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# SIMULLATION OF A FUZZY CONTROLLER FOR AUTONOMOUS VEHICLE IN COMPLEX AND DYNAMICALLY CHANGING ENVIRONMENTS

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***Abstract:*** *This article presents the development of a fuzzy controller for an autonomous vehicle (Autonomous Mobile Robots - AMR, Auto Guided Vehicles - AGV, Autonomous Vehicles for Disabled – AVD). In order to choose the better procedure to obtain the obstacle avoidance behavior, two different techniques are used: inhibitive rules and proportional behavior selector. The vehicle's behavior with these techniques are simulated in an environment with obstacles and in narrow passages. In all cases, a cruiser velocity is used during the path. The obtained results show that, as expected, the fuzzy controller with inhibitive rules presents better performance than the other technique. The vehicle moves without zigzag, the number of obstacles present in the environment has no influence in its performance and for narrow passages, with or without obstacles, the vehicle needs to reduce the cruiser velocity and adapt the obstacle avoidance set to improve the performance.*

***Keywords***: *Fuzzy Controller, Inhibition Rules, Autonomous Vehicle.*

## 1. INTRODUCTION

Autonomous vehicles are programmable systems performing a multitude of tasks. Today, they are intended for material handling, transportation (people and load), decontamination, fire fighting, rescuing and many others hazardous activities. Autonomous navigation is essentially a trajectory control problem. In general terms, the control system must execute a given task, such as reaching a target, while avoiding obstacles. The intrinsic difficulties of the autonomous navigation problem have captivated many artificial intelligent researchers who have found it to be of considerable challenge (Fabro & Gomide, 1996). Navigation control of autonomous mobile vehicles is a research area that can be divided into two main approaches: global path planning, based on a priori complete information about the environment, and local path planning, based on sensory information in uncertain environment where the size, shape and location of obstacles are unknown (Beom & Cho, 1995). The navigator is a navigation and obstacle avoidance controller that generates the steering and velocity commands for the vehicle.

Global path planning methods can solve the path planning problems for completely known environments. But, they can not be used for navigation in complex and dynamically changing environments, where unknown obstacles may be located on a priori planned path. To overcome these difficulties, methods considering real-time environment information from sensors must be considered.

Local path planning methods uses information of the sensors (like optical sensors, ultrasonic, sonar and laser) to provide environmental information for the vehicle's navigator. Based on sensor readings, the vehicle should be able to perform local path planning and to take appropriate control actions. Conflict can appear, e.g.: go to goal position vs. obstacle avoidance.

Fu & Liu (1990) used a graph search algorithm ("visibility graph") to finding a minimum-distance collision-free path in a 2D environment. Wang & Tsai (1991) used a modified version of the least-mean-square-error classifier in pattern recognition to compute a local collision-free path for navigation in indoor corridors. Feng & Krogh (1991) proposed an algorithm for path planning that uses a feedback solution, where the on-line sensor data can be used to generate dynamically the steering commands for the vehicle. Zapata *et al.* (1994) developed a method for fast outdoor mobile robots based on deformable virtual zone. The mobile robot has no model of its environment but can measure any intrusion of information (proximity-type information) in the direction of its own motion.

But, conventional controls are not suitable for navigation in complex and dynamically changing environments where unknown obstacles may be located on a priori planned path. Conflict of objectives, like go to goal position versus obstacle avoidance, can appear. To overcome these problems, many approaches have recently been developed using fuzzy sets and neural networks. Beom & Cho (1995) used reinforcement learning to tune a fuzzy rule base, and to obtain adaptive behavior during interaction with the environment. Baxter & Bumby (1995) used a fuzzy logic controller, inhibitive rules and the rule spreading and windowing techniques for the navigation in presence of obstacles. Fabro & Gomide (1996) used a self-organising neuro-fuzzy controller and a proportional behavior selector. The aim of this work is to compare two different approaches to obtain the obstacle avoidance behavior in complex and dynamically changing environments: inhibitive rules previous shown in (Becker & Dedini, 1997) and a proportional behavior selector (Becker & Dedini, 1998).

## 2. FUZZY CONTROLLER

The use of fuzzy logic in controls is well documented in literature. Initially the input variables are fuzzified and linked, via a set of linguistic rules, to the fuzzy output during the composition and encoding stages. The fuzzy output is then defuzzified to produce a crisp output value. The approach adopted here is to have guidance plans for the vehicle expressed as fuzzy rules and continually apply these rules so as to be able to react appropriately in face of changing conditions. By adopting such a fuzzy logic based controller, only the initial and the final positions of the vehicle are specified and a set of linguistic rules is used to guide the vehicle to its goal, taking any necessary action to avoid obstacles on its way.

