Probabibstic Robot Navigation in Partially Observable Environments*

Reid Simmons and Sven Koenig
Carnegie Mellon University
School of Computer Science
Pittsburgh, PA 15213-3890
reids@cs emu edu, skoenig@cs emu edu

Abstract

Autonomous mobile robots need very reliable navigation capabilities in order to operate unattended for long periods of time This paper reports on first results of a research program that uses par tially observable Markov models to robustly track a robot s location in office environments and to direct its goaJ-onented actions The approach explicitly maintains a probability distribution over the possi ble locations of the robot taking into account var IOUS sources of uncertainly including approximate knowledge of the environment and actuator and sensor uncertainty A novel feature of our approach is its integration of topological map information with approximate metric information We demon stcate Itw robustness of this appiorch «\ controlling an actuaJ indoor mobile robot navigating corridors

1 Introduction

We are interested in the task of long term autonomous navigation in an office environment (with corridors foyers and rooms) While the slate of the art in autonomous office navigation is fairly advanced it is not generdlly good enough to permit robots lo traverse corridors for long periods of time without getting lost Evidence for this can be seen in recent AAA1-sponsored robot competitions [Konolige 1994 Simmons 1995] where the robots often got confused as to where they were and had difficulty relocalizing once that occurred

We contend that navigation can be made more reliable by having the robot explicitly represent spatial and sensor uncertainty To this end we have developed a navigation technique that uses Markov models lo robustly track the robot's position and direct ils course A partially observable Markov decision process (POMDP) model is constructed from topological information about the connectivity of the environment, approximate distance information plus sensor and actuator characteristics The Markov model estimates the position of the robot in the form of probability distributions The probabilities are updated when the robot reports that it has moved or turned, and when it observes features such as wails and corridor junctions To direct the robot s behavior, a planner associates a directive (e g turn or stop) with every Markov stale Whenever the probability distribution of the Markov model is updated the total probability mass for each directive is calculated, and the robot executes the one with the largest probability mass

Our approach has several features that make it well-suited for the office navigation task It explicitly accounts for uncertainty in actuation sensor data and their interpretation and the robot s position It can utilize all available sensor informa lion to track position and is particularly amenable to adding new sources of sensor information It seamlessly combines topological and metric map information enabling the robot to utilize as much or as little metric information as nhas avail able It is also very reactive - once the robot believes it has strayed from the nominal (optimal) path it will automatically execute corrective actions On the other hand n is relatively immune lo temporary uncertainly in position For example even if the robot does not know for certain which of two parallel comdors it is traversing H does not stop and replan as long as the control directives associated with both corridors are the same In this way it can continue making progress towards its desired goal while at the same lime collecting sensor readings to help disambiguate its true location

An important aspect of this work is that it must run in real time on board an actual robot Problems include not only how to model the navigation problem as a POMDP but also how to deal with memory and time constraints While still preliminary our experimental results both in simulation and on the actual robot, are encouraging In particular they indicate that the approach produces very robust navigation even when using estimates of the actual sensor and action models While, to date, we have concentrated more on implementation and validation aspects of the approach our work opens up new application areas for more theoretical results in the area of planning with Markov models, including some of our own group s work tChnsman, 1992, Goodwin, 1994 Koenig and Simmons 1994]

2 Related Work

Most recent work in robolic office navigation has used a *landmark based* approach that relies on topological maps

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whose nodes correspond to landmarks (locally distinctive places) such as corridor junctions and whose edges indicate how the robot should navigate between nodes [Kortenkamp and Weymouth, 1994 Kuipers and Byun, 1988] This ap proach is attractive because it does not depend on geometric accuracy and is reactive to sensed features of the environment (the landmarks) It suffers however, from problems of sensors occasionally not detecting landmarks and of sensor *aliasing* (not being able to distinguish between similar landmarks) On the other hand, using purely metric maps is vulnerable to inaccuracies in both the map making and dead-reckoning abilities of the robot While some researchers augment topological maps with approximate metric information such information is primarily used to resolve topological ambiguities [Kuipers and Byun 1988 Mataric 1991 Simmons, 1994] In contrast our Markov model approach seamlessly integrates topological landmark-based informa lion and approximate metric information

