Fuzzy Environment Mapping for Robot Navigation Based on Grid Computing

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***Abstract*—In order to navigate autonomously, a mobile robot needs to build an environment map where the robot is navigating. Currently, the sensors are mounted on the robot to detect if the obstacles exist and then the map immediate surrounding of the robot is built to help for navigation path planning. The map created by this method is a local map that may cause global navigation problem which a global coverage map is needed to solve such a problem. In this study, a sensor network is deployed for building global environment map. All the sensor locations are assumed known. The navigation space is divided into grids and a grid is to be detected if obstacles exist by one or a number of sensors. Fuzzy set concept is used to introduce a tool useful for sensor perception. Those sensors work as a team to explore all the space and then the global fuzzy map is constructed. The experiments show that the fuzzy map is more practical and helps the path planning problem to be solved more efficiently.**

***Keywords*—autonomous mobile robot, sensor network, fuzzy set concept.**

I. Introduction

The applications of mobile robot are getting more important. The autonomous robot can do works without continuous human guidance, for example, cleaning floors. Some applications use autonomous robots to collect data in the places where people is hard to reach, for example, sea depths. The basic requirement for a robot to have the ability of autonomy is it can understand its environment [4, 7-8]. The robot needs to localize itself first and then generates map to understand its environment. The map is built according to the uncertain data that is collected by the sensors mounted on the robot. Lots of the researches use ultrasonic sensor to detect the obstacles and build map based on the probabilistic model [10]. The most seen probabilistic model is occupancy grids framework which is introduced by Elfes [6]. The basic assumption for occupancy grids is the environment has binary structure, i.e. that each grid cell is either occupied or empty [12]. Based on the occupancy grids method, there are researches that use sensor fusion technique to generate more accurate map [1, 9, 13]. Some other studies use fuzzy set concept for robot perception [11], and the fuzzy map is defined as the fuzzy set of grid, whose membership function quantifies the possibility for each grid to belong to an obstacle. Since fuzzy logic is robust with dealing with uncertainty, the fuzzy map that built according to the uncertain sensor data is efficient to the robot navigation [10].

Once the environment map is generated, the navigation path can be planned to guide the autonomous robot. However, the robot using the above methods to build environment map only gain the information on the scale of a few meters to the robot. In fact, this only solves the problem of obstacles avoidance [2]. In larger scare space, the robot has global navigation problem since the robot cannot the goal state from its initial position. For example, a service robot in museum may work as a guide to lead visitors to a special destination. There might be unpredictable and dynamic obstacles in the robot navigation space. Since the robot has only local environment information, the robot will not know the dynamic obstacles appear in advance until it is near the obstacles. This causes the path planning inefficient. In fact, this is very like traveling in a city. If one could get the newest traffic information of entire city in advance, he will avoid getting into the traffic jam area.

Wireless sensors became cheaper in the recent years that allow more application development is based on the sensor network. Batalin et al. [2] proposed a framework of robot navigation using a sensor network embedded in the environment to solve the global navigation problem. In [MRN], a probabilistic model is adopted for sensors to build the best possible path for robot navigation.

In this paper, a method that uses sensor network to build an environment map is proposed. However, the proposed method to build the map is based on fuzzy set concept rather than probabilistic. A static sensor network is pre-deployed in the indoor environment where robot is navigating. The environment is divided into grids, and a single grid is to be

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detected if obstacles exist or not by one or a number of sensors. All sensor locations are assumed known and they will send collected data back to the server to build a fuzzy global map. Since the sensor network is keeping monitoring the entire environment, the server can update the fuzzy map that results the best possible navigation path also updated in real time mode. The experiments show that the proposed method provides an efficient method for navigation path planning.

The remaining parts of this paper are organized as follows. Section 2 introduces related works on map building. Section 3 describes the proposed method and section 4 provides experimental evidence. Section 5 concludes the paper.

