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# TRAJECTORY PLANNING FOR AUTONOMOUS VEHICLE IN UNCERTAIN ENVIRONMENT USING EVIDENTIAL GRID

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**Abstract:** This paper considers the path planning problem for an autonomous vehicle given uncertain knowledge about the surrounding environment. We propose to use evidential occupancy grid to deal with sensor uncertainties. Our aim is to develop a planning approach based on clothoid tentacles allowing a vehicle to move autonomously and safely in an environment which is not perfectly known a priori and in which static obstacles are present.

*Keywords:* Autonomous vehicle, Path planning, Evidential occupancy grid.

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## 1. INTRODUCTION

Whether driving on highways or exploring in the middle of a war zone, autonomous vehicles must have the capacity to rapidly and robustly planify a trajectory in very uncertain environment. The uncertainty comes from : imperfect knowledge of the vehicle model [Xu et al. 2014], environment sensing and environment predictability [Aoude et al. 2010; Sun et al. 2014]. To solve environment predictability, Partially Observable Markov Decision Process (POMDP) [Foka and Trahanias 2005; Brechtel et al. 2014; Gindele et al. 2015] offers a framework for autonomous robot navigation in dynamic environments. With this approach, the state of a car’s environment can be estimated and the development of traffic situations can be predicted. In [Bonnin and Kummert 2012], the authors present a system able to predict the future behavior of the ego-vehicle in an inner-city environment; based on a manually constructed decision tree, the developed system recognizes the class of the situation that a traffic participant is facing. This approach doesn’t predict other vehicles position or heading and their future directions which is vital in motion planning.

This paper addresses problems involving uncertainty in sensing and how to integrate this uncertainty in trajectory planning. For the autonomous vehicle applications, the perception system serves to model the environment in the proximity of the host vehicle. For modeling the environment, the occupancy grids have become the dominant paradigm for environmental modeling in mobile robotics. An occupancy grid map is a tessellated grid in which each cell stores fine grained, quantitative information regarding which areas of a robots operating environment are occu-

ried and which are empty. Specifically, each individual cell in the grid records a confidence factor that the particular cell is occupied. Such maps are extremely useful for mobile robotic applications as they facilitate tasks such as navigation, path planning, localization and collision avoidance.

The main challenge in implementing the grid-based approach is how to deal with the uncertainties originating from the imprecise sensor readings, imprecise prior information and absence of information. In the literature, the Bayesian framework is the most popular method to tackle this problem by representing the uncertainties by means of probability as in [Elfes 1989; Coue et al. 2006; Adarve et al. 2012]. This framework has the advantages of being simple thus fast to implement. In recent years, the framework of belief function to deal with uncertainties gathers more and more attention. It is a generalisation of the Bayesian framework. Thus a new branch of constructing the perceptual grids which is called evidential approach becomes another research hotspot. The approach was proposed in [Pagac et al. 1998] to interpret sonar data into grid values, while in [Yang and Aitken 2006; Moras 2013; Yu et al. 2014] the authors used this framework for lidar sensors. According to the reported results one can remark that this approach brings new features to the mapping process: applications oriented combination operators for information fusion, new method of the management of conflict information, and flexible decision making methods.

In this paper, we propose to deal with uncertainty of environment sensing by using the information provided by evidential grid to choose the best trajectory to execute. The path planning part is based on the clothoid tentacles approach detailed in [Mouhagir et al. 2016b].

The paper is organized as follows: Section 2 presents the concept of evidential grids. In Section 3, we explain how to consider the uncertainty in evidential grids in trajectory planning with tentacles. The simulation results based on data taken from SCANeR™Studio simulator are discussed in Section 4. Finally, conclusions and perspectives are given in Section 5.

## 2. EVIDENTIAL OCCUPANCY GRID

The evidential occupancy grids gather more and more attention in the literature. In [Pagac et al. 1998; Yang and Aitken 2006], the authors adopt the evidential approach to deal with uncertainties for perception grids. All these works report some performance improvements or some new features. Another interesting point is that different sensors are used in these works, sonars, lidars, etc, proving the efficiency and effectiveness of the evidential occupancy mapping approach. Each cell of an evidential occupancy grid is a mass function (or belief function) giving the belief on occupancy.

