Inteligencia Artificial 17(53) (2014), 13-23

INTELIGENCIA ARTIFICIAL

http://journal.iberamia.org/

Autonomous navigation with deadlock detection and avoidance

Guido M. Sanchez[1,2,3], Leonardo L. Giovanini[1,2,4]

[1]Center for Signals, Systems and Computational Intelligence, Faculty of Engineering and Water Sciences, Universidad Nacional del Litoral, Santa Fe, Argentina

[2]National Council for Scientific and Technological Research, Argentina

[3]gmsanchez@conicet.gov.ar

[4]lgiovanini@fich.unl.edu.ar

Abstract This paper studies alternatives to solve the problem of autonomous mobile robots navigation in unknown indoor environments. The navigation system uses fuzzy logic to combine the information obtained from range sensors and the navigational data to plan the robot's movements. The strategy is built upon five modules: *i)* target following, *ii)* obstacle avoidance, *iii)* possible path, *iv)* deadlock detection and *v)* wall following. Given a possible path and obstacles near the environment of the robot, the controller will modulate the output velocity in order to go to the target and avoid collisions. In case of dead lock situations, a method that enables the robot to detect, escape and reach the target is proposed. The performance and behavior of the proposed navigational system was evaluated through simulations in different conditions, where the effectiveness of the proposed method is demonstrated and compared with previous results.

Keywords: autonomous navigation, deadlock detection, fuzzy logic.

1 Introduction

One of the main objectives in mobile robotics is the design of autonomous robots: robots that can be told what to do without having to tell them how to do it. A major challenge faced by such robots is to make sure that their actions are executed correctly and reliably, despite the dynamics and inherent uncertainty of the working space.

A possible solution to this problem is to combine both path planning and path tracking, this approach is known as *motion planning with complete information*. This method requires to know the environment before the motion starts and then the algorithm transforms this information into proper motion trajectories. Li et al. [9] uses a genetic algorithm for optimum path planning, focusing on the shortest distance criterion. Several other optimization methods have been developed to solve the optimum path-planning problem [4, 8, 13, 16, 22]. While this approach is well suited for structured environments, cannot be used in any real world situations, mainly because sometimes objects cannot be described or because one doesn't know which object is going to be where and when.

If the robot has to move in an environment that is not predesigned and/or has no complete prior information, we are in the scope of *motion planning with incomplete information*. In this case, the robot must use real-time sensing and sensor data processing to gather information about the surroundings. Generally, the robot moves reacting to obstacles while trying to get to the target. Typical examples of

ISSN: 1988-3064(on-line)

these techniques include potential-field methods [3] and fuzzy approaches [1, 2, 5, 17, 18, 20, 21]. Because the source of information is mainly local, these methods have the drawback that are prone to get trapped in deadlock situations [1, 2, 17, 18] and because of this, particular attention is paid to the deadlock problem.

When the robot is in a deadlock situation –also called *local minima*, *limit cycle* or *infinite loop*–, it will repeat indefinitely the same trajectory unless this is detected. This problem has been addressed using three types of approach: *i)* the boundary-following approach [1], *ii)* the virtual subgoal approach [19, 20] and *iii)* the behavior integration approach [11, 17]. Boundary-following approaches generally detect a deadlock when the robot makes a sharp turn or when all sensors detect short obstacle distances. Then, the robot follows the boundary of the obstacle until an escape criterion is satisfied. This strategy can get trapped following a boundary indefinitely if the escape criterion fails to activate and may lead to rather inefficient paths because there is no way to choose the right boundary-following direction. Virtual subgoal approaches typically detect a deadlock whenever the robot makes a sharp turn or when the robot visits the same location more than one time. Then, the robot generates a new subgoal to escape the deadlock and returns the original goal when an escape criterion is satisfied. These methods may overproduce virtual subgoals leading to a deadlock arising from conflictive subgoals. Behavior integration approaches usually make a map that models the surroundings of the robot, while a planning and a reactive module suggest a direction to escape from the deadlock and a direction that avoids obstacles, respectively. These behaviors are then integrated to drive the robot to the goal. Building a map of the traversed path may be an issue when the system requires low memory and processing capabilities, like a microcontroller or a small computer.