Some navigation techniques represent uncertainly in position using models that presume a certain probability distribution typically Gaussian [Kosake and Kak, 1992, Smith and Cheeseman 1986] While such models are efficient to encode and update they are not ideally suited for office navigation In particular due to sensor aliasing one often wants to encode the belief that the robot might be in one of a number of non-conliguouslocations This cannot be represented precisely using Gaussian distributions but is quite easy for our Markov models On the other hand we need to lessellale space into discrete states, rather than representing position using real numbers Thus there is a tradeoff between the precision and expressiveness of the different models We contend that for office navigation however that die added expressiveness of the Markov models outweighs the decrease in precision from discretization

Like our own work several researchers have investigated Bayesian approaches for probabilistic planning and execution monitoring in office navigation [Nourbakhsh *el al* 1995] use a partially observable Markov model approach similar to ours but do not utilize any metric information The states of the robot are either at a topological node or somewhere in a connecting comdor In contrast our approach can use estimates of how far the robot has traveled and sensor reports that occur within a corridor to further constrain the robot s location For example knowing that two corridor junctions are approximately 5 meters apart enables the robot to estimate when it is in the vicinity of the second junction even if it misses seeing the junction

Most of the other Bayesian approaches rely on metric maps [Kirman *a al*, 1991] and [Nicholson and Brady 1994] use approaches based on temporal belief networks With such methods the size of die models grows linearly with the amount of temporal lookahead, which limits their use to rather small lookaheads [Dean *et al* 1993] use robot navigation as an example to describe a planning and monitoring algonmm dial uses a totally observable Markov model which assumes that the location of the robot is always known precisely [Hu and Brady, 1994] use Bayesian techniques to detect unforeseen obstacles in an otherwise completely known environments

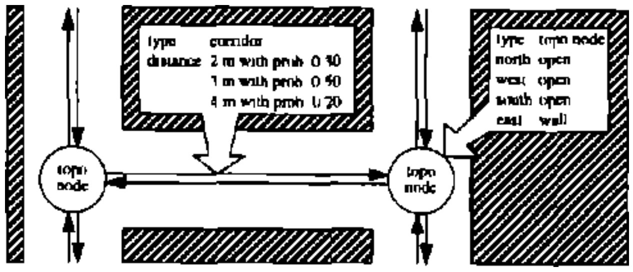


Figure 1 Augmented Topological Map

3 Constructing the Markov Models

Before describing how we construct Markov models of an office environment, we introduce some terminology A finite Markov model consists of a finite set of states S a finite set of actions A a set of actions $A(s) \subseteq A$ for each state $s \in S$ that can be executed in that state, and transition probabilities $p(s'|s,a)$ for all s $s' \in S$ and $a \in A(s)$ (the probability that the new stale is y if action *a* is executed in slate *s)* We also define a set of sensors $\imath \in I$ The sensors are characterized by observation probabilities $p_\imath(o|s)$ for all $s \in S$ and $o \in O(\imath)$ (the probability that sensor / reports feature *o* when the robot is in state *s)* Note that Markov models assume that the transition and observation probabilities are determined only by the current state of the robot (the "Markov assumption)

In our case, the Markov model is partially observable be cause the robot may never know exactly which slate it is in Instead it maintains a belief of its current state in form of a probability distribution *p{s)* over die slates $s \in S$ The probability distribution is updated in two ways When an action report *a* is received indicating a move or turn, the new probabilities become

$$p_{posterior}(s) = K \times \sum_{s' \in S | a \in A(s')} p(s|s', a) \times p_{prior}(s')$$

where A" is a normalization factor to ensure that the probabil iiies all sum to one (this is necessary because not all actions are defined for all states) When a sensor report *o* is received from sensor *i* indicating that a feature has been detected the probabilities become

$$p_{posterior}(s) = K \times p_\imath(o|s) \times p_{prior}(s)$$

The Markov model is constructed from three sources of information the topology of the environment (which we presume can be easily obtained) general knowledge about office environments (such as that corridors are straight and perpendicular to each other) and approximate metric knowledge (obtained either from rough measurements or from general knowledge, such as the fact that, in our building, corridors are two meters wide and all doorways are between two and ten meters apart)

The map information is initially encoded as a graph of nodes and edges (Figure 1) A node represents a junction between corridors (and/or doorways or foyers) Nodes are connected by a pair of directed edges which are augmented widi approximate length information in the form of a probability distribution over possible lengths Rooms and foyers (not shown) are also represented in the map

