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FUZZY TRACKING METHODS FOR MOBILE ROBOTS

This chapter deals with the application of fuzzy logic to autonomous navigation of mobile robots. Two different tracking problems are considered: tracking of previously computed explicit paths, and tracking of walls and other natural features in the robot environment. Fuzzy logic allows the management of heuristic rule base knowledge, imprecise information from sensors, and the uncertainties in the knowledge about the environment. The Chapter includes the application of the tracking methods to the mobile robots RAM-1 and AURORA.

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25.1 INTRODUCTION

The number of applications of fuzzy logic to mobile robot and autonomous vehicle control has increased significantly in the last years. The most well known arguments supporting fuzzy control are the ability to cope with imprecise information in heuristic rule based knowledge and sensor measurements, the interpolative nature of the fuzzy controllers, and the flexibility in the definition of non linear control laws.

Motion planning and control of autonomous vehicles involves several problems related with environment perception and representation, path planning, path tracking, velocity control and low level motion control. This paper deals with the applications to the mobile robot tracking of references, which include:

- a) tracking of explicit previously defined paths, using dead reckoning and navigation sensors.
- b) tracking of walls and other natural features in the environment using external sensors.

In a) the tracking objective is to generate the control commands for the vehicle to follow the previously defined path by taking into account the actual position and the constraints imposed by the vehicle and its lower level motion controllers. Fuzzy logic can be used both to supervise conventional path trackers, as proposed in [1], and for direct fuzzy control. This Chapter considers the second case. That is, the fuzzy controller directly generates the steering command from the sensor inputs [2].

The approach b) is related with fuzzy reactive approaches for mobile robot navigation. In this case the controller inputs are provided by the external sensors.

The chapter is organized as follows. The following section is devoted to fuzzy direct explicit path tracking. The section includes the description of the method and the application to the mobile robot RAM-1. The next section is related to reactive navigation. Fuzzy tracking is considered in the framework of a behavior based architecture for mobile robot control. The application of this method to the AURORA mobile robot is considered in the next section. The two last sections of the Chapter are for the Conclusions and References.

25.2. FUZZY EXPLICIT PATH TRACKING

The application of fuzzy control methods to solve the tracking of explicit paths is motivated by difficulties to apply in real time realistic control laws derived from complex kinematics and dynamic models. Explicit path tracking is based on position estimation produced by the mobile robot's dead reckoning system. This estimation is not very accurate but allows the vehicle controller to quickly close the control loop. The general scheme for fuzzy path tracking is shown in Figure 25-1.

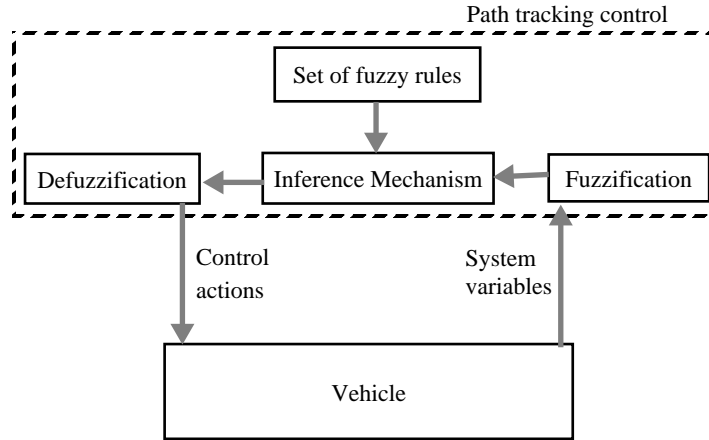


Figure 25-1: Fuzzy path tracking.

In this section the problem of steering the vehicle to track a previously defined path in spite of external perturbations is considered. This path can be defined off-line prior to navigation or computed on-line by the autonomous navigation system. Today several path generation methods can be applied in real time, providing a path with good kinematic properties to be followed by the real vehicle [3].

25.2.1 DESCRIPTION

The inputs to the fuzzy controller are variables defining the state of the vehicle with respect to the path, and the output is the steering command to be executed by the low-level motion controllers. Consider a goal point in the path at a look-ahead distance away as shown by Figure 25-2a [4]. The goal point has a negative x coordinate (negative Δx) and the path tangent in this point (path heading) is the same as the vehicle's heading (zero heading in the vehicle's coordinate frame or $\Delta\phi = 0$). Then, the vehicle must be turned to the left by a certain amount as shown in Figure 25-2a.

Consider now the situation illustrated by Figure 25-2b. In this case Δx is zero, but $\Delta\phi$ is positive and the vehicle must be turned again to the left by a certain amount. It seems clear that fuzzy logic could be used to interpret this heuristic in order to generate the steering command γ_d from the values of Δx and $\Delta\phi$.

In addition to Δx and $\Delta\phi$, it is advantageous [5] to consider as antecedents the distance between the vehicle and the nearest point in the path Δs , the difference between the curvature at the goal point and the robot's curvature $\Delta\gamma$, and the vehicle's velocity v . The curvature has to be increased when $\Delta\gamma$ is positive, and decreased when the error in curvature is negative. When velocity is high, the desired curvature should change in a smooth way. When Δs is shorter the

curvature can change more abruptly. When conflicts appear in applying the above heuristic rules, the error in position Δx will be the most significant, while the error in curvature will be the least.

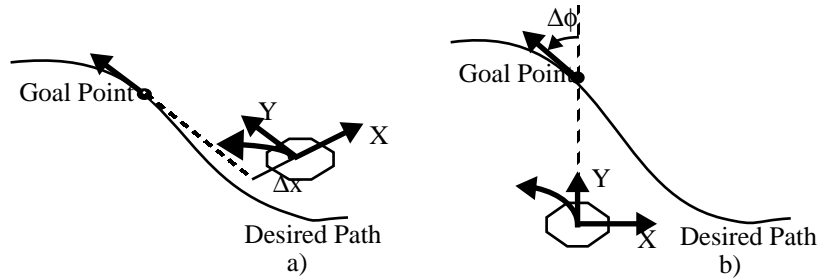


Figure 25-2: Motivation of the fuzzy path tracking strategy.

