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Fault detection via recurrence time statistics and one-class classification☆

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ABSTRACT

Predictive maintenance has emerged as a fundamental practice to preserve production assets in many industrial environments. Of a wide set of approaches, vibration analysis is one of the most used for high-speed rotating machinery, especially when fault detection is to be automatic. Traditionally, this task has been studied as a classification problem using data extracted from the frequency domain. This approach, however, has two main limitations: (a) manufacture and mounting procedures can vary the vibration spectra of a machine, even when these share the same design; and (b) incipient fault signatures may be concealed in the frequency domain by noise and vibration from other parts of the system. For these reasons, the application of a classifier obtained for one machine to another machine is pointless, making early fault detection difficult. In this paper, a bearing fault detection problem is tackled using one-class classifiers and features extracted from vibration capture in the time domain using recurrence time statistics. We also describe a study of the behavior of the proposed method in real conditions. Our method shows high detection accuracy accompanied by a reduced number of false positives and negatives.

1. Introduction

Predictive maintenance aims at increasing the cost efficiency of a plant by reducing maintenance expenditure. In contrast with classical approaches, predictive maintenance tries to determine the status of equipment through continuous or periodic monitoring of signals that describe its status. Early fault detection avoids fatal breakdowns and facilitates cost-effective maintenance scheduling. Nowadays, predictive maintenance technologies are considered essential to extending equipment life, reducing maintenance costs and enhancing asset exploitation [4]. The fault management process can be divided into four main stages [28]: (1) *detection*, in which a system component failure is detected; (2) *isolation*, in which information is obtained about cause and possible spatial location of the failure; (3) *evaluation*, in which failure severity is quantified, and (4) *prognosis*, in which the remaining life of the system is estimated.

In this paper, we focus on the first stage, detection. Detection models are traditionally classified in one of two categories. In *model-based fault detection* approaches, access to input $u(t)$ and output $y(t)$ for the monitored system is assumed to be possible. Monitored in order to detect deviations is the discrepancy between the behavior of a model of the system and the actual system itself [11,15,26,34]. In *signal-based fault detection* approaches, the availability of the system input $u(t)$ is not assumed and detection is only based on the system output $y(t)$. This second approach is more broadly applicable in real scenarios where fault detection must be performed without detailed design data for the machinery. Fault detection tackled from a signal-based perspective has three fundamental stages.

(1) Feature extraction. Descriptive features are extracted from the available output $y(t)$. These should be sensitive to changes in system dynamics for a fault to be detected. This fundamental stage governs the final accuracy of the detection strategy [15,23].

(2) Normal state discrepancy measurement. When new data $y(t)$ is received, its description based on feature extraction must be compared with data representative of a non-faulty state. This particular stage has been a hot topic in the pattern-recognition community in recent years. However, most research to date [5,7,16,19,22,24,36] has tackled this stage as a two- or multi-class classification problem based on the availability of fault examples. This is not, however, a common eventuality in many real-life applications. Few studies to date have taken into account this

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challenge [29]. When this stage is considered as a novelty detection or one-class classification problem, the output is a discrepancy measure between the normal state represented by the trained one-class model and the current state. This measure will be the input of the next stage.

(3) Discrepancy analysis. A final decision needs to be made in this final stage, based on the sequence of obtained discrepancies. More challengingly, a purely binary decision is not acceptable, as can be elicited from the latest certification standards for machinery monitoring systems [10]. Hence, automatic means of assessing fault evolution are necessary.

When dealing with high-speed rotating equipment, vibration analysis is one of the most effective methods of evaluating its condition, detecting defects and avoiding critical failures. In the last decade, detection has evolved from visual inspection by human experts to automated methods that use advanced signal-processing techniques and pattern-recognition models such as neural networks, fuzzy logic and data-driven empirical and physical modeling [12]. As equipment begins to fail, it typically exhibit symptoms that suitable methods will indicate as failure precursors. Combining sensors with predictive maintenance techniques can avoid unnecessary equipment replacement, save costs and improve process safety, availability and efficiency. The impact of advances in this field becomes immense when we take into account the ongoing growth in the markets for certain kinds of rotating machinery, such as windmill power generation (with cumulative power of 185 GW worldwide in 2010). In this scenario, planned and corrective maintenance is a prohibitive burden.

The case of fault detection based on vibration captured in complex machinery falls in the *signal-based fault detection* category, since typically only the vibration signals are available. We focus specifically on bearing faults as detected from vibration data. Feature extraction in this area has mostly been based on frequency space analysis and it is only recently that a growing interest has become evident in automatic detection based on features extracted from the time domain signal. Classical approaches to the time domain have focused on statistical measures and models specifically intended for stationary processes; these tend to average transient vibrations such as those of bearings and usually overlook incipient fault symptoms, more suitable to time-invariant processes [6].

