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This paper presents the mathematical and probabilistic framework we now use for evidence grids. It gives the history of the grid representation, and its relation to other spatial modeling approaches. It discusses earlier formations and their limitations, and documents several extensions. A list of open issues and research topics is then presented, followed by a literature survey.

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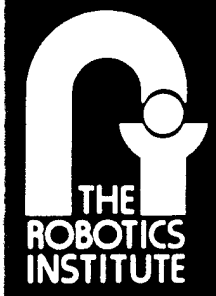

Carnegie Mellon University

The Robotics Institute

Technical Report

Robot Evidence Grids

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Robot Evidence Grids

Abstract

The evidence grid representation was formulated at the CMU Mobile Robot Laboratory in 1983 to turn wide angle range measurements from cheap mobile robot-mounted sonar sensors into detailed spatial maps. It accumulates diffuse evidence about the occupancy of a grid of small volumes of nearby space from individual sensor readings into increasingly confident and detailed maps of a robot's surroundings. It worked surprisingly well in first implementation for sonar navigation in cluttered rooms. In the past decade its use has been extended to range measurements from stereoscopic vision and other sensors, sonar in very difficult specular environments, and other contexts. The most dramatic extension yet, from 2D grid maps with thousands of cells to 3D grids with millions, is underway.

This paper presents the mathematical and probabilistic framework we now use for evidence grids. It gives the history of the grid representation, and its relation to other spatial modeling approaches. It discusses earlier formulations and their limitations, and documents several extensions. A list of open issues and research topics is then presented, followed by a literature survey.

1 Introduction

Early approaches to computer vision attempted to identify lines and vertices in images and infer the boundaries of objects. Stereoscopic vision sometimes contented itself with identifying small distinctive patches, presumed to be parts of object surfaces, in multiple views of scenes. The traditional approach suffers from brittleness, because the existence of objects is decided quickly, from small, noise prone, quantities of data. All is well when these snap decisions happen to be correct, but frequently chance properties of the signal produce incorrect indications, invalidating the entire subsequent chain of inferences. Prior to devising the evidence grid approach, we guided mobile robots through obstacle courses by stereoscopic patches, and experienced such brittle failures about every hundred meters of travel.

We were forced to abandon the notion of locating object features as the initial step of sensory processing when we decided to use inexpensive Polaroid sonar rangefinders to map robot surroundings. These sensors register the distance of the nearest sound reflector within a wide 30 field of view, providing general information about the occupancy of large areas without localizing features. Representing the robot's surroundings by a grid of small cells, enabled us to represent and accumulate the diffuse information from sonar readings into increasingly confident maps. Occasional sensor errors had little effect, and the approach did not exhibit the brittleness of the feature based methods.

We have found evidence grids generally useful with various sensors and tasks requiring detailed geometric modeling of the world, but have applied them mostly to planning and traversing obstacle-avoiding paths for mobile robots. We usually give the robot no *a priori* knowledge of the geometry of its environment and assume that most of the world is static. We favor inexpensive sensors because we anticipate applications in cost-critical near-future commercial robots. We are less sensitive to computing cost because we anticipate continuing rapid declines in that component.

The evidence grid approach represents the robot's environment by a two or three dimensional regular grid (see Figure 1). In each cell is stored the evidence (or probability), based on accumulated sensor readings, that the particular patch of space is occupied. Many of our sensors report the distance

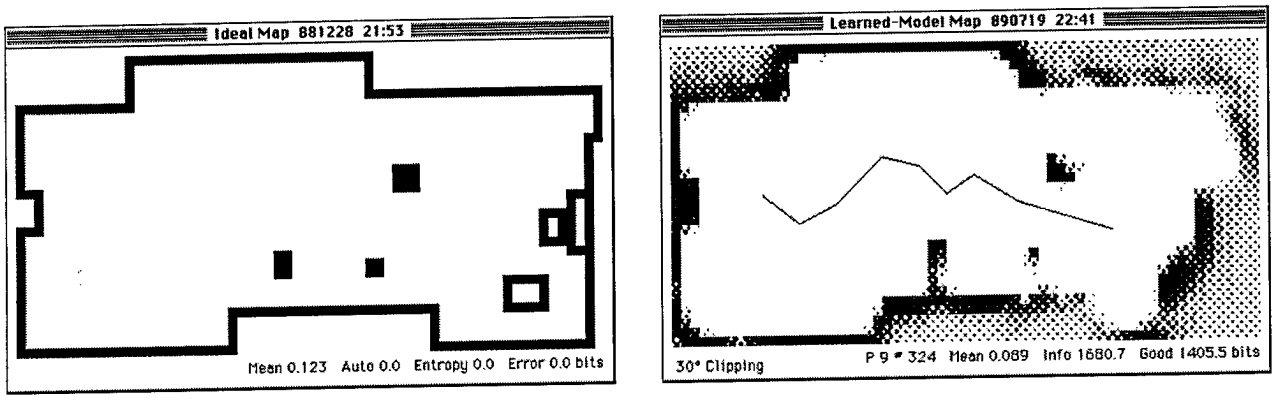

FIGURE 1 *Example evidence grids. The left grid is an ideal of a simulated room, similar to our own laboratory. The right is the result of processing after a simulated traverse by a robot with a ring of 36 sonar sensors. The path of the robot is superimposed on the grid. From [Moravec-Blackwell93].*

to the nearest object in a given direction. Given the robot's position, we increase the probabilities in the cells near the indicated object and decrease the probabilities between the sensed object and the sensor (since it is the *first* object in that direction). The exact amount of increase or decrease to the various cells in the vicinity of the sight line forms the *sensor model.* Figure 2 shows an example sensor model that might be appropriate for a Polaroid sonar rangefinder.

The evidence grid approach has proven itself especially useful with wide angle sonar range finders that are among the least expensive and most practical sensors for industrial and perhaps home robots. One of our earliest runs is shown in Figure 3 (see [Elfes87]). It used the Neptune robot with a Denning sonar ring with 24 sensors. In this run Neptune took a reading from each sensor, planned a path to the goal, travelled 2 meters along the path and repeated until it reached the goal.

A brief overview of the remainder of the paper follows.

In Section 2, other methods are described and contrasted with evidence grids. The evidence grid approach, although computationally expensive, provides more robust and reliable navigation than other methods used to date.

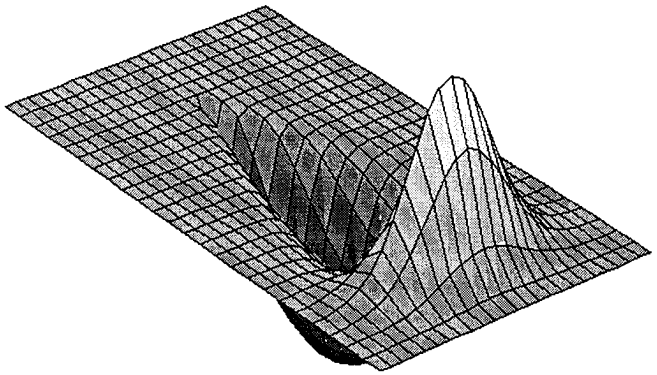

FIGURE 2 *Example Sensor Model. A range reading reports the distance to the nearest object in a given direction. For sonar, this object can be anywhere within a relatively wide beam. The sensor model describes exactly how much to increase or decrease the probability at a given location relative to the position and direction of the sensor and the reported range.*

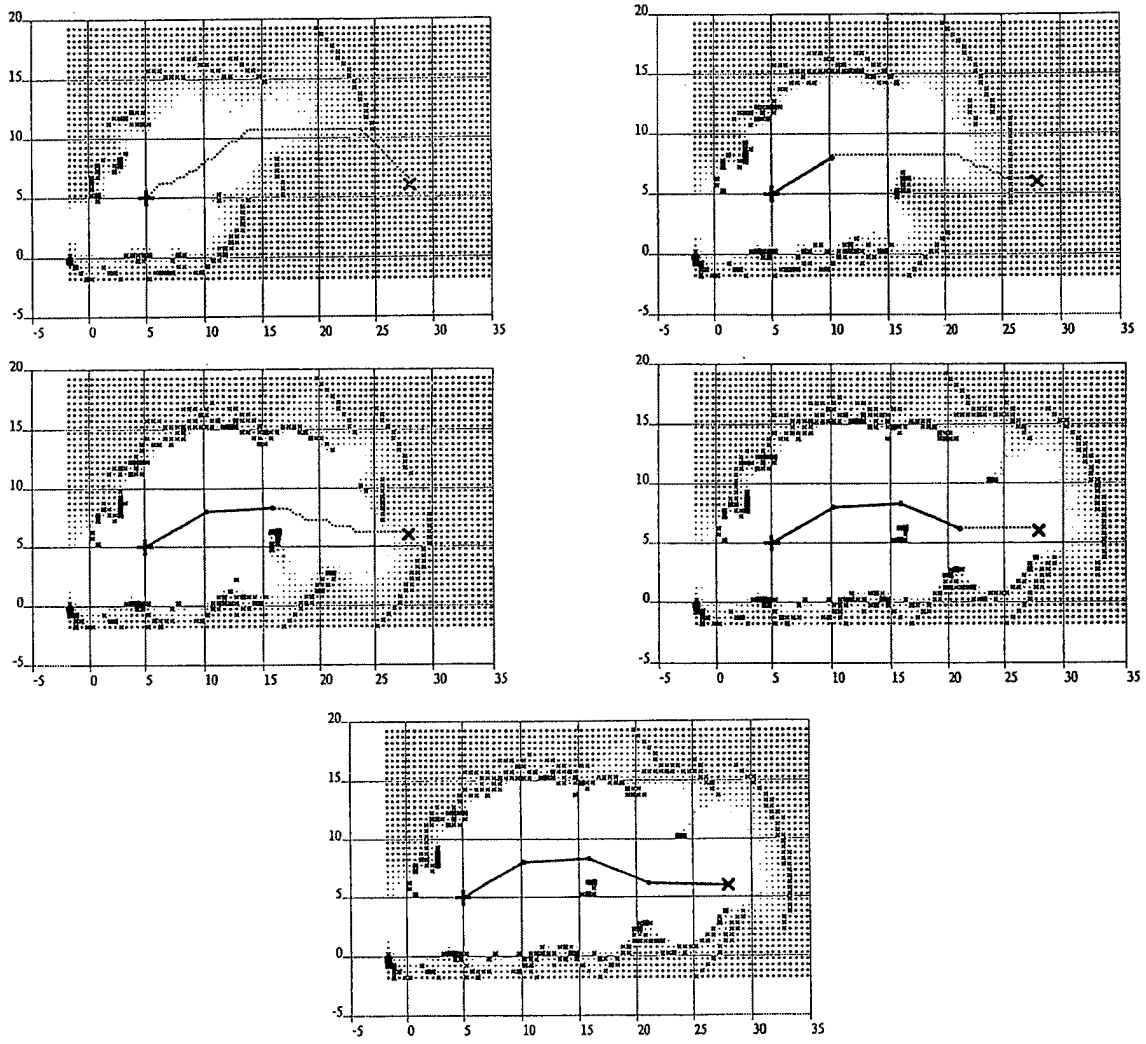

FIGURE 3 *Overhead view of the evidence grid built by a sonar guided robot traversing out laboratory. The scale marks are in feet. Each point on the dark trajectory is a stop that allowed the onboard sonar ring to collect twenty four new readings. The forward paths were planned by an A* path planner working in the grid as it was incrementally generated. From [Elfes87].*

Section 3 presents the Bayesian probability framework for the approach. A representation for the probability that simplifies computation is derived. Using this representation, we first precompute the sensor model, storing it in a table. Then, to incorporate a new sensor reading we simply take values from the table and project and add them to the evidence grid. We have also found a way of comparing two maps: we calculate the logarithm of the probability that two maps represent the same situation.

Section 4 discusses previous formulations and their problems. The evidence grid framework has gone through several changes since it was first introduced in 1983, and these previous formulations are discussed, along with reasons for modifying them. Our lab and others at CMU have conducted many runs in various conditions, each demonstrating competent navigation and the robustness of the approach.

Section 5 explains several extensions which have been explored at CMU. This includes a sensor model derived from a probabilistic model of wave propagation (the *context sensitive* method), the automatic learning of sensor models, the explicit modeling of surface orientation and sensor fusion. Also discussed are path planning, autonomous exploration, matching evidence grids and visualization of 3D evidence grids.

Section 6 details several open research topics These include the use of 3D evidence grids, the *unsupervised* learning of sensor models, the use of stereo vision and other sensors with evidence grids, sensor fusion, and a host of higher level navigation issues. Also mentioned are explicit models for systematic errors, the use of evidence grids in position estimation, the matching of grids, object identification and the incorporation of other object properties.

Finally, this report concludes with an annotated bibliography of all evidence grid related articles known to the author.

2 Related Work in Robot Navigation

Current robot navigation algorithms can be divided into two categories, model based systems that maintain internal representations of their surroundings, and reactive ones that act reflexively on their current sensory input. Most present model-based systems are "geometric," constructing point, line or surface descriptions from sense data at an early stage of processing [Faugeras93]. They have the disadvantage that decisions about surface existence and location must be made very quickly, from small amounts of sense data collected in a short time interval, with a consequent high probability of error. Errors are subsequently processed with too little extra information to weed them out reliably. In our experience, geometric programs are brittle, working well for a while, then failing dramatically when early incorrect identifications fool error checks, and amplify to a large effect. They do work effectively if the sensor data is very clean, lowering sensing uncertainties and consequent failure probabilities. A number of partially successful, but error sensitive, geometric programs fed from sonar data have appeared, for example [Crowley89], [Leonard90], and [Drumheller91].

The 1980s saw much effort and expense applied to obtaining clean navigational data from scanning laser rangefinders (see, for example, [Hebert88], [Singh-Keller91], [Singh-West91]). These systems quickly reduce the range data to topographic geometry of oncoming terrain, on which they evaluate possible paths. Some even simulate simplified vehicle dynamics on each prospective path [Daily88]. As noise in the sensor data rises, geometric and range map methods become ineffective. Since they draw conclusions about the world during early stages of processing, the probability of an incorrect conclusion rises. Later stages of processing, working with an incorrect description of the world, often fail spectacularly.

In reflexive controllers, local environmental cues trigger behaviors, and fast data flow dilutes transient sensory errors. Reflexive robots include almost all pre-computer machines and most practical computer-controlled ones, including trolleys that are started and stopped by limit switches and wire, and line and beacon following machines. They do many things very well, and have made a come back with the realization of the problems of geometric model-based techniques. Even model-based robots benefit from fast reflexive components [Brooks90], [Mataric92]. However, their willingness to change behavior when new sensor information contradicts old is also their downfall. Their lack of any "big picture" of where they are in relation to things in the world leads to simple behaviors which can get them trapped by occasional unlucky arrangement of objects, and leave them literally going around in circles.

We invented the evidence grid approach in 1983, to handle data from inexpensive Polaroid sonar devices, whose wide beams leave angular position ambiguous. These sensors are notorious for their

transient misreadings and for being confused by smooth surfaces such as walls, which act like mirrors. Instead of registering objects, the grid method accumulates occupancy evidence for an array of spatial locations, slowly resolving ambiguities as the robot moves. This allows the robot to integrate disparate readings over time, taken from different locations and even with different sensors. We first used the method to interpret measurements from a ring of 24 Polaroid sonar transducers carried on board a mobile robot autonomously navigating in a cluttered laboratory. It was surprisingly successful compared with our earlier experiences in similar environments using stereo-vision based programs that mapped points on objects as error distributions in space. The method also worked on a tree-lined path, in a coal mine, with stereo vision range data, and it successfully fused stereo and sonar. We are now able to learn the sensor model, and can train the program to work nicely in specular surroundings, and superbly elsewhere.

3 The Mathematical Details of the Approach

Let $p(A \mid B)$ represent our best estimate of the likelihood of situation A given that we have received information B. A and B mean either "a certain region of space is occupied" (written o), "a certain region of space is unoccupied" (written $\bar{o}$), or they represent a sensor reading. By definition, $p(A|B) = p(A \wedge B)/p(B)$. Plain $p(A)$ represents our estimate of A given no new information. The alternative to situation A is written $\bar{A}$ (not A).

