Diagnosis Tool for Motor Condition Monitoring

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***Abstract*—In the modern industrial environment there is increasing demand for automatic condition monitoring. With reliable condition monitoring, faults such as mechanical motor failures could be identified in their early stages and further damage to the system could be prevented. Successful monitoring is a complex and application-specific problem, but a generic tool would be useful in preliminary analysis of new signals and in verification of known theories. A generic condition diagnosis tool is introduced in this paper. The tool is based on discriminative energy functions which reveal discriminative frequency-domain regions where failures can be identified. The tool was applied to induction motor bearing fault detection and succeeded in finding characteristic frequencies which allow accurate detection of bearing faults.**

***Index Terms*—Condition monitoring, fault detection, Fisher linear discriminant, induction motor, Gabor filters, pattern recognition, signal processing.**

I. Introduction

Condition monitoring and diagnosis are important tasks in modern industrial systems having a high degree of automation. Existing industrial systems already have a variety of sensor and control signals that can be used for monitoring. Of particular importance would be automatic detection and recognition of faults, such as motor failures, where an early warning of failure can prevent escalation of the problem and larger damages. One useful application area is motor bearing damage detection using a stator current signal [1]–[3].

Condition monitoring has mainly been studied within specific applications and not many generic methods exist. The monitoring usually requires specific knowledge of the underlying system. For example, in a stator current monitoring the condition is often monitored at pre-calculated characteristic frequencies at which faults are likely to cause changes. However, such information is not necessarily available or easily discovered and, thus, a generic method which could find the significant frequencies of interest would be of considerable value.

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In this paper, a method and a general diagnosis tool are proposed. The method can discriminate between two classes of signals using statistical discrimination measures for time-frequency features, i.e., Gabor filter responses. The method utilizes global information, namely, power spectra of the filter responses. The tool is intended to be used by engineering researchers to analyze differences between signals of normal and damaged motors and to identify the present condition. In experiments, the tool was successfully applied to detect bearing damage in induction motors using measurements of the stator current or vibration.

II. Condition Monitoring

Condition monitoring is an important issue in many fields, including railways [4], power delivery [5], and electrical machines and motors [2], [6]. Condition monitoring can be defined as a technique or process of monitoring the operating characteristics of a machine so that changes and trends of the monitored signal can be used to predict the need for maintenance before a breakdown or serious deterioration occurs, or to estimate the current condition of the machine.

Condition monitoring has become increasingly important, for example, for energy companies. The normal undisturbed operation of electrical equipment in power stations is very important. An unexpected fault or shutdown can result in a serious accident and financial loss for the company. Energy companies must find ways to avoid failures, minimize downtime, reduce maintenance costs, and lengthen the lifetime of their equipment. With reliable condition monitoring, machines can be utilized in a more optimal fashion [5].

Time-based maintenance follows a schedule to decide when maintenance is to be done. This leads to inefficiencies because either the maintenance may be done needlessly early or a failure may happen before scheduled maintenance takes place. Condition monitoring can be used for condition based maintenance, or predictive maintenance.

A. Example: Induction Motor Bearing Damage

Induction motors are a widely studied subject in condition monitoring [2], [6]. There are several different methods for recognizing failures. The most widely studied methods in bearing condition monitoring are based on measurements of vibration, acoustic noise, or temperature. Vibration- and stator-current-based methods seem to be some of the most popular. When monitoring bearing damage in induction motors, the characteristic frequencies of bearing damage are often used to monitor certain frequency components in either vibration or stator current signals.

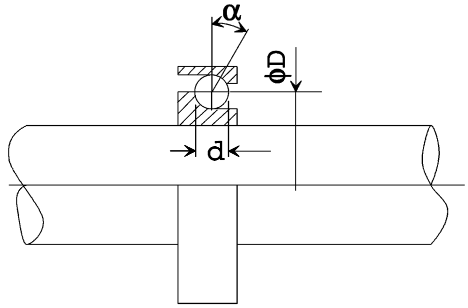

Fig. 1. Geometry of an angular contact ball bearing.

Bearing faults cause vibrations in an electric motor. When the rolling element passes the defective groove, a small radial movement is caused and the movement affects a resonance in the stator frame. The vibration can be measured by velocity transducers or accelerometers. The total vibration energy does not necessarily change for a bearing fault as compared to a no-fault situation, since normal mechanical and magnetic asymmetries already cause considerable vibrations.

