Fusion of Fuzzy Behaviors for Autonomous Robots *

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Abstract

A new methodological approach to solve the problem of integrating different behaviors in autonomous robots is developed in this paper. It relies on the succesful integration of several fuzzy relational algorithms [Zadeh 73], each one specialized in a different task. The whole system is based on a continiously act on sensor data (reactive) approach. The problem is how to get an intelligent behavior from low level reactive controllers. Our assumption is that we can obtain adecuate response to unkown external situations from the fusion of basic actions.

In this way, we present a new architecture for autonomous robots consisting on two levels. The firs one are the basic actions, also called instincs, that are implemented like fuzzy logic controllers specifically designed to respond to a particular stimuli. For example, avoiding obstacles or reaching a position. The fusion process is a modified fuzzy version of the subsumption architecture [Brooks 86]. The second level is the fusion module, which has been developed in several steps. The first one is a simple system based on crisp intervals that choose one of the behaviors. The second one is a linear combinator system, based on the previous one, but considering the similarity of the outputs to fusion some behaviors when it is possible. The last one is based on a fuzzy decision module that is able to fusion the outputs in a natural way.

This new architecture has been tuned on a simulator and then tested on a real robot named Khepera. In the simulator it is possible to prove each behavior separately, taking into account only the corresponding stimulus to a behavior. In the real world the architecture ability to solve new situation is tested trough the fusion of the output of the lonely behaviors. At the end of the paper the result of each architecture in the simulator and in the real world is presented.

1

1 Introduction

The problem of building autonomous mobile robots able to carry out useful tasks in real world has been faced since the beginning of the Artificial Intelligence Field However, aproaches based on the classical paradigms (abstraction, planning, heuristic search, etc.) failed and the sub-field of intelligent robotics remained in a theorical stage till the end of the 80's.

In these last years there has been a change, most autonomous robots are now been built under a new paradigm: *reaction*, which stands by intelligence resulting of the interaction with the environment. In this way, autonomous robot intelligence will be a result of its interaction with the real world through its sensors and actuators.

So, our architecture is based on two main ideas, the first one is that autonomous robots must rely its base-activities on a reactive aproach. This means that the behavior of the robot will be the result of the not optimal fusion of diferent "behaviors" designed to continuosly act on real-time sensory data. The second one is that it has been demostrated that fuzzy logic is a robust enviroment for the development of highly efficient controllers. So, the "behaviors" refered on the previous paragraph may be constructed as groups of fuzzy rules.

The organization of the rest of this paper is as follows. Section II presents the motivation of this research and a historical review of the problems and solutions in this field. Section III presents the control of a simple system by a Fuzzy Logic Control (FLC) and the basic behaviors represented by particular FLCs. In Section IV we propose a new general methodology for the integration of the basic behaviors presented in the previous section implemented as FLC, although it is possible that these behaviors were built by another kind of system such as neural networks, finite state machines, etc. Section V is devoted to show the potentiality of our general methodology presenting an example of a particular application consisting of two behaviors to the control of a real robot. This section also explains all the particularities of each behavior and the various fusion systems tested. Real experiments carried out are also examined in this section proving the validity and evaluating the performance of this behavior-based architecture. Section VI contains some concluding remarks.

2 Reactive robots

Since the first days of the knowledge field named *Artificial Intelligence* there has been a temptation to imitate human way of thinking, more precisely the way we think our mind works: It has been supposed that our mind builds an abstract model of the real world, planifies in this abstract world and decides which actions should carry out. This idea has led *Artificial Intelligence* to a top-down design, which implies the necesity of knowledge representation and reduces intelligence to a problem of heuristic search in the abstract world.

Artificial Intelligence influence on the robotics field caused intelligent robots were built following these ideas. So, robots were designed to construct an elab-

orated world model, to make its plans on this abstract world and to execute its plans on the real world. One of the best know robots built according to this ideas is Shakey the robot [Nilsson 84].

