A Reliability Analysis of Airport Noise Monitoring Data Based on Evidence Theory

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***Abstract*----With the scale of airport transportation expanding, the level of airport noise pollution is worsening, therefore, installing airport noise monitoring system has been an important method for a lot of airport to monitor the surrounding noise environments. In order to know well the operation of various monitoring points around the airport, this paper presents an assessment model of airport noise monitoring data reliability based on evidence theory. The model makes use of the relationship of every monitoring noise data in the same flight events to construct the basic probability assignment function, and then combines evidence using the improved rule. Experimental results show that the model can assess the reliability of the various monitoring points accurately, and when an exception of monitoring points occurs, the proposed model based on improved rule is superior to those based on the existing rules.**

***Index Terms*—Evidence Theory, Relationship, Reliability, Airport Noise Event**

I. Introduction

Currently, the airport noise monitoring system has been installed in major airports of many developed countries. The Beijing Capital International Airport and major airports of Taiwan and Hong Kong have also used similar systems. This system can monitor aircraft noise by setting up 20 to 40 fixed monitoring points around the airport from day to night， and provide more reliable environmental data for comprehensively controlling the airport noise. However, this kind of fixed monitoring point has high costs, high environmental requirements and poor stability. Furthermore, airport noise monitoring data is interspersed environmental noise generated by other noise sources (such as wind noise, construction noise, etc.), therefore, assessing the reliability of monitoring data becomes particularly important.

Airport noise levels are generally associated with a variety of factors, but a period of time noise information monitored by aware devices are with complementary in different spatial locations[1]. According to the relationships among noise data produced by different monitoring points, it is theoretically possible to derive the reliability of noise data produced by target monitoring points. Because noise data produced by a single monitoring point is not convincing, using different monitoring points as many as possible to verdict the reliability of noise data produced by target monitoring point is needed, and then these results are combined before final decision, which is called multi-source information fusion problem. There are many commonly used multi-source information fusion methods, typically Bayesian method and evidence theory. Compared with the Bayesian, evidence theory does not require a priori probability and can also satisfy even weaker axiom system than probability theory. Because airport noise monitoring data has the characteristics of huge data, it is difficult to obtain priori probabilities. Therefore, evidence theory is more suitable for assessing reliability of noise data. Judgment and fusion process based on evidence theory is shown in Fig. 1.

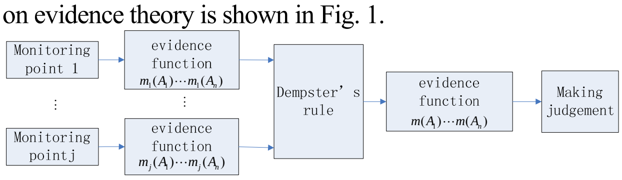

Figure 1. Judgment and fusion process based on evidence theory

In Fig. 1, the reliability levels of noise data produced by target monitoring point are divided into $A_i, \cdots, A_n$. $m_j(A_1), \cdots, m_j(A_n)$ represent belief functions of monitoring point j for $A_i, \cdots, A_n$ respectively. $m(A_1), \cdots, m(A_n)$ represent belief functions after the noise data of the target monitoring points is combined.

The rest of the paper is organized as follows. Section II presents the basics of D-S evidence theory. In Section III, we are going to discuss the problems of evidence theory, and then a new combination rule will be introduced in Section IV. Section V presents an assessment model of airport noise monitoring data reliability and there is an example about it in

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Section VI. Finally, I conclude the paper in Section VII.

II. BASICS OF THE D-S EVIDENCE THEORY

D-S evidence theory is proposed by Dempster [2], and is systematically improved by Shafer [3]. By now, evidence theory with its powerful expression and processing capability of uncertain information is widely used in uncertain reasoning [4], multi-sensor information fusion [5,18], pattern recognition[19], uncertain information decision [6,17] and target identification, etc.

We review a few concepts commonly used in the D-S evidence theory. Let $\Theta=\{\theta_1,\theta_2,\cdots,\theta_n\}$ called the frame of discernment be a finite set.

Definition 1. A basic probability assignment(BPA) is a mapping $m: 2^{\Theta}\rightarrow[0,1]$ that satisfies 1） $0\le m(A)\le 1$; 2） $m(\varnothing)=0$， $\varnothing$ represents empty set; 3） $\sum_{A\in 2^{\Theta}} m(A)=1$.

