Bijoy K. Ghosh*, Tzyh Jong Tarn*, Ning Xi**, Zhenyu Yu***, Di Xiao****

Robotic Motion Planning and Manipulation in an Uncalibrated Environment

The authors analyze planning and control problems in "Robotic Manipulation" in an uncalibrated environment consisting of a PUMA 560 robotic manipulator, a rotating turntable equipped with an encoder and a CCD camera based vision sensor fixed permanently on the ceiling. It is assumed that a part with a known shape but unknown orientation is placed on the turntable which is rotating with an unknown motion dynamics. Furthermore, the calibration parameters are *a priori* assumed to be unknown. The objective is to track the rotating part with an *a priori* specified relative orientation. The task considered is of importance in various problems concerning industrial automation, such as part-feeding and tool-changing.

Keywords: Multisensor Fusion, virtual rotation, parallel guidance, event base

In this paper we study the problem of *Motion Planning* and *Manipulation* in an uncalibrated environment with *Multisensor Fusion*. An important aspect in our study is the special role played by *Vision*. In many instances, we emphasize, vision alone is not sufficient, and one must combine visual information together with one or more additional sensory inputs, leading to many multisensor Fusion-Based algorithms discussed in this paper. Before we elaborate on these algorithms, a few background and somewhat historical remarks are in order. Control of robot manipulators, with vision in the feedback loop, has an exciting history starting with the pioneering work of Hill and Park [1], Weiss, Sanderson and Neuman [2]. Subsequent work in this area has focused on *Visual Servoing*, wherein the emphasis is to visually locate the position and orientation of a part and to control a robot manipulator to grasp and manipulate the part. If the part is not stationary, then the process of locating the part and repositioning the robot must be performed utilizing *Feedback Control*, that has been subsequently studied in [3] and [4] and many references therein. Use of vision in the feedback loop has many advantages over the more direct *look and go* approach. Some of the advantages are that a visually guided robot is more flexible and robust and has the potential to perform satisfactorily even under structural uncertainty. This is evidenced by the proposed *Controlled Active Vision* scheme introduced by Papanikolopoulos et al. [5], where the goal is to accomplish the task in spite of

*Washington University, One Brookings Drive, Saint Louis, MO 63130-4899. **Department of Electrical Engineering, 2120 Engineering Building, Michigan State University, East Lansing, MI 48824-1226. ***DSP Digital Control Systems Applications, Texas Instruments-Houston, Houston, TX. **** FANUC Robotics North America, Inc., 48309-3253. This work was partially supported by the Department of Energy under grant number DE-FG02-90ER14140 and by National Science Foundation under grant number CAD-9404949, IRI-9796287, IRI-9796300 and Sandia National Laboratories Contract No. AC 3752-C. Electronic mail for correspondence is ghosh@zach.wustl.edu.

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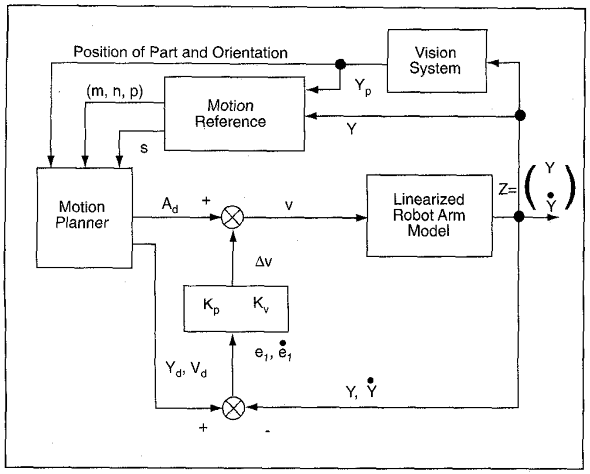

Figure 1. A block diagram for tracking showing feedback signal to the motion planner.

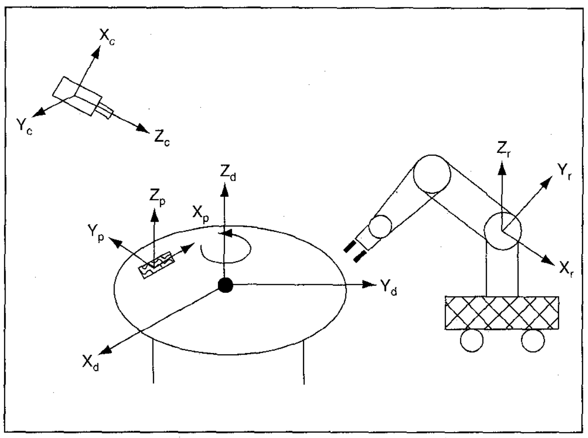

Figure 2. A typical manufacturing workcell.

environmental and target related unknown and possibly changing factors.

