Use of Sensors in Programmable Automation*

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Technical Note 122

Introduction

If previous studies[1-4] are any indication, there is a national need to develop advanced automation techniques to increase industrial productivity and to enhance the well-being of workers by eliminating hard, dangerous, and dull jobs. Although an ultimate goal might be a completely automated factory in which design, planning, scheduling, and manufacturing are all under computer control, automation will probably evolve slowly with the development of the appropriate technology.

One day, however, repetitive jobs in labor-intensive operations will be performed by computer-controlled machines supervised by a small, highly trained group of operators who will set up and program each job, modify procedures to fit the particular circumstances, change over for new batches or models, maintain the equipment, and cope with breakdowns and stoppages. Thus, the system will "time-share" the operators, augmenting their capacity to do useful work by relieving them of the need to perform relatively low-level jobs that can best be done by machines.

In this paper we are concerned with the application of sensor-mediated programmable automation to material-handling, inspection, and assembly operations in batch-produced, discrete-part manufacturing. These operations, which are still highly labor-intensive, have been estimated to represent over half the total cost of product manufacturing costs in the United States.[1]

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Programmable automation consists of a system of multidegree-of-freedom manipulators (commonly known as industrial robots) and sensors under computer control, which can be programmed, primarily by software, to perform specified jobs in the manufacturing process and can be applied to new (but similar) jobs by reprogramming. The capabilities of such programmable systems differ sharply from those of conventional "fixed" or "hard" automation systems, in which special-purpose machines are designed to perform only specific repetitive tasks. This is particularly important where production runs are small and where different models may have to be produced frequently.

Most industrial robots in use today are point-to-point manipulators, which perform a variety of "pick and place" material-handling jobs and spot welding. The remaining industrial robots are continuous-path manipulators, which are used in arc welding, paint spraying, and so on. A major limitation of these manipulators is their primitive sensory feedback.[5] In particular, commercially available industrial robots have neither contact sensors (force, torque, and touch sensors) as aids to manipulation, nor noncontact sensors (visual and range sensors) as aids to recogniton, inspection, or manipulation of workpieces. Extensive research in machine intelligence, a branch of computer science, has provided tools, techniques, and concepts that are directly relevant to this class of problems. This work originated in a number of "hand-eye" and robot programs[6-13] that developed and demonstrated fairly complex systems of integrated effectors and sensors to guide a manipulator by using computer-processed contact and noncontact sensory feedback.

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However, machine intelligence research has been primarily directed at finding general methods that demonstrate principles, and relatively little attention has been paid to questions of computational cost and program complexity—questions that are of major importance to industrial applications. For example, the goal of most visual scene-analysis programs has been the identification of all the objects in a scene, regardless of orientation, with parts of some objects occluded by other objects, and under varying and rather difficult illumination conditions. Under these conditions computer programs that can barely cope with fairly simple scenes are huge, difficult to code and modify, and time consuming; hence, they require large computers. On the other hand, recognition of a relative small number of parts, one at a time against a controlled background and under controlled illumination, can be accomplished by algorithms that will run quickly on a small computer.

Experienced machine-intelligence scientists have just begun to apply their knowledge to the constrained and therefore simplified problems of programmable automation in the factory. A number of research and development programs[14-18] are now in being with the specific goals of exploring, applying, and expanding machine-intelligence techniques and concepts to programmable automation. Concurrently, inexpensive yet powerful minicomputers and microcomputers are now becoming available, making it possible to control integrated sensor-manipulator systems that can be economically justified.

Needs for sensors

Extending the present capabilities of "pick-and-place" industrial robots will require a considerable improvement in their capacity to perceive and interact with the surrounding environment. In particular, it is desirable to develop sensor-mediated, computer-controlled interpretive systems that can emulate human capabilities. To be acceptable by industry, these hardware/software systems must perform as well or better than human workers. Specifically, they must be inexpensive (provide an acceptable return on investment), fast (comparable to average speed of human workers), reliable (error and failure rates considerably lower than those of humans), and suitable for the factory environment.

Sensor needs can be broadly divided into three areas of application: visual inspection, finding parts, and controlling manipulation.

Visual inspection. Here we are concerned only with an important subset of visual inspection: the qualitative and semiquantitative type of inspection performed by human vision rather than by measuring instruments. Such inspection of parts or assemblies includes identifying parts; detecting of burrs, cracks, and voids; examining cosmetic qualities and surface finish; counting the number of holes and determining their approximate locations and sizes; assessing completeness of assembly; and so on. Sensory methods being developed for augmenting industrial robot systems can also be applied effectively to inspection that requires accurate mensuration, but these applications will not be considered here.

Visual inspection occupies many workers in factories. *Explicit* inspection, performed by workers whose sole job is to inspect parts, subassemblies, and assemblies, has been estimated to represent approximately 10 percent of the total labor cost for all durable goods.[19] This cost is second only to that of assembly operations, which is approximately 22 percent of the total cost. It is fair to assume that the majority of these inspection tasks are done visually.

Implicit visual inspection is performed by assemblers to ascertain that the assembled workpieces are the correct ones, are complete, and have not been damaged. This task represents a small but essential part of the assembly function. Adding defective or wrong workpieces to an assembly that may have acquired a considerable value will produce costly scrap or require expensive correction later.

The wide variety of significant characteristics that are routinely examined visually by humans indicates the complexity of the processing that must be performable by automated systems. It is evident that a large library of computer programs will have to be developed to cope with the numerous classes of inspection. To avoid the lengthly and costly programming for every new inspection job, this library must be made generally available to all manufacturing industries.

Finding parts. Where fixed or hard automation is justified for high-volume mass production, workpieces must be positioned and oriented with considerable precision, usually at high cost for special jigging. For material-handling and assembly operations in the unstructured environment of the great majority of factories, it will probably be necessary to "find" workpieces—that is, to determine their positions and orientations and sometimes also to identify them. It is possible to preserve workpiece orientation throughout the manufacturing process by suitable jigging or special palletizing. However, the cost entailed with this approach may not be justified, especially if batches are small or product modifications are frequent.

