Fault Detection System Using Acoustic Particle Velocity based on Gaussian Mixture Models and Mel-Cepstral Parameters

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Introduction

The detection of faulty parts is of fundamental importance for end of line (EOL) tests. Most available EOL techniques are based on analysis of either sound emission, or vibration generated by the studied equipment. Sound signatures can be analysed in order to distinguish between good and defective product samples. However, acoustic measurements are often not viable on a production line due to high levels of background noise and reverberation.

For the case of rotating machinery, the vibration signal can be affected by mechanical defects, i.e. in bearings or meshes, as well as by defects in the driven moving parts. On the other hand, the acoustic emission can be very low, and in many cases masked by the background noise, preventing the application of sound pressure based solutions.

The use of particle velocity transducers offers a significant advantage over traditional testing techniques, providing all measurements can be carried out in the proximity of the vibrating surface. It was shown in [1] that the particle velocity level is proportional to the surface vibration and is hardly affected by high background noise levels [2].

In this paper the use of particle velocity sensors for fault detection and classification is proposed using Gaussian Mixture Models (GMM) along with short-term Mel-Frequency Cepstral Coefficients (MFCC).

Theory

The acoustic particle velocity in the normal direction near to the vibrating surface is hardly affected by background noise and reflections for three reasons [2]:

- The particle velocity level, due to vibration of the surface itself, is high because of near field effects.
- The particle velocity level due to background noise is usually low because many objects have high surface impedance. The incoming and reflected sound waves are almost equal in strength but opposite in phase thus they interfere destructively.
- Particle velocity sensors are directional and can be pointed towards the vibrating surface, reducing noise contributions from other directions.

In 1994, the Microflown sensor was invented, which can directly measure acoustic particle velocity and source strength even in reverberant environments.

Gaussian Mixture Models

Gaussian Mixture Models (GMM) have been used for many applications of pattern recognition. It was 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 [3].

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 is composed by a sum of N Gaussian distributions. The parameters of a model j are represented by:

$$\lambda_j = \{w_i, \mu_i, \Sigma_i\} \qquad i = 1, ..., N \tag{1}$$

where w_i and μ_i are the weight and mean of the distribution, and Σ_i is the covariance matrix.

The classification task is split in two steps, training and testing.

Training

In the training phase, the parameters of the model λ_j are obtained using the Expectation-Maximisation (EM) algorithm [4] for each class. The weight, mean and covariance parameters found using the EM algorithm maximizes the likelihood of belonging to certain class j.

Testing

In the testing phase, an unknown signal is compared to both GMMs, the faulty λ_F and the normal λ_N class models. Given a sequence of K feature vectors in a segment $X = \{\vec{x}_1, ..., \vec{x}_K\}$, a scoring function is given by the log-likelihood ratio (LLR) [4]:

$$\Lambda(X) = \log\left[p\left(\frac{X}{\lambda_F}\right)\right] - \log\left[p\left(\frac{X}{\lambda_N}\right)\right] \tag{2}$$

A decision threshold Λ_θ is adjusted to minimise the trade-off between false negatives (rejecting faulty samples) and the false positives (accepting good samples). Figure 1 shows the LLR histogram for the two classes and the estimated threshold.

Feature extraction

The feature extraction technique applied in this paper is based on Mel-Frequency Cepstral Coefficients

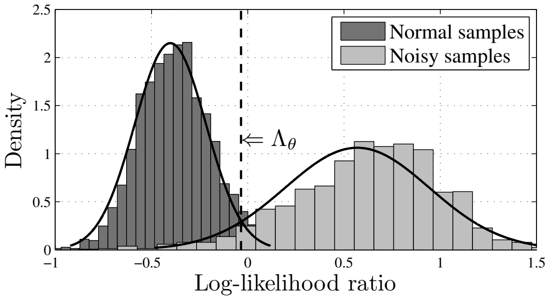

Figure 1: LLR histogram estimated from a subset of normal and faulty frames in the testing procedure. $\Lambda_\theta(x)$ indicates a decision threshold of the algorithm.

(MFCC) [3]. MFCC vectors contain time-frequency information of the signal, which is widely used for extracting linear and non-linear features.

The analysed signal is segmented in frames using short overlapped windowing functions. Next, the power spectrum of each frame is filtered using a *mel*-scale filter bank. It is then transformed to the cepstral domain by taking logarithms and applying the *Discrete Cosine Transform* (DCT) [3].

The resulting coefficients are the MFCCs that describe the power spectral envelope. Dynamic features are captured to assess coefficient changes between frames, i.e. computing the 1st and 2nd derivatives, known as Delta and Delta-Delta.

Experimental setup

The proposed method has been applied to the classification of actuators driving air valves in a factory environment with high background noise. Particle velocity sensors were placed near the actuators to capture anomalous vibrations induced by mechanical defects in valves and the actuator itself. The multiple actuators of the machinery units being assessed were operating under different loads.

The dataset was separated into two classes: normal and noisy. The normal class was composed of 20 samples, whilst the noisy class was composed of 38 samples.

The duration of each test sample was 5 seconds. All signals were preprocessed to reduce the influence of the factory noise, filtering them with an autoregressive-model (AR).

MFCC-based GMM method parameters

The method was tested with several parameter combinations. The feature extraction process used a window frame of between 32 to 512 samples (3.8 ms to 61.4 ms), with 50% overlap. The number of MFCCs use was between 2 and 16. The frequency range of interest was between 50 Hz and 3.5 Khz.

Furthermore, the number of GMM mixtures employed in the classification process was between 2 and 12. The features were also tested after applying a z-score normalisation.

Results

The classifier performance was assessed by averaging the results of a 5-fold cross-validation scheme [5] repeated 5 times. Table 1 shows the accuracy including 95% confidence intervals(CIs), F1-score, and Area Under the Curve (AUC) for several configurations. Accuracy describes the classifier ratio of successful predictions. The F1-score is a performance indicator based upon the relevance of the results. The AUC estimates the relative performance of binary classifier compared to a random classifier.

Table 1: Performance results for several parameters

Results	**MFFCs / GMMs / Frame length**		
	16/2/128	12/4/64	8/2/64
Accuracy	99.82±0.9	99.46±2.1	99.02±2.2
F1-score	99.83	99.52	98.95
AUC	0.999	0.999	0.998

The results shows an accuracy of over 99%, which seems to be dependent upon the number of MFCCs used. However, a larger dataset should yield a better estimation of the classifier performance and the optimal parameter configuration.

Conclusion

A GMM-MFCC method based upon acoustic particle velocity measurements has been proposed to perform end of line tests for rotating machinery in a noisy factory environment. The results shows excellent performance for detecting faults that are subject to different loads and dynamic changes.

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