A characteristic frequency of bearing failure can be calculated from the bearing geometry (Fig. 1). The characteristic vibration frequency is the inverse of time between occurrences of bearing impulses. An outer race defect causes an impulse when a ball or roller passes the defect and rotational frequency of the damage can be calculated from

$$f_o = \frac{N}{2} f_r \left(1 - \frac{d}{D}\cos\alpha\right) \tag{1}$$

where N is the number of balls or rollers, f_r is the rotational speed of the rotor, d is the diameter of the ball, D is the pitch diameter, and α is the contact angle of the rolling element. Respectively, the frequency for a defect on the inner race is

$$f_i = \frac{N}{2} f_r \left(1 + \frac{d}{D}\cos\alpha\right). \tag{2}$$

The ball spin frequency can be calculated from

$$f_b = \frac{N}{2d} f_r \left(1 - \left(\frac{d}{D}\right)^2 \cos^2\alpha\right) \tag{3}$$

and the cage fault frequency from

$$f_c = \frac{1}{2} f_r \left(1 + \frac{d}{D}\cos\alpha\right). \tag{4}$$

The frequencies in (1)–(4) are valid for ideal bearings; in practice, the rolling element slides in addition to its rotation. This can be taken into account by using a sliding factor e which is typically between 0.8–1.0. In both the literature and practice the equations are often replaced by approximate equations [7] which can be used when the exact bearing geometry is not known. A characteristic frequency using approximate formula for an outer race defect is

$$f_o = 0.4 N f_r \tag{5}$$

and for an inner race defect

$$f_i = 0.6 N f_r. \tag{6}$$

Measuring the stator current is also a potential choice for detecting faults, since rotor eccentricity causes changes in the stator current. It should be noted that there are always eccentricities in the rotors, but the eccentricities change in the case of a fault. The characteristic frequency of a bearing defect establishes new current components which are present at the frequencies

$$f_{ib} = |f \pm m \cdot f_{vb}|, \qquad m = 1, 2, 3, \ldots \tag{7}$$

where f is the supply frequency and f_{vb} is the frequency of the vibration caused by the fault [1].

The bearing damage characteristic frequencies can be used for monitoring by measuring signals, either vibration or stator current, and computing energies at the characteristic frequencies. A fault will cause a change in the energy of some or all frequency bands. There are some problems associated with using characteristic frequencies in this manner. The equations are approximations, in reality a fault may cause a larger change to other frequencies. Also, some of the characteristic frequencies might be masked by other noise sources in the motor which make the characteristic frequencies unusable for the monitoring. Thus, a method for finding discriminative frequencies automatically in signals would be useful. In addition, automatically discovered frequencies could be used for verifying models of faults, such as the bearing fault characteristic frequency equations.

III. Identifying System Condition

A. Condition States

A system condition state depends on operating parameters and system health. For example, in the case of induction motors the condition state changes when the load or motor speed changes (operating parameters), and also in response to faults or wearing of motor parts over a longer time (system health). Condition monitoring applications often work by first segmenting the signal to stationary parts and these are used to identify the current system condition [8].

In the following discussion it is supposed that the motor condition stays stationary during measurement, i.e., there are no changes in load or speed. In practice, the operating conditions change and segmentation is needed to distinguish between changing conditions. Segmentation has been studied in the case of stator current monitoring in [2].

B. Feature Selection

Feature extraction is used to find simple features describing the measured signals. Subsequently, best features and their parameters for classification can be selected using discriminative energy functions.

Two sets of signals, $x_k(t)$ and $y_k(t)$, represent examples from two classes, C_1 and C_2, respectively. The sub-index k denotes a measurement number, $k = 0, 1, \ldots, N_1 - 1$ for C_1 and $k = 0, 1, \ldots, N_2 - 1$ for C_2. It is assumed that the signals are measured during the same system mode, i.e., operating parameters such as rolling speed and load are constant, and that the discriminative information is present at a frequency band where the behavior of the two types of signals differs. With these assumptions, it is sufficient to apply a bandpass filter $\psi(t)$ and the two classes can be distinguished based on filter responses. Furthermore, since the state is constant, it is assumed that the signals are stationary and, thus, the time information can be ignored and global information such as power spectra

$$\int_{-\infty}^{\infty} |\psi(t) * x_k(t)|^2 dt \quad \text{and} \quad \int_{-\infty}^{\infty} |\psi(t) * y_k(t)|^2 dt \tag{8}$$

can be utilized. Because of the assumptions concerning the type of discriminative information, the problem is reduced to finding the optimal values for the central frequency f and bandwidth γ of a bandpass filter. A normalized Gabor filter (e.g., [9]) can be used as the bandpass filter ψ. A normalized Gabor filter can be defined as

$$\psi(t) = \frac{|f|}{\gamma\sqrt{\pi}} e^{-(\frac{f}{\gamma})^2 t^2} e^{j2\pi f t} \tag{9}$$

where f denotes the central frequency and γ controls the time duration and frequency bandwidth of the filter.

IV. Statistical Discriminative Measures

Statistical discriminative measures are used to find differences between signals. Discriminative energy functions should have large responses on filter parameter (f, γ) values which provide a good discrimination of signals [10].

