AN APPROACH DESIGNING AUTONOMOUS ROBOT NAVIGATION SYSTEM BASED ON BEHAVIOR COORDINATION

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ABSTRACT

Robot navigation using fuzzy behavior is suited in unknown and unstructured environment in which each behavior have an individual task. This paper deals with an approach designing autonomous robot navigation system based on fuzzy behaviors including *collision avoidance, wall-following, go-to-target*. The proposed hierarchy of fuzzy behaviors is used to fuse the command in which each behavior is a fuzzy inference system and its outputs are fuzzy sets. Its inputs are information fused from sensors using fuzzy directional relationship. The simulation results with some statistics show that the system works correctly.

Keywords: robot navigation, fuzzy directional relation, fuzzy inference system, mobile robot, behavior hierarchy.

1. INTRODUCTION

Fuzzy behaviors with capable of making inferences are well suited for mobile robot navigation because of uncertainty of the environment. The hierarchy of behaviors is a widely applied methodology to divide the system into several smaller subsystem in which each subsystem is a fuzzy behavior. The partitioning may guarantees real-time performance with a large rule-base by reducing the complicated level of inference system.

Recently, there are many approaches to design a hierarchy of behaviors applied in robotics applications. Brooks [1] proposed an approach to built behavior control paradigm based on decomposing the problem of autonomous control by task. E. Petriu [11] proposed the hierarchy of behaviors based neuro-fuzzy controller by using sonar sensors to detect obstacles. The module of command fusion fuses the output of fuzzy inference systems of behaviors and then defuzzify to obtain the crisp value. Thongchai [3] built behaviors to execute individual tasks and the output of them is fused command based on the priority degree of each behavior. John Yen

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[4] proposed the approach to fuse the output fuzzy set of behaviors into a final fuzzy set and defuzifying to get the crisp command value.

The paper deals with an approach in designing autonomous robot navigation system based on behavior coordination using fuzzy logic system. Behaviors are built as *collision avoidance, wall-following, go-to-target, turn-around* in which each behavior is a fuzzy inference system. Collision avoidance behavior is used to avoid obstacles detected by robot. Wall-following behavior is used to navigate the robot moving along to the wall. Reach-target is used to locate and to navigate the robot reaching the target. Turn-around only is used in case robot is not able moving. So rule-base is enough smaller to implement the task in real time. The extended fuzzy directional relationship computed from range sensors [5, 6] is one of inputs of fuzzy behaviors. Because of modeling the environment using information from range sensors and fuzzy directional relationship, may be there are many entities of the same type of fuzzy behaviors (in case there are many obstacles) at the time. Authors have developed idea in designing the hierarchy of fuzzy behaviors to fuse command from many entities of individual behaviors. The hierarchy has two layers. The first is used to fuse command from entities of the same type. And three outputs corresponding three types of behaviors are fused by the second fusion layer. The output of the second fusion layer is defuzzified to achieve the crisp value for navigating robot.

The paper is organized as follows: Section 2 introduces fuzzy inference process, an overview on behavior-based mobile robot navigation, the extended fuzzy directional relationship. Section 3 introduces the proposed approach to design the hierarchy of behaviors for robot navigation. Section 4 shows some simulation results and section 5 is conclusion and future works.

2. BACKGROUND

2.1 Fuzzy inference system

A fuzzy inference system essentially defines a nonlinear mapping of the input data vector into a scalar output, using fuzzy rules. The mapping process involves input/output membership functions, fuzzy logic operators, fuzzy if-then rules and aggregation of output sets and defuzzification. We generally have M fuzzy “IF-THEN” rules, where the l^{th} rule has the form:

$$R^l\text{: IF } x_1 \text{ is } A_1^l \text{ AND } x_2 \text{ is } A_2^l \ldots \text{ AND } x_p \text{ is } A_p^l \text{ THEN } y \text{ is } B^l \quad (1)$$

where $x_i \in X_i$ ($i = 1, 2, \ldots, p$) be universes, $y \in Y$ are linguistic variables representing for input set, A_i^l's, B^l are fuzzy subsets having membership functions be $\mu_{X_i}(x)$, $\mu_Y(y)$ of antecedent and consequent sets, respectively. The rule represents fuzzy relation between the input space $X_1 \times X_2 \times \ldots \times X_p$ and the output space Y.

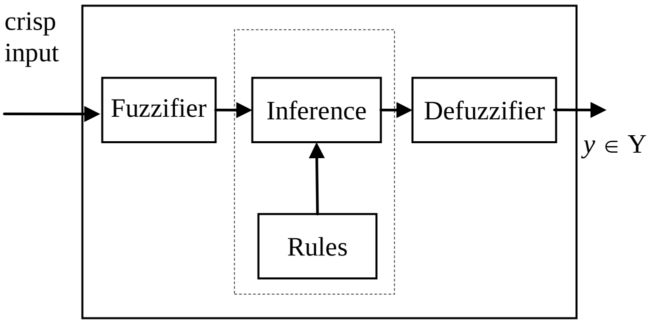


Fig. 1: *The structure of fuzzy logic system.*

The fuzzier maps the crisp input into the fuzzy set being input of inference engine. The inference engine combines rules and gives a mapping from fuzzy input sets into fuzzy output sets. Multiple antecedents in rules are connected by the t-norm operator (corresponding to intersection of sets) as following:

$$\mu_{B^l}(y) = \mu_{X_1 \times X_2 \times \ldots \times X_p \to Y}(y) = \mu_Y(y) \circ \lfloor \mu_{X_1}(x_1) \circ \mu_{X_2}(x_2) \circ \ldots \circ \mu_{X_p}(x_p) \rfloor \tag{2}$$

where ° is t-norm operator being minimum operator or product operator. Provider that having *N* rules of *M* rules are fired, then multiple fired rules may be combined by using the *t*-conorm operator (corresponding to union of sets) as following:

$$\mu_B(y) = \mu_{B^1}(y) \bullet \mu_{B^2}(y) \bullet \ldots \bullet \mu_{B^M}(y) \tag{3}$$

where • is t-conorm operator being maximum operator.

