Journal of Applied Sciences

ISSN 1812-5654

Journal of Applied Sciences 13 (21): 4749-4753, 2013
ISSN 1812-5654 / DOI: 10.3923/jas.2013.4749.4753

A New Local Path Planning Approach for Mobile Robot with Blind Zone

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Abstract: Path planning for mobile robot with blind zone, caused by limited sensing capability, is a difficult and practical problem, from which most local path planning approach is suffering. In this study, entry point has introduced to represent the free road which may guide the robot to find the gaps between obstacles. So that, the priory detected free road which has fallen in to blind zone, could be memorized and a new local path planning approach is proposed. By the memorizing, the historical sensor information, is infact partly memorized. By tracking the entry point in blind zone and estimating the probability distribution using uncented kalman filter, the influence of blind zone is reduced. All entry points are then evaluated using a evaluate function. So that both the current sensor information and the historical sensor information are making used. Compared with the traditional local path planning approaches, this approach avoid the trap problem and the hover problem came with the blind zone. Simulations have proved the effect.

Key words: Mobile robot, local path planning, free road, blind zone

INTRODUCTION

Benefit from the mobility, mobile robot shows great potential market in many fields like industry, discovery and service. However in practice, it is often the case that robot has to work in unknown environment with limited sensing ability and the blind zone which can not be covered by the sensors, exists. So path planning with blind zone in unknown environment should be fully considered.

Path planning is focus on leading the robot to its destination in an optimal and safe way. Many researches focus on this area, thus several groups of techniques have been proposed. According to the information relied on, the exiting techniques would be divided into three types: global path planning, local path planning and hybrid path planning.

Generally, Global path planning plan a path relies on a "map" which are extracted from the environmental information(Meyer and Filliat, 2003). Typically, the "map" includes the following types: Voronoi diagram (Bhattacharya and Gavrilova, 2008), regular grid, generalized cones, quad-tree, vertex graph, road map (Bhattacharya and Gavrilova, 2008) and Visibility Graph (Lozano-Perez and Wesley, 1979). With the "map", the global path planning then employ a path finding algorithm to finish the planning task. Some most popular path finding algorithm including: graph searching algorithms like A*, D*, D*lite (Sun *et al*., 2010), intelligent optimization algorithms like genetic algorithm (Manikas *et al*., 2007), particle swarm optimization (Saska *et al*., 2006), ant colony system (Garcia *et al*., 2009) and sampling-based algorithms (Bhattacharya and Gavrilova, 2008). Most path finding algorithms are capable to survey the whole "map", thus most global path planning approaches are capable to find the most optimal path. How ever, the survey is time-consuming and prior knowledge of the environment is essential. Consequently, the adaptability of most global path planning approaches to unknown environment in reality is poor.

In contrast, local path planning only rely on the environmental information around which are generally provided by the sensor on board. Several classical approaches have been proposed. The Potential Field approach (Khatib, 1986) developed by Khatib which benefit from its simpleness, may be the most popular one. It guides the robot move along the gradient of a potential field where the obstacle repulses the robot while the destination attracting it. The VFF (Virtual Force Field) and VFH (Vector Field Histogram) (Ulrich and Borenstein, 2000) approaches developed by Borenstein *et al.* (200) improved the performance in narrow valley and decreased the probability of falling into local minimal. The fuzzy logical control methods (Wang and Liu, 2008) guide the robot using driving experience of human being. They proposed some good performance and are easy to be applied. The dynamic window approach, developed by Fox *et al.* (1997), controls the motion of the robot according to its driving ability and the influence of the obstacles. So that, the motion command proposed by the dynamic window approach is feasible and safe. In general, local path

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plannings are efficient enough to be executed online while only sensor information is needed. Thus, these approaches proposed good ataptability in unknown or changing environment.

Both the two aforementioned types of path planning approaches have their own strong points and weak points. Thus the hybrid path planning approaches (Chang and Yamamoto, 2008), combined both of them, are developed. Most of these approaches can be classifed into two types based on the combination method. The sub target based approaches (Chang and Yamamoto, 2008), guide the local path planning using a subtarget chosen from a global path. The behavior based approaches (Tarokh, 2008), treat the results of its two path planning modules as a behavior. Then the the final behavior of the robot could be incorporated from the global behavior and the local behavior. Hybrid path planning obtains moderate adaptability to the environment, benifit from the local path planning part. However, they still relies on both the map and the localization which are difficult to be got in unknown environment.

