Mechanical Systems and Signal Processing 70-71 (2016) 932–946

Contents lists available at ScienceDirect

Mechanical Systems and Signal Processing

journal homepage: www.elsevier.com/locate/ymssp

Introducing passive acoustic filter in acoustic based condition monitoring: Motor bike piston-bore fault identification

D.P. Jena [a,*], S.N. Panigrahi [b]

[a] Department of Industrial Design, National Institute of Technology Rourkela, Orissa, 769008, India
[b] School of Mechanical Sciences, Indian Institute of Technology Bhubaneswar, Bhubaneswar 751 013, India

ARTICLE INFO

Article history:
Received 25 October 2014
Received in revised form
30 May 2015
Accepted 27 September 2015
Available online 23 October 2015

Keywords:
Passive Acoustic Filter
Condition monitoring
Quincke tube
Helmholtz resonator
Genetic Algorithm (GA)
Support Vector Machine (SVM)

ABSTRACT

Requirement of designing a sophisticated digital band-pass filter in acoustic based condition monitoring has been eliminated by introducing a passive acoustic filter in the present work. So far, no one has attempted to explore the possibility of implementing passive acoustic filters in acoustic based condition monitoring as a pre-conditioner. In order to enhance the acoustic based condition monitoring, a passive acoustic band-pass filter has been designed and deployed. Towards achieving an efficient band-pass acoustic filter, a generalized design methodology has been proposed to design and optimize the desired acoustic filter using multiple filter components in series. An appropriate objective function has been identified for genetic algorithm (GA) based optimization technique with multiple design constraints. In addition, the sturdiness of the proposed method has been demonstrated in designing a band-pass filter by using an n-branch Quincke tube, a high pass filter and multiple Helmholtz resonators. The performance of the designed acoustic band-pass filter has been shown by investigating the piston-bore defect of a motor-bike using engine noise signature. On the introducing a passive acoustic filter in acoustic based condition monitoring reveals the enhancement in machine learning based fault identification practice significantly. This is also a first attempt of its own kind.

1. Introduction

Every system is unique in itself and requires specific formulation of signal processing methodology pertinent to the system or faults under investigation [1–3]. So far, the piston-bore defect identification based on engine noise signature has not been addressed profoundly. Although various methodologies have been proposed for acoustic based condition monitoring of similar applications, suitability of such techniques are known to be highly reliant on the type of application and the quantity and quality of parameters that are monitored [4–9]. From the literature, it is also worth noticing that when expert systems are developed based on real-time data, robustness of such systems depend crucially on the nature of the signal signatures, signal parameters used to train the system and the total number of training samples [5,10–12].

The performance of supervised learning technique highly hinges on the number of parameters and numbers of training samples [2,12]. However, use of higher numbers of parameters need high computational time which is not desired. In order to achieve adequate performance of expert system using lower number of parameters an optimized filtering is required at

* Corresponding author at: Department of Industrial Design, National Institute of Technology Rourkela, Orissa, 769008, India.
E-mail address: dpj10@iitbbs.ac.in (D.P. Jena).

http://dx.doi.org/10.1016/j.ymssp.2015.09.039
0888-3270/

the time of signal acquisition. So, a passive acoustic filter has been introduced before the acoustic sensor. The corresponding enhancement in the proposed acoustic based condition monitoring has been demonstrated.

In implementing real time condition monitoring systems, so far, no one has attempted to explore the possibility of implementing passive acoustic filters in acoustic based condition monitoring as a preconditioner. In an intention of introducing passive acoustic filters as preconditioner in the acoustic based condition monitoring, literature covering analysis and design of passive filters has been reviewed and summarized below.

