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The Combined Use of Evidence Theory and Vague Sets to Interpret Multimodal Inspection Data

Bai Hua
School of Mechatronics Engineering
Harbin Institute of Technology
Harbin, China
baihua@hit.edu.cn

***Abstract*— Several measurement modalities have been applied for the safety and reliability evaluation of complex system. A great deal of information can be obtained by multimodal inspection. But different sensors can only capture part of the exterior and interior geometry since the limitations of its involved physical phenomena. So a challenging problem is how to effectively interpret the available multimodal inspection data, especially when the data show vague, uncertain and even conflict information. In this paper, a combined vague sets/ D-S evidence theory approach is proposed to make more reasonable inferences using multi-source information fusion. Since the D-S theory shares the similar form in the fundamental definition of the measure of a proposition to that in the definition of grade membership of an element in vague sets, the relationship between the true-membership function and false-membership function of vague sets and belief/plausibility functions of D-S theory is discussed. Based on the feature of vague sets, the true-membership function and false-membership function are used to describe the belief level of fusion target. Then they are combined by an enhanced combination algorithm based on D-S evidence conventional combination rule. Finally, an example is conducted to demonstrate the effectiveness of the proposed combined vague sets/ D-S evidence theory. According to its firm mathematical foundation, the proposed approach can express and handle uncertain and vague information effectively, and can be applied to fuse any bodies of multimodal inspection data without changing the recursive combination algorithm.**

***Keywords*—multimodal inspection; data fusion; vague sets**

I. INTRODUCTION

It is well known that different multimodal inspection provide complementary information on flaws or pending failures of the system. Each sensor only identifies a particular kind and amount of information because of the involved physical phenomena, different sensors can only capture part of the exterior and interior geometry. With the need of evaluation and analysis the safety and reliability for complex system, it's necessary to use multiple sensors to acquire all information about the system being inspected, in particular, when the system failure are extreme or catastrophic in nature. For example, PIRAT is an advanced multimodal robot inspection system for inspecting, monitoring, and evaluating of buried pipeline condition developed by an Australia research institute, which holds CCTV, laser scanner, and sonar scanner, can provide quality data on pipeline condition, including pipe geometry, vertical and horizontal deflections, structural deficiencies, and location and extent of defects[1]. So a challenging problem has arisen with regard to effectively interpreting and integrating the available multimodal inspection data, especially when the data show vague, uncertain and even conflict information.

Evidence inference theory has been extensively applied in the field of data fusion, due to its advantage of uncertainty expression, measuring and integration. But when the fusion target is vague and imprecise, that is to say, the focal elements in the framework of discriminate have fuzziness, it is difficult to fuse the information based on the conventional evidence theory, for example, in pipeline condition assessment, how to evaluate and distinguish the area of goodness, fairness and poorness of a segment buried pipe. Some researchers take advantage of fuzzy sets and evidence theory to express and handle uncertain and fuzzy information. In [2], a D-S belief structure is viewed as providing incomplete information about an underlying fuzzy measure, and a class of fuzzy measures can be seen as possible completions of a D-S belief structure. A fuzzy-valued definition for the belief, plausibility, and probability functions was proposed in [3] for mass assignments in evidence theory. In [4], Zadeh's fuzzy sets were extended into a mathematical structure "evidence set" by using evidence theory, and the belief, plausibility, and probability functions were fuzzy-valued defined.

The key concept of classical fuzzy set is the degree of membership, which describes the degree that an element belongs to a fuzzy set. However, the degree of membership can only reflect one aspect of an element, the degree of non-membership, indicating the degree that an element does not belong to a fuzzy set, can not be included in the classical fuzzy set. In 1993, Gau and Buehrer proposed a vague sets theory [5], in which the relation between the element and set in the universe of discourses is the relation "belong to in certain level degree". Vague sets can express support, opposite and unknown information of objects (no-support and no-opposition), but fuzzy sets only can express support or opposition information of objects, and cannot express its unknown degree information. Compared with fuzzy sets, vague sets are more effective in accurately expressing the fuzzy information.

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Combined with the advantage of vague sets, this paper proposed a combined vague sets/ D-S theory. The reminder of the paper is organized as follows: the basic concepts of evidence theory and the schemes for basic probability reassignment considering the evidence importance are introduced in section 2, the vague sets and the combined vague sets/ D-S theory is presented in section 3. In section 4, the proposed method is applied to evaluate a buried pipeline condition. Some final remarks of the proposed method are concluded in section 5.

