

Ultrasonic Sensor based Fuzzy Obstacle Avoidance Behaviors

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Abstract— The fuzzy controller provides a mechanism for combining sensor data from all ultrasonic sensors which present different information. An intelligent mobile robot that implements concepts of fuzzy logic, mobile robotics, and behavior-based artificial intelligence has been developed. The main features of the robot are to navigate freely in an unknown environment and avoid the other objects as obstacles. A combination of ultrasonic sensors is used to facilitate navigation and obstacle avoidance. The fuzzy behavior producer is embedded in an 8-bit chip, which is programmed in assembler. The control software implements behavior-based artificial intelligence, where the robot's overall intelligence is made up of layers of several simple and primitive behaviors similar to those observed in animals. The obstacle avoidance behaviors are successfully implemented by formulating a set of fuzzy rules.

Keywords— Fuzzy controller, mobile robot, ultrasonic sensor.

I. INTRODUCTION

The implementation of complex artificial systems can be approached by decomposing the global tasks into several simpler, well-specified behaviors that are easier to design and can be tuned independently of each other. These behaviors are implemented as several levels included in a hybrid reactive architecture. The robot achieves every control objective and the robot trajectory is smooth in spite of the interaction between several behaviors, unexpected obstacles and the presence of noise. Robot behaviors can be implemented as a set of fuzzy rules which mimic expert knowledge in specific tasks in order to model expert knowledge [1], [2], [3], [4], [5], [6]. Usually people do not need precise, numerical input information to make a decision, but they are able to perform highly adaptive and robust control. Fuzzy logic is known to be an organized method for dealing with imprecise data. It is suitable for situations where there is a lack of precision. It attempts to apply a human-like way of thinking in the application areas. A fuzzy system is usually designed by interviewing an expert and formulating his implicit

knowledge of the underlying process into a set of linguistic variables and fuzzy rules. When designing a behavior based mobile robot, expert knowledge is also needed to plan and implement the desired behaviors. Behaviors usually emerge from implicit knowledge of the underlying process that can be converted into a set of linguistic variables and fuzzy rules. When designing behaviors for a robot, a tedious and unreliable trial and error approach is often used. In this study, fuzzy logic is applied to a behavior based mobile robot with ultrasonic sensors. The fuzzy controller provides a mechanism for combining sensor data from all ultrasonic sensors which present different information. The obstacle avoidance behaviors are successfully implemented by formulating a set of fuzzy rules.

II. BACKGROUND

The use of fuzzy logic in the design of navigation behaviors for a mobile robot is nowadays quite popular [7]. The set of behaviors that are being implemented can include, e.g. the following of walls, corridors or the avoidance of obstacles. There is not however an established way of designing the rule bases of these behaviors. A lot of approaches use expert knowledge to decide on the response of the behavior according to its objective but without defining that objective explicitly. Usually people do not need precise, numerical information input to make a decision, but they are able to perform highly adaptive control. Behaviors usually emerge from implicit knowledge of the underlying process that can be converted into a set of linguistic variables and fuzzy rules.

A. Behavior-Based Approaches

In behavior-based robotics, the robot acts out some basic behaviors similar to that of animals by simply reacting to its sensory inputs. Some common behaviors that employed by researchers include wall following, light seeking, obstacle avoidance and

target approaching. From the success of these and other creative behaviors, the subsumption architecture has emerged, which provides a structured approach of combining simple behaviors to exemplify an artificial intelligence. This approach is known as behavior-based artificial intelligence [8]. The subsumption architecture is a way of organizing an intelligent system by means of layering task-achieving behaviors without recourse to world models or sensor fusion. In this architecture, behaviors are arranged in levels of priority where triggering a higher level behavior suppresses all lower level behaviors. The designer determines the priority order of the behaviors and devises an arbitration scheme to further resolve conflicting behaviors. A behavior-based control architecture can be organized horizontally which shows that each behavior has full access to all sensor readings and processes its own command to control the mobile robot.