The development of the fuzzy controller is conveniently divided into two parts: navigation control, and obstacle avoidance control. An important principle is adopted at the outset: the obstacle avoidance structure should always be active but should not affect the normal operation of the vehicle unnecessarily. This principle requires that the navigation control and obstacle avoidance be a carefully integrated control structure so as to prevent conflicts between the navigation control and obstacle avoidance control. The controller uses "max-min" inference and the correlation minimum encoding technique to give a wide range of output values.

### 2.1 Basic navigator controller

The basic navigation controller is responsible for moving the vehicle form start position to its goal position defined in terms of ($x_f$, $y_f$, $\theta_f$), see Fig. 1.

To achieve this control, five principles were adopted in the development of the navigation control sets (Baxter & Bumby, 1995):

1. If the vehicle is *long way* from the goal position, steer so as to head straight towards it, that is: $\theta_{he} \rightarrow 0$;
2. If the vehicle is a *medium distance* from the goal attempt to move the vehicle to line up behind the goal heading towards it, that is $\theta_{fe} \rightarrow 0$;
3. If the vehicle is a *small distance* from the goal position, try to line up directly with the center-line, that is: $\theta_{he}$ e $\theta_{fe} \rightarrow 0$;
4. If the vehicle is *not orientated to succeed* steer away from the goal for a new approach;
5. If the vehicle is *almost on top of the goal position* try to achieve the demanded final orientation , that is: $\theta_{oe}$ or $\theta_{he} + \theta_{fe} \rightarrow 0$.

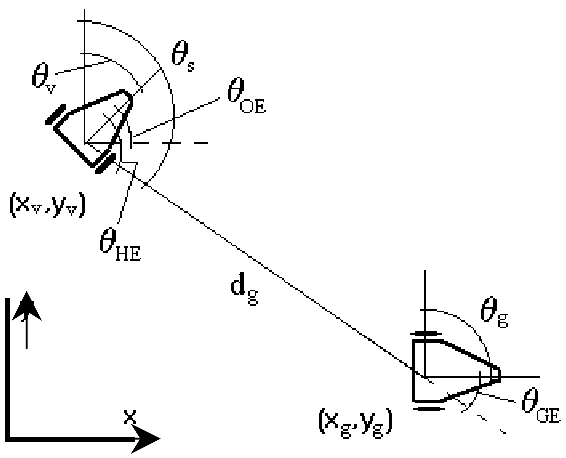



Figure 1 - State variables and global coordinate system.

The following Equations derive the values of the state variables from the global coordinates of the vehicle and its goal:

$$\theta_s = \tan^{-1}\left(\frac{y_f - y_r}{x_f - x_r}\right) \tag{1}$$

$$\theta_{fe} = \theta_s - \theta_f \tag{2}$$

$$\theta_{he} = \theta_r - \theta_s \tag{3}$$

$$\theta_{oe} = \theta_r - \theta_f \tag{4}$$

Such navigation control principles allowed the input fuzzy sets are shown in Figs. 2 to 5 and the linguistic names for distance and error angles sets are shown on Tables 1 and 2, respectively. To see more clearly the interaction between the fuzzy rule sets, they are conveniently represented by a fuzzy associate memory bank matrix on Tables 3 to 6.

Table 1 - Linguistic names for distance.

| Set Label | ZE | S | M | L |
|---|---|---|---|---|
| Set Name | Zero | Small | Medium | Large |

Table 2 - Linguistic names for error angles.

| Label | Set Name | Label | Set Name |
|---|---|---|---|
| NA | Neg. Away | PA | Pos. Away |
| NB | Neg. Big | PB | Pos. Big |
| NP | Neg. Perpend. | PP | Pos. Perpend. |
| NL | Neg. Large | PL | Pos. Large |
| NM | Neg. Medium | PM | Pos. Medium |
| NS | Neg. Small | PS | Pos. Small |
| NVS | Neg. Very Small | PVS | Pos. Very Small |
| NZ | Neg. Zero | PZ | Pos. Zero |

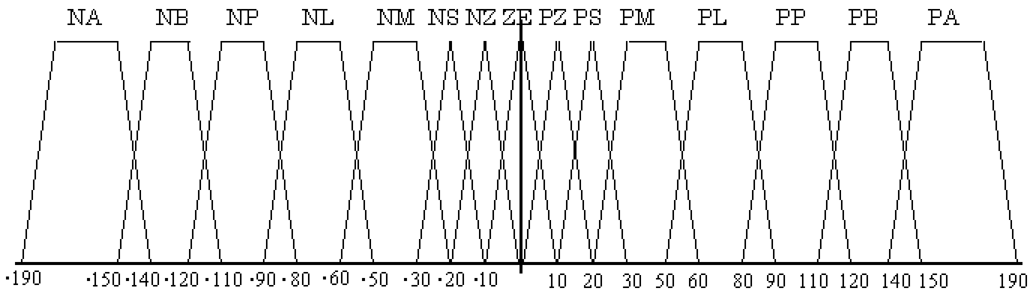



Figure 2 - Fuzzy set definition for $\theta_{fe}$.