II. RELATED WORKS

This section describes works related to map building for autonomous robot.

A. Occupancy Grid Map of the Environment

Occupancy grids method is based on the assumption that the environment has binary structure, that is, each grid cell is either occupied or empty [12]. The probability that a certain grid is occupied will converge to 1 if standard occupancy grids method is employed. This is not always justified especially as the grid cells which are partly covered. Fig. 1 shows an example in which a grid is partly covered by an obstacle and the probability of this grid will converge to 1 if the sensors of the robot repeatedly detect the obstacle. In top picture of fig. 1, the color of black represents high likelihood that the cell is occupied. However, since the obstacle only covers 10% of this cell, a coverage value of 0.1 would be a better approximation of the true situation. The bottom picture of Fig. 1 uses gray color to represent lower likelihood that the cell is occupied.

B. Sensor Network

The smart environment needs information about its surroundings. Now, this information needed by smart environments can be provided by distributed wireless sensor networks.

The basic works and challenges of a sensor network are: detecting the relevant quantities, monitoring and collecting the data, assessing and evaluating the information, formulating meaningful user displays, and performing decision-making and alarm functions. There are also lots of researches that work on the following fields: network deployment, sensor localization [3, 5], communication protocols and power management.

The application of sensor network is enormous. For example, physical properties such as pressure, temperature, humidity and flow can be measured by sensor networks.

C. Robot navigation using a Sensor Network

Occupancy grids method is a well-known method to solve robot navigation problem. However, while the robot can not observe the goal state from its initial position, the robot navigation becomes inefficient. Several studies have been proposed to address this problem of global navigation [MRN 3, 4, 5]. However, none of above methods deals with highly dynamic environment.

Batalin et al. [2] proposed a framework that using sensor network to solve the global navigation problem. The system from [2] does not need the environment to be static and the design principle is the sensor network serves as the communication, sensing and computation medium for the robots, whereas the robots provide actuation. Following is a brief introduce of the system approach from [2].

In Batalin's study, the robot does not have a pre-deployed environment map and the robot is not necessary to compute the navigation path itself. The system approach relies on a pre-deployed sensor network with determined transition probabilities. Sensor nodes will guide the robot to navigate in its environment. Navigation directions are computed within the network using value iteration that is an algorithm of computing the utilities for node's state. The robot communicates with sensor nodes in the network locally, and makes navigation decisions based on which node it is near.

The most interesting idea in [2] is to compute the action policy distributively in the sensor network. The idea is that every node use value iteration algorithm to update its utility and computes the best navigation action for a robot in its neighborhood on its own.

Since all the computing work is in the network, the processors that robot equips with can have more power to do other important job.

D. Fuzzy Grid Map of Environment

Fuzzy logic is usually used to handle two different kinds of uncertainty [10]. The first one is vagueness that is associated with the difficulty in characterizing a particular concept or property with a crisp set. The second one is lack of evidence to see that whether a given element is a member of a particular crisp set. Environment detection or path planning from sensors is an example of the second kind of uncertainty.

For example, the basic idea of occupancy grid map building is to determine for each grid cell of environment whether it belongs to the occupied set or empty set. We can define the entire environment is the universal set U which is the union of the occupied set O and the empty set E. However, based on the basic occupancy grids method, if each grid cell is partly occupied, there will be no path for robot to go.

The empty set E and the occupied set O should be defined as fuzzy sets over the universal U, and their membership functions are μ_E and μ_O, respectively. For each $g \in U$, the two values $\mu_E(g)$ and $\mu_O(g)$ are needed to be computed as fuzzy map is building.

It is intuitive that the fuzzy map, that information about the risk of collision for each grid cell of the environment, will be more accurate if the measurement locations where the sensors on the robot collect a series of range readings are numerous and well distributed.

