FEATURE GROUP OPTIMIZATION FOR MACHINERY FAULT DIAGNOSIS BASED ON FUZZY MEASURES

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Abstract: With the development of modern multi-sensor based data acquisition technology often used with advanced signal processing techniques, more and more features are being extracted for the purposes of fault diagnostics and prognostics of machinery integrity. Applying multiple features can enhance the condition monitoring capability and improve the fault diagnosis accuracy. However, an excessive number of features also increases the complexity of the data analysis task and often increases the time associated with the analysis process. A method of bringing some efficiency into this process is to choose the most sensitive feature subset instead. Fuzzy measures are helpful in this regard and have the ability to represent the importance and interactions among different criteria. Based on fuzzy measure theory, a novel feature selection approach for machinery fault diagnosis is proposed in this paper. A heuristic least mean square algorithm is adopted to identify the fuzzy measures using training data set. Shapley values with respect to the fuzzy measures are applied as importance indexes to help choose the most sensitive features from a set of features. Interaction indexes with respect to the fuzzy measures are then employed to remove the redundant features. Vibration signals from rolling element bearing test rig are used to validate the method. The results show that the proposed feature selection approach based on fuzzy measures is effective for fault diagnosis.

Key Word: Fault diagnosis, Feature selection, Fuzzy measures, Importance index; Interaction index

1 INTRODUCTION

The task of condition monitoring and fault diagnosis for modern machinery is becoming increasingly complex as the machines become more automated and complicated. Fortunately, with the development of modern multi-sensor technology and advanced signal processing techniques, the increasing complexity of the tasks of diagnostics and prognostics of these machines can now be managed more meaningfully.

The task of condition monitoring and fault diagnosis usually results in a probabilistic result with a level of uncertainty. According to information fusion theory, information uncertainty can be reduced by applying multi-source information [1]. Hence, condition monitoring and fault diagnosis capability can be enhanced by applying multiple features. However, an excessive number of features on the other hand also increases the difficulties of data analysis and usually escalates maintenance cost. In fact, using all the features for monitoring and diagnosis purposes is also unnecessary as the contribution of each feature varies in a range. Some of them may be of little use to a specific troubleshooting process. Thus, selecting the most valuable feature subset is extremely important.

Various methods have been applied for feature selection purposes. Sub-optimal methods are more widely used than optimal methods. Although sub-optimal methods can generally produce optimal or near-optimal results in most real application cases, they cannot guarantee optimal results. The most frequently used sub-optimal feature selection algorithms are sequential forward search, sequential backward search, plus-L-minus-R and floating search, etc [2].

The exhaustive search is a universal optimal method. It produces an optimal solution by testing all the possible feature combinations. However, as the number of feature combinations increases exponentially with the number of features, this method becomes difficult to implement for high dimension feature space [3] [4] [5]. The only method other than exhaustive search still capable of yielding an optimal result is the branch and bound (BB) based algorithm. However, its application is also conditional. This method is only limited to monotonic criteria. Furthermore, its converging speed is highly dependent on the data sets [3]. To enhance its performance, BB algorithms have been improved by some researchers [6, 7].

Classical set theory and probability theory have been widely applied for dealing with uncertainty problems. Fuzzy set theory and fuzzy measure theory are two more general mathematical methods. Fuzzy methods are more effective than traditional clustering methods in handling fault features which are imprecise, with the boundaries among different failure modes usually being ambiguous in their mapping space. Fuzzy methods describe fault patterns in a non-dichotomous way which is similar to the manner in which human beings process vague information. As an outgrowth of classical measure theory, Fuzzy Measure (FM) and Fuzzy Integral (FI) theory has been applied to pattern recognition [8] [9] [10], image
processing [11] [12] [13] and information fusion [14] and have the advantage that they are able to represent importance of criteria and certain interactions among them.

This paper presents a novel optimal feature selection approach for machinery fault diagnosis based on the fuzzy measure theory. It is suitable for low feature space problems. A heuristic least mean square algorithm (HLMS) is adopted to identify the fuzzy measures from training data set. Shapley values with respect to the fuzzy measures are computed and applied as importance indexes to choose the most sensitive features from a number of features. Interaction indexes with respect to the fuzzy measures are then employed to remove the redundant features. Vibration signals from rolling element bearings are used to validate this method. The results show that the proposed feature selection approach based on fuzzy measures is effective for fault diagnosis and is agreeable with feature subset obtained through other method.

The rest part of this paper is organised as follows. In section 2, the definition of fuzzy measures and related concepts, such as Shapley value and interaction index, are briefly introduced. In Section 3 a heuristic least mean square algorithm for identifying 2-additive fuzzy measures is introduced. A novel approach for fault diagnosis feature optimisation based on fuzzy measures is proposed in section 4. Section 5 presents the results of the experimental evaluation. Discussions based on the results are presented in Section 6, and Section 7 draws the conclusion.

2 FUZZY MEASURE, CHOQUET FUZZY INTEGRAL, IMPORTANCE INDEX AND INTERACTION INDEX

A fuzzy measure on the set $X$ of criteria is a set function

$$\mu : P(X) \rightarrow [0,1]$$

satisfying the following axioms:

1) \( \mu(\emptyset) = 0, \mu(X) = 1 \)

2) \( A \subseteq B \subseteq X \) implies \( \mu(A) \leq \mu(B) \)

where \( X = \{x_1, \ldots, x_n\} \) is the set of criteria, \( P(X) \) is the power set of \( X \), i.e. the set of all subsets of \( X \). Here \( \mu(A) \) represents the weight of importance of the set of criteria \( A \). \( \emptyset \) denotes the empty set.

The 2-additive fuzzy measure is a special kind of fuzzy measure. It is defined by

$$\mu(K) = \sum_{i=1}^{n} a_i x_i + \sum_{\{i,j\} \subseteq X} a_{ij} x_i x_j , \quad (1)$$

where \( K \subseteq X \). For any \( K \subseteq X \) and \( |K| \geq 2 \) with \( x_i=1 \) if \( i \in K \), otherwise \( x_i=0 \).

As \( \mu_i = a_i \) for all \( i \), the general form for the 2-additive fuzzy measure can be formulated as

$$\mu(K) = \sum_{\{i,j\} \subseteq K} \mu_{ij} - (|K| - 2) \sum_{i \in K} \mu_i \quad (2)$$

for any \( K \subseteq X \) and \( |K| \geq 2 \). It can be seen from the expression that the 2-additive fuzzy measure is determined by the coefficients \( \mu_i \) and \( \mu_{ij} \).

The 2-additive fuzzy measures need \( n(n+1)/2 \) coefficients to be defined. The general number of coefficients required to be defined for \( k \)-order additive fuzzy measures is \( \sum_{j=1}^{k-1} \binom{n}{j} \).

Fuzzy measures can describe any of the three interactions between two criteria A and B:

3 Synergetic interaction, which can be represented by

$$\mu(A \cup B) > \mu(A) + \mu(B) , \quad (3)$$