For example, present industrial robots cannot cope with the problem of picking up parts, one at a time, from a bin containing many randomly oriented parts. Such bins are used for temporary storage and for transportation of parts from station to station in many factories. It is highly unlikely that a very expensive replacement for this function will be implemented in most factories, especially for small batches or for parts that emerge from processes that inherently produce disorder, such as tumble polishing and plating.[20]

The inability of existing industrial robots to adapt to random positions and orientations of parts greatly limits their usefulness in material-handling and assembly operations. Further, if robot systems are to replace people currently doing these jobs, then these systems must also be able to perform the kind of qualitative and semiquantitative inspection tasks described previously. Thus, it is necessary to augment existing robots with visual sensors to be able to determine the identity, position, and orientation of parts and to perform visual inspection as needed. Up to the present, such sensors have been optical or electro-optical and have consisted of television cameras (vidicon and solid state) and several types of scanning systems that measure intensity and range data.

Controlling manipulation. Manipulation of workpieces and tools for material handling and assembly jobs requires many basic operations, such as grasping, holding, orienting, inserting, aligning, fitting, screwing, turning, and so on. In a completely structured environment it may be possible to perform all these operations in a feed-forward manner with no sensory control or correction needed.

It is instructive to note that human manipulation, being imprecise, depends almost entirely on sensory feedback to control both simple and complex manipulative operations. In general, the human worker makes use of both noncontact (visual) sensing and contact (force, torque, or touch) sensing. There is little doubt that a blind worker can perform many manipulative tasks using contact sensing alone. However, he cannot easily perform most inspection functions, cannot readily cope with unexpected instrusions into his work space, and would generally require a far more structured situation to equal the performance of a sighted worker.

On the basis of these observations, it appears useful to consider the use of both contact and noncontact sensors in manipulator control and to try to assess where each sensor is most appropriate. One approach is to divide the sensory domain into coarse and fine sensing, using noncontact sensors for coarse resolution and contact sensors for fine resolution. For example, in acquiring a workpiece that may be randomly positioned and oriented, a visual sensor may be used to determine the relative position and orientation of the workpiece rather coarsely, say, to one tenth of an inch. From this information the manipulator can be positioned automatically with a precision matching that of the visual sensor. The somewhat compliant fingers of the manipulator hand, bracketting the workpiece, will now be close enough to effect closure, relying on touch sensors to stop the motion of each finger when a specified contact pressure is detected. After contacting the workpiece without moving it, the compliant fingers have flexed no more than a few thousandths of an inch before stopping. The touch sensors have thus performed fine resolution sensing and have compensated for the lack of precision of both the visual sensor and the manipulator. This task, which is quite common, illustrates the relative merits of each sensory modality and the advantages of using both. It appears likely that the combined use of these sensors and the associated computer hardware and software will be cost effective within a short time.

Other common applications for contact sensors, which implicitly entail fine resolution or precision sensing, include:

- Collision avoidance, using force sensors on the links and hand of a manipulator. Motion is quickly stopped when any one of preset force thresholds is exceeded.
- Packaging operations in which parts are packed in orderly fashion in tote boxes. Force sensors can be used to stop the manipulator when its compliantly mounted hand touches the bottom of the box, its sides, or neighboring parts. This mode of force feedback compensates for the variability of the positions of the box and the parts and for the small but important variability of the manipulator positioning.
- Insertions of pegs, shafts, screws, and bolts into holes. Force and torque sensors can provide feedback information to correct the error of a computer-controlled manipulator. Again, one may first use visual sensors with relatively coarse resolution to find the hole, bring the peg to an edge of the hole (perhaps partially inserted), and then align the peg with the hole by moving in a direction that minimizes the measured binding force and torque.

By reducing the field of view, it is possible to increase the resolution of noncontact sensors to approach that of contact sensors. This method may be too slow because of the large number of fields required to cover a given area of interest and the excessive amount of computation. However, this limitation may be overcome by using a fixed, wide field of view to find the target and a movable, narrow field of view to obtain high resolution. Alternatively, mounting a small optical sensor on the hand of a manipulator will provide reasonably high resolution over the small but very important field of view close to where it is most needed. It would then be possible for the manipulator to follow especially identified lines, or to control its motion based on the location of holes or fiduciary marks. It is likely that this "eye-in-hand" mode of operation can be applied successfully to situations that require positioning of intermediate precision.

Contact sensors

As discussed earlier, contact sensing of force, torque, and touch can be usefully combined with visual sensing for many material-handling and assembly tasks. For certain classes of manipulation, however, visual sensors will not be used.[21,22] Here are some examples:

- The workpieces cannot be seen because of occlusion or lack of sufficient light.
- The visual sensors are busy doing other tasks.
- Instances in which processing of contact sensory data is simpler or faster than that of visual sensory data.

The functions of contact sensors in controlling manipulation may be classified into the following basic material-handling and assembly operations:[21,23]

- Searching—detecting a part by sensitive touch sensors on the hand exterior without moving the part.
- Recognition—determining the identity, position, and orientation of a part, again without moving it, by sensitive touch sensors with high spatial resolution.
- Grasping—acquiring the part by deformable, roundish fingers, with sensors mounted on their surfaces.
- Moving—placing, joining, or inserting a part with the aid of force sensors.

Force and torque sensors. There are basically three methods for sensing forces (and torques) for controlling a manipulator, depending on their location:

- Measuring the forces acting on the joints of the manipulator without adding special sensors.
- Measuring the forces acting between the last link of the manipulator and its hand by means of a wrist force sensor.
- Measuring the force exerted by the manipulator hand on a workpiece by means of a separate pedestal sensor.

Measurement of joint forces and torques. The force and torque acting on each joint of a manipulator can be sensed directly. If the joint is driven by an electric dc motor, then sensing is done by measuring the armature current; if the joint is driven by a hydraulic motor, then sensing is done by measuring the back pressure. Two examples in which joint forces were measured follow.

Inoue[24] programmed a manipulator to insert a peg into a hole, using force sensing at the manipulator joints. Paul[25] programmed the Stanford arm to assemble a water pump consisting of a base, a gasket, a top, and six screws. Joint forces were computed from measurements of motor currents. His program included compensation for gravity and inertial forces. Force feedback was used to locate holes for inserting two pins that were later used to align the gasket.

