AN APPLICATION OF TOOL INSERTION USING MODEL BASED VISION

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Abstract

This paper presents an application of tool insertion using model based vision. The requisite technologies, including model representation, sensor calibration and error quantification are discussed. These techniques are applied to a nuclear servicing task in a physical mock-up of a steam generator.

1. INTRODUCTION

Tool insertion is a class of problems that mate two non-compliant parts in the presence of geometric uncertainty. For a subclass of tool insertion, an accurate model of the tool, its mating receptacle, and its surrounding environment contains sufficient information to drive the task. For these tool insertion problems a model does exist, but is not always accurate enough to enable reliable manipulation.

Model based vision offers one solution to the problem of reducing model uncertainty and providing precise scene data. Using sensors, an approximate model is corrected until it is sufficiently accurate for manipulation. Achieving model accuracy requires the application of a number of techniques such as sensor calibration, sensor error estimation and the identification of spurious sensor data.

In this paper, model based vision is shown to be a viable solution to a tool insertion problem for the nuclear servicing industry. The development of a complete model based tool insertion system including sensor calibration, image processing, error estimation and methods for motion planning in the presence of sensor dropout is discussed.

2. PRIOR WORK

The development of manipulation for model based tool insertion requires that vision systems for model correction be developed, and that the manipulator be driven based on model information. Much work has been done in robotics toward the development of automated manipulation systems, the references cited here are certainly not all inclusive, but offer an overview of the technologies that influenced our work.

Mitchell [4] studied planning/learning systems for manipulation tasks such as moving a block along a wall. A vision system detected the location and orientation of the block in the scene and planning algorithms commanded manipulator motion to achieve some goal. The robot refined its understanding of the manipulation task through its failures.

Allen [1] performed both contact and non-contact sensing of three dimensional objects and illustrated the necessity of multisensor integration to achieve reliable reconstruction information. Tactile feedback augmented a stereo vision system to determine object shape. The work demonstrated the advantages of combining multisensor feedback to achieve better reconstruction of the manipulator workspace.

Our work uses sensor feedback to establish the state of the manipulation environment and uses this information to guide a manipulator in performing some task. Multi-sensor integration provides an estimate of the state of the manipulation environment that was unachievable with a single sensor. The current work specializes and integrates these component technologies into a functional system.

3. APPLICATION OF THE SYSTEM

Perception driven manipulation has not yet progressed to the point of generalization, therefore discussion of the tool insertion system would be unclear without some discussion of the intended application.

This work was motivated by the desire to automate servicing operations in nuclear steam generators. A steam generator exchanges heat between the superheated radioactive primary loop water and the secondary loop water. In Figure 1, the primary loop water enters the left hand side of the channelhead. The water is forced up through U-shaped tubes that are pressed into the tubesheet, an 18 - 24 inch thick metal slab which caps the

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channelhead. The secondary water which surrounds these tubes is boiled over into steam to drive the turbine.

It is critical to radiation containment to keep the boilertubes in good repair; the nuclear servicing industry targets the tubesheet as a critical failure area. Much inspection and repair is performed from the channelhead, where high radiation levels force the use of remote manipulators.

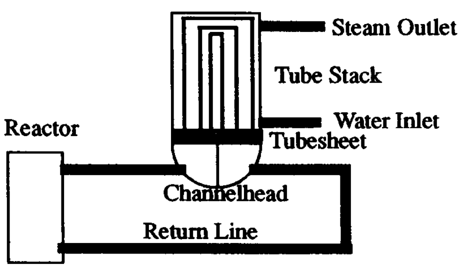

Figure 1: A Steam Generator

Steam generator servicing (See Figure 2) with a typical robotic arm requires that the base be inserted through a manway door and docked to the tubesheet. After the base has been secured, the remaining arm links are drawn completely into the channelhead. The arm is then in a position to allow its end effector to reach tubesheet holes for inspection and/or repair tasks.

