Computational Improvements in the Multivalued Fuzzy Behavior Control System for Robot Navigation

Yanan Zhao, Majura F. Selekwa, Emmanuel G. Collins, Jr.,
Department of Mechanical Engineering
Florida A&M University - Florida State University
Tallahassee, FL 32310
email: yzhao@eng.fsu.edu, majura@eng.fsu.edu, ecollins@eng.fsu.edu

***Abstract*— Multivalued fuzzy behavior control systems for robot navigation have demonstrated more system robustness against sensor and environmental uncertainty and changes in behavioral priorities than univalued fuzzy behavior control systems. However, a major concern for the implementation of multivalued systems is the computational burden associated with the fuzzy inference and deffuzification process. This paper presents a multivalued fuzzy behavior control system for robot navigation using singletons instead of fuzzy set consequences. The proposed implementation with singleton consequences greatly reduces the space required for data storage and speeds up the control computation while providing a simple way of fusing the behavioral commands. Simulation results show that the singleton implementation yields a navigation trajectory that is roughly the same as or even better than that of the original system that uses fuzzy set consequences. Real-time implementation at high speed is possible with this new type of fuzzy model because of the increased computational efficiency.**

I. Introduction

Fuzzy logic provides efficient tools for robot navigation because of its ability to handle the uncertainty in the robot information [3]. In recent years there has been a growing interest in behavioral fuzzy methods [1], [4], [7], [8], [11]. One of the major difficulties in implementing behavioral robotics is that of fusing the behavioral reactions when there are several conflicting behaviors. Depending on the behavior structure and the fusion process, fuzzy behavior control systems can be generally grouped into two categories: the univalued fuzzy behavior systems and the multivalued fuzzy behavior systems [8].

A general structure of the univalued behavior control systems is shown in Figure 1, where each of the behaviors uses the environmental information to determine the control command that satisfies its particular objective, e.g., obstacle avoidance, path following, goal seeking, etc. Each behavior responds by triggering only one command signal, i.e., the behavior is "univalued". The command signal for one behavior does not take into consideration the command of another behavior. If the system has several behaviors with conflicting responses, these behaviors compete for the control of the robot, i.e., each behavior seeks to satisfy its own interests. The "selfishness" structure of these behaviors has been cited as one of the leading causes for robot navigation failures in cases of conflicting behavioral interests [5], [6], [8].

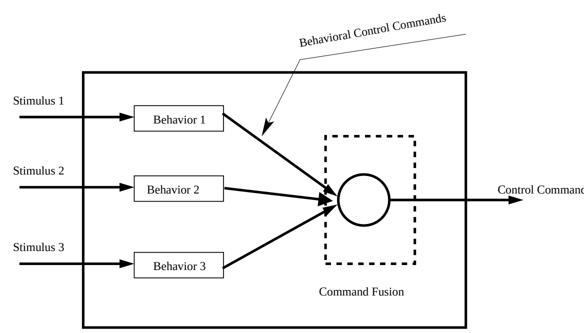

Fig. 1. The General Structure of Univalued Behavioral Control Methods

A multivalued fuzzy behavior design and fusion for robot navigation control was proposed recently [8]. This method removes the effects of "selfishness" of the individual behaviors by denying them the ability to control the robot by themselves without regard to the interests of other behaviors in the system.

Figure 2 shows the general architecture of the multivalued behavior system. The system is made up of two blocks; the advisory block and the command block. The control command is generated centrally by the command block. The available control command alternatives are known to both the advisory and the command block. The advisory block is made up of several behaviors, each of which is always active. Each behavior determines the relative importance of each of the available command alternatives in satisfying its control objectives. The command block accepts all responses from the advisory block about the available command alternatives. The responses from all behaviors for each of the command alternatives are fused to get the resultant preference by using an intersection operation. The command alternative that gets the highest resultant preference is the one that best satisfies all behaviors; it is eventually picked by the command block

Prepared through collaborative participation in the Robotics Consortium sponsored by the U. S. Army Research Laboratory under the Collaborative Technology Alliance Program, Cooperative Agreement DAAD 19-01-2-0012. The U. S. Government is authorized to reproduce and distribute reprints for Government purposes notwithstanding any copyright notation thereon.

and sent to the robot actuators. This process ensures that no behavior is ignored. For a fuzzy behavior system the data input to the individual behaviors is fuzzy, the recommendations passed to the command fusion unit are all fuzzy, and the output of the command fusion unit is also fuzzy. The final fuzzy command is defuzzified to obtain a crisp command suitable for control actions.

