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A Vision System Planner for Increasing the Autonomy of the Extravehicular Activity Helper/Retriever

submitted by

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1.0 Introduction

The need for intelligent robots that are able to assist with operations in space will continue to increase as the human presence in extraterrestrial environments expands.[1-6] There are several reasons why the development of such robotic devices, operating with varying degrees of autonomy, will be a critical step toward achieving this goal. Foremost among these reasons is that extended operations in space by humans require complex life support systems and shielding from hazards such as radiation. This means that the time which an astronaut may devote to tasks outside an orbiting vehicle or space station is an exceptionally valuable resource that should be allocated to tasks requiring a high degree of human intelligence.

Many of the tasks that will be required to achieve a particular goal will not demand such high levels of intelligence, however. For example, a crew member that is servicing a satellite or space station might need a particular tool or replacement unit to be fetched. This is a task that would be appropriately delegated to a spatially mobile robot that has the ability to recognize objects, estimate their spatial poses, grasp, and retrieve them. These are precisely the types of objectives that the Extravehicular Activity Helper/Retriever (EVAHR) is envisioned to achieve.

The EVAHR is a robotic device currently being developed by the Automation and Robotics Division at the NASA Johnson Space Center to support activities in the neighborhood of Space Station Freedom. Its primary responsibilities will be to retrieve tools, equipment, or other objects which may become detached from the spacecraft, or to rescue a crew member who may have been inadvertently de-tethered. Later goals will include cooperative operations between a crew member and the EVAHR, such as holding a light to illuminate a work area, exchanging an Orbital Replacement Unit (ORU), or maintaining equipment.

In order to be able to perform such tasks, it is clear that the EVAHR must be able to reason about its operational environment based on the input obtained from one or more sensors. This input is generally extracted from sensors that are capable of providing intensity and/or range information, and there are advantages and drawbacks for each of these sensory domains depending on the processing goal or the types of objects about which reasoning is to be performed. For example, a laser scanner is directly able to extract three-dimensional coordinates from an observed object whereas considerable computationally complex processing is necessary if only an intensity based imaging system is employed using a classical method such as shape-from-shading. These three-dimensional coordinates can be used to recognize the object based on its geometry or to estimate its spatial pose (location and orientation). On the other hand, certain objects, such as those covered with highly reflective material do not provide good return signals for the laser scanner, thus minimizing its usefulness in such cases. However, there are certain intensity based algorithms that make the estimation of spatial pose a straightforward and computationally inexpensive process if the right geometry exists among four or more extracted features in the intensity image.

The examples cited in the preceding paragraph are illustrative of the need for a Vision System Planner (VSP) that is capable of selecting a sensor based on knowledge of sensor capabilities and object characteristics. The justifications for a VSP extend far beyond sensor selection, however, since once a sensor has been selected it may need to be reoriented to obtain a better view of a target object. In some cases, physical characteristics of the sensor such as scanning rate or effective resolution may need to be altered so that the data can be acquired more rapidly or such that feature location estimates can be improved. Once a sensor has been selected and configured for the task at hand, the VSP should also be capable of selecting an appropriate algorithm to achieve the current vision system goal based on what is known about the sensor configuration, the characteristics of the objects being reasoned about, and the state of the operational environment as represented in a world model. Figures 1 and 2 show the fundamental functional components of the VSP and its relationship to the higher level Task Planner.

The remainder of this report is divided into four sections that describe research progress toward the development of such a Vision System Planner and make recommendations for future related research. Section 2 reviews the initial study of the vision system architecture. The details of the initial VSP design are documented in a paper entitled "A Vision System Planner for the Extravehicular Activity Retriever"[7] which was published in the *Proceedings of the International Conference on Intelligent Autonomous Systems*, and thus section 2 may be skipped by the reader who has read that paper or who is familiar with the research performed during the summer of 1992. Section 3 details the implementation phase of the follow-on research in which many of the approaches developed in the initial study were realized on available intensity image processing hardware mounted on a mobile robot platform. Section 4 extends the study of the vision system architecture beyond the limitations of the available sensory and robotic hardware by incorporating synthetically generated range images and demonstrates how a moderate amount of range data processing can facilitate the recognition process. Section 5 discusses how the vision system can plan sequences of actions relating to object recognition and object pose estimation using complementary sensors and a variety of algorithmic options to accomplish a current visual objective and makes recommendations for continuing research relating to the Vision System Planner.

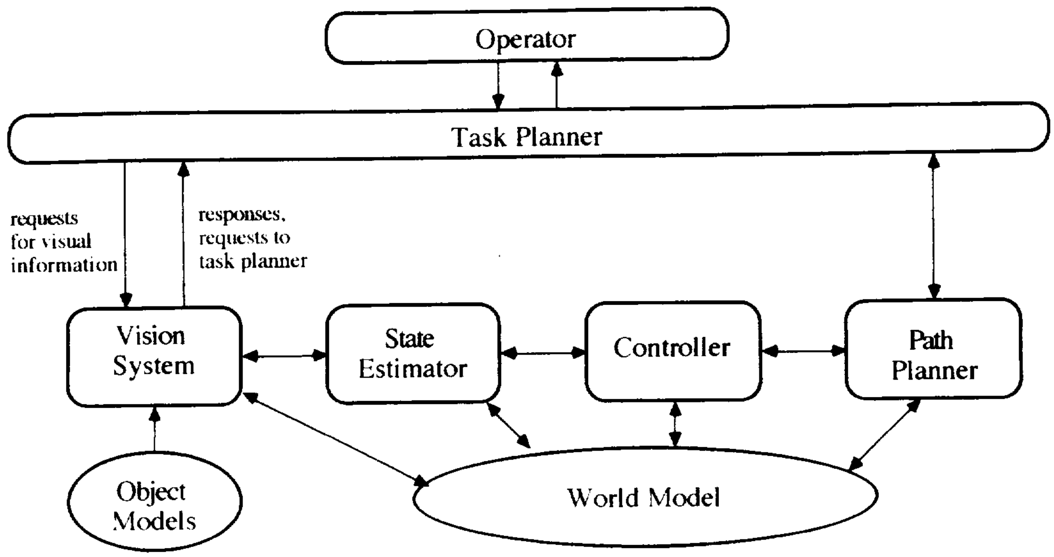


Figure 1: Planning System Architecture

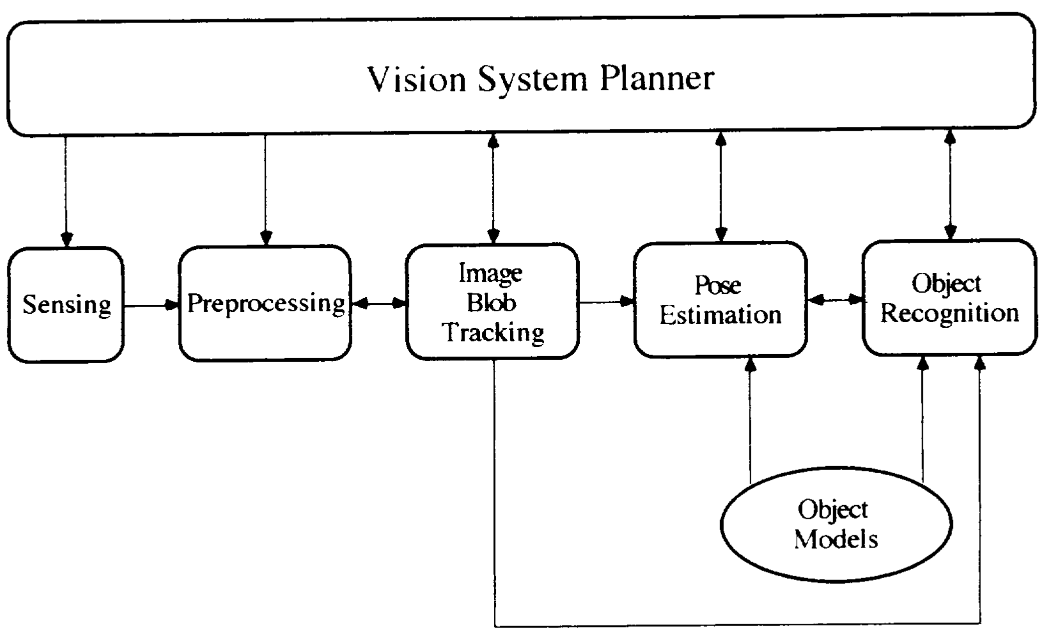


Figure 2: Vision System Components

2. Vision System Planner Design Considerations

2.1 Background for the Initial Design of VSP

The planning mechanisms developed for the initial VSP were founded on the assumption that there should be at least two visual sensors which provide intensity and range images. There are several reasons why such a multisensory approach is desirable, three of which are particularly significant. First, the availability of sensors with complementary capabilities permits the VSP to select a sensor/algorithm combination that is most appropriate for achieving the current visual goal as specified by the task planner. Second, if the sensor that the VSP would normally select as its first choice to achieve the goal is either unavailable or inappropriate for usage because of some current constraint, it may be possible to perform the desired task using the other sensor to achieve the same goal, albeit perhaps by accepting a penalty in performance. Finally, instances may occur for which it is desirable to verify results from two different sensory sources rather than relying on the inferences based on data obtained from a single sensor.

The first of the above motivations addresses the need to achieve the visual goal in the most effective manner by allowing the VSP to choose among sensors with complementary capabilities. For example, if it is desired to distinguish between two objects of similar structure with the color of the objects being the primary differentiating feature, then it is apparent that the color camera should be used as the primary sensor. On the other hand, if the size and/or geometry of the objects are most useful for determining identity, then it is important to be able to expeditiously extract and process three-dimensional coordinates. Clearly, this is a task that would be most properly assigned to the laser scanner. Similarly, tasks involving pose estimation[8], object tracking[9] and motion estimation[10] would more appropriately involve invoking the laser scanner as the primary sensor. The initial versions of these submodules are under development and are to be tested in a reduced gravity environment using NASA's KC-135 aircraft[11].

The previous example involving the need for three-dimensional coordinates is illustrative of a case in which the primary sensor (the laser scanner) is engaged to extract the required information. However, there may be cases for which the laser scanner cannot be used to obtain range information because (a) the object to be processed is covered with a highly specularly reflective material thus preventing acquisition of good return signals, (b) the laser scanner is currently assigned to another task, or (c) the laser scanner is temporarily not functioning properly. For such instances, it is highly desirable to provide a redundant capability by using the other sensor if possible. The classical method for determining three-dimensional coordinates from intensity images involves a dual (stereo vision) camera setup in which feature correspondences are established and the stereo equations are solved for each pair of feature points. Although the assumed configuration has only one intensity image camera, this alternative mechanism for computing range values is in fact possible for the VSP to achieve by requesting the task planner to reposition the EVAHR such that the camera's initial and final positions are offset by a known baseline distance. Of course, there is a penalty in performance if this (pseudo) stereo vision method is chosen, since the EVAHR must be moved and feature correspondences computed. However, it is nevertheless important to have such a redundant sensing capability for the reasons previously mentioned and to be able to independently verify the results obtained from one sensor or to increase the confidence of those results.

Aside from selecting an appropriate sensor, it is may also be possible to alter certain physical characteristics of the sensor such as the effective resolution and scanning rate. In the case of the laser scanner, images can be acquired at rates (and resolutions) varying between 2.5 frames per second (256 x 256 pixels) to 10 frames per second (64 x 256 pixels). The capability to select a faster frame rate with a penalty in resolution becomes significant if it is important to be able to sense and process data rapidly, as in the case of motion parameter estimation. On the other hand, if an object is relatively stationary and finer features are to be sensed, then higher resolution with a lower frame rate would be chosen. Hence, a vision system planner should be able to select a sensor as well as its relevant parameters (e.g. scanning rate, resolution, zoom factor, orientation).

Once an appropriate sensor has been selected and configured, the next step is to focus attention on the object(s) and to apply a preprocessing algorithm that will effectively achieve the current goal. Focusing attention is important because it reduces the amount of image data that must be processed for the immediate task. If the task is tracking an image blob that corresponds to an object of interest, and the image blob merges with another blob or disappears due to occlusion, then the object's predicted location (computed by the adaptive image blob tracker) is central to assisting in the segmentation of sub-blobs.[9] The selection of a pose estimation algorithm is directly dependent on the model being processed.[8] There are two fundamental classes of algorithms that are currently employed, namely object-based and image-based (multi-view) pose estimation. If an object contains curved surfaces (e.g. a cylinder) then an image-based approach is taken, by which the occluding contours derived from several views of the object that were recorded on a tessellated sphere are used as the basis for matching the observed object's outline. If the object has a polyhedral structure (no curved surfaces) then an object-based pose estimation algorithm is employed, by which features extracted from images are matched against model features in a CAD data base. For situations in which the object is very close to the sensor (e.g. during grasping), the pose may be estimated on subparts of the entire object rather than the entire object. Similarly, for purposes of recognition, the subset of object features selected and the algorithm chosen are also a function of the size of objects in images.

Proximity to target objects will affect not only the features selected for recognition and pose estimation but will strongly influence the confidences associated with the results computed. For example, a typical scenario might involve a case in which the EVAHR is close enough to a target object to hypothesize its class based on color, but too far away to definitively recognize its geometric structure using laser scanner data. In this case, the VSP would tentatively identify the object (using color) and would advise the task planner to move closer to the object so that a laser scanner image with higher resolution can be obtained. The confidence of the initial hypothesis would then be strengthened (or perhaps weakened) depending on the conclusion reached by processing the range data at close proximity. This capability is illustrative of the necessity for the VSP to be able to plan high level vision tasks as well as to be able to interact (interface) with the higher level task planner in order to reposition the EVAHR. Hence, at the highest level of vision system planning, the VSP will be responsible for task scheduling and resource planning.

The fundamental architecture for the Vision System includes modules which are designed to detect, recognize, track, and estimate the pose of objects. Upon receiving a request from the main task planner to achieve one of these objectives, the Vision System Planner determines an appropriate sequence of goals and subgoals that, when executed, will accomplish the objective. The plan generated by the VSP will generally involve (a) choosing an appropriate sensor, (b) selecting an efficient and effective algorithm to process the image data, (c) communicating the nominal (expected) results to the task planner or informing the task planner of anomalous (unexpected) conditions or results, and (d) advising the task planner of actions that would assist the vision system in achieving its objectives. The specific plan generated by the VSP will primarily depend on knowledge relating to the sensor models (e.g. effective range of operation, image acquisition rate), the object models (e.g. size, reflectivity, color), and the world model (e.g. expected distance to and attitude of objects). The next subsection presents the resulting plans generated by the VSP for several different scenarios.

2.2 Scenarios Illustrating the Operation of the VSP

The operation of the prototype VSP that was initially designed and implemented can best be understood by examining the plans generated for various scenarios. For purposes of illustration, the initial state of the world is always assumed to be that there are three objects somewhere in front of the EVAHR. One of the objects is an Orbital Replacement Unit (ORU) with a known uniform color. For cases in which the EVAHR VSP needs to search for the ORU, the hemisphere in front of the EVAHR is searched in the spiraling manner shown in Figure 3. The task planner (perhaps in consultation with the human operator) selects an angular field of view (i.e. zoom factor) for the color camera which affects (in an inversely proportional manner) the number of hemispherical sectors that must be searched (i.e. the smaller the angular field of view, the larger the number of hemispherical sectors). For example, if the angular field of view is chosen to be 45^o, sectors near the center of the forward hemisphere (sectors 1-6 in Figure 3) are searched and if the ORU is not found, the extreme sectors (7-14) are searched in that order.

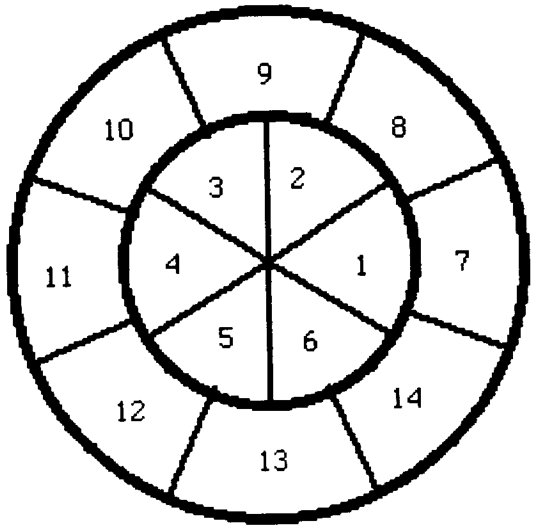


Figure 3: hemispherical sector search order

The scenarios that follow illustrate situations involving object detection, recognition, range estimation, and obstacle notification.

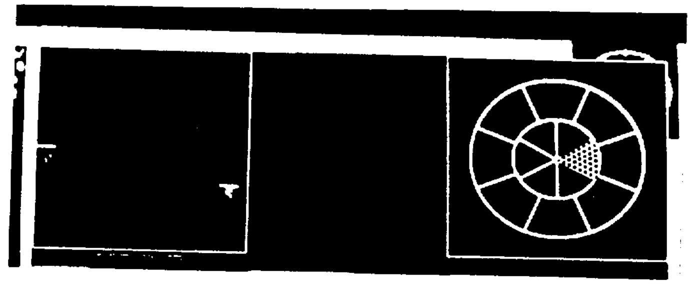
Scenario 2.2.1

Command received by the VSP: Search in front of the EVAHR for an ORU.