II. EVIDENCE THEORY

A. Basics of Dempster-Shafer Theory

In D-S theory[6], a finite nonempty set of mutually exclusive alternatives is called the *frame of discernment*, denoted byΘ. The *basic probability assignment* (BPA), represented by m, reflects a degree of belief in a hypothesis or the degree to which the evidence supports the hypothesis, and can be represented with the following equations:

$$\begin{aligned} &\sum_{\Psi\subseteq\Theta} m(\Psi)=1; \\ &m(\phi)=0; \\ &0\le m(\Psi)\le 1, \textit{for all} \quad \Psi\subseteq\Theta \end{aligned} \tag{1}$$

The quantity $m(\Theta)$ is a measure of that portion of the total belief that remains unassigned after commitment of belief to all subsets of Θ. If $m(\Psi) = s$, and no BPA is assigned to other subsets of Θ, then $m(\Theta) = 1 - s$. Thus, the remaining BPA is assigned to Θ itself, but not to the negation of a subset Ψ, which represents *ignorance*.

For example, consider the frame of discernment is *Good, Fair, Bad,* denoted as $H = \{H_1, H_2, H_3\}$, which represents three condition states of a buried pipe. Assuming the information obtained indicates that $m(\{H_1\}) = 0.5$, $m(\{H_2\}) = 0.3$, i.e., the degree to which the evidence supports condition states H_1/*Good* and H_2/*Fair* is 50% and 30% respectively. Hence, BPA assigned to *ignorance* is $m(H) = 1 - (0.5 + 0.3) = 0.2$. It can then be interpreted that the set of all conditions states $\{H_1, H_2, H_3\}$ possess 20% unassigned probability based on available incomplete evidence.

From the BPA, the upper and lower bounds of an interval can be defined. The lower bound, *Belief* for a set A, is defined as the sum of all the BPAs of the proper subsets *(B)* of the set of interest *(A)* ($B\subseteq A$). The upper bound, Plausibility, is the sum of all the basic probability assignments of the sets *(B)* that intersect the set of interest *(A)* ($B\cap A\neq\varnothing$). Formally, they can be represented as the followings:

$$\begin{aligned} Bel(A) &= \sum_{B|B\subseteq A} m(B) \\ Pl(A) &= \sum_{B|B\cap A\neq\phi} m(B) \end{aligned} \tag{2}$$

Obviously, *belief* function represents the degree that one believes in A. *Plausibility* function represents the degree that one believes A is not false. It is easy to obtain the conclusions:

$$\begin{aligned} &Bel(\phi)=m(\phi)=0 \\ &Bel(\Theta)=\sum_{B\subseteq\Theta} m(B)=1 \\ &Pl(A)=1-Bel(\sim \mathrm{A}) \end{aligned} \tag{3}$$

Where $\sim A$ represents the complementary set of A. $Bel(\sim A)$ reflects the belief degree of $\sim A$. For all subset A of the frame of discernment, it holds $Pl(A)\ge Bel(A)$. $Bel(A)$ and $Pl(A)$ is interpreted as bounds on the probability. *Belief* function represents the maximal value that all epistemic uncertainty believes the probability. *Plausibility* function represents the highest plausible value of the probability.

Assume there exist two bodies of evidence in Θ, and that they provide two basic probability assignments to a subset $\Psi$of Θ, i.e. $m_1(\Psi)$ and $m_2(\Psi)$. To obtain a combined probability $m_{12}(\Psi)$, the D-S theory provides an combination rule defined below:

$$\begin{aligned} m_{12}(\Psi) &= \frac{\sum_{A\cap B=\Psi,\forall A,B\subseteq\Theta} m_1(A)m_2(B)}{1-K} \\ \textit{where} \quad K &= \sum_{A\cap B=\phi,\forall A,B\subseteq\Theta} m_1(A)m_2(B) \end{aligned} \tag{4}$$

In this combination rule, $m_{12}(\Psi)$for hypothesis Ψ is computed from m_1 and m_2 by adding all products of the form $m_1(A)$ and $m_2(B)$ where A and B are selected from the subsets of Θ in all possible ways such that their intersection is Ψ. K reflects the conflicting situations where both $m_1(A)$ and $m_2(B)$ are not zero, but the intersection $A\cap B$ is empty or void set.