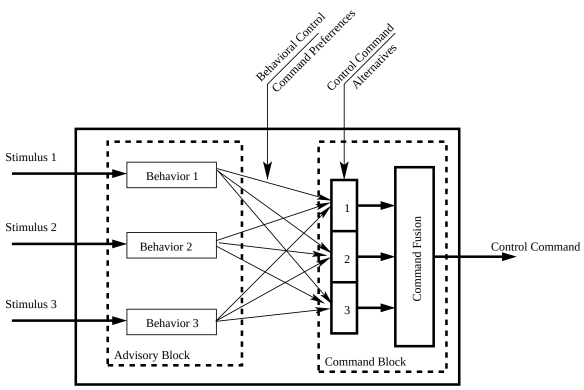

Fig. 2. The General Structure of a Multivalued Behavioral Control System

Extensive simulation tests on multivalued behavior fuzzy architecture have demonstrated that it is in general more robust with regard to sensor and environmental uncertainty, and changes in behavioral priorities [2]. However, a major concern for the multivalued architecture is the computational burden in processing information carried by the fuzzy sets; since requirements for both the computation time and data storage space are heavy. This brings up difficulties in real-time implementation particularly when the robot is to travel at high speeds, which may call for specialized, additional hardware [4].

This paper presents an approach that greatly reduces the computational cost, while maintaining the "unselfishness" feature of the multivalued architecture. Instead of using triangular or trapezoidal shaped fuzzy sets, singletons are used as consequences for each of the behaviors. The main advantage of using singletons is the computational simplicity and hence the potential for real-time implementation. Fuzzy systems with singleton consequences, also known as the Sugeno Type fuzzy systems, have been used in several mobile robot navigation and helicopter control problems [4], [9], [10], [12]. In addition, since its defuzzification formula is linear in the consequent parameters, the Sugeno Type fuzzy system has also been widely applied in the study of neuro-fuzzy systems.

The remainder of the paper is organized as follows. Section II describes the multivalued fuzzy behavior control architecture. Section III introduces the modified architecture with singleton output and provides a performance comparison. Concluding remarks are given in Section IV.

II. The Multivalued Fuzzy Behavior System for Navigation Control

Under the multivalued fuzzy behavior control paradigm, the navigation control problem is broken into two parallel control activities: the heading control and the speed control. The heading control activity controls the heading direction while the speed control activity controls the speed of the robot. Each control activity is controlled by one multivalued fuzzy behavior control system as described in Section I.

In implementation, the command alternatives are defined as fuzzy sets over the universe of discourse of the reactions in each control activity. In achieving their behavioral objectives, the individual behaviors do not choose a single fuzzy set from this universe of discourse but rather, they express the importance of each. This structure enables information from all behaviors to reach the command block, which chooses the command that best fits the interests of all behaviors.

A. Implementation of the Multivalued Fuzzy Behavior System by Using Consequent Fuzzy Sets

This section gives a brief description on the design of the multivalued fuzzy behavior system using fuzzy set consequences. The overall system has five behaviors: 1) goal-seeking, (2) obstacle avoidance, (3) the left edge tracking, (4) right edge tracking, and (5) overturning avoidance. The heading control uses four behaviors while the speed control uses two behaviors. The obstacle avoidance behavior runs in both the heading control activity and the speed control activity, and the overturning avoidance behavior runs on the speed control activity only; the remaining behaviors are for the heading control only. Each of these behaviors uses sensory information to determine its course of action. The obstacle avoidance and edge tracking behaviors use range finding sensors to determine distances to the nearest obstacle or path edges; the goal seeking behavior uses compass measurements to determine the direction of the goal; and the overturning avoidance behavior uses a speedometer to determine the robot speed.