B. Fuzzy Control

The theory of fuzzy control has been extensively researched in various fields of engineering. The concept of fuzzy logic was conceived by Lotfi Zadeh, a professor at the University of California at Berkeley, and presented as a way of processing data by allowing partial set membership rather than crisp set membership or non-membership [9]. This approach to set theory was not applied to control systems until the 70's due to insufficient small-computer capability prior to that time. Professor Zadeh reasoned that people do not require precise, numerical information input, and yet they are capable of highly adaptive control. If feedback controllers could be programmed to accept noisy, imprecise input, they would be much more effective and perhaps easier to implement. U.S. manufacturers have not been so quick to embrace this technology while the Europeans and Japanese have been aggressively building real products around it.

Fuzzy logic is a problem-solving control system methodology that lends itself to implementation in systems ranging from simple, small, embedded micro-controllers to large, networked, multi-channel PC or workstation-based data acquisition and control systems. It can be implemented in hardware, software, or a combination of both. Fuzzy logic provides a simple way to arrive at a definite conclusion based upon vague, ambiguous, imprecise, noisy, or missing input information. Fuzzy logic approach to control problems mimics how a person would make decisions.

Fuzzy logic incorporates a simple, rule-based "IF X AND Y THEN Z" approach to a solving control problem rather than attempting to model a

system mathematically. The fuzzy logic model is empirically-based, relying on an operator's experience rather than their technical understanding of the system. The terms used in fuzzy logic are imprecise and yet very descriptive of what must actually happen. Fuzzy logic is capable of mimicking the decision an expert might have made for a control process but at very high rate.

Fuzzy logic requires some numerical parameters in order to operate, e. g. what is considered as significant error and significant change-in-error. But exact values of these numbers are usually not critical unless very responsive performance is required in which case empirical tuning would determine them.

Fuzzy logic was conceived as a better method for sorting and handling data but has proved to be an excellent choice for many control system applications since it mimics human control logic. It can be built into anything from small, hand-held products to large computerized process control systems. It uses an imprecise but very descriptive language to deal with input data more like a human operator. It is very robust and forgiving of operator and data input and often works when first implemented with little or no tuning.

III. BEHAVIOR-BASED FUZZY OBSTACLE AVOIDANCE DESIGN

By using behavior-based control architecture, the robot developed in this study is organized so that each behavior has full access to its corresponding sensor readings and processes its own command to control the mobile robot. Several levels of competence are implemented on the robot. The lowest level has the highest priority. The final command depends on if the behaviors that have higher priority have been triggered. The robot described in this study has six levels of competence, target following, obstacle avoidance, joystick command executing, emergent behavior after contacting with obstacles, trajectory tracking and emergent stop. A high-level behavior may require intelligent control techniques such as fuzzy control. The focus of this study is only the development of the obstacle avoidance behaviors that are implemented by using fuzzy logic control.

A. The Developed Fuzzy Controller

A block diagram of the fuzzy controller is shown in Fig. 1. The data from ultrasonic sensors are the distances between the sensors and the objects. All ultrasonic sensors send data to the inputs of the fuzzy controller embedded in the chip on the robot. The fuzzy controller has eight inputs and two outputs. It is designed to output the moving speed

v and turn angle ϕ that will be used to actuate the motors controlled by the lower level of finite state machines which will output the desired behaviors.

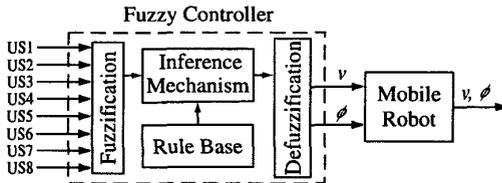


Fig. 1. Block diagram of the fuzzy controller.

