Ultrasound Environment Classification Based on Fuzzy Model

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Abstract. The fuzzy model based on the centreline ultrasound signal is pro-posed to solve the poor orientation of ultrasonic sensors in the environment modelling in this paper. The locations of ultrasonic arc feature points were extracted and distinguished. For the problem of poor resolution of split type ultrasonic sensors, fuzzy algorithm is applied to identify the obstacle such as line, corner, or arc structure. Ultrasound environment map based on fuzzy is constructed and the maximum distance and angle deviation is 1.2cm and 3°, showing that the accuracy of obstacle classification based on ultrasound and Fuzzy is improved.

1. Introduction

Because most of the environments that robots face cannot be known in advance, autonomous identification of the environment and mapping is necessary. The environmental modeling based on ultrasonic signal has broad application prospect in indoor service robot since ultrasonic sensor is the earliest development sensor with mature technology and has the advantages of the high precision of small range measurement, no harm to human body, low cost of transforming products, etc.

Research of ultrasonic environment modeling can be divided into three aspects, as grid map[1,2], topological map[3] and geometric feature map[4].To form the geometric feature map, features such as straight lines, corner, and arcs from environments is extracted and combined. The main algorithms of feature extraction include Range of Constant Depth Method(RCD)[5], Arc-Transversal Median(ATM) and Triangulation-Based Fusion (TBF). Many ultrasonic environment modeling in the form of feature maps have emerged in recent years, because the geometric feature map not only has the ability to accurately acquire the necessary information for positioning, but also has a low storage space occupancy rate[6,7]. Heinen[8] used Gaussian mixture model to represent the surrounding environment and proposed a new feature environment map algorithm which has the advantages of small memory usage and high processing speed avoiding the discrete error in fast calculation. Hesham Ismail and Balakumar Balachandran[9] applied revolving measurement data with double ultrasonic sensor and proposed a fusion algorithm of environment feature extraction. The circular arc feature extraction algorithm was combined with the Hough transform-based TBF algorithm and advantages of those algorithms were fully developed. SJ Lee[10] proposed a new ultrasonic feature structure, which uses an ultrasonic data correlation method to extract circular sets of convex corner of objects. The integrated circle center of each set is used as a EKF-SLAM roadmap. The above method can realize the discrimination of angles and arcs, thus the problem of complex indoor environment modeling was solved.

In this paper, by analyzing the geometric features of revolving platform scanning, a fuzzy algorithm is proposed to extract and classify ultrasonic signals. Finally, the environmental modeling based on revolving ultrasonic signals is realized.

2. Experiment Measurement Based On Ultrasound

In experiment, the ultrasonic signal is collected by a four array ultrasonic sensors, fixed in a rotary motor. Figure 1 shows the experiment measurement platform. The typical distance data of the obstacles is shown in figure 2.
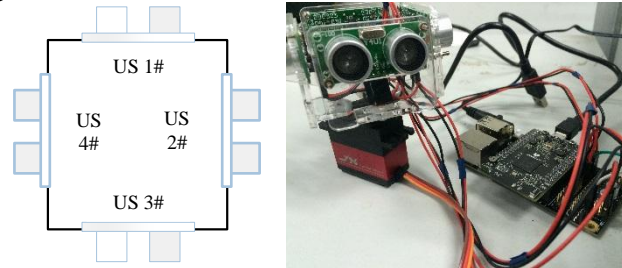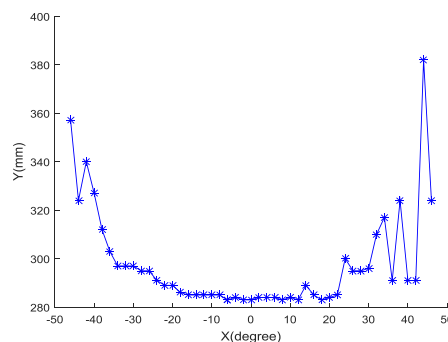
Figure 1. Experiment measurement

