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Dempster-Shafer evidence theory for multi-bearing faults diagnosis

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ABSTRACT

Support vector machines (SVMs) are frequently used in automated machinery faults diagnosis to classify multiple machinery faults by handling a high number of input features with low sampling data sets. SVMs are well known for fault detection that involves binary fault classifications only (i.e., healthy vs. faulty). However, when SVMs are used for multi-faults diagnostics and classification, they result in a drop in classification accuracy; this is because the adaptation of SVMs for multi-faults classifications requires the reduction of the multiple classification problem into multiple subsets of binary classification problems that result in many contradictory results from each individual SVM model. To overcome this problem, a novel SVM-DS (Dempster-Shafer evidence theory) model is proposed to resolve conflicting results generated from each SVM model and thus increase the classification accuracy. The analysis of results shows that the proposed SVM-DS model increased the accuracy of the fault diagnosis model from 76% to 94%, as SVM-DS continuously refines and eliminates all conflicting results from the original SVM model. The proposed SVM-DS model is found to be more accurate and effective in handling multi-faults diagnostic and classification problems commonly faced in the industries, as compared to the original SVM method.

1. Introduction

Bearings remain one of the most vital mechanical components of rotating machinery. They are essential for ensuring the integrity of such machinery. Bearing fault can lead to total machine breakdown and costly downtime. Thus, the past decades have seen increasingly rapid advances in the field of bearing fault diagnosis. Various methods have been developed for bearing fault diagnosis, such as vibration analysis (Gelman et al., 2014), acoustic analysis (Jena and Panigrahi, 2015), and thermal imaging interpretation (Janssens et al., 2015). Vibration spectra analysis has been proven to be the most efficient health monitoring and diagnostic method for rotating machinery (Chen et al., 2013). Various vibration signal processing tools have been introduced, namely wavelet analysis, empirical mode decomposition, and the Hilbert-Huang transform. These signal processing methods advanced from non-adaptive to self-adaptive signal analysis (Hui et al., 2013). The capabilities of vibration analysis also progressed from qualitative analysis to quantitative analysis (Cui et al., 2016). For instance, earlier bearing fault diagnostic methods were developed to identify the conditions of the bearing (i.e., healthy or faulty), but recent diagnostic methods are meant to determine the severity of the bearing fault (e.g., fault size). However, the effectiveness of these diagnostic methods is highly dependent on the experience and knowledge of the operator of the machine.

In recent years, there has been increasing interest in using an artificial intelligence (AI) approach for machinery fault diagnosis. This approach provides a more consistent diagnostic result based on a trained AI structure and thus leads to a more automated fault diagnosis system that eliminates any human intervention. An AI algorithm attempts to establish a relationship between the input (i.e., data captured by sensors) and the output (i.e., conditions of the machine) of the collected data. Subsequently, the trained algorithm can provide an output based on new input data. Although AI-based machinery fault diagnosis provides more consistent diagnostic results, its accuracy is still highly dependent on the AI algorithm applied to analyze the input data. In other words, the accuracy of diagnostics based on artificial neural networks (ANNs), self-organizing maps (SOMs), support vector machines (SVMs), the Hidden Markov Model (HMM), particle filtering, regression analysis and fuzzy logic, and the Bayesian technique could be completely different. Previous studies have reported SVMs to be superior to other AI algorithms in fault diagnosis because they can handle a high number of input features with a small sampling data set (Kankar et al., 2013; Jedliński and Jonak, 2015; Zhang et al., 2015). However, SVMs were designed for two-class (binary) problem classification. Jegadeeshwaran and Sugumaran (2015) reduced the multi-faults classification of automobile hydraulic brake system fault diagnosis into a multi-layer binary classification (i.e., decision tree). One major drawback of this approach is that if data were classified wrongly in the initial layer, then they will be misclassified in the second layer, since the classification accuracy is highly dependent on the architecture

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of the decision tree. Keskes et al. (2013) also reduced the multi-faults classification of a rotor bar into binary problems that first classified the conditions of the rotor bar (i.e., healthy and faulty) and then classified the severity of the broken rotor bar (i.e., one or two broken rotor bars). One question that must be posed is how this model classifies the severity of broken rotor bars if there are more than two levels of severity.

Different strategies exist in the literature regarding SVMs for multi-faults classification, including one-versus-one, one-versus-all, binary tree, error correcting output code, and directed acyclic graphs (Cheong et al., 2004). However, most research on SVM multi-faults classification has emphasized the use of the one-versus-one (Wang et al., 2014) and one-versus-all (Liu et al., 2013; Baccarini et al., 2011) strategies. These strategies require more than one SVM structure for multi-faults classification. Therefore, different SVM models may provide contradictory results. Together, these research studies indicate that their machine learning models will simply treat the first result as the final decision without further refining the conflicting results. This paper proposes a novel method to increase the accuracy of SVM multi-faults classification by eliminating conflicting results using Dempster-Shafer (DS) evidence theory.

