Machine Vibration (1996) 5:154–162

Machine Vibration

Unsupervised Pattern Classifier for Abnormality-Scaling of Vibration Features for Helicopter Gearbox Fault Diagnosis

Vinay B. Jammu[1], Kourosh Danai[1] and David G. Lewicki[2]

[1]Department of Mechanical Engineering, University of Massachusetts, Amherst, Massachusetts, USA [2]Vehicle Propulsion Directorate, U.S. Army Research Laboratory, NASA Lewis Research Center, Cleveland, Ohio, USA

A new unsupervised pattern classifier is introduced for on-line detection of abnormality in features of vibration that are used for fault diagnosis of helicopter gearboxes. This classifier compares vibration features with their respective normal values and assigns them a value in [0, 1] to reflect their degree of abnormality. Therefore, the salient feature of this classifier is that it does not require feature values associated with faulty cases to identify abnormality. In order to cope with noise and changes in the operating conditions, an adaptation algorithm is incorporated that continually updates the normal values of the features. The proposed classifier is tested using experimental vibration features obtained from an OH-58A main rotor gearbox. The overall performance of this classifier is then evaluated by integrating the abnormality-scaled features for detection of faults. The fault detection results indicate that the performance of this classifier is comparable to the leading unsupervised neural networks: Kohonen's Feature Mapping and Adaptive Resonance Theory (ART2). This is significant considering that the independence of this classifier from fault-related features makes it uniquely suited to abnormality-scaling of vibration features for fault diagnosis.

Keywords: Condition monitoring; Diagnostics; Gearbox; Vibration

1. Introduction

Present helicopter gearboxes are significant contributors to both maintenance costs and flight safety incidents. Power trains comprise almost 30% of maintenance costs and 22% of mechanically related malfunctions that often result in loss of life and aircraft [1]. Therefore, improved fault diagnosis of helicopter gearboxes is important for saving lives and reducing maintenance costs. Fault diagnostic systems which can detect failures reliably and rapidly will eliminate the need for routine disassembly of the gearbox and allow scheduling of maintenance before a catastrophic failure occurs.

Fault diagnosis of helicopter gearboxes (like most rotating machinery) is based upon vibration monitoring. Since detecting gearbox faults based on the raw vibration signal is usually difficult, features of vibration such as the Root Mean Square (RMS), Kurtosis, Skewness, etc. are extracted to identify various types of faults. A considerable effort has been directed towards development of signal processing schemes for identification of individual features that would be affected by specific faults in the gearbox [2–8]. However, such a one-to-one approach to fault diagnosis has not been feasible because of the complexity of the gearbox, diversity and severity of component faults, presence of noise in the measured vibration, and variations in the operating conditions.

A more comprehensive approach to fault diagnosis which compensates for some of the difficulties of the one-to-one approach is the multiple-feature approach. The common means of feature integration in this approach is pattern classification through connectionist networks [9–12], where the decision regions representing various faults are defined by the connection weights of these networks. Connection weights are usually formed through supervised training using a sample set of feature–fault data. Fault diagnosis is then performed by classifying the vibration features into the decision regions that represent various faults. An important property of connectionist networks is their ability to form decision regions with non-linear boundaries which enables them to represent non-linear relations between features and faults. Their disadvantage, however, is their reliance on supervised learning, which requires feature–fault data for training. Since training data are usually not available and

Correspondence and offprint requests to: K. Danai, Department of Mechanical Engineering, University of Massachusetts, Amherst, Mass, 01003-2210, USA

through expensive experiments, supervised diagnostic networks are limited in applicability.

In order to avoid the prior training required by supervised diagnostic networks, the authors have proposed an unsupervised network that incorporates the knowledge of gearbox structure for diagnosis [13]. The inputs to this Structure-Based Connectionist Network (SBCN) are abnormality-scaled vibration features (see Fig. 1). Therefore, a method needs to be developed to identify and scale the abnormality of vibration features. This paper introduces the unsupervised pattern classifier designed for this purpose. This classifier performs abnormality-scaling of each feature by relying solely on its value from the normal operation of the gearbox. As such, it is referred to as Single Category-Based Classifier (SCBC) to signify its independence from feature values associated with faulty conditions. In order to perform abnormality-scaling, the SCBC compares features with weights representing their normal-mode values, and if they are 'sufficiently different', assigns values between 0 and 1 to characterize their degree of deviation from the weight values. While the SCBC has a unique design that is specific to the problem at hand, many of its features are similar to those in Kohonen's Feature Mapping (KFM) [14] and Adaptive Resonance Theory (ART2) [15]. For example, like KFM, it uses Euclidean distance as a measure of similarity between the features and their normal-mode values, or similar to ART2, it does not require the abnormal values of features for classification.