A. First-Order Statistics

If the dominant difference between two classes is simply their magnitude level on some frequency band, the first-order statistics are sufficient. The features are extracted using the power spectra in (8) and the expectation values $E[\cdot]$ of the power spectra act as a basis for the discrimination

$$\begin{aligned} \mu_x &= E\left[\int_{-\infty}^{\infty} |\psi(t) * x_k(t)|^2 dt\right] \\ \mu_y &= E\left[\int_{-\infty}^{\infty} |\psi(t) * y_k(t)|^2 dt\right]. \end{aligned} \tag{10}$$

A new signal is classified to a class whose expectation value is closer to the energy of the filtered signal and, thus, the farther apart the expectation values μ_x and μ_y are in (10), the more discriminative they are. Now, a discrimination energy function can be formed by calculating the distance between the expectation values of the two classes

$$E_1 = \frac{1}{2}(\mu_x - \mu_y)^2. \tag{11}$$

B. Second-Order Statistics

If there are several frequency bands where the contents of the classes C_1 and C_2 are dissimilar, then the band where the separation of the classes is most evident should be selected. The first-order approach (E_1) simply selects the frequency band where the distance between the expectations is largest, but neglects the variance information, and thus, a significant overlap of the class probabilities may exist. The second-order statistics can be utilized to find a solution where distributions of the features are as separate as possible.

In the second-order statistics an assumption must typically be made about forms of probability distributions $p_x(n)$ and $p_y(n)$ of the two classes which describe the deviation of the feature values.

It was assumed in this study that the features are extracted from signals measured during a constant operation mode where the variance in the measurements is caused by a large number of unknown independent sources. It can, thus, be assumed that the form of the probability distribution of the measurements is Gaussian. If the distributions $p_x(n)$ and $p_y(n)$ are Gaussian, both classes are uniquely defined by their expectations (μ_x, μ_y) and variances

$$\begin{aligned} \sigma_x^2 &= E\left[\left(\int_{-\infty}^{\infty} |\psi(t) * x_k(t)|^2 dt - \mu_x\right)^2\right] \\ \sigma_y^2 &= E\left[\left(\int_{-\infty}^{\infty} |\psi(t) * y_k(t)|^2 dt - \mu_y\right)^2\right]. \end{aligned} \tag{12}$$

Fisher's discriminant ratio (FDR) can be used for the Gaussian probabilities to measure the distance between the distributions [11]

$$\mathrm{FDR}(p_x(n), p_y(n)) = \frac{(\mu_x - \mu_y)^2}{\sigma_x^2 + \sigma_y^2}. \tag{13}$$

Using the divergence measure in (13) a discriminative energy function can be defined as

$$E_3 = \frac{1}{2}\left(\frac{(\mu_x - \mu_y)^2}{\sigma_x^2 + \sigma_y^2}\right)^2. \tag{14}$$

For compatibility with previous studies, E_1 and E_3 are used to denote the discriminative energy functions [12]. Using the discriminative energy functions, the optimal filter parameters can be drawn from

$$\arg\max_{\gamma,\ f} E_i \tag{15}$$

using the gradient information.

C. Classifying New Signals

Since the sample probability distributions are established, it is natural to use a Bayesian classifier to classify the new signals. Features used to establish the classifier are the bandpass filtered power spectra of measurements $x_k(t)$ and $y_k(t)$ in (8) belonging, respectively, to the classes C_1 and C_2. The distributions are defined by the expectation values and variances, and a new sample can be classified based on its maximal class specific posteriori value by the Bayesian classification rule [10]. The *posteriori* value acts also as a confidence value.

D. Practical Considerations

1) Efficient Implementation: Computing the numerical values of the discrimination energy functions E_1 and E_3 in (11) and (14) may turn out to be very time consuming if the number of signals, N_1 and N_2, or the discrete length of the signals is large.

For discrete signals, the computation of the expectation values in (10) can be reduced to the equations

$$\mu_x = \frac{1}{N_1}\sum_k \sum_u \Psi^2(u) X_k(u) X_k^*(u)$$
$$\mu_y = \frac{1}{N_2}\sum_k \sum_u \Psi^2(u) Y_k(u) Y_k^*(u) \quad (16)$$

where $\Psi(u)$, $X_k(u)$, and $Y_k(u)$ are the Fourier transforms of $\psi(t), x_k(t)$, and $y_k(t)$, and N_1 and N_2 are the number of signals in the classes C_1 and C_2. Exact numerical values of the mean values μ_x and μ_y used by both E_1 and E_3 can be computed efficiently. The value of $\Psi(u)$ does not depend on k in the calculation of μ_x and μ_y in (16). Thus, computation of values

$$\frac{1}{N_1}\sum_k X_k(u) X_k^*(u) = X(u)$$
$$\frac{1}{N_2}\sum_k Y_k(u) Y_k^*(u) = Y(u) \quad (17)$$