For the two occupancy cases of a cell, o (the cell is occupied) and $\bar{o}$ (the cell is empty), and new information M (say, derived from a sensor measurement), the above definition immediately gives us:

$$\frac{p(o|M)}{p(\bar{o}|M)} = \frac{p(M|o)}{p(M|\bar{o})}\frac{p(o)}{p(\bar{o})} \qquad \textbf{(Equation 1)}$$

This easy-to-prove formula is related to Bayes theorem. Now suppose we have some information M_1 that we've already processed into a map, i.e. we have $p(o|M_1)$, and we wish to integrate some new measurement M_2 to find $p(o|M_1 \wedge M_2)$. In order to make the analysis tractable we'll assume the new measurement is independent from all previous information. However, we don't mean $p(M_1 \wedge M_2) = p(M_1)p(M_2)$, since if M_1 indicates that the cell is occupied then we would hope M_2 would be more likely to indicate the same thing. Instead what we mean is, *given that the cell is occupied,* the probabilities of getting reading M_1 is independent of getting M_2, and similarly for the cell being unoccupied:

$$\begin{aligned} p(M_1 \wedge M_2|o) &= p(M_1|o)p(M_2|o) \\ p(M_1 \wedge M_2|\bar{o}) &= p(M_1|\bar{o})p(M_2|\bar{o}) \end{aligned} \qquad \textbf{(Equation 2)}$$

Another way to look at this assumption is that we only assume that the sensor's *errors* are independent from one reading to the next. Combining this with a double application of Equation 1, we get

$$\frac{p(o|M_1 \wedge M_2)}{p(\bar{o}|M_1 \wedge M_2)} = \frac{p(o|M_1)p(M_2|o)}{p(\bar{o}|M_1)p(M_2|\bar{o})} = \frac{p(o|M_1)p(o|M_2)}{p(\bar{o}|M_1)p(\bar{o}|M_2)}\frac{p(\bar{o})}{p(o)} \qquad \textbf{(Equation 3)}$$

We generally assume that the *a priori* probability of cell occupation is 1/2, i.e. $p(o) = p(\bar{o}) = 0.5$, so that the last factor above cancels out. When the information M_2 is a sensor reading, the value $p(M_2 \mid o)/p(M_2 \mid \bar{o})$, for all cells and all possible readings, is called the *sensor model.* In other words, the sensor model is a function which attaches a number ($p(M_2 \mid o)/p(M_2 \mid \bar{o})$) to every combination of sensor reading and cell location, relative to the sensor. Note that this assumes the sensor is isotropic in its

world position and pointing direction; in general, the sensor model is a function of 1) the sensor reading, 2) the location and orientation of the sensor and 3) which cell we're updating. Also note that, while the sensor reading M_2 may represent a continuous number indicating distance from the sensor, in general we can say that each time we poll the sensor, it returns an element from some set, and that M_2 ranges over all elements of that set.

The sensor model is usually independent of the current map and can be stored in tables. A further speed up can be achieved if we use the logarithm of the above probability ratio (itself known as the *odds*). In *log odds*, the combining formula is changed from a multiplication to a simple addition, and the log odds can be considered *weight of evidence*. Properly scaled, eight bit integers appear adequate for storing the sensor model's weight-of-evidence values. That we only need a single addition per cell, combined with the high regularity of the array structure of the grid, allows for very simple and fast evidence painting algorithms. We have incorporated these ideas into a very fast implementation [Moravec92b] that has only three additions and a bounds test in the inner loop.

3.1 Match, Score and Entropy

For several reasons, we may wish to compare two maps to see how similar they are. For example, to provide a merit value for the automatic learning of sensor models, we compare a reconstructed map with a (usually hand made) ideal one. In the following we assume that the two maps are co-located, that is they are aligned to the same position and orientation, so that cell A_i from grid A and B_i from grid B both describe the same physical volume, for all i. Our *match* value is calculated in the following way. The probability that two maps represent the same world is equal to the product of the probabilities that each corresponding pair of cells represents the same value. Each number in our maps represents the probability that the cell is occupied. So the probability that two cells A_i and B_i are both occupied is just $A_i \times B_i$. The probability that they are both empty is $\overline{A}_i \times \overline{B}_i$. The probability that they are the same is the sum of these cases: $A_i \times B_i + \overline{A}_i \times \overline{B}_i$. The probability that two maps represent the same thing is then the product $\prod_i (A_i \times B_i + \overline{A}_i \times \overline{B}_i)$ over all the cells of the maps. Generally this will be a ridiculously tiny number. To get a number of reasonable magnitude, and incidentally an information measure in bits, we take $\log_2$ of this probability. By adding 1 to each term, we see that two cells that are identical and maximally confident (either exactly 1 or 0) score as 1, while a cell in an unknown state (1/2), scores 0 when compared to any values. We call the sum of these logs the *Match* between the maps.

$$\begin{aligned} \text{Match} &= n + \log_2\left(\prod_i A_i B_i + \overline{A}_i \overline{B}_i\right) \\ &= \sum_i [1 + \log_2(A_i B_i + \overline{A}_i \overline{B}_i)] \end{aligned}$$

(Equation 4)

Match is generally a small number that climbs slowly to the number of cells in the map as the maps being compared both become more certain (the probabilities approach 0 or 1) and become identical to each other.

When a *Match* is calculated between a reconstructed map and its perfect ideal (which contains either 0, 1 or 1/2 in every cell), we call the result the *Score*. The perfect knowledge of the world this requires is easily obtained in simulation, and can be available in physical runs if the environment is carefully measured by hand, or by a very reliable and high resolution calibrated sensor. Even if the ideal is not known, one can reason that if a reconstructed map has a probability of p in a cell, it should be the case

that a fraction p of the time the ideal map should have a 1 in that place, and a 0 the other $\bar{p}$ of the time. This reasoning allows us to calculate an average expected *Score* for a map, even when the ideal map is unknown. We call this the *Entropy*. A bit of algebra reveals its equivalence to the classical definition:

$$\text{Entropy} = \sum [1 + p_i \log_2(p_i) + \bar{p}_i \log_2(\bar{p}_i)] \qquad \textbf{(Equation 5)}$$

If the probabilities in a reconstructed map are a completely accurate representation of the robot's true state of incomplete knowledge, then the map's *Score* would be equal to its *Entropy*. If the magnitude of *Score* is greater than *Entropy*, then the map can be said to be overconfident.

A totally undifferentiated map, where all the cells have the same probability value p, has maximum *Score* when the p is equal to the number of cells in the ideal map that are 1 divided by the total number of cells, i.e. when the probability is equal to the occupancy density of the ideal. But *Entropy* is maximum when $p = 0.5$ and drops towards 0 as p goes to either 0 or 1.

In summary, the *Match* between two maps (for a given relative displacement) is the log of the probability that the maps represent the same world. The *Match* of a map to an *a priori* ideal map is called its *Score*; learning can be done by trying to maximize score. *Match* of a map with an ideal whose distribution of 1s and 0s reflects the map's probabilities gets the average expected *Score*, which we call the *Entropy*. When an ideal map doesn't exist, we can maximize *Entropy* instead, for example, during exploration.

4 Evidence Grids at the Mobile Robot Laboratory

Between 1973 and 1984 the Mobile Robot Lab's approach to robot navigation, rooted in a thesis at Stanford University, used multibaseline stereo vision that tracked surrounding features to negotiate and map obstacle courses. Our 1979 program drove the Stanford Cart robot through 30 meter obstacle courses successfully about three times in four, consuming several hours of 1 MIPS processing en route. Most failures were due to clusters of mismatched features which, by chance coincidence, passed geometric consistency tests and confused navigational estimations. Inadequate modeling of uncertainties, in too few basic measurements, made the program brittle.

We refined the approach between 1980 and 1984 at CMU, using new robots [Thorpe86], [Moravec85], [Podnar84], [Moravec83]. Better algorithms for key steps boosted speed and navigational precision [Matthies89], but the brittleness remained, indicating that our representations were incapable of adequately modeling stereo mismatch errors.

In 1983 we accepted a contract from a small mobile robot company to navigate robots carrying inexpensive Polaroid sonar range sensors [Kadonoff86], [*Denning]. The sonar units' range readings are laterally ambiguous with a broad beam, making them unsuitable for pinpointing features, as required in the stereo based approaches. In response we invented evidence grids, which had several advantages. Uncertainty from all sources, for instance both statistical range inaccuracies and totally erroneous readings, could be implicitly represented in the complex evidence patterns, unlike the simple covariance ellipses in the old program. We hand-modeled sonar evidence patterns by crudely imitating the sensitivity diagrams in the Polaroid documentation. Despite this and many other adhoceries, our first experiments with the approach yielded spectacular results.

After ten years of development, the Cart program was still unreliable at crossing a room, but the very first grid program succeeded every time [Elfes87]. The approach worked indoors in rooms and corridors, and outdoors on a tree lined path [Elfes89b] (see Figure 4).

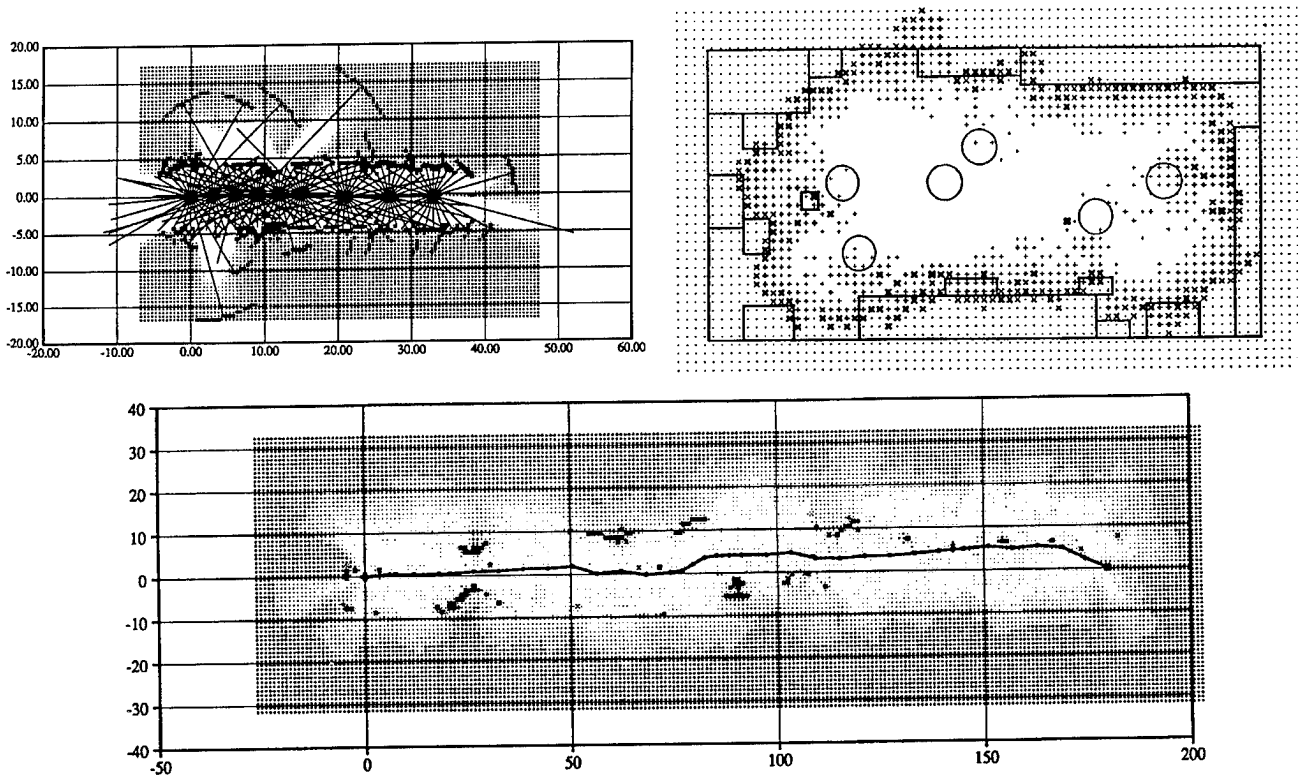

FIGURE 4 *Some early runs of using the evidence grid framework. The upper left shows a run in a hallway where some of the doors are open. The upper right is in our lab. At the bottom is a run on a tree lined path; the trees are clearly visible.*

An early formulation [Moravec-Elfes] stored two numbers per cell, the certainty or confidence that a cell was empty (*Empty*) and the certainty or confidence that it was occupied (*Occupied*). Both were zero when nothing was known about the cell, and contradictory information would lead to both being near one. In this formulation the operations performed on the empty and occupied probabilities are not symmetrical. The reason is that in the occupied ridge of a sonar reading (see Figure 2) all we know is that there is at least one object somewhere in the ridge, whereas in the empty region we know that there can't be anything in any part of it. Therefore the *Occupied* values are scaled by 1-*Empty* and normalized before being added to the map.

An analysis of the steps in this method, as well as the work of Ken Stewart of MIT and Woods Hole [Stewart89], revealed that one number per cell, representing the probability that the cell is occupied, will suffice. The only difference between the representations was the normalization step on the occupied ridge in the original formulation but not in the newer one. Experience has shown no significant difference in performance.

When we first formulated evidence grids with one number per cell, we had an *ad hoc* combining formula [Moravec88], namely that to increase the certainty in a cell we would use $C_x := C_x + M_x - C_x M_x$, where C_x is the certainty for cell x and M_x is the sensor model. To decrease the certainty we used $C_x := C_x (1 - M_x)$. Extending and reasoning in this formulation was difficult because there was no mental framework in which to proceed. Our new framework grounded in probability theory makes this obsolete.

The name of the approach has changed as well. First called occupancy grids, we realized that we could store evidence for things other than occupancy information in the grid, things such as surface orientation or color. So the name was changed to certainty grids. However, since the name for what we store in the grids (the log of the odds) is "evidence", we've renamed the approach yet again to evidence grids.

In the current formulation we always initialize the map to a background probability of 0.5. In most maps however, we expect there to be fewer occupied cells than empty ones, so we experimented with the idea of initializing the map to a lower background value [Moravec88]. The drawback is that the map combining formula becomes a little more complicated, because you must remember which maps have this background probability, since the same background in two maps does *not* represent independent information. As well, the first reading in any area swamps the very small amount of information in the background, so the added benefit is negligible. A background probability of 0.5 has proven to be much more convenient.

5 Extensions of the Evidence Grid framework explored at CMU

In 1988 we developed a sensor model using a probabilistic model of wave propagation which depends on values already in the map. This *context sensitive* method is more computationally expensive and exhibited no clear advantage in map quality.

Smooth surfaces can deflect sonar pulses, resulting in lost or improperly long ranges. This "specular reflection" problem is the most serious systematic error encountered with sonar, affecting almost all readings in confined spaces bounded by smooth walls. Our otherwise successful early grid programs, using hand-made sensor models, fail completely in highly specular conditions. We have solved this problem in a number of ways.

One approach is to store in each cell, not just the probability that the cell is occupied, but rather k probabilities corresponding to the hypotheses "this part of space contains a surface at angle θ", for k discrete values of θ.

Another approach is to run the robot in an area with high specular reflection for which we have ground truth, and then solve for the sensor model that produces the best map.

Accurate perception is only half the problem. Our goal is competent navigation, and we describe work we have done on path planning by using an A* search that finds a path that minimizes the probability of collision. After each move, new sensor data is acquired and the path replanned. Finally, we describe some work in exploration, namely navigation and obstacle avoidance without any pre-specified goal location.

5.1 The Context Sensitive Approach

In the context sensitive method [Moravec-Cho89] we calculate the sensor model from an incremental description of the process of making a range measurement, for example, sonar wave propagation. When we talk of calculating the sensor model, we mean calculating $p(R|o_i)/p(R|\overline{o_i})$ for every cell i in the path of the beam, where $p(R \mid o_i)$ is the probability of getting the reading we got, given that the cell is occupied (see the mathematical derivation in Section 3 above). We model our sensor as emitting a signal which hits each of the cells in its path in order of their distance from the sensor, until it detects an occupied cell. For now, assume that the identity of this cell is returned by the sensor. This detection isn't perfect. There is a less than certain probability that a signal will halt at an occupied cell

when it gets there ($p(\text{halt}_j \mid o_j$, arrived at j)), and a "false alarm" probability that it halts at an empty cell given that it got there ($p(\text{halt}_j \mid \overline{o_j}$, arrived at j)).

The first step is to sort the cells in order of their distance from the sensor. We know that the signal went through all the cells from 1 to R-1 without halting, and then finally halted at cell R. So:

$$p(R|o_j) = \left(\prod_{i=1}^{R-1} p(\overline{\text{halt}_i}|o_j)\right) p(\text{halt}_R|o_j), \text{ and } p(R|\overline{o_j}) = \left(\prod_{i=1}^{R-1} p(\overline{\text{halt}_i}|\overline{o_j})\right) p(\text{halt}_R|\overline{o_j}) \qquad \textbf{(Equation 6)}$$

Note that, when $i \neq j$, $p(\text{halt}_i \mid o_j)$ is independent of j. We can write $p(\text{halt}_i \mid o_j) = p(\text{halt}_i) = p(\text{halt}_i \mid o_i)p(o_i) + p(\text{halt}_i \mid \overline{o_i})p(\overline{o_i})$. Although $p(\text{halt}_i \mid o_i)$ and $p(\text{halt}_i \mid \overline{o_i})$ are independent of the current map, $p(\text{halt}_i \mid o_j)$ (= $p(\text{halt}_i)$) isn't (for $i \neq j$). Therefore, the value added into the grid depends on the current content of the grid, hence the name *context-sensitive.*

So far we have assumed that we know the identity of cell R. However, in general we only know that R is among some set of cells $R_1 \ldots R_n$, with associated probabilities $p_1 \ldots p_n$. In this case Equation 6 becomes:

$$\frac{v(R|o_j)}{v(R|\overline{o_j})} = \frac{\sum_{k \leq n} p_k p(\text{halt}_k|o_j) \prod_{i=1}^{k} p(\overline{\text{halt}_i}|o_j)}{\sum_{k \leq n} p_k p(\text{halt}_k|\overline{o_j}) \prod_{i=1}^{k} p(\overline{\text{halt}_i}|\overline{o_j})} \qquad \textbf{(Equation 7)}$$

This formula is the context-sensitive method. In its stated form it takes time proportional to the cube of the sensor volume, as opposed to the linear time of the context-free method. Algebraic simplifications reduce this time to linear outside of cells $R_1 \ldots R_n$, and quadratic within $R_1 \ldots R_n$.