In this paper we develop an autonomous navigation system for mobile robots in unknown environments, where the robot must be capable to go from a starting point A to a target point B. The information available to the robot is limited to its own position and those of the starting point A and target point B. Also, the robot is capable of detecting its own distance to obstacles. This information should be sufficient to reach the objective position. The proposed navigation system was developed using fuzzy logic, which has proved to be an appropriate tool to design robust systems in presence of noise [5, 15, 20] and signal processing tools [14] for detecting the deadlock situation.

In an attempt to meet these objectives, we make the following restrictions: *i)* we consider the navigation of a single mobile robot, *ii)* the robot does not generate maps of the traversed path, and *iii)* the environment is assumed to be a flat indoor environments without slippage between the wheels of the robot and the floor.

The main contribution of this article is a procedure for the identification of the deadlock situation during the robot's traversal. The proposed method uses only the distance to the target d_t and the autocorrelation function to detect if the robot is in a deadlock. Once a deadlock situation is detected, a wall-following behavior makes the robot escape from the deadlock.

The organization of the article is as follows. Section 2 presents the system configuration. Section 3 describes the fuzzy based navigation system and Subsection 3.4 describes the deadlock detection and avoidance strategy. Section 4 shows the simulation results obtained using the described method and Section 5 presents the conclusions.

2 System Configuration

To achieve autonomous behavior, some of the most important tasks of mobile robots are acquiring the information of the surrounding environment and self localization. In order to control a mobile robot to reach its goal without colliding any obstacle, the robot must be equipped with some sensors to sense the environment and transfer that information to the robot to interpret the sensed information. The commonly used sensors on mobile robots are ultrasonic sensors, CCD cameras, infrared sensors, laser sensors, global positioning systems and so on. Because the ultrasonic sensor has many characteristics such as cost-effective, simple operation, easy implementation in hardware and little information processing, it has gotten widely used in mobile robots. Therefore, we adopt ultrasonic sensors to detect obstacles' distance and the mobile robot's direction. Figure 1(a) show the robot sensor configuration where we can see that five sensors are arranged to cover 180°. The great quantity of low cost Inertial Measurement Units (IMU) and Global Positioning System (GPS) modules being built enable us to choose a set of

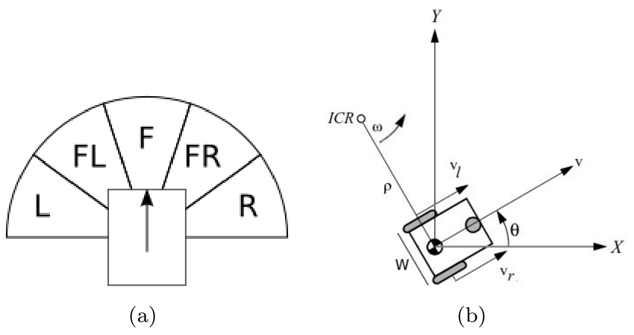


Figure 1: (a) Robot sensor configuration. (b) Robot coordinate system.

IMU+GPS sensors that will enable us to know the position and orientation of the vehicle with minimum error.

There are two coordinate systems: world coordinate system depicted by XOY and robot local coordinate system depicted by xoy, the relationship between these two coordinate systems and the relationship of control variables are shown in Fig. 1(b). The robot is modeled as a differential drive wheeled mobile robot, which is one of the most popular ways to drive indoor mobile robots. There are two main wheels, each of which is attached to its own motor. A third wheel placed in the rear to passively roll along while preventing the robot from falling over [7]. We can vary the trajectories that the robot takes by varying the velocities υ_l and υ_r of the two wheels.

When the mobile robot moves in the unknown environments, the distance to the target d_T and the steering angle θ_g can be computed from the robot current position and target positions in global coordinate.

3 The navigation system

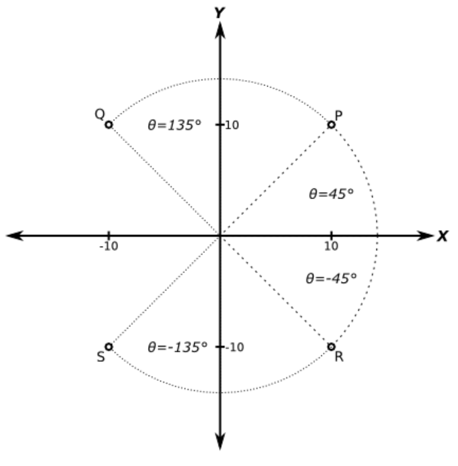
The robot moves in an environment with unknown obstacles. In the following we will ignore all the problems related to position uncertainty (such as wheels drifting), by assuming that a sufficient accurate self-localization subsystem is available. This enables us to use odometry methods to calculate the robot and the target position at every moment. Besides this, the only other source of information available to the robot are the range sensors.

