Mobile Robot Navigation using a Sensor Network

by Maxim A. Batalin, Gaurav S.Sukhatme, Myron Hattig



Min- Ulk Kim
The ory of Computation Laboratory Konkuk University Ћttp://tc.konkuk.ac. Kr/ minuk@konkuk.ac.kr 2007.12 .12

## Agenda

- Introduction
- Previous Work
- Probabilistic navigation
- Experiments
- Conclusion
- References
- Appendices

Introduction

## Introduction

- Navigation is a fundamental problem in mobile robotics.
- Navigation problems
- local-deals with navigation on the scale of a few meters
- global-deals with navigation on a larger scale in which the robot cannot observe the goal state from its initial position
- There are many solutions.
- But their approaches assume that a map is given a priori.



## Introduction

- Our approacf's properties
- The sensor network is pre-deployed into the environment
- The network are synchronized in time.
- The robot does not have a pre-decided environment map or access to $\mathcal{G P S}$, IMU or a compass.
- The environment is not required to be static.
- The robot does not perform localization or mapping.
- The robot does not have to be sophisticated.
- The primary computation is performed distributively in the sensor network, the only sensor required is for obstacle avoidance.


## Previous Work

- Coverage, Exploration and Deployment by a Mobile Robot and Communic ation Network(2004)
- Maxim A. Batalin, Gaurav S.Sukhatme
- Deployment of network
- Probabilistic navigation
- Navigation field
- Ifis paper is just experimental report of previous work.

Probabilistic navigation

## Probabilistic navigation

- In order for the robot to be able to navigate through the environment from $\mathcal{A}$ to $\mathcal{B}$, the robot should choose an action that maximizes its chances of getting to its goal.
- Our approacfirelies on a pre-deployed sensor network with determined transition probabilities.


## Probabilistic navigation

- Transition probabilities are probability of arriving at s' given that the robot started at s and commanded action a
- Actions $=\{$ East, West, South, North $\}$
- $s$ is start point(node)
- s'is next point(node)
$P\left(s^{\prime} \mid s, a\right)$
- If we want that every nodes have the transition probabilities about their neighbor, Robot should explore whole network.


Probabilistic navigation

Planning

## Probabilistic navigation

- When the navigationgoal is specified, the node that is closest to the goal triggers the navigation field computation.
- During this computation, every node probabilistically determines the optimal direction in which the robot should move, when in its vicinity.


Probabilistic navigation

- When the navigation goal is specified, the node that is closest to the goalsend Start Computation packet.
- Nodes that receive the Stat Computation packet initialize utility.
- The utility of the goalnode is set to $\underline{1}$ and of the other nodes to $\underline{0}$.
- Every node in the networkupdates its utility and computes the optimal navigation action of its own.

$$
\begin{gathered}
U_{t+1}(s)=C(s, a)+\max _{a \in A(s)} \sum_{s^{\prime} \in S-s} P\left(s^{\prime} \mid s, a\right) \times U_{t}\left(s^{\prime}\right) \\
\pi(s)=\arg \max _{a \in A(s)} \sum_{s^{\prime} \in S-s} P\left(s^{\prime} \mid s, a\right) \times U\left(s^{\prime}\right)
\end{gathered}
$$

## Probabilistic navigation

$$
U_{t+1}(s)=C(s, a)+\max _{a \in A(s)} \sum_{s^{\prime} \in S-s} P\left(s^{\prime} \mid s, a\right) \times U_{t}\left(s^{\prime}\right)
$$

- where $C(s, a)$ is the cost associated with moving to the next node. Ulsually $\leq-1 / k$ where $k$ is the number of nodes.
- This is an iteration model.
- The utility update equations have to be executed until the desired accuracy is acfieved. For practicalreasons, the accuracy in our algorithm is set to $\underline{10^{-3}}$, which requires a reasonable number of executions of the utility update equation per node(Approx. 20).


## Probabilistic navigation

- Example: When the navigationgoal is specified to 9

- 1. Start Computation packet is sent by 9 to its ne ighbors


## Probabilistic navigation

- Example: When the navigationgoal is specified to 9

$C(s, a)=-\frac{1}{10}<-\frac{1}{k}=-\frac{1}{9}$ where $k$ is the number of nodes
- 2. Node that receive SC packet starts updating its utility.
- If neighbors of all nodes are known exactly, then $\mathcal{P}\left(s^{\prime} \mid s, a\right)=1$
- In this paper, every node is preprogrammed with information about its neigfibors.


## Probabilistic navigation

$\pi(s)=\arg \max$
$a \in A(s)$

$$
P\left(s^{\prime} \mid s, a\right) \times U\left(s^{\prime}\right)
$$

- After the utifities are computed, every node computes an optimal policy for itself according to this equation.
- The computed optimal action is stored at each node and is emitted as part of a suggestion packet that the robot would receive if in the vicinity of the node.