In this section, the necessities of an AI approach in automatic bearing fault diagnosis have been explained. The following section considers the limitations and drawbacks of SVM multi-faults classification. The DS evidence theory for machinery fault diagnosis will be introduced in Section 3. The methodology for bearing data collection will be described in Section 4. Section 5 discusses the features used for faults classification. Section 6 compares the performances of different strategies in SVM multi-faults classification and evaluates the performance of the SVM-DS model. Finally, this paper will conclude with a discussion of the effectiveness of the SVM-DS model in eliminating the conflicting results generated by SVMs.

2. Limitations and drawbacks of SVMs for multi-faults classification

SVM is a supervised machine learning method that relies on statistical learning theory. The capabilities of this learning method in handling high input features with small samples are beneficial for fault diagnosis (Kankar et al., 2013). SVM creates a hyperplane that allocates the majority of points of the same class in the same side while maximizing the distance between the two classes to this hyperplane (Baccarini et al., 2011). Eq. (1) describes the position of a hyperplane (Konar and Chattopadhyay, 2011). The position of the hyperplane will be determined by the vector $\mathbf{w}$ and the scalar b.

$$f(x) = \mathbf{w}^T x + b \tag{1}$$

Fig. 1 shows an example of a hyperplane created by SVM for two classes (i.e., healthy and faulty) by two features (i.e., skewness and kurtosis) using a Gaussian radial basis function (RBF) kernel. Hsu et al. (2010) proposed that an RBF kernel function be the first-try kernel function for an SVM model. Chen et al. (2014) also found that an RBF kernel leads to better test accuracy compared to a polynomial kernel. However, in this study, several SVM kernel functions (e.g., RBF, quadratic, polynomial) were used in order to determine the best kernel function for bearing fault classification purposes.

SVMs have been developed to classify two classes (binary) of a problem by multiple features. For instance, a typical SVM is only able to classify an issue into “A” or “B” and “true” or “false.” As the case study in this paper involves four bearing conditions, namely healthy, rolling element fault, inner raceway fault, and outer raceway fault, a multi-faults classification approach was therefore employed in this study. Two common multi-faults classification strategies are the one-versus-one and one-versus-all strategies. Eqs. (2) and (3) show the number of the models required for one-versus-one and one-versus-all strategies, respectively. However, only one training model is required for two classes if the one-versus-all strategy is employed.

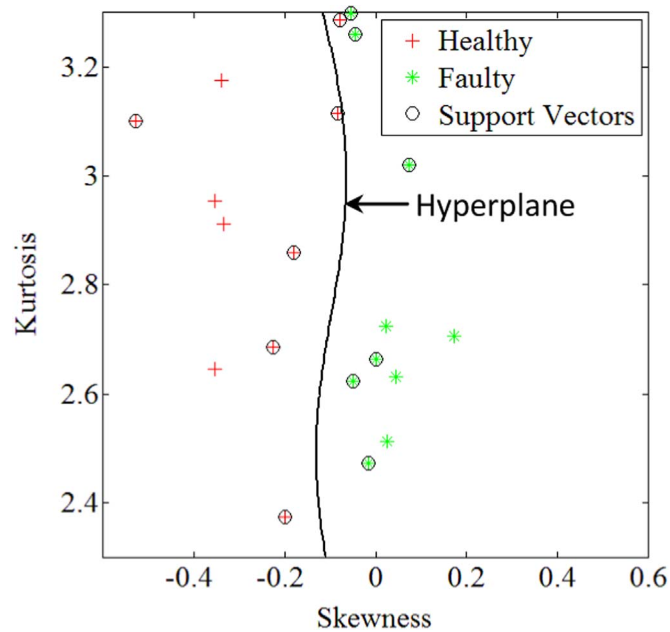

Fig. 1. SVM's decision boundary.

$$\text{Number of Model} = \frac{\text{No. ofClasses} \times (\text{No. of Classes} - 1)}{2} \tag{2}$$

$$\text{Number of Model} = \text{No. of Classes} \tag{3}$$

Chang and Lin (2011) developed a library for support vector machines, LIBSVM. They implemented a one-versus-one strategy in multi-faults classification. A voting strategy was used in the library for classification. In other words, each binary classification model will be considered as a vote that can be cast for any class (decision). Then, the class with the maximum number of votes will be the final decision. They were aware of the drawback of this method, which is that no decision can be made if there is more than one class with identical votes. However, in this library, they decided to choose the first class among all identical classes. The situation of a one-versus-all strategy is similar to that of a one-versus-one strategy, that is, no decision can be made if the results are contradicted, but the number of the models required for the one-versus-all strategy is smaller. The examples of the conflicting results generated by each multi-faults classification strategy are illustrated in Tables 1 and 2. This study examines both strategies.

To classify completely all four bearing conditions, six different one-versus-one SVM models and four different one-versus-all SVM models were developed, which resulted in multiple SVM results for the same data input. This study shows that the results of each of the SVM models may be inconsistent, which could lead to conflicting results. In this case, the SVM classification model was found to be indecisive in providing one conclusive result for the particular data input. Therefore, the DS algorithm is proposed to overcome this pitfall. The DS algorithm essentially acts as the agent for the SVM, which results in

Table 1
An example of results generated by SVM (one-versus-one strategy).

Sample	Votes (Total 6 votes)				Final decision
	Class A	Class B	Class C	Class D	
1	6	0	0	0	Class A
2	1	3	1	1	Class B
3	1	1	2	2	Conflict