The concept of *Multisensor Fusion* is to combine data from multiple sensors to obtain inferences that may not be possible from a single sensor alone. There are many different schemes of Multisensor Fusion in the literature, see for example [6], [7] and many references therein. As opposed to the traditional approach of Multisensor Fusion-Based Servoing, where the sensory information automatically generates the feedback control, we propose in this paper a Multisensor Fusion-Based Planning, where the sensory information automatically feeds the motion planner (see Figure 1). The motion planning schedule is generated autonomously, as a result, and the robot controller gains K_p and K_v simply would adjust the input to compensate for any online errors in the position and orientation of the robot end effector. This simplifies the problem of controller synthesis while relegating the computational burden from the controller to the motion planner. On the other hand, the planner has an additional structure, since it now receives (multi) sensory inputs from "vision" and other encoders (not shown in the figure).

EXPERIMENTAL SETUP

For the purpose of experiments, we consider a manufacturing workcell as shown in Figure 2. The workcell is equipped with a rotating conveyor (equipped with encoders that measure the rotation angle), a robotic manipulator and a computer vision system with a single CCD camera. The precise relative positions of the camera, robot and the conveyor are assumed to be unknown. In spite of the lack of calibration data, the objective is to compute the instantaneous position and orientation of a part placed on the turntable, with respect to the coordinate system attached to the base frame of the robot. The second objective is to feed the above information to a motion planner which in turn provides the required control to the robot manipulator. The planner computes the relevant position, velocity and acceleration profile that the robot end effector needs to follow in order to achieve the desired task, which in our experiment is to pick up a part from the rotating conveyor.

In order to achieve planning and execution of the above prescribed task we make some assumptions about the workcell which we now describe. The precise position and orientation of the camera with respect to the robot coordinate frame are assumed unknown. Additionally, the precise position and orientation of the rotating conveyor with respect to the robot coordinate frame are also assumed unknown. The plane of the conveyor and the horizontal plane of the base frame of the robot are assumed to be parallel. The part is assumed to have a known simple shape. In particular, we assume that observing feature points placed on the top surface of the part enables one to determine the orientation of the part. The entire workcell is assumed to be in the view field of the camera. The center of the conveyor and a reference point on the conveyor is also assumed to be observed by the camera. Finally, the intrinsic parameters, namely the focal length, etc., of the camera are assumed to be known.

The technical contents of the paper are now summarized. Since the camera has not been selectively placed at any specific known position in the workcell, we propose a *virtual rotation algorithm* that would virtually rotate the camera to a vertical position with respect to the rotating conveyor. The process of virtual rotation enables us to calibrate the position of the camera. Since the position and orientation of the part on the conveyor are assumed unknown, we subsequently describe an algorithm to compute this. This is first done assuming that the height of the part is negligible, compared to its dimension. Subsequently we consider parts with feature points that are at a certain height above the conveyor. All of this is described in the next section.

In the subsequent sections of this paper, we consider the problem of *robot calibration. A priori*, the position of the robot is assumed unknown with respect to the coordinate frame attached to the conveyor. The associated calibration parameters are computed by observing feature points on the end effector of the robot. Our final problem is to derive a control law for tracking a rotating part on the conveyor. This is achieved by synthesizing a plan for the robot to approach the rotating target with a prescribed orientation. In doing so, we implement a *parallel guidance* controller, which guides the end effector to move parallel to the conveyor above the rotating part. In order to avoid actuator saturation, an error reduction term is added to the position and velocity of the part to form a desired position, velocity and acceleration profile that the end effector would follow. The error reduction term is carefully reduced to zero using both *time based* and *event based* approaches (see [11] for details about event based approach) leading to an implementable tracking control law that avoids actuator saturation. We conclude with a description of various experimental implementations.

ESTIMATION AND CALIBRATION

Virtual Rotation

As indicated before, we assume that the camera has been placed at an unknown position in the workcell. We now describe a virtual-rotation algorithm to ascertain the relative position of the camera with respect to the coordinate frame of the conveyor. Note that any point on the conveyor undergoes a circular trajectory as the conveyor rotates. The image of such a circular trajectory is an ellipse on the image plane of the camera. The shape of the ellipse depends on the relative orientation of the camera with respect to the normal vector to the plane of the conveyor. The virtual-rotation algorithm hinges on the simple fact that under a suitable transformation, the elliptic image of the circular trajectory can be rotated back to a circle. This transformation can then be applied to the entire image so that the transformed image is what the camera would have seen if its optical axis was perpendicular to the conveyor. From this special *top view* of the camera, the relative position and orientation of the part with respect to the rotating conveyor can be easily obtained. The details of the steps involved in virtual rotation are described as follows (see Figure 3).

Consider a set of i reference points on the image plane. At first, a rotation of the camera around its optical center is applied to transform the image of the center of the conveyor to the center of the image plane. Next we obtain parameters that describe the ellipse traced out by the i^{th} reference point on the image plane. Recursive least squares fitting algorithm is used for this purpose. Subsequently, a rotation around z-axis of the camera is applied to transform the major axis of the ellipse on the image plane to a position parallel to the y-axis of the image plane. Note that this would automatically place the minor axis along the x-axis. Finally, a rotation of the camera around the y-axis of the image plane is applied to transform the ellipse to a circle. This circle would automatically have its center on the x-axis of the image plane.

