Visual Map Making for a Mobile Robot

Rodney A. Brooks
MIT Artificial Intelligence Lab
545 Technology Square, Cambridge, Mass 02173.

Abstract. Mobile robots sense their environment and receive error laden readings. They try to move a certain distance and direction, and do so only approximately. Rather than try to engineer these problems away it may be possible, and may be necessary, to develop map making and navigation algorithms which explicitly represent these uncertainties, but still provide robust performance. The key idea is to use a relational map, which is rubbery and stretchy, rather than try to place observations in a 2-d coordinate system.

1. Introduction

We are interested in building mobile robot control systems useful for cheap robots (i.e., on the order of the price of an automobile) working in unstructured domains such as the home, material handling in factories, street cleaning, office and hotel cleaning, mining and agriculture. The same capabilities can be useful for robots, which do not have to be so cheap to be economically feasible, and which do tasks like: planetary exploration, space station maintenance and construction, asteroid mining, nuclear reactor operations, military reconaissance and general military operations.

For all these applications a robot must wander around an unstructured environment. If it is able to build and maintain a map by itself its functionality within the environment will be much improved. In this paper we examine some problems faced by such a robot.

We first state some starting points for the research we are engaged in. In some cases they are quite different from the working assumptions made by other mobile robot researchers. As we go we will compare our approach to those of [Moravec 1983]'s rover project and [Giralt et al 1983]'s Hilaire. These are the most advanced examples of mobile robot projects.

2. Dogma

1. We do not believe that a robot can perform many useful tasks if it models its world as a projection in a two dimensional plane. Nor does it suffice to decorate those projections with "height-of-feature" information. The world a robot must operate in is inherently three dimensional even if it can locally move in only a two dimensional plane. Many objects in the world are small enough that the robot can see over the top of them, but not so small that it can roll or step over them. On the other hand some objects hang over space that is navigable by the robot. Such objects can not always be ignored. They may on occasion block the robot's view of landmarks for which it is searching. They may have surfaces that the robot wishes to interact with; e.g., a table top that it can reach up to and dust, or a deck that the robot can get to via some stairs or a ramp.

2. Almost all mobile robot projects have had as one of their underlying assumptions that it is desirable to produce a world model in an absolute coordinate system. However all sensors and control systems have both systematic and random errors. The former can be dealt with by calibration techniques (although these are often time consuming and are confounded on mobile robots by the fact that the robot itself is not fixed to any coordinate system). The latter are always present. It is usual to model some worse case bounds on such errors but this will not always suffice (e.g. mismatches in stereo vision can produce depth measurements with error magnitude the full range of depths which can be measured). In any case the bounded errors at least must be dealt with in building models of the world and using them. A number of approaches have been taken to this problem:

a. Ignore it. This has only been successful in the most toylike of worlds.

b. Use fixed reference beacons. This implies that the environment is either structured for the robot's benefit in the case that beacons are explicitly installed, or that the environment has been pre-surveyed for the robot's benefit in the case that known positions of existing beacons (e.g. power outlets) are used.

c. Some sort of inertial navigation device is used to determine accurately where the robot is in the global coordinate system. These sensors have a large number of disadvantages, including high cost (although proponents say they will be down from \$100K to about \$5K in only a few years), drift requiring recalibration to some global reference every few hours, long startup time for gyroscope based sensors, errors too large for use on a small scale such as within a factory or house, and uncertain behavior when subject to high jerk components (such as a tank crossing ditches, or your child playing tag with the vacuum cleaner robot).

d. Almost all wheeled mobile robots come equipped with shaft encoders on their steering and drive mechanisms. In a perfect world with no slip or slide between wheels and ground surface readings from these sensors would provide an extremely accurate estimate of robot position. Unfortunately wheels slip and slide with magnitudes that are functions of, at least, wheel velocity and acceleration, exact ground surface composition and shape, wheel load, and tire wear. These aspects can all be modelled but the surface the robot runs on must be restricted or there will still be errors with essentially the same magnitude. Of course such techniques will be less accurate on legged vehicles.

e. Landmarks are chosen by the robot and used as reference points when next seen, to update the robot position estimate. The landmarks must be chosen for recognizability within some expected uncertainty area.