1) The heading control activity and the related behaviors: The control command for the heading control activity is the heading angular change $\Delta\theta$. In the design of [8], five fuzzy sets shown in Figure 3 were defined for $\Delta\theta$. The fuzzy labels in this figure are: Large Right Turn (LRT), Slight Right Turn (SRT), No Turn (NT), Slight Left Turn (SLT), and Large Left Turn (LLT). Each behavior i assigns a relative importance to each command alternative j by some parameter $\alpha_{i,j} \in [0, 1]$; the more the value, the more the importance. This parameter is also expressed by fuzzy sets on the interval [0, 1]. As shown in Figure 4, three fuzzy sets are used with the linguistic symbols: Not Acceptable (NA), Favored (F), and Highly Favored (HF). The structure of the multivalued control system for the heading control is illustrated in Figure 5. A brief description of each behavior is given below.

The obstacle avoidance behavior: The obstacle avoidance behavior uses range sensor measurements to determine the possible movements in the forward or backward directions. Its design is such that this behavior becomes effective when an obstacle is observed in some neighborhood of the robot. The general form of fuzzy rules for forward motion is:

$$\begin{aligned}&\textbf{IF}(\text{Forward Range Sensors })\textbf{THEN}\\&\qquad(\alpha_{1,1} \text{ and } \alpha_{1,2} \text{ and } \alpha_{1,3} \text{ and } \alpha_{1,4} \text{ and } \alpha_{1,5}).\end{aligned} \quad (1)$$

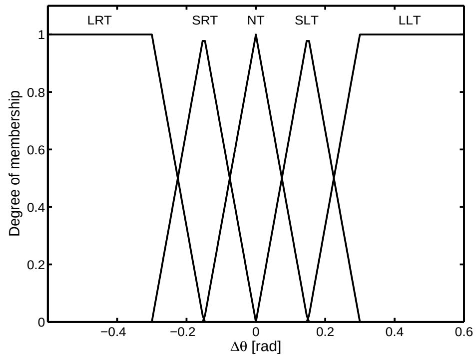

Fig. 3. The Fuzzy Sets for the Heading Control Command

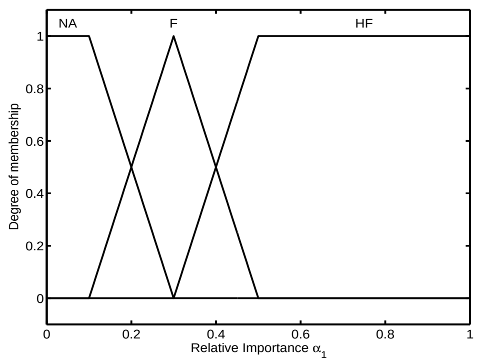

Fig. 4. The Fuzzy Sets for the Measure of Relative Importance

Similarly, for backward motion the rules are

$$\textbf{IF}(\text{Backward Range Sensors })\textbf{THEN}$$
$$(\alpha_{1,1} \text{ and } \alpha_{1,2} \text{ and } \alpha_{1,3} \text{ and } \alpha_{1,4} \text{ and } \alpha_{1,5}). \tag{2}$$

The right and the left edge tracking behaviors: The edge tracking behaviors are effective when the robot is within some specified distance from an edge. The stimuli to these behaviors are the lateral sensor range measurements. Each behavior is implemented by fuzzy rules of the form:

$$\textbf{IF}(\text{Left/Right Range Sensors })\textbf{THEN}$$
$$(\alpha_{i,1} \text{ and } \alpha_{i,2} \text{ and } \alpha_{i,3} \text{ and } \alpha_{i,4} \text{ and } \alpha_{i,5}). \tag{3}$$

