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# Coordination of Distributed Fuzzy Behaviors in Mobile Robot Control

Eddie Tunstel†
CAD Laboratory for Intelligent & Robotic Systems
Department of Electrical and Computer Engineering
University of New Mexico
Albuquerque, NM 87131 USA

**ABSTRACT**

Mobile robot navigation can be achieved using a control system comprised of a collection of special-purpose motion routines, or behaviors. In order to exhibit robust autonomous performance, a suitable strategy for coordinating the behaviors must be adopted. This paper describes an approach to behavior coordination and conflict resolution within the context of a hierarchical architecture of fuzzy behaviors. This architecture can be viewed as a network of distributed intelligent behaviors in which coordination is achieved using weighted decision-making based on behavioral degrees of applicability. Aspects of the coordination and conflict resolution procedures that are based on generalized concepts from fuzzy control are discussed. The strategy is appropriate for fuzzy control of systems that can be represented by hierarchical or decentralized structures.

## 1. INTRODUCTION

Fuzzy logic is a powerful tool for use in intelligent control of dynamic systems, if for no other reason, then simply because control problems are essentially problems of decision making. Some of the advantages of using fuzzy logic controllers (FLCs) are that they are robust in the presence of system and external perturbations, easy to design and implement, and efficient for representing knowledge for systems that deal with continuous variables [1]. Fuzzy controllers have been successfully used in a number of industrial plants and processes, and are sometimes the more favorable controller even when classical controllers are applicable. However, there are potential limitations to the conventional fuzzy controller when intended for use in distributed intelligence systems that can be represented by hierarchical or decentralized structures.

The conventional FLC architecture typically employs a single rule-base representing the control policy for a given plant. During any given control cycle all rules in the fuzzy rule-base are sequentially processed. Consequently, the cardinality of the fuzzy rule base has a direct influence on the real-time performance of the control system. This is a minor concern for real-time control of systems requiring relatively small numbers of rules (e.g. less than twenty). For systems that require a significantly larger number of rules, the conventional implementation can potentially suffer from degraded real-time performance. This is a major concern for control of distributed intelligence systems that are represented as hierarchical or decentralized structures (or can be decomposed as such). Examples of such systems are autonomous mobile robots, corporate decision-making entities, social systems, electric power systems, and large-scale systems in general.

Recent research has shown that for the conventional FLC the cardinality of the fuzzy rule-base increases exponentially with the number of system variables [2, 3]. Alternative rule structures have been proposed that represent a fuzzy rule-base as a *hierarchy* of rules for which the cardinality of the rule-base increases only linearly with the number of system variables. Similar results were produced in [4] where hierarchically structured rules based on fuzzy partitions of the state space were introduced. Thus, it is possible to overcome the aforementioned limitation of conventional FLCs and facilitate practical implementations of more complex FLCs by employing alternative rule structures.

In this paper, an alternative architecture is described for facilitating the incorporation of fuzzy control theory into the framework of *behavior control* for mobile robots. In particular, an approach to behavior coordination and conflict resolution for navigation in dynamic and possibly unstructured environments is presented. Examples of such environments are office settings, automated factories, natural terrain, and planetary surfaces. Autonomy is achieved within a hierarchical architecture of fuzzy rule-bases which can be viewed as a network of distributed intelligent behaviors.

## 2. FUZZY BEHAVIOR CONTROL

Autonomous control of mobile robots is traditionally achieved based on a functional decomposition of tasks following a sequential sense-plan-act cycle. Due to the sequential processing of functional modules, computational bottlenecks are common, particularly in the planning modules. Alternative control approaches are modeled after natural processes and advocate a behavioral decomposition of tasks. Such approaches are associated with what has come to be known as the behavior control paradigm. The paradigm has grown out of an amalgamation of ideas from ethology and control theory

† On leave from NASA Jet Propulsion Laboratory, USA.

[5-7]. The high-level motion control system is decomposed into a set of special-purpose behaviors that achieve distinct tasks when subject to particular stimuli. Clever coordination of individual behaviors results in the emergence of more intelligent behavior suitable for dealing with complex situations. Behavior control systems have demonstrated reductions in computational requirements without sacrificing robust autonomous performance [8].

