Adaptive Fuzzy-Behavior Hierarchy for Autonomous Navigation

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Abstract

Adaptive behavioral capabilities are necessary for robust navigation in non-engineered environments. A control approach to adaptive behavior is described which exploits the approximate reasoning facility of fuzzy logic. In particular, a behavior-based architecture for hierarchical fuzzy control of mobile robots is presented. Its structure is described as well as mechanisms of control decision-making which give rise to adaptive behavior. Control decisions result from a consensus of recommendations offered only by behaviors that are applicable to current situations. Indoor navigation examples demonstrate the practicality of the approach and reveals characteristics of multiple behavior interaction.

1 Introduction

Real-time intelligent controllers are required to achieve the level of autonomy necessary in unstructured or "non-engineered" domains such as office settings, automated factories, and natural terrain. As a result, motion control research in mobile robotics is steering toward advances beyond fixed-path tracking and teleoperation and closer to true autonomy. The very nature of autonomy dictates the need for some capacity of adaptive behavior. In support of research efforts to endow mobile robots with adaptability sufficient for autonomous navigation, we are concentrating on providing an approximate reasoning capability as a resource for intelligence. We advocate fuzzy logic control techniques as a means to this end. For mobile robots intended for tracking or teleoperation, classical control techniques can be applied without much difficulty. However, as environmental structure and task constraints are removed from the problem domain, the need for increased autonomy mandates the development of higher-level intelligent controllers. Fuzzy logic is particularly well suited for implementing such controllers due to its capabilities of inference and approximate reasoning under uncertainty.

This paper describes a hierarchical fuzzy control approach to local navigation for autonomous mobile robots. A behavior-based control architecture is presented that is structured as a hierarchy of fuzzy logic rule-bases which enables distribution of intelligence amongst a number of special-purpose *fuzzy-behaviors.* The fuzzy-behavior hierarchy represents a conceptual model of an embodied behavior system and its behavioral relationships. A coordination scheme based on fuzzy logic is also described which employs a mechanism for weighted decision-making based on contextual behavior activation. This coordination scheme is responsible for continuous behavioral adaptation in response to goal information and instantaneous sensory input.

An overview of fuzzy logic control is given followed by a discussion of fuzzy behavior control, synthesis, and hierarchical organization. We then describe mechanisms of behavior modulation and associated interactions. Finally, performance of the adaptive behavior hierarchy is demonstrated in simulated navigation tasks involving behavior interaction with emphasis on aspects of the decision-making process that give rise to adaptive behavior.

2 Fuzzy Logic Control

Fuzzy control is one of the more active areas of application of fuzzy logic and the underlying fuzzy set theory introduced by Zadeh [1]. Fuzzy logic controllers (FLCs) are intelligent control systems that smoothly interpolate between rules, i.e. rules fire to continuous degrees and the multiple resultant actions are combined into an interpolated result.

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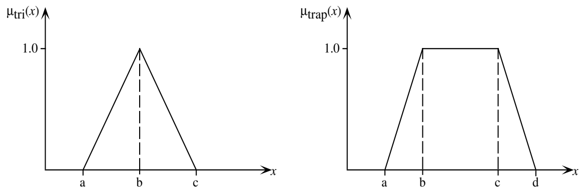

Figure 1: Typical membership functions.

A fuzzy set may be represented by a mathematical formulation known as a membership function. That is, associated with a given linguistic variable (e.g. *speed*) are linguistic values or fuzzy subsets (e.g. *slow*, *fast*, etc.) expressed as membership functions which represent uncertainty, vagueness, or imprecision of values of the linguistic variable. This function assigns a numerical degree of membership to a crisp (precise) number. More precisely, over a given universe of discourse (relevant numerical range) X, the membership function of a fuzzy set $\tilde{A}$, denoted by $\mu_{\tilde{A}}(x)$, maps elements $x \in X$ into a numerical value in the closed unit interval, i.e.

