

A Method for Anomaly Detection for Non-stationary Vibration Signatures

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ABSTRACT

Vibration signatures contain information regarding the health status of the machine components. One approach to assess the health of the components is to search systematically for a list of specific failure patterns, based on the physical specifications of the known components (e.g. the physical specifications of the bearings, the gearwheels or the shafts). It is possible to do so, since the manifestation of the possible failures in the vibration signature is known a priori. The problem is that such a list is not comprehensive, and may not cover all possible failures. The manifestation of some failure modes in the vibration signature may be less investigated or even unknown. In addition, when more than one component is malfunctioning, unexpected patterns may be generated. Anomaly detection tackles the more general problem: How can one determine that the vibration signatures indicate abnormal functioning when the specifics of the abnormal functioning or its manifestation in the vibration signatures are not known a priori? In essence, anomaly detection completes the diagnostics of the predefined failure modes. In many complex machines (e.g. turbofan engines), the task of anomaly detection is further complicated by the fact that changes in operating conditions influence the vibration sources and change the frequency and amplitude characteristics of the signals, making them non-stationary. Because of that, joint time-frequency representations of the signals are desired. This is different from other vibration based diagnostic techniques, which are designated for stationary signals, and often focus on either the time domain or the frequency domain.

For the purpose of this article, we will refer as TFR (time-frequency representation) to all 3D representations which employ on one axis either time, or cycles, or RPM, and on the other axis either frequency, or order. The proposed method suggests a solution for anomaly detection by analysis of various TFRs of the vibration signals (primarily

the RPM-order domain).

In the first stage, TFRs of healthy machines are used to create a baseline. The TFRs can be obtained using various methods (Wigner-Ville, wavelets, STFT, etc). In the next stage, the distance TFR between the inspected recording and the baseline is computed. In the third stage, the distance TFR is analyzed and the exceptional regions in the TFR are found and characterized. A basic classification of the anomaly type is suggested. The different stages of analysis: creating baselines, computing the distance TFR, identifying the exception regions, are illustrated with actual data.

1. INTRODUCTION

Monitoring of vibrations can be used to detect machine faults, including roller bearing degradation, gearwheels degradation, eccentricity, mechanical looseness, unbalance, misalignment, oil film bearing instabilities, structural resonance, and cracked rotors. In most methods, the detection is based on comparison of vibration levels at specific frequencies to reference or “baseline” values, representing the healthy cases. The specific frequencies used for tracking are defined separately for each failure mode of each component. Detection of all the possible failure modes of a machine implies definition of all the possible failure modes of all components including all the relevant combinations of failure modes such that all the frequencies of interest will be covered. In spite of the fact that many failure modes can be pre-defined with their associated patterns, the definition and listing of all the frequencies of interest is a very complex task, often impossible. In order to complete the diagnostic process when only a part of the frequencies of interest can be predefined, an anomaly detection algorithm is required.

Diagnostics of rotating machinery during regular operation involves in many cases analysis of non-stationary signals. This is because rotating speeds, loads, and environmental conditions vary (in some cases rapidly) with time. Often, even the assumption of quasi-stationarity may not be appropriate. In such an environment, an efficient way to evaluate condition indicators may be based on time-

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frequency or time-order representations that reveal the evolution of the spectra with time. The time-frequency or time-order representations (TFR) can be computed using different techniques of signal processing such as Short Time Fourier Transform (STFT), Wavelets decomposition or Wigner-Ville representations (see Polyshchuk et al 2002, Juluri & Swarnamani 2003, Yang & Ren 2004, Bradford 2006, Klein et al 2011).

Usually the TFRs are representations of the vibration signal or its derivatives (synchronic average, envelope, pre-whitened signals, etc.) in the RPM-frequency or RPM-order domains (see Antoni & Randall 2002, Antoni et al 2004, Sawalhi & Randall 2008, Klein et al 2012). TFRs are widely used in scientific and industrial applications for visual inspection of vibrations. The primary problem of the visual inspection is that in complex machinery, the TFR contains a huge amount of information and it is difficult to sort out and focus on the relevant information manually.