It is well known that not all the evidences have the same importance in decision making. Some evidences are more importance than others. Conventional D-S theory does not differentiate the importance of different evidences. In multimodal inspection data fusion, since different inspect data can be regarded as different evidence, which make different contributions to the condition description of target, evidence importance should be considered in data fusion. Generally, the evidence importance can be denoted by weight factor. Considering the weight factor of evidence importance, the basic probability assignment of the evidence should be reassigned.

B. Schemes for weight Nornalization and Basic Probability Assignment

In reality, not all the evidences have the same importance in fusing multimodal data. Generally, multimodal inspection data can be performed with prior knowledge about the strengths and weaknesses of the modalities at detecting specific defects or dimensions.

In multi information fusion process, data obtained from different sensors was fused in data level first. To evaluate the safety and reliability of in-service equipment, decision level fusion is needed. The data level fusion result describes a feature of equipment as a certain condition grades. Multiple data need to be integrated to make a reasonable decision on safety and reliability condition. Suppose N distinctive condition grades are defined that collectively provide a complete set of standards for assessing a feature, represented as $H=\{H_1\ H_2 \cdots\ H_n \cdots\ H_N\}$. Several features need to be considered to evaluate the equipment safety and reliability. A given evaluation for an feature e_i is mathematically denoted as $\beta_{n,i}$, Where $\beta_{n,i}\ \ge 0$, $\sum_{n=1}^{N}\beta_{n,i}\le 1$. $\beta_{n,i}$ denotes a degree of belief to which the feature e_i is assessed to the grade H_n. Let $m_{n,i}$ be a BPA representing the degree to which the feature e_i

supports the hypothesis that the equipment safety and reliability is assessed to the grade H_n. Considering the weight of the feature e_i as ω_i, then $m_{n,i}$ is calculated as follows:

$$m_{n,i} = \omega_i \beta_{n,i} \quad (5)$$

To distinguish the weight influence on remaining probability assignment, some mathematical conversion is needed. Let $m_{H,i}$ be a remaining probability unassigned to any individual grade after all the N grades have been considered for assessing the general features as far as e_i is considered. It is decomposed into two parts [7], $\overline{m}_{H,i}$ *and* $\widetilde{m}_{H,i}$, where

$$\begin{aligned} m_{H,i} &= 1 - \sum_{n=1}^{N} m_{n,i} = \overline{m}_{H,i} + \widetilde{m}_{H,i} \\ \overline{m}_{H,i} &= 1 - \omega_i; \\ \widetilde{m}_{H,i} &= \omega_i (1 - \sum_{n=1}^{N} \beta_{n,i}) \end{aligned} \quad (6)$$

$\overline{m}_{H,i}$ will be zero if e_i dominates the evaluation, and will be one if the weight of e_i is zero. That is to say, $\overline{m}_{H,i}$ represents the degree to which other features can play a role in the condition assessment. It should be assigned to individual grades in a way that is dependent upon how all factors are weighted and assessed. $\widetilde{m}_{H,i}$ is caused due to the incompleteness in the assessment for feature e_i. $\widetilde{m}_{H,i}$ is zero if $\sum_{n=1}^{N} \beta_{n,i} = 1$, and $\widetilde{m}_{H,i}$ is proportional to w_i and will cause the subsequent assessment to be incomplete.

C. *Enhanced Combination Algorithm*

To combine the features e_i and e_j, an enhanced combination algorithm with weight normalization is summarized based on (4), (5) and (6). For computational purpose, an "intersection table" with values of probability assignment along the rows and columns, respectively, is constructed in table1 to develop the enhanced combination algorithm.

