ROLLING ELEMENT BEARING FAULT DIAGNOSIS IN ROTATING MACHINES OF OIL EXTRACTION RIGS

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ABSTRACT

This paper presents vibration analysis techniques for fault detection in rotating machines. Rolling element bearing defects inside a motor pump are the subject of study. Signal processing techniques, like frequency filters, Hilbert transform, and spectral analysis are used to extract features used later as a base to classify the condition of machines. Also, pattern recognition techniques are applied to the obtained features to improve the classification precision. In a previous work, a graphic simulation was used to produce signals to illustrate the idea of the method. In this work we examine the performance of this method for monitoring bearing condition when applied to rotating machines of oil rigs, that is, when applied to real problems.

1. INTRODUCTION

Detecting or even preventing failures in complex machines usually benefits in terms of economy and security [16]. Continuous technological development contributes to the increase of the lifetime of a rolling bearing. However, defects can occur due to the great number of critical processes where bearings are employed. The precocious diagnosis of possible faults constitutes an important activity to prevent more serious damages. Predictive maintenance [14], from the analysis of vibration signals produced by the process, allows to monitor and make conclusions about the operational state of the machine, in addition to that allows taking appropriate measures to extend the time of use, and to minimize costs resultant from the machine's downtime.

The objective of the signal analysis is the discovery of discriminative features that allow the identification of problems in their early stages. In particular, bearing problems manifest in alterations of the vibration patterns of the machines. Especially for defects in rolling element bearings *envelope detection* [7] is an indicated technique because the mechanic defects in components of the bearing manifest themselves in periodic beatings, overlapping the low frequency vibrations of the entire equipment, for instance caused by unbalance of the rotor of the pump. The Hilbert transform [19] plays an important role in the sequence of steps of the analysis. The main idea is the separation of the defect frequency and the natural frequency of the beating by demodulation.

In a previous work [8], experimental and computationally simulated data were used to illustrate the idea and effectiveness of the vibration signal analysis and envelope method to identify incipient failures of rolling bearing. Many publications [6, 15] have also discussed the detection of bearing faults but only using well behaved data from a controlled laboratory environment. When an experimental benchmark is used, the fault classes are perfectly known. This permits a doubtless labeling of the data sample for supervised learning. Machine simulations can assist in several aspects of system operation and control, being useful to do preliminary investigations about the capability of the method, though it cannot completely simulate all real-world situations. It is worth to mention that there are a few papers which have investigated rolling bearing faults analyzing some case studies [2, 11] and also looked at complex cases, for instance, from helicopter gearboxes that provide a particularly difficult situation with respect to bearing diagnostics [12].

In this paper we are interested in investigating a well-known method for monitoring the bearing condition applied to real world data obtained from rotating machines of oil extraction rigs. Certainly, more sophisticated research related analysis techniques have been developed, but the one presented here is implemented in the majority of commercial and diagnostic systems. Therefore we focus our attention on how this technique will behave in a real world situation. The availability of significant amounts of real data from oil extraction rigs has motivated this work. To the best of our knowledge this is the first work to investigate bearing condition diagnosis method with statistically significant amounts of real data in this context.

Most industrial rotating machinery contains components which will produce additional noise and vibration whereas a simulated environment is almost free from external vibrations. There are a number of factors that contribute to the complexity of the bearing signature that could not be simulated. Real bearing faults were used to supply this gap. The results suggest that this technique is robust enough to be satisfactorily applied to a real life fault recognition application given accurate information about rolling bearing condition. We furthermore compare some classifier algorithms by ROC analysis [4], a classifier performance evaluation tool beyond the usually employed classification accuracy.

The rest of the paper is organized as follows: In section 2, the vibration analysis in rotating machines is shortly described. In section 3 real examples are shown and some discussions about them are made. The adopted classification methodology is described in section 4. Section 5 presents the results and comparisons of classifier's performance followed by conclusions in section 6.

2. VIBRATION ANALYSIS IN ROTATING MACHINES

Motor pumps, due to the rotating nature of their internal pieces, produce vibrations. Accelerometers strategically placed at points next to bearings and motors allow the displacement, velocity or acceleration of the machine over time to be measured, thus generating a discrete signal of the vibration level. Fig. 1 shows a typical positioning configuration of accelerometers on the equipment. In general, the orientations of the sensors follow the three main axes of the machine, that is, vertical, horizontal, and axial.