Approaches a, b, and c above are ruled out for us because of costs or our unstructured domain. We are left with inaccurate motion estimates and the need for visual landmark recognition. Compare this to the *Hilare* project at Toulouse [Giralt et al 1983].

The Hilare project is probably the most complete and advanced of any mobile robot projects. They have produced by far the best non-vision based results. It uses methods b

CH2152-7/85/0000/0824\$01.00 © 1985 IEEE

(infrared beacons), d (shaft encoders), and e (a directable laser range finder) from above to try to produce as accurate as possible a model of the environment in an absolute coordinate system. Even with an elaborate error tracking system and the use of fixed beacons errors still accumulate to the point where they are forced to break up observed objects into pieces and let the pieces change relative coordinates (i.e. the observed objects get deformed in the model relative to what was observed), to maintain a consistent position model [Chatila and Laumond 1985] The underlying problem is that worse case error needs to be assumed in placing things in an absolute coordinate system, and cumulative worse cases soon lead to useless models globally.

We use no global or absolute coordinate system. We do not ignore errors nor do we use beacons or inertial navigation systems. Instead we will use only local coordinate systems with relative transforms and error estimates. We use shaft encoder readings and visibility analysis and landmark recognition to build a consistent and accurate world model. In the future we might use a compass as these are cheap and from theoretical considerations it appears that a compass may provide a large amount of useful information.

3. Some mobile robot projects make no real attempt to model the environment on the basis of their perceptions. Such robots will necessarily have limited capabilities. Other projects, especially those based on indoor robots, which have made serious attempts to model the environment from perceptions have often assumed that the world is made up of polyhedra. This assumption manifests itself in two ways:

a.The perception system produces models of the world whose primitives are polyhedra.

b.The environment in which the robot is allowed to roam is constructed out of large planar surfaces with typically less than 100 planes in the complete environment of the robot.

In fact since most projects have used 2 dimensional representations of the world they often actually model the world as polygons, and the artificial worlds are constructed from vertical planes reaching from the ground to above the range of the sensors.

When algorithms developed under such assumptions and test in such domains are applied to more realistic worlds, they break down in two ways:

a.Time performance degrades drastically if there are any algorithms with even moderate time complexity as a function of the number of perceived surfaces. A quadratic algorithm can be fatal and even a linear algorithm can have unpleasant consequences.

b.More seriously, the mapping between the world and its perceived representation usually becomes very unstable over slight changes in position, orientation or, in the case of vision, illumination.

The second of these points can be disastrous for two reasons:

i.It becomes much more difficult to match a new perception with an existing partial model of the world. Straightforward matching of edges to edges and vertices to vertices no longer suffices.

ii.If the representation of free space is based on object faces (e.g., [Chatila 1982] has the most complete example of such a scheme) providing defining edges of convex polygons, then such representations get almost hopelessly fragmented into many, many convex polygons which extend distances many times the size of the object, and which have no semantic relevance, besides being completely unstable.

For the reasons we will build no artificial environments. The robot must exist in a "real" environment that humans inhabit and have constructed for their own use. We need to tackle the representation problems with multiple scales of representation to filter out the small high frequency perturbations of the environment which have no real effect on tasks to be performed within that environment.

It is important to remember the following:

A representation of the world is not something from which the world need be reconstructable. Rather a representation of the world is a statement of facts deducable from observations, and ideally includes enough facts that anything deducable from past observations is also deducable from the representation. A representation is not an analgous structure to the world; it is a collection of facts about the world.

4.Many groups building mobile robots are relying on sonar sensors (usually based on the Polaroid sensor used for autofocusing their cameras) as their primary source of thhree dimensional information about the world. The reasons for choosing such sensors seem to be:

a.they give direct digital readings of depth, or distance to first echo, and as such

b.they seem to require very little processing to produce a two dimensional description of the world, which means

c.they produce almost real-time data with very cheap processors, and

d.the sensors themselves are cheap so they can be hung all over the robot giving $360°$ sensing without the need for mechanical scanning.