The defuzzifier produces a crisp output from the fuzzy set that is the output of inference engine. There are many methods of defuzification such as centroid, maximum-decomposition, center of maxima or height defuzzification.

2.2 Behavior-based robot navigation

Behavior models have been widely used in advanced robotic system operating in uncertainty dynamic environment, combining information from many sensors. Behavior hierarchy, has developed to navigate robot more flexibility, involves many ordered behaviors. The main components of this architecture are behavior entity that is responsible for only a very narrow task of robot navigation. Each behavior only receives the information needed for its task. Fuzzy inference systems (FIS) have used to make behaviors.

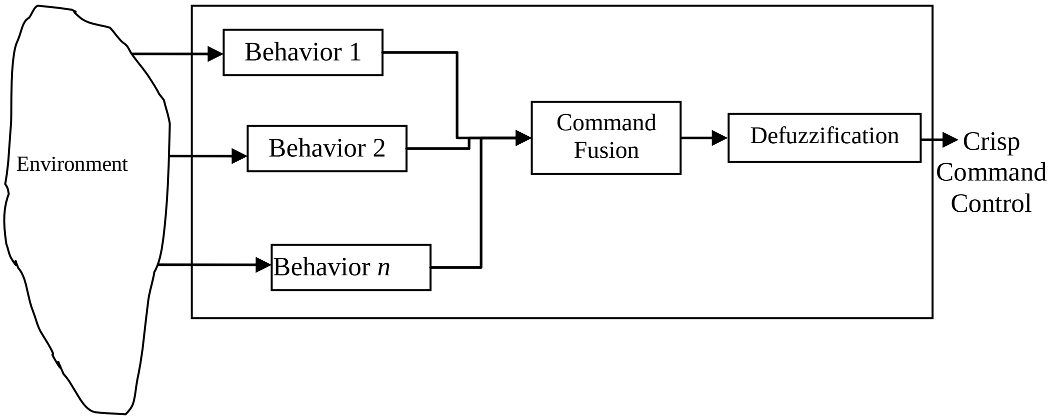


Figure 2 is model of behavior hierarchy for mobile robot navigation. Each behavior gets fuzzy outputs by using FIS having inputs are information received from environment by identified sensors. The output of behaviors, be fuzzy sets, are fused command or defuzzified. The final is a crisp value used to control robot.

There are some approaches fusing command from fuzzy outputs ([2 - 4]) and almost of approaches are based on two methods: fusing command from fuzzy sets before defuzzification or fusing command from crisp values after defuzzification (Figure 3). See that two methods fusing command have results being different.

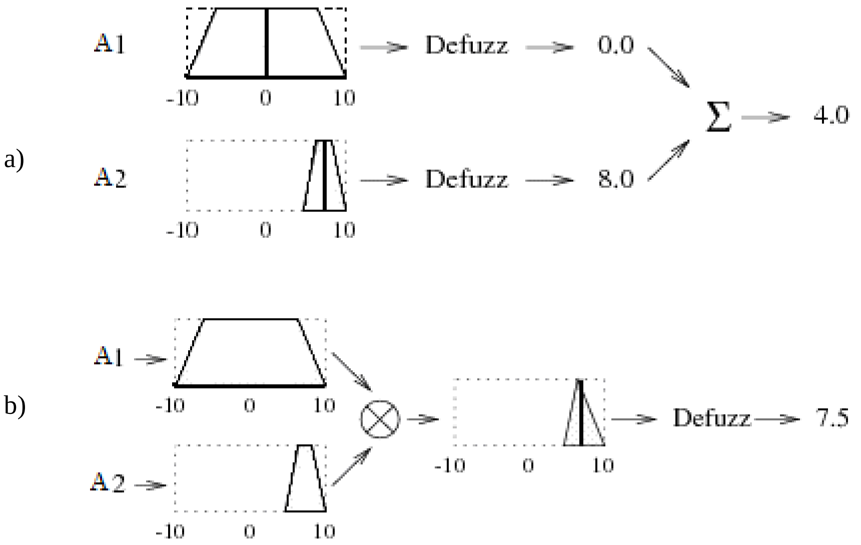


Fig. 3: *Two methods of command fusion, a) fusing from defuzzified crisp values b) fusing from fuzzy set before defuzzification.*

2.3 The extended fuzzy directional relation

Fuzzy directional relation has developed by Keller and Matsakis [5 - 7] from idea on the relation of position between two area objects. Fuzzy directional relationship of A, B objects is computed based on the truth value of proposition like "*A is in direction α of B*". There are many proposed approach to compute truth value of the above proposition as neural network [6], angle histogram [8] or F-histogram [5]. These approaches permit processing of vector data as well as raster data and to be suitable for modeling environment in robotic applications. In [5], Matsakis proposed F-histogram method that the relative position of an object A with regard to another object B is represented by a function F_{AB} from *IR* into IR_+. For any direction θ, the value $F_{AB}(\theta)$ is the total weight of the arguments that can be found in order to support the proposition "A is in direction θ of B". F_{AB} may be an F-histogram of constant forces (F_0-histogram) or F-histogram of gravitational forces (F_2-histogram). Matsakis proposed an algorithm computing F-histogram and fuzzy spatial relationship for vector data be enough fast in real time (more detail in [7]).