The virtual rotation algorithm, as outlined above, provides not only a technique to calculate the relative position and orientation of the part, but also a method to compute the orientation of the optical axis of the camera with respect to the vertical line. This algorithm, therefore, has been used in both *camera calibration* and in *localizing the part* on the conveyor.

Multi-Sensor Integration and Part Localization

We have already indicated how virtual rotation algorithm can be utilized to obtain the relative position and orientation of a part on the conveyor. In fact, the algorithm computes the projection of a part on the conveyor plane along the optical axis of the camera. Thus if the height of the part is negligible, compared to the length and width of the part, the position and orientation of the part can be ascertained from its projection on the conveyor plane.

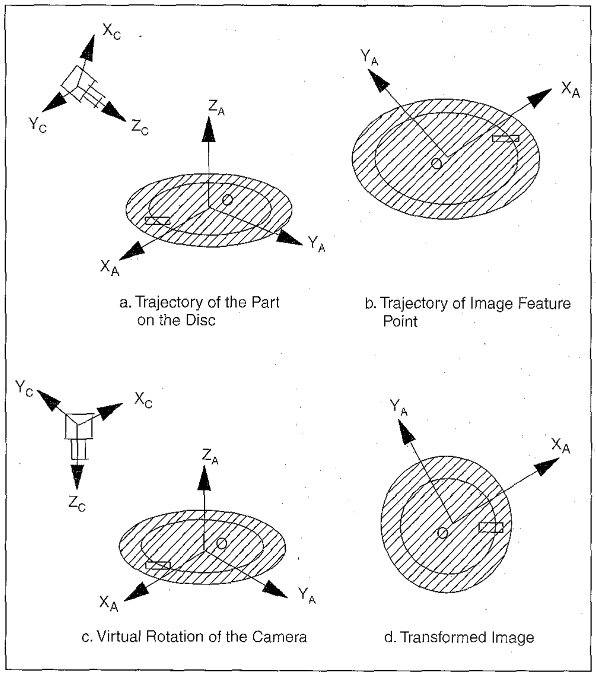

Figure 3. The virtual rotation scheme.

If the height of the part is not negligible, the feature point observed on the part may be assumed to be at a certain height h from the conveyor plane (see Figure 4). Thus if r_1 is the true position of the feature point, the virtual rotation algorithm provides the coordinates of the projection r on the conveyor and computes the line joining r and r_0. It is not possible to compute h from this data alone. However, by observing the same feature points at various instants of time (at least two are required), and by repeated application of the virtual rotation algorithm, one computes a linear relation between the height and the cartesian co-ordinates of the point r. The height h is readily computed using least squares approximation. For details we would refer to [10].

What we have outlined so far is that for a planar or for a non-planar part, it is possible to compute the positions of feature points on the part, using repeated application of the virtual rotation algorithm. The relative position and orientation (relative with respect to the rotating axis on the conveyor) of the part on the conveyor can therefore be ascertained. For the purpose of tracking the moving part, it is necessary to compute the absolute position and orientation of the part (absolute with respect to a fixed axis on the conveyor). This is achieved by fusing information with an encoder sensor on the rotating conveyor. The details are now explained.

Assume that we have two co-ordinate frames on the conveyor, one of them is stationary and the other is rotating with

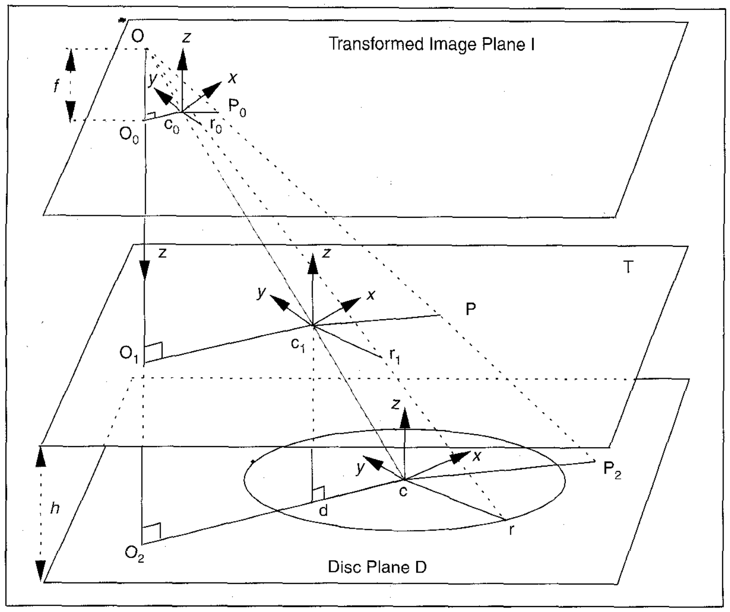

Figure 4. Determining the position of a point from its image using virtual rotation.

