USE OF FUZZY TEMPORAL RULES FOR AVOIDANCE OF MOVING OBSTACLES IN MOBILE ROBOTICS

M. Mucientes, R. Iglesias, C. V. Regueiro, A. Bugarín, P. Cariñena and S. Barro
Grupo de Sistemas Inteligentes
Departamento de Electrónica y Computación
Universidad de Santiago de Compostela
15706 Santiago, Spain
{manuel, rober, carlos, alberto, puri, senen}@dec.usc.es

Summary

A fuzzy control system has been developed for the avoidance of moving objects by a robot. Due to the displacement of this moving object, it is necessary to carry out temporal reasoning with the aim of responding suitably with regard to the tendency of the moving object, employing for this a fuzzy temporary reasoning profile that we denominate Fuzzy Temporal Rules. The system has been subjected to a complete simulation process, and certain results are commented upon and an example is presented.

Keywords: Robot navigation, Moving obstacles avoidance, Fuzzy Temporal Rules, Fuzzy control.

1 INTRODUCTION

An area of robotics in which great advances have been made in recent years, but in which many complex problems still remain to be solved, is the endowment of mobile robots with sufficient autonomy to pursue their goals while overcoming the imperfectly predictable problems - including moving obstacles - that are presented by environments that have not been tailored to their needs. The difficulty of this enterprise stems from the robot's model of the environment inevitably being incomplete, imprecise or faulty due to the modifications that real environments are likely to undergo (including continuous modification by moving obstacles) and the limited precision, accuracy and reliability of the robot's sensors (a problem that can be exacerbated by environmental noise).

The majority of research into the avoidance of mobile objects in robotics have been focused on attempting to estimate future positions of the obstacles with the aim of recalculating the robot's trajectory. Various different techniques have been used for this. Thus Chang [3] uses neural networks in order to obtain the moving objects' future positions, whilst Elnagar [4] uses an autoregressive model. In other works the robot travels towards its goal and in order to avoid collision with the moving object only how far this is away from the robot and its relative position is taken into consideration. Garnier [5] and Pratihar [6] use fuzzy controllers to this end

All these systems have in common the impossibility of reasoning out the behaviour of the moving object (which is reflected in the changes of velocity and/or turning) over time.

This paper describes a knowledge-based control system for the avoidance of the collision of a robot with a moving object in a restrictive environment (the robot moves along a passageway). For this we have introduced expert knowledge into the system, which demands the valuation of the occurrence of certain events (significant changes in the values of variables) within a determined, albeit fuzzy, temporal reference (e.g. *"in the last few seconds the robot's speed has been slow"*). For this reason it has been necessary to use a paradigm belonging to fuzzy temporal reasoning which we denominate FTR (Fuzzy Temporal Rules) [1, 2]. In this manner it is possible to valuate the current setting in which the robot is found, along with previous scenarios (recent values histories), which is decisive for taking the correct decisions to avoid collision.

2 DESCRIPTION OF THE CONTROL SYSTEM

In the problem that has been tackled, a robot travels along a passageway some 4 metres wide, and in which there is a free-moving mobile object. Based on the position coordinates, velocity and advance angle of the robot and the position of the mobile object, all the input system control variables are calculated.

The system has been exhaustively validated in the setting of Nomad 200 robot simulation; the range of the ultrasonic sensors (6 metres) and the finite dimensions of the space in which both objects move (passageway 4 metres wide) have been taken into account. Furthermore, possible imprecision in the measurements of the position of the mobile object by the ultrasonic sensors has also been simulated, this being considered as an error that depends on the distance between the robot and the mobile object, and can reach as much as 10%.