Since the vehicle cannot correct the errors that it has with the nearest point in the path to follow, the goal point is chosen some distance ahead D from the nearest point. This distance is measured over the desired path in order to make the search easier (see Figure 25-3). The lookahead distance allows the vehicle to anticipate since it knows the path to follow in advance. A larger lookahead distance implies smoother control but it also means worse tracking. A smaller lookahead can reduce the tracking errors; however, command control increases and can even become unstable. So, it would be useful to consider the lookahead as a parameter that has to be adjusted depending on the vehicle's situation with respect to the desired path. Changes in the lookahead distance must be accomplished smoothly in order to change the desired curvature in the same way from one control period to the next.

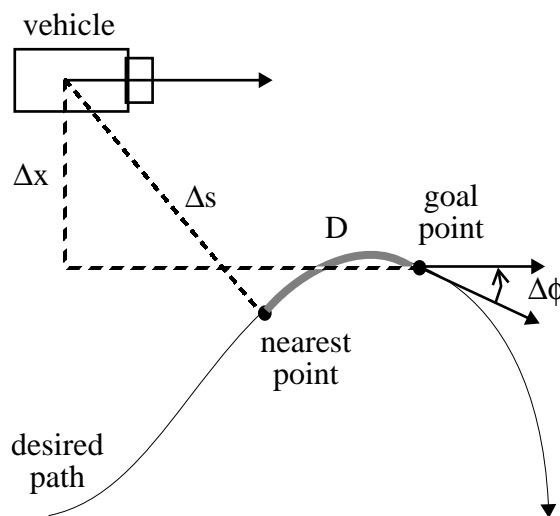


Figure 25-3: Variables of the fuzzy controller.

The influence of the antecedents on the lookahead distance is the following:

- Larger errors in position, orientation or curvature imply that the lookahead D should be increased, while smaller ones should give a decrease in D .
- As the vehicle moves faster, D should be increased. The opposite occurs when the vehicle decreases its velocity.
- The lookahead D has to be increased when Δs is bigger, and decreased when Δs is smaller.

In case of conflict in applying the above rules, the worst case that increases D would be considered the dominant.

Thus, a set rules such as

R_i : If Δx is NEGATIVE_LARGE and $\Delta\phi$ is POSITIVE, $\Delta\gamma$ is ZERO, v is MEDIUM and Δs is SMALL, then γ_d is POSITIVE_LARGE and D is MEDIUM.

are used, where SMALL, POSITIVE, NEGATIVE_LARGE, MEDIUM and NEAR_ZERO are labels associated with the corresponding variables and R_i is the i -th rule of the set of fuzzy rules of the controller. These labels are represented by fuzzy subsets. The set of fuzzy rules represents a fuzzy relation into the antecedents and consequents.

From the control law point of view, the fuzzy direct controller is defined by a nonlinear function:

$$(\gamma_d, D) = \Phi(\Delta x, \Delta\phi, \Delta\gamma, \Delta s, v)$$

Then, the controller inputs are the vehicle's lateral errors with respect to the goal point in the path to follow, which are: errors in position Δx , orientation $\Delta\phi$, and curvature $\Delta\gamma$, the vehicle's distance to the nearest point in the path Δs , and the mobile robot's speed v . The outputs are the lookahead distance D and the steering command γ_d . Figure 25-4 shows the scheme of the fuzzy direct path tracking method.

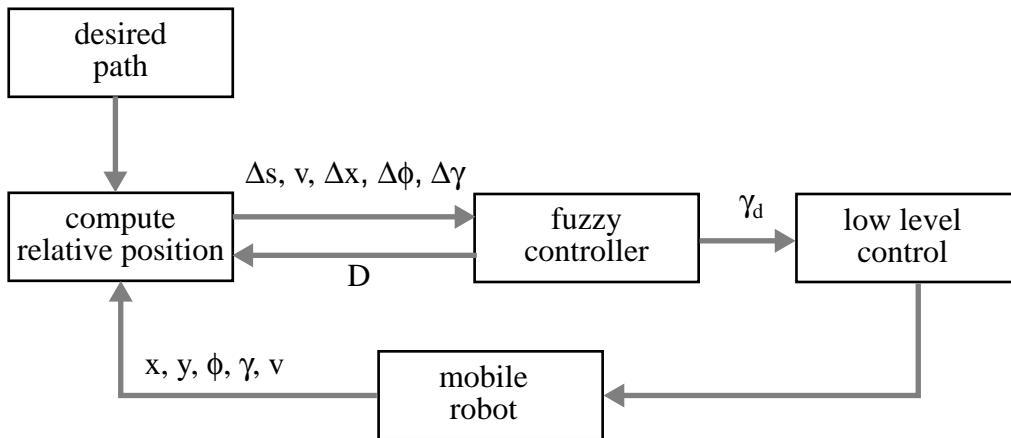


Figure 25-4: Fuzzy direct path tracking.

25.2.2 APPLICATION TO RAM-1

RAM-1 is an autonomous mobile robot designed as a testbed for the automatization of surveillance, manipulation and small part transportation [6]. The RAM-1 vehicle (see Figure 25-5), has four wheels located in the vertices of a rhomb with a diagonal in the longitudinal axis. The two parallel wheels are driven by DC motors. The front and rear wheels are steered by a DC motor with a kinematic rigid link. The locomotion system can provide a zero turning radius. For path tracking the front and rear wheels are steered and the parallel wheels are used with differential drive. The top speed, that is 1.6 m/sec, only can be reached when the vehicle moves along a straight line, and automatically decreases as the curvature of the vehicle increases. The steering time constant for the RAM-1 was measured to be 0.1 seconds. RAM-1 has several sensors including a scanner laser, 2 video cameras, a sonar ring and navigation sensors. The RAM-1 control architecture is shown in Figure 25-6.



Figure 25-5: The autonomous mobile robot RAM-1.

