Obstacle Detection Using Fuzzy Integral-Based Gaze Control for Mobile Robot

Seung-Beom Han, Jeong-Ki Yoo, and Jong-Hwan Kim

Abstract Obstacle detection is one of key issues in robotics because robots should avoid obstacles not to collide with or use them to obtain some information in the environment. Decision making for a proper gaze direction to get more information is also an important issue when there are many obstacles, in particular, dynamic obstacles. To deal with these issues, this paper proposes fuzzy integral-based gaze control for obstacle detection of mobile robots. The fuzzy measures are calculated with the preference degree for five criteria about obstacle detection and the fuzzy integral decides a final gaze direction using the fuzzy measure values and partial evaluation values with respect to the five criteria. Computer simulation demonstrates the effectiveness of the proposed algorithm.

Key words: Obstacle detection, fuzzy integral, gaze control.

1 Introduction

Obstacle detection is one of important issues for mobile robots. It influences obstacle avoidance, path planning, map building and so on. There are many researches on obstacle detection for mobile robots [1, 2] and visually impaired people [3, 4, 5]. Gaze control is usually researched for giving an attention to a specific object in robotics [6, 7]. It is also used to get more useful information with a limited number of sensors in an environment while navigating [8, 9, 10]. Researches on multi-criteria decision making have been carried out considering user's preference and relationships among criteria using λ-fuzzy measure and Choquet fuzzy integral [11, 12, 13]. The Choquet fuzzy integral could be used in gaze control.

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This paper proposes fuzzy integral-based gaze control for mobile robots to detect obstacles and to explore widely and efficiently in a dynamic environment. λ-fuzzy measure is employed to denote the preference degree for five criteria about obstacle detection. The final gaze direction is decided by the Choquet fuzzy integral using the fuzzy measure values and partial evaluation values with respect to the five criteria.

This paper is organized as follows. Section 2 presents the fuzzy measure and the fuzzy integral. In Section 3, fuzzy integral-based gaze control of mobile robots for obstacle detection is proposed. Computer simulation and results are presented in Section 4. Finally, conclusion and future works follow in Section 5.

2 Fuzzy Measure and Fuzzy Integral

The fuzzy integral is one of multi-criteria decision making methods. The correlation between criteria is calculated by the fuzzy measure. And then, the global evaluation of candidates are calculated by the fuzzy integral using the fuzzy measure values and partial evaluation values with respect to criteria.

To compute the fuzzy measure, weights of criteria are calculated using diamond pairwise comparison diagram shown as Fig. 1 [13]. The shapley value of the fuzzy

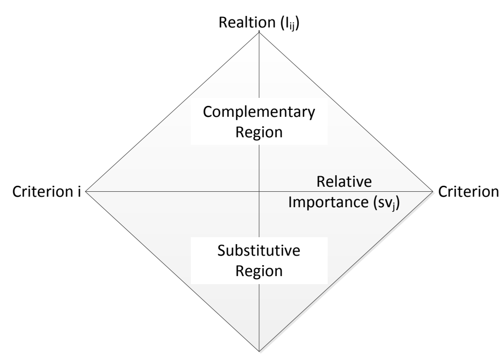

Fig. 1 Diamond pairwise comparison diagram

measure g, sv_i and sv_j, for the lateral axis in diamond pairwise comparison diagram is defined as

$$\begin{aligned} sv_i &= \{\mathrm{g}(\{C_i\}) + \mathrm{g}(\{C_i, C_j\}) - \mathrm{g}(\{C_j\})\}/2 \\ sv_j &= \{\mathrm{g}(\{C_j\}) + \mathrm{g}(\{C_i, C_j\}) - \mathrm{g}(\{C_i\})\}/2, \end{aligned} \tag{1}$$

where C_i and C_j are criteria, and i and j are the index of criteria.

Weights of criteria w_i are identified by eigenvalue of the ordinal AHP's pairwise comparison matrix. The ordinal AHP's pairwise comparison matrix is defined as

$$C = \begin{pmatrix} c_{11} & \cdots & c_{1n} \\ \vdots & \ddots & \vdots \\ c_{n1} & \cdots & c_{nn} \end{pmatrix}, \tag{2}$$

where $c_{ij} = sv_i/sv_j$, $c_{ii} = 1$, $c_{ji} = 1/c_{ij}$, and n is the number of criteria.