Most implementations of robot behavior control employ behaviors that perform non-fuzzy data processing and binary logic-based reasoning. In this work, each behavior is encoded as a fuzzy rule-base with a distinct control policy governed by fuzzy inference. Thus, each fuzzy behavior is similar to the conventional FLC in that it performs an inference mapping from some input space to some output space. If X and Y are input and output universes of discourse of a behavior with rule-base size $n$, the usual fuzzy if-then rule takes the following form

$$\text{IF } x \text{ is } \tilde{A}_i \text{ THEN } y \text{ is } \tilde{B}_i \quad (1)$$

where $x$ and $y$ represent input and output fuzzy linguistic variables, respectively, and $\tilde{A}_i \in X$ and $\tilde{B}_i \in Y$ ($1 \leq i \leq n$) are fuzzy sets representing linguistic values of $x$ and $y$. Typically, the input $x$ refers to sensory data and y to actuator control signals. In general, the antecedent consisting of the proposition "$x$ is $\tilde{A}_i$" could be replaced by a conjunction of similar propositions; the same holds for the consequent "$y$ is $\tilde{B}_i$". Fuzzy behaviors consist of a finite set of such rules.

The lowest-level behaviors are simple, self-contained behaviors that serve a single purpose by operating in a reactive fashion. Alone, their capability would be insufficient for autonomous navigation. These simple behaviors are building blocks for more intelligent fuzzy behaviors. Overall robot intelligence is distributed amongst the individual behaviors in a hierarchical structure as described below.

### 2.1 Hierarchy of Distributed Behaviors

In the spirit of the behavior control paradigm, we decompose autonomous system behavior into a bottom-up hierarchy of increased behavioral complexity in which *primitive* behaviors reside at the lowest level of hierarchy. The lowest level of behavior is referred to here as the primitive level. Within this framework a finite set of primitive behaviors can be combined synergistically to produce more intelligent *composite* behaviors in service of goal-directed operations. As an example, consider the driver-automobile system as an autonomous system operating in a dynamic environment. Consider further the act of turning a corner at a moderate speed (say, 55 km/h) as a composite behavior, and the acts of decelerating, braking, and steering as primitive behaviors. Then we can interpret the turning behavior as a synergism of the behaviors in the primitive level, each operating at varying levels of activation. In Figure 1 each circle represents a behavior.

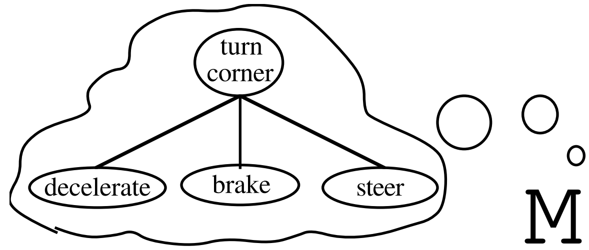



Figure 1. Possible hierarchy of a turning behavior

A typical hierarchy for indoor navigation might be arranged as in Figure 2. This figure implies that goal-directed navigation can be decomposed as a behavioral function of `goal-seeking` (collision-free navigation to some location) and `route following` (assuming some direction is given perhaps in the form of a path plan). These behaviors can be further decomposed into primitive behaviors as shown, with dependencies indicated by the adjoining lines. `Wall following` and `obstacle avoidance` are self-explanatory. The `doorway` behavior implies one that can guide a robot through narrow passageways with very shallow depth (in the visual image sense). The `goto` behavior will direct a robot to navigate along a straight line trajectory to a particular location. Note that the decomposition of behavior for a given mobile robot system is not unique. Consequently, suitable behavior repertoires and associated hierarchical arrangements are arrived at following a subjective analysis of the system and the task domain.