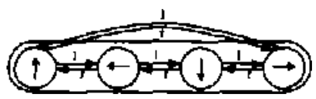


Figure 2 Group of Four Markov States

The rest of this section describes how the augmented topological map is compiled into a Markov model

Modeling Locations

Each Markov state encodes both the orientation and location of the robot To insulate the model from low-level control aspects (such as turning to avoid obstacles) we encode the commanded heading of the robot rather than its instantaneous orientation Since our corridors are straight and perpendicular to each other it is sufficient to discretize orientation into the four compass directions North South, East, West The spatial locations of the robot are also discretized While more fine-grained discretizations yield more precise models they also result in more memory requirements and more time-consuming computations We use a resolution of one meter which we have found to be sufficient

Since our Markov states encode both orientation and lo cation four states are needed lo fully represent each spatial location Three actions are modeled turning right 90 de grees (r) turning left 90 degrees (/) and going forward one meter (/) Right and left turn actions are defined for every state (Figure 2) Since they correspond lo changes in commanded heading and not to changes in position, we have found it sufficient lo model them determinislically Some states also have "forward' actions defined for transitioning from location to location (note that forward actions are not defined for stales that face walls) Dead-reckoning uncertainty is modeled by a self-transition that is, the forward action transitions with some probability from a Male into itself

Modeling Corridors

Our representation of topological edges is a key to our approach If the edge lengths are known exactly, it is simple lo model the ability to traverse a corridor with a Markov cain that has forward actions between those states whose onenta lions are parallel to the corridor axis (Figure 3a) The model becomes more complex when only approximate edge lengths are known While one approach is to represent a corridor edge by a single Markov state [Nourbakhsh *et al* 1995] this loses die ability lo utilize dead-reckoned information in doing position estimation

Another approach is lo model an edge as a set of parallel Markov chains, each corresponding to one of the possible lengths of the edge (Figure 3b) The transition probabilities into the first state of each chain are the same as the probability distribution over edge lengths associated with the topological map (see Figure 1) Each forward transition after that is deterministic (modulo dead-reckoning uncertainly — note that the identity transitions are not shown in these figures) While this representation best captures the actual structure of the environment it is relatively inefficient the number of stales is quadratic in the maximum length of the edges

As a compromise between fidelity and efficiency, our current implementation models edges by collapsing the parallel chains in a way that we call the come from" semantics (Figure3c) In this representation thespattal location of aMarkov