The following is the method to compute the degree of truth of a proposition like "*A is in direction 0 of B*". For another value of α, you can simply perform the computations described below on the shifted histogram, $F_r^{AB}(\theta + \alpha)$. The set of directions is divided into four quadrants as shown in Fig.4. The forces $F_r^{AB}(\theta)$ of the outer quadrants ($\theta \in [-\pi, -\pi/2] \cup [\pi/2, \pi]$) are elements which weaken the above proposition; the forces of the inner quadrants ($\theta \in [-\pi/2, 0] \cup [0, \pi/2]$) are elements which support the proposition. Some forces of the third quadrant are used to compensate the contradictory forces of the fourth one. The proportion of these compensatory forces is defined by some angle θ_+. Forces of the second quadrant are used in a similar way to compensate the contradictory forces of the first one. The amount of these compensatory forces is defined by θ_-. The remaining forces are called the effective forces. The "average" direction α_r*(RIGHT)* of the effective forces is then computed.

Finally, the degree of truth of "*A* is to the right of *B*" is set to $\mu(\alpha_r(\text{RIGHT}))\times b_r(\text{RIGHT})$. In this expression, b_r*(RIGHT)* denotes the percentage of the effective forces (i.e. the sum of the effective forces divided by the sum of all forces), and μ the membership function of a fuzzy set that can be employed to define a family of fuzzy directional relations between points.

Choose θ_+ so that

$$\text{If } \int_{-\frac{\pi}{2}}^{\pi} (\theta - \frac{\pi}{2}) F_r^{AB}(\theta) d\theta \geq 0 \text{ then } \int_{\theta_+}^{\pi} (\theta - \frac{\pi}{2}) F_r^{AB}(\theta) d\theta = 0 \tag{4}$$

Otherwise $\theta_+ = -\pi/2$.

In a similar way: Choose θ_- so that

$$\text{If } \int_{-\pi}^{\pi/2} (\theta + \frac{\pi}{2}) F_r^{AB}(\theta) d\theta \geq 0 \text{ then } \int_{-\pi}^{\theta_-} (\theta + \frac{\pi}{2}) F_r^{AB}(\theta) d\theta = 0 \tag{5}$$

Otherwise $\theta_- = \pi/2$.

Thence, b_r(RIGHT) is given by the following:

$$\text{If } \theta_+ > \theta_- \text{ then } b_r(\text{RIGHT}) = \frac{\int_{\theta_-}^{\theta_+} F_r^{AB}(\theta) d\theta}{\int_{-\pi}^{\pi} F_r^{AB}(\theta) d\theta} \tag{6}$$

Otherwise b_r(RIGHT) = 0.

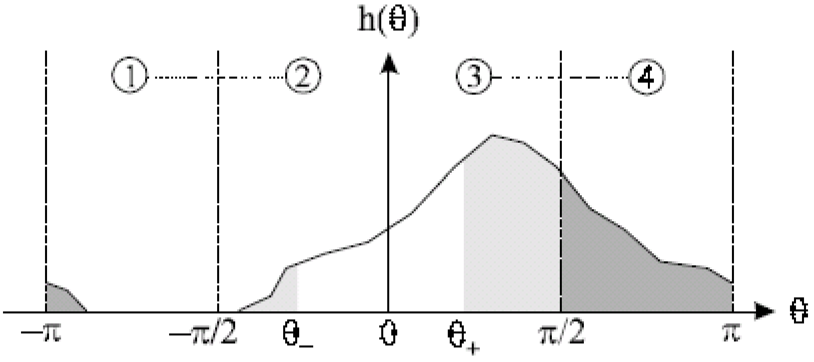


Fig. 4: *The example of forces.*

In [9], the F-histogram method was extended by developing the origin proposition and determining the degree of truth of proposition like "*A is on left/right in direction α of B*". This extending is suitable with designing behaviors of robotic navigation problems. Authors proposed a method to compute the extended fuzzy directional relationship (μ_{AB}) that is the degree of truth of the above proposition based on Matsakis' F-histogram. This value has to presenting both of left property and right property of A object in direction α of B object and so μ_{AB} takes value from -1 to 1, i.e. $\mu_{AB} \in [-1, 1]$. The μ_{AB} value may be positive or negative relies on r_S ratio computed as following:

$$r_S = \frac{\int_{\alpha}^{\pi+\alpha} F_r^{AB}(\theta) d\theta}{\int_{-\pi+\alpha}^{\alpha} F_r^{AB}(\theta) d\theta} \tag{7}$$

where $F_r^{AB}(\theta)$ is the scalar resultant of forces that tends to move B in direction θ. α is the current direction.

3. DESIGNING FUZZY BEHAVIORS

3.1 Modeling environment from range sensors

This section is to describe using range sensors arranged on robot to build an approximate representation of the environment surrounding the robot. Each sonar sensor returns a range value being the distance from the robot to obstacle according to the direction of the sensor. The range values are used to model the environment by building approximate polygons of corresponding obstacles because sonar sensor can't determine the thickness of obstacles. In [7], M. Skubic proposed an approach building the polygons of obstacles using range sensor readings. When sonar sensor *S* returns a range value, indicating that an obstacle is detected. Thus, a single trapezoid object is built in the center of cone S.

In the case of two adjacent sensors return, we use Skubic's approach [7] to assess whether they are from a single obstacle or multiple obstacles. The following distance measure is used to determine two objects are closer enough to form one object or two separate objects.