Definition 2. Let m_1 and m_2 be two BPAs defined on frame Θ which are derived from two distinct sources. Let the combined BPA be $m=m_1\oplus m_2$ by Dempster's rule of combination where $\oplus$ represents the operator of combination. Then

$$m(C)=\begin{cases}\dfrac{\sum_{A_i\cap B_j=C} m_1(A_i)m_2(B_j)}{1-k}, & C\neq\varnothing\\ 0, & C=\varnothing\end{cases} \quad (1)$$

when $A_i\in 2^{\Theta}$ ， $B_j\in 2^{\Theta}$ ， $C\in 2^{\Theta}$ ； $k=\sum_{A_i\cap B_j=\varnothing} m_1(A_i)m_2(B_j)$.

III. THE PROBLEMS AND RESEARCH STATUS

Dempster's rule is the core of D-S evidence theory. It is assumed that all the evidence sources are reliable, but it is difficult to meet in practice. When there are conflicts among the information sources, the application of Dempster's rule tends to produce counter-intuitive results.

Example 1. $\Theta=\{A,B,C\}$

$$m_1(A)=0.9 \quad m_1(B)=0.1 \quad m_1(C)=0$$

$$m_2(A)=0 \quad m_2(B)=0.1 \quad m_2(C)=0.9$$

It can be seen that the evidence m_1 and m_2 is highly contradictory, but the combination result according to Dempster's rule is $m(A)=0$, $m(B)=1$, $m(C)=0$. The above result is contrary to common sense, because a very low reliability proposition B has the maximum trust after combination.

Due to poor natural factors and human interference, judgments from different monitoring points are often highly conflicting. In order to solve the combination problem of highly conflicting evidence, researchers have proposed many improved methods which can be divided into two categories: one is to modify the classic Dempster's rule. It means the redistribution of the conflict when the evidence conflicts, and the typical research works are made by yager [7], Sun Quan [8], etc. Another is to keep the classical combination rule, since it has solid mathematical foundation. However, evidence sources need to be amended to reduce the amount of conflicting information before combination, and the typical works are made by Murphy[9], Deng Yong [10,11], etc. Because the improved combination rules break excellent features (such as commutative and associative) of the rule, for practical reasons, we select the second category.

Murphy's method is a modification of the model without changing the Dempster's rule. Murphy proposes a combination rule of evidence mean: first of all, the basic probability assignments of n pieces of evidence are arranged, then combine them for n-1 times using Dempster's rule. Compared with other methods, Murphy's method can deal with conflicting evidence combination and has faster convergence speed. But Murphy's method is obviously inadequate for multi-source information, which only makes simple average without considering the linkages between evidence.

Deng Yong's method introduces a Josselme distance function[12] based on Murphy's method to measure the degree of similarity between the bodies of evidence, and then the levels of each evidence supported by other evidence are obtained. The supported levels are used as weight of evidence, and then each of evidence is weighted averaged and combined by Dempster's rule. Deng Yong's method inherits all the advantages of Murphy's method, and has a stronger robustness and faster convergence speed.

IV. A NEW COMBINATION RULE

Classical Dempster's rule uses value k to characterize the degree of conflict among the evidence. As the two rules in Example 1, in which value k equals 0.99 that indicates two pieces of evidence highly conflicting. However, the literature [13] considers that the value k is not an accurate measure of the level of the conflict between two pieces of evidence. For example:

Example 2. Let the pair of BPAs from two distinct sources on frame $\Theta=\{A_1,A_2,A_3,A_4,A_5\}$ be:

$$m_1(A_i)=0.2, \quad i=1,2,3,4,5$$

$$m_2(A_i)=0.2, \quad i=1,2,3,4,5$$

If we follow the above convention in Dempster's rule and use the value k as the quantitative measure of conflict in beliefs, then the two BPAs in the pair could be classified as in conflict since k=0.8. This conclusion is obviously wrong because we know already that these two BPAs completely agree with each other. Liu considered that pignistic probability function can better characterize the degree of conflict among the evidence [13].