can be made in advance, and now

$$\mu_x = \sum_u \Psi^2(u) X(u)$$
$$\mu_y = \sum_u \Psi^2(u) Y(u). \quad (18)$$

A fast calculation of the variances σ_x^2 and σ_y^2 in E_3 is more difficult because the terms cannot be separated. Other than near the central frequency f the Gabor filter coefficients are, however, negligible. Therefore, a good estimate of the variances can be calculated by including only an interval where the filter yields at least some minimum response ϵ as

$$\sigma_x^2 = \frac{1}{N_1 - 1}\sum_k \left[\sum_{u \in U_\epsilon} \Psi^2(u) X_k(u) X_k^*(u) - \mu_x\right]^2,$$
$$\sigma_y^2 = \frac{1}{N_2 - 1}\sum_k \left[\sum_{u \in U_\epsilon} \Psi^2(u) Y_k(u) Y_k^*(u) - \mu_y\right]^2$$
$$U_\epsilon = \{u \mid \Psi(u) \geq \epsilon\}. \quad (19)$$

2) Measuring Gaussianity: Since the current method is based on the Gaussianity assumption it must first be verified. Kurtosis is a fourth-order statistic and has been used to examine Gaussianity of distributions. Normalized kurtosis with adjustment to bias is [13]

$$k(x) = \frac{E\{(x-m)^4\}}{[E\{(x-m)^2\}]^2} - 3 \quad (20)$$

where m is the mean of x. Kurtosis is zero for Gaussian distribution. Distributions having negative kurtosis are sub-Gaussian, e.g., uniform or multimodal distributions, and positive kurtosis are super-Gaussian. A typical super-Gaussian distribution has a sharp peak and long tails.

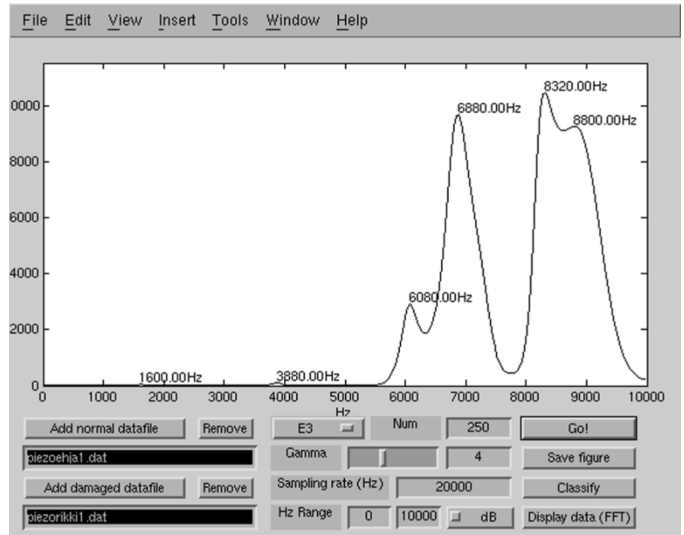

Fig. 2. Diagnosis tool user interface (UI).

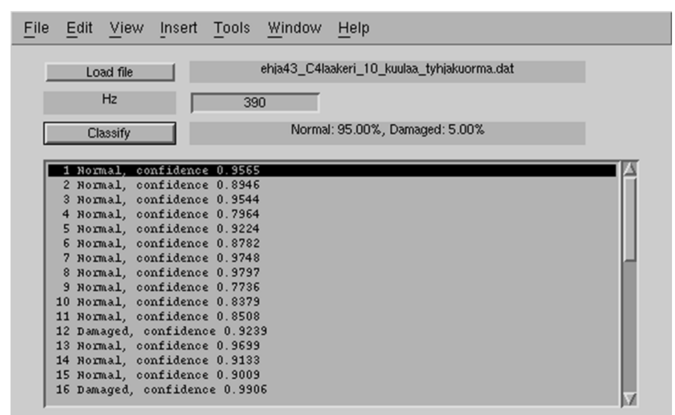

Fig. 3. Diagnosis tool classifier UI.

V. Diagnosis Tool

The proposed tool can be used to find discriminative frequencies between two classes of signals. The tool can also be used for verification of existing theories by checking if the discriminative energies are found at correct frequencies [14].

A diagnosis tool was implemented based on the proposed discriminative energy functions. The tool can be used to find optimal filter parameters in (15) to discriminate between two different conditions.

The tool shown in Fig. 2 is intended for use by diagnosis engineering researchers. The user can inspect differences in power spectra of two classes using discriminative energy functions (11) and (14). Furthermore, new signals can be classified based on the stored signal data using a classifier module (Fig. 3). The user can manually select frequency and bandwidth or the tool can automatically search for the most discriminative frequency and bandwidth. The classifier gives also a confidence value for the classification result (Bayesian *posteriori*).