the conveyor. Assume that the position of the conveyor cane be described by $\theta(t)$, which is the angle between the x-axes of the two coordinate frames. We measure the angle $\theta(t)$ by an encoder sensor. Assume that the position of the centroid of a part with respect to the rotating coordinate frame on the conveyor be represented by x_a which we assume to have been obtained from the virtual rotation algorithm already described. The position $x_d(t)$ of the part with respect to the fixed coordinate frame is given by

$$x_d(t) = R_z(\theta(t))x_a \tag{1}$$

where

$$R_z(\theta(t)) = \begin{bmatrix} \cos\theta(t) & -\sin\theta(t) & 0 \\ \sin\theta(t) & \cos\theta(t) & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{2}$$

represents a rotational transformation around the z-axis.

The equations (1) and (2) reflect how the absolute position information $x_d(t)$ is obtained through fusing the relative position information x_a together with the encoder measurement $\theta(t)$. Similar transformation can be obtained for the orientation matrix as well. Differentiating both sides of (1) yields

$$\dot{x}_d(t) = \Omega(\dot{\theta})R_z(\theta)x_a \tag{3}$$

where $\Omega(\dot{\theta})$ can be easily calculated. Equation (3) shows that the velocity of a part on the conveyor can be obtained by fusing relative information x_a with encoder measurement $\theta(t)$ and $\dot{\theta}(t)$, the speed of rotation of the conveyor. In fact the speed can also be measured or estimated by the encoder.

Because the relative position of a part with respect to the conveyor has been assumed not to change with time, the absolute position, orientation and velocity of the part are updated at the same rate the encoder measurements are taken. In fact since the encoder measurements are updated at a very high frequency, it is possible to obtain absolute information in real time, without requiring that the relative information be updated at a high frequency. Computational burden on the vision-based algorithm is therefore greatly reduced.

ROBOT CALIBRATION

In this section, we turn our attention to the robot and recall that we do not assume position and orientation of the base of the robot to be known *a priori*. This would typically be the situation if a mobile robot has traveled into an uncalibrated workspace. The goal of this section is to attempt to localize the robot using *vision* once again. We assume that there are feature points on the end effector of the robot that are visible by the camera. The calibration coordinates are computed from this information. The details are described as follows.

In order to determine the relation between stationary frame on the conveyor and the base frame on the robot, we need to describe a set of points in both frames since the two frames are related by

$${}^bP = {}^bR_d\,{}^dP + {}^bT_d,$$

where ${}^bP$ and ${}^dP$ are the coordinates of a point in the base frame on the robot and the stationary frame on the conveyor, respectively. Since the plane of the conveyor and the base plane of the robot are assumed to be parallel, it is readily seen that there is just one unknown in the rotation matrix ${}^bR_d$. Of course, additionally there is a set of three unknowns in the translational vector ${}^bT_d$. Thus every feature point on the end effector provides a set of three equations in four unknowns. The equations can be readily written once the coordinates ${}^bP$ and ${}^dP$ are known. Fortunately, from reading encoders of the robot, the coordinates ${}^bP$ of points on the end-effector with respect to the base frame of the robot can be obtained. We now describe a procedure to calculate ${}^dP$ using the vision system and applying once again the virtual rotation algorithm. Note, however, that we need at least a set of two points to obtain the four unknown parameters uniquely.

Since the feature point on the end effector is visible by the camera, we can use virtual rotation algorithm to localize the feature point up to a line, i.e., the coordinates of the point are obtained as a function of the height of the point from the conveyor plane. If we assume that this height is known, or equivalently if we assume that the distance between the conveyor plane and the base plane of the robot is known (recall that they are already parallel, by assumption), then ${}^dP$ is readily computed.

If, on the other hand, we assume that the distance between the conveyor plane and the base plane of the robot is unknown *a priori* although we continue to assume that they are parallel, then this distance has to be estimated. This problem is much harder, compared to, for example the computation of height of a feature point on the rotating part, because the height of a feature point on the end-effector does not remain fixed as the end-effector moves. Thus, an algorithm using repeated application of the virtual rotation, cannot be used in this case. We therefore propose a new algorithm. This algorithm can be implemented, in particular, using two or three feature points. In what follows, we shall describe the case with two points.

