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AGV Decision Making Subsystem Based on Modified Dempster-Shafer Evidence Theory and Fuzzy Logic

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***Abstract*—The AGV decision making subsystem directly affects the performance of the vehicle. The information it uses can be classified into "Objective Information" and "Subjective Information" two major groups. To fuse these two kinds of information, we propose a novel framework for decision in this paper. In the framework, an effective method based on the modified Dempster-Shafer evidence theory was used to make the fusion of the objective and subjective information. In addition, we used fuzzy logic to quantify the subjective information. The experiment shows the proposed method can solve the vagueness and uncertainty of information and achieve decision exactly and credibly.**

I. INTRODUCTION

Intelligent Vehicle acquires multisensory data to sense the environment and is a combination of environmental awareness, decision making and multiclass driver assistance [1, 2]. The decision making subsystem directly affects the performance of Autonomous Ground Vehicle (AGV). In AGV system, the information for decision can be classified into two major groups: "Objective Information" and "Subjective Information". The classification is mainly based on the fact that whether the prior information of human is needed. Therefore, the data we acquire through the sensors built in the vehicles is the objective information. The experience of experts and the knowledge related to the task is considered to be the subjective information. Generally, based rules or decision tree would be established to make the decision based on the fusion of objective information irrespective of the subjective information. However we think the subjective information is also useful to make the final decision.

The objective information from various sensors is usually imperfect, disparate and even inconsistent. There are many ways to make the data fusion and the dominating two are the Bayesian method and the Dempster-Shafer method [3]. Unlike the Bayesian inference, the Dempster-Shafer theory allows each source to contribute information in different levels of detail [3, 4]. The evidence theory is one of these method fusion has similar reasoning logic with human. D-S theory has become a promising and popular approach to data fusion especially in the last few years. In our experiment we used modified evidence theory to fuse the data and overcome the problem in fusing conflicting data by the classical D-S theory[5-9]. For the subjective information, the main problem is the quantification of vague language information. In this paper, we used fuzzy logic to quantify the vague information. Provided people's feeling can be adopted as a kind of instrumentation [10], we use the modified evidence approach to fuse the objective information and the subjective information finally.

The rest of this paper is organized as follows: in Section II, the classical evidential belief reasoning, the modified evidence theory and the fuzzy logic are discussed. Section III provides the description of our decision making system. In Section IV, the details of the experiment as well as the results analysis are provided. Finally, Section V presents the concluding remarks for this paper.

II. BASIC THEORY OF EVIDENCE THEORY AND FUZZY LOGIC

A. Classical Dempster-Shafer Evidence Theory

The theory of belief functions initiated from Dempster's work and was then mathematically formalized by Shafer toward a general theory of reasoning based on evidence[11, 12]. Dempster-Shafer evidence theory defines the frame of discernment which represents all possible states of a system and is a set of hypotheses Θ defined as follows:

$$\Theta = \{A_1, A_2, \cdots, A_n\} \tag{1}$$

The power set 2^Θ represents the set of all possible subsets of Θ and the definition is shown as follows:

$$2^\Theta = \begin{Bmatrix} \varnothing, \{A_1\}, \{A_2\}, \cdots, \{A_n\}, \{A_1 \cup A_2\}, \\ \{A_1 \cup A_3\}, \cdots, \Theta \end{Bmatrix} \tag{2}$$

Dempster-Shafer evidence theory defines the basic probability mass to represent the confidence of the evidence. The mass can be formalized as a function as follows:

$$m : 2^\Theta \to [0,1] \tag{3}$$

The function has two properties:

$$\begin{aligned} &1.m(\varnothing) = 0 \\ &2.\sum_{X \in 2^\Theta} m(X) = 1 \end{aligned} \tag{4}$$

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Using m , belief function and plausibility function are defined respectively:

$$Bel_j(A)=\sum_{B\subseteq A} m_j(B) \quad \text{and} \quad Pl_j(A)=\sum_{A\cap B\neq\varnothing} m_j(B) \tag{5}$$

