A Concept for the Dependable Operation of Autonomous Robots by Means of Adaptive Fuzzy Rules

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Abstract
In this paper, a specific concept to implement adaptive fuzzy rules systems is described. This is achieved by integrating weight factors directly into the membership functions of the rules. The resulting possibility to change the influence of individual rules is discussed in detail. The scheme also supports the systematic growing of specialized mutants from existing rules. In this way, a combination of precautious behaviour, and more specialized, e.g. also performance-related operations, can be achieved. Some examples of rule schemes illustrate the potential of the concept.

1 Introduction

For autonomous robots moving in environments which are partially or mostly unknown, the impact of sudden conditions or events that might disturb the gait of the robot or other aspects of its operation, can produce effects which are equivalent to the impairing influence of component faults. Especially, sudden changes in the ground surface (holes, steps, channels, edges etc.) which are not easily detectable, might affect the robot´s actual movement, and, by leading to accidents, impair its health. So, there is the need to achieve robustness against such unknown, undesired external effects, according to the principles of Organic Computing, as e.g. self-organization [1, 2].
Especially for such situations, the classical artificial intelligence techniques, based on organizing expert knowledge in a fixed set of behavioural rules, have turned out to be insufficient. As an alternative, the use of fuzzy rules has also been considered for autonomous robots. Using ordinary fuzzy rule systems, however, implies as disadvantage that the win of experience that might be gained during robot operation cannot be exploited to further optimize the control system. Here, a combination with adaptive strategies might be a remedy. To prepare this discussion, first, in section 2.1, the basic operational principles of fuzzy rule systems are shortly introduced. Then in section 2.2 a specific approach for an adaptive fuzzy rule base organization is described. Section 2.3 outlines the advantages of the approach for developing, from such rules, again more specialized mutations.

2 Adaptive Fuzzy Rule Bases

2.1 Basic Principles of Fuzzy Rule Systems
Fuzzy rule systems are utilized to enable decision-making based on vague, “fuzzy” information [3]. Let us sketch the basic working principle of fuzzy rule systems by the example of an autonomous robot which receives certain input signals from the values of which decisions have to be derived about the values of output signals controlling certain actuators for moving the robot.
Here, it is usually (except for the case of disturbed signals which we shall not consider here) not the problem that the values of the input signal variables are not distinct (i.e. they usually possess distinct, “crisp” values), but to interpret them in a distinct manner, i.e. the semantics of the signal value might be “fuzzy”.
So, to draw conclusions in such a situation, as a first step of the fuzzy decision calculus, the crisp input signal values which are to be used for deciding about the actuator operation, are “fuzzified” into so-called linguistic variables, which have, as their values, fuzzy terms like e.g. “warm” “ cold”, “great” “middle”, “fast”, “slow” etc. This mapping is implemented by a so-called membership function F the value of which, from the interval [0,1], gives a “degree of intensity”, i.e. how strongly a given crisp value is corresponding to a fuzzy term of a linguistic variable. Fuzzy rules are setting such linguistic variables into relation with other linguistic variables that are to govern the output control signals, which then e.g. might trigger the intensity of action of certain actuators.
For ease of understanding we confine here the discussion to the simple case where in the left and

right side of rules just one fuzzy term appears. In Figure 1 as an illustrating example, the membership functions F1 and F2 of two fuzzy terms x1 and x2, respectively, of a linguistic variable v are shown. As type of these functions, the classical tri-angle functions are considered; everywhere outside the triangle region, the value of these functions is 0 [4]. A second linguistic variable w depends on v according to the two fuzzy rules

R1: **IF** v=x1 **THEN** w=y1

and

R2: **IF** v=x2 **THEN** w=y2.