Figure 2. Typical distance data of the obstacles

3. Fuzzy model and application

In actual conditions, the ultrasonic arc fluctuates greatly, and it is difficult to distinguish the source of different feature points. To solve the above problem, a fuzzy algorithm was proposed. The advantage of fuzzy theory is to reduce the data accuracy requirements, and data classification can be achieved through the probability distribution of data and the correlation between data features. As shown in figure 3, the principle of fuzzy algorithm is that by fuzzing the width of ultrasonic arc and fuzzy reasoning with the boundary state of ultrasonic arc and processing it with defuzzification module, the type of geometric feature that can be recognized by computer is obtained finally. The ultrasonic arc width membership can be expressed and the graph is shown in figure 4.
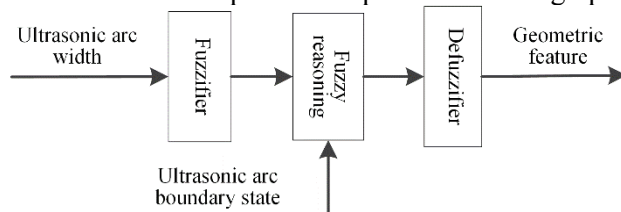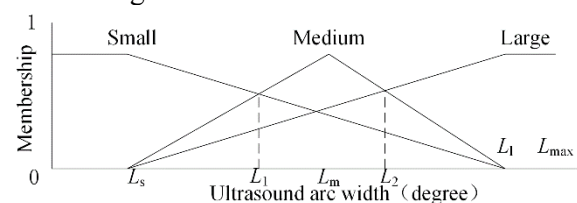
Figure 3. Principle and process of fuzzy model   **Figure 4.** Membership of ultrasound arc width

3.1. Language Conversion

3.1.1.Ultrasonic arc width. According to the ultrasonic arc model, the arc width of the ultrasound is related to the geometric features. In combination with the actual measurement of the ultrasonic sensor, generally, the surface has a maximum arc width, and the arc width of the cylindrical surface is reduced

accordingly. The effective arc of convex corner and the concave corner width is the smallest because of the poor recognition ability. The width of the ultrasonic arc can be expressed in table 1.

Table 1. Numerical form of ultrasonic arc width fuzzy state

State	Small	Medium	Large
Value	0	1	2

(2) Boundary of ultrasound arc

The boundary reflects whether the ends of arc are shielded by other ultrasonic arcs. The blocked ultrasonic arc will reduce part of the arc length, thus affecting the judgment of the arc state. The boundary is shown in table 2.

Table 2. Numerical form of boundary states

State	Unobstructed	Left front	Right front	Front
Value	0	1	2	3

(3)Geometric Features

As shown in table 3, geometric features classified include angle, cylinder, plane with value of 0~2.

Table 3. Numerical form of geometric features

State	Corner	Cylinder	Plane
Value	0	1	2

3.2. Data Fuzzification

In order to fuzzify the ultrasonic arc width, it is divided into three categories: large, medium, and small. Three categories of maximum membership threshold corresponding to arc width are set. The critical arc width of different categories is related to the maximum width of the ultrasonic arc.

3.3. Reasoning and defuzzification

3.3.1. Reasoning. The boundary states as the influencing factor of the ultrasonic arc width play a key role in the judgment of geometric features in fuzzy reasoning. A boundary state of 0 means that it is not occluded, a boundary state of 1, 2 means that one side is occluded, and a boundary state of 3 means that both sides are occluded. For each fuzzy arc width, the system has a boundary state corresponding to it. Different boundary states will redefine the types of membership in the current arc width. The reasoning process is as follows. When the arc width is 0, the membership of small width type drops by 0.25 and the membership degree in the rises by 0.25 if the boundary condition is 1, 2. The small membership degree decreases by 0.3 and the large membership degree increases by 0.3 if the boundary condition is 3.When the arc width is 1, the membership degree of medium width type decreases by 0.2 and the large one increases by 0.2 if the boundary condition is 1, 2. The membership of medium decreases by 0.3, and the large membership degree increases by 0.3 if the boundary condition is 3.

*3.3.2. Defuzzification.*When the maximum membership degree is μ_0, the ultrasonic arc comes from the angular feature and the output of the system is 0; when the maximum membership degree is μ_1, the ultrasonic arc comes from the cylindrical feature and the output of the system is 1; when the maximum membership degree is μ_2, the ultrasonic arc comes from the plane feature, and the output of the system is 2.

4. Environment classification with fuzzy algorithm

For the classification of the environmental obstacles, the feature of lines, arcs, and angles need to be identified. After the multi-position measurement data were obtained, the interference is eliminated by preprocessing data points, and the ultrasonic arc clustering with different characteristics is carried out.

4.1. Ultrasound collection and data preprocess
Figure 5 is the schematic diagram of the indoor environment used for modeling in this experiment. There is a cylinder with a radius of 37 mm as an obstacle to detect the ability of the arc modeling.

In experiment, a total of 10 locations were scanned and the data was visualized in the MATLAB. As shown in figure 6, the red circle represents the measurement position of rotating platform, and dotted line represents the platform movement trajectory. The figure shows a large number of discrete points around the distribution environment, due to the poor ability of the sensor to identify the concave corner. The ultrasonic arc representing the concave corner feature is not located in the actual concave position, but in the direction of the concave corner in the form of discrete or small arcs.

