Rover Visual Obstacle Avoidance

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Abstract

The Stanford AI Lab cart is a remotely controlled TV equipped mobile robot. A computer program has driven the cart through cluttered spaces, gaining its knowledge of the world entirely from images broadcast by the onboard TV system.

The cart uses several kinds of stereo to locate objects around it in 3D and to deduce its own motion. It plans an obstacle avoiding path to a desired destination on the basis of a model built with this information. The plan changes as the cart perceives new obstacles on its journey.

The system is reliable for short runs, but slow. The cart moves one meter every ten to fifteen minutes, in lurches. After rolling a meter it stops, takes some pictures and thinks about them for a long time. Then it plans a new path, executes a little of it. and pauses again.

It has successfully driven the cart through several 20 meter courses (each taking about five hours) complex enough to necessitate three or four avoiding swerves. Some weaknesses and possible improvements were suggested by these and other, less successful, runs.

INTRODUCTION

A run of the avoider system begins with a calibration of the cart's camera. The cart is parked in a standard position in front *of* a wall of spots. A calibration program notes the disparity in position of the spots in the image seen by the camera with their position predicted from an idealized model of the situation. It calculates a distortion correction polynomial which relates these positions, and which is used in subsequent ranging calculations.

The cart is then manually driven to its obstacle course (littered whith large and small debris) and the obstacle avoiding program is started. It begins by asking for the cart's destination, relative to its current position and heading. After being told, say, 50 meters forward and 20 to the right, it begins its maneuvers. It activates a mechanism which moves the TV camera, and digitizes nine pictures as the camera slides in precise steps from one side to the other along a 50 cm track.

A subroutine called the *interest operator* is applied to the one of these pictures. It picks out 30 or so particularly distinctive regions (features) in this picture. Another routine called the *correlator* looks for these same regions in the other frames. A program called the *camera solver* determines the three dimensional position of the features with respect to the cart from their apparent movement image to image.

The *navigator* plans a path to the destination which avoids all the perceived features by a large safety margin. The program then sends steering and drive commands to the cart to move it about a meter along the planned path. The cart's response to such commands is not very precise. The camera is then operated as before, and nine new images are acquired. The control program uses a version of the correlator to find as many of the features from the previous location as,possiblc in the new pictures, and applies the camera solver. The program then deduces the cart's actual motion dunng the step from the apparent three dimensional shift of these features. Some of the features are pruned during this process, and the interest operator is invoked to add new ones.

This repeats until the cart arrives at its destination or until some disaster terminates the program. Figure la and lb document uie cart's internal world model at two points during a sample run.

CAMERA CALIBRATION

The camera's focal length an geometric distortion are determined by parking the cart a precise distance in front of a wall of many spots and one cross. A program digitizes an image of the spot array, locates the spots and the cross, and constructs a a two dimensional polynomial that relates the position of the spots in the image to their position in an ideal unity focal length camera, and another polynomial that converts points from the ideal camera to points in the image. These polynomials arc used to correct the positions of perceived objects in later scenes.

The algorithm begins by determining the array's approximate spacing and orientation. It trims the picture to make it square, reduces it by averaging to 64 by 64, calculates the Fourier transform of the reduced image and takes its power spectrum, arriving at a 21) transform symmetric about the origin, and having strong peaks at frequencies corresponding to the horizontal and vertical and half-diagonal spacings. with weaker peaks at the harmonics. It multiplies each point *[ij]* in this transform by point [-*j.t]* and points [*j-ij+ i*\ and *[i+jj-il* effectively folding the primary peaks onto one another. The strongest peak in the 90 degree wedge around the y axis gives the spacing and orientation information needed by the next part of the process.

The interest operator described later is applied to roughly locate a spot near the center of the image. A special operator examines a window surrounding this position, generates a histogram of intensity values within the window, decides a threshold for separating the black spot from the white background, and calculates the centroid and first and second moment of the spot. This operator is again applied at a displacement from the first centroid indicated by the orientation and spacing of the grid, and so on, the region of found spots growing outward from the seed.

A binary template for the expected appearance of the cross in the middle of the array is constructed from the orientation/spacing data from the Fourier transform. I"he area around each of the found spots is thresholded on the basis of the expected cross area, and the resulting two valued pattern is convolved with the cross template. The closest match in the central portion of the picture is declared to be the origin.