Plan generated by the VSP:

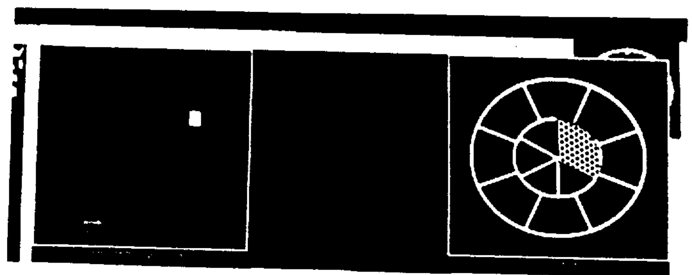
1. Search the hemisphere in front of the EVAHR by activating the color camera, fixing the effective focal length and spiraling outward from the center until the object is found (Figures 4a, 4b).

2. If the ORU is found, terminate the spiraling search and iteratively refine the estimate of where the object is located by adjusting the sensor gimbals toward the object and reduce the field of view (telephoto zoom) until the object is centered and large in the image (Figures 4c, 4d). If the ORU was not found, the VSP reports failure, after which there are several actions that could be taken. First, the forward hemisphere could be rescanned at higher magnification (a slower process since more scans will be required). Second, the forward hemisphere could be rescanned with increased illumination (requiring a decision to be made regarding the desirability in terms of overall objectives and power consumption by the illumination source). Finally, the VSP could request the Task Planner to rotate the EVAHR by 180 degrees and scan the rear hemisphere.



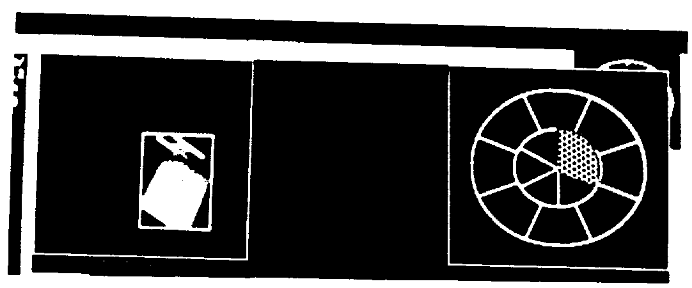
Teleoperator command: *RGB search for ORU*
Field of view angle = 50°
Scan angle = 45°

Figure 4a: search of sector 1 for ORU



VSP response: *ORU was found in sector 2*
Area of object was 150 pixels

Figure 4b: search of sector 2 for ORU

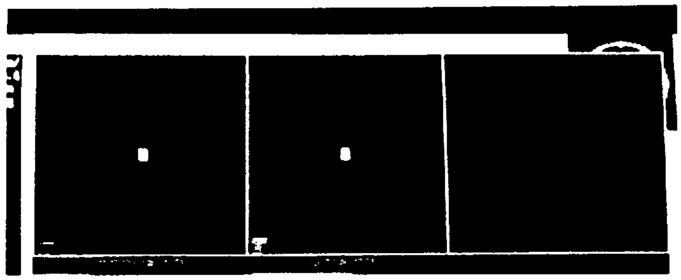


VSP action: *Reorienting camera gimbals*
Setting field of view to 7°

Figure 4c: first gimbal and zoom refinement

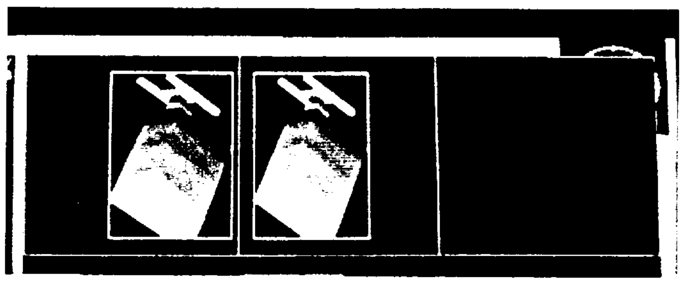
VSP action: *Reorienting camera gimbals*
Setting field of view to 4°

Figure 4d: second gimbal and zoom refinement



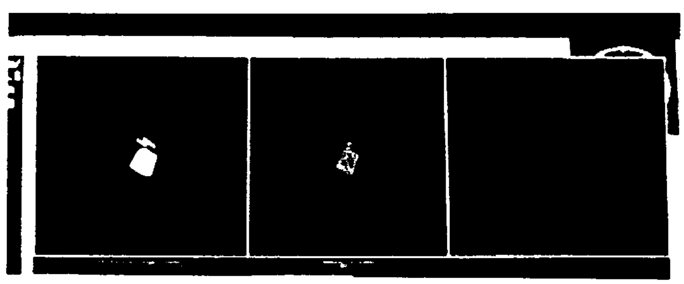
Teleoperator command: *estimate range to ORU using laser scanner*
VSP response: *estiamted range to ORU is 18.5 feet*

Figure 5: laser scanner range estimation



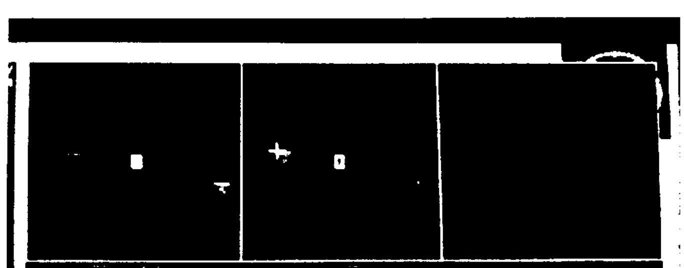
Teleoperator command: *estimate range to ORU using pseudo-stereo*
VSP response: *estimated range to ORU is 18.5 feet*

Figure 6: pseudo-range estimation



Teleoperator input: *move EVAR along optical axis*

Figure 7: moving EVAR toward the ORU



Teleoperator input: *check for obstacles in field of view*
VSP action: *obstacle located (identified by cursor)*

Figure 8: checking for obstacles prior to moving EVAR

Scenario 2.2.2

Command received by the VSP: Determine the distance to the ORU, no sensor specified.

Plan generated by the VSP:

1. Locate the ORU as in Scenario 2.2.1 using the color camera.
2. Examine the object model for an ORU and determine which sensor is the most appropriate to be used. In this case, since an ORU is not specularly reflective the laser scanner is chosen.
3. Examine that part of the laser scanner image that corresponds to the region belonging to the ORU in the color image and compute the distance to those range image elements (Figure 5).

Scenario 2.2.3

Command received by the VSP:
Determine the distance to the ORU, but force the estimation of distance using single camera lateral stereo vision.

Plan generated by the VSP:
1. Locate the ORU as in Scenario 2.2.1 using the color camera.
2. Move the EVAHR left a known distance, take an image, and record the location of the ORU in that image. Then move the EVAHR right a known distance, take an image, and record the location of the ORU in that image.
3. Using triangulation (stereo vision with two cameras separated by a known baseline distance) compute the distance to the ORU (Figure 6).

Scenario 2.2.4

Command received by the VSP:
Determine the distance to the ORU and move toward the ORU along the optical axis of the color camera until the EVAHR is a specified distance (D) away from it.

Plan generated by the VSP:
1. Locate the ORU as in Scenario 2.2.1 using the color camera.
2. Estimate the distance to the ORU (D_{oru}) using the laser scanner.
3. Compute a vector along the optical axis of the color camera whose length is (D_{oru} - D). Transform that vector into EVAHR coordinates and move to that position, maintaining the same attitude (Figure 7).

Scenario 2.2.5

Command received by the VSP:

As in Scenario 2.2.4, determine the distance to the ORU and check to determine whether any other objects in the field of view are closer to the EVAHR than the ORU prior to moving toward it.

Plan generated by the VSP:

1. Locate the ORU as in Scenario 2.2.1 using the color camera.
2. Estimate the distance to the ORU using the laser scanner.
3. Search the range image for values that lie outside of the region containing the ORU and report a potential obstacle if any of the values indicate distances between the EVAHR and the ORU. The cursor in Figure 8 shows the potential obstacle.

2.3 Deficiencies of the Initial VSP

For purposes of developing an initial architecture for the Vision System Planner, it was assumed that objects could be recognized based on a single monolithic color that was sensed by an RGB camera. The prototype VSP did not make use of features that might be extracted from range images that are potentially very useful for separating objects into geometric classes based on, for example, surface geometry or size. Furthermore, there was no attempt to combine information from the two sensory domains in order to disambiguate object recognition choices.

The complementary use of object geometry and color can easily be illustrated by considering a set of four simple objects which are a red cube, a blue cube, a red cylinder, and a blue cylinder. If, by processing a range image of one of these objects, it is determined that there are two or more visible planar surfaces, then clearly the object must be either a red or blue cube, but only examining a color image of the scene will determine which. On the other hand, if at least one non-planar surface is observed, then the object must be one of the cylinders, with color again being the differentiating feature. Hence, features based on range and color images provides a potentially powerful combination for recognition purposes. It is realized, of course, that current technology does not provide the capability to sense accurately registered RGB and range images. However, it is possible to extract features from registered range and reflectance images and to apply similar principles if the objects to be recognized have features that can be identified in the intensity images. This potential will be discussed in the next section which concentrates on object recognition in the intensity domain and implementation on an actual mobile robot platform.

3.0 Implementation and Studies of the Initial VSP on a Mobile Robot Platform

3.1 Hardware Implementation of the Initial VSP

The prototype VSP was completely developed using simulated sensors and hence the results obtained were under the most ideal of processing conditions. This meant that many "real world" issues did not arise such as those having to do with finding a specific object in cluttered visual backgrounds or dealing with sensor problems such as a camera that is out of focus. These problems are in fact significant issues that must be dealt with by the VSP, considering that there will be times when the earth with its oceans, clouds and continental land masses of varying colors will be the visual background for an object. Furthermore, the object, depending on its distance to the camera, may very well be out of focus.

With the goals of testing, validating, and expanding the functionalities of the prototype Vision System Planner in a non-simulated environment, a Mobile Robot Platform (MRP) was developed. The hardware available for this testbed MRP consisted of the following components.

1. A TRC LabMate mobile robot with three degrees of freedom provided general mobility for the other components. The LabMate can move about the floor (x and y translation) or rotate about a vertical (z) axis (Figure 9a).
2. A rotary carousel was attached to the top of the LabMate. This provided pan/tilt capabilities for the camera that was mounted on it (Figure 9b).
3. A color camera with separate red, green, and blue (RGB) output signals which was mounted atop the rotary carousel provided the primary sensing capability.
4. An Image Technology image processing system was used as the primary hardware unit for digitizing, displaying and processing multiband images.
5. A Silicon Graphics GTX 210 workstation hosted and controlled all of the above devices.

It should be noted that relative to the capabilities of the prototype VSP, the hardware available for the testbed MRP provided only color sensing capabilities. Hence, there was no facility for directly sensing range images via, for example, a laser scanner. Thus, the issues relating to range sensing were studied separately using simulated images with the results documented in section 4.

3.2 Complexities Introduced in Scenarios Involving Actual Color Images

The basic outline for planning to achieve goals relative to the scenarios discussed in section 2 was followed using the MRP with the exception that no range sensor was available. As has been pointed out previously, this could represent an actual situation in which a normally available range sensor has become nonfunctional or has been temporarily allocated for another purpose. In any