Another important feature of SCBC, which is similar to ART2, is its on-line adaptation capability whereby the weight values are updated so as to cope with changes due to noise and variations in process conditions. In general, without sample features associated with faulty cases it is very difficult to distinguish abnormalities due to noise from those caused by faults. Accordingly, there is always the risk that the weights may be inadvertently replaced with those associated with a faulty case. In order to improve reliability of adaptation in SCBC, the weights are updated with regard to the status of other features. Adaptation in SCBC is performed in two stages: *primary adaptation* and *secondary adaptation* [15].

In primary adaptation, a weight is updated to be closer to the value of the feature classified as normal. In secondary adaptation, the weights associated with the rest of the features are updated to be closer to their current values if this feature was classified as normal, and to be away from their current values if the feature was classified as abnormal. Primary adaptation is designed to cope with drift in feature values due to process variations. Secondary adaptation on the other hand, is incorporated so as to achieve homogeneity in classification. The rationale for secondary adaptation is that if the majority of features are classified as normal, then the gearbox is healthy and the minority features are classified as abnormal due to noise. So, the normal values of these minority features need to be updated to improve homogeneity in classification. Both primary adaptation and secondary adaptation are recursively performed using a set of recent feature vectors so as to avoid dominance of individual feature vectors in adaptation and better capture the drift in vibration features.

The performance of the SCBC is tested in abnormality-scaling of experimental vibration features obtained from an OH-58A helicopter main rotor gearbox. For this, vibration data reflecting the effect of various faults were processed through a microcomputer customized for vibration signal processing to obtain features of vibration. These vibration features were then abnormality-scaled by SCBC as a prerequisite for fault diagnosis. In this paper, in order to test the performance of SCBC, the abnormality-scaled features were evaluated for fault detection. For this purpose, these features were weighted and integrated. The detection results obtained compare favourably to those obtained from KFM and ART2 methods, which is reassuring given that SCBC is considerably less constrained in its applicability due to its independence from fault-related features.

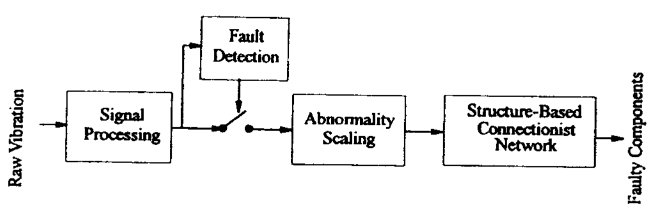

Fig. 1. Overview of fault detection and diagnosis in the proposed structure-based diagnostic system.

2. Single Category-Based Classifier (SCBC)

The design of the Single Category-Based Classifier (SCBC) is best described in the context of the problem constraints. This classifier is required to classify individual vibration features according to their level of abnormality, which is not readily possible by either of the two unsupervised pattern classifiers: Kohonen's Feature Mapping (KFM) [14] and Adaptive Resonance Theory (ART2) [15]. KFM performs classification by measuring the distance of the feature vector from the centre of various decision regions formed during an off-line training phase. As such, KFM is limited in applicability due to its need for feature values associated with the fault category. The other method of unsupervised pattern classification, Adaptive Resonance Theory (ART2), classifies a feature vector as normal unless it is 'sufficiently different' [15] from its nominal value. 'Sufficient difference' in ART2 is measured by a 'vigilance' ρ as:

$$\rho_j = \sum_{i=1}^{n} f(s_i, w_{ij}) \tag{1}$$

where the function f determines the match between the feature s_i and the weight value w_{ij} associated with the jth decision region. The advantage of ART2 over KFM is that it does not require any sample features associated with the fault category. Its drawback, however, is that it categorizes feature values that are multiples of the weight w_{ij} within the same category. A limitation that is common to both KFM and ART2 is that they are not designed for scalar classification, which is a requirement in abnormality-scaling of individual features for fault diagnosis.

