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Autonomous Bearing Tone Tracking Algorithm

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ABSTRACT

To date, much of the research done in the field of condition monitoring of rotating machinery is conducted in the frequency domain. The frequency domain analysis specifically for bearings is based on extracting features from the spectrum of the vibration signature. These features are mostly based on the amplitude at the bearing tones along with their sidebands and high order harmonics. Therefore, it is important to determine the location of the mentioned bearing tones in the spectrum accurately and automatically. For the case of ball bearings this process can be problematic due to slippage of the rolling elements and variations in the angle of contact. These may cause the bearing tone to deviate from its nominal value.

To this day, the common practice for bearing diagnostics is based on the vibration level at the analytical bearing tones or involvement of experts to identify the true location of the bearing tone. In this research an autonomous algorithm for bearing tone extraction, based on pattern matching, was developed. The proposed algorithm is based on the common assumption that the spectrum of a faulted bearing contains a certain known pattern of prominent peaks. The algorithm "scans" the entire spectrum and determines the frequency value which has the highest correlation to the mentioned pattern.

The proposed algorithm was validated and its capabilities are illustrated using experimental data. This algorithm is able to assist any diagnostic approach towards automatic and reliable feature extraction process, both for physics based and data driven approaches.

1. INTRODUCTION

Condition based monitoring (CBM) has become a dominant approach in maintenance as it can save resources and manpower while improving safety. The general concept of CBM is monitoring the machine`s components and estimating its current health condition.

This research focuses on the field of rotating machines, and specifically in the field of bearings since bearings are highly prone to faults. A fault in a bearing can cause malfunction of the entire machine, leading to failure and environmental damage (Randall, 2011).

One of the common approaches for monitoring the condition of bearings is vibration analysis. This approach is based on the assumption that a faulted bearing will generate an impulse followed by a dynamic response each time a component encounter with the fault. By analyzing this vibration signature, the fault severity can be estimated (Malla and Panigrahi, 2019).

Vibration analysis in the frequency domain is one of the common approaches in the field of bearings. This approach assumes that the spectrum of a healthy bearing will be relatively "clean" while a faulted bearing has unique prominent peaks in the spectrum according to the rate of the impulses. These frequencies are named bearing tones which can be calculated based on kinematic equations. This assumption was firstly modelled and discussed by (McFadden and Smith, 1984).

Most frequency domain analysis methods are based on manipulating the spectrum around the bearing tones. Zhang et al. reviewed several diagnostic approaches and demonstrated a method which tracks the amplitude of the peak at the bearing tone and utilizes it to estimate the fault size, which is related to the bearing condition (Zhang et al., 2022). There is a great need to determine the precise location of the bearing tone automatically. This demand applies for physics-based and/or data-based approaches which utilize manipulations around the peaks for feature extraction. For instance, Nissim et al. used features which are based on the location of the bearing tones (Nissim et al., 2021). These approaches are highly sensitive to the location of the analyzed peaks as it may affect the results. Therefore, the accuracy of the peak location is important.

For the best of our knowledge, only limited research provides algorithms for this purpose. A paper which was published by (Kass, Raad, and Antoni, 2019) displayed an algorithm for bearing tone detection. It is aimed to detect small deviations of the bearing tone due to slippage of the rolling elements. In many applications these deviations are significantly larger than those caused by slippage. This study proposes a new algorithm for bearing tone determination which can handle large deviations in noisy spectrum. The algorithm can assist frequency domain diagnostic approaches.

The article is organized as follows. Chapter 2 presents the required background for the understanding and establishment of the suggested algorithm. Chapter 3 presents the algorithm inputs and procedure followed by a demonstration in Chapter 4. Lastly, Chapter 5 summarizes the work.

2. Background

A bearing contains four components, an inner race, an outer race, rolling elements and a cage. In the case of a fault in one of these components a specific frequency, named bearing tone, will rise in the spectrum. The bearing tone can be calculated analytically based on kinematic equations. BPFO is the ball pass frequency on the outer race, BPFI is the ball pass frequency on the inner race, FTF is the fundamental train frequency and BSF is the ball spin frequency.

$$BPFO = \frac{f_r}{2} \cdot n \cdot \left[1 - \left(\frac{B_d}{P_d}\right) \cdot \cos(\beta)\right] \tag{1}$$

$$BPFI = \frac{f_r}{2} \cdot n \cdot \left[1 + \left(\frac{B_d}{P_d}\right) \cdot \cos(\beta)\right] \tag{2}$$

$$FTF = \frac{f_r}{2} \cdot \left[1 - \left(\frac{B_d}{P_d}\right) \cdot \cos(\beta)\right] \tag{3}$$

$$BSF = f_r \cdot \frac{P_d}{B_d} \cdot \left[1 - \left(\frac{B_d}{P_d}\right)^2 \cdot \cos(\beta)^2\right] \tag{4}$$

Where f_r is the rotating speed, n is the number of balls, B_d is the ball diameter, P_d is the pitch diameter and β is the angle of contact.