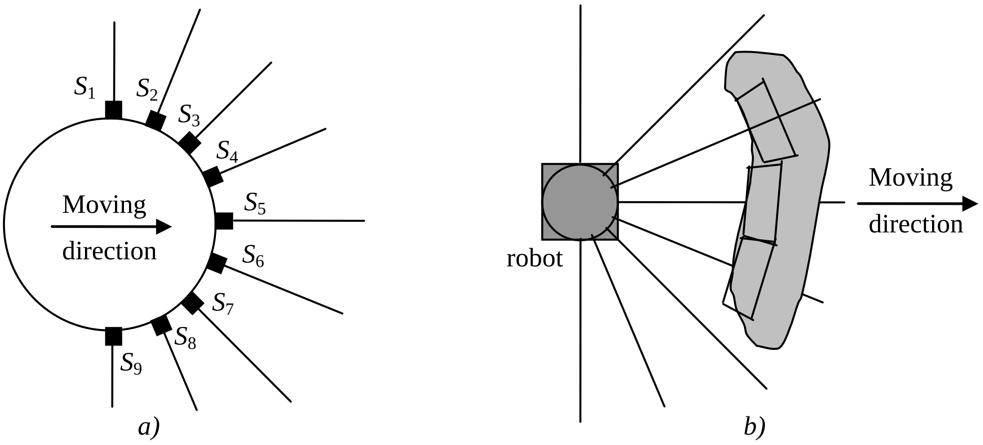
$$\sqrt{s_1^2 + s_2^2 - 2s_1 s_2 \cos(\alpha)} \tag{8}$$

where s_1 is the reading from sonar sensor S_1

s_2 is the reading from sonar sensor S_2(adjacent to S_1)

α is the angle between the axes of two adjacent sonar cones.

We use 9 sonar sensors being arranged on an half of ring (Fig. 5a). So the angle between the axes of two adjacent sonar cones is π/8. The figure 5b is the example that explains in modeling the environment with having only one actually objects but there are two objects built from sonar sensor readings. The trapezoid made from the S_4 reading and the trapezoid S_5 are not closer enough to combine, so they are two separate objects. But the trapezoids S_5 and S_6 are closer enough and there is only one object formed.



a) *b)*

***Fig. 5:** The arrangement of sonar sensors (a) and an example on modeling obstacles surrounding the robot (b).*

3.2 Building fuzzy behaviors

We use four basic behaviors for navigating robot as go-to-target, collision avoidance, wall-following and turn-around. Each behavior gets information of the environment modeled from range sensors and undertake individual task. In above mentioned model, may be there are many obstacles built from range sensor readings so each behavior may be use many times corresponding to the obstacle detected by robot. We proposed the hierarchy (fig. 6) to fuse command from behaviors.

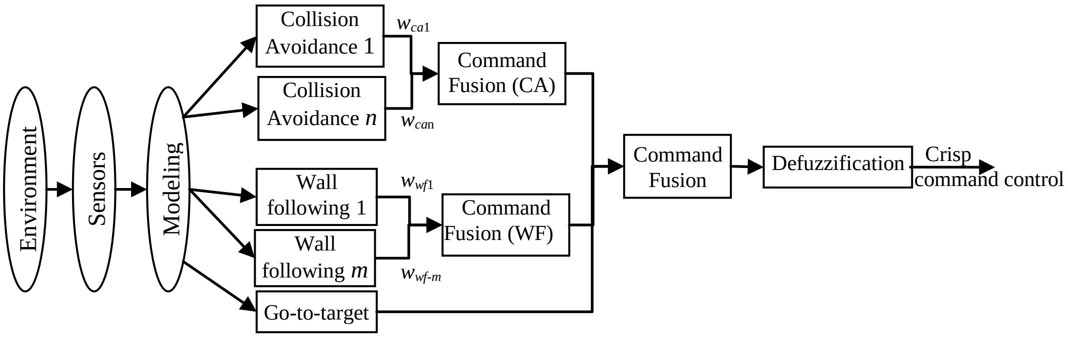


Fig. 6: *The hierarchy of behaviors to fuse command.*

The hierarchy of behaviors in figure 6 has four layers: behavior-layer, the first fusion layer, the second fusion layer and defuzzification layer. The behavior-layer contains all of basic behaviors and each type of behavior may be have many entities ($n \geq 0$, $m \geq 0$) based on the number of detected obstacles. The first fusion layer is used to fuse command from the same behaviors, so there are two command fusers for collision-avoidance behaviors and wall- following behaviors. Each behavior has a value of weight (taking value in [0, 1]) to evaluate the degree of importance in the overall navigating command. The value of weight is computed by a fuzzy inference system. The second fusion layer fuses commands from entities of the first layers. The crisp command control is output of the defuzzification layer that has the input being the output of the second fusion layer. The turn-around behavior is used to control robot in case impossible moving.

3.2.1 Collision avoidance behavior

This is most important behavior of a mobile robot. The behavior is built based on fuzzy inference system using the modeled information of environment. The collision avoidance behavior uses two inputs being the extended fuzzy directional relationship [9] and range to the obstacle. The fuzzy rule of the behavior has the form as following:

IF *FDR* is $\boldsymbol{A_1}$ AND *Range* is $\boldsymbol{B_1}$ THEN *AoD* is $\boldsymbol{C_1}$

where A_1, B_1, C_1 are fuzzy subsets of linguistic variables.