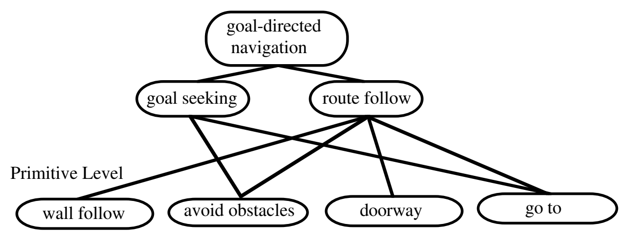



Figure 2. Hierarchical behavior decomposition for indoor navigation

## 3. Fuzzy Behavior Coordination

An important problem arises when behaviors compete for control of the robot or when competing behaviors recommend conflicting control actions. This occurs frequently during any sufficiently complex navigation task. In the jargon of behavior control the problem is referred to as behavior arbitration. It consists of coordination of multiple task-achieving behaviors and conflict resolution amongst them. A common approach to this problem employs a prioritization scheme wherein the control recommendation of only one behavior among several competing behaviors is taken; recommendations from the remaining behaviors are ignored [6, 8]. An alternative approach is proposed here that takes into account the recommendations of all applicable behaviors.

Behavior coordination is achieved by introducing a scheme for weighted decision-making and rule-base (behavior) selection. The mechanism for weighted decision-making is embodied in a concept called the *degree of applicability* which is a linguistic measure of the instantaneous level of activation of a behavior. Fuzzy rules of composite behaviors are formulated to include weighting consequents which govern the degree of applicability of primitive behaviors at a lower level. We refer to these as applicability rules. Let $\mathcal{B}_c$ be a composite behavior comprised of $N_p$ primitive behaviors. Then the degree of applicability, $\alpha_p$, of primitive behavior p ($p = 1, 2, \ldots, N_p$) is specified in the consequent of applicability rules of the form

$$\text{IF } x \text{ is } \tilde{A}_i \text{ THEN } \alpha_p \text{ is } \tilde{D}_i \qquad (2)$$

where $\tilde{A}_i$ is defined as before. The fuzzy set $\tilde{D}_i$ represents the linguistic value (e.g. "high") of the degree of applicability of primitive behavior p to the situation prevailing during the current control cycle. It is defined over the unit interval, [0, 1]. This feature allows certain robot behaviors to influence the overall behavior to a greater or lesser degree as required by the current system goal. Thus, behavior coordination is accomplished using meta-rules that provide a form of the ethological concepts of inhibition and dominance observed in animal behavior. Behaviors with partial applicability can be said to be inhibited, while behaviors with maximal applicability can be said to dominate.

As described here, the degrees of applicability are analogous to neuronal activation levels. Effects similar to neuron threshold activation can easily be implemented with the use of α-cuts of fuzzy sets (this 'α' is not to be confused with the degree of applicability). An α-cut of a fuzzy set, A, defined over a universe U, is a crisp set, $A_\alpha$, containing all the elements of U with membership grade in A greater than or equal to α [9]. Formally,

$$A_\alpha = \{x \in X \mid \mu_A(x) \geq \alpha\} \qquad (3)$$

where $\mu_A(\bullet)$: $X \longrightarrow [0,1]$ is a membership function of fuzzy set A. To utilize α-cuts for implementing thresholding behavior activation, we consider the rule-strength of an applicability rule. If the α-cut of the fuzzy set resulting from evaluation of the rule's consequence is null, then the rule recommends that the level of activation for the behavior is zero. Thus, the rule recommends that the behavior be activated (to degree $\tilde{D}_i$) only if the rule-strength equals or exceeds a threshold α.

### 3.1 Coordination Procedure

The coordination of fuzzy behaviors is done in the framework of fuzzy logic theory via operations on fuzzy sets. In order to briefly describe the process we will concentrate on a single composite behavior, $\mathcal{B}_c$, which can be decomposed into primitive behaviors $\beta_1$ and $\beta_2$ ($N_p = 2$). We do this without loss of generality since the following description also applies when $N_p > 2$, and across additional composite behaviors. Consider a given control cycle during which $\mathcal{B}_c$ dictates that the applicabilities of $\beta_1$ and $\beta_2$ are say, $\alpha_1 = 0.25$ and $\alpha_2 = 0.75$ respectively. Fuzzy rules of each applicable primitive behavior are processed yielding output fuzzy sets, $\tilde{o}_1$ and $\tilde{o}_2$ (see Figure 3). These output fuzzy sets are equivalent to the result produced by rule-base evaluation in conventional FLCs *before* applying the defuzzification operator.