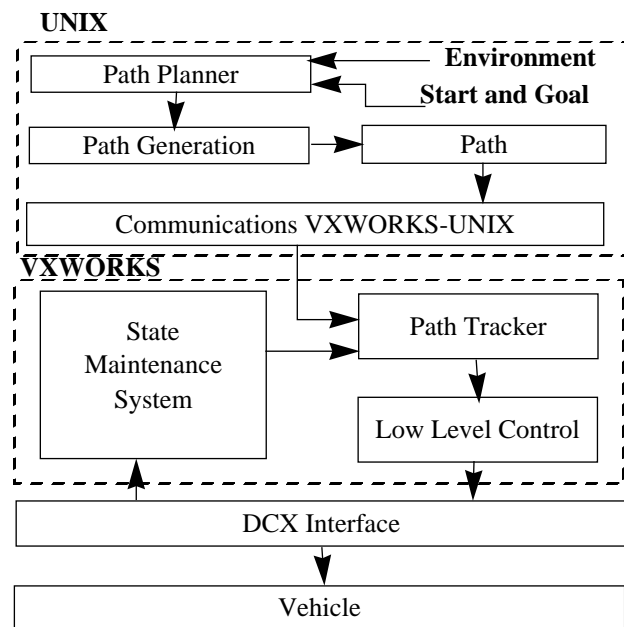


Figure 25-6: RAM-1 control architecture.

The steps that have been taken to build the RAM-1 fuzzy controller are the following:

- Representation in a rule based form of the heuristic knowledge described above.
- The use of a RAM-1 simulation program in real time that allows testing and improving the fuzzy controller very easily, quickly and without danger.
- Apply the fuzzy controller to the real vehicle and, eventually, tuning some parameters.

The fuzzy controller is embedded in the real time controller of the vehicle, which runs on conventional hardware, and is programmed in the C language. The real time controller can compensate for perturbations, such as terrain irregularities, while tracking a path.

Direct fuzzy control provides smooth transitions on the variation of curvature and of the lookahead distance between one control period and the next (20 msec. for RAM-1). Path tracking is robust, even when the mobile robot begins far from or badly orientated to the desired path. Experimental results with the RAM-1 show an excellent performance and a robust behavior with large speed variations.

Several experiments have been done confirming the above comments. Figure 25-7 shows the results in the tracking of a reference path at a speed of 1.4 m/s when RAM-1 starts 1.8 meters away ($\Delta x = -1.8$) with a zero error in orientation and curvature. The efficiency of the method can be observed when tracking a difficult path with sharp curves.

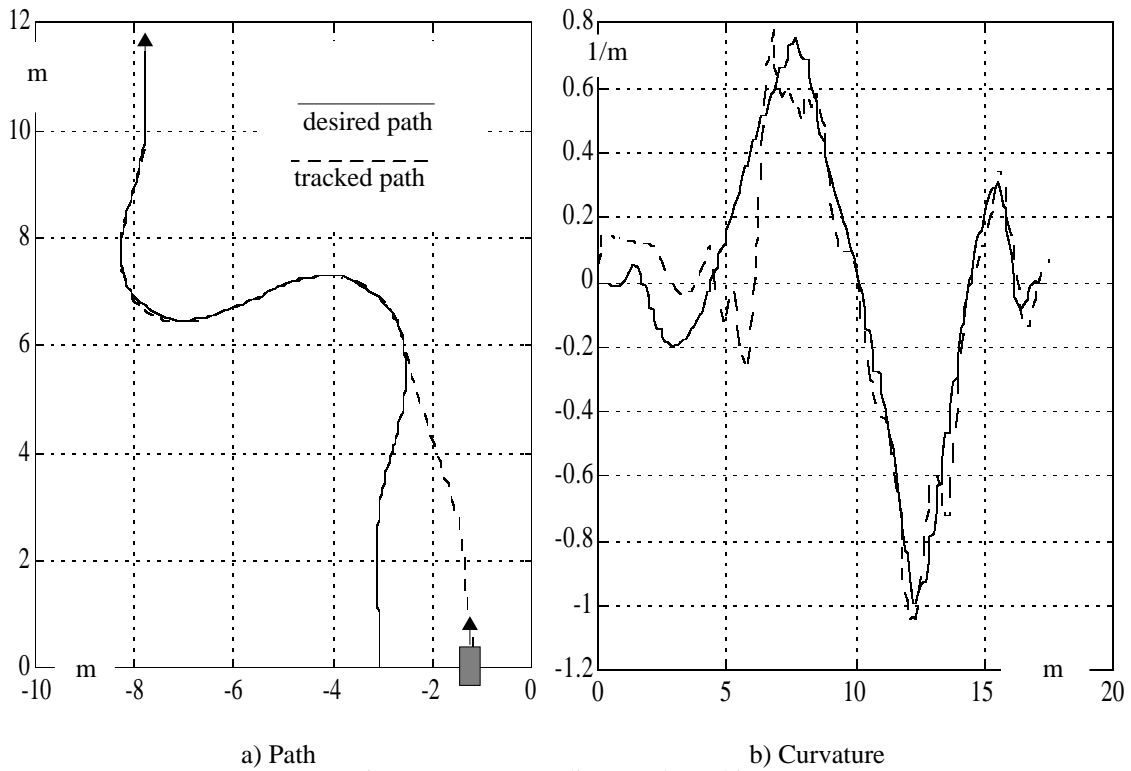


Figure 25-7: Fuzzy direct path tracking.

25 3. FUZZY TRACKING FOR BEHAVIOR BASED ARCHITECTURES

Mobile robots are increasingly required to navigate and perform purposeful autonomous tasks in more complex domains, where the environment is uncertain and dynamic. These requirements demand reactive capacity in their navigation systems in order to attain speed and reliability, which implies a strong dependency on sensed information about the robot's surroundings. Therefore, these applications require full use of the dynamic capabilities of sensor systems, which result from the exchange of information between different sensors, each taking limited or partial observations of the environment [7].

Much of the work on reactive navigation has been inspired by the layered control system of the subsumption architecture [8], which tightly couples sensing and action. The emergent behavior of the robot is the result of the cooperation of independent reactive modules, each one specialized in a particular basic behavior. This approach of competing and cooperative agents has also been applied in a fuzzy frame [9]. However, since reactivity alone does not suffice to meet the needs of real world tasks, hybrid solutions have been devised that blend low level reactive behaviours with a high level plan, used to supervise overall mission execution by activating and deactivating behaviours either sequentially [10] or by means of fuzzy transitions [11].