The navigation system consists of three main components: *i)* target tracking, that finds a set of desired directions from the current robot and target positions; *ii)* obstacle avoidance, that finds a set of disabled directions from the data available from the range sensors; and *iii)* get possible direction, that combines the fuzzy conclusions of the previous modules to find a direction that takes into account both the desired and the disabled direction.

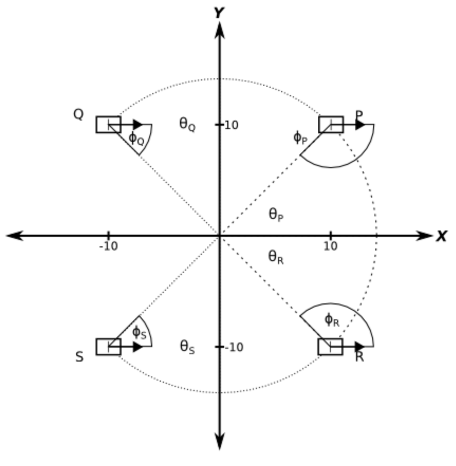
3.1 Target tracking

This behavior finds a set of desired directions from the robot actual orientation θ_r, which can be obtained at every time interval from the robot actual position (x_r, y_r) and the target position (x_T, y_T). The desired steering angle θ_g required to align the robot to the target is calculated from this data. The angle θ_g is then translated to a steering set named R (right), FR (front-right), F (front), FL (front-left) and L (left).

We use the function `atan2` to calculate the angle θ_t of a point to the origin of coordinates. In terms



(a)



(b)

Figure 2: (a) Rotation angle from the coordinate system origin. (b) Robot rotation angles.

of the standard **arctan** function, whose range is $(-\pi/2, \pi/2)$, it can be expressed as follows:

$$\theta_t = \operatorname{atan2}(y,x) = \begin{cases} \arctan(\frac{y}{x}), & x > 0 \\ \pi + \arctan(\frac{y}{x}), & y \geq 0,\, x < 0 \\ -\pi + \arctan(\frac{y}{x}), & y < 0,\, x < 0 \\ \frac{\pi}{2}, & y > 0,\, x = 0 \\ -\frac{\pi}{2}, & y < 0,\, x = 0 \\ \text{undefined}, & y = 0, x = 0 \end{cases} \tag{1}$$

Figure 2(a) shows the angle θ_t obtained by measuring the **atan2** function on points located in every quadrant. It can be seen that when $y > 0$, the function measures the positive angle and when $y < 0$ it measures the negative angle. θ_t is angle measured from the origin of coordinates of the frame of reference (in our case, the target position) to the robot. In order to know the angle θ_r that represents the angle from the point where the robot is located to the origin of coordinates (see Figure 2(b)), we calculate

$$\theta_r(y,x) = \begin{cases} \pi + \theta_t, & \theta_t < 0 \\ -\pi + \theta_t, & \theta_t \geq 0 \end{cases} \tag{2}$$

the steering angle θ_r tells us *how much* the robot must turn to be aligned with the center of coordinates.

In the general case where the robot is located at a point (x_r, y_r) with orientation ϕ and must head to the target point (x_T, y_T) (see Figure 2(b)), we must do a coordinate translation:

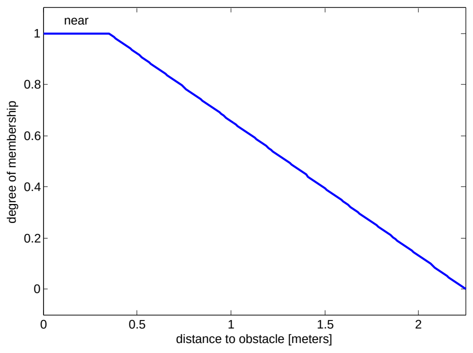
$$x' = x_r - x_T \tag{3}$$

$$y' = y_r - y_T \tag{4}$$

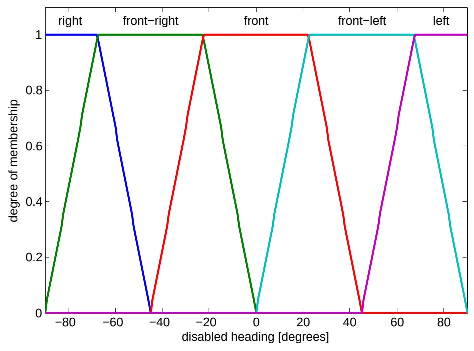
this operation sets the origin at the point $O : \{x_T, y_T\}$. To calculate the steering angle θ'_r when the robot heading is ϕ, we have