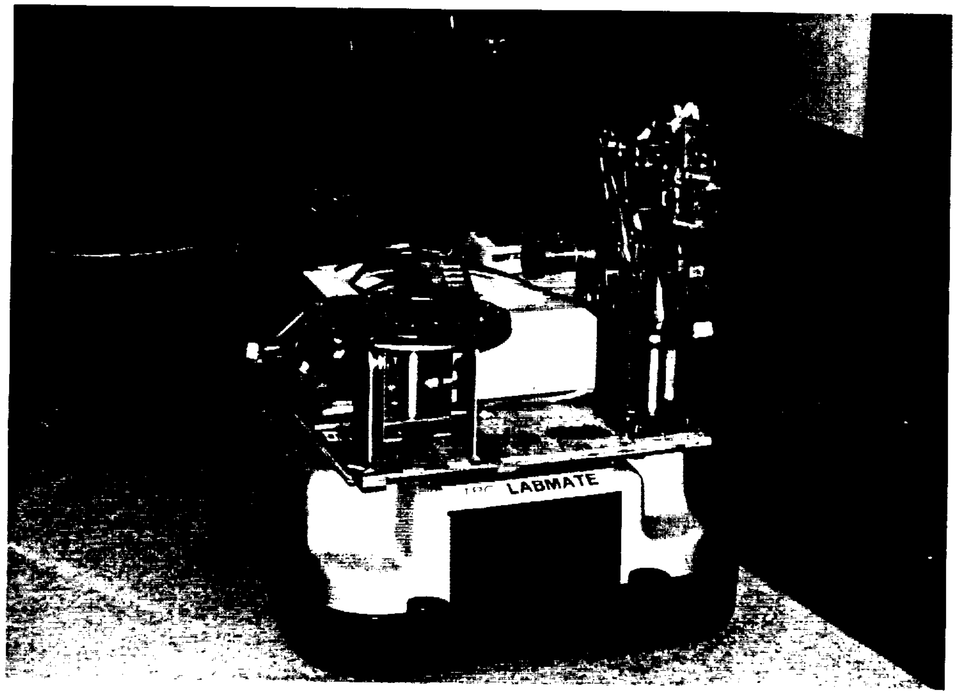


Figure 9a: The Mobile Robot Platform

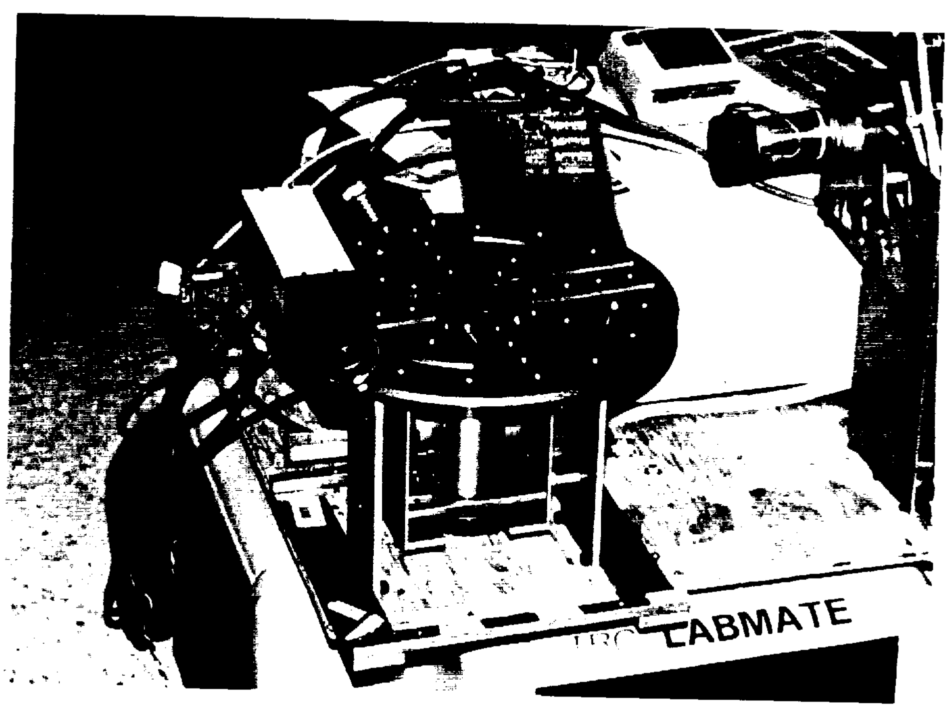


Figure 9b: The Rotary Carousel with RGB Camera

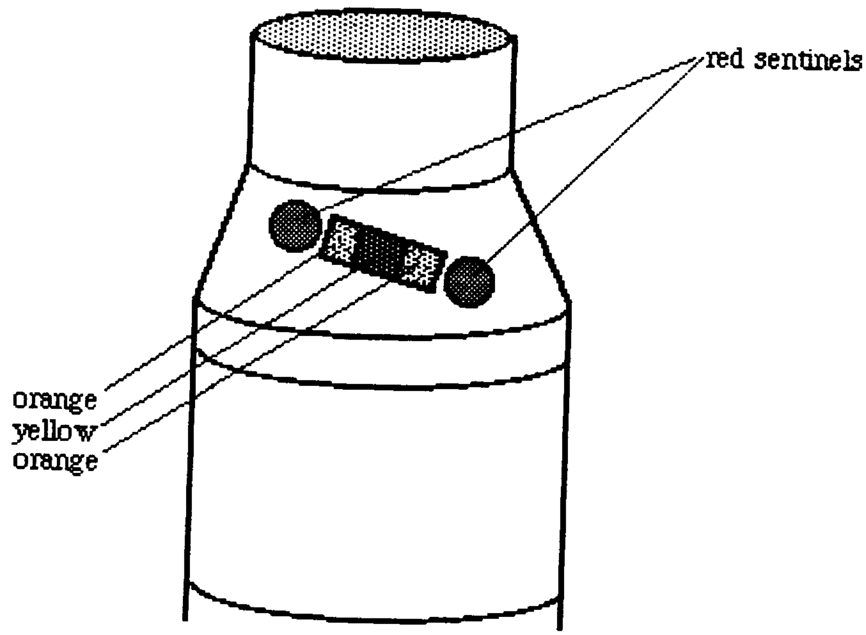


Figure 10a: Truss Coupler Identifier Markings

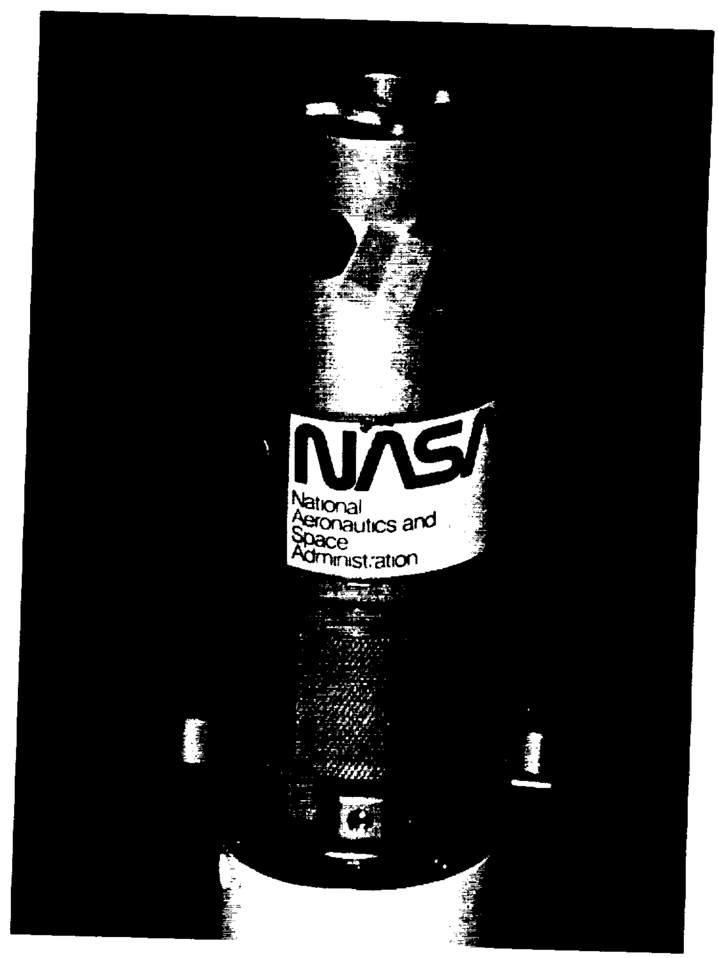


Figure 10b: Actual Truss Coupler with Identifier Markings

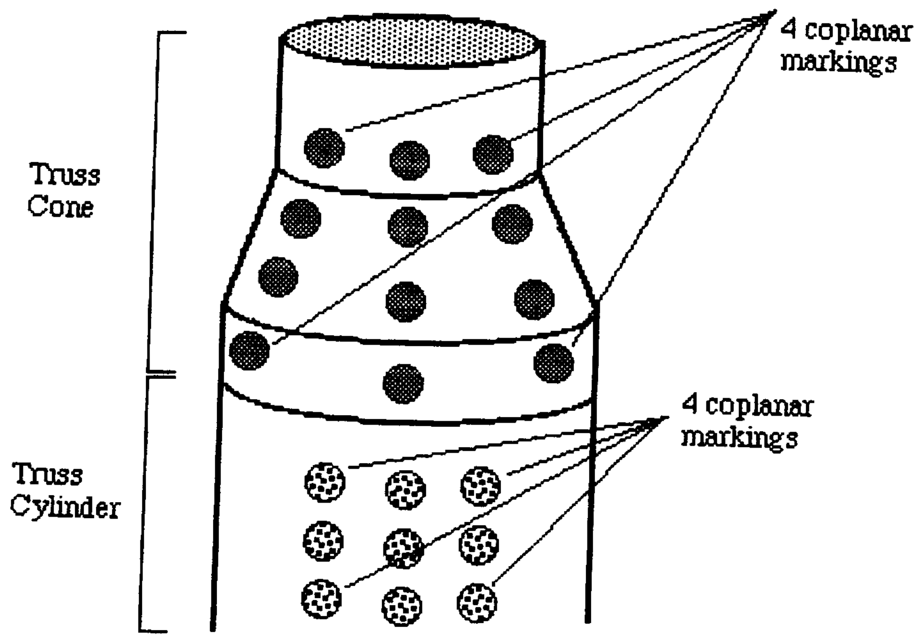


Figure 11a: Truss Coupler Pose Estimation Markings

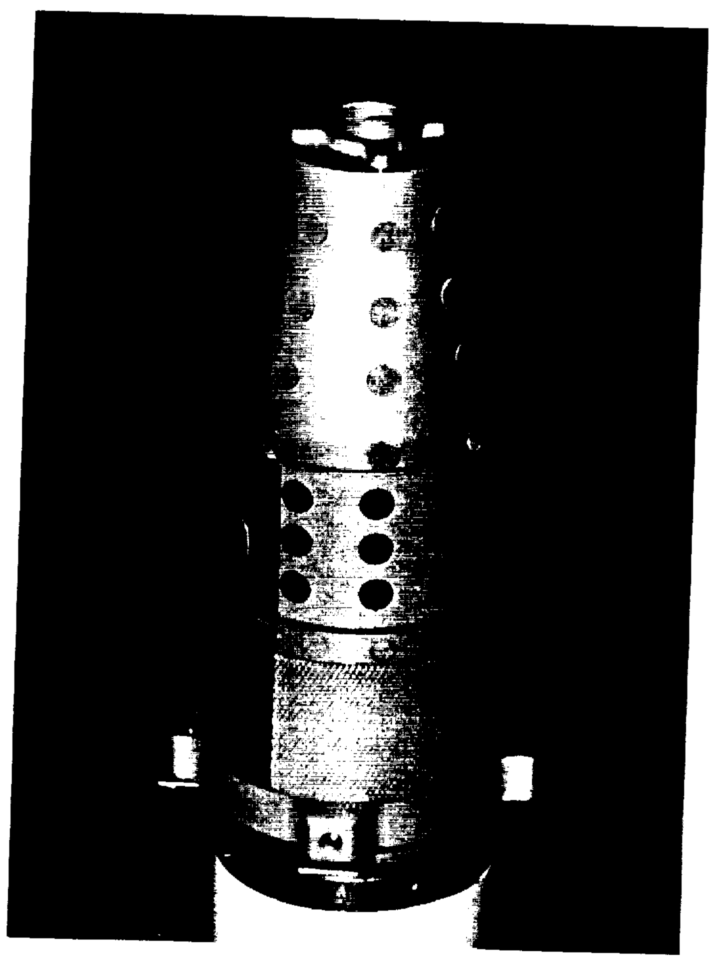


Figure 11b: Actual Truss Coupler with Pose Estimation Markings

event, for the scenarios that follow all plans are based only on information extracted from RGB images.

With this restriction in mind, this means that object recognition and/or pose estimation must be achievable using only intensity information. The lack of direct range sensing capability for achieving such goals should not, however, be necessarily viewed as unduly restricting the capabilities of the VSP for the following reasons. First, if there are significant colored features on an object, they may in fact expedite recognition in preference to complex processing of dense range images. Second, if these identifiable features share a special geometry, then estimating pose based on the intensity image may be more straightforward than if the range image is used as the basis for pose estimation. The utility of using intensity domain features can be particularly well illustrated by examining the truss coupler shown in Figures 10a,b and 11a,b.

Figures 10a and 10b show the upper conic structure of a truss coupler that has been marked with 5 colored regions. The outer most of these colored patterns are two red circles that serve as sentinel markings to delineate the boundaries of an interior pattern of encoded colored rectangles, which in this case are orange and yellow. Relative to the task of finding an object of interest in an RGB image, the red circles serve as markings that tell the vision system that there may be an object of interest in their proximity. This is, of course, not a certainty since other objects with a color similar or identical to the sentinels may be observed, but such sentinel markings serve as a clue to assist in restricting the search neighborhood.

The use of sentinel markings in the RGB domain was employed as a substitute for other methods that could be used if range images were available. To illustrate, consider a scenario in which an object is sought with the earth in the background. If range sensing were available, the detection of an object would be straightforward, assuming that the object were within the operational range of the sensor, since there would be no meaningful return signal from any source other than the target object. In the absence of a range image, however, it would be necessary to use only the color image to distinguish the object from a background that would consist of a myriad of colors. This is the fundamental purpose of the sentinel markings, but again, they are not sufficient by themselves to guarantee that an object of interest has been detected.

The mechanism by which a target object is detected is to seek the interior color coded set of rectangles that lies between the sentinel markings. For the case of the truss coupler cone shown in figures 10a and 10b, there are three such colored markings which can take on any of 4 colors (yellow, orange, blue, green). Hence, the identities of up to 24 (= 4 * 3 * 2) different objects could be encoded in this fashion, assuming that ambiguous (symmetric) patterns are to be avoided. This method of color encoding is analogous to bar coding the object except that no active scanner is required. The processing of the color bar code is performed as follows:

1. Locate all regions in the image that have the same color as the sentinel markings. Record the centroids of these regions as the locations of potential sentinels.

2. Search along the line segment joining a pair of potential sentinel centroids for regions having known bar code colors. If there are no unexamined sentinel pairs, exit.

3. If the intervening region colors do not match known bar code colors or produce an unknown bar code combination, reject the candidate pair of potential sentinels, select another candidate pair and repeat the process starting at step 2. Otherwise, continue on to step 4.

4. If the intervening region color combination is a known configuration, record the object's identity, record its identity and location and go back to step 2.

Assuming that a target object's color encoded identifier is visible, the above object segmentation and identification algorithm works quite well as long as the object is close enough to the camera such that each colored bar projects onto a few hundred pixels in a well focused image. When such is not the case, the VSP is nevertheless able to locate the target object, but must plan actions that compensate for poor focus or viewing the object at large distances. In particular, there are three cases which cause varying degrees of complexity in the planning process when attempting to locate specific objects. These cases involve (a) an object in close proximity that is completely in focus, (b) an object in close proximity that is moderately out of focus, and (c) an object that is completely out of focus. The plans generated by the VSP to find the target object for each of these scenarios follow.

3.3 Example Scenarios

Scenario 3.3.1

The truss coupler is close to the MRP and would be in focus if the camera were pointed toward it.

Command received by the VSP:

Search the forward hemisphere for the truss coupler and any other known objects and report the locations of these objects when finished.

Plan generated by the VSP:

1. Using the spiral search technique, examine the forward hemisphere for pairs of sentinel markings. Whenever a color bar code for any known object is recognized, record its location.

2. Report the locations of all recognized objects to the task planner.

Scenario 3.3.2

The truss coupler is close to the MRP but would be moderately out of focus if the camera were pointed toward it.

Command received by the VSP:

Search the forward hemisphere for the truss coupler and any other known objects and report the locations of these objects when finished.

Plan generated by the VSP:

1. Using the spiral search technique, examine the forward hemisphere for pairs of sentinel markings. Whenever a color bar code for any known object is recognized, record its location. For this scenario involving an out of focus target object, however, it is quite possible that the intervening colors between the sentinel markings will blend together and will prevent identification of the sought target object even though the sentinel markings were found. In this case, one of two different plans will be generated, depending upon the level of autonomy requested by the task planner. If the task planner permits operator intervention, the VSP will request that the camera be focussed. It should be noted that in a situation with more sophisticated hardware, this could be done automatically since the VSP could estimate the distance of the target object with a range finder and then adjust the camera's focus accordingly. On the other hand, if refocusing is precluded, the VSP will request the task planner to move the MRP toward the target object under the assumption that the lens focus setting has been fixed at approximately 1 meter. Since the task planner will know the locations of all objects in the forward hemisphere (ala Scenario 1 above), this maneuver can be executed by treating the objects as obstacles to be avoided.
2. Upon repositioning the MRP to a location approximately one meter away from the truss coupler, the VSP again examines the candidate object's color code, which should now be in focus, and reports success or failure in locating it. Figure 12 illustrates a case in which the VSP successfully found an initially out of focus truss coupler after notifying the task planner to move the MRP toward it.

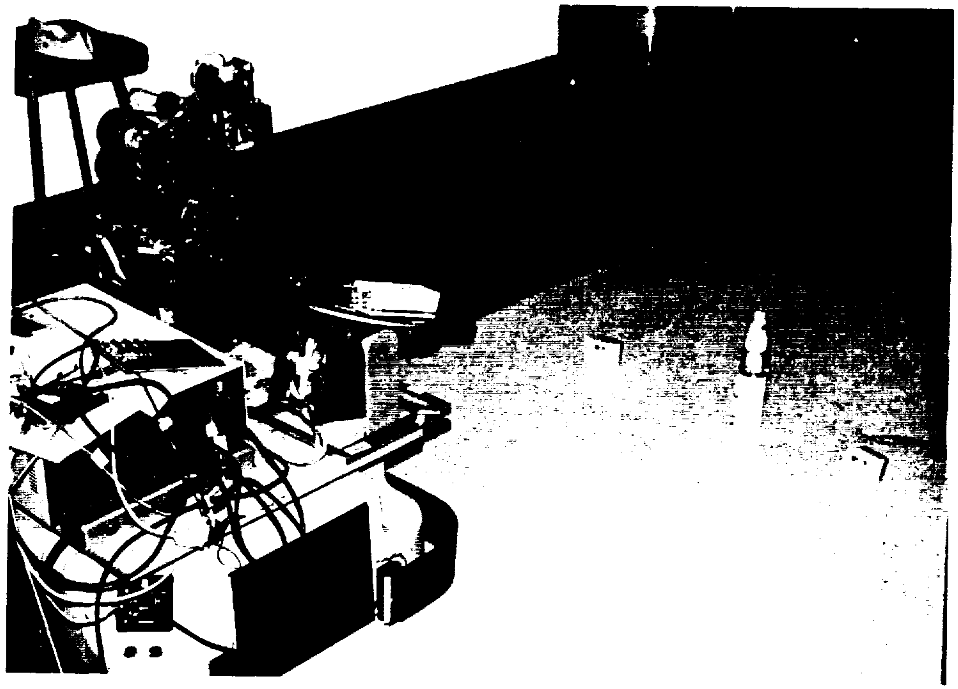


Figure 12: Configuration of MRP Relative to Truss Coupler after Executing VSP Plan

Scenario 3.3.3

The truss coupler would be totally out of focus if the camera were pointed toward it, or too far away to be identified as even a candidate, or is not in the forward hemisphere of the MRP.

Command received by the VSP:

Search the forward hemisphere for the truss coupler and any other known objects and report the locations of these objects when finished.

Plan generated by the VSP:

1. As in the previous two scenarios, the truss coupler would be sought by searching for its sentinel markings and the appropriate intervening color code.
2. If no candidate sentinels are found, the VSP cannot request the task planner to move the MRP to a more advantageous position with any degree of confidence based on observed data. Hence, it asks for refocusing of the camera and for the MRP to be pointed in the general direction of the target object.
3. Once step 2 is performed, the actions outlined in Scenario 2 can be followed to achieve the desired goal.

The above scenarios illustrate the VSP's ability to plan and execute actions that compensate for an out of focus camera or an object that is at a distance that makes identification difficult. Inherent in these actions, however, is the need to be able to estimate the distance to the object so that refocusing can occur or the MRP can be moved toward the object. For the current implementation, distance estimation was based on knowledge of the focal length of the camera and the distance between the sentinel markings on the target objects as embedded in the model knowledge base. This method suffers from two significant deficiencies, however. First, in order to estimate distance to the object, the camera must be relatively near the plane that is the perpendicular bisector of the line joining the sentinel markings. Second, and perhaps more importantly, although two markings are sufficient to base an estimate of distance upon, at least four markings are required for complete six degree-of-freedom pose estimates. With this in mind, objects like the truss coupler were also marked with colored features such as those shown in Figures 11a and 11b and a study of the quality of results was undertaken.

3.4 Intensity Based Pose Estimation

The technique for estimating the spatial pose of the truss coupler is based on the algorithm described by Hung, Yeh and Harwood.[12] This method requires three prerequisite conditions in order for the algorithm to be applicable. First, the effective focal length of the camera must be known. Second, the target object must have four coplanar points, no three of which are colinear.

Finally, the distances between each pair of the four points must be known and recorded in the model. If these prerequisite conditions are met, then the complete six degree-of-freedom spatial pose of the object can be determined by observing the locations of the four points in the image plane. The method involves only simple vector inner and cross products and the solution of linear equations.

For the specific case of the truss coupler shown in Figures 11a and 11b, the markings shown were placed on non-planar surfaces. However, the four outer markings shown at the corners of the twelve marker pattern lie in the same three-dimensional plane and therefore meet the criterion that is necessary to apply the Hung-Yeh-Harwood algorithm.

Nine tests with actual images of the truss coupler were run. These tests were divided into three groups which varied the pose of the truss coupler by rotating it about the conic axis, translating it along the conic axis, and changing its distance from the camera. From these tests, two conclusions can be drawn that directly affect the architecture of the VSP. First, in order to minimize sensitivity of the pose estimate to local pixel noise, the target object should fill a large portion of the image plane. Second, the camera should be positioned relative to the target points such that its optical axis is perpendicular to the plane containing the four points. The latter condition is particularly important since on curved objects like the truss coupler, markings on the "horizon" of the surface produce projected image plane coordinates that are very sensitive to minor variations in their extracted positions.