A healthy bearing should not generate any impulses in the vibration signature and consequently no prominent peaks are expected in the spectrum while the spectrum of a faulted bearing will contain prominent peaks at the bearing tones. Due to the Fourier transform properties, these peaks will appear along with their harmonics.

Another phenomenon is the Amplitude Modulation (AM), which is caused by load variations (loading zone or unbalance of the shaft). This phenomenon occurs when a signal with frequency f_{tone} is modulated by a signal a frequency f_m, usually the bearing tone will be modulated by the shaft rotation frequency. Therefore, in addition to the bearing tone peaks we can expect sidebands in f_m distance from the bearing tone as a result of AM. These sidebands will also appear with their harmonics, e.g., $f_{tone} \pm f_m, f_{tone} \pm 2f_m, \ldots, f_{tone} \pm nf_m$.

Overall, assuming a faulted bearing with a bearing tone of f_{tone} and a modulating frequency of f_m, the pattern illustrated in Figure 1 is expected to appear in the spectrum. This pattern only includes two harmonics with three sidebands and may include many more.

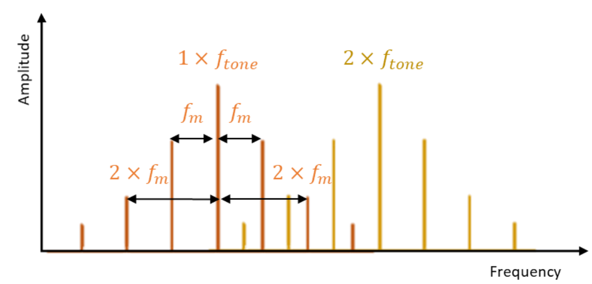

Figure 1. Expected pattern of a faulted bearing.

As mentioned before, many approaches utilize the spectrum around its bearing tones in order to acquire information about the bearing health condition. Eq. (1)-(4) are based on two assumptions which do not necessarily apply for real cases and might cause the real bearing tone to deviate from its analytical value.

The first assumption is rolling without slippage. The slippage of the rolling elements in the bearing can be explained by the fact that each rolling element is loaded differently depending on its position. As a result, each element tries to rotate at a different velocity yet the cage forces them to remain in equal distance by causing slippage (Randall, Antoni, and Chobsaard, 2001). Another research conducted by (Pennacchi et al., 2011) concludes that the amount of slippage in bearing may change according to the operating conditions, bearing type and the bearing tone of interest. For instance, the BPFI will be more affected by slippage than the BPFO. Another assumption is that the angle of contact β is constant at the nominal value. In many cases the angle of contact varies from its nominal value depending on the ratio between the axial and radial loads and operating conditions. These changes of the angle of contact might change the bearing tone significantly as can be deduced from Eq. (1)-(4). Therefore, it is required to locate the true bearing tones in every vibration record. When the change of the bearing tone is large, e.g., for large variations in the angle of contact, or when there are many peaks in the vicinity of the bearing tone, the task becomes more challenging.

3. BEARING TONES LOCATION ALGORITHM

The proposed algorithm Bearing Tones Location (BTL) is based on pattern matching, since it is assumed that the spectrum of a faulted bearing will contain prominent peaks which match a pattern similar to the illustration in Figure 1.

Since the spectrum may include many peaks related to other components (shafts, gears, etc.), the BTL search for the defined pattern simultaneously which aids to avoid irrelevant peaks. In cases where the spectrum contains numerous peaks related to other components, filtering methods can be applied to remove the discrete frequencies from shafts, gears and rotors.

The BTL "scans" the entire spectrum and finds the frequency value which has the highest correlation to the expected pattern. Once the bearing tone is determined, the BTL calculates the result score by evaluating the statistical distance of the whole pattern based on the selected bearing tone to the alternative patterns. The higher the distance the more reliable the determination is.