Some methods of anomaly detection in TFRs have been proposed using different approaches (see below). In general, a statistical analysis of the spectrogram values or the over threshold values is used for detection of anomalies. This requires a definition of the probability density function (PDF) and an evaluation of the PDF parameters (differently for different zones of the TFR). There were different assumptions regarding the nature of the probability density function for spectrum or spectrogram values; Huillery et al (2008) show that for spectrograms and STFTs, when using Hanning windowing, the χ^2 PDF (central or non-central for deterministic peaks) is adequate for detection of exceptions. Bechhoefer et al (2011) discussed Rayleigh PDFs for spectrum values and Nakagami PDFs for sums of Rayleigh distributed values. Clifton & Tarassenko (2009) showed that the PDF in spectrogram bins is approximately Gamma and that its tail can be described by a Gumbel distribution representing extremum values distribution. Hazan et al (2012 and 2013) proposed Peak Over Threshold (POT) and Frequency Dependent Peak Over Threshold (FDPOT) methods which were based on the assumption that the values exceeding a threshold can be approximated by a Generalized Pareto distribution.

The current paper proposes an automatic procedure for anomaly detection which is adequate for all types of TFRs. The analysis algorithm emphasizes only the exceptions relative to the “baseline” or the reference TFR, allowing effective masking of huge amounts of less relevant information.

The “baseline” is a statistical characterization of the TFRs derived from a set of healthy machines. The exceptions relative to the baseline are then examined to detect relevant regions corresponding to significant anomalies. In the first section of the article, we will describe the statistical characterization stage, or the baseline generation. Then we will show the algorithm for emphasizing the exceptions in

the analyzed TFR (relative to the baseline). Next, we will explain the algorithm for automatic detection and classification of the exceptional regions. The algorithm is demonstrated with an example of a seeded test data, in which the presented algorithm was able to detect the fault without using any prior knowledge on the nature of the fault or the physical dimensions of the faulty part.

2. BASELINE GENERATION

The baseline is generated from a set of TFRs recorded in a set of healthy machines. In essence, the baseline is a statistical characterization of the data distribution in each cell of the TFR matrix:

$$\mu_{i,j} = \frac{1}{N} \sum_{n=1}^N P_{i,j,n} \quad \sigma_{i,j} = \frac{1}{N} \sqrt{\sum_{n=1}^N P_{i,j,n}^2} \quad (1)$$

where: $\mu_{i,j}$ is the average of values in cell i,j , $\sigma_{i,j}$ is the standard deviation of the values in cell i,j , N is the number of TFRs in the baseline, and $P_{i,j,n}$ is the value of the spectrum n in cell i,j .

It is highly advisable to use similar operating conditions for baseline generation. This allows a better representation of the healthy population, hence a higher reliability in detecting anomalies. To illustrate that, let us consider slow acceleration versus fast acceleration in a jet engine. In our experience, the two cases differ significantly in their vibration patterns even at the same RPM. Evidently, loads vary significantly, some of the resonances that are excited during a slow acceleration may not be present at a fast acceleration, and there are also differences in the amplitude of peaks at characteristic frequencies. Combining both cases of fast and slow accelerations in the same baseline model may lead to a significant reduction in discrimination abilities of the condition indicators.

Thus, it is essential to decide which operating conditions can be combined in the same baseline. This can be achieved by a relatively simple statistical hypothesis testing procedure, combined with a physical understanding of the load variations in the different operating conditions.

Various other technical issues should be addressed during the implementation of the baseline algorithm.

First, all the TFRs need to have the same scale. This can be achieved either by interpolation of the existing TFRs to a new common scale, or by calculation of the TFRs using a predefined common scale. The predefined common scale is achieved by calculating the TFRs at predefined ranges of rotating speeds and similar frequency/order resolution.

If interpolation is used, one should be careful not to introduce artifacts to the data when the time scale does not fit the variation rate of the load. For example, when the time resolution or RPM resolution is too low compared to the acceleration rate, and adjacent spectra differ abruptly in

amplitude, the interpolated spectrum may generate an erroneous baseline TFR with high variances.

Another issue is how to set a correct scale. A higher resolution in time or RPM will provide better detection capabilities, but setting the resolution too high may leave some time segments of the TFR too short for a reliable spectrum calculation. The scale should be adapted to the operating modes of the inspected machinery so that most of the TFR will be calculated correctly.