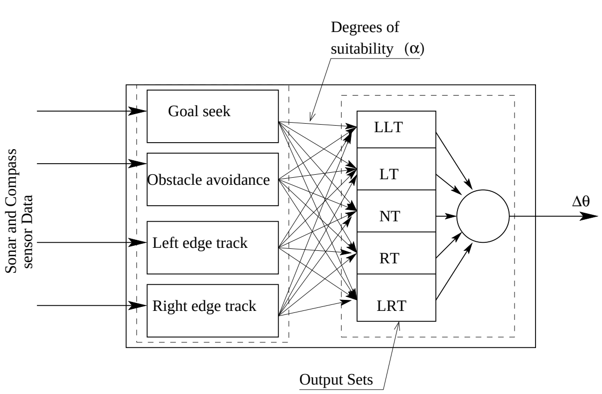

Fig. 5. The Multivalued Behavioral Control System for Heading Control Activity

where $i = 2, 3$, corresponding to either left edge tracking or right edge tracking

The goal seeking behavior: The goal seeking behavior directs the robot to a specific predefined target. It uses compass measurements to determine the relative heading direction Φ, and range measurements to determine the distance to the nearest path edge or obstacle. These range measurements are necessary to stop the behavior from forcing the robot to traverse obstacles to the target. It is implemented by fuzzy rules of the form:

$$\textbf{IF}(\Phi \text{ and Range Sensors})\textbf{THEN}$$
$$(\alpha_{4,1} \text{ and } \alpha_{4,2} \text{ and } \alpha_{4,3} \text{ and } \alpha_{4,4} \text{ and } \alpha_{4,5}). \tag{4}$$

For all of the above behaviors, the outputs $\alpha_{i,j}$ for $(i = 1, 2, \cdots, 4)$ and $(j = 1, 2, \cdots, 5)$ are fuzzy sets as in Figure 4. For detailed definitions of inputs of each behavior please refer to [8].

The command block: The command block receives proposals $\alpha_{i,j}$ that are forwarded by individual behaviors i for each control command alternative j. These proposals are fused by the command block by using the intersection operation

$$\alpha_j = \bigcap_i \alpha_{i,j}. \tag{5}$$

Each α_j is a measure of the importance of each command alternative j. The final control command $\Delta\theta$ is determined by the command block using fuzzy rules of the form

$$\textbf{IF}(\alpha_{\mathbf{1}} \text{ and } \alpha_{\mathbf{2}} \text{ and } \alpha_{\mathbf{3}} \text{ and } \alpha_{\mathbf{4}} \text{ and } \alpha_{\mathbf{5}})\textbf{THEN}(\Delta\theta). \tag{6}$$

2) The speed control activity and related behaviors: The speed control activity determines whether the speed should be increased or decreased; its control command is the speed change Δv. There are only two behaviors in this activity: the obstacle avoidance behavior and the overturning avoidance behavior. As in the case of the heading control activity, each behavior i assigns a relative importance $\mu_{i,j} \in [0, 1]$ to each of the command alternatives j. The fuzzy sets for $\mu_{i,j}$ are same as those for $\alpha_{i,j}$ in Figure 4. Detailed description of this algorithm is given in [8].

B. Computational Cost for Implementation with Fuzzy Sets

The above multivalued architecture has been extensively tested in an environment crowded with obstacles [8], and has been compared with a univalued architecture [2]. The results obtained demonstrate that the approach is very promising. However, a major concern about this method is the amount of computations that must be performed because of its Mamdani structure. Figure 6 shows the command fusion process among different behaviors. Here, the heading control activity is taken as an example. The process is similar for speed control activity.

At each sampling period, the command block takes the advice from four behaviors as the measures of relative importance $\alpha_{i,j}$; each of them is represented by fuzzy sets as shown in the first four rows of Figure 6. In the implementation of [8], each fuzzy set is represented by 101 sample points along the range of [0, 1]; therefore for $i = 4$ and $j = 5$ a total of

$(4 \times 5 \times 101)$=2020 data points are passed to the command block at each instant. Then the fuzzy "AND" operation is taken to obtain the relative importance α_j (see (5)), i.e., a new set of 101 sample points is obtained representing α_j, the measure of the importance of each command alternative j. The obtained data are as shown in the last row in Figure 6. Each of the resulting fuzzy sets α_j is defuzzified to obtain a crisp value, shown as diamonds in the most left two figures in the last row, and straight lines in the three right figures (see Figure 6). The five crisp values obtained are the inputs for the final control command fuzzy system that determines the heading angle change $\Delta\theta$.

