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WIND TURBINE GEARBOX FAULT DETECTION USING MULTIPLE SENSORS WITH FEATURE LEVEL DATA FUSION

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ABSTRACT

Fault detection in complex mechanical systems such as wind turbine gearboxes remains challenging, even with the recently significant advancement of sensing and signal processing technologies. For example, the non-stationary nature of the wind load may require the joint time-frequency domain feature extraction methods for the signals collected from the gearbox. In this paper, a harmonic wavelet based method is adopted, and a speed profile masking technique is developed to account for tachometer readings and gear meshing relationship. In such a way, those features with fault-related physical meanings can be highlighted. While multiple sensors yield redundant features, we fuse them through a statistical weighting approach based on principal component analysis. The fused data are fed to a simple decision making algorithm to verify the effectiveness. Using experimental data collected from a gearbox testbed emulating wind turbine operation, we can detect gear faults statistically for a given confidence level.

INTRODUCTION

Engineers have used vibration based analysis for decades to evaluate performance of complex mechanical systems such as rotating machineries. There are many challenges for detecting fault conditions, since faults occur primarily at the materials level but their effects can only be observed indirectly at a system level. Another problem is the many-to-many relationship between faults and the observable quantities at macroscopic system level, e.g., vibration amplitude. The accuracy of the empirical techniques may be significantly subject to human interpretation. In recent years, along with the rapid advancements of microelectronics and information technologies, innovative monitoring and diagnosis systems have emerged. Although visual inspections are still needed in certain situation, vibration and acoustic emission signals become main inputs in many cases. Those signals are easily accessible by small yet sensitive sensors of different types. Even when individual sensor's performance is compromised due to cost or energy constraints, multiple sensors can be deployed for information redundancy. Utilizing signal processing algorithms, an intelligent monitoring scheme can enable the implementation of a condition-based maintenance (CBM) philosophy [1].

Signal processing has been playing a critical role in gearbox monitoring and fault detection, especially when raw data are collected in a noisy observing environment [2]. It is well known that the vibration and acoustic emissions produced by a gearbox contains important diagnostic and prognostic information about the condition of the gears. The key is to extract damage-sensitive features from those signals and perform statistical analysis of these features for decision making. The Fourier transform as a signal representation method, though widely used, provides only the global frequency information averaged over the entire time span. To preserve time information in the signal, wavelet analysis has been utilized to transform a signal into the joint time-frequency domain. Each wavelet coefficients represents how well the input signal correlates with a windowed basis function called wavelet. For different applications, a variety of wavelets have been adopted, e.g., Haar, Daubechies, Mexican Hat, Gabor and Morlet wavelets. Generally speaking, wavelet analysis is capable of extracting time-frequency features from complex signals [3]. However, choosing a specific wavelet remains empirical in many engineering applications.

In a multi-sensor setup, data fusion can improve the ability to detect, characterize, and eventually identify fault conditions. Despite extensive research on mechanical models, pattern recognition, neural network, and other signal processing techniques for individual sensor, relatively less research has been conducted on fusion of multi-sensor data for condition monitoring [4]. The sensor-level data fusion is mainly raw data alignment, denoising, normalization, and resampling, etc. Techniques such as frequency banding and time-domain averaging are commonly adopted at this lowest level to insure data quality and provide sensor self-check. Other examples can be found in [5]. When features are extracted from the raw data, through wavelet analysis for example, it becomes feature-level data fusion. Next, determining the health of the monitored system based on the fused features involves decision-level data fusion. There are statistical, voting or neural network based algorithms developed at this level [6], where decisions are weighted, blended and quantified as indicators of fault existence. The data fusion methodology discussed in this paper will be focused on the feature level. In a gearbox application, features extracted respectively from accelerometers, microphones and tachometer measurement may cover one aspect/area/property of the overall condition. When combined, these features may provide a better characterization of the condition or reduce the size of the critical feature subspace for easier decision-making.

To quantify the severity of fault or malfunction, statistical indices can be calculated from the extracted features. Common scalar indices include [7] root-mean-square deviation (RMSD), mean absolute percentage deviation (MAPD), covariance (Cov) and correlation coefficient (CC). In this paper we adopt a straightforward statistical decision making algorithm to demonstrate the effectiveness of our data fusion algorithm.

