D-S Evidence Theory Applied to Fault Diagnosis of Generator Based on Embedded Sensors

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Abstract - In the monitoring system of power plant, the method of gathering real time data of sensors is often adopted. It not only increases the communication burden of monitoring system but also results in erroneous transmitting due to worse electromagnetism environment. For overcoming these shortcomings, we adopt a new approach --- using embedded multisensors and D-S evidence theory. This method has been applied to the monitoring system of JiLin FengMan Power Plant successfully.

Keywords: Embedded sensors, data fusion, Dempster-Shafer evidence theory.

1 Introduction

1.1 Embedded Sensors

In the traditional monitoring system of power plant[1], to realize online system monitoring and fault diagnosis, it is necessary to collect real time data from data gathering system in the power plant through advanced network communication technology. In this process, for example, when we collect data of temperature sensors, the temperature value will be firstly transformed into electrical signal and then be sent to the monitoring center in the form of analogue value. Sometimes these data can be transmitted in the form of digital value, but that is often done through simple sampling and quantifying. Furthermore there is intense electromagnetic disturbance in industrial environment, errors will be introduced into the signal regardless of analogous transmitting or digital transmitting in any time. If the monitoring center evaluates current situation based on these “color data”, an incorrect judgment is often made. At the same time, it also increases the communication quantity of monitoring system because of continuous real time data transmitting and decreases monitoring center’s management performance. To resolve this problem, we adopt embedded sensors to collect data. Embedded sensors can preprocess the continuous and real time values measured from field equipments. Then the monitoring center can gather data form the sensors periodically. Moreover the embedded sensors can engender a local judgment about the state of the monitored equipment and then transmit to the monitoring center. Therefore the embedded sensors possess some intelligent function in this monitoring architecture. Because transmitted data is only a judgment value, it can be sent in a short code form. In case of disturbance, it also can be sent repeatedly. Thereby we can get high reliability data that may reach up to zero error code rate. But for the monitoring center, it acquires less information than that of traditional monitoring architecture and tend to make mistakes. In order to settle this problem, we apply a sort of fusion algorithm which matches the embedded sensors judgment. It can achieve better monitoring and detection performance.

Architecture of embedded sensors is shown in figure 1:

1.2 Fundamentals of Data Fusion:

Data fusion is a process of management, control and decision-making with computer based on all data sources. Initial definition of data fusion is given by the department of defense of USA[2].

Waltz and Llinas supplement and modify the definition in literature[2]. Their definition about data fusion is correlative to military application. In fact, the study on data fusion is concerned with a great deal of subject and the most important subject is study on artificial intelligent technology. At present the study on artificial intelligent technology is attached more importance and becomes a bottleneck of much technology development. In addition, research on data fusion will facilitate the study on artificial intelligent technology. Now fusion technology has been applied to civil application and so it should have a more general definition. It is believed that a general and accurate definition will be derived at last with the thorough research on data fusion.

Study of functional fusion model depends on its application’s background deeply. A general requirement on functional model of data fusion system is represented
in literature [3]: In the fusion system, information which all data sources possess should be made full use of in every fusion process. Furthermore, the function which each datum has in its local treatment should integrate organically with other part. So that, while the local treatment is very close to intuitive experience, efficiency of each datum wouldn’t be decreased when it comes into other process of the fusion system. Namely, all counterparts of the system have obtained harmony and unification. The most difficult work to achieve the upper performance is how to find algorithms and tools that can make full use of information possessed by measured data. It will cover much research theme and has close relationship with its application context. In this paper, we attempt to resolve fusion problem of fault diagnosis by using D-S evidence theory for utilizing information sufficiently to reach the upper object.

The definition of data fusion at functional level develops with the development of fusion research. Initially it is divided into three parts: pixel level, characteristic level and decision-making level[4]. In the application of fault detection and diagnosis, fusion of data layer involves direct data treatment and necessary analysis. For instance, signal filtering, spectrum analysis and wavelet analysis etc. In this paper, fusion on data layer is implemented in embedded sensors through some matured detection algorithms or artificial neural networks[5][6]. Fusion at characteristic level involves efficient judgment from the fusion results on data layer. Generally it corresponds to diversified fault diagnosis algorithms. In this study, we mainly discuss fusion algorithm at characteristic level. Fusion at decision-making level corresponds to all sorts of countermeasures based on fault diagnosis results: such as fault isolation, operation in lower performance and so on. The three fusion level suit for fault alarm, fault diagnosis and fault isolation separately in functional character[7].