### 2.1 Evidential framework

The theory of belief functions, also known as Dempster-Shafer theory (DST), was proposed by Dempster [Dempster 1976], and developed, among others, by Shafer [Shafer 1976] and Smets [Smets 2005]. This formalism gained its popularity thanks to various interesting properties. DST not only generalizes the probability theory, but the possibility theory as well.

In the theory of Dempster-Shafer, a frame of discernment  $\Omega$  is defined to model a specific problem. In the occupancy grid framework, the frame of discernment is defined as:  $\Omega = \{O, F\}$ , referred as the states (occupied or free) of each cell. The power set is defined as  $2^{|\Omega|} = \{\emptyset, F, O, \Omega\}$ , with  $|\Omega|$  is the cardinality of the set.

For quantitatively supporting the cell states, a mass function (also referred as basic belief assignment *BBA*) is calculated and provides four beliefs  $[m(F) m(O) m(\Omega) m(\emptyset)]$ , where  $m(A)$  represents respectively the quantity of evidence that the space is *Free*, *Occupied*, *Unknown* or *Conflict*.

The function  $m$  returns values in the range of  $[0, 1]$  and satisfies the condition:

$$\sum_{A \subseteq \Omega} m(A) = 1$$

$m(\emptyset)=0$ , for a normalized mass function.

A powerful application of evidential theory is the fusion of different sources of information. The following section presents some combination rules.

### 2.2 Combination rules

The combination rules enable to fuse information from different sources. Herein, the sources of information should be defined in the same frame of discernment to use the following rules.

The Transferable Belief Model (TBM) conjunctive rule and Dempster's rule are noted  $\cap$  and  $\oplus$ , respectively. They are defined as follows: Let  $m_1$  and  $m_2$  be two given mass functions describing the occupancy belief of the same cell, and let  $m_1 \cap m_2$  and  $m_1 \oplus m_2$  be the result of their combination by  $\cap$  and  $\oplus$ . We have:

$$m_{1 \cap 2}(A) = \sum_{B \cap C = A} m_1(B) m_2(C), \quad \forall A \subseteq \Omega \quad (1)$$

and, assuming that  $m_{1 \cap 2}(\emptyset) \neq 1$ :

$$m_{1 \oplus 2}(A) = \begin{cases} 0 & \text{if } A = \emptyset \\ \frac{m_{1 \cap 2}(A)}{1 - m_{1 \cap 2}(\emptyset)} & \text{otherwise} \end{cases} \quad (2)$$

The normalization process in Dempster's rule has the effect of distributing the belief from the conflict to the other propositions, according to their respective mass.

### 2.3 Evidential occupancy grids

We consider in the following the ego-centered evidential grids built from the sensor model described in [Moras et al. 2011]. This approach uses two grids. The *ScanGrid* is created from sensor data, *Lidar* points provide information about the state of the scanned cells. The masses assignment respects the least commitment principle: the cells containing a lidar point are occupied, the cells between the sensors and the occupied cells are free and the other are *unknown*. The value of masses depends of the resolution of the grids and sensor performances. The second grid is the *MapGrid* that fuses the new *ScanGrid* at each perception step. The fusion rule is based on the conjunctive rule that can provides conflicting mass. The conflicting mass can be analysed before the normalization stage. In order to give more importance to newer *ScanGrid*, a discounting function is applied to the *MapGrid* before the fusion.

Based on this principle, several sensor models were proposed [Yu et al. [2014]]. After the *MapGrid* processing, a cell contains a mass function  $[m(\emptyset) m(F) m(O) m(\Omega)]$ . The value of  $m(\Omega)$  represents the uncertainty,  $m(\emptyset)$  the conflict resulting from a combination of free mass  $m(F)$  and occupied mass  $m(O)$ . A decision process can be applied to decide the state of the cell. To clarify the above definition, here we show some mass distributions as examples:  $[m(\emptyset) m(F) m(O) m(\Omega)] = [0.0.0.7.0.3]$  indicates an *Occupied* cell with 0.7 as a belief, the rest of the mass is in *Unknown*.  $[m(\emptyset) m(F) m(O) m(\Omega)] = [0.0.6.0.0.4]$  shows we have belief 0.6 in *Free* state, the rest of mass are in *Unknown*.