In our early experience, this method performed comparably to (actually a little worse than) the context free approach. However, it has been extended by Lim and Cho outside our lab, who have achieved much better results in highly specular environments ([Cho90],[Lim90], [Lim93], and [Lim94]) .

5.2 The Automatic Learning of Sensor Models

The effect that most seriously limits robot sonar navigation is sonar's tendency for specular reflection. When a wave encounters a surface less rough than its wavelength, the wave will reflect like light off a mirror. In our early experiments we hand-constructed a sensor model from an *ad hoc* interpretation of the technical specifications of our sonar sensors. In a cluttered room, where there was little specular reflection, this worked fine, but in the hallway outside it failed spectacularly (see the second map in the left column of Figure 7). We have tried two approaches to dealing with specular reflection: the automatic learning of sensor models [Moravec-Blackwell93] and learning in the context of explicitly modeled surface orientation.

Recall (from the discussion of Equation 3) that the sensor model is a function of the sensor reading, R, and the location of the cell relative to the sensor, which in our case is represented by a two dimensional position (x, y). For each combination of reading and position, we associate a ratio of probabilities. The position (x, y) is measured from the location of the sensor, with the y axis designating the sensor's direction. Initially we created a discrete sensor model, sampling the x, y and R values. Each

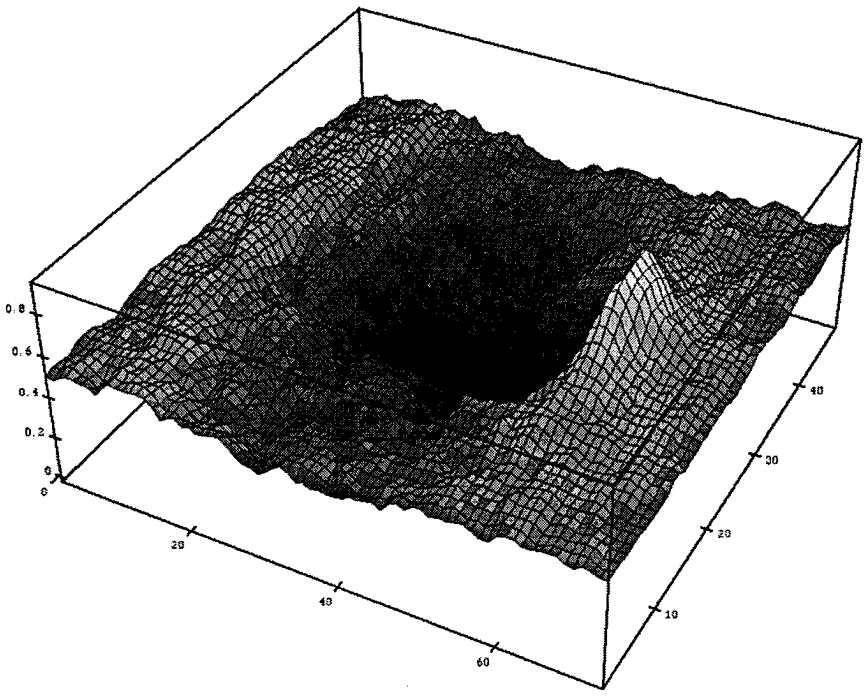

FIGURE 5 *This sensor model was produced from 740 readings between 10 and 11 feet, out of a total of 20,000 readings. The readings were collected by a simulated sonar transducer moving at random in a simulated room. The transducer is located about 80% towards the left end of the diagram, looking towards the right. See the text for more details.*

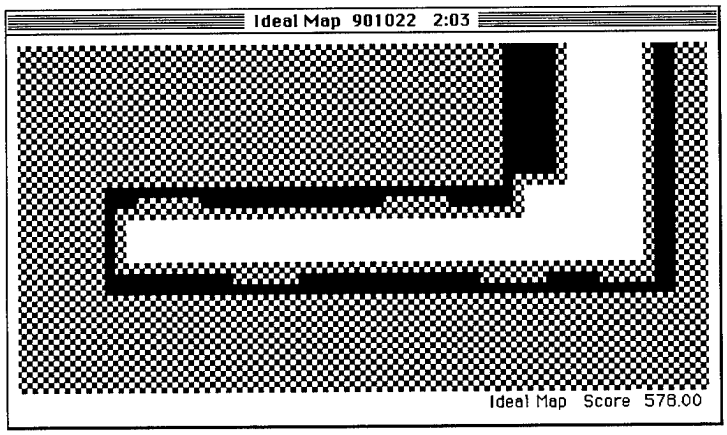

FIGURE 6 *The layout of the simulated lab used to create the sensor model in Figure 5.*

cell was a separate parameter to be adjusted by the learning algorithm. With this large a number of parameters we needed a large amount of data, so we turned to simulation.

The probability profile in Figure 5 was produced from the 740 readings whose range was between 10 and 11 feet, out of 20,000 total readings of all ranges. The readings were collected by a simulated sonar transducer moving at random in the space, resembling our 30 foot long laboratory, shown in Figure 6.

The probability profile is a graph of x and y vs. probability, for a fixed value of R=10 feet. The transducer is located about 80% towards the left end of the diagram, looking towards the right. The hollow pit in front of the transducer represents the "probably empty" interior volume of a range reading. The hump at the right edge of the pit is the range surface. The complete sensor model consists of about 30 such probability distributions, each representing a different range interval from 1 to 30 feet.

This model-free learning approach has its problems. It needs a huge amount of data, gives a statistically noisy result, and does not in any way compensate for the fact that individual readings don't give entirely independent information. Its learns problematical quirks in the training sample, for instance occupancy correlations outside the known field of view of the sensor.

In response we developed a parameterized closed form sensor model that incorporates what is known *a-priori*. The detailed shape of the model is controlled by a small number of parameters in a function that maps x, y and R to probability. For a given set of parameters, the sensor model would be created, and would used to interpret data collected from a robot run down a hallway to produce an evidence grid. By computing the *match* of this resulting grid with a hand-crafted ideal map, we'd compute a *score* for the map (see Section 3.1). The parameters were adjusted to maximize this score.

Figure 7 shows maps produced from a data set of 648 sonar measurements collected with a Denning sensor ring [Kadonoff86] mounted on our Uranus robot [Blackwell91]. A set of 27 readings was taken at each foot of travel down the center of a long narrow (28 foot by 4 foot) leg of an L shaped corridor. For a particular set of parameters, a grid was created from the readings and the associated sensor model. The accuracy of this grid was assessed by calculating the matching *Score* (see Section 3) between this map and a hand made ideal map created from measurements of the hallway.

The first map in the figure is this ideal map which has a perfect score: 578 correct bits. The robot traversed the horizontal part of the L shape. The next map was constructed with a naive, *ad hoc* sensor model that works well in our cluttered lab. The remaining maps are reconstructions with increasingly good scores, excerpted from thousands encountered in our computer program's search, which took several days on a Sparc 2 workstation to search a 9 parameter space. The final map scores about 425, and is easily good enough for most navigational purposes.

Since that time (1990) we have made several advances. The learning technique used previously simply searched each axis in turn, by taking a number of evenly spaced samples. However, we realized that we could compute the derivative of the score with respect to each parameter without much extra work. And we found that, as a function of each parameter, the score was quite smooth, along most axes looking simply like a parabola. This lead us to use the BFGS quasi-Newton optimization method ([Zhu95], [Dennis83]), which found the maximum score much more quickly, in hours rather than days.

In an attempt to get a better score, we created a new parameterized formula for the sensor model. The previous model was formulated in probability, i.e. as a function of $x, y, \theta \rightarrow [0,1]$. However, during the reformulation, several considerations led us to calculate the log odds directly. First, we want to differentiate the formula with respect to log odds, which means the derivative will be simpler and, hopefully, "smoother" if the formula is simple when expressed in log odds. Also, it's more natural to have formulae go to zero at infinity, rather than 0.5, and such formulae are easier to combine. Finally, we noticed a simple result when working in log odds: when scaling the sensor model in log odds, the best match occurs when the match value equals the entropy.

The new sensor model (with 21 parameters), combined with conjugate gradient search, produced a sensor model with a score of 551 out of a maximum of 578... but which overfit to the data (see Figure 8)[1]. It could get away with this because the map calculation counted a probability of 0.5 in the ideal map as a "don't care". In light of this, it appears that a better match value is the sum of squared

FIGURE 8 *A map with a score of 552 out of a possible 578, created with a new learning method. While correctly declaring the hallway empty and walls occupied, it has overfitted to the data by declaring areas it can't sense as either occupied or empty instead of unknown. It could do this since the values it chooses for "unknown" areas don't affect the score.*

differences in probability. The overfitting also demonstrates the importance of testing the new sensor model on data separate from the test data.

5.3 Modeling of Surface Orientations

Specular reflection is a largely systematic effect. For a given surface, a proper sonar echo will be received when the beam is close to the perpendicular, and not received at more glancing angles. These different expectations can be separated if grid cells, instead of a single hypothesis of occupancy, represent multiple surface orientation hypotheses. In this approach [Takada93], a 2D grid of the environment is augmented with an extra dimension, effectively associating a vector with each spatial location. Each element of this vector is a probability that the area is occupied by a surface of a certain orientation. Typically 8 or 16 angles were represented, ranging from 0° to 180°. 180 is sufficient since a surface can only be viewed from only the front.

When the sonar beam is perpendicular to a surface it is much more likely to give an accurate reading than when it strikes the surface at a glancing angle. Hence, the following sensor model was used:

$$p_\theta(M|o) = p_0(M|o)k^{|\theta - 90°| - 90°}, \qquad \textbf{(Equation 8)}$$

where θ is the angle of the surface relative to the beam's direction of travel (so that θ=0 represents a perpendicular surface), k>1 controls the rate of drop off, and $p_\theta(M|o)$ is the probability of getting reading M, given that the cell under consideration is occupied by a wall of orientation θ. Two different values of k were used, one in the empty hollow of the sensor model and one in the occupied ridge.

1. In fact, in one run a map with a score of 577.91 was found, but parameter values were lost.

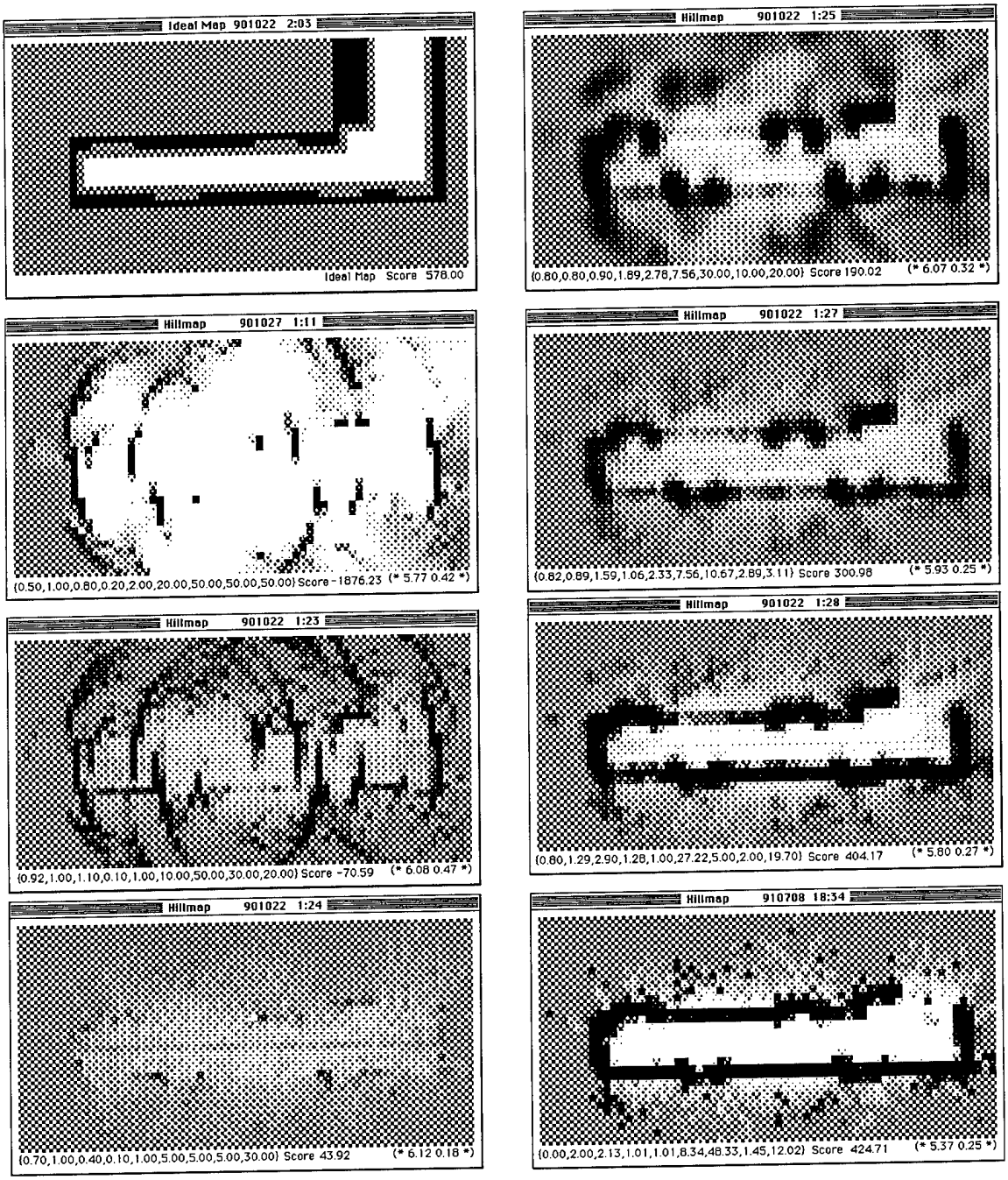

FIGURE 7 *Maps produced from one data collection run of Uranus down the hallway. The first map is the ideal map, the 50% checkerboard pattern representing "don't know". The one below it is the reconstruction using our naive parameters for the sensor model. The remaining maps are reconstructions from the program's search, with the 9 parameters shown below in braces. The correctness of the reconstruction compared to the ideal map is its* score. *From [Moravec-Blackwell93]*

Learning was performed in this orientational framework just as in the pure occupancy framework, only with the addition of the 2 "k" orientational parameters to the original 9.

To calculate the match value, a single occupancy probability for each cell was needed, which had somehow to be derived from the 8 or 16 orientation probabilities. Two formulas were tried, the "probabilistic union" and the "harmonic mean," defined as:

(Probabilistic Union) **(Equation 9)**

$$p(o|M) = 1 - \prod_{\theta}(1 - p_{\theta}(o|M))$$

$$p(o|M) = 1 - \frac{N}{\sum_{\theta}\frac{1}{1 - p_{\theta}(o|M)}}, \text{ (Harmonic Mean)} \quad \textbf{(Equation 10)}$$

In this experiment, modeling surface orientations didn't significantly improve the best match score, and in some cases the score was slightly worse. However, in one run, when the sensor model that was trained in the specular environment was used in a non-specular environment, it did better than the analogous model in the simple occupancy scheme. It was also shown that the probabilistic union outperforms the harmonic mean.

5.4 Sensor Fusion

Sensor fusion, the combining of information about the same location from different sensors, is rather difficult in most perception and navigation frameworks, but is very straightforward with evidence grids. In fact, this is one of the framework's major strengths. The combining equation is independent of the particular sensor used, and the properties of associativity and commutativity make the order of combination immaterial. A single, centralized map can be updated by measurements from both sonar and stereoscopic vision range measurements, or separate maps can be maintained for each sensor and integrated into a single map as needed. In our experiments the latter approach was used.

The individual and combined maps shown in Figure 9 illustrate three facets of the integration process [Elfes-Matthies87], [Matthies-Elfes88], [Moravec88]. First, the sensors *complement* each other, with one sensor providing information about areas inaccessible to the other sensor (Figure 9e). Second, the sensors can *correct* each other, when weak false inferences made by one sensor coincide with strong true inferences made by the other. For example, sonar makes strong statements about emptiness of regions, but weaker statements about occupied areas. Stereo statements can be strong or weak, depending on the distance to or distribution of features in the image. Figure 9(f) shows a case where a region seen as occupied by sonar is correctly cleared by stereo. Similarly, sonar can recover information about featureless areas, whereas stereo cannot. This is the case in Figure 9(f), where the left edge of a barrel is invisible to stereo because of low contrast against the background; the barrel is, however, detected by sonar.