These observations are relevant to the Vision System Planner because it is not known in advance how close the camera should be to the object in order that it should occupy a large region of the image plane. However, as shown in the initial study, it is possible to use range images to estimate the distance and to use this estimate as the basis to execute a move toward the target object to produce a viewpoint that is close enough. The more difficult problem is to achieve a viewpoint such that the optical axis is nearly perpendicular to the plane of the four markings since this would involve at least an approximate knowledge of the rotational parameters of the object. However, if the object possessed multiple quadruplets that could be uniquely identified, then there would be a redundancy built into the model by which its pose could be estimated. For cylindrical or conic objects, this technique would be particularly appropriate since their poses are uniquely determined by the location of a point on the axis and the orientation on the axis itself. Hence, if multiple sets of points were evenly distributed around the cylindrical or conic section, it would always be possible to determine the pose of the object by selecting an "inner"set (in the image plane) that is most likely to satisfy the optical axis perpendicularity constraint. This method of pose estimation will be discussed within the context of an expanded VSP architecture later.

4.0 Synthetic Range Image Processing

4.1 Model Feature Learning and Object Recognition Overview

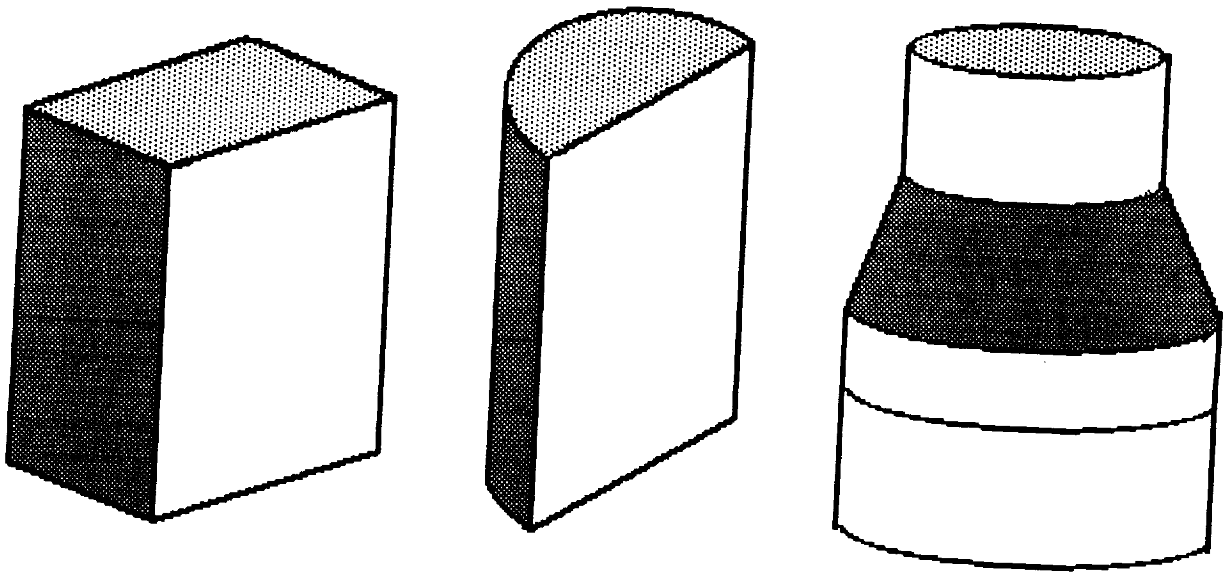
It has been previously pointed out that range image processing can directly provide information that is useful for recognition, pose estimation and repositioning of the vision system and that there are both advantages and disadvantages to employing such a sensor. Foremost among the advantages are the ability to directly extract distances to an object without extensive image processing (e.g. establishing stereo correspondence in two intensity images). However, higher level goals such as recognition and pose estimation may still require significant processing of the range image in order to extract features such as the surface type (planar, conic, cylindrical, spherical, etc.) The segmentation of objects into their component surfaces is particularly computationally intensive since multidimensional decoupled Hough transforms are typically required[13]. It is therefore appropriate to consider methods of object classification and pose estimation that make use of the best elements of each domain considering the following principles:

1. Recognition of objects based only on their geometric or topological characteristics is too difficult if only intensity images are used due to the three-dimensional transformations to which they may be subjected.
2. Certain low level operations in the range domain are relatively inexpensive. Among these are the computation of local surface normals.
3. The general segmentation of an object into all of its component surfaces using range images is computationally too expensive, but it is possible to rapidly segment the planar surfaces of the object.
4. Certain objects may be recognized by comparing the number of visible planar and nonplanar surfaces and the areas of each with those of known models. Hence, such knowledge can be used to constrain the identities of objects in an appropriately structured recognition search tree.

With the above principles in mind, a set of range processing primitives was developed that can separate observed objects into geometric classes as follows:

1. For test purposes, three types of objects are used. These include the cube, cut cylinder and truss coupler shown in figure 13. Synthetic range images of these objects as they can appear in arbitrary orientations are then generated.
2. In the learning phase, these objects are shown to the range data processing system in many different orientations such that object oriented model structures are automatically constructed and revised as each scene is presented. The goal of the learning phase is to develop a set of topological and geometric conditions that can be used to constrain each object when attempts are made to recognize it later.
3. During the recognition phase, the information extracted from the range image is compared

against that embodied in the learned object models. Candidate models are then included or excluded from the potential recognition set based on range data features such as how many planar surfaces are visible, how many curved surfaces are visible, the size of each planar surface, the size of the curved surfaces, and the total visible surface area. It should be noted that because of the computational expense involved, no attempt is made to determine whether curved surfaces are cylindrical, conic or otherwise. Hence, the algorithms only provide a basis or framework for further refinement of the identities of the objects based on more expensive range image processing or using features in the intensity image. Because of the extreme expense of processing the range images, it is believed that the most effective manner to proceed is by combining intensity based features with knowledge gleaned from a rough classification based on planar/nonplanar topologies.



Cube

Cut Cylinder

Truss Coupler

Figure 13: Models for Range Data Processing

4.2 Range Image Processing

In both the learning and recognition phases it is necessary to segment the data into planar and nonplanar regions so that the number of such regions and their respective areas can be determined. The way that this is done is as follows:

1. Let each range image value be represented as a homogeneous vector $V = [x\ y\ z]$. Then, if this range value belongs to the plane with equation $ax + by + cz - d = 0$, clearly $P \bullet V = d$ where planar normal vector $P = [a\ b\ c]$.

2. Now if $V_1, V_2, \ldots, V_9$ are vectors that represent point coordinates in the 3 X 3 neighborhood of a central range pixel, and $P \bullet V_i = d$ for i = 1, 2, ..., 9 it is possible to set up the following set of linear equations that computes a local planar normal based on this neighborhood:

Let $M = [\, V_1 \; V_2 \ldots V_9]$ be a 3 row, 9 column matrix of range image values and let $D = [\, 1 \; 1 \ldots 1 \,]$ be a row vector containing 9 1's.

Then, if the 9 points all belong to the same plane with equation $ax + by + cz = d$,

$$[a\;b\;c]\, M = D$$

and it is possible to compute a least squares solution for $[a\;b\;c]$ by using a pseudo-inverse of M by observing that

$$[a\;b\;c]\, M\, M^t = D\, M^t$$

$$[a\;b\;c]\, (M\, M^t)\, (M\, M^t)^{-1} = D\, M^t\, (M\, M^t)^{-1}$$

$$[a\;b\;c] = D\, M^t\, (M\, M^t)^{-1}$$

The value of d can then be computed as $d = ax + by + cz$ where $[x\;y\;z]$ is the value of the central range pixel.

In order to determine where there are planar regions within a range image, local plane equations are computed across a grid that effectively overlays the range image and those range pixels that contributed to (nearly) identical plane equations are collected into separate lists that support these individual plane equations. The remaining range pixels that do not strongly support the existence of a plane equation are grouped into a list of non-planar range pixels that are deemed to support the existence of one or more curved surfaces. Again, it is important to note that no attempt is made to perform any surface segmentation that is more sophisticated than separating planar and non-planar surfaces due to the associated computational costs.

Once a range image has been processed, several useful features relating to the observed object are recorded. In the learning phase, these features are used as the basis for refining the known object model. During the recognition phase, they are used to satisfy constraints that must be met in order to select a viable model. The specific features computed for an observed object are:

1. the number of visible planar surfaces (≥ 0)
2. the number of visible curved surfaces ($= 0$ or 1)
3. the area of the visible planar surface with the smallest area
4. the area of the visible planar surface with the largest area
5. the total visible planar area
6. the total visible surface area for the entire object

The next subsection demonstrates how these features can be used as the basis for learning about the topology and geometry of the object.

4.3 Learning model features

The basic philosophy employed for developing models is to embody in the model descriptors viewpoint dependent constraints that facilitate rapid identification. Hence, no global description of an object is constructed or used. To illustrate why this is done, consider the three objects in Figure 13. If three planar surfaces are ever viewed, it can be categorically stated that the observed object is a cube since the maximum number of visible planar surfaces for the cut cylinder and truss coupler are 2 and 1, respectively. Similarly, if at least one curved surface is observed, then the object cannot be the cube and it will be necessary to use some other discriminating feature(s) to determine whether it is the cut cylinder or the truss coupler. For none of these cases is it necessary to have a global descriptor of each object that describes its entire unified topology and geometry. It is, however, important to judiciously select a set of viewpoints that sufficiently constrains the potentially observable features so that it is known, for example, that a cube will always have at least 1 and at most 3 visible planar surfaces, while a cut cylinder will have 1 and 2, respectively. The learning mechanism actually employed can be illustrated by examining the image sequences shown in Figures 14-16.

Figure 14a shows the unprocessed synthetic image for a cube when three of its planar faces are visible. After applying the plane extraction algorithm described in section 4.2, three surfaces with the normals shown in Figure 14b are derived. The areas of these planar faces and the visible area is recorded in the initial model for the cube. This learning phase is followed by the two examples shown in Figures 14c and 14d that demonstrate that certain viewpoints relative to the object may result in fewer than 3 planar faces being visible.

For the cut cylinder, a similar learning sequence is provided. Figures 15a and 15b cause the system to learn that at most 2 planar faces and 1 curved surface may be visible. After presenting the views shown in Figures 15c and 15d, it is learned that as few as 1 planar surface may be visible and Figure 15e demonstrates that no curved surfaces may be visible. In addition, another view that presents only the half-cylindrical side refines the model knowledge such that it is known that no planar regions may be visible. The full learning sequence for a truss coupler, part of which is illustrated by Figures 16a-16d, produces a model that represents knowledge that one or no planar or curved surfaces may be visible.