We usually use the Dempster's rule of combination to fuse evidence from sensors. It combines the multiple masses in the following manner:

$$\begin{aligned} & m(A)=m_1\oplus m_2\oplus\cdots m_n(A)= \\ & \sum_{A_1\cap A_2\cap\cdots A_n=A}\prod_{i=1}^{n} m_i(A_i) \\ & m(\varnothing)=m_1\oplus m_2\oplus\cdots m_n(\varnothing)=0 \\ & k=\sum_{A_1\cap A_2\cap\cdots A_n=\varnothing}\prod_{i=1}^{n} m_i(A_i),k\neq 1 \end{aligned} \tag{6}$$

B. *Modified Evidential Belief Reasoning*

In general, classical evidence theory performs well while dealing with data sources without conflicting information. Otherwise, the result will be obviously unreasonable. This kind of modified method preprocesses the data source before applying the Dempster's rule of combination. In classical method, all the data sources are considered to be with the identical importance. The main idea of the modified approach is that the importance of evidence may be different. We can define the weight of each piece of evidence based on the distance of the evidence [13-15].

Mathematically, consider w to represent the weight of evidence. We call the evidence with the highest reliability the primary evidence and the rest evidence the secondary evidence [16]. The weight of the primary evidence is 1. We assign the weight of the secondary evidence based on the reliability relative to the primary evidence. The reliability of the evidence derived from the expert advice and the analysis of the sensor performance. Consider the frame of discernment $\Theta=\{A_1,A_2,\cdots,A_n\}$. The number of sources of information is k and the belief function is $m_i(i=1,\cdots,k)$ respectively. Suppose the evidence v is the primary evidence with the reliability R_v and the secondary evidence R_i . The weight w_i of the evidence i is derived from R_v and R_i :

$$w_i=\frac{R_i}{R_v}\left(0\leq w_i\leq 1,i=1,2,\cdots,k\right) \tag{7}$$

The weighted mass of the evidence i is:

$$\begin{aligned} & m'(A_i)=w_i m(A_i) \\ & m'(\Theta)=w_i m(\Theta)+(1-w_i) \end{aligned} \tag{8}$$

C. *Fuzzy Logic*

Fuzzy set theory proposed by Zadeh [17, 18] in 1965 is a kind of theoretical reasoning scheme for dealing with imperfect data [3]. The foundation of fuzzy logic is natural language which can help us to make full use of expert information [10]. Mathematically speaking, consider F to represent a fuzzy set in the domain of discourse U . The fuzzy set F can be defined by the membership function as follows:

$$\mu_F(x)\in[0,1],\forall x\in U \tag{9}$$

Therefore vague or partial sensory data can be fuzzified by using a gradual membership function. There are many ways to generate the membership function [19], such as dual contrast compositor method, statistical testing method and intuitive approach. Fuzzy dual contrast compositor method[20] is a practical way to generate the membership function. Consider $f_y(x)$ to respect the relative membership degree of x while taking y as the standard and $f_x(y)$ to respect the membership degree of y while taking x as the standard. The assignment of $f_y(x)$ and $f_x(y)$ need to follow the Table I below:

TABLE I. ASSIGNMENT OF THE RELATIVE MEMBERSHIP DEGREE

Membership Degree of x Compared to y	$f_y(x)$	$f_x(y)$
Same	1	1
Slightly Bigger	1	3
Significantly Bigger	1	5
Prominent Bigger	1	7
Absolutely Bigger	1	9
Between Two Neighboring Judgments	1	2,4,6 or 8

Relative priority degree matrix G can be constructed to calculate the membership degree. The matrix G is defined as follows:

$$G=\begin{bmatrix} f(x/x) & f(x/y) & f(x/z) & \cdots \\ f(y/x) & f(y/y) & f(y/z) & \cdots \\ f(z/x) & f(z/y) & f(z/z) & \cdots \\ \vdots & \vdots & \vdots & \vdots \end{bmatrix} \tag{10}$$