Definition 3. [14] Let m be a BPA on Θ. Its associated pignistic probability function $BetP_m:\Theta\rightarrow[0,1]$ is defined as

$$BetP_m(A)=\sum_{W\subseteq\Theta,A\in W}\frac{1}{|W|}\frac{m(W)}{(1-m(\varnothing))},\forall A\in\Theta \quad (2)$$

$BetP_m(A)$ gives the all values which represent that each of pignistic probability of A is true. For Example 1, $BetP_{m_1}(A)=0.9$, $BetP_{m_2}(A)=0$, and the difference of them is $|BetP_{m_1}(A)-BetP_{m_2}(A)|=0.9$. The value is so great and proves that the conflict is large. For Example 2, $BetP_{m_1}(A)=0.2$, $BetP_{m_2}(A)=0.2$, and the difference of them is $|BetP_{m_1}(A)-BetP_{m_2}(A)|=0$. It can be seen that the differences between the evidence represented by pignistic probability function are more in line with the actual situation. Jiang Wen averages value k and evidence distance to measure the degree of conflict [15]. In fact, what the value k measures is different from distance function. The distances between the evidence characterize the differences between evidence; however value k is original definition about conflicts of evidence. Which is good or bad, it is still controversial [16]. Based on the above analysis, new metrics of evidence conflict are defined as follows.

Definition 4. [14] Let m_1 and m_2 be two BPAs on frame Θ , and let $BetP_{m_1}$ and $BetP_{m_2}$ be the results of two pignistic transformations from them respectively. Then

$$difBetP_{m_1}^{m_2}=\max_{A'\subseteq\Theta}(|BetP_{m_1}(A')-BetP_{m_2}(A')|) \quad (3)$$

is called the distance between betting commitments of the two BPAs.

There are many methods to measure the degree of conflict between evidence besides value k and pignistic probability function. Josselme distance function in the literature [10,11] presented by Deng Yong can also get good results. Liu compares them in the literature [13].

Example 3. Let us consider two pairs of BPAs on a frame with five elements:

1st pair $m_1^1(A,B)=0.8$ $m_1^1(C)=0.1$ $m_1^1(D)=0.1$

$m_2^1(A,B)=0.1$ $m_2^1(C)=0.1$ $m_2^1(D)=0.8$

2nd pair $m_1^2(A)=0.8$ $m_1^2(B,C,D,E)=0.2$

$m_2^2(\Theta)=1.0$

Let BPAs be basic probability assignment function for comparison, and let d_{BPA} and $difBetP$ be the distance of evidence computing by Josselme distance function and pignistic probability function. The results are shown in Table I.

TABLE I.
COMPARISON OF d_{BPA} AND $difBetP$ OF THE TWO PAIRS OF BPAS

BPAs	d_{BPA}	$difBetP$
m_1^1 , m_2^1	**0.70**	0.700
m_1^2 , m_2^2	**0.721**	0.600

Intuitively, we can see that there are a certain conflicts between two groups of evidence. The degree of conflict in the first pair of evidence is clearly greater than that in the second pair. However, the result calculated by Josselme distance function is inconsistent with the actual situation. Pignistic probability function, therefore, is more suitable to measure the distance of evidence.

In summary, this paper introduces pignistic probability function to construct a new method to combine conflict evidence based on method of Deng Yong. Suppose that the collection of evidence provided by n sources of evidence is $E=\{E_1,E_2,\cdots,E_n\}$, and the weight vector is $W=\{w_1,w_2,\cdots,w_n\}$. The algorithm is as follows:

Step1 The degree of evidence $difBetP_i^j$ is calculated between evidence E_i and other evidence $E_j\,(j=1,2,\cdots,i-1,i+1,\cdots,n)$ according to equation (3);

Step2 $\sup_i^j=1-difBetP_i^j$ is calculated, which is the level of evidence E_i supported by other evidence $E_j\,(j=1,2,\cdots,i-1,i+1,\cdots,n)$;

Step3 The overall support of each piece of evidence $\sup_i=\sum_{j=1,j\neq i}^{n}\sup_i^j$ is obtained; thereby a support vector $Sup=\{\sup_1,\sup_2,\cdots\sup_n\}$ is also obtained;

Step4 The support is normalized and weight of each piece of evidence is $w_i=\frac{\sup_i}{\sum_{i=1}^{n}\sup_i}$ obtained, and then a weight vector $W=\{w_1,w_2,\cdots,w_n\}$ is constituted;

Step5 All pieces of evidence weighted averaged by weight vector are combined using Dempster's rule for n-1 times.