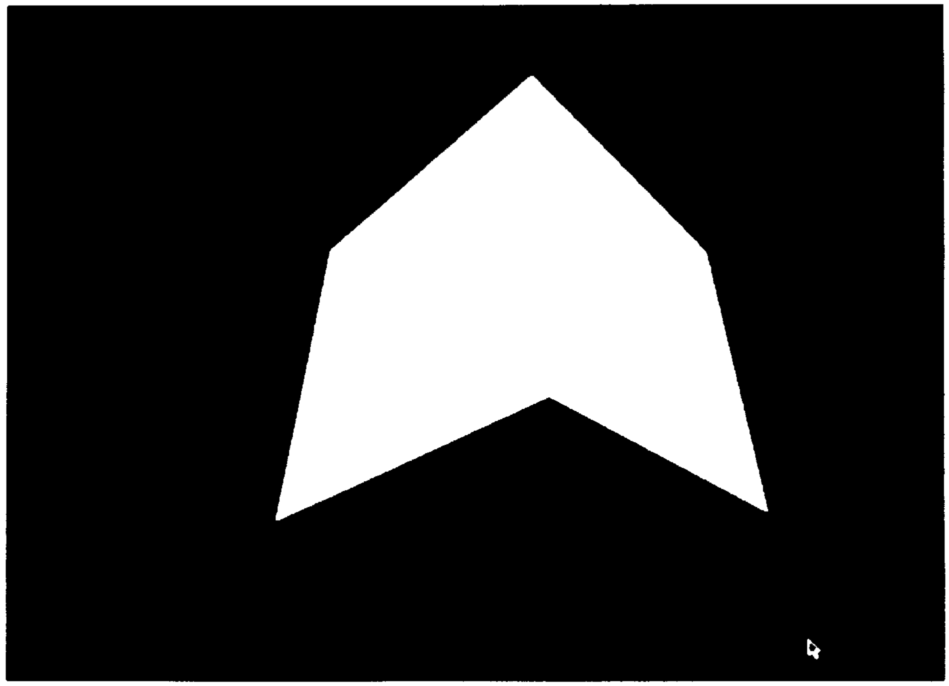


Figure 14a: Cube Showing Three Planar Faces

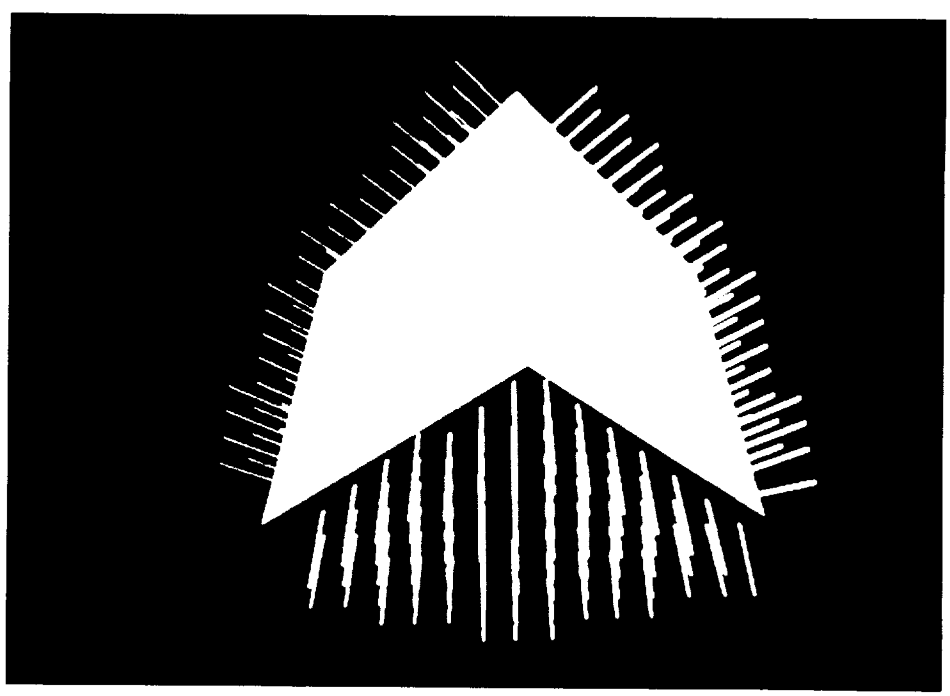


Figure 14b: Cube Showing Surface Normals for Three Planar Faces

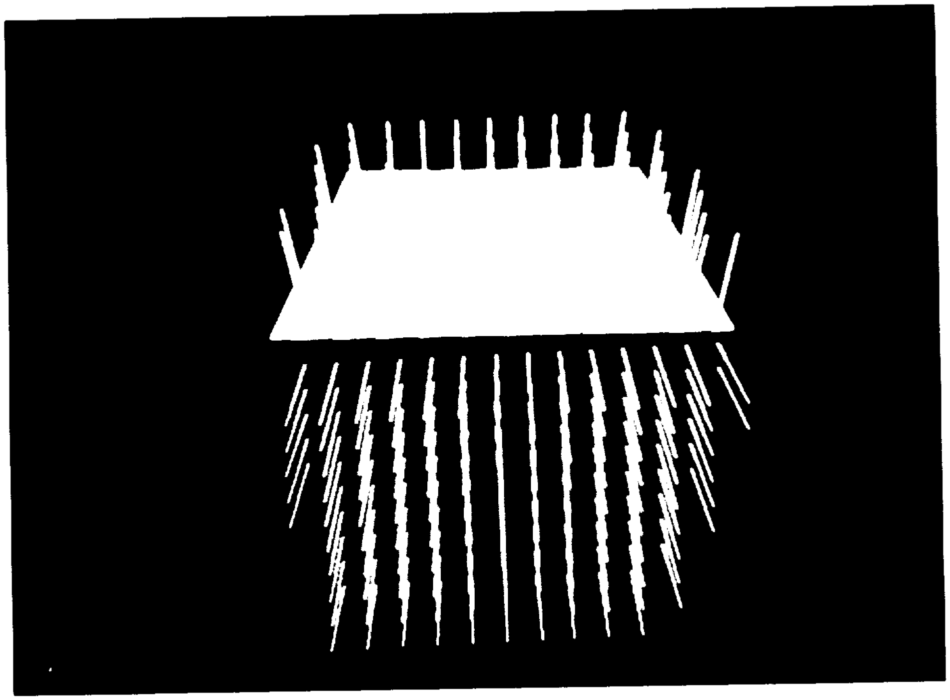


Figure 14c: Cube Showing Surface Normals for Two Planar Faces

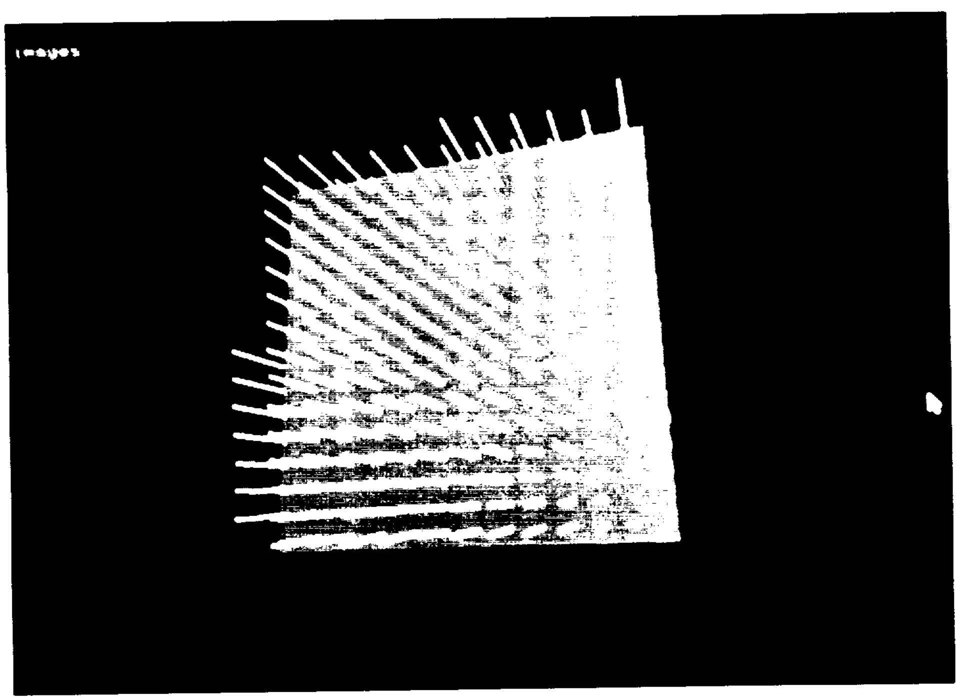


Figure 14d: Cube Showing Surface Normals for a Single Planar Face

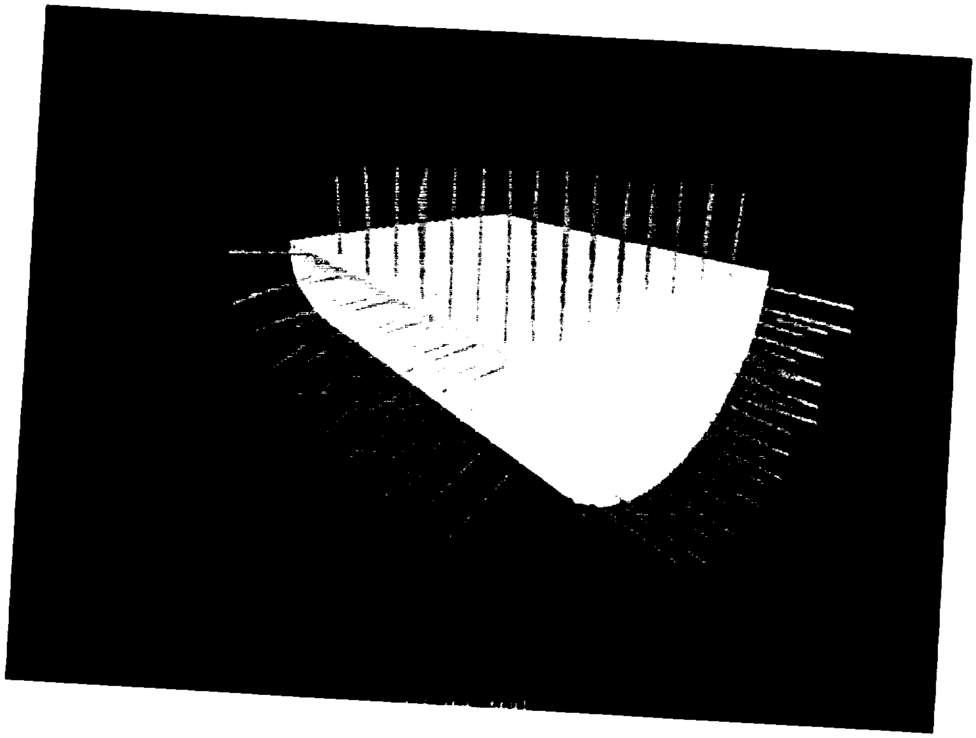


Figure 15a: Cut Cylinder Showing One Curved and Two Planar Surfaces

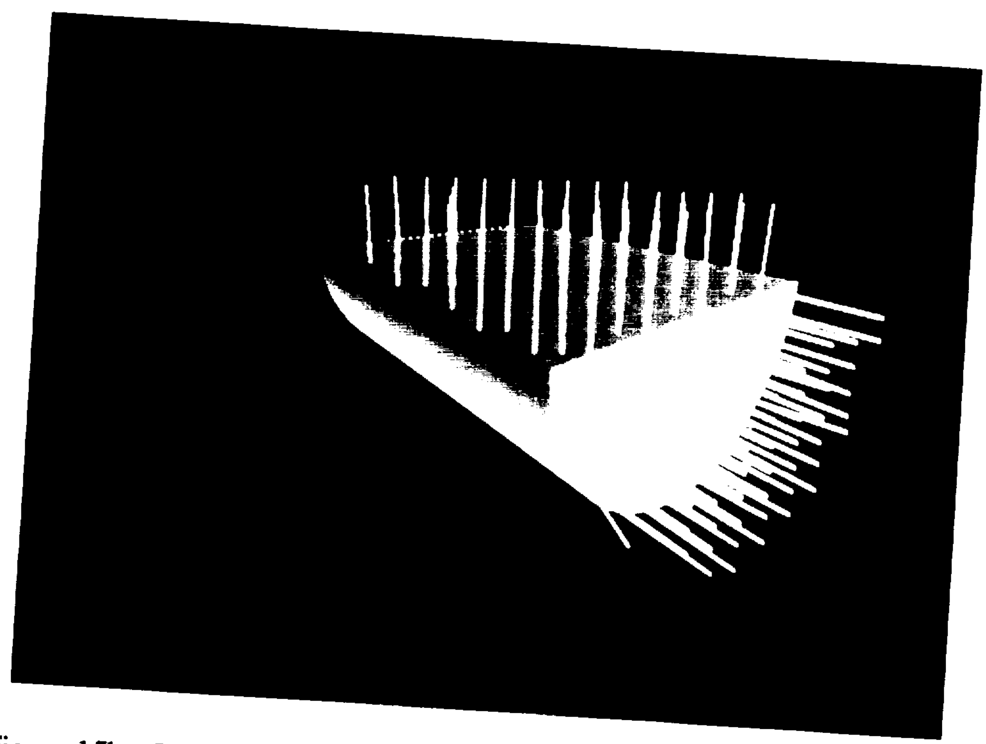


Figure 15b: Cut Cylinder Showing Surface Normals for Two Planar Surfaces

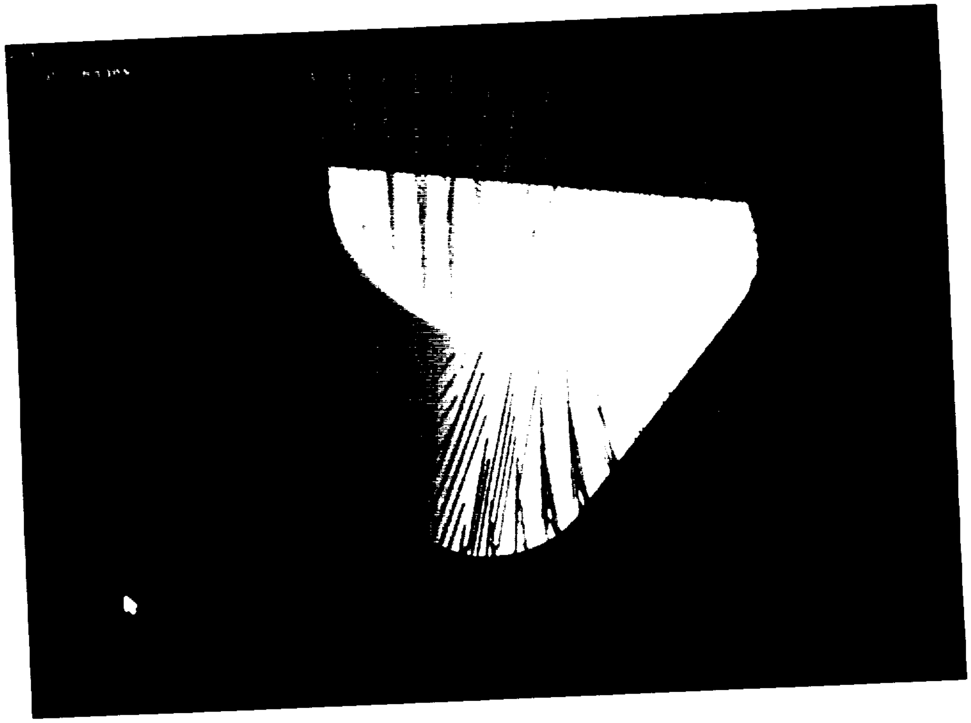


Figure 15c: Cut Cylinder Showing One Planar and One Curved Surface

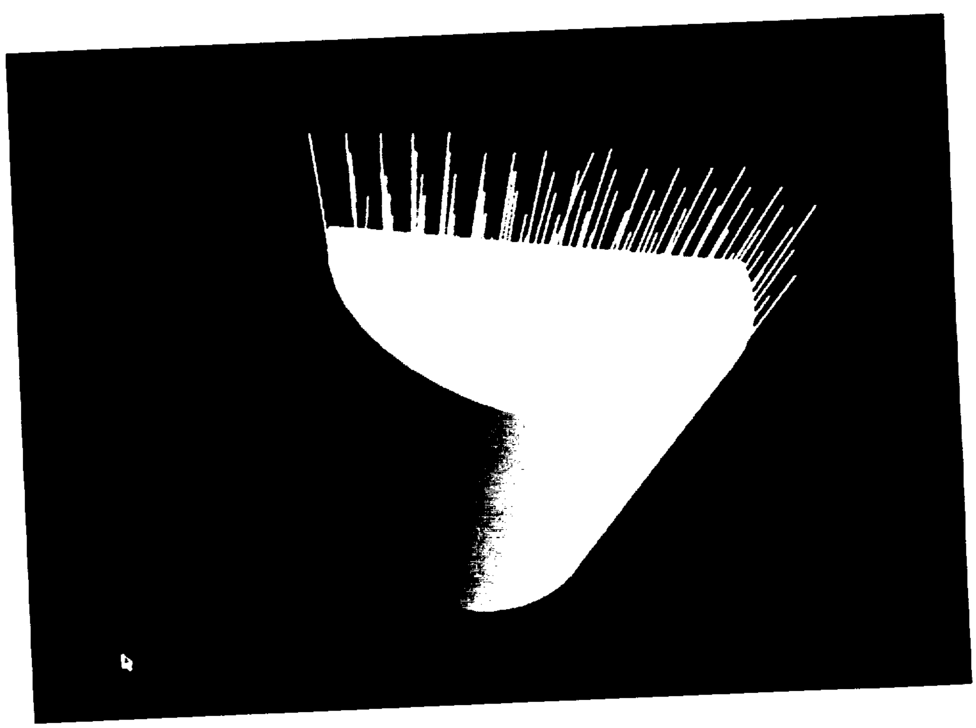


Figure 15d: Cut Cylinder Showing Surface Normals for Visible Planar Surface

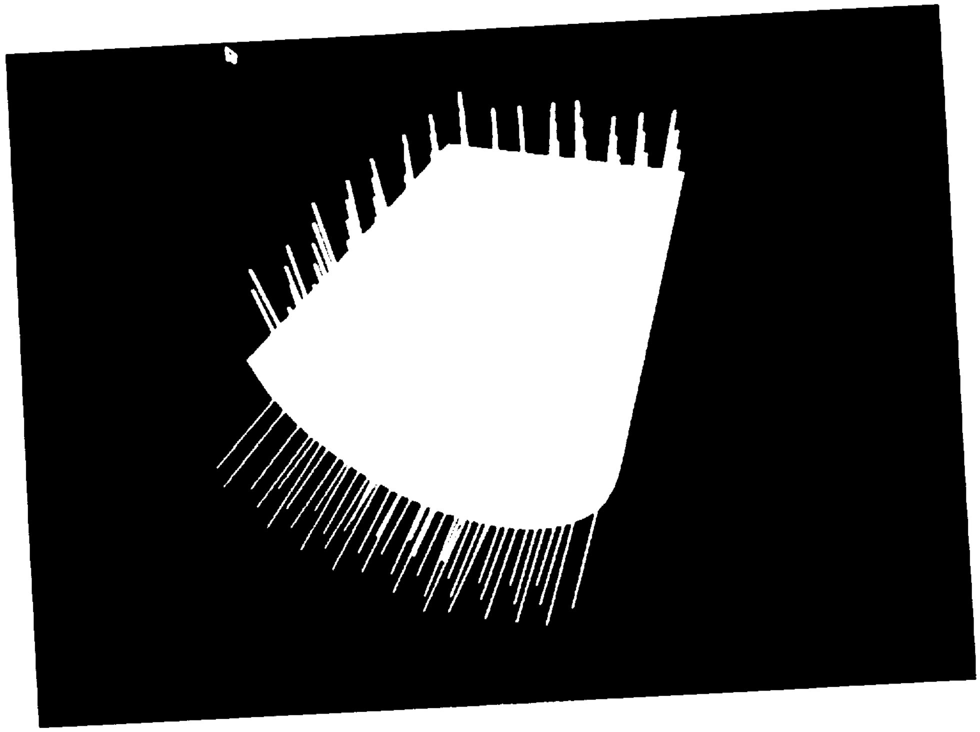


Figure 15e: Cut Cylinder Showing Surface Normals for Two Visible Planes

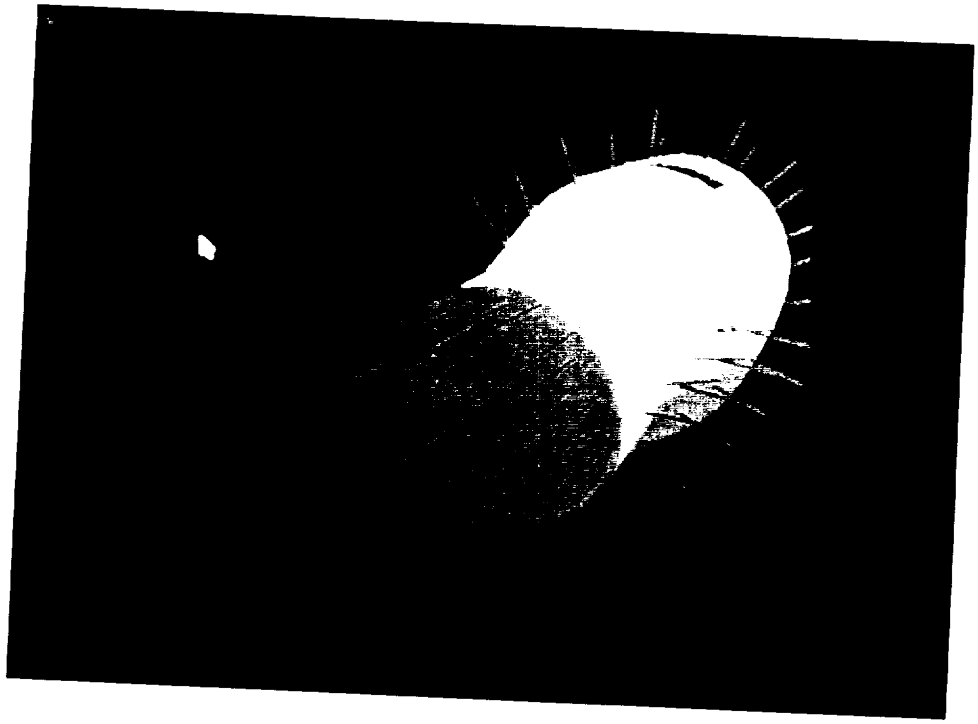


Figure 16a: Truss Coupler Showing One Planar Face and Curved Surfaces

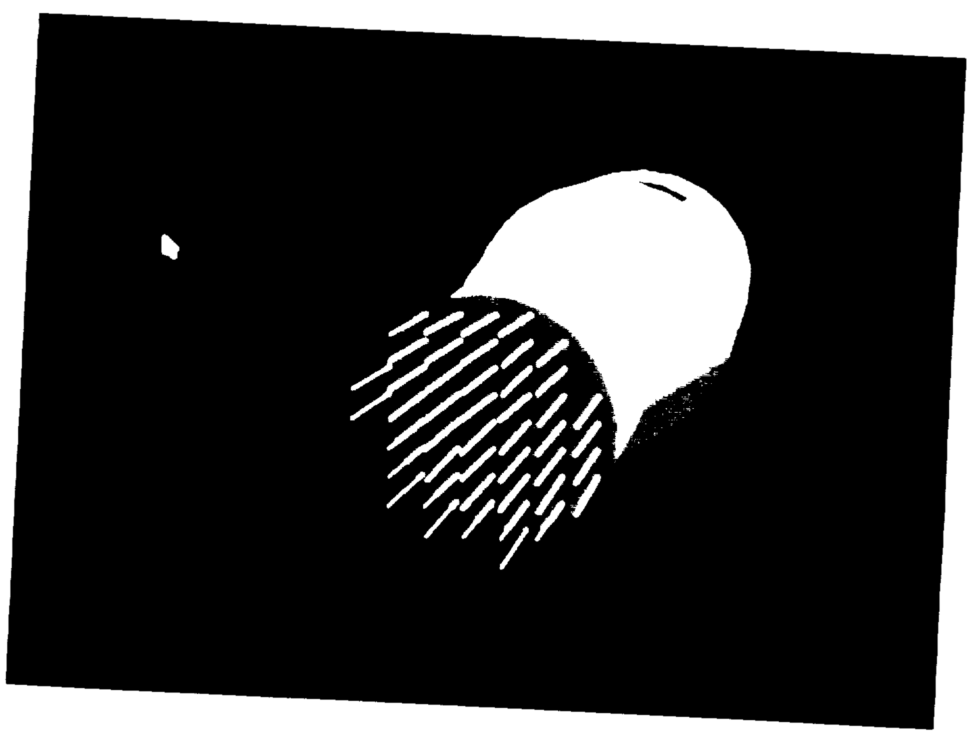


Figure 16b: Truss Coupler Showing Surface Normals for Visible Planar Face

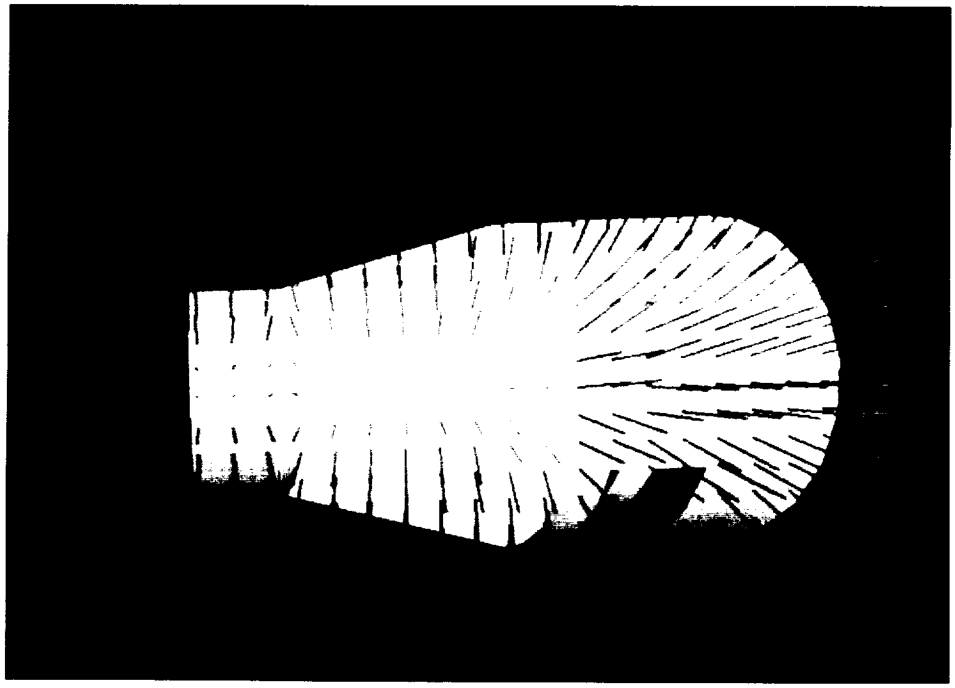


Figure 16c: Truss Coupler Showing Only Curved Surfaces

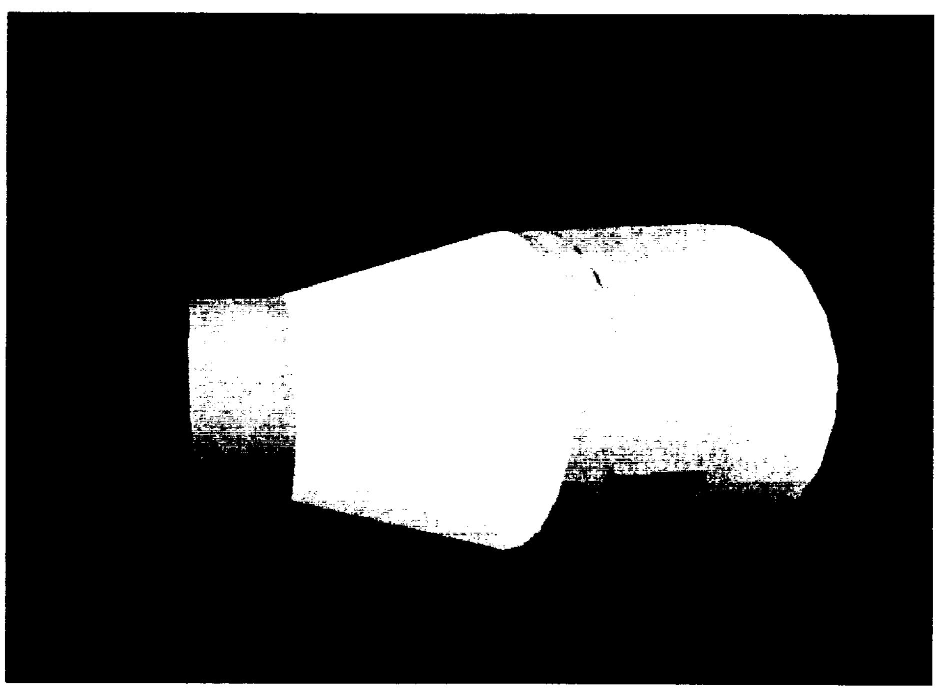


Figure 16d: Truss Coupler Showing Absence of Planar Surface Normals

4.4 Range Image Based Object Recognition

The learned features described in section 4.2 were used as the basis for discriminating among the cube, cut cylinder and truss coupler in various spatial poses like those illustrated by Figures 14-16. The system performed as expected, with the most useful features being the numbers of visible planar and curved surfaces and their respective areas. For certain views that did not produce a rich set of useful features, the system was unable to determine the identity of the viewed object. For example, the semi-circular planar region of the cut cylinder and the circular region of the truss coupler are very nearly the same area. Hence, if only these surfaces are visible, the system as it currently exists cannot distinguish between them and additional differentiators are necessary.

One possibility for such differentiating features would be to examine not only the topology of each surface but the structure of its bounding edges. Since the cut cylinder face is bounded by edges that are linear and semi-circular and the truss coupler surface is bounded by circular edges, these would be sufficient additional features to distinguish between these objects if such limited viewpoint dependent information were available. For certain cases, however, it will be necessary to obtain additional views, perhaps using a different sensor, in order to recognize an object or to estimate its pose. The augmentation of the current system with additional features and viewpoints and the combining of intentisy and range domains are the subject of the next section.

5.0 Vision System Planner Recommendations

As the result of experiments undertaken with both actual and synthetic sensor data, the following general principles were developed and used as the basis for recommending modifications to the Vision System Planner architecture. Figures 17-20 illustrate the basic recommended flows for sensor/algorithm decisions relating to object detection, recognition, pose estimation and iteratively improving the confidences of recognition and pose estimation.