But the obtention of actor data (command reference values) from sensor data (observation variables) for autonomous mobile robot navigation is a complex task. One interesting approach aiming to reduce complexity and to add flexibility is to deal with a fuzzy system that encapsulates sets of rules in modules and performs inference in parts, with intermediate fuzzy variables [12][13]. For instance, the basic navigation level in the mobile robot control architecture could be divided into two groups of fuzzy rules: The first one would provide a fuzzy interpretation of the sensed data appropriate for each particular navigation concern, while the aim of the second group, a set of navigation behaviors, would be to generate a reference value for the navigation of the robot according to the fuzzy sensor interpretation of the environment. Figure 25-8 sketches the main components of this basic navigation level, in which each behavior makes use of a particular fuzzy interpretation of the sensors needed to accomplish its goal.

The focus of the remaining part of this chapter is on how basic reactive behaviours for navigation can be implemented by means of fuzzy rulebases, considering issues of both measurement (fuzzy range sensor fusion) and action (fuzzy tracking of sensed features). By way of illustration, a real application with the AURORA mobile robot and some experiments are presented.

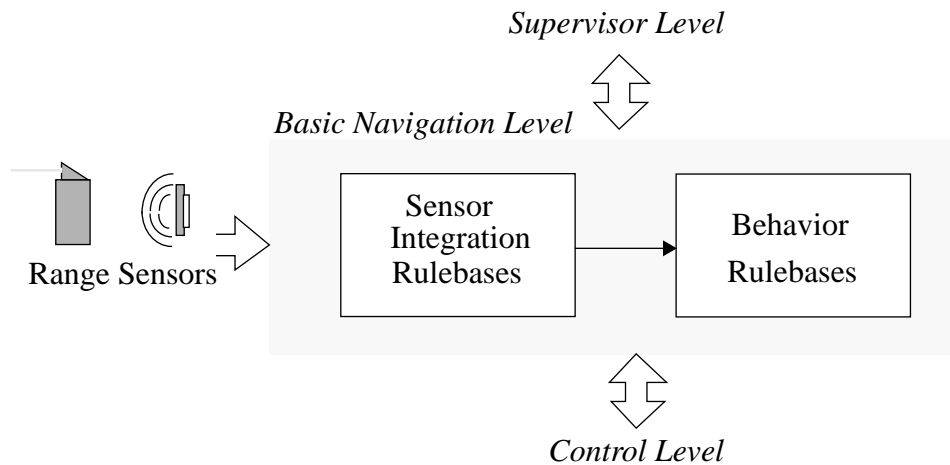


Figure 25-8: The basic navigation level.

25.3.1. FUZZY SENSORS FOR NAVIGATION BEHAVIORS

Different range sensors usually applied in mobile robot navigation, like laser scanners, sonars and infra-red, offer distinct characteristics in reliability, operating limits, accuracy, bearing angle, operating frequency, and last but not least, cost. Robotic applications usually require the combination of sensory data from multiple sources so that reliable and robust interpretations of the environment are available for navigation and operation. The integration of disparate sensory information in order to obtain a coherent description of the world around the robot is rather complex. Fuzzy logic provides a promising way for dealing with conflicts, complementary information, and other issues involved in sensor coordination. Furthermore, a fuzzy description of the sensed environment can be integrated in a fuzzy navigation system.

The nature of sensor interpretation also depends on the use given to it. By adopting a reactive approach, the aim of the system is not to build a map of the environment from an integration of all sensed information [14], but to obtain some immediate indication about the presence of objects around the robot. The meaning given to that indications is task-dependent and environment-dependent, since some of the characteristics of task and environment are used implicitly for navigation. When dealing with tracking of environmental features such as walls, corridors and corners, an interesting solution is to use just global information, obtained from the integration of different sensors, about particular regions around the robot, e.g. its front and both sides. It must be noted that for task-oriented navigation in open environments it should be necessary to have long range information as well, so that long range targets can be detected.

The problem of multiple-sensor processing is fit for a fuzzy approach, since it implies dealing with uncertainty in three different and combined ways:

- Uncertainty in the distance to surrounding objects, which can be modelled by terms such as “far” or “close”. It arises from the inaccuracy of sensors, that are very sensitive to such external factors as the quality of the reflecting surfaces or environmental conditions such as light and temperature.
- Uncertainty about the reliability of sensed data from which the distance can be inferred. Sonars, for instance, provide multiple erroneous readings and do not always detect the presence of objects. Despite stochastic models, it is not always possible to feasibly estimate the reliability of an individual sensor. However, an estimation can be inferred from a combined interpretation by the degree of agreement between different redundant sensors.
- Mobile applications involve specific sources of uncertainty: the distance to surrounding objects varies during the measurement process due to the robot’s motion, and when data are available for use they are not completely up-to-date, because of the time required for obtention and processing.

From the navigation point of view, several efficient reactive systems have been implemented which make use of range sensor information of an homogeneous type (ultrasonic rings, spinning laser range finders,...). Nevertheless, an appropriate combination of several sources of sensor data may offer more information with increased reliability, but still an homogeneous interpretation is preferable to be immediately used by the reactive navigation system. In other words, the design of a particular navigation behavior (e.g. wall following) is quite simple if it makes use of just one input (i.e. the distance to the wall) provided by a single sensor, whereas by using inputs from more sensors the behavior should be more reliable, but at the expense of increased complexity.

As a result of this, the introduction of a model based on virtual fuzzy sensors offers a reliable solution for the integration of disparate sensor information with an autonomous navigation system. A virtual fuzzy sensor provides a fuzzy range estimation that results from fusing information produced by a set of heterogeneous real sensors (that can be complementary in range, redundant, of different quality, etc.) covering the region assigned to it. From the navigation point of view there would be no difference between using the data from a sonar ring or from a virtual ring of homogeneous fuzzy sensors, except for the improved reliability of the latter solution.