One can find detailed analogies of filtering properties of various passive acoustic filters to those of digital filters [13]. In general, parameters affecting the acoustic impedance dictate the acoustic properties of a passive filter. In recent years, numerous analytical solutions have been reported for estimating acoustic transmission loss (TL) of various types and shapes of filters [14–16]. The use of transfer matrix technique facilitates designers to design a wide range of filters with minimal acceptable error. If the filter is not a multiply connected one, on multiplying transfer matrix of each sub component the resultant transfer matrix for the whole desired filter can be achieved. For estimating acoustic TL of such a filter, it is required to have transfer matrix for each of its sub components [14,16].

After this present section of introduction, Section 2 explains the design of acoustic based expert system and its application in piston-bore fault detection. The concept of designing a passive acoustic band-pass filter and introducing in acoustic based condition monitoring has been demonstrated in Section 3. The last section summarizes some important observations of the present experimental research.

2. Development of the acoustic based expert system

In the present work the most common engine defect, commonly branded as the piston-bore defect, which is also known to have direct impact on the quality of the exhaust, has been addressed. A sample of a defective piston-bore pair of a vehicle is shown in Fig. 1(a) and (b). This work has been inspired by the near super-human ability of auto mechanics in identifying this defect just by carefully listening to the sound coming from the vehicle. Therefore, in an attempt to mimic their working style, an expert system has been developed that broadly follows the stages of appropriate signal filtering, statistical learning and feature based classification.

For automatic fault detection, development of a robust supervised learning system is desired. In the proposed acoustic based expert system, a supervised statistical learning mechanisms has been established. Out of many methods, artificial neural network (ANN) and support vector machine (SVM) have been widely adopted to tackle similar types of systems. With an intention to develop an expert system for automatic piston-bore fault identification using engine noise signal, an expert system based on ANN and SVM have been developed separately, and have been investigated on experimental data. The performance of six of the most preferred conventional parameters that are used in statistical learning systems to tackle similar problems, has been demonstrated. A variant of artificial neural network (ANN) and support vector machine (SVM) has been implemented to set up a robust expert system suitable for natural workshop environment. These stages of implementation are explained in detail in subsequent sections.

2.1. Multi-layered feed forward back propagation neural network

Artificial neural network (ANN) is considered to have enough potential to build a fairly acceptable system model even with insufficient knowledge about the system. ANN gains knowledge through an adaptive learning process by adjusting its weights by observing a series of inputs and the corresponding outputs. This process is usually called the training of an ANN. There are various types of neural network models based on different kernel functions. Feed-forward back-propagation neural network (FBNN) structure is a widely used one in machine fault diagnosis and condition monitoring purposes [17,18,11]. In this study, a multi-layer (with 10 hidden layers) feed-forward back-propagation neural network (FBNN) is designed and used. An analogous network, with six inputs, one hidden layer and two outputs, is shown in Fig. 2(a).

The general rule of selecting number of hidden layers depends on the number of inputs and outputs, i.e., it is taken to be equal to two third of the total number of inputs and outputs. However, the quality of approximation hinges highly on the

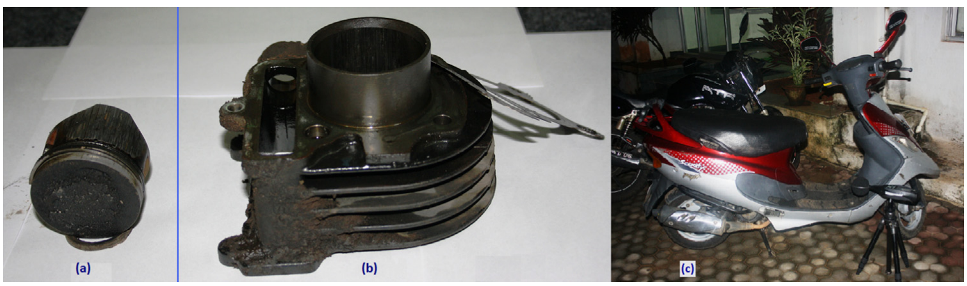

Fig. 1. Experiment; (a) sample faulty piston of DV-II, (b) sample faulty bore of DV-II, and (c) noise data acquisition using Bruel Kjaer 2270®.