Since the location of the fault is unknown, the BTL is designed to determine different bearing tones using their corresponding patterns, each pattern includes a different set of harmonics and sidebands corresponding to different failure modes, e.g., defect on outer race or inner race or ball, etc. It is important to note that the BTL will produce a meaningful result only if such pattern exists in the spectrum, otherwise the score (statistical distance from the alternatives) will be low.

The process of scanning the spectrum for a pattern can be conducted in two ways. The first way is searching for the whole pattern, from the first harmonic to a high harmonic defined as an input to the algorithm. The second way is by scanning different sets of harmonics each time. For each set, the BTL determines the most probable location of the bearing tone for this specific set, and the final bearing tone is determined to be the location found in the set which produced the highest total amplitude. The second scanning process helps to detect the bearing tone in case a small number of peaks are prominent in the spectrum.

There is a tradeoff which needs to be taken in account when defining the pattern for the BTL. When the pattern contains more harmonics and more sidebands, the pattern gets richer and the result will be more reliable since the odds for accidental high correlation between the pattern and the spectrum decreases. If the pattern is too rich, meaning that it includes more harmonics and sidebands than what rises in the spectrum, the score might be affected since it will sum a lot of irrelevant bins. The recommended pattern should include the minimal amount of harmonics and sidebands which can provide a reliable result.

For visualization, in Figure 2 two arbitrary frequency values were examined and matched to a pattern consisting of one harmonic with one sideband. It can be seen that by summing the amplitude of the spectrum matching the red pattern the total corresponding amplitude is higher than the case of the green pattern, in this example the red pattern is more likely to represent the bearing tone.

The spectrum of the vibration signature is calculated using DFT, hence the frequency axis is discrete and divided into "bins". Since the frequency resolution is constant, each bin in the first harmonic corresponds to n bins in the n^{th} harmonic. Therefore, to determine the bearing tone with the highest accuracy, for every approach, it is best to find the highest harmonic and divide it by the corresponding harmonic number.

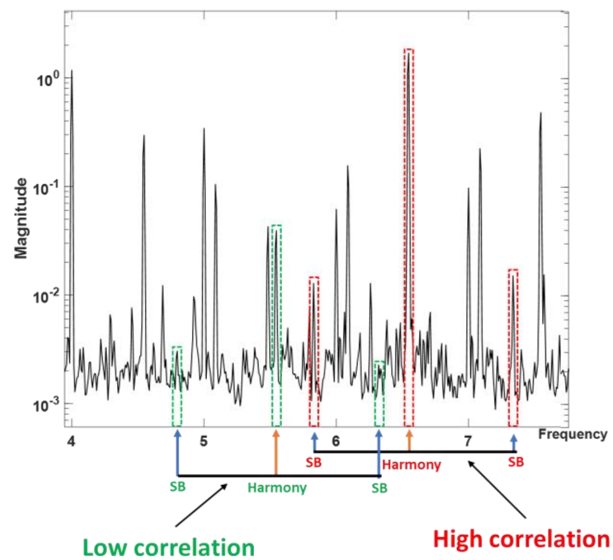

Figure 2. General pattern matching example.

3.1. Algorithm Inputs

In the following subchapter, the BTL inputs will be presented and explained. Note that for the next section, the term "harmonic" refers to the harmonic and its corresponding sidebands.

- Analytical bearing tone

The kinematic bearing tone can be calculated using the rotating speed and the geometry of the bearing using Eq. (1)-(4).

- Range of the first harmonic

Since the experimental bearing tone may deviate from the analytical value, this input defines the search range around the analytical bearing tone. To set this input properly a preliminary evaluation of the variations of the angle of contact β and changes due to slippage are required. The search range is not necessarily symmetrical and has no limitation, but it may affect the score and run-time of the algorithm.

For bearings with no axial load the only cause for deviation is slippage, therefore a search range of 1% is mostly sufficient. For the case of a bearing with axial load the search range should increase according to the possible variations of the contact angle.

- Number of harmonics in the set

This input determines the number of harmonics in the set that the algorithm will scan. The number of harmonics has to be bigger than one.

- Maximum harmonic

If the chosen scanning approach is by using different sets of harmonics, then this input determines the highest harmonic in the search range. This number is equal or larger than the number of harmonics in the set. This value affects the different patterns that the algorithm scans, For example if the maximum harmonic is 10 and the number of harmonics in the pattern is 4, the algorithm will scan the following - harmonics 1:4,2:5,...,7:10.