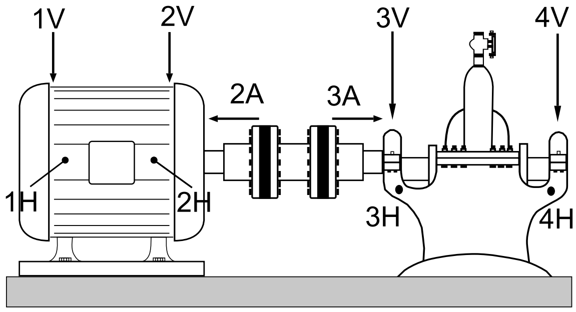

Figure 1: Motor pump with extended coupling between motor and pump. The accelerometers are placed along the main directions to capture specific vibrations of the main axes. (H=horizontal, A=axial, V=vertical.)

In the presence of bearing defects there are vibrations that overlap the signals of normal operation conditions. Besides that, faults from other problems of the machinery can also occur. An example are the lower frequency vibrations which typically occur in case of unbalance of the rotating parts of the pump. Whenever a collision between a defect and some bearing element happens, a short duration pulse is produced. This pulse excites the natural frequency of the bearing, resulting in an increase of the vibrational energy.

2.1 Faults Model

The structure of a rolling bearing allows establishing a model of possible faults. Fig. 2 illustrates a basic model of a bearing with the rolling elements, the inner and outer raceways, and the cage. The bearings, when defective, present charac-

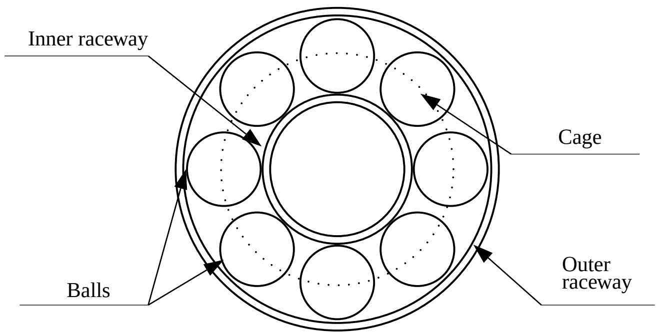

Figure 2: Sectional view of a bearing model [9].

teristic frequencies depending on the localization of the defect [9]. Defects in rolling bearings can be foreseen by the analysis of vibrations, detecting spectral components with the frequencies (and their harmonics) typical for the fault. There are five characteristic frequencies at which faults can occur. They are the shaft rotational frequency F_{S}, fundamental cage frequency F_{C}, ball pass inner raceway frequency F_{BPI}, ball pass outer raceway frequency F_{BPO}, and the ball spin frequency F_{B}. The characteristic fault frequencies, for a bearing with stationary outer race, can be calculated by the following equations [9]:

$$F_{\mathrm{C}} = \frac{1}{2}F_{\mathrm{S}}\left(1 - \frac{D_b\cos(\theta)}{D_c}\right) \tag{1}$$

$$F_{\mathrm{BPI}} = \frac{N_B}{2}F_{\mathrm{S}}\left(1 + \frac{D_b\cos(\theta)}{D_c}\right) \tag{2}$$

$$F_{\mathrm{BPO}} = \frac{N_B}{2}F_{\mathrm{S}}\left(1 - \frac{D_b\cos(\theta)}{D_c}\right) \tag{3}$$

$$F_{\mathrm{B}} = \frac{D_c}{2D_b}F_{\mathrm{S}}\left(1 - \frac{D_b^2\cos^2(\theta)}{D_c^2}\right) \tag{4}$$

where D_b is the ball diameter, θ is the load angle based on the ratio of axial to radial load, D_c is the cage diameter, and N_b is the number of balls. These equations consider that the rolling elements do not slide, but roll over the race's surfaces. Of course, there is virtually always some slip and these equations give a theoretical estimate which would vary by 1-2% from the actual values [12]. These frequencies will only be present in the vibration spectrum when the bearings are really defective or, at least, when their components are subject to tensions and deformations that can induce a fault.