If for a crisp input c, the value of F(c) is larger than 0, c is said to fulfil the left hand side of the rule. As a consequence, the rule is activated. The result of this activation is an area, produced by truncating the area under the membership function of the right side´s fuzzy term, at height F(c) (see Fig. 1).
Usually all rules, for which the fuzzy transforms of the crisp input fulfil the left side of those rules, are concurrently activated. For the crisp value c of v shown in Fig. 1, the left hand sides of both of the rules are fulfilled, i.e. both of the rules are active. Carrying out the first rule for the crisp value c means that the area under the membership function of y1 is truncated at the height F1(c), creating the area A1. In a corresponding way, for rule R2 the area A2 is resulting. The common concurrent processing step of all activated rules is also called a fuzzy inference of the fuzzy rule system. To obtain, for one inference, a common result reflecting the influence of all rules activated in this case, the union of the mentioned areas is formed. As both rules in Fig. 1 are active, the common result area is given by the union of A1 and A2. In a final step, from this area as the output result of an inference of the fuzzy rule base, again a crisp signal value for controlling an actuator has to be gained. This is carried out e.g., as one classical method, by computing the "center of gravity" of the mentioned area; from the – crisp – coordinates of this center of gravity then the desired crisp actuator control signal is directy derived. A detailed description of the working principles sketched here can, e.g., be found in [4].

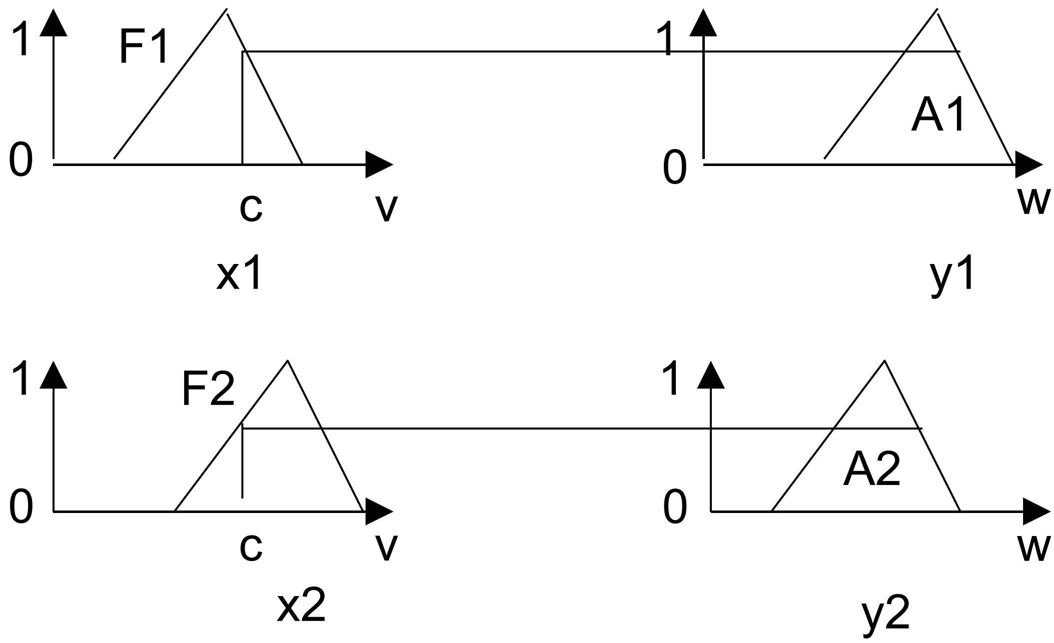

Fig. 1 Left side: membership functions F1 and F2 of two fuzzy terms x1 and x2, respectively, of an input v; right side: membership functions of an output function w depending on x1 and x2 by means of the fuzzy rules R1: "**IF** v=x1 **THEN** w=y1" and R2: "**IF** v=x2 **THEN** w=y2".
For the crisp value c of v, as result we obtain the union of the two areas A1 and A2 which are cut out by the two shown horizontal lines at height F1(c) and F2(c).