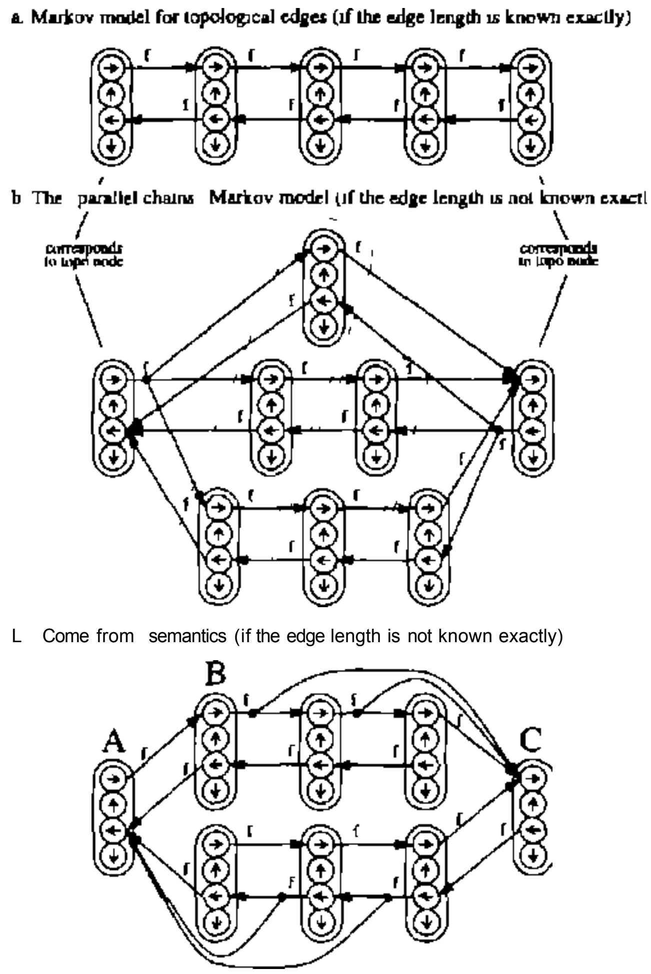


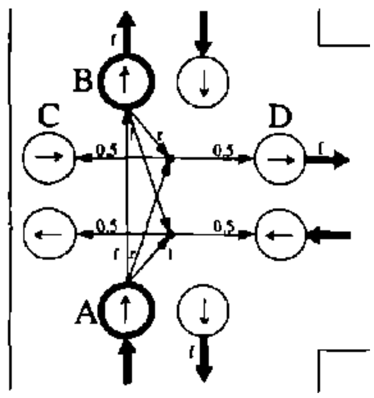
Figure 3 Representations of Topological Edges

state is known relative to the topological node from which the robot comes, but its location relative to the end of the chain is uncertain (c g stale B is 1 meter from A, but is between 1 and 3 meters from C) For each stale the forward transition probabilities are derived from the edge length probability dis tnbutions When edge length uncertainty is large the come from semantics can save significant space over the 'parallel chains ' representation For example for an edge between 2 and 10 meters long the come from semantics needs only 80 stales to encode the edge compared lo 188 for the "parallel chains

Each edge in the come from" semantics is actually repre sented using two chains one for each of the comdor directions Thus, if the robot travels some distance and then turns around the model limits the positional uncertainty as the robot travels back to the last topological node This is particularly useful when the robot realizes it has missed a junction, and turns around to head back

Modeling Junctions and Doorways

Unfortunately we cannot represent comdorjunctions simply with a single group of four Markov states since the spatial resolution of a Markov state is one meter but our corridors are two meters wide



(for claniy only actions from the highlighted nodes arc shown)

Figure 4 Representation of Corridor Junctions

While one approach would be to represent junctions using [our (two by two) groups of four Markov stales each we achieve nearly the same result with four groups of two states each which both saves space and makes the model simpler (Figure 4) The basic idea is that turns within a junction are non deterministic with equal probability of transitioning to one of the two slates of the appropriate orientation in the lunction For example in entering the junction of Figure 4 from the South the robot would first encounter slate A then stale B if it continues to move forward If it then turns right it would be facing East and would transition to either stales C or D with equal probability This models agrees with how the robot actually behaves in junctions In particular it captures the uncertainty thai arises due to the facr that the robol turns with a non zero turn radius

Doorways can be modeled much more simply since the width of our doors is approximately the resolution of the Markov model A single exact-length edge (Figure la) leads ihrough a door into a room Similarly lo [Nourbakhsh *el al* 1995] doorway edges have an associated probabilityp mat the door is open Then the observation probabilities associated with seeing a doorway are

$$p_i(o|\text{door}) = p \times p_i(o|\text{open-door}) + (1-p) \times p_i(o|\text{closed-door})$$

Modeling Foyers and Rooms

We arc developing adequate models for large open spaces (layers and rooms) Currently we lessellale a foyer into a matrix of locations From each location, The forward action has some probability of transitioning straight ahead but also some probability of self-transitioinng and moving to diagonally adjacent states While this model corresponds well with our observations about how the robot actually performs in such spaces it is deficient in that it requires the exact length and width of the foyer Although this model could also be used to represent rooms it is probably overly complex for that purpose wc are currenlly leaning towards representing rooms using a single group of four slates each of which has a high probability of self-transitiomng

4 The Navigation System Architecture

The overall system architecture consists of five main components (Figure 5) The robot controller performs local obstacle avoidance while trying to travel along a commanded heading

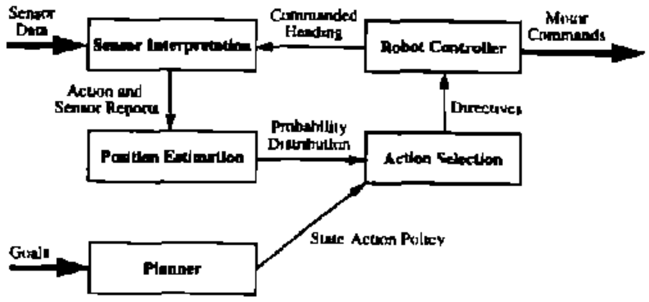


Figure 5 Navigation System Architecture

The sensor Inlerpretation component converts raw data from the wheel encoders and sonar into higher-level action reports (heading changes and disiance traveled) and sensor reports (features delected) Position estimation uses these reports and the Markov model lo maintain a belief about the current location of the robot Action selection uses this probability distribution along with a goal-directed policy produced by the planner to choose directives which arc sent to the controller to change the robot s heading or make it stop These directives are also fed back lo sensoT interpretation, since interpretation of features is often heading specific

