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Evidence fusion-based framework for condition evaluation of complex electromechanical system in process industry

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ABSTRACT

Evaluation of the condition of complex electromechanical systems in the process industry is one of the most important purposes of condition monitoring, and is an indispensable step to ensure safe operation and comprehensive coverage capabilities of a system. However, there are still difficulties in obtaining a precise evaluation result from uncertain, incomplete and even conflicting system monitoring data, and this is a key step for condition evaluation. Since evidence theory has shown high efficiency in handling uncertain information, an evidence fusion-based framework for condition evaluation has been presented in this paper to improve the certainty and precision of evaluation decisions by fusing features extracted from different sources of evidence. The proposed framework contains key points for condition evaluation that are driven by data, and evidence fusion is at the core of this method. First, the frame of discernment has been automatically constructed using time-series based clustering. Second, a kernel density estimation based non-parametric method for determining the basic probability assignment of evidence has been proposed. After combination, the conditions can be evaluated using pignistic probability. An actual condition evaluation requirement of complex electromechanical systems in the process industry has been used to verify the effectiveness of the proposed framework and to compare it with existing methods. This framework can handle common problems of condition evaluation and overcome some drawbacks of other existing similar methods since no particular distribution is assumed and a prior knowledge of system conditions is not required. Furthermore, it can be flexibly used in many engineering applications.

1. Introduction

Condition evaluation of complex electromechanical systems in the process industry is an important step for safe operation and comprehensive coverage of systems. However, it is still difficult to obtain precise evaluation results from uncertain, incomplete and even conflicting system monitoring data, which is the main purpose of condition evaluation.

As a technique that is used to integrate heterogeneous data from different sources, information fusion has attracted much attention from researchers and has been used in many applications [4,7]. Irrespective of the specific application, the aim of information fusion is to increase certainty and precision by combining both uncertain and imprecise information. There are several available mathematical theories for measuring the uncertainty and imprecision of data, such as the probability theory, rough sets, evidence theory, etc.. Among these, the Dempster-Shafer evidence theory (D-S theory), proposed by Dempster [8] and extended by Shafer [39], is one of the most effective mathematical tools for handling information that is imprecise, uncertain, and incomplete [48]. Even though it has been widely applied in information fusion fields [9,15,26,37,41,49,53], there are still some basic problems that need to be completely addressed. The key issue in D-S theory is lack of reasonable and effective methods of establishing the frame of discernment and obtaining basic probability assignment (BPA). Several methods have been proposed to automatically estimate the frame of discernment. In the work of Hégarat-Mascle [28], each source considered all of the hypotheses and it was defined on a discernment frame which was a subset of the common frame. In the work of Janez [21], the discernment frame was derived in an unsupervised way using the intersections between the hypotheses that were independently distinguished by individual sources. Schubert [38] has constructed alternative frames of discernment from input belief functions based on the assumption that the core of each belief function is a subset of the as-of-yet unconstructed frame of discernment. Rekik et al. [35] have proposed a method for updating the discernment frame as and when new information is available from new source. Smets and Kennes [40] argued that irrational fusion results are mainly due to an incomplete knowledge base when reliable sensors are available, so they proposed the con-

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cepts of the closed world and the open world. Deng [12] proposed a basic framework of generalized evidence theory to address conflict management in the open world. In his theory, $\emptyset$ is regarded as an element with the same properties as the other elements, which represents an unknown, but un-common, empty element.

Many authors have tried to solve the problem of obtaining BPAs using different methods. Yang et al. [51] have proposed a new method to represent the total degree of uncertainty of a given body of evidence based on the average distance between the belief interval of each singleton and the most uncertain case. Yager [50] has investigated this problem using fuzzy measures, and has compared the uncertainty of each fuzzy measure. Zhu et al. [56] have proposed a method based on fuzzy membership degrees to derive mass values. Jiang et al. [23] have presented an improved method for determining the similarity measure between generalized fuzzy members, and have proposed a new method to obtain BPA. Xu et al. [47,48] have proposed a method based on the assumption of a normal distribution and an improved method based on Gaussian process regression to obtain the BPAs. The specific assumption of distribution limits the application of this method. Jiang et al. [24] have proposed a method to determine the generalized BPA in an open world. A pessimistic strategy based on the differentiation degree between the models and the sample was defined to yield the BPAs for known targets. Based on the Shannon entropy, a new entropy named as Deng entropy has been proposed [13] to measure the uncertainty degree with basic probability assignment.