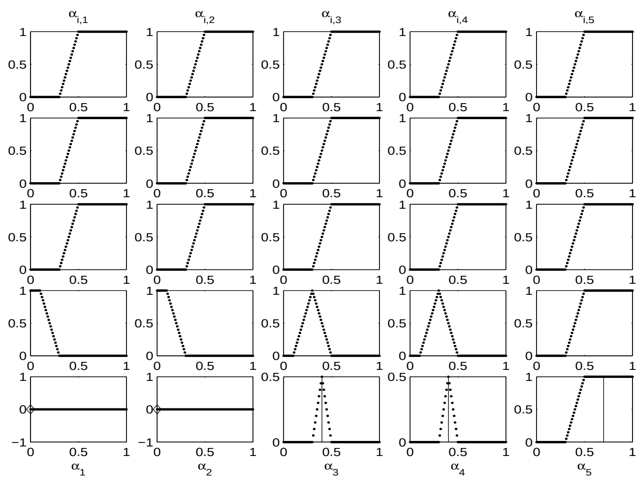

Fig. 6. The Fusion Process with Fuzzy Sets Output

This implementation process is not computationally effective, especially when it is compared with the univalued architecture (Figure 1) where only crisp values are used for command fusion. To reduce the computation and storage burden while keeping the same architecture, the number of data points that the command block receives must be reduced. The next section describes how the data points are reduced by using singleton consequences for all fuzzy rules.

III. Fuzzy Behaviors with Singleton Consequences

Each behavior is redesigned as a Sugeno type fuzzy system with singleton consequences, which are obtained by transforming the previously defined Mamdani fuzzy systems for each behavior. The transformation is performed by determining the centroids of the fuzzy sets in the Mamdani type system and using the obtained values as singletons for the Sugeno type system. Recall that the membership functions for the fuzzy sets defined for every $\alpha_{i,j}$ consist of three fuzzy sets as shown in Figure 4 where NA is the trapezoidal shape defined as $y = trapmf(x, [0, 0, 0.1, 0.3])$, F is the triangular shape defined as $y = trimf(x, [0.1, 0.3, 0.5])$, and HF is also the trapezoidal shape defined as $y = trapmf(x, [0.3, 0.5, 1, 1])$. Here, $trapmf$ and $trimf$ are Matlab Fuzzy Logic Toolbox commands describing membership functions. After transformation, the centroids for these membership functions are determined to represent the three singletons with respective

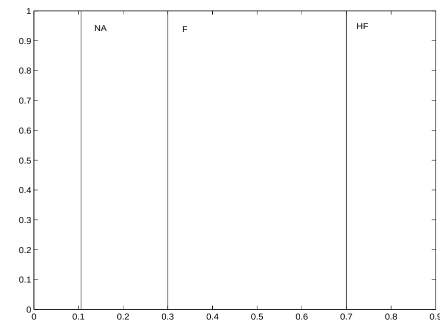

Fig. 7. The Transformed Singleton Output Membership Functions

values NA=0.1056, F=0.3 and HF= 0.69975, as shown in Figure 7.

This new design simplifies the command fusion process among different behaviors by sending only one data point to the command block instead of the 101 data points for each $\alpha_{i,j}$ as shown in the the first four rows of Figure 8. This one data is the defuzzified result of each $\alpha_{i,j}$. Then α_j is obtained by taking the minimum of $\alpha_{i,j}$ for $(i = 1, 2, \cdots, 4)$, i.e., $\alpha_j = \min(\alpha_{i,j})$. The obtained values of α_j are shown by the last row of Figure 8. By comparing with the process in Figure 6, it is clear that this new approach greatly reduces both the data storage and computation requirements.