Fig. 1 illustrates the concept of evidential grid. The left grid is an evidential occupancy grid where the green color shows the free cells (navigable), the red shows the occupied cells, while the blue represents conflicting cells and the black represents unexplored cells (unknown). The color intensity reflects the certainty degree. The right grid is a binary grid computed from evidential one, with the value '0' for *free* cells and '1' for *occupied* cells. after the decision process. We consider that the state is occupied if  $f_s$  (threshold) cells inside the state are occupied, otherwise it is considered as a free state. Instead of binary grid, we propose to use evidential grid where the mass is assigned to

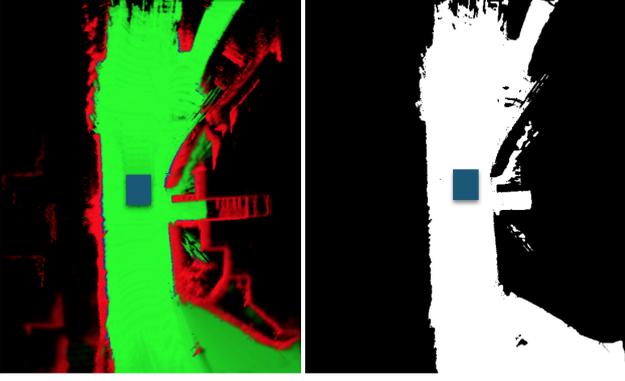


Fig. 1. From evidential grid to binary grid. The blue rectangle represents the vehicle position.

all subset of the domain which able this theory to represent uncertainty and conflict.

### 3. PLANNING WITH UNCERTAINTY

The local trajectory planning goal is the computation of an obstacle free local trajectory while following a desired global reference trajectory defined on a global map.

#### 3.1 Trajectory planning with clothoid tentacles

Our planning approach is based on using a set of virtual antennas called tentacles in the egocentered reference frame related to the vehicle. Tentacles are a geometrical shape which models the dynamically feasible trajectories of the vehicle. Several forms of tentacles exist: circular tentacles [Hundelshausen et al. 2008] and clothoid tentacles [Himmelsbach et al. [2011]; Chebly et al. 2015]. In our work, we use clothoid tentacles because this method considers the current steering angle of the vehicle and make smooth variations in the vehicle dynamic variables such as the yaw rate, the sideslip angle and the steering angle.

Clothoid is a curve whose curvature varies linearly with curvilinear abscissa, also known as an Euler spiral, Cornu spiral or linarc. Its expression is presented by (Equ.3):

$$\rho = \frac{2}{k^2}s \quad (3)$$

where  $\rho$  is the clothoid curvature,  $s$  is the curvilinear abscissa and  $k$  is a constant, representing the clothoid parameter.

For a fixed speed, all the tentacles begin at the center of gravity of the vehicle and take the shape of clothoid. Tentacles of the extremity correspond respectively to the positive and negative maximal value (Equ. 4) of the reached steering angle which the vehicle can make at the current speed without losing stability.

$$\rho_{max} = \frac{a_{max}}{V_x^2} \quad (4)$$

where  $a_{max}$  is the maximum lateral acceleration. The length of tentacles increases with the increase of the speed. We assume that all tentacles generated for a given speed  $V_x$  have the same length.

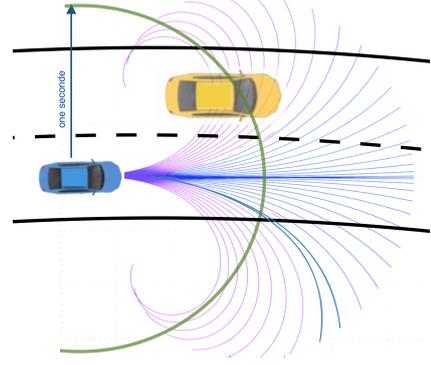


Fig. 2. The concept of classifying tentacles as undrivable only in case of being occupied within a speed-dependent crash distance (see main text). In this case, some drivable tentacles remain, allowing a pass of the car.

After generating all tentacles in the egocentred occupancy grid related to the vehicle, the next step is to choose the best tentacle to execute using different criteria.

#### 3.2 Choosing the best tentacle

In order to choose the best tentacle to execute, we use the information provided by the occupancy grid. First we classify tentacles as navigable or not navigable. We define a security area as the distance over one seconde with the ego-vehicle speed. If a tentacle is obstacle free in this security area, we classify as a navigable one, otherwise it's not navigable (see Fig. 2).