GEARBOX DYNAMICS EXPERIMENTAL SETUP

Gearbox is typical rotating machinery that serves as a major dynamic component in most mechanical systems. There are often multiple pairs of meshing gears in each gearbox mounted on rotating shafts, while the shafts themselves require bearings and fixtures to be installed. Many types of mechanical faults and failures can occur in a gearbox, for example, surface wear, misalignment, eccentric or crack gears. Vibration and acoustic sensor signals collected from such a system may reveal partial information about its running operating condition. With the aid of advanced signal processing techniques, our goal is to achieve autonomous condition monitoring.

One challenge for wind turbine gearbox condition monitoring comes from the non-stationary nature of its operation, as the energy source, the wind load, is often a time-varying quantity. A direct consequence would be that harmonic based method like Fourier transform cannot be used effectively. Instead, time-frequency methods such as wavelet analysis become a natural choice [8]. To obtain real-time running conditions of a gearbox with or without faults, we use a gearbox dynamics simulator manufactured by SpectraQuest. It consists of a 3HP motor controlled via USB by a software package on PC, a gearbox with 3 shafts and 2 pairs of meshing gears, and a voltage controlled magnetic brake. According to the diagram shown in Figure 1, we can see that the two-stage gearbox is a speed reducer, in which the input speed is first reduced to its 40% and then reduced to its 30%. A built-in tachometer measures the rotational speed of the input shaft. In addition, we use one PCB accelerometer and two PCB microphones to record the vibration and acoustic signals. All the sensor readings are converted into digital signals and recorded onto PC through a dSPACE system with an ADC board.

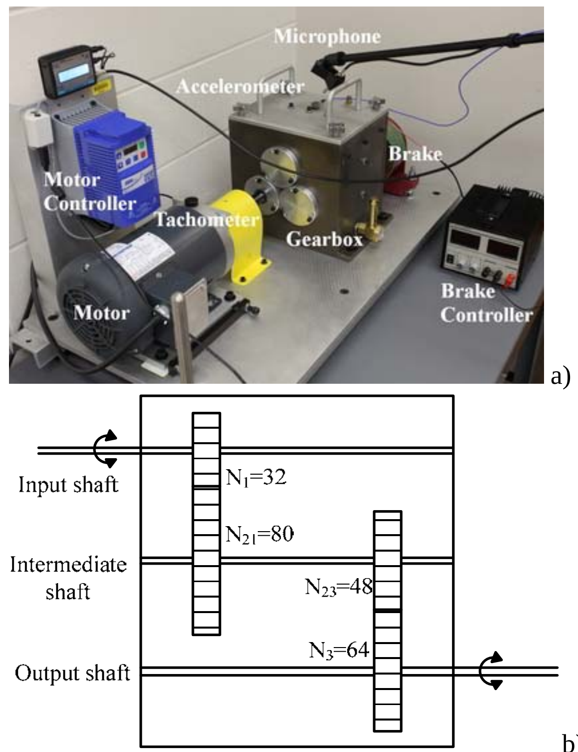


Figure 1. a) Gearbox dynamics simulator; and b) Gear mesh schematics.

To emulate the non-stationary wind load condition, we create a speed profile in the driver controller software. Starting from zero speed, the motor first accelerates to 1500rpm within 2 sec, remains for 1 sec, and then decelerates to zero within 1 sec. This speed profile may mimic a testing process from start-up to shut-down. A typical signal collected from the accelerometer is shown in Figure 2 together with its frequency spectrum. Since the signals are non-stationary, the frequency spikes on the spectrum do not necessarily correspond to harmonics. A time-frequency domain method is thus needed for feature representation.