To simplify the implementation, this fuzzy logic controller is divided into eight separate fuzzy logic controllers of the same structure except that the rule bases are different. Thus only a single 1-input-2 output fuzzy logic controller is needed to be implemented. The input universe of discourse are exactly same for the eight separate fuzzy logic controllers because the eight ultrasonic sensors have the same properties. Therefore there is no need to adjust the values of the gains for the input variable. The fuzzy behavior producer is embedded in an 8-bit chip, which is programmed in assembler.

B. Fuzzification

Altogether there are eight ultrasonic sensors installed on the robot. Four sensors are in the front, two are on the back and on each side there is one sensor. as shown in Fig. 2.

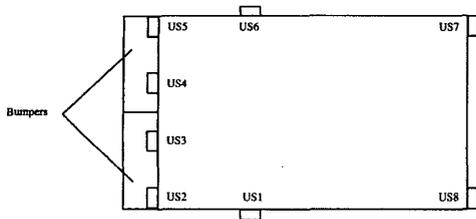


Fig. 2. The ultrasonic sensors arrangement on the robot.

The fuzzification procedure maps the crisp input values to the linguistic fuzzy terms with the membership values between 0 and 1. In most fuzzy decision systems, non-fuzzy input data is mapped to fuzzy sets by treating them as trapezoid membership functions, Gaussian membership functions, sharp peak membership functions, triangle membership functions, etc. In this paper, we use three membership functions for each ultrasonic sensor. Fig. 3 shows the input membership functions that are used for all the eight ultrasonic sensors.

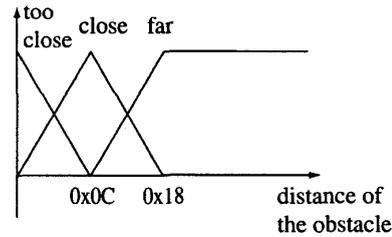


Fig. 3. Input membership functions.

These input membership functions are defined according to the ultrasonic collision avoidance behaviors. The ultrasonic collision avoidance is performed on three levels. The first level defines that the obstacles are too far away from the robot so that it is not necessary for the robot to avoid any obstacles. The second level enables the robot to turn away from obstacles which are detected to be close, but not too close. This means the robot will only try to turn away from obstacles. The third level of avoidance is when obstacles are determined to be too close, the robot will swerve sharply away from the obstacle until it is no longer determined to be too close.

C. Inference Mechanism

The inference mechanism is responsible for decision making in the control system using approximate reasoning. It is used to combine the fuzzy "IF-THEN" with the fuzzy rule base, and to convert input information into output membership functions. The inference mechanism emulates an expert's decision-making knowledge in interpreting and applying knowledge about how to perform the control tasks. The knowledge can be implemented as a fuzzy rule-base. The rules use the expert's experience and control engineering knowledge. The rule base stores the rules governing the input output relationship of the proposed fuzzy controller. The control rules are designed based on experiment results. Six rules are formulated for each of the ultrasonic sensors. Table I shows the rules for all the eight ultrasonic sensors.

The obstacle avoidance behavior has been designed to avoid unexpected obstacles wherever the robot goes. The behavior to avoid obstacles should have a higher priority than the navigation behaviors considering that the robot can avoid any obstacles while the robot is following a moving target.

Taking into account the locations of all the eight ultrasonic sensors, if there is an obstacle close to the left side of the robot (but not too close), the

TABLE I
RULE TABLE FOR THE ULTRASONIC SENSORS.

	sensor value		
	far	close	too close
v_1	0	positive	positive fast
ϕ_1	0	right	more right
v_2	0	negative	negative fast
ϕ_2	0	right	more right
v_3	0	negative	negative fast
ϕ_3	0	right	more right
v_4	0	negative	negative fast
ϕ_4	0	left	more left
v_5	0	negative	negative fast
ϕ_5	0	left	more left
v_6	0	positive	positive fast
ϕ_6	0	left	more left
v_7	0	positive	positive fast
ϕ_7	0	left	more left
v_8	0	positive	positive fast
ϕ_8	0	right	more right

robot should turn a little bit right in order to avoid colliding with the obstacle. If the obstacle is too close to the robot's left side. The robot should turn right more to avoid the obstacle, as illustrated in Fig. 4.