Table1 Intersection table

	$e_{I(2)}$	e_i: $\{H_1\}(m_{1,i})$	···	$\{H_n\}(m_{n,i})$	$\{H\}(\widetilde{m}_{H,i})$	$\{H\}(\overline{m}_{H,i})$
e_j	$\{H_1\}(m_{1,j})$	$\{H_1\}(m_{1,i}\, m_{1,j})$	···	$\{\varnothing\}(m_{n,i}\, m_{1,j})$	$\{H_1\}(\widetilde{m}_{H,i}\, m_{1,j})$	$\{H_1\}(\overline{m}_{H,i}\, m_{1,j})$
	···	···	···	···	···	···
	$\{H_n\}(m_{n,j})$	$\{\varnothing\}(m_{1,i}\, m_{n,j})$	···	$\{H_n\}(m_{n,i}\, m_{n,j})$	$\{H_n\}(\widetilde{m}_{H,i}\, m_{n,j})$	$\{H_n\}(\overline{m}_{H,i}\, m_{n,j})$
	$\{H\}(\widetilde{m}_{H,j})$	$\{H_1\}(m_{1,i}\widetilde{m}_{H,j})$	···	$\{H_n\}(m_{n,i}\widetilde{m}_{H,j})$	$\{H\}(\widetilde{m}_{H,i}\, \widetilde{m}_{H,j})$	$\{H\}(\overline{m}_{H,i}\, \widetilde{m}_{H,j})$
	$\{H\}(\overline{m}_{H,j})$	$\{H_1\}(m_{1,i}\overline{m}_{H,j})$	···	$\{H_n\}(m_{n,i}\overline{m}_{H,j})$	$\{H\}(\widetilde{m}_{H,i}\, \overline{m}_{H,j})$	$\{H\}(\overline{m}_{H,i}\, \overline{m}_{H,j})$

The combined probability assignment are generating as follows:

$$\begin{aligned} \{H_n\}: m_{n,I(2)} &= \left(m_{n,i}m_{n,j} + \widetilde{m}_{H,i}m_{n,j} + \overline{m}_{H,i}m_{n,j} + m_{n,i}\widetilde{m}_{H,j} + m_{n,i}\overline{m}_{H,j} \right) \Big/ (1 - K_{I(i+1)}) \\ \{H\}: \widetilde{m}_{H,I(2)} &= (\widetilde{m}_{H,i}\widetilde{m}_{H,j} + \overline{m}_{H,i}\widetilde{m}_{H,j} + \widetilde{m}_{H,i}\overline{m}_{H,j}) / (1 - K_{I(i+1)}) \\ \{H\}: \overline{m}_{H,I(2)} &= \overline{m}_{H,i}\overline{m}_{H,j} / \left(1 - K_{I(i+1)}\right) \\ K_{I(i+1)} &= \sum_{t=1}^{N} \sum_{l=1, l\neq t}^{N} m_{t,i} m_{l,j} \end{aligned} \quad (7)$$

Where $m_{n,I(2)}$ is the combined probability assignment for the grade H_n generated by aggregating the features e_i and e_j; $\widetilde{m}_{H,I(2)}$ is the combined probability assignment for H due to the possible incompleteness in the condition assessment for features e_i and e_j, and $\overline{m}_{H,I(2)}$ for H due to the combined relative importance of features e_i and e_j.

After all L features have been aggregated, the combined degrees of belief are generated by assigning $\overline{m}_{H,I(L)}$ back to all individual grades proportionally using the following normalization process:

$$\begin{aligned} \{H_n\}: \beta_n &= \frac{m_{n,I(L)}}{1 - \overline{m}_{H,I(L)}} \\ \{H\}: \beta_H &= \frac{\widetilde{m}_{H,I(L)}}{1 - \overline{m}_{H,I(L)}} \end{aligned} \quad (8)$$

β_n generated in (8) is the degree of belief to which grade H_n is assessed, and β_H is the unassigned degree of belief representing the extent of incompleteness in the assessment.

III. COMBINED D-S THEORY AND VAGUE SETS APPROACH

A. *Vague sets theory*

Let X be a space of objects, with a generic element of X denoted by x. A Vague Sets A in X is characterized by a truth-membership function t_A and a false-membership function f_A. $t_A(x)$ is a lower bound on the grade of membership of x derived from the evidence for x, and $f_A(x)$ is a lower bound on the negation of x derived from the evidence against x. $t_A(x)$ and $f_A(x)$ both associate a real number in the interval [0,1] with each object in X. In general,

$$t_A(x) + f_A(x) \leq 1 \quad (9)$$

This approach bounds the grade of membership of x to a subinterval $[t_A(x), 1 - f_A(x)]$ of [0,1]. In other words, the exact grade of membership $\mu_A(x)$ of x may be unknown, but it is bounded by

$$t_A(x) \le \mu_A(x) \le 1 - f_A(x) \quad (10)$$

For example, the health condition of a pipe is divided into three states, i.e. *good, fair, bad,* denoted as $H = \{H_1, H_2, H_3\}$. The pipe condition belongs to each state can be described as vague sets. Assuming the information obtained is written as $[t_{H_1}, 1-f_{H_1}]$= [0.5, 0.8], i.e. t_{H_1}=0.5, and $1-f_{H_1}$=0.8. That is to say, based on the obtained information, the grade of membership for H_1/*Good* is 0.5, against H_1/*Good* is 0.2, and 0.3 is unassigned because of the uncertain and inaccurate information.