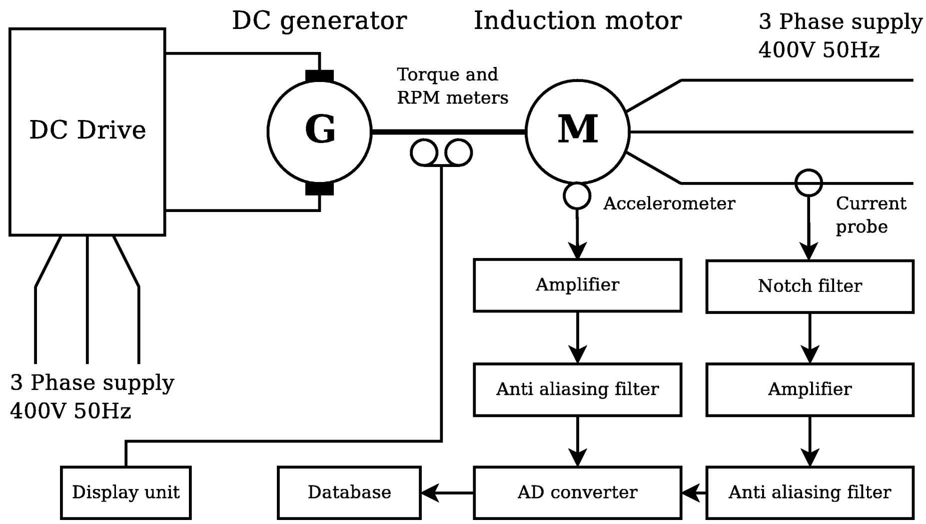

Fig. 4. Measurement system configuration for bearing damage detection.

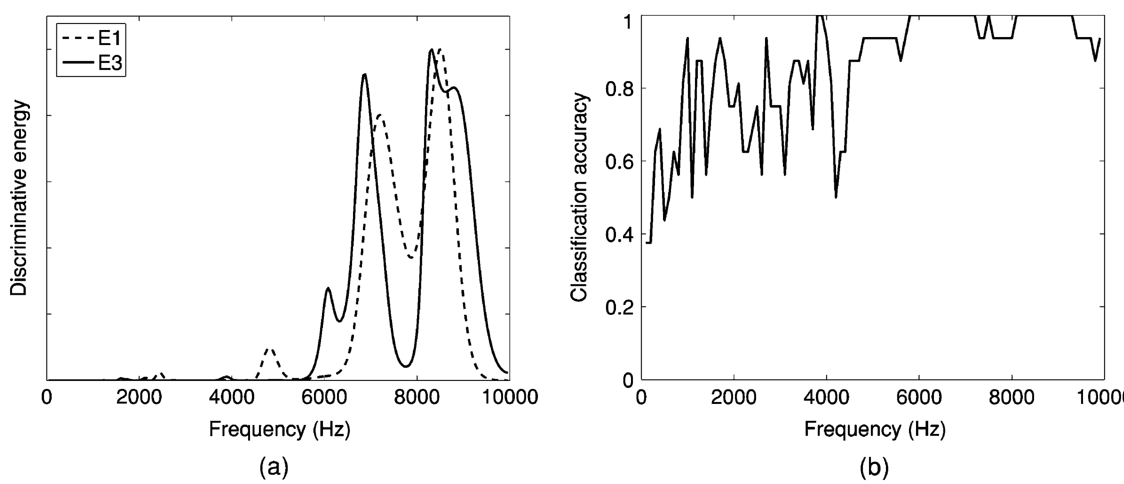

Fig. 5. Discriminative energy functions and Bayesian classification accuracy for motor vibration measurements of induction motors. (a) E_1 and E_3. (b) Bayesian classifier.

VI. Experiments

A. Experimental Setup

In the experimental setup, a 15-kW four-pole induction motor (ABB M2 AA 160 L4) was loaded with a converter-driven dc motor. The motors were connected together with a toothed belt and a bearing-supported axle with a band coupling. The bearings of the induction motor were single-row deep groove ball bearings, type 6209. Measurements were recorded for eight bearings: three healthy and five with radial holes of 2 or 5 mm in the outer race. The bearings were of three different types of internal radial clearance. The clearances of the tighter bearings were less than 20 μm from the center position. The clearances of the looser bearings were between 30–45 μm. The motor air-gap length was 0.5 mm. The stator current was measured from one phase with a current clamp. A notch filter with stop bands at 50, 250, and 350 Hz was used in order to decrease the total amplitude of the signal before a 16-bit AD conversion with a sampling frequency of 3 kHz. In addition, radial vibration was measured with a piezoelectric accelerometer in order to verify the actual bearing pass frequency (analysis was done using the envelope spectrum method). The measurement configuration is illustrated in Fig. 4.

B. Bearing Damage Detection Based on Motor Vibration

The data used for bearing damage detection based on motor vibrations consisted of measurements of motors in a normal condition (C_1) and motors with bearing damage (C_2). Both classes contained eight measurements of a duration of 1.65 s with a sampling rate $f_s = 20$ kHz.