The following example illustrates the general process of this combination method.

Example 4. Let the pair of BPAs from five distinct sources on frame $\Theta=\{A,B,C\}$ be:

$m_1(A)=0.5$ $m_1(B)=0.2$ $m_1(C)=0.3$

$m_1(A)=0$ $m_1(B)=0.9$ $m_1(C)=0.1$

$m_1(A)=0.55$ $m_1(B)=0.1$ $m_1(C)=0.35$

$m_1(A)=0.55$ $m_1(B)=0.1$ $m_1(C)=0.35$

$m_1(A)=0.55$ $m_1(B)=0.1$ $m_1(C)=0.35$

Respectively, the three pieces of evidence are combined based on Dempster's rule, Murphy, Jiang Wen, Deng Yong and improved method of combination in this paper. The results are shown in Table II:

TABLE II.
COMPARISON OF COMBINATION RULES

	m_1,m_2	m_1,m_2,m_3	m_1,m_2,m_3,m_4	m_1,m_2,m_3,m_4,m_5
Dempster	$m(A)=0$	$m(A)=0$	$m(A)=0$	$m(A)=0$
	$m(B)=0.8571$	$m(B)=0.6316$	$m(B)=0.3288$	$m(B)=0.1228$
	$m(C)=0.1429$	$m(C)=0.3684$	$m(C)=0.6712$	$m(C)=0.8772$
Murphy	$m(A)=0.1543$	$m(A)=0.3500$	$m(A)=0.6027$	$m(A)=0.7958$
	$m(B)=0.7469$	$m(B)=0.5224$	$m(B)=0.2627$	$m(B)=0.0932$
	$m(C)=0.0988$	$m(C)=0.1276$	$m(C)=0.1346$	$m(C)=0.1110$
Jiang Wen	$m(A)=0$	$m(A)=0.2331$	$m(A)=0.2354$	$m(A)=0.2236$
	$m(B)=0.2509$	$m(B)=0.0574$	$m(B)=0.0332$	$m(B)=0.0308$

	$m(C)=0.0418$	$m(C)=0.1571$	$m(C)=0.1353$	$m(C)=0.1251$
	$m(\Theta)=0.7072$	$m(\Theta)=0.5523$	$m(\Theta)=0.5960$	$m(\Theta)=0.6205$
Deng Yong	$m(A)=0.1543$	$m(A)=0.5816$	$m(A)=0.8060$	$m(A)=0.8909$
	$m(B)=0.7469$	$m(B)=0.2439$	$m(B)=0.0482$	$m(B)=0.0086$
	$m(C)=0.0988$	$m(C)=0.1745$	$m(C)=0.1458$	$m(C)=0.1005$
Improved	$m(A)=0.1543$	$m(A)=0.6330$	$m(A)=0.8260$	$m(A)=0.8974$
	$m(B)=0.7469$	$m(B)=0.1852$	$m(B)=0.0303$	$m(B)=0.0050$
	$m(C)=0.0988$	$m(C)=0.1818$	$m(C)=0.1437$	$m(C)=0.0977$

As can be seen from Table II, Dempster combination rule can not solve the conflict evidence effectively. The basic probability assignment function of A is always 0, although other evidence is inclined to A. Murphy's method can not recognize A correctly until the fourth piece of evidence is added. Jiang Wen's method is too conservative, although no false result is generated, but it still can not get the correct result. The recognition effect of DengYong and improved method is better, and when the third piece of evidence is added, the correct result is generated. But the focusing capability of the improved method is better than DengYong's. And it is mentioned in Section III, the result of DengYong's method is sometimes counter-intuitive, so the improved method is better regardless of the focusing capability or accuracy.