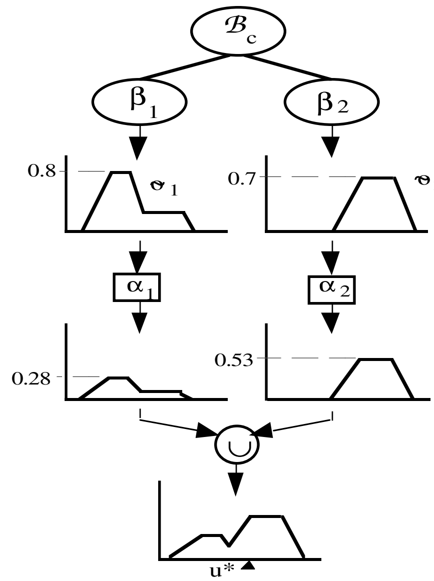



Figure 3. Fuzzy coordination of behaviors

Following the consultation of individual primitive behaviors, each fuzzy behavior output is weighted by the corresponding degree of applicability. Thus, $\beta_1$ and $\beta_2$ are activated to degrees $\alpha_1$ and $\alpha_2$. Here, the behavior activation is accomplished via scalar multiplication of the output fuzzy sets by the appropriate degree of applicability. This is equivalent to the conjunction of a crisp set of height α with the output fuzzy set. The resulting fuzzy sets are then aggregated using an appropriate t-conorm operator ('max' is usually used in fuzzy logic control), and defuzzified to yield a crisp output, $u^*$, that is representative of the intended coordination of behavior.

In this procedure, multiplication by α expresses the relative applicability of a primitive behavior to the current situation, while the scalar α represents the weight of the behavior in the aggregated control decision. Operators other than multiplication can be used to achieve a similar effect. Yager [10] refers to such operators as importance transformations and suggests a general class of them for both t-norm and t-conorm aggregations. The illustration of this hypothetical example, shown in Figure 3, reveals that the output of $\mathcal{B}_c$ is influenced more by its dominant primitive behavior (in this case $\beta_2$) as intended. This coordination procedure is a generalization of the idea of rule weighting in a single rule base to rule-base weighting among multiple rule-bases. Control recommendations from each applicable behavior are considered in the final decision. In the general case, the resultant control action can be thought of as a consensus of recommendations offered by multiple experts.

In some instances, it may be evident from current sensory data that only one particular robot behavior is fully applicable ($\alpha = 1$). In such cases, coordination simply reduces to behavior selection as is done in conventional behavior arbitration and alternative approaches to fuzzy adaptive control [11, 12]. We refer to this as switching coordination since behaviors are alternately switched on and off. When the state of the world satisfies the conditions for activation of a single behavior, or several, there is no need to process rules from behaviors that do not apply (as is done in the conventional FLC architecture). Processing rules from irrelevant behaviors would result in unnecessary consumption of computational resources and possible introduction of "noise" into the decision-making process. In our approach, there are no conceivable circumstances under which the totality of rules in the entire system will be consulted during a given control cycle.

## 4. Behavior Conflict Resolution

In the framework of fuzzy logic theory, conflict resolution is handled implicitly in the mechanics of the conventional fuzzy inference and defuzzification processes. That is, conflicting fuzzy outputs from individual rules are aggregated and defuzzified (resolved) to yield non-fuzzy control actions. In a similar manner as for coordination, we use fuzzy set theory to generalize this concept to resolve conflicts among conflicting *rule-bases*, i.e. behaviors. The manner in which this is done depends on whether there is partial or full conflict among competing behaviors.