$$\theta'_r = \theta_r - \phi \tag{5}$$

To guarantee that θ_g is the minimum steering angle of the two possible turn directions (left and right), we must compare both left and right turn angles and then keep the minimum. Given θ_{g1} and θ_{g2} as the



(a)



(b)

Figure 3: a) Membership function for every sensor. b) Membership functions for the output variable θ_d.

steering angles of each direction, we have

$$\begin{aligned} \theta_{g1} &= \theta'_r \\ \theta_{g2} &= \begin{cases} \theta_{g1} + 2\,\pi, & \theta_{g1} < 0 \\ \theta_{g1} - 2\,\pi, & \theta_{g1} \geq 0 \end{cases} \end{aligned} \tag{6}$$

Once we get the pair of steering angles, we choose the one with minimum absolute value

$$\theta_g = min\{|\theta_{g1}|, |\theta_{g2}|\} \tag{7}$$

and translate θ_d to the set of desired directions R, FR, F, FL and L. The fuzzy rules that perform this translation are:

- IF θ_g *is close to* -90, THEN desired-heading *is* R.
- IF θ_g *is close to* -45, THEN desired-heading *is* FR.
- IF θ_g *is close to* 0, THEN desired-heading *is* F.
- IF θ_g *is close to* 45, THEN desired-heading *is* FL.
- IF θ_g *is close to* 90, THEN desired-heading *is* L.

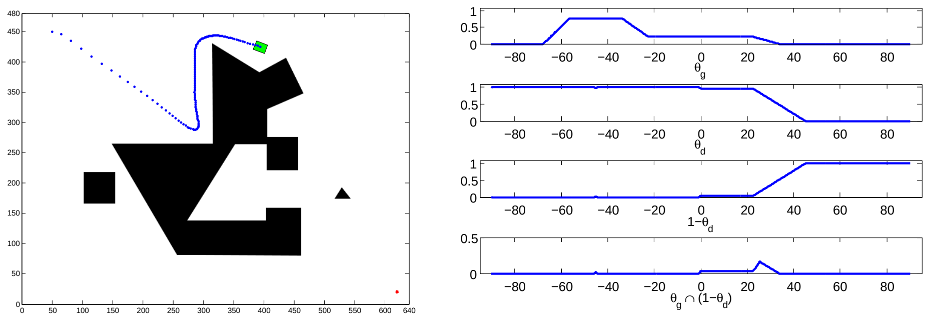
3.2 Obstacle avoidance

This behavior determines the direction θ_d in which the robot should be heading to avoid obstacles. It uses the data available from the range sensors to represent the level in which a given direction (L, FL, F, FR or R) has an obstacle near or not by measuring the degree of membership of each sensed distance to a fuzzy set which we call "near" (see Fig. 3(a)). Each sensor has a steering label (see Fig. 3(b)) that is scaled according to the proximity of obstacles, thus determining the degree of traversability in the vicinity of the robot.

3.3 Possible direction

This module combines the fuzzy conclusions of the *target tracking* and *obstacle avoidance* components. We want the robot to be heading towards a direction that takes into account both the desired and the disabled direction. To do this, we realize the following fuzzy operations:

$$\theta_p = \theta_g \text{ AND NOT } \theta_d \tag{8}$$
$$= \theta_g \cap (1 - \theta_d) \tag{9}$$



(a) (b)

Figure 4: The fuzzy system in action. (a) The robot near obstacles. (b) The output of each of the fuzzy components.

Figures 4(a) shows the robot with obstacles in the right, while Fig. 4(b) shows the output of each of the fuzzy systems, where we can see that θ_g is trying to make the robot go to the right, while θ_d is disabling this set of directions. The *possible direction* module combines these fuzzy sets in a way that makes the robot turn approximately 25° to the left.