Where $f(x/y)$ represents the relative priority degree and is given by:

$$f(x/y)=\frac{f_y(x)}{\max\{f_x(y),f_y(x)\}},\forall x,y\in U \tag{11}$$

The membership degree of x is minimum value of each line in matrix G and is computed as follows:

$$f\left(x/X\right)=\min_{y\in U}\left\{f\left(x/y\right)\right\},\forall x\in U \tag{12}$$

III. AGV DECISION MAKING SUBSYSTEM

Multisensory data is needed for AGV to build the environment perception system [21, 22]. After the data acquisition, we control the actions of AGV through the decision system. Our work is an endeavor to investigate the data fusion and the decision making task. The framework of the overall autonomous vehicle is shown in Fig. 1. The decision making subsystem synthesizes the information from different sources including the subjective information.

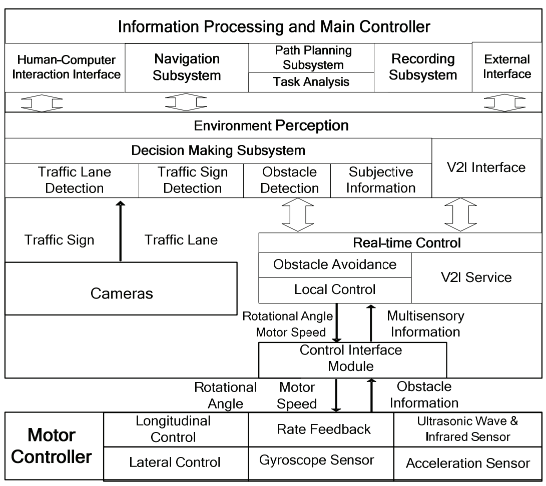

Figure 1. Framework of the overall autonomous vehicle.

A. Framework of Decision System

The framework of the overall decision system is shown in Fig. 2.

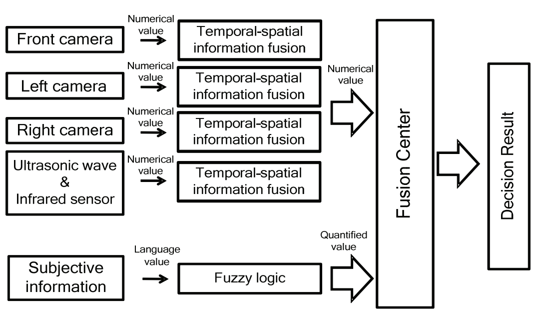

Figure 2. Framework of the decision system.

The framework of the decision system can be divided into three parts: the objective information processing, the subjective information processing and the decision fusion center. We make the decision as Fig. 2 shows: firstly, we conduct the temporal-spatial information fusion of the objective information. Secondly, we quantify the subjective information by using fuzzy logic. Finally, we add our subjective information as evidence support to the decision, which would reflect experience and knowledge of experts on the execution of AGV in certain environment.

B. Temporal-spatial Information Fusion

In our experiment, three cameras were used to collect the environment information. After filtering, template matching and line detection, we got the data of the traffic sign, traffic lane and obstacle. In addition, the ultrasonic wave sensor and infrared sensor were used to detect the obstacle. However, in the temporal-spatial information fusion[23, 24], the old and new data will be inconsistent. This kind of conflicting data will be very likely obtained when the state of the system changes. To overcome this problem, we use modified evidence theory to fuse the conflicting data.

Multiple measurements were conducted to improve the accuracy of the result. Consider k to represent the number of the measurement and $w_i\left(i=1,2,\cdots,k\right)$ to represent the weight of every measurement. Because the newest measurement can reflect the environment better, we choose the newest measurement as the primary evidence. We can calculate the weight of all the evidence by using the modified evidence theory and use the Dempster's rule of combination to fuse the data.

C. Quantification of Subjective Information

The subjective information can be treated as a piece of evidence which indicates our support to some element in the frame of discernment. It can be obtained from experienced experts with concrete knowledge related to the task. However, subjective information is usually described by natural language. For instance, the car should be a bit slow if we prefer a smooth ride. If we want to use this kind of information, it is necessary that these vague words should be quantified before making the decision.