III. FUZZY MAP BUILDING

This study is using an ultrasonic rangefinders sensor network to build a fuzzy map. The environment where the service robot navigation is divided into grids and each grid is detected continually by a group of sensor (there may be one or a number of sensors in a group). Each sensor's location is assumed known and it will send its collected information back to the server which is called central control device (*CCD*) to build the map. The *CCD* builds a single local grid map based on the fuzzy set concept and then merges all local grid maps into a global map. The *CCD* also takes responsibility for solving the problem of path planning and sending signal to guild the robot.

Ultrasonic sensors working principle is to generate ultrasonic wave and to see if the echo occurs. Fig. 2 shows a sensor is generating ultrasonic wave to detect obstacles, and we can see that the wave form of a radiation cone and the wave will be reflected back by objects that is in radiation cone.

There are three sources of uncertainty happen while the obstacles are detected by sensors. The first and the most important one is the measured distance is affected by an error.

The above uncertainty can be transferred to a fuzzy model to express the state of points belonging to the radiation cone. In this paper, the method of how to set up fuzzy model refers to the work in [FM].

The state of points that insider the radiation cone may be fuzzy. That is, it seems the state of the points is occupied; on the other hand, it seems the state is empty. Tow fuzzy membership functions can be defined to describe this situation.

$$f_\varepsilon(d,r)=\begin{cases} k_\varepsilon & 0 \le d < r-\Delta r \\ k_\varepsilon(\frac{r-d}{\Delta r})^2 & r-\Delta r \le d < r \\ k_\varepsilon & d \ge r \end{cases} \quad (1)$$

$$f_o(d,r)=\begin{cases} 0 & 0 \le d < r-\Delta r \\ k_o\left[1-(\frac{r-d}{\Delta r})^2\right] & r-\Delta r \le d < r+\Delta r \\ 0 & d \ge r+\Delta r \end{cases} \quad (2)$$

f_ε is the membership function of measuring the degree of the state of empty, whereas f_o is to measure the degree of the state of occupied. r is the radius of radiation cone. d is the distance that sensor to the detected object. Δr is the distance of the vicinity to r. k_ε and k_o are two pre-defined maximum constants for membership functions, respectively.

The second uncertainty is caused by the ultrasonic wave intensity decreasing. However, this uncertainty is not considered in this study. We assume wave intensity is uniform inside the radiation cone.

The last uncertainty is caused by multiple reflections. This results in the increasing of d. Fig. 3 shows an example of multiple reflections. In order to reduce the possible affection of multiple reflections, a radial modulation function f_r as in (3) that is also proposed by [FM] is adopted.

$$f_r(d)=1-\frac{1+h\tan(2(d-d_v))}{2} \quad (3)$$

d_v is a pre-defined constant that is used to weaken the confidence of measurement. Fig. 4, 5 and 6 show above functions.

For a single sensor S_i reading, two fuzzy sets E_i and O_i is generated. E_i the empty fuzzy set for S_i. O_i is occupied fuzzy set .the membership functions for E_i and O_i are $E_i(d_i)=f_\varepsilon(d_i,r_i)f_r(d_i)$ and $O_i(d_i)=f_o(d_i,r_i)f_r(d_i)$, respectively. $E_i(d_i)$ represents the empty degree of the detected area, and $O_i(d_i)$ represents the occupied degree of the area.

If a single grid cell C is monitored by a group of sensor, then the empty fuzzy set E and occupied fuzzy set O for C are the union of E_i and O_i, respectively.

$$E=\cup_i E_i \quad (4)$$

$$O=\cup_i O_i \quad (5)$$

Now, we can get the safe area and unsafe area from E and O. The ambiguous area in the cell C is defined as:

$$A=E\cap O \quad (6)$$

The indeterminate area is defined as those neither empty nor occupied:

$$I=\overline{E}\cap\overline{O} \quad (7)$$

The safe area is defined as:

$$S=E^2\cap\overline{O}\cap\overline{A}\cap\overline{I} \quad (8)$$

E^2 means "very empty". The unsafe area is defined as:

$$U=\overline{S} \quad (9)$$

After the safe and unsafe areas being defined for a single grid, the global fuzzy map can be constructed.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