Two least-squares polynomials (one for X and one for Y) of third (or sometimes fourth) degree in two variables, relating the actual positions of the spots to the ideal positions in a unity focal length camera, arc then generated and written into a file. The polynomials arc used in the obstacle avoider to correct for camera roll, tilt, focal length and long term variations in the vidicon geometry.

INTEREST OPERATOR

The cart vision code deals with localized image patches called features. A feature is conceptually a point in the three dimensional world, but it is found by examining localities larger than points in pictures. A feature is good if it can be located unambiguously in different views of a scene. A uniformly colored region or a simple edge is not good because its parts are

indistinguishable. Regions such as corners, with high contrast in orthogonal directions are best

New features in images are picked by a subroutine called the *interest operator.* It tries to select a relatively uniform scattering of good features, to maximize the probability that a few features will be picked on every visible object by returning regions that arc local maxima of a directional variance measure. Featureless areas and simple edges, which have no variance in the directior of the edge, are thus avoided.

Directional variance is measured over small square windows. Sums of squares of differences of pixels adjacent in each of four directions (horizontal, vertical and two diagonals) over each window are calculated, and the window's interest measure is the minimum of these four sums. Features are chosen where the interest measure has local maxima. The chosen features are stored in an array, sorted in order of decreasing interest measure.

Once a feature is chosen, its appearance is recorded as series of excerpts from the reduced image sequence. A window (6 by 6 in the current implementation) is excised around the feature's location from each of the variously reduced pictures. Only a tiny fraction of the area of the original (unreduced) image is extracted. Four times as much of the x2 reduced image is stored, sixteen umes as much of the x4 reduction, and so on until at some level we have the whole image. The final result is a scries of 6 by 6 pictures, beginning with a very blurry rendition of the whole picture, gradually zooming in linear expansions of two to a sharp closcup of the feature.

Weaknesses

The measure is able to unambiguously reject edges only if they are oriented along the four directions of summation. Edges with intermediate direction give non-zero values for all four sums, and arc sometimes incorrectly chosen as interesting. The operator especially favors intersecting edges. These arc sometimes corners or cracks in objects, and are very good. Sometimes they arc caused by a distant object peering over the edge of a nearby one and then they are very bad. Such spurious intersections do not have a definite distance, and must be rejected during camera solving.

CORRELATION

Deducing the 3D location of features from their projections in 2D images requires that we know their position in two or more such images. The *correlator* is a subroutine that, given a feature description produced by the interest operator from one image, finds the best match in a different, but similar, image. Its search area can be the entire new picture, or a rectangular sub-window.

The search uses a coarse to fine strategy that begins in reduced versions of the pictures. Typically the first step takes place at the xI6 (linear) reduction level. *The* 6 by 6 window at that level in the feature description, that covers about one seventh of the total area of the original picture, is convolved with the search area in the correspondingly reduced version of the second picture. The 6 by 6 description patch is moved pixel by pixel over the approximately 15 by 16 destination picture, and a correlation coefficient is calculated for each trial position. The position with the best match is recorded. The 6x6 area it occupies in the second picture is mapped to the x8 reduction level, where the corresponding region is 12 pixels by 12. The 6 by 6 window in the x8 reduced level of the feature description is then convolved with this 12 by 12 area, and the position of best match is recorded and used as a search area for the x4 level. The process continues, matching smaller and smaller, but more and more detailed windows until a 6 by 6 area is selected in the unreduced picture. The window sizes and other parameters are sometimes different from the ones used in this example.

STEREO

Slider Stereo

At each pause on its computer controlled itinerary the cart slides its camera from left to right on the 52 cm track, taking 9 pictures at precise 6.5 cm intervals. Points are chosen in the fifth (middle) of these 9 images, either by the correlator to match features from previous positions.-or by the interest operator. The camera slides parallel to the horizontal axis of the (distortion corrected) camera co-ordinate system, so the parallax-induced displacement of features in the 9 pictures is purely horizontal.