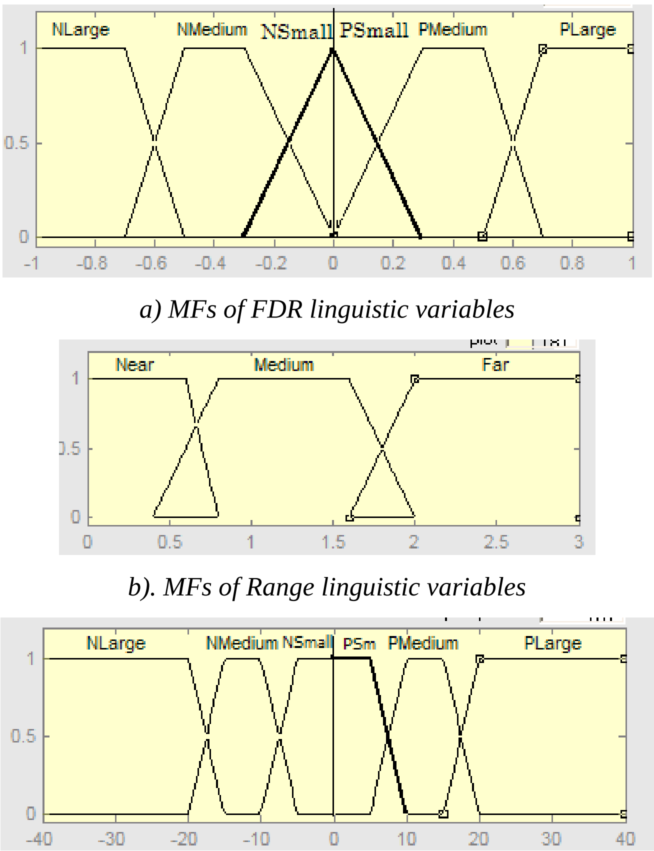
The fuzzy directional relation has six linguistic values (Negative Large-NL, Negative Medium-NM, Negative Small-NS, Positive Small-PS, Positive Medium-PM and Positive Large-PL) with membership functions in figure 7a. The range from robot to obstacle is divided in three subsets: Near, Medium and Far with membership functions in figure 7b. The output of fuzzy if-then is a linguistic variable representing for angle of deviation, has six linguistic variables the same the fuzzy directional relation with the different membership functions in figure 7c. The rule-base and membership functions of linguistic variables are described more detail in table 1.

3.2.2 Wall-following behavior

The wall-following behavior is also a fuzzy inference system with the fuzzy rule having the form as following:

IF *the obstacle* is $\boldsymbol{A_1}$ AND *Range* is $\boldsymbol{B_1}$ THEN *Angle of Deviation* is $\boldsymbol{C_1}$

The position relation between the robot and obstacles is computed from obstacles built by S_1, S_2, S_8 and S_9 sensors. The mentioned position relation, that is left or right, is fuzzy spatial relationship between the robot and the obstacle (more detail in [5, 6]). So rule base of wall-following behavior is as following:



a) MFs of FDR linguistic variables

b). MFs of Range linguistic variables

c) MFs for AoD linguistic variables

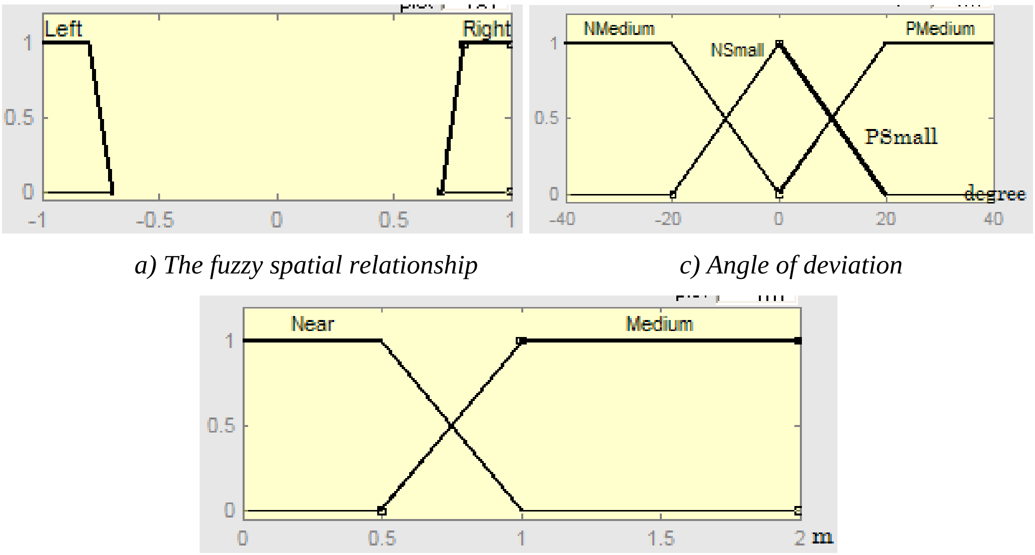
Fig. 7: *MFs of linguistic variables of the collision avoidance behavior.*

Table 1. *Rule base of FLC for collision avoidance behavior.*

FDR	Range	AoD	FDR	Range	AoD
NS	N	PL	PS	N	NL
NS	M	PM	PS	M	NM
NS	F	PS	PS	F	NS
NM	N	PM	PM	N	NM
NM	M	PM	PM	M	NM
NM	F	PS	PM	F	NS
NL	N	PM	PL	N	NM
NL	M	PS	PL	M	NS
NL	F	PS	PL	F	NS

FDR	Range	Angle of Deviation
Left	Medium	Positive Small
Right	Medium	Negative Small
Left	Near	Positive Medium
Right	Near	Negative Medium

The membership functions of the linguistic variables are described as following:



a) The fuzzy spatial relationship

c) Angle of deviation

b) Range

Fig. 8: *Membership functions of fuzzy subset of linguistic variables.*

3.2.3 Reach-target behavior

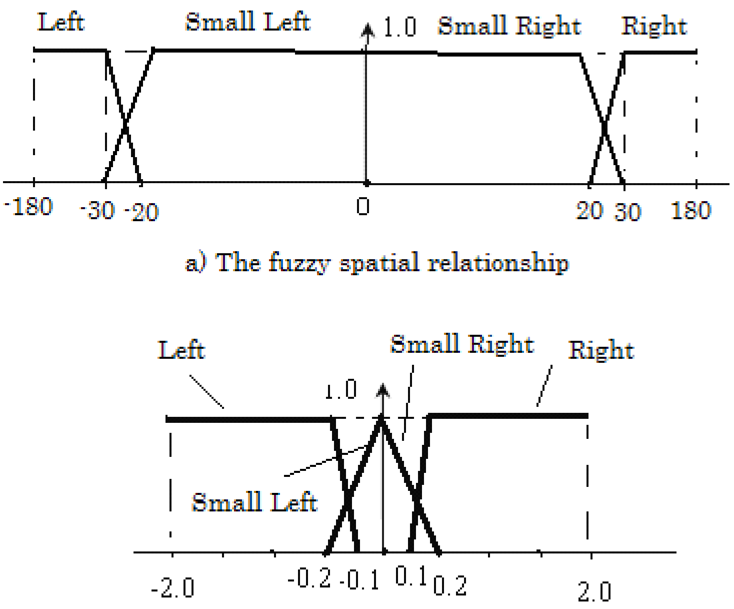
The reach-target behavior is a fuzzy inference system with the fuzzy rule having the form as following:

IF *the obstacle* is $\boldsymbol{A_1}$ THEN *Angle of Deviation* is $\boldsymbol{B_1}$

The positive relation between obstacles has four linguistic values (Left, Small Left, Small Right, and Right) with membership function described in figure 9a. The output is angle of deviation having four fuzzy subsets with membership function in figure 9b.

So the rule base of reach-target behavior is described as following:

FDR	Angle of Deviation
Left	Right
Small Left	Small Right
Small Right	Small Left
Right	Left



a) The fuzzy spatial relationship

b) The angle of deviation

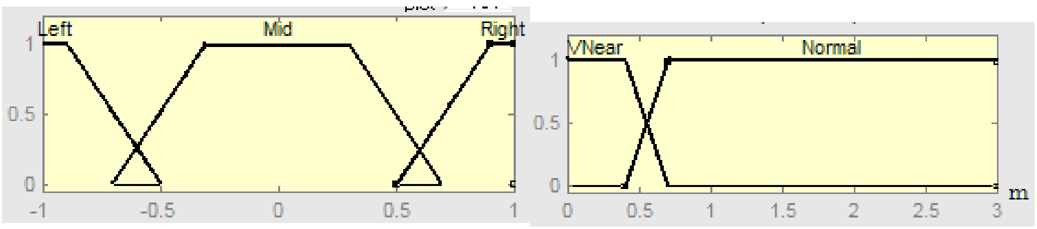
Fig. 9: *Membership functions of fuzzy subset of linguistic variables.*

3.3 Computing the weight of behavior

The weight of each fuzzy behavior is to assess the effect of the behavior on the result of navigation. Obstacles built by S_1, S_2 or S_9, S_{10} (be on left or right of robot) affects the wall-following behavior more than collision avoidance behavior. Beside, obstacles being on the moving direction of robot affect collision avoidance behavior more than other behaviors. In order to estimate the weight of fuzzy behaviors, we use a fuzzy inference system with two inputs being fuzzy directional relationship and range to obstacle. So the rule has the format as following:

If *FSR* is **A** AND *range* is **B** then **C**

in which A, B are one of fuzzy subsets of the linguistic variable FSR and range, respectively, C is a fuzzy behavior. The linguistic variable FSR has three fuzzy subsets: *Left*, *Mid*, *Right* with membership functions $\mu_{\text{Left}}(x)$, $\mu_{\text{Mid}}(x)$, and $\mu_{\text{Right}}(x)$, respectively, as figure 10a. The linguistic variable range has two fuzzy subsets: *Near* and *Normal* with membership functions $\mu_{\text{Near}}(x)$ and $\mu_{\text{Normal}}(x)$ (fig. 10b).



a) FSR

b) Range

Fig. 10: *Membership functions of linguistic variables.*

The weights of behaviors are computed as:

$$w_{\mathrm{WF}} = (\mu_{\mathrm{Left}}(x_1) \circ \mu_{\mathrm{Normal}}(x_2)) \bullet (\mu_{\mathrm{Right}}(x_1) \circ \mu_{\mathrm{Normal}}(x_2)) \tag{9}$$

$$w_{\mathrm{CA}} = \mu_{\mathrm{Mid}}(x_1) \circ \mu_{\mathrm{Normal}}(x_2) \tag{10}$$

$$w_{\mathrm{Round}} = \mu_{\mathrm{Near}}(x_2) \tag{11}$$

where ° is t-norm operator and • is t-conorm opertator.

3.4 Command fusion and defuzification

The fusion layer is to fuse the fuzzy conclusions of previous layer into a combined fuzzy command. In our model, there are two layers of fusion. With the first layer, we use a *t-norm* or *t-conorm* operator to fuse the fuzzy conclusions of entities of the behavior, as following:

The fusion of collision avoidance (CA) behaviors:

$$\mu_{CA}(x) = (\mu_{CA\text{-}1}(x) \circ w_{CA\text{-}1}) \bullet (\mu_{CA\text{-}2}(x) \circ w_{CA\text{-}2}) \bullet \ldots \bullet (\mu_{\mathrm{CA}\text{-}n}(x) \circ w_{CA\text{-}\mathrm{n}}) \tag{12}$$

where • is t-conorm operator being maximum operator and ° is t-norm operator and $w_{\mathrm{CA\text{-}i}}$s are computed according to (10).

The fusion of wall-following (WF) behaviors:

$$\mu_{WF}(x) = (\mu_{WF\text{-}1}(x) \circ w_{WF\text{-}1}) \circ \ldots \circ (\mu_{WF\text{-}m}(x) \circ w_{WF\text{-}m}) \tag{13}$$

where ° is t-norm operator being either minimum operator or product operator and $w_{\mathrm{WF\text{-}i}}$s are computed as (9).

Note that we have three types of behaviors in which the command of go-to-target (GT) and wall-following behaviors is the *desired-direction* and the command of collision avoidance behavior is the *disallowed-direction*. The turn-around with the weight computed in (11) is only used in case robot is not able to move. Using the method of J.Yen [4] in fusing commands from two behaviors, the t-norm is used with three inputs:

$$\mu(x) = \mu_{WF}(x) \circ \mu_{GT}(x) \circ (\text{NOT } \mu_{CA}(x)) = \mu_{WF}(x) \circ \mu_{GT}(x) \circ (1 - \mu_{CA}(x)). \tag{14}$$

where ° is t-norm operator being either minimum operator or product operator.