2.2 Adaptive Fuzzy Rule Systems

Quite a lot of work has been dedicated to research on neuro-fuzzy rule systems, where the basic fuzzy rules are optimized by training them via neural nets [5]. As a consequence, a "collective" learning of the rule system is implemented; i.e. the contribution of an individual rule to the success of the entire rule base system cannot be identified any more. Just in the recent years, also more attention is being paid to other kinds of fuzzy rule adaptation [6].
In the approach introduced here, the individual influence of each fuzzy rule is considered and exploited. To do so, as a basis we need a metric measuring the tendencies of success or failing of the robot in solving certain movement tasks. To establish such a metric, we consider a small number of central,

critical parameters of the autonomous robot, as e.g. the inclination angle of the main robot body, battery power consumption, temperature at servo motors, number (or weighted sum) of components diagnosed to be partially or completely faulty. Their values are mapped into a scalar function, the so-called general health function ghf. For each instance of the fuzzy rule system, the effect of the resulting movement is checked whether it has increased or decreased the ghf, or whether it has left it (approximately) unchanged. Correspondingly, this change of ghf is reflected by updating the influence of the rules which had been active during the instance. To enable such changes, to each rule an additional weight factor w_r is associated. The weight factor governs the rule in the way that the membership function F of the fuzzy term at the rule´s left hand side, is transformed into

$$F_w = \mathrm{Min}\,(F \; * \; w_r,\, 1)$$

This formula reflects the condition that the maximum of the membership function at most can be 1; this latter case represents the strongest activity of the rule that is possible. Thus, we have created a mechanism to change the truncation height mentioned above, and, correspondingly, also to change the result area under the membership function at a rule´s right hand side. In Figure 2, for the example treated in Fig. 1, now the membership function of x1 has been scaled down by a weight factor. It can be seen that correspondingly the result area changes. Thus, also the union of the two result areas is changing.

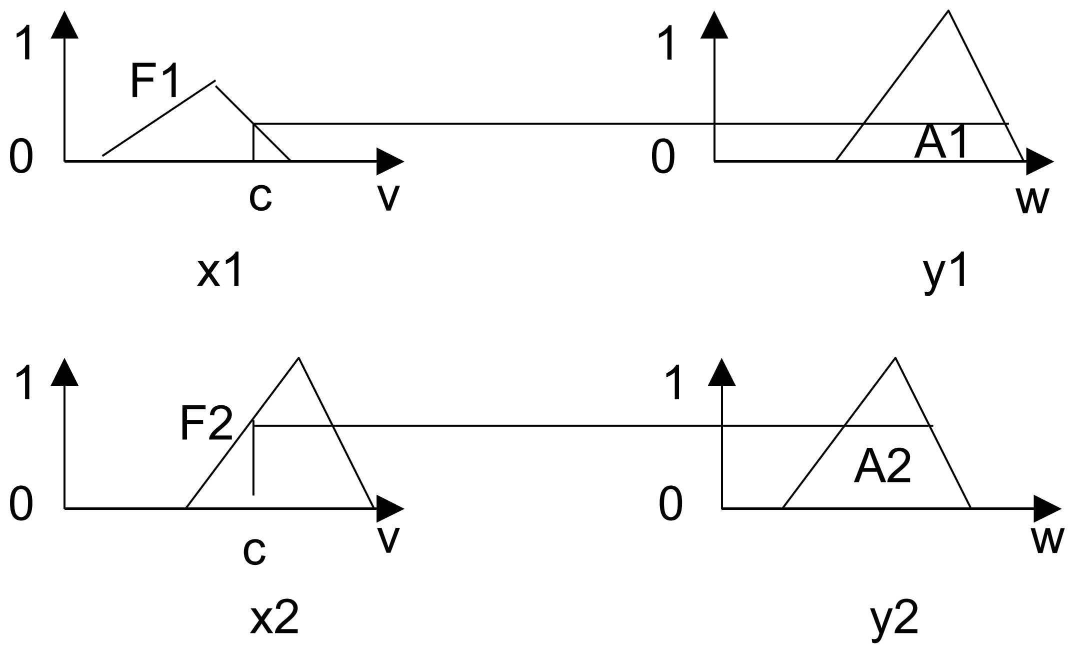

Fig. 2 For the example presented in Fig. 1, now the membership function F1 of x1 is scaled down by a weight factor, whereas F2 is left unchanged. This causes a change of the area A1, and, thus, also, of the entire result area, formed by the union of A1 and A2