The correlator looks for the points chosen in the central image in each of the eight other pictures. The search is restricted to a narrow horizontal band. This has little effect on the computation time, but it reduces the probability of incorrect matches. In the case of correct matches, the distance to the feature is inversely proportional to its displacement from one image to another. The uncertainty in such a measurement is the difference in distance a shift one pixel in the image would make. The uncertainty varies inversely with the physical separation of the camera positions where the pictures were taken (the stereo baseline). Long baselines give more accurate distance measurements.

After the correlation step the program knows a feature's position in nine images It considers each of the 36 (= 9 choose 2) possible image pairings as a stereo baseline, and records the estimated (inverse) distance of the feature in a histogram. Each measurement adds a little normal curve to the histogram, with mean at the estimated distance, and standard deviation inversely proportional to the baseline, reflecting the uncertainty. The area under each curve is made proportional to the product of the correlation coefficients of the matches in the two images (in central image this coefficient is taken as unity), reflecting the confidence that the correlations were correct. The distance to the feature is indicated by the largest peak in the resulting histogram, if this peak is above a certain threshold. If below, the feature is forgotten about.

The correlator sometimes matches features incorrectly. The distance measurements from incorrect matches in different pictures arc not consistent When the normal curves from 36 pictures pairs arc added up. the correct matches agree with each other, and build up a large peak in the histogram, while incorrect matches spread themselves more thinly. Two or three correct correlations out of the eight will usually build a peak sufficient to offset a larger number of errors. In this way eight applications of a mildly reliable operator interact to make a very reliable distance measurement

Motion Stereo

After having determined the 3D location of objects at one position, the computer drives the cart about a meter forward. At the new position it slides the camera and takes nine pictures. The correlator is applied in an attempt to find all the features successfully located at the previous position. Feature descriptions extracted from the central image at the last position arc searched for in the central image at the new stopping place.

Slider stereo then determines the distance of the features so found from the cart's new position. The program now knows the 3D position of the features relative to its camera at the old and the new locations. Its own movement is deduced from 3D co-ordinate transform that relates the two.

The program first eliminates mis-matches in the correlations between the central images at two positions. Although it doesn't yet have the co-ordinate transform between the old and new camera systems, the program knows the distance between pairs of feature positions should be the same in both. It makes a matrix in which element [*i,j]* is the aosolute value of the difference in distances between points i and / in the first and second co-ordinate systems divided by the expected error (based on the one pixel uncertainty of the ranging). Fach row of this matrix is summed, giving an indication *of* how much each point disagrees with the other points. The idea is that while points in error disagree with virtually all points, correct positions agree with all the other correct ones, and disagree only with the bad ones. The worst point is deleted, and its effect is removed from the remaining points in the row sums. This pruning is repeated until the worst error is within the error expected from the ranging uncertainty.

After the pruning, the program has a number of points, typically 10 to 20. whose position error is small and pretty well known. The program trusts these, and records them in its world model, unless it had already

done so at a previous position. The pruned points are forgotten forevcrmorc.

The 3d rotation and translation that relates the old and new cart position is then calculated by a Newton's method iteration that minimizes the sum of the squares of the distances between the transformed first co-ordinates and the raw co-ordinates of the corresponding points at the second position, with each term divided by the square of the expected uncertainty in the 3D position of the points involved.

PATH PLANNING

The cart vision system "models" objects as simple clouds of features. If enough features are found on each nearby object, this model is adequate for planning a non-colliding path to a destination. The features in the cart's 3D world model can be thought of as fuzzy ellipsoids, whose dimensions reflect the program's uncertainty of their position. Repeated applications of the interest operator as the cart moves cause virtually all visible objects to be become modelled as clusters of overlapping ellipsoids.

To simplify the problem, the ellipsoids arc approximated by spheres. Those spheres sufficiently above the floor and below the carts maximum height are projected on the floor as circles. The can itself is modelled as a 3 meter circle. The path finding problem then becomes one of maneuvering the cart's 3 meter circle between the (usually smaller) circles of the potential obstacles to a desired location. It is convenient (and equivalent) to conceptually shrink the cart to a point, and add its radius to each and every obstacle. An optimum path in this environment will consist of cither a straight run between start and finish, or a series of tangential segments between the circles and contacting arcs (imagine loosely laying a string from start to finish between the circles, then pulling it tight).