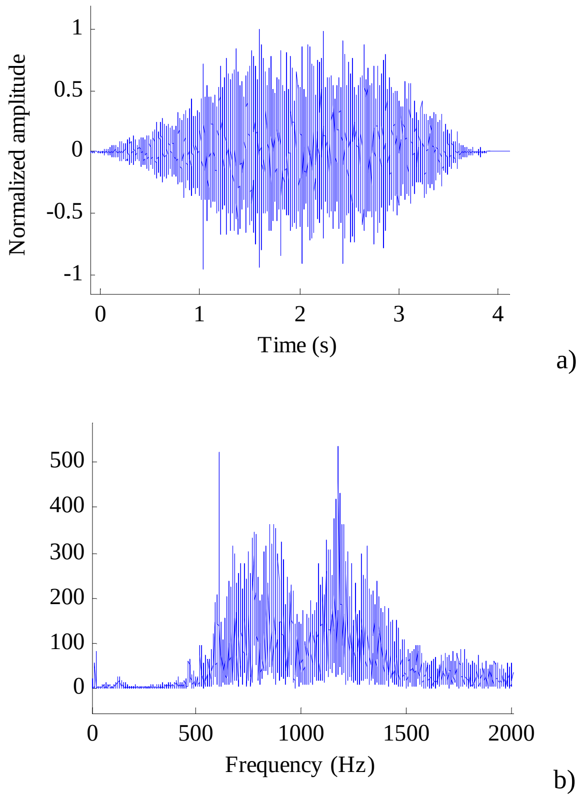


Figure 2. a) A typical sensor signal; and b) Its frequency spectrum.

HARMONIC WAVELET BASED SIGNAL REPRESENTATION

Newland [9, 10] derived the family of generalized harmonic wavelets,

$$w_{mnk}(t) = w_{mn}(t - \frac{k}{n-m}) \\ = \frac{\exp\left[in2\pi(t-\frac{k}{n-m})\right] - \exp\left[im2\pi(t-\frac{k}{n-m})\right]}{(n-m)i2\pi t} \quad (1)$$

where m and n are the level parameters, $0 \le m < n$, and the integer k denotes the translation parameter within the level (m,n). Harmonic wavelets are compact and complete in the frequency domain. Each wavelet level (m,n) covers the frequency range $(m2\pi, n2\pi)$ so that it forms an ideal bandpass filter with its Fourier transform as

$$W_{mnk}(\omega) = \begin{cases} \frac{1}{(n-m)2\pi} e^{-i\omega\frac{k}{n-m}} & m2\pi \le \omega \le n2\pi \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

We can see that it is a square window function, i.e., constant in a certain octave band and zero elsewhere. Harmonic wavelet transform combines the advantages of the short-time Fourier transform and the continuous wavelet transform. Signal analysis can thus be restricted to specific frequency bands with known physical meanings. This partially explains why harmonic wavelet has been chosen for many vibration based condition monitoring and fault detection applications [11, 12].

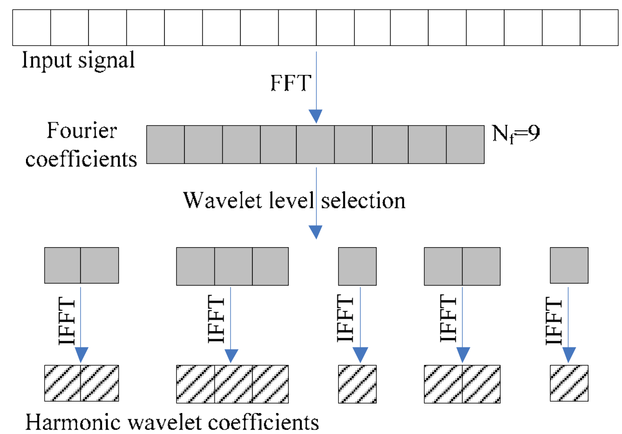


Figure 3. Schematic illustration of FFT based Harmonic wavelet computation (N=16).

Another advantage of harmonic wavelets is that the coefficients can be calculated through a FFT/IFFT based algorithm. For a given signal $s(t)$ represented by the time series $s(r)$, $r = 0,1,\ldots,N-1$, the corresponding complex wavelet coefficients can be expressed as [13]

$$a_{mnk} = \sum_{l=0}^{n-m-1} F(m+l)\exp(\frac{i2\pi kl}{n-m}), \quad k = 0,1,\ldots,n-m-1 \quad (3)$$

where $F(q)$, $q = 0,1,\ldots,N-1$ are the Fourier coefficients defined as

$$F(q) = \frac{1}{N}\sum_{r=0}^{N-1} s(r)\exp(-\frac{i2\pi rq}{N}) \quad (4)$$

The selection of wavelet levels (m,n) can be arbitrary, but each selection, e.g., $\{(m_0,n_0),(m_1,n_1),\ldots,(m_{L-1},n_{L-1})\}$, must begin with $m_0 = 0$ and continue with touching (but not overlapping) pairs until $n_{L-1} = N_f$, where N_f corresponds to the Nyquist frequency and L denotes the number of levels. Figure 3 illustrates the above process with a sample input signal of 16 data points.