$$\mu_{\tilde{A}}(x) : X \rightarrow [0,1]. \tag{1}$$

Within this framework, a membership value of zero corresponds to an element which is definitely not a member of the fuzzy set, while a value of one corresponds to the case where an element is definitely a member of the set [2]. Typical membership functions used to express uncertainty in the system variables of fuzzy logic control systems take on triangular and trapezoidal shapes (or variants thereof) given by Equations (2) and (3), respectively, where a, b, c, and $d \in \Re$. These are illustrated in Figure 1.

$$\mu_{tri}(x) = \begin{cases} 0 & : \; x < a \\ \frac{(x-a)}{(b-a)} & : \; a \leq x \leq b \\ \frac{(a-x)}{(b-a)} & : \; b \leq x \leq c \\ 0 & : \; x > c. \end{cases} \tag{2}$$

$$\mu_{trap}(x) = \begin{cases} 0 & : \; x < a \\ \frac{(x-a)}{(b-a)} & : \; a \leq x < b \\ 1 & : \; b \leq x \leq c \\ \frac{(c-x)}{(d-c)} & : \; c < x \leq d \\ 0 & : \; x > d. \end{cases} \tag{3}$$

Implementation of a fuzzy controller requires assigning membership functions for inputs and outputs. Inputs to a fuzzy controller are usually measured variables, associated with the state of the controlled plant, that are fuzzified (assigned membership values) before being processed by an inference engine. The heart of the controller inference engine is a set of *if-then* rules whose antecedents and consequences are made up of linguistic variables and associated fuzzy membership functions. Consequences from different rules are numerically aggregated by fuzzy set union and then collapsed (defuzzified) to yield a single crisp output as the control signal for the plant. For a more detailed introduction to fuzzy control, fuzzy set operations, and the concepts of fuzzification, inference, aggregation, and defuzzification see one of [2, 3].

3 Behavior-based FLC

The behavior control paradigm grew out of an amalgamation of ideas from ethology, control theory and artificial intelligence [4, 5]. Under this paradigm, one decomposes high-level motion control into a set of special-purpose behaviors that achieve distinct tasks when subject to particular stimuli. The paradigm was initially proposed by Brooks [5] who realized behaviors as finite state automata to control a mobile robot through arbitrated competition and cooperation.

3.1 Fuzzy-behavior synthesis

In contrast to behaviors in non-fuzzy behavior controllers, fuzzy-behaviors are synthesized as fuzzy logic rule-bases, i.e. collections of a finite set of fuzzy if-then rules. Each behavior is encoded as a fuzzy rule-base with a distinct mobile robot control policy governed by fuzzy inference. Thus, each fuzzy-behavior is similar to a conventional fuzzy logic controller 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 a rule-base of size n, the usual fuzzy if-then rule takes the following form

$$IF \; x \; is \; \tilde{A}_i \; THEN \; y \; is \; \tilde{B}_i \tag{4}$$

where x and y represent input and output fuzzy linguistic variables, respectively, and $\tilde{A}_i$ and $\tilde{B}_i$ ($i = 1...n$) are fuzzy subsets representing linguistic values of x and y. In the mobile robot controller, the input x refers to sensory data or goal information; y refers to motor control signals or behavior activation levels. In general, the rule antecedent consisting of the proposition "x is $\tilde{A}_i$" could be replaced by a conjunction of similar propositions; the same holds for the rule consequent "y is $\tilde{B}_i$". Fuzzy-behaviors consist of a finite set of such rules. Thus far the hierarchy has been implemented to act in an

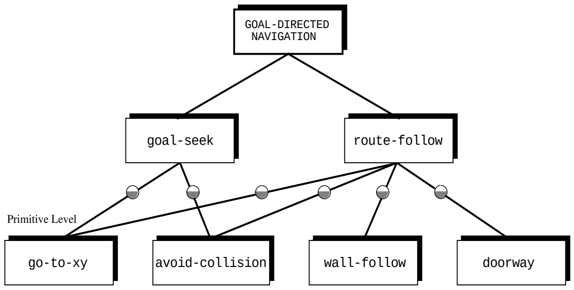

Figure 2: Mobile robot behavior hierarchy.

intelligent supervisory mode atop low-level classical PID controllers by issuing appropriate set-points as recommended by the fuzzy-behavior system.