2.1 Abnormality-Scaling

The schematic of the Single Category-Based Classifier (SCBC) is shown in Fig. 2. The inputs to SCBC are features $s_i(t)$, $i = 1,\dots,n$, and its outputs are abnormality-scaled features $f_i(t)$ with values between 0 and 1. The value of 0 indicates normality, and the other extreme of 1 denotes complete abnormality. The weights of the SCBC w_i represent the normal values of the features, which are initially set equal to the first set of feature values supplied to the SCBC.

Classification in SCBC is performed by first measuring the distance of each feature $s_i(t)$ from its weight value w_i, and then normalizing it into the range [0,1] using a 'matching factor' ϕ_i, defined as (see Fig. 3):

$$\phi_i(t) = 1 - \exp\frac{-(s_i(t) - w_i)^2}{w_i^2} \tag{2}$$

A ϕ_i value of 0 indicates that the feature value matches the weight value precisely, and a value of 1 indicates that it deviates considerably. Note that the exponential function used here is not unique and that other functions which can map the distance into the range [0,1] can also be used for the matching factor. Since during normal operation of the gearbox, noise in the features causes drifts in the normal values, a threshold θ is considered to account for such drifts within the noise level. The threshold θ is used to hard-limit $\phi_i(t)$ in SCBC as:

$$\phi_i(t) = \begin{cases} o & \text{if } \phi_i(t) < \theta \\ \phi_i(t) & \text{otherwise} \end{cases} \tag{3}$$

In the above relationship, the threshold θ is obtained as:

$$\theta = \frac{1}{n}\sum_{i=1}^{n}\left(1 - \exp\frac{-[max(s_i) - \mu_i]^2}{\mu_i^2}\right) \tag{4}$$

where $max(s_i)$ denotes the maximum value of the ith feature in a set of κ samples of this feature recorded during normal operation, and μ_i represents its mean, estimated as

$$\mu_i = \frac{1}{\kappa}\sum_{t=1}^{\kappa} s_i(t) \tag{5}$$

The matching factor defined by Eq. 2 squashes any positive value in $[0, \infty]$ into the range [0, 1]. As such, only very large deviations in feature values will be scaled to the value of 1. Since such large deviations in feature values are uncommon for gearboxes, the value of matching factor is further scaled to yield abnormality-scaled feature values $f_i(t)$ as (see Fig. 3):

$$f_i(t) = f_{min} + \exp[\alpha^* \phi_i(t)] \tag{6}$$

where f_{min} represents the minimum abnormality value assigned to any feature that violates the threshold θ, and α controls the slope of the exponential curve. Since $f_i(t)$ is defined to have a value between 0 and 1, it is set to 1 when $f_i(t)$ in Eq. (6) exceeds the value of 1.

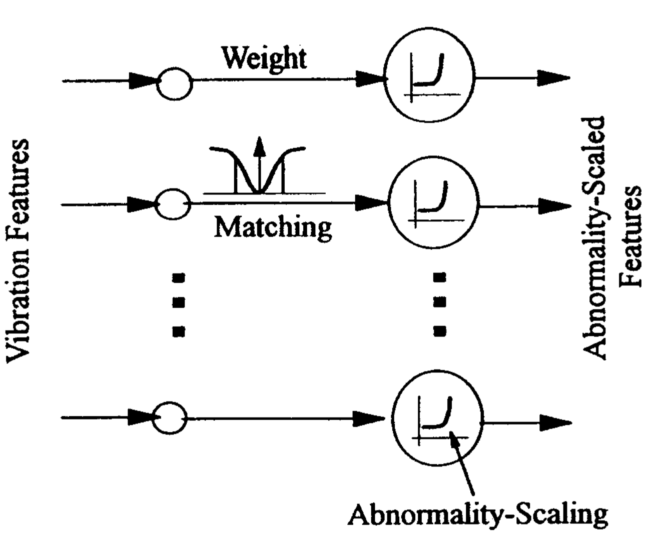

Fig. 2. Schematic of the SCBC.

