Obstacle recognition of indoor blind guide robot based on improved D-S evidence theory

Dongqing Du¹,a, Jinyong Xu¹,b, Yan Wang¹,c*

¹School of Mechanical and Electrical Engineering, Guilin University of Electronic and Technology, Guilin, GuangXi, 541004, China

aemail: 19012201007@mails.guet.edu.cn, bemail: xujinyong62@163.com, cemail: yanwang@guet.edu.cn

Abstract. The ability to recognize obstacles with high accuracy is an important guarantee for the safe driving of indoor blind guide robots. In order to improve the accuracy of the indoor blind guide robot's recognition of obstacles, a sensor data fusion method based on D-S evidence theory of the genetic algorithm is proposed. The system uses ultrasonic sensors, infrared sensors, and lidar to collect environmental information. Under the premise of determining the weight range of various sensors, the genetic algorithm is used to optimize each weight and the optimized weight is substituted into D-S evidence theory for data fusion. In application, the determination of the weight of evidence is the key to weighting and fusion of evidence. Through the comparison of the two fusion results, under the same conditions, the method proposed in this paper has an accuracy of 0.94 for the obstacle recognition of the indoor guide robot, which is 33.0% higher than the result of unweighted fusion. The algorithm can also be used for obstacle detection in other systems.

1. Introduction

The indoor blind guide robot is a comprehensive control system that integrates multiple functions such as environment perception, positioning and navigation, and autonomous obstacle avoidance. In an unknown and complex indoor environment, the key to autonomous navigation for blind guide robots is to have good obstacle recognition capabilities. Many universities and research institutions at home and abroad are conducting research on the obstacle recognition of blind guide robots.

The detection and recognition of obstacles is mainly through various sensors. The sensors used are roughly divided into two categories, one is passive sensors, such as vision sensors, which obtain obstacle images through the camera and perform corresponding processing; the other is active sensors, namely ultrasonic sensors, infrared sensors, etc., which judge whether there is an obstacle ahead by the time difference between the transmitted signal and the received signal. The performance of different sensors is different, and the applicable occasions are also different. The visual sensor has a wide detection range and large amount of information, but it is easily affected by the external environment such as light; the lidar has strong detection direction, but the cost is high; the ultrasonic sensor has good environmental adaptability but poor directionality[1]. According to the characteristics of ultrasonic reflection intensity on different obstacles, foreign scholars Dvorak and others, the robot studied has a high ability to recognize obstacles in complex environments[2]. Al-Kaff and others detect the feature points of obstacles through a monocular camera, compare the area of the obstacle with the position of the robot, and detect whether the obstacle will cause a collision[3]. Domestic scholar Yu et al. used the method of combining the optical flow sensor and the improved Artificial potential field
method to realize the obstacle detection of the aircraft\cite{4}. However, when the robot is in a complex
environment, a single sensor has poor ability to detect obstacles, and the obtained sensor information
has a large error; multi-sensor information fusion technology greatly improves the robot's obstacle
recognition ability\cite{5}. Google Driverless Car’s fully autonomous vehicles are equipped with multiple
vision sensors and lidar sensors for obstacle recognition\cite{6}. Document 7 uses the combined Kalman
filter method to fuse the information from the vision sensor, ultrasonic sensor and infrared sensor, and
uses the fusion result as the obstacle detection result\cite{7}. As one of the most mature methods of
information fusion, D-S evidence theory has significant advantages in uncertainty reasoning\cite{8}. In
order to improve the accuracy of obstacle identification of indoor blind guide robots, an improved D-S
evidence theory based on the genetic algorithm is proposed to fuse the information collected by the
sensors.

2. Improve D-S evidence theory
The D-S evidence theory has significant advantages in the information fusion of the same type of
sensor, but in a multi-sensor system, due to the different credibility of different sensors, the direct
fusion of the data of various sensors will make the results inaccurate\cite{8}. Some studies have put forward
a weighted D-S evidence theory method, whose evidence assignment is based on expert experience
and adopts a fixed weight method\cite{9}. This method is highly subjective and easily leads to human
intervention in the fusion result, which makes the fusion result lose its objectivity. Therefore, we
propose the genetic algorithm based weight optimization method that combines expert experience,
which not only refers to expert opinions, but also ensures the objectivity of weights.

In this paper, the genetic algorithm is used to optimize the weight of evidence obtained by each
group of sensors, to find the optimal weight of each group of evidence, and then to fusion information.

The framework of improved D-S evidence theory based on the genetic algorithm is as follows: (1)
Producing a population. (2) Perform genetic operations to find the optimal weight within the range.
After reaching the number of iterations, the algorithm stops and finds the optimal weight. (3) The
optimal weights found are weighted according to the method of literature 9 to meet the requirements
of the D-S evidence theory combination rule for the same weight of evidence\cite{9}. (4) According to the
D-S evidence theory, the result of obstacle recognition is obtained.

