Fuzzy Decision Making on Direction Changes of Water Pollution Monitoring Underwater Robots

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Abstract: - Fuzzy decision making on trajectory direction changes of pollution monitoring robots is addressed in this paper. Measured pollution densities and the possible existence of obstacles are used as the two fundamental data. While pursuing water pollution monitoring tasks, underwater robots may experience serious difficulties due to various kinds of obstacles in the water. Therefore, one of the major concerns for underwater robots is to detect and recognize obstacles in advance for natural and smooth movements without collision. Trajectory direction changes of a robot should be made so that the robot can move in the direction that the measured pollution data is increased most, especially when there are no obstacles. When there are obstacles along the robot's path in the polluted area, proper trade-off should be made between the steepest ascending direction of pollutant densities and the possibilities of collision with obstacles or traps in them. Our experimental results show that underwater robots, which change the direction following the proposed fuzzy decision results, make their movement to the area of higher pollution density without collision.

Key-Words: - Fuzzy Decision Making, Water Pollution Monitoring, Trade-off, Obstacle Recognition

1 Introduction

Since there are various kinds of water plants and trashes, obstacle detection and collision avoidance are the primary and crucial tasks for underwater robots to make smooth and natural movements. The robots need to detect the obstacles in advance and move without collision. Robots make appropriate propulsion direction changes to avoid collision based on the IR distance sensor data. Analyzing image data of the target areas to recognize possible obstacles is the basic method in the water. Despite advantages of image systems, such as cameras and sonar, there are many kinds of situations where image data cannot be properly applied. The common reasons for this restriction are the limited capabilities of processors, ranges of short distances, and adverse underwater conditions to get sufficient image data.

For one of the practical applications of underwater robots, a new method of the water pollution mapping and tracking system by using a fish robot based on ubiquitous sensor networks is introduced [1]. In the water pool imitating the similar situation such as the diffusion of a real water pollution source, the robot searches higher reflected light intensity from the bottom of the tank with different colors to track the highest level position.

Fuzzy decision making on trajectory direction changes of monitoring robots is proposed, which is based on two fundamental data of the measured pollution and the possible existence of obstacles. Underwater robots may experience serious difficulties in doing water pollution monitoring tasks due to various kinds of obstacles in the water. When there are obstacles along the robot's path in the polluted area, appropriate trade-off methods should be applied between the steepest ascending direction of pollutant densities and the possibilities of collision or traps in the obstacles. Our experimental results show that underwater robots, which change direction following the proposed fuzzy decision results, make their movement to the area of higher pollution density without collision.

In section 2, a robot for the water pollution monitoring and tracking system is presented. The estimation and recognition of obstacles using distance sensors are covered in section 3. The simulation of water pollution circumstances and the actuating control of robots for monitoring are given in section 4. Fuzzy decision making on direction changes of pollution is proposed in section 5. Experimental results are given in section 6, followed by conclusion.

2 Underwater Robots

We have constructed several types of fish-shaped underwater robots in our lab. The robots that have various structures and shapes of real fish imitate the ways the real fish swim. For instance, four servo motors are used at the caudal fin of the robot for propulsion and horizontal direction control. Distance sensors, which are mounted at the front and two sides of the head, measure the distance to an obstacle. Every signal is processed based on the MSP430F149 by TI. User commands and sensor data are transmitted between the fish robot and a host notebook PC either by Bluetooth modules or by an RF module, which depends on operation depth. A fish robot is shown in Fig. 1.

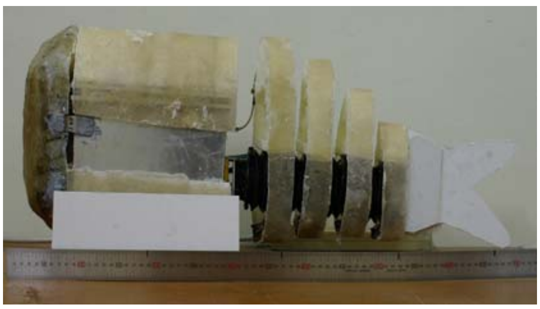


Fig. 1. Underwater fish-shape robot

The infrared distance sensor, regardless of obstacle color, size and angle, is generally used to measure the distance between the robot and an obstacle. Three infrared distance sensors, GP2D12s, are used to measure the distance from the fish robot to the wall or obstacles. The detectable range is reduced to about 12-30cm underwater, though the range is 10-80cm in the air. The configuration of the sensors on the fish robot's body is shown in Fig 2.

Since obstacle avoidance is the most important in mobile robot, whether it is wheel based or not, lots of previous studies have presented a variety of methods and applications [2, 3, 4, 5].

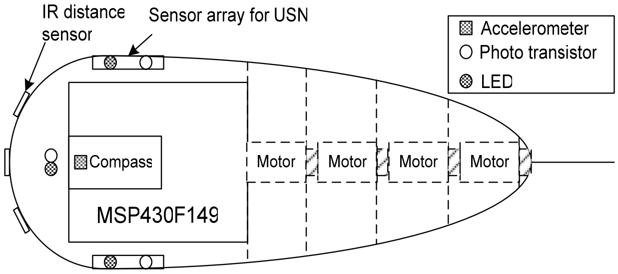


Fig. 2. Sensor configuration on a fish robot

Table 1. Specifications of a fish robot

Item	Specification
Length	73Cm
Width	12.5Cm
Height	22.5Cm
Weight	4950g
Length of tail fin	42Cm
Maximum angle of tail fin	80°
Minimum rotation radius	31Cm
Maximum speed	70Cm/sec
Maximum torque of motors	7.4KgCm at 6V
Angular speed of motors	300°/sec

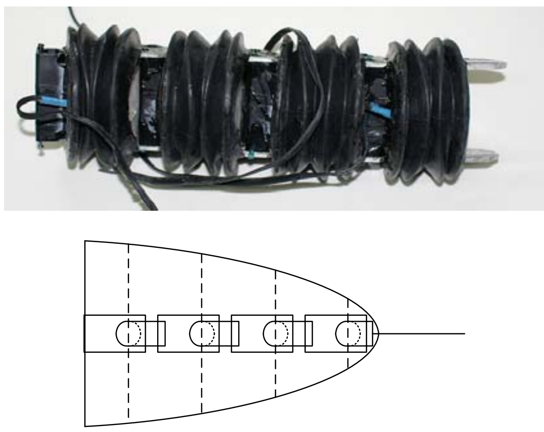
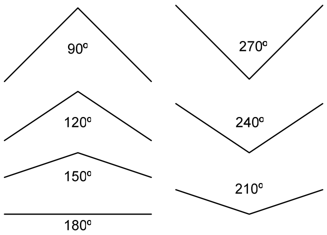


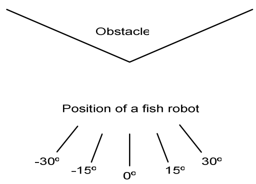
Fig. 3. Lower body and caudal fin of a fish robot

3 Recognition of Obstacles

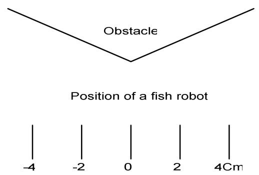
Obstacle models, which consist of two planes, are assumed to be simple to find the basic characteristics of the randomness of obstacles. The angles range from 90 to 270 degrees in the water tank as shown in Figure 4(a). Underwater robots can approach obstacles with different angles and shifts of obstacles as shown in (b) and (c).



(a) plane angles of obstacles



(b) rotation of obstacle

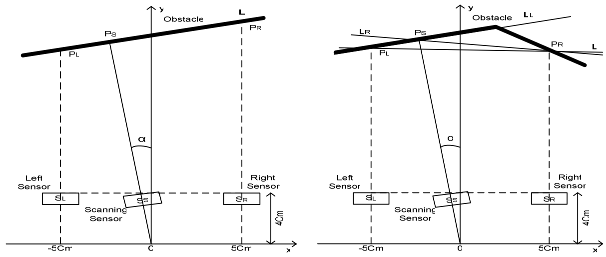


(c) shift of obstacle

Fig. 4. Various shapes and positions of obstacles

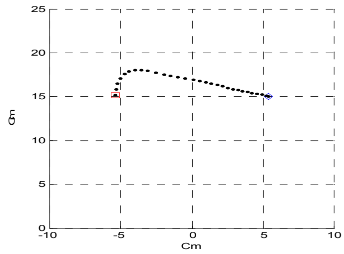
Figure 5 shows geometric relationships of sensor data for an obstacle example. Let the lines passing through P_L and P_R be **L**, P_L and P_S be $\mathbf{L}_L$, P_S and P_R be $\mathbf{L}_R$, and the slopes of the lines be m, m_L, m_R, respectively. The estimations of the plane angle of an obstacle, rotation and shift of an obstacle, distance to an obstacle are made from the measurements of the three IR sensors.

While a robot is moving there is a considerable level of noise due to waves, vibration of the actuators or the scanning motor itself. Therefore the discrepancy of the scanning sensor data should be compensated using the distance data of the fixed sensors at both ends. We propose a method that transforms the raw shape data from the scanning sensor to the real obstacle shape irrelevant to the rotation and shift of the obstacle using the distance data of the fixed sensors.

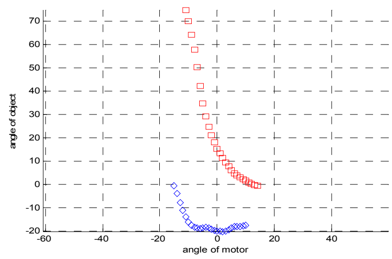


(a) Obstacle without corner (b) Obstacle with a corner

Fig. 5. Geometric relationship of sensor system



(a) Scanned data



(b) Estimated angles from left and right end points

Fig. 6. Angles of an obstacle from two left and right points to each scanned point

In Figure 6(a), scanned data for an obstacle which has a 90 degree corner is shown in a dotted line. Estimated angles from the far left measurement are denoted by a line made up of squares, and the estimated angles from the far right measurement are denoted by a line made up of diamonds, as shown in Figure 6(b). The data denoted in a line of diamonds shows almost constant -20° as the motor angle changes from +11° to -8°. We assume this constant angle to be m_R. The line of squares indicates +74° at the motor angle of -11° and then it drops sharply. We assume the average of the first three angles to be m_L. Therefore, the estimated obstacle angle is about 89°, and the corner point is measured at the average of -11° and -8°.

Figure 7 shows reconstructed results when the obstacle which has 120° is rotated in five different ways.

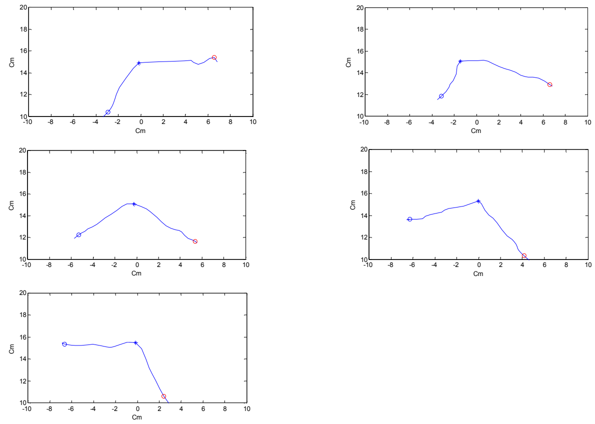


Fig. 7. Reconstruction and feature points of the same angle obstacle in five positions

4 Tracking Direction Control

A new system we propose is that a fish robot tracks the water pollution source autonomously in the real circumstance. We made an artificial model circumstance similar to the real circumstance. It is general that a water pollution source diffuses widely and in a circular pattern at static condition, for example, in the lakes and sea, except in the rivers which have strong stream.

The fish robot can detect higher reflection intensity to infrared among the different colors that are reflected from the bottom to an LED light source. In order to search the place showing higher intensity, we need to make the fish robot's head swing periodically to find a wide area for one period swimming. The basic strategy for tracking is a swing of the body. The robot changes the direction to find higher intensity of reflection to the light source.

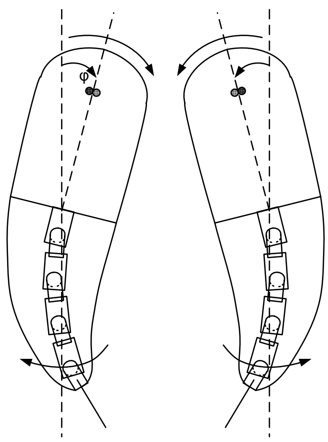


Fig. 8. Head swings due to tail fin movement

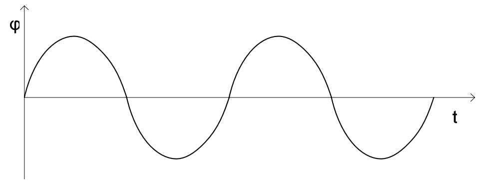


Fig. 9. Patterns of head swing

Equation (1) shows general swim function.

$$A_i(t) = K_i Am_i \sin(2\pi ft - \theta_i) + \Delta_i(t) \qquad (1)$$

A_i is the angle of $i^{\text{-th}}$ tail motor, K_i is amplitude factor, Am_i is amplitude, f is frequency of caudal fin, θ_i is phase delay of $i^{\text{-th}}$ motors, and Δ_i is deflection angle for slow and quick turn. We use 10 degree maximum amplitudes of angle and 35 degree phase delays for general swim. Swim frequency is 0.5Hz.

The fish robot's ability to search for a wide area while swimming is considered as the basic strategy of tracking higher pollution intensity. The intensity of infrared in swing trajectory is measured by the sensor, and the highest intensity is found during the half cycle of each swing. When the highest intensity is found at the right side, the robot must change the direction to the right. Thus, Δ_i in equation (1) must be decreased for direction change to the right, while it must be increased for direction change to the left. The fish robot continuously changes the direction for the place which shows higher reflection intensity to the light source and it can find the highest intensity place. For an autonomous tracking, simple commands are used for direction changes; for example, 'If the intensity of the left side is higher than the right side, then turn left,' 'If the intensity of the right side is higher than the left side, then turn right,' and 'If the intensity of one side is similar to the other side, go straight.' Though these simple and concrete commands produce good results for tracking, it is impossible to apply these oral commands to our microcontroller in a sophisticated way. Thus, for easy implementation of the controller, a simple fuzzy logic is used in our study.

5 Fuzzy Decision Making on Direction Changes

Fuzzy decision making on trajectory direction changes of monitoring robots should be introduced for easy implementation of the controller. We use two fundamental data of the measured pollution and the possible existence of obstacles in real situations. Underwater robots may face serious difficulties doing water pollution monitoring tasks due to various kinds of obstacles in the water. When there are obstacles along the robot's path in the polluted area, appropriate trade-off methods should be applied between the steepest ascending direction of pollutant densities and the possibilities of collision with the obstacles or traps in them.

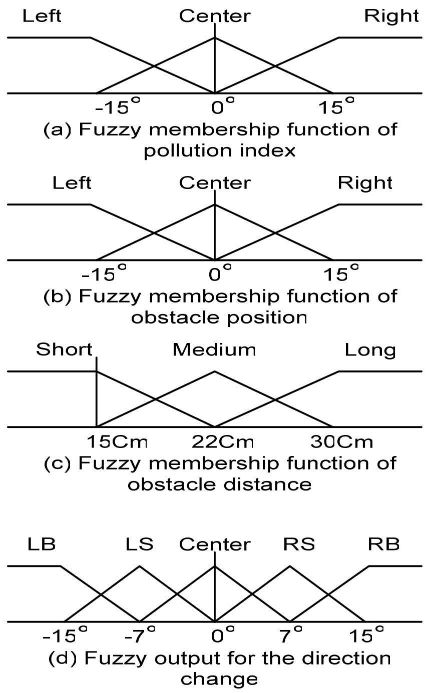


Fig. 10. Fuzzy membership functions inputs and control output variables

Since both measured data of obstacles and pollution intensities have ambiguity in nature, measured inputs and control outputs are described by fuzzy variables as shown in Fig. 10. The 'Left', 'Center', and 'Right' in Fig. 10(a) mean that the intensities of pollution index in left, center, and right side are higher than any other ranges, respectively. The corresponding fuzzy variables are represented in Fig. 11. The direction control of the tail fin considering both obstacles and pollution density is carried out using fuzzy inference. The fuzzy rules are summarized in Table 2. In the table, *O.S.* represents Obstacle Status, *P.I.* is Pollution Index and *X* is 'don't care'. *Left*, *Center*, and *Right* are the input positions of an obstacle. *Short*, *Medium*, and *Long* express distances from a sensor to the obstacle. Every output in Table 2 has two directions: *Temporal Direction* and *Main Direction*. *Main Direction* is the output variable when there are no obstacles while *Temporal Direction* is the one when an obstacle is detected.

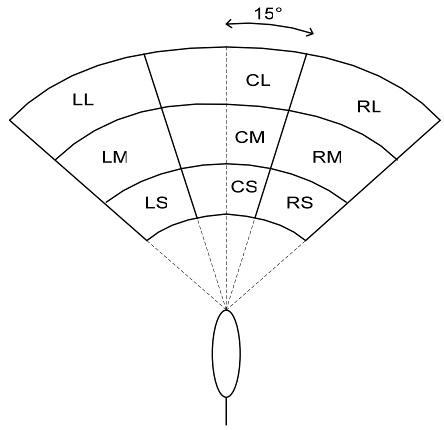


Fig. 11. Fuzzy variables of direction and distance for obstacles

Table 2. Fuzzy rules for direction changes

O.S. \ P.I.		Left	Center	Right
Left	**S**hort	RB/LB	RB/CT	RB/RB
	Medium	RS/LB	RS/CT	RS/RB
	Long	X/LB	RS/CT	RS/RB
Center	**S**hort	LB/LB	RB/CT	RB/RB
	Medium	LB/LB	RS/CT	RB/RB
	Long	LS/LB	RS/CT	RS/RB
Right	**S**hort	LB/LB	LB/CT	LB/RB
	Medium	LS/LB	LS/CT	LS/RB
	Long	LS/LB	LS/CT	X/RB

(*RB*: Turn Right Big, *RS*: Turn Right Small, *CT*: go Center, *LS*: Turn Left Small, *LB*: Turn Left Big)

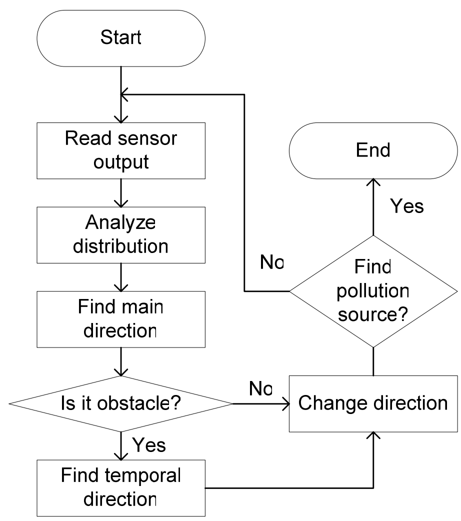


Fig. 12. Flow chart for the direction changes

Examples of fuzzy rules are as follows;

* R1: If *P.I.* is *Left* and *O.S.* is *LS*, then *Temporal Direction* is *RB* and *Main Direction* is *LB*.
* R2: If *P.I.* is *Left* and *O.S.* is *LM*, then *Temporal Direction* is *RS* and *Main Direction* is *LB*.
* R3: If *P.I.* is *Left* and *O.S.* is *LL*, then *Temporal Direction* is *X* and *Main Direction* is *LB*.

Typical experimental results of trajectories for directional fuzzy control are denoted in dots in Fig. 13. They show successful collision avoidance while searching for higher pollution density areas.

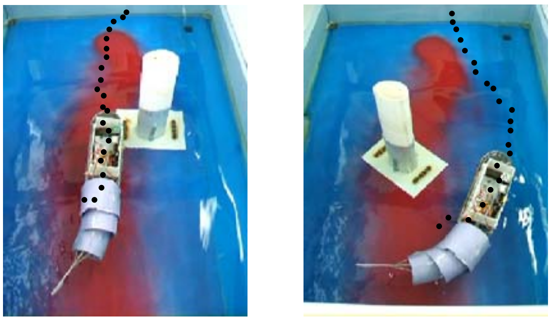


Fig. 13. Experiments of direction fuzzy control

6 Conclusion

Fuzzy decision making on trajectory direction changes of pollution monitoring robots is addressed in this paper. We use two fundamental data of the measured pollution and the possible existence of obstacles. When there are obstacles along the robot's path in the polluted area, proper trade-off should be made between the steepest ascending direction of pollutant densities and the possibilities of collision with the obstacles or traps in them. Our experimental results show that underwater robots, which change the direction following the proposed fuzzy decision results, make their movement without collision to the area of higher pollution density.

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References:

[1] Daejung Shin, Seung Y. Na, Jin Y. Kim and Seong-Joon Baek, "Water Pollution Monitoring system by Autonomous Fish Robots," *WSEAS Trans. on SYSTEM and CONTROL*, Issue 1, Vol. 2, 2007, pp. 32-37.

[2] Seung Y. Na, Daejung Shin, Jin Y. Kim, and Su-Il Choi, "Collision Recognition and Direction Changes Using Fuzzy Logic for Small Scale Fish Robots by Acceleration Sensor Data," *FSKD 2005*, LNAI 3614, 2005, pp. 329-338.

[3] G. Antonelli, S. Chiaverini, R. Finotello, R. Schiavon, "Real-time path planning and obstacle avoidance for RAIS: an autonomous underwater vehicle," *IEEE Journal of Oceanic Engineering*, Vol. 26, Issue 2, 2001, pp. 216-227.

[4] Y. Petillot, T. Ruiz, I. Tena, D. M. Lane, "Underwater vehicle obstacle avoidance and path planning using a multi-beam forward looking sonar," *IEEE Journal of Oceanic Engineering*, Vol. 26, Issue 2, 2001, pp. 240-251.

[5] R. Wai, P. Chen, "Intelligent tracking control for robot manipulator including actuator dynamics via TSK-type fuzzy neural network," *IEEE Trans. on Fuzzy Systems*, Vol. 12, 2004, pp. 552-560.

[6] J. Yu, M. Tan, S. Wang, E. Chen, "Development of a Biomimetic Robotic Fish and Its Control Algorithm," *IEEE Trans. on Systems, Man, and Cybernetics-Part B*, Vol. 34, 2004, pp. 1798-1810.

[7] J. Liu, H. Hu, "Mimicry of Sharp Turning Behaviours in a Robotic Fish," *Proceedings of the 2005 IEEE International Conference on Robotics and Automation*, Spain, 2005, pp. 3329-3334.

[8] J. R. Jang, "ANFIS: Adaptive-network-based fuzzy inference system," *IEEE Trans. Syst., Man, Cybern.*, Vol. 23, 1993, pp. 665-685.

[9] M. Panella, A. S. Gallo, "An Input-Output Clustering Approach to the Synthesis of ANFIS Networks," *IEEE Trans. on Fuzzy Systems*, Vol. 13, No. 1, 2005, pp. 69-81.

[10] K. Kiguchi, T. Tanaka, T. Fukuda, "Neuro-fuzzy control of a robotic exoskeleton with EMG signals," *IEEE Trans. on Fuzzy Systems*, Vol. 12, 2004, pp. 481-490.