Sensing joint forces directly has the advantage of not requiring a separate force sensor. However, the force (or torque) between the hand and its environment is not measured directly. Thus, the accuracy and resolution of this measurement are adversely affected by the variability in the inertia of the arm and its load and by the nonuniform friction of the individual joints.[26]

Wrist force sensors. A wrist force sensor measures the three components of force and three components of torque between the hand and the terminal link of the manipulator. Basically, a wrist force sensor consists of a structure with some compliant sections and transducers that measure the deflection of the compliant sections along three orthogonal axes as a result of the applied force and torque. There are different types of force transducers, such as strain gage, piezoelectric, magnetostrictive, magnetic, and others.[21-27] The most common of these is the strain-gage transducer, which is inexpensive, reliable, and rugged.

A wrist sensor employing four beams with ball joint mounts and strain gages was built at Draper Laboratory and found by Groome[28] to have a resolution of only 4 binary bits because of hysteresis in the ball joints. Goto[29] built a compliant wrist force sensor with cross springs and strain gages and used the sensor to control insertion of a 1/2-inch-diameter polished cylinder into a vertical hole with 7- to 20-micron clearance in less than 3 seconds. The insertion operation was based on two types of compliance: active compliance, whereby sensed forces are used to command the manipulator to correct positional or orientational errors, and passive compliance, whereby such errors are corrected by the reaction forces between the workpieces.

Figure 1 illustrates a typical strain-gage wrist force and torque sensor. The sensor, with seven-bit resolution, was built at Stanford Research Institute[14] for the Stanford arm. The sensor is made of a milled 3-inch-diameter aluminum tube, having 8 narrow elastic beams with no hysteresis. The neck at the end of each beam transmits a small bending torque and thus increases the strain at the other end of the beam where two foil strain gages (shown as black rectangles) are cemented. The two strain gages are connected to a potentiometer circuit whose output is proportional to a force component normal to the strain-gage planes, and is automatically compensated for variation in temperature.

The wrist sensor measures the three components of force and three components of torque in a Cartesian coordinate system (x, y, z) attached to the manipulator hand. As shown in Figure 2, the hand coordinates x, y, and z are also called, respectively, "lift," "sweep," and "reach," when referring to forces or translations, and "turn," "tilt," and "twist" when referring to torques or rotations.

A wrist force sensor made of milled aluminum cylinder and foil strain gages cemented to beams was built by Watson and Drake.[30] Using extensional strain gages and strain-gage shear bridges, they were able to use only three beams.

A hand with sensors for a Unimate manipulator performing material handling was built by Hill and Sword.[14,31] The sensors included a wrist force sensor, using compliant elements and potentiometers to sense the relative displacement of the hand, as well as touch and proximity sensors. Figure 3 shows a sequence of actions illustrating the use of this hand in orderly packing of water pumps into a tote box: The Unimate moves rapidly to a previously taught starting position (a) and then moves slowly down until a threshold z force is sensed (b), up 1/2 inch, along the $-x$ direction until a threshold x force is sensed (c), along the $+x$ direction 1 inch, along the $+y$ direction until a y threshold is sensed, along the $-y$ direction 1/2 inch, and down until a threshold z force is sensed (d); it then opens the fingers to release the pump and moves quickly to acquire the next pump (e).

Pedestal force sensor. A pedestal force sensor, forming a base for assembly operations, was also built by Watson and Drake.[22,30] The sensor measures the three components of force and three components of torque that are applied to a workpiece mounted on the pedestal.

The pedestal force sensor is shown in Figure 4. Its frame consists of three aluminum plates, about 40 cm square and 2.5 cm thick. The middle plate is connected to the top plate by four strain-gage force transducers that are set vertically and to the bottom plate by four similar transducers that are set horizontally. The sensor has a 4000:1 dynamic range (12-bit resolution). It was used at Draper Laboratory to perform peg-in-hole experiments.

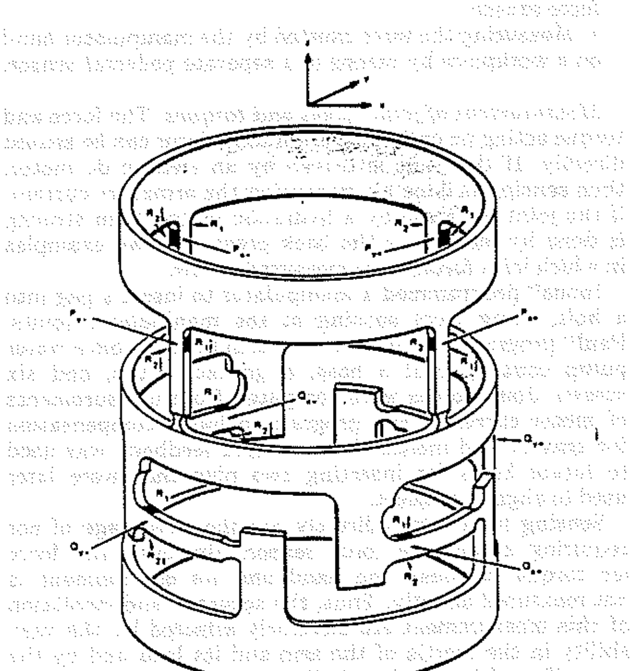

Figure 1. Strain gage wrist sensor.

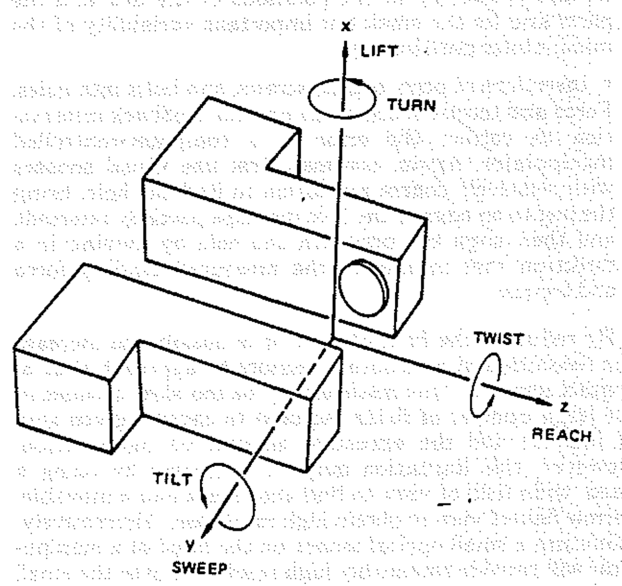

Figure 2. Hand coordinates.