As stated, in unknown environment, local path planning is a proper kind of choice. However, most of the traditional approaches have not fully considered the blind zone. As a result, the priory selected motion target would be immediately abolished while it has been fallen in to blind zone. Thus, in this study, we discuss a local path planning approach to navigate the robot with blind zone, in unknown environment, where neither the map nor the localization information is available.

PROBLEM STATEMENT

Let's mount a coordinate system on the robot where the orientation of the robot is 90°, counter-clockwise is the positive direction. Assuming the robot is moving in an unknown environment with neither the map nor the localization of itself is available. More than that, it can only detect objects located in a specific area whose angle covers a specific range (i.e., SICK laser ranger finder can only cover 0~180 degree).Assuming the robot can cover 0~180 degree, then the area whose angle covers 180~360 degree is a blind zone. Traditional local path planning approaches were not designed for such blind zone. So, they are more likely to be trapped or hovered while blind zone exits.

Assuming differential driven robot is used. For commonly used sensors like sonar, camera etc., they are impossible to observe through obstacles, so several assumptions are made as follow:

- The robot is treated as a point-like differential droved vehicle while the obstacles are enlarged by safe range
- The location of the destination is always available which is $Ta(r_T, \phi)$. The sensor can provide information of obstacles enlarged by a safe range, as: O_i $(r_{oi}, \phi_{oi}, \phi_{i1} \phi_{ir},)$

PATH PLANNING APPROACH

Free road and entry point: For more efficiency, the information needed in path planning is expected to be compressed.

Definition 1: Free road is a radial which dose not intersect with any obstacle region, or two obstacle regions are intersect on it but their least distance are differed so much, that the robot is capable to travel through between them.

Definition 2: Entry point denoted by $F(r, \phi)$ is a point on a free road which are both nearest to the boundary point of the obstacle region near by and to the robot. r, ϕ are the polar coordinates of F.

Definition 3: Entry point probability denoted by P is the probability of a specific location to be an entry point.

The area in the coordinate system, covered by the sensors, is called unblind zone. For a blind zone, some parts may be detected before while the others may not be. So the undetected parts are called undetected areas while the detected parts are called memorized areas. The entry points in the memorized area are memorized. Figure 1 shows the blind zone which include two memorized areas.

In an unblind zone, points can only get two entry point probability: The minimal probability 0, the max probability $P_{max}(P_{max} = 1)$. The point in obstacle region will get $P = 0$ because it is impossible to found an entry point in an obstacle region. The point in free space will get P_{max} because it is very possible to find one there. For a point in an undetected area, it is unable to decide the entry point probability, thus we set it to a little value P_b. For a point in a memorized area as it has been detected, we can evaluate the possibility according to the historical sensor data. Considering the case shown in Fig. 2, on time t-1, the pose of the robot is implied by the coordinate system R_{t-1} and the entry point $F_{t-1}(r_{t-1}, \phi_{t-1})$ is also found there. On time t the pose of the robot has changed to R_t and the coordinate of F_{t-1} in R_t has been changed to $F_t'(r_t', \phi'_t)$ which is estimated according to the Eq. 1. In Eq. 1, x', y_t' are the Cartesian coordinates of F_t' which can be calculated according to Eq. 2. In Eq. 2, x_d, y_d are