The controller is made up of three modules (figure 1): in the first of these ("obstacle course evaluation") the tendency of the object is deduced, valuating its recent position and velocity values by means of FTRs. Essentially, this entails valuating whether the obstacle tends to go before or after the robot, or whether it shows no clear tendency in these two senses. The second module ("behaviour selection") selects the most suitable behaviour for the robot to avoid collision. In order to do so, it uses, amongst other variables, the estimated tendency of the previous block. There are up to seven components that may be selected in this module. Amongst these are: *give way* (the robot lets the moving object pass by), *pass in front* (the robot attempts to pass before the moving object) and *observe*. In the latter situation, the robot maintains its velocity (in module and direction); this is normally due to the tendency of the mobile object not being clear.

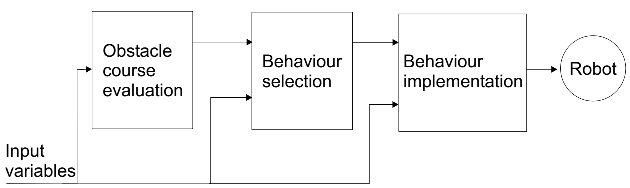

Figure 1: Schematic diagram of the control system.

Finally, the last block ("behaviour implementation"), given the current location of the robot (its position with respect to the walls of the passageway, its speed, the collision time and the moving objects's angle of incidence) establishes the optimum way of implementing this behaviour. Angular velocity and linear acceleration control variables are obtained as output of this module, and these are sent to the robot three times a second. With these values the robot will turn and vary its advance velocity in order to avoid collision. The latter two blocks described are made up of conventional fuzzy rules.

The avoidance of collision is based, to a good degree, on the accurate estimation of the tendency (first block), due to which this task is especially critical in the process. In this sense, it is of utmost importance to have explicit knowledge on how to carry out this task. In order to do so, new representational models have to be adopted which adapt themselves faithfully to the manner in which an expert would express his knowledge on the problem to be solved, due to which we have adopted a suitable knowledge and reasoning representation model (FTR)

Due to its special interest, the remainder of the paper will focus on the description of this first module of the controller. In order to do this, we briefly describe in section 3 the paradigm of FTRs, which is the knowledge and reasoning representation formalism that is used in the obstacle course evaluation module, in section 4 we give examples of how it is applied to obstacle course evaluation, and in section 5 we describe the performance of the system in a typical simulation run.

3 FUZZY TEMPORAL RULES

The obstacle course evaluation module uses FTRs of the kind described in previous papers [1, 2]. In these rules, a generic antecedent proposition has the form

$$X\ is\ A\ for\ Q\ of\ T \tag{1}$$

where X is a non-temporal variable such as velocity that takes as its values fuzzy sets defined on a universe U, A is a linguistic label associated with a possible value of X, T is a time reference (either a fuzzy instant or a fuzzy interval), and Q is a quantifier such as *all* or *most*.

Calculation of the current degree of fulfillment of the proposition, $DOF(\tau_{now})$ starts with the calculation of the spatial compatibility, $sc(\tau_k)$, between X and A at each time point τ_k in the support of T:

$$sc(\tau_k) = \bigvee_{u \in U} \mu_{\tilde{A}}(\tau_k, u) \wedge \mu_A(u) \tag{2}$$

where $\mu_{\tilde{A}}(\tau_k, u)$ is the membership function associated (by direct fuzzification or otherwise) with the value that is observed at time τ_k for X, $\mu_A(u)$ is the membership function associated with A, $\wedge$ is the t-norm *minimum* and $\vee$ the t-conorm *maximum*. $DOF(\tau_{now})$ is then obtained by combining $sc(\tau_k)$ and μ_T (the membership function defining the time reference T) in a way that depends on the value of Q. If Q is *any point* (*"for Q of" = in*),

$$DOF(\tau_{now}) = \bigvee_{\tau_k \in Supp(\mu_T)} sc(\tau_k) \wedge \mu_T(\tau_k) \tag{3}$$

where $Supp(\mu_T)$ is the support of μ_T. If Q is *all* (*"for Q of" = "for all of"*),

$$DOF(\tau_{now}) = \bigwedge_{\tau_k \in Supp(\mu_T)} sc(\tau_k) \vee (1 - \mu_T(\tau_k)) \tag{4}$$