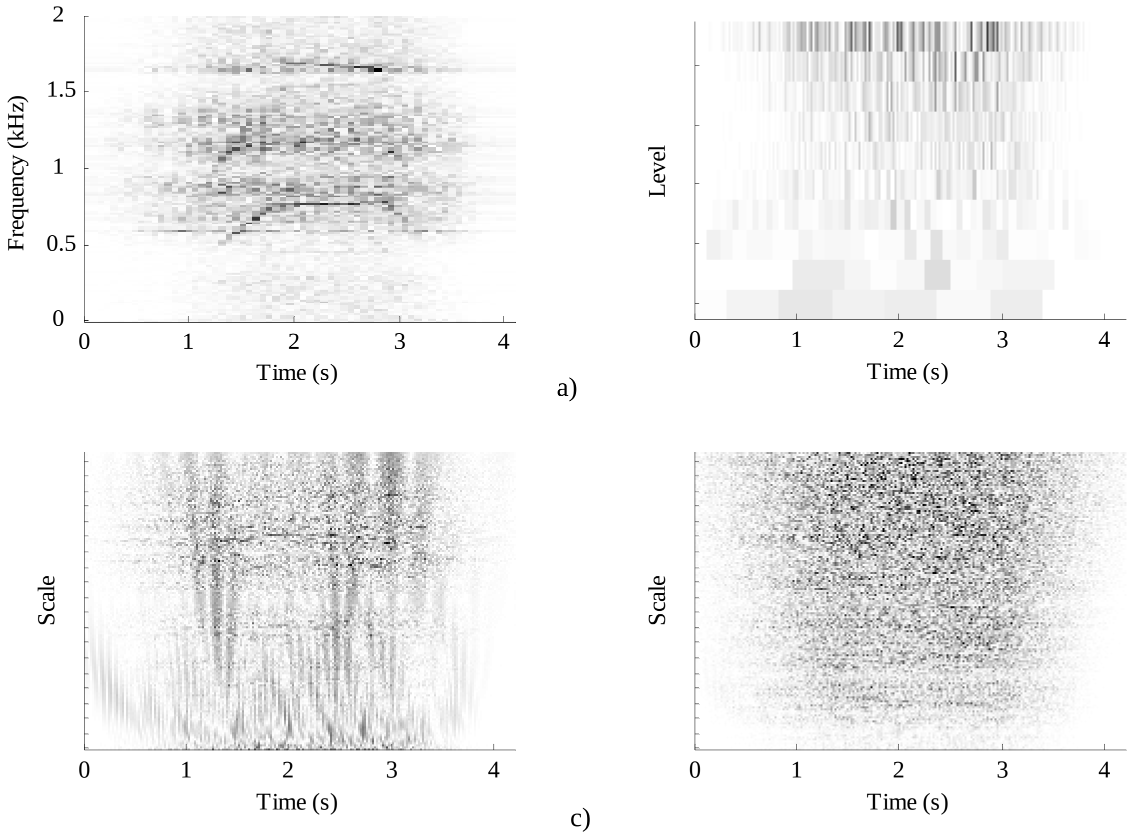


Figure 4. Time-frequency representation using a) harmonic wavelet, b) discrete DB4 wavelet, c) continuous DB4 wavelet, and d) continuous MORLET wavelet.

Comparing the time-frequency maps using different wavelets as shown in Figure 4, we can see that only on the harmonic wavelet map there is a recognizable pattern similar to the predefined motor speed profile: accelerating for the first 2 seconds, remaining steady for the third second, and decelerating for the last second. Since the vertical axis corresponds to frequency, we can further identify that specific profile around 500-800 Hz, which matches exactly the gear mesh frequency of the gear pair on the input and intermediate shafts. The other three wavelet maps are plotted using MATLAB's wavelet toolbox, none of which can reveal features with physical meanings.