3. DISTANCE TFR

When a new data is available, the TFR is interpolated to obtain the same scale as the scale that was used during baseline generation. A new representation, the distance TFR, is calculated, where each cell represents the corresponding distance from the model of healthy machines.

The distance TFR emphasizes the cells that deviate from the distribution of healthy machines (see Figure 1 and Figure 2).

Mahalanobis distance is used for comparison (Eq. 2).

$$D_{i,j} = \frac{P_{i,j} - \mu_{i,j}}{\sigma_{i,j}} \quad (2)$$

where: $D_{i,j}$ is cell i,j in the distance TFR, $P_{i,j}$ is the corresponding cell in the TFR of the new data, $\mu_{i,j}$ is the mean of i,j cell in the baseline, and $\sigma_{i,j}$ is the baseline standard deviation of the corresponding cell.

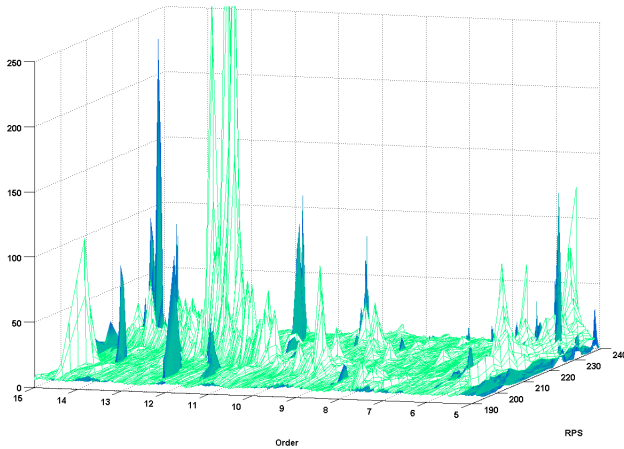


Figure 1. Comparison between baseline and a newly obtained TFR in the RPS-order domain (RPS – Rotation Per Second). The white surface represents the baseline ($\mu+3\sigma$) and the dark green surface represents the inspected TFR.

The distance TFR represents the distance of the actual TFR from the healthy population in terms/units of standard deviations, i.e. it contains data that is statistically normalized. The way the distance is calculated does not imply a specific probability distribution.

Faults of mechanical components generate specific known vibration patterns such as characteristic frequencies with sidebands due to modulation. Appropriate algorithms allowing diagnostics of components based on TFRs can recognize these patterns automatically (such an algorithm operating on the distance TFR was proposed for detection of faulty bearings in Klein et al 2012).

In other cases where the exceptions do not follow a specific pattern it will not be possible to associate the failure with one of the mechanical components. Nevertheless, automatic diagnostics of abnormal behavior can be performed with good reliability and detection capabilities.

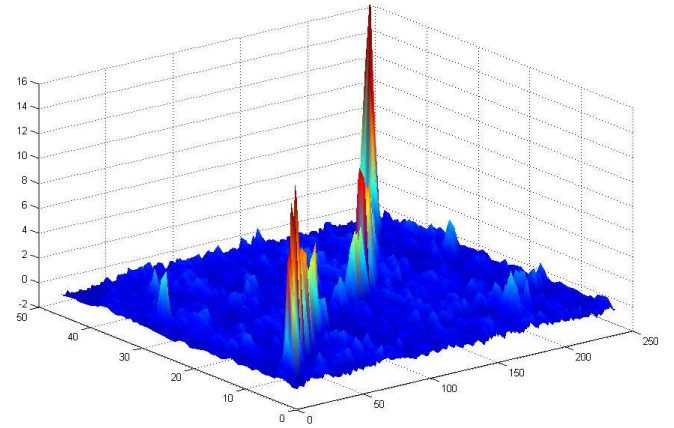


Figure 2. Illustration of the distance TFR

4. DETECTION OF EXCEPTIONAL REGIONS

The goal of the algorithm is to identify continuous regions of exceptional cells. The algorithm flowchart is described schematically in Figure 3.

First a surface defining the threshold for each cell is defined. Then the exceptional cells exceeding the local threshold are found. The exceptional cells are grouped into continuous regions. The number of cells and volume of each exceptional region are calculated and compared to the criteria defined for identification of anomalies.