Moreover, the modularity of this approach allows that new behaviors can be added to cope with new tasks or environmental requirements, which in turn may require the introduction of new virtual fuzzy sensors in the rulebase to meet their particular perception requirements. This is very interesting from the designer's point of view, since simple independent behaviors and virtual sensors consisting of a reduced number of fuzzy rules can be easily developed and tested before being merged into a comprehensible navigation control system.

25. 3.2. APPLICATION TO THE AURORA MOBILE ROBOT

This section presents the implementation of fuzzy reactive navigation behaviours for AURORA, a mobile robot which is equipped with a sensing system based on ultrasonic sensors for autonomous navigation. Ultrasonic sensors can be adjusted to work at different range distances and can thus be combined to sense both the immediate surroundings (a few centimeters) and mid-range distances (a few meters) from the robot.

AURORA (see Figure 25-9) is a non-holonomic autonomous wheeled mobile robot for greenhouse operations designed and built at the Málaga University to perform operations in greenhouses [15]. AURORA must be capable of operating in a variety of different greenhouses without imposing any alterations on them at all. The locomotion system is a modification of the RAM-1 dual configuration [6]. The mechatronic system consists of an octagonal mobile platform 80 cm in width and 140 cm in length that accommodates a spraying device, the power system, standard electronic and computer enclosures, and a variety of sensors for intelligent operation and navigation.



Figure 25-9: The AURORA mobile robot.

For autonomous navigation, AURORA carries an heterogeneous configuration of ultrasonic sensors that was chosen considering the characteristics of constrained environments, where the robot has to navigate through narrow spaces among a high obstacle density [16]. Instead of a typical ring of homogeneous sonars, its sensor configuration is a combination of three different types of sonars placed at different heights on the front half of the robot, covering the ranges shown in Figure 25-10. The number and types of sonars that have been used are the following: four Short-Range Digital (SRD) sensors, two Mid-Range Digital (MRD) sensors, and four Mid-Range Analog (MRA) sensors. It must be noted how analog range sensors are combined with digital ones, that do not provide a range measurement but a truth value, depending on the presence or not of an object within its working range. Technical details about these types of ultrasonic sensors are presented in Table 25-1.

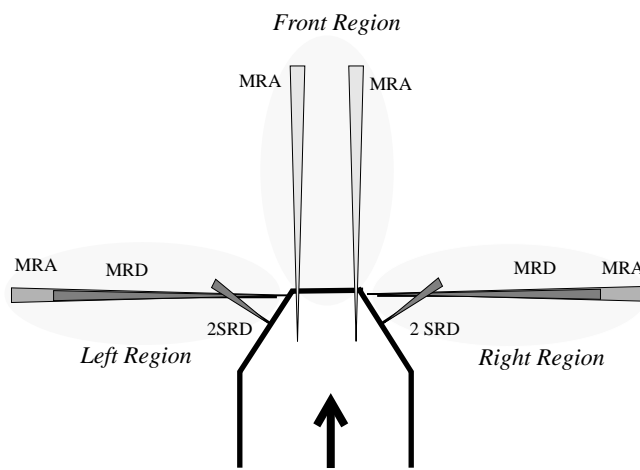


Figure 25-10: Operating range limits of ultrasonic sensors.

Table 25-1: Technical specifications of ultrasonic sensors.

	SRD	MRD	MRA
Sensing range	6 to 30 cm	20 to 100 cm	20 to 130 cm
Switching frequency	8 kHz	4 kHz	4 kHz
Ultrasonic frequency	400 kHz	200 kHz	200 kHz
Repeat accuracy	$\pm 0,45$ mm	$\pm 1,5$ mm	± 2 mm
Resolution	-	-	5 mm
Angle	5°	5°	5°

This is a case where sensor fusion is necessary in order to produce an immediate sensorial interpretation of the robot's surroundings. The fact that all sensors are ultrasonic somehow simplifies the problem of fuzzy sensor fusion, but their heterogeneity allows that the results presented here could be extended, without much effort, for the integration of different kinds of range sensing devices.

The concept of behavior based fuzzy navigation system presented above is illustrated by Figure 25-11, that shows the sets of basic navigation behaviours and virtual fuzzy sensors implemented for AURORA. The following sections describe the design and implementation of some of these modules, together with some illustrative experimental results.

