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ACOUSTIC PARTICLE VELOCITY FOR FAULT DETECTION OF ROTATING MACHINERY USING TACHLESS ORDER ANALYSIS

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The detection of faulty parts is of fundamental importance during the manufacturing process. Most traditional acoustic techniques for fault diagnosis are based on analysis of the sound pressure emitted by the device. However, the performance of such methods are strongly limited for industrial scenarios due the presence of high levels of background noise. Furthermore, to carry out fault detection in rotating machinery, the exact measure of rotational speed of the shaft is required. The placement of a specific tachometer for this purpose is not often possible at the end of the assembly line due to time or spatial constraints. Particle velocity sensors are a non-contact solution that are able to capture surface vibration and can therefore be used to simultaneously quantify the vibro-acoustic behavior of a device and to perform order tracking. In addition, they provide better signal to noise ratio as they are less affected by background noise when measurements are performed close to the radiating surface.

This paper presents the application of a single 3D acoustic particle velocity sensor for fault detection in rotating machinery under factory conditions with high levels of background noise. The implemented method is able to perform tachless order analysis and make use of Gaussian mixture models for the fault classification. The proposed method provides evidence for the viability of particle velocity-based solutions for end of line control applications in noisy conditions.

1 INTRODUCTION

In recent years, end-of-line (EOL) tests are required for most NVH applications in order to detect defective parts during the manufacturing process. Traditionally, subjective rating has been used as a standard for estimating the quality of the object tested. However, results are often biased, possibly leading to contradictory scores depending on the person testing. As a result, there is an growing trend of developing EOL solutions based on objective criteria that correlate well with controlled subjective scores.

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The vibro-acoustic signature of a device has proven useful for detecting problems and classifying manufacturing defects [1]. The signature is highly dependent upon the excitation and load, which can reveal a series of problems relative to operating condition. Each defect should be assessed differently, linking the measured quantity to the physical cause of the problem. Understanding the root cause allows for designing test procedures that capture a particular vibro-acoustic behaviour related to the defect.

For the case of rotating machinery in particular, it is know that the vibro-acoustic signature of rotating machinery relates to periodic events, such as a rotating shaft, gear-mesh or ball-bearing movement. For that reason, many diagnosis techniques, like order analysis, require an exact measure of the rotational speed of the shaft. Traditionally, direct measurement of the shaft requires the placement of tachometers, which needs set-up time and proper handling to avoid errors during the measurement. However, during end of line testing, direct measurement is not possible due to time constraints or shaft location not being accessible after assembly. The extraction of rotational speed information from the vibro-acoustic signal (tachless) would allow order analysis features to be obtained without a dedicated tachometer sensor.

Moreover, conventional techniques that are based upon the sound emitted at a certain distance in a controlled environment, are often not viable on a production line. The high levels of background noise and reverberation, along with low excitation emitted by the source, prevent the gathering of acoustic data in-situ, reducing the suitability of sound pressure based solutions. In contrast, the use of acoustic particle velocity transducers offers a significant advantage over pressure-based testing techniques. Measurements performed in the proximity of the device are proportional to the surface vibration [2] and hardly affected by noise generated by the surrounding machinery [3].

This paper shows that a single 3D acoustic vector sensor can be used for fault detection and classification of rotating devices during end of line testing. The proposed non-contact approach extracts instantaneous RPM information to obtain the vibro-acoustic signature in the order domain for several excitation loads. Firstly, the procedure for tachless order tracking and analysis is described, followed by some examples of fault assessment and feature extraction based on order analysis are illustrated. Finally, the fault classification method based on Gaussian Mixture Models (GMM) is outlined.

2 ORDER ANALYSIS OF ROTATING MACHINERY

The vibro-acoustic behaviour of a machine varies greatly depending upon the operational speed and load. Many noise control strategies rely upon the direct link that can often be established between the noise emitted and the rotational speed. Most of the components that comprise the device are likely to cause periodic excitations at frequencies which are integer multiples of the main rotational speed. This key relationship can be used as an indication to identify the main sources of noise. The frequency assessment of vibro-acoustic signals as a function of rotational speed is usually referred to as order analysis [1].

The transformation from the time domain to the order domain requires a precise estimation of the machine rotational speed and a suitable signal processing method. The following sections cover these aspects, describing the techniques that were implemented for the application studied in this paper.