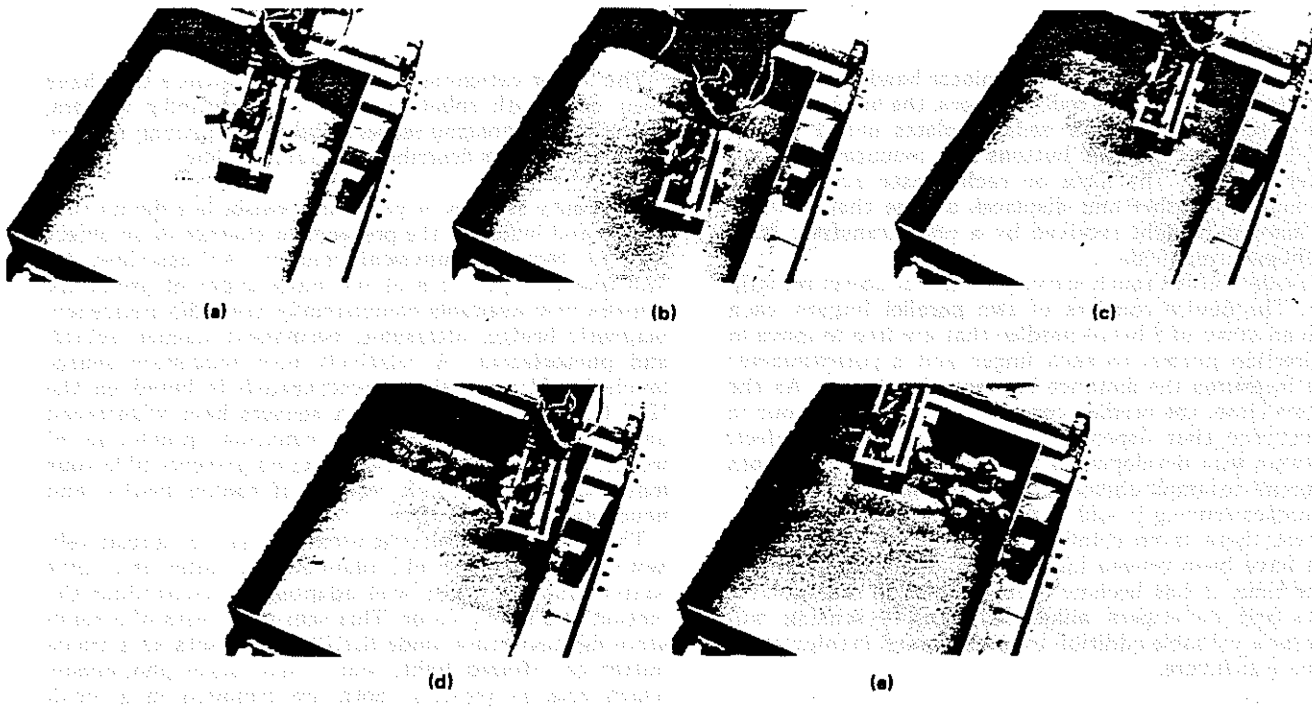

Figure 3. Force sensor control of manipulator hand in pump packing.

Touch sensors. Touch sensors are used to obtain information associated with the contact between the finger(s) of a manipulator hand and objects in the workspace. They are normally much lighter than the hand and are sensitive to forces much smaller than those sensed by the aforementioned force sensors.

Touch sensors may be mounted on the outer and inner surfaces of each finger. The outer sensors may be used to search for an object and possibly determine its identity, position, and orientation. Outer sensors may also be used for sensing unexpected obstacles and stopping the manipulator before any damage can occur. The inner mounted sensors may be used to obtain information about an object before it is acquired and about grasping forces and workpiece slippage during acquisition.

Touch sensors may be classified into two types, binary and analog.

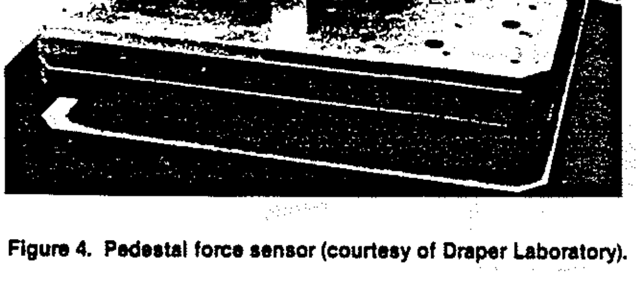

Figure 4. Pedestal force sensor (courtesy of Draper Laboratory).

Binary touch sensors. A binary touch sensor is a contact device, such as a switch. Being binary, its output is easily incorporated into a computer controlling the manipulator.

A simple binary touch sensor consists of two microswitches, one on the inner side of each finger. Paul[25] used such a sensor to determine whether a part was present or absent and to center the hand over it during automated assembly of a water pump. With the addition of a position potentiometer that measures the distance between the two fingers, this primitive sensor can also be used to classify a small set of parts by determining some of their dimensions.

Ernst,[6] who pioneered sensor-mediated manipulation under computer control, built a two-fingered hand with both binary and analog touch sensors. However, he later found that binary touch sensors were far more useful and he used the analog touch sensors primarily as binary sensors.

Goto[23] built a hand with two fingers, each having 14 outer contact sensors and 4 inner, pressure-sensitive, conductive-rubber sensors. He used the touch information to acquire blocks randomly located on a table and pack them tightly on a pallet.

Garrison and Wang[32] built a gripper with 100 pneumatic snap-action touch sensors located on a grid with 0.1- by 0.1-inch centers. The sensors consisted of contact terminals, a thin metal sheet with elastic shallow spherical domes, and a flexible insulating rubber sheet on the outside. Physical contact is sensed when external pressure exceeds a preset threshold, causing the activation of a snap-action switch consisting of a dome and a terminal.

Analog touch sensors. An analog touch sensor is a compliant device whose output is proportional to a local force. Analog touch sensors are usually mounted on the inner surface of the fingers to measure gripping forces and to extract information about the object between the fingers.

Hill and Sword[26] built a manipulator hand with a wrist force sensor and analog touch sensors: the hand is shown in Figure 5. Seven outer sensing plates and a matrix of 3-by-6 inner sensing buttons are mounted on each finger (or jaw). The force on each sensor acts against a compliant washer and displaces a vane that controls the amount of light received by a phototransistor from a light-emitting diode.

