Hierarchical Fuzzy Behavior-Based Control of a Multi-Agent Robotic System

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Abstract

A hierarchical fuzzy behavior-based architecture for the control of a multi-robot system is presented. The arbitration of distinct behaviors is achieved by weighing each behavior according to its applicability to the current control cycle. This applicability is determined using global constraints. Combining fuzzy logic and behavior-based control increases the systems adaptability and robustness. Simulation results of the proposed methodology are discussed and a future hardware implementation is outlined.

1. Introduction

Multi-agent mobile robotic systems extend the capabilities of single mobile robots enabling both new solutions to old problems and new problems solved. They also pose new constraints on the control system. The group architecture of a cooperative robotic system is the infrastructure of the implementation of the collective behaviors. It determines the system capabilities and its limitations (Cao *et al.,* 1997). One of the key features of the group architecture of a system is the control methodology, i.e. how conflicts are resolved and how the joint capabilities of the multi-robot apparatus are utilized.

Synthesizing and analyzing group behaviors from individual interactions is one of the great challenges of both ethology and artificial intelligence (Mataric, 1995). A hierarchical fuzzy behavior-based control architecture for a multi-robot system is proposed. Combining fuzzy logic and behavior-based control enhances the capabilities of both theories. Fuzzifying the behavior-based control increases the diversity of the emergent, composite behaviors and therefore increases the complexity level the system can achieve. It allows for a more robust, adaptive and smoother control. On the other hand, implementing fuzzy control using a hierarchical

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behavior-based model lowers the number of necessary rules drastically, making the implementation of complex systems using fuzzy logic feasible. The proposed methodology was successfully simulated in software and a hardware realization is currently underway.

Control of mobile robotic systems in an unstructured environment poses many challenging problems. Fuzzy control presents a logical choice since it is a convenient tool for handling real world uncertainty (Jamshidi, 1996, ch. 7). Fuzzy controllers are robust in the presence of perturbations, efficient for continuous systems and relatively easy to design and implement (Mamdani, 1993). A major drawback of conventional fuzzy systems is that the rule base dimension rises exponentially with the number of variables. One common method of addressing this problem in complex systems is implementing a hierarchy of rules in which rules are subdivided into groups processed sequentially (Raju *et al.,* 1991). The hierarchical fuzzy behavior-based paradigm takes advantage of the same mechanism but it uses separate rule bases that are hierarchically processed.

Behavior-based control has grown out of an amalgamation of ideas from ethology, control theory and artificial intelligence (Brooks, 1986, 1990). Robotic controllers consist of a collection of special purpose *behaviors* that achieve distinct tasks e.g. "*Avoid-Obstacle*" maintains the task of preventing collision with obstacles. Coordination between behaviors results in the emergence of more intelligent and complex behaviors. Several methods have been implemented for achieving behavior coordination (Arkin and Balch, 1998). Behavior fusion forms a weighted sum of the output of distinct behaviors. It degenerates to behavior switching by giving a unit weight to one behavior and zero to the others. Behavior-based control is well suited for a real world, unstructured environment since no modeling is involved, "The world is it own best model" (Brooks, 1990), and the behaviors react in a straightforward fashion to stimuli from the environment. The research effort here is focused on finding ways for increasing achievable task complexity (Brooks, 1990).

Much of the recent research activity in the field of cooperative robotics implements behavior-based control. Mataric (1995) studied the synthesis of group behaviors based on a minimal set of low–level behaviors termed *basis behaviors*. The *basis behaviors* serve as building blocks for more complex behaviors. Arkin and Balch (Arkin, 1992; Arkin and Balch, 1998) studied schema based reactive systems and use fusion for behavior coordination. Parker (1998) tries to enhance system adaptability and fault tolerance by implementing several behavior sets in a multi robot architecture, ALLIANCE (and L-ALLIANCE). The behavior sets are activated according to motivational behaviors. At any given time only one behavior set may be active.