2.2 Envelope Analysis

The defect detection based on the frequencies of (1) to (4) follows a set of consecutive stages usually denominated as envelope detection [5, 7]. The envelope is an important signal processing technique that helps in the identification of the bearing defects, extracting characteristic frequencies from the vibration signal of the defective bearing. The objective is the isolation of these frequencies and their harmonics, previously demodulated by the Hilbert transform. With this analysis it is possible to identify not only the occurrence of faults in bearings, but also identify possible sources, like faults in the inner and outer race, or in the rolling elements.

The first step in amplitude demodulation is signal filtering with a band-pass filter to eliminate the frequencies associated with low frequencies defects (for instance unbalance and misalignment) and eliminating noise. The frequency band of interest is extracted from the original signal using a FIR filter [5, 10] in the time domain. The selection of the demodulation band was based on the SKF industry filter standard (500Hz-10kHz). Although it is difficult to properly designate the filter band to filter out a complete vibration mode, it is out of the scope of this paper to investigate techniques for the optimal choice of the demodulation band to separate the bearing signal from masking noise, such as Spectral Kurtosis [1, 13]. The vibration signals of interest have repetitive high frequency manifestations as a consequence of the excitation of high frequency resonances in regular intervals. These free vibrations generated by the bearing defects are modulated in amplitude by the sequence of repetitive impacts and by the damping effect.

The direct frequency analysis of the signals does not provides much information [5], because in the high frequency bands there is noise and other defects mixed with the characteristic frequencies of bearing faults. These repeating frequencies are, however, easily measured in the signal envelope. The envelope detection method (or amplitude demodulation) provides an important and effective approximation to analyze fault signals in high frequency vibrations and can be calculated by the Hilbert transform [19]. Given a signal $h(t)$ in the time domain, the Hilbert transform is the convolution of $h(t)$ with the signal $\frac{1}{\pi t}$:

$$\widetilde{h}(t) := \mathscr{H}\{h(t)\} := h(t) * \frac{1}{\pi t} = \frac{1}{\pi}\int_{-\infty}^{\infty} h(t)\frac{d\tau}{t-\tau}. \quad (5)$$

The envelope of the signal in the discrete form is then given by:

$$\mathscr{E}[k] = \sqrt{h^2[k] + \widetilde{h}^2[k]} \quad (6)$$

After the calculus of the spectrum of the envelope, with the knowledge of the bearing properties, a classification module is responsible for the diagnosis of the possible fault.

The presence of new peaks in the spectrum, that were not exact multiples of the shaft rate, was the first indication that a bearing problem likely existed because true bearing defects emit frequencies that are non-synchronous with running speed. In the initial failure stage, the fundamental frequencies are rarely visible in the velocity spectrum and the greater amplitudes occur only at high order harmonics. No external feature, such as temperature or audible noise, is altered. Maintenance of the motor pump is not required in this stage. As the defect progresses, a small increase in energy on the regions of natural frequencies of bearings is noticed. In this stage it is possible to identify the presence of one of the five characteristic fault frequencies by envelope analysis. In the next failure stage the temperature increases and more and more fault frequencies harmonics are observed, and the number of sidebands around on both characteristic frequencies harmonics and natural bearing frequencies become greater.

3. REAL DATA: ANALYSIS AND DISCUSSION

Usually, research papers in the literature exhibit their results based on experimental data or even simulated data to corroborate the effectiveness of a given method. This is due to the limited amount of vibration data available in this area. Real data cannot be easily gathered. Hence, to investigate the performance of the previously presented fault detection method for the diagnosis of real rolling element bearing failure, real acquisitions were obtained from various oil production plants. Measurements were regularly taken during five years from 25 different oil platforms operating along the Brazilian coast. A total amount of 3700 acquisitions was collected. Of this total, only 1000 examples had some type of defect attributed by a human operator relying on his experience. The remainder represented normal operational conditions. Each acquisition labeled as a fault presents some kind of defect (not only bearing fault) that can be divided into electrical, hydrodynamic, and mechanical failures, and may present several types of defects simultaneously.

The considered motor pumps are composed of one-stage horizontal centrifugal pumps coupled to an AC electric motor. The measurements are collected at different points, all in machine bearing housings, to detect various types of defects. Also, vibrations are measured along axial, horizontal, and vertical directions. Vibration signals are collected by means of a closed, proprietary vibration analyzer equipped with a sensor in the time domain and vibrational signal techniques were applied within the system.

