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Health diagnostics using multi-attribute classification fusion

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ABSTRACT

This paper presents a classification fusion approach for health diagnostics that can leverage the strengths of multiple member classifiers to form a robust classification model. The developed approach consists of three primary steps: (i) fusion formulation using a k-fold cross validation model; (ii) diagnostics with multiple multi-attribute classifiers as member algorithms; and (iii) classification fusion through a weighted majority voting with dominance approach. State-of-the-art classification techniques from three broad categories (i.e., supervised learning, unsupervised learning, and statistical inference) were employed as member algorithms. The diagnostics results from the fusion approach will be better than, or at least as good as, the best result provided by all individual member algorithms. The developed classification fusion approach is demonstrated with the 2008 PHM challenge problem and rolling bearing health diagnostics problem. Case study results indicated that, in both problems, the developed fusion diagnostics approach outperforms any stand-alone member algorithm with better diagnostic accuracy and robustness.

1. Introduction

Real-time health diagnostics and prognostics interpret data acquired by smart sensors, and utilize these data streams in making critical operation and maintenance decisions (Licht and Deshmukh, 2003). Effective health diagnostics provides enormous benefits such as improved system safety, reliability, and reduced costs for the operation and maintenance of complex engineered systems. Maintenance and life-cycle management is an area that can significantly benefit from the improved design and maintenance activities, as it constitutes a large portion of system overhead costs in many industries (Dekker, 1996). For example, unexpected system breakdowns in the manufacturing and service sectors could be prohibitively expensive since they immediately result in loss of production and poor customer satisfaction. Thus to reduce and possibly eliminate such problems, it is important to accurately assess the health condition of an operating system in real time through effective health diagnostics.

Research on condition monitoring addressed these challenges by assessing system degradation states utilizing sensory information from the functioning system. Monitoring of system health state (HS) changes over time provides valuable information about the performance degradation of system components (Ebeling, 1997; Coit and Jin, 2000; Elsayed, 2000), that can be used for critical maintenance decision makings. Condition monitoring has been successfully applied to many engineering systems such as bearings (Alguindigue et al., 1993; Li et al., 1999; Huang et al., 2007; Zhang, 2010), machine tools (Martin, 1994), transformers (Macian et al., 2003), engines (Booth and McDonald, 1998), aircraft wings (Zhao et al., 2007), and turbines (Breikin et al., 2005). In the literature, there are two categories of approaches in general that have been employed for health diagnostics, namely machine learning techniques and statistical inference techniques. The machine learning-based health diagnostics approaches can be further divided into supervised learning, unsupervised learning and semi-supervised learning techniques. In addition to the aforementioned machine learning-based approaches, statistical inference-based algorithms can also be used to classify system HSs based on statistical distances such as the Mahalanobis distance (Wang et al., 2010), the k-nearest neighbor method (KNN) (Zhang and Srihari, 2004) and the k-mean clustering method (Alsabti et al., 1997). Significant advancements in diagnostics area have been achieved by applying classification techniques based on machine learning or statistical inferences, resulting in a number of classification methods, such as back-propagation neural networks (BNNs) (Huang et al., 2007; Srinivasan et al., 2007; Samanta, 2004; Saxena and Saad, 2007; Yang et al., 2005), deep belief networks (DBNs) (Arel et al., 2010; Tamilselvan et al., 2011), support vector machines (SVMs) (Samanta, 2004; Saimurugan et al., 2010; Ge et al., 2004; Abbasion et al., 2007; Sun et al., 2004; Geramifard et al., 2010), self-organizing maps (SOMs) (Wong et al., 2006), and Mahalanobis distance (MD) classifiers (Wang et al., 2010). Some researchers combined two or more of existing techniques to form hybrid classification models thus

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Acronyms

BNN	back-propagation neural network
DBN	deep belief networks
DC	dominant classifier
GA	genetic algorithm
HS	health state
MD	Mahalanobis distance
RBM	restricted Boltzmann machine
RUL	remaining useful life
SOM	self-organizing map
SVM	support vector machine
WMVD	weighted majority voting with dominance