Changing of the weight factor of a rule by an increment or decrement, respectively, should depend on

- the resulting amount of change of the general health function after the inference (either toward “success” or toward “failure”) where that rule was active;
- the influence of the considered rule among the other activated rules of that inference (measured in terms of its result area compared to the union of the result areas of all active rules of the inference).

A further modification of the update strategy for the weight factors results, if the change of the weight factors is constructed as a non-linear function of the entities mentioned aboved. E.g. marginal changes of the ghf could be responded by a sub-linear change of weight factors, or completely neglected. Also, if the value of the resulting membership function at the left side of a fuzzy rule is already close to 1, the result of this saturation could be reflected by a sub-linear change of the weight factor. Combining these two additional principles, a sigmoid curve for the change of the weight factor, depending on the change of the ghf, would result.

The approach described here so far, is mainly dependability-oriented, i.e. its aim is to keep the general health function within the required stability range, or to improve it. However, it cannot be stressed too strongly that the concept can be extended to reflect also the general success of robot operations, by corresponding changes in the weights of successful rules. Such a success could e.g. be the timeliness of the robot, i.e. reaching certain coordinates in the operation field of the robot within a given time bound. Here as additional constraint, also the successful carrying of a given specific load within such a time bound could be required. Other performance aspects to be considered might be the consumption of resources, as long no critical point of exhaustion is reached.

These aspects have to be measured by an additional performance metric. By combining that metric and the ghf metric, we would extend the approach to a performability-oriented strategy. Alternatively, key performance issues, as e.g. timeliness, could directly be integrated into the general health function, expressing that this property is a part of the robot´s health.

2.3 Deriving More Precise Rules

The described mechanism can also be used to grow up detailed rules from more vague original ones. Such an original vague rule can be characterized as follows: The membership function of its left hand side is relatively flat, i.e. it has a broad range where it is larger than 0, and, on the other hand, also a relatively low peak. In addition, experimentally mutations of this rule are produced, where the left hand side membership function has a narrower range, but a higher peak. Fig. 3 shows the example of a "mother" rule R1 with a membership function F1 at its left hand side, and two mutants R1* and R1**. The triangle regions of the membership functions F1* and F1** of their left hand sides, are situated within the triangle region of F1.