If Q is intermediate between *any point* and *all*, then the linguistic quantification method of Zadeh [7] is used:

$$DOF\ (\tau_{now}) = \mu_Q \left(\frac{\sum_{\tau_k \in Supp(\mu_T)} sc(\tau_k) \wedge \mu_T(\tau_k)}{\sum_{\tau_k \in Supp(\mu_T)} \mu_T(\tau_k)} \right) \tag{5}$$

where μ_Q is the membership function of Q.

4 APPLICATION TO AVOIDANCE OF MOVING OBSTACLES

Three conclusions can be drawn by the FTRs of the obstacle course evaluation module: that the obstacle is *giving way* to the robot to avoid collision, that the obstacle is aiming to *pass in front* of the robot to avoid collision, or that the obstacle is *indifferent* to the robot (i.e. it maintains either a steady course or an erratic course uncorrelated with the possibility of collision). These conclusions are drawn for an estimate of whether and how soon collision will occur; from information of which side of the robot the obstacle is approaching from (to avoid what would essentially be duplication of rules, all reasoning is carried out as if it approaches from the left; if it actually approaches from the right, the input variables are subjected to a transformation that is later taken into account by the robot's behavior modules); and from evaluation of the recent history of the *non-collision index* (*nci*), a variable that quantifies how far from head-on any collision will be, and which is calculated from the radii, position and velocity of the robot and obstacle, and the distance between them. Values of the *nci* in the interval [-1, 1] predict that there will be a collision (which affects the left-hand side of the robot if $nci > 0$, the right-hand side if $nci < 0$), values > 1 and < -1 that the robot will leave the obstacle to its left and right respectively.

For an approach of the obstacle from the left side of the robot, an increase of the *nci* could be produced by the following four causes: increase of the robot's velocity, decrease of the obstacle's velocity, turn of the robot to its right or turn of the obstacle to its right

An example of the reasoning that takes place in this module is the rule

"IF
collision_time is medium AND *collision_status_change is increase in approximately the_last_3_seconds* AND *nci_trend is not_decreasing for all of approximately the_last_2_seconds*
THEN
obstacle_aim is to_give_way" (6)

Here *collision_status_change* is a fuzzy variable that is set to *increase* if in successive reasoning cycles the value of *nci* changes from less than -1 to greater than -1, to *decrease* if *nci* changes from greater than +1 to less than +1, and to *neutral* otherwise. The variable *nci_trend* takes fuzzy values defined on the universe of possible changes in the value of *nci*.

Note that what is evaluated is the consistent non-collision-oriented behavior of the obstacle over a period of several seconds, not just a single acceleration, deceleration or change of direction. The reason for this can be understood by considering the case of a obstacle approaching from the left that suddenly accelerates: an analysis of whether this acceleration tends to avoid or favour collision requires the processing of detailed information about the magnitude of the acceleration and the course of the obstacle and the robot, and in any case may be invalidated by the behaviour of the obstacle during the next few instants. Assessment of what appears to be the "intention" of the obstacle, as shown by consistent behaviour over a reasonable period, is less precise, but affords more robust conclusions.

On the other hand, the alternative of using mean values of variables does not allow the detection of variations produced over a small number of cycles, whilst the use of derivatives does not permit reasoning with immediately prior values.

5 AN EXAMPLE

With the aim of illustrating the behaviour of the robot in avoiding moving objects we will now give an example taken from one of many situations analysed. In all cases, in order to increase the realism of the simulation, we have worked with different degrees of error in the knowledge of the position of the moving object. For example, figure 2 shows the real trajectory of the moving object and the one employed by the robot for a maximum error percentage of 10% of the distance between the robot and the moving object.