Notation

$\alpha(t)$	learning coefficient
a_i	target classification decision of ith training data point
$AC_{i,j}$	target classification decision matrix of jth HS for ith fold
b	bias of the hyper plane
b_i	bias of the ith neuron
c	total number of classifier methods used in fusion process, where $1 \le m \le c$
C	penalty parameter
$CC_{i,j}$	multi-attribute classifier decision matrix of jth HS for ith fold
$d_{l,m}$	classification decision of mth classifier for lth training data point
$h(\bullet)$	neighborhood function
h_i	state of the ith neuron in hidden layer
$inc_{m,j}$	classification decision of mth classifier as jth HS of the incoming data point
k	total number of folds used for fusion formulation, where $1 \le i \le k$
$\boldsymbol{\mu}_j$	mean vector of the training data
$P(\bullet)$	probability distribution function
q_i	ith class label
r	total number of training data points in each fold, where $1 \le l \le r$
$\mathbf{S}_j$	covariance matrix of the training data
T	classification fusion decision of the incoming data point
u_i	state of the ith neuron
v_i	state of the ith neuron in visible layer
w	normal vector of the hyper plane
$w_{i,j}$	synaptic weight between the ith and the jth neurons
$wt_{m,j}$	weight value of mth classifier in classifying jth HS
x_i	p-dimensional vector
ξ_i	slack variable

achieving better diagnostics performances. Zhang (2010) proposed a bearing fault diagnostics methodology using multi-scale entropy (MSE) and adaptive neuro-fuzzy inference system. Saimurugan et al. (2010) presented a multi-component fault diagnostics of a rotational mechanical system based on decision trees and support vector machines.

Despite successful applications in various engineering fields, a key challenge for health diagnostics resides in the implicit relationship between sensory signals and system HSs, which makes it difficult to develop a generic robust health diagnostics approach. Additionally, there are many factors affecting the efficacy of a diagnostics system, such as the dependency of a diagnostics algorithm's accuracy on the number of training data points, the variability in manufacturing conditions, and large uncertainties in environmental and operational conditions. Thus, it is extremely difficult, if not impossible, to have a single diagnostics algorithm that could work well for all possible diagnostics applications. Therefore, leveraging strengths of different algorithms to form a robust unified algorithm (Polikar, 2006) could potentially increase the efficacy of health diagnostics substantially. In the literature, there are generally two categories of algorithm fusion techniques based on the combination strategy used for fusion: consensus and learning (Gao et al., 2010), which combine estimates from multiple individual algorithms to form a single fusion output. By consensus approach, Breiman (1996, 2001) employed bagging method to determine a class label with major voting by multiple classification algorithms, and used random forest to improve the performance of bagging by combining with random feature selection scheme. By learning approach, Boosting (Schapire, 1990), Adaboost (Freund and Schapire, 1997), and rule ensemble (Friedman and Popescu, 2008) have been developed to form different training strategies of member algorithms in order to achieve a better fusion algorithm. These algorithm fusion techniques have been applied to a wide variety of research fields, such as in the development of committees of neural networks(Perrone and Cooper, 1993; Bishop, 2005), metamodeling for the design of modern engineered systems (Zerpa et al., 2005; Goel et al., 2007; Acar and Rais-Rohani, 2009), discovery of regulatory motifs in bioinformatics (Hu et al., 2006), detection of traffic incidents (Chen et al., 2009), transient identification of nuclear power plants (Baraldi et al., 2011), fault diagnostics of electronics (Tamilselvan et al., 2013), and development of ensemble Kalman filters (Evensen, 2003). In addition, the authors' early work has also employed algorithm fusion for rolling element bear health diagnostics (Tamilselvan and Wang, 2013). Similar to health diagnostics applications, an ensemble prognostics approach has also been developed (Hu et al., 2012) by combining multiple prognostics member algorithms to predict the remaining useful life (RUL). This approach utilized the k-fold cross validation (CV) process to evaluate the error of each member algorithm and computed the ensemble RUL prediction as a weighted sum of multiple RUL predictions by member algorithms.

Due to the diversified learning ability of the classifiers and the implicit relationships between sensory signals and system HSs, there is no single classifier that can diagnose all HSs effectively. There is an existence of different dominant classifiers (DCs) for classifying different HSs. Research on fusion diagnostics does not use a dominant member algorithm for each HS and utilize the advantages of the different member algorithms in developing a classification fusion system to diagnose different HSs. Therefore, there is a critical need of developing new fusion process by utilizing the advantages of dominant member algorithm for each HS and further provide a general framework to combine the results of different diagnostic approaches into a robust unified diagnostic decision. This paper presents a multi-attribute classification fusion system that leverages the strengths of multiple member classifiers to form a robust classification model for health diagnostics. The developed approach for health diagnostics includes three primary steps: (i) fusion formulation using the k-fold CV; (ii) diagnostics using multiple multi-attribute classifiers as member algorithms; and (iii) classification fusion using a weighted majority voting with dominance (WMVD) approach. The rest of the paper is organized as follows. Section 2 presents the proposed multi-attribute classification fusion system. Section 3 gives a brief introduction to the multi-attribute classification member algorithms selected in this study. Section 4 presents the