1. For the detection of objects without recognition and/or pose estimation, the most appropriate sensor to select under general circumstances is the laser scanner. The primary reason for this conclusion is that segmentation of objects as viewed by a color camera becomes extremely difficult if a colorful background (e.g. the earth) is present. Hence, in the most general cases, it is preferable to attempt to detect anomalies in depth data rather than in color images.

2. For the recognition of objects a two pronged approach that combines range and intensity images is advantageous. From a geometric structural approach, the recognition of generalized curved objects from range images is too computationally expensive, even to perform surface segmentation. However, as was shown in the previous section, a limited amount of range processing to extract the planar surfaces and their areas can provide the basis to group objects into broad categories. Once this is done, key intensity features can be examined either in the reflectance image for the laser scanner or in that of the color camera to refine the identity of the object. For example, suppose that a planar and a non-planar surface are extracted from a range image. This is a situation that could arise if either the cut cylinder and the truss coupler were viewed as in Figures 15d and 16b. The resulting confusion between the two models could be resolved simply in the intensity image by noting that the planar surface of the truss coupler is not bounded by any straight line segments, whereas the planar surface of the cut cylinder has a semicircular and a linear boundary. In another case, colored (bar code) patterns could be used as the discriminating factor. Hence, applying information obtained from both range and intensity domains would differentiate the two models.

3. The manner by which spatial pose is estimated should be a function of the visible surface characteristics for the observed object. If only planar surfaces are observed, then the vertices at which these planar surfaces intersect can provide sufficient features upon which to compute pose using the locations of these features as extracted from the range image. For curved objects such as the truss coupler, however, computationally difficult problems relating to the extraction of surface type (e.g. cylinder, cone, etc.) arise. It is therefore advisable to consider using markings on the objects that facilitate applying one or more of the computationally simple intensity domain pose estimation algorithms such as that of Hung, Yeh and Harwood. An object like the truss coupler could be marked redundantly such that at least four coplanar noncolinear feature points would always be visible. This approach avoids problems associated with the computation of parameters for curved surfaces and potential occlusion of a single set (of 4) pose estimation feature points.

4. Finally, there may be cases for which there is a low confidence for the identity or estimated pose of an object as determined above. This may be due to a goal that minimizes processing in order to avoid computationally expensive feature extraction during the recognition phase. However, if a reliable pose has been estimated, the location of features in each image may be predicted and the search space can be considerably constrained. Hence, it is appropriate to loop back through both the recognition and pose estimation phases further refining estimates of feature correspondences and pose parameters based on predicted and verified features.