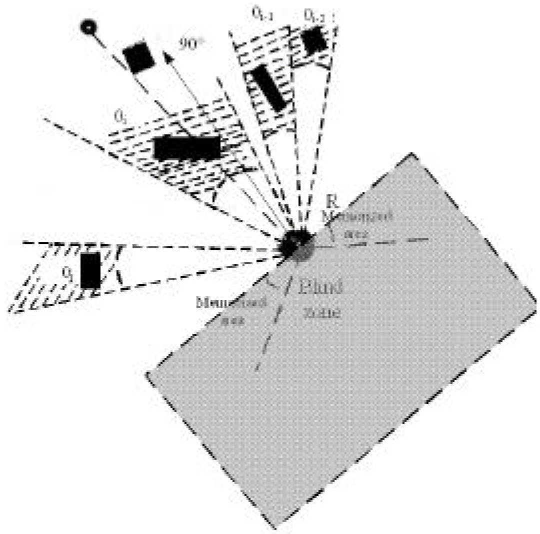

Fig. 1: Robot and its detection to the environment

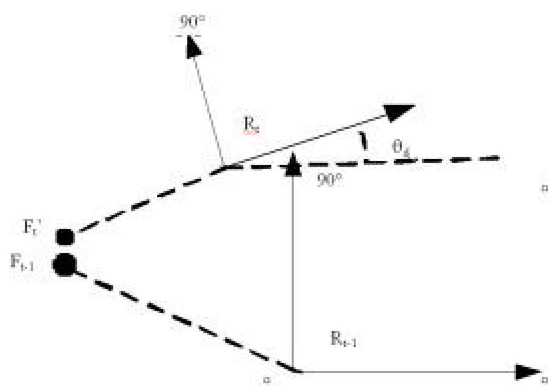

Fig. 2: Estimation of the entry point

coordinates of the origin point of R_t in the coordinate system R_{t-1}. θ_d is the deflection angle of R_t refers to R_{t-1}. x_d, y_d, θ_d can then be calculated according to the moving distances of the left and right wheel separately:

$$r_t' = \sqrt{x_t' + y_t'} \qquad \phi_t' = \text{atn}(y_t', x_t') \tag{1}$$

$$\begin{pmatrix} x_t' \\ y_t' \end{pmatrix} = \begin{pmatrix} \cos\theta_d & \sin\theta_d \\ -\sin\theta_d & \cos\theta_d \end{pmatrix} \left(\begin{pmatrix} x_{t-1} \\ y_{t-1} \end{pmatrix} - \begin{pmatrix} x_d \\ y_d \end{pmatrix} \right) \tag{2}$$

Unfortunately, with the travel length of the robot growing, the entry point probability of F_t is gradually decreased because of many factors in reality (like the noisy encoder information). Let $\tilde{F}_t \sim N(F_t', \delta_{Ft})$ denote the entry point probability of F_t conforming to a Gaussian disstribution whose expectation is F_t' and the variance is δ_{Ft}. Let $\tilde{u}_t \sim N(Ut, du)$ denotes the odometer information polluted by control noise where U_t is the expectation, $\ddot{a}_u$ is the variance. Let the Gaussian noise $\tilde{Q}_{t-1} \sim N(0, dQ)$ denotes the error in the estimation. Then a prediction model as shown in Eq. 3 could be established:

$$\tilde{F}_t = f(\tilde{F}_{t-1}, \tilde{u}_k) + \tilde{Q}_{t-1} \tag{3}$$

In Eq. 3, the function f() is composed of the Eq. 2. Then uncented kalman filter (Jargani *et al*., 2009) could be applied to estimate the distribution of $\tilde{F}_t$ and also the probability of F_t'.

Free road searching: A so called "free road ϕ" implies that the angle of the free road is ϕ, so does the "entry point ϕ". A "best free road ϕ_S"is the best one, we are searching, whose angle is ϕ. If the destination is located on a free road, then it is nature to choose $\phi_S = \phi_T$, otherwise a searching step is needed. As the following shows, the searching process is divided into several parts:

- Search for the best free sector in the unblind zone, find the free road candidates (I = 1, 2...) (Gao and Sun, 2009)
- For all candidate free roads , their entry points F_i and the entry point possibilites P_i could be found according to Eq. 3
- For entry point F_i in blind zone, it could be estimated according to the Eq. 2. The entry possibilities can then be calculated according to Eq. 3
- Evaluate all entry points and search the best free road using Eq. 4. Then the best free road is the one the best entry point belongs to

An entry point is in fact represents a free road and its entry position. The best entry point belongs to the best free road. For an entry point F(r, ϕ), we introduce a evaluate function as Eq. 4 shows. Here, ϕ is the angle of the entry point to be evaluated. P is the entry point possibility of F. ϕ_{st-1} is the angle of the best free road found in one time step before. $\Delta(\phi_1,\phi_2)$ is a function that computes the absolute angle difference betweenand. The three weights k_1, k_2, k_3 decide the priority of three requirements they are: The goal oriented behavior requirement, motion commit to current orientation requirement, motion commit to previous selection requirement. In the following simulations, they are 0.5, 0.2, 0.2. The best entry point is the one gets the minimal evaluation which implies it get the maximum entry possibility while it satisfied the three requirements stated above best:

$$\text{cost}(\phi) = [k_1\Delta(\phi, \phi_T)+k_2\Delta(\phi, \phi_{st-1})+k_3\Delta(\phi, 90)](1-P) \quad (4)$$