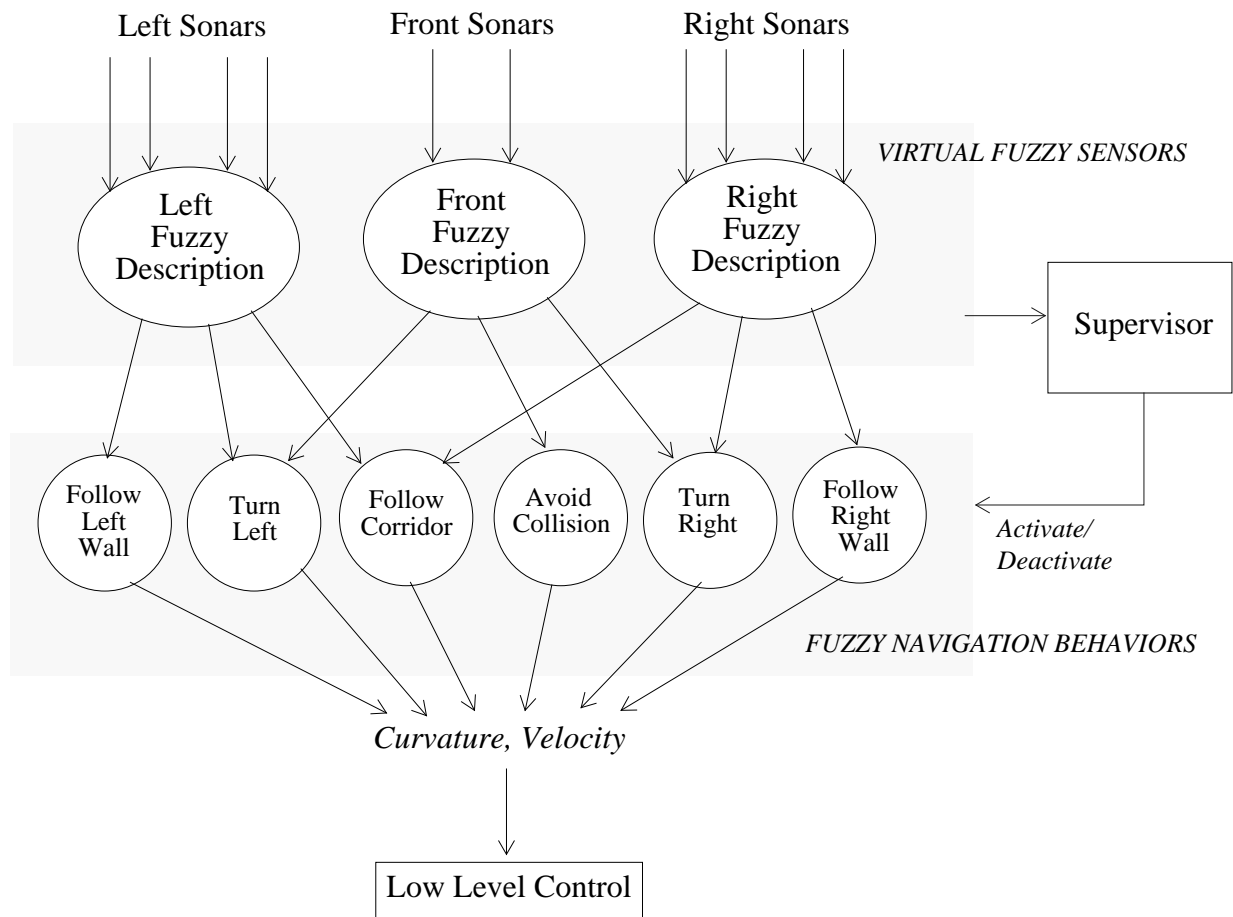


Figure 25-11: Elements of fuzzy navigation with sensor fusion.

SENSOR INTEGRATION

In the presented application, the sensor configuration allows for the definition of three fuzzy sensors, covering three regions around the front half of the robot, as can be seen in Figure 25-10. The front area is covered by two similar sensors, separated by a distance so that they provide complementary information. The side areas are covered by a mixture of disparate sensors, so they offer an interesting case for sensor fusion, and will be considered below in more detail.

Each fuzzy system dedicated to sensor interpretation must obtain a conclusion about the existence or proximity of objects around the robot from the information provided by a set of heterogeneous ultrasonic sensors. A major cause for uncertainty in the distance to surrounding objects arises from the fact that some of the sensors used in this robot are digital, i.e. they merely provide two-valued information about the presence of an object within a range, and the

possibility of having an object is the same along the whole working range of the sensor. Nevertheless, this range can be easily represented by a fuzzy set, and through sensor fusion, that uncertain information, insufficient to produce an accurate description of the environment, can be used to add reliability to that from analog sensors.

Heuristic knowledge about each kind of sensor can be introduced in the fuzzy sensor rulebase so that a feasible result is inferred. In the particular case of ultrasonic sensors, there are two types of erroneous readings: First, analog sensors may provide an erroneous range, and second, a sensor, either analog or digital, may be mistaken about the presence or not of an object. Besides, a sonar detecting something is more reliable than other that does not. With the exception of echoes and multiple reflections, when an ultrasonic sensor detects the presence of something is because something is really there; on the other hand, sensors do not always detect the presence of an object, depending on the quality or the angle of the reflecting surface. For that reason, an heuristic approach to deal with sonar reliability, when some kind of redundancy is available, is to give more credibility to those sensors that detect something, while relying less on those that failed to detect it. One way to represent this knowledge is to assign each rule a weight corresponding to its relative reliability with respect to other rules, according to the following criteria:

- Rules for digital sensors have a lower value, depending on the range covered.
- Rules for close ranges have the highest values, and they decrease according to distance. The closer a range detected, the more reliable it will be. Reflected beams make a longer fly and result in erroneous distant readings.

The fuzzy rulebase designed for the side fuzzy sensors (which can be used for both left and right sides, since their configuration is symmetrical) consists of 12 rules with decreasing weights along the range of the analog sensor, and two additional rules for the digital sensors. Figure 25-12 shows an example of some of these rules with their membership functions and how they are activated by a particular set of input data (MRA= 0.27, SRD1 =1, SRD2 = 0, MRD = 1). The output defuzzified value (0.479 in the presented example) is the result of applying the Max-Dot/Height method, whose value is given in the following equation:

$$v^* = \frac{\sum_{i=1}^n \alpha_i H_i C_i W_i}{\sum_{i=1}^n \alpha_i H_i W_i}$$

where v^* is the defuzzified output value, α_i is the degree of membership computed for the premise of rule i , W_i is the weight assigned to rule i , H_i is the height of the membership function assigned to the consequent v in rule i , and C_i is the center of gravity of the membership function assigned to v in rule i .

