

# Autonomous navigation with deadlock detection and avoidance

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**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.

## 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. [8] 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, 7, 12, 15, 21]. 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 these techniques include potential-field methods [3] and fuzzy approaches [1, 2, 5, 16, 17, 19, 20]. Because the source of information is mainly local, these methods have the drawback that are prone to get trapped in deadlock situations [1, 2, 16, 17] 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 [18, 19] and *iii*) the behavior integration approach [10, 16]. 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, 14, 19] and signal processing tools [13] 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.

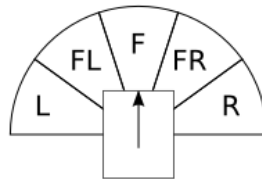
The main contribution of this article is a procedure for the identification of the deadlock situation during the robot's traversal. The proposed method uses

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

**Fig. 1.** Robot sensor configuration.

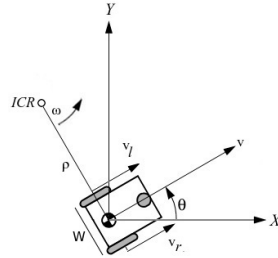


### 2.1 Sensors Arrangement

To achieve autonomous behaviors, one of the most important tasks of mobile robot is acquiring the information of the surrounding environments. 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 robot 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 robot. Therefore, we adopt ultrasonic sensors to detect obstacles distance and the mobile robots direction. Figure 1 show the robot sensor configuration where we can see that five sensors are arranged to cover  $180^\circ$ .

### 2.2 Coordinate System and Control Variable

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. 2. The robot is modeled as a differential drive wheeled mobile robot. We

**Fig. 2.** Robot coordinate system.

can vary the trajectories that the robot takes by varying the velocities  $v_l$  and  $v_r$  of the two wheels.

When the mobile robot moves in the unknown environments, the distance to the target  $d_t$  and the steering angle  $\theta_t$  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

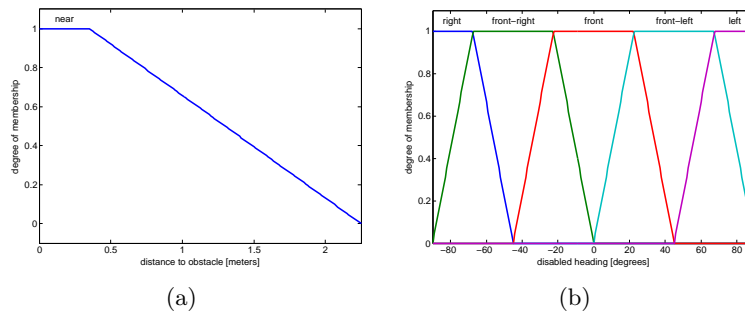
This behavior finds a set of desired directions from the robot actual orientation  $\theta_r$ , which can be obtained at every time interval from the robot actual position  $(x_r, y_r)$  and the target position  $(x_T, y_T)$ . The rotation angle  $\theta_g$  required to align the robot to the target is calculated from this data. The angle  $\theta_g$  is then translated to a steering set named RIGHT, FRONT-RIGHT, FRONT, FRONT-LEFT and LEFT. The fuzzy rules that perform this translation are:

- IF  $\theta_g$  is close to -90, THEN desired-heading is R.
- IF  $\theta_g$  is close to -45, THEN desired-heading is FR.
- IF  $\theta_g$  is close to 0, THEN desired-heading is F.

- IF  $\theta_g$  is close to 45, THEN desired-heading is FL.
- IF  $\theta_g$  is close to 90, THEN desired-heading is L.

### 3.2 Obstacle avoidance

This behavior determines the direction  $\theta_d$  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.



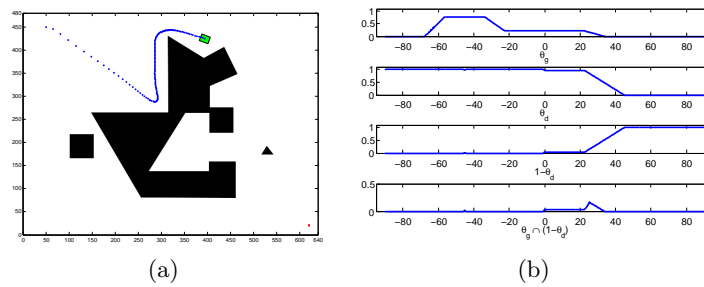
**Fig. 3.** a) Membership function for every sensor. b) Membership functions for the output variable  $\theta_d$ .

### 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:

$$\begin{aligned}\theta_p &= \theta_g \text{ AND NOT } \theta_d & (1) \\ &= \theta_g \cap (1 - \theta_d) & (2)\end{aligned}$$

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  $\theta_g$  is trying to make the robot go to the right, while  $\theta_d$  is disabling this set of directions. The *possible direction* module combines these fuzzy sets in a way that makes the robot turn approximately  $25^\circ$  to the left.