In our work, a method based on the fuzzy theory was used to quantify the subjective information. We can get the membership mass $f\left(X/\Theta\right)$ by using the fuzzy dual contrast compositor method mentioned in Section II. Firstly, the assignment of membership degree can be generated based on the Table I. Secondly, we construct the relative priority degree matrix to calculate the membership degree. Finally, we choose the minimum value of each line in matrix as the membership degree. However, the membership degree needs to be normalized and should have a subjective oriented mass assignment function as the function m. In contrast to the D-S evidence theory we assign a subjective mass Fm which equals to the normalized membership degree of each element.

$$Fm\left(X\right)=\frac{f\left(X/\Theta\right)}{\sum_{X\subset\Theta}f\left(X/\Theta\right)} \tag{13}$$

And the subjective mass function has three qualities as follows:

$$\begin{aligned}&1.Fm(\varnothing)=0\\&2.Fm(\Phi)=0\\&3.\sum_{X\in 2^{\Theta}} Fm(X)=1\end{aligned} \tag{14}$$

The subjective Fm is just like the confidence, which represents the support we give to the decision. According to the modified evidence theory, we can also assign the weight of the subjective information so that we can change its influence on the decision result.

IV. Experimental Results

In our experiment, we made several scaled autonomous vehicles, which have 3 cameras, 1 ultrasonic wave sensor, 1 infrared sensor, 1 gyroscope sensor, 1 acceleration sensor and 1 encoder sensor installed, as shown in Fig. 3.

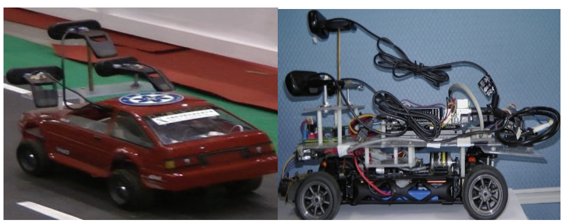

Figure 3. Scaled autonomous vehicle.

To test the performance of the vehicles, we constructed the scaled transportation environment [25-29]. The environment is combination of various traffic elements such as straight lain, turning, bridge, traffic signs and obstacles, as shown in Fig. 4.

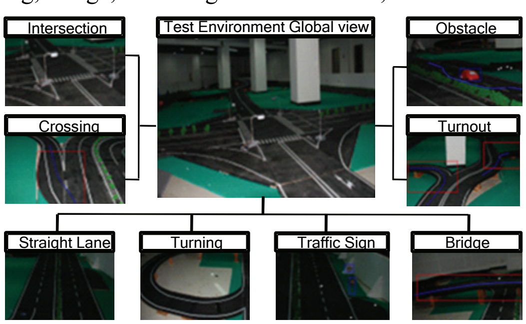

Figure 4. Testing environment composed of various structured way.

The frame of discernment for the detection is shown as follows:

$$\Theta=\{O_1,O_2,O_3\} \tag{15}$$

In the frame Θ, O_1, O_2 and O_3 represent that the car will stop, change lane or go further based on the environment perception information, respectively. As to the objective information, we conducted the temporal-spatial information fusion, as shown in Table II. Firstly, we used the recognition accuracy as the reliability of each sensor. In our experiment, 3 cameras, 1 ultrasonic wave sensor and 1 infrared sensor are used to detect the environment and the recognition accuracy of them is 40%, 32%, 40%, 24% and 28%, respectively. Therefore, the information of the front camera was the primary evidence. The weight of the five sensors w_S is (1, 0.8, 0.7, 1, 0.6). As to every sensor, we gather the data twice and the weight w_T of the measurement period T is (1, 0.5). Secondly, the corresponding mass functions can be accessed by computing the similarity between the calculated result and the element of the frame Θ. Finally, we made the temporal-spatial information fusion based on the modified evidence algorithm.

From the result we can see that there are two similar choices. That is to say we can go further or change lane. This kind of situation will occur in the decision very often as a result of we have two or more feasible choices in certain situation. In this case, the subjective information is needed. However, in traditional approach, we usually manually decide which one to choose without any quantitative analysis.