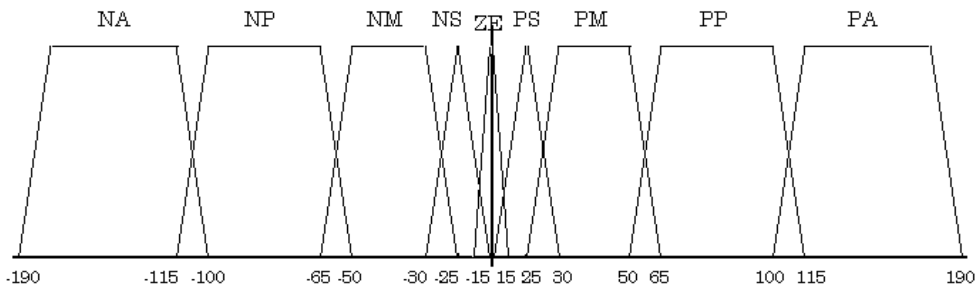



Figure 3 - Fuzzy sets definition for $\theta_{he}$ and $\theta_{oe}$.

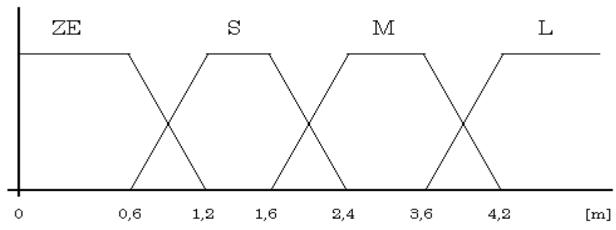



Figure 4 - Fuzzy set definition for $d_f$ (distance to goal).

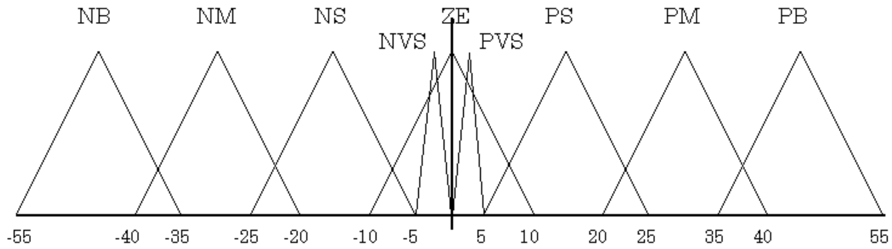



Figure 5 - Fuzzy set definition for $\theta_{output}$.

Table 3 - Fuzzy associate memory matrix for $d_f$ (ZE).

| | | $\theta_{fe}$ | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | PA | PB | PP | PL | PM | PS | PZ | ZE | NZ | NS | NM | NL | NP | NB | NA |
| | PA | ZE | ZE | ZE | ZE | ZE | ZE | ZE | ZE | ZE | ZE | ZE | ZE | ZE | ZE | ZE |
| | PP | ZE | ZE | ZE | NB | NB | NB | NB | NM | NB | NB | NB | NB | ZE | ZE | ZE |
| | PM | NB | NB | NB | NB | NB | NB | NS | NS | NS | NB | NB | NB | NB | NB | NB |
| | PS | NS | NS | NS | NS | ZE | NM | NVS | NVS | NVS | NM | ZE | NS | NS | NS | NS |
| $\theta_{oe}$ | ZE | PS | PS | PM | PM | PS | PS | ZE | ZE | ZE | PS | PS | PM | PM | NS | PS |
| | NS | PS | PS | PS | PM | PM | PS | PVS | PVS | PVS | PS | PM | PM | PS | PS | PS |
| | NM | PB | PB | PB | PB | PB | PB | PS | PS | PS | PB | PB | PB | PB | PB | PB |
| | NP | ZE | ZE | ZE | ZE | ZE | ZE | ZE | PM | ZE | ZE | ZE | ZE | ZE | ZE | ZE |
| | NA | ZE | ZE | ZE | ZE | ZE | ZE | ZE | ZE | ZE | ZE | ZE | ZE | ZE | ZE | ZE |

Table 4 - Fuzzy associate memory matrix for $d_f$ (S).

