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A Robust Algorithm for Local Obstacle Avoidance

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***Abstract*— This paper concerns with real-time local obstacle avoidance for mobile robots. We use probabilistic clearance approach to avoid obstacles efficiently and for sharper turning and more time for the navigator to detect additional nearby obstacles. A combination of probabilistic clearance matrix with a Gaussian weighing is used to overcome sudden increase in probabilistic clearance value, which is mainly because of errors in the reading due to low-cost sensors such as the ultrasonic proximity sensors, thus making the algorithm suitable for developing low cost navigators as well. Before taking any decision for movement, the algorithm takes into consideration the nearby environment also for better results. The algorithm is designed in such a way that the navigator chooses a path having less number of obstacles thus reducing the probability of collision to a very high extent.**

The Algorithm has been successfully implemented and extensively tested on an autonomous robot at Delhi College of Engineering, India.

***Index Terms*— Gaussian, Probabilistic Clearance, Navigator, Obstacle Avoidance**

I. Introduction

Obstacle avoidance is in itself a challenging field of Robotics and the most basic requirement of any autonomous navigator. While talking about an autonomous navigator we are concerned about its real time capabilities. A navigator should be robust enough to avoid obstacles efficiently in real time to avoid any undesired collision. Just avoiding an obstacle is not enough but avoiding it smoothly and efficiently in both indoor and outdoor environment is what is needed. We are interested in high speed operation of outdoor and indoor mobile robots for various applications. The main problem behind autonomous navigation is detecting and locating obstacles and steering between the obstacles efficiently. Here we consider issues related to collision avoidance while navigation so that a robot can avoid obstacles in front of it in sufficient time.

Real time collision avoidance for mobile robots is an interesting concept, and a large number of methods have been developed for different applications. In case of indoor robots, they move at speeds where we do not bother about the dynamics of the robot [3]. The remarkable methods for these kind of robot navigation are Borestein and Koren's Vector Field Histogram (VFH) [7][8], dynamic window approach [6] and the curvature lane approach [4]. Fajen and Warren have proposed a model for obstacle avoidance by humans [5] which was again modified by Hammer et al [3].

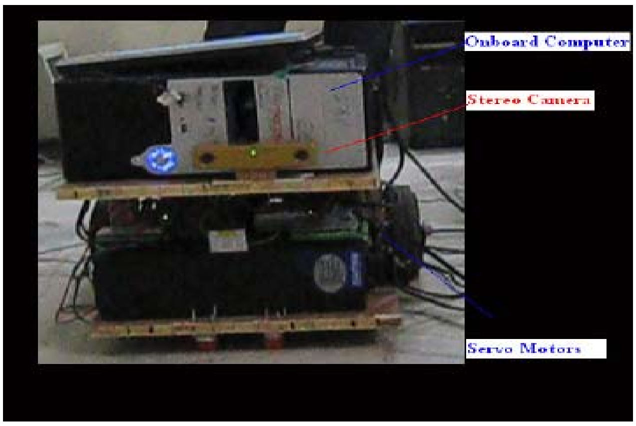
Puneet et al [1] proposed a probabilistic clearance approach which takes into account the effective clearance value which in turn is a function of relative angle with respect to the present heading and the distance of the obstacle for each region. The sector with the highest value of probabilistic clearance is decided as the destination sector. The approach successfully avoids obstacles in real-time but the major drawback of this algorithm is that due to its greedy approach it succumbs to isolated high values which are generally erroneous readings or undesired calculated values. Here we present a solution for this problem by using a modified form of Gaussian weighing function. The proposed approach incorporates the probabilistic clearance values of the neighboring sectors in order to avoid traps due to sudden rise in the clearance value.

The paper is organised as follows. Section II explains and critically analyses the previous approach. It also explains the new approach along with the different weighing functions. The results are discussed in section III while the last section gives the references

II. The description

A. System Architecture

The algorithm proposed has been successfully tested on an autonomous robotics platform at Delhi College of Engineering, India. We used PGR library and Intel OpenCV Library along with Microsoft Visual Studio for programming. The robot is equipped with Ultrasonic Sensors, Stereo Vision Camera, Laser Range Finder and GPS.