- Modulating frequency

The modulating frequency determines the distance of the sidebands expected to rise around the bearing tone harmonics. In most cases the amplitude modulation will occur due to shaft unbalance or fluctuations of the load, meaning that the modulating frequency is usually the shaft rotation frequency.

- Number of sidebands

This input determines the number of sidebands around each harmonic in the expected pattern that the algorithm will scan. The higher the number the more specific the pattern will be. For most cases 1-3 sidebands is sufficient to create a specific enough pattern.

3.2. Algorithm Procedure

The general scheme of the algorithm is presented in Figure 3 as a block diagram, each step of the BTL will be explained throughout this subchapter. The procedure will be described according to the general case of using different sets. When the number of harmonics in the set is equal to the maximum number of harmonics the algorithm works on one set.

First, the BTL builds the desired pattern to search for and defines the search range and the sets of harmonics.

Since high resolution is desired, the BTL will find the frequency bins which correspond to the deviation range around the highest harmonic in the specific set, these will be noted as $bins = \{i \in 1,2,3 \dots N\}$.

For every bin i in this range the BTL will find the matching bins of lower harmonics and their associated sidebands and will sum their amplitudes. This step is conducted for each harmonic in the defined set, summing all of their amplitudes to the matching bin which will result in an amplitude A_i.

Once this procedure is done for each bin, the bearing tone is determined to be the bin which corresponds to the highest total amplitude divided by the highest harmonic number n in the set as can be seen in Eq. (5).

$$bearing\ tone = \frac{\operatorname{argmax}(A_i)}{n} \tag{5}$$

After the bearing tone is determined, the score of the result is estimated by calculating the Z Score of the amplitude of the chosen bin according to Eq. (6).

$$ZS = \frac{\max_i(A_i) - \mu}{\sigma} \tag{6}$$

Where μ is the average and σ is the standard deviation of the sum of amplitudes in the different bins, respectively. The Z-Score measures the prominence of the amplitude corresponding to the chosen bin relative to all other bins. This correlates to the distance of the chosen bin amplitude from the mean amplitudes σ, thus correlates to the confidence of the result.

After the bearing tone and the result score value are found according to the current set of harmonics, the same procedure is conducted using the next set which includes different harmonics. After the procedure is done for each set, the bearing tone which has the highest amplitude value is chosen.

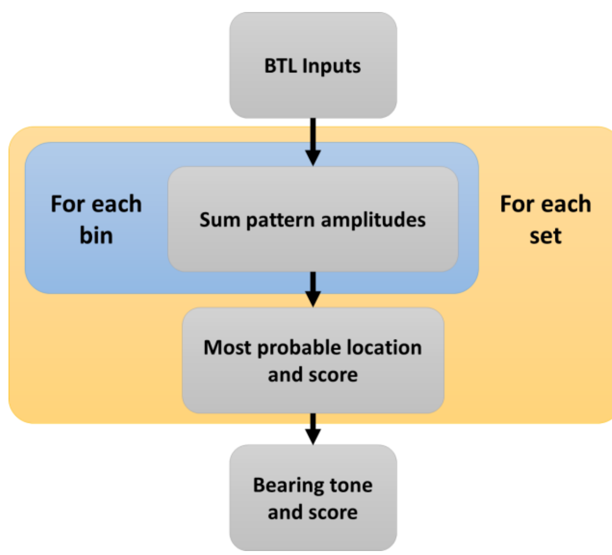

Figure 3. Algorithm scheme

4. DEMONSTRATION

To demonstrate the algorithm efficiency and to further explain the required inputs, two experiments were conducted. Throughout each experiment the vibration signature was recorded. Each vibration recording was processed according to the methodology presented in Figure 4. Eventually, the spectrum of the recording was obtained in the order domain instead of the frequency domain by calculating the spectrum after angular resampling. The angular resampling corrects the effect of fluctuations in rotating speed since the bearing tone will be normalized to cycles instead of time. Then the envelope of the signal is calculated to emphasize the bearing related phenomena. The final step is estimating the Power Spectral Density (PSD) of the envelope. These processing steps are not mandatory and the BTL can be applied on any spectrum in the order/frequency domain. Yet, when applying it in the frequency domain the peaks will be smeared on several bins which might affect the accuracy of the result.