The classification method of functional model of data fusion comes mainly from military applications. It will be different in other applications. However, in a broad manner, lower part of fusion model involves treatment of local data. On the contrary, the higher part of fusion model involves treatment of macroscopical and entire judgment or evaluation. Algorithms adopted by the two parts of fusion model is also different ------ for the lower part, structural and formular analysis methods are adopted through some matured signal processing approaches. For the higher part, usually AI is adopted and so it can simulate the thinking way of people and get a right judgment and evaluation on current situation.

By applying data fusion technology to fault detection and diagnosis system, we can achieve precise estimation about equipment state or “health” status, enhance belief quantity, decrease fuzzy level, improve detection performance and take full advantage of resource of sensor network[8][9].

1.3 Fundamentals of Dempster -Shafer Theory

In the fusion process of fault diagnosis, Bayes theory is often adopted[3][8][9] Bayes clings to classical probability theory and has rigorous logic. However, while the theoretical conclusion deduced from Bayes theory is applied to practical system, it is not very perfect and is difficult to get expectant results. The reason is that much hypothesis has been made to simplify the inferring process. Whereas in practical application, these hypothesis will not come true entirely. Therefore it results in errors of experiment. For example, while computing uncertainty of every sensor’s judgment, prior probability distributing function and conditional probability distributing function of every measured variable should be known beforehand. Nevertheless it is impossible to obtain precise probability distributing function. Consequently we adopt a sort of fault diagnosis algorithm that do not need exact probability distributing function ------ Dempster-Shafer evidence theory.

In this paper we propose a method to combine data supplied by several sources using Dempster-Shafer rule. The Dempster-Shafer Theory offers an interesting tool to combine data supplied by data sources more or less reliable by managing their imprecision and uncertainty. The D-S theory has been used in many applications as in Pattern recognition and Image Analysis. But in fault diagnosis applications, D-S theory is adopted scarcely. Therefore, by means of D-S theory, we plan to resolve special problem that can not be settled perfectly by some other algorithms of fault diagnosis.

In this section, a brief overview of the Evidence’s Theory is given.

The D-S theory uses a frame of discernment which is a set interpreted as a set of mutually exclusive propositions. The correlated propositions are assumed to be expressed as subsets of the frame \( \Omega \) which is assumed to be a finite set. A mass function over \( \Omega \) also known as a basic probability is m function:

\[
2^\Omega \rightarrow [0,1]
\]

where \( m(\emptyset) = 0 \), and

\[
\sum_{x \in A} m(A) = 1 \quad (1)
\]

The knowledge about the problem induces a basic belief assignment that allows to define a belief function.

Hypothetic subsets \( \Omega_i \) of \( \Omega \) \( (m(\Omega_i) > 0) \) are called focal elements of \( m \). From this Basic belief assignment \( m \), the credibility \( Bel(\Omega_i) \) and plausibility \( Pl(\Omega_i) \) can be computed from the following equations:

\[
Bel(\Omega_i) = \sum_{A \supseteq \Omega_i} m(A) \quad (2)
\]

\[
Pl(\Omega_i) = \sum_{A \supseteq \Omega_i} m(A) \quad (3)
\]

The value \( Bel(A) \) quantifies the strength of the belief that event \( A \) occurs. These functions (m, Bel and Pl) are derived from the concept of lower and upper bounds for a set of compatible probability distributions. In addition, Dempster-Shafer theory allows the fusion of several sources using the Dempster’s combination operator. It is defined like the orthogonal sum (commutative and associative) in terms of the following equations:

\[
m(\Omega_i) = m_1(\Omega_i) \oplus \cdots \oplus m_m(\Omega_i) \quad (4)
\]

For two sources \( S_i \) and \( S_j \), the aggregation of evidence for a hypothesis \( \Omega_i \subseteq \Omega \) can be expressed as follows:
Where $c$ is defined by:

$$
\text{The normalization coefficient } c \text{ evaluates the conflict between two sources.}
$$

$$
c = 1 - \sum_{A_i \cap C = \emptyset} m_i(A) \cdot m_j(C)
$$

between two sources.