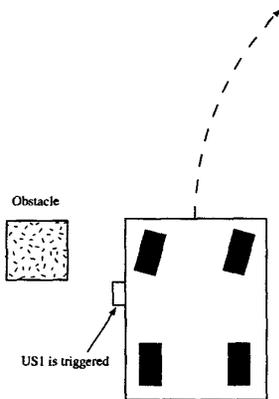


Fig. 4. Obstacle avoidance behavior for the obstacle on the left side.

If there is an obstacle in the left front of the robot, the robot should reverse and go backward. Furthermore, it should turn right a little bit so that after it goes backward, it can go forward again and pass the obstacle on its right side and will not bump into the obstacle again, as illustrated in Fig. 5.

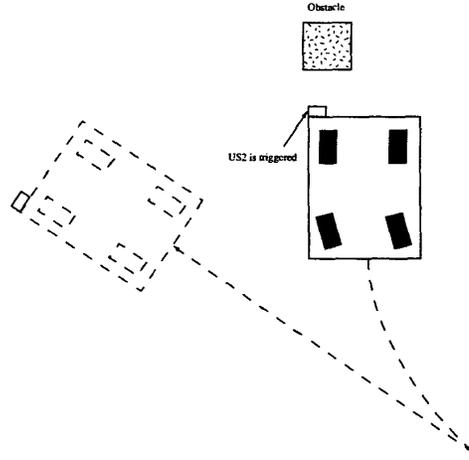


Fig. 5. Obstacle avoidance behavior for the obstacle in the left front of the robot.

All the other obstacle avoidance behaviors are evolved in the same way.

D. Defuzzification

The defuzzification procedure maps the fuzzy output from the inference mechanism to a crisp signal. There are many methods that can be used to convert the conclusions of the inference mechanism into the actual output of the fuzzy controller. Each provides a means to choose a single output based on either the implied fuzzy sets or the overall implied fuzzy set chosen. We use the "center of gravity" (COG) defuzzification method for combining the recommendations represented by the implied fuzzy sets from all the rules. Let b_i denote the center of the membership function of the consequent of rule (i) and $\int \mu_{(i)}$ denote the area under the membership function $\mu_{(i)}$. The COG method computes μ^{crisp} to be

$$\mu^{crisp} = \frac{\sum_i b_i \int \mu_{(i)}}{\sum_i \int \mu_{(i)}} \quad (1)$$

Fig. 6 shows the output membership functions for v and Fig. 7 shows the output membership functions for ϕ . $\int \mu_{(i)}$ can be easily computed because here symmetric triangular output membership functions that peak at one and have a base width of w are used. Simple geometry can be used to show that the area under a triangle "chopped off" at a height of h is equal to $w(h - \frac{h^2}{2})$.

Because the output membership functions are symmetric, it will be the case that the center of

the implied fuzzy set will be the same as the center of the consequent fuzzy set from which it is computed. If the output membership functions are not symmetric, then their centers, which are needed in the computation of the COG, will change depending on the membership value of the premise. This will result in the need to recompute the center at each time instant.

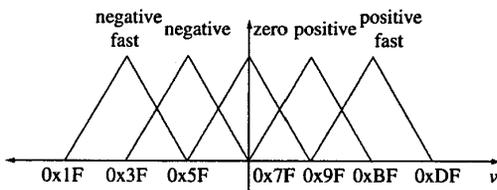


Fig. 6. Output membership functions for the velocity.

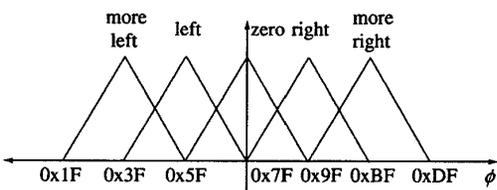


Fig. 7. Output membership functions for the turn angle.