B. Combined Vague sets/ D-S evidence theory

A challenging problem in interpretation multimodal inspection data is how to effectively deal with the available data, which show uncertain, vague even conflict information. Some theories are developed to describe such information, but different theories describe uncertainty and ignorance in different ways, which have more or less common characteristics. Both the D-S theory and vague sets theory are such ones that have close correlation with each other, and many conclusions in either D-S theory or vague sets theory may be applied to solving the problems in the counterpart field [8].

Belief and *plausibility* are two functions that describe the lower and upper bounds of one believe the proposition *A*. *Belief* function represents the maximal value that all epistemic uncertainty believes the proposition *A*. It reflects the degree that one believes *A* is true; *Plausibility* function represents the highest plausible value of the proposition. It can be interpreted as the degree that one believes *A* is not false. So the Difference between *Belief* and *plausibility* represent the uncertainty of *A*. In other words, the difference represents the portion of belief that neither one can believes nor disbelieve the proposition. With this interpretation, the D-S theory makes a similar form in the fundamental definition of the measure of a proposition to that in the definition of grade membership of an element in vague sets theory. If elements in vague sets theory are concretized to be subsets of a total set and the grade membership of the subsets are redefined according to those of D-S theory, the vague sets becomes D-S theory.

Based on the above opinion, we can construct a pair for a proposition *A*: [*Bel(A), Pl(A)*]. This form is very similar to that of vague set: [$t_A(x)$, $1-f_A(x)$]. Such correspondence can be easily found: $A \leftrightarrow x$;

$$Bel(A) \leftrightarrow t_A(x); \quad Bel(\sim A) \leftrightarrow f_A(x) \quad (11)$$

In D-S theory, if A is a focal element, its basic probability assignment *m(A)* has the same value with *Bel(A)*. From the equation (11), we can get that *m(A)* has the same value with t_A. Then the *basic probability assignment* can be represented as:

$$m_{H_n,i} = \omega_i t_{n,i} \\ \bar{m}_{H,i} = 1 - \omega_i; \\ \tilde{m}_{H,i} = \omega_i (1 - \sum_{n=1}^{N} t_{n,i}) \quad (12)$$

With the similarity between D-S theory and Vague Sets, an enhanced approach based on (7) and (12) is proposed to interpret multimodal inspection data.

IV. SAMPLE CASE ANALYSIS

The deterioration of buried pipe is a physical manifestation of the ageing process, which influenced by many factors, such as the pipe materials, stability and composition of surrounding soils, car load-carrying capacity of road surface, internal flow rate and aggressiveness of transported water, etc.

Based on the multimodal inspection data, we can get some features that can manifest the deterioration condition of a segment pipe, such as internal corrosion depth, crack width, change in alignment, and tuberculation.

Suppose there are four features (that is (1) internal corrosion depth, (2) crack width, (3) change in alignment, (4) tuberculation) getting from the multimodal inspection result, which associated with the pipe safety and reliability condition evaluation for a segment of buried pipe. And the condition states of a pipe can be divide into three states, i.e. $H=\{H_1/good, H_2/fair, H_3/bad\}$. Subjective judgment is used to identify, classify, and/or rate pipe defect factors. The evaluations of each feature described in the form of vague sets are listed in table2.

Table 2 evaluations described in vague sets

Factor		{Good/ H_1}	{Fair/ H_2}	{Bad/ H_3}
No.	*weight*			
1	0.3	[0.2, 0.45]	[0.55, 0.8]	[0, 0.25]
2	0.3	[0, 0.3]	[0.3, 0.6]	[0.4, 0.7]
3	0.1	[0, 0.3]	[0.5, 0.8]	[0.2, 0.5]
4	0.3	[0.25, 0.55]	[0.45, 0.75]	[0, 0.3]

As discussed in section 3, the lower and upper bounds of belief could be described by the pair of *Bel(A)* and *Pl(A),* as well as the pair of $t_A(x)$ and $1-f_A(x)$, as shown in (11)and (12). So the corresponding probability assignments in the form of belief and plausibility function are listed in table3.