3.2 Hierarchy of fuzzy-behaviors

A collection of *primitive behaviors* resides at the lowest level. These are simple, self-contained fuzzy controllers that serve a single purpose by operating in a reactive (non-deliberative) or reflexive (memoryless) fashion. Via fuzzy inference, they perform nonlinear mappings from different subsets of the robot's sensor suite to (typically, but not necessarily) common actuators. As designed, a single behavior operating alone would be insufficient for autonomous navigation tasks. Such primitive behaviors are building blocks for more intelligent *composite behaviors* implemented as fuzzy decision systems. That is, they are combined synergistically to produce intelligent behavior(s) suitable for accomplishing goal-directed navigation.

Indoor mobile robots should be capable of collision-free navigation in static and dynamic environments. Several capabilities are necessary to achieve this including collision avoidance, self and goal localization, and traversal through indoor features such as halls, doorways, and densely cluttered spaces. A behavior hierarchy encompassing these capabilities is shown in Figure 2. This figure implies that goal-directed navigation can be decomposed as a behavioral function of `goal-seek` (collision-free navigation to some location) and `route-follow` (assuming some direction is given perhaps in the form of waypoints or a path plan). These behaviors can be further decomposed into the primitive behaviors shown, with dependencies indicated by the adjoining lines. The purposes of `wall-follow` and `avoid-collision` are implied by their names. The `doorway` behavior implies one that can guide a robot through narrow passageways in walls. The `go-to-xy` behavior will direct a robot to navigate along a straight line trajectory to a particular location. Interconnecting circles between composite behaviors and the primitive level represent weights and activation thresholds of associated primitive behaviors (described below).

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 environment.

4 Behavior Modulation

During execution of adaptive behavior, complex interactions occur when more than one primitive behavior is active. This interaction can take the form of behavioral cooperation or competition. These forms of behavior are not perfectly distinct; they are extremes along a continuum [6].

We define *behavior modulation* as the continuous adjustment or adaptation of behavior activation levels in a multi-behavior or multi-agent system. Behavior modulation is achieved in this work by a mechanism of weighted control decision-making embodied in a concept called the *degree of applicability* (DOA) — a measure of the instantaneous level of activation of a motion behavior. Fuzzy rules of composite behaviors are formulated to include weighting consequents which modulate the DOAs of primitive behaviors at a lower level. We refer to these as applicability rules. The DOA, α, of a primitive behavior is specified in the consequent of applicability rules of the form

$$IF\ x\ is\ \tilde{A}_i\ THEN\ \alpha\ is\ \tilde{D}_i \qquad (5)$$

where $\tilde{A}_i$ is defined as in (1). $\tilde{D}_i$ is a fuzzy subset representing the linguistic value (e.g. *high*, *low*, etc) of the behavior's DOA to the situation prevailing during the current control cycle. It is defined over the closed unit interval, [0, 1]. In general, a composite behavior, c, will include applicability rules with a consequent of the form "α_p is $\tilde{D}_i$" for each primitive behavior p modulated by c. Thus for all p, $\alpha_p \in [0, 1]$ is determined by fuzzy inference as the output of an associated composite behavior. This feature allows certain robot behaviors to influence the overall behavior to a greater or lesser degree as required by the current situation and goal. It serves as a form of adaptation since it causes the control policy to dynamically change in response to goals, sensory input, and internal state. The behavior hierarchy, then, is a dynamic nonlinear mapping from situations to actions rather than a static non-linear mapping represented by a fixed set of fuzzy rules. The DOA not only dictates the amount of influence a behavior has on overall robot behavior, but is also used to implement thresholding behavior activation.