Let (x_i, y_i, z_i) $(i=1,2)$ be coordinates of two points on the end-effector (with respect to the camera frame) with associated coordinates on the image plane of the camera given by (X_i, Y_i) where $(x_i, y_i, z_i) = (X_i z_i / f, Y_i z_i / f, z_i)$. Note that the z-coordinates of the two points can be measured in the base frame coordinates of the robot and so is their difference d. After virtually rotating the camera, the difference between the z-coordinates of the two points has the same magnitude in each of the camera frame and the base frame. Without any loss of generality we therefore assume that $z_1 - z_2 = d$ is known from the robot encoders. Likewise, we assume that the distance s between the two points on the end-effector can be measured in the robot base frame and continues to be same in the camera frame. We therefore obtain the following quadratic equation:

$$(X_1 z_1 - X_2 z_2)^2 + (Y_1 z_1 - Y_2 z_2)^2 + f^2 (z_1 - z_2)^2 = f^2 s^2 \qquad (4)$$

which can be solved for z_2 for a pair of solutions. In practice, the problem itself guarantees that one real solution exists. Hence, the quadratic equation of z_2 must have two real solutions. However, in many cases we can recover z_2 uniquely since the point should be in front of the camera, i.e., $z_2 > 0$.

The algorithm can be repeated with three feature points, pairwise. Analogously, in this case, we obtain a triplet of quadratic equations which, in general, would have an unique solution, common to all the three equations. The relation between the base frame of the robot and the fixed frame on the conveyor can be easily computed and the details are omitted.

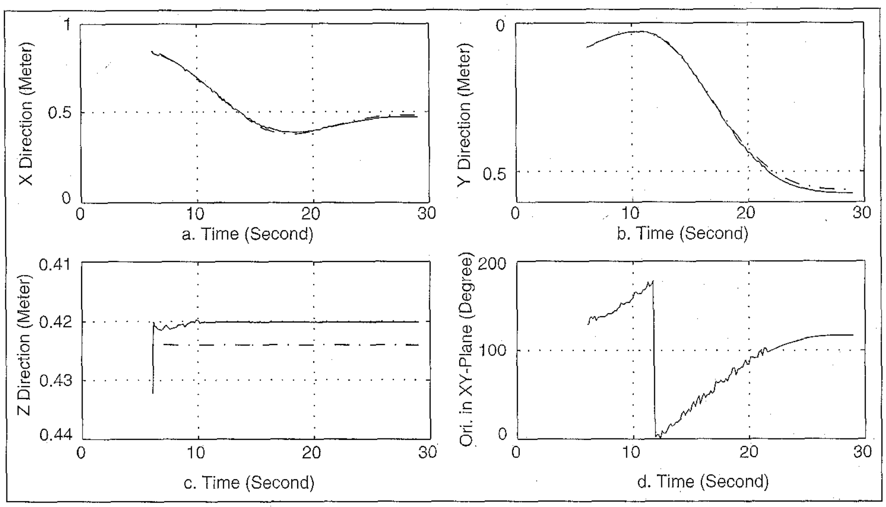

Figure 5. Estimated and actual pose of the part for the case where the distance of the end-effector from the conveyor is unknown.

ROBOT PLANNING AND CONTROL

In this section, we divert our attention to the control problem which is of independent interest. The task considered is to control the end effector so that it is able to track a moving part on the rotating conveyor. The tracking controller should be robust with respect to positional inaccuracies of the end effector and is synthesized by using the concept of parallel guidance. This involves moving the end effector synchronously with the rotating part at a given fixed distance and gradually reducing the distance to zero. The controller is actuated by the error between the position and orientation of the end effector and the part. Unfortunately however, the true error signal, if used, would lead to actuator saturation. Hence the error signal is carefully planned and modified by the motion planner. An error reduction term is added to the position and velocity of the target to form a modified desired position, velocity and acceleration profile for the robot. When the error reduction term is carefully planned, it guarantees a time optimal and robust robot motion with a prescribed bounded control. The planner, we show, can be implemented in both *time based* and *event based*. In particular, our approach leads to a new event based tracking scheme for the robot. We would like to refer to [8], [9] for details of the structure of the event based controller particularly the structure of the *motion reference module* (see Figure 1). The vector (m,n,p) is the direction vector that the end effector needs to follow to approach the part on the conveyor and the parameter s is the event base with respect to which the control signals are computed and implemented.

Robot Control

The dynamic model of a robot arm is given by

$$D(q)\ddot{q} + C(q, \dot{q}) + G(q) = \tau \qquad (5)$$

where q, $D(q)$, $C(q, \dot{q})$, $G(q)$ and τ are respectively the joint angle vector, the inertia matrix, the load related to centripetal and Coriolis forces, the load related to gravity, and the joint torque vector. The joint torque has to satisfy the following constraints

$$\tau_{i,\min}(q,\dot{q}) \le \tau_i \le \tau_{i,\max}(q,\dot{q}) \quad i = 1,2,\ldots m \qquad (6)$$

where m is the number of joints. The output is given by $Y = H(q) = (X,\theta)^t$ where $X \in \Re^3$ and $\theta \in \Re^3$ represent the position and orientation of robot end-effector. Let us consider the nonlinear feedback control law given by

$$\tau = D(q)J^{-1}(q)(A_d + K_v(V_d - \dot{Y}) + K_p(Y_d - Y) - \dot{J}(q)q) + C(q,\dot{q}) + G(q) \qquad (7)$$

where $J(q)$ is the Jacobian of $H(q)$ with respect to q; K_v and K_p are gain parameters for velocity and position, respectively. It is assumed that the robot has six joints. It can be shown that if A_d, V_d and Y_d satisfy the constraints $\dot{Y}_d = V_d$ and $V_d = A_d$, then by proper choice of K_v and K_p, the closed-loop system is stable and the tracking error will vanish asymptotically provided the induced joint torque is within the limit specified by (6). The problem of robot motion planning considered here is to design A_d, V_d and Y_d so that the robot end effector would track the motion of a part.