Unfortunately sonar sensors also have many drawbacks which force many such groups to spend a great deal of effort overcoming them. The major drawbacks are:

a.the beam is either wide giving ambiguous and sometimes weak returns or when the beams are more focused it is necessary to have either very many sensors or to mechanically scna witha smaller number of them.

b.sonar returns come from specular reflections (i.e. mirror-like reflections int he visible spectrum) and thus the emitted sound pulse often skims off a surface leading to either no return, or a secondary return giving the depth of an object seen (heard) ina mirror, rather than in the line of sight (hearing), and

c.because of these problems large amounts of processing turn out to be necessary to get even moderately low noise levels in the data, defeating one of the original reasons for choosing sonar sensing, and lastly

d.sonar is not useable over large distances without much higher energy outputs than that of the standard cheap sensors making it much more hardware expensive and also subject to errors due to atmospheric effects.

A final problem with sonar is that it is not useable on the surface of the Moon or Mars nor in space outside of a pressurized vehicle.

For these reasons we prefer to use the natural alternative of passively sensing electromagnetic radiation in the near visible range. It suffers from none of the drawbacks we have listed above, although it does have its own; such as the need for large amounts of computation for even the simplest of data extractions.

We will however consider using sonar for tasks for which it is suited. For example it is an excellent sensor for monitoring local obstacles, missed by the visual sensor, as the robot moves along. Thus it acts as a backup safety sensor only. The Hilare project [Giralt et al 1983] is another projects which has come to similar conclusions concerning the proper role of sonar.

5. We are interested in building *artificial beings* in the sense described by [Nilsson 1983]. A robot purchased from Sears must work reliably for at least many months, and hopefully many years. It must work under the "control" of a completely unskilled, unsophisticated and untrained operator; i.e., the purchaser (you!). It must operate sensibly and safely under a large class of unforseen circumstances (some quite bizarre). To achieve such performance we may make only a minimal set of assumptions about the environment. The control software must be reliable in a sense orders of magnitude more complex and sophisticated than that which is normally considered under the banner of "software reliability". We suspect new hardware architectures will be necessary, besides software developments to meet these challenges.

2.1 *The task*

Our mobile robot is a circular platform with three wheels which always steer together and can point int any direction. It has sonar sensors and stereo TV cameras on board. Its environment is restricted to indoors but we plan to let it wander anywhere within our Lab. We want to use vision to build reliable maps of the world which are suitable for navigating about the world. We plan on using a system of [Khatib 1983] to provide a robust lower level control system avoiding local obstacles through acoustic sensing.

The only assumptions made about the robot in the rest of this paper are that it can move in any direction and it uses stereo vision to provide a sparse depth map (in particular we consider the use of a [Moravec 1983] style feature point depth map). No consideration is given to the use of acoustic sensors.

The algorithms described in this paper have not been implemented and therefore have not been tested on real data. In some cases only a computational problem has been formulated and no algorithm is given here.

3. Major Issues

A visually guided mobile robot inhabits a mental world somewhat different from the real world. Its observations do not exactly match the real world. Its physical actions do not occur exactly as intended. The task of navigating around the world can be eased by having the world map based on primitives suitable for navigation. The map should also be constructable from visual observations.

3.1 *Uncertainty*

Observations of the world are uncertain in two senses, providing two sources of uncertainty. Action in the world is also uncertain leading to a third source of uncertainty.

(a) There is inherent error due to measuring physical quantities. In particular, a pixel raster as used in computer vision enforces a minimal spatial resolution at the sensor beyond which there is no direct information. Physical constraints, such as continuity of surfaces in the world or averaging an identified event over a number of pixels, can be used to obtain sub-pixel accuracy of certain measurements, but the finite amount of information present ultimately can not be escaped. For the purposes of this paper we will only consider single pixel accuracy at best. For stereo vision this discretizes the possible depth measurements into a small number of possibilities, based on the maximum disparity considered by the algorithm. The error in depth measurements, increases with the distance from the cameras and the possible nominal values become more sparse.

(b) There may be errors in stereo matching. Thus a depth point may be completely wrong.

(c) When a robot is commanded to turn or go forward it does not carry out the action completely accurately. If drive shaft encoders are used then the best possible accuracy is to within on encoder count. If this were the only source of error it could almost be ignored as shaft encoders can be built with many thousands of marks resulting in very small physical errors. The real source of error is wheel slippage on the ground surface. This can be reduced somewhat with very accurate dynamic models, and accurate knowledge of the ground surface and wheel characteristics.

Our approach is to take explicit account of the first source of observational uncertainty in the design of all algorithms and to use the principle of least commitment to handle it in a precise and correct manner. The second source is handled more heuristically, by making the algorithms somewhat fault tolerant.