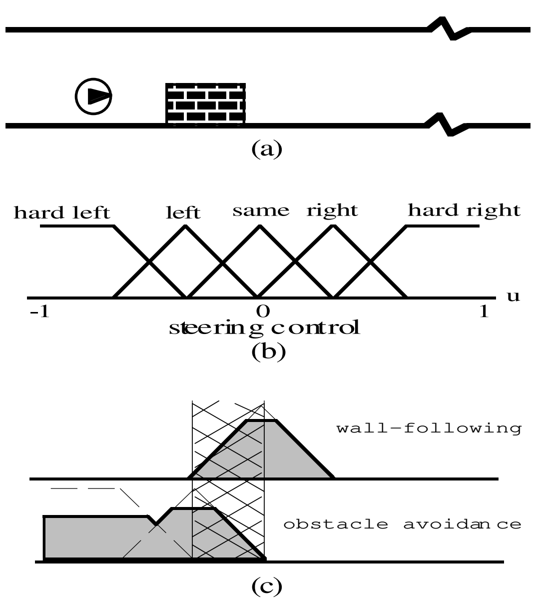



Figure 4. Partial behavior conflict

In mobile robot navigation we are often concerned with behavior conflicts. For example, we can imagine the necessity to resolve conflicts between avoiding obstacles and following a wall when navigating in a cluttered corridor. Such a situation is illustrated in Figure 4a where the objective requires following the right-wall. Assuming the robot travels at a constant speed, a representative partition of the universe of discourse for steering control is as shown in Figure 4b. Based on this partition, plausible fuzzy steering output recommendations are shown in Figure 4c for wall-following and obstacle avoidance. The `wall-following` behavior recommends proceeding in the current direction (recall that primitive behaviors serve their single purpose; they are not cognizant of the purpose of other behaviors). The `obstacle avoidance` behavior opts to turn left (or hard-left depending on the frontal proximity of the obstacle). Also shown is a region of overlap between these fuzzy outputs indicating a partial behavioral conflict. Due to such overlap, situations of partial conflict are not significantly distinguishable from general cases requiring behavior coordination. Therefore, partial behavior conflict is handled as described in the previous section.

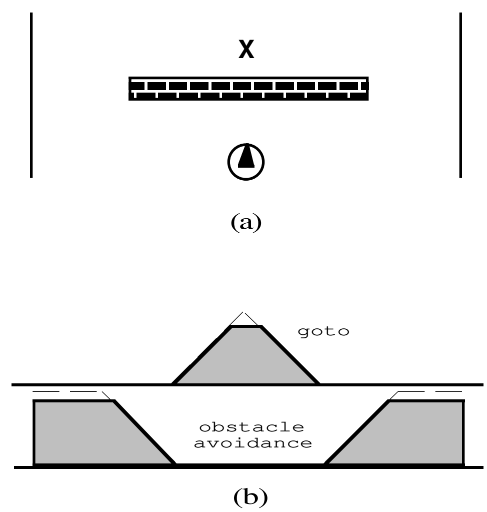


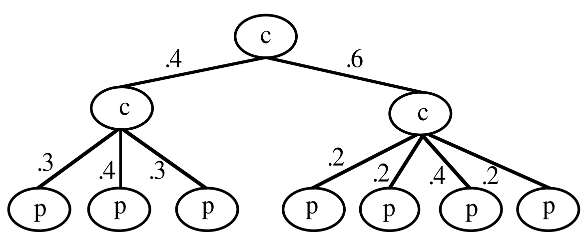

Figure 5. Full behavior conflict

Alternatively, consider the situation shown in Figure 5 in which goal-seeking and obstacle avoidance behaviors are interacting. In this case, the objective is to navigate to a specified goal (indicated by the '`X`'). However, the robot's direct path is blocked and a decision must be made to proceed by turning right or left. Based on the same steering control partition of Figure 4b, plausible fuzzy control outputs are indicated in Figure 5b. Here, the `goto` behavior urges the robot to proceed straight towards the goal. The `obstacle avoidance` behavior suggests going left *or* right. In this case there is no overlap and the behaviors are fully conflicting. If we aggregate and defuzzify these fuzzy recommendations using common defuzzification methods (e.g. center of gravity, or mean of maxima) the result would be to proceed straight, thus leading to collision with the obstacle. This will occur even if a higher degree of applicability was assigned for obstacle avoidance.