Takeda[13] built a touch sensing device for object recognition. The device consists of two parallel fingers, each with an array of 8-by-10 needles that are free to move in a direction normal to each finger and a potentiometer that measures the distance between the fingers. As the fingers close, the needles contact the object's contour in a sequence that depends on the shape of the object. Software was developed to use the sensed touch points to recognize simple objects, such as a cone.

Contact sensing is still in a highly experimental stage. As yet there is no commercial line of contact sensors that have been proved in industrial application. At the same time, it has become quite evident to manipulator users and developers alike that contact sensing will become a valuable addition to programmed manipulation in the near future.

Noncontact sensors

As previously discussed, noncontact sensors are potentially useful in identifying and finding parts in sensor-controlled manipulation and in visual inspection.

The major categories of noncontact sensors that have been used with robot systems are proximity sensors, electro-optical imaging sensors, and range-imaging sensors. These sensors are described separately below.

Proximity sensors. A proximity sensor is a device that senses and indicates the presence or absence of an object without requiring physical contact. As described by *Machine Design*,[34] five of six major types of proximity sensors now available commercially are radio frequency, magnetic bridge, ultrasonic, permanent-magnet hybrid, and photoelectric. A relatively new solid-state sensor (made by Micro Switch Incorporated) is based on the Hall Effect. These noncontact sensors have widespread use, such as for high-speed counting, protection of workers, indication of motion, sensing presence of ferrous materials, level control, reading of coding marks, and noncontact limit switches.

The modern photoelectric proximity sensor, a relatively new version of the old photoelectric tube and light source, appears to be well adapted for controlling the motion of a manipulator. This sensor consists of a solid-state light-emitting diode (LED), which acts as a transmitter of infrared light, and a solid-state photodiode, which acts as receiver: both are mounted in a small package. As shown in Figure 6, the sensitive volume is approximately the intersection of two cones in front of the sensor. This sensor is not a rangefinder because the received light is not only inversely proportional to the distance squared but is also proportional to the target reflectance and the cosine of the incidence angle, both

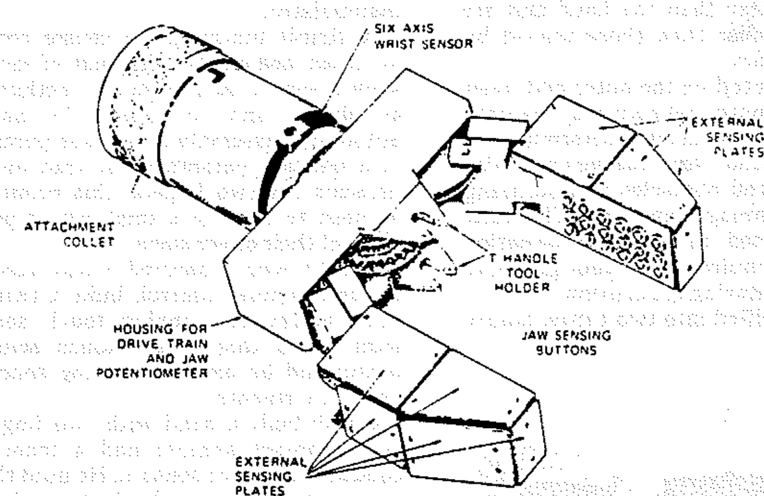

Figure 5. Hand with wrist force sensor and analog touch sensors.

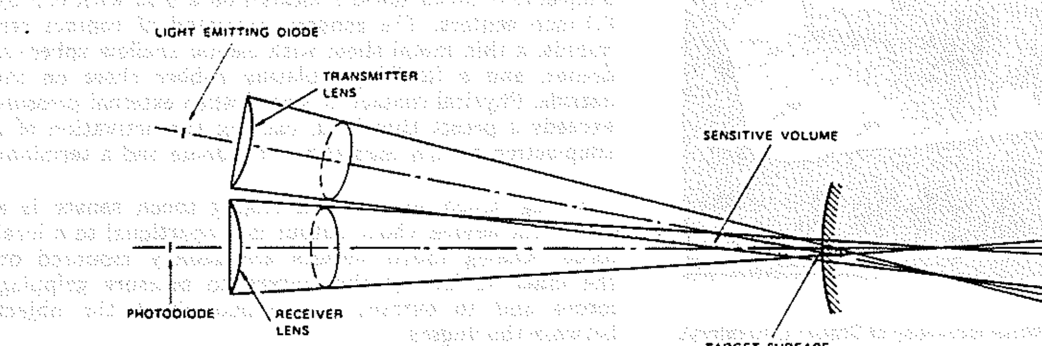

Figure 6. Proximity sensor.

of which may vary spatially. However, if the reflectance and incidence angle are fixed, then the distance may be inferred with suitable calibration. Usually, a binary signal is generated when the received light exceeds a threshold value that corresponds to a predetermined distance. Furthermore, the sensor will detect the appearance of a moving object in a scene by sensing the change in the received light. Such devices are sensitive to objects located from a fraction of an inch to several feet in front of the sensor.

A proximity sensor, interfaced to a control computer, was used to stop the motion of an industrial robot in its approach to within a predetermined distance of a given solid surface.[14] If a "stop" signal to the moving hand is initiated before contact with the surface is made, there is time to stop the industrial robot without damage. This is far superior to the use of a mechanical limit switch for manipulator protection.

A more interesting application of multiple photoelectric proximity sensors used to control the positioning of a manipulator is described by Johnston.[35] Lateral positioning of a hand was controlled by signals from two sensors to center the hand over the highest point of an object. Bejczy[36] described the potential use of proximity sensors for three-dimensional control of the hand and suggested several control algorithms.

Electro-optical imaging sensors. Until recently, electro-optical imaging sensors have provided the most commonly used "eyes" for industrial robots and visual inspection. Standard television cameras, using vidicons, plumbicons, and silicon target vidicons, have been interfaced with a computer and have provided the least expensive and most easily available imaging sensors. These cameras scan a scene, measure the reflected light intensities at a raster of, say, 320-x-240 pixels (picture elements), convert these intensity values to analog electrical signals, and feed this stream of information serially into a computer—all within 1/60 of a second. These signals may be either stored in the computer core memory for subsequent processing or processed in real time "on the fly," with consequent reduction of memory requirements.