| | | $\theta_{fe}$ | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | PA | PB | PP | PL | PM | PS | PZ | ZE | NZ | NS | NM | NL | NP | NB | NA |
| | PA | ZE | ZE | ZE | NS | NS | NM | NM | NM | NB | NB | NB | NB | NB | NB | NB |
| | PP | PS | ZE | ZE | NS | NS | NS | NM | NM | NB | NB | NB | NB | NB | NB | NB |
| | PM | PM | PS | ZE | ZE | NS | NS | NS | NM | NM | NS | NS | NM | NB | NB | NB |
| | PS | PB | PB | PM | PS | ZE | ZE | ZE | NS | NS | NS | NS | NM | NB | NB | NB |
| $\theta_{he}$ | ZE | PB | PB | PB | PM | PM | PS | ZE | ZE | ZE | NS | NM | NM | NB | NB | NB |
| | NS | PB | PB | PB | PM | PS | PS | PS | PS | ZE | ZE | ZE | NS | NM | NB | NB |
| | NM | PB | PB | PB | PM | PS | PS | PM | PM | PS | PS | PS | ZE | ZE | NS | NM |
| | NP | PB | PB | PB | PB | PB | PB | PB | PB | PM | PS | PS | PS | ZE | ZE | NS |
| | NA | PB | PB | PB | PB | PB | PB | PB | PB | PM | PM | PS | PS | ZE | ZE | ZE |

Table 5 - Fuzzy associate memory matrix for $d_f$ (M).

| | | $\theta_{fe}$ | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | PA | PB | PP | PL | PM | PS | PZ | ZE | NZ | NS | NM | NL | NP | NB | NA |
| | PA | ZE | ZE | ZE | NS | NS | NS | NS | NB | NB | NB | NB | NB | NB | NB | NB |
| | PP | PS | PS | ZE | ZE | ZE | NS | NS | NM | NM | NM | NM | NM | NB | NB | NB |
| | PM | PM | PM | ZE | ZE | ZE | ZE | PS | NS | NS | NM | NM | NM | NB | NB | NB |
| | PS | PB | PB | PM | PB | ZE | ZE | ZE | NS | NS | NS | NM | NM | NB | NB | NB |
| $\theta_{he}$ | ZE | PB | PM | PM | PS | PS | ZE | ZE | ZE | ZE | ZE | ZE | NS | NM | NM | NB |
| | NS | PB | PB | PB | PM | PS | PS | PS | ZE | ZE | ZE | ZE | NS | NM | NB | NB |
| | NM | PB | PB | PB | PM | PM | PS | PS | PS | PS | ZE | ZE | ZE | ZE | NM | NM |
| | NP | PB | PB | PB | PM | PB | PM | PM | PS | PS | PS | ZE | ZE | ZE | NM | NS |
| | NA | PB | PB | PB | PB | PB | PB | PB | PS | PS | PS | PS | PS | ZE | ZE | ZE |

Table 6 - Fuzzy associate memory matrix for $d_f$ (L).

| | | $\theta_{fe}$ | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | PA | PB | PP | PL | PM | PS | PZ | ZE | NZ | NS | NM | NL | NP | NB | NA |
| $\theta_{he}$ | PA | NM | NM | NM | NM | NM | NM | NM | NB | NB | NB | NB | NB | NB | NB | NB |
| | PP | NM | NM | NM | NM | NM | NM | NM | NB | NB | NB | NB | NB | NB | NB | NB |
| | PM | NS | NS | NS | NS | NS | NS | NS | NM | NM | NM | NM | NM | NM | NM | NM |
| | PS | ZE | ZE | ZE | ZE | ZE | ZE | ZE | NS | NS | NS | NM | NM | NM | NM | NM |
| | ZE | ZE | ZE | ZE | ZE | ZE | ZE | ZE | ZE | ZE | ZE | ZE | ZE | ZE | ZE | ZE |
| | NS | PM | PM | PS | PS | PS | PS | PS | PS | ZE | ZE | ZE | ZE | ZE | ZE | ZE |
| | NM | PM | PM | PM | PM | PM | PM | PM | PM | PS | PS | PS | PS | PS | PS | PS |
| | NP | PB | PB | PB | PB | PB | PB | PB | PB | PM | PM | PM | PM | PM | PM | PM |
| | NA | PB | PB | PB | PB | PB | PB | PB | PB | PM | PM | PM | PM | PM | PM | PM |

A cruiser velocity (0.35 m/sec) is used during the path and the fuzzy velocity controller is used only in the final approach. In other words, the controller slows the AVD down only as it approaches the goal position: *"IF distance to goal position is SMALL then velocity is SLOW"*. If the vehicle is in a very complex environment (with several obstacles around, like in a narrow passage), the cruiser velocity is reduced to 0.10 m/sec. In order to choose the better procedure to obtain the obstacle avoidance behavior, two different techniques are used: inhibitive rules and proportional behavior selector.