Defuzzification is the process of converting a fuzzy command into a crisp command. We use the centroid defuzzification method that the domain of the fuzzy A set, $x \in X$, is discretized into N points, $x_1, x_2, \ldots, x_N$ and the centroid is given as

$$c_A = \frac{\sum_{i=1}^{N} x_i \mu_A(x_i)}{\sum_{i=1}^{N} \mu_A(x_i)} \tag{15}$$

or $$c_A = \frac{\int_{x \in X} x\mu_A(x)dx}{\int_{x \in X} \mu_A(x)dx} \tag{16}$$

4. SIMULATION RESULTS

We have implemented above-mentioned results based on object oriented model by VC++. Obstacles managed according to polygon are modeled as in figure 11. During the movement of the robot in the environment, the robot uses 9 sensors (be arranged on half of ring) to detect obstacles (as Fig. 11). In our approach, there are two types of obstacles: real obstacle and “virtual” obstacle. The “virtual” obstacles are modeled by the above mentioned approach using sonar sensors so may be there are many “virtual” obstacles from only one real obstacle. Our approach only uses these “virtual” obstacles to navigate the robot.

The result of the approach is represented in figure 12. The program runs fast enough for interactive, real-time execution on a Pentium III PC. The tasks of modeling obstacles, computing histograms and referencing to compute angle of deviation are executed faster than the movement of the robot, so there is no delay in simulation displayed to user.

We implement the experiment to test the robustness of the proposed approach by using the degree of sensor noise. The simulated sensor noises are characterized by a uniform probability distribution in the interval [-*dxn*, *dxn*] where d is real distance returned by a sensor, and *n* is the sensor noise rate [4]. We use the following three metrics to measure the performance of the robot navigator: *Safety measure* is to measure the percentage of successful simulation runs that robot can reach target without hitting any obstacle. *Smoothness measure* is to measure the smoothness of the moving route of the robot, is computed by the average of angle of deviation made by robot. *Optimized measure* is to measure the rate of the length of the route made by robot and real distance from the starting point to the target.

We have simulation results by implementing of 100 pairs of starting point and target in above environment. The table 2 show results of the collision avoidance behavior been tested in the case only having one obstacle. The table 3 shows the results of the system in above environment with data 100 pairs of starting and target. The figure 12 shows an example of implementing the wall-following behavior. The simulation results show that the robot is able to avoid obstacle in case the sensor noise is very high.

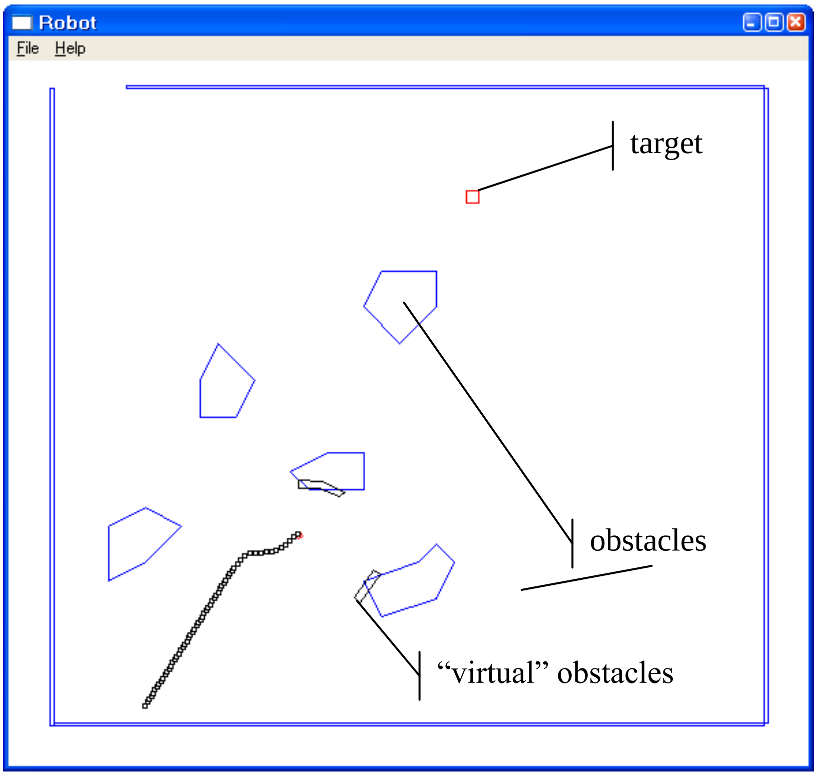


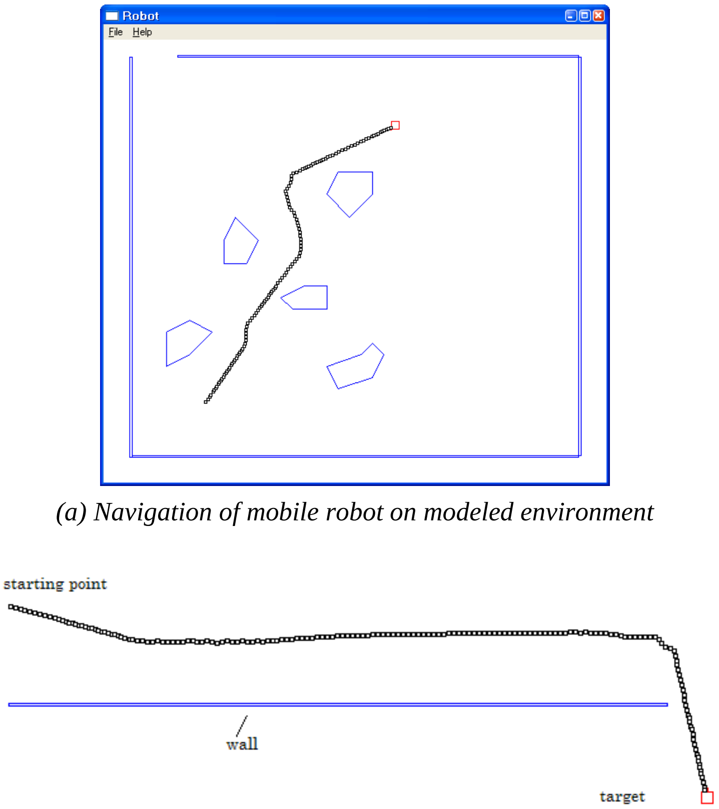
Fig. 11: *The environment is modeled to simulate the result of our approach.*