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

### 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* [11], *limit cycle* [1, 17] 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. [17] detects a deadlock whenever the robot makes a sharp turn while Yang et al. [19] 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. [17] 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. [19] experimental results are all with simple maps, where the anti-deadlock mechanism cannot be properly evaluated. Krishna et al. [9] uses a fuzzy classification scheme coupled to Kohonens self-organizing map and fuzzy ART network determines this classification and Wang et al. [16] builds a memory grid map which records the environmental information and the robot experience while traversing the map. Ordonez et al. [11] 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  $\theta_t$  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

$$R(j) = \sum_n x_n \bar{x}_{n-j}. \quad (3)$$

If the signal is periodic with period  $P$ , the autocorrelation  $R$  will attain a maximum at sample lags of  $\pm nP$ , where  $n \in \mathbb{Z}$  [13]. 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  $M_1 = R(P)$ , we can check the periodicity of the signal through

$$\frac{M_1}{M_0} \geq \tau, \quad (4)$$

where  $\tau$  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
   $p \leftarrow is\_periodic(d10)$ ;
  if  $\neg p$  then
     $p \leftarrow is\_periodic(d20)$ ;
  end
  if  $\neg deadlock\_status \wedge p$  then
     $deadlock\_status \leftarrow True$ ;
  else
     $deadlock\_status \leftarrow False$ ;
  end
end

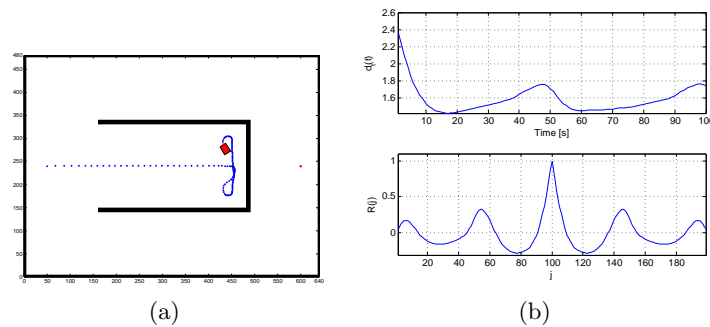
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**Algorithm 1:** Periodicity detection algorithm

### 3.5 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 maintaining a quick response and a small storage space. In



**Fig. 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).

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.

### 3.6 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  $\beta$  is a real valued constant.

### 3.7 Algorithm

The main navigation algorithm can be seen in algorithm 2.

## 4 Simulation results

We ran different experiments on various deadlock-prone maps from Wang et al. [16] 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.



```

while  $d_t \geq \text{MIN\_DISTANCE}$  do
  acquire sensor readings;
  if deadlock situation then
    while  $d_t \geq d_i$  do
      compute wall follow direction;
      wall follow;
    end
  else
    compute target direction  $d_p$ ;
    go to target;
  end
end

```

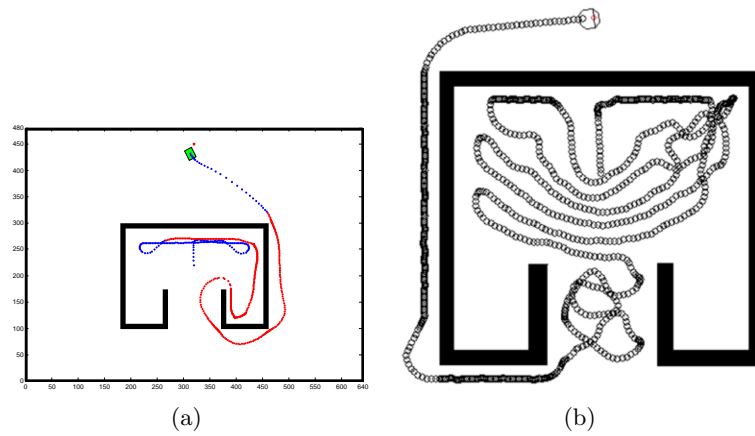
**Algorithm 2:** Navigation algorithm

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 [18] and Krishna and Kalra’s method [9]. 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.

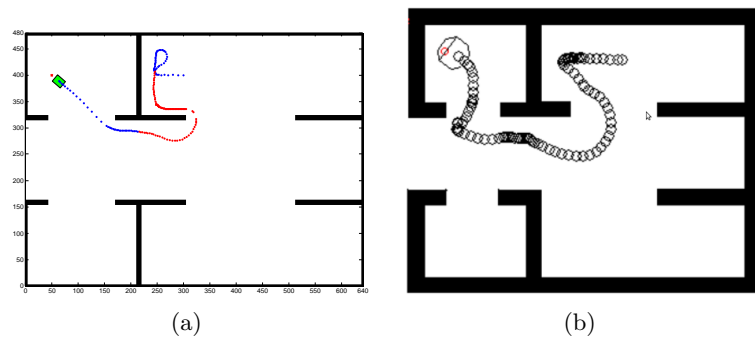
We next compare our algorithm in a concave environment shown in Fig. 7(a) where we can see that we get similar results that the ones in Fig. 7(b). In Wang et al. it is shown that Krishna and Kalra’s method reaches the target, but chooses a wall boundary that leads to a longer traversed path. It is very difficult to choose the correct boundary to follow without making maps or remembering the past as the minimum risk method does.

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.

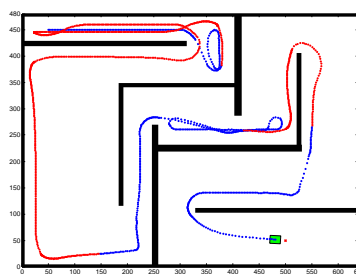
Our method exhibits a behavior similar to Krishna and Kalra’s and the minimum risk method, but is worth to mention that it neither uses a Kohonens self-organizing map nor makes a grid of the traversed path. In this way, the proposed scheme is much simpler while maintaining the effectiveness. The only 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.



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



**Fig. 7.** In a concave environment. (a) Our method. (b) Minimum risk method.



**Fig. 8.** Our method in a complicated environment.

## 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 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.

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