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A classifier fusion system for bearing fault diagnosis

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ABSTRACT

In this paper, a new strategy based on the fusion of different Support Vector Machines (SVM) is proposed in order to reduce noise effect in bearing fault diagnosis systems. Each SVM classifier is designed to deal with a specific noise configuration and, when combined together – by means of the Iterative Boolean Combination (IBC) technique – they provide high robustness to different noise-to-signal ratio. In order to produce a high amount of vibration signals, considering different defect dimensions and noise levels, the BEAring Toolbox (BEAT) is employed in this work. The experiments indicate that the proposed strategy can significantly reduce the error rates, even in the presence of very noisy signals.

1. Introduction

Although the visual inspection of time- and frequency-domain features of measured signals is adequate for identifying machinery faults, there is a need for a reliable, fast and automated procedure of diagnosis (Samanta et al., 2004). Due to the increasing demands for greater product quality and variability, short product life-cycles, reduced cost, and global competition, automatic machine condition monitoring (MCM) has been gaining importance in the manufacturing industry (Liang et al., 2004). MCM systems allow for a significant reduction in the machinery maintenance costs, and, most importantly, the early detection of potential faults (Guo et al., 2005). Mass unbalance, rotor rub, shaft misalignment, gear failures and bearing defects are exemples of faults that may lead to the machine's breakdown (Samanta et al., 2004).

Besides the detection of the early occurence and seriousness of a fault, MCM systems may also be designed to identify the components that are deteriorating, and to estimate the time interval during which the monitored equipment can still operate before failure (Lazzerini and Volpi, 2011). These systems continuously measure and interpret signals (e.g., vibration, acoustic emission, infrared thermography, etc.), that provide useful information for identifying the presence of faulty symptoms.

The focus of this work is in rotating machines, which usually operate by means of bearings. Since they are the place where the basic dynamic loads and forces are applied, bearings represent a critical component. A defective bearing causes malfunction and may even lead to catastrophic failure of the machinery (Tandon and Choudhury, 1999). Vibration analysis has been the most employed methodology for detecting bearings defects (Thomas, 2011). Each time a rolling element passes over a defect, an impulse of vibration is generated. On the other hand, if the machine is operating properly, vibration amplitude is small and constant (Alguindigue et al., 1993). Another methodology successfully applied to this problem has been the acoustic emission (AE) (Elmaleeh and Saad, 2008; Tandon and Choudhury, 1999).

Automatic bearing fault diagnosis can be viewed as a pattern recognition problem, and several systems have been designed using well-known classification techniques, such as Artificial Neural Networks (ANNs) and Support Vector Machines (SVM). When these systems employ real vibration data obtained from bearings artificially damaged, they have to cope with a very limited amount of samples. Furthermore, with exception of a few works (Guo et al., 2005; Jack and Nandi, 2002) – which consider a validation set, besides the training and test sets –, the choice of the system's parameters, including the feature selection step, too often has been done by using the same datasets employed to train/test the classifiers. This may lead to biased classifiers that will hardly be able to generalize on new data. Another important aspect that has been little investigated in the literature is the presence of noise, which disturbs the vibration signals, and how this affects the identification of bearing defects (Lazzerini and Volpi, 2011).

In this paper, a classification system based on the fusion of different SVMs is proposed to detect early defects on bearings in the presence of high noise levels. Each SVM classifier is designed to deal with a specific noise configuration and, when combined together – by using the Iterative Boolean Combination (IBC) technique (Khreich et al., 2010) – they provide high robustness to different noise-to-signal ratio.

In order to produce a high amount of bearing vibration signals, considering different defect dimensions and noise levels, the BEAring Toolbox (BEAT) is employed in this work. BEAT is dedicated to the simulation of the dynamic behaviour of rotating ball bearings

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in the presence of localized defects, and it was shown to provide realistic results, similar to those produced by a sensor during experimental measurements (Sassi et al., 2007).

This paper is organized as follows. Section 2 presents the state-of-the-art in automatic bearing fault diagnosis. Section 3 describes the experimental methodology, including datasets, measures used to evaluate the system performance, and the IBC technique. Finally, the experiments are presented and discussed in Section 4.

2. The state-of-the-art in automatic bearing fault diagnosis

Fig. 1 illustrates the general structure of a bearing. It is composed of six components: housing, outer race (OR), inner race (IR), rolling elements (RE) (i.e., rollers or balls), cage and shaft (Guo et al., 2005). As previously mentioned, the interaction of defects in rolling element bearings produces impulses of vibration. As these shocks excite the natural frequencies of the bearing elements, the analysis of the vibration signal in the frequency-domain, by means of the Fast Fourrier Transform (FFT), has been an effective method for predicting the health condition of bearings (Tandon and Choudhury, 1999).

Each defective bearing component produces frequencies, which allow for localizing different defects occurring simultaneously. BPFO (Ball Pass Frequency on an Outer race defect), BPFI (Ball Pass Frequency on an Inner race defect), FTF (Fundamental Train Frequency) and BSF (Ball Spin Frequency) – as well as their harmonics, modulating frequencies, and envelopes – are examples of frequency-domain indicators, calculated from kinematic considerations – that is, the geometry of the bearing and its rotational speed (Sassi et al., 2007).

