

# A Health Diagnosis Model for Sluices based on the Improved Evidence Combination Algorithm

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**Abstract.** The traditional evidence theory is mainly used to solve the fusion problem with consistent or low conflict evidences. When the evidences are obvious conflicted, the traditional evidence theory may lead to unreasonable diagnosis results. In order to solve the information uncertainty in the health diagnosis of sluices and the obvious conflicts in the evidences in the diagnosis process, an improved evidence combination algorithm is applied to diagnose the health status of a sluice, which considers the conflict as a local conflict and takes into account the assignment of conflict information between the health states of conflict production when integrating the evidences. The example shows that the improved evidence combination algorithm can deal with the problem of evidence conflict more reasonably, and reflect the health state of the sluice more truly, which provides a new method for diagnosing sluices behavior.

## 1. Introduction

As an important tool for dealing with uncertain problems, the evidence theory can integrate uncertain multi-source information by using the trust function and combination rules [1], thereby weakening the adverse effects of information uncertainty on the diagnosis results. The health diagnosis of sluice is a complex problem with multi-layers, which means that many indicators and uncertainty are based on multi-source monitoring information. Therefore it is appropriate to diagnose the healthy state of sluices by using the evidence theory.

In the field of engineering health diagnosis, Ma Fuheng [2] et al. adopted the modified information fusion method based on evidence theory to analyze the measured seepage data and study the identification and analysis method of the seepage warning of the earth-rock dam. Tao Congcong [3] et al. applied the evidence theory-based information fusion method to the analysis of the monitoring data of Qingtongxia Dam and diagnosed the health status of the Qingtongxia Dam. He Jinping [4] et al. proposed a new fusion coefficient calculation formula for dam health diagnosis, and established a multi-effect fusion model for the health diagnosis of high arch dams based on the improved evidence theory.

At present, there are two main disadvantages in the application of the traditional evidence theory to the engineering health diagnosis. First of all, the diagnostic indicators (evidences) are equally important with little consideration on the difference in the importance degree; secondly, the traditional evidence theory is mainly applicable to dealing with the fusion problem with consistent or low conflict evidences. When the evidences are obvious conflict, the traditional evidence theory may lead to unreasonable diagnosis results. Therefore, this paper preprocesses the evidence information based on the concept of weight, and adopts an improved evidence combination algorithm to study the health diagnosis method of sluice, making the results more practical.



## 2. Improved Evidence Combination Algorithm

*Dempster* combination rule is the basic synthesis rule of the evidence theory. It reassigns the trust value  $K$  of the conflict part between the evidences to the non-conflict propositions in the evidences by normalization, so it ignores the conflict between the evidences in order to realize normalization. *Yager* combination rule removes the normalization process and assigns the conflict part between the evidences to the identification framework, so it is reasonable to deal with the low conflict situation. However, in the health diagnosis of sluices, the evidences provided by the monitoring data may be highly conflicting. At this time, the applicability of the above synthetic rules is not ideal. In fact, the conflict of evidence itself is a reflection of the uncertainty of information, which cannot be completely ignored. A new combination method is needed in dealing with the high conflict evidence.

For this reason, the paper reduces the impact of evidence conflict on the results of health diagnosis from two aspects: the first is to consider the importance of evidence in the combination of evidences based on the concept of weight, so as to highlight the role of important evidence and weaken the role of the secondary evidence; the second is to consider the conflict as a local conflict and take into account the assignment of conflict information between the health states of conflict production when combining the evidences, so as to make the assignment of conflict information more realistic.

### 2.1. Basic Trust Assignment Function Based on Weight

In the sluice health diagnosis, different diagnosis indexes (evidences) have different effects on it, so the importance of the evidence should be different in the process of evidence combination.