V. An Assessment Model Of Airport Noise Monitoring Data Reliability

We have a number of noise data monitored by monitoring points every second. Excavate relationship of noise data between the monitoring points using classical Apriori algorithm, and then association rules base is constructed. The form of association rules is *pi-tm=[x,y]->pj-tn=z（sup，conf）*. It means that if the noise decibel values of the monitoring point *pi* at time *tm* ranging between *x* to *y*, then the noise decibel value of monitoring points *pj* at time *tn* is deduced as *z*, and the support and confidence of this rule are *sup* and *conf*. Based on the known association rule and the new combination rule in section III, an assessment model of airport noise monitoring data reliability is established, whose flow chart is as follows:

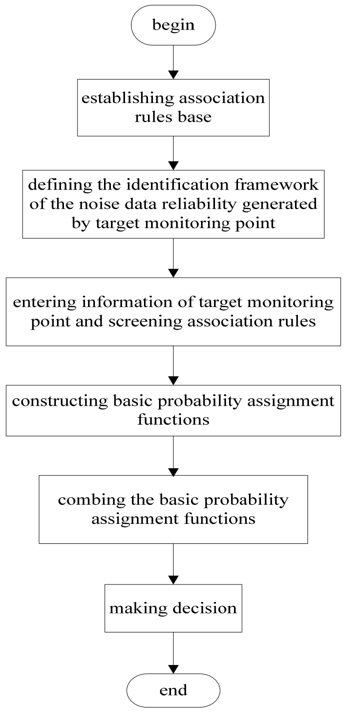

Figure II. The flow chart of assessment model

TABLE III.
DATABASE TABLE STRUCTURE

Attribute	Description
ID	Unique identification of association rules
PRE_POINT	The No. of previous monitoring points
PRE_TIME	The time of previous monitoring points
PRE_VALUE	The noise value of previous monitoring points
RESULT_POINT	The No. of target monitoring points
RESULT_TIME	The time of target monitoring points
RESULT_VALUE	The noise value of target monitoring points
SUP	The support of association rules
CONF	The confidence of association rules

Now each step in the model is described in detail:

(1) Association rule base of Noise data is established, database table structure is shown in Table III, and the association rules *pi-tm = [x, y] -> pj-tn = z (sup, conf)* are introduced into the database table.

(2) The identification framework is established. The levels of reliability of the target monitoring points are divided into four categories, measured value of *pj* is denoted as *real*, predictive value of *pj* by association rules is denoted as *z*. Set three thresholds are *p, q, r*（*p<q<r*）.

If *z* is located within the *real* ± *p*, measured value is considered reliable, and denoted as A;

If *z* is located in [*real-q, real-p*) or (*real* + *p, real* + *q*], measured value is considered a little reliable, and denoted as B;

If *z* is located in [*real-r, real-q*) or (*real+q, real+r*], measured value is considered less reliable, and denoted as C;

If *z* is located out of *real* ± *r*, the measured value is considered unreliable, and denoted as D.

(3) Association rules whose target monitoring points is RESULT_POINT and time is RESULT_TIME from the association rule base are screened. Then these association rules are grouped by RESULT_POINT and RESULT_TIME and arranged in descending order according to support then confidence.

(4) For each PRE_POINT, association rules are matched one by one in order to find out whether the noise data generated by the flight incident in PRE_TIME is between PRE_VALUE. The pseudo code of this process is as follows:

```
For every PRE_POINT
    For every PRE_TIME
        For every association rule of this PRE_TIME
            If the noise data monitored at PRE_TIME is
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                between PRE_VALUE in this flight
                incidence then
                    the BPA of focal element that includes
                    RESULT_VALUE in this association
                    rule adds up CONF
            End If
        End For
        If association rule is matched successful and BPA
            is generated then
                Break
        End If
    End For
    If association rule is matched unsuccessful and
        BPA is not generated then
        unknown term of BPA of this monitoring point is
        equaled 1
    End If
End For
```

(5) Combine these pieces of evidence using combination rule in section III, and make the type with highest probability be the final decision.

The following example illustrates the general process of this model.

Example 5. Now evaluate measured data produced by monitoring point *p11* at time *t35* whether or not reliable. Association rules matched with *p11* are selected from the association rules base and some association rules related to *p10, p12 and p13* are obtained. Set the threshold values *p* = 3dB, *q* = 5dB, *r* = 8dB. Noise data is mined by Apriori and association rules base is established, and the base is shown in Table IV. Then the table is grouped and arranged according to (3), and the result is shown in Table V.