It is worth noting that the shock amplitude is directly related to the defect dimension: the bigger the defect, the bigger the shock.

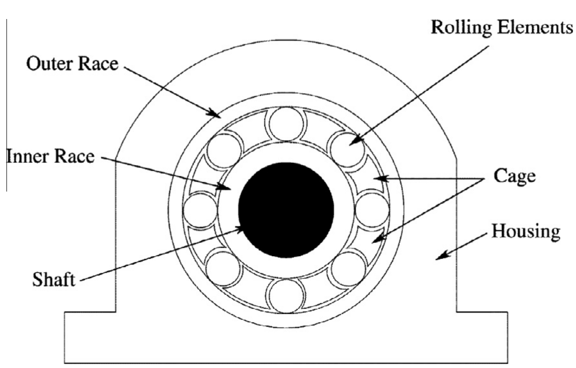

Fig. 1. Typical roller bearing, showing different component parts. Adapted from Jack and Nandi (2002).

Fig. 2 presents an example of a defect located in the outer race and its corresponding vibration signal.

Not only frequency- but also time-domain indicators have been widely employed as input features to train a bearing fault diagnosis classifier. Time-domain indicators are adimensional, and allow for representing the vibration signal through a single scalar value. For instance, *peak* is the maximum amplitude value of the vibration signal, RMS (Root Mean Square) represents the effective value (magnitude) of the vibration signal and Kurtosis describes the impulsive shape of the vibration signal. Table 1 presents the effectiveness (advantages and disadvantages) of some time-domain indicators in describing the presence (or absence) of faulty symptoms (Kankar et al., 2011; Sassi et al., 2008; Tandon and Choudhury, 1999).

A bearing fault diagnosis system may be designed to provide different levels of information about the defect (s). The first and simpler issue investigated in the literature is the detection of the presence or absence of a defect (Jack and Nandi, 2002; Samanta et al., 2004). The second issue is the determination of the defect location, which may occur in different components of a bearing (Alguindigue et al., 1993; Bhavaraju et al., 2010). Often, the type of defect is considered along with the defect location. For instance, some authors consider the following classes: sandblasting of IR/OR, indentation on the roll, unbalanced cage (Lazzerini and Volpi, 2011; Volpi et al., 2010), crack on IR/OR, spall on IR/OR, spalls on rollers (Widodo et al., 2009), generalized fault of two balls (Alguindigue et al., 1993), etc.

Finally, the severity of a bearing defect is the last and perhaps the most difficult information to be predicted. Through this information, it may be possible to estimate the duration during which the equipment can still operate safely. In the literature, this issue has been partially investigated, by associating a different class to each defect dimension (Cococcioni et al., 2009a, 2009b; Widodo et al., 2009). Cococcioni et al. (2009a), for example, have employed three classes for describing the seriousness of an "indentation on the roll", namely, light (450μm), medium (1.1 mm) and high (1.29 mm). The drawback of this strategy is that other defect dimensions are not considered by the classifier. A more suitable solution would be the estimation of defect dimensions as a regression problem.

Table 2 presents a summary of different systems reported in the literature, with their respective employed classification techniques, types of signal, descriptors (features), types of defects and datasets. It is important to mention that the bearing defects may be categorized as distributed or local. Distributed defects are due to unavoidable manufacting imperfections, such as surface roughness, waviness, misaligned races and off-size rolling elements (Sassi et al., 2007), whereas localized defects include cracks,

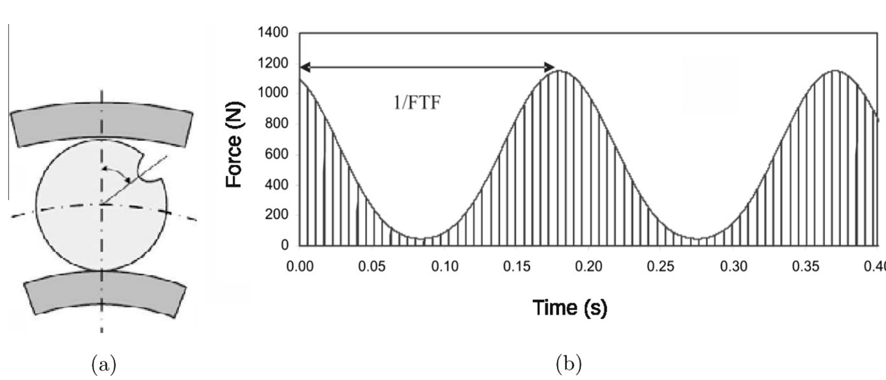

Fig. 2. Example of a hypothetical defect located in the rolling element (a) and its corresponding shock impulses (b), where FTF is the Fundamental Train Frequency (or cage frequency). Adapted from Sassi et al. (2007).