In the past few years several solid-state area-array cameras, competitive with the above vacuum tube type of television cameras, have become commercially available. These small, rugged, and potentially reliable cameras are fabricated using modern large-scale-integration silicon technology and will probably become the dominant electro-optical sensors for industrial applications. The photo-active chip of an area-array camera consists of photodiodes, usually charged-coupled devices,[17] whose number at present varies from 32x32 to 320x512 for different requirements of resolution. These cameras operate in a raster-scan mode, similar to that of the vidicon television cameras, and produce two-dimensional images of scenes.

A one-dimensional solid-state camera, using a linear diode array that varies from 16 to 1872 elements, is also available commercially. This device can perform a single linear scan and is very useful for sensing objects that are in relative motion to the camera, such as workpieces moving on a conveyor belt. An example is shown in Figure 7, where a connecting rod moves past the viewing station and top-view and side-view linear scans are performed by two linear diode arrays, each scan initiated by a repetitive signal from a position sensor (incremental encoder) that is coupled to the moving conveyor belt. For each scan, values of light intensity at a fixed number of discrete points are measured, converted into electrical signals, and sent to a computer. These signals are either processed in real time or stored in memory until the image of the entire workpiece is obtained for subsequent processing.

Another large class of electro-optical sensors, which differ in several important characteristics from the above cameras, has been used primarily in advanced "hand-eye" artificial intelligence research projects.[7-9] These sensors include the image dissector camera, the cathode-ray flying spot scanner, and the laser scanner. They have been described and compared with the more common vidicon type of television cameras in reviews by Earnest[38] and Chien and Snyder.[39] These electro-optical sensors can be programmed to image selected areas of the field of view in a random access manner, as contrasted with the prescribed "raster scan" acquisition of the ordinary television camera. In many instances this method of operation permits the acquisition, storage, and processing of only the relevant data in a field of view. The image dissector,

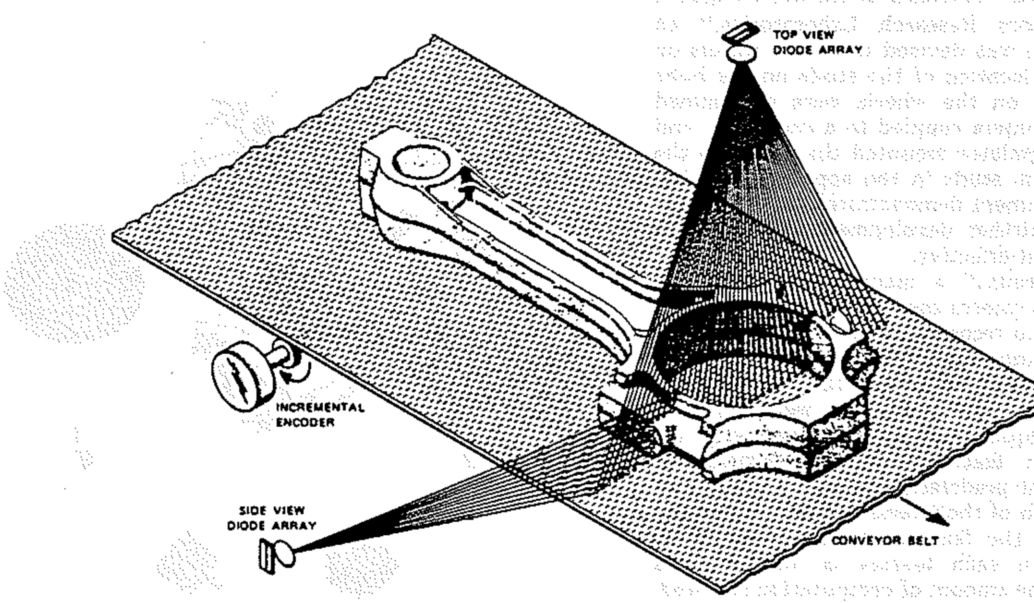

Figure 7. Obtaining orthogonal views of a moving part by two linear diode arrays.

however, has low sensitivity, requiring high levels of illumination, and is relatively expensive; for these reasons it has not attained widespread acceptance. Nevertheless, one commercial company[40] has adapted the image dissector for visual inspection and recognition and alignment of parts, and claims to be able to make noncontact measurements to a precision of less than 1 micron and to recognize and determine position of parts at speeds of 1000 frames per second.

As noted previously, recognition of parts and determination of their positions and orientations are often requirements for manipulating parts in material-handling and assembly operations. Researchers working in "hand-eye" programs have made use of electro-optical imaging sensors to identify, locate, and manipulate simple objects. A few examples follow:

• At Stanford University,[41] a television camera fitted with color filters was used to identify four colored blocks. Using a computer program that extracted edges and vertices, the position and orientation of each block was determined, thus providing the information needed to stack the blocks according to certain rules.

• At the University of Nottingham,[42] the identity, position, and orientation of flat workpieces were determined, one at a time, from a top-view image obtained by a television camera. The camera and a manipulator were mounted on a turret in the same fashion as lens objectives are mounted on a common turret of a microscope. After the identity, position, and orientation of each workpiece had been determined, the manipulator rotated into a position coaxial with the original optical axis of the camera lens and acquired the workpiece.

• At Hitachi Central Research Laboratory,[43] prismatic blocks moving on a conveyor belt were viewed, one at a time, using a vidicon television camera. A low-resolution image (64x64 pixels) was processed to obtain the outline of each block. A number of radius vectors from the center of area of the image to the outline were measured and processed by a minicomputer to determine the identity, position, and orientation of each block. The block was then picked up, transported, and stacked in an orderly fashion by means of a simple suction-cup hand whose motion was controlled by the minicomputer.

• At General Motors Research Laboratories,[44] an experimental system was devised to mount wheels on an automobile. The location of the studs on the hubs and the stud holes on the wheels were determined using a television camera coupled to a computer, and then a special manipulator mounted the wheel on the hub and engaged the studs in the appropriate holes. Although this experiment demonstrated the feasibility of a useful task, further development is needed to make this system cost-effective.