The main problem of this kind of systems was its slowness, they spent most of its processing time creating world models and much less time in planning. The solution to this slowness was to use highly structured worlds in which robots could easily build its world models. So, robots built following this principle were hardly able to move in carefully prepared laboratories, but if they were tested on the real world, they failed.

Since the late 80's a growing number of people have started to worry about robots could work on the real world. These robots would have to face problems like uncertain sensors, unpredicted environment, changing world, etc. These requirements made people adopt a *reactive* approach, meaning that there is no need for abstraction and planning [Brooks 91], when building intelligent robots.

One classical instance of this kind or architectures is the *subsumption architecture* [Brooks 86], where the key idea is to use the world as its best model. The willing of this architecture is to build autonomous robots that co-exist with humans, but instead of using a central system, with sensor modules as inputs and actuators modules as outputs, it uses a descomposition by activity aproach. So, each activity or behavior connects sensing to action. This means that these layers must decide when to act for themselves, they are not just subrutines to be invoked by a central planner.

The subsumption architecture uses finite state machines to implement the behaviors. We propose a different approach based on fuzzy logic reasoning. The original architecture has been modified in two ways. In first place we design the behaviors in a fuzzy way, this is due to the fact that fuzzy rules are nearer to human language than state finite machines. In the second place, we have developed a method to fusion the outputs instead of choosing one of them.

3 Fuzzy Reasoning

Therefore, the first step should be to select adequate descriptions of the information returned by the robot sensors, "analogous" to those formulated by humans when they describe perceived objects. The fuzzy representation scheme provides a convenient conceptual framework to deal with this kind of knowledge. Thus, a generic input can be represented as a set, defined as an abstract symbolic structure with slots $(f_1, f_2, ..., f_n)$, which are features characterizing the information from a sensor. For example, a sensor is able to return two kinds of information, the angle and the distance from a object, there were two slots f_1 (angle) and f_2 (distance).

Each $f_i \in F_i$, where F_i is the feature space that defines the possible numerical values range of f_i . In this example we have to features: $angle \theta_i \in \Theta$ and the distance $d_i \in D$. Θ is the angular space and its range is $r_{\theta_i} = \theta_i \in [0 - 2\pi]$. D is the metric espace, its range is $r_{d_i} = d_i \in [0 - \infty]$.

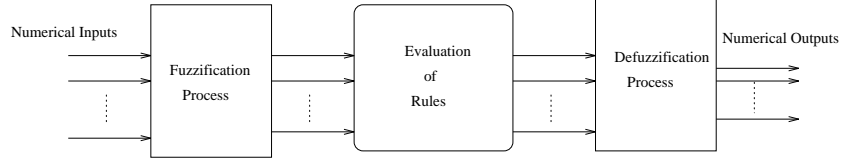To face the intrinsic uncertainty that underlies the appearance of perceptual

Figure 1: Fuzzy Logic Controller

features (distorted after the sensor acquisition process), the numerical values of the input could be mapped into qualitative symbolic labels, through a fuzzification process [Zadeh 73], transforming the features of an input into linguistic variables. In our example, we could define the two inputs (angle and distance) and the two outputs (linear and angular velocity) linguistic variables.

A linguistic variable [Zadeh 73] is a variable whose values are sentences in a natural or artificial language, that is, a concatenation of atomic terms: labels (adjectives), hedges (modifiers such as very, much, slightly, etc), the negation and markers (parentheses). The meaning of a linguistic variable is defined as the fuzzy subset for which the value of the linguistic variable serves as a label. A fuzzy subset A of a universe of discourse U is characterized by a membership function $\mu_A : U \rightarrow [0,1]$ which associates with each element $y \in U$, a number $\mu_A(y)$ which represents the degree of membership of $y \in A$. The operation of fuzzification (application dependent) has the effect of transforming a nonfuzzy set or quantity into a fuzzy set. It is worth noting at this point, that the value of, for example, the linguistic variable color (a natural label such as green) represents a much less precise meaning than the numerical value of the wavelength of the green color.