Several researchers have applied fuzzy logic to behavior-based control of single and multi-robot control. Glorennec (1997) presented a multi-robot system in which each robot has a mechanism termed Local Supervisor (LS) that switches between two behaviors: mobile robot avoidance and fixed-obstacle avoidance (and goal seeking). Both behaviors and LS are fuzzy. Ghanea-Hercock and Barnes (1996) proposed a fuzzy multi-layer controller in which a fuzzy rule base adjusts the relative weighting of each behavior. The fuzzy control layer takes direct sensory input and applies negative feedback on the utility (importance) of selected behaviors. This paper takes a more generic approach providing a common framework to fuzzy multi-robot control. Tunstel (1996), Michaud *et al*. (1996) and Moreno *et al*. (1993) have formulated hierarchical fuzzy behavior-based control for a single mobile robot. This paper extends their methodology to the multi robot control field. Each robot is modeled independently using the hierarchical fuzzy behavior-based control methodology and intelligent group behaviors emerge from the interaction between the robots.

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The rest of the paper is organized as follows: Section 2 outlines the control methodology, Section 3 describes the simulation environment and results obtained, Section 4 discusses the simulation results and outlines future software and hardware implementations.

2. The Control Methodology

Primitive behaviors are low-level behaviors that typically take inputs from the robot's sensors and send outputs to the robot's actuators forming a nonlinear mapping between them. *Composite behaviors* map between sensory input and/or global constraints and the Degree Of Applicability (DOA) of relevant primitive behaviors. The DOA is the measure of the instantaneous level of activation of a behavior. The primitive behaviors are weighted by the DOA and aggregated to form composite behaviors. This is a general form of behavior fusion that can degenerate to behavior switching for DOA =0 or 1 (Tunstel, 1996).

At the Primitive level, behaviors are synthesized as fuzzy rule bases, i.e. a collection of fuzzy if-then rules. Each behavior is encoded with a distinct control policy governed by fuzzy inference. If X and Y are input and output universes of discourse of a behavior with a rule-base size n, the usual fuzzy if-then rule takes the following form:

$$\text{IF x is } A_i \text{ THEN y is } B_i$$

where x and y represent input and output linguistic variables, respectively, and A_i and B_i (i=1...n) are fuzzy subsets representing linguistic values of x and y. Typically x refers to sensory data and y to actuator control signals. The antecedent and the consequent can also be a conjunction of propositions (e.g. IF x_1 is $A_{i,1}$ AND… x_n is $A_{i,n}$ THEN…).

At the Composition level the DOA is evaluated using a fuzzy rule base in which global knowledge and constraints are incorporated. An activation level (threshold) at which rules become applicable is applied to the DOA giving the system more degrees of freedom. The DOA of each primitive behavior is specified in the consequent of applicability rules of the form:

$$\text{IF x is } A_i \text{ THEN } \alpha_j \text{ is } D_i$$

where x is typically a global constraint, $\alpha_j \in [0,1]$ is the DOA and A_i and D_i, respectively are the fuzzy set of linguistic variables describing them. As in the former case the antecedent and consequent can also be a conjunction of propositions.

At each control cycle the DOA of each behavior is determined, then the fuzzy rules of applicable behaviors are processed yielding respective output fuzzy sets. The output sets are multiplied by the corresponding DOA, yielding weighted fuzzy sets. The resulting fuzzy sets are aggregated using the arithmetic sum and defuzzified using the centroid method.

In order to develop the framework for multi-robot control, a case study approach was taken in which several behaviors were defined and composed. *Safe-Homing* behavior depicted in Fig 1 enables the robots to move towards a given position without colliding with stationary obstacles or

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other robots. It is composed of the primitive behavior *Homing,* i.e. moving towards a given position and the composite behavior *Safe-Wander*, i.e. moving about without colliding with stationary obstacles or other robots. *Safe-Wander* is composed of three primitive behaviors*: Avoid- Obstacle* for avoiding stationary obstacles, *Avoid-Kin* for avoiding other robots and *Wander-Randomly* to ensure coverage of search area and avoiding dead-lock situations.