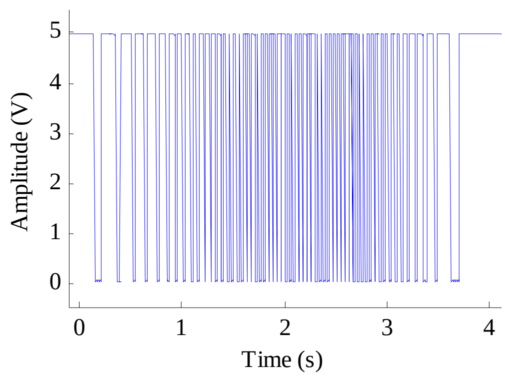
FEATURE HIGHLIGHTING USING SPEED PROFILE MASKING

We have extra information regarding the running condition of a gearbox from the built-in tachometer. Such information can be utilized to enhance the time-frequency features from the harmonic wavelet coefficients. As mentioned, there are two pairs of gears mounted in the gearbox. The first pair connects the input and intermediate shafts, and the other pair connects the intermediate and output shaft. Figure 5 shows a segment of signal from the tachometer mounted on the input shaft. The speed profile can be easily converted into Hz. Along with the gear mesh relationship, we can then derive the rotation speed of each shaft and the gears on it. The gear mesh frequency is defined as the product of the shaft speed and the tooth number. It can expressed as

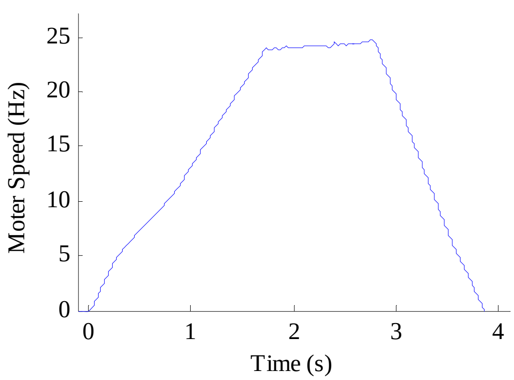
$$GMF = v_{\text{gear}} \times N_{\text{gear}} = v_{\text{pinion}} \times N_{\text{pinion}} \tag{5}$$

where v_{gear} (v_{pinion}) is the gear (pinion) rotation speed in Hz and N_{gear} (N_{pinion}) is the gear (pinion) tooth number. Also, since the tooth number of each gear is known, we can calculate rotation speed of other shafts if we know the speed of the input shaft.

Through the study of rotating machineries, engineers have accumulated empirical knowledge about gearbox dynamics. It has been demonstrated that certain frequency components are of high interest for fault diagnosis [14]. If the running condition is stationary, experienced engineer may identify gearbox faults based on the frequency spectrum of measured signals. To name a few, the shaft speed and its multiples, as well as the gear mesh frequency and its multiples sidebanded by the shaft speed, are all of high interest. Using the converted tachometer reading, we can then construct a *mask* to extract the critical features from the harmonic wavelet map. Figure 6 shows a contracted mask, where blue lines correspond to the critical frequency components for the first gear pair, whereas the dotted lines correspond to the second gear pair. Here we include 1x and 2x shaft frequencies, as well as 1x and 2x gear mesh frequencies sidebanded by 1x shaft frequency. In practice, we also need, say, 2% relaxation to account for unavoidable experimental variations.



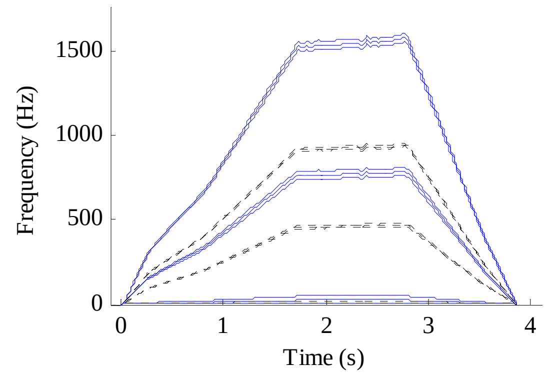
a)