## 2.2 Inhibitive rules

The obstacle avoidance is added to the controller by a set of inhibitive rules of the form: *"IF obstacle is AHEAD LEFT then DO NOT steer ZERO, NEGATIVE SMALL, ...*". This type of rule set reduces the activation of an output set rather than increasing it, as would be the case if a positive avoidance rule were used. The aim of the inhibitive rules is to produce a mask vector that, when multiplied by the fuzzy vector, give an overall output vector. The mask vector contains values indicating how acceptable each possible steering angle set is in view of the proximity of obstacles. The input sets for the obstacle avoidance controller are linked to particular areas of the certainty grid relative to the vehicle. The area covered by a set is the area that the vehicle would occupy if a particular output set was activated. Each rule links one or more of these input sets to a degree of inhibition of the corresponding output steering angle set which ranges from 0, total inhibition, to 1, no inhibition. Sets covering areas close to the vehicle have the greatest inhibitive effect and prevent any activation of their linked output set, while more distant sets merely reduce the activation.

Table 7 - Avoidance rules set (Becker & Dedini, 1997).

| Rule | Obstacle Position | Inhibitive Rules |
|---|---|---|
| P1 | $-100° \le \theta_{obstacle} \le -35°$ | PB, PM, PS, PVS and NVS |
| P2 | $-40° \le \theta_{obstacle} \le -20°$ | PB, PM, PS, PVS and NVS |
| P3 | $-25° \le \theta_{obstacle} \le -5°$ | PB, PM, PS, PVS, ZE, NVS and NS |
| P4 | $-10° \le \theta_{obstacle} \le 10°$ | PM, PS, PVS, ZE, NVS, NS and NM |
| P5 | $5° \le \theta_{obstacle} \le 25°$ | PS, PVS, ZE, NVS, NS, NM and NB |
| P6 | $20° \le \theta_{obstacle} \le 40°$ | PVS, NVS, NS, NM and NB |
| P7 | $35° \le \theta_{obstacle} \le 100°$ | PVS, NVS, NS, NM and NB |

Table 8 - Degree of inhibition **x** distance to obstacle.

| Distance [m] | $d \ge 4$ | $4 < d \le 3$ | $3 < d \le 2$ | $2 > d$ |
|---|---|---|---|---|
| inhibition | 1,0 | 0,8 | 0,5 | 0 |

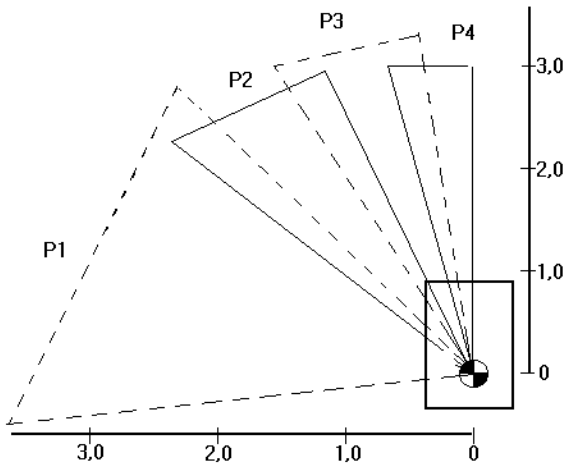
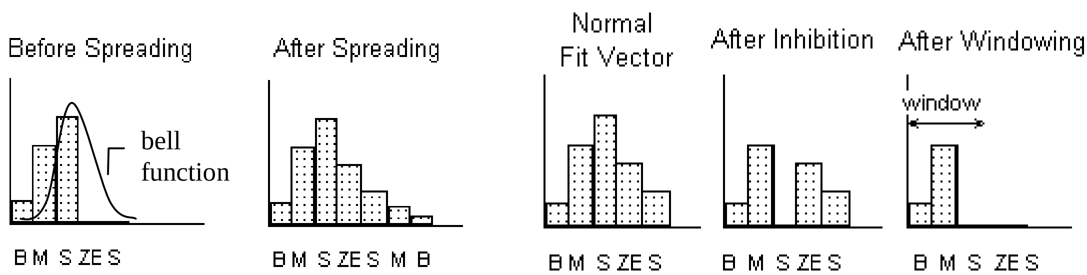



Figure 6 - Avoidance sets areas.