There are a number of factors that contribute to the complexity of the bearing signature that could not be simulated but must be taken into consideration. Only with real data it is possible to work under real environment conditions. We will show and analyze some real examples to illustrate how the theory appears in practice. First of all, variations of the bearing geometry and assembly make it impossible to precisely determine bearing characteristics frequencies. The fault severity progress can alter the bearing geometry, contributing to the increase of complexity of the diagnosis process. Operating speed and loads of the shaft greatly affect the way and the amount a machine vibrates causing bearing basic frequencies to deviate from the calculated value. In a real-world environment, the motor speed cannot keep rotating at a constant F_S precisely. This fluctuation can be caused by external factors such as the performance of the controller, noise, and disturbance in the power system. It is important to consider band frequency range around the characteristic frequencies. Consequently these range needs to be large enough to solve this problem without creating another one.

Fault signature appear to be very different at advanced stages of severity. As the bearing gets worse the number of sidebands increase. What may have started out as a relatively sharp peak may appear to be spreading out to cover a wider frequency range [17]. The raise of sidebands can be seen in Fig. 3 indicating that the condition of this bearing is worsening.

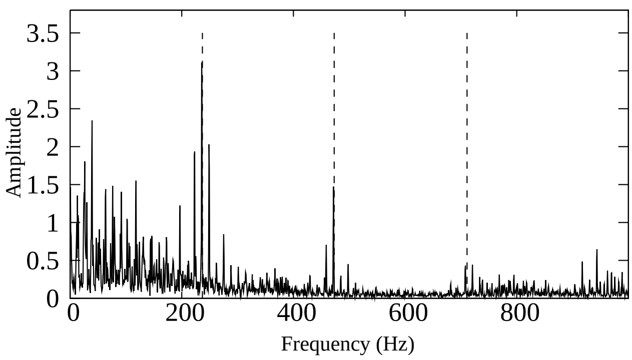

Figure 3: F_C sidebands around F_{BPO} harmonics (represented as dashed line)

The vibration signature of Fig. 4 shows the existence of multiples of the rolling bearing cage characteristic frequency indicating that the bearing condition is critical.

The real data has an additional difficulty due to a lot of random vibration components from other parts of the machine than the bearing being examined. The band-pass filter and envelope analysis techniques are useful to reduce the noise influences. Sometimes, when the signals are very noisy, mainly caused by some kind of looseness, neither filtering nor envelope analysis can do anything to improve the quality of the processed signal. Fig. 5 illustrates this case.

Another problem happens when some of the harmonic components unrelated to bearing conditions coincide in fre-

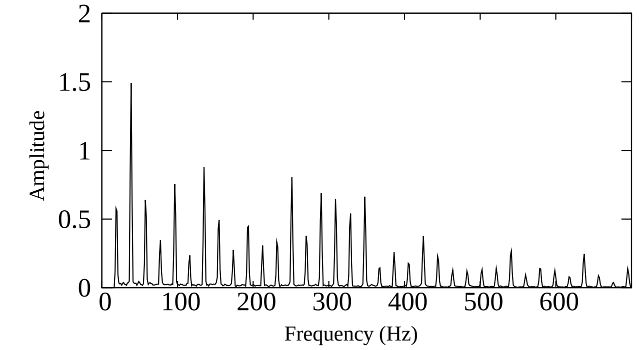

Figure 4: Damaged bearing with many fundamental cage frequency harmonics.

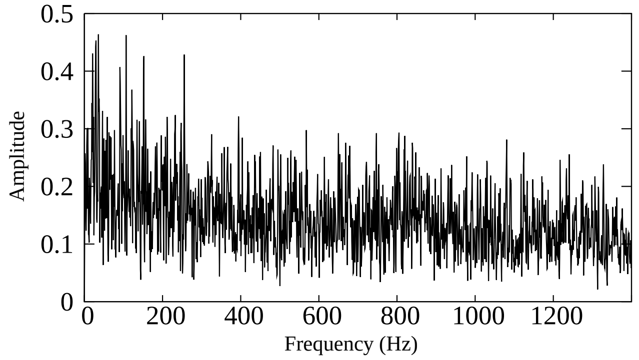

Figure 5: Noisy envelope spectrum.

quency with the bearing vibration components creating obstacles to identifying the type of defect. In the worst cases, even the increase of resolution in the envelope spectrum would not help to distinguish the different families of harmonics. This is not only a challenge when conceiving an automatic pattern recognition based classifier, but also an almost insurmountable obstacle to a human expert.