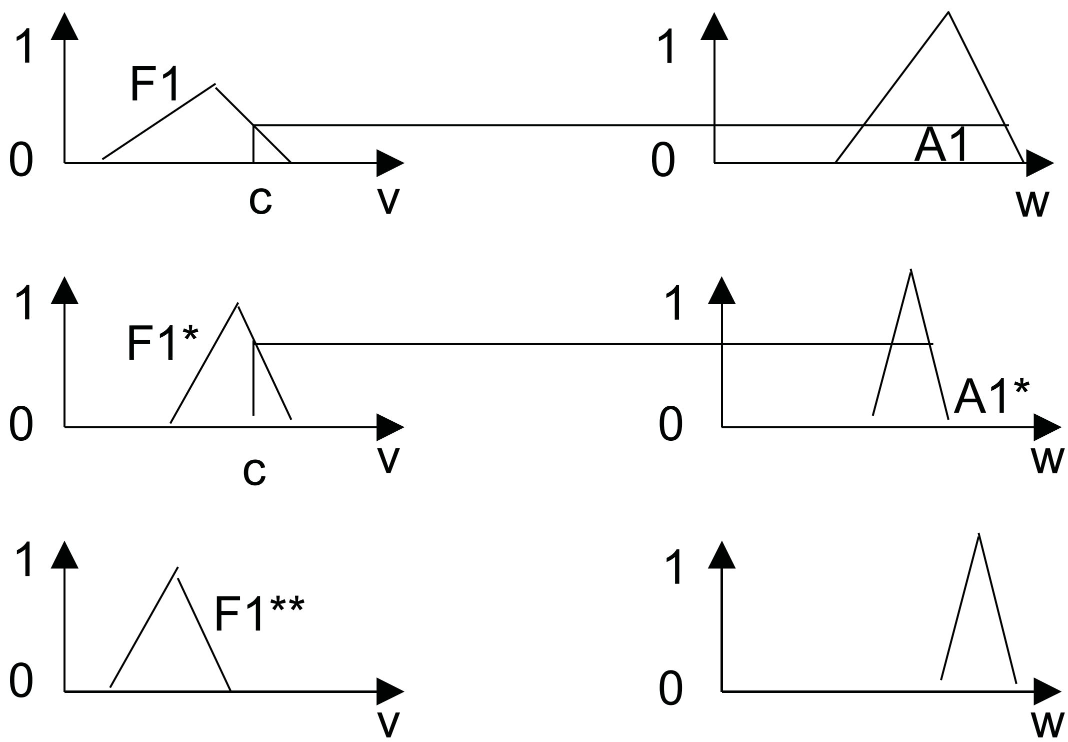

Fig. 3 Example of a rule R1 and two "specialized" mutants R1* and R1** of it, with corresponding membership functions F1, F1* and F1**. For the shown crisp value c, rule R1 and R1* are fulfilled and active, whereas R1** is passive, as F1**(c) is 0.

The use of such more specialized versions of the rule, together with the original vague rule, is monitored, and according to success or failure tendency, the influence of the mutants is changed by updating their weight factors. So, under the shelter of the mother rule some successful child rules might grow up, whereas other, less successful child rules loose their influence and might finally be negligible. Fig. 4 as example shows a case, where the influence of the mother rule R1 has increased (peak of F1 increased), the influence of the mutant R1* strongly increased to the saturation value (peak of F1* equaling 1), whereas the influence of the second mutant R1** is much weaker (peak of F1** considerably smaller).