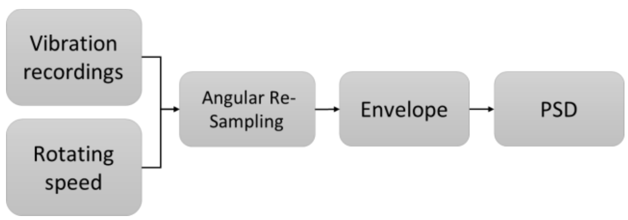

Figure 4. Signal processing methodology.

For the first example the test rig included a deep groove bearing fitted on a shaft, rotated in 40 [Hz]. The bearing was being radially loaded by 200 [N] flywheels and was artificially induced by a fault on the outer race. After the signal processing procedure was applied, the spectrum obtained is presented in Figure 5 in the order domain.

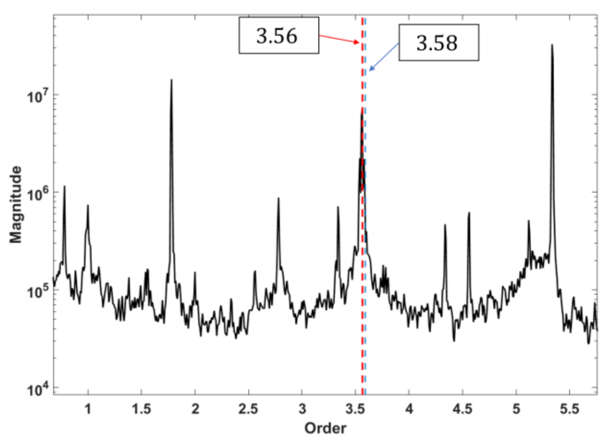

Figure 5. First example of the algorithm.

Using the geometric parameters of the bearing the analytical BPFO bearing tone is $3.586\ order$ and is presented in a blue dashed line in . The algorithm was applied with inputs of the analytical bearing tone, a 1% of the analytical bearing tone as search range, 8 harmonics and 1 sideband of 0.4 order (FTF). The bearing tone was determined to be $3.5625\ order$ as can be seen in a red dashed line with a deviation of 0.64% from the analytical bearing tone, with a Z Score of 8.52.

For the second example an endurance test was conducted, the test rig included an angular contact bearing fitted on a shaft rotating in a constant speed of 166 [Hz] and loaded axially by 5500 [N]. A random recording was processed using the procedure presented and the obtained spectrum is presented in Figure 6. Using the geometric parameters of the bearing the analytical BPFI bearing tone is $6.58\ order$ and is represented by a blue dashed line in Figure 6. The algorithm was applied with inputs of the analytical bearing tone, a 1.5% of the analytical bearing tone as deviation range, 10 harmonics and 2 sidebands of 1 order (shaft rotation). The bearing tone was determined to be $6.51\ order$ as can be seen in a red dashed line in Figure 6, its sidebands are marked with red dotted lines. Observing the spectrum, it can be seen that even though it is relatively clean around the first harmonic and the determination of the bearing tone is simple, the deviation from the analytical bearing tone is significant at 1.06%. The Z Score of this result is 9.72 making the determination considerably confident.

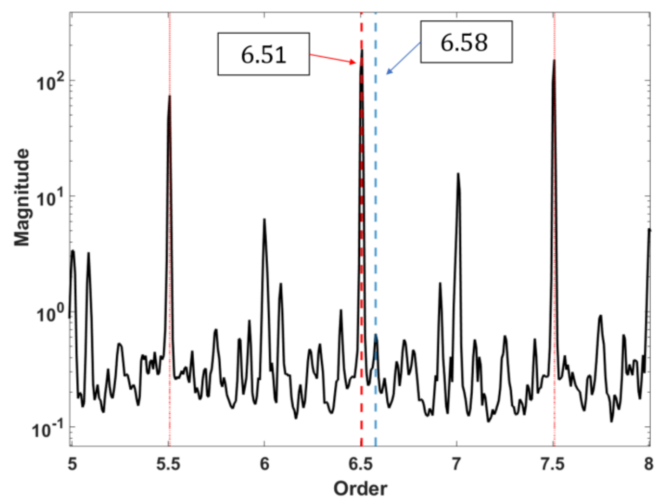

Figure 6. Example of the algorithm result.

It is also noticed that by using the analytical bearing tone for further analysis the results will not reflect the amplitudes of the peaks excited by the faulty bearing. Even though the task of locating the bearing tone in the first harmonic is quite simple, the resolution gained from this process is limited and can also affect any further analysis. The BTL was applied on many more recordings and was thoroughly validated with various fault cases and operating conditions and is successfully capable of determining the bearing tone.