3.4 Deadlock detection and avoidance

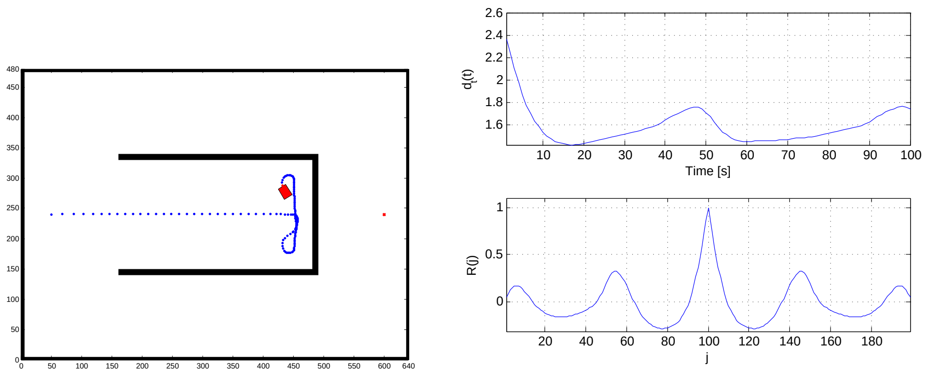
Since the robot does not remember the location visited before and the navigation algorithm is based only on local information, it can get trapped in local minima commonly called *deadlock* [12], *limit cycle* [1, 18] or *infinite loop* [6]. While trapped in this situation, the robot will repeat indefinitely the same trajectory unless this is detected and deal with this situation.

Xu et al. [18] detects a deadlock whenever the robot makes a sharp turn while Yang et al. [20] detects a deadlock when all sensors detect small distances to obstacles, both of them produce a set of subgoals that help escape the deadlock until an escape criterion is met. The algorithm proposed by Xu et al. [18] obtains good results, although in some complicated environments the algorithm may produce a significant quantity of subgoals. It is worth mentioning that Yang et al. [20] experimental results are all with simple maps, where the anti-deadlock mechanism cannot be properly evaluated. Krishna et al. [10] uses a fuzzy classification scheme coupled to Kohonen's self-organizing map and fuzzy ART network determines this classification and Wang et al. [17] builds a memory grid map which records the environmental information and the robot experience while traversing the map. Ordonez et al. [12] uses a virtual wall approach. Our proposed method uses the distance to the target d_t to detect if the robot is in a deadlock. At every time interval the navigation algorithm calculates the distance d_t and orientation θ_t of the robot to the target. If we store the last N records we could think of the distance as a signal over time d_t and see how this behaves in different situations, being the main case of interest how this signal behaves when the robot is in a deadlock situation.

When the robot is in an obstacle free environment , the distance would initially be D_0 and it would decrease down to 0 . However, when facing a deadlock situation the robot travels indefinitely along the deadlock loop (see Fig. 5(a)) and the measurements of the distance d_t will then become periodic, as shown in Fig. 5(b). The usual method for deciding if a signal is periodic and then estimating its period is the autocorrelation function. The discrete autocorrelation R at lag j for a discrete signal x_n is defined by

$$R(j) = \sum_n x_n \, \overline{x}_{n-j}. \tag{10}$$

If the signal is periodic with period P, the autocorrelation R will attain a maximum at sample lags of $\pm nP$, where $n \in \mathbb{Z}$ [14]. We can see in Fig. 5(a), that the size of the traversed path is 148 centimeters and the period of the autocorrelation signal $R(j)$ in Fig. 5(b) is 148. By calling $M_0 = R(0)$ and $M_1 = R(P)$,



(a) (b)

Figure 5: The robot in a typical deadlock-prone scenario. (a) Simulation results. (b) Evolution of the measured distance through time (top) and its autocorrelation (bottom).

we can check the periodicity of the signal through

$$\frac{M_1}{M_0} \geq \tau, \tag{11}$$

where τ is a real valued constant defined by the variance of the system noise. If this check gives positive results we can change the robot's behavior to *wall-follow* and escape the deadlock.

```
begin
    $p \longleftarrow is\_periodic(d10)$;
    if $\neg p$ then
        $p \longleftarrow is\_periodic(d20)$;
    end
    if $\neg deadlock\_status \wedge p$ then
        $deadlock\_status \longleftarrow True$;
    else
        $deadlock\_status \longleftarrow False$;
    end
end
```