But, there are some problems with using inhibitive rules and center of gravity defuzzification: the resultant output would still be to steer straight on as compromise between going left or right round the obstacle. To guarantee that the defuzzified output will not fall within one of inhibited sets, sliding window defuzzification is used. To provide alternative suggestions, in the situation when all the output sets activated by the navigation controller are inhibited by the obstacle avoidance rules, a technique called rule spreading is used (Baxter & Bumby, 1995). The rule spreading operates by using a bell function to add activation values to all the entries in the fuzzy fit vector, depending on their distance from the activated sets. The activation of the *r*th set is multiplied by $e^{-k(i-r)^2}$ and added to the activation of the *i*th set, see Fig. 7-a. The sliding window defuzzification technique involves locating the set with the maximum activation and then applying fuzzy centroid defuzzification to this set and its immediate neighbors (defined by the window width), see Fig. 7-b.




(a) (b)

Figure 7 - Examples of Rule Spreading (a) Slide Windowing application (b).

### 2.3 Proportional behavior selector

In this case, a new fuzzy rule set is also used to make the obstacle avoidance (collision controller). The selector takes its decision based on measurements of proximity of the target (goal position) and the obstacle as follows. When an obstacle brings near, the navigation controller output is inhibited and the collision controller output is stimulated: the selector must avoid obstacles, independently of target position. This situation occurs when the vehicle is near to the obstacles, but far from the target. When the vehicle is closer to the target than to any obstacle, the selector must go towards the target, independently of obstacles. And, when the target position is very closer to an obstacle, the selector must find a compromise solution between the actions to be taken (Becker & Dedini, 1998). The formulae are:

$$\text{Collision: } \alpha_c = d_{obst} . e^{0.1(d_{obst} - 15)} \qquad \text{Navigation: } \alpha_n = d_f . e^{0.1 d_f} \tag{5}$$

Let $u_c$ and $u_n$ be the defuzzified control actions from the fuzzy collision avoidance controller and the fuzzy navigator controller, respectively. Thus the output control action $u$ to be adopted is determined by:

$$u = u_c \frac{\alpha_c}{(\alpha_c + \alpha_n)} + u_n \frac{\alpha_n}{(\alpha_c + \alpha_n)} \tag{6}$$

The output angle set for the collision controller is the same used in previous case (inhibition rules). So, the structures of the fuzzy controllers (block diagrams) with the application of inhibition rules and collision avoidance controller are shown on Fig. 8.

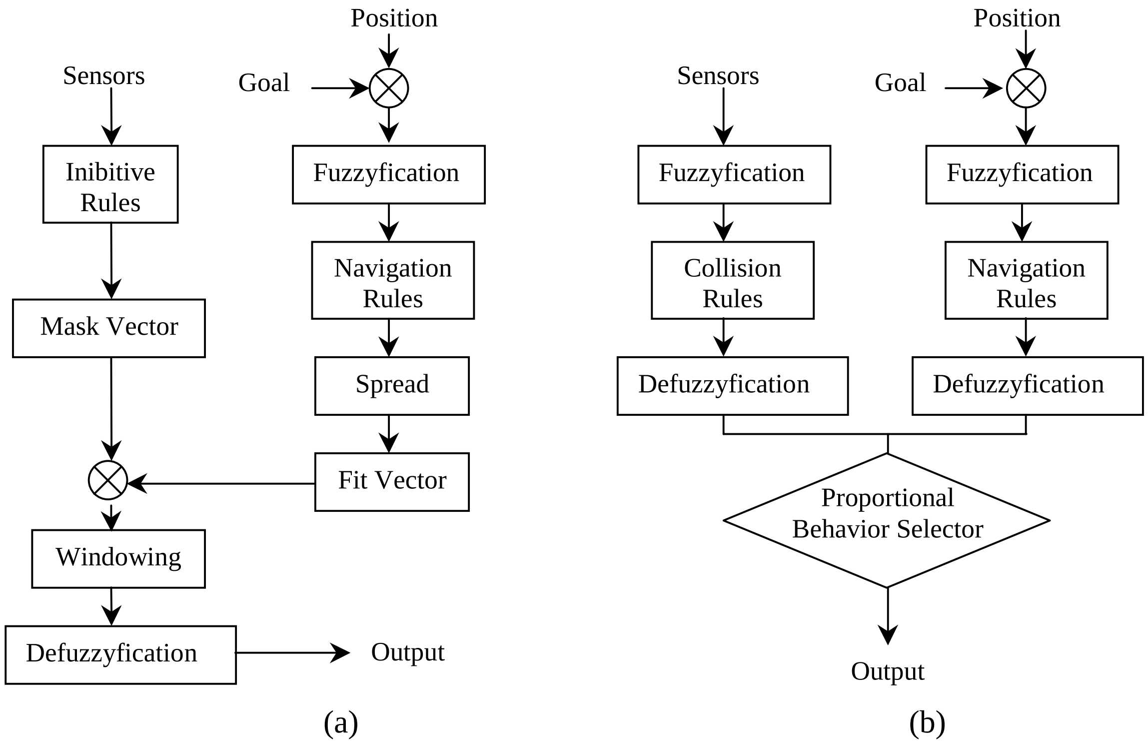



Figure 8 - Block diagram of the controller with the application of IR (a) and PBS (b).