And the hierarchy diagram is estimated using agglomerative hierarchical clustering method. ϕ_s transformation is used to calculate the fuzzy measure efficiently as follows:

$$\phi_s : [0,1] \times [0,1] \to [0,1],$$
$$\phi_s(\xi,u) = \begin{cases} 1 & \text{if } \xi = 1 \text{ and } u{>}0 \\ 0 & \text{if } \xi = 0 \text{ and } u{=}0 \\ 1 & \text{if } \xi = 1 \text{ and } u{=}1 \\ 0 & \text{if } \xi = 0 \text{ and } u{<}1 \\ \frac{s^u-1}{s-1} & \text{other cases} \end{cases}, \tag{3}$$

where $s = \frac{(1-\xi)^2}{\xi^2}$, $u = \sum_{i\in A} \omega_i$. ω_i is the weight of criterion, and ξ is interaction degree.The fuzzy measure $\mathtt{g}$ is identified, as follows:

$$\mathtt{g}(X) = \phi_s(\xi_R, \sum_{P\subset R} u_P^R), \tag{4}$$

$$u_P^R = \begin{cases} w_i, \text{ where } i \in P & \text{if } |P| = 1 \text{ and } i \in X \\ 0 & \text{if } |P| = 1 \text{ and } i \notin X \\ \phi_s^{-1}(\xi_R, \phi_s(\xi_P, \sum_{V\subset L} u_V^P) \times T_P^R & \text{other cases} \end{cases}, \tag{5}$$

$$T_P^R = \frac{\phi_s(\xi_U, \sum_{i\in L} \omega_i)}{\phi_s(\xi_L, \sum_{i\in L} \omega_i)}, \tag{6}$$

where R is root level set and $\phi_s^{-1}(\xi,r)(\xi \in (0,1))$ is the inverse function of $\phi_s(\xi,r)$. U and L denote an upper level set and a lower level set in the hierarchy diagram, respectively.

Finally, Choquet fuzzy integral calculates the global evaluation of each candidate gaze direction using the fuzzy measure values and partial evaluation value, $\mathtt{h}$ [14].

$$\int_X \mathtt{h} \circ \mathtt{g} = \sum_{i=1}^{n} (\mathtt{g}(E_i) - \mathtt{g}(E_{i+1}))\mathtt{h}(x_i), \tag{7}$$

where $\mathtt{h}(x_1) \le \ldots \le \mathtt{h}(x_n)$, $E_i = \{x_i, x_{i+1}, \ldots, x_n\}$ and $\mathtt{h}(x_0) = 0$, for $x_i \in X$ and $i = 1, \ldots, n$.

3 Fuzzy Integral-Based Gaze Control for Obstacle Detection

Fuzzy integral-based gaze control of mobile robots for obstacle detection is processed as in as Fig. 2. Fuzzy measures are calculated from the user-defined preference. A mobile robot obtains obstacle information (distance, size, velocity and so on) through the sensor system. The candidate gaze directions are calculated by visibility check. Finally, Choquet fuzzy integral decides the gaze angle using the fuzzy measure values and partial evaluation values.

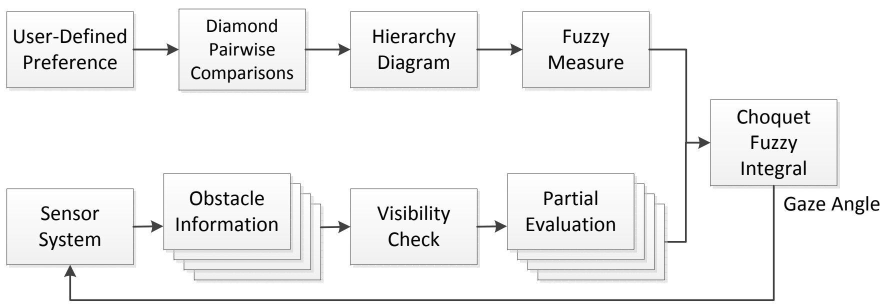

Fig. 2 Fuzzy integral-based gaze control for obstacle detection

3.1 Criteria for Obstacle Detection

In this paper, five criteria are proposed for obstacle detection: distance-based, size-based, velocity-based, uncertain area-based and localization-based criteria. A distance between the robot and the obstacle is an important factor for detection. The partial evaluation function for distance-based criterion C_d is defined as follows:

$$H_d = 1 - \frac{i_{sd}}{n_{obs}}, \tag{8}$$

where i_{sd} and n_{obs} denote the index of the sorted list into the close distance order and the number of obstacles, respectively.