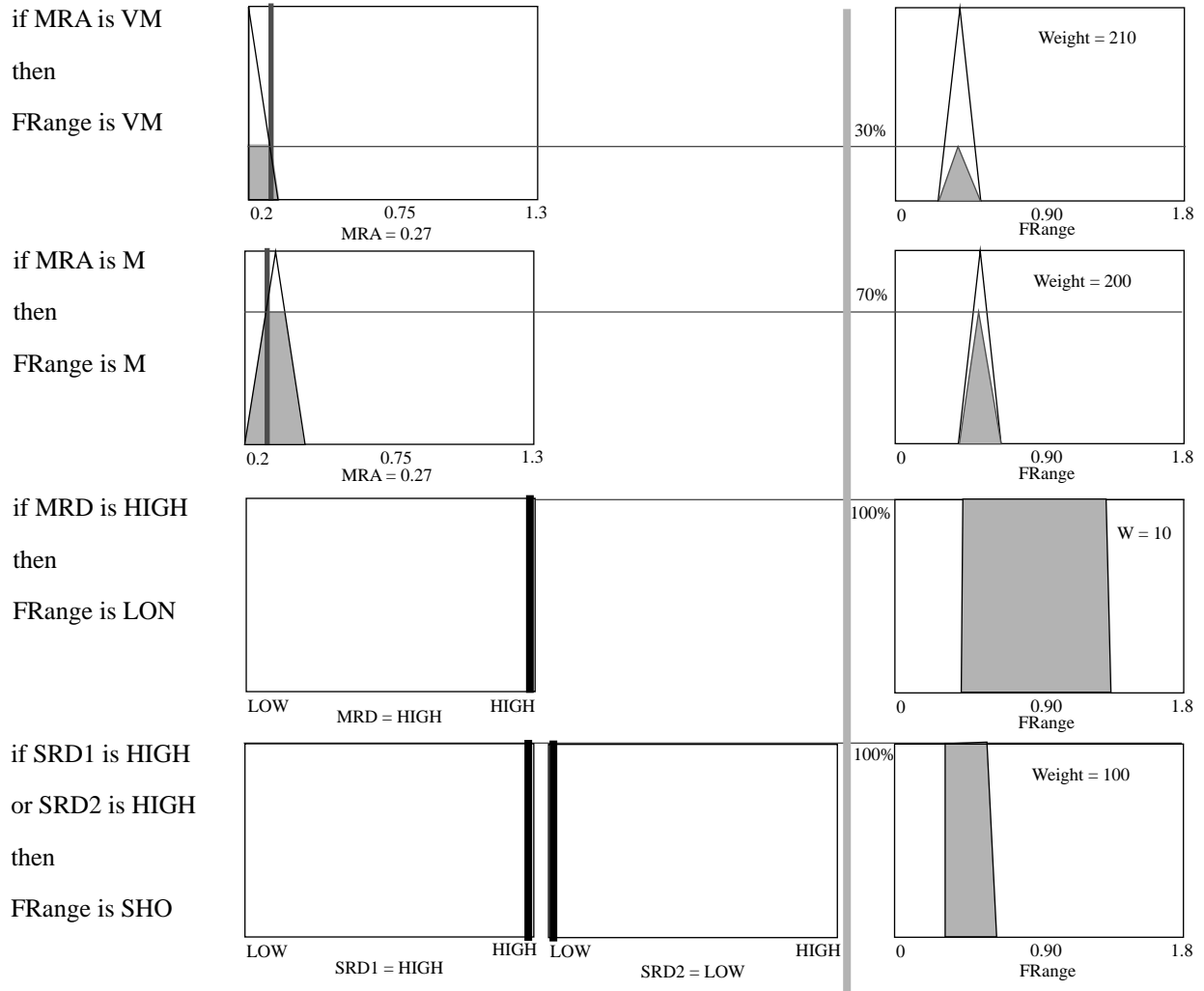


Figure 25-12: Fuzzy outputs of each active rule of the side fuzzy sensor

Figure 25-13 shows the result for the side fuzzy sensor while the robot diverged from a wall as compared with the original readings from all side sensors (analog and digital). If any of the digital sensors fails to detect anything, the incidence on the result is very small. On the other hand, if the failing sensor is the analog one (i.e. the less uncertain), the result is not accurate, but still offers a rough approximation to reality.

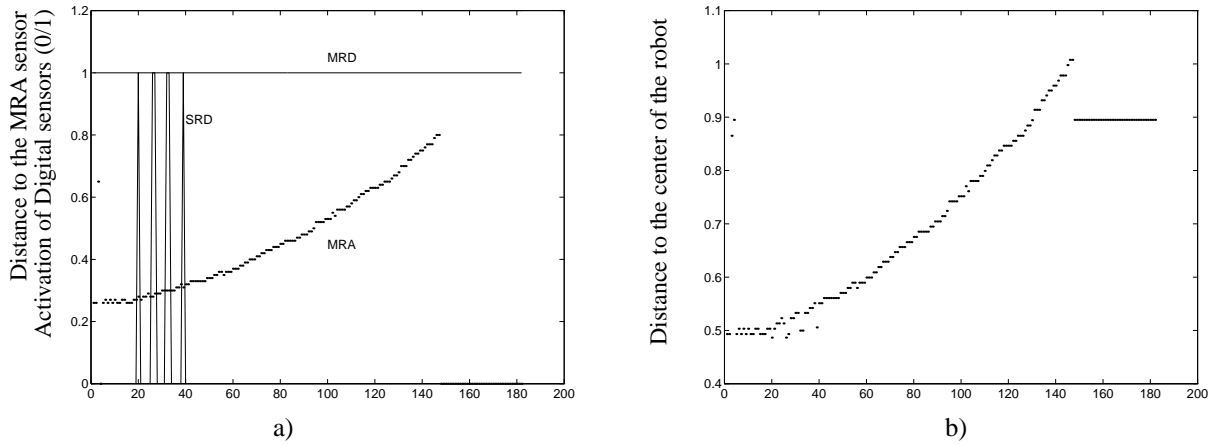


Figure 25-13: Experimental results a) with the side sensors and b) the fuzzy sensor.

Figure 25-13 a shows how the side analog sensor fails to detect a lateral obstacle in the last section of readings. The fuzzy sensor (Figure 25-13b) provides integrated data, referred to the center of the robot, from all side sensors, using information from the digital ones to compensate the erroneous readings of the analog.

TRACKING NATURAL FEATURES

The use of the virtual fuzzy sensors presented above allows the design of much simpler navigation behaviors, such as wall following, corridor following or turning.

Such is the case of the set of rules shown in Table 25-2, which are used for wall tracking. Two inputs are defined, the first one is the distance that must be kept as reference while following the wall. For the sake of simplicity in task specification, this is a crisp variable with only three possible values: Very Close, Close and Middle. The second input is that of the virtual fuzzy sensor providing the distance to the wall, which has been defined by means of five triangular fuzzy sets. The output is a reference value for the curvature of the robot, which is defined by five triangular sets in the universe of discourse $[-0.8, 0.8]$. The defuzzification method used for these rules has been the center of gravity of the unioned scaled output. The corridor following behavior is similar, but it receives inputs from two fuzzy sensors, representing distances to walls at both sides of the robot.