2.1 Tachless RPM tracking

Tachometers are typically used to measure the shaft speed of rotating machinery by counting the amount of pulses per shaft revolution. Although their accuracy can be high, the installation of such sensors may not be suitable for applications where time is limited, such as end-of-line tests [4]. Several tachless order tracking methods have been proposed, firstly using sound pressure in a car interior [5] and more recently measuring surface acceleration [6]. The former technique is limited to environments with a very high signal-to-noise ratio, whereas the latter method requires attaching a transducer to the vibrating structure, a process that may be unsuitable for certain applications. As an alternative, the use of acoustic particle velocity is hereby proposed. As pointed out above, the normal acoustic particle velocity measured close to a high impedance surface is less affected by background noise than sound pressure. On the other hand, a non-contact solution that is able to capture surface vibration and simultaneously quantify the acoustic output of a device is very useful for estimating the noise impact of a machine in its operational environment.

The acoustic signal captured in the vicinity a complex device often contains a combination of strong tonal components proportional to the main rotational speed, and broadband noise caused by mechanisms of a random nature, such as flow-induced vibrations. An order tracking algorithm has been developed based on some of the ideas proposed for pitch extraction of polyphonic music [7, 8] and speech [9]. It should be noted that in the case studied, the amplitude of most of the orders may be apparent at certain speeds or loads, but it cannot be assumed to be higher than that of the random noise during the whole test. As a result, the main aim of the algorithm designed is to extract tracking information from the harmonic series in order to minimize the error between a polynomial model and the measurement data. The tracking algorithm can be summarized by the steps shown in Figure 1.

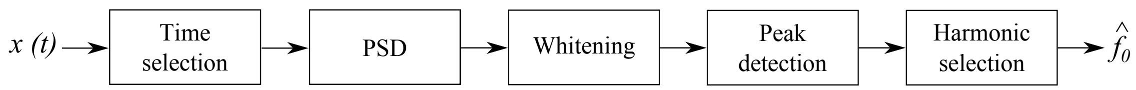

Figure 1. Flow chart of the steps involved in the RPM tracking process.

Firstly, the power spectral density (PSD) of a short time section of the measurement data is computed. Following this, a whitening procedure is applied in order to suppress timbral information and thus increase the uniformity of the signal. The whitening coefficients were calculated from a smoothed version of the spectrum using a long median-based filter. The signal is then compared to a relative threshold, obtaining a selection of the main frequency peaks. The harmonic sum that maximizes the total energy and at the same time minimizes the model error is then selected to compute the instantaneous rotating frequency. This process is repeated across the entire time data. Finally, polynomial curve fitting is applied to compute the RPM for every data sample.

2.2 The order spectrum

When analyzing rotating machinery it is often desirable to study excitation as a function of harmonics or orders of the shaft speed [1]. If the data acquired is synchronized with the rotational speed, the Fourier transform of the signal will directly lead to the order spectrum, i.e.

$$X(\Omega) = \int x(\phi) e^{-j\Omega\phi} \mathrm{d}\phi \tag{1}$$

where Ω is the evaluated order and ϕ is the shaft angle. Although analog phase-locked systems were formerly used for this purpose, practical limitations lead to the search for alternative digital solutions. Nowadays, the most extensively used method to convert the data to the order domain is by resampling the recorded signals using the corresponding rotational speed via digital interpolation. However, significant improvements can be obtained by using the Velocity Synchronous Discrete Fourier Transform (VSDFT) introduced by Borghesani et al. [10]. The order domain conversion of the VSDFT is derived from the fundamental relationship shown in Equation 1, applying a change in the domain of integration, i.e.

$$X(\Omega) = \int x(t)\omega(t)e^{-j\Omega\phi(t)}\mathrm{d}t \tag{2}$$

where $\omega(t)$ denotes the instantaneous shaft speed. The implementation of the above expression requires the discretization of both order and time domain, i.e.

$$\mathrm{VSDFT}[k] = \frac{\Delta t}{\Theta}\sum_{n=0}^{N-1} x[n\Delta t]\omega[n\Delta t]e^{-j\Omega[k\Delta\Omega]\phi[n\Delta t]}\mathrm{d}t \tag{3}$$

where Θ is a normalization factor related to the acquisition time window in the angular domain. In practice, $\omega[n\Delta t]$ is extracted from the RPM tracking procedure explained above. On the other hand, $\phi[n\Delta t]$ can be estimated using numerical integration on $\omega[n\Delta t]$. Figure 2 shows an example of the conversion from the time-frequency domain to the RPM-order domain using the VSDFT.