The results for discriminative energies E_1 and E_3 with classification results are presented in Fig. 5. Classification was conducted using the Bayesian classifier leaving one measurement out at a time, repeating for all measurements. Both discriminative energy functions have clear peaks near 7000 and 8500 Hz [Fig. 5(a)]. The classification accuracy is 100% with the same frequencies. Theoretically, the characteristic frequency of the bearing fault (101 Hz) should have a clear discrimination between normal and damaged bearings, but in practice the motor's mechanical vibration characteristics prevent this and, in addition, other vibration factors disturb the low frequencies.

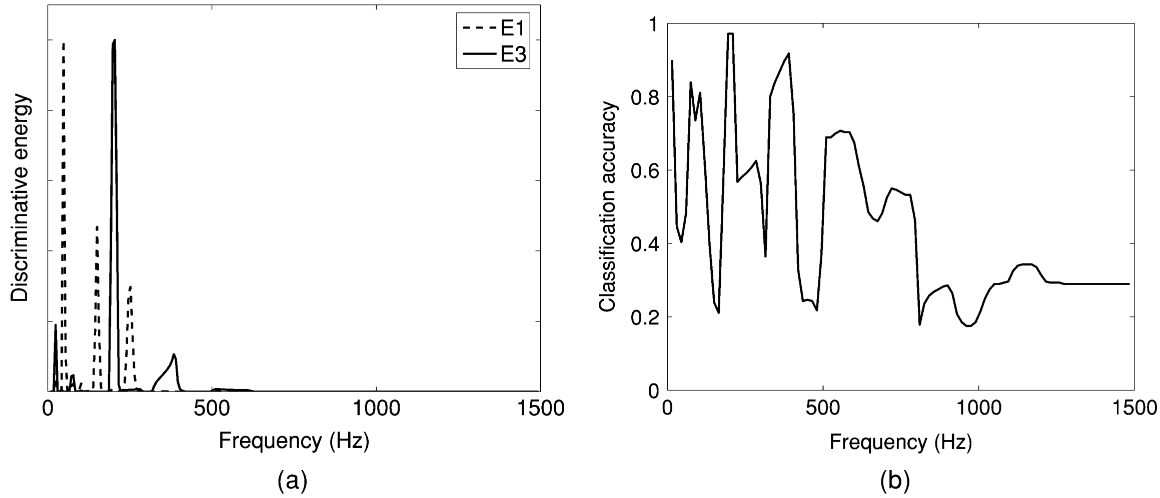

Fig. 6. Discriminative energy functions and Bayesian classification accuracy for stator current signals of induction motors with large bearings (minimum internal clearance 30 μm), big bearing failure (5-mm hole), and without load (characteristic frequency approximately 101 Hz). (a) E_1 and E_3. (b) Bayesian classifier.

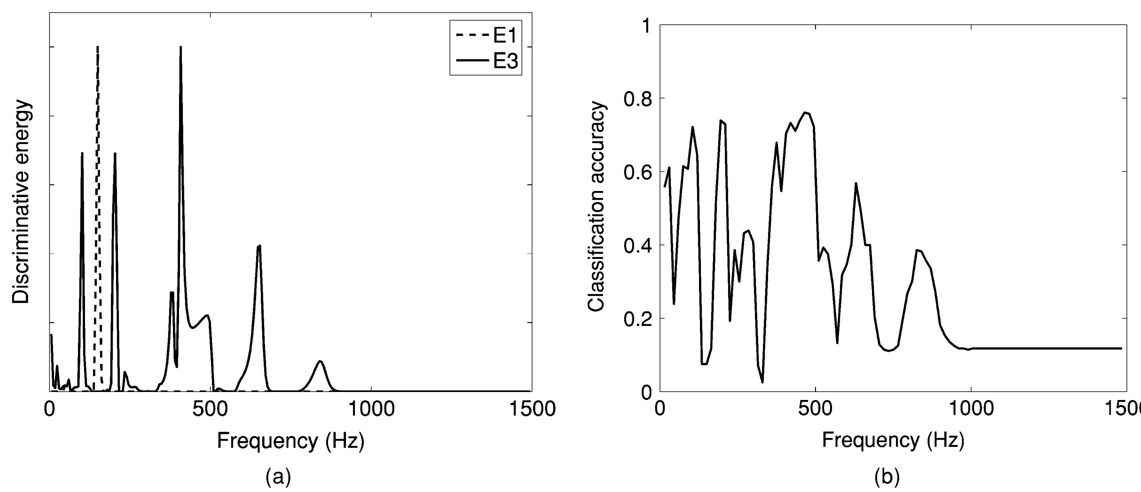

Fig. 7. Discriminative energy functions and Bayesian classification accuracy for stator current signals of induction motors with large bearings (minimum internal clearance 30 μm), big bearing failure (5-mm hole), and with load (characteristic frequency approximately 101 Hz). (a) E_1 and E_3. (b) Bayesian classifier.