Table 25-2: Fuzzy Inference Rules for Wall Following

<i>REFERENCE</i>	<i>MEASURED RANGE</i>				
	TOOCLOSE	VCLOSE	CLOSE	MIDDLE	FAR
VCLOSE	PM	Z	N	NM	NM
CLOSE	PM	P	Z	N	NM
MIDDLE	PM	PM	P	Z	NM

Figure 25-14 shows the physical layout of an experiment in which AURORA accomplished the task “Follow close right wall, turn right and follow close right wall.” Figure 25-15 shows the measures provided by the “right fuzzy sensor” and the vehicle’s curvature during the experiment. The result produced by the fuzzy right sensor is used to generate the curvature commands by the navigation behaviors involved in the task. The 2.5/m peak in curvature corresponds to the turn, which takes place when the fuzzy sensor detects free space at the right.

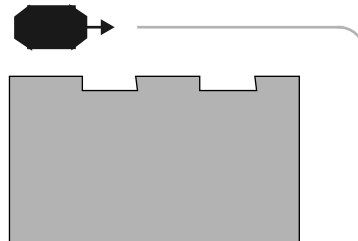


Figure 25-14: Physical layout of the experiment.

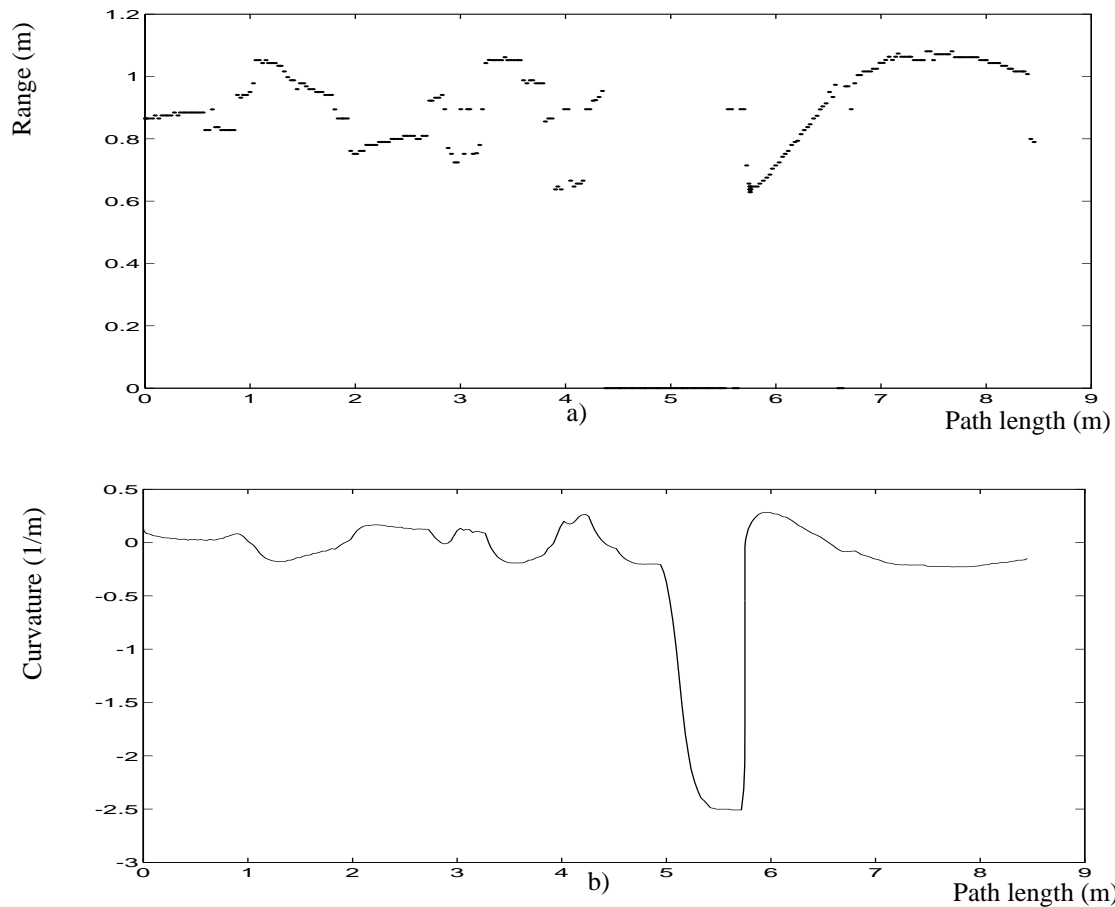


Figure 25-15: Experimental results a) Measures provided by the “Right fuzzy sensor”. b) Vehicle’s curvature.

After several tests with this setup, AURORA repeatedly detected the same environmental landmarks specified in the task (corridor, turning point and wall), accomplishing the mission independently of the robot’s starting position or the exact path followed.

25.4 CONCLUSIONS

Fuzzy logic can be used for both path tracking of paths previously computed by path planners and tracking of walls and other natural features encountered in the robot environment. In the first case a fuzzy controller implements heuristic rules to generate the steering commands to take or maintain the path from the knowledge of the vehicle’s position and orientation provided by dead reckoning and navigation sensors. The fuzzy controller also updates the lookahead distance on the path to track, which is the critical parameter in path tracking. Thus, the resulting fuzzy con-

troller is robust and can obtain good performance for both compensating the effect of perturbations (e.g. due to terrain interaction) and tracking sharp paths. The implementation of this strategy in the RAM-1 mobile robot has validated these conclusions.

On the other hand, fuzzy rules can be efficiently used to implement basic reactive behaviors based on external sensor information. Particularly, this Chapter shows how the so called “virtual fuzzy sensors” offer a reliable solution for the integration of disparate sensor information in an autonomous navigation system. This virtual sensor provides a fuzzy range estimation that results from fusing information from a number of heterogeneous real sensors. The efficiency and robustness of this approach have been demonstrated in wall tracking experiments with the AURORA mobile robot using three types of ultrasonic sensors. Some results are also included in the Chapter.

The same approach will be implemented in the near future for other different navigation behaviors such as following corridors and avoid collisions. Furthermore, fuzzy logic will be also used to coordinate the different behaviors in the reactive architecture.

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