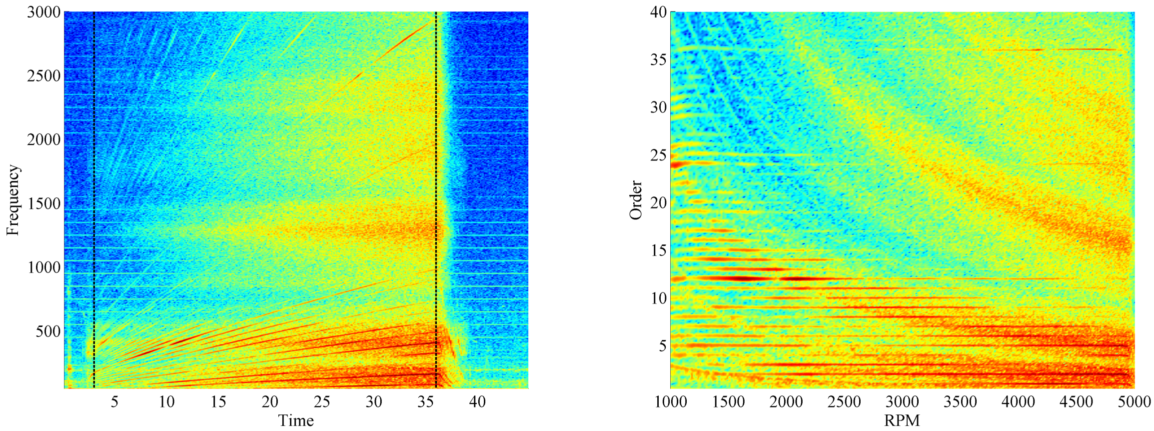

Figure 2: Example of a time-frequency domain representation during the run-up (left). Equivalent RPM-order domain representation (right) with the performed tachless order tracking.

3 FAULT ASSESSMENT AND FEATURES EXTRACTION

Multiple test procedures are usually required to assess different defects under specific operating conditions. Each procedure aims to extract features that are related to the type of problem evaluated. The latter application of a probabilistic model allows for the detection of manufacturing defects, as shown in Section 4.

For the case studied, several evaluation criteria were developed to asses different defects of rotating machinery. For the sake of clarity, this section is focused on only two of the procedures: unbalance and vibro-acoustic anomalies.

3.1 Unbalance

Unbalance is mainly caused by a misalignment between the local centre of mass and the rotating axis. This deviation induces forces rotating at the shaft speed that may excite the structure of the device. Even a small misalignment during the manufacturing process could yield unbalance problems and therefore excessive vibrations.

In practice, unbalance generates a significant power increment at the first harmonic of the rotating shaft speed, being more apparent at higher excitations. The implemented detection method uses the acoustic particle velocity signals acquired during a run-up in three orthogonal directions. The maximum level reached in the first order in each sensor is used as a feature vector, addressing structural resonances in every direction. In the figure 3 a comparison of the first order response of an unbalanced and a balanced device is shown.

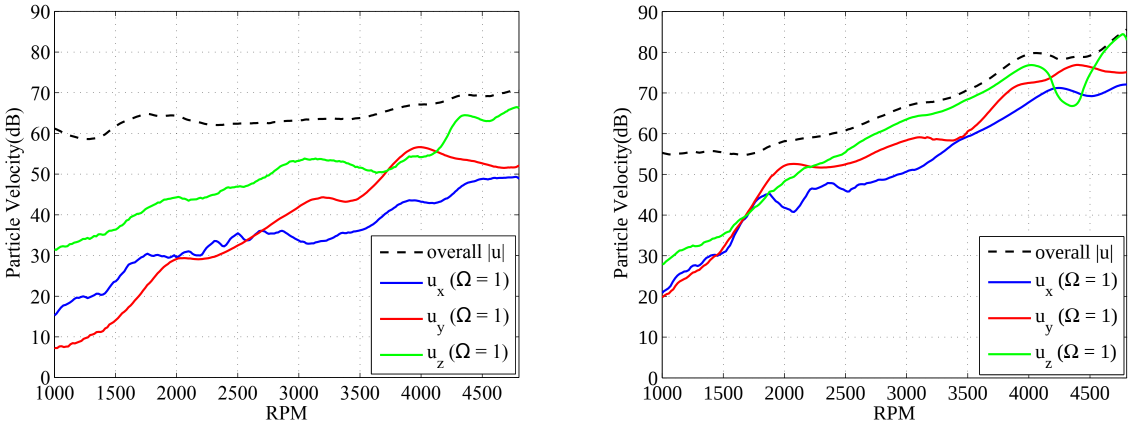

Figure 3: Comparison of balanced (left) and unbalanced (right) sample. First order energy in the velocity directions u_x, u_y, u_z compared with the overall energy $|\mathbf{u}|$.