B. The algorithm

Taking range data in the form of (r, theta), we can calculate the probabilistic clearance value [1] of a particular sector using following equation:

$$P_i = \frac{(\boldsymbol{Ri})^{\alpha}\ (|\cos(\boldsymbol{\theta i})|)^{\beta}}{\sum_{j\epsilon\Omega} (\mathbf{Rj})^{\alpha}\ \ (|\cos(\boldsymbol{\theta i})|)^{\beta}} \qquad (1)$$

Where, $\mathbf{P}_i$ is the probabilistic clearance value of the ith sector, $\boldsymbol{Ri}$ is the range value of ith sector, $\boldsymbol{\theta i}$ is the angle of the ith sector with respect to heading of the robot and $\boldsymbol{\Omega}$ represents the set of all sectors. $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ represents the tuning parameters. Here the forward movable area is divided into n angular sectors each of width φ such that n= 180/φ.

Here the probabilistic clearance value is calculated for each sector using the effective coordinate and alignment values. The sector with the maximum range and least angular separation to the robots heading is supposed to be the sector with the highest probability clearance. The robot at each step then moves to the sector with highest probability clearance. In spite of the simplicity of this algorithm it works efficiently in many real-world scenarios. But an inherent drawback of the algorithm is its greedy approach. At each step, it moves to the region with highest probability clearance without any thought of the clearance in neighboring sectors. This increases the chance of collision due to two major factors, (1) an isolated high probabilistic clearance value which is actually due to a noisy data that is received from the sensor, (2) the navigator finally reaches an environment dense with obstacles and avoids an alternate path having lesser obstacles.

The above said problem can be explained mathematically as follows: Consider the following Probabilistic clearance value P(x) versus sectors graph:

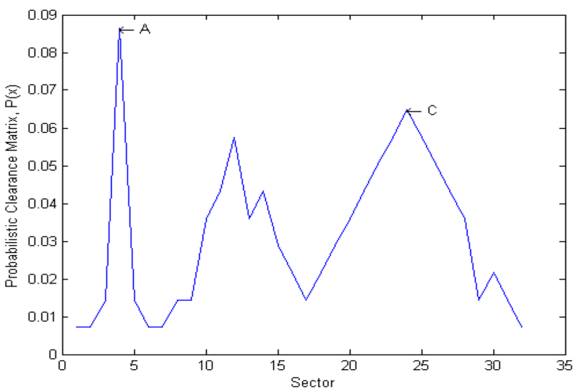


Fig 1

As is clear from the graph, P(x) has a maximum value at the fourth sector i.e. point A. Using the earlier approach [1], the robot will choose this as the destination sector. Although it is easy to tell that the robot should navigate to sector 24 where although P(x) is slightly less but its neighbors have high probability clearance and hence the robot is in a clear and safe area.

Another problem is that when ultrasonic sensors are used on the robot, there is a high chance of getting erroneous readings [2]. Since P(4) i.e. point A, is an isolated high value, it might be that it is an error.

To overcome the above said problems we need to take into account the probabilistic clearance of the neighboring sectors while calculating the probabilistic clearance of a particular sector. In this approach first of all the probabilistic clearance matrix is calculated using equation 1. Then the value of P(x) is modified in accordance with the value at its neighbors (x-1), (x+1), (x-2), (x+2) and so on to obtain modified probabilistic clearance matrix Q(x). To obtain sector values of this modified matrix, we take weighted average of the original matrix with a weighing function Gxi(x) centered at sector xi. In a nutshell, we calculate new probabilistic clearance value for a particular sector by taking a weighted average of values of the neighborhood sectors. Mathematically, it is represented as:

$$Q(xi) = \sum_{x=0}^{n} P(x) * Gxi(x) \qquad (2)$$

$$Q(x) = \sum_{xi=0}^{n} Q(xi) \qquad (3)$$

Here, Gxi(x) denotes the value of weighing function at point x when it is centered at point xi.

C. Weighing Function

The novelty in the new improved approach is the introduction of a Weighing function. As is clear from the last section, the desired properties of the weighing function Gxi(x) are:

1) The weighing function Gxi(x) denotes the weight at point x for the function centered at point xi.
2) The weight/value of the function at a point should depend on the Euclidian distance of the point from its center.
3) The value should be unity at the center and should decrease with an increase in distance. The value being approximately zero for points at large distances.
4) Equidistant points should have equal weights. Hence the value of the weighing function at points (x+t) and (x-t) should be same.