Algorithm 1: Periodicity detection algorithm

3.4.1 Selecting the window size

The window size plays a critical role in the correct behavior of the deadlock detection algorithm. Small window sizes will detect small sized deadlocks, but will fail to catch the periodicity of big sized deadlocks. On the other side, using a large window will enable us to detect big sized deadlocks, but it will spend much more time until a small sized deadlock fills the window and the deadlock detection method detects the periodicity. Thus, there is a trade-off between the window size N, the suspected periodicity size and the time spent to detect the deadlock situation.

We chose to implement a constant size, multi-window approach. The first window is the signal d_t and the others being downsampled versions of the first. We can downsample d_t as many times as we want and we can run our detection algorithm in parallel through all the windows. This enables us to detect deadlocks of various sizes while mantaining a quick response and a small storage space. In our experiments we chose to use two windows of size $N = 100$, named d_{10} and d_{20}. The second window being the downsampled version of the first, keeping every second sample of the signal and discarding the others. By doing this, we ensure to keep the windows size small enough while catching periodicities of two different sizes that are appropriate for the map sizes we work with. The method used to check if the robot is in a deadlock situation is shown in algorithm 1.

3.5 Wall following

Once the robot knows it is in a deadlock situation it can change its behavior and try to escape from it. We chose to implement a fuzzy logic wall following controller. When the deadlock detection algorithm checks positive, we store the distance to the target d_t as the deadlock distance d_l and the robot follows a wall until $d_t \leq d_l$ and $|\theta_p| < \beta$, where β is a real valued constant.

3.6 Algorithm

The navigation algorithm is described in algorithm 2. The pseudocode shows the integration of the tasks described through this Section. After acquiring the sensors readings, the algorithm checks if it is in a *deadlock situation*. According to these results, the algorithm uses the *wall following* or the *target tracking*, *obstacle avoidance* and *possible direction* behaviors to reach the target. This process is then repeated until a distance criterion is met.

```
while $d_t \geq$ MIN_DISTANCE do
    acquire sensor readings;
    if deadlock situation then
        while $d_t \geq d_l$ do
            compute wall follow direction;
            wall follow;
        end
    else
        compute target tracking direction;
        compute obstacle avoidance direction;
        compute possible direction;
        go to target;
    end
end
```

Algorithm 2: Navigation algorithm

4 Simulation results

We ran different experiments on various deadlock-prone maps from Wang et al. [17] and compared our algorithm with the "minimum risk method" proposed in this work. The blue lines show the robot traveling in the normal goal-oriented behavior while the red lines show the deadlock-detection and wall-following behavior.

We first compare our method in concave environments. Figure 6(a) detects a deadlock before making entering the first repetition of the infinite loop. It then follows the left wall until the escape criterion is met and reaches the target. Figure 6(b) shows the result of the minimum risk method. The robot exhibits a so-called "trial and return" phenomenon and manages to escape the deadlock. In Wang et al. there are comparison with virtual target methods [19] and Krishna and Kalra's method [10]. While the first fails to reach the target, the second exhibits a similar behavior as our method by using a fuzzy classification scheme coupled to Kohonen's self-organizing map (SOM) and fuzzy ART network to determine the deadlock situation. This requires to train the SOM to learn typical landmarks that are expected to occur in a general environment. However, all the experiences of spatio-temporal patterns cannot be modeled through the landmarks learnt offline. Under some situations this can result in the robot not getting aware of its trapped condition and because of this, a Fuzzy ART network is added to dynamically add new patterns to the knowledge base. This architecture is more complicated than our approach, which has only to calculate an autocorrelation.