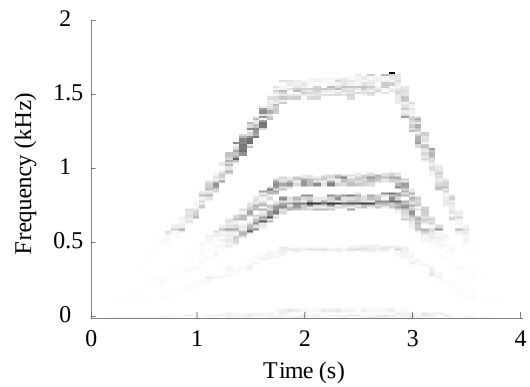
b)

Figure 5. a) A typical tachometer signal; and b) Its converted speed profile in Hz.

Compared to the wavelet map prior to the masking as shown in Figure 4, we can see that most characteristics have been extracted while stationary noise or unrelated frequency components, such as those caused by the cooling fan, are thrown away.



a)



b)

Figure 6. a) Speed profile mask constructed from tachometer signal; b) Time-frequency features extracted using the constructed mask.

FEATURE LEVEL MULTI-SENSOR DATA FUSION

Each recorded time series can generate an array of time-frequency features through the above procedure. Thus, a multi-sensor data collection will generate 3 arrays of features simultaneously. To evaluate the running condition of the gearbox based on all the information available, we need to further fuse the features from different sensors.

Instead of simply averaging the features, here we use a statistical method based on the principal component analysis (PCA). PCA is a multivariate statistical procedure that transforms a number of correlated variables into a smaller number of uncorrelated new variables called the principal components [15]. The first principal component accounts for as much of the variation in the data as possible, and each succeeding component explains as much of the remaining variability as possible. To be exact, the first principal component is along the direction with the maximum variance, and the second component is constrained to lie in the subspace perpendicular to the first component. Within the subspace, the second component points to the direction of maximum variance. And the third component is taken in the maximum variance direction in the subspace perpendicular to the first two, and so on.

Consider a block of data denoted by a $K \times L$ matrix $\mathbf{X}$, each column vector represents a K-dimensional signal. The covariance matrix $\mathbf{C} = \tilde{\mathbf{X}}\tilde{\mathbf{X}}^{\mathbf{T}} / (L-1)$ can be calculated from $\tilde{\mathbf{X}} = \begin{bmatrix} \mathbf{x}_1 - \boldsymbol{\mu} & \mathbf{x}_2 - \boldsymbol{\mu} & \cdots & \mathbf{x}_L - \boldsymbol{\mu} \end{bmatrix}$, where vector $\boldsymbol{\mu}$ consists of the sample mean μ_k along each dimension ($k = 1, 2, \ldots, K$). We can find an orthonormal matrix (eigenvectors) $\mathbf{V} = \begin{bmatrix} \mathbf{v}_1 & \mathbf{v}_2 & \cdots & \mathbf{v}_K \end{bmatrix}$ and a diagonal matrix (eigenvalues) $\mathbf{D} = \mathrm{diag}(\lambda_1, \lambda_2, \ldots, \lambda_K)$ such that $\mathbf{CV} = \mathbf{VD}$. Without loss of generality, the eigenvalues are often arranged in descending order $\lambda_j \geq \lambda_{j+1}$ for $j = 1, 2, \ldots, K-1$.

Suppose we have two feature vectors $\mathbf{x}_1$ and $\mathbf{x}_2$, then both $\mathbf{V}$ and $\mathbf{D}$ are of dimension 2×2. Consider the first eigenvector $\mathbf{v}_1$ that corresponds to the largest eigenvalue λ_1, we can have the weights for fusing the two features as $w_1 = \mathbf{v}_1(1)$ and $w_2 = \mathbf{v}_1(2)$ such that

$$\mathbf{x}_{\text{fused}} = w_1 \mathbf{x}_1 + w_2 \mathbf{x}_2 \tag{6}$$

where $\mathbf{x}_{\text{fused}}$ is the fused feature vector. This PCA based data fusion method can also be applied segment by segment, though segment size may affect fusion performance.