TABLE II. Temporal-Spatial Information Fusion

Sensors	w_S	T	w_T	O_1	O_2	O_3	Θ
Front Camera	1	1	1	0.09	0.45	0.42	0.05
		2	0.5	0.11	0.40	0.37	0.13
Left Camera	0.8	1	1	0.06	0.43	0.39	0.11
		2	0.5	0.01	0.48	0.49	0.01
Right Camera	0.7	1	1	0.04	0.37	0.39	0.20
		2	0.5	0.08	0.52	0.36	0.04
Ultrasonic	1	1	1	0.10	0.47	0.35	0.08
		2	0.5	0.01	0.35	0.58	0.07
Infrared Sensor	0.6	1	1	0.01	0.33	0.50	0.17
		2	0.5	0.03	0.45	0.50	0.02
Result				0.007	0.524	0.468	0.001

To overcome this problem, here we use the fuzzy logic method mentioned in section III to quantify our subjective information. There are mainly two factors to be considered:

- The strategy priority, which will be different if tasks are not the same.
- The prior knowledge of the whole environment.

For instance, if the task is to get to the destination safely, we would like to choose a safer way of driving the car rather than some other way which may carry certain risks, such as make a lane change. In this way, the experts figured out the relative priority degree, as shown in Table III.

TABLE III. Relative Priority Degree

	O_1	O_2	O_3
O_1	1	1	1/7
O_2	1/3	1	1/5
O_3	1	1	1

We used fuzzy dual contrast compositor method to ascertain the fuzzy membership function and add our subjective information with the equal weight w_F to make the decision, as shown in Table IV.

TABLE IV. FUSION RESULTS OF SUBJECTIVE AND OBJECTIVE INFORMATION

Information	w_F	O_1	O_2	O_3	Θ
Objective Information Fusion Result	1	0.007	0.524	0.468	0.001
Subjective Information		1/7	1/5	1	0
Normalized Subjective Information	1	0.106	0.149	0.745	0
Final Result		0.002	0.183	0.815	0

To make the final decision for the detection, we set 0.6 as the threshold for the value of belief function. When the following conditions are satisfied, a hard decision is made:

$$\max\left(Bel\left(O_i\right)\right) \geq 0.6\left(i=1,2,3\right) \tag{16}$$

The result indicates that we distinguished the two similar choices and obtain quantitative result. In addition, we can change the value of the weight of the subjective information and the result is shown in Fig. 5.

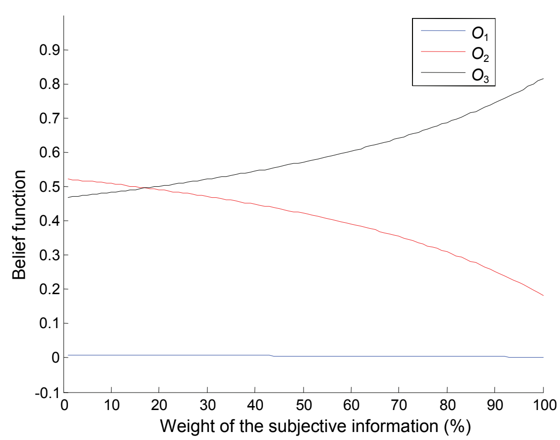

Figure 5. Effect of the weight of the subjective information.

The result indicates that the more we increase the weight of the subjective information, the more the result would be influenced. In real applications, we can use the fuzzy logic method to assign an appropriate value of weight with the guidance of experts.

V. CONCLUSION

This article discusses the framework of AGV decision making subsystem. The key point of our decision system is the fusion of the objective information and the subjective information. The problems of conflicts caused by unbalance of importance of multiple data sources are solved through reducing the weights of the less reliable data sources. In addition, subjective information is quantified based on fuzzy logic. From the experiment results we can find that the decision based on the data fusion can reflect the multisensory data fusion result as well as our subjective experience. The next step is to implement more intelligent system and more effective algorithms which can realize autonomous driving.

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