Big size obstacles should be focused in detection. The partial evaluation function for size-based criterion C_s is defined as follows:

$$H_s = 1 - \frac{i_{ss}}{n_{obs}}, \tag{9}$$

where i_{ss} denotes the index of the sorted list into the big size order.

Fast dynamic obstacles should be observed closely in order to detect certainly. The partial evaluation function for velocity-based criterion C_v is defined as follows:

$$H_v = 1 - \frac{i_{sv}}{n_{obs}}, \tag{10}$$

where i_{sv} denotes the index of the sorted list into the fast velocity order.

Keeping gaze on only detected obstacles disturbs to explore environment. So the robot should look around to detect new obstacles. To obtain uncertain area, sample points locate the front of a robot. And sample points in gaze area change from uncertain points to certain points. The partial evaluation function for uncertain area-based criterion C_u is defined as follows:

$$H_u = \frac{n_{up}}{1+n_{sp}}, \tag{11}$$

where n_{up} and n_{sp} denote the number of uncertain sample points and the number of whole sample points, respectively.

The accurate position of the robot leads to obtain the accurate positions of obstacles. Because the robot calculates the positions of obstacles using the own position. Unscented Kalman filter-based SLAM (UKF-SLAM) is used to estimate the position of the robot [15]. The partial evaluation function for localization-based criterion C_l is defined as follows:

$$H_l = \frac{\sigma}{\tau}, \tag{12}$$

where σ and τ denote the magnitude of robot position components in the error covariance matrix which is computed by UKF-SLAM and a user-defined normalization factor, respectively.

3.2 *Weights of Criteria and Fuzzy Measure*

Shapley value of the fuzzy measure g, sv_i and sv_j, and the Murofush and Soneda's interaction index I_{ij} are obtained through Grabisch's graphical interpretation as shown in Fig. 3. The ordinal AHP's pairwise comparison matrix and weights are shown as Table 1. The identified fuzzy measures using the process explained Section 2 are provided in Table 2.

Table 1 Ordinal AHP's pairwise comparison matrix and weights

	C_d	C_s	C_v	C_u	C_l	w_i
C_d	1.0000	2.2030	1.4729	0.9863	0.9863	0.2406
C_s	0.4539	1.0000	0.6471	0.3669	0.5583	0.1092
C_v	0.6789	1.5455	1.0000	1.9828	1.3912	0.2449
C_u	1.0139	2.7253	0.5043	1.0000	0.9954	0.2073
C_l	1.0139	1.7910	0.7188	1.0046	1.0000	0.1980