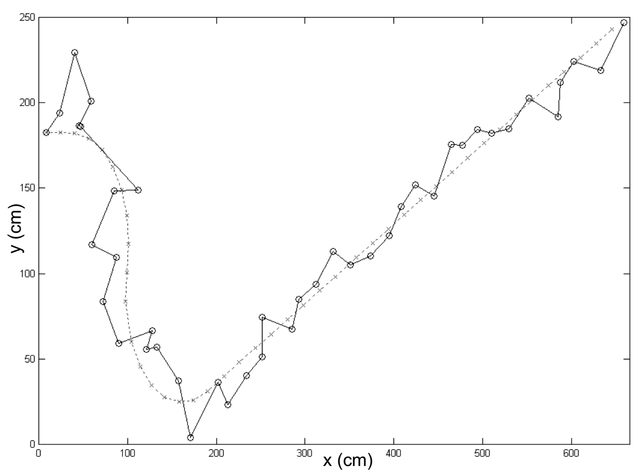

Figure 2: Trajectory of the moving object (real (**x**··**x**) and employed by the robot (**o-o**)).

Figure 3 shows the history of an obstacle that was initially moving quite fast (50 cm/s), approaching from the left side of the robot, on a course that would have led it to cross in front of the slowly moving robot (25 cm/s). In this figure, a greater concentration of marks indicates lower velocity (of the robot or the moving obstacle) while a smaller concentration reflects higher velocity. At point A the obstacle turned right, bringing it first onto a collision course. The rule described in expression (6) correctly detected this trend.

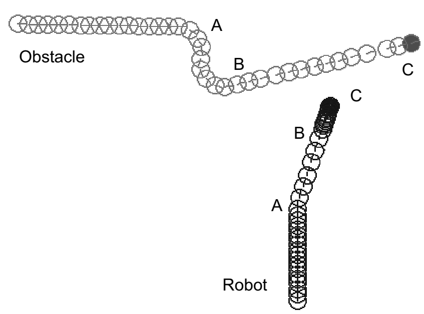

Figure 3: Example. A, B and C are different positions of the robot and the obstacle along a time interval.

The behaviour selection module of the robot responded by choosing *to_pass_in_front*, behaviour that in this situation was implemented by turning a few degrees to the right and accelerating.

A short time later the obstacle turned left (point B) and advanced at full speed (60 cm/s); although this behaviour actually put it once more on a collision course, the following rule interpreted it as showing an intention to pass in front of the robot:
"IF
collision_time is short AND *collision_status_change is decrease in approximately the_last_2_seconds* AND *nci_trend is not_increasing for all of approximately the_last_second*
THEN
obstacle_aim is to_pass_in_front" (7)

The robot's response to this latter interpretation was to select the behaviour *give_way*, which for short collision time is implemented by braking hard.

Simulations of other situations, involving a wide range of obstacle and robot speeds and obstacle trajectories, have confirmed the ability of the system to prevent collision. Anyway, final validation will be carried out by hardware implementation in the robot Nomad 200.

6 CONCLUSIONS

In this paper, we have described the implementation of a fuzzy control system for the avoidance of moving obstacles that go towards a robot. An important characteristic of the 131 rules that make up the system is that in the obstacle course evaluation module an explicit assessment of the time is needed. In order to carry out this assessment in a correct manner, we have used a new fuzzy knowledge model, which we have called Fuzzy Temporal Rules [1, 2]. With this approach, it is possible to evaluate a variable along a given time interval. This is precisely what is needed for the analysis of the moving obstacle's behaviour over time, as this behaviour can be highly variable in the time period considered. Furthermore, the projection of the knowledge is more direct using this model than with other strategies, thus facilitating the acquisition and subsequent tuning of the knowledge base. The proposal of FTRs supposes a new contribution to the field of fuzzy control. Its validation in a real-time complex application, such as the one shown in this paper, clearly demonstrates its interest and usefulness.

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