3.2 *Map primitives*

[Brooks 1983a] introduced a new representation for free space, useful for solving the find-path problem for a convex polygon. (See [Brooks 1983b] for an extension to the case of a manipulator with revolute joints.) The key idea is to represent free space as *freeways*, elongated regions of free space which naturally describe a large class of collision-free straight line motions of the object to be moved. Additionally there is a simple computation for determining the legal orientations (i.e. those where the moving object stays completely within the freeway) of the object while it is moved along a freeway.

Using freeways as a map representation for a mobile robot has a number of positive aspects. These are:

1. Visual observations provide natural freeway descriptions. If the robot can see some point in the distance, then it must be the case that there are no obstacles along the line of sight from the robot to that observed point. We will call this the *Visibility Constraint.*

2. For a simple circular robot, such as ours, navigability of a freeway depends only on its minimum width.

3. Freeway descriptions of free space do not rely on having each point of free space represented uniquely. Freeway representations are naturally overlapping. It is not necessary to know that two descriptions of pieces of free space are refering to the same place; the map can still be useful for navigation tasks.

It should be noted however that not all of free space is best described by elongated primitives. Some places are best described as convex regions. We will include such regions in our map, and refer to them as *meadows.*

3.3 *Combining these ideas*

These ideas can be combined in a map representation by avoiding the use of a 2-d coordinate system. Instead, only relationships between parts of the map are stored, in a graph representation. The relationships include estimates on their associated uncertainties.

Consider figure 1. It is one aspect of a map built by a mobile robot as it has moved from some place A, to place B, and so on to place E. It tried to travel in straight lines between places. The representation uses a 2-d coordinate system, so that straight lines in the map correspond to straight line paths in the world. It did not know the places beforehand but has been labelling them as it goes. Suppose it has been using nominal distances travelled and nominal angles turned, to give nominal 2-d coordinates for A, B, etc. Given that these values include errors there may be three physical positions for E, that give rise to the same measurements mad by the robot in moving from D. Any coordinates chosen for E implicitly add unsupported conclusions to the map. It can not be known whether the path from D to E crossed the path from A to B, went via place B, or crossed the path from B to C.

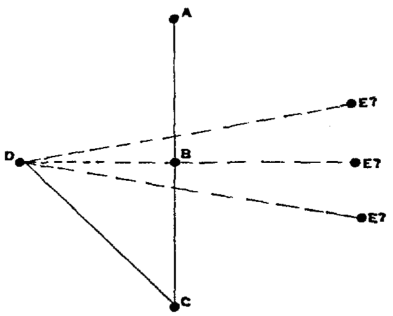

Figure 1. Metric information leads to incorrect represenatations when the information contains uncertainty.

A better approach then is to use an abstract graph as in figure 2 where the arcs, which represent straight line motions in the real world, are not represented as straight lines in the model, but are simply arcs with labels. For instance, arc BC is labelled with the robot's estimate of the distance it travelled. Intersections of arcs in this representation are purely an artifact of our attempt to draw the graph on paper. It will be possible however, to determine from the arc labels that the path represented by arc DE somewhere crossed the path followed by the robot from A to C.

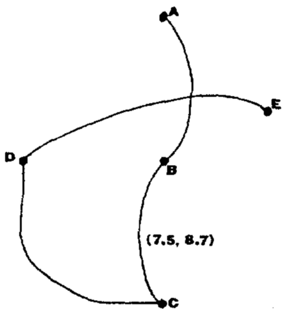

Figure 2. A better representation. The graph is not embedded in the 2-d plane, except for the purpose of drawing this diagram.

4. Dealing with Uncertainty

If a mobile robot is moving in a flat two dimensional world, and if it has a labelled direction as forward then its space of possible locations and orientations is a three dimensional *configuration space* [Lozano-Pérez 1983]. We can label its axes x, y, and θ. When the robot is at two dimensional coordinates (x_0, y_0) with orientation θ_0, its configuration corresponds to point (x_0, y_0, θ_0) in configuration space. For now lets refer to such a configuration as P_0.