• At Osaka University,[45] a machine-vision system, including a television camera coupled to a minicomputer, has been developed to recognize a variety of industrial parts, such as gasoline-engine parts, when viewed one at a time on a conveyor. Resolution of 128x128 elements digitized into 64 levels of gray scale were used. In lieu of the usual sequence of picture processing, extraction of relevant features, and recognition, the system makes use of predetermined part models that guide the comparison of the unknown part with stored models, suggesting the features to be examined in sequence and where each feature is located. This procedure reduced the amount of computation required. Further, by showing sample parts and indicating important features via an interactive display, an operator can quickly train the system for new objects, the system generating the new models automatically from the cues given by the operator. The system is said to recognize 20 to 30 complex parts of a gasoline engine. Recognition time and training time were 30 seconds and 7 minutes, respectively.

• At Stanford Research Institute[11,12] a hardware/software system under minicomputer control has been developed that determines the identity, position, and orientation of each workpiece placed randomly on a table or on a moving conveyor belt and, using a Unimate industrial robot, acquires that workpiece and moves it to its destination. The electro-optical sensors employed include a solid-state 100x100 area-array camera and a solid-state 128x1 linear array camera. A workpiece is recognized by using either a method based on measuring the entire library of features ("nearest-reference" classification) or a method based on sequential measurement of the minimum number of features that can distinguish one workpiece from the others ("decision-tree" classification). Selection of the distinguishing features for the second method is done automatically by simply showing a prototype to the viewing station of the system. The decision-tree classification method was applied to recognition of different workpieces, such as foundry castings, water-pump parts, and covers of electrical boxes. For example, showing the water-pump parts in Figure 8 resulted in automatic generation of the decision tree in Figure 9, where x_1, x_3, x_4, and x_7 are a subset of the set of features x_1 through x_7 (perimeter; square root of area; total hole area; minimum, maximum, and average radius from center of area to outline; and the ratio x_1/x_2), which are invariant to the position and orientation of a part. The feature selected at each tree node is the most distinguishing feature for dividing the group of part candidates into two subgroups. The subgroup to be followed during recognition time will depend on the measured value of that feature. This process is repeated recursively until a terminal node is reached and the unknown part is identified. In all cases, either training (tree building) or recognition was achieved in much less than 1 second.

• At Stanford Research Institute, Agin[14,46] developed an interactive programming system to aid the program-

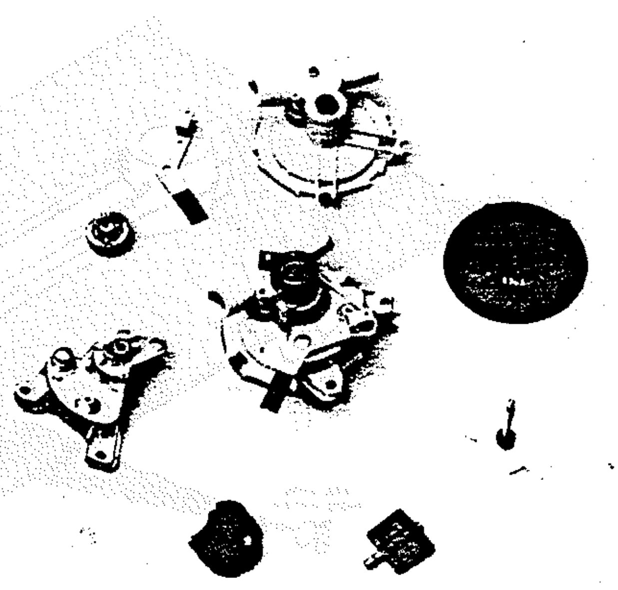

Figure 8. Water pump parts.

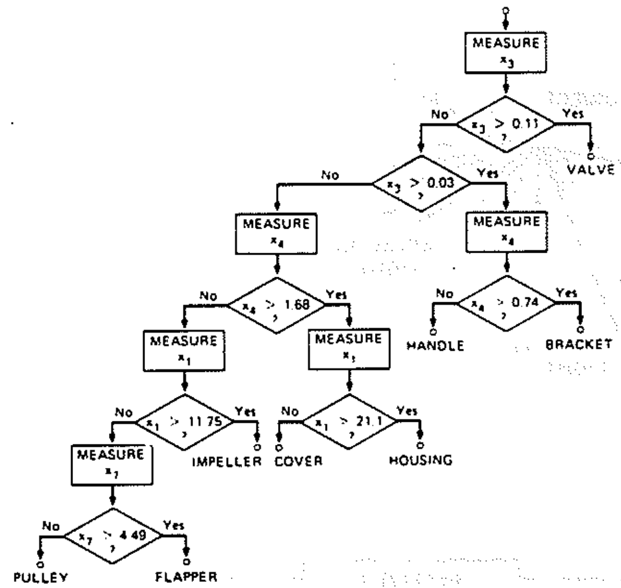

Figure 9. Decision tree for water pump parts.

mer in constructing an inspection strategy for each inspection job. The operator has the use of a graphics terminal, a light pen, and a library of image-processing and feature-extraction routines. A typical inspection job, which at present is done by human vision only, is to ascertain that the number and placement of electrical contacts on lamp bases, such as shown in Figure 10, is correct. An acceptable lamp base has two contacts that are separated and positioned with specific tolerance with respect to an insertion guide pin on the side. The result of the automated inspection is shown in Figure 11, where crosses indicate rejection and a plus sign indicates acceptance. Note that the inspection was performed while two lamp bases were touching. It is estimated[48] that lamp bases can be inspected at a rate of about 6 per second, using a PDP-11/40 minicomputer with a linear diode array camera.

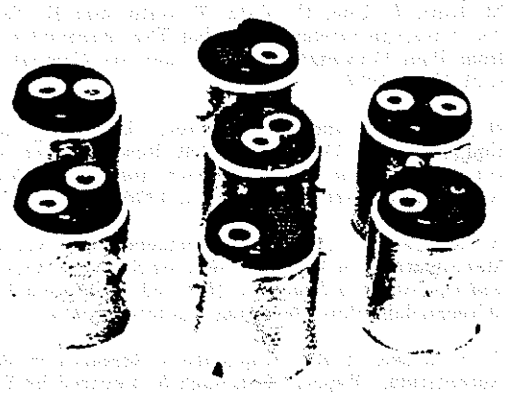

Figure 10. Lamp bases.