Considering these factors, a modified Gaussian function in one-dimension is found to be the best option. It is represented mathematically as:

$$Gxi(x) = \exp(-(x - xi)^2) \qquad (4)$$

It is centered at (xi) and equals unity at the center. Also for sufficiently large Euclidean distance of point (x) from point (xi), the function approximately equals zero. Some of the values of this function are:

$$\exp(-1) \approx 1.0000$$

$$\exp(-4) \approx 0.3679$$

$$\exp(-9) \approx 0.0183$$
$$\exp(-16) \approx 0.0001$$
$$\exp(-25) \approx 0.0000$$

Hence it is found that,

$$Gxi(x) \approx 0, \ when \quad (x - xi) > 4$$

It possesses all the required characteristics but, there are many more functions which satisfy these criteria. Some of them are as follows:

$$Gxi(x) = \frac{a}{(x-xi)^k + a} \quad (5)$$

$$Gxi(x) = 1 + (x - xi)^{-k} \quad (6)$$

$$Gxi(x) = \frac{1}{(1+(x-xi))^k} \quad (7)$$

For sample, probabilistic clearance matrix P(x), corresponding modified probability clearance matrix Q(x) is obtained. Out of various weighing functions, the Gaussian function is the best suited. Only Gxi(x) = 1/(1+(x-xi)^2) comes close to the Gaussian function as is clear from the figure 2, but this function decreases very slowly in comparison to the Gaussian function and hence gives a significant weight to even far-off neighbors. This is computationally extensive as well since a lot of neighbors are considered. For Gaussian function, not more than 4 neighbors on either side are taken into consideration as explained above.

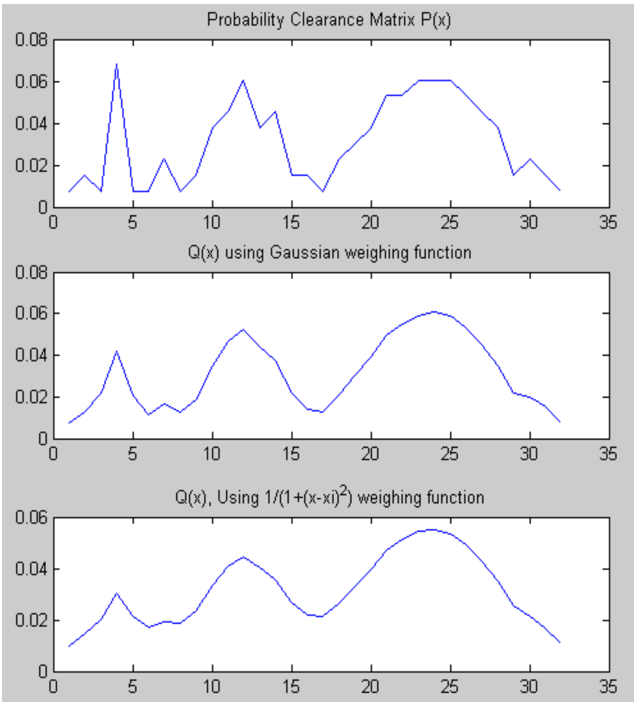


Fig 2

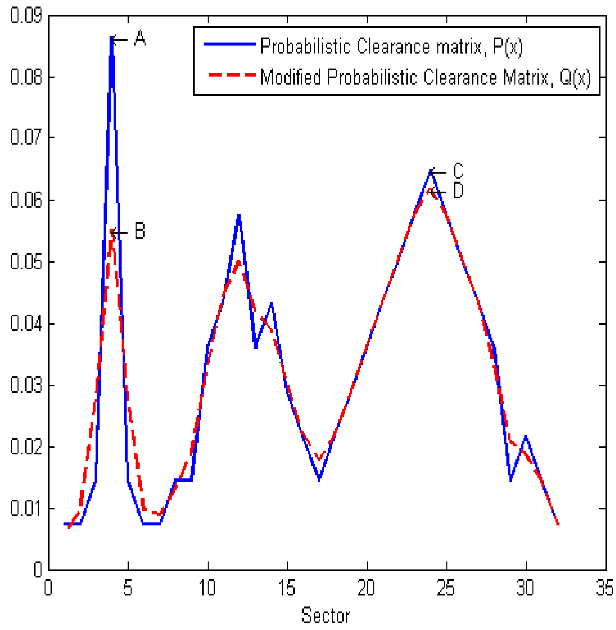
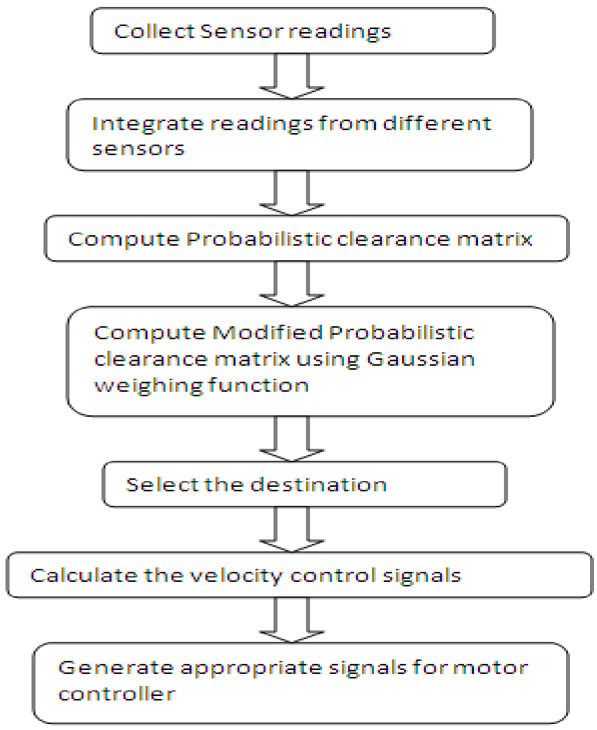