Suppose the robot has configuration P_0, and it re-orients by angle η then travels distance d. Its new configuration would be:

$$P_1 = (x_0 + d\cos(\theta_0 + \eta), y_0 + d\sin(\theta_0 + \eta), \theta_0 + \eta).$$

However there is always error associated with the robot's motion. Typical errors might be $\pm 5°$ angular error and $\pm(5 + 0.05d)$ centimeters, in distance error, as a function of the distance travelled.

4.1 *Uncertainty manifolds*

We have shown that P_1 can not be uniquely identified. Instead P_1 can range over an *uncertainty manifold* (see figure 3) in configuration space. If the range of possible values for d is $[d_l, d_h]$ and for η is $[\eta_n - \alpha, \eta_n + \alpha]$ then the uncertainty manifold is:

$$\begin{aligned} M_1(x_0, y_0, \theta_0) = & \qquad\qquad (1) \\ \{\, (x_0 + d\cos(\theta_0 + \eta), & \, y_0 + d\sin(\theta_0 + \eta), \theta_0 + \eta) \\ & \mid d \in [d_l, d_h], \eta \in [\eta_n - \alpha, \eta_n + \alpha] \,\}. \end{aligned}$$

Notice that this is a two dimensional manifold in three dimensional space.

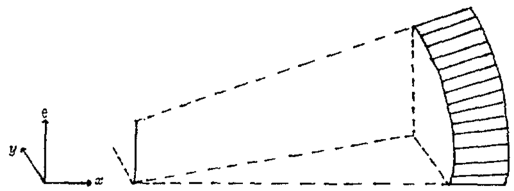

Figure 3. An uncertainty manifold arising from an uncertain motion in an uncertain direction.

A simple question, but nevertheless a useful one to ask while exploring the world, is "Am I back some place I've already been?", which, without loss of generality, can be simplified to "Am I back where I started?". Given that each individual motion is uncertain, it will be necessary to take into account the cumulative uncertainty, and in fact, without further sensing, the toughest question that can be answered is "Is it plausible that I am back where I started?". We will call this the *am-I-there-yet* question.

The uncertainty manifold resulting from two motions can be written as

$$C_{12}(x_0, y_0, \theta_0) = \bigcup_{(x,y,\theta) \in M_1(x_0,y_0,\theta_0)} M_2(x, y, \theta) \qquad (2)$$

and from two motions:

$$C_{123}(x_0, y_0, \theta_0) = \bigcup_{(x,y,\theta) \in C_{12}(x_0,y_0,\theta_0)} M_3(x, y, \theta)$$

(Note that this is different from an incorrect forumlation given in [Brooks 1984].) We call the manifolds C_{12}, C_{123}, etc., "cascaded manifolds". These manifolds are three dimensional and "solid"; i.e., they have a non-empty interior. The surfaces of these manifolds become progressively harder to express as the number of motions increase.

One approach to answering the am-I-there-yet question is to introduce three more variables for each motion (besides nominal angles and distances and bounds on errors in each), and write explicit conjunctions of symbolic inequalities of the form

$$P_1 \in M_1(x_0, y_0, \theta_0),$$

$$P_2 \in C_{12}(x_0, y_0, \theta_0),$$

etc. Note that each P_i introduces three more variables. Then we can add the constraints

$$(x_0, y_0, \theta_0) \in C_{12\ldots n}(x_0, y_0, \theta_0), \tag{3}$$

and, using the methods of [Brooks 1983] ask whether all the constraints are together satisfiable. This is *forward reasoning* with constraints. Additionally one would like to be able to use auxiliary information, such as from landmarks, to be able to assert inequalities such as (3). Then one would use the symbolic bounding algorithms from the above paper to determine the implications in terms of constraints on the actual physical values of angles of re-orientation and distances travelled. This is *backward reasoning* with constraints. Unfortunately this approach doesn't work well because of the presence of so many trigonometric terms.

4.2 *Approximating uncertainty manifolds*

A second approach, used more successfully in reasoning about uncertainties in assembly processes, is to use bounds on trigonometric functions, such as

$$\sin\alpha \le \sin(\eta - \eta_n) \le \eta - \eta_n$$

for $\eta \ge \eta_n$ and

$$1 - \frac{1}{2}(\eta - \eta_n)^2 \le \cos(\eta - \eta_n) \le 1$$

This has the effect of making an individual 2-d manifold M_i a little fuzzy, giving it some three dimensional volume. This makes the resulting manifolds (e.g. equation (2)) a little nicer in form. Unfortunately, again the constraint propagation methods fail because of the large number of cascading variables.