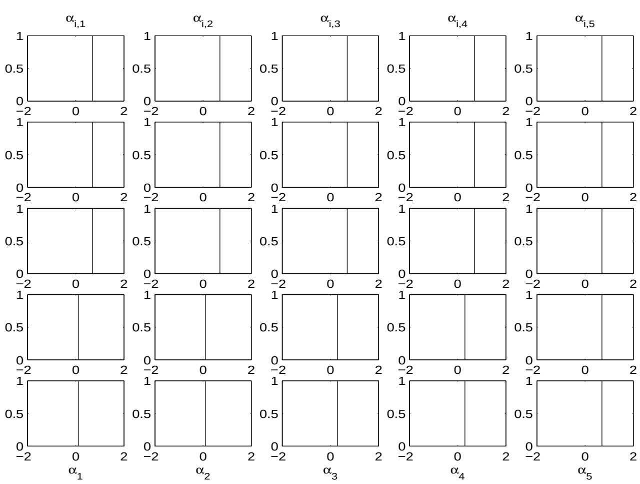

Fig. 8. The Command Fusion Process with Singleton Outputs

A. Comparison of the Two Types of Fuzzy Systems

To ascertain that the transformed singleton system is equivalent to the original fuzzy set system, the output surfaces for the two systems were compared. It was seen that the transformation from the fuzzy sets to singletons does not distort the integrity of the original system. Figure 9 shows the solution surface for $\alpha_{4,3}$ in the goal seeking behavior using fuzzy sets, and Figure 10 shows the equivalent surface in the transformed singleton system. As seen from these figures, the surface of the transformed singleton system is roughly the same as that of the original system, with only a small reduction in information. Comparisons of the output surfaces for the other fuzzy behaviors show the same similarity.

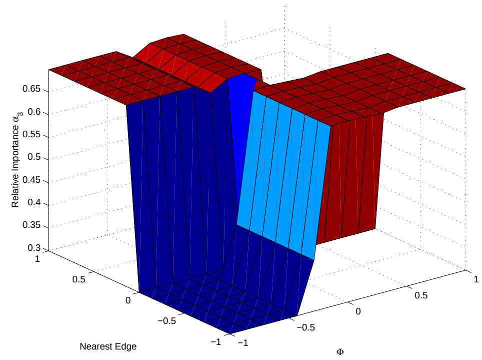

Fig. 9. Output Surface of the Fuzzy Set Consequences System

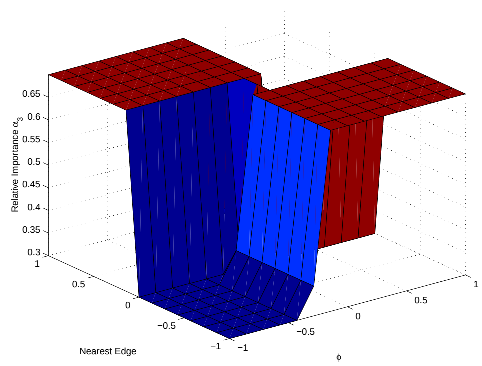

Fig. 10. The Output Surface of the Singleton Consequences System

Table I provides a comparison of α_j values obtained for the two types of systems at two sampling instants: instant 1 and instant 4. It is seen that even though the amplitude of the values are not the same, the trends of the values are the same. At the 1st sampling time, the maximum measure of relative importance for both systems is α_5, while at the 4th sampling time, the maximum measure of relative importance for both systems is α_4.

