant \( z \). From the instantaneous \( x, y, z \) information of the end-effector, the unknown surface can be created. The major question is how much movement should be generated at each joint so that the normal distance in the \( z \) direction is kept constant. In other words, how much control voltage should be given to each actuator of the manipulator? As mentioned earlier, the optical sensor provides information about the normal distance to the surface. Therefore, the control scheme should provide the input voltage to the actuator based on the sensor information. At the same time, it should learn from past experience and provide a more optimal input control that minimizes possible errors and/or overshoots.

The learning scheme based on experience was proposed by Kawamura et al. [1]. Their idea was to have the robot repeat a motion several times and use the errors from each iteration for enhancement of performance in the next iteration. Figure 5 shows a block diagram of this learning scheme. Convergence to the desired state based on this scheme is guaranteed by the following analysis.

Assume that the response of a time-varying system, \( x(t) \), at the \( i \)th iteration is given by the following equation for \( x_{i}(t) \), and the error between the desired response, \( x_{d}(t) \), and the actual response at the \( i \)th iteration is defined as \( e_{i}(t) \).

\[
x_{i}(t) = g(t) + \int_{0}^{t} h(t, \tau) u_i(\tau) d\tau \quad (2)
\]

\[
e_{i}(t) = x_{i}(t) - x_{d}(t) \quad (3)
\]

The control input, \( u_i(t) \), at the next iteration is related to the control value of the current iteration by the following equation, where the control input has been written in discrete form.

\[
u_{i+1}(k) = u_i(k) + G e_i(k + 1)
\]

\[
\frac{1}{T} H[e_i(k + 1) - e_i(k)] \quad (4)
\]

Namely, the learning effort in the next trial is the sum of previous trial effort, a proportional learning effort, and a derivative learning effort. In Eq. (4), \( G \) and \( H \) are proportional and derivative learning gain matrices. They may be time varying or constant. In the case of variables \( G \) and \( H \), we refer to the scheme as "adaptive learning control." Figure 5 shows a block diagram of the control loop for an autonomous machine. In order to show that this learning format yields complete learning after the required number of trials, one needs to show that the learning error, \( e_i(k) \), goes to zero as the number of trials, \( i \), increases substantially.

If the discrete form of Eq. (2) is written for the \( i \)th and \( (i+1) \)th iterations and substituted in Eq. (3) to evaluate the error at these two iterations, then the following equation can be derived, where the usual properties hold for the transition matrix \( \Phi \).

\[
e_{i+1}(k + 1) - e_i(k + 1)
\]

\[
= - \sum_{j=0}^{k} \Phi(k + 1, j + 1)
\]

\[
\cdot B(j)[u_{i+1}(j) - u_i(j)] \quad (5)
\]

Substituting Eq. (4) into Eq. (5) and separating the \( G \) and \( H \) components of the summation and the last term of the \( G \) component gives the following, where \( e_i(j + 1) = e_i(j + 1) - e_i(j) = \epsilon_i(j) \).

\[
e_{i+1}(k + 1)
\]

\[
= e_i(k + 1) - A(k) \sum_{j=0}^{k-1} \Phi(k, j + 1)
\]

\[
\cdot B(j) [u_{i+1}(j) - u_i(j)]
\]

\[
+ B(k) G e_i(k + 1)
\]

\[
- B(k) G e_i(k + 1) - A(k) \sum_{j=0}^{k-1} \Phi(k, j + 1)
\]

\[
\cdot B(j) H [e_{i+1}(j) - e_i(j)] \quad (6)
\]

In order to guarantee learning completion, i.e., \( e_{i+1}(k) \) is less than \( e_i(k) \), Eq. (6) must be analyzed. By considering the largest values of the terms in this equation over all components at a given time step, upper bounds for the learning gains can be obtained. This is achieved by taking the Euclidean norm on both sides of Eq. (6).

\[
||e_{i+1}(k + 1)|| 
\]

\[
\leq \left\{ ||I - B(k) G|| + ||A(k)|| \sum_{j=0}^{k-1} \Phi(k, j + 1) \right\} ||e_i(k + 1)|| + \left\{ ||A(k)|| \sum_{j=0}^{k-1} ||\Phi(k, j + 1)|| \cdot B(j) H ||e_i(k + 1)|| \right\}
\]

Equation (7) now can be rewritten as

\[
||e_{i+1}(k + 1)|| \leq \rho ||e_i(k + 1)|| \quad (8)
\]

where

\[
\rho = \alpha + \beta ||e_i(k + 1)||/||e_i(k + 1)||
\]

and

\[
\alpha = ||I - B(k) G|| + ||A(k)|| \sum_{j=0}^{k-1} ||\Phi(k, j + 1) B(j) G||
\]

\[
\beta = ||A(k)|| \sum_{j=0}^{k-1} ||\Phi(k, j + 1) B(j) H||
\]

In order to achieve complete learning, the \( G \) and \( H \) matrices have to be chosen such that \( 0 < \rho < 1 \). It should be noted that in the case of learning effort being dependent on the error only and not its derivative, i.e., \( H = 0 \), the preceding results reduce to those of Togai and Yamano [4]. Furthermore, if the original \( A \) matrix is stable, i.e., \( ||A(k)|| < 1 \), then the maximum convergence speed can be obtained when the norm \( ||I - B(k) G|| \) is zero. This is because for a stable \( A \) matrix, after a large number of iterations, \( \alpha \) would approach \( I - BG \). It can be seen from Eq. (8) that the smaller \( \alpha \) the faster the convergence, resulting in better learning. By an appropriate choice of \( G \) and \( H \), one can make \( \rho \) to be less than 1. However, if the machine operates under high-speed conditions with
maneuvering from low accelerations to high accelerations in different directions, then \( \|\dot{\gamma}(j + 1)\| \) may be very large. This is the case where an infinite acceleration is physically required. For example, having a robot end-effector maneuver around a 90-deg corner requires very high acceleration. In such cases, it is better to lower the proportional learning gain to prevent any overshoots, but increase derivative gain to compensate for speed of response. In this case, an adaptive learning scheme is required [7].