The program converts the problem to a shortest path in graph search. There are four possible paths between each pair of obstacles because each tangent can approach clockwise or counterclockwise. Each tangent point becomes a vertex in the graph, and the distance matrix contains sums of tangential and arc paths, with infinities for blocked or impossible routes. The cart program was occasionally run using this exact procedure, but more often with a faster approximation that made each obstacle into two vertices (one for each direction of circumnavigation).

A few other considerations were essential in the path planning. The charted routes consist of straight lines connected by tangent arcs, and are thus plausible paths for the cart, which steers like an automobile. This plausibility is not necessarily true of the start of the planned route, which, as presented thus far, docs not take the initial heading of the cart into account. The plan could, for instance, include an initial segment going off 90 degrees from the direction in which the cart points, and thus be impossible to execute. This is handled by including a pair of "phantom" obstacles along with the real perceived ones. The phantom obstacles have a radius equal to the cart's minimum steering radius, and are placed, in the planning process, on either side of the can at such a distance that after their radius is augmented by the cart's radius (as happens for all the obstacles), they just touch the cart's centroid. and each other, with their common tangents being parallel to the direction of the carts heading. They cfTcctivcly block the area made inaccessible to the cart by its maneuverability limitations.

Path Execution

After the path to the destination has been chosen, a portion of it must be implemented as steering and motor commands and transmitted to the cart. The control system is primitive. The drive motor and steering motors may be turned on and ofT at any time, but there exists no means to accurately determine just how fast or how far they have gone. The current program makes the best of this bad situation by incorporating a model of the cart that mimics, as accurately as possible, the cart's actual behavior. Under good conditions, as accurately as possible means about 20%; the carl is not very rcpcatablc, and is affected by ground slope and texture, battery voltage, and other less obvious externals.

The path executing routine begins by excising the first .75 meters of the planned path. This distance was chosen as a compromise between average cart velocity, and continuity between picture sets. If the cart moves too far between picture digitizing sessions, the picture will change too much for reliable correlations. This is especially true if the cart turns (steers) as it moves. 'The image seen by the camera then pans across the field of view. The cart has a wide angle lens that covers 60 degrees horizontally. The .75 meters, combined with the turning radius limit (5 meters) of the cart results in a maximum shift in the field of view of 15 degrees, one quarter of the entire image.

The program examines the cart's position and orientation at the end of the desired .75 meter lurch, relative to the starting position and orientation. The displacement is characterized by three parameters; displacement forward, displacement to the right and change in heading. In closed form the program computes a path that will accomplish this movement in two arcs of equal radius, but different lengths. The resulting trajectory has a general "S" shape. Rough motors timings arc derived from these paratmetcrs. The program then uses a simulation that takes into account steering and drive motor response to iteratively refine the solution.

CONCLUSION

Many years ago I chose the line of research described herein intending to produce a combination of hardware and software by which the cart could visually navigate reliably in most environments. For a number of reasons, the existing system is only a first approximation to that youthful ideal.

One of the most serious limitations is the excruciating slowness of the program. In spite of my best efforts, and many compromises, in the interest of speed, it takes 10 to 15 minutes of real time to acquire and consider the images at each lurch, on a lightly loaded KL-10. This translates to an effective cart velocity of 3 to 5 meters an hour. Interesting obstacle courses (2 or three major obstacles, spaced far enough apart to permit passage within the limits of the cart's size and maneuverability) are at least 15 meters long, so interesting cart runs take from 3 to 5 hours, with little competition from other users, impossibly long under other conditions.

During the last lew weeks of the AI lab's residence in the D.C Power building, when the full fledged obstacle runs described here were executed, such conditions of light load were available on only some nights, between 2 and 6 AM and on some weekend mornings. The cart's video system battery lifetime on a full charge is at most 5 hours, so the limits on field tests, and consequently on the debug/improve loop, were strictly circumscribed.

Although major portions of the program had existed and been debugged for several years, the complete obstacle avoiding system (including fully working hardware, as well as programs) was not ready until two weeks before the lab's scheduled move. The first week was spent quashing unexpected trivial bugs, causing very silly cart behavior under various conditions, in the newest parts of the code, and recalibrating camera and motor response models.