Secondly, we need to choose from the navigable tentacles one to execute using different criteria. As it was presented in [Mouhagir et al. 2016b], we modeled the decision problem as a MDP-like problem. We attribute reward regarding three criteria:

- (1) Occupancy criterion: Since we need to judge every tentacle about its occupancy, we discretize each tentacle by using circles (their diameter represent the width of the vehicle with a margin of security) (Fig. 3). Then, we give positive reward to circles (states) free from obstacles, and negative reward for the occupied circles.

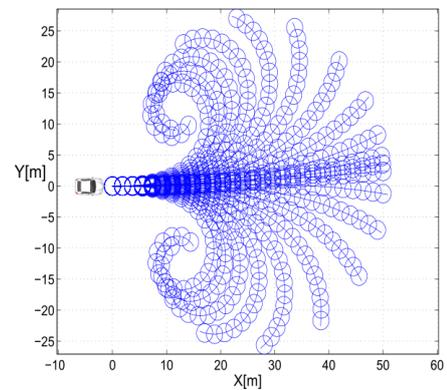


Fig. 3. Decomposing each tentacle into several circles.

- (2) Trajectory criterion: To calculate the reward to be attributed to states with regard to their closeness to the global reference trajectory, defined for example by

GPS waypoints and a global map, we calculate the lateral displacement between the tentacles and the reference trajectory at different points of the tentacle. These points are chosen in function of the crash distance. The crash distance  $l_c$  is the distance needed to stop a vehicle traveling with a speed  $V_x$ , with a maximum longitudinal deceleration  $a_m = 1.5 m/s^2$  that maintains passenger comfort; it is calculated by Equation 5 (where  $l_s$  is a security margin)

$$l_c = \frac{V_x^2}{2a_m} + l_s \quad (5)$$

- (3) Overtaking criterion : In the case of the presence of an obstacle in front of the vehicle, the tentacles of the left receive an additional reward since the overtaking is done by the left.

For trajectory and overtaking criteria, we used the same reward as presented in [Mouhagir et al. 2016a]. Then the tentacle reward is:

$$R(tentacle) = \sum_{k=0}^{n_s} \gamma_t^k R(s_k|trajectory) + \sum_{k=0}^{n_s} \gamma_o^k R(s_k|occupancy) + \sum_{k=0}^{n_s} \gamma_f^k R(s_k|free) + R(left) \quad (6)$$

where  $\gamma_t$ ,  $\gamma_o$  and  $\gamma_f$  (Equ. 6) are discount factors that can be used to change the behavior of our approach, and that represent distance attenuation of each kind of reward.  $n_s$  is the number of state per tentacle,  $s_k$  is the state number  $k$  in the tentacle.

For occupancy criterion, we used binary grid with the value '0' for *free* cells and '1' for *occupied* cells. We consider that the state is occupied if  $f_s$  (threshold) cells inside the state are occupied, otherwise it is considered as a free state. Instead of binary grid, we propose to use evidential grid where the mass is assigned to all subset of the domain which able this theory to represent uncertainty and conflict.

The states definition in our MDP-like model helps us to discretize the environment ahead the vehicle. To use information provided by the evidential grid, we superimpose the states on the grid (the state is a circle). This superimposing gives a matrix which contains several cells. Each cell contains 4 beliefs (Fig. 4).

We dispose of matrix englobing each state (circles around the vehicle), each cell of the matrix provide mass about the occupancy.

In order to define a reward regarding the occupancy of the state, we propose to process cells information using four different rules. We consider that each cell is a source of information about the occupancy of the state. All cells are defined in the same frame of discernment.

- Conjunctive rule
- Dempster's rule
- Mean of the mass
- Occupied and unknown cells number

For each rule, we attribute a different reward (Equations 6 to 9, where  $a_1, a_2, a_3, a_4$  are weighting parameters see Table 1):

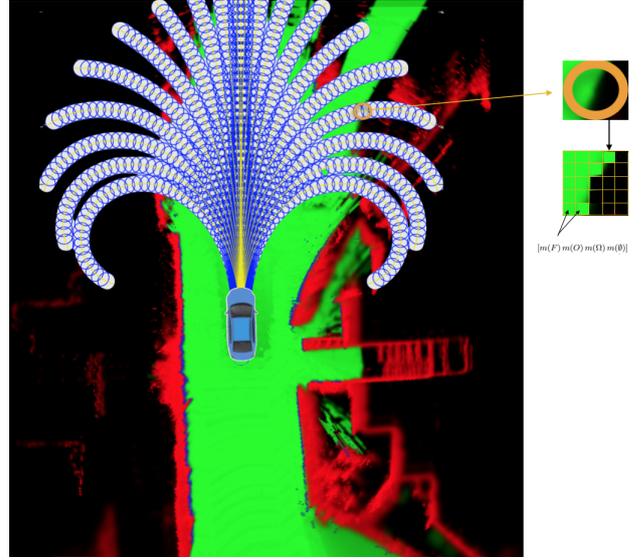


Fig. 4. The superposition of the tentacles on the grid. Each tentacle is a set of circles.