DOAs of a set of primitive robot behaviors convey their respective utilities. Evaluation of these utilities performed by the composite behaviors endows the robot with motivational autonomy [7]. Collectively, these mechanisms allow robots to exhibit behavioral responses throughout the continuum. This is in contrast to non-fuzzy behavior arbitration which typically employs fixed priorities that allow only one activity to influence the robot's behavior during a given control cycle.

4.1 Handling multiple behaviors

Multi-behavior coordination is done in the framework of fuzzy logic theory – via operations on fuzzy sets [8]. Fuzzy rules of each applicable primitive behavior are processed yielding respective output fuzzy sets for motor velocity set-points. These output fuzzy sets are equivalent to the result produced by rule-base evaluation in conventional fuzzy controllers *before* applying the defuzzification operator. Following the consultation of applicable primitive behaviors, each fuzzy behavior output is weighted by the corresponding DOA. The resulting fuzzy outputs for motor velocities are aggregated using an appropriate fuzzy union operation and defuzzified to yield a crisp velocity set-point representative of the intended coordination of behavior. This procedure is a generalization of the idea of *rule* weighting in a monolithic rule-base to *rule-base* weighting among multiple rule-bases. In this way, control recommendations from each applicable behavior are considered in the final decision.

An additional flexible feature of the architecture lies in the choice of an appropriate operator for consolidating multiple control recommendations. We focus on the t-conorm, or generalized fuzzy union operator of fuzzy set theory. Recall that primitive rule-base outputs are fuzzy sets, and an aggregation across rule-bases must be performed to produce an overall control output. As the selection of the t-conorm used for *rule-base* aggregation dictates how anything approaching a consensus will be made, available options should be considered.

We consider the following t-conorms: bounded sum, arithmetic maximum, probabilistic sum, and the Sugeno S_λ family ($\lambda \geq -1$) which is one of a variety of parameterized families of aggregation operators [9]. Their definitions follow respectively, where $a \in [0,1]$, $b \in [0,1]$, and $U(a,b)$ denotes the t-conorm operator.

$$U(a,b) = \min(1, a+b) \quad (6)$$

$$U(a,b) = \max(a,b) \quad (7)$$

$$U(a,b) = a + b - ab \quad (8)$$

$$U(a,b,\lambda) = \min(1, a+b+\lambda ab) \quad (9)$$

The selection of the above set of t-conorms was based on their computational simplicity (i.e. no division or exponent operations required).

5 Examples and Discussion

In this section, we examine representative results of adaptive behavior controlled by the fuzzy-behavior hierarchy. The mobile robot is modeled after LOBOt, a custom-built base with a 2-wheel differential drive and two stabilizing casters. It measures 75 cm tall and 60 cm in width. The outputs from the behavior hierarchy are right and left wheel speeds; the inputs to the hierarchy are the goal location and subsets of sensor readings. The robot's sensor suite includes optical encoders on each driven wheel and 16 ultrasonic transducers arranged primarily on the front and sides.

5.1 Goal-seeking

Figure 2 shows that the composite `goal-seek` behavior arises from synergistic interaction between `go-to-xy` and `avoid-collision` behaviors. Alone, `avoid-collision` would merely display cyclic collision-free behavior in the immediate vicinity of the robot's initial location, while `go-to-xy` would display a taxic reaction that propels the robot toward the goal irregardless of obstacles in its path.