Finally, the sensors can *conflict* by making strong statements about the same space. This moves the region towards "unknown", which is valuable for later planning, since it correctly signals the fact

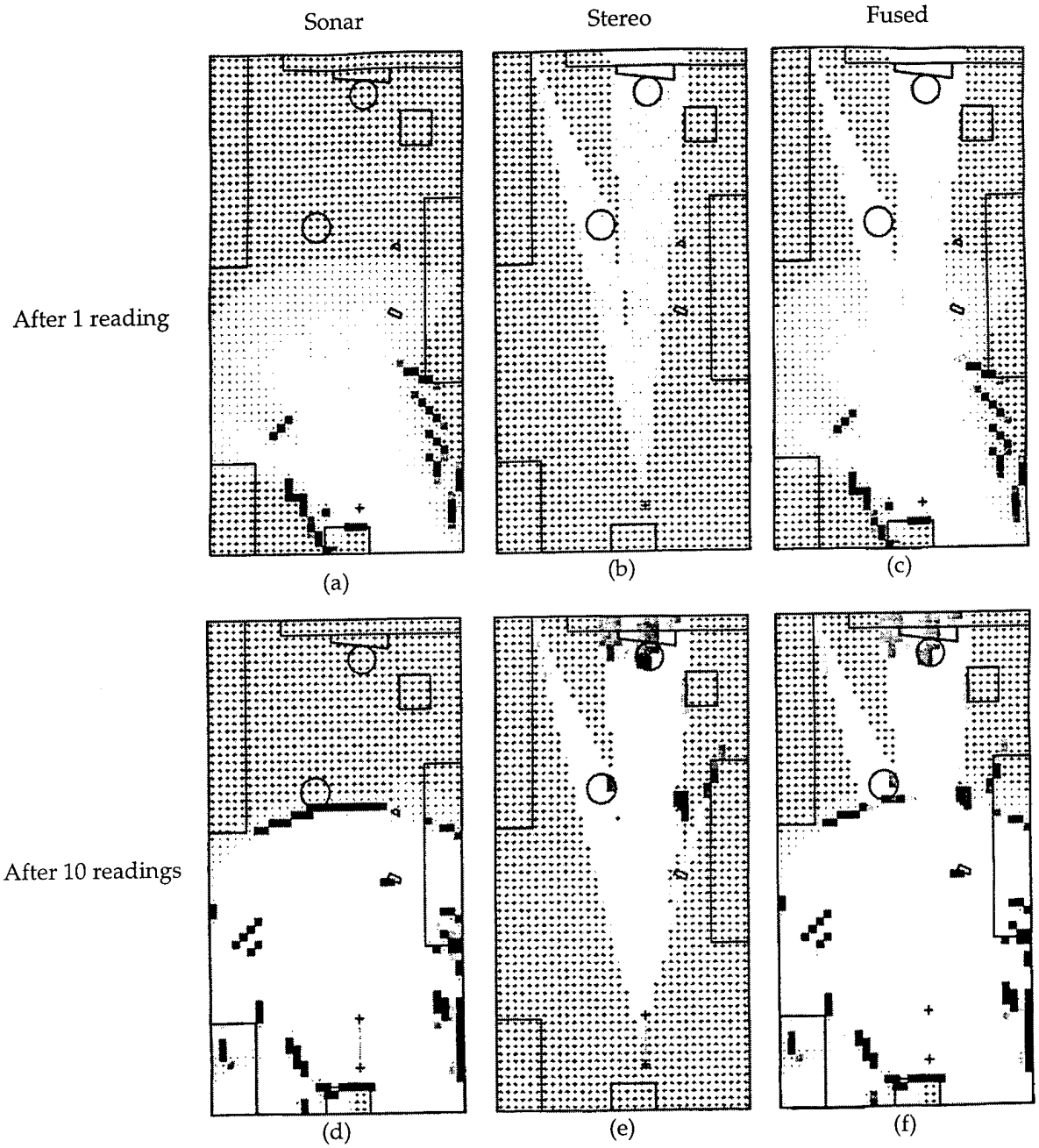

FIGURE 9 *Fusion of Sonar and Stereo. Fusion is trivial in the evidence grid framework: we simply add the log odds of corresponding cells. The "+" marks the location of the robot, which moved in a straight line taking readings at evenly spaced intervals. From [Matthies-Elfes88], [Elfes-Matthies87], and [Moravec88]*

that sensor information does *not* provide an unambiguous interpretation for a given area. Future systems may detect such conflicts and use them to direct the attention of the sensors.

5.5 Path Planning

Given an evidence grid and start and end points, the goal of path planning is to find an efficient path from the start to the goal that avoids obstacles. Early work in this domain [Thorpe84] concentrated on *path relaxation:* given an existing path that's longer than necessary or contains sudden, jerky movements, find a similar path that's better.

However, later work focused directly on path planning. To find a path we perform an A* search (see any introductory AI textbook, such as [Luger89]), with the nodes of the search being the cells of the grid. For the cost of the path we use the log of the probability of collision along the path plus a constant times the path length,

$$g(\text{path}) = \int_{\text{path}} (\log(1-p) + k) \ , \qquad \textbf{(Equation 11)}$$

and for our heuristic estimate of the cost from some location to the goal we use k times the euclidean distance from the node to the goal. Note that our heuristic is admissible, and so the search is guaranteed to find the path with the smallest cost.

In most of our programs, the successors of any cell were simply its 8 neighbors [Elfes87]. However, this produces jagged paths in many conditions. In a later experiment, the set of "neighbors" was expanded [Goang-Tai Hsu, 1989, unpublished] to include all cells within some distance from the current point, with the integral taken over the straight line from the center of the current cell to the center of the destination cell. This produced much more natural and efficient paths, at the expense of some extra computation.

5.6 Exploration

After the work on path planning (see above), some experiments in exploration were performed [Jie Yang, 1990, unpublished]. The goal of the exploration module was to try to make the grid as polarized (each cell close to one or zero) as possible. We used entropy (see Section 3) as our polarization measure which the robot would try to maximize.

We chose a small number (8 or 16) of points equally spaced around the robot. At each point we calculated the entropy in a small window surrounding that point. Then we take a reading and incorporate it into the grid, and then recalculate the entropies. The point with the greatest change in entropy was then made the goal and the path planner was invoked to guide the robot to that point. The procedure was repeated until all points had a high entropy, that is, there was nothing left to explore in the local area.

The results of a typical simulation run are shown in Figure 10. The robot started on the right by taking a reading with its 32 simulated sonar sensors. This changed the entropy in some areas more than others; the area with the greatest change was to the left and slightly up from the robot. It then moved to the x in that direction and repeated the process until all of the immediate vicinity is explored. This stopping condition doesn't guarantee that the whole map has been explored, and in our example run the bottom right near the starting area was partially unexplored. However, the vast majority of the area was explored. Also, entropy will change less in directions with nearby walls, since only a smaller area (the part in front of the wall) can change. Therefore, this method naturally avoids walls and other objects.

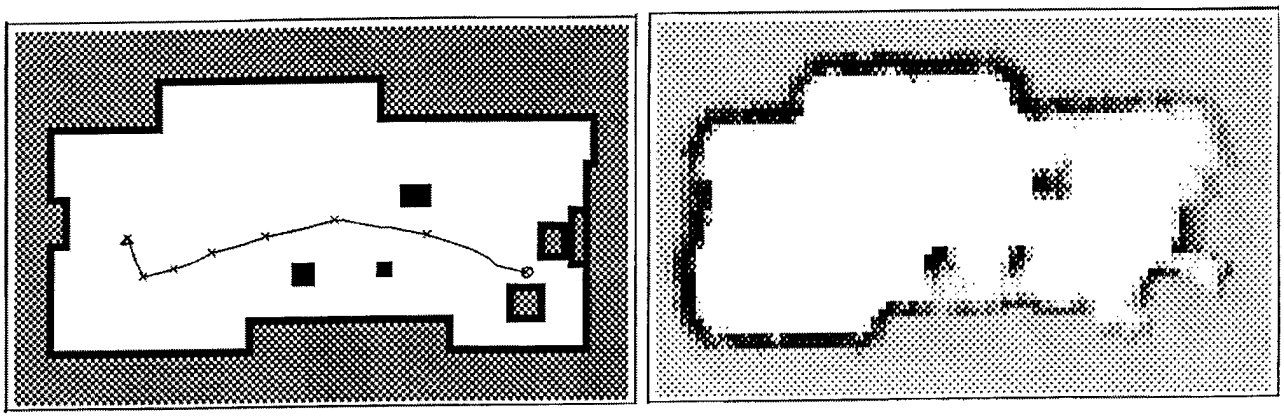

FIGURE 10 *Exploration in a simulated world. The robot started in the lower right and always moved in the direction in which the sensors registered the biggest change. When the sensors registered no significant change, the robot stopped.*

5.7 Grid Matching

Given two grids of the same area built at different times, it is possible to deduce the relative robot position by finding the displacement and rotation that brings one into alignment with the other. We call this process *grid matching*. Our approach [Elfes87] starts by scaling each cell of both maps so that each cell contains $2p - 1$, where p is that cell's probability of occupancy. This way, cells whose occupancy is unknown contain 0, cells which are probably empty are negative, and those that are probably occupied are positive. For a given displacement and rotation we define the goodness of match as the sums of the products of corresponding cells in the two maps. Our goal is then to find the displacement and rotation which minimizes this measure. To speed up the search, we note that most of the information in the maps is in the occupied cells, and the number of such cells is typically on the order of the square root of the total number of cells. By only transforming the occupied cells of each map to the other and summing over those, much time is saved.

Another approach we used in 1986 used complete maps and a coarse to fine matching strategy. It generated a hierarchy of reduced resolution versions of each map, in half-scale steps. A rough estimate of the best match was found by matching the lowest resolution maps (whose dimension typically was 8×8 cells). It then improved on this estimate by matching the next higher resolution, searching only in the vicinity of the original match. Continuing in this way it quickly found a near optimal match at the highest resolution. Optionally, it could improve the final resolution to a fraction of cell by means of a polynomial interpolation. A program of this type in 1986 was able to match two 32×32 maps in three seconds on an 8MHz Motorola 68000 processor of the type found on early Denning robots and in the original 128K Macintosh computer [Moravec 1986, unpublished].

5.8 Visualization of 3D Grids

We are in the process of applying what we have learned from working with 2D grids to ones in 3D. Not only does this leap multiply the size of the grid by the resolution of third dimension, but it tempts us to increase the resolution in the other dimensions. 2D maps blur together the differences of horizontal planes at different heights, and are practically limited to an effective resolution of about ten centimeters. 3D grids, without such ambiguity, could, in principle, be much finer, leading us to con-

sider $128 \times 128 \times 128$ grids in3D compared to typical 64×64 maps in 2D, a 500-fold increase in the number of cells. Such large grids were computationally unfeasible until the recent appearance of workstations in the 100 MIPS speed and 100 megabyte memory range. Even with them, we find it necessary to devise very efficient algorithms and shortcuts to assemble 3D grid guided robots that could move at tolerable speeds. We are in the process of doing so. One problem is visualizing the robot's internal knowledge of its surroundings.

By visualizing an evidence grid, we mean displaying the grid to the user so she can see the information contained in it. Visualizing evidence grids is important for a number of reasons, including debugging, and communicating and understanding results. While visualizing 2D evidence grids is straightforward, an adequate method for visualizing 3D grids is not obvious. One approach is to simply threshold: declare all cells over $p = 0.5$ to be opaque and the rest transparent. In practice the threshold should probably be set lower to ensure "unknown" regions are transparent. Rendering such a grid can then be easily done by many graphics packages. However, a lot of information is lost this way, so in some exploratory work we investigated an alternative method (see Figure 11). In this implementation the cells of the grid are treated as if filled with a fog whose density depends on the occupancy probability. For rendering purposes, each cell is defined by two parameters, the color of the cell and the "weight" of the cell. When light passes through a cell on the way to the virtual camera, each component (R, G or B) is modified using the following formula:

$$light \leftarrow \text{cell\_color} \times \text{weight} + light \times (1 - \text{weight}) \qquad \textbf{(Equation 12)}$$

In our implementation we made cells with $p = 1$ red (weight 0.7), $p = 0.5$ white (weight 0.01), and $p = 0$ blue (weight 0.01). Values for intermediate probability simply used a linear interpolation.

The rendering was slow to the point of aggravation. Even our fastest implementation, which avoided floating point operations by using a fixed point (integer) representation, took 20 seconds to render a $100 \times 100 \times 100$ grid on a Sparc 10. In future we plan to explore precomputing a thresholded image which can be manipulated at higher speeds.

6 Open Issues

The work is ongoing. Here is a partial list of open research questions.

- **3D Evidence Grids** We have barely begun work with 3D grids. Our Polaroid-sonar-based 2D grids have a few thousand cells each representing an area about six inches square. A typical robot run in such a space involves under a thousand range measurements. A good resolution 3D grid has over a million cells, needing on the order of a million 3D sensory data points for good definition. We briefly contemplated a tilting sonar ring, but Polaroid sonar cannot providing this much data. Recent progress suggests stereo cameras a promising sensor for general applications, since a single set of stereo images can provide tens of thousands of range values. Most operations such as learning and matching, are made very challenging by the number of cells and the extra of degrees of freedom. For example, even visualizing 3 dimensional grids is a non-trivial problem. We have already created efficient code for adding new readings into a grid, given the grid and the sensor model [Moravec92b]. We have also written a program that accurately characterizes distortion and rectifies wide angle images for stereo vision.
- **Unsupervised Learning** Methods for learning sensor models were described above. All required an accurate ideal map given to the program *a priori*, presumably measured by hand or created with a different, high precision sensor. Such maps are hard to generate in 3D. It

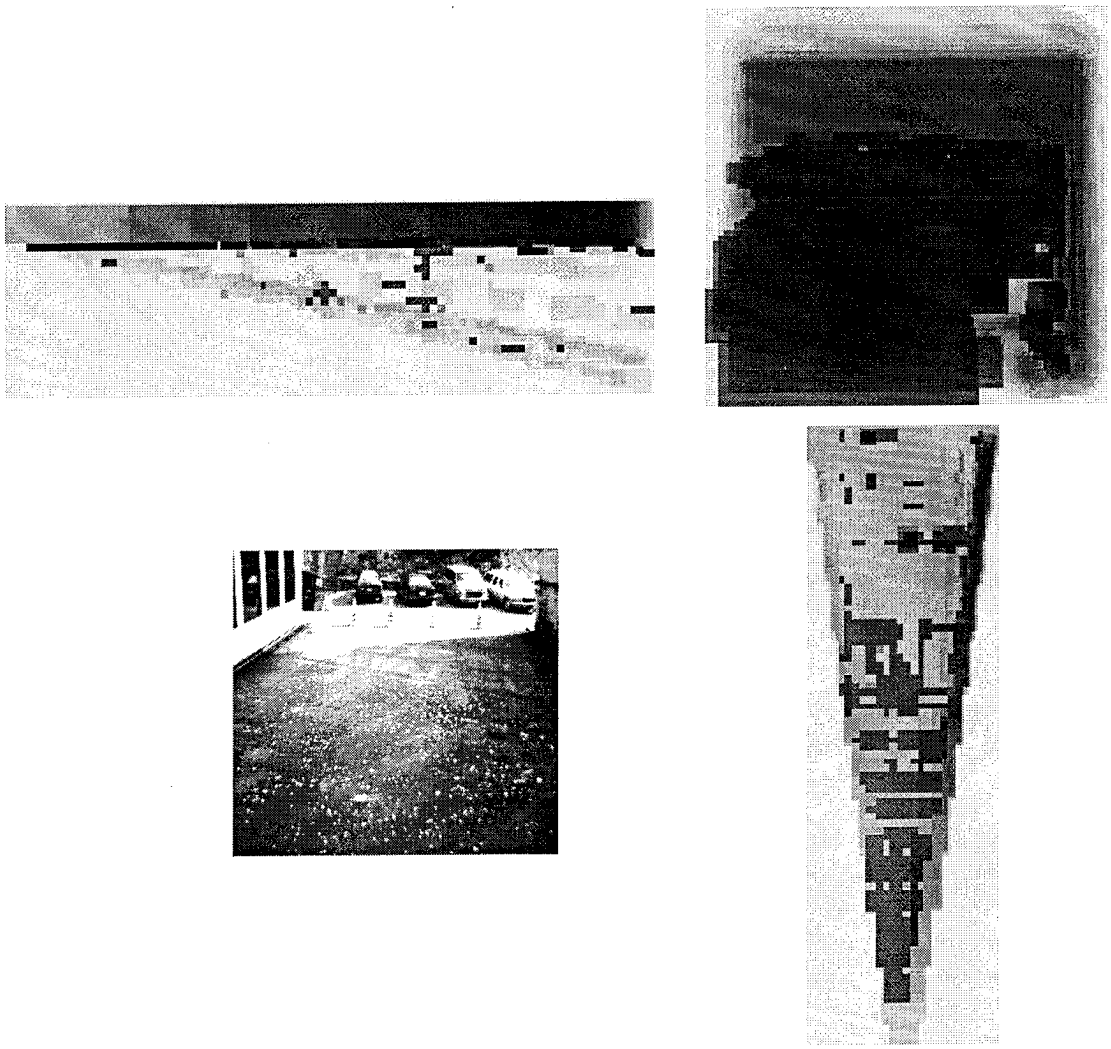

FIGURE 11 *Visualization of Three Dimensional Evidence Grids. The grid displayed here was created from 3 stereo images of parking lot, one of which is shown above. The image on the top left is a side view of the resulting grid; the pavement is a red horizontal line, with a blue space above it. The noise below the pavement resulted from several spurious stereo matches near the edge of the stereo images. In the upper right is a view from roughly the same location as the stereo camera; the dark two thirds is red, becoming bluer red farther up the image (further back). The top view (bottom right) shows patchy red watered down by the blue above it.*

may be possible to learn the sensor model without such a map. The key idea is to notice that a good sensor model will not lead to many contradictory readings, where one reading increases a cell and another reading decreases it. At the same time, it shouldn't achieve this by leaving the map undecided. Learning sensor models without an a priori map may be possible by finding the sensor model which maximizes some combination of consistency and information content. This kind of ideal-map-free unsupervised learning would also allow the sensor model to be easily and automatically updated to accommodate changing sensor characteristics.