## Probabilistic navigation

- Example: Compute optimalaction at each nodes

- 3. At node 8, I will choose West direction because 9's utility is bigger than 7's utility.

Probabilistic navigation
$\mathcal{N a v i g a t i o n}$

## Probabilistic navigation

- Note that deployed sensor ne tworkdiscretizes the environment.
- Now we should navigate the robot.
- There are 3 pfiases.
- 1. Robot accepts command which is given by current node.
- 2. Robot moves 'forward'using the $\mathcal{V} \mathcal{F H}$ algoritfim for local navigation and obstacle avoidance.
- 3. During this phase the current node switches and the navigation algorithm start from phase 1 again.
- In this manner, the robot can navigate to goal wherever it locates. This is the node-wise approach.


## Probabilistic navigation

- Suppose initially current node is set to node 1.
- Node 1 suggests the robot to go forward direction.
- In $M_{2}$ are a, current node will be changed to node 2.
- And node 2 will suggest the robot to go left direction.
- Then, How can we switch current node to node 2?



## Probabilistic navigation

- This is the solution about switching current node based on processing signal strengtr values.
- Adaptive $\mathcal{D e}$ lta Percent



## Probabilistic navigation

- Tfis algoritfin fias 4 pfases.
- 1. Compute an initial maximum average $\mathcal{A}_{\text {im }}$-an average of the first is amples.
- 2. Compute a running ave rage $\mathcal{A}_{r}$ which is an ave rage of $j$ consecutive samples.
- 3.If $\mathcal{R}=\mathcal{A}_{r} / \mathcal{A}_{\text {im }}<\mathcal{M}$, where $\mathcal{M}$ is the thresfold value, then return from the algorithm. Put $\mathcal{R}$ into list $\mathcal{L}_{\mathbb{R}}$.
- 4. If y consecutive elements of $\underline{\mathcal{L}}_{\text {d }}$ are in nondecreasing order, then return y and quit the algorithm, else repeat 2~4.
- Incase, severalnodes returned from the algoritfm, pick the node with the smallest ratio and switch to it.
- Experimentally we determined threshold $\mathcal{M}=0.65$.

Experiments

## Experiments

- We conducted experiments at Intel Researcf facilities.
- We used
- a Pioneer 2DX mobile robot.
- with $180^{\circ}$ laser range finder used for obstacle avoidance
- a base station(Mic a 2 mote)
- for communication with the sensor network



## Experiments

- The sensor network of 9 nodes was pre-deployed.
- Every node is preprogrammed with information about its neightors.


Experiments

- The environment itself resembles a regular cubicle office. Like environment with narrow corridors (about lm), changing topology, crowded with people and obstacles.
- Figure 5 shows the mobile robot and one of the deployed nodes in the experimental environment.



## Experiments

- The experimental scenario that we consider for navigation is alarm fandling.
- An alarm occurs when a certain node detects an event.
- The task of the robot is to navigate from the 'home base'(around node 1) towards the triggered alarm.
- Requirements for the successfulexperiment
- navigation field should yield shortest paths
- robot should stop within 3 m of the goal node

Experiments

- We conducted 10 experiments for 5 different goal nodes.
- This is representative trajectories that the robot took on its route from the start.

<Goal 3 >

<Goal 5 >

<Goal $6>$

<Goal $8>$

<Goa lg >


## Experiments

- Table I shows the final distances from the robot to the goal nodes after the robot has signaled that it had comple ted navigation.
- The robot was able to navigate to the correct goalnode in all cases.

TABLE I
Experimental data (distance to goal at finish, in meters). Five GOALS, TEN EXPERIMENTS PER GOAL.

| Trial | Goal 3 | Goal 5 | Goal 6 | Goal 8 | Goal 9 |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | 0.7 | 1.4 | 0.78 | 2.9 | 0.96 |
| 2 | 0.82 | 1.26 | 0.86 | 1.6 | 0.96 |
| 3 | 0.94 | 1.45 | 0.72 | 1.62 | 1.35 |
| 4 | 0.91 | 1.41 | 0.91 | 2.4 | 1.26 |
| 5 | 0.85 | 1.4 | 0.87 | 1.4 | 1.21 |
| 6 | 0.97 | 1.39 | 1.3 | 2.1 | 1.24 |
| 7 | 0.85 | 1.01 | 0.85 | 1.7 | 0.95 |
| 8 | 0.98 | 1.55 | 0.88 | 2.8 | 1.51 |
| 9 | 0.89 | 1.5 | 0.55 | 1.79 | 1.4 |
| 10 | 0.66 | 1.04 | 1.02 | 2.1 | 0.92 |
| Average | 0.86 | 1.34 | 0.87 | 2.04 | 1.17 |

## Conclusion

- We fiave presented an algoritfin that allows the robot to navigate using a deployed sensor network.
- without a map, GPS, IMA, compass
- The navigation occurs through node-wise motion from node to node on the path.