To simulate the vehicle behavior in complex environments, the software MatLab was used. Simulations are made in an environment with 10 obstacles for the two techniques: inhibition rules (IR) and proportional behavior selector (PBS). In both cases, a cruiser velocity (0.35m/sec) was used during the path. The figures next show the path of the vehicle and the output signal of the fuzzy controller (steering angle in degrees). The simulations in a narrow passage used a cruiser velocity of (a) 0.1 m/sec and (b) 0.2 m/sec, and the obstacle avoidance set was adapted (reduced).

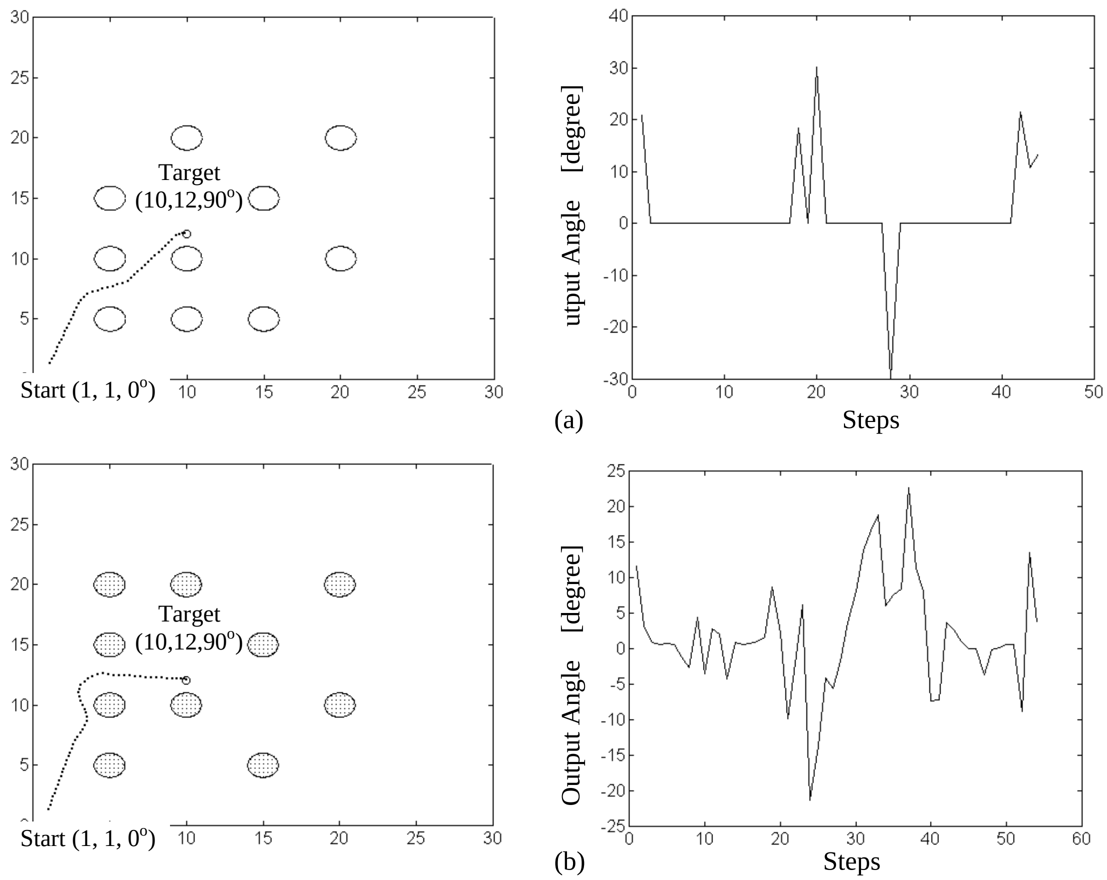



Figure 9 – Fuzzy controller with IR (a) and PBS (b) – Target (10, 12, 90°).