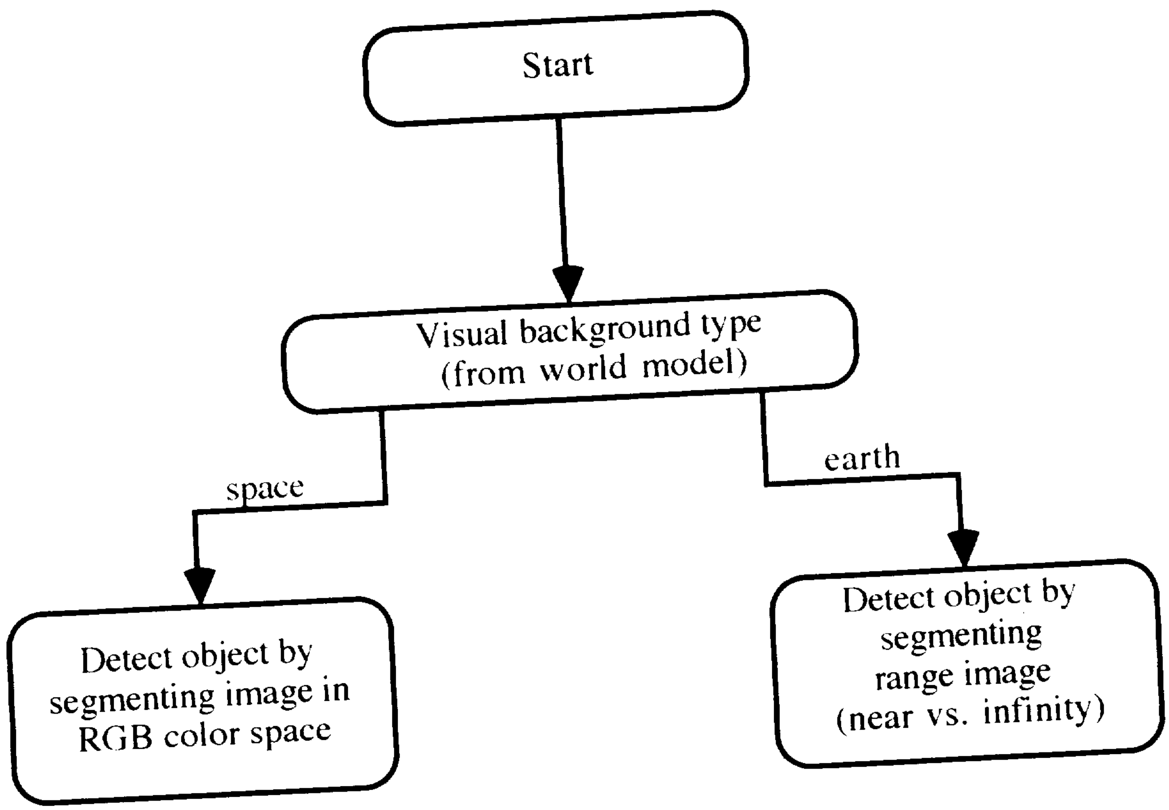


Figure 17: Object Detection

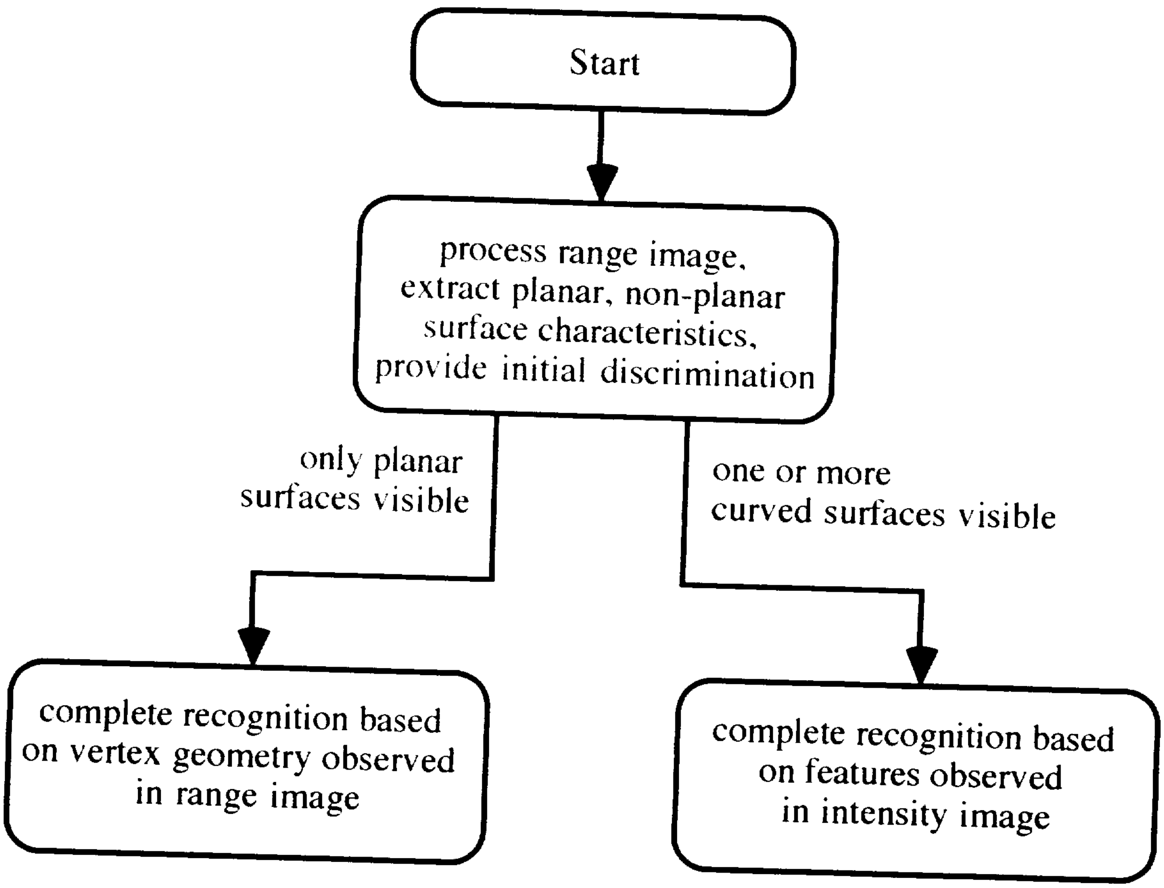


Figure 18: Object Recognition

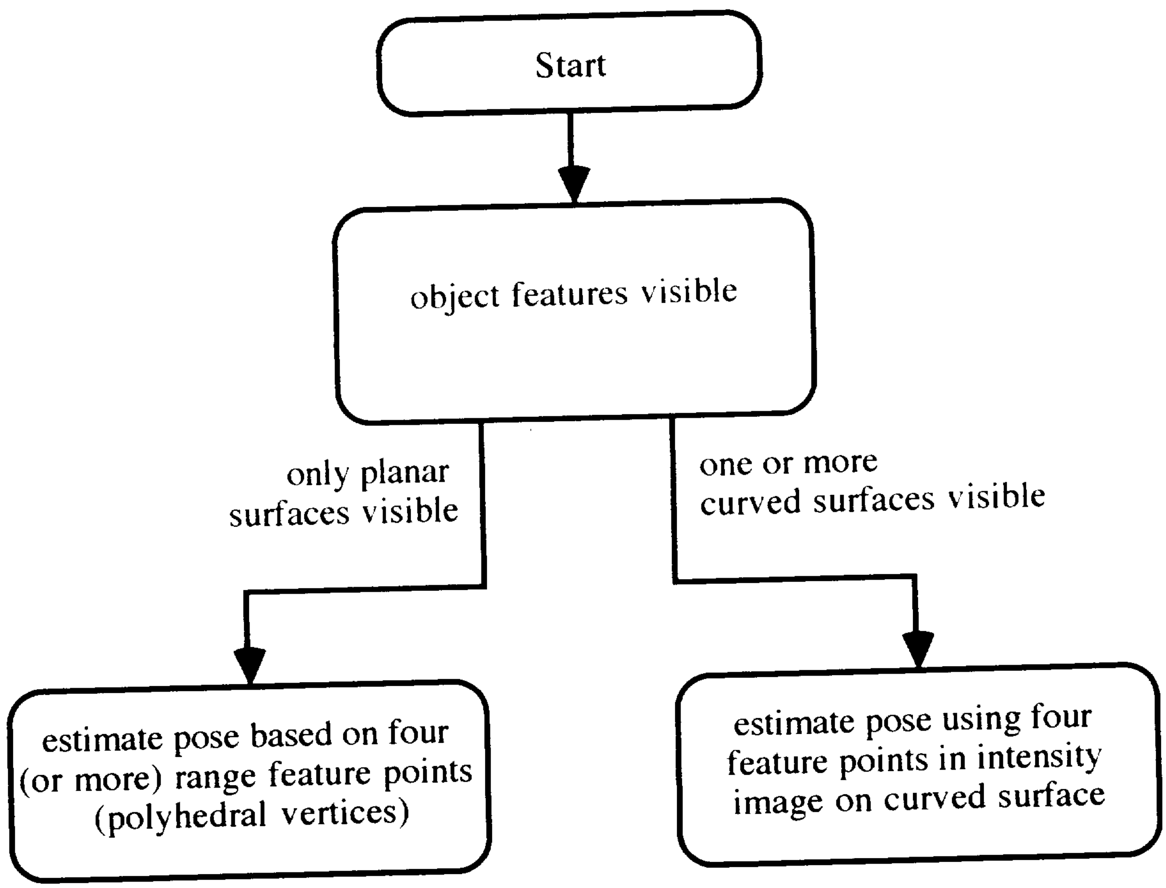


Figure 19: Spatial Pose Estimation

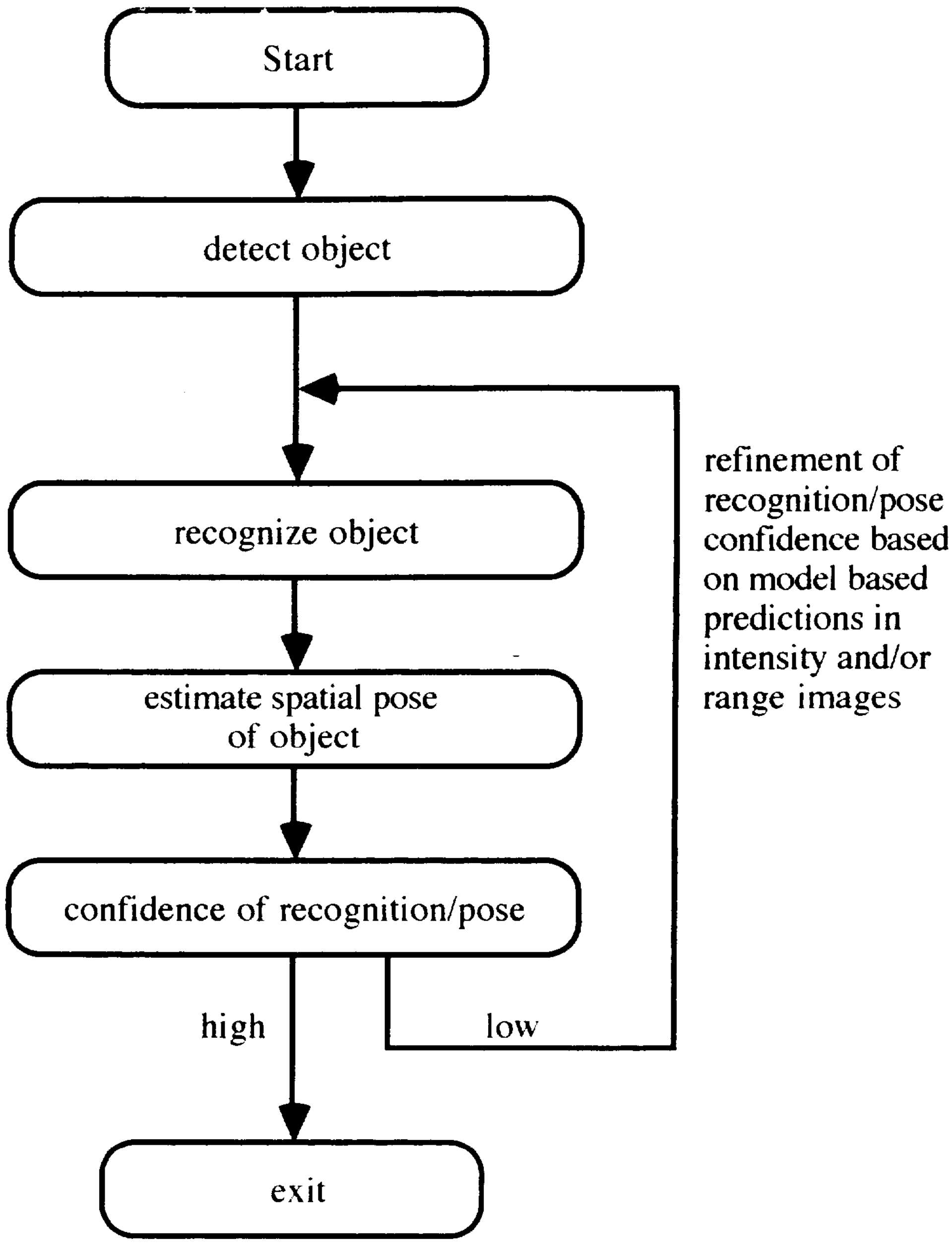


Figure 20: Object Detection, Recognition, and Pose Estimation

The combination of the above planning paradigms as illustrated by Figure 20 is intended to be an iterative process by which a confidence measure is computed based on the currently estimated pose and identity of an object. The confidence measure should generally be based upon the computed error (e.g. RMS) between observed feature locations in the image and their locations as predicted by the current pose/identity hypothesis, and it should be iteratively refined as additional features are sought in new views. In essence, this is analogous to what happens when the Vision System Planner seeks an out-of-focus truss coupler in scenario 3.3.2. However, the fact that the VSP continues its search for the truss coupler is currently motivated only by the fact that color bar combinations are sought. There is a clear need to use features from range images (e.g. planar/nonplanar surfaces, surface area, etc.) to prune the recognition tree and to couple pose estimation algorithms to predict image features that could be used to modify confidences in the iterative process.

For example, when the Vision System Planner was seeking the truss coupler as described for the various scenarios in section 3, color images were the only available sensory input. Two of the three objects in front of the Mobile Robot Platform in Figure 12 had only planar surfaces visible and one showed a curved surface. Of course, surface curvature is not easily determined from intensity images. However, as was demonstrated in section 4, if a laser range finder had been available the cubes would have been immediately rejected based on their surface characteristics. Had this capability existed, a tentative identification of the object as a truss coupler could have been made. Based on the tentative identification from range image features, the model knowledge base would have revealed that its spatial pose could be estimated based on four coplanar non-colinear (i.e. Hung-Yeh-Harwood) feature points in the intensity image. The estimated spatial pose in tandem with knowledge of the sensor models would have made it possible to backproject the object model into the intensity and/or range images to predict other features or to modify the confidence of the recognition/pose combination. Hence, combining information from both sensory domains would provide a capability that is greater than the sum of the capabilities strictly obtainable from intensity or range sensory domains and algorithms.

6.0 Summary and Conclusions

In order to increase the autonomy of the Extravehicular Activity Helper/Retriever, it is necessary for the Vision System Planner to be able to select an image sensor or invoke an image processing algorithm that will achieve a goal in an expeditious manner. The primary criteria for selecting the sensor or algorithm should be based upon

a. what is known about the object being sought (the object model),
b. what is known about the operational environment (the world model),
c. what is known about the capabilities of the sensor, and
d. what is known about the capabilities of the processing algorithm.

The results obtained using actual images from a color camera mounted on the Mobile Robot Platform and synthetically generated range images demonstrate that each sensory domain has inherent strengths that should be exploited and inherent weaknesses that should be avoided when circumstances warrant. More important, however, is the capability of each sensory domain to complement or enhance the capability of the other, particularly if an approach to iteratively refine the confidences associated with identification and pose is taken.

Acknowledgement

Philip Schlump, who is a first year Ph.D. student in the Computer Science Department at the University of Wyoming, designed, constructed and programmed the Mobile Robot Platform in addition to developing and testing the color vision algorithms described in section 3. His dedicated assistance in this project is gratefully acknowledged.

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A Vision System Planner for the Extravehicular Activity Retriever[†]

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Abstract

The Extravehicular Activity Retriever (EVAR) is a robotic device currently being developed by the Automation and Robotics Division at the NASA Johnson Space Center to support activities in the neighborhood of the Space Shuttle or Space Station Freedom. As the name implies, the Retriever's primary function will be to provide the capability to retrieve tools and equipment or other objects which have become detached from the spacecraft, but it will also be able to rescue a crew member who may have become inadvertently de-tethered. Later goals will include cooperative operations between a crew member and the Retriever such as fetching a tool that is required for servicing or maintenance operations.

This paper documents a preliminary design for a Vision System Planner (VSP) for the EVAR that is capable of achieving visual objectives provided to it by a high level task planner. Typical commands which the task planner might issue to the VSP relate to object recognition, object location determination, and obstacle detection. Upon receiving a command from the task planner, the VSP then plans a sequence of actions to achieve the specified objective using a model-based reasoning approach. This sequence may involve choosing an appropriate sensor, selecting an algorithm to process the data, reorienting the sensor, adjusting the effective resolution of the image using lens zooming capability, and/or requesting the task planner to reposition the EVAR to obtain a different view of the object.

An initial version of the Vision System Planner which realizes the above capabilities using simulated images has been implemented and tested. The remaining sections describe the architecture and capabilities of the VSP and its relationship to the high level task planner. In addition, typical plans that are generated to achieve visual goals for various scenarios are discussed. Specific topics to be addressed will include object search strategies, repositioning of the EVAR to improve the quality of information obtained from the sensors, and complementary usage of the sensors and redundant capabilities.

1. Introduction

There has been considerable research that relates to the development of specialized robotic devices that are designed to operate in exterrestrial domains. These devices cover a broad spectrum of operational characteristics. At the less autonomous end of the spectrum are telerobots and telemanipulators that are controlled by a human operator, and which, to a significant degree, depend on human reasoning and intervention in order to be able to accomplish high level tasks.[1] At the more autonomous end of the spectrum are robots that must be able to sense and reason about their environments, and which will then plan and achieve a goal or set of goals. The degree of autonomy that is required is frequently mandated by the proximity of the human operator to the robotic device, particularly if significant time delays necessarily exist in the human-robot loop. For example, it would be impractical for a walking rover on the surface of the planet Mars to depend on a teleoperator to specify each step to be taken, since the round trip signal time can be up to 45 minutes.

The CMU Ambler is one such highly autonomous robot designed to explore the distant rugged terrain of another planet in a highly mobile, reliable and efficient manner.[2] The Ambler constructs a terrain map using a laser range scanner as its primary sensor and plans the movements of its six legs based on local three-dimensional constraints. Both the manner of locomotion and the ability to sense the environment are in contrast to Robby, a planetary rover that uses stereo vision to derive terrain information and is capable of navigating around and over obstacles using six articulated wheels.[3]

The EVA Retriever, on the other hand, is intended to operate in relatively close proximity to a human operator and thus does not have to operate under severe constraints that impose highly autonomous operation, such as large communication delays. However, it is nevertheless very desirable for the Retriever to exhibit a great degree of autonomy in order to allow the operator to be free to attend to other tasks. Phase I and II studies demonstrated the fundamental design components and capabilities for the EVAR using a Precision Air Bearing Floor (PABF) to simulate the frictionless environment of space.[4,5] The EVAR demonstrated that it was capable of self-location (relative to a fixed structure), locating a target object to be retrieved, and grasping and retrieving the target object using a system design that included five major functional subsystems which were: perception, world model, reasoning, sensing and acting.[6]

The ability to sense and perceive objects in the vicinity of the EVAR is, of course, central to any interaction with the environment since the EVAR must be able to detect and recognize objects prior to reasoning about them and executing actions involving them. It is therefore important for a vision system to provide autonomous or semi-autonomous robots with information that describes the surrounding environment, but it should also be able to plan and execute actions that solve visual problems efficiently and effectively. In order to achieve its objectives the Vision System should be able to call on other modules, for example, to request that the EVAR be repositioned or reorieted in order to obtain a better view of an object.

The preliminary architecture that has been developed to embody these control objectives is shown in Figure 1. From a software design standpoint, the highest level or supervisory planner is the Task Planner. The Task Planner oversees the actions of several subplanners, one of which is the Vision System Planner. Each of these subplanners can be considered to be an expert with special knowledge regarding how to solve problems within its particular domain. When commanded to do so by the Task Planner, a subplanner will determine a method for achieving the specified goal given its knowledge of the current state of the world and it will then communicate the result of executing the planned action back to the Task Planner.

Although each subplanner is subservient to the Task Planner, it may nevertheless ask for assistance from the Task Planner if such assistance would help it achieve the specified goal. For example, if the Task Planner requests the Vision System Planner to recognize an object and the robot on which the vision hardware is mounted is poorly positioned to sense the object, the VSP may request the Task Planner to cause the robot to be moved. If the Task Planner honors the request from the VSP, it would then send commands to other subplanners (involving navigation and control) to move the robot so that the Vision System can accomplish the objective originally requested by the Task Planner.

The Vision System module itself (Figure 2) should be a self-contained entity capable of accomplishing many types of objectives such as object detection, recognition, tracking and pose estimation. A typical plan that would be formulated to achieve one of these goals would involve choosing an appropriate sensor, selecting an algorithm to process the data, and

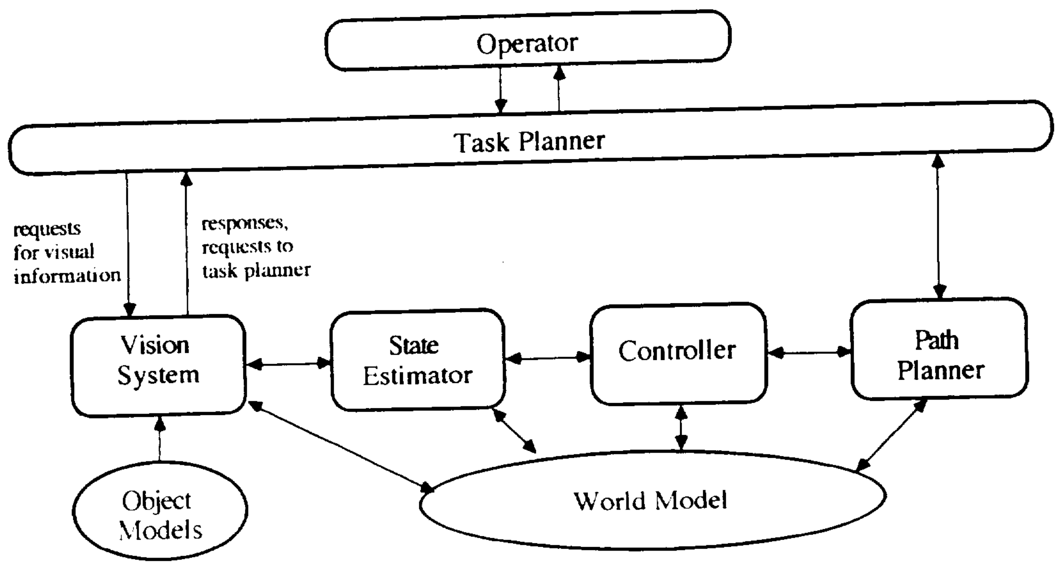


Figure 1: Planning System Architecture

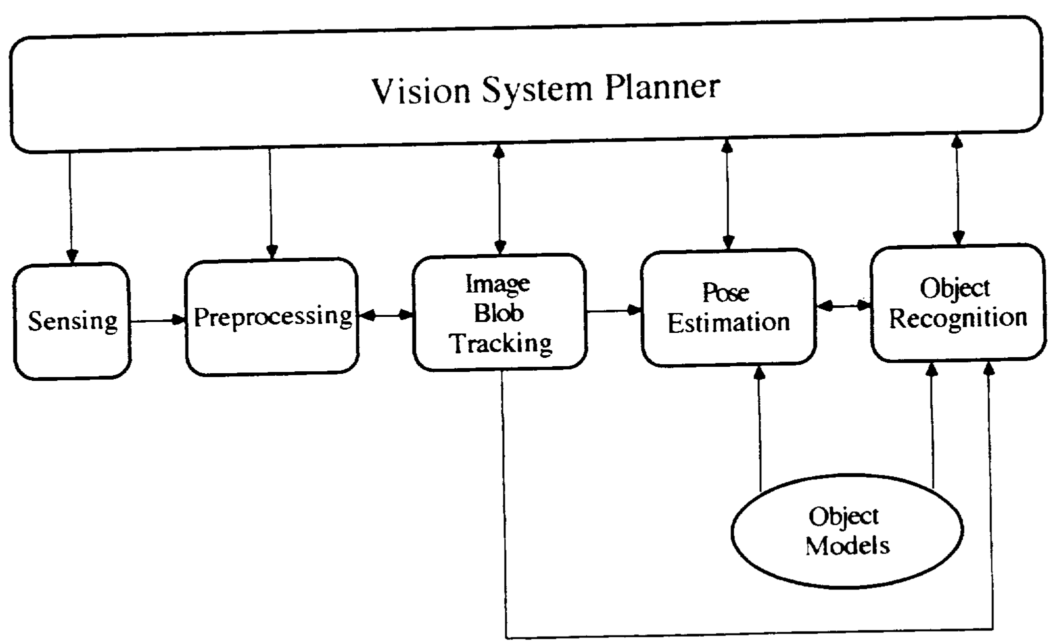


Figure 2: Vision System Components

communicating the results or a request for assistance to the Task Planner. The remaining sections discuss a suggested architecture for such a Vision System within the context of the Extravehicular Activity Retriever.