In this example, the robot's task is sensor-based navigation from some location to a designated goal inside a hypothetical indoor layout not unlike a warehouse or office building. The robot is not provided with an explicit map, however, it is cognizant of the notion of a two-dimensional Cartesian coordinate system. Its path is not pre-planned; it is executed in response to instantaneous sensory feedback. Its initial state is at a docking/charging station with pose $(x\ y\ \theta)^T = (11.7m\ 12.3m\ \frac{\pi}{2}rad)^T$. The goal is located at $(1.5m, 1m)$. We ran the simulated navigation using each of the operators defined above to examine the relative impact that

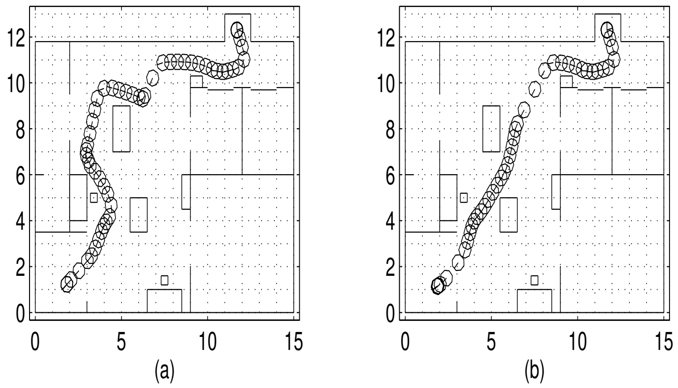

Figure 3: Goal-seeking using different t-conorms.

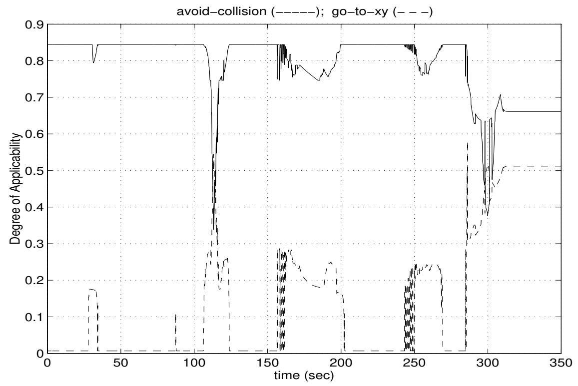

Figure 4: Behavior modulation during goal-seeking.

each has on motion decisions made during the run. That is, the fuzzy outputs of `go-to-xy` and `avoid-collision` were aggregated using Equations (6)–(9). The resulting path taken by the robot using the bounded sum is shown in Figure 3a; dimensions are meters. The robot simultaneously achieves the goals of reaching the target location *and* avoiding collisions. The paths resulting from using maximum and probabilistic sum were very similar to the bounded sum case. However, the decisions made as a result of applying the S_λ family for $\lambda \geq 1$ were clearly different as revealed by the alternative path shown in Figure 3b for $\lambda = 1$. The ensemble of control decisions made over the course of this run led to a more direct path to the goal. The results were similar for $\lambda > 1$. Thus, possible variations in system behavior can be determined through examination of the effects of the chosen fuzzy union operator on multi-behavior decision-making.

In Figure 4, the behavioral modulation during traversal of the path in Figure 3a is shown as the

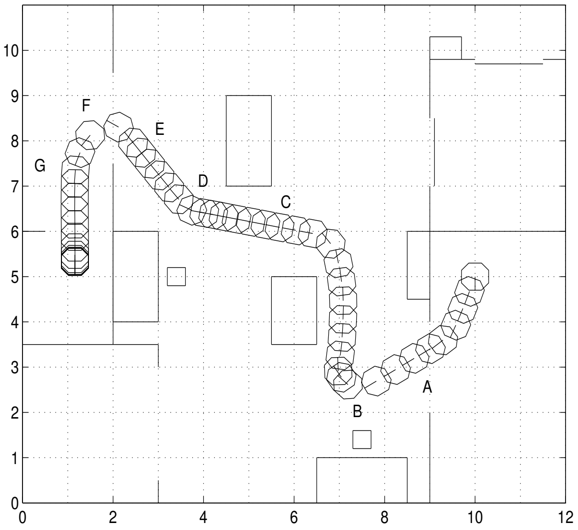

Figure 5: Route-following using waypoints.

temporal evolution of the DOAs, α_{ac} and α_{gt}, of each primitive behavior. The interaction dynamics shows evidence of brief bouts of competition (overlapping oscillations) and cooperation with varying levels of dominance. Initially, `avoid-collision` has the dominant influence over the robot's motors. It virtually maintains dominance throughout the task due to the relative clutter in the environment. The first bout of competition corresponds to the robot's approach towards the obstacle located at $(5, 8)$; the second bout occurs as it enters the goal room. Elsewhere, the applicabilities vary continuously reflecting the levels of activation recommended by the behavior control system.