TABLE IV.
THE ASSOCIATION RULES BASE

ID	PRE_POINT	PRE_TIME	PRE_VALUE	RESULT_POINT	RESULT_TIME	RESULT_VALUE	SUP	CONF
1	p12	t7	[71,75]	p11	t43	64	0.25	0.75
2	p12	t6	[71,75]	p11	t44	64	0.3333	0.5714
3	p13	t27	[76,80]	p12	t2	72	0.25	0.75
4	p12	t3	[71,75]	p11	t43	64	0.25	0.6
…	…	…	…	…	…	…	…	…
100	p11	t41	[61,65]	p13	t38	61	0.25	0.375
…	…	…	…	…	…	…	…	…

TABLE V.
THE GROUPED AND ARRANGED ASSOCIATION RULES BASE

ID	PRE_POINT	PRE_TIME	PRE_VALUE	RESULT_POINT	RESULT_TIME	RESULT_VALUE	SUP	CONF
819	p10	t98	[56,60]	p11	t35	58	0.25	0.75
543	p10	t99	[56,60]	p11	t35	58	0.25	0.75
…	…	…	…	…	…	…	…	…
949	p12	t9	[71,75]	p11	t35	61	0.3333	0.3636
950	p12	t9	[71,75]	p11	t35	58	0.25	0.2727
…	…	…	…	…	…	…	…	…
134	p13	t30	[71,75]	p11	t35	61	0.3333	0.6
698	p13	t29	[56,60]	p11	t35	51	0.25	1
…	…	…	…	…	…	…	…	…

Follow the process of the model and eventually obtain the following three pieces of evidence:

$m_1(A) = 0.75 \quad m_1(B) = 0 \quad m_1(C) = 0 \quad m_1(D) = 0$

$m_1(\Theta) = 0.25$

$m_2(A) = 0.6363 \quad m_2(B) = 0 \quad m_2(C) = 0 \quad m_2(D) = 0$

$m_2(\Theta) = 0.3637$

$m_3(A) = 0.6 \quad m_3(B) = 0 \quad m_3(C) = 0 \quad m_3(D) = 0$

$m_3(\Theta) = 0.4$

Respectively, the three pieces of evidence are combined based on Dempster's rule, Murphy, Jiang Wen, Deng Yong and improved method of combination in this paper. The results are shown in Table VI:

TABLE VI.
RESULTS OF COMBINING EVIDENCE

	$m(A)$	$m(B)$	$m(C)$	$m(D)$	$m(\Theta)$
D-S	0.9636	0	0	0	0.0364
Murphy	0.9614	0	0	0	0.0386
Jiang Wen	0.8279	0	0	0	0.1721
Deng Yong	0.9610	0	0	0	0.0390
Improved	0.9610	0	0	0	0.0390

As can be seen from Table VI, when the evidence has no major conflict, these methods can obtain more accurate results. It is assumed that point *p13* is matched nothing, the three pieces of evidence are as follows:

$m_1(A) = 0.75 \quad m_1(B) = 0 \quad m_1(C) = 0 \quad m_1(D) = 0$

$m_1(\Theta) = 0.25$

$m_2(A) = 0.6363 \quad m_2(B) = 0 \quad m_2(C) = 0 \quad m_2(D) = 0$

$m_2(\Theta) = 0.3637$

$m_3(A) = 0 \quad m_3(B) = 0 \quad m_3(C) = 0 \quad m_3(D) = 0$

$m_3(\Theta) = 1$

Then the combination results are as shown in Table VII:

TABLE VII.
RESULTS OF COMBINING EVIDENCE INCLUDING UNKNOWN INFORMATION

	$m(A)$	$m(B)$	$m(C)$	$m(D)$	$m(\Theta)$
D-S	0.9091	0	0	0	0.0909
Murphy	0.8444	0	0	0	0.1556
Jiang Wen	0.5381	0	0	0	0.4619
Deng Yong	0.8953	0	0	0	0.1047
Improved	0.9000	0	0	0	0.1000

As can be seen from Table VII, although there is a piece of evidence including unknown information, these methods can also obtain better results. But Jiang Wen's method is too conservative. Then it is assumed that point *p13* is abnormal, leading to the first evidence conflicts with other evidence. Therefore the point is matched a piece of false association rule. The three pieces of evidence are as follows:

$m_1(A) = 0.75 \quad m_1(B) = 0 \quad m_1(C) = 0 \quad m_1(D) = 0$

$m_1(\Theta) = 0.25$

$m_2(A) = 0.6363 \quad m_2(B) = 0 \quad m_2(C) = 0 \quad m_2(D) = 0$

$m_2(\Theta) = 0.3637$

$m_3(A) = 0 \quad m_3(B) = 0 \quad m_3(C) = 0 \quad m_3(D) = 1$

$m_3(\Theta) = 0$

Then the three pieces of evidence are combined according to five methods, and the results are shown in Table VIII:

TABLE VIII.
RESULTS OF COMBINING CONFLICT EVIDENCE

	$m(A)$	$m(B)$	$m(C)$	$m(D)$	$m(\Theta)$
D-S	0	0	0	1.000	0
Murphy	0.6490	0	0	0.3317	0.0193
Jiang Wen	0	0	0	0.0967	0.9033
DengYong	0.9246	0	0	0.0477	0.0278
Improved	0.9628	0	0	0.0085	0.0287

As can be seen from Table VIII, when there is a conflict of evidence, Dempster's rule often gets the wrong results. Jiang Wen's methods cannot make judgments. Murphy, Deng Yong and the improved method can get the correct results, but the focusing capability of improved method is better.

VI. AN EXAMPLE

A group of reliable noise monitoring data is selected from May 1, 2010 to May 10 ,2010 of a domestic airport, and noise data produced by B738 from the same flight route is screened out. The level of reliability of measured data produced by monitoring point *p11* at time *t35* is assessed using Dempster's rule, Murphy, Jiang Wen, Deng Yong and improved method of combination in this paper. Experimental data and threshold settings are the same as in Example 5. The assessment results of the event are made by using statistics, and experimental results are shown in Table IX.

TABLE IX.
RESULTS OF NOISE DATA RELIABILITY ASSESSMENT

	D-S	Murphy	Jiang Wen	Deng Yong	Improved
Reliable	76.9%	76.9%	61.5%	76.9%	76.9%
A little reliable	7.7%	7.7%	0	7.7%	7.7%
Less reliable	0	0	0	0	0
Unreliable	0	0	0	0	0
Uncertain	15.4%	15.4%	38.5%	15.4%	15.4%

As can be seen from Table IX, when all the data is reliable, five methods can more accurately infer the reliability of the target monitoring noise data, and no error inference. Only Jiang Wen's method is too conservative. As the aircraft routes slight error and limited amount of data, there is also a small part of the data which cannot be clearly distinguished.

The condition of the above experiments is that all the experimental noise data is reliable, but in actual application a monitoring point data abnormal may exist. Main exception reasons include: firstly, monitoring equipment loses and there exists a certain error between noise data after calibration and the original data; Secondly, monitoring data includes interference of external factors, superimpose surrounding ambient noise in addition to aircraft noise. Now a group data containing the above exception is selected from the airport noise monitoring data, and leading to contain conflicting evidence. Then combine them using the five methods. The experimental results are shown in Table X.

TABLE X.
RESULTS OF ABNORMAL NOISE DATA RELIABILITY ASSESSMENT

	D-S	Murphy	Jiang Wen	Deng Yong	Improved
Reliable	53.8%	61.5%	46.2%	69.2%	76.9%
A little reliable	7.7%	7.7%	0	7.7%	7.7%
Less reliable	0	0	0	0	0
Unreliable	23.1%	0	0	0	0
Uncertain	15.4%	30.8%	53.8%	23.1%	15.4%

As can be seen from Table X, when there is conflicting evidence, Dempster's rule will be error and the result is in less reliable; Jiang Wen's method is without error judgments, but too conservative; The combination effect of Murphy, Deng Yong, and improved method is more accurate, and the recognition ability of improved method is better than both of them. As already mentioned, Deng Yong's method has counter-intuitive results in certain circumstances, the improved method, therefore, has also better accuracy.

VII. CONCLUSIONS

This article uses the evidence theory to airport noise monitoring data reliability assessment. The existing combination rules of evidence theory are improved and an assessment model of airport noise monitoring data reliability based on the improved combination rule is established. Experiments show that the improved method is better than existing methods. On this basis, the proposed assessment model can also assess the reliability of the monitoring data more accurately, with a stronger practicality.

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