In the health diagnosis of sluices, the identification framework of the health state can be defined as:  $\Theta = \{\text{normal, basically normal, abnormal, disordered}\} = \{H_1, H_2, H_3, H_4\}$  [5]; it is assumed that there are  $n$  diagnostic indexes, that is,  $n$  evidences, written as  $X = \{x_1, x_2, \dots, x_n\}$ , so the basic trust of  $n$  evidences ( $x_i$ ) for health states ( $H_j$ ) within the identification framework is written as:

$$M = [m_{ij}] \quad (i=1, 2, \dots, n; j=1, 2, 3, 4) \quad (1)$$

The weight of evidence is written as  $\{p_1, p_2, \dots, p_n\}$ . The greater the role of evidence in the health diagnosis of sluices, the bigger the weight is. Thus, it can be defined as:

$$\alpha_i = p_i / p_{\max} \quad (i=1, 2, \dots, n) \quad (2)$$

$\alpha_i$  is a conversion coefficient, and the reduction coefficient is used to reallocate the basic trust of each evidence.

$$m_{ij}^* = \alpha_i m_{ij} \quad (3)$$

$m_{ij}^*$  is the basic trust of each of the evidences after reassignment. Since the sum of  $m_{kj}^*$  of all elements in the identification framework  $\Theta$  is less than 1 for the evidence ( $x_k$ ) after reassignment, not meeting the requirement of basic trust assignment function, an additional definition is required:

$$m_{kj}^*(U) = 1 - \sum_{j=1}^4 m_{kj}^* \quad (4)$$

where  $U$  is the basic trust of complete uncertainty. Formula (3) and (4) form a new basic trust assignment function that considers the importance of evidence.

### 2.2. Improvement of the Combination Algorithm

At present, the conflict is mainly handled by regarding it as the global conflict and implementing global assignment within the identification framework  $\Theta$ , but the method is very rough. Therefore, the paper regards the conflict as a local conflict [6], starts from its source, determines the assignment space of conflict, and assigns it between the health states of conflict production in accordance with the conflict value. It is not general. The improved combination formula can be expressed as:

$$\begin{cases} m(A) = \sum_{\substack{B \cap C = A \\ B, C \subseteq \Theta}} m_1(B)m_2(C) + \sum c(A) \\ c(A) = \frac{m_1(A)}{m_1(A) + m_2(X)} m_1(A)m_2(X) \end{cases} \quad (5)$$

where  $c(A)$  is the part that assigned to A by local conflicts, in which  $A \cap X = \emptyset$ .

The improved combination algorithm is based on the idea that the conflict is completely available. It makes full use of all the information provided by the evidence. When dealing with the high conflict evidence, the method has obvious advantages in reasonable results, simple calculation and fast convergence speed.

### 3. Engineering Example

A large sluice hub is equipped with a 16-hole sluice. In order to monitor the safety of the sluice, surface horizontal displacement, surface vertical displacement, joint opening degree, sluice uplift pressure and subgrade reaction are arranged.

#### 3.1. Basic Trust

The identification framework of the health status of the sluice  $\Theta = \{H_1, H_2, H_3, H_4\} = \{\text{normal, basically normal, abnormal, disordered}\}$ , and the diagnosis evidence of the health state  $X = \{x_1, x_2, x_3, x_4, x_5\} = \{\text{surface horizontal displacement, surface vertical displacement, joint opening degree, sluice uplift pressure and subgrade reaction}\}$ . Among them, surface horizontal displacement mainly considers uneven settlement. According to the qualitative and quantitative analysis of the long-term monitoring data of the monitoring effect quantities (evidence), the initial basic trust of the evidence on the identification framework is shown in table 1.

Table 1. Initial Basic Trust of the Evidences.

Diagnosis Index	Normal (H <sub>1</sub> )	Basically normal (H <sub>2</sub> )	Abnormal (H <sub>3</sub> )	Disordered (H <sub>4</sub> )
Surface Horizontal Displacement (x <sub>1</sub> )	0.20	0.70	0.10	0
Uneven Settlement (x <sub>2</sub> )	0.25	0.60	0.15	0
Joint Opening Degree (x <sub>3</sub> )	0.10	0.25	0.65	0
Sluice Uplift Pressure (x <sub>4</sub> )	0.10	0.50	0.40	0
Subgrade Reaction (x <sub>5</sub> )	0.15	0.40	0.45	0

From Table 1, the initial basic trust of most of the monitoring effect quantities (evidence) on the health states is consistent, but the initial basic trust of the seepage monitoring effect quantities (x<sub>4</sub>, x<sub>5</sub>) is obviously lower than that of the deformation effect quantities (x<sub>1</sub>, x<sub>2</sub>), and the initial basic trust of the joint opening degree (x<sub>3</sub>) on the abnormal (H<sub>3</sub>) is obviously lower than that of other effect quantities. Thus, there are obvious conflicts between evidences.