2 Fault Diagnosis Model and Experiment

2.1 Architecture of Fusion Model

Measured value space of sensors is divided into two different characteristic sections. A judgment criterion can be formed through necessary alternation processing of the characteristic section and obtained information. We may adopt binary proposition judgment for simple fault detection. For a special fault mode, on the premise of binary proposition, the observation space is divided into two sections --- $Z_0$ and $Z_1$. If the observation value (or transformed characteristic value) locates in $Z_0$ section, no fault happening can be assumed. Otherwise decision of fault happening will be made. By selecting suitable judgment section, low error code rate of repeated experiment can be obtained. In the fusion of detection layer, we can realize the upper elementary work of fault detection and give an alarm.

In the fusion of characteristic layer, results of detection layer and some diagnosis knowledge of diagnosed object are necessary. The diagnosis knowledge originates from all sorts of prior knowledge. Contrast with the former proposition and examining the measured value, proposition matches the measured value will be made. By combining fusion results of diagnosis knowledge with fusion results of detection layer to finish fusion process on characteristic layer, we can implement the diagnosis process of fault diagnosis system.

Firstly, in every cycle of measuring data, fusion credibility assignment of all sensors is computed. Secondly general fusion credibility assignment based on the obtained fusion credibility assignment of all cycles is computed.

$$
m(P) = \frac{1}{c} \sum_{A_i \cap P \neq \emptyset} m(A_i), \quad P \subseteq \emptyset
$$

$$
c = 1 - \sum_{A_i \cap \emptyset \neq \emptyset} m(A_i)
$$

In this study, one kind of architecture based on embedded sensors is adopted. The kernel fusion algorithm is to compute credibility assignment of multisensors in multi-cycle. The credibility assignment means the extent to which each possible result is believed in the fusion center. It is like the probability of classical statistical theory.

The fusion architecture is shown in figure 2:

The following is formulas of computing the general fusion credibility assignment based on the known fusion credibility assignment of all cycles: $m(A_i)$ represents credibility assignment of proposition $A_i$ in the $i$th cycle.

![Figure 2 Architecture of data fusion](image-url)
2.2 Experiment Analysis:

The following is an fault diagnosis example of generator stator winding temperature\(^{[10]}\).

For the generator, its cooling system of stator winding and rotor and measuring points of monitoring operation parameters is shown in figure 3:

After the cooling water in the cooling water tank is pumped to the radiator by cooling water pump (one pump is in normal working state, the other is in backup state), it will flow from stator winding to rotor winding and then return back to cooling water tank. While the cooling water passing the radiator, its heat energy is transferred to the radiator, which attain the purpose of lowering temperature.

There are the following five kinds of causes to produce alarm: circulation water valve shut by error (F1), low pressure of circulation water (F2), cooling water valve shut by error (F3), cooling water pump lose electricity and backup pump not switched (F4), generator’s three phase current is out of balance or other electric fault (F5). Relationship between causes of alarm and operation parameters is shown in figure 4.

These five causes can be regard as proposition of temperature fault diagnosis. Altogether there are three groups of data of sensors sent to the fusion center. Separately they are obtained from the embedded sensors that derived from measured parameters about the safety state of current system. Each group of data is composed of a six dimensions vector of binary space. Process of fusion is as follows: Firstly, combining the three groups of data in each cycle, namely, computing orthogonal sum of credibility assignment of each proposition based on D-S evidence theory rule. Secondly, computing general credibility assignment on the basis of credibility assignments of each cycle. Finally judgment about fault state is educed. Vector representation of every proposition is shown in table 1:
Table 1 Vector representation of every proposition