It should be noted that the robustness of this scheme depends on the choice of the \( G \) and \( H \) matrices. If the \( A \) and \( B \) matrices include unmodeled dynamics, the learning scheme would converge provided the system is stable. Furthermore, as a result of implicit accumulation in the formulation of control input, the noise effects can be eliminated provided noise is stationary and has a zero mean.

In terms of the manipulator control, Eq. (4) provides the next iteration control input for every joint in terms of the previous control and the feedback of the angular position and angular velocity of that joint. In order to synchronize the three functions, i.e., learning process, path planning, and the manipulator motion, three counters are used in the control scheme. Therefore, the overall control scheme goes through the following steps:

1. Read stored x-y plane path and desired z distance.
2. Read in the learning scheme coefficients \( G \) and \( H \).
3. Move the end-effector to the start of the planned path.
4. Activate all counters.
5. Activate the learning scheme.
6. Save the data and go back to step 2.

Activation of the learning scheme in step 5 requires seven substeps: (a) read in the last point in the path, (b) obtain the current joint positions and velocities, (c) calculate the next step control input, (d) find the error in the z direction, (e) calculate the current z position, (f) use inverse kinematics to find joint information, and (g) calculate the next iteration control input for every joint. It should be noted that, because of the learning control structure, only one "pass" of control inputs is required to be stored for calculation of the next pass input.

**Experimental Results**

The preceding learning control scheme combined with the optical sensor was implemented on the GE-P50 robot. The objective was to track different unknown surfaces generated by the adjustable surface fixture shown in Fig. 6. This mechanism provides flexibility in forming different shape surfaces. It can provide a sinusoidal surface with peak-to-peak amplitude of 25 cm, with the peaks being separated by as much as 40 cm. The results are very satisfactory. They are presented in terms of how well the manipulator can track the surface and, by increasing the number of iterations, how well the learning is achieved. Figure 7 shows the results of the learning scheme on the reconstruction of a sinusoidal surface. The manipulator starts its motion from one side of the surface and tries to keep a 2-cm distance in the vertical direction, from the surface at all times. One of the system counters is used to develop a linear point-to-point path for the end-effector motion, and the distance error at each point of the path is recorded in the memory of the controller. Initially, constant learning gains were used, but it took more than 10 iterations for the robot to recognize the surface. Therefore, adaptive gains, which vary proportionally to the error and its derivative, are used. As shown, after seven iterations, the surface is very well learned. Figure 8 shows three-dimensional images of other variations of the flexible surface. In this case, the surface in the x direction is divided by the robot controller into a set of stripes. The controller moves the end-effector 1 cm forward in the x direction every time it goes through one pass in the y-z plane. The learning controller has been able to reconstruct the surface shape very accurately even though constant learning gains are used. If variable gains were used, a reduction in the number of trials over the surface would have resulted.

**Conclusion**

In an effort to proceed further toward the development of an autonomous machine, a learning controller was developed that utilizes past experience and current error in system states to calculate input for the next iteration. An optical sensor using a single emitter and eight detectors provides information regarding environmental variations to the controller. This study shows the feasibility of integrating optical sensory information and a learning scheme to develop more intelligence for industrial manipulators and to adapt to unexpected events. Furthermore, the results of this study can help lead to control schemes for processes such as automatic brushing, deburring, painting, and seam tracking. Such a control scheme could also be implemented in high-precision automatic measurements and for knowledge-based development about unknown surfaces and objects.

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References


Rahmat Shoureshi is an Associate Professor and Chairman of the Manufacturing and Material Processing area in the School of Mechanical Engineering at Purdue University. He completed his graduate studies at the Massachusetts Institute of Technology in 1981. His research interests include active and semiactive control of distributed parameter systems, including flexible structures (e.g., automobiles and aircraft) and acoustic plants; intelligent control and diagnostic systems using analytical/symbolic processors and neural networks; and manufacturing automation, including autonomous machines and robotic manipulators. He is the recipient of the 1987 American Automatic Control Council Eckman Award for outstanding contributions to the field of automatic control. Currently, he is involved in several industrial and government research studies.

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Warren Stevenson is a Professor and Chairman of the Systems, Measurement, and Control Group in the School of Mechanical Engineering at Purdue University. His research is directed toward applications of optical methods for measurement. He was one of the early workers in the field of laser velocimetry and has applied this technique to studies of fluid flow, combustion, and solid surface motion. Presently, much of his research is concerned with studies of optical sensors for automated systems. He has been active professionally in the optics community and is the 1989 President of the Laser Institute of America.

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