The optimization problem is formulated as:

\[
\begin{align*}
& \text{min} : \quad - | \max \{ \min \{ m(T_0) - m(T_j) \} \} | \\
& \text{find} : \quad i \\
& \text{s.t.} : \quad i = 1, 2, \ldots, n - 1 \\
& m(T) = \begin{cases} \\
0 & T = \emptyset \\
\sum_{A_i \subseteq T_j = T} m_i^0(A_i) m_j^0(B_j) & \forall T \subset \theta, T \neq \emptyset \\
(1 - K) & \end{cases} \\
& K = \sum_{A_i \neq B_j = \emptyset} m_i^0(A_i) m_j^0(B_j) < 1 \\
& m(T_0) - m(T_j) > 0 \\
& 0 \leq t_i \leq 1, \sum_{i=1}^{n} t_i = 1, \quad t_i^{\min} \leq t_i \leq t_i^{\max}
\end{align*}
\]  

The above formula (1) is the objective function of the genetic algorithm. The purpose of evidence
fusion is to identify the target, that is, the difference between the combined basic probability
assignment of the identified target and other targets is the largest, so that the optimal weight found
makes the basic probability assignment \( m(T_0) \) get a maximum. In order to ensure that the maximum
value obtained is the optimal choice, the pessimistic principle is adopted when making uncertain
decisions. In the formula, \( n \) is the number of propositions, \( T_0 \) is the recognition target, and \( m(T) \) is the
composite basic probability assignment of other propositions.
The source of evidence provided by the sensor is $E_1, E_2, ..., E_n$.

The above formulas (2) (3) (4) (5) is the constraint condition of the genetic algorithm. The above formulas (2) (3) is the weighted expression of the basic probability assignment function in D-S evidence theory, used to fuse evidence $E_1$ and evidence $E_2$. Reference 9 explains in detail the conversion method of the basic probability assignment function after weighting.

The above formula (4) is a limitation of the basic probability distribution function obtained after optimizing the weights, and guarantees that the combined probability distribution assignment obtained by optimizing is larger than the probability distribution assignment of other propositions.

The above formula (5) is the limitation on the weight of evidence. In this formula, $\nu$ is the weight of each evidence, and $t^\text{max}_j$ and $t^\text{min}_j$ are the upper and lower limits of the weight range.

3. Multi-sensor obstacle recognition system

3.1. Multi-sensor combination

Most of information obtained by using a single sensor is limited, and it cannot accurately identify the indoor environment, and it has been unable to meet the requirements of obstacle recognition for the blind guide robot. The use of multiple sensors has greatly improved the robot's ability to obtain environmental information, and the accuracy of obstacle recognition has also been improved. In this paper, ultrasonic sensors, infrared sensors and lidar are used to fuse the collected data, so as to realize the obstacle recognition of the blind guide robot in the indoor environment.

Ultrasonic sensors have high frequencies, short wavelengths, and good directivity. They have great advantages in low-speed and short-distance measurements; however, ultrasonic sensors have low measurement accuracy and are easily affected by noise. The cost of infrared sensor is relatively low, but the accuracy is not high, it is easily affected by light, and the error when used alone is relatively large. Lidar has high detection accuracy, but has a long response time. Combining the advantages of the three sensors, through multi-sensor information fusion, the recognition method can have the advantages of wide spatial coverage, long time coverage, and high reliability.

3.2. Sensor layout

The research object is a blind guide robot whose mechanical body is a four-wheel drive car. Due to the unique working nature of the ultrasonic sensor and the infrared sensor, it can only judge whether there are obstacles in front of the sensor. In order to realize the obstacle recognition of various directions of the indoor guide robot, we install the ultrasonic sensor and the infrared sensor in the front of the guide robot. On the left and right sides, the obstacles on the left and right and in front of the blind guide robot are detected respectively; the lidar is installed on the top of the body of the blind guide robot for auxiliary detection.

4. Application of D-S Evidence in Obstacle Recognition of Indoor Guide Robot

4.1. Application of Unweighted D-S Evidence Theory

Under ideal circumstances, the sensor can detect whether there are obstacles in the surrounding environment, but the actual situation is more complicated, and the control chip may not be able to accurately obtain the information of each sensor, such as: the sensor transmitting device fails; the sensor receiving device fails; the signals of each sensor interfere with each other; the ranging sensor receives a clear signal, but the transmission is wrong. In order to make the signal more reliable, we sample two cycles of the signal for data fusion of D-S evidence theory. The existence recognition framework is \{obstacle (A), barrier-free (B), uncertain (C)\}.

The basic probability assignment of the two-period measurement data is shown in Table 1.
Table 1 Two-period measurement evidence of three types of sensors and their probability assignment table

| Identification framework | Ultrasonic sensor | Infrared sensor | Lidar sensor |
|--------------------------|-------------------|----------------|-------------|
| First cycle              | A     | 0.550 | 0.350 | 0.100 | A     | 0.380 | 0.400 | 0.220 | A     | 0.600 | 0.300 | 0.100 |
| Second cycle             | B     | 0.450 | 0.400 | 0.150 | B     | 0.350 | 0.350 | 0.300 | B     | 0.520 | 0.380 | 0.100 |

The fusion process is the single-source time-domain fusion first, and then the multi-source airspace fusion as the Figure 1 shows.