Broader bounding volumes for the uncertainty manifolds, with fewer parameters, and with simpler interactions, are needed if we are to make use of them in either forward or backward reasoning.

4.3 *Cylinders in configuration space*

The projection of the uncertainty manifold (1) into the x–y plane is can be bounded in the x–y plane by a circle with radius

$$\frac{(d_l + d_h)^2}{4\cos^2\alpha} - d_l d_h$$

centered distance

$$\frac{d_l + d_h}{2\cos\alpha}$$

from the start of the motion. We can then bound the complete manifold in configuration space by a cylinder sitting above the bounding circle with have constructed, and ranging from $\eta_n - \alpha$ to $\eta_n + \alpha$ in height.

A bounding cylinder B has four parameters and is a function of three variables (just as a manifold M_i itself is a function of position and orientation of its root point in configuration space). The four parameters are distance d, radius r, central orientation η, and orientation radius α.

Suppose that $B_{d_1,r_1,\eta_1,\alpha_1}(x, y, \theta)$ bounds $M_1(x, y, \theta)$, and that $B_{d_2,r_2,\eta_2,\alpha_2}(x, y, \theta)$ bounds $M_2(x, y, \theta)$. Then it turns out we can bound the cascaded manifold

$$C_{12}(x_0, y_0, \theta_0)$$

by the bounding cylinder:

$$B_{d_{12},r_{12},\eta_{12},\alpha_{12}}(x_0, y_0, \alpha_0)$$

where

$$d_{12} = \sqrt{{d_1}^2 + {d_2}^2\cos^2\alpha_2 + 2d_1d_2\cos\eta_2\cos\alpha_2}$$

$$r_{12} = d_2\sin\alpha_2 + r_1 + r_2$$

$$\eta_{12} = \eta_1 + \eta_2$$

$$\alpha_{12} = \alpha_1 + \alpha_2$$

Now we are able to cascade many motions together without increasing the complexity of our representation for the amount of uncertainty which results. The penalty we pay is that our bounds are sometimes rather generous.

Figure 4 shows the projection of bounds on uncertainty manifolds produced by four successive motions into the x–y plane. After the last, the am-I-there-yet question has an affirmative answer, i.e. "maybe", relative to the point of origin.

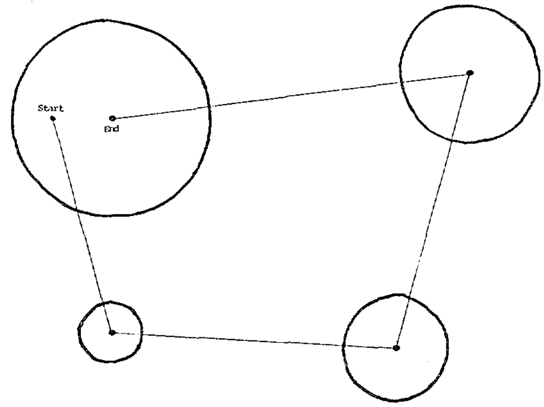

Figure 4. An example of forward reasoning, deciding that it is plausible that the robot is back where it started.

In figure 5 we see an example of backward reasoning. Suppose we have used forward reasoning to determine that it is plausible that the robot is in the same circular meadow from which the journey commenced. It might be plausible that the robot is in other meadows too. In any case the plausibility condition cuts down the number of possible meadows the robot might be in. If there are some visual landmarks associated with the meadow then perhaps one of the hypotheses can be verified (if a similar landmark is visible in another meadow then the forward reasoning will sometimes provide the disambiguation). So suppose such reasoning does indeed determine that the robot is in the original meadow. The intersection of the uncertainty cylinder cross section and the meadow determines a smaller region where the robot really might be. We bound that with a circle to produce a new uncertainty cylinder. If orientation information was gleaned from the landmark observation then that can be used to cut down the cylinder's range in the θ direction. This projection of this cylinder is illustrate in figure 5.