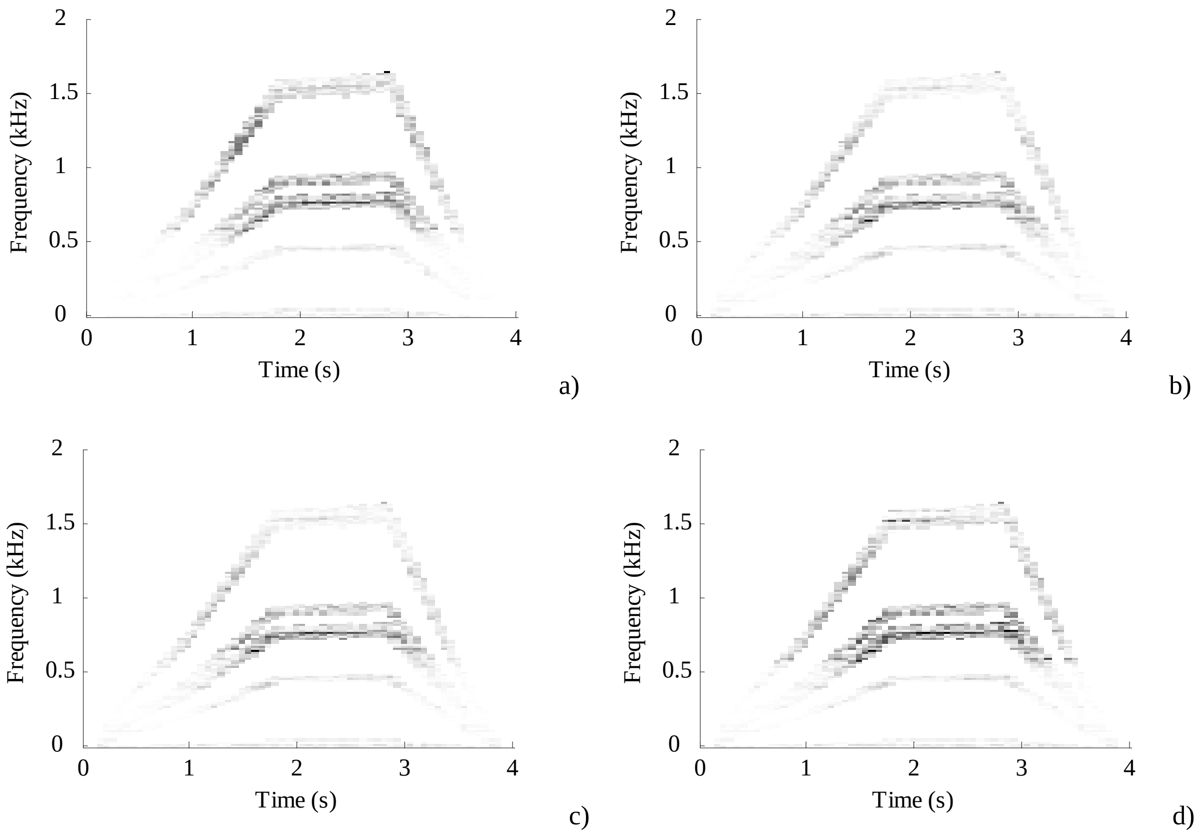


Figure 7. Harmonic wavelet features extracted from a) accelerometer, b) microphone #1, and c) microphone #2. d) Fused features from all above.

STATISTICAL DECISION MAKING

Suppose now we have a baseline library, in which features for a healthy gearbox are stored. After a testing process, a new signal is collected from a gearbox under an unknown condition. The decision should be made about the gearbox by comparing the new features with the baseline features. Since we cannot guarantee a perfectly synchronized signal for each data collection, we need to align the new signal along with those in the baseline library. It is a normal practice to use the Generalized Cross Correlation with Phase Transform (GCC-PHAT) as presented by [16] and [17]. Given two time series $x_i(n)$ and $x_j(n)$ the GCC-PHAT is defined as

$$\hat{G}_{PHAT}(f) = \frac{X_i(f) X_j^*(f)}{\left| X_i(f) X_j^*(f) \right|} \tag{7}$$

where $X_i(f)$ and $X_j(f)$ are the Fourier transforms of the two signals and * denotes the complex conjugate. The time delay for these two inputs is estimated as

$$\hat{d}_{PHAT} = \arg\max_{d} \hat{R}_{PHAT}(d) \tag{8}$$

where $\hat{R}_{PHAT}(d)$ is the inverse Fourier transform of $\hat{G}_{PHAT}(f)$. Harmonic wavelet features are then extracted from the shifted signal using the above mentioned method.