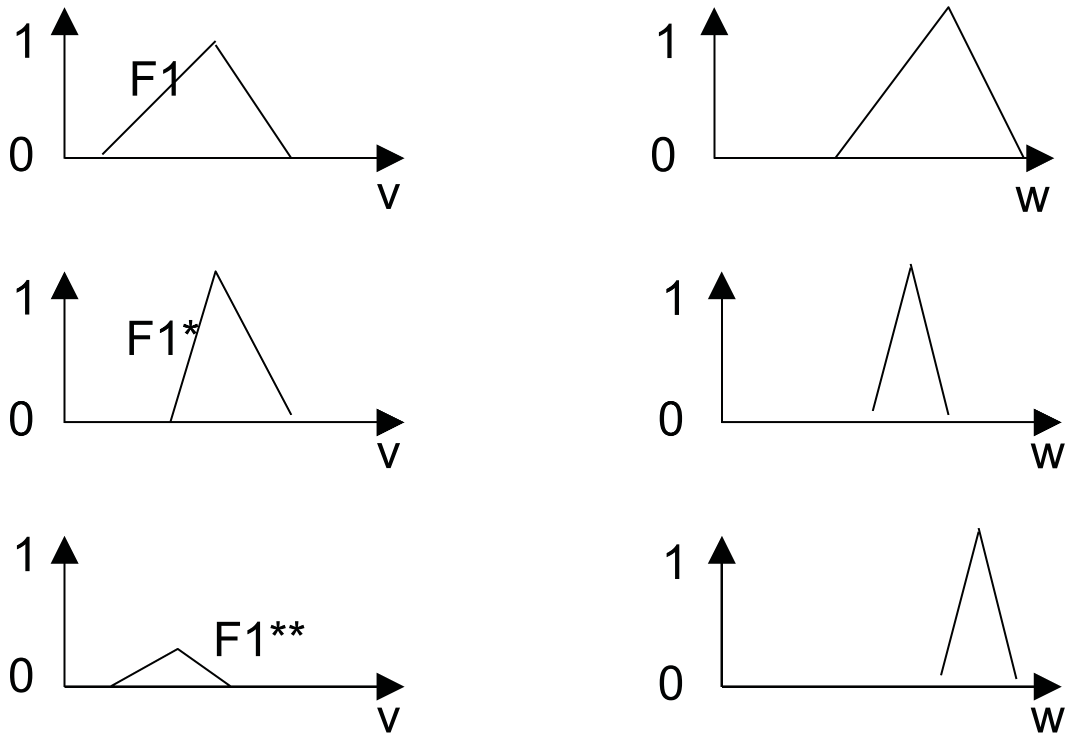

Fig. 4 Case where, compared to Fig. 3, the influence of mutant R1* has grown, whereas that one of mutant R1** has strongly decreased.

So, the sketched scheme allows that as a first phase of robot operation in an environment not completely known, a set of relatively general, precaution-oriented rules is tried. The influence of the successful rules among them remains, and is, in addition, gradually superimposed by the influence of more specialized mutants of them. I.e. from an given initial start-up rule base, the robot control develops by a self-organizing process, as required by the principles of Organic Computing.

With regard to the strategy for creating, for a given specialized mutant, competitor mutants to be compared with it, little pre-knowledge is needed. Simply, initially an assumption has to be made about the position behaviour of their fuzzy terms´ triangle regions: E.g., for a given mutant like R1* in Fig. 3, its right hand side fuzzy term is placed in the left part of its mother rule´s triangle region. Now, if we create a competitive mutant with a triangle region of its left hand side, placed more to the right as that one of R1*, should the same also hold for its right side ("monotonous" behaviour of the spectrum of competing mutants) or the other way round (anti-monotonous behaviour)? In Fig. 3, e.g., the triangle regions of the fuzzy terms F1 and F2 show an anti-monotonous behaviour.

If an initial mutant turns out to be very unsuccessful, the value of its weight approaches 0; i.e. the influence of the mutant is marginal or completely vanishing. In this case, to replace this mutant, also a quite alternative rule can be created: Here the alternative property means that, for given, identical left hand sides of both mutated rules, their right hand side fuzzy terms are quite different: I.e. in terms of their triangle regions, these regions are placed into opposite parts of their mother rule´s triangle region. E.g. for a new mutant R*** which is to replace the failing mutant R** of Fig. 3, the triangle region of its right hand side fuzzy term should be placed into the left part of its mother´s right hand side triangle region.

It has to be noted that simultaneous creation of such quite different, "antagonistic" mutants should be avoided, since, due to their identical left hand side fuzzy terms, they are activated always concurrently, and, because of their symmetric placement with respect to their mother rule´s triangle region, the area effects of this activation would compensate each other (see Fig. 5).