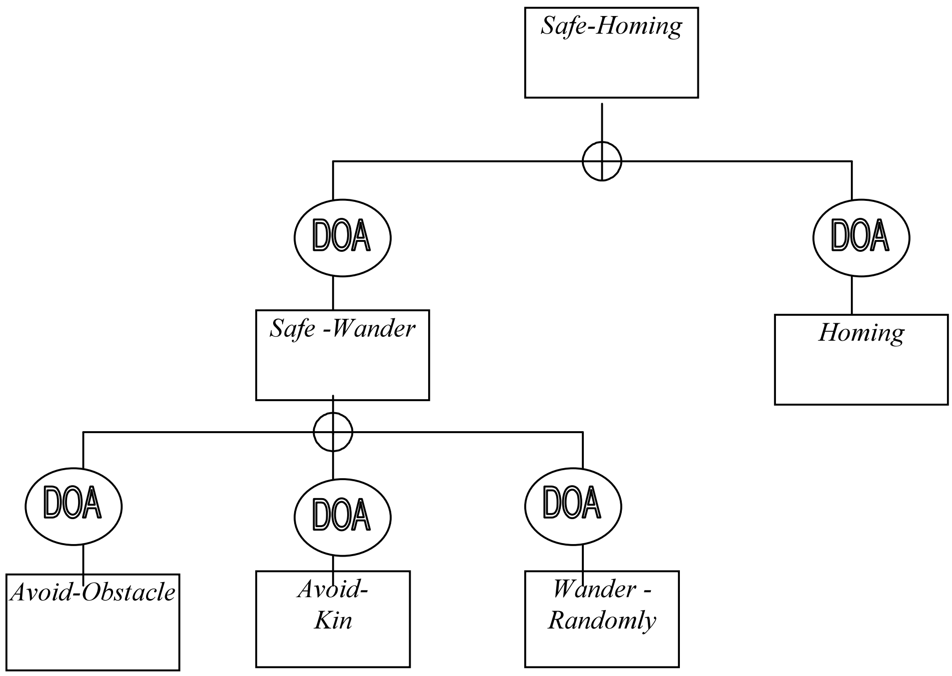

Fig. 1: Decomposition of *Safe-Homing* behavior

Avoid-Obstacle takes as inputs the distances to the nearest obstacle in front and on both sides of the robot and activates the robot's actuators. An example of a rule is:

IF front is TOO_CLOSE AND left is TOO_CLOSE AND right is FAR THEN speed is VERY_SLOW AND angle is TURN_RIGHT

Avoid-Kin operates in a similar way, taking only the distance and angle to the nearest robot. *Wander-Randomly* causes the robot to move forward with rotational directives issued randomly. *Homing* takes as inputs the robot's current position and the target position.

The composite behavior *Safe-Wander* changes the DOA of *Avoid-Obstacle*, *Avoid-Kin* and *Wander-Randomly*, according to the distance to the nearest obstacle and robot and the composite behavior *Safe-Homing* changes the DOA of *Homing* and *Safe-Wander.*

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3. Simulation

The multi-robot simulation consists of a 2D environment populated by two distinct objects: Robots and stationary objects. The robots are modeled as having circular shapes. The obstacles are modeled as polygons. The robots are capable of translational and rotational motion. They possess range sensing abilities: sonar and near IR range sensors with noisy perturbations are coarsely modeled. The near IR sensors have a limited range and a random range detection error up to ±10% of the reading. The sonar sensors poses a wider sensing range but have a dead zone for close proximity objects. They have a random range detection error of up to ±10% and a random phase error of up to ±10-deg is inserted randomly in 50% of the readings. We assume that the robots can distinguish between other robots and stationary objects. At each time cycle the robot senses the environment and fuses the sensor readings. Sensor fusion is achieved by summing weighted values of the sensor readings according to equation 1.

$$R(t) = IR(t)\left(1 - \frac{1}{1+e^{-(IR(t)-R_m)}}\right) + S(t)\left(\frac{1}{1+e^{-(S(t)-R_m)}}\right) \qquad (1)$$

Where:

R(t) is the fused range value
IR(t) is the near IR reading
S(t) is the sonar reading
R_m is a constant

The DOAs of the robots behaviors are evaluated by the composite behaviors and applicable behaviors (i.e., with a DOA that is higher then the activation threshold) are evaluated and aggregated. Finally, the robot executes the recommended motion.