Table 3 corresponding probability assignments

Factor		{Good/ H_1}	{Fair/ H_2}	{Bad/ H_3}	{Θ/H}
No.	*weight*	$m_{1,i}$	$m_{2,i}$	$m_{3,i}$	$m_{H,i}$
1	0.3	0.2	0.55	0	0.25
2	0.3	0	0.3	0.4	0.3
3	0.1	0	0.5	0.2	0.3
4	0.3	0.25	0.45	0	0.3

Considering the weight influence on each factor, the weight normalized probability assignments are given in table4.

Table 4 description after weight normalization

Factor		{Good/H_1}	{Fair/ H_2}	{Bad/ H_3}	{Θ/H}	
No.	*weight*	$m_{1,i}$	$m_{2,i}$	$m_{3,i}$	$\bar{m}_{H,i}$	$\tilde{m}_{H,i}$
1	0.3	0.06	0.165	0	0.7	0.075
2	0.3	0	0.09	0.12	0.7	0.09
3	0.1	0	0.05	0.02	0.9	0.03
4	0.3	0.075	0.135	0	0.7	0.09

From (7), combining the first two factors, we can calculate the conflict parameter $K_{I(2)} = 0.0324$, combined probability assignments *m* as:

$m_{1,I(2)} = 0.049; \quad m_{2,I(2)} = 0.222; \quad m_{3,I(2)} = 0.096$

$\widetilde{m}_{H,I(2)} = 0.007; \quad \overline{m}_{H,I(2)} = 0.626$

Then combining the above result with the third factor can get:

$m_{1,I(3)} = 0.0461; \quad m_{2,I(3)} = 0.2526; \quad m_{3,I(3)} = 0.1053$

$\widetilde{m}_{H,I(3)} = 0.002; \quad \overline{m}_{H,I(3)} = 0.5958$

At last, combining the above result with the forth factor:

$m_{1,I(4)} = 0.089; \quad m_{2,I(4)} = 0.329; \quad m_{3,I(4)} = 0.087$

$\widetilde{m}_{H,I(4)} = 0.001; \quad \overline{m}_{H,I(4)} = 0.494$

From(8), the combined degree of belief are calculated by:

$$\beta_1 = \frac{m_{1,I(4)}}{1-\overline{m}_{H,I(4)}} = \frac{0.089}{1-0.494} = 0.17559; \quad \beta_2 = 0.65174; \quad \beta_3 = 0.17263$$

$$\beta_H = \frac{\widetilde{m}_{1,I(4)}}{1-\overline{m}_{H,I(4)}} = 0.00004$$

So the final internal surface condition evaluation for a segment of buried pipe considering the associated factors is concluded as {Good/0.176, Fair/0.652, Bad/0.172}.

The degree of incompleteness in the above evaluation result is 0.00004. Compared with the three original incomplete assessments, where the uncertainty is 0.25 or 0.3, the overall incompleteness is significantly reduced due to the relatively complete assessments in other factors. It is also noted that the commutativity of multiplication in the combination algorithm ensures that the combination process yields the same value regardless of the order in which the two pieces of evidence are combined, so changing the order of combining the three factors does not change the final result at all.

V. Conclusion

Multimodal inspection approach is applied for the safety and reliability evaluation for complex system. Since a great deal of information can be obtained by multimodal inspection result, a challenging problem has arisen with regard to effectively interpreting and integrating the available multimodal inspection data, especially when the data show vague, uncertain and even conflict information. Evidence theory is an effective way to deal with multi-source information fusion. But in traditional D-S evidence theory, the relation between elements and sets in the *frame of discernment* is belonged to or not belonged, which is a kind of relationship between crisp sets. So it is difficult to describe and aggregate the uncertain and vague information rely on the traditional D-S theory. In this paper, taking advantage of vague sets and D-S evidence theory, a combined vague sets/evidence theory approach is proposed to interpret and integrate multimodal inspection data.

Based on the properties of vague sets theory and D-S theory, the similarity between vague sets and the *belief* and *plausibility* function is discussed. To effective express uncertainty and reduce the computational complexity for combining multi information, an enhanced combination algorithm is developed. Based on the data level fusion result, different features can be described as different vague sets, and then represented them with *belief* and *plausibility* forms. By use of the enhanced combination algorithm, all the features will be aggregated to evaluate the safety and reliability of a equipment. An example is given to illustrate the proposed approach step by step and the result demonstrates the effectiveness of the proposed method. According to its firm mathematical foundation, the proposed approach can express and handle uncertain and vague information effectively, and can be applied to fuse any bodies of multimodal inspection data without changing the recursive combination algorithm.

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