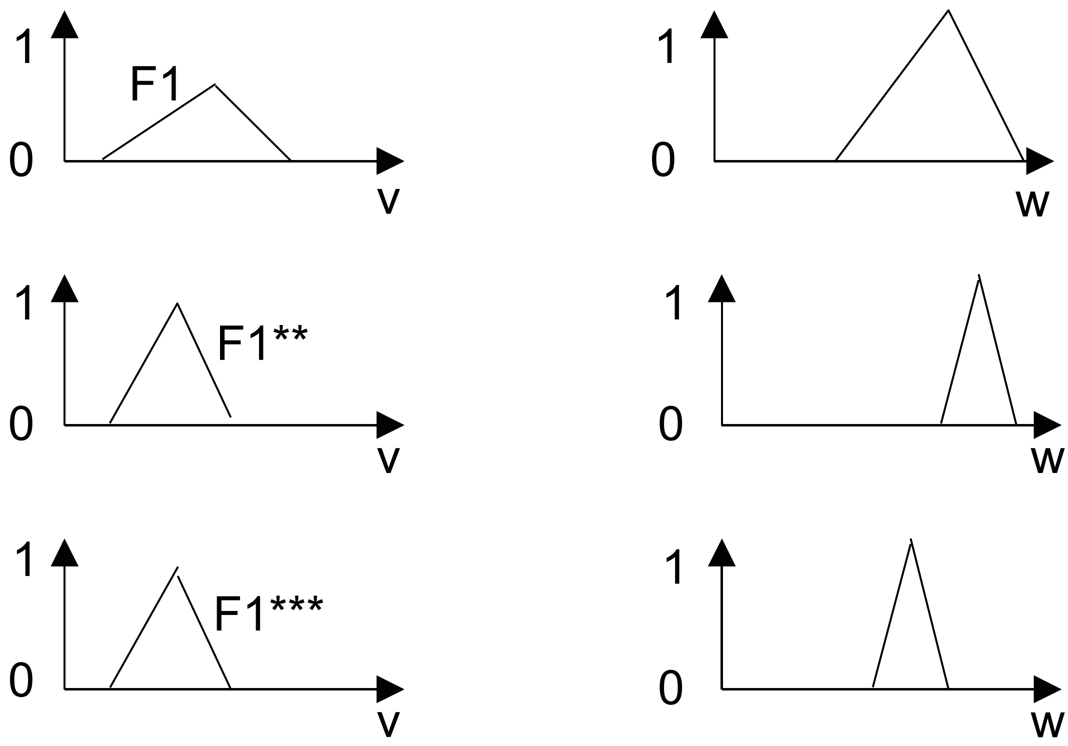

Fig. 5 Creation of two antagonistic rules R1** and R1***. As can be seen, the triangle regions of their right hand sides are situated symmetrically with regard to that one of the mother rule R1. So, for all truncation heights, the center of gravity of the union of their result areas with that one of the mother rule R1, is identical to the center of gravity of the mother rule´s result area alone; i.e. the area effects of the two mutants are compensating each other.

Fig 6 shows, as a simple evolution example, the resulting behaviour of competing mutants of a rule R. It It can be seen that first, at time t_1, the rule R is created, with a medium initial maximum of its left hand side membership function. As the success of rule R evolves quite well (timepoint t_2) specialized mutants R* and R** of R are derived. At timepoint t_3, R** has moderately lost influence. But, due to missing success, the influence of mutant R* has declined and and tends towards final vanishing. Thus, as a compensating attempt, now, at timepoint t_4, an additional mutant R*** is created which is antagonistic to R*. At timepoint t_5, it can be seedn that this mutation turns out to be the most successful rule among the created mutants.
An alternative to the need that antagonistic mutants must be creately sequentially, could be to create them simultaneously, but with clearly different initial weight factors. As a consequence, however, the competition between the two antagonistic mutants usually would take longer time, until one of them has been driven into a marginal role. Such fine-grain effects are to be studied by future analyses. Also, it will be the focus of future research to investigate, by simulation, the behaviour of autonomous robots, under the control an adaptive fuzzy rule set, in a more detailed physical environment.

3 Conclusion and Outlook

In this paper, a specific concept has been described to implement adaptive fuzzy rules systems, by integrating weight factors directly into the membership functions of the rules. The scheme also supports the systematic growing of specialized mutants from existing rules. In this way, a combination of precautious behaviour, and more specialized, prerformance-related operations can be achieved.
It will be the focus of future research to investigate, by simulation, the behaviour of autonomous robots, under the control of adaptive fuzzy rules, in a more detailed physical environment.