3.2 Vibro-Acoustic Anomalies

Anomaly detection deals with the determination of abnormal functioning of a device. In the case of rotating devices, fault detection using the vibro-acoustic signal could be challenging provided that the defect could be non-stationary, only appearing at certain operating conditions.

The proposed method obtains statistical features from the rpm-order representation, calculated from a set of measurements of devices with normal behavior, of the vibro-acoustic signal during run-up. Based on this, a probabilistic model, as shown in Section 4, is built. The anomalous devices are assumed to show significantly different vibro-acoustic behavior and therefore to have a lower probability of belonging to the normal device model.

The features extracted are the mean and maximum values reached during the run-up in a representative set of orders. These two features were shown to be sufficient to detect anomalies in the devices.

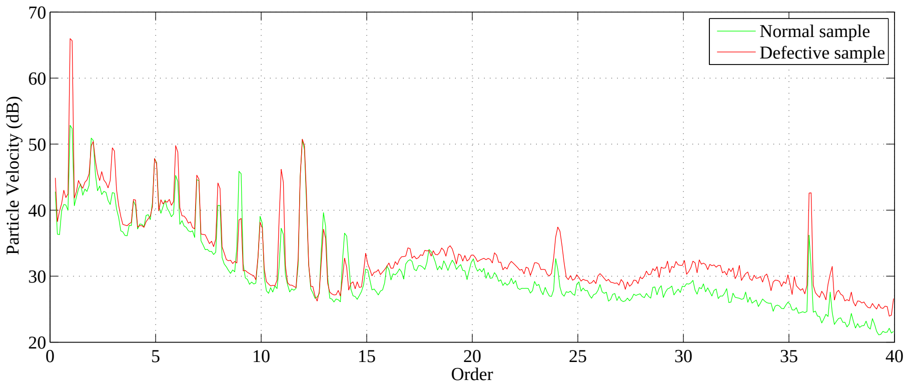

Figure 4: Comparison of the mean order power during a run-up of a normal sample (green) and a defective sample (red).

4 CLASSIFICATION

4.1 Gaussian Mixture Models

Gaussian Mixture Models (GMM) have been used for many pattern recognition applications. It is a statistical model that has been shown to be robust for the classification of dynamic signals, making it very suitable for the classification of vibration data subject to load and fault severity variations [11, 12].

A GMM is used to model the features of a signal class, i.e. faulty or normal. It represents the probability density function (*PDF*) of the observed class and comprises a weighted sum of G Gaussian distributions:

$$p(X \mid \lambda_m) = \sum_{j=1}^{G} \omega_j p_j(X) \tag{4}$$

where λ_m is the mixture model, ω_j is the weight of the j-th Gaussian component with a multivariate probability distribution given by [13]

$$p_j(X) = \frac{1}{\sqrt{(2\pi)^{N_f} \left|\Sigma_j\right|}} e^{-\frac{1}{2}\left[(X-\mu_j)' \Sigma_j^{-1} (X-\mu_j)\right]} \tag{5}$$

where w_j, μ_j and Σ_j are the weight, the mean and the covariance matrix of the distribution, and $X = \{\vec{x}_1, ..., \vec{x}_{N_f}\}$ is the sequence of N_f feature vectors in the analysed segment.

The GMM for the given class model m is represented by

$$\lambda_m = \{w_j, \mu_j, \Sigma_j\} \qquad j = 1, ..., G \tag{6}$$

where w_j and μ_j are the weight and mean of the distribution, and Σ_j is the covariance matrix.

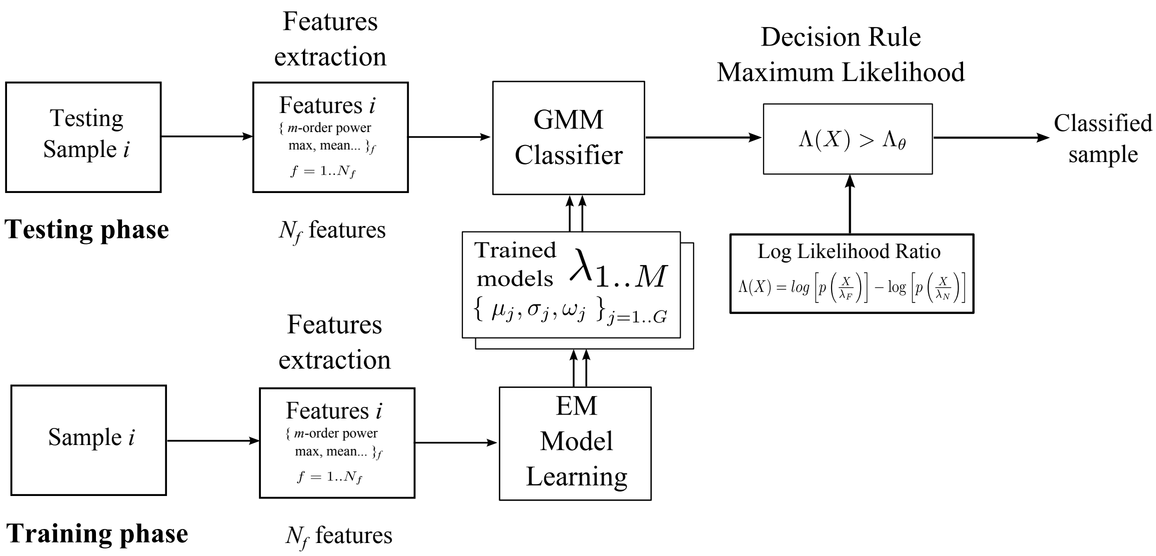

Figure 5. Flow chart of the steps involving the testing procedure

4.2 Training

In the training phase, the parameters of the model λ_m are obtained using the Expectation-Maximisation (EM) algorithm [13] for each class. The model parameters $\{w_j, \mu_j, \Sigma_j\}$ are found using the EM algorithm to maximize the likelihood of a sample belonging to certain class m. The estimation of model parameters, i.e. the number of mixtures G, was done using 10-fold cross-validation [14].

4.3 Testing

In the testing phase, a score is obtained for an unknown signal using the GMMs. Given a sequence of N_f feature vectors in a segment $X = \{\vec{x}_1, ..., \vec{x}_{N_f}\}$, a scoring function is given by log-likelihood ratios (LLR) for two different testing scenarios [13]:

- *Anomaly detection*: A score indicating that the sample belongs to the normal class model λ_{1N}:
$$\Lambda_1(X) = \log\left[p\left(X \mid \lambda_{1N}\right)\right] \tag{7}$$

- *Good/Faulty detection*: A score indicating that the sample belongs to the faulty λ_{2F} class model or the normal λ_{2N} class models:
$$\Lambda_2(X) = \log\left[p\left(X \mid \lambda_{2F}\right)\right] - \log\left[p\left(X \mid \lambda_{2N}\right)\right] \tag{8}$$

The decision thresholds $\Lambda_{\theta 1}$ and $\Lambda_{\theta 2}$ are adjusted to discriminate between normal and anomaly samples in the first case, and to minimise the trade-off between false negatives (rejecting faulty samples) and the false positives (accepting good samples) in the second case:

$$\Lambda_1(X) \underset{normal}{\overset{anomaly}{\lesseqgtr}} \Lambda_{\theta 1}, \qquad \Lambda_2(X) \underset{good}{\overset{faulty}{\lesseqgtr}} \Lambda_{\theta 2} \tag{9}$$

With regard to the testing procedures shown in Section 3, it should be noted that the unbalance test uses the score function $\Lambda_1(X)$ for good/faulty sample detection, and the anomaly test uses the score function $\Lambda_2(X)$ for abnormal sample detection.

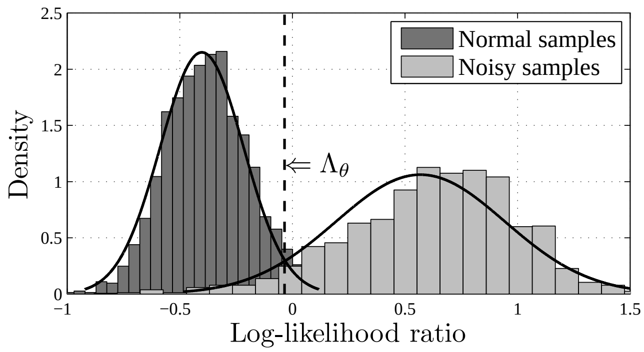

Figure 6: An example of a Log-Likelihood Ratio (LLR) histogram and decision threshold (Λ_θ).

5 CONCLUSION

A fault detection method for rotating machinery based upon tachless order analysis using a 3D acoustic particle velocity sensor has been proposed. The use of single probe enables not only the quantification of vibro-acoustic emissions and the detection of noise and vibration problems but also the tracking of the operational speed of rotation. The method was able to perform fault classification and anomaly detection using Gaussian Mixture Models. In addition, the proposed technique is capable of working in the presence of high background noise. This proves the viability of particle velocity sensors for end of line fault detection using automated quality control systems in factory conditions.

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