5.2 Route-following

In the hierarchy of Figure 2 `route-follow` employs capabilities of several primitive behaviors. We demonstrate its performance in a navigation task utilizing the same primitives with the addition of `wall-follow`. For this example different start and goal locations are used and a designated route is specified by three additional waypoints to the goal. The initial state is $(x\ y\ \theta)^T = (10m\ 5m\ -\frac{\pi}{2}rad)^T$; the goal is located at $(1.2m, 5.2m)$. Waypoints between these locations are

$$(7.5, 2.5) \rightarrow (3.5, 6.5) \rightarrow (2.0, 8.5)$$

The resulting route is shown in Figure 5 and the corresponding DOAs for each primitive behavior are shown separately in Figure 6. Labels A–G in

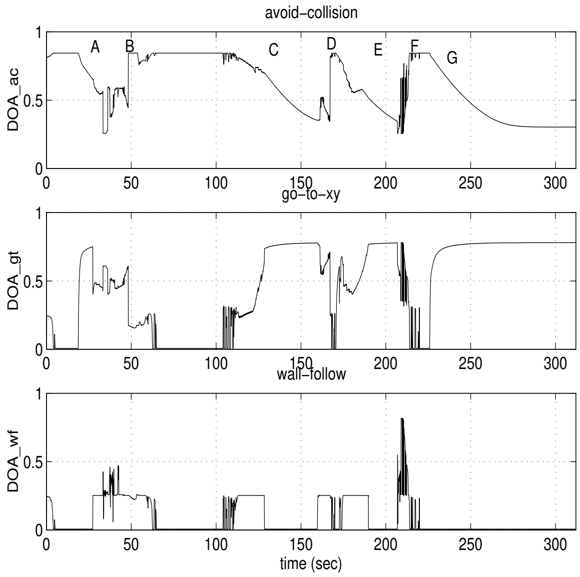

Figure 6: Behavior modulation during route-following.

each figure indicate a correlation between robot position along the route and the DOAs applied at that instant.

At point A as the robot exits the start room all three primitive behaviors compete for control. At B α_{ac} takes over as the dominant behavior while approaching the first waypoint. After avoiding an obstacle, α_{gt} becomes dominant at C on approaching the second waypoint. Dominance modulates between α_{ac} and α_{gt} through competition while traversing through D and E where the robot adjusts its heading towards the goal room. Interactions among the three primitive behaviors resurface at F where α_{wf} briefly takes over. It becomes inactive at G giving way to α_{ac}, and finally to α_{gt} on direct approach to the goal. During the majority of the task each primitive behavior is active to varying degrees influencing the overall robot behavior in response to goals, sensory input, and internal state.

6 Conclusion

The hierarchy of fuzzy-behaviors provides an efficient approach to synthesis of adaptive behavior capabilities necessary for robust autonomous navigation by mobile robots. Its practical utility lies in the decomposition of overall behavior into sub-behaviors that are activated only when applicable. When conditions for activation of a single behavior (or several) are satisfied, there is no need to process rules from behaviors that do not apply. The mechanism for weighted decision-making provides a suitable framework for situated adaptation in autonomous mobile robots. This approximate reasoning-based approach to behavior control appears to have potential as a conceptual model of intelligent behavior and behavioral relationships. It is useful for autonomous sensor-based navigation involving both goal-seeking and route-following.

Acknowledgement

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