However, a damaged bearing appears to cause a very clear effect at high frequencies, which leads to both E_1 and E_3 finding discriminative frequencies.

C. Bearing Damage Detection Based on Stator Current

The data used for the stator current experiments consisted of stator current signals measured with motors in a normal condition (C_1) and motors with bearing damage (C_2). Measurements were done with no load connected to the motor and with a full load. For both cases there were 280 measurements, 160 belonging to C_1 and 120 to C_2, of a duration of 11.0 s with a sampling rate $f_s = 3000$ Hz. The measurements were divided into groups of 40 based on the measurement setups and the Bayesian classification was done by leaving a set of 40 measurements out at a time, repeating for all sets.

Discriminative energies E_1 and E_3 and classification results for motors with no load are presented in Fig. 6. In this case, discriminative energy peaks by E_1 and E_3 are at clearly different frequencies. The first-order statistic-based E_1 does not seem to find meaningful discriminative information from the data, but emphasizes the motor supply frequencies. The second-order statistic E_3 has its maximum near the first harmonic (202 Hz) of the damage characteristic frequency (101 Hz). The Bayesian classifier also has the maximum accuracy in the same frequency band.

TABLE I
CLASSIFICATION RESULTS

	No load		Full load	
	Frequency	Correct	Frequency	Correct
Characteristic freq.		97.9%		62.5%
1st peak of E_3	201.6 Hz	96.4%	408.0 Hz	73.4%
2nd peak of E_3	23.4 Hz	87.9%	101.4 Hz	70.0%
3rd peak of E_3	386.4 Hz	91.8%	203.4 Hz	80.4%
3 highest peaks of E_3		100.0%		77.1%

Discriminative energies E_1 and E_3 and classification results for motors with a full load are presented in Fig. 7. This is a much more difficult situation since the full load causes various disturbances, but it corresponds to the normal situation in industry. The characteristic frequency and its harmonics have almost the same discriminative information E_3 [Fig. 7(a)]. The classification accuracy was maximal at a few characteristic frequency harmonics, but is considerably worse than without load [Fig. 6(b)].