Relative Importance	Sampling Instant 1		Sampling Instant 4	
	Fuzzy-Set	Singleton	Fuzzy-Set	Singleton
α_1	0.0000	0.1056	0.4000	0.1575
α_2	0.0000	0.1056	0.4000	0.3000
α_3	0.4000	0.3000	0.6506	0.4068
α_4	0.4000	0.3000	**0.6878**	**0.5930**
α_5	**0.6998**	**0.6998**	0.4000	0.3000

TABLE I

COMPARISON OF OBTAINED α_j

B. Comparison of Simulation Results

Computer simulation experiments were carried out to study the effectiveness of the proposed implementation and compare it with the original implementation that uses fuzzy set consequences. The simulation represents the motion of a differentially driven mobile robot in a hypothetical warehouse of dimension 150m by 130m [11]. A kinematic model of the robot is used; the forces that acts on the robot are not considered. The robot is assumed to have a total of eighteen sensors that surround it over $360°$. Several simulation scenarios were run using both the fuzzy set-based and the singleton-based systems. A sample of the obtained results from these simulations are tabulated in Table II.

Case No.	Start Position	Target Position	Computation Time		No. of Iterations	
			Singleton	Fuzzy-Set	Singtn.	Fz-Set
1	(15, 10, 0)	(117, 123)	3.8530	26.5380	191	190
2	(117, 123, $\frac{\pi}{2}$)	(15, 10)	4.6780	33.0840	232	236
3	(140, 10, $\frac{\pi}{2}$)	(15, 10)	3.5900	25.1140	177	178
4	(110, 80, $\frac{-\pi}{2}$)	(15, 10)	4.0070	26.7990	197	192
5	(100, 65, $\frac{\pi}{2}$)	(15, 10)	3.6090	25.4470	178	182
6	(50, 100, $\frac{-\pi}{2}$)	(15, 10)	3.0730	23.2730	150	166
7	(140, 10, $\frac{\pi}{2}$)	(10, 85)	3.7240	25.8830	184	185
8	(25, 110, 0)	(140, 25)	4.2860	32.1530	208	229
9	(15, 10, 0)	(10, 100)	3.4210	30.1800	170	215

TABLE II

COMPARISON OF FUZZY SET-BASED AND SINGLETON-BASED SYSTEMS. THE THIRD ELEMENT IN THE START POSITION INDICATES THE ROBOT ORIENTATION RELATIVE TO THE HORIZONTAL AXIS IN RADIANS.

These results show that the singleton consequences yield a system that runs faster than the fuzzy set consequences and reduces the computation time by more than 85%. However, the systems use almost the same number of (although the singleton tend to use fewer) iterations to complete the movement as shown in last two columns of the Table. In most cases the trajectories resulting from the two controllers are almost identical as shown in Figure 11. In this figure, and also in Figure 12, the solid line represents the trajectory due to the singleton system, while the dashed line represent the trajectory of the fuzzy set outputs. It is worth mentioning that the singleton system tends to generate a more smooth trajectory as seen in Figure 12, which corresponds to scenario 9 of Table II; in this scenario, the path with the singleton output implementation is significantly shorter.

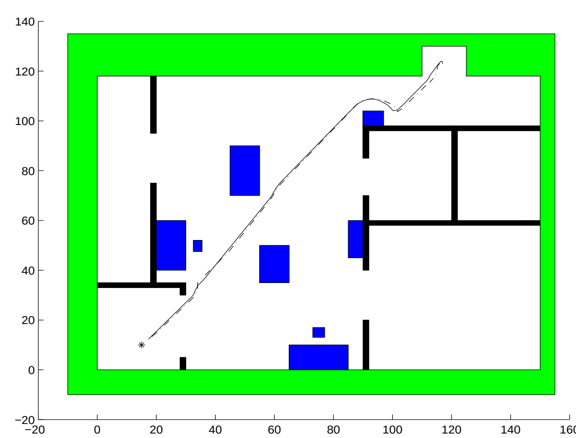

Fig. 11. Comparison of the Robot Trajectories for Movement from Position (117,123) to Position (15,10)

IV. CONCLUSIONS

It is acknowledged that multivalued fuzzy behavior architectures for robot navigation control provide a promising approach to robot navigation in uncertain environments. However, their design tends to be computationally intensive