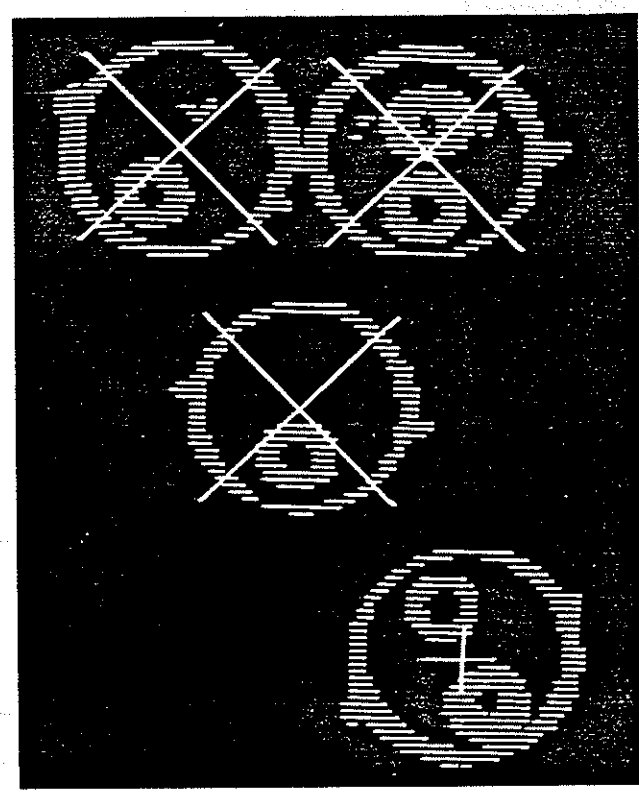

Figure 11. Display of lamp base inspection.

Range-imaging sensors. A range-imaging sensor measures the distances from itself to a raster of points in the scene. Although range sensors are used for navigation by some animals (e.g., the bat), hardly any work has been done so far to apply range image to control the path of a manipulator. This situation may change in the future however, as the technological and economical difficulties currently entailed with range-imaging sensors are overcome.

Different range-imaging sensors have been applied to scene analysis in various research laboratories.[47-59] These sensors may be classified into two types, one based on the trigonometry of triangulation and the other based on the time of flight of light (or sound).

Triangulation range sensors are further classified into two schemes, one based on a stereo pair of television cameras (or one camera in two locations),[47-50] and the other based on projecting a sheet of light by a scanning transmitter and recording the image of the reflected light by a television camera.[51-54] Alternatively, the second scheme may transmit a light beam and record the direction of the reflected light by a rocking receiver. The first scheme suffers from the difficult problem of finding corresponding points in the two images of the scene.[47-49] Both schemes have two main drawbacks: missing data for points seen by the transmitter but not by the receiver and vice versa,[55] and poor accuracy for points that are far.[50]

The above drawbacks are eliminated by the second type of range-imaging sensor using a laser scanner, which is also classified into two schemes: one based on transmitting a laser pulse and measuring the arrival time of the reflected signal,[56] and the other based on transmitting amplitude modulated laser beam and measuring the phase shift of the reflected signal.[59] A simplified block diagram of the latter sensor is shown in Figure 12. The transmitted

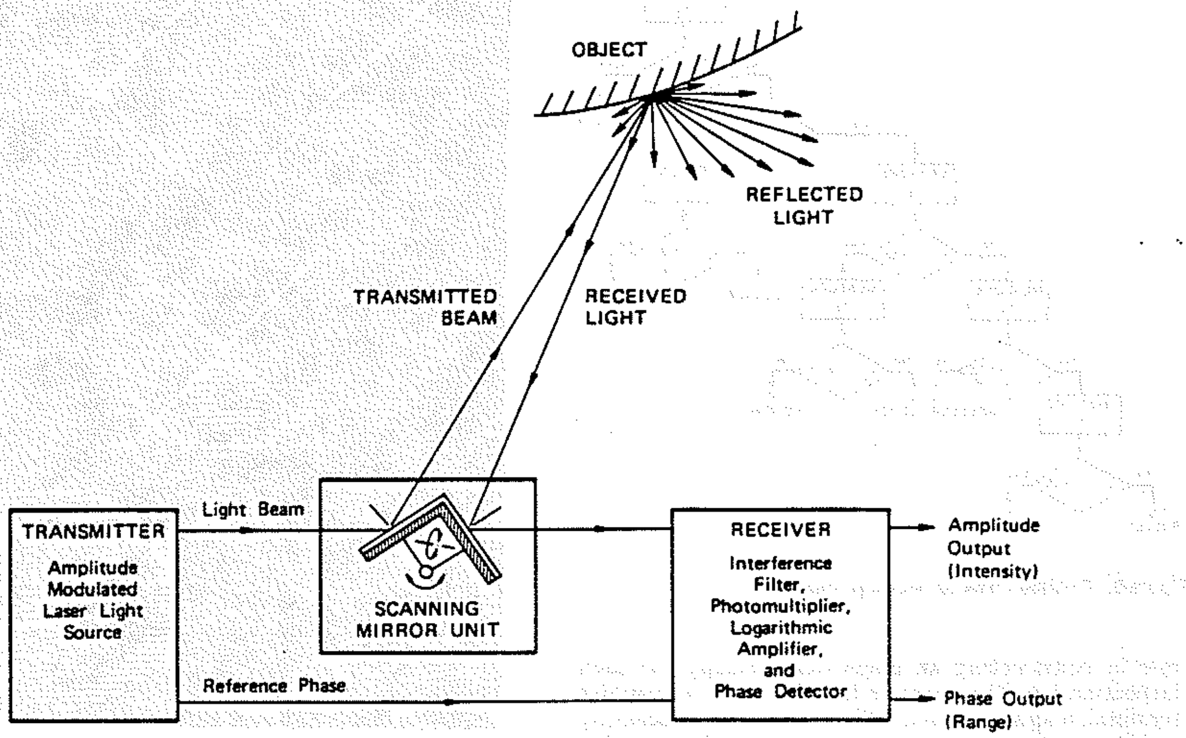

Figure 12. Simplified block diagram of a range imaging sensor.

beam and the received light are essentially coaxial.

Range-imaging sensors have been applied so far primarily to object recognition. However, they are also very suitable for other tasks, such as finding a factory floor or a road, detecting obstacles and pits, and inspecting the completeness of subassemblies.[58,59]

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