4. CLASSIFICATION METHODOLOGY

Since each considered example always presents at least one kind of defect (not only bearing defect), the approach to deal with this multilabel classification problem was to generate a binary rolling bearing classifier in the following way: all examples without any bearing fault constitute the negative class while the examples containing at least one kind of bearing defect belong to the positive class. The training base was created considering that each acquisition is formed by all signals collected by each sensor placed on each bearing housing of the motor pump. Since the machine normally has four bearing housings and each one has a distinct rolling bearing, each acquisition provided four examples to the training base. Table 1 shows the proportion of positive and negative examples where the positive class means the class of examples containing any rolling element bearing defect and the negative class is the class of examples that have no bearing fault.

There are two important steps in the fault detection process. The first is to perform signal processing to generate the feature vector used in the subsequent classification step and the second step consist of inducing a classifier. In this work we extract features from some important bands of the envelope spectrum. We consider narrow bands around the first, the second, the third, the fourth, and the fifth harmonic of each characteristic frequency. Another useful information used was the RMS (root mean square) calculated from the spectrum of acceleration and from the envelope spectrum of each measurement point.

Table 1: Class distribution of the examples

Class	*A priori class distribution*
Negative (without bearing fault)	87.79%
Positive (with any bearing fault)	12.21%

Pattern recognition techniques [18], especially *feature selection*, is useful to reduce the number of features and to avoid the presence of irrelevant information, facilitating the subsequent classification. In this work we use the *Sequential Forward Selection* strategy [18]. After all features have been extracted and selected, the next step is the induction of a classifier algorithm.

5. RESULTS

We will present some experimental results with real data from rotating machines of oil rigs conducted. A statistically significant amount of real examples were available. Each considered acquisition present some kind of fault, for instance misalignment, unbalance, flow turbulence, bearing, and so on. Normal examples, that is, examples without any defect were not used in this experiments. An examples is called “normal” when the level of overall RMS is less than a pre-set threshold. Doing a simple pre-processing, we could distinguish a faulty example from an example in good condition without training a classifier. (A high RMS value does not necessarily mean a bearing failure.) With these experiments we will be able to conclude if the envelope analysis together with pattern recognition techniques really provide a powerful method to determine if a bearing is defective or not.

An empirical comparison with various classifier models [3,18], was made and the 10-fold “Cross Validation” method was used to estimate the error rate. Table 2 shows the result of the performance estimates experiences of various classifiers: 5-Nearest-Neighbor (5-NN), Multi-Layer Perceptron (MLP), and Support Vector Machine (SVM). For the SVM classifier we used the radial basis as the kernel function, set the cost parameter to 0.5, and set the gamma value to 8.

Table 2: Accuracy rate regarding only the selected features.

Classifier	*Accuracy rate*
5-Nearest-Neighbor	91.09%
Multi-Layer Perceptron	92.32%
Support Vector Machine	91.49%

An alternative way to compare the classifier’s performance is shown in Fig. 6 which is an ROC graph [4] with the three classifiers presented in Table 2. Each point representing one classifier. It is a technique for visualizing, organizing and selecting classifier based on their performance in a two-dimensional space where the true positive rate (also called hit rate or recall) is plotted on the *Y* axis and the false positive rate is plotted on the *X* axis.

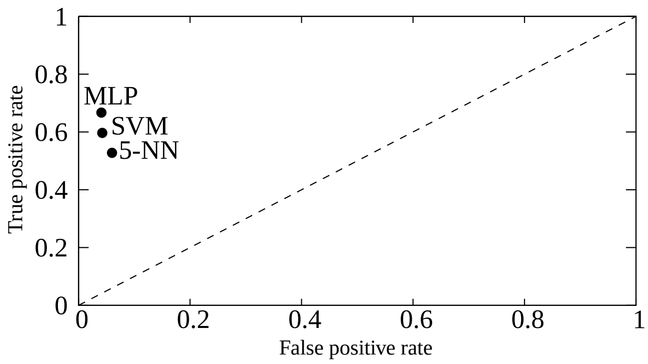

Figure 6: The ROC graph showing three classifiers.

One classifier is supposed to be better than the other if it is to the northwest of the first. Any classifier on the diagonal is said to follow a random guessing strategy while a classifier below the diagonal performs worse than random guessing and may be said to have useful information, but applying it in an incorrect way. The ROC analysis is very important to compare classifiers considering unbalanced classes problem, such as a machine fault diagnosis since the number of negative class examples is almost always greater than the positive ones. Metrics such as accuracy are sensitive to changes in class distribution.