As proof of concept we implemented the behavior of *Safe-Homing* (Fig. 1). The primitive behaviors (*Avoid-Obstacle, Avoid-Kin, Wander-Randomly* and *Homing)* are shown in Fig 3. *Safe-Wander* behavior is shown in Fig. 2 Note that the tracks are different in Fig 2a and 2b due to the random nature of *Wander-Randomly* and the errors in the sensor readings. Finally *Safe-Homing* is shown in Fig. 4. The results obtained are good in the sense that no collisions were detected and the robots reached their target using a reasonable path.

2a) 2b)

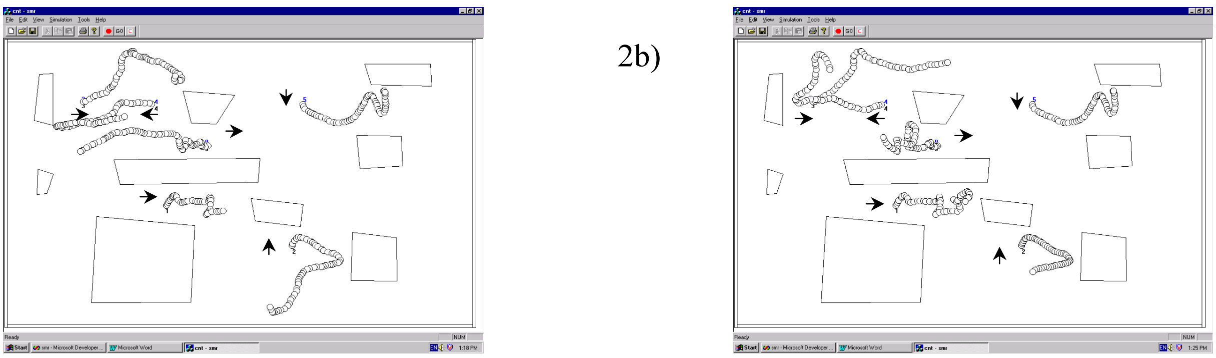
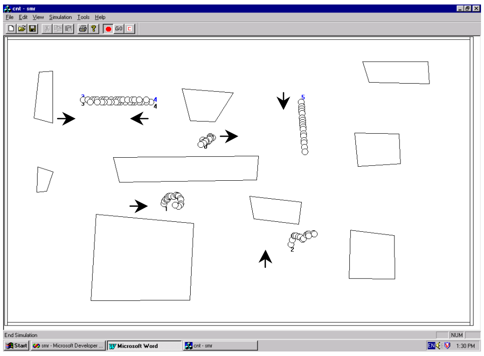


Fig. 2: Robot tracks generated using *Safe-Wander* behavior. Initial positions and orientation indicated by arrows.

3a)



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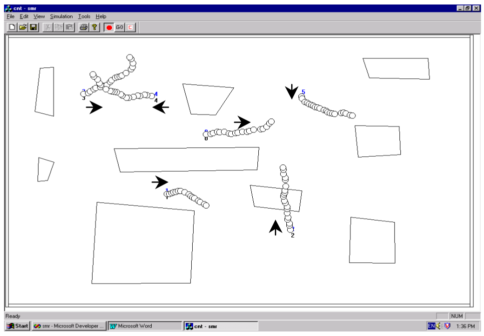

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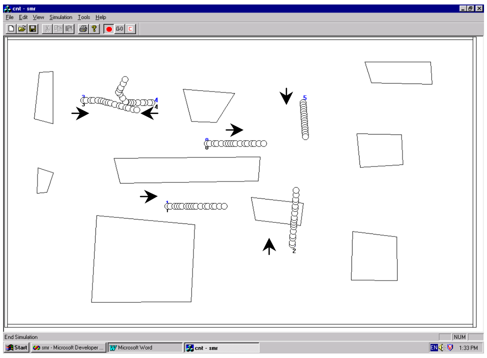