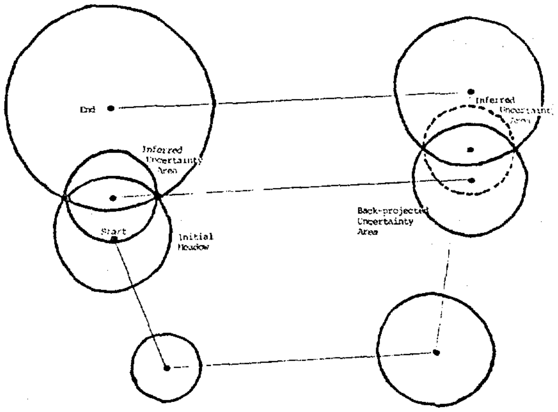

Figure 5. Backward reasoning. Additional information indicated the robot was in the meadow. The dashed circle shows bounds where the robot really must have been before.

Now we can use backward reasoning, and ask "What are all the points I could have been at, before the last motion and gotten into this new uncertainty cylinder?". This does not involve shrinking the cylinder by subtracting the uncertainly cylinder of the last motion, rather it involves cascading its inversion through the origin of configuration space. The resulting uncertainty cylinder, is shown in figure 5. Since the robot got to the third observation point by travelling forward around the path, it must have been in the intersection of the two cylinders before the fourth motion. Now a new uncertainty cylinder can be constructed to bound that intersection. It specifies an uncertainty relationship between the start of the journey, and any observations which were made after the third stop. Thus it ties down some of the rubbery map just a little bit better, and the effects of this additional constraint will be able to be used in later references to the map. Notice that the backward reasoning can continue from the last uncertainty cylinder we constructed. Soon however the uncertainties will become so large that no new information will be gained.

This technique was independently developed under another name by [Chatila and Laumond 1985] They call it *fading*.

5. Conclusion

In this paper we examined some problems which must be solved by a mobile robot which explores an unknown environment, building a map from visual observations. In particular we introduced a symbolic map representation whose primitives are suited to the task of navigation, and which is explicitly grounded on the assumption that observations of the world are inaccurate and control of the robot is inaccurate.

Acknowledgements

This research was partially supported by DARPA under contract N00014-80C-0505 and partially supported by an IBM Junior Faculty Development Award.

References

[**Brooks 1982**] Rodney A. Brooks, *Symbolic Error Analysis and Robot Planning* in **International Journal of Robotics Research**, vol 1, no. 4, 29-68.

[**Brooks 1983a**] Rodney A. Brooks, *Solving the Find-Path Problem by Good Representation of Free Space* in **IEEE Systems, Man and Cybernetics**, SMC-13, 190-197.

[**Brooks 1983b**] Rodney A. Brooks, *Planning Collision Free Motions for Pick and Place Operations* in **International Journal of Robotics Research**, vol 2, no. 4, 19-44.

[**Brooks 1984**] Rodney A. Brooks, *Aspects of Mobile Robot Visual Map Making* in **Preprints of the Second International Symposium of Robotics Research**, Kyoto, 287-293.

[**Chatila and Laumond 1985**] Raja Chatila and Jean-Paul Laumond, *Position References and Consistent World Modeling for Mobile Robots* in these proceedings.

[**Giralt et al 1983**] Georges Giralt, Raja Chatila and Marc Vaisset, *An Integrated Navigation and Motion Control System for Autonomous Multisensory Mobile Robots* in **Proceedings of the First International Symposium on Robotics Research**, Bretton Woods, New Hampshire, to be published by MIT press.

[**Khatib 1983**] Oussama Khatib, *Dynamic Control of Manipulators in Operational Space* in **Sixth IFTOMM Congress on the Theory of Machines and Mechanisms**, New Delhi.

[**Laumond 1983**] Jean-Paul Laumond, *Model Structuring and Concept Recognition: Two Aspects of Learning for a Mobile Robot* in **Proceedings IJCAI-83**, Karlsruhe, West Germany, 839–841.

[**Lozano-Pérez 1983**] Tomás Lozano-Pérez, *Spatial Planning: A Configuration Space Approach* in **IEEE Transactions on Computers**, (C-32):108–120.

[**Moravec 1983**] Hans P. Moravec, *The Stanford Cart and the CMU Rover* in **Proceedings of the IEEE**, (71)872–884.

[**Nilsson 1983**] Nils J. Nilsson, *Artificial Intelligence Prepares for 2001* in **The AI Magazine**, 7-14