6. CONCLUSION

In this work we employed signal processing and pattern recognition techniques to classify faults in bearings. The envelope analysis provides the feature vector used in the subsequent classification steps. On the contrary to the majority of the works that study the fault detection problem, we investigate the rolling element bearing fault diagnosis method based on envelope analysis applied to real world data obtained from several different oil platforms. Preliminary analysis were done and some common problems were exhibited. The results has suggest that this method can satisfactorily be used on diagnosis process even in a real environment.

In the near future we will examine these real examples more closely in order to improve the performance of the classifiers refining the adopted techniques. Moreover, more robust techniques than the traditional envelope analysis will be used. Further investigations not only on rolling bearing failure but also on others faults, such as unbalance, misalignment, flow turbulence, and cavitation will be reported soon.

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REFERENCES

[1] J. Antoni and R. B. Randall. The spectral kurtosis: application to the vibratory surveillance and diagnostics of rotating machines. *Mechanical Systems and Signal Processing*, 20:308–331, 2006.

[2] T. Barszcz and R. B. Randall. Application of spectral kurtosis for detection of a tooth crack in the planetary gear of a wind turbine. *Mechanical Systems and Signal Processing*, 23:1352–1365, 2009.

[3] C. Cortes and V. Vapnik. Support vector network. *Machine Learning*, 20:273–297, 1995.

[4] T. Fawcett. An introduction to ROC analysis. *Pattern Recognition Letters*, 27:861–874, 2006.

[5] T. A. Harris and A. G. Piersol. *Harris's Shock and Vibration Handbook*. McGraw-Hill, 5th edition, 2002.

[6] B. Li, M. Y. Chow, Y. Tipsuwan, and J. C. Hung. Neural-network-based motor rolling bearing fault diagnosis. *IEEE Transactions on Industrial Electronics*, 47(5):1060–1069, 2000.

[7] P. D. McFadden and J. D. Smith. Vibration monitoring of rolling element bearings by the high frequency resonance technique - a review. *Tribology International*, 17:1–18, 1984.

[8] E. Mendel, L. Z. Mariano, I. Drago, S. Loureiro, T. W. Rauber, F. M. Varejao, and R. J. Batista. Automatic bearing fault pattern recognition using vibration signal analysis. *Proceedings of the IEEE International Symposium on Industrial Eletronics*, pages 955–960, 2008.

[9] R. K. Mobley. *Root Cause Failure Analysis (Plant Engineering Maintenance Series)*. Butterworth-Heinemann, 1999.

[10] A. V. Oppenheim, R. W. Schafer, and J. R. Buck. *Discrete-Time Signal Processing*. Prentice-Hall, 2nd edition, 1998.

[11] S. Orhan, N. Aktürk, and V. Çelik. Vibration monitoring for defect diagnosis of rolling element bearings as a predictive maintenance tool: Comprehensive case studies. *NDT&E International*, 39:293–298, 2006.

[12] R. B. Randall. Detection and diagnosis of incipient bearing failure in helicopter gearboxes. *Engineering Failure Analysis*, 11:177–190, 2004.

[13] N. Sawalhi and R. B. Randall. Spectral kurtosis optimization for rolling element bearings. *Proceedings of Eighth Internation Symposium on Signal Processing and Its Application*, 2:839–842, 2005.

[14] C. Scheffer and P. Girdhar. *Pratical Machinery Vibration Analysis and Predictive Maintenance*. Elsevier, 1st edition, 2004.

[15] J. R. Stack, T. G. Habetler, and R. G. Harley. Fault-signature modeling and detection of inner-race bearing faults. *IEEE Transactions on Industry Applications*, 42(1):61–68, 2006.

[16] P. J. Tavner and J. Penman. *Conditiong Monitoring of Electrical Machines*. Wiley, 1987.

[17] Technical Associates of Charlotte. *Vibration Analysis Level II*. 1997.

[18] S. Theodoridis and K. Koutroumbas. *Pattern Recognition*. Academic Press, Inc., Orlando, FL, USA, 3rd edition, 2006.

[19] V. Čížek. Discrete Hilbert transform. *IEEE Transactions on Audio and Electroacustics*, 18(4):340–343, 1970.