Psychoacoustic Approach to Machine Fault Diagnosis

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A method for machine diagnosis, based on acoustic signals, is proposed. The method is based on psychoacoustic modelling, which simulates the ability of human aural analysis. The solution approach combines psychoacoustic pre-processing, feature-extraction modules, and feature-evaluation modules. Feature-extraction methods are defined for the detection of stationary and dynamic acoustic phenomena. Stationary features are appropriate for diagnosing machines that emit continuous sounds, and defects are reflected in altered sound patterns. Dynamic features are suitable for the detection of transient phenomena, such as collisions, etc. Statistical procedures, based on asymmetrically defined fault-detection margins, are proposed for an evaluation of extracted features. An application of the method for the diagnosis of industrially produced compressors is discussed. Noxious space defect and lubrication defect are diagnosed by a stationary approach during the normal operation of compressors. Various mechanical defects in the supporting spring system are diagnosed by extracting dynamic features for collision detection. Compressor defects are successfully recognised through the proposed method.

1. INTRODUCTION

Modern industrial production, based on machining processes, requires reliable condition-monitoring procedures. Through the proper monitoring of machines, a harmful machine breakdown and, consequently, a loss of production can be prevented. Various sensory signals – such as acoustic emission, temperature, vibration, and forces – can be monitored in order to estimate the machine's condition.[1,2] Machinery fault diagnosis, based on vibroacoustic signals, is currently receiving considerable attention.[3-5] Components of rotating machinery that suffer from wear can be diagnosed through the appropriate methods.[6-8]

Machine-structure-borne sound is also very informative for condition monitoring and fault diagnosis. Human operators can often diagnose machine defects while the machine is in operation, by simply performing an aural inspection. Such a method requires a clear distinction between sound patterns of normal and abnormal machine operation. Various successful applications of acoustic-based machine fault detection are reported in the literature. Tsao et al. applied a neural network to acoustic signatures of induction motors in order to recognise motor faults.[9] Li et al. proposed a neural-network-based expert system for machine fault diagnosis in which acoustic power spectra and statistical moments were used as input features.[10] Sound analysis with an extraction of features for particular defect types was proposed by Benko et al. and the method was applied to a vacuum cleaner fault diagnosis.[11] Lin applied a Morelet wavelet, for the extraction of the features of machine sounds for the purposes of machine fault diagnosis.[12] An application of a hidden Markov model, which is a successful method for speech recognition, was proposed for the diagnosis of mechanical faults.[13] The idea of an electronic stethoscope was proposed by Tse et al., in which a direct analysis of machine sound for machine fault diagnosis is based on continuous wavelet transformation and on trajectory parallel measures.[14]

In this paper, we propose a method for automatic acoustic-based machine diagnosis that resembles an artificial ear. The method is based on psychoacoustic modelling, which describes the ability of human aural analysis.[15] Psychoacoustic models combine several signal-processing stages for simulating aspects of transformation in the auditory periphery.[16] A pre-processing stage combines an array of independent band-pass filters with signal rectification and with low-pass filtration. This stage roughly simulates the transformation of mechanical oscillations of the basilar membrane into receptor potentials in the inner hair cells. Further stages combine non-linear adaptation for compression and high sensitivity for fast temporal variations. Finally, signals are analysed by a decision device.

The proposed method combines psychoacoustic modelling with simple signal-processing routines. The method is suitable for detection of both stationary and dynamic acoustic phenomena. For the former, faults can be detected in machines that emit continuous sounds, – defects occur only as slight alterations from a basic buzz pattern. For the latter, dynamic acoustic phenomena, such as transients caused by collisions and other events, can be detected.

This article is organised as follows: a solution approach is introduced first, which is followed by a description of psychoacoustic pre-processing. The next section presents feature-extraction methods for detecting stationary and dynamic acoustic phenomena. Extracted features are then evaluated by statistical procedures that diagnose a normal or faulty state. A section with industrial applications presents two case studies that illustrate stationary and dynamic sound recognition. Both case studies address the production of commercial compressors and focus on the recognition of various defect types.

2. SOLUTION APPROACH

The proposed method of automatic aural detection of machining phenomena consists of three successive modules which are schematically shown in Fig. 1.

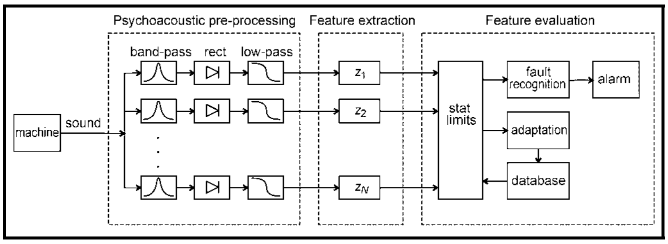

Figure 1. Solution approach to automatic aural machine fault diagnosis.

Acoustic signals are first pre-processed by a psychoacoustic module that includes a series of band-pass filters, half-wave rectifiers, and low-pass filters. This results in low-pass filtered envelopes for each frequency band. The envelopes are fed into a feature-extraction module, where informative features, characteristic of either stationary or transient phenomena, are extracted through simple signal-processing steps. The feature-evaluation module combines a comparison of extracted features with a database, the detection of faulty conditions, the adaptation of a database, and a possible alarm.

3. PSYCHOACOUSTIC PRE-PROCESSING

The input stage of the psychoacoustic pre-processing module consists of an auditory gammatone filter bank, as proposed by Patterson et al.[17] The gammatone filter bank roughly simulates the transformation of mechanical oscillations of the basilar membrane into receptor potentials in the inner hair cells. The filter bank is designed as a set of parallel band-pass filters, in which each is tuned to a different frequency.

The efficient filter bank implementation by Slanley was used in our analysis.[18] The filter bank is defined by the following parameters: sampling frequency f_s, starting frequency f_0, and number of filters N. An example of