In order to reduce the influence of the interference points on the ultrasound arc clustering, the data needs to be filtered. The similar distance points that one's number less than 4 are selected and cleared as the interference point. The removal result is shown in figure 7. It can be seen that the discrete points are cleared and the ultrasonic arcs representing the line features and arc features are displayed clearly.
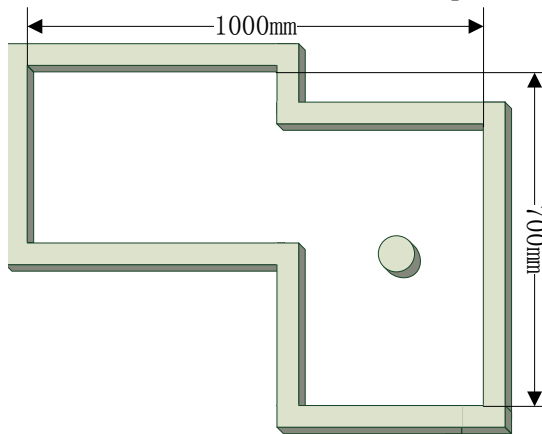

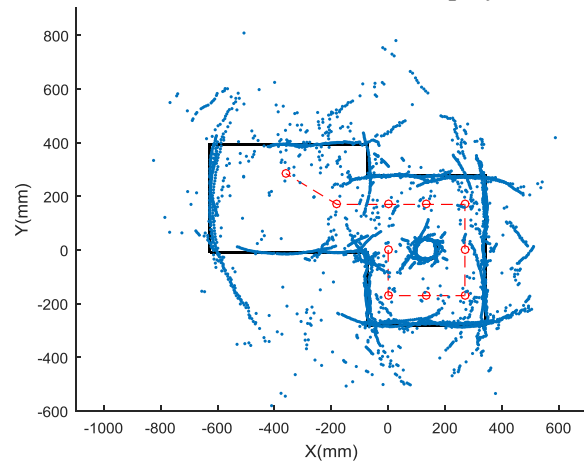**Figure 5.** Schematic diagram of the indoor environment

Figure 6. Result of multi-position ultrasound scanning

4.2. Fuzzy feature point acquisition
In experiment, we need to collect many environmental features such as plane, cylinder, convex corner, and use fuzzy algorithm to extract and classify feature points. Firstly, the preprocessed data points are clustered according to the differential distance clustering method. Since there is no interference from outliers, the width of most ultrasonic arcs is regularly distributed according to the source of the features. The width of the plane is the widest, the cylinder is the second, and the angle is the shortest. After clustering, the least squares polynomial fitting is to extract the minimum distance and the result is shown in figure 8.

The clustered ultrasonic arc width and the boundary state are the input of fuzzy classification algorithm, and classified line features, arc features and corner features are the output. The result of fuzzy classification is shown in figure 9.

Data associations are set for the line feature points, arc feature points, and corner feature points related to geometric features. The data association classifies feature points in units of lines, arcs, and points by the geometric association of multi-position features. In experiment, 8 straight line feature point sets, 1 arc feature point set and 1 corner feature point set were formed by classification. Since the corner feature points in the figure that correspond to the secondary measurement intersections are only located at the lower convex corner, the remaining locations do not meet the requirements to be cleared,

so there is only one corner feature point set. In addition, the unmatched data in the fuzzy classification is rematched, achieving 100% matching rate in experiment.

4.3. Construction of multi-feature map

The straight-line fitting method is used to process the set of straight line feature points at each position. 8 straight lines are generated, and the intersections between the straight lines are calculated. Least squares curve fitting is performed on the arc feature point set to generate an arc. The nearest point of intersection of the two ends of the line is taken as the position of the optimal corner feature which serves as the two endpoints of the line. Finally, a complete environment map as shown in figure 10 is generated.
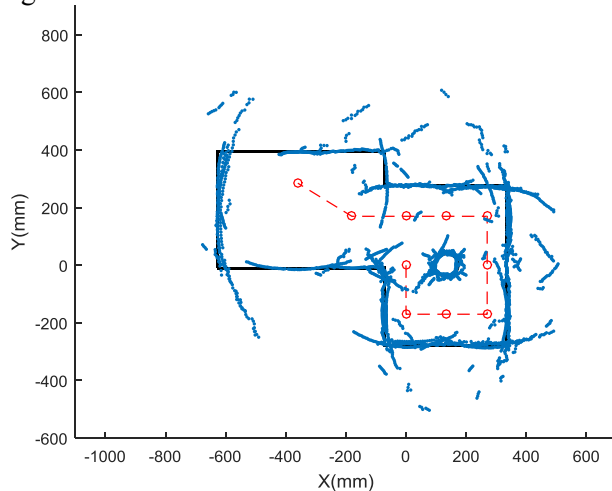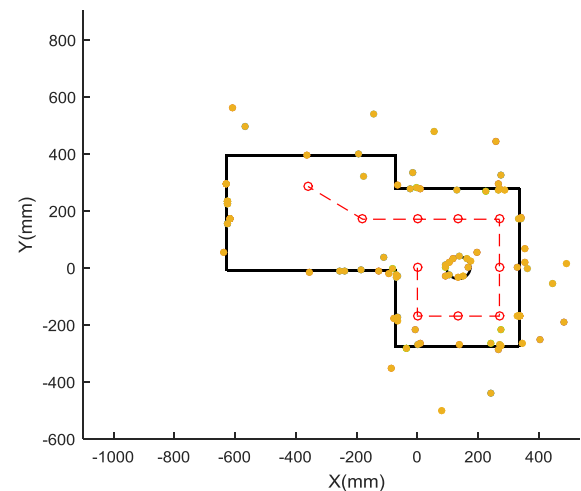