- **Stereo** Stereo, especially in 3D grids, promises to be much more robust and reliable than traditional stereo, which is prone to momentary mismatches. Also, traditional stereo throws away a lot of information when it returns only the best match. In the evidence grid framework there is no need to declare one match as "the answer" and ignore the rest: for each pair of pixels along the epipolar line in the two images we can create a confidence value, and add that to the map.
- **Other Sensors** Any sensor that returns geometric information, such as laser range finders or proximity sensors, can be integrated into the evidence grid framework.
- **Sensor Fusion** Although we have demonstrated combing sonar and stereo in 2D, the results are expected to be much more spectacular in 3D, where the stereo isn't restricted to a narrow horizontal field of view. And other combinations of sensors should be investigated as well.
- **High Level Navigation** Robot navigation is one of the most important applications of robot evidence grids. So far, we have only created grids about the size of a room or a length of hallway. Creating larger grids presents problems both because of their memory requirements, and because dead reckoning error increases at these bigger scales. Some issues that arise when attempting higher level navigation are:
  - **Recognizing Previously Visited Areas** Suppose a robot travels around a rectangular hallway. Because of accumulative positioning (dead reckoning) errors, it won't be able to tell from its wheel encoders alone that it has returned. The problem of simultaneously creating a higher level map and determining whether you're in a part you've seen before is crucial to practical applications of evidence grids.
  - **Identifying Features Needed for Navigation** When navigating, the robot needs to know which areas are passible and which aren't, which openings lead where, and possibly even the detection of walls which break an area into "regions", and the classification of those regions as rooms, hallways, etc.
  - **Identifying Areas That Are Likely To Change or To Remain The Same** When a robot needs to go from a hallway to a room, it needs to find the door into the room and detect whether the door is open or closed. It should know that, even if the door was closed last time (and so presumably those cells are labelled "occupied"), it may be worth the robot's while to go check the door to see if it's open now.
  - **Interaction Between Path Planning and Plan Execution** Typically, evidence grids don't notice highly dynamic objects, such as people moving in a corridor, and so path planning and execution algorithms need to take this into account. For example, path planning might be done in the evidence grid (which only weakly renders moving objects) and might be executed by a purely reactive system. If the robot drifts too far from the planned path it should stop and replan.
- **Models for Systematic Errors** The derivation of the formula for adding new readings into the grid assumed that all errors in the readings were independent. However, there are many cases where this is not true. Although there are various ways around this problem, explicit models of such systematic errors would be a much more powerful solution and probably make for the most accurate and informative grids from a given set of readings.
- **Position Estimation** A largely unexplored problem is: given a small set of readings taken near your current location, and a map made previously from a large set of readings, find your current location. You'd want to take into account your dead reckoned position, even though some error will be associated with it. A related extension would be to develop an algorithm that decides what direction to aim the sensor to help disambiguate position.

- **Grid Matching** Related to position estimation is the problem of efficiently matching two grids of the same area that were produced at different times from different sets of readings, i.e. finding the displacement and rotation(s) that bring the coordinates of one grid into alignment with those of the other. This is moderately challenging in 2D, and even more interesting in 3D.
- **Object Identification** A fine grained grid of a room should provide enough information for the robot to identify objects by shape. This is especially difficult since usually part of the object may be hidden by other objects or the wall, so that we must deal with partial occlusion. One approach to object recognition might be to learn the "signatures" of the object in the grid. The probabilistic nature of the grid is a help, since it indicates unknown areas that can be ignored in a match.
- **Incorporating Other Object Properties** For many tasks beyond navigation it helps to record the color of objects, the orientation of the surfaces in the cells, or any other object properties that could be put into the cells.

7 Annotated Bibliography of Evidence Grid Related Work

The following is a selection of papers relevant to the Evidence Grid framework. Although this list tries to be as complete as possible, no doubt some omissions remain.

[Beckerman90]

Author Beckerman, M.; Oblow, E.M.;
Oak Ridge Nat. Lab., TN, USA

Title Treatment of systematic errors in the processing of wide-angle sonar sensor data for Robotic navigation

Source IEEE Transactions on Robotics and Automation (USA); vol.6, no.2; April 1990; pp. 137-45

Abstract A methodology has been developed for the treatment of systematic errors that arise in the processing of sparse sensor data. A detailed application of this methodology to the construction, from wide-angle sonar sensor data, of navigation maps for use in autonomous robotic navigation is presented. In the methodology, a four-valued labeling scheme and a simple logic for label combination are introduced. The four labels Conflict, Occupied, Empty, and Unknown are used to mark the cells of the navigation maps. The logic allows for the rapid updating of these maps as new information is acquired. Systematic errors are treated by relabeling conflicting pixel assignments. Most of the new labels are obtained from analyses of the characteristic patterns of conflict that arise during the information processing. The remaining labels are determined by imposing an elementary consistent-labeling condition.

[Blackwell91]

Author Blackwell, Mike
Pittsburgh, Pa.: Carnegie Mellon University, The Robotics Institute

Title The Uranus mobile robot

Source Technical report. Carnegie Mellon University. The Robotics Institute; CMU-RI-TR-91-06

Abstract The Uranus mobile robot was built by Carnegie Mellon University's Mobile Robot Lab to provide a general purpose mobile base to support research in to indoor robot navigation. As a base, it provides full mobility, along with support for a variety of payloads, such as sensors and computers. This report details the design and maintenance of Uranus's me-

chanical, electrical, and software systems, and is intended to serve two purposes. First, it acts as documentation for the robot. Second, it offers a perspective in to mobile robot design, showing the decisions, trade-offs and evolution that are involved in the design of a system of this complexity. Hopefully, others building similar systems will be able to profit from our experience.

[Borenstein88a]

Author Borenstein, J.; Koren, Y.;
Dept. of Mech. Eng. & Appl. Mech., Michigan Univ., Ann Arbor, MI, USA

Title Real-time obstacle avoidance for fast mobile robots

Source CAD/CAM Robotics and Factories of the Future. 3rd International Conference (CARS and FOF '88) Proceedings, B. Prasad Ed.; Southfield, MI, USA; 14-17 Aug. 1988; pp. 144-8 vol.3

Abstract A real-time obstacle avoidance approach for mobile robots has been developed and tested on an environmental mobile robot. The approach enhances the basic concepts of the potential field method by representing obstacles in a two-dimensional certainty grid that is especially suited to the accommodation of inaccurate real-time sensor data (such as that produced by ultrasonic sensors), as well as sensor fusion. Experimental results on a mobile robot running at 0.78 m/sec demonstrate the power of the new algorithm.

[Borenstein88b]

Author Borenstein, J.; Koren, Y.;
Dept. of Mech. Eng. & Appl. Mech., Michigan Univ., Ann Arbor, MI, USA

Title High-speed obstacle avoidance for mobile robots

Source Proceedings IEEE International Symposium on Intelligent Control 1988, Stephanou, H.E., Meystel, A. and Luh, J.Y.S. Ed.; Arlington, VA, USA; 24-26 Aug. 1988; pp. 382-4

Abstract A real-time obstacle avoidance approach for mobile robots has been developed and implemented. This approach permits the detection of unknown obstacles simultaneously with the steering of the mobile robot to avoid collisions and the advance of the robot toward the target. The approach, called the virtual force field technique, integrates two known concepts: certainty grids for obstacle representation and potential fields for navigation. This combination is especially suitable for the accommodation of inaccurate sensor data (such as those produced by ultrasonic sensors) as well as for sensor fusion, and it allows continuous motion of the robot without stopping in front of obstacles. Experimental results from a mobile robot running at a maximum speed of 0.78 m/s demonstrate the power of the proposed algorithm.

[Borenstein89]

Author Borenstein, J.; Koren, Y.;
Adv. Technol. Lab., Michigan Univ., Ann Arbor, MI, USA

Title Real-time obstacle avoidance for fast mobile robots

Source IEEE Transactions on Systems, Man and Cybernetics (USA); vol.19, no.5; Sept.-Oct. 1989; pp. 1179-87

Abstract A real-time obstacle avoidance approach for mobile robots has been developed and implemented. It permits the detection of unknown obstacles simultaneously with the steering of

the mobile robot to avoid collisions and advance toward the target. The novelty of this approach, entitled the virtual force field method, lies in the integration of two known concepts: certainty grids for obstacle representation and potential fields for navigation. This combination is especially suitable for the accommodation of inaccurate sensor data as well as for sensor fusion and makes possible continuous motion of the robot with stopping in front of obstacles. This navigation algorithm also takes into account the dynamic behavior of a fast mobile robot and solves the local minimum trap problem. Experimental results from a mobile robot running at a maximum speed of 0.78 m/s demonstrate the power of the algorithm.

[Borenstein95]

Author Borenstein, J.
Adv. Technol. Lab., Michigan Univ., Ann Arbor, MI, USA

Title DOE Project History at UM - Mobile Robots Research

Source http://www-personal.engin.umich.edu/~johannb/history1.html

Descrip Describes the history of Mobile Robots research at the Advanced Technology Lab. Includes pages on the *Virtual Force Field* and *Vector Field Histogram* obstacle avoidance methods as well as others.

[Christensen94]

Author Christensen, H.I.; Kirkeby, N.O.; Kristensen, S.; Knudsen, L.; Granum, E.;
Inst. of Electron. Syst., Aalborg Univ., Denmark

Title Model-driven vision for indoor navigation

Source Robotics and Autonomous Systems (Netherlands); vol.12, no.3-4; April 1994; pp. 199-207

Abstract For navigation in a partially known environment it is possible to provide a model that may be used for guidance in the navigation and as a basis for selective sensing. In this paper a navigation system for an autonomous mobile robot is presented. Both navigation and sensing is built around a graphics model, which enables prediction of the expected scene content. The model is used directly for prediction of line segments which, through matching, allow estimation of position and orientation. In addition, the model is used as a basis for a hierarchical stereo matching that enables dynamic updating of the model with unmodelled objects in the environment. For short-term path planning a set of reactive behaviours is used. The reactive behaviours include use of inverse perspective mapping for generation of occupancy grids, a sonar system and simple gaze holding for monitoring of dynamic obstacles. The full system and its component processes are described and initial experiments with the system are briefly outlined.

[Cho90]

Author DongWoo Cho;
Dept. of Mech. Eng., Pohang Inst. of Sci. & Technol., South Korea

Title Certainty grid representation for robot navigation by a Bayesian method

Source Robotica (UK); vol.8, pt.2; April-June 1990; pp. 159-65

Abstract Development of sensor knowledge representation by the use of a certainty grid has been extensive and shown the usefulness of the grid-based concept for robot navigation. Yet the

methodology was not perfect. The paper introduces the Bayesian formula into the certainty grid representation to overcome some difficulties of ad hoc formula that has been the only way of updating the grids. The complete derivation of the proposed updating formula is given and proved to be able to accurately identify the simulated world. Also, the paper suggests two updating models: context-sensitive and context-free. Both of them were shown to be usable through simulation in real world modeling.

[De Almeida89]

Author De Almeida, R.; Melin, C.;
Dept. Genie Informatique, Univ. de Technol. de Compiegne, France

Title Exploration of unknown environments by a mobile robot

Source Proceedings of an International Conference. Intelligent Autonomous Systems 2, Kanade, T., Groen, F.C.A and Hertzberger, L.O. Ed.; Amsterdam, Netherlands; 11-14 Dec. 1989; pp. 715-25 vol.2

Abstract The aim of the paper is to define a software architecture allowing a mobile robot to explore an unknown territory. The finality of the active learning is to build a geometric map of the mobile robot environment using its sensors. This map is a grid where each cell is labelled empty, unknown or occupied; from it, a road map is built by the cartographer module. The navigator module plans the exploration using these two maps. Obstacle avoidance is assured by a local navigator using sensor data returned by the observer module.

[Dodds90]

Author Dodds, D.R.

Title Terrain classification in navigation of an autonomous mobile robot

Source Mobile Robots V; Boston, MA, USA; 8-9 Nov. 1990;
Proceedings of the SPIE - The International Society for Optical Engineering; vol.1388; 1991; pp. 82-9

Abstract The authors describe a method of path planning that integrates terrain classification (by means of fractals), the certainty grid method of spatial representation, Kehtarnavaz Griswold collision-zones (N. Kehtarnavez, 1989), Dubois Prade fuzzy temporal and spatial knowledge (D. Dubois, 1989) and nonpoint sized qualitative navigational planning. An initially planned ('end-to-end') path is piecewise modified to accommodate known and inferred moving obstacles, and includes attention to time- varying multiple subgoals which may influence a section of path at a time after the robot has begun traversing that planned path.

[Elfes86]

Author Elfes, Alberto
Pittsburgh, Pa.: Carnegie Mellon University, The Robotics Institute

Title A Sonar Based Mapping and Navigation System

Source 1986 IEEE International Conference on Robotics and Automation, San Francisco, CA, April 7-10, 1986; vol. 2, pp. 1151-56

Abstract This paper describes a sonar-based mapping and navigation system for autonomous mobile robots operating in unknown and unstructured surroundings. The system uses sonar

range data to build a multi-leveled description of the robot's environment. Sonar maps are represented in the system along several dimensions: the *Abstraction* axis, the *Geographical* axis, and the Resolution axis. Various kinds of problem-solving activities can be performed and different levels of performance can be achieved by operating with these multiple representations of maps. The major modules of the Dolphin system are described and related to the various mapping representations used. Results from actual runs are presented, and further research is mentioned. The system is also situated within the wider context of developing an advanced software architecture for autonomous mobile robots.

[Elfes87]

Author Elfes, Alberto
Pittsburgh, Pa.: Carnegie Mellon University, The Robotics Institute

Title Sonar-Based Real-World Mapping and Navigation

Source IEEE Journal of Robotics and Automation; IEEE J. Robot. Autom. (USA); vol.RA-3, no.3; A07; June 1987; pp. 249-65

Abstract A sonar-based mapping and navigation system developed for an autonomous mobile robot operating in unknown and unstructured environments is described. The system uses sonar range data to build a multileveled description of the robot's surroundings. Sonar readings are interpreted using probability profiles to determine empty and occupied areas. Range measurements from multiple points of view are integrated into a sensor-level sonar map, using a robust method that combines the sensor information in such a way as to cope with uncertainties and errors in the data. The sonar mapping procedures have been implemented as part of an autonomous mobile robot navigation system called Dolphin. The major modules of this system are described and related to the various mapping representations used. Results from actual runs are presented, and further research is mentioned. The system is also situated within the wider context of developing an advanced software architecture for autonomous mobile robots

[Elfes89a]

Author Elfes, Alberto
Pittsburgh, Pa.: Carnegie Mellon University, The Robotics Institute

Title Occupancy Grids: A Probabilistic Framework for Mobile Robot Perception and Navigation

Source Ph.D. Thesis, Electrical and Computer Engineering Dept., Carnegie-Mellon University, 1989.

Abstract In this thesis we introduce a new framework for spatial robot perception, real-world modeling, and navigation that uses a stochastic tessellated representation of spatial information called the *Occupancy Grid*. The Occupancy Grid is a multi-dimensional random field that maintains probabilistic estimates of the occupancy state of each cell in a lattice. To recover a sensor-based map of the robot's environment, the cell state estimates are obtained by interpreting the incoming range readings using probabilistic sensor models that capture the uncertainty in the spatial information provided by the sensor. A Bayesian estimation procedure allows the incremental updating of the Occupancy Grid, using readings taken from several sensors and over multiple points of view. Additional estimation methods provide mechanisms for composition of multiple maps, integration of information from different sensors, decision-making, and handling of robot and sensor position uncertainty. The resulting Occupancy Grids provide dense descriptions of the robot's environment, are robust

under sensor uncertainty and errors, and can be used directly for navigation and other robotic tasks.