E. Recombination of the Output of the Divided Fuzzy Controllers

The behavior of the robot to stimulus detected by the ultrasonic sensors depends on the output of the fuzzy controller corresponding to various stimulus and which sensor is being triggered. Any stimulus detected by the sensors is treated as a force vector pushing the robot. A resultant direction vector is calculated by

$$\begin{aligned} v &= \frac{1}{8} \sum_{i=1}^8 v(i), \\ \phi &= \frac{1}{8} \sum_{i=1}^8 \phi(i), \end{aligned} \quad (2)$$

in which $v(i)$ and $\phi(i)$ are the output of the eight separate fuzzy controllers. v and ϕ are the resultant velocity and turn angle. It can be seen that the resultant direction vector is determined by all the sensors triggered and the output of the fuzzy controller. The robot is made to go in that direction. Given this concept of resultant vectors, if an

object is detected only by a sensor on the left side, the robot would turn to the right. This means that if an object was detected to be equally close on both sides the robot would go straight, because the ϕ component of the two vectors would cancel out.

IV. EXPERIMENTS

In order to test the performance of the system in the real world different tasks have been carried out. The first one is to activate each of the behaviors triggered by only one ultrasonic sensor separately in its own context of applicability in order to tune the linguistic variables of the rule base. This tuning process has been based on expert knowledge gained from the results from several trials. After that, the robot is put into the outdoor environment to navigate randomly which requires the combination of all the behaviors triggered by all sensors in order to test the performance of the whole system. The robot reaches the control objective in spite of the presence of noise in the sensor data. When several sensors are triggered, the transition between behaviors is smooth and the robot adapts its behavior according to the current context. The experimental result of this fuzzy obstacle avoidance behavior approach is promising. If there is no obstacle around the robot, the robot will execute the higher level commands, e.g. following the moving target captured by the vision system. If there is an obstacle detected in the front left of the robot, the obstacle avoidance behaviors defined by the fuzzy rules will emerge. The robot will go backward and turn right. If there are obstacles on every side of the robot. The robot will stay there and wait until there is no obstacle in front of it or there is no obstacle behind it. The developed mobile robot demonstrates satisfactory ability to navigate autonomously. Fig. 8 shows that the developed robot is moving around an outdoor environment while avoiding bumping into obstacles.

V. CONCLUSION

Intelligent control techniques for robotic systems have been used with some success in a wide variety of applications. Intelligent control system of a robot can be constructed by using fuzzy behavior-based control, which decomposes the control system into several elemental behaviors, and each one is realized by fuzzy reasoning. It is introduced in this paper that symbolic representations can be coupled with behavior-based robot systems. The behavior-based control system is implemented with subsumption architecture, which is a class of behavior-based systems, and the obstacle avoidance module of this subsumption architecture is realized with fuzzy

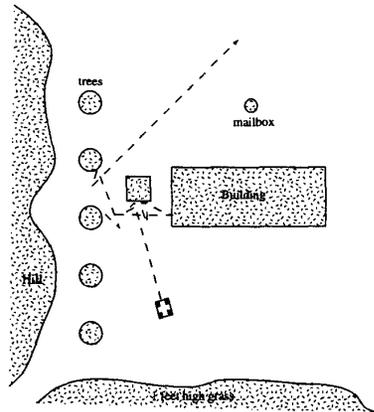


Fig. 8. Random navigation with obstacle avoidance behaviors in outdoor environment.

logic. The fundamental idea in applying the fuzzy logic to this behavior-based system is that the behaviors generated from the symbol representations are to be extracted from the sensor-motor coordination defined by a set of fuzzy rules. The proposed method is applied to the obstacle-avoidance problem of the developed mobile robot and the effectiveness of the method is illustrated through experiment results.

Acknowledgments

This work was supported by Natural Sciences and Engineering Research Council (NSERC) and Material and Manufacturing Ontario (MMO) of Canada. The authors gratefully acknowledge the assistance and cooperation provided by Applied AI Systems, Inc. Carp, Canada.

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