The final week was devoted to serious observation (and filming) of obstacle runs. Three full (about 20 meter) runs were completed, two indoors and one outdoors. Two indoor false starts, aborted by failure of the program to perceive an obstacle, were also recorded. The two long indoor runs were nearly perfect

In the first, the cart successfully slalomed its way around a chair, a large cardboard icosahedron, and a cardboard tree then, at a distance of about 16 meters, encountered a cluttered wall and backed up several times trying to find a way around it.

The second indoor run involved a more complicated set of obstacles, arranged primarily into two overlapping rows blocking the goal. The cart backed up twice to negotiate the light turn required to go around the first row, then executed several steer forward / back up moves, lining itself up to go through a gap barely wide enough in the second row. This run had to be terminated, sadly, before the cart had gone through the gap because of declining battery charge and increasing system load.

The outdoor run was less successful. It began well; in the first few moves the program correctly perceived a chair directly in front of the camera, and a number of more distant cardboard obstacles and sundry debris. Unfortunately, the program's idea of the cart's own position became increasingly wrong. At almost every lurch, the position solver deduced a cart motion considerably smaller than the actual move. By the time the cart had rounded the foreground chair, its position model was so far off that the distant obstacles were replicated in different positions in the carts confused world model, because they had been seen early in the run and again later, to the point where the program thought an actually existing distant clear path was blocked. I restarted the program to clear out the world model when *the* planned path became too silly. At that time the cart was four meters in front of a cardboard icosahedron, and its planned path lead straight through it. The newly reincarnated program failed to notice the obstacle, and the cart collided with it. I manually moved the icosahedron out of the way, and allowed the run to continue. It did so uneventfully, though there were continued occasional slight errors in the self position deductions. The cart encountered a large cardboard tree towards the end of this journey and detected a portion of it only just in time to squeak by without colliding.

The two short abortive indoor runs involved setups nearly identical to the two-row successful long run described one paragraph ago. The first row, about three meters in front of the cart's starting position contained a chair, a real tree (a small cypress in a planting pot), and a polygonal cardboard tree. The cart saw the chair instantly and the real tree after the second move, but failed to see the cardboard tree ever. Its planned path around the two obstacles it did sec put it on a collision course with the unseen one. Placing a chair just ahead of the cardboard tree fixed the problem, and resulted in a successful run. Never, in all my experience, has the code described in this thesis failed to notice a chair in front of the cart.

Flaws Found

These runs suggest that the system suffers from two serious weaknesses. It does not see simple polygonal (bland and featureless) objects reliably, and its visual navigation is fragile under certain conditions. Examination *of* the program's internal workings suggests some causes and possible solutions.

Bland Interiors

The program sometimes fails to see obstacles lacking sufficient high contrast detail within their outlines. In this regard, the polygonal uee and rock obstacles 1 whimsically constructed to match diagrams from a 3D drawing program, were a terrible mistake. In none of the test runs did the programs ever fail to see a chair placed in front of the cart, but half the time they did fail to see a pyramidal tree or an icosahedral rock made of clean white cardboard. These contrived obstacles were picked up reliably at a distance of 10 to 15 meters, silhouetted against a relatively unmoving (over slider travel and cart lurches) background, but were only rarely and sparsely seen at closer range, when their outlines were confused by a rapidly shifting background, and their bland interiors provided no purchase for the interest operator or correlator. Hvcn when the artificial obstacles were correctly perceived, it was by virtue of only two to four features. In contrast, the program usually tracked five to ten features on nearby chairs.

In the brightly sunlit outdoor run the artificial obstacles had another problem. Their white coloration turned out to be much brighter than any "naturally" occurring extended object. These super bright, glaring, surfaces severely taxed the very limited dynamic range of the carts vidicon/digitzer combination. When the icosahedron occupied 10% of the cameras field of view, the automatic target voltage circuit in the electronics turned down the gain to a point where the background behind the icosahedron appeared nearly solid black.

Confused Maps

The second major problem exposed by the runs is glitches in the cart's self-posmon model. This model is updated after a lurch by finding the 3D translation and rotauon that best relates the 3d position of the set of tracked features before and after the lurch. In spite of the extensive pruning that precedes this step, (and partly because of it. as is discussed later) small errors in the measured feature positions sometimes cause the solver to converge to the wrong transform, giving a position error beyond the expected uncertainty. Features placed into the world model before and after such a glitch will not be in the correct relative positions. Often an object seen before is seen again after, now displaced, with the combination of old and new positions combining to block a path that is in actuality open.