To dale the work reported here has focused on position estimation and action selection The robol controller and sensor interpretation components are essentially the same as those used in our previous work in landmark based navigation [Simmons 1994] and wc have not yet pul significant effort into the planner

Robot Controller

The main task of the robot controller is to head in a given direction while avoiding obstacles To do that, it uses a po (ential field approach lArkin 1987] in which obstacles arc represented as repulsive forces and the desired heading is an attractive force The robot sums the force vectors and locally moves in that direction modulating its speed if necessary lo avoid collisions

The directives supplied to the controller are to make it stop go and change heading While the Markov model represents turns and moves as discrele actions in reality the robol does not stop to turn, but continually moves forward even while turning In addi'ion heading changes are cumulative so that two successive right turn directives for instance results in a smooth 180 degree turn

Sensor Interpretation

The task of the sensor interpretation component is lo convert the continual motion of the robot into discrete action reports and to produce sensor reports from the raw sensor data that indicate the observation of high-level features such as walls and corridor openings

The sensor interpretation component periodically receives reports from the robot s *dead reckoning* which uses internal sensors (wheel encoders) lo estimate position and orientation This information is combined with the robol s commanded heading to produce a virtual odomeler that keeps track of the distance traveled along that heading This is needed so that the distance the robol travels in avoiding obstacles is

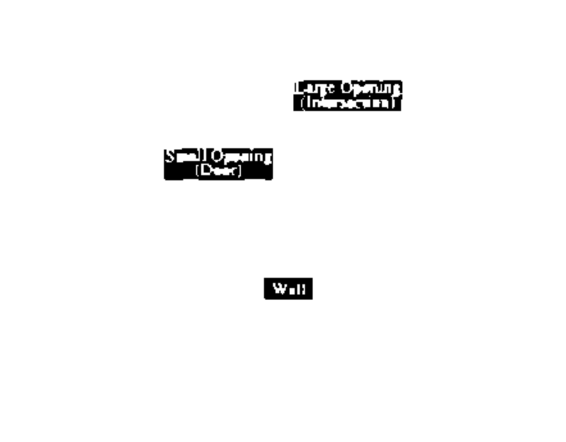


Figure 6 Occupancy Grid with Corridor Features

not counted in determining how far it has traveled along a corridor After each meter of cumulative travel the sensor interpretation reports that one forward action has occurred Similarly, the robot controller reports when Us commanded heading has changed and this is reported (in units of 90 degree turns) to the position estimation component

Sonar readings are bundled into three virtual sensors' that report observations of walls and openings of various sizes (small medium and large) in front of the robot and to its immediate left and right An occupancy grid [Elfes 1989] which probabilistically combines sonar sensor readings taken over time as the robot travels is used lo filter noisy sensor readings and produce a more global view of the robot s surroundings (Figure 6) The occupancy grid is processed by projecting a sequence of rays perpendicular to the robot s commanded heading (thus, it is independent of the robot's actual orientation) until they intersect an occupied grid cell The rays are then analyzed geometrically If the end points of the rays can be fit to a line reasonably well 0 e with a small chi-squared statistic) then a wall has been detected with high probability An opening is indicated by a contiguous sequence of long rays

Position Estimation

The virtual sensor and action reports are used to update the probability distribution over the Markov slates according to the update rules shown in Section 3 These rules need the transilion probabilities for actions $p(s'|s_1)$ and the observation probabilities for virtual sensors $p_i(o|s)$ The transition probabilities are derived from edge length distributions in the map plus knowledge of dead-reckoning uncertainty The observation probabilities must be estimated or learned To simplify the problem rather than characterizing each individual state, we characterize classes of states, such as wall open (corridor junctions), closed-door and open-door Then we create a table containing feature/state class pairs that encode the probability that the sensor reports a given feature when the robot is next to that particular class of states For example the left virtual sensor is partially characterized by

$$\begin{aligned}
&p(\texttt{wall}|\texttt{open}) &&= 0\,05\\
&p(\texttt{small_opening}|\texttt{open}) &&= 0\,20\\
&p(\texttt{medium_opening}|\texttt{open}) &&= 0\,40\\
&p(\texttt{large_opening}|\texttt{open}) &&= 0\,30\\
&p(\texttt{nothing}|\texttt{open}) &&= 0\,05
\end{aligned}$$