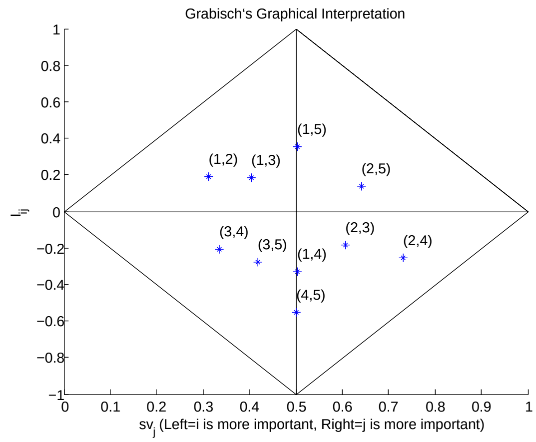

Fig. 3 User-defined diamond pairwise comparison diagram

Table 2 Identified fuzzy measures

A	g(A)	A	g(A)	A	g(A)	A	g(A)
$\{\emptyset\}$	0.000000	$\{4\}$	0.241472	$\{5\}$	0.231136	$\{4,5\}$	0.454150
$\{1\}$	0.278492	$\{1,4\}$	0.497724	$\{1,5\}$	0.488340	$\{1,4,5\}$	0.690813
$\{2\}$	0.129732	$\{2,3\}$	0.360844	$\{2,5\}$	0.350951	$\{2,4,5\}$	0.564397
$\{1,2\}$	0.396275	$\{1,2,4\}$	0.606101	$\{1,2,5\}$	0.597120	$\{1,2,4,5\}$	0.790906
$\{3\}$	0.283160	$\{3,4\}$	0.502019	$\{3,5\}$	0.492651	$\{3,4,5\}$	0.694780
$\{1,3\}$	0.535572	$\{1,3,4\}$	0.734273	$\{1,3,5\}$	0.725768	$\{1,3,4,5\}$	0.909281
$\{2,3\}$	0.400743	$\{2,3,4\}$	0.610212	$\{2,3,5\}$	0.601246	$\{2,3,4,5\}$	0.794703
$\{1,2,3\}$	0.642325	$\{1,2,3,4\}$	0.832502	$\{1,2,3,5\}$	0.824361	$\{1,2,3,4,5\}$	1.000000

where 1:C_d, 2:C_s, 3:C_v, 4:C_u, 5:C_l.

4 Simulation Environments and Results

In this simulation, there were a mobile robot, static obstacles, dynamic obstacles and one goal in an environment, as shown Fig. 4. The small red circle located (0,0) is the initial position of the mobile robot and big blue circles are obstacles. The size of the blue circle means the size of obstacle and the length of the blue line in the blue circle indicates the speed of the obstacle. The red hexagon is the goal point for the mobile robot to arrive at. The mobile robot assumed to have a RGB-D camera which can move to a desired pan/tilt angle. In Fig. 4, a red trapezoid denotes view area. The robot could obtain obstacle information (distance, size, velocity) only within the view area. The robot moved at a speed of 30.0 cm/s and the period of detection process was 100.0ms. The control noise of the mobile robot about the moving distance and angle is assumed Gaussian noise. Its mean was 5.0 cm/s, 1.0°. The observation noise from RGB-D camera about the distance and angle is also assumed Gaussian noise and its mean was 5.0 cm, 10.0°.

In this simulation, the proposed algorithm was applied 10 times to analyze results of obstacle detection. The average of root mean square error (RMSE) and standard deviations (STD) for the obstacle position error and the robot position error are

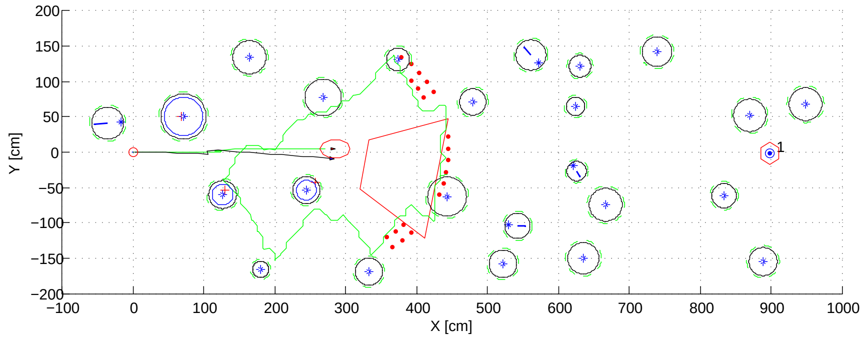

Fig. 4 Simulation environment

shown in Table 3. The obstacle position error was the distance between the detected obstacle position and the real obstacle position. The robot position error was the distance between the estimated robot position from UKF-SLAM and the real robot position.

Table 3 Simulation results

	RMSE (*cm*)	STD (*cm*)
Obstacles	20.3	16.1
Robot	14.8	12.3

Consequently, the obstacle position error and the robot position error were not big. If weights of criteria are optimized, the results with the smaller error can be obtained.

5 Conclusion

This paper proposed the fuzzy integral-based gaze control of mobile robots for obstacle detection. It makes a mobile robot explore widely and efficiently in a dynamic environment. For the effective detection, five criteria were proposed: distance-based, size-based, velocity-based, uncertain area-based and localization-based criteria. To calculate weights of criteria, diamond pairwise comparison diagram were used and then fuzzy measures were identified. The global evaluations of all the candidate gaze directions were calculated through the Choquet fuzzy integral using fuzzy measures and partial evaluation values. Computer simulation demonstrated the effectiveness of the proposed algorithm in obstacle detection.

Performance improvement should be needed. Real experiments with the mobile robot will be performed as a further work. Also, obstacle avoidance algorithms will be incorporated into the proposed obstacle detection algorithm for navigation in real environment.

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