This problem showed up mainly in the outdoor run. I've also observed it indoors in past, in simple mapping runs, before the entire obstacle avoider was assembled. There appear to be two major causes for it, and a wide range of supporting factors.

Poor seeing, resulting in too few correct correlations between the pictures before and after a lurch, is one culprit. The highly redundant nine eyed stereo ranging is very reliable, and causes few problems, but the non-redundant correlation necessary to relate the position of features before and after a lurch, is error prone Sometimes the mutual-distance invarianee pruning that follows is overly agressivc. and leaves too few points for a stable least squares co-ordinate fit.

The outdoor runs encountered another problem. The program ran so slowly that shadows moved significantly (up to a half meter) between lurches, Their high contrast boundaries were favorite points for tracking, enhancing the program's confusion.

Simple Fixes

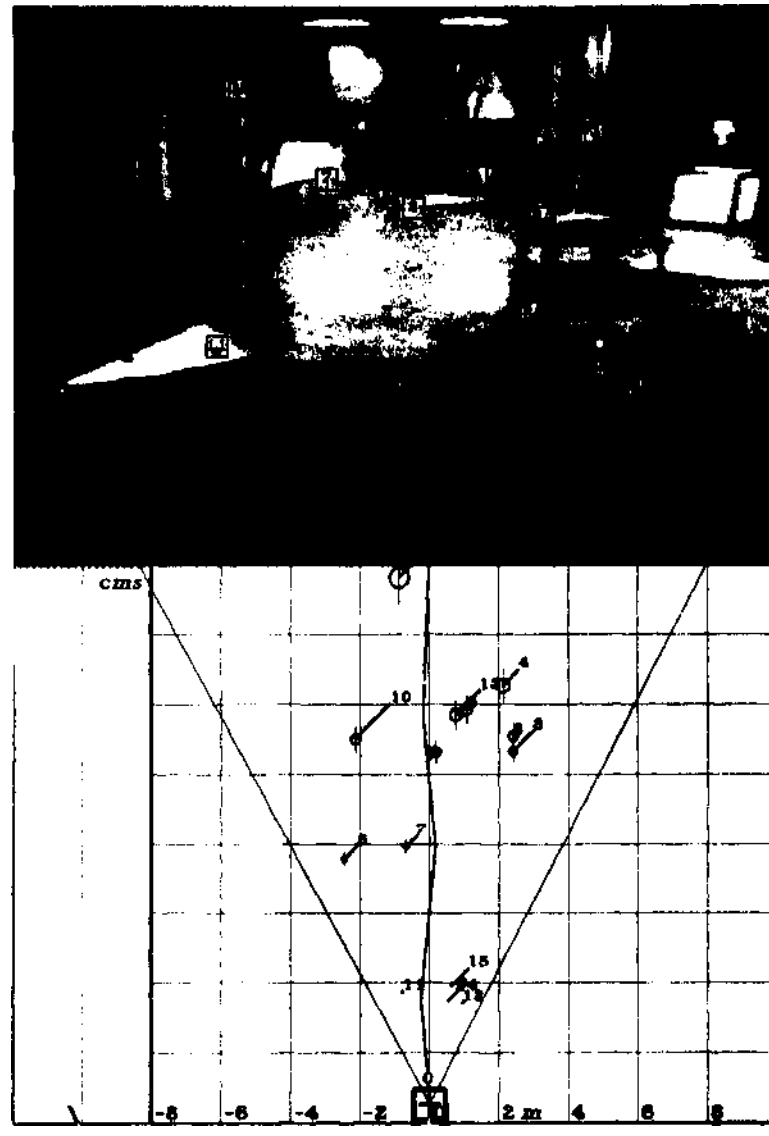
Though elaborate (and thus far untried in our context) methods such as edge matching may greatly improve the quality of automatic vision in future, subsequent experiments with the program revealed some modest incremental improvements that would have solved most of the problems in the test runs.