Searching for over threshold values as an only criterion was found to be insufficient. To avoid false alarms, there was a need to screen out noise phenomena in single cells, and highlight exceptions only if they belong to continuous and sizeable regions. To accomplish that, the algorithm is searching for exceptional regions satisfying the following additional criteria:

- The number of cells N_k , in a continuous region k , should exceed a minimum value – to avoid consideration of spurious peaks.
- The volume V_k ($V_k = \sum_{i,j \in k} D_{i,j}$) of an exceptional region k should exceed a minimum value. The volume represents a measure of the number of cells and their

values. We want to guarantee that at least one of these is large enough to be considered as significant.

- The total volume of exceptions $\sum_k V_k$ should exceed a minimum value. The total volume represents the number of exceptional regions and their mean volume giving the option to define at what level we will consider the TFR as exceptional.

These criteria allow sufficient flexibility to tune the detection algorithm and adapt it to different needs. For example, if we suspect that the distance of peaks (from the baseline of healthy machines) maybe of low amplitude, we may want to set the threshold to a low value (e.g. $T_{i,j} = 3\sigma$), and to compensate it by setting a large threshold for the number of cells in a region and/or the minimum volume of a region.

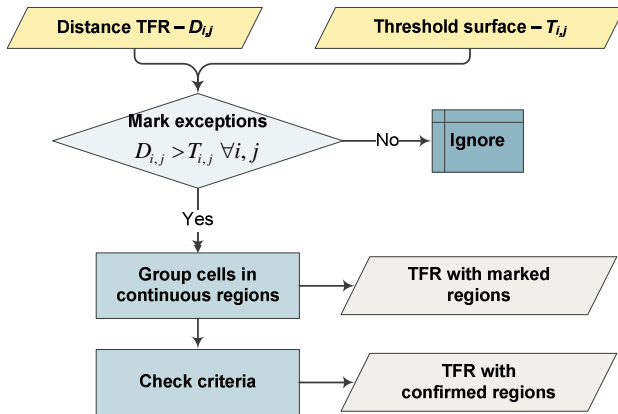


Figure 3. Algorithm flowchart

It is important to note that the proposed solution for general anomaly detection should attempt to cover several types of TFRs. For example, when a fault exists in a rotating component like a bearing or a gearwheel, we would expect to detect several exceptional regions, each related to a specific harmonic or a sideband (each region will contain several cells covering different rotating speeds). The exceptional regions can be detected in the order domain, but they can be better emphasized in the order domain of the dephased signal or in the order domain of the envelope (see Antoni & Randall 2002, Antoni et al 2004, Sawalhi & Randall 2008, Klein et al 2009, Bechhoefer et al 2011).

4.1. Definition of the threshold surface

The selection of threshold values is important and influences the reliability of anomaly detection. The threshold can be constant for all the cells of the TFR, defining a plane parallel to the time frequency plane, or can vary defining any positive surface.

Several considerations affect the selection of the threshold surface:

First, it is possible to use the threshold surface for masking out effects of faults discoverable by the direct search algorithms. For example, faults in specific gearwheels are discoverable in some specific frequencies/orders. We may want to set very high threshold values to the corresponding frequencies/orders to mask out these effects.

The second consideration for selection of the threshold surface is the type of the probability distribution function (PDF) of the healthy population belonging to the baseline. It is also possible that the PDF parameters differ from one cell to another. The determination of these parameters for each cell may require a large data set of healthy TFRs.

Because we are using the distance TFR, which is already normalized, the threshold for several types of PDFs can be constant and generic. This is true for Rayleigh, χ^2 , and Gamma PDFs.

One last word on threshold selection: Because thresholds are not the sole parameter used (the algorithm also uses the criteria of area and volume, i.e. number of exception cells and accumulated sum of values), the proposed method is relatively tolerant to imperfections in selecting the thresholds. The algorithm was applied on several TFRs of healthy machines, using relatively low thresholds, without triggering false alarms.

4.2. Classification of anomalies

The algorithm for anomaly detection targets faults which are not covered in the direct search algorithms. It can be used as a start point to learn about and define new patterns to search for, thus enlarging the knowledge about faults in a specific machine. The detection of anomalies should be amended with an examination of experts and field feedback on the status of the machine.