In this paper, we propose a condition evaluation framework for complex electromechanical systems in the process industry which is based on evidence fusion. A clustering technique is used to divide the training data into exhaustive and exclusive clusters, and a frame of discernment is adaptively constructed which contains the individual clusters. The union of the individual clusters is regarded as the ignorance. The features of each individual cluster are extracted and applied as the evidence in the evidence theory. A kernel-based density estimation is used to calculate the probability density function (PDF) of the features of each object in the frame of discernment. Then, the BPAs are obtained based on the estimated PDFs. Finally, the rule of evidence combination is performed, which is followed by calculating the pignistic probability to make a final decision. Our framework can handle the problems of condition evaluation and overcome some drawbacks of other existing similar methods since no particular distribution is assumed and a prior knowledge of system conditions is not required.

The organization of the rest of this paper is as follows. Section 2 briefly presents clustering, kernel density estimation, D-S theory and pignistic probability transformation. Section 3 describes the processing procedures of the evaluation framework, in particular, the construction of the frame of discernment based on clustering and obtaining the BPAs based on kernel density estimation. Section 4 verifies the effectiveness of the proposed framework for condition evaluation problems. The conclusions are presented in Section 5.

2. Preliminaries

2.1. Dempster–Shafer evidence theory

Dempster–Shafer evidence theory is a generalization of the probability theory. Due to its ability to deal with uncertain and imprecise information, it has been applied in many fields, such as decision making [6,11,19], risk assessment [10,15], classification [29,30], and others. [1]. Formally, the evidence theory can be simply presented as follows.

The first definition in evidence theory is the frame of discernment (FOD), which contains N exhaustive and exclusive hypotheses and it can be represented as $\Theta = \{H_1, H_2, \cdots, H_N\}$. $P(\Theta)$, the power set composed of 2^N propositions A of Θ, can be denoted as:

$$P(\Theta) = \{\emptyset, \{H_1\}, \{H_2\}, \cdots \{H_N\}, \{H_1 \cup H_2\}, \cdots, \Theta\} \quad (1)$$

where $\emptyset$ is regarded as the empty set. In general, the hypotheses can be viewed as possible or uncertain targets, and the FOD is a set of these targets. The N subsets containing only one element are called singletons.

The mass function m is a mapping of $P(\Theta)$ to [0, 1], which satisfies the following conditions:

$$\sum_{A \in P(\Theta)} m(A) = 1; m(\emptyset) = 0 \quad (2)$$

The mass function m is also named as basic probability assignment (BPA). $m(A)$ denotes the supporting degree of all relevant and available evidence for A. In evidence theory, $m(A)$ is determined by all relevant and available evidence based on a combination rule. If $m(A) > 0$, A is called a focal element.

The combination rule of the D-S theory is an operation for combining different BPAs to yield a new BPA. For instance, assume that m_1 and m_2 are two mass functions derived from two different evidence sources in the same FOD. Then, the fused BPA can be obtained using the following formula:

$$m(A) = \frac{\sum_{B \cap C = A} m_1(B) m_2(C)}{1 - k} \quad (3)$$

$$k = \sum\nolimits_{B \cap C = \emptyset} m_1(B) m_2(C) \quad (4)$$

where A is a focal element of m_1 and m_2, B is a focal element of m_1 and C is a focal element of m_2. The term k represents conflict between the sources of evidence under a specific basic probability mass function. It is an accumulation of the products of the mass function of all sets where the intersection is null. The larger the value of k, the more conflicts between the sources, and the less informative their combination will be(P. D. [48]).

2.2. Time series-based clustering

The first step in applying evidence theory is constructing the FOD. Within the process industry, processes are typically multimodal, and each stable condition has specific dynamics and duration times [54,55]. The intrinsic condition modes are consistent with the singletons in the discernment frames, and the essence of discernment frame construction is to obtain the intrinsic condition of the complex electromechanical system. Furthermore, when expert knowledge of a process is not available, unsupervised learning methods are usually adopted. For this purpose, conventional time-series clustering algorithms have been adopted.

As a data mining technique, clustering can place similar data elements into related or homogeneous groups without advance knowledge of the definition of each of the groups [2]. It is used as a solution to classify large volumes of data when early knowledge of the classes is not available. Clustering has been applied in many fields, such as novelty detection [34], dynamic change recognition [18] and pattern discovery [20].

Time-series data can be partitioned in an unsupervised way using time-series clustering. Given a dataset of n time-series data points $D = \{X_1, X_2, \cdots, X_n\}$, time-series clustering will partition D into $C = \{c_1, c_2, \cdots, c_k\}$ groups in such a way that homogeneous time-series are grouped together based on certain similarity measures. Each c_i is a cluster, where $D = \bigcup_{i=1}^{k} C_i$ and $c_i \cap c_j = \emptyset$ for $i \neq j$.

Stable modes are established depending on the desired productivity or product quality and they have stable characteristics for a long time. Consequently, each mode can be described using a single statistical mode.