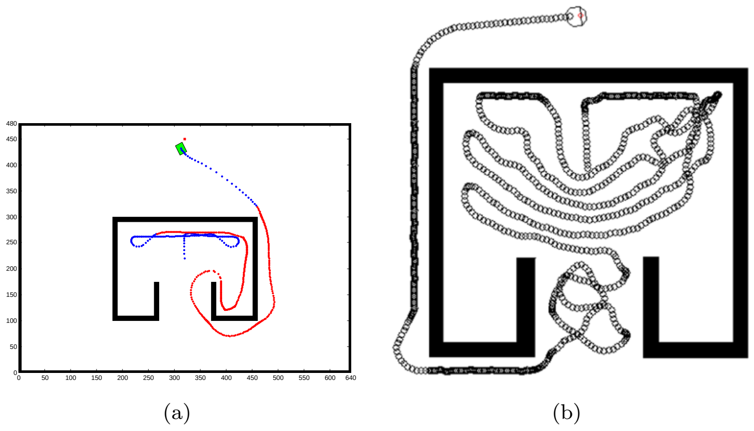

(a) (b)

Figure 6: In large concave and recursive U-shaped environment. (a) Our method. (b) Minimum risk method

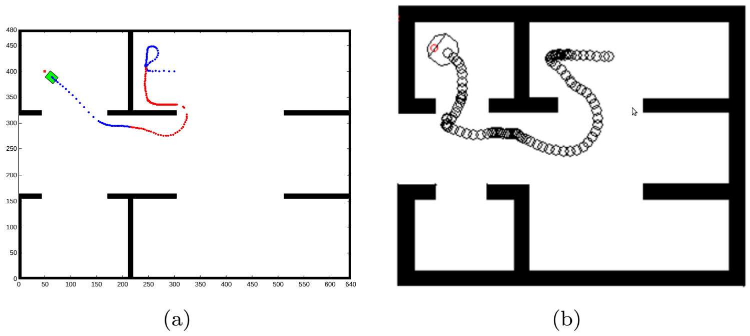

(a) (b)

Figure 7: In a concave environment. (a) Our method. (b) Minimum risk method.

We next compare our algorithm in a concave environment shown in Fig. 7(a) where we can see that we get similar results that the ones in Fig. 7(b). In Wang et al. it is shown that Krishna and Kalra's method reaches the target, but choses a wall boundary that leads to a longer traversed path. It is very difficult to choose the correct boundary to follow without making maps or remembering the past as the minimum risk method does. Although the results are similar, we must emphasize that our algorithm does not build maps of the traversed path or surroundings. It is able to reach the target only using the distance to the target d_t and the autocorrelation function, a much simpler approach.

We finally test our algorithm in a complicated environment shown in Fig 4. We can see that the proposed method is capable of reaching the target. It detects and escapes from two different sized deadlocks during the traversal of the environment.

Our method exhibits a behavior similar to Krishna and Kalra's and the minimum risk method, but is worth to mention that it neither uses a Kohonen's self-organizing map nor makes a grid of the traversed path. In this way, the proposed scheme is much simpler while maintaining the effectiveness. The only extra data needed is the distance to the target d_t and a deadlock can be detected by checking the autocorrelation of the vector that stores the last N distances.

5 Conclusions

The proposed method is effective and enables the robot to escape from deadlock situations while using as little data as the distance to the target. The obtained results are comparable with methods that use

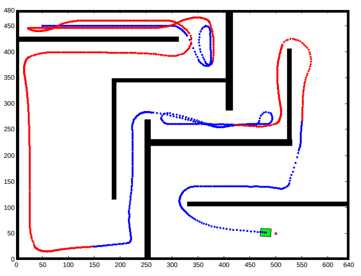


Figure 8: Our method in a complicated environment.

more complex schemes.

It is extremely difficult to guarantee that a selected direction will ensure to leave the deadlock situation once detected. Without further information nothing guarantees that following a wall to the right is better than following it to the left. In unknown environments optimal navigation distance is not known, but travel time can be reduced by controlling the robot's velocity. The simulation results shown in Section 4 show that the robot reaches every target describing a smooth trajectory. If the method is aimed to be used for long-distance navigation, another information sources should be added, such as a GPS or an IMU unit to compensate the odometry errors.

References

[1] Ranajit Chatterjee and Fumitoshi Matsuno. Use of single side reflex for autonomous navigation of mobile robots in unknown environments. *Robotics and Autonomous Systems*, 35(2):77 – 96, 2001.

[2] Wang Dongshu, Zhang Yusheng, and Si Wenjie. Behavior-based hierarchical fuzzy control for mobile robot navigation in dynamic environment. In *Control and Decision Conference (CCDC), 2011 Chinese*, pages 2419–2424. IEEE, 2011.

[3] Shuzhi S. Ge and YJ Cui. Dynamic motion planning for mobile robots using potential field method. *Autonomous Robots*, 13(3):207–222, 2002.