The classification of anomalies should allow as much as possible hints on their origin and nature. The hints can be based on the type of TFR in which the anomaly was detected (e.g. TFR of the raw vibration signal, TFR of the synchronous average, TFR of the resampled signal, TFR of the dephased signal, etc.), as well as the range of frequencies or orders.

The simplicity of the algorithm and the fact that only the threshold surface depends on the assumed PDF makes it useful and easy to apply in different TFRs and different configurations.

5. EXAMPLE OF ALGORITHM PERFORMANCE

The example is based on data recorded during a seeded fault back to back test in a turbofan engine. The fault was introduced on the outer race of a bearing in which the inner race rotates at a speed proportional to shaft A rotating speed. The example demonstrates that the algorithm was able to detect the fault, without using any prior knowledge on the

nature of the fault or the physical dimensions of the faulty bearing.

The presented method was applied to TFRs consisting of RPM-orders spectrograms. The spectrograms used were based on PSDs. The PSDs were calculated in consecutive periods of fixed length, during accelerations and decelerations of a turbofan engine with similar rotating speed gradients.

The presented results were based on spectrograms calculated with similar order resolution and varying RPM resolution. A study of the variations of the spectra levels in the healthy records revealed that the variations of the peak levels did not exceed the random error of the PSDs in bins of 5 Hz. Therefore, the periods for each PSD calculation were defined such that the rotating speed variations will be of maximum 5 Hz and the interpolation of the RPM axis was applied in bins of 3Hz.

The statistics of the baseline were calculated on 28 spectrograms from healthy runs.

Figure 4 shows a part of the RPM-order spectrogram of the vibration signal from a run with the faulty bearing. Some energetic ridges corresponding to the shaft A harmonics and background noise can be observed (the highest ridges can be observed at orders above 35). As well, some harmonics of shaft B rotating speed can be observed.

Figure 5 shows the distance TFR (based on the RPM-order spectrogram and corresponding baseline) calculated on the same data as in Figure 4. A pattern that was not visible in the regular spectrogram becomes evident after distance calculation. The shaft harmonics that are clearly observable at orders above 35 in Figure 4 are not seen in Figure 5. This means that the vibration levels corresponding to both shafts harmonics were close to the baseline of healthy systems and not exceptional.

As one can see from comparison of Figure 4 and Figure 5, the distance TFR is a helpful tool for visual inspection of TFRs. It emphasizes only the suspicious locations and allows a significant reduction of information for manual scan.