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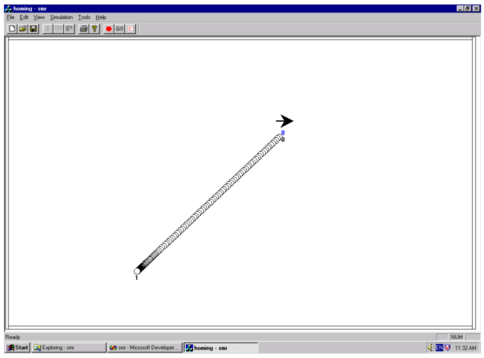
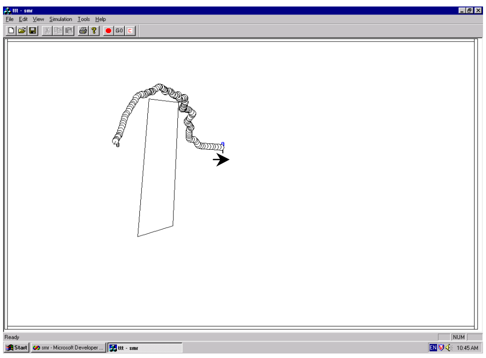


Fig. 3: Robot tracks generated using singly primitive behaviors: a) *Avoid-Obstacle* behavior, b) *Wander-Randomly* behavior, c) *Avoid-Kin* behavior, d) *Homing* behavior. Initial positions and orientation indicated by arrows.

4a)



4b)

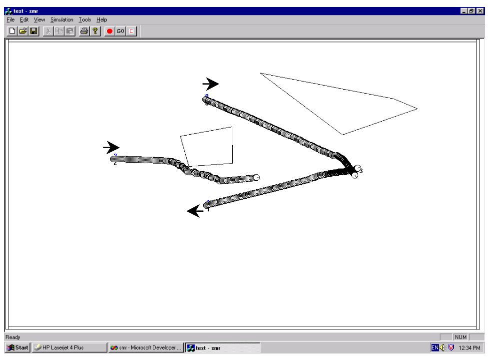


Fig. 4: Robot tracks generated using *Safe-Homing* behavior. Initial positions and orientation indicated by arrows.

4. Conclusion

A hierarchical fuzzy behavior approach to cooperative robotics has been implemented in simulation. This promising method allows synthesizing group behaviors capable of tackling complex tasks such as group terrain navigation. Our technique employs fuzzy logic to achieve smoother, more adaptive behavior interaction.

The intuitive representation of knowledge as fuzzy rule bases and the hierarchical structure facilitate design and analysis of composite behaviors by breaking down the controller into manageable blocks (Miller, 1956) and explicitly showing the behavioral interrelationships.

Our ongoing research endeavors include the validation of the more complex sets of behaviors, both in simulation and on an actual robotic platform. Simulation enables a more rapid development of behaviors using heuristics and automated optimization techniques such as genetic algorithms and neural networks.

The robotic platform under construction will initially be composed of two similar mobile robots, based on a M68HC11 micro-controller board (the Handyboard™). The robots will have onboard sonar and near-IR range sensors and will be capable of wireless communication with each other and with a fixed PC. The sessile computer may take the roles of a GPS and of a home base (e.g. for recharging and sample return). A prototype of the robot is presented in Fig 5.

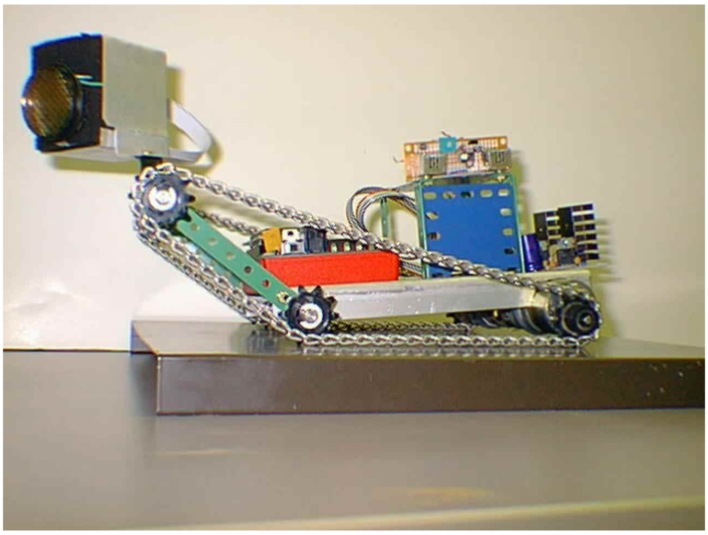


Fig. 5: A prototype of the robotic platform

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