We explore the application of statistical measures from the chaos and fractal theory field [8] as an alternative to using classical fault detection statistics. Specifically, recurrence time (RT) statistics [9] extracted from vibration time signals for the machinery are used as features. An historic dataset of normal captures preprocessed by RT statistics is used to construct a one-class classifier. A one-class classifier based on extreme statistics is used [21], as it has the advantages of having a reduced set of just two hyperparameters and has demonstrated high classification accuracy in comparison with other standard one-class classifiers.

The paper is organized as follows: in Section 2 and Section 2.1 RT statistics, the T1 index and a methodology for selecting hyperparameters are described; in Section 3, the EVOC one-class classifier model [21], to be used as the detection model, is explained; in Section 5 empirical evidence of the suitability of the proposed model for fault detection is reported and some of its key properties are highlighted; finally, Section 6 concludes the paper.

2. Recurrence time statistics

In the past years, the study of bearing fault detection in the frequency space has been studied thoroughly and the principles for detecting the faults both manually and automatically have been well established [33]. However, it is a well known fact, when the fault is incipient or the system where the bearing is embedded is too complex, vibration features due to bearing faults are concealed by the vibration signature of the rest of the system and noise. This fact usually makes early fault detection task in frequency domains very difficult. In recent years, the interest in automatic bearing fault detection research has moved towards studying how information in the time domain signals can be exploited for early detection of bearing faults. In recent years, traditional linear and nonlinear time series analysis techniques combined with other signal detection techniques have been used (see, for example, the work in [30]). Machinery vibration generation processes (and more specifically, faulty bearing vibration generation [6]) are known to be non-stationary dynamic processes: hence, the problem can be viewed as a change of dynamics, as has been studied for many years [8]. Many specially designed indexes for characterizing the dynamics of nonlinear and chaotic systems have been proposed, and their applicability as features in bearing fault detection is an improvement that, as yet, has to be fully studied.

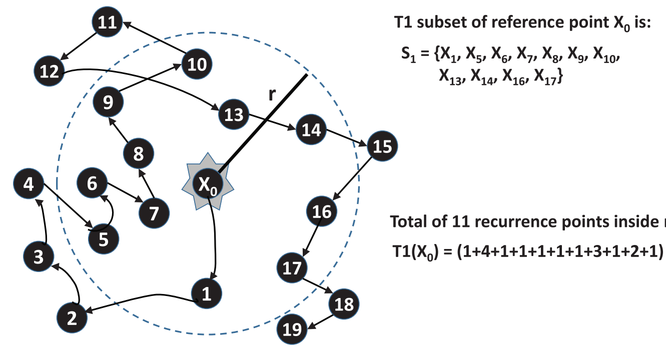

Fig. 1. Recurrence Time Statistics calculation illustration.

RT statistics is a method rooted in chaos theory [8] that assumes that the process under study is fully described by scalar time series $\{x(i), i = 1, 2, \dots, M\}$, where i is the time index. According to Takens' embedding theory [32], the corresponding m dimensional phase space can be recovered by constructing vectors from the time series, $X_k = [x(k), x(k+L), x(k+2L), \dots, x(k+(m-1)L)]$, where L is the time delay. This vector sequence $\{X_k, k = 1, 2, \dots, N\}$ constitutes a trajectory in the phase space with $N = M - (m-1)L$. Under normal circumstances, a dynamic process remains close to a fixed attractor. Thus, the time required for a dynamic process to return to an attractor close to the initial one (Poincaré recurrence time) can be used as a sign that the process has changed. To measure this time, we proceed as follows:

1. Fix an arbitrary reference point X_0 in this constructed phase space, and consider the ball centered at that point of radius r: $B_r(X_0) = \{\|X_j - X_0\| \leq r \mid j \in [1, N], j \neq 0\}$
2. Denote the ordered subset of the trajectory that belongs to $B_r(X_0)$ by $S_1 = \{X_{t_1}, X_{t_2}, , X_{t_i}, \cdots \mid t_i \in [1, N], t_{i+1} > t_i\}$. These points are called Poincaré recurrence points.
3. Calculate the Poincaré recurrence times, which are defined as $\{T1(i) = t_{i+1} - t_i, i = 1, 2, \dots\}$. The T1 index of this reference point X_0 is the mean of the generated T1 set.

Finally, the overall T1 of the whole phase space is the average of the T1 indexes for all the reference points. Fig. 1 illustrates the T1 generation of one reference point [18].

According to Takens' embedding theory, if the attractor dimension is D (possibly a non-integer), then a constructed phase space, with an embedding dimension of $m > 2D + 1$ (where m should be an integer) reveals the underlying dynamics. In the next section we describe a method to approximate the embedding dimension of a vibration generation process.