[Elfes89b]

Author Elfes, Alberto
Pittsburgh, Pa.: Carnegie Mellon University, The Robotics Institute
Title Using Occupancy Grids for Mobile Robot Perception and Navigation
Source Computer, vol. 22, no. 6, June 1989, pp. 46-57

Abstract This article reviews a new approach to robot perception and world modeling that uses a probabilistic tessellated representation of spatial information called the *occupancy grid*. The occupancy grid is a multi-dimensional random field that maintains stochastic estimates of the occupancy state of the cells in a spatial lattice. To construct a sensor-derived map of the robot's world, the cell state estimates are obtained by interpreting the incoming range readings using probabilistic sensor models. Bayesian estimation procedures allow the incremental updating of the occupancy grid using readings taken from several sensors over multiple points of view.

[Elfes-Matthies87]

Author Elfes, A.; Matthies, L.;
Dept. of Comput. Sci., Carnegie-Mellon Univ., Pittsburgh, PA, USA
Title Sensor integration for robot navigation: combining sonar and range date in a grid-based representation
Source Proceedings of the 26th IEEE Conference on Decision and Control; Los Angeles, CA, USA; 9-11 Dec. 1987; pp. 1802-7 vol.3

Abstract The problem of integrating noisy range data from multiple sensors and multiple robot positions into a common description of the environment is considered. A cellular representation, called the occupancy grid is proposed as a solution. Occupancy grids are used to combine range information from sonar and one-dimensional stereo into a two-dimensional map of the vicinity of a robot. Each cell in the map contains a probabilistic estimate of whether it is empty or occupied by an object in the environment. These estimates are obtained from sensor models that describe the uncertainty in the range data. A Bayesian estimation scheme is used to update the existing map with successive range profiles from each sensor. This representation is simple to manipulate, treats different sensors uniformly, and models uncertainty in the sensor data and in the robot position. It also provides a basis for motion planning and creation of higher-level object descriptions.

[Faibish92]

Author Faibish, S.; Abramovitz, M.;
Rafael, Haifa, Israel
Title Perception and navigation of mobile robots
Source Proceedings of the 1992 IEEE International Symposium on Intelligent Control (Cat. No.92CH3110-4); Glasgow, UK; 11-13 Aug. 1992; pp. 335-40

Abstract The authors present a method of navigation for mobile robots, based on perception of the unknown environment, that is similar to a blind man's behavior. The perception uses data

from different types of sensors, combined in a probabilistic occupancy map of the close surroundings of the robot. A global map of the workspace is constructed and updated at each step by the navigation algorithm, using the latest perception. The navigation algorithm is suited for indoor as well as outdoor applications. It computes the optimal path based on the last updated map of the workspace and the present position estimate of the robot with respect to the goal position. The algorithm consists of two stages: global path planning and local obstacle avoidance.

[Firby92]

Author Firby, R.J.; Christianson, D.; McDougal, T.;
Dept. of Comput. Sci., Chicago Univ., IL, USA

Title Fast local mapping to support navigation and object localization

Source Sensor Fusion V; Boston, MA, USA; 15-17 Nov. 1992;
Proceedings of the SPIE - The International Society for Optical Engineering; vol.1828; 1992; pp. 344-52

Abstract A robot must have an internal representation of the local space it occupies to use for both navigation and obstacle localization. In addition, it must be possible to build and update the map in real-time so that it can be used in feedback control loops. A robot's notion of local space must bridge the gap between symbolic and continuous control. To satisfy both real-time constraints and the needs of high-level navigation and object recognition, the map building system must use a simple representation that can be computed quickly yet will support the construction of more involved maps over longer timescales. A complete system also requires control behaviors that can use the simple representation to drive the robot through its immediate surroundings in service of higher-level local navigation goals generated from the more detailed map. This paper describes a system based on building simple geometric occupancy maps from multiple sensors in real-time and using them for control. The mapping and local navigation algorithms presented were used to control the University of Chicago mobile robot at the AAAI-92 robot Competition.

[Good92]

Author Good, T.T.;
Dept. of Comput. Sci., Brown Univ., Providence, RI, USA

Title Blank-map orienteering for a mobile robot using certainty grids

Source Mobile Robots VII; Boston, MA, USA; 18-20 Nov. 1992;
Proceedings of the SPIE - The International Society for Optical Engineering; vol.1831; 1993; pp. 631-42

Abstract The author uses a robot based certainty grid to maintain map information generated from eight fixed sonars to compare three robot navigators. The certainty grid includes a variety of averaging and weighting techniques to improve sonar accuracy and reduce noise. The navigators are constrained by two design parameters: they should not use domain specific knowledge and the navigators and mapper are independent. Navigation decisions are based solely on the internal map. Each navigator uses a weighting function to determine a potential for each grid element and navigates by minimizing the potential over the robot's immediate surroundings. Local route selection is performed in real time while traveling as the local navigator continuously re-evaluates the path with new information from the certainty grid. The navigators differ in their methods of global route selection. One uses inter-

mediate destinations and backtracking to handle dead ends. The other two incorporate dead end information directly into local route selection, one with intermediate destinations and the other without them

[Gourley94]

Author Gourley, C.; Trivedi, M.;
Dept. of Electr. & Comput. Eng., Tennessee Univ., Knoxville, TN, USA

Title Sensor based obstacle avoidance and mapping for fast mobile robots

Source Proceedings of the 1994 IEEE International Conference on Robotics and Automation; Part: vol.2; San Diego, CA, USA; 8-13 May 1994; pp. 1306-11 vol.2

Abstract This paper describes one aspect of a project whose goal is to move a robot in an unknown environment and find pipes to decommission. While moving through the environment a low level map, in the form of an occupancy grid, along with detailed location of pipes in the environment are obtained. This paper deals only with the low level "reflex" of obstacle avoidance that is performed while the robot moves along its path as well as some of the higher level tasks involved in path planning and robot motion in order to negotiate through a hazardous environment. The overall high level interaction with the system is made as simple and user friendly as possible using a graphical interface to control high level tasks. All low level communications and processing are transparent. The robot used for experimentation is a wheeled mobile platform equipped with many different sensors including ultrasonic range sensors and cameras. A quick and efficient obstacle avoidance algorithm has been developed using sixteen ultrasonic range sensor and one infrared proximity sensor.

[Graham92]

Author Graham, J.H.;
Dept. of Eng. Math. & Comput. Sci., Louisville Univ., KY, USA

Title A fuzzy logic approach for safety and collision avoidance in robotic systems

Source Ergonomics of Hybrid Automated Systems III, Brodner, P. and Karwowski, W. Ed. Proceedings of the Third International Conference on Human Aspects of Advanced Manufacturing and Hybrid Automation; Gelsenkirchen, Germany; 26- 28 Aug. 1992; pp. 493-8

Abstract A major factor which has limited the application of robots in industrial and human service applications has been the lack of robust sensing and control algorithms for detection and prevention of collision conditions. This paper discusses an approach to the collision avoidance control of robots using a fuzzy logic methodology for the integration of sensory input data from the robot's environment. The paper presents a formulation of the collision avoidance problem using the occupancy grid formulation, and discusses the use of a combination of Dempster-Shafer inference and fuzzy logic in fusing the sensory information and making robot movement decisions. This hybrid approach utilizes the strengths of both systems to provide an effective and computationally tractable result.

[Hughes92]

Author Hughes, K.; Murphy, R.;
Dept. of Comput. Sci., Univ. of South Florida, Tampa, FL, USA

Title Ultrasonic robot localization using Dempster-Shafer theory
Source Neural and Stochastic Methods in Image and Signal Processing; San Diego, CA, USA; 20-23 July 1992;
Proceedings of the SPIE - The International Society for Optical Engineering; vol.1766; 1992; pp. 2-11

Abstract The authors present a method for ultrasonic robot localization without a prior world models utilizing the ideas of distinctive places and open space attraction. This method was incorporated into a move-to-station behavior, which was demonstrated on the Georgia Tech mobile robot. The key aspect of the approach was to use Dempster-Shafer theory to overcome the problem of the uncertainty in the range measurements returned by the sensors. The state of the world was modeled as a two element frame of discernment Theta: empty and occupied. The world itself was represented as a grid, with the belief in whether a grid element was empty or occupied set to total ignorance (don't know) at the beginning of the robot behavior. A belief model of the range readings was used to compute the belief of points in the environment being empty, occupied, or unknown. Experiments demonstrated that the robot was able to localize itself with a repeatability of 1.5 feet in a 33 foot square room, regardless of the starting position within the open space.

[Ianigro92]

Author Ianigro, M.; D'Orazio, T.; Lovergine, F.P.; Stella, E.; Distante, A.;
Istituto Elaborazione Segnali e Immagini, CNR, Bari, Italy
Title Real-time obstacle avoidance based on sensory information
Source Mobile Robots VII; Boston, MA, USA; 18-20 Nov. 1992;
Proceedings of the SPIE - The International Society for Optical Engineering; vol.1831; 1993; pp. 62-73

Abstract Detecting unexpected obstacles and avoiding collisions is an important task for any autonomous mobile robot. The authors describe an approach using a sonar-based system that they have used in an indoor autonomous mobile system. The logical design of this system is shown, followed by a description of how it builds a knowledge of the environment. The information collected of the environment can be used for many applications like real-time obstacle avoidance, environment learning, position estimation. This method builds up two kind of maps: a occupancy grid which contains the probability value of each cell to be occupied and an orientation map which contains the expected orientation of the surface of each cell in the occupancy grid. Methods for filtering raw sensor data before using it for map generation together with experimental results are shown

[Jones93a]

Author Jones, J.P.;
Oak Ridge Nat. Lab., TN, USA
Title Real-time construction and rendering of three-dimensional occupancy maps
Source Applications of Artificial Intelligence 1993: Machine Vision and Robotics; Orlando, FL, USA; 14-16 April 1993;
Proceedings of the SPIE - The International Society for Optical Engineering; vol.1964; 1993; pp. 249-56

Abstract This paper describes a preliminary sensory system for real-time sensor-based robot navigation in a three-dimensional, dynamic environment. Data from a laser range camera are processed on an iWarp parallel computer to create a 3D occupancy map. This map is rendered using raytracing. The construction and rendering consume less than 800 milliseconds.

[Jones93b]

Author Jones, J.P.;
Oak Ridge Nat. Lab., TN, USA

Title Real-time construction of three-dimensional occupancy maps

Source Proceedings of 1993 IEEE International Conference on Robotics and Automation; Atlanta, GA, USA; 2-6 May 1993; pp. 52-7 vol.1

Abstract An experimental study of parallel algorithms for constructing 3- D occupancy maps is described. Data from a laser range camera are processed on an iWarp parallel computer. The resulting 3-D map is rendered using raytracing. The construction and rendering consume less than 800 ms.

[Jorgensen87]

Author Jorgensen, C.C.;
Oak Ridge Nat. Lab., TN, USA

Title Neural network representation of sensor graphs in autonomous robot path planning

Source IEEE First International Conference on Neural Networks, Caudill, M. and Butler, C. Ed.; San Diego, CA, USA; 21-24 June 1987; pp. 507-15 vol.4;

Abstract A continuous-valued associative neural network used for anticipatory robot navigation planning in partially learned environments is discussed. A navigation methodology is implemented in four steps. First, a room is represented as a lattice of connected voxels (voice elements) formed by dividing navigation space into equal-sized volumetric cells. Each voxel is associated with a simulated neuron. The magnitude of a neuron's activation corresponds to a probability of voxel occupancy calculated from a series of sonar readings taken by an autonomous robot. Neurons are trained with a series of room patterns derived from varying robot sensor perspectives. At another time, the robot is exposed to a single perspective of one of the rooms and utilizes the sensor return as a cue to prompt associative recall of a best guess of the complete interior of the room. A two-step path planning operation is then invoked that uses line-of-sight readings and anticipated global information to form a trial path plan. The planning process merges a nearest neighbor grid cell technique and a simulated-annealing gradient descent method to optimize transversal movements. In the final step, the path is followed until a mismatch between the estimated room and the actual sensor returns indicate incorrect anticipation. Implementation of the method on a hypercube computer is discussed, along with memory-computation trade-off requirements.

[Laliberte94]

Author Laliberte, T.; Gosselin, C.M.;
Dept. de Genie Mecanique., Laval Univ., Que., Canada

Title Efficient algorithms for the trajectory planning of redundant manipulators with obstacle avoidance

Source Proceedings of the 1994 IEEE International Conference on Robotics and Automation; Part: vol.3; San Diego, CA, USA; 8-13 May 1994; pp. 2044-9 vol.3

Abstract This article presents a path planning strategy for redundant serial manipulators working in a cluttered environment. Developed in a practical context of telemanipulation, the algorithm, which sacrifices the capability of solving very difficult trajectories for efficiency, allows a human to control a robot at a higher level, in Cartesian space. The model of the environment is provided by a 3D vision system as an occupancy map. An iterative process guides the end effector towards its goal with the help of discrete potential fields, which reduce the number of local minima. The motion of the manipulator is calculated using the velocity inversion of a redundant manipulator, which optimizes the distance to obstacles. The algorithm includes joint limit constraints, collision detection and heuristics for the solution of typical difficult cases, thereby leading to a high success rate. A simulator has been developed to test the algorithms.

[Lang89]

Author Lang, S.Y.T.; Korba, L.W.; Wong, A.K.C.;
Lab. for Biomed. Eng., Nat. Res. Council of Canada, Ottawa, Ont., Canada

Title Characterizing and modeling a sonar ring

Source Mobile Robots IV; Philadelphia, PA, USA; 6-7 Nov. 1989;
Proceedings of the SPIE - The International Society for Optical Engineering; vol.1195; 1990; pp. 291-304

Abstract Effective sensor integration requires knowledge of the characteristics of all sensor subsystems. This type of meta- knowledge can originate from theoretical models of the physical processes involved in the sensing, from actual testing of the sensory system or from a combination of both. This paper describes the collection and analysis of experimental data from an actual sonar ring. The effective beam pattern is mapped and modeled for the eight possible setting combinations of pulse width and gain profiles, using three different sizes of targets. The beam cross sectional characteristics are also analyzed to show the effective signal strength and its effect upon error in the depth readings. The performance of the system is highly dependent upon surface texture and orientation, and other tests of the sonar ring illustrate the types of artifacts which arise in the actual use of the system. The test results can be used to provide better certainty values in certainty grid representations, or used to build a boundary representation from a composite scan which integrates the data from the scans at different settings. The test results are shown graphically.

[Lee94]

Author Jang Gyu Lee; Chung, H.;
Dept. of Control & Instrum. Eng., Seoul Nat. Univ., South Korea

Title Global path planning for mobile robot with grid-type world model

Source Robotics and Computer-Integrated Manufacturing (UK); vol.11, no.1; March 1994; p p. 13-21

Abstract This paper presents a new methodology for global path planning for an autonomous mobile robot in a grid-type world model. The value of a certainty grid representing the exist-

ence of an obstacle in the grid is calculated from readings of sonar sensors. In the calculation, a way of utilizing three sonar sensor readings at a time is introduced, resulting in a more accurate world model. Once the world model is obtained, a network for path planning is built by using the model. The global paths, defined as the shortest paths between all pairs of nodes in the network, are calculated. A fast algorithm using a decomposition technique is proposed for real-time calculation. The new methodology has been implemented on the mobile robot whose role is to transport materials in a flexible manufacturing system. The results show that the proposed method of certainty grids satisfactorily represents a precise environment, including the locations of obstacles. Thus, the robot successfully comprehends its surroundings, and navigates to its destinations along optimal paths.

[Lim90]

Author Jong-Hwan Lim; Dong-Woo Cho;
Korean Inst. of Electr. Eng., Seoul, South Korea

Title Sonar-based certainty grids for autonomous mobile robots

Source Transactions of the Korean Institute of Electrical Engineers; Trans. Korean Inst. Electr. Eng. (South Korea); vol.39, no.4; April 1990; pp. 386-92

Abstract This paper describes a sonar-based certainty grid, and the probabilistic representation of uncertain and incomplete sensor knowledge, for autonomous mobile robot navigation. They use sonar sensor range data to build a map of the robot's surroundings. This range data provides information about the location of the objects which may exist in front of the sensor. Here, a new method using a Bayesian formula is introduced, which enables one to overcome some difficulties of the ad-hoc formula that has previously been the only way of updating the certainty grids. This new formula can be applied to other kinds of sensors as well as the sonar sensor. The validity of this formula in the real world is verified through simulation and experiment.