The issue of unseen cardboard obstacles turns out to be partly one of over-conservatism on the program's part. In all cases where the cart collided with an obstacle it had correctly ranged a few features on the obstacle in the prior nine-eyed scan. The problem was that the much more fragile correlation between vehicle forward moves failed, and the points were rejected in the mutual distance test. Overall the nine-eyed stereo produced very few errors If the path planning stage had used the pre-pruning features (still without incorporating them permanently into the world model) the runs would have proceeded much more smoothly. All of the most vexing false negatives, in which the program failed to spot a real obstacle, would have been eliminated. There would have been a very few false positives, in which non-existent ghost obstacles would have been perceived. One or two of these might have caused an unnecessary swerve or backup. Hut such ghosts would not pass the pruning stage, and the run would have recovered after the initial, non-catastrophic, glitch.

The self-position confusion problem is related, and in retrospect may be considered a trivial bug When the path planner computes a route for the cart, another subroutine takes a portion of this plan and implements it as a sequence of commands to be transmitted to the cart's steering and drive motors. During this process it runs a simulation that models the cart acceleration, rale of turning and so on. and which provides a prediction of the cart's position after the move. With the current hardware the accuracy of this prediction is not great, but it nevertheless provides much a prion information about the carts new position. This information is used, appropriately weighted, in the least-squares coordinate system solver that deduces the carts movement from the apparent motion in 3D of tracked features. It is not used, however, in the mutual distance pruning step that proceeds this solving. When the majority of features have been correctly tracked, failure to use this information does not hurt the pruning Hut when the seeing is poor, it can make the difference between choosing a spuriously agreeing set .of mis-tracked features and the small correctly matched set

Incorporating the prediction into the pruning, by means of a heavily weighted point that the program treats like another tracked feature, removes almost all the positioning glitches when the program is fed the pictures from the outdoor run.

Figure 1a:

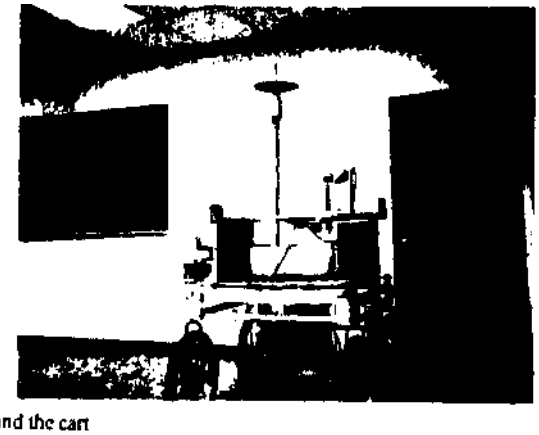


This and the following diagram arc plan views of the can's world model at obstacle run stopping positions.

In this first view, one step into a run. the can has (by the program's reckoning) travelled a little under a meter. The program has noted a number of objects; a chair in the foreground, pieces of cardboard on the floor, an icosahedron. a refrigerator, a cardboard tree, and some other things. It has deduced that the chair, the icosahedron and the tree arc real obstacles, and has planned a path which slaloms around them (the cardboard in the foreground has been ignored because it lies on the floor).

The grid cells arc two meter squares, conceptually on the floor. The cart's own position is indicated by the small heavy square, and by the graph, indicating height, calibrated in centimeters, to the left of grid. Since the can never actually leaves or penetrates the floor, this grapn provides an indication of the overall accuracy. The irregular, tick marked, line behind the cart's position is the past itinerary of the cart as deduced by the program. Each tick mark represents a stopping place. The picture at top of the diagrams is the view seen by the TV camera. The two rays projecting forward from the cart position show the horizontal boundaries of the camera's field of view (as deduced by the camera calibration program). The numbered circles in the plan view arc features located and tracked by the program. The centers of the circles are the vertical projections of the feature positions onto the ground. The size of each circle is the uncertainty (caused by finite camera resolution) in the features position. The length of the 45 degree line projecting to the upper right, and terminated by an identifying number, is the height of the feature above the ground, to the same scale as the floor grid. The features are also marked in the camera view, in the guise of numbered boxes. The thin line projecting from each box to a lower blob is a stalk which just reaches the ground, in the spirit of the 45 degree lines in the plan view. The irregular line radiating forwards from the carl is the planned future path. This changes from slop to stop, as the cart tails to obey instructions properly, and as new obstacles are detected. The small ellipse a short distance ahead of the cart along the planned path is the planned position of the next stop.