These probabilities indicate that junctions are most commonly delected as medium-sized openings but can often be seen as large or small openings (although they are hardly ever confused for walls) The observation probabilities of the feature nothirg which is used to indicate that a sensor has made no determination are chosen so that if the sensors reports nothing the overall probability distribution is unaffected While these values represent our best guesses, we have implemented learning algondims to determine action transition and observation probabilities more precisely

In general forward actions tend to increase positional uncertainty due to non deterministic transitions, while observanons tend to decrease it In certain cases however, the effects of a forward action can dramatically decrease uncertainty This occurs when there is some probability that the robot is in slates with no forward actions $(f \notin A(s))$ Such stales are prevalent — for instance all states within a corridor whose orientation is perpendicular to the axis of the corridor (see Figure 3) In practice, this effect can be seen when the robot turns at an intersection Before the turn there is often some probability thai the robot has not yet reached the intersection After the robot has turned and successfully moved forward a bit the probability that it is still in the original corridor drops to zero We believe this is a major factor in keeping the positional uncertainty low, even when the robot travels long distances

When incorporating sensor reports, care must be taken to preserve the Markov assumption Since reports by the same sensor at the same location are not independent (since they depend on the same occupancy grid cells), multiple reports cannot be aggregated Instead we retract the old sensor report before updating with the new report which can be done easily as long as no action updates occur between the two reports

Action Selection

To control the robot s goal-directed behavior our planner (see below) associates a directive $d(s) \in D$ with each Markov state (note these should not be confused with the set of actions *A(s)* defined for the Markov model) The four directives are change heading by 90 degrees (turn right) -90 degrees (turn left) 0 degrees (go forward) and stop The action selection component chooses new directives based on the probability distribution of the Markov model

A straightforward strategy is to choose the directive associated with the stale s that has the highest probability [Nourbakhsh *el al* 1995] While this strategy may be adequate when each topological entity is associated with a single Markov stale, it does not work well in our models For example, since comdor junctions are modeled using several states for each orientation, it is reasonable to consider all of their recommendations when deciding which directive to issue

A selection strategy with this property is the "best-action strategy in which the *probability mass* of each directive is calculated and the one with the highest total probability is chosen

$$\arg\max_{d \in D} \sum_{s \in S | d(s) = d} p(s)$$

A variation on this is the 'best-above threshold' selection strategy which chooses the best directive only if its probability mass is above some threshold otherwise the current directive remains in effect We have investigated this strategy because we thought it would reduce the chances of making wrong moves due to spunous false positive sensor reports Experimental evidence, however, both in simulation and with the real robot, indicate that the 'best-action' strategy is in fact superior in reducing the number of erroneous moves

Reinforcement learning researchers such as [Chnsman, 1992 Tenenberg et al 19921 often use other voting schemes, such as the following Let *gd(s,d)* be the shortest distance from state $s \in S$ to the goal if the robot executes directive $d \in D(s)$ and then behaves optimally The strategy chooses ihe directive with the smallest expected goal distance

$$\arg\min_{d \in D} \sum_{s \in S} p(s) gd(s, d)$$

This scheme allows one for example to choose the second best action if all stales agree on the second best action but disagree on the best action While this scheme is attractive wc did not implement it because it would require substantial changes to our path planner

Planning

While opportunities abound for applying probabilistic planning techniques to this problem we currently use a very sim pie symbolic path planner a variant on the one used for our landmark based navigation

The planner uses A* search in the augmented topological map to find a path to the goal It uses this plan skeleton to assign preferred headings to the edges and nodes in the map based on the expected total travel distance to the goal and estimates about how long it takes to turn Directives are then associated with the Markov stales a go forward directive is assigned to each state whose orientation is the same as the preferred heading of its associated topological entity The remaining states are assigned actions that will turn the robot towards the desired heading Finally a slop directive is assigned to the goal state and to nearby states (which helps to increase the total probability mass of the slop directive when the robot reaches the goal)