2.2 Adaptation

After each round of classification of the vibration features, the weight values in the SCBC are updated so as to cope with noise and small variations in the operating conditions. Adaptation is carried out in two stages. In the first stage, called primary adaptation, a network weight is adapted if the feature associated with it is classified as normal. In the second stage, referred to as secondary adaptation [15], the rest of the weights are adapted to achieve homogeneity in the abnormality-scaled values, thus increasing the likelihood of all of them being classified as normal or abnormal. Achieving this homogeneity, however, needs to be carried out with respect to specific feature groups, because individual gearbox faults do not necessarily cause abnormality in all the features. For example, a gear fault will be reflected only by the features related to the gear and is not expected to cause abnormality in bearing features. In order to preserve the functionality of individual groups of features (i.e., general features, gear features, bearing

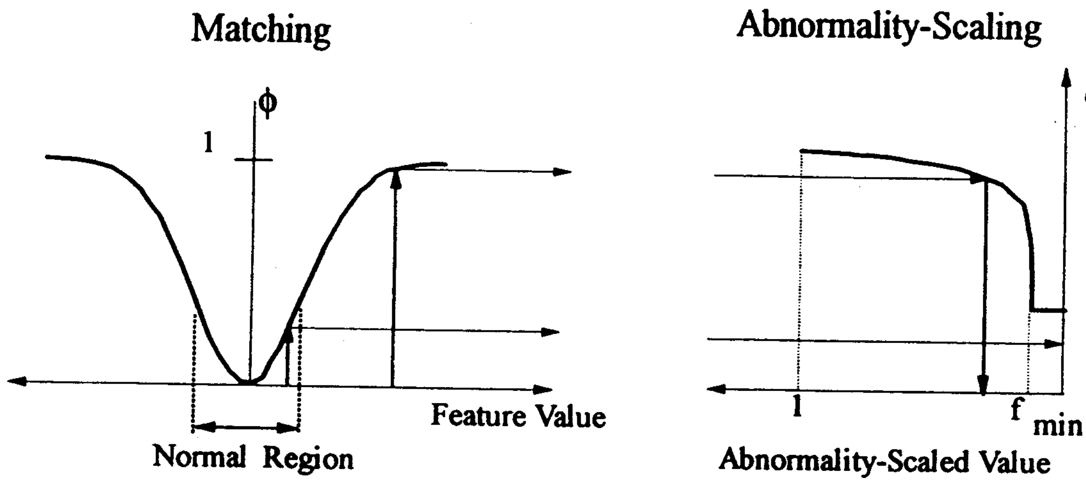

Fig. 3. Matching and abnormality-scaling in SCBC.

features), secondary adaptation is performed exclusively for each feature group.

Adaptation in SCBC is performed as follows: let w_I represent the weight which is presently being updated and w_i the remaining weights in the group. In primary adaptation, the weight value w_I is modified according to the relationship

$$w_I = w_I + \delta w_I \tag{7}$$

where

$$\delta w_I = \begin{cases} \eta[s_I(t) - w_I] \text{if } f_I(t) = 0 \\ 0 \qquad \text{otherwise} \end{cases} \tag{8}$$

The parameter η in Eq. (8) denotes the learning rate.

For secondary adaptation, if the majority of features are classified as normal, then the weight values associated with the features classified as abnormal will be adjusted such that the likelihood of all the features being classified as normal is increased for the same feature values. Secondary adaptation is performed as

$$w_i = w_i + \delta w_i \text{ for all } i \neq I \tag{9}$$

where

$$\delta w_i = \begin{cases} \eta\Lambda[s_i(t) - w_i] & \text{if } f_I(t) = 0 \\ -\eta\Lambda[s_i(t) - w_i] & \text{otherwise} \end{cases} \tag{10}$$

In secondary adaptation, the amount by which the weight values are adjusted is controlled by a neighbourhood function Λ [14] which is assigned a value between 0 and 1. A value of 0 is used for inputs with no noise, and a value at the other extreme of 1 is used for unreliable features with large amounts of noise. Usually in practice the value of Λ is set less than 0.5. For each round of primary adaptation (Eqs (7) and (8)), I is varied to include all the features in the group. If the jth group of features contains m_j features, then primary adaptation is applied by varying I from 1 to m_j to cover all the weight values w_I in the jth feature group. For each I, the remaining weight values w_i in the group (i = 1 to m_j and $i \neq$ I) are adapted using secondary adaptation according to Eqs (9) and (10).