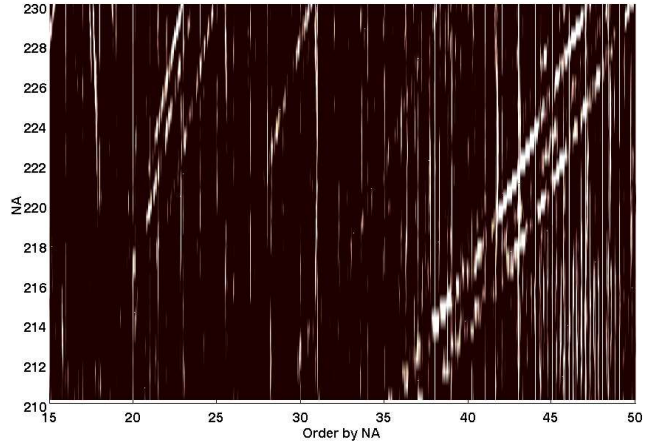


Figure 4. RPM-Order spectrogram

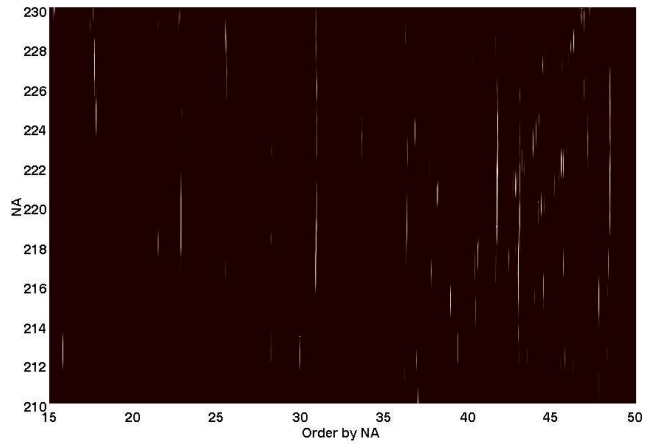


Figure 5. Distance TFR of the RPM-Order spectrogram

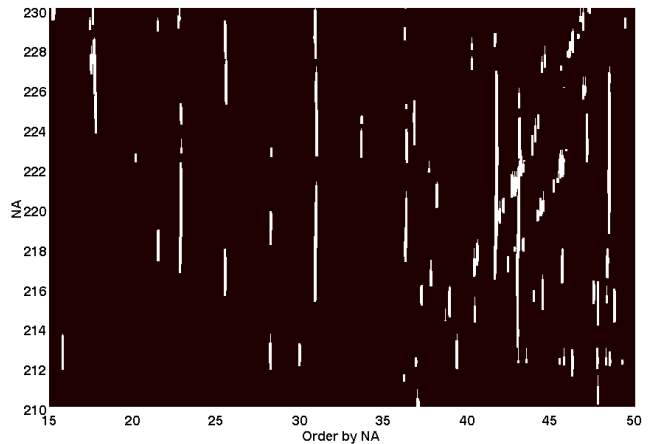


Figure 6. Exceptions found in the distance-TFR of the RPM-Order spectrogram

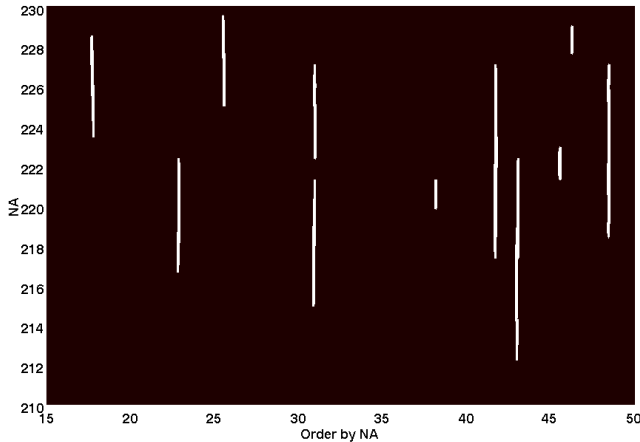


Figure 7. Exceptions confirmed in the distance-TFR of the RPM-Order spectrogram

Figure 6 shows the contours of the exceptional continuous regions found after the comparison with the threshold surface. Figure 7 shows the contours of the confirmed regions after application of all the criteria (i.e. the number of cells and the volume). It can be easily observed that in Figure 7 only the peaks related to the faulty bearing remain, and that their location indicates a very clear pattern that is easy to identify and diagnose.

6. SUMMARY AND CONCLUSIONS

A method for analysis and diagnosis of non-stationary TFRs of vibro-acoustic data was proposed.

The method can be applied on any type of TFR, regardless of the analyzed signal or the method of the TFR calculation. The key idea of the method is the detection of the exceptional regions in the distance TFR (deviation from the baseline TFR).

The method was demonstrated, using RPM-order spectrograms, for diagnosis of a damaged bearing in a seeded fault test of a turbofan engine (without relying on the specific physical information of the bearing). The method of extracting the exceptional regions was described. It was shown that the proposed method is effective for detection of the abnormal behavior resulting from a faulty bearing.

It seems that the distance TFR is a powerful tool in detecting anomalies and emphasizing abnormal behavior.

The distance TFR proved effective in emphasizing exceptions in a noisy environment, including unknown damage or anomalies of any kind.

Last, the distance TFR can be used efficiently by experts for visual inspection and diagnostics of exceptions. Since the distance TFR emphasizes only the ridges or regions that deviate from the baseline population statistics, masking out the irrelevant data, it is easier and a more focused tool for

visual inspection compared to the original time frequency representation.