[Lim93]

Author Jong Hwan Lim; Dong Woo Cho;
Dept. of Mech. Eng., Pohang Inst. of Sci. & Technol., South Korea

Title Experimental investigation of mapping and navigation based on certainty grids using sonar sensors

Source Robotica (UK); vol.11, pt.1; Jan.-Feb. 1993; pp. 7-17

Abstract A mapping and navigation system based on certainty grids for an autonomous mobile robot operating in unknown environment is described. The system uses sonar range data to build a map of the robot's surroundings. The range data from sonar sensor are integrated into a probability map that is composed of two dimensional grids which contain the probabilities of being occupied by the objects in the environment. A Bayesian model is used to estimate the uncertainty of the sensor information and to update the existing probability map with new range data. The resulting two dimensional map is used for path planning and navigation. In this paper, the Bayesian updating model which was successfully simulated in the earlier work is implemented on a mobile robot and is shown to be valid in the real world by experiment. This paper also proposes a new path planning method based on weighted distance, which enables the robot to efficiently navigate in an unknown area

[Lim94]

Author Jong Hwan Lim; Dong Woo Cho;
Dept. of Mech. Eng., Cheju Nat. Univ., South Korea

Title Specular reflection probability in the certainty grid representation

Source Transactions of the ASME. Journal of Dynamic Systems, Measurement and Control (USA); vol.116, no.3; Sept. 1994; pp. 512-20

Abstract A new method for solving the specular reflection problem of sonar systems has been developed and implemented. This method, the specular reflection probability method, permits the robot to construct a high quality probability map of an environment composed of specular surfaces. The method employs two parameters, the range confidence factor (RCF) and orientation probability. The RCF is the measure of confidence in the returning range from a sensor under reflective environment, and the factor will have low value for long range information and vice versa. Orientation probability represents the surface orientation of an object. Bayesian reasoning is used to update the orientation probability from the range readings of the sensor. The usefulness of this approach is illustrated with the results produced by our mobile robot equipped with ultrasonic sensors.

[Matthies-Elfes88]

Author Matthies, L.; Elfes, A.;
Carnegie-Mellon Univ., Pittsburgh, PA, USA

Title Integration of sonar and stereo range data using a grid-based representation

Source Proceedings of the 1988 IEEE International Conference on Robotics and Automation; Philadelphia, PA, USA; 24-29 April 1988; pp. 727-33 vol.2

Abstract The authors use occupancy grids to combine range information from sonar and one-dimensional stereo into a two-dimensional map of the vicinity of a robot. Each cell in the map contains a probabilistic estimate of whether it is empty or occupied by an object in the environment. These estimates are obtained from sensor models that describe the uncertainty in the range data. A Bayesian estimation scheme is applied to update the current map using successive range readings from each sensor. The occupancy grid representation is simple to manipulate, treats different sensors uniformly, and models uncertainty in the sensor data and in the robot position. It also provides a basis for motion planning and creation of more abstract object descriptions.

[Matthies-Elfes89]

Author Matthies, L.; Elfes, A.;
Dept. of Comput. Sci., Robotics Inst., Carnegie-Mellon Univ., Pittsburgh, PA, USA

Title Probabilistic estimation mechanisms and tessellated representations for sensor fusion

Source Sensor Fusion: Spatial Reasoning and Scene Interpretation; Cambridge, MA, USA; 7-9 Nov. 1988;
Proceedings of the SPIE - The International Society for Optical Engineering; vol.1003; 1989; pp. 2-11

Abstract Two fundamental issues in sensor fusion are (1) the definition of model spaces for representing objects of interest and (2) the definition of estimation procedures for instantiating representations, with descriptions of uncertainty, from noisy observations. The authors

show that random field models provide attractive, alternative representations for the problem of creating spatial descriptions from stereo and sonar range measurements. For stereo ranging, they model the depth at every pixel in the image as a random variable. Maximum likelihood or Bayesian formulations of the matching problem allow one to express the uncertainty in depth at each pixel that results from matching in noisy images. For sonar ranging, they describe a tessellated spatial representative that encodes spatial occupancy probability at each cell. They derive a probabilistic scheme for updating estimates of spatial occupancy from a model of uncertainty in sonar range measurements. These representations can be used in conjunction to build occupancy maps from both sonar and stereo range measurements. They show preliminary results from sonar and single-scanline stereo that illustrate the potential of this approach. They conclude with a discussion of the advantages of the representations and estimation procedures used over approaches based on contour and surface models.

[McDonnell90]

Author McDonnell, J.R.; Page, W.C.;
US Naval Ocean Syst. Center, San Diego, CA, USA

Title Mobile robot path planning using evolutionary programming

Source Conference Record. Twenty-Fourth Asilomar Conference on Signals, Systems and Computers, Chen, R.R. Ed. (Cat. No.90CH2988-4); Pacific Grove, CA, USA; 5-7 Nov. 1990; pp. 1025-9 vol.2

Abstract Evolutionary programming provides a framework for generating algorithms which emulate natural evolution. A description is given of the use of evolutionary programming for global path planning in two dimensions. Safe paths are planned in cluttered environments modeled with a certainty grid representation. The results indicate that evolutionary programming yields a safe path if one exists

[Mobasseri88]

Author Mobasseri, B.G.; Adams, W.J.;
Dept. of Electr. Eng., Villanova Univ., PA, USA

Title Real-time spatial occupancy map generation using multiresolution shadow casting

Source Optics, Illumination and Image Sensing for Machine Vision III; Cambridge, MA, USA; 8-9 Nov. 1988;
Proceedings of the SPIE - The International Society for Optical Engineering; vol.1005; 1989; pp. 88-94

Abstract Path planning comprises a significant task in robot vision problems. The issue involves navigating from point A to B, avoiding obstacles on the way and satisfying other possible optimality criteria. Among the many path planning algorithms, multiresolution techniques based on hierarchical tree structures, e.g. quadtrees, have shown great potential. The paper presents a technique whereby a quadtree-based spatial occupancy map is generated in real time, making an online path planning task feasible.

[Mobasseri89a]

Author Mobasseri, B.G.;
Dept. of Electr. Eng., Villanova Univ., PA, USA

Title Path planning under uncertainty from a decision analytic perspective

Source Proceedings. IEEE International Symposium on Intelligent Control 1989 (Cat. No.89TH0282-4); Albany, NY, USA; 25-26 Sept. 1989; pp. 556-60

Abstract Previous work has used a certainty grid for navigation and path planning. In the present work, the author attempts to formulate the path planning problem under uncertainty from a decision analytic perspective. Paths are generated based on the planner's preferences and expected utilities of actions. A proposed cost structure, controlled by a strategy index, can simulate attitudes ranging from risk aversion to risk seeking. Experimental results demonstrate how path length and path risk are traded off based on this index. The proposed framework for navigation under uncertainty has proven to be a powerful tool in encoding subjective preferences in path planning. With a solid theoretical foundation such as decision analysis and utility and game theory, uncertain spatial and other knowledge terms can be assimilated in the overall plan. The preliminary results so far have shown a promising outlook for further expansion of this technique to real-world problems.

[Mobasseri89b]

Author Mobasseri, B.G.;
Dept. of Electr. Eng., Villanova Univ., PA, USA

Title Incorporating subjective measures in robot motion planning

Source Mobile Robots IV; Philadelphia, PA, USA; 6-7 Nov. 1989;
Proceedings of the SPIE - The International Society for Optical Engineering; vol.1195; 1990; pp. 340-8

Abstract Path planning can be grossly defined as the problem of reaching a goal from a starting position, avoiding collisions and satisfying one or more optimality criteria. A prerequisite to such planning is the availability of an occupancy map either as a priori information or generated online. Recent work has shown that such information can at best be obtained within a probabilistic framework, hence exact occupancy status is never known with absolute confidence. This paper presents a formal framework for formulating path planning under uncertainty. It is shown that paths compete not just on the basis of physically measurable parameters but also on the basis of collision risk. There emerge circumstances requiring a formulation of underlying subjective trade-offs among competing paths with the added element of risk. A set of experimental results shows the actual implementation of the proposed path planner inside a certainty grid.

[Moravec85]

Author Moravec, Hans P.
Robotics Inst., Carnegie Mellon Univ., Pittsburgh, PA, USA

Title Autonomous Mobile Robots Annual Report 1985

Source Carnegie Mellon University, Robotics Institute Technical Report CMU-RI-TR-86-4

[Moravec88]

Author Moravec, Hans P.
Robotics Inst., Carnegie Mellon Univ., Pittsburgh, PA, USA

Title Certainty Grids for Sensor Fusion in Mobile Robots

Source Sensor Devices and Systems for Robotics, Alicia Casals, ed., Springer-Verlag, Berlin, 1989, pp 243-276. Also in AI Magazine v9#2, Summer 1988, pp 61-77. Earlier version in *Proceedings JPL Workshop Telerobotics* (Pasadena, CA), Jan. 1987.

Abstract A numerical representation of uncertain and incomplete sensor knowledge we call Certainty Grids has been used successfully in several of our past mobile robot control programs, and has proven itself to be a powerful and efficient unifying solution for sensor fusion, motion planning, landmark identification, and many other central problems. We had good early success with ad-hoc formulas for updating grid cells with new information. A new Bayesian statistical foundation for the operations promises further improvement. We propose to build a software framework running on processors onboard our new Uranus mobile robot that will maintain a probabilistic, geometric map of the robot's surroundings as it moves. The "certainty grid" representation will allow this map to be incrementally updated in a uniform way from various sources including sonar, stereo vision, proximity and contact sensors. The approach can correctly model the fuzziness of each reading, while at the same time combining multiple measurements to produce sharper map features, and it can deal correctly with uncertainties in the robot's motion. The map will be used by planning programs to choose clear paths, identify locations (by correlating maps), identify well known and insufficiently sensed terrain, and perhaps identify objects by shape. The certainty grid representation can be extended in the time dimension and used to detect and track moving objects. Even the simplest versions of the idea allow us fairly straightforwardly to program the robot for tasks that have hitherto been out of reach. We look forward to a program that can explore a region and return to its starting place, using map "snapshots" from its outbound journey to find its way back, even in the presence of disturbances of its motion and occasional changes in the terrain.

[Moravec92a]

Author Moravec, Hans P.;
Carnegie Mellon Univ., Robotics Institute, Pittsburgh, PA, USA

Title 2D Evidence Grid Code in C

Source available from the author, hpm@cs.cmu.edu, and from http://www.frc.ri.cmu.edu/~hpm/s2d/

[Moravec92b]

Author Moravec, Hans P.;
Carnegie Mellon Univ., Robotics Institute, Pittsburgh, PA, USA

Title VOLSENSE (3D Evidence Grid Program)

Source available from the author, hpm@cs.cmu.edu, and from http://www.frc.ri.cmu.edu/~hpm/s3d/

Abstract A 1992 sabbatical year at supercomputer manufacturer Thinking Machines Corporation in Cambridge, resulted in a surprisingly efficient program for updating 3D evidence grids with additional sensor data. A log-odds representation makes the basic update operation an integer addition. By assuming sensor symmetry about the view axis, 3D distributions of

individual sensings are stored as 2D arrays representing radial slices. These slices are swept into cylinders when used, intersecting successive z grid planes in the 3D map in a series of ellipses. The mapping from radius, distance coordinates in the slices differs from one z plane to the next only in a few additive constants, allowing it to be precomputed outside the main loop, which itself requires less than ten operations, none more expensive than integer addition, per cell updated. An efficient bounding calculation outside the loop limits the updates to those that cause changes, typically occupying a cone within the evidence cylinder. Additional efficiencies exploit a four-way symmetry in the elliptical slices, and various coding and incremental computation techniques. The central evidence accumulation can process about 200 wide-beam sonar, or 4000 narrow-beam stereo-vision rangings per second in a 128x128x128 world representing a cube 10 meters on a side, on a SPARC-2 uniprocessor. This is fast enough now for experimental robots, and is suitable for practical robots when 100 MIPS microprocessors become available later this decade. The package also contains procedures for building sensor models controlled by 15 parameters, for comparing 3D maps, and various utilities.

[Moravec-Blackwell93]

Author Moravec, H.P.; Blackwell, M.;
Robotics Inst., Carnegie Mellon Univ., Pittsburgh, PA, USA

Title Learning Sensor Models for Evidence Grids

Source CMU Robotics Institute 1991 Annual Research Review, 1993, pp.8-15.

Abstract Evidence grids (aka. occupancy, probability and certainty grids) are a probabilistic, finite-element representation of robot spatial knowledge. The grids allow the efficient accumulation of small amounts of information from individual sensor readings into increasingly accurate and confident maps. Each sensor measurement is translated, via a sensor model, into a spatial evidence distribution that is added to a grid representing the robot's surroundings. In our first applications of the method, on a mobile robot with a ring of 24 Polaroid sonar transducers autonomously navigating a cluttered room, we constructed the sensor model from a cursory examination of the Polaroid literature. Despite the ad-hoc model, the grid approach worked far better than an older program, a decade in development, that used a geometric model. It successfully navigated cluttered rooms, most hallways, a coal mine and outdoors. The original program failed in a smooth-walled narrow corridor, where most sonar pulses, deflected by mirrorlike walls, indicated overlong ranges. The evidence grid method might be able to slowly accumulate evidence from such data, if only the sensor model accurately represented the modest information contained in a reading, as our ad-hoc model did not. This paper reports on a learning program that finds good models automatically. The sensor model is formulated as a closed form expression shaped by several parameters. The parameters are adjusted, in a hill-climbing process, that maximizes the match between a hand-constructed ideal map and a map built by the model with data from a robot test run in the mapped area. Using this approach with a 9- parameter function a program using several weeks of Sparc1+ workstation search time was able to produce a crisp, correct map of the difficult smooth hallway, from data that produces an unrecognizable splatter when interpreted by our original ad-hoc sensor model.

[Moravec-Cho89]

Author Moravec, H.P.; Cho, D. W.;
Robotics Inst., Carnegie Mellon Univ., Pittsburgh, PA, USA

Title A Bayesian Method for Certainty Grids
Source Working notes of AAAI 1989 Spring Symposium on Robot Navigation, Stanford, CA, 1989, pp. 57-60.

Abstract In earlier work we introduced a probabilistic, finite-element representation of robot spatial knowledge we call "certainty grids". The grids allow the efficient accumulation of small amounts of information from individual sensor readings into increasingly accurate maps of a robot's surroundings. Early experiments using the method to interpret measurements from a ring of 24 Polaroid sonar transducers carried on board an autonomously navigating mobile robot were surprisingly successful, compared with our earlier experiences with stereo-vision based programs that mapped points on objects as error distributions in space. These older programs enabled a robot to map and traverse cluttered 30 meter obstacle courses, succeeding about three times in four attempts. By contrast the grid method accomplished a similar task with a vanishingly small failure rate. We then used the grid approach to a stereo-vision equipped robot, also with excellent success. A subsequent experiment integrated sonar and vision data, generating maps with correct features not found in those from either sensor alone. These encouraging early results were obtained using ad-hoc statistical models and methods. We then developed a Bayesian statistical foundation for grid updates. A key result of this derivation was a combining formula for integrating two independently derived maps of the same area, or for adding a new reading to a developing map. This combining formula incorporated in one expression (and improved on) several different parts of the ad-hoc approach. In this paper we introduce a more specialized Bayesian combining formula for inserting range readings into maps. The formula is suitable for sonar, stereo, laser, proximity and touch measurements. By making use of the property of this kind of sensor that nearby objects occlude distant ones, the new (context-sensitive) formula manages to extract more information from a reading than the older (context-free) version. To insert a sensor reading, the context free method has a computational cost linear in the number of grid cells in the sensitive volume of the sensor. The context-sensitive formula has a cost dominated by a term quadratic in the volume of range uncertainty of the reading. Using simulated data, we compare the performances of the context-free formula, the context-sensitive one used incrementally, and the context-sensitive formula operating in a "batch" mode, in which every reading of a batch serves as context for all the others. Given the same input, the context-sensitive formula produces slightly better maps than the context-free method, and the batch mode does better than the incremental mode. But typically the differences are small. A few more readings processed by the cheaper context-free method can compensate for its slightly less efficient use of each reading. The paper also shows how this approach allows sensor models to be learned as a wandering robot equipped with several sensors gathers experiences. As an example, a sonar-type sensor whose characteristics are initially completely unknown is well characterized after experiencing as few as 1000 random range measurements in a world well mapped by other sensors.

[Moravec-Elfes85]

Author Moravec, H.P.; Elfes, A.E.;
Robotics Institute, Carnegie Mellon University, PA, USA
Title High Resolution Maps from Wide Angle Sonar
Source Proceedings of the 1985 IEEE International Conference on Robotics and Automation, St. Louis, March, 1985, pp 116-121;

Abstract We describe the use of multiple wide-angle sonar range measurements to map the surroundings of an autonomous mobile robot. A sonar range reading provides information concerning empty and occupied volumes in a cone (subtending 30 degrees in our case) in front of the sensor. The reading is modelled as probability profiles projected onto a rasterized map, where somewhere occupied and everywhere empty areas are represented. Range measurements from multiple points of view (taken from multiple sensors on the robot, and from the same sensors after robot moves) are systematically integrated in the map. Over- lapping empty volumes reinforce each other, and serve to condense the range of occupied volumes. The map definition improves as more readings are added. The final map shows regions probably occupied, probably unoccupied, and unknown areas. The method deals effectively with clutter, and can be used for motion planning and for extended landmark recognition. This system has been tested on the Neptune mobile robot at CMU.