A simulation test is set up to build the global fuzzy map. The experimental area is a square of $5m\times 5m$. Each grid is $0.25m\times 0.25m$ and is marked a unique ID as shown in Fig. 7. Each grid is monitoring by a group of 4 ultrasonic sensors. k_ε is set to 0.15; k_o is set to 0.25; the sensor reading radius is set to $0.3m$; Δr is set to $0.15m$ and d_v is $1.2m$. The sensor sends the collected data back to central control device. We put obstacles in grid 2, 21 and 22. Fig. 8 shows the standard occupancy grids map that generated by central control device. Since the standard occupancy grids method use binary structure, a grid that partly covered is still considered as fully occupied. Fig. 9 shows that some safe area is between grid 21 and grid 22. If the robot's body is smaller than the width of safe area, it still can pass grid 22.

The second test is to prove that our proposed method can solve the global navigation problem. In fig. 10, the robot is asking to navigate from grid 1 to grid 121 in time point t_1. There is no obstacle in time t_1, and we assume that the best way is go straight from grid 1 to grid 121. Fig. 11 shows that a set of dynamic obstacles appear In time t_2 , and the robot is in grid 41 at that time. The robot that its sensing ability is limited by its sensors may not detect the obstacles until it gets into the grid 101. If this happens, the robot needs to go back to grid 61 to choose another way to the goal. However, the proposed fuzzy map is generated in real time mode, the central control device understands the newest global environment and can send signal immediately to guide the robot to another navigation path.

The above two experiments show that the proposed fuzzy map is more practical especially in a larger indoor environment. Though the maps generated based on probability theory also gain lots success, the fuzzy sets concept provides a more comprehensive and easier way to construct the application model.

V. Conclusions

The autonomous robot needs to understand environment where the robot is navigating. There are many researches proposed map building methods to solve the problem. Generally speaking, most of them use probabilistic model to build maps, and global navigation problem is also solved based on probabilistic model. However, there is no research using fuzzy set concept cooperated with a wireless sensor network to build a global map. In this study, environment is divided into grids and a group of sensor is monitoring a single grid. The sensors work as a team and send the collected data back to the central control device to generate the fuzzy map. Thus, the robot is not necessary to be sophisticated. The experiments show that the fuzzy map is more practical. Since our research is focus on the map generated, the other issues for robot navigation such as sensor communication and path planning are assumed to work well with the fuzzy map generating. In order to make a more robust navigation system, the next step is to develop an optima path planning algorithm that is very suitable for the fuzzy map.

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References

[1] A. Amditis, A. Polychronopoulos, N. Floudas and L. Andreone, "Fusion of infrared vision and radar for estimating the lateral dynamics of obstacles," *Information Fusion*, vol. 6, pp.129-141, June 2005.

[2] M. A. Batalin, G.S. Sukhatme and M. Hattig, "Mobile robot navigation using a sensor network," *Proc. IEEE International Conference on Robotics and Automation*, New Orleans, LA, vol. 1, pp.636-641, April 2003.

[3] J.A. Castellanos, J.M.M. Montiel, J.Neira, J.D.Tardos, "Sensor influence in the performance of simultaneous mobile robot localization and map building," *Experimental Robotics IV*, Springer-Verlag, pp.287-296, 2000.

[4] G. Dissanayake, H. Durrant-Whyte, and T. Bailey, "A computationally efficient solution to the simultaneous localisation and map building (SLAM) problem," *Proc. IEEE International Conference on Robotics and Automation*,. Albuquerque, USA, pp.1009-1014, April 2000.

[5] M.W.M.G. Dissanayake, P. Newman, H.F. Durrant-Whyte, "A solution to the simultaneous localization and map building problem," *IEEE Transactions on Robotics and Automation*, vol. 17, no. 3, pp.229-241, 2001.