ABBREVIATIONS

RPM	Rotations Per Minute
TFR	Time-Frequency Representation
STFT	Short Time Fourier Transform
PDF	Probability Density Function
PSD	Power Spectral Density
POT	Peak Over Threshold
FD POT	Frequency Dependent Peak Over Threshold

REFERENCES

- Antoni, J. & Randall, R. B., (2002). Differential Diagnosis of Gear and Bearing Faults, *Journal of Vibration and Acoustics*, Vol. 124 pp165-171, April 2002.
- Polyshchuk, V. V., Choy, F. K. & Braun, M. J., (2002). Gear Fault Detection with Time-Frequency Based Parameter NP4, *International Journal of Rotating Machinery*, 8(1), 57-70, 2002.
- Juluri, N. & Swarnamani, S., (2003). Improved accuracy of Fault Diagnosis of Rotating Machinery using Wavelet De-noising and Feature Selection, *Proceedings of ASME Turbo Expo 2003*, Power for Land, Sea and Air, June 16-19, 2003, Atlanta, Georgia, USA.
- Antoni, J., Bonnardot, F., Raad, A. & El Badaoui, M., (2004). Cyclostationary modeling of rotating machine vibration signals, *Mechanical Systems and Signal Processing* 18 (6), pp. 1285-1314, 2004.
- Yang, W. X. & Ren, X. M., (2004)., Detecting Impulses in Mechanical Signals by Wavelets, *EURASIP journal on Applied Signal Processing*, pp 1156-1162, 2004.
- Bradford, S. C., (2006). Time-Frequency Analysis of Systems with Changing Dynamic Properties, Ph.D. Thesis, *California Institute of Technology, Pasadena, California*, 2006.
- Huillery, J., Millioz, F. & Martin, N., (2008). On the description of spectrogram Probabilities with a Chi-Squared Law, *IEEE Transactions on Signal Processing* 56, 6 (2008) pp. 2249-2258.
- Sawalhi, N. & Randall, R. B., (2008). Localised fault diagnosis in rolling element bearings in gearboxes, *Proceedings of The Fifth International Conference on Condition Monitoring and Machinery Failure Prevention Technologies – CM/MFPT*, 2008.
- Clifton, D. A. & Tarassenko, L., (2009). Novelty detection in jet engine vibration spectra, *Proceedings of the 6th International Conference on Condition Monitoring and Machine Failure Prevention Technologies*, 2009.
- Klein, R., Rudyk, E., Masad, E. & Issacharoff, M., (2009). Emphasizing bearing tones for prognostics, *The Sixth International Conference on Condition Monitoring and Machinery Failure Prevention Technologies*, pp. 578-587, 2009.

- Bechhoefer, E., He, D. & Dempsey, P., (2011). Gear health threshold setting based on probability of false alarm, *Proceedings of the Annual Conference of the Prognostics and Health Management Society*, 2011.
- Klein, R., Masad, E., Rudyk, E. & Winkler, I. (2011). Bearing diagnostics using image processing methods, *Proceedings of Surveillance 6*, Compiegne, October 2011.
- Klein, R., Rudyk, E. & Masad, E. (2012). Bearing diagnostics in non-stationary environment, *International Journal of Condition Monitoring*, March 2012.
- Hazan, A., Verleysen, M., Cottrell, M., Lacaille, J. & Madani, K. (2012). Probabilistic outlier detection in vibration spectra with small learning dataset, *Mechanical Systems and Signal Processing*, 2012.
- Hazan, A. & Madani, K., (2013). Frequency-Dependent Peak-Over-Threshold algorithm for fault detection in the spectral domain, *ESANN 2013*, Bruges: Belgium, 2013.

BIOGRAPHY

Renata Klein received her B.Sc. in Physics and Ph.D. in the field of Signal Processing from the Technion, Israel Institute of Technology. In the first 17 years of her professional career, she worked in ADA-Rafael, the Israeli Armament Development Authority, where she managed the Vibration Analysis department. In the decade that followed, she focused on development of vibration based health management systems for machinery. She invented and managed the development of vibration based diagnostics and prognostics systems that are used successfully in combat helicopters of the Israeli Air Force, in UAV's and in jet engines. Renata is a lecturer in the faculty of Aerospace Engineering of the Technion, and in the faculty of Mechanical Engineering in Ben Gurion University of the Negev. In the recent years, Renata is the CEO and owner of "R.K. Diagnostics", providing R&D services and algorithms to companies who wish to integrate Machinery health management and prognostics capabilities in their products.