[Moreno91]

Author Moreno, L.; Salichs, M.A.; Gachet, D.;
Univ. Politecnica de Madrid, Spain

Title Fusion of proximity data in certainty grids

Source Parallel and Distributed Computing in Engineering Systems; Tzafestas, S., Borne, P. and Grandinetti, L. Ed. Proceedings of the IMACS/IFAC International Symposium; Corfu, Greece; 23-28 June 1991; pp. 269-74

Abstract The present work deals with the different methods to fuse new sensors information about the environment in certainty grid environment modeling. The Probabilistic Estimation and some combination rules based on the Dempster-Shafer theory of evidence are analyzed and their possibilities compared. The present work has been developed under the Esprit-2483 Panorama project.

[Moreno92]

Author Moreno, L.; Puente, E.A.; Salichs, M.A.;
Dept. Ingenieria de Sistemas y Autom., Univ. Politecnica de Madrid, Spain

Title World modelling and sensor data fusion in a nonstatic environment. Application to mobile robots

Source Intelligent Components and Instruments for Control Applications; Ollereo, A. and Camacho, E.F. Ed. Selected Papers from the IFAC Symposium; Malaga, Spain; 20-22 May 1992; pp. 433-6

Abstract Describes a world modelling method which is able to integrate static and moving objects existing in dynamic environments. The static world is modelled by using an occupancy grid. The method is capable of modelling several moving objects. Whereas measurements belonging to actual targets are processed using a Kalman filter to yield optimum estimates, all other measurements are used to create or maintain multiple hypothesis corresponding to possible mobile objects. The viability of the method has been tested in a real mobile robot. Portions of this research has been performed under the EEC ESPRIT 2483 Panorama Project.

[Mori94]

Author Mori, T.; Fukuda, H.; Kamei, K.; Inoue, K.;
Ritsumeikan Univ., Kyoto, Japan

Title An environment modeling method by sensor fusion for an indoor mobile robot

Source Transactions of the Institute of Electrical Engineers of Japan, Part C (Japan); vol.114-C, no.5; May 1994; pp. 603-8

Abstract Describes a sensor fusion system which uses monocular vision and a sonar sensor to recognize an environment for an indoor mobile robot. In the authors' system the environment is represented by using the occupancy grids that Elfes (1989) has proposed. The occupancy grids are two-dimensional tessellations of space into cells where each cell contains a probabilistic estimate of its occupancy. Since they supply a common underlying representation for the interpretation of qualitatively different sensors, they also provide a natural framework for sensor integration. In order to cope with the weakness of each sensor, the occupancy grids derived from camera and sonar are integrated into a local map using a Bayesian estimation procedure. The weakness of vision is errors in distance due to shadows and reflections, while sonar errors in width are due to beam width. Further, local maps made at different locations are integrated into a global map for robot navigation.

[Poloni95]

Author Poloni, M.; Ulivi, G.; Vendittelli, M.;
Dipartimento di Inf. e Sistemistica, Rome Univ., Italy

Title Fuzzy logic and autonomous vehicles: experiments in ultrasonic vision

Source Fuzzy Sets and Systems (Netherlands); vol.69, no.1; 13 Jan. 1995; pp. 15-27

Abstract The opportunities offered by fuzzy logic to build maps for robot navigation are investigated. Characteristics of points of the space (occupied, free, uncertain, etc.) are easily expressed through set theoretical operations. Real-world experiments validate the approach. The experimental set-up is based on modified Polaroid ultrasonic sensors; however, the approach can be easily extended to incorporate other kinds of sensors.

[Puente91]

Author Puente, E.A.; Moreno, L.; Salichs, M.A.; Gachet, D.;
Dept. Ingenieria de Sistemas y Autom., Univ., Politecnica de Madrid, Spain

Title Analysis of data fusion methods in certainty grids application to collision danger monitoring

Source Proceedings IECON '91. 1991 International Conference on Industrial Electronics, Control and Instrumentation (Cat. No. 91CH2976-9); Kobe, Japan; 28 Oct.-1 Nov. 1991; pp. 1133-7 vol.2

Abstract The authors focus on the use of the occupancy grid representation to maintain and combine the information acquired from sensors about the environment. This information is subsequently used to monitor the robot collision danger risk and take into account that risk in starting the appropriate maneuver. The occupancy grid representation uses a multidimensional tessellation of space into cells, where each cell stores some information about its state. A general model associates a random vector that encodes multiple properties in a cell state. If the cell property is limited to occupancy, it is usually called occupancy grid. Two main approaches have been used to model the occupancy of a cell: probabilistic estimation

and the Dempster-Shafer theory of evidence. Probabilistic estimation and some combination rules based on the Dempster- Shaffer theory of evidence are analyzed and their possibilities compared.

[Santos94]

Author Santos, V.; Goncalves, J.G.M.; Vaz, F.;
Joint Res. Centre, Commission of the Eur. Communities, Ispra, Italy

Title Perception maps for the local navigation of a mobile robot: a neural network approach

Source Proceedings of the 1994 IEEE International Conference on Robotics and Automation; Part: vol.3; San Diego, CA, USA; 8-13 May 1994; pp. 2193-8 vol.3

Abstract Sensorial perception is a key issue for the problem of robot local navigation, that is, the immediate or short-range motion planning, reacting only to the free space around the robot, without requiring a pre-defined trajectory plan. Therefore, local navigation requires no environment model and relies entirely on sensorial data. Commonly used sensors such as ultrasonic ranging devices, are known for their associated problems: specular reflections and crosstalk, essentially. However if sensors are used in an appropriate number and geometric lay-outs, the resulting spatial redundancy offers the possibility of overcoming some of those problems. This paper deals with these problems by means of special perception maps using ultrasound data. A generalized grid serves as the base of maps, and its cells have simply binary values: free or occupied. The relation between the topology of the perception map and the environment is a determinant factor for accurate reasoning. A 3- layer feedforward neural network is used to perform the mapping between sensorial scans and grid occupancy. It was verified that the neural network handles most of the situations of specular reflections, and gives good perception maps for mid- range distances. Changes in environment, such as obstacles in vehicle's trajectory, have also been detected, which stresses the network's ability to generalize.

[Schiele94a]

Author Schiele, B.; Crowley, J.L.;
LIFIA, Inst. Nat. Polytech. de Grenoble, France

Title A comparison of position estimation techniques using occupancy grids

Source Robotics and Autonomous Systems; (Netherlands); vol.12, no.3-4; April 1994; pp. 163-71

Abstract A mobile robot requires a perception of its local environment for both sensor-based locomotion and for position estimation. Occupancy grids, based on ultrasonic range data, provide a robust description of the local environment for locomotion. Unfortunately, current techniques for position estimation based on occupancy grids are both unreliable and computationally expensive. This paper reports on experiments with four techniques for position estimation using occupancy grids. A world modeling technique based on combining global and local occupancy grids is described. Techniques are described for extracting line segments from an occupancy grid based on a Hough transform. The use of an extended Kalman filter for position estimation is then adapted to this framework. Four matching techniques are presented for obtaining the innovation vector required by the Kalman filter equations. Experimental results show that matching of segments extracted from both the local and global occupancy grids gives results which are superior to a direct matching of grids, or to a mixed matching of segments to grids.

[Schiele94b]

Author Schiele, B.; Crowley, J.L.;
LIFIA-IMAG, Grenoble, France

Title A comparison of position estimation techniques using occupancy grids

Source Proceedings of the 1994 IEEE International Conference on Robotics and Automation; Part: vol.2; San Diego, CA, USA; 8-13 May 1994; pp. 1628-34 vol.2

Abstract A mobile robot requires perception of its local environment for both sensor based locomotion and for position estimation. Occupancy grids, based on ultrasonic range data, provide a robust description of the local environment for locomotion. Unfortunately, current techniques for position estimation based on occupancy grids are both unreliable and computationally expensive. This paper reports on experiments with four techniques for position estimation using occupancy grids. A world modeling technique based on combining global and local occupancy grids is described. Techniques are described for extracting line segments from an occupancy grid based on a Hough transform. The use of an extended Kalman filter for position estimation is then adapted to this framework. Four matching techniques are presented for obtaining the innovation vector required by the Kalman filter equations. Experimental results show that matching of segments extracted from the both the local and global occupancy grids gives results which are superior to a direct matching of grids, or to a mixed matching of segments to grids.

[Schultz95]

Author Schultz, Alan; Grefenstette, John;

Title Continuous localization using evidence grids

Source NCARAI Technical Report AIC-95-024, Naval Research Laboratory, Washington, DC, USA.

Abstract Not Available.

[Singh93]

Author Singh, K.; Fujimura, K.;
Dept. of Comput. & Inf. Sci., Ohio State Univ., Columbus, OH, USA

Title Map making by cooperating mobile robots

Source Proceedings of 1993 IEEE International Conference on Robotics and Automation; Atlanta, GA, USA; 2-6 May 1993; pp. 254-9 vol.2

Abstract The problem of map making using cooperating multiple heterogeneous mobile robots is investigated. The mobile robots vary in size and capabilities in terms of speeds to navigate through the region and sensor ranges to acquire information about the region. The robots are assumed to have sufficient memory to store the map and to be able to communicate with each other. An algorithm is presented for map making by multiple mobile robots in a cooperative manner. The authors' approach makes use of an occupancy grid and completes a map to a specified resolution. The algorithm is discussed in detail, and its feasibility is demonstrated by simulation results for the case of two cooperating mobile robots.

[Takada93]

Author Takada, Ryohei
Mechanical Technology R&E Center, Nippon Steel Corporation, Chiba, Japan

Title Modeling Surface Orientation in 2D Evidence Grids

Source Nippon Steel Corporation, Mechanical Technology R&E Center, Technical Report 93-026

Abstract The evidence grid approach (aka certainty grids or occupancy grids) has proven itself very useful in constructing maps from inexpensive wide-beam sonar range finders mounted on mobile robots. Sonar works well in rough surroundings, but is unreliable in reflective environments of hard flat surfaces that act as acoustic mirrors. An automatic tuning (learning) process has produced sensor evidence functions that construct quite good maps in reflective environments by making only small map adjustments for each individual, often erroneous, reading. This conservative tuning, however, gives less than optimal performance in non-mirror environments. By extending the grid approach from evidence of simple occupancy to evidence of possible surface orientations, we attempted to model the systematic nature of reflective sonar errors to produce a system that works well in both reflective and diffusive surroundings. Results of these experiments show the validity of the approach and suggest future research directions.

[Tanabe91]

Author Tanabe, M.; Maeda, Y.; Yuda, M.; Takagi, T.;
Lab. for Int. Fuzzy Eng. Res., Yokohama, Japan

Title Path planning method for mobile robot using fuzzy inference under vague information of environment

Source Fuzzy Engineering Toward Human Friendly Systems; Terano, T., Sugeno, M., Mukaidono, M. and Shigemasu, K. Ed.; Yokohama, Japan; 13-15 Nov. 1991; pp. 758-69

Abstract Path planning based on vague information of the environment is discussed. In this method the abstracted motion of planning is taken into consideration. The vague environment information is taken into consideration as vague map, defined using a certainty factor. Human knowledge described as fuzzy rules used in the planning process.

[Vacherand94]

Author Vacherand, F.;
Dept. Syst. CENG, CEA, Centre d'Etudes Nucleaires, de Grenoble, France

Title Fast local path planner in certainty grid

Source Proceedings of the 1994 IEEE International Conference on Robotics and Automation; Part: vol.3; San Diego, CA, USA; 8-13 May 1994; pp. 2132-7 vol.3

Abstract A real time local path planner is designed and developed. It is based on a specific environment modeling with square grid tessellation. Because of different motion requirements to achieve a mission, several path planners are developed that do forward or reverse motions and maneuvers. The motion planning problem is formulated as the problem of motion of a point in a reduced sub-set of the configuration space. The implementation use intensively cellular automaton paradigm to compute the different stages of the processing

[Van Dam93a]

Author van Dam, J. W. M.; Krose, B. J. A.; Groen, F. C. A.;
Fac. of Math. & Comput. Sci., Amsterdam Univ., Netherlands

Title Transforming occupancy grids under robot motion

Source Artificial neural networks, S. Gielen and B. Kappen, ed, Springer-Verlag, pp. 318
http://www.fwi.uva.nl/research/neuro/projects/fusion.papers.html

Abstract This paper addresses the problem of how occupancy values from one occupancy grid can be used to calculate occupancy values in another grid, where the latter is rotated and/or translated with respect to the former. The mapping is described in terms of a neural network, of which the parameters are learned form examples. An activation function is derived taking into account that the input and output values represent probabilities. It is also determined how many points should be taken in a learning sample to optimize learning speed.

[Van Dam93b]

Author van Dam, J. W. M.; Krose, B. J. A.; Groen, F. C. A.;
Fac. of Math. & Comput. Sci., Amsterdam Univ., Netherlands

Title A neural network that transforms occupancy grids by parallel Monte-Carlo estimation

Source Computing Science in The Netherlands, H. A. Wijshoff, ed., CWI, Amsterdam, pp. 121-131
http://www.fwi.uva.nl/research/neuro/projects/fusion.papers.html

Abstract To represent the working environment of an autonomous mobile robot, occupancy grids can be used. This paper addresses the problem of how occupancy values from one occupancy grid can be used to calculate occupancy values in another grid, where the latter is rotated and/or translated with respect to the former. The mapping is described in terms of a neural network, of which the parameters are learned from examples. An activation function is derived taking into account that the input and output values represent probabilities in the occupancy grid. It is shown that the network performs a parallel Monte Carlo estimation of multiple volumes. It is also determined how many points should be taken into account in a learning sample to optimize the learning speed.

[Van Dam94]

Author Van Dam, J.W.M.; Krose, B.J.A.; Groen, F.C.A.;
Fac. of Math. & Comput. Sci., Amsterdam Univ., Netherlands

Title Transforming the ego-centered internal representation of an autonomous robot with the cascaded neural network

Source Proceedings of 1994 IEEE International Conference on MFI '94. Multisensor Fusion and Integration for Intelligent Systems; Las Vegas, NV, USA; 2-5 Oct. 1994; pp. 667-74
http://www.fwi.uva.nl/research/neuro/projects/fusion.papers.html

Abstract This paper addresses the problem how the ego-centered internal representation of a robot is to be transformed upon robot movement if the robot's environment is represented in an occupancy grid. The transformation rules are derived and it is shown that for a single change in the robot's position, the parameters of this transformation can best be estimated with Monte Carlo sampling. A neural network architecture is introduced as a computational model of the Monte Carlo estimation method, which can calculate estimates of all parameters in parallel. The cascaded neural network is an extension to this architecture, which is

capable of learning the relation between the change in the robot's configuration and the parameters of the corresponding transformation of occupancy grids.

[Weigl93]

Author Weigl, M.; Siemiatkowska, B.; Sikorski, K.A.; Borkowski, A.;
Inst. of Fundamental Technol. Res., Polish Acad. of Sci., Warsaw, Poland

Title Grid-based mapping for autonomous mobile robot

Source Robotics and Autonomous Systems (Netherlands); vol.11, no.1; May 1993; pp. 13-21

Abstract A mapping module for the mobile robot equipped with the ultrasonic range finder is presented. The environment is described by a grid of cells that can be either free or occupied. A two-stage processing of data coming from the sonar is proposed: first, the readings are filtered and composed into the local model, then the latter is aggregated into the global map. In order to account for random errors the formulae based upon Shafer theory are employed. The proposed procedure is able to reproduce correctly the indoor environment as documented by the results of tests performed on a prototype robot

[Yamauchi96]

Author Yamauchi, Brian.;
Institute for the Study of Learning and Expertise, Palo Alto, CA, USA

Title Mobile Robot Localization in Dynamic Environments Using Dead Reckoning and Evidence Grids

Source http://robotics.stanford.edu/people/yamauchi/
Submitted to the 1996 IEEE International Conference on Robotics and Automation.

Abstract None.

[Zapata90]

Author Zapata, R.; Jouvencel, B.; Lepinay, P.;
Lab. d'Autom. de Microelectron. de Montpellier, Univ. des Sci. et Tech. du Languedoc, France

Title Sensor-based motion control for fast mobile robots

Source Intelligent Motion Control; Kaynak, O. Ed. Proceedings of the IEEE International Workshop (Cat. No.90TH0272-5); Istanbul, Turkey; 20-22 Aug. 1990; pp. 451-5 vol.2

Abstract This paper addresses the motion planning problem for fast mobile robots evolving in ill-structured and dynamic environments. First, several theoretical aspects of the sensor and geometric fusion are investigated. Unknown environments are modelled with a spherical grid in which cells are either empty or occupied. A connectivity graph is obtained by merging neighboring occupied cells. Next, the navigation control structure based on the potential field method is described. By this method it is possible to take into account both an a priori model and sensor information, by adding artificial forces due to the known part of the world, to distance information coming from sensors. Finally, the paper discusses the implementation of this sensor-integrated motion control structure for controlling a fast outdoor mobile robot (5 m/s to 10 m/s) in an unknown world.

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