In the figure: \( m_{ij} \) is the basic probability assignment of the \( j \)-th period of the \( i \)-th sensor (\( i=1,2,3; j=1,2 \)); \( m_i \) is the basic probability assignment of the \( i \)-th sensor after two-period time domain fusion (\( i=1,2 \)); \( m \) is the basic probability assignment of spatial fusion after three types of sensors time domain fusion.

Figure 1 Two-period temporal and spatial fusion of three types of sensors

Table 2 Time domain fusion probability assignment table of three types of sensors

| Identification framework | Ultrasonic sensor | Infrared sensor | Lidar sensor |
|--------------------------|-------------------|----------------|-------------|
| A                        | 0.610             | 0.390          | 0.710       |
| B                        | 0.350             | 0.410          | 0.260       |
| C                        | 0.040             | 0.200          | 0.030       |

Table 3 Assignment table of spatial fusion probability after time domain fusion of three types of sensors

| Identification framework | A     | B     | C     |
|--------------------------|-------|-------|-------|
| Fusion result            | 0.630 | 0.260 | 0.110 |

4.2. Application of D-S Evidence Theory Based on Improved Genetic Algorithm

The method based on the genetic algorithm to improve D-S evidence theory is verified.

According to expert experience obtained from the failure rate of various sensors, the weight range assigned to ultrasonic sensors is (0.4, 0.65), and the weight range assigned to infrared sensors is (0.08, 0.20), and the weight assigned to lidar The value range is (0.25, 0.45).

Using the genetic algorithm, the optimal weights are found within the weight range, which are 0.5559, 0.3140, and 0.1301 respectively.

Substituting the data in Table 2 into the improved D-S evidence theory based on the genetic algorithm for fusion, the fusion results obtained are shown in Table 4.

Table 4 Optimized weighted fusion results

| sensor           | Weigh of evidence | A     | B     | C     |
|------------------|-------------------|-------|-------|-------|
| Ultrasonic sensor| 1                 | 0.610 | 0.350 | 0.040 |
| Infrared sensor  | 0.234             | 0.820 | 0.100 | 0.078 |
| Lidar sensor     | 0.565             | 0.830 | 0.150 | 0.020 |
| Fusion result    |                   | 0.940 | 0.060 | 0     |
Comparing the evidence fusion results without weights in Table 3 and the evidence fusion results with optimized weights in Table 4, the evidence fusion results with optimized weights can more clearly identify the target, and verify the effectiveness of the algorithm, at the same time, the accuracy of the indoor blind guide robot to identify surrounding obstacles is improved, making the blind travel safer.

5. Conclusions
This paper proposes a method based on the genetic algorithm to improve the D-S evidence theory, which improves the accuracy of obstacle recognition of indoor blind guide robots. By fusing the information of ultrasonic sensor, infrared sensor and lidar, the genetic algorithm is used to optimize the weight range of expert experience, and an optimal weight is obtained, which is substituted into D-S evidence theory for data fusion. Numerical experiments show that the fusion result obtained by this algorithm possesses a higher obstacle recognition rate. The recognition rate of obstacles is 0.94. The recognition rate is 33.0% higher than that of the fusion result without weights, which improves the recognition rate of obstacles and safety when the blind guide robot works in a complex indoor environment.

Acknowledgements
This research was financially supported by Guilin Science and Technology Plan Project (20190211-14); Innovation Project of GUET Graduate Education (2018GCZX009).

References
[1] Zhai Guangyao. Obstacle Detection of Tram Based on Information Fusion of Millimeter Wave Radar and Machine Vision[D]. Soochow University, 2018.
[2] Dvorak J S, Stone M L, Self K P. Object detection for agricultural and construction environments using an ultrasonic sensor[J]. Journal of Agricultural Safety & Health, 2016, 22(2): 107-119.
[3] Al-Kaff A, Garcia F, Martin D, et al. Obstacle detection and avoidance system based on monocular camera and size expansion algorithm for UAVs [J]. Sensors, 2017, 17(5): 1061.
[4] Yu Chaofan, Sun Jianhui. A Real-time obstacle avoidance system for multi-rotor unmanned aerial vehicle based on optical flow sensor[J]. Computer Applications and Software, 2018, 35(01): 206-210.
[5] Ning Jiangkun. Research on the Obstacle Avoidance Control Algorithm for Autonomous vehicles [D]. Xi'an Technological University, 2016.
[6] Poczter S L, Jankovic L M. The Google Car: driving toward a better future [J]. Journal of Business Case Studies (Online), 2014, 10(1): 7.
[7] Wang Zhongli, Niu Ying. Obstacle detection of robot based on multi-sensor information fusion [J]. China Test, 2017, 43(08): 80-85.
[8] Miao Yanzi, et al. D-S evidence theory fusion technology and its application [M]. Beijing: Electronic Industry Press, 2013.
[9] Liu Haiyan, Zhao Zonggui, Ba Hongxin. Multisensor target identification method based on weight evidence combination[J]. Journal of PLA University of Science and Technology (Natural Science Edition), 2005(06): 521-524.