Robot Tracking with Planned Error Reduction

The main problem in robot tracking is to eliminate the position and velocity error between the robot end effector and the part by controlling the robot. An obvious tracking plan would be to choose

$$Y_d = Y_p(t),\ V_d = V(t),\ A_d = \dot{V}_d$$

which is to let the desired motion be the motion of the part. However, if such a plan is used to control the motion of the robot, the required control will be large when the initial error in position, orientation and velocity between the part and the robot is large. A large value of the position error can easily cause the command torque to exceed the upper limit and force the lower level controller to shut down. In order to circumvent the problem of dealing with a large value of the initial error, a new tracking plan is proposed in the form of

$$\begin{Bmatrix} Y_d = Y_p(t) + Y_e(t) \\ V_d = \dot{Y}_d = V_p(t) + \dot{Y}_e(t) \\ A_d = \dot{V}_d = A_p(t) + \ddot{Y}_e(t) \end{Bmatrix} \qquad (8)$$

where Y_e is an *error reduction term* that is set to $Y(0)$-$Y_p(0)$ at the time tracking starts and is gradually reduced to zero according to a plan. The proposed plan is based on optimal control, [12] and controls the robot to move at the same speed of the part while the position error is gradually reduced to zero according to an error reduction plan.

After the error reduction term is added to the target position, the initial positional error is set to be zero to guarantee that the control will not be out of range while tracking starts. The error reduction term would be planned so that the initial positional error would be reduced with a feasible control command.

The torque demand of a planned motion depends on the planned path, speed and acceleration and is usually difficult to meet. An often adopted method for motion planning is to specify a conservative constant speed and acceleration limit based on the off line kinematics and dynamic workspace analysis. Let us assume that the constraints on the desired motion are given by $\|V_d\| \le v_m$ and $\|A_d\| \le a_m$. We also assume from prior knowledge that the motion of the target satisfies the constraints $\|V_p\| \le v_{mp}$ and $\|A_p\| \le a_{mp}$. It follows from (8) that a conservative constraint on the error-reduction term planned error would be $\|\dot{Y}_e\| \le a_m - a_{mp}$ and $\|\ddot{Y}_e\| \le a_m - a_{mp}$. It is now reasonable to assume $v_{mp} \le v_m$ and $a_{mp} \le v_m$ in order for the robot to be able to keep track of the target.

In our experiments, the control has been implemented

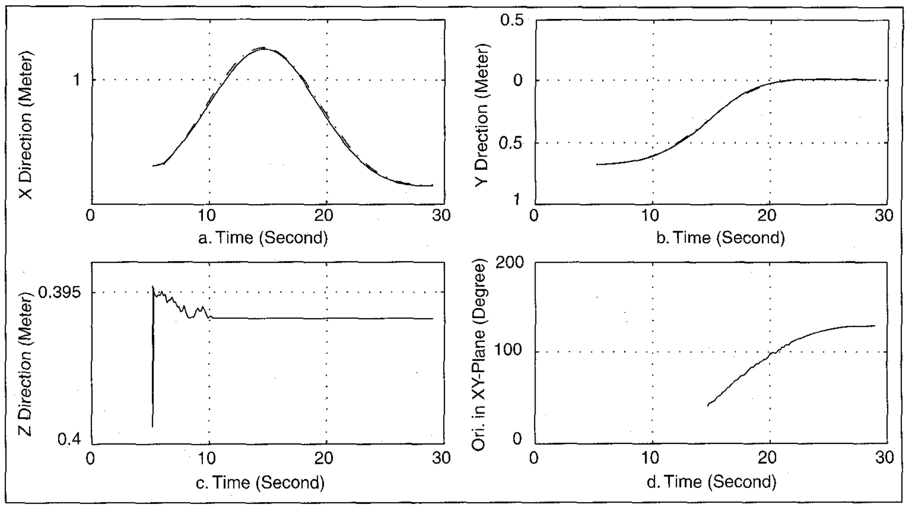

Figure 6. Estimated and actual pose of the part for the case where the distance of the end-effector from the conveyor is known and height of the part is 4 cm.

both in time-base and in event-base. The details on the implementation has been omitted (see [9] and [10]). We would also refer to [11] for some general introduction to *event based control*. To summarize the main contribution of this section, we have implemented a dynamic tracking controller with a feedback to the motion planner. The overall closed loop system is stable and robust.