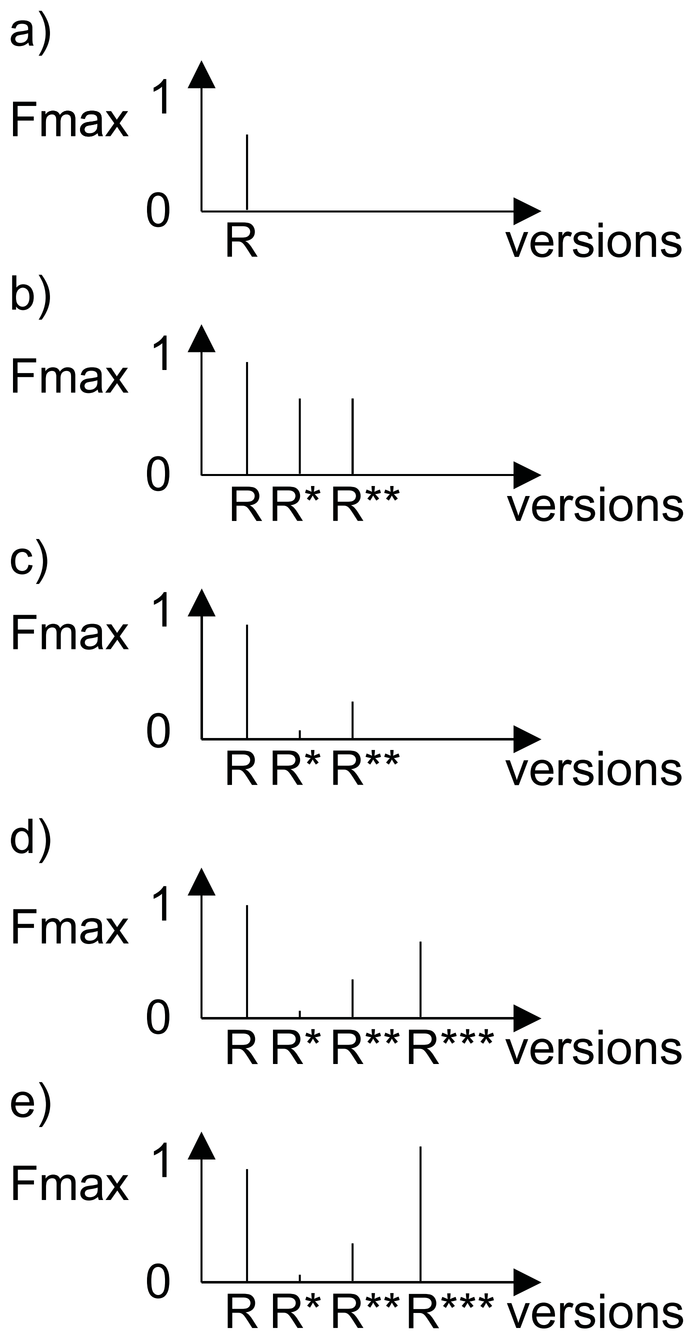

Fig. 6 Example of the evolution of the maximum values of the membership functions, for several versions of a rule:

a) At timepoint t_1 a more general rule R is created, with an initially medium weight of its left hand side fuzzy term´s membership function.

b) Until timepoint t_2 R has considerably increased its influence (maximum of the membership function grown to nearly 1); now two specialized mutants of R, R* and R**, are created, both with the same medium initial value of the membership function maximum.

c) At timepoint t_3 it is observed that the influence of R* has decreased to a marginal role; also the influence of R** has decreased.

d) Thus, at timepoint t_4 as an alternative, a rule R*** which is antagonistic to R*, is created.

e) At timepoint t_5 it has turned out that the mutant R*** is the most successful version.

Finally, it cannot be stressed too strongly that the application of the sketched adaptive fuzzy rule base organization is not confined to the area of robot control; it can be applied also for the control of other autonomous systems, e.g. software agents, or, also to organizational systems.

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