Using these concepts, for each f_i, for instance the distance d_i, a linguistic variable Lf_i, in the example could be "distance from the robot to the nearest object", is introduced with its set of values $\{lf_i1, lf_i2, ..., lf_imi\}$, whose cardinality is mi. Each term lf_ij in the set, labels a fuzzy subset in the universe of discourse F_i, with membership function $\mu_{lf_ij}(f_i)$. Values of membership function of a label are related to the difficulty of attributing this label to a particular input of a sensor. The fuzzification operation adopted, affecting the numerical input f_i, will result in its transformation into a fuzzy singleton, fuzzy subset whose support is a single point in F_i, with membership function equal to one.

A Fuzzy Relational Algorithm (FRA) will store the knowledge required to obtain the global parameters of movement through a fuzzy reasoning process, based on the linguistic features provided by a sensor. The FRA will be composed of a finite set of fuzzy conditional statements whose form is $IF(Lf_i \ is \ lf_ij)$ $THEN(LVEL \ is \ lv_k)$, where the antecedent are conjunctions and/or a disjunctions of fuzzy statements about the linguistic variables Lf_i, and the consequents are fuzzy statements about LVEL, linguistic global linear or angular velocity, whose value set is $\{lv_1, lv_2, ..., lv_n\}$. The Mamdani implication has been chosen to assign a meaning to these fuzzy conditional statements: the fuzzy subset of

ordered pairs (f_i, v), with $f_i \in F_i$ and $v \in VEL$, of the Cartesian product of $lf_i j \times lv_k$ with a degree of membership given by $min(\mu_{lf_{i_j}}(fi), \mu_{lv_k}(v))$. v is the defuzzification of LVEL and VEL represents its numerical domain (universe of discourse of LVEL).

The final aspect that has to be considered is the inference strategy to manipulate the knowledge contained in the FRA, in order to achieve a global movement of the robot. The compositional rule of inference (CRI), proposed by Zadeh[Zadeh 73], (approximate extension of the familiar rule of modus ponens), serves us as inference mechanism to obtain the fuzzy subset induced in VEL by a fuzzy statement with the form Lf_i is $lf_i r$, through each conditional statement of the FRA. That is the fuzzy subset of VEL whose membership function is obtained after max-min product of discretized versions of $\mu_{lf_i r}(di)$ and $\mu_{lf_i j} \times \mu_{lv_k}(f_i, s)$, represented as (relational) matrices [Zadeh 73]. As there can be several conditional statements forming the FRA, the meaning of LVEL will be the intersection of the intermediate meanings resulting from each application of the CRI (min of all the induced consequent membership functions). Finally, the adopted defuzzification process on LSIM will be a modified version of the Centre of Gravity procedure, this method treats the rules separately. Each rule produces a level of activation in the output labels, λ_i . Let $\{C_l v_k\}$ be the numerical representatives of each label, $\{lv_i\}$ (e.g. the centres of gravity). Then, the output is taken as a type of weighted sum:

$$linear\ velocity = \frac{\sum_{i=1}^{n} (\lambda_i \times C_l v_i)}{\sum_{i=1}^{n} \lambda_i}$$

4   Multilevel Fuzzy Reasoning

The goal of this research is to show that intelligent behavior of a robot can emerge from simple behaviors implemented as sets of fuzzy rules. Our architecture have n basic actions represented by fuzzy systems, FLC (Fuzzy Logic Control) and a decission-making unit. For a world configuration, each FLC obtains a reaction depending on its behavior. The decission module obtains one output from these reactions.

The decision-making module, in a primary architecture, it chooses one behavior (one output) from all the FLC. This selection is critical and the inputs for the decision have not a perfect matematical descripcion, using a fuzzy decisor we want to model the human decision-making behavior. In summary, we have two fuzzy aspects in our architecture, one are the fuzzy behaviors and the other is the fuzzy decision-maker.