[4] Yanrong Hu and Simon X Yang. A knowledge based genetic algorithm for path planning of a mobile robot. In *Robotics and Automation, 2004. Proceedings. ICRA'04. 2004 IEEE International Conference on*, volume 5, pages 4350–4355. IEEE, 2004.

[5] G.S. Huang, C.K. Tung, and J.C. Ciou. To achieve the path planning of mobile robot for a correct destination and direction using fuzzy theory. In *Industrial Electronics, 2009. ISIE 2009. IEEE International Symposium on*, pages 1737–1742. IEEE, 2009.

[6] K. Madhava Krishna and Prem K Kalra. Solving the local minima problem for a mobile robot by classification of spatio-temporal sensory sequences. *Journal of Robotic Systems*, 17(10):549–564, 2000.

[7] Steven Michael LaValle. *Planning algorithms*. Cambridge university press, 2006.

[8] Qing Li, Xinhai Tong, Sijiang Xie, and Yingchun Zhang. Optimum path planning for mobile robots based on a hybrid genetic algorithm. In *Hybrid Intelligent Systems, 2006. HIS '06. Sixth International Conference on*, pages 53–53, 2006.

[9] Qing Li, Wei Zhang, Yixin Yin, Zhiliang Wang, and Guangjun Liu. An improved genetic algorithm of optimum path planning for mobile robots. In *Intelligent Systems Design and Applications, 2006. ISDA'06. Sixth International Conference on*, volume 2, pages 637–642. IEEE, 2006.

[10] K Madhava Krishna and Prem K Kalra. Perception and remembrance of the environment during real-time navigation of a mobile robot. *Robotics and Autonomous Systems*, 37(1):25–51, 2001.

[11] Javier Minguez and Luis Montano. Sensor-based robot motion generation in unknown, dynamic and troublesome scenarios. *Robotics and Autonomous Systems*, 52(4):290–311, 2005.

[12] Camilo Ordonez, Emmanuel G. Collins Jr., Majura F. Selekwa, and Damion D. Dunlap. The virtual wall approach to limit cycle avoidance for unmanned ground vehicles. *Robotics and Autonomous Systems*, 56(8):645 – 657, 2008.

[13] Ruan Qiuqi et al. A gene-constrained genetic algorithm for solving shortest path problem. In *Signal Processing, 2004. Proceedings. ICSP'04. 2004 7th International Conference on*, volume 3, pages 2510–2513. IEEE, 2004.

[14] Lawrence R Rabiner and Ronald W Schafer. *Digital processing of speech signals*, volume 19. IET, 1979.

[15] A. Saffiotti. The uses of fuzzy logic in autonomous robot navigation. *Soft Computing-A Fusion of Foundations, Methodologies and Applications*, 1(4):180–197, 1997.

[16] Jianping Tu and Simon X Yang. Genetic algorithm based path planning for a mobile robot. In *Robotics and Automation, 2003. Proceedings. ICRA'03. IEEE International Conference on*, volume 1, pages 1221–1226. IEEE, 2003.

[17] Meng Wang and James NK Liu. Fuzzy logic-based real-time robot navigation in unknown environment with dead ends. *Robotics and Autonomous Systems*, 56(7):625–643, 2008.

[18] WL Xu. A virtual target approach for resolving the limit cycle problem in navigation of a fuzzy behaviour-based mobile robot. *Robotics and Autonomous Systems*, 30(4):315–324, 2000.

[19] WL Xu and SK Tso. Sensor-based fuzzy reactive navigation of a mobile robot through local target switching. *Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on*, 29(3):451–459, 1999.

[20] X. Yang, M. Moallem, and R.V. Patel. A layered goal-oriented fuzzy motion planning strategy for mobile robot navigation. *Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on*, 35(6):1214–1224, 2005.

[21] John Yen and Nathan Pfluger. A fuzzy logic based extension to payton and rosenblatt's command fusion method for mobile robot navigation. *Systems, Man and Cybernetics, IEEE Transactions on*, 25(6):971–978, 1995.

[22] Soh Chin Yun, V. Ganapathy, and Lim Ooi Chong. Improved genetic algorithms based optimum path planning for mobile robot. In *Control Automation Robotics Vision (ICARCV), 2010 11th International Conference on*, pages 1565–1570, 2010.