[6] A. Elfes, "Occupancy grids: A stochastic spatial representation for active robot perception," *Proc. Conference on Uncertainty in AI*, Los Alamitos, CA, USA, pp.60-70, July 1990.

[7] J.-S. Gutmann and K. Konolige, "Incremental mapping of large cyclic environments," *Proc. International Symposium on Computational Intelligence in Robotics and Automation*, Monterey, CA, USA, pp.318-325, Nov. 2000.

[8] D. H¨ahnel, D. Schulz, and W. Burgard, "Map building with mobile robots in populated environments," *Proc. IEEE International Conference on Intelligent Robots and Systems*, Lausanne, CH, USA, pp.496-501, October 2002.

[9] C. Martin, E. Schaffernicht, A. Scheidig and H.-M. Gross, "Multi-modal sensor fusion using a probabilistic aggregation scheme for people detection and tracking," *Robotics and Autonomous Systems*, vol. 54, issue 9, pp.721-728, September 2006.

[10] G. Oriolo, G. Ulivi, and M. Vendittelli, "Fuzzy maps: A new tool for mobile robot perception and planning," *Journal of Robot System*, vol. 14, no. 3, pp.179-197, 1997.

[11] A. Saffioti, "The uses of fuzzy logic in autonomous robot navigation : a catalogue raisone," *Soft Computing*, vol. 1, no. 4, pp.180-197, November 1997.

[12] C. Stachniss and W. Burgard, "Mapping and exploration with mobile robots using coverage maps," *Proc. IEEE International Conference on Intelligent Robots and Systems*, Las Vegas, NV, USA, pp.476-481, October 2003.

[13] Z. Yi, H.Y. Khing, C.C. Seng, and Z.X. Wei, "Multi-ultrasonic sensor fusion for mobile robots," *Proc. IEEE Intelligent Vehicles Symposium*, Dearborn, MI, USA, pp.387-391, October 2000.

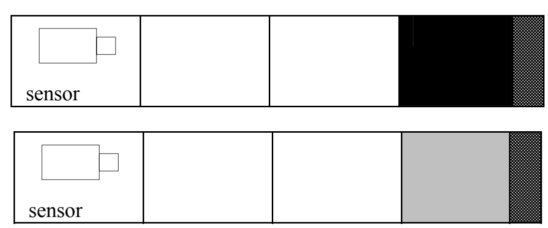

Figure 1. The right handest grid is partly covered by an obstacle. However, the top map that made by occupancy grids method consider that grid fully occupied. The lower one is a better approximate of the true situation.

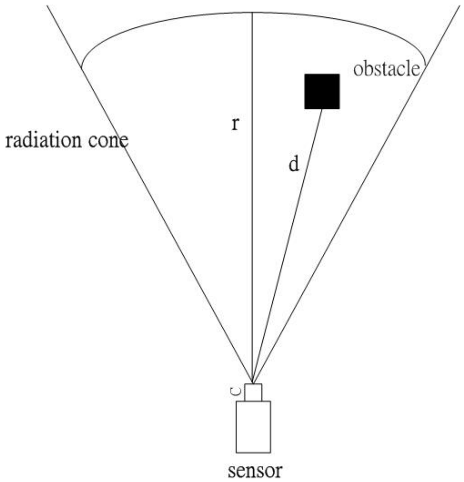

Figure 2. The sensor radiation cone. An obstacle is inside the radiation cone.