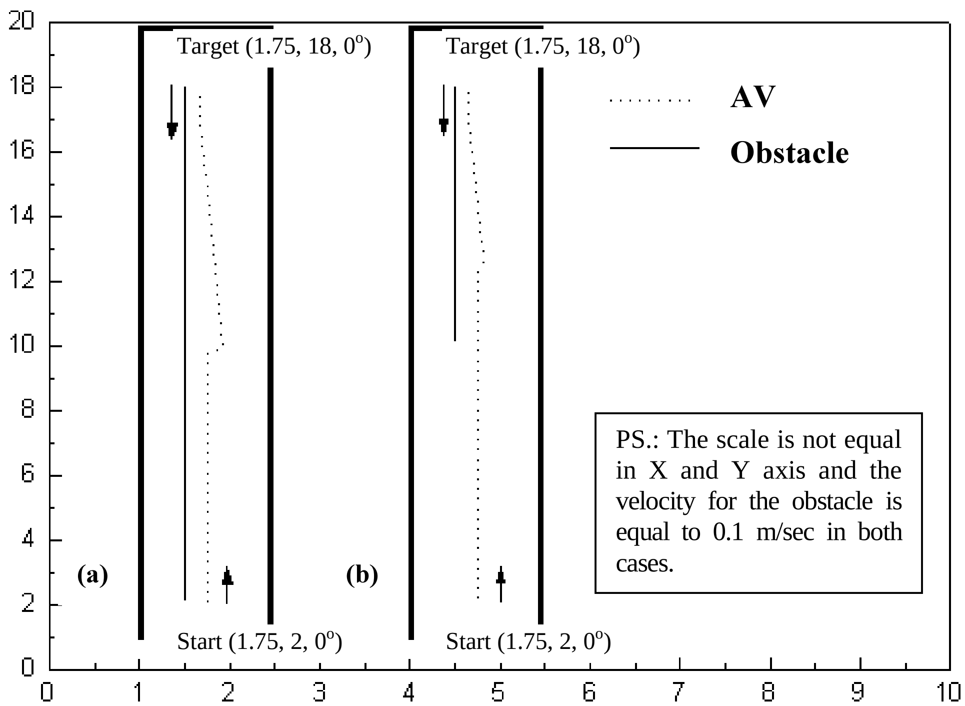



Figure 10– Autonomous Vehicle (AV) behavior in a narrow passage with a Mobile Obstacle (MO), (a) cruiser velocity equal to 0.1 m/sec and (b) cruiser velocity equal to 0.2 m/sec.

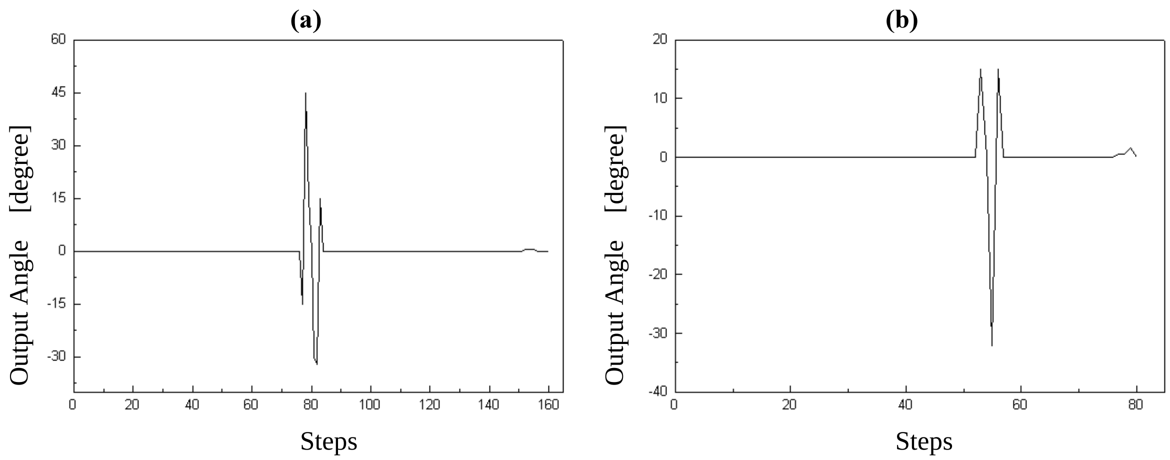



Figure 11 – Output Angle of the fuzzy controller (a) cruiser velocity = 0.1 m/sec and (b) 0.2 m/sec.

## 3. CONCLUSIONS

This work showed two different techniques to obtain the obstacle avoidance behavior in autonomous vehicles: the use of inhibitive rules and the use of a proportional behavior selector. In both cases, the same fuzzy navigator is used. The fuzzy controller with inhibition rules produces a better control action. It provides the obstacle avoidance and navigation behavior as the vehicle moves to goal without the need for an absolute path defined before movement starts and without the vehicle zigzag. The fuzzy navigator has a great number of fuzzy rules, due to the predetermined final orientation. In other applications, where the vehicle mustn't have a final orientation, the number of fuzzy rules is smaller. The narrow passage problem was approached. In this situation the controller changes the cruiser velocity and adapts the obstacle avoidance set to improve the vehicle performance. It is necessary to do experimental tests to validate the fuzzy controller.

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