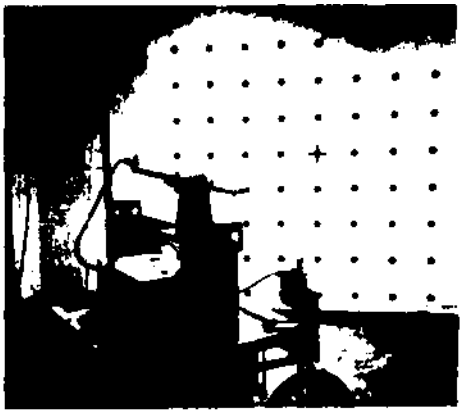
The room



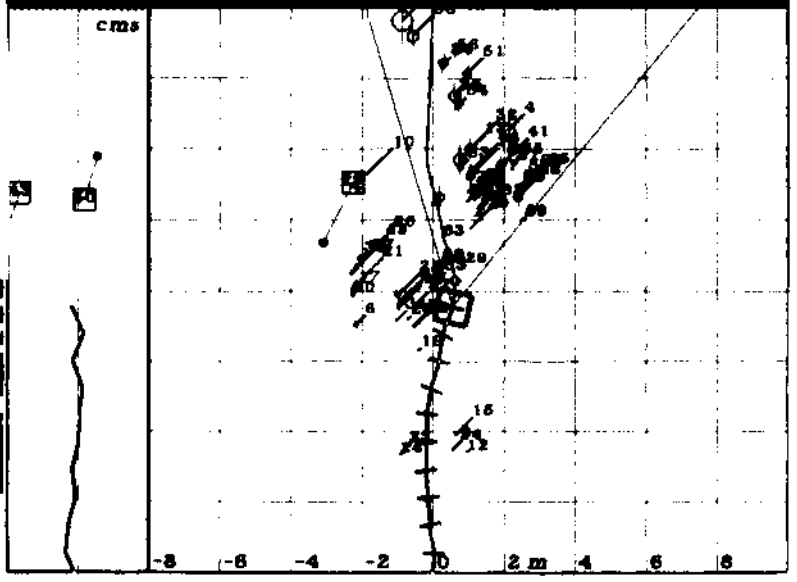
and the cart

Figure 1b:

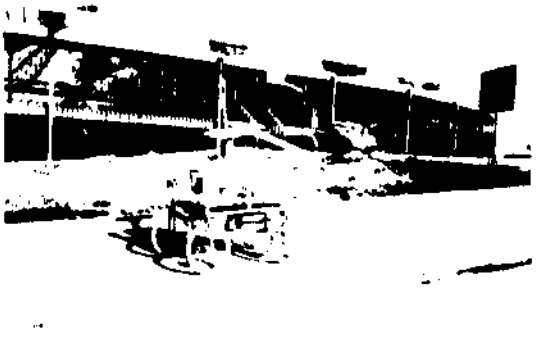
After the II'th lurch the cart has rounded the chair, the icosahedron and is planning to round the cardboard tree. The wold model has suffered som accumulated drift error, and the oldest acquired features are considerably misplaced. Also misplaced, due to human error, is the carts destination, which is about a meter behind the far wall of the room. The cart backed up a number of times later in this run trying to get around it, when il found planned paths blocked by newly observed portions of the wall.

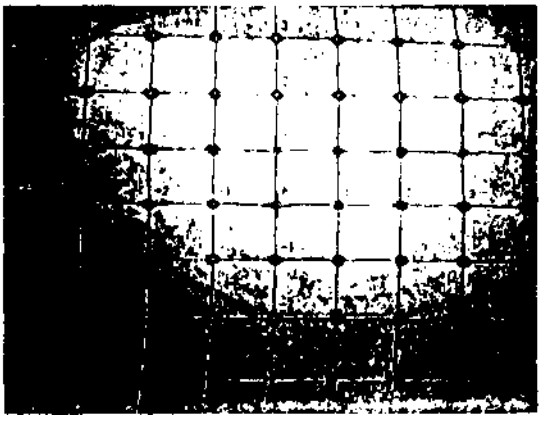


The calibration pattern



Outdoors





Calibration-polynomial distorted grid superimposed on the spot image from which it was calculated.