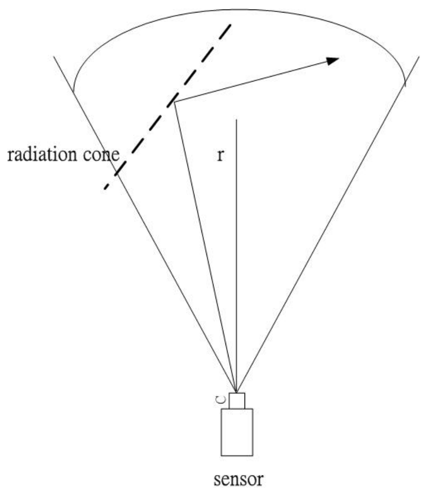

Figure 3. Multiple reflections may occur in this figure.

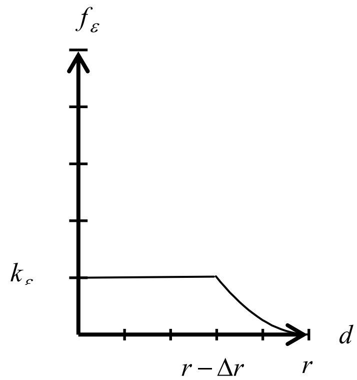

Figure 4. The fuzzy member function for f_ε.

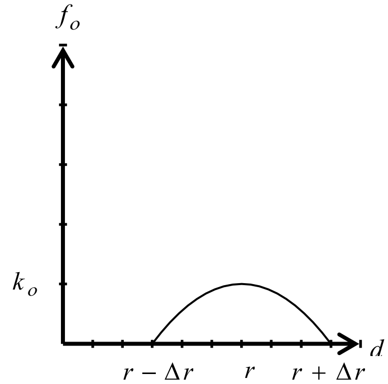

Figure 5. The fuzzy member function for f_o.

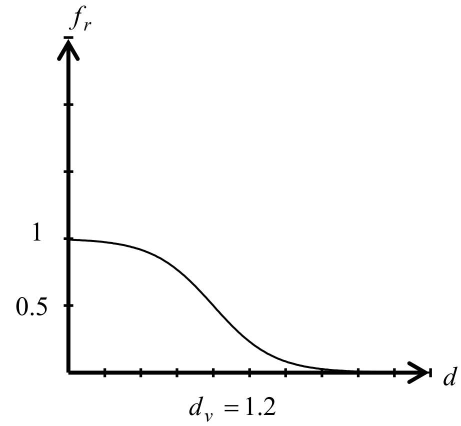

Figure 6. The radial modulation function.

1	2	3	…	…	20
21	22	23	…	…	40
41	42	43	…	…	60
…	…	…	…	…	…
…	…	…	…	…	…
381	382	383	…	…	400

Figure 7. The entire environment is 5mX5m, and each grid cell is 0.25mX0.25m. Each grid is monotering by 4 sensors. The sensor is put on the vertex of the grid. There are obstacles in grid 2, 21, and 22.

1	2	3	…	…	20
21	22	23	…	…	40
41	42	43	…	…	60
…	…	…	…	…	…
…	…	…	…	…	…
381	382	383	…	…	400

Figure 8. The environment map that generated by standard occupancy grids method. If a robot is in grid 1, it will find itself no way to go out.

1		3	…	…	20
		23	…	…	40
41	42	43	…	…	60
…	…	…	…	…	…
…	…	…	…	…	…
381	382	383	…	…	400

Figure 9. The fuzzy map shows that the safe area (in light grey color) still exists in grid 2, grid 21 and grid 22. The dark grey area is considered as unsafe area.

1	2	…
21	22	…
41	42	…
61	62	…
81	82	…
101	102	…
121	122	…
…	…	…

Figure 10. There is no obstacle exists in entire environment at time t_1. The best path for robot navigation from grid 1 to grid 121 is shown in figure.

1	2	…
21	22	…
41	42	…
61	62	…
81	82	…
101	102	…
121	122	…
…	…	…

Figure 11. The obstacles appear .in time t_2. The robot is in grid 41 at that time and it may not dectect the obstacle until it goes into grid 101 if the robot use local map. In this case, the robot only goes back to grid 61 to choose another way to go.