- (1) Conjunctive rule:

$$Reward_{occupation} = a_1m(F) + a_2m(O) + a_3m(\Omega) + a_4m(\emptyset) \quad (7)$$

The conjunctive rule is used if all sources of information are telling the truth. By applying this rule, we obtain a consensus between all sources of information.

- (2) Dempster's rule:

$$Reward_{occupation} = a_1m(F) + a_2m(O) + a_3m(\Omega) \quad (8)$$

The normalization process in Dempster's rule has the effect of distributing the belief from the conflict to the other propositions, according to their respective mass

- (3) Mean of the mass

$$Reward_{occupation} = a_1mean_m(F) + a_2mean_m(O) + a_3mean_m(\Omega) \quad (9)$$

- (4) Cells number

$$Reward_{occupation} = a_1Nb(F) + a_2Nb(O) + a_3Nb(\Omega) \quad (10)$$

with  $Nb(F)$  for example refers to the number of free cells.

## 4. SIMULATION RESULTS

To compare The use of evidential grid instead of the binary grid, we used an exemple of an evidential grid with a lot of uncertainty (Fig. 5). We generated a set of 41 tentacles on each grid. To compute the reward with an evidential grid we used the *Conjunctive* rule.

With the binary grid, the uncertain cells are considered as occupied. With an error detection as in Fig. 5, the algorithm will choose a tentacle of the right which don't include an obstacle because the left and middle tentacles passes by an uncertain cells (Fig. 6).

With the evidential grid, having an uncertainty represents an additional information that we choose to penalize but less then an obstacle. The algorithm don't try to avoid uncertain cells like occupied cells. In this case, the selected



Fig. 5. An evidential grid created using a *Lidar* 4 nappes. The green color shows the free cells, the red shows the occupied cells and the black represents unexplored cells (unknown). The yellow circle includes a error detection because of snow on the *Lidar*.

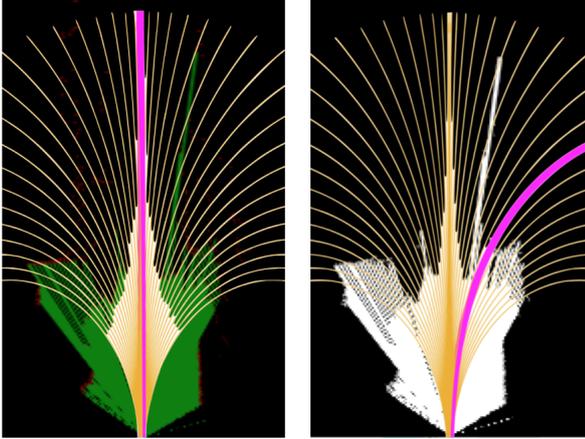


Fig. 6. The left grid is an evidential grid, the selected tentacle is on pink. The right grid is a binary grid, the selected tentacle is on pink.

tentacle is the nearest to the reference trajectory even if it includes some uncertain cells.

#### 4.1 System set-up

To validate the algorithm, we use SCANeR™Studio simulator to get data for simulation. The data was processed in *Matlab*. From this simulator data, we created a global map with a reference trajectory, the navigable space on black and the occupied one on white. We positioned two static obstacles (Fig. 7). The obstacles are represented by circles of diameter  $2.5\text{ m}$ .