SIMULATION STUDY

In this section, we have created a 3D environmental model according to our laboratory and the simulation software "webots" is used. As assumed, the robot in simulation can only detect the objects located in the unblind zone whose angle covers 0~180 degree and the distance is less than 8 m. The bird view of the environmental model is showed in Fig. 3. The robot was initially located at a point S and tried to reach the destination Ta while there were four boards stand between S and Ta.

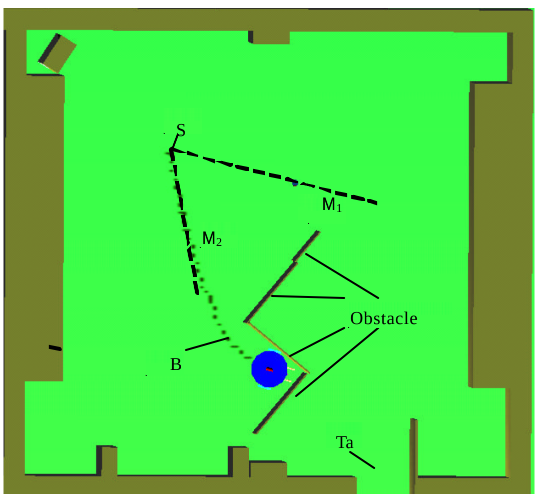

Fig. 3: With VFH+, treat the blind zone as obstacle region

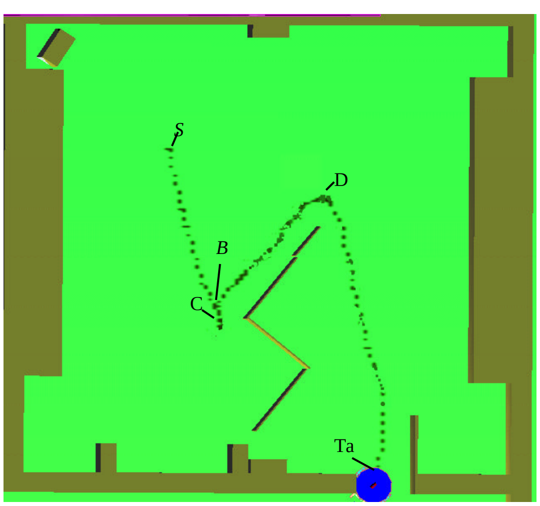

Fig. 4: Simulation with the proposed approach

VFH+ is a rapid, effective and widely used approach. So it's chose to compare with the proposed approach. However, VFH+ has not considered the blind zone. Thus we treat the blind zone as free space for VFH+. The simulation result has shown in Fig. 3, where the black dots denote the track of the robot.

At the begging of all the simulations, the robot is located at S and it has found two candidate free roads andas the dashed line shows. The robot then chose as the best free road. In Fig. 3 the robot has then failed to find free road while it moved to the point B and the robot is out of control and collision happened.

Figure 4 shows a simulation with the proposed approach. Similarly, at the begging, the robot has chose as the best free road and moved to the point B. But as the entry point of the free road has already been memorized, the robot will turned back and moving towards the entry point around the point C. Finally, the robot moves around the point C and successfully achieved Ta.

CONCLUSION

In this study, a local path planning is proposed which focused on the situation that blind zone exists. By introducing entry point, the free roads may be memorized. By using a unscented kalman filter, the entry point probability can then be calculated. So that, the error in estimating the entry point in memory could then be considered. By using a evaluate function, the best entry point could then be found. Compared with traditional local path planning approach, the historical sensor information is considered. Benefit from that, the proposed approach can avoid the robot to be trapped or be hovered.

ACKNOWLEDGMENTS

This project was supported by the Special Funds for Basic Scientific Research of Central Colleges, Chang'An University (CHD 2011JC176, CHD2011JC105, CHD2011 TD-15), China Postdoctoral Science Foundation (2013M 531999) and the National Natural Science Foundation of China (51108040).

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