For the construction of the whole system, the first step is to design each single FLC to be able of controlling a autonomous robot in a predetermined way. In this way, to design a FLC we need to :

- Define input and output variables, that is, determine which phenomenous will be observed and which control action have to be considered,

- Define the way in which the observations of the world are expressed as
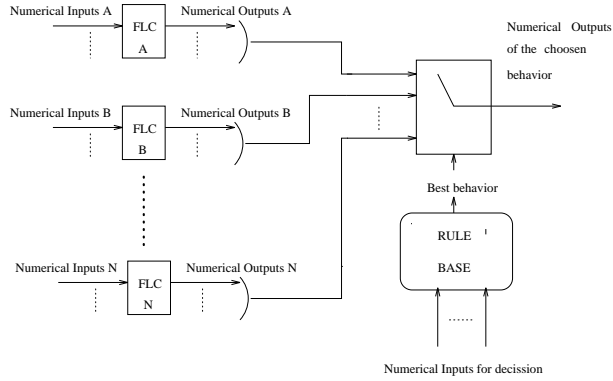
Figure 2: 0/1 System

fuzzy sets,

- Design the rule base,

- Determine the way to which fuzzy outputs can be transformed into numerical control actions.

The system inputs are perceptions of the world but not the same ones for all the FLC. One behavior is based on a particular world vision, for example a behavior as "avoid obstacles" needs to have consciousness about the distance to the obstacles around the robot, another behavior as "classify an object" need to recognize a shape and to matching from all the forms stored in the robot.

To finish this first step, we prove each FLC in a environment prepared to transmit a single stimulus, so the robot only needs one behavior to act. Through these experiments it is necessary to fine the FLC for a right performance. In this phase, it is possible to modify the inputs, the membership functions of the input and the rule base.

The second step is to built a system able to find a good output for a determined robot situation in the world. In a previous phase we try with a system that chooses only a behavior, and because that, the output from the choosen behavior. This decission module is named as "0/1 SYSTEM".

This system is not able to obtain a behavior, whose output corresponds to an intermediate state from all the FLCs, when they have similar outputs. To mix several outputs it is possible to do a linear combination of the outputs. Then, if each FLC has a v_i output and the decision-making module is able to realize that all the FLCs want the robot to go to the same direction, but the decision-making module is not able which behaviors is chosen for that situation the system can obtain one output using a matematical formula as $v_t otal = \sum_{i=1}^{n} (\alpha_i \times v_i)$.

A problem of this system is the definition of the inputs and a matematical description of these inputs, to decide which behaviors have to be stimulated.Next
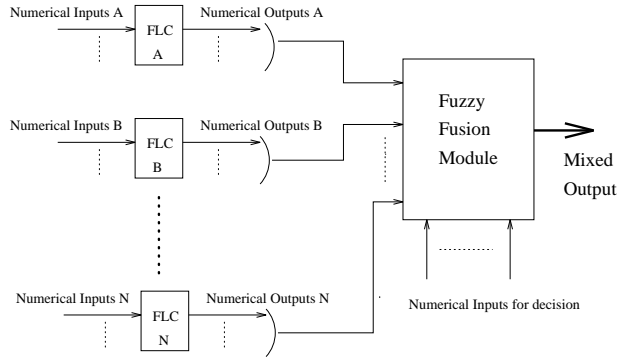
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Figure 3: Fuzzy Fusion Process

problem to solve is the inputs and its matematical descripcions. We present in this work a fuzzy module that permits a not exactly definition of the input, and it is possible to make the decision in a way analogous to the human thinking.

The problem of which inputs are neccesary to generate a right response depends on each robot, its objetive, and the number of implemented behaviors. In particular, for a robot that wants "to pursue an object" and "to avoid obstacles" the inputs of the decision module is the descripcion of the environment to permit a reaction for in order not to crash with obstacles. In the next section we present a real case and all details to better understand the fuzzy decision module.