The docking problem is formulated as follows. The arm operates in a world that contains a single plane of holes equally spaced in a 2-D grid (the tubesheet). Tubesheet manufacturing tolerances cause significant deviation of the holes' spacing within the grid. The operator specifies four holes, the robot finds the holes and inserts its base, a four pronged clamping device, into the holes. The system must therefore be able to correctly determine the position and orientation of the holes relative to the manipulator and automatically perform the insertion.

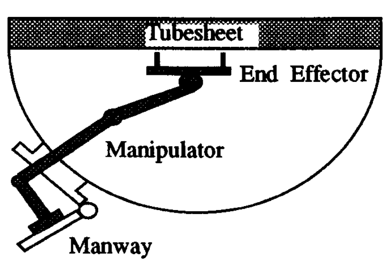

Figure 2: The Channelhead

4. VISION BASED TOOL INSERTION

Model based vision is a method by which an uncertain model is corrected until it is sufficiently accurate to drive the given task. Calibration of the sensors is necessary to eliminate systematic error, and uncertainty models are needed for the remaining random effects.

A complete tool insertion system requires:

- Representation of the model
- Extraction of model parameters from sensor data
- Quantification of sensor error
- Transformation of sensor error to model error
- Sensor calibration techniques
- Motion planning for sensor drop out recovery

The body of this paper visits each of these topics as a component technology, then relates them as an aggregate system in a technical insertion scenario. While each of these technologies is required in a complete system, the specific technique is application dependant. The requisite technologies are discussed in the context of the general problem, the insertion of a four pronged tool into four specific holes in a plane, using a vision corrected CAD model.

4.1. Representation of the Model

The channelhead environment is represented by a CAD model, which stores the three dimensional scene information, and displays it in pseudo 3-D. A "correct" model renders the current state of the manipulation environment with sufficient information to allow safe manipulator interaction. In our case sufficient information includes:

- Resolution of the mating ambiguity.
- Sufficient model accuracy to allow precision mating of the two components.

Mating ambiguity arises in that there are four possible end effector orientations that will allow a mate, only one of which is deemed correct. There is insufficient initial model accuracy for docking because the exact locations of the four prescribed holes is not known. Although the holes lie in a known pattern, they exhibit some random deviation from their expected positions which, if ignored, is sufficient to prevent insertion.

4.2. Extraction of Model Parameters

Two types of sensor are employed to measure the hole locations, as shown in Figure 3. A triad of range sensors describe the attitude and height of the tubesheet and a single-camera vision system determines hole locations within that plane.

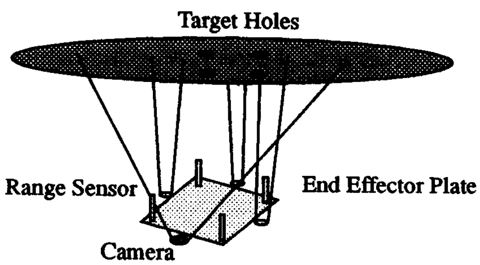

Figure 3: Sensor Configuration

Computer vision techniques are used to find the locations of the centers of each of the holes. For each point in an image, a Canny[2] edge detector assigns a confidence value which corresponds to the likelihood that that point comprises part of an edge. A threshold is empirically set to account for lighting conditions, noise, and to filter out weak edges. After thresholding, the remaining points are run through a calibration formula which transforms them from image coordinates to robot world coordinates. (See Sensor Calibration, section 4.4) A Hough [3] transform, tailored for circle finding, locates the centers of the holes. The Hough transform was chosen over other algorithms because it is robust to missing or spurious data.

After the centers of the image holes have been calculated, the CAD model is updated. A nearest neighbor algorithm matches the holes found in the image to the hole locations predicted by the model. The new locations are returned for model update.

4.3. Quantification and Transformation of Error

Each of the range sensors has an associated inaccuracy which imparts error to the range measurements and consequently to the tubesheet parameters. Euclidean geometry can be used to transform the range readings to parameters; the transformation of error is less straightforward. Smith and Cheeseman [7] described a method for transforming Gaussian uncertainty through a chain of geometric frames.