Our planner and the voting heuristics used in action selec lion arc clearly inferior compared lo optimal POMDP solu tions (in which directives are assigned to probability distributions rather than individual states) For example, unlike POMDP algorithms, our planner cannot decide to take actions whose only purpose is lo gather information Sometimes however it can be advantageous to gamer additional informa lion thai helps the robot to reduce positional uncertainty, even if that requires it to move away from the goal temporarily

At present however it is infeasible lo determine even approximate POMDP solutions given the size of our stale spaces and our real-time constraints [Lovejoy 1991] [Cassandra *el at* 19941, for instance report that their POMDP method can solve a problem with 23 stales in under half an hour while the model for just half of one floor of our building has over 1000 slates We still intend to explore POMDP algorithms however given recent advances in approximate algorithms [ParT and Russell 19951 and the hope that the restricted topology of our Markov models might make them more amenable to efficient solutions

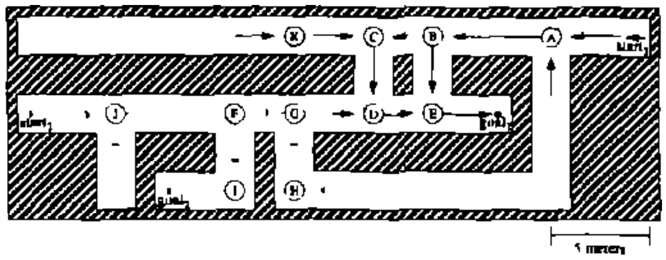


Figure 7 An Office Comdor Environment

	best action			best above threshold		
path	freq	time s	speed cm/s	freq	time s	speed cm/s
ABE	12	68 2	25 7	5	63 6	27 5
ABCDE	3	79 7	29 5	8	81 0	29 0
ABCKCDE	—	—	—	2	104 1	N/A

5 Experiments

While Markov models are expressive and relatively efficient thev make strong independence assumptions Empirical evidence is needed to determine whether mthiscase theMarkov assumption is satisfied well enough to yield good, reliable navigation performance In this section we report on experiments in two environments for which the Markov assumption is only an approximation a realistic simulation of a prototypical office comdor environment and an actual mobile robot navigating in our building The same navigation code is used for both sels of experiments since the simulator and the robot have the exact same interfaces

5 1 Experiments with the Simulator

Two navigation experiments were performed wilh the robot simulator in the comdor environment shown in Figure 7 The topological map has 17 nodes and 36 directed edges We modeled the uncertainty of the length of a topological edge as a uniform distribution over the interval ranging from 80 to ISO percent of the real length of the edge The resulting Markov model has 1184 Markov slates The initial positional uncertainty for both experiments is minimal the initial probability for the robot s aciual location is about 90 percent The remaining probability mass is distributed in the vicinity of ihe actual location

In the first experiment the task was to navigate from start j lo *goal]* The preferred headings assigned by our planner are shown with solid arrows Note that the preferred heading between B and C is towards C because even though the goal distance is a bil longer, this way Ihe robot does not have to turn around if il overshoots B We ran a lolal of 15 trials for both the best action and the best-above-threshold strategies all of which were completed successfullv (Table 1)

The robot has to travel a rather long distance from *start]* before its first turn Since this distance is uncertain and comdor openings are occasionally missed the robol occasionally overshoots B and then becomes uncertain whether it is re ally at C or B However, since the same directive is assigned to both nodes this ambiguity does not need to be resolved the robot turns left in both cases and then goes straight The

path	best-action freq	best-action time s	best-action speed cm/s	best-above threshold freq	best-above threshold time s	best-above threshold speed cm/s
JFI	11	60 6	28 9	8	65 4	26 8
JFGFI	2	91 5	25 7	—	—	—
JFGHGFI	1	116 0	23 7	5	120 2	22 9
JFGFGFI	1	133 0	22 2	—	—	—
JFGDGFI	—	—	—	2	176 5	N/A

Table 2 Experiment 2

Figure 8 Wean Hall at CMU

same thing happens when it gets to D since it thinks it may be at either D or E The robot eventually corrects its beliefs when after turning left and traveling forward, and it detects an opening lo its left At this point the robot becomes fairly certain that it is at E A purely landmark based navigation lechnique can easily get confused in this situation since it has no expectations about seeing this opening, and can only attribute it to sensor error (which in this case, is incorrect)