For each cell of the global map, we affect 4 masses depending on its occupancy. If the cell with the coordinate  $(i, j)$  is on the navigable space,  $m[i, j] = [m(F) m(O) m(\Omega) m(\emptyset)]$ , where  $m(F) = \text{rand}(0.5, 1)$  (random number between 0.5 and 1),  $m(O) = 0$ ,  $m(\Omega) = 1 - m(F)$  and  $m(\emptyset) = 0$ . If the cell is on the occupied space;  $m(O) = \text{rand}(0.5, 1)$ ,  $m(F) = 0$ ,  $m(\Omega) = 1 - m(O)$  and  $m(\emptyset) = 0$ . We can see in Fig. 1, the right and left borders of the road and behind obstacles in the evidential grid represent a lot of uncertainties. In order to represent this uncertainty, if the cell is in the road borders or behind obstacles;  $m(\Omega) = \text{rand}(0.5, 1)$ ,  $m(F) = 1 - m(\Omega)$ ,  $m(O) = 0$  and  $m(\emptyset) = 0$ . In every time step, we update the grid.

For each sampling time, we dispose of a local occupancy grid of  $800 \times 800$  cells. The cell is represented by a square of

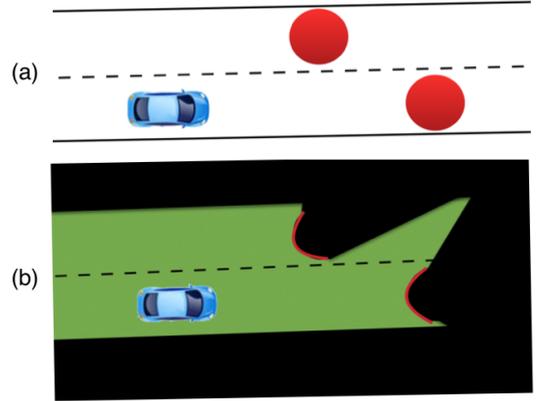


Fig. 7. Scenario test from SCANeR™Studio simulator. (a): the obstacles are represented by red circles. (b) This figure represents an evidential grid; the navigable space is in green, the occupied space in red and unknown in black.

$25\text{ cm}$ . The state is represented by circles of diameter  $2.5\text{ m}$ . The matrix including the state is a matrix of  $10 \times 10$ , then we dispose of 100 cells as a source of information for each state. The table below contains the parameters of different combination rules.

Rule	$a_1$	$a_2$	$a_3$	$a_4$
Conjunctive	20	-20	-1	-50
Dempster	20	-50	-1	-
Mean	10	-50	-1	-
Cell-number	20	-50	-2	-

Table 1. Parameters of different combination rules.

#### 4.2 Results

In order to demonstrate the difference between combination rules, we tested all different rules on the same scenario. We set the ego vehicle velocity to  $10\text{ m/s}$ , we positioned the obstacles.

We tried at first the scenario with a binary grid, the ego-vehicle couldn't overtake the second obstacle, because the algorithm didn't find any navigable tentacles, in this case, it choses to brake.

The Fig. 8 shows the behavior of the ego-vehicle with different combination rules using an evidential grid. the main difference between those several combination rules are time computing and the distance  $d$  between the obstacle and the vehicle after returning to the reference trajectory (see Fig. 8). The computing time is calculated for a road of length  $200\text{ m}$

Rule	Conjunctive	Dempster	Mean	Cell-number
Time (s)	320	460	125	96
$d(\text{m})$	25	32	12	15

Table 2. Time computing and distance  $d$  for different combination rules.

Conjunctive and Dempster combination rule are not suitable for real-time application. The return to the reference trajectory take more time than the Mean and Cell-number Combination rules.

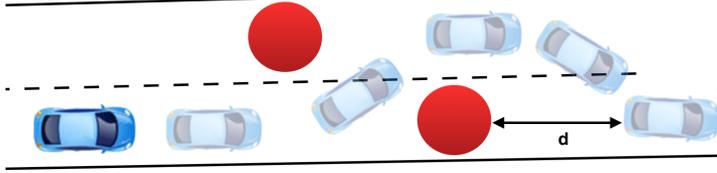


Fig. 8. The behavior of the ego-vehicle using the evidential grid.

The main advantage of the proposed algorithm is to planify a trajectory while taking into consideration the uncertainty of the environment. The use of evidential grid provide informatoion about the unknown which enable us to process it differently from the occupied space.

## 5. CONCLUSION AND PERSPECTIVES

In this work, the goal is to integrate uncertainty of the environment in the planning trajectory using evidential grid. The simulation results show good performance of our algorithm in avoiding obstacles under uncertainty and underline the difference between using an evidential grid instead of a binary grid . Among the perspectives, we aim to test the algorithm with more different scenarios and implement it in a robotized vehicle. We also aim to use a control approach to execute the selected tentacle.

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