2. Vision System Planner Design Considerations

The planning mechanisms developed are founded on the assumption that there should be at least two visual sensors which provide intensity (color) and range images. There are several reasons why such a multisensory approach is desirable, three of which are particularly significant. First, the availability of sensors with complementary capabilities permits the VSP to select a sensor/algorithm combination that is most appropriate for achieving the current visual goal as specified by the task planner. Second, if the sensor that the VSP would normally select as its first choice to achieve the goal is either unavailable or inappropriate for usage because of some current constraint, it may be possible to perform the desired task using the other sensor to achieve the same goal, albeit perhaps by accepting a penalty in performance. Finally, instances may occur for which it is desirable to verify results from two different sensory sources.

The first of the above motivations addresses achieving the visual goal in the most effective manner by allowing the VSP to choose among sensors with complementary capabilities. For example, if it is desired to distinguish between two objects of similar structure with the color of the objects being the primary differentiating feature, then it is apparent that the color camera should be used as the primary sensor. On the other hand, if the size and/or geometry of the objects are most useful for determining identity, then it is important to be able to expeditiously extract and process three-dimensional coordinates. Clearly, this is a task that would be most properly assigned to the laser scanner. Similarly, tasks involving pose estimation[7], object tracking[8] and motion estimation[9] would more appropriately involve invoking the laser scanner as the primary sensor. The initial versions of these submodules have already been developed and will be tested in a reduced gravity environment using NASA's KC-135 aircraft during the coming year[10].

The previous example involving the need for three-dimensional coordinates is illustrative of a case in which the primary sensor (the laser scanner) is engaged to extract the required information. However, there may be cases for which the laser scanner cannot be used to obtain range information because (a) the object to be processed is covered with a highly specularly reflective material thus preventing acquisition of good return signals, (b) the laser scanner is currently assigned to another task, or (c) the laser scanner is temporarily not functioning properly. For such instances, it is highly desirable to provide a redundant capability by using the other sensor if possible. The classical method for determining three-dimensional coordinates from intensity images involves a dual (stereo vision) camera setup in which feature correspondences are established and the stereo equations are solved for each pair of feature points. Although the current simulated configuration has only one intensity image camera, this alternative mechanism for computing range values is in fact possible for the VSP to achieve by requesting the task planner to reposition the EVAR such that the camera's initial and final positions are offset by a known baseline distance. Of course, there is a penalty in performance if the (pseudo) stereo vision method is chosen, since the EVAR must be moved and feature correspondences computed. However, it is nevertheless important to have such a redundant sensing capability for the reasons previously mentioned and to be able to independently verify the results obtained from one sensor or to increase the confidence of those results.

Aside from selecting an appropriate sensor, it is may also be possible to alter certain physical characteristics of the sensor such as the effective resolution and scanning rate. In the case of the laser scanner, images can be acquired at rates (and resolutions) varying between 2.5 frames per second (256 x 256 pixels) to 10 frames per second (64 x 256 pixels). The capability to select a faster frame rate with a penalty in resolution becomes significant if it is important to be able to sense and process data rapidly, as in the case of motion estimation. On the other hand, if an object is relatively stationary and finer features are to be sensed, then higher resolution with a lower frame rate would be chosen. Hence, a vision system planner should be able to select a sensor as well as its relevant parameters (e.g. scanning rate, resolution, zoom factor, orientation).

Once an appropriate sensor has been selected and configured, the next step is to focus attention on the object(s) and to apply a preprocessing algorithm that will effectively achieve the current goal. Focussing attention is important because it reduces the amount of image data that must be processed for the immediate task. If the task is tracking an image blob that corresponds to an object of interest, and the image blob merges with another blob or disappears due to occlusion, then the object's predicted location (computed by the adaptive image blob tracker) is central to assisting in the segmentation of sub-blobs.[8]

The selection of a pose estimation algorithm is directly dependent on the model being processed.[7] There are two fundamental classes of algorithms that are currently employed, namely object-based and image-based (multi-view) pose estimation. If an object contains curved surfaces (e.g. a cylinder) then an image-based approach is taken, by which the occluding contours derived from several views of the object that were recorded on a tesselated sphere are used as the basis for matching the observed object's outline. If the object has a polyhedral structure (no curved surfaces) then an object-based pose estimation algorithm is employed, by which features extracted from images are matched against model features in a CAD data base. For situations in which the object is very close to the sensor (e.g. during grasping), the pose may be estimated on subparts of the entire object rather than the entire object. Similarly, for purposes of recognition, the subset of object features selected and the algorithm chosen are also a function of the size of objects in images.

Proximity to target objects will affect not only the features selected for recognition and pose estimation but will strongly influence the confidences associated with the results computed. For example, a typical scenario might involve a case in which the EVAR is close enough to a target object to hypothesize its class based on color, but too far away to definitively recognize its geometric structure using laser scanner data. In this case, the VSP would tentatively identify the object (using color) and would advise the task planner to move closer to the object so that a laser scanner image with higher resolution can be obtained. The confidence of the initial hypothesis would then be strengthened (or perhaps weakened) depending on the conclusion reached by processing the range data at close proximity. This capability is illustrative of the necessity for the VSP to be able to plan high level vision tasks as well as to be able to interact (interface) with the higher level task planner in order to reposition the EVAR. Hence, at the highest level of vision system planning, the VSP will be responsible for task scheduling and resource planning.

The fundamental architecture for the Vision System includes modules which are designed to detect, recognize, track, and estimate the pose of objects. Upon receiving a request from the main task planner to achieve one of these objectives, the Vision System Planner determines an appropriate sequence of goals and subgoals that, when executed, will accomplish the objective. The plan generated by the VSP will generally involve (a) choosing an appropriate sensor, (b) selecting an efficient and effective algorithm to process the image data, (c) communicating the nominal (expected) results to the task planner or informing the task planner of anomalous (unexpected) conditions or results, and (d) advising the task planner of actions that would assist the vision system in achieving its objectives. The specific plan generated by the VSP will primarily depend on knowledge relating to the sensor models (e.g. effective range of operation, image acquisition rate), the object models (e.g. size, reflectivity, color), and the world model (e.g. expected distance to and attitude of objects). The next section presents the resulting plans generated by the VSP for several different scenarios.

3. Scenarios and Results

The operation of the prototype VSP that was designed and implemented can best be understood by examining the plans that it generates for various scenarios. For purposes of illustration, the initial state of the world is always assumed to be that there are three objects somewhere in front of the EVAR. One of the objects is an Orbital Replacement Unit (ORU) with a known color. For cases in which the EVAR VSP needs to search for the ORU, the hemisphere in front of the EVAR is searched in the spiralling manner shown in Figure 3.

The task planner (perhaps in consultation with the human operator) selects an angular field of view (i.e. zoom factor) for the color camera which affects (in an inversely proportional manner) the number of hemispherical sectors that must be searched (i.e. the smaller the angular field of view, the larger the number of hemispherical sectors). For example, if the angular field of view is chosen to be 45°, sectors near the center of the forward hemisphere (sectors 1-6 in Figure 3) are searched and if the ORU is not found, the extreme sectors (7-14) are searched in that order.

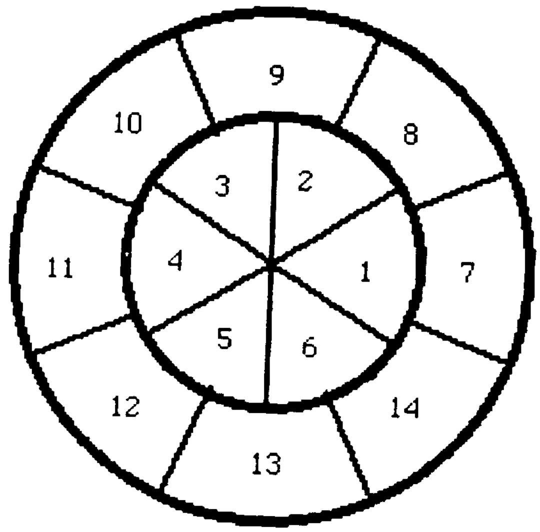


Figure 3: hemispherical sector search order

The scenarios that follow illustrate situations involving object detection, recognition, range estimation, and obstacle notification.

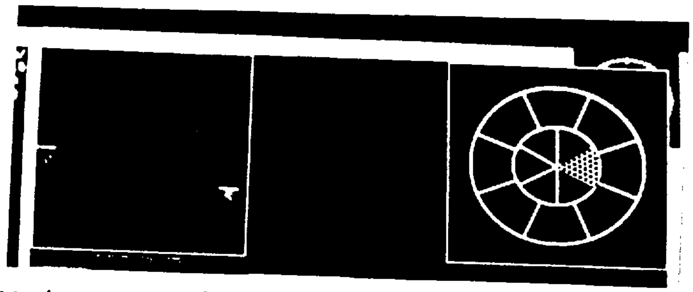
3.1 Scenario 1

Command received by the VSP: Search in front of the EVAR for an ORU.

Plan generated by the VSP:

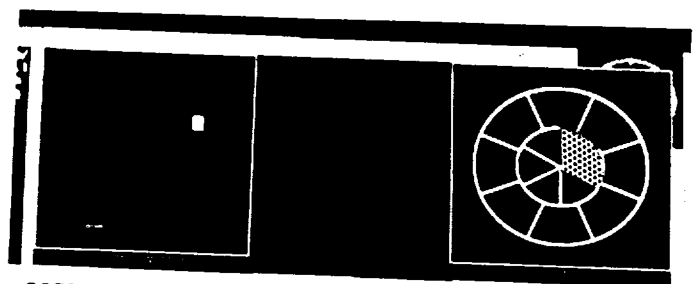
1. Search the hemisphere in front of the EVAR by activating the color camera, fixing the effective focal length and spiralling outward from the center until the object is found (Figures 4a, 4b).

2. If the ORU is found, terminate the (spiralling) search and iteratively refine the estimate of where the object is located by adjusting the sensor gimbals toward the object and reduce the field of view (telephoto zoom) until the object is centered and large in the image (Figures 4c, 4d). If the ORU was not found, the VSP reports failure, in which there are several actions that could be taken. First, the forward hemisphere could be rescanned at higher magnification (a slower process since more scans will be required). Second, the forward hemisphere could be rescanned with increased illumination (requiring a decision to be made regarding the desirability in terms of overall objectives and power consumption by the illumination source). Finally, the VSP could request the Task Planner to rotate the EVAR by 180 degrees and scan the rear hemisphere.



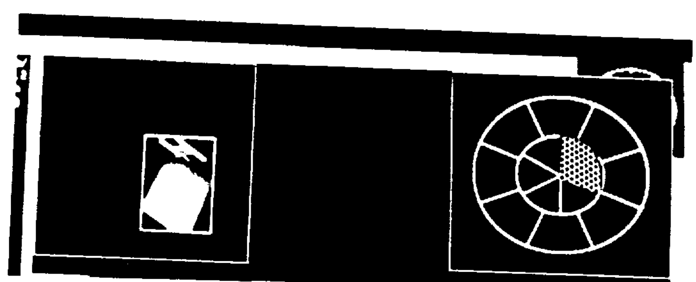
Teleoperator command: *RGB search for ORU*
Field of view angle = 50°
Scan angle = 45°

Figure 4a: search of sector 1 for ORU



VSP response: *ORU was found in sector 2*
Area of object was 150 pixels

Figure 4b: search of sector 2 for ORU

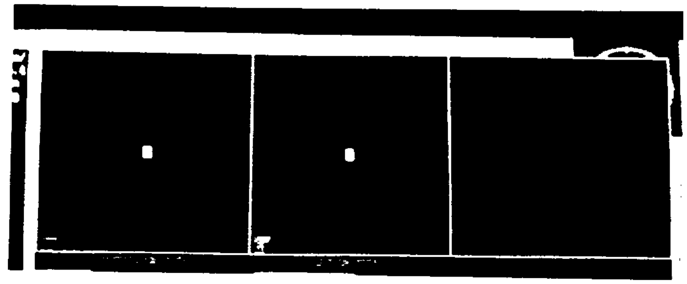


VSP action: *Reorienting camera gimbals*
Setting field of view to 7°

Figure 4c: first gimbal and zoom refinement

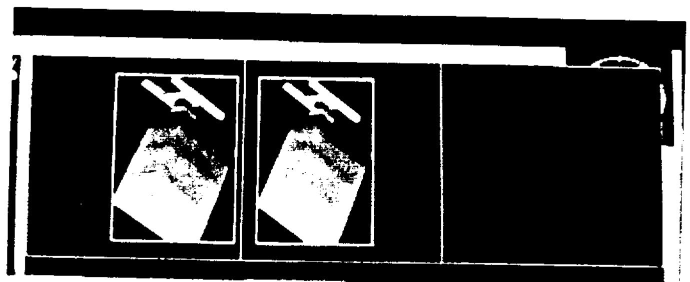
VSP action: *Reorienting camera gimbals*
Setting field of view to 4°

Figure 4d: second gimbal and zoom refinement



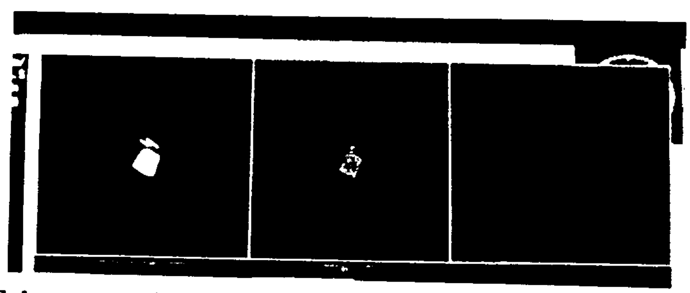
Teleoperator command: *estimate range to ORU using laser scanner*
VSP response: *estiamted range to ORU is 18.5 feet*

Figure 5: laser scanner range estimation



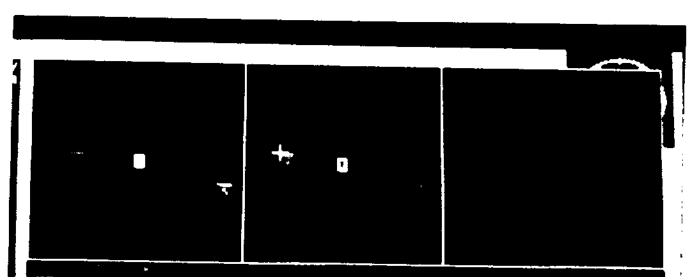
Teleoperator command: *estimate range to ORU using pseudo-stereo*
VSP response: *estimated range to ORU is 18.5 feet*

Figure 6: pseudo-range estimation



Teleoperator input: *move EVAR along optical axis*

Figure 7: moving EVAR toward the ORU



Teleoperator input: *check for obstacles in field of view*
VSP action: *obstacle located (identified by cursor)*

Figure 8: checking for obstacles prior to moving EVAR

3.2 Scenario 2

Command received by the VSP: Determine the distance to the ORU, no sensor specified.

Plan generated by the VSP:

1. Locate the ORU as in Scenario 1 using the color camera.
2. Examine the object model for an ORU and determine which sensor is the most appropriate to be used. In this case, since an ORU is not specularly reflective, the laser scanner is chosen.
3. Examine that part of the laser scanner image that corresponds to the region belonging to the ORU in the color image and compute the distance to those range image elements (Figure 5).

3.3 Scenario 3

Command received by the VSP:
Determine the distance to the ORU, but force the estimation of distance using single camera lateral stereo vision.

Plan generated by the VSP:

1. Locate the ORU as in Scenario 1 using the color camera.
2. Move the EVAR left a known distance, take an image, and record the location of the ORU in that image. Then move the EVAR right a known distance, take an image, and record the location of the ORU in that image.
3. Using triangulation (stereo vision with two cameras separated by a known baseline distance) compute the distance to the ORU (Figure 6).

3.4 Scenario 4

Command received by the VSP:
Determine the distance to the ORU and move toward the ORU along the optical axis of the color camera until the EVAR is a specified distance (D) away from it.

Plan generated by the VSP:

1. Locate the ORU as in Scenario 1 using the color camera.
2. Estimate the distance to the ORU (D_{oru}) using the laser scanner.
3. Compute a vector along the optical axis of the color camera whose length is (D_{oru} - D). Transform that vector into EVAR coordinates and move to that position, maintaining the same attitude (Figure 7).

3.5 Scenario 5

Command received by the VSP:
As in Scenario 4, determine the distance to the ORU and check to determine whether any other objects in the field of view are closer to the EVAR than the ORU prior to moving toward it.

Plan generated by the VSP:

1. Locate the ORU as in Scenario 1 using the color camera.
2. Estimate the distance to the ORU using the laser scanner.
3. Search the range image for values that lie outside of the region containing the ORU and report a potential obstacle if any of the values indicate distances between the EVAR and the ORU. The cursor in Figure 8 shows the potential obstacle.

4. Conclusions and Future Work

An initial version of the Vision System Planner has been implemented and tested using simulated input from a color camera and laser scanner. The VSP has been shown to be capable of planning the fundamental tasks required for the vision system, namely object detection, recognition, range estimation, obstacle detection and advising the task planner for repositioning of the EVAR. The next phase of the research will involve implementing the VSP on robotic hardware that is capable of repositioning the sensor(s) and moving about in its environment in a laboratory setting. Beyond this goal of moving from simulated environments to physical domains, the primary goal will be to increase the autonomy of the VSP such that less teleoperator input is required.

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