In the second experiment the robot had to navigate from *start-i* to *goal2* The preferred headings for this task arc shown with dashed arrows Again we ran 15 trials lor both action selection strategies (Table 2)

For reasons that are similar to those in the first experiment the robot can confuse G with F If at is at G but thinks it is probably at F it turns right and goes forward However when it detects the end of the corndor but does noi detect a right comdor opening it realizes that it must be at H rather man I Since the probability mass has now shifted, it turns around and goes over G F and I to the goal This shows that our nav igation lechnique can gracefully recover from misjudgements based on wrong sensor reports - even if it takes some lime lo correct its beliefs It is important to realize that this behavior is not triggered by any explicit exception mechanism but results automatically from the way the position estimation and action selection interact

53, Experiments with Xavier

Xavier our indoor mobile robot is buill on an RWI B24 base and includes bump sensors sonars a laser range sensor and a color camera on a pan-tilt head Control perception and planning are all earned out on two on-board mulli-processing 486-based machines

As mentioned the probabilistic navigation system uses a modified version of the planner and essentially the same robot controller and sensor interpretation components as our landmark-based navigation system Thus, differences in performance can be directly attributed to the different navigation approaches In addition to facilitate comparisons we ran Xavier along the same routes as reported in [Simmons 1994] In particular the robot traversed from point S to G and back again (Figure 8) in some trials (45 meters each way) and in some circumnavigated around the building (150 meters)

The topological map used lo represent the corridors in Figure 8 has 95 nodes and 180 directed edges As with the simulator trials the edge lengths ranged uniformly from 80 to 150 percent of the real comdor length The resulting Markov model has 3348 states

In 25 trials (mostly back and forth between points S and G) the robot successfully reached its goal in 22 cases averaging 30 cm/s while traversing a total of over a kilometer In two of those cases the robot missed seeing a junction, but turned back when it realized it had probably gone too far and successfully continued This success rate of 88% compares favorably with ihe 80% rate reported in [Simmons 1994]

The main difference is thai lhe probabilistic navigation scheme uses all available sensor information to help locali?e itself For example while the probabilistic navigation uses the robot s dead reckoning to directly constrain its po sition estimates the land mark-based navigation uses metric information in only two ways it ignores landmarks that are reported before a minimum distance has been traveled and turns around after a maximum distance Similarly the prob abilistic navigation scheme utilizes all sensor reports, while the land mark-based scheme pays attention only to those features that might correspond to the expected landmark One effect of this is that the probabilistic navigation scheme tends lo turn the robot earlier when entering a junction it often gets enough confidence from a single sensor report while the land mark-based scheme needs several (eg seeing both an opening lo the side and the end of the corridor ahead) before it decides to turn

The few remaining failures are attributable to two sources Occasionally the action selection heuristics enter a limit cycle and continually lurn the robot (we suspect this is due to a software bug) More fundamental is that the local obstacle avoidance will especially in foyers move the robot a signih cant distance orthogonally lo its commanded heading Since this is not currently reported the robot s position estimation becomes very inaccurate We can remedy this by reporting side motions and adding a slide action lo the Markov model that will cause the appropriate state transitions

6 Future Work and Conclusions

This paper has presented our first efforts al using partially observable Markov models (POMDPs) for autonomous office navigation The approach enables a robot to utilize all its sensor information both positional and feature based in order to robustly track its location A simple path planner and action selection heuristics are used lo direct the robot s goal heading Advantages of this approach include the ability to account for uncertainty in the robol s initial position actuator uncertainly sensor noise, and uncertainly in the interpretation of thesensordata Also by integrating topological and metric information the approach easily deals with uncertainty arising from incomplete descriptions of the environment

We are extending this work in several directions We have implemented methods, based on EM learning techniques that passively refine metnc map information as well as the sensor and action models and will be testing it with Xavier In addition we are developing improved learning techniques that are more resistant to violations of the Markov assumption We intend to pursue planning and action selection algorithms that approximate optimal POMDP policies and to compare meir performance to the greedy heunstics descnbed here Finally, we inlend to add new sources of sensor information pnmanly vision-based feature detectors

The implemented probabilistic navigation system has demonstrated its reliability, both in simulation and on Xavier even in the face of significant uncertainty We believe that such probabilistic navigation techniques hold gTeat promise for getting robots reliable enough to operate unattended for long penods of time in complex uncertain environments

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