<table>
<thead>
<tr>
<th>Sequence Number</th>
<th>Signification</th>
<th>Vector Representation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>circulation water valve shut by error</td>
<td>110000</td>
</tr>
<tr>
<td>2</td>
<td>low pressure of circulation water</td>
<td>111000</td>
</tr>
<tr>
<td>3</td>
<td>cooling water valve shut by error</td>
<td>100101</td>
</tr>
<tr>
<td>4</td>
<td>cooling water pump lose electricity, backup pump not switched</td>
<td>100111</td>
</tr>
<tr>
<td>5</td>
<td>generator's current is out of balance / other electric fault</td>
<td>100000</td>
</tr>
<tr>
<td>6</td>
<td>Unidentified reason 1(F6)</td>
<td>000000</td>
</tr>
<tr>
<td>7</td>
<td>Unidentified reason 2(F7)</td>
<td>111111</td>
</tr>
</tbody>
</table>

Table 2 Two cycle’s credibility assignment data

<table>
<thead>
<tr>
<th>Cycle</th>
<th>Sensor Group 1</th>
<th>Sensor Group 2</th>
<th>Sensor Group 3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>F2 F5 F7</td>
<td>F1 F2 F7</td>
<td>F2 F5 F6</td>
</tr>
<tr>
<td>1</td>
<td>0.5 0.2 0.3</td>
<td>0.6 0.3 0.1</td>
<td>0.3 0.5 0.2</td>
</tr>
<tr>
<td>2</td>
<td>0.7 0.1 0.2</td>
<td>0.5 0.3 0.2</td>
<td>0.5 0.3 0.2</td>
</tr>
</tbody>
</table>

In this case, we only implement fusion computing of two cycles. The two cycle’s credibility assignment data is grouped in table 2. Through the upper formula, it is easy to compute the three group sensors’ credibility assignment of each proposition in the first cycle and the second cycle:

First Cycle:

\[ m_1(F_1) = 0.18; \]
\[ m_1(F_2) = 0.12; \]
\[ m_1(F_3) = 0; \]
\[ m_1(F_4) = 0; \]
\[ m_1(F_5) = 0.7; \]
\[ m_1(F_6) = 0; \]
\[ m_1(F_7) = 0; \]

Second Cycle:

\[ m_2(F_1) = 0.28125; \]
\[ m_2(F_2) = 0.28125; \]
\[ m_2(F_3) = 0; \]
\[ m_2(F_4) = 0; \]
\[ m_2(F_5) = 0.4375; \]
\[ m_2(F_6) = 0; \]
\[ m_2(F_7) = 0; \]

Thereby we can obtain two cycle’s general credibility assignment data for fusion proposition:

\[ m(F_1) = 0.135; \]
\[ m(F_2) = 0.03375; \]
\[ m(F_3) = 0; \]
\[ m(F_4) = 0; \]
\[ m(F_5) = 0.83125; \]
\[ m(F_6) = 0; \]
\[ m(F_7) = 0; \]

From the results of fusion, it is obvious that possible cause giving rise to alarm is F5 --- electric fault or imbalanced current. Certainly, this is only a simple example in special situation. In the practical operation of system, credibility assignment of each proposition is more complex, but we can compute their uncertainty in the form of digital value through D-S evidence theory, and eventually get quite exact judgment. In literature [10], an approach applying cause and effect judgment method is applied to resolve fault diagnosis. However, when the diagnosed system is much more complicated and has diversified fault phenomena, the combination number of causes and effects of the diagnosis system will increase in geometric progression. So it is expected that in the situation of complicated system we can get more precise results than that of adopting method of cause and effect in literature [10]. Therefore it is an effective
attempt to use D-S evidence theory to resolve uncertainty inferring problem of fault diagnosis.

3 Conclusions

D-S evidence theory is an important method in uncertainty deducing theory. In this study, we get an anticipative purpose by applying D-S evidence theory to fault diagnosis of generator temperature. Sequential research is going to study application of knowledge mining in data fusion, namely, how to mine new useful knowledge from field measured data for fault diagnosis in order to realize more accurate data fusion.

References:

1. Li Xianwei. *Discussion on Remote Large Generator's Online Monitor and Diagnosis System*, ShanXi Electric Technology, 1999, 1