(Comentar el dibujo y especificar que fusionamos tenemos que discutirlo: - Decidimos una salida con un modulo fuzzy - Hacemos una combinaci'on linel con un sistema fuzzy - Hacemos algo maravilloso con un sistema fuzzy lo que decidamos aqu'i hay que llevarlo al abstract)

5   A real two-level architecture

The teorical architectured presented in the previous section has been developed on a simulator and tested on a real robot. We have used a simulator of this robot, named SRA [Nuria 94], which has been developed at Universidad Carlos III. This simulator lets us to design a simple environment to test several implementations of a behavior before proving some of the best in the real robot.

The robot used in our experiments is the mini-robot named KHEPERA [Mondada 93], developed at LAMI 4. Khepera is a mini-robot, 5.5 cm diameter, designed as technological demostrator. It owns eight infra-red proximity sensors, two motors with encoders, and the possibility of working autonomously or connected to a computer via a serial cable.

We describe the whole system in two steps. In the first one each behavior is implemented (subsection 5.1). In the second one different decision-making
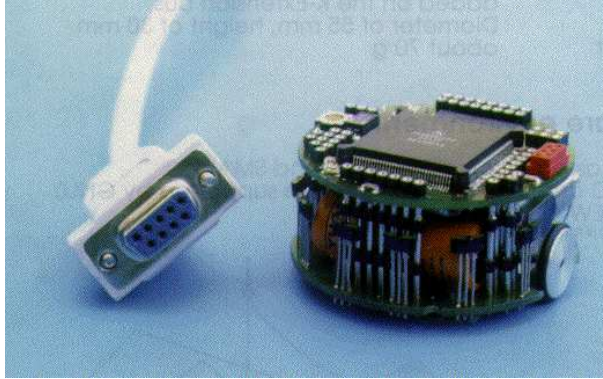
Figure 4: The mini-robot Khepera

modules are presented, beginning with a 1/0 SYSTEM, and proving lately with a linear combination to finish with a fuzzy decision proccess (subsection 5.2).

5.1 The "alone" behaviors

In a first experiment we have implemented a simple behavior named "Avoid". This group of fuzzy rules makes the robot wander through the world without crashing with any obstacle. The set of rules was first tested on a the Khepera simulator. The system inputs are distances returned from the infrared sensors in particular it is possible use only three of these sensors. The outputs are the new robot speeds for each motor wheel. The rules that implement the behavior are shown in the figure 7. Once the rules seemed to work properly in the simulator, the same set of rules was tested on the real robot.

Then, we have developed another behavior named "Follow" which makes the robot follow a mobile object. (!!OJO!!!!)To implement this instinct on the simulator we have simulated two sensors that do not exist on the real robot. These sensors return the distance and the angle towards the movile object.

Using these sensors the set of rules of the figure **??** have been tested ....