Table 2. *The simulation results of CA behavior.*

Noise rate	Smoothness measure	Safety measure	Optimized measure
0.0	1.65	1.0	105.06 %
0.2	1.69	1.0	104.81 %
0.4	1.75	1.0	105.71 %
0.6	1.90	1.0	104.95 %
0.8	2.17	1.0	105.35 %
1.0	2.33	1.0	105.58 %

Table 3. *The simulation results of the system in above environment.*

Noise rate	Smoothness measure	Safety measure	Optimized measure
0.0	2.61	1.0	110.00 %
0.2	2.78	0.99	112.47 %
0.4	2.75	1.0	113.23 %
0.6	2.90	1.0	111.38 %
0.8	3.50	1.0	113.56 %
1.0	3.52	1.0	112.71 %



(a) Navigation of mobile robot on modeled environment

(b) Implementing of wall-following behavior

Fig. 12: *The result of the proposed approach.*

5. CONCLUSION

We have developed an approach in designing autonomous robot navigation system based on fuzzy behaviors using the extended fuzzy spatial relation. By using sonar sensor arranged on an half of ring, the robot may be detect obstacles and determine the range and the degree of extended fuzzy spatial relation between obstacles and robot. These parameters are used as inputs of fuzzy behaviors and then by using behavior hierarchy to fuse command output of behaviors to navigate robot. We also proposed a hierarchy of behaviors to fuse command from fuzzy behaviors before defuzzifying. The approach is implemented in above mentioned environment by using many pairs of starting and target points to test the robustness of the model. The result is good and robot be able avoid all of obstacles in case the sensor noise rate is very high.

The next goals of this research will be to develop approaches more intelligent as type-2 fuzzy logic system being to manage uncertainty better or adaptive neuro-fuzzy inference system based this behavior hierarchy. The important goal is to apply the result of this research for outdoor robot designed by using PC-104, sonar sensors and GPS for locating the position in the unknown environment.

REFERENCES

1. Brooks, R.A. (1986), A Robust Layer Control System for a Mobile Robot, IEEE Journal of Robotics and Automation, vol. 2, No. 1, pp. 14-23.
2. Ye, C. and Wang, D. (2001), A Novel Behavior Fusion Method for the Navigation of Mobile Robots, Proceedings of IEEE International Conference on Systems, Man, and Cybernetics, Nashville, TN, pp. 3526-3531.
3. Thongchai, S., Suksakulchai, S., Wilkes, D.M., and Sarkar N. (2000), Sonar Behavior-Based Fuzzy Control for a Mobile Robot, Proceedings of the IEEE International Conference on Systems, Man and Cybernetics.
4. Yen, J. and Pfluger, N. (1995), A fuzzy logic based extension to Payton and Rosenblatt's command fusion method for mobile robot navigation, IEEE Trans. Systems, Man and Cybernetics, 25(6), pp. 971-978.
5. Matsakis, P. and Wendling, L. (1999), A New Way to Represent the Relative Position of Areal Objects, *PAMI* (*IEEE Trans. on Pattern Analysis and Machine Intelligence*), vol. 21, No. 7, pp. 634-643.
6. Bondugula, R., Matsakis, P., and Keller, J. (2004), Force Histograms and Neural Networks for Human-Based Spatial Relationship Generalization, NCI 2004 (IASTED Int. Conf. on Neural Networks and Computational Intelligence), Grindelwald, Switzerland, February 2004, Proceedings.
7. Skubic, M., Matsakis, P., Chronis, G., and Keller, J. (2003), Generating Multi-level Linguistic Spatial Descriptions from Range Sensor Readings Using the Histogram of Forces," *Autonomous Robots*, vol. 14, No. 1, pp. 51-69.
8. Miyajima, K. and Ralescu, A. (1994), Spatial organization in 2D segmented images: representation and recognition of primitive spatial relations, Fuzzy Sets and Systems, 65(2/3), pp. 225-236.
9. Ngo, L.T., Pham, L.T., and Nguyen, P.H. (2006), Extending fuzzy directional relationship and applying for mobile robot collision avoidance behavior", International Journal of Advanced Computational Intelligence & Intelligent Informatics, vol. 10, No.4.

10. Payton, D., Rosenblatt, J., and Keirsey, D. (1990), Plan Guided Reaction, IEEE Trans. System, Man and Cybernetics, vol. 20, No.6, pp. 1370-1382.

11. Rusu, P., Petriu, E.M., Whalen, T.E., Cornell, A., and Spoelder, H.J.W. (2003), Behavior-Based Neuro-Fuzzy Controller for Mobile Robot Navigation, IEEE Trans. on Instrumentation and Measurement, vol. 52, No. 4, pp. 1135-1140.

12. Ngo, L.T., Pham, L.T., and Nguyen, P.H. (2006), An Approach in the Design Hierarchy of Fuzzy Behaviors for Mobile Robot Navigation", Proceedings of International Symposium on Management of Engineering (ISME06), Japan, March 2006.