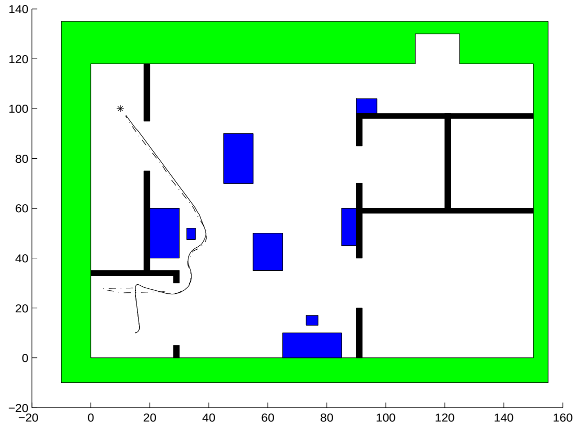

Fig. 12. Comparison of the Robot Trajectories for Movement from Position (15,10) to Position (10,100)

because of the massive data that must be processed. This paper has presented a design approach that transforms the fuzzy set consequences into singleton consequences in a multivalued fuzzy behavior control system. The resulting system is not only computationally fast but also tends to yield more smooth performance than the counterpart fuzzy set consequences system. It is seen that the transformed fuzzy systems can reduce the computational time by more than 85% without degrading the performance.

DISCLAIMER

The views and conclusions contained in this document are those of the authors and should not be interpreted as representing the official policies, either expressed or implied, of the Army Research Laboratory or the U. S. Government.

REFERENCES

[1] E. Aguirre and A. González. Fuzzy Behaviors for Mobile Robot Navigation: Design, Coordination and Fusion. *International Journal of Approximate Reasoning*, 25:225–289, 2000.

[2] J. Q. Combey. Comparison of univalued and multivalued fuzzy behavior systems for autonomous robot navigation control. Master's thesis, Florida A & M University, Tallahassee, Florida, 2003.

[3] D. Driankov and A. Saffiotti. *Fuzzy Logic Techniques for Autonomous Vehicle Navigation*. Physica-Verlag Heidelberg, New York, 2001.

[4] S. G. Goodridge, M. G. Kay, and R. C. Luo. Multilayered Fuzzy Behavior Fusion for Real-Time Reactive Control of Systems with Multiple Sensors. *IEEE Transactions on Industrial Electronics*, 34(3):387–394, 1996.

[5] D. W. Payton, J. K. Rosenblatt, and D. M. Keirsey. Plan Guided Reaction. *IEEE Transactions on Systems, Man, and Cybernetics*, 20(6):1370–1382, Dec, 1990.

[6] J. Rosenblatt. *DAMN: Distributed Architecture for Mobile Navigation*. Ph.D. Thesis, Carnegie Mellon University Robotics Institute, Pittsburgh, PA, 1997.

[7] A. Saffiotti. Fuzzy Logic in Autonomous Robotics: Behavior Coordination. In *Proceedings of the IEEE International Conference on Fuzzy Systems, Bercelona, Spain*, pages 573–578, July, 1997.

[8] M. F. Selekwa and E. G. Collins. A Centralized Fuzzy Behavior Control for Robot Navigation. In *Proc. IEEE International Symposium on Intelligent Control, Houston Texas*, pages 602–607, October 2003.

[9] M. Sugeno. On Stability of Fuzzy Systems Expressed by Fuzzy Rules with Singleton Consequents. *IEEE Transactions on Fuzzy Systems*, 7(2):201–224, April 1999.

[10] M. Sugeno, T. Murofushi, T. Mori, T. Tatematsu, and K. Tanaka. Fuzzy Algorithmic Control of a Model Car by Oral Instructions. *Fuzzy Sets and Systems*, 32(2):207–219, 1989.

[11] E. Tunstel. Mobile Robot Autonomy Via Hierarchical Fuzzy Behavior Control. In *Proceedings of the 6th International Symposium on Robotics and Manufacturing (ISRAM'96), Montpellier, France*, pages 837–842, May, 1996.

[12] H. Wang, K. Tanaka, and M. Sugeno. Design and analysis of fuzzy control systems: A systematic-theoretic approach. Workshop S-2 at the 2001 American Control Conference, June 2001. Arlington, Virginia.