5.2 Fusion of behaviors

With the two behaviors developed, it is neccesary to make a decision module integrating the two responses. One of the FLC has three distances as inputs, which is a limited vision of the surronding world. The other FLC uses the distance and the angle to the object that the robot pursues as inputs. The two outputs are the speeds of each wheels. From this point, it is possible to make a 0/1 SYSTEM that chooses between the two outputs, the best one for a determined situation. As we want that robot to follow the object, provided that it avoids the obstacles found in its way, the inputs are the same as in the "avoid" behavior. In the moment that a obstacle is very near and there is
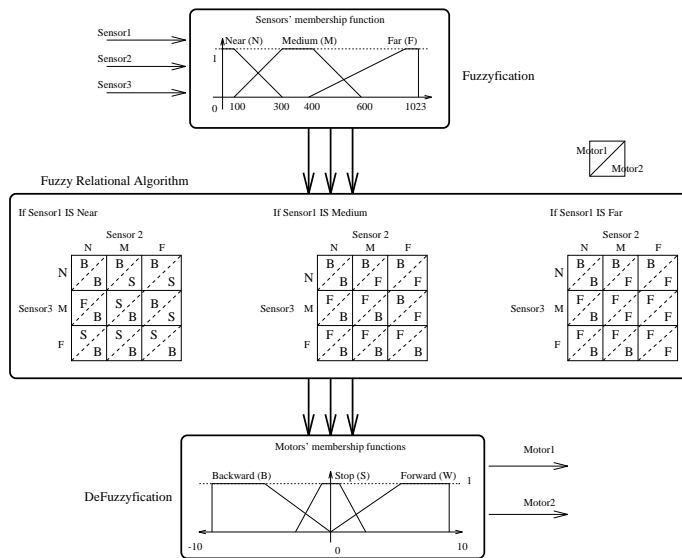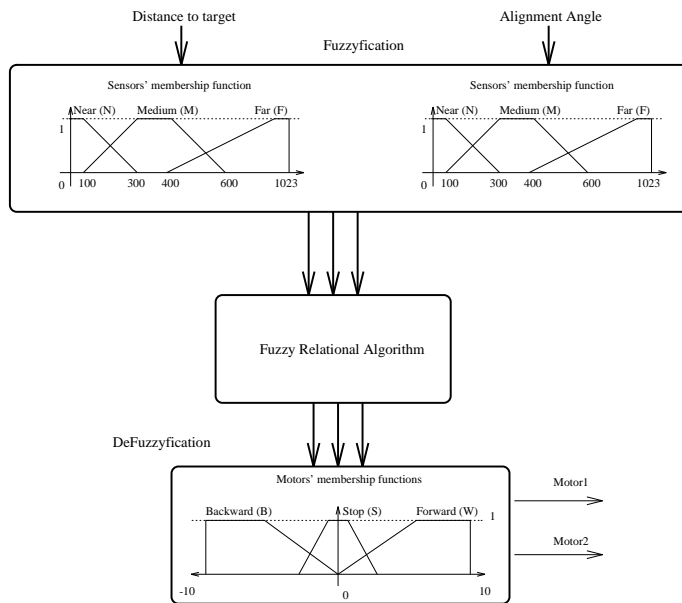
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Figure 5: FLC to avoid obstacles
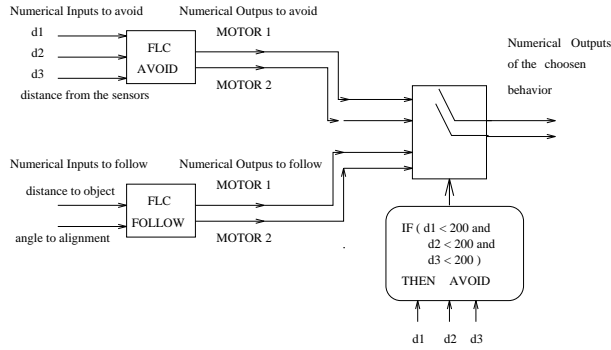

Figure 6: FLC to follow a object

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Figure 7: The first decision module. A 0/1 SYSTEM

danger of colission the system is controlling for the FLC avoid. To know that, it is sufficient with the three distances. The system is representing in the figure ??.

The rules of the system are...

The result are...

(Como vamos a hacer la combinacion lineal)

(Como vamos a hacer el sistema fuzzy)

6 Conclusions and Future Work

A new methodology, based on fuzzy logic concepts and a subsumption architecture, has been introduced to integrate a different behaviors. Moving from the use of quantified variables towards the use of the type of linguistic description employed by humans, we acquire the capability to deal with the robot control, which may be considered too much complex to be susceptible to analysis in convencional mathematical terms.

In this work a theorical architecture is presented and it is implemented on a real robot in a real world. The system capability is then tested and its result proves a better performance than a system with no fuzzy information about the behaviors and about the decision-making module.

Future works may include, on one side, the possibility of having more sensors. With a superior perception of the environment the robot has more information and it will be able to take a better solution. This is very complex using a matematical decision module, but with a fuzzy system it would be easy, as long as adding more inputs does not implies a exponential growing of the complexity.

On the other side, the possibility of making a cooperating system can be considered. In this case, our system should be integrated as part of a complex architecture including communication and high level reasoning. Our aim is to study the ability of robots to solve problems in a cooperative way.

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