The adaptation algorithm presented in Eqs (7)–(10) is biased towards the most recent feature vector if only this vector were used for adaptation. Ideally, adaptation should be performed using all the feature vectors that pertain to the current operating conditions. But as the number of available feature vectors for each operating condition progressively increases, adaptation based on all the features becomes computationally demanding. As a compromise, in SCBC only the β most recent feature vectors are utilized for each adaptation sweep such that adaptation is performed iteratively over the β most recent feature vectors. The learning rate η is progressively reduced for each adaptation iteration.

3. Experimental

The effectivness of SCBC is evaluated using experimental vibration data from an OH-58A helicopter main rotor gearbox (see Fig. 4). In this section, the experimental setup and signal processing of the vibration are described.

3.1 Setup

Vibration data were collected at the NASA Lewis Research Center as part of a joint NASA/Navy/Army Advanced Lubricants Program [16]. Various component failures in the OH-58A main rotor transmission were produced during accelerated fatigue tests. The vibration signals were recorded from eight piezoelectric accelerometers (frequency range of up to 10 kHz) using an FM tape recorder. The signals were recorded once every hour, for about one to two minutes per recording (using a bandwidth of 20 kHz). Two magnetic chip detectors were also used to detect

2. Bradley SJ. Gearbox vibration problem exposed during flight testing, IMechE Conference Transactions, Second International Conference on Gearbox Noise, Vibration, and Diagnostics, London, UK, November 1995
3. Futter DN. Vibration monitoring of industrial gearboxes using time domain averaging, IMechE Conference Transactions, Second International Conference on Gearbox Noise, Vibration, and Diagnostics, London, UK, November 1995
4. McLean RF, Lim KP, Fleming JS. A diagnostic technique for gearbox monitoring, IMechE Conference Transactions, Second International Conference on Gearbox Noise, Vibration, and Diagnostics, London, UK,November 1995
5. Astridge DG. Gearbox noise and vibration – review of opportunities for improving safety and reliability, Proc. of the Institute of Mechanical Eng., First International Conference on Gearbox Noise and Vibration, University of Cambridge, UK, April 1990
6. Stewart RM. Through-life monitoring of transmission systems, Proc. of the Institute of Mechanical Eng., First International Conference on Gearbox Noise and Vibration, University of Cambridge, UK, April 1990
7. Mertaugh LJ. Evaluation of vibration analysis techniques for detection of gear and bearing faults in helicopter gearboxes, Proc. of Mechanical Failure Prevention Group 41st Meeting, Oct. 1986, pp. 28–30
8. Mcfadden PD, Smith JD. A signal processing technique for detecting local defects in a gear from signal average of the vibration, in Proc. of the Institute of Mechanical Engineers, 1985; 199 (c4): 287–292
9. Chin H, Danai K, Lewicki DG. Pattern classifier for fault diagnosis of helicopter gearboxes, J of IFAC Control Eng. Practice, 1993; 1 (5): 771–778
10. Kazlas PT, Monsen PT. LeBlanc MJ. Neural network-based helicopter gearbox health monitoring system, IEEE-SP Workshop on Neural Networks for Signal Processing, Linthicum, MD, Sep. 1993
11. Solorzano MR, Ishii DK, Nickolaisen NR, Huang WY. Detection and classification of faults from helicopter vibration data using recently developed signal processing and neural network techniques, Advanced Technology Development Branch, Naval Ocean Systems Center, San Diego, Nov. 1991
12. Penter AJ, Lewis DC. Build quality inspection of repaired and new gearboxes, Proc. of the Institute of Mechanical Eng., First International Confernce on Gearbox Noise and Vibration, University of Cambridge, UK, April 1990
13. Jammu VB, Danai K, Lewicki DG. Diagnosis of helicopter gearboxes using structure-based networks, Proc. of American Control Conference, Seattle, WA, June 1995, pp. 1632–1627
14. Kohonen T. Self-Organization and Associative Memory, Springer-Verlag, Berlin, 1989
15. Carpenter GA, Grossberg S. ART2: Self-organization of stable category recognition codes for analog input patterns, Applied Optics, 1987
16. Lewicki DG, Decker HJ, Shimski JT. Full-scale transmission testing to evaluate advanced lubricants, NASA TM-105668, AVSCOM TR-91-C-035, 1992
17. Stewart Hughes Limited, MSDA user's guide, Tech. Report, Southampton, UK, 1986
18. Chin H. Vibration analysis of an OH-58A main rotor transmission, Tech. Report, Department of Mechanical Engineering, University of Massachusetts, Amherst, MA 1992