EXPERIMENTAL RESULTS

Our experimental set up is now described. The manipulator is one of the two PUMA 560 robotic manipulators separately controlled by two UMC controllers from Motion Tek. The two controllers interface with the main computer, a four processor SGI IRIS 4D/VGX work-station, through shared memory. High level planning and control algorithms such as the multiple sensor integration algorithm, the vision algorithm with an implicit calibration and the parallel tracking algorithm discussed in this paper are all implemented on SGI work-station, making full utilization of its computing power. Schunk grippers are mounted on the manipulators to grasp parts to be manipulated. The conveyor rotates around a fixed axis. There is an encoder attached to the motor to generate measurement of the angle and speed of rotation of the conveyor. The resolution of the encoder is $(576\times10^3)/2\pi$ lines per radian. The rotation of the conveyor is independently controlled by a spare channel on one of the Motion Tek controllers. Two markers are placed on the conveyor with one of them at the center of rotation. These two markers represent the x axis of the attached coordinate frame. They are identified as reference points by vision algorithm in determining the relative position and orientation of a part placed on the conveyor. The

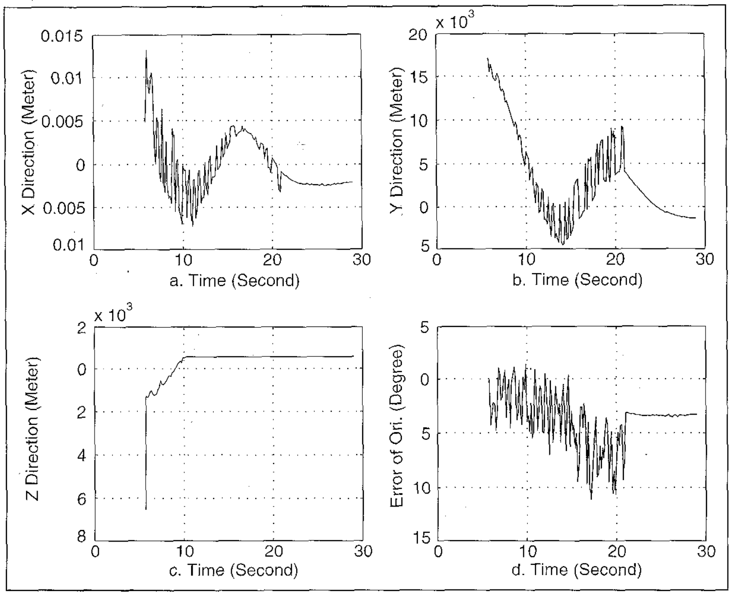

Figure 7. Estimated and actual pose of the part for the case where the distance of the end-effector from the conveyor is known and height of the part is 7 cm.

vision system consists of two cameras in a stereo setup, an Intelledex IntelleVue vision processor, a black and white monitor and a development system on PC. Only one camera is used in this experiment. In order to allow communication between Intelledex vision processor and the SGI IRIS 4D/VGX workstation, a parallel interface between them was developed. The task of the vision system is to identify the image coordinates of the markers representing the reference points and the outline of a part. Note that the outline of the part is not marked with markers. The results are then transferred to SGI workstation to be further processed or directly used in the guidance of robot motion. The Intelldex vision processor is based on a 16 MHz Intel 80386 CPU with Intel 80287 co-processor. There are 6 256×256×8 bit image buffers, 2 of which can be used as image grabbers for direct image acquisition. Image resolution is 256×240 (although the cameras have a pixel array of 422×490). The display has 256 gray levels while the digitizer can only distinguish 64 gray levels.

In Figures 5, 6, and 7 results of our experiments have been shown. For lack of space, only results pertaining to the estimation of position and orientation of the part has been shown. In Figure 5 we assume that the height of the end effector from the conveyor plane is unknown, whereas in Figures 6 and 7, this height is assumed to be known together with the height of the part. In almost all the trials of the experiments that we have performed, knowing the height has led to a robust estimate of the robot calibration parameters and has resulted in improved success rate. The position errors obtained are within 1cm and the orientation errors are less than 5 degrees.

CONCLUSIONS

In this paper we demonstrate the advantage of using visual sensing in a multiple sensor integration mode in order to manipulate parts in a typical manufacturing workcell that is composed of a robot manipulator, a rotating conveyor and a camera system. Even though the visual computations are performed in low rate, part position and orientation information can still be updated at the rate of the feedback loop using an additional encoder sensor. We also demonstrate a practical tracking algorithm which pays attention to the fact that the torque that the robot control system can supply is bounded. The proposed algorithm is primarily based on error feedback with an extra error reduction term added in order to force the required torque requirement to remain within acceptable bounds. The proposed control scheme has been implemented in both time and event base.