Figure 7. Result after data preprocessing

Figure 8. Result of distance minimum point extraction
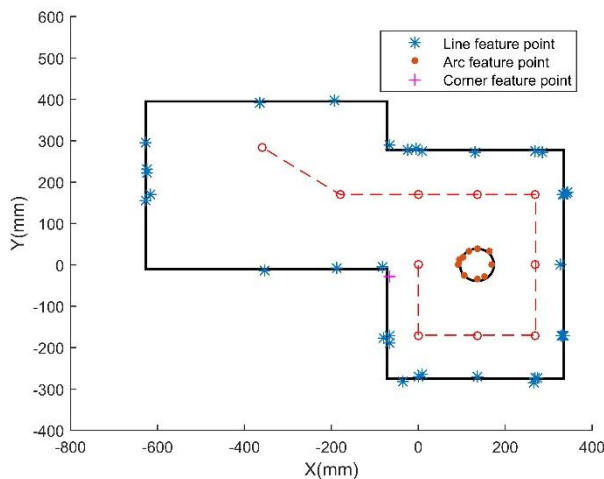

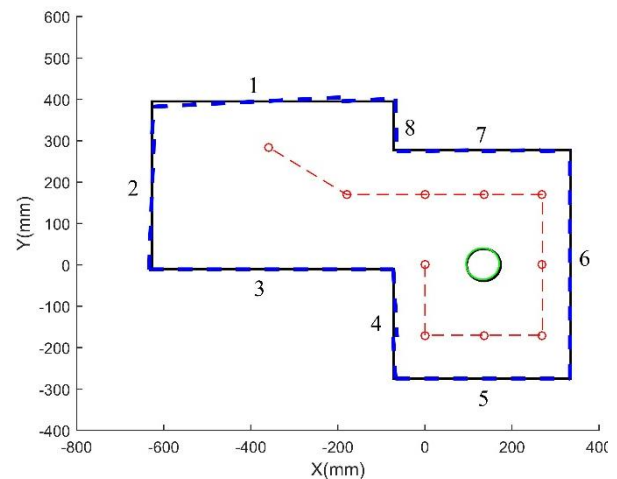**Figure 9.** Classification result of fuzzy

Figure 10. Constructed environment map

By comparing the original boundary with the boundary generated by the fuzzy algorithm, the maximum distance deviation and the angle deviation can be obtained, as shown in table 4. We can see in the farthest measurement distance 1000mm range, the distance deviation of the 1st boundary is the largest, reaching 12.8 mm, and the angle deviation is 3°; the 5th boundary has the smallest distance deviation, only 0.5 mm, and angle deviation is 0°. Because there is only one feature point in the 8th boundary, data association cannot be performed after fuzzy classification. In this case, the distance deviation is 7 mm and the angle deviation is 1°. Therefore, fuzzy algorithm can realize complex map construction with high accuracy and multiple features in the case of split revolving ultrasonic scanning.

Table 4. Deviation result

Boundary index	Maximum distance deviation(mm)	Angle deviation(°)
1	12.8	3
2	6.7	2
3	1.0	0
4	7.8	3
5	0.5	0
6	1.8	0
7	3.8	1
8	7.0	1

5. Conclusion

In this paper, the feature extraction algorithm via ultrasound sensor is proposed. This method solves the problem of feature point location error and feature matching error. A fuzzy extraction algorithm is proposed to solve the problem that the feature location error because of the low resolution and large fluctuation of measurement for ultrasonic sensor. Compared with the physical map, the maximum distance deviation constructed by the ultrasound signal is 1.2 cm and the maximum angle deviation is 3 °, so the accuracy of the fuzzy algorithm is improved to meet with requirements of environmental modeling.

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