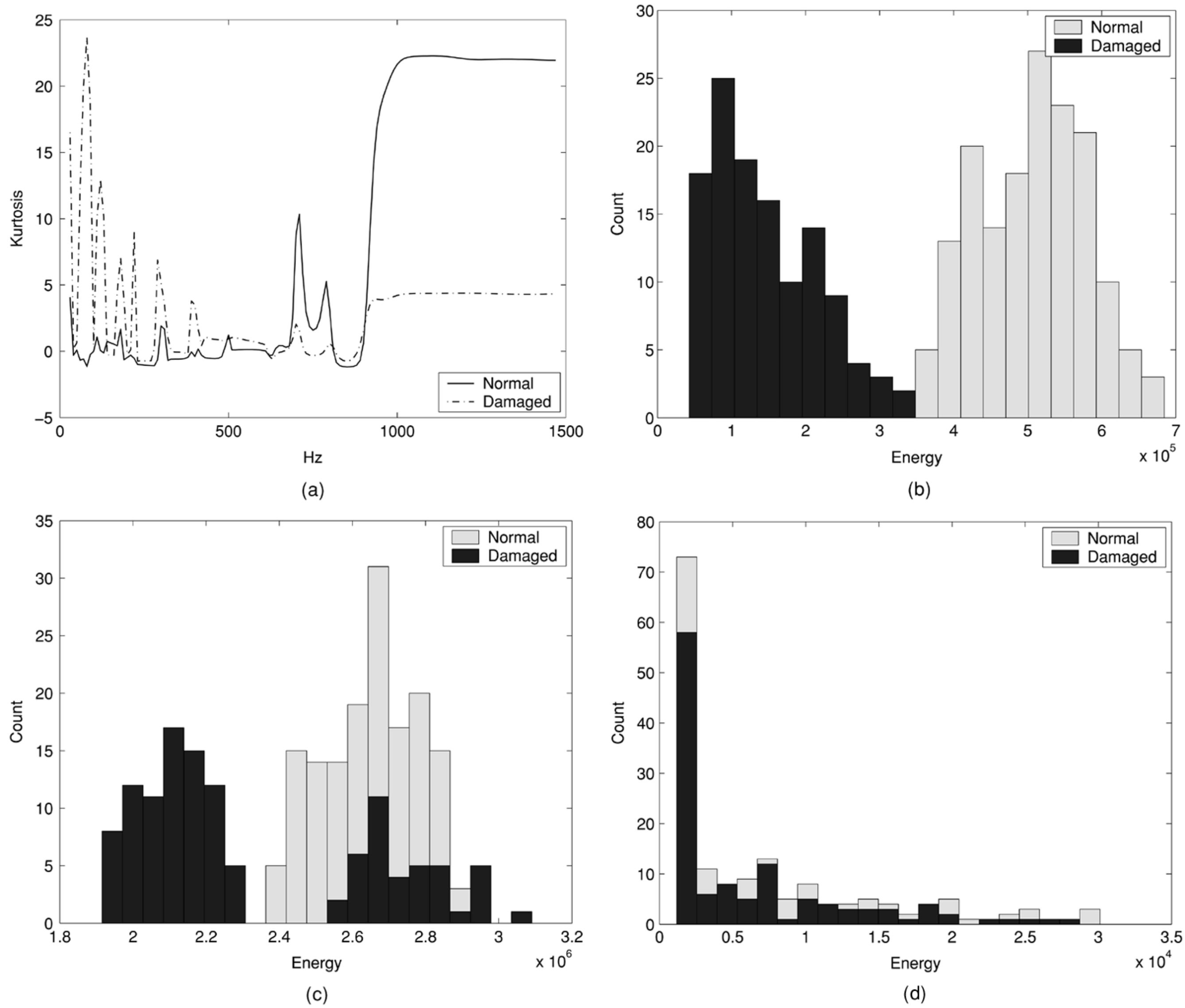

Fig. 8. Stator current measurements. (a) Kurtosis of features. (b) Features of two classes at 200 Hz (Gaussian). (c) Features of two classes at 420 Hz (multimodal). (d) Features of two classes at 1120 Hz (non-Gaussian).

In both of these cases there was a clear difference between E_1 and E_3. E_1 tends to find frequencies with the highest power and does not take into account that frequencies may often also have a high variation which makes them an unreliable choice for classification. On the other hand, E_3 also considers variations and, thus, the frequencies it finds often have more relevance for classification. In both cases E_3 provided frequencies with the best accuracy in the classification. Furthermore, E_3 verified the characteristic frequency theory of bearing failures [1].

D. Comparative Results

For comparison the stator current based tests were conducted by utilizing the characteristic frequencies in (5)–(7). These frequencies have been successfully used for the detection of bearing failures, for example, by Yazici and Kliman in [2].

Only the selection of frequencies used for classification was changed while other details were kept the same: the calculated characteristic frequencies were used instead of frequencies selected by the discriminative energy functions. Ten frequency components were calculated from (7) and features at the calculated frequencies were classified with the Bayesian classifier.

The classification results at frequencies selected by the discriminative energy functions and bearing damage characteristic frequency equations are presented in Table I. Classification was done using the three highest peaks of E_3, both separately and combined, and compared to the classification results for the characteristic frequencies. Characteristic frequencies provided an accuracy of 97.9% correct classification for motors with no load. The classification with the most discriminative frequency of E_3 provided a slightly worse accuracy of 96.4%, but 100% accuracy was achieved for a combination of the three most discriminative frequencies. For motors with full-load classification with characteristic frequencies provided an accuracy of only 62.5% while all of the three most discriminative frequencies provided better classification, up to 80.4%.

E. Verifying Gaussianity

The Fisher discriminant is based on the Gaussian probability densities. For other density types densities must be explicitly estimated, for example, by using Gaussian mixture models, and the Fisher discriminant must be replaced, for example, with the Kullback–Leibler divergence (E_2 in [15]). However, this study was limited to Gaussian distributions, and now validity of the Gaussian assumption is considered in the conducted experiments.

For the stator current data, the Gaussianity was measured with kurtosis in (20). Kurtoses of the two classes are shown in Fig. 8(a). At certain frequencies kurtosis deviates significantly from zero and for those frequencies also the divergence measures fail and the classification cannot provide accurate results. However, by inspecting feature values at locations where discriminative energy is maximal one can observe small kurtosis and also good separation of the two classes [Fig. 8(b)]. By inspecting other parts where kurtosis is large, e.g., due to multimodality [Fig. 8(c)] or non-Gaussian distributions [Fig. 8(d)], it seems that no better classification accuracy could be achieved and the assumption of the type of discriminative information seems to be correct.

Without the load connected to the motors, the results were very accurate and classification accuracy of 100% was achieved at best. With full load the results were significantly worse, about 80% at the best. However, the results using the most discriminative frequencies found by E_3 were clearly better than those using the theoretical characteristic frequencies used in literature.

VII. Conclusion

In this paper, a tool for condition diagnosis was proposed. The tool aims to be generic and not tied to a specific application; it can automatically find frequencies and bandwidths that discriminate between any two signal sets. The most obvious use of the tool is verifying models that describe behavior and physical causes of mechanical failures. The usability was verified with real data in the conducted experiments where consistent results with theory were achieved: the tool found the bearing damage characteristic frequencies or their harmonics.

There are also many potential improvements; for example, the stationary assumption of signals can be relaxed by applying a segmentation to handle also nonstationary signals. The method also lacks generality due to its Gaussianity assumption, but it still succeeds in many practical situations. The Gaussianity limitation can be overcome by the proposed extensions using Gaussian mixture models and the Kullback–Leibler divergence. These improvements will be studied in the future versions of the tool.

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