To further present the complexity of locating the bearing tone at higher resolution, the same spectrum is presented around the 10th harmonic in Figure 7. As can be seen, the spectrum presents many peaks which represent different harmonics and their corresponding sidebands. The 9th harmonic is marked with a blue dashed line and its sidebands are marked with blue dotted lines, same goes for the 11th harmonic marked in green. The 10th harmonic which we desire is marked in red. In high orders, sidebands of different harmonics can overlap one another and cause confusion making the task of determining the bearing tone becomes very complicated, emphasizing the need to search for the entire pattern match. The location of the 10th harmonic of analytical BPFI bearing tone is marked in a light blue dashed line and its sidebands are marked as blue arrows above the spectrum.

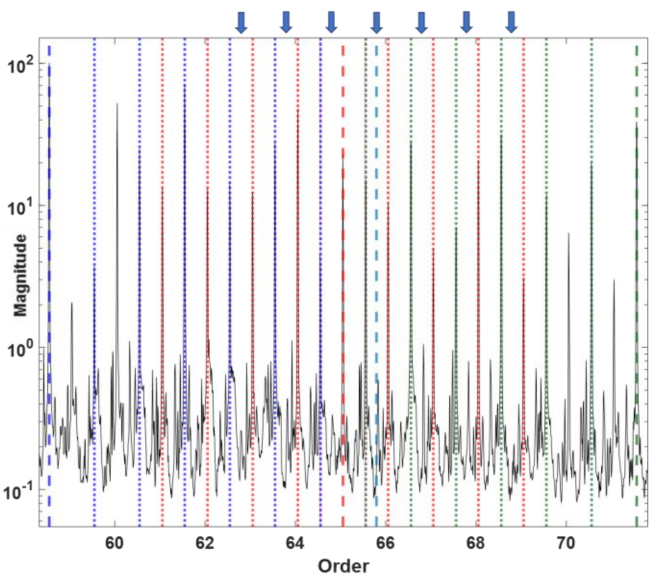

Figure 7. Second example with higher harmonics.

It is important to mention that the deviations from the analytical bearing tone will linearly increase when examining higher harmonics, which will affect any further analysis and may cause erroneous conclusions regarding the bearing health condition.

5. Summary

In this article the BTL algorithm was introduced. It determines the bearing tone of a bearing with known geometry. It is based on the assumption that a faulted bearing will produce a pattern of prominent peaks in the spectrum of the vibration signal. This pattern is defined based on the bearing faulted component. The bearing tones, i.e., the frequencies of interest, might deviate from their nominal value since bearings are prone to slippage and load variations. These deviations can cause unreliable results of any further analysis. The BTL algorithm is able to determine the bearing tone automatically and accurately and evaluate the confidence of the determination.

Both the reliability and the uniqueness of the BTL algorithm result from scanning the entire spectrum for the specific pattern, which is assumed to rise in case of a fault. The BTL algorithm can be applied on every spectrum in the frequency or order domain with any pre-processing stages. The proposed algorithm was validated and its capabilities are illustrated using experimental challenging data. This algorithm is able to assist any diagnostic approach towards automatic and reliable feature extraction, both for physics based and data driven based approaches.

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Alon Sol received his B.Sc. degree in Mechanical engineering from Ben-Gurion University of the Negev. Currently, he is a M.Sc. student. His study focuses on vibration analysis of rolling element bearing. His main areas of research are signal processing, dynamic behavior of bearings and data analysis.

Eyal Madar received his B.Sc. and M.Sc. degree in Mechanical Engineering from Ben-Gurion University of the Negev. Currently, he is a Ph.D. student. His study focuses on characterization the dynamic behavior of faulted bearings by using physical based models vibration analysis. His main areas of research interest are dynamic modelling, signal processing and data analysis.

Dr. 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 UAVs 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.

Prof. Jacob Bortman joined the academic faculty of Ben-Gurion University of the Negev in September 2010 as a full Professor. Prof. Bortman spent thirty years in the Israel Air Force (IAF), retiring with rank of Brigadier General. His areas of research in the Dept. of Mechanical Engineering include: Health usage monitoring systems (HUMS); Conditioned based maintenance (CBM); Usage and fatigue damage survey; Finite Element Method; and Composite materials.