The problem just described is important not only in navigation tasks but in most tasks requiring reasoning among fully conflicting alternatives. A common solution is to select a designated *default* alternative, or to randomly select one action from the set of conflicting alternatives. A control action could also be selected based on some criteria such as minimum required control effort. Currently, we deal with this problem by designating a right-turn as the default alternative. More flexible approaches based on fuzzy logic defuzzification methods have been proposed in the literature. Yager introduces a method for defuzzification that utilizes nonmonotonic conjunction [13] of fuzzy sets representing allowed control actions and control actions recommended by the rule-base. In the example given here, the allowed control actions are left or right; the recommended action is straight. The nonmonotonic conjunction is coupled with the random generation defuzzification method [10] to achieve defuzzification under constraints. Pfluger et al [14] also proposed a solution based on their centroid of largest area defuzzification strategy. In future work we plan to adopt such methods as an alternative to the commonsense reasoning approach of the right-turn policy.

## 5. Implementation Issues

The development of the coordination strategy and the overall hierarchical architecture has revealed aspects of the implementation that the control system designer must address. These are design options whose relative performance advantages are under investigation. Namely, is it more advantageous to implement the degree of applicability concept using fuzzy logic as opposed to crisp logic? And, should the degree of applicability concept be implemented at all levels of hierarchy?




.4(.3 + .4 + .3) + .6(.2 + .2 + .4 + .2) = 1 (0r 100%)

Figure 6. Percentage distribution of applicability

The first is a question of whether or not additive weighting should be used to achieve coordination. With additive weighting, the decision-making responsibility for a given composite behavior is distributed as a true *percentage* among its primitive behaviors. This idea is depicted in Figure 6 where labels 'c' and 'p' designate composite and primitive behaviors, respectively, in a hypothetical hierarchy. The numerical labels indicate crisp degrees of applicability associated with behaviors at subsequent levels. This option has the property that

$$\sum_{\mathcal{B}\in B_k} \alpha = 1.0 \qquad (4)$$

where $\mathcal{B}$ is a behavior in the set, $B_k$, of all behaviors at level $k$ of the hierarchy. If the assignment of the degree of applicability is based on fuzzy logic (as described earlier) then this property does not hold necessarily. The fuzzy logic approach emphasizes the relative *weight* of integral behaviors in the motion control decision as opposed to percentage of responsibility.

At its current stage the hierarchy of behaviors is comprised of three levels, similar to that shown in Figure 2. The degree of applicability is implemented at the primitive level while switching coordination is used at the higher level (e.g. between goal-seeking and route-following in Figure 2). Thus far, simulation results have demonstrated acceptable performance. Nevertheless, in future work a comparison will be made between this approach and a strategy utilizing fuzzy coordination throughout the hierarchy.

For behavior coordination, the advantage of additive weighting relative to the fuzzy logic approach is not yet clear. Results comparing the different options will be the subject of a subsequent paper.

## 6. Summary

A hierarchical fuzzy control methodology has been described for mobile robot navigation. Aspects of behavior coordination and conflict resolution are the main focus in this paper. In particular, the concept of behavioral degree of applicability as a basis for behavior coordination has been discussed. The hierarchy of distributed fuzzy behaviors provides an alternative approach for controlling systems with many rules. It is suitable for controlling systems that can be represented by hierarchical or decentralized structures. While this paper has described coordination of intelligent behavior in the context of robot motion control, the ideas have a broader scope. A formal exposition of similar ideas in the context of multi-attribute decision-making can be found in [15].

The performance of the approach is under investigation via simulation and real-world experiments of mobile robot behavior in indoor navigation tasks. The implementation of α-cuts for thresholding activation of primitive behaviors is also being incorporated into the architecture. Experimental results of this research will reveal the relative advantages of various implementation issues articulated herein. These include methods for assigning degrees of applicability for behavior coordination, and utilization of the concept throughout the entire hierarchy of behaviors.

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