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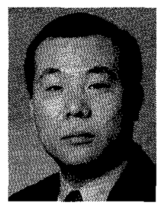
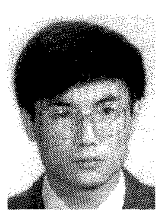
Bijoy K. Ghosh received a bachelor's degree in Electrical and Electronics Engineering from Birla Institute of Technology and Sciences, Pilani, India in 1977, a master's degree in Electrical Engineering from Indian Institute of Technology, Kan-

pur, India with specialization in Control Systems in 1979 and a PhD in Engineering from the Decision and Control group of the Division of Applied Sciences at the Harvard University, Cambridge, USA in 1983. Since 1983, he has been a Professor in the Systems, Science and Mathematics department and Director of the Center for BioCybernetics and Intelligent Systems at Washington University with research interests in the area of Multivariable Control Theory, Machine Vision, Robotic Manufacturing. In 1988, Dr. Ghosh received the American Automatic Control Council's Donald P. Eckman Award in recognition of his outstanding contribution in the field of Automatic Control. He was a visiting fellow at Osaka University, and Tokyo Institute of Technology respectively during the years 1992 and 1995. In 1993, he was the United Nations Development Program fellow under the TOKTEN program and visited the Indian Institute of Technology, Kharagpur. In 1997 he received the Japan Society for the Promotion of Science invitation fellowship and visited Tokyo Denki University. Dr. Ghosh is a Senior Member of the IEEE.

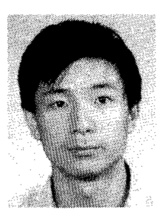
T. J. Tarn received the Dr. of Science degree in Control Systems Engineering from Washington University, Saint Louis, MO. He is currently a Professor in the Department of Systems Science and Mathematics and the Director of the Center for Robotics and Robotics and Automation at Washington University. An active member of the IEEE, he served as the President of the IEEE Robotics and Automation Society, 1992-93, the Director of the IEEE Division X (Systems and Control), 1995-96, and a member of the IEEE Board of Directors, 1995-96. At present he serves as a member of the nomination committee of the IEEE Board of Directors. He also serves as both Chairman of the Management Committee and an Editor of the IEEE/ASME Transactions on Mechatronics and as a Board member of the IEEE Neural Network Council. He received the NASA Certificate of Recognition for the creative development of a technical innovation on "Robot Arm Dynamic Control by Computer" in 1987. The Japan Foundation for the Promotion of Advanced Automation Technology presented him with the Best Research Article Award in March, 1994. He also received the best paper award at the 1995 IEEE/RSJ International Conference on Intelligent Robots and Systems, and the Distinguished Member Award from the IEEE Control Systems Society in 1996. He is the first recipient of both the Nakamura Prize (in recognition and appreciation of his contribution to the advancement of the technology on intelligent robots and systems over a decade) at the 10th Anniversary of IROS in Grenoble, France, 1997 and the Ford Motor Company best paper award at the Japan/USA Symposium on Flexible Automation, Otsu, Japan, 1998. In addition, he was featured in the Special Report on Engineering of the 1998 Best Graduate School issue of US News and World Report. Dr. Tarn is a Fellow of the IEEE.



Ning Xi received his D.Sc. degree in Systems Science and Mathematics from Washington University in St. Louis, Missouri in December, 1993. He received his M.S. degree in computer science from Northeastern University, Boston, Massachusetts, and B.S. degree in electrical engineering from Beijing University of Aeronautics and Astronautics. Currently, he is an assistant professor in the Department of Electrical and Computer Engineering at Michigan State University. Dr. Xi received the Excellent Research Award from the Japan Foundation for the Promotion of Advanced Automation Technology in March, 1995. He also received the Best Paper Award in IEEE/RSJ International Conference on Intelligent Robots and Systems in August, 1995. Dr. Xi was the recipient of The Anton Philips Best Student Paper Award in 1993 IEEE International Conference on Robotics and Automation. In addition, he has received the National Science Foundation CAREER Award. Currently, his research interests include robotics, manufacturing automation, intelligent control and systems.



Zhenyu Yu received the B.S. degree in 1982, and the M.S. degree in 1985, both in Automatic Control from Beijing University of Aeronautics and Astronautics. He received the M.S. degree in 1992, and the Dr. of Science degree in 1995, both in Systems Sciences and Mathematics from Washington University in St. Louis, MO. Since 1995, he has been with Texas Instruments, in Houston, TX. He is currently a DSP Digital Control Systems Applications engineer. His job responsibilities include study and promotion of applications of Digital Signal Processor (DSP) in digital control and digital motor control systems.



Di Xiao received the B.S. degree in Mechanical Engineering in 1984 and M.S. degree in Control Theory and Applications in 1989, both from Beijing University of Aeronautics and Astronautics, P.R. China, and the D.Sc. degree in Systems Science and Mathematics from Washington University, U.S.A. Since September of 1997, he has been with Fanuc Robotics North America, Inc. His research interests include motion planning, control theory and applications.