According to the importance of different diagnostic indexes, their weights are determined to be  $\{p_1, p_2, p_3, p_4, p_5\} = \{0.25, 0.20, 0.10, 0.20, 0.25\}$ . The reduction coefficient  $\alpha_i = \{1, 0.8, 0.4, 0.8, 1\}$  of the evidences are calculated by Formula (2). Then, the basic trust of the evidences after assignment is calculated by Formula (3) according to  $\alpha_i$ , as shown in Table 2, in which U represents the basic trust of complete uncertainty.

Table 2. Basic Trust of the Evidences after Reassignment.

Diagnosis Index	Normal (H <sub>1</sub> )	Basically normal (H <sub>2</sub> )	Abnormal (H <sub>3</sub> )	Disordered (H <sub>4</sub> )	U
Surface Horizontal Displacement (x <sub>1</sub> )	0.20	0.70	0.10	0	0
Uneven Settlement (x <sub>2</sub> )	0.20	0.48	0.12	0	0.20
Joint Opening Degree (x <sub>3</sub> )	0.04	0.10	0.26	0	0.60
Sluice Uplift Pressure (x <sub>4</sub> )	0.08	0.40	0.32	0	0.20
Subgrade Reaction (x <sub>5</sub> )	0.15	0.40	0.45	0	0

From Table 2, among the basic trust of the evidences after reassignment, the basic trust of two most important evidences (x<sub>1</sub>, x<sub>5</sub>) remains the same, that of the least important evidence (x<sub>3</sub>) changes greatly, in which the basic trust assigned to the complete uncertain state (U) is 0.60, thus achieving the purpose of weakening the secondary evidence.

### 3.2. Evidence Combination

The improve combination algorithm shown in Formula (5) is applied to calculate the basic trust of the evidences reassigned in Table 2. The results are shown in Table 3. At the same time, in order to verify the rationality and effectiveness of the improved combination algorithm, *Dempster* combination formula and *Yager* combination formula are adopted to calculate the data in Table 2. The combination results are also listed in Table 3.

Table 3. Combination Formula Fusion Results

Combination Method	Normal	Basically normal	Abnormal	Disordered	U
<i>Dempster</i> Combination Formula	0.0028	0.9370	0.0602	0	0
<i>Yager</i> Combination Formula	0.0001	0.0065	0.0004	0	0.9930
Improved Combination Formula	0.0490	0.6084	0.2323	0	0.1103

### 3.3. Health Diagnosis

According to Table 3, the information provided by the diagnosis results of different combination methods are obviously different when there are clear conflicts in the evidences provided by the sluice monitoring information.

(1) *Dempster* combination method completely ignores the conflict between the evidences. As a result, the diagnosis results are highly concentrated at “basically normal”. In practical application, it easily makes the sluice managers neglect the “abnormal” component in the sluice safety, which is not conducive to the safety management of sluices.

(2) *Yager* combination method completely assigns the conflicting information to unknown items, leading to the obviously large value of unknown items. As a result, it is unable to obtain definite results.

(3) The improved evidence combination algorithm well deals with the conflict assignment problem among the evidences. The diagnosis results show that the sluice is “basically normal”, but the “abnormal” component can not be ignored. It is consistent with the actual situation, and it is also helpful to remind the sluice managers of paying attention to the unsafe factors of the sluice.

#### 4. Conclusion

When there are obvious conflicts in the evidences, *Dempster* combination rules ignore the conflict between the evidences in order to meet the requirement for normalization, and *Yager* combination rules may lead to the failure in obtaining clear diagnosis results due to the cancellation of the normalization process. In order to solve the problem of evidence conflict in the evidence theory, the paper applies the improved evidence combination algorithm to diagnose the health state of the sluice when there are obvious conflicts in the evidences provided by the monitoring information. The example shows that the improved evidence combination algorithm can more accurately reflect the health status of the sluice.

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