## References

- M.A. Batalin and G.S.Sukhatme, "Coverage, exploration and deployment by a mobile robot and communic ation network," in The $2^{\text {nd }}$ Intl. Workshop on Information Processing in Sensor $\mathfrak{N e}$ tworks(IPS $\mathfrak{X}$ '3), Palo Alto, 2003, pp.376-391
- M. A. Batalin and G.S.Sukhatme, "S ensor Network6ased Multi-Robot Task Allocation," in IEEE/RSI Int. Conf. on Intelligent Robots and Systems (IROS '́3), Las Vegas, 2003, pp.1939-1944
- I. Ulrich and g. Borenstein, "VFF*: Localobstacle Avoidance with Look-Ahe ad Verification,"in IEEE int. Conf. on Robotics and Automation, 2000, pp.2505-2511


## Appendices

## Appendix $\mathcal{A}: \mathcal{N}$ ode Arcfitecture

- It is not exactly the same architecture used in this paper.
- But it helpful to understand.
- This arcfitecture is used when an alarm event may be occurred different nodes concurrently.
- It assume that there are several robots.
- Robot fas a compass.



## Appendix $\mathcal{A}: \mathcal{N}$ ode Arcfitecture

- $\operatorname{ALAR} \mathcal{M}(a, w, f c)$
- Id of the node that detected the alarm
- Weight
- Hop count
- If a node receives an $\operatorname{ALARM}$ $m s g$, the alarm is placed on the [ist
- Every node maintains a current alarm variable, which is the element of $\mathcal{L}$ with largest utility.



## Appendix $\mathcal{B}: V \mathcal{F} \mathcal{H}^{*}$

- This is an enfancement version of earlier developed Vector Field Histogram $(\mathcal{V F H})$ method for mobile robot obstacle avoidance.
- Earlier version $V \mathcal{F} \mathcal{H}+$ sometimes fails.
- Figure 1 shows a situation where a mobile robot trave ls down a corridor and encounters two obstacles in its path.
- Obstacles are shown in black, while the configuration space is gray.

<Fig. 1 >

Appendix $\mathcal{B}: \mathcal{V F} \mathcal{H}^{*}$

- The large circle drawn in a dashed line shows the approximate distance at which an obstacle triggers an avoidance maneuver.
- At the position sfrown in the example, $\mathcal{V F H}+$ detects $\underline{2}$ openings.
- Unfortunately, both trajectories $\mathcal{A}$ and $\mathcal{B}$ appe ar equally appropriate to $\mathcal{V F H}+$.
- In problematic situations like this, $\mathfrak{V F} \mathcal{F}+$ would thus select the appropriate direction on average only 50\% of the time.


## Appendix $\mathcal{B}: \mathcal{V} \mathcal{F} \mathcal{H}^{*}$

- $\mathcal{V F H}^{*}$ algoritfin overcomes problematic situations like this one most of the time by combining $\mathcal{V F} \mathcal{H}+$ with the $\mathcal{A}^{*}$ search algoritfm.
- Figure 5 shows the trajectories of $\mathcal{V F H}^{*}$ with 4 different goaldeptr values.


Figure 5: VFH* trajectory with: a) $n_{g}=1$, b) $n_{g}=2$, c) $n_{g}=5$, and
d) $n_{g}=10$.

## Appendix $\mathcal{B}: V \mathcal{F} \mathcal{H}^{*}$

- Figure 5 shows that the higher $n_{g}$ is selected, the better $\mathcal{V F} \mathcal{H}^{*}$ performs.
- However, this improvement is at the expense of computational time.
- Table 1 shows an execution time comparison based on the Guide Cane's embedded computer, a PC 486 running at 66 $\mathfrak{M H z}$.

| $\boldsymbol{n}_{\boldsymbol{g}}$ | $\mathrm{T}_{\text {average }}$ | $\mathrm{T}_{\text {maximum }}$ |
| :---: | :---: | :---: |
| 1 | 3 ms | 6 ms |
| 2 | 5 ms | 11 ms |
| 3 | 8 ms | 22 ms |
| 4 | 10 ms | 39 ms |
| 5 | 12 ms | 82 ms |
| 10 | 30 ms | 242 ms |

Table 1: VFH* execution time.
A blind person walks with the GuideCane.

## Appendix $\mathcal{B}: V \mathcal{F} \mathcal{H}^{*}$

- $V \mathcal{F H}^{*}$ which is a localobstacle avoidance algoritfm that uses look-ahead verification can consider more than the robot's immediate surroundings.
- While $\mathcal{V G H}^{*}$ has the same obstacle avoidance performance as $\mathcal{V F} \mathcal{H}+$ for regular obstacles, VFFH is also capable of dealing with problematic situations that would require the robot to substantially slow down or even stop.