Fig 3

In figure 3, solid blue color line graph represents the probabilistic clearance graph using the previous approach [1] and broken red color line graph represents the probabilistic clearance graph using the proposed approach. Clearly, in the modified probabilistic clearance matrix Q(x), obtained after using Gaussian weighing function, the effect of an isolated high peak at point A in P(x) has been reduced to point B and now the point D has the highest value showing the destination sector as the sector number 24 which is the most suitable sector for the movement of the navigator.

D. *The Flow Chart*



Flowchart

III. Conclusions And Results

The proposed approach has been successfully implemented and tested on an autonomous robot– an Unmanned Ground Vehicle at Delhi College of Engineering, India. This approach effectively avoids all obstacles in real time. An added advantage from the last approach is that apart from just avoiding obstacles, it also finds itself in a clear and safe environment. This advantage is particularly useful in case of dynamic obstacles. If the robot maneuvers very close to obstacles then there is a high probability that if the obstacle shifts even slightly, it will collide with the robot.

Also, the robot responds to a cluster of high probabilistic clearance value while ignoring single (possibly erroneous) data points. This prevents the robot to be trapped due to positive peaks depicting sudden clearance in environment, which is effectively due to noise in sensor data.

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References

[1] Puneet Kumar, Neha Kumari, Shivangi Srivastava, "Probabilistic approach for Autonomous Navigation using Stereo Vision," *The proceedings of the 2009 International Conference on Software technology and Engineering*, indexed by world scientific, ISBN-13 978-981-4289-97-9 (pbk), pp184-188.
[2] J. Borenstein, Y. Koren, "Obstacle Avoidance with ultrasonic sensors," *IEEE Journal of Robotics and Automation*, Vol. RA-4, No. 2, pp. 213-218.
[3] Bradley Hamner, Sanjiv Singh, and Sebastian Scherer, "Learning obstacle avoidance parameter from Operator Behavior," *Journal of Field Robotics* 23(11/12), 1037-1058(2006), Wiley Inter science.
[4] R. Simmons, "The curvature velocity method for local obstacle avoidance," *IEEE International Conference on Robotics and Automation*, Minneapolis, MN, April 1996.
[5] B. Fajen, W. Warren(2003), "Behavioral dynamics of steering, obstacle avoidance, and route selection," *Journal of experimental psychology: Human perception and Performance*, 29(2), pp. 343-362.
[6] D. Fox, W. Burgard, S. Thrun, "The dynamic window approach to collision avoidance," *IEEE Robotics and automation Magazine* 1997, 4(1), pp. 23-33.
[7] J. Borenstein, Y. Koren, "The vector field histogram – Fast obstacle avoidance for mobile robots," *IEEE Journal of Robotics and Automation* Vol 7, No 3, June 1991, pp. 278-288.
[8] J. Borenstein, Y. Koren, "Motion Control Analysis of a Mobile Robot," Transactions of ASME, *Journal of Dynamics, Measurement and Control*, Vol. 109, No. 2, 1987, pp. 73-79.

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