Treating each reading as a random variable with some uncertainty, the problem is to transform the uncertainties from one frame of reference to another, and to transform the sensor uncertainties to model parameter uncertainties. Smith and Cheeseman's method uses a covariance matrix to represent the sensor uncertainty, and transforms the sensor uncertainty through the geometry of the manipulator chain.

This method transforms the individual sensor reading and uncertainty. However, sensors typically measure scene attributes from many locations and at many different orientations during manipulation, requiring a robust method for determining the best possible parameter estimate, while reducing the total parameter uncertainty. The Kalman filter is a well known technique for merging multiple measurements with unbiased random error. The Kalman filter is appropriately suited to error estimation in this application because a number of discrete readings are taken, a consensus estimate is desired, and a statistical method for dealing with sensor drop-out is needed. The Kalman filter updates the estimate by performing a weighted average of the current estimate and the new sensor readings; the readings with the lower associated uncertainty receive a greater weight.

4.4. Sensor Calibration

The camera and its associated electronics introduce lens distortion and electronic timing offsets to the image; high accuracy measurements require the calculation of the characteristic camera parameters. The use of a camera as a metric device also requires that its location and orientation in free space be determined. Tsai [8] describes a camera calibration technique which addresses both problems. There are six "extrinsic" parameters, three translational and three rotational. Six "intrinsic" parameters serve to characterize the camera model: focal length, two distortion coefficients, the computer image coordinates for the origin, and the timing uncertainty factor. The focal length is calculated because the nominal focal length is not precise enough for accurate measurements. The two distortion coefficients are the coefficients from the first two terms in the Taylor's series expansion which describes radial distortion. The uncertainty scale factor describes the hardware timing bias between the sensing equipment and the image acquisition hardware.

The strength of this calibration technique lies in the camera model characterization. The elimination of nonlinear distortion is especially critical to the accurate measurement of object characteristics.

4.5. Motion Planning for Sensor Drop Out

Sensor drop out occurs when a sensor fails to return reasonable data. The causes of sensor drop out vary with the sensor, but can include range limitations, occlusion, noise, etc. A statistical method for ignoring uncertain data exists with the Kalman filter, but the manipulator must be moved into a position where the sensors can collect valid data.

In our application, range sensor drop out occurs when a sensor is aligned with a hole such that it misses the nearby tubesheet surface and its signal fails to reflect from the void. Individual sensor failures can be used to derive motion trajectories that will move the sensor to the nearest configuration that enables all three range sensors to collect accurate data

The problem is formulated as a search for the nearest end effector configuration parallel to the tubesheet that causes all three range sensors' footprints to fall on planar areas of the tubesheet. Hole positions are assumed to be known accurately enough for a topological search. The model is then searched until a configuration is found. This process repeats until a configuration without sensor dropout is found.

The search space is the set of all possible configurations of the end effector. A grid structure is imposed on the configuration space to tessellate the space into a set of nodes to be searched using a hierarchical data structure (an octree [6]) to represent the configuration space. The A* search algorithm [5] is employed to find a sequence of nodes in the search space that connects start node to goal node while minimizing distance.

5. SYSTEM PERFORMANCE

A research analog to the servicing task was used to characterize the system's performance. The analog consisted of an industrial arm fitted with a camlock end effector, a tubesheet replica, piezo electric range sensors and a remote head CCD camera. The CAD system ran on an SGI personal IRIS while the remaining processing was performed by a Sun SPARCstation.

The range system determined the attitude of the tubesheet to within 0.1 degrees. The vision system located each hole within an image to an accuracy of at least 0.1 inches. Over a series of 20 trials, the robot consistently docked four 0.7 inch diameter pegs into 0.8125 inch diameter holes. A typical dock took about 10 minutes which includes the significant settling time of the industrial arm. This time could be reduced to 4 minutes through software optimization and use of a modern nuclear servicing arm.

6. CONCLUSIONS

Model based vision is a viable solution to many tool insertion tasks. This work goes beyond formulation of component technology to implementation of a complete system. Although there were insufficient docks to provide meaningful statistical data, the performance indicates that an industrial implementation of this technology would provide a practical solution to the tool insertion problems encountered in nuclear servicing tasks.

7. REFERENCES

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