The decision making process is based on Student's t-test, assuming the each feature point follows a normal distribution. Suppose there are k feature arrays in the baseline library, and $a_1, \ldots, a_k$ are the feature points from each array but corresponds to the same time-frequency location on the harmonic wavelet map. Let $\bar{a} = (a_1 + \cdots + a_k)/k$ be the sample mean, and $S^2 = \frac{1}{k-1}\sum_{i=1}^{k}(a_i - \bar{a})^2$ be the sample variance. For a new feature point a_t, the T statistic can be calculated as

$$T = \frac{a_t - \bar{a}}{S/\sqrt{k}} \tag{9}$$

It is known that the T follows a Student's t-distribution. The $(1-\alpha)$-upper confidence limit $UCL_{1-\alpha}$ can be calculated using the following equation:

$$\mathrm{UCL}_{1-\alpha} = \bar{a} + \frac{t_{\alpha,k-1}S}{\sqrt{k}} \tag{10}$$

where $t_{\alpha,k-1}$ is the critical t-distribution value with $k-1$ degrees of freedom. If the calculated T value exceeds the upper confidence limit, we can conclude that, with the confidence level of $1-\alpha$, the test feature a_t is statistically different from the baseline. In other words, we can claim with $1-\alpha$ confidence that the condition of the test gearbox is unhealthy. Decisions on fault cases may be made by further analyzing the T values projected back to the wavelet map.

CONCLUDING REMARKS

In this paper, we present a collection of feature extraction and multi-sensor data fusion techniques for fault detection in complex mechanical systems such as wind turbine gearboxes. Time domain raw data are collected from our gearbox dynamics test bed, when a healthy or faulty gear has been installed. A harmonic wavelet based method is chosen to handle the complexity caused by the non-stationary nature of wind load. We also developed a speed profile masking technique to account for tachometer readings and gear meshing relationship. The highlighted features from multiple sensors are then fused through a statistical weighting approach based on principal component analysis. Finally a simple decision making algorithm is employed to verify the effectiveness of the entire scheme. Using experimental data collected from a gearbox test bed, gear faults can be detected statistically for a given confidence level.

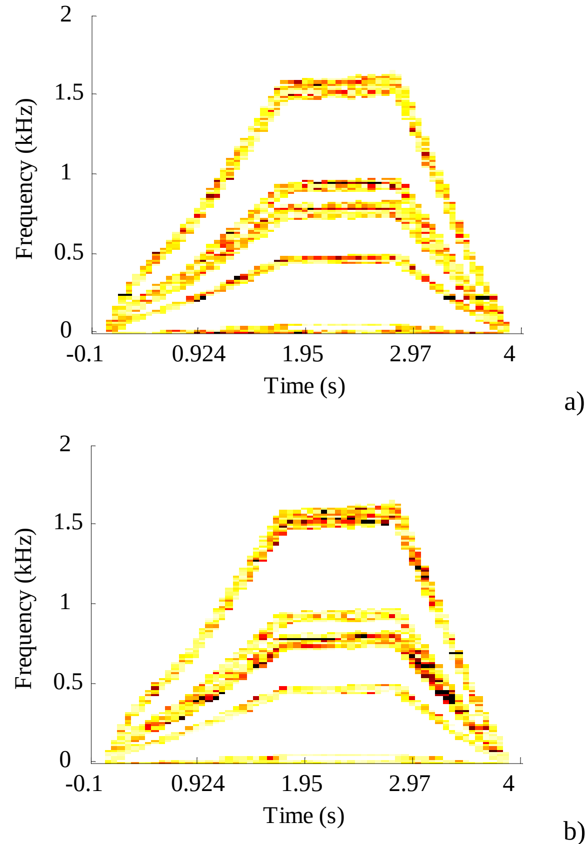


Figure 8. T statistic calculated for features corresponding to (a) healthy, and (b) faulty test gearbox.

ACKNOWLEDGMENTS

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