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.

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].

Table 1. Specifications of a fish robot

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

Fig. 1. Underwater fish-shape robot

Fig. 2. Sensor configuration on a fish robot

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).

![Figure 4](image)

(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 \( P_S \) be \( L_P \), \( P_L \) and \( P_S \) be \( L_P \), \( L_P \), and \( L_P \) be \( L_P \), and the slopes of the lines be \( m_L \), \( m_S \), \( m_S \), \( m_S \), 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.

![Figure 5](image)

(a) Scanned data

(b) Estimated angles from left and right end points

Fig. 5. Geometric relationship of sensor system

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 \( m_S \). 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.

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.

Equation (1) shows general swim function.

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

Where, $A_i$ is the angle of $i^{th}$ tail motor, $K_i$ is amplitude factor, $Am_i$ is amplitude, $f$ is frequency of caudal fin, $\theta_i$ is phase delay of $i^{th}$ motors, and $\Delta_i$ 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.

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.

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.

![Fuzzy membership functions inputs and control output variables](image)

![Fuzzy membership function of pollution index](image)

![Fuzzy membership function of obstacle position](image)

![Fuzzy membership function of obstacle distance](image)

![Fuzzy output for the direction change](image)

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

**Fig. 11. Fuzzy membership function of pollution index**

**Fig. 12. Flow chart for the direction changes**

Table 2. Fuzzy rules for direction changes

<table>
<thead>
<tr>
<th>O.S.</th>
<th>P.I.</th>
<th>Left</th>
<th>Center</th>
<th>Right</th>
</tr>
</thead>
<tbody>
<tr>
<td>Left</td>
<td>Short</td>
<td>RB/LB</td>
<td>RB/CT</td>
<td>RB/RB</td>
</tr>
<tr>
<td></td>
<td>Medium</td>
<td>RS/LB</td>
<td>RS/CT</td>
<td>RS/RB</td>
</tr>
<tr>
<td></td>
<td>Long</td>
<td>X/LB</td>
<td>RS/CT</td>
<td>RS/RB</td>
</tr>
<tr>
<td>Center</td>
<td>Short</td>
<td>LB/LB</td>
<td>RB/CT</td>
<td>RB/RB</td>
</tr>
<tr>
<td></td>
<td>Medium</td>
<td>LB/LB</td>
<td>RS/CT</td>
<td>RB/RB</td>
</tr>
<tr>
<td></td>
<td>Long</td>
<td>LS/LB</td>
<td>RS/CT</td>
<td>RS/RB</td>
</tr>
<tr>
<td>Right</td>
<td>Short</td>
<td>LB/LB</td>
<td>LB/CT</td>
<td>LB/RB</td>
</tr>
<tr>
<td></td>
<td>Medium</td>
<td>LS/LB</td>
<td>LS/CT</td>
<td>LS/RB</td>
</tr>
<tr>
<td></td>
<td>Long</td>
<td>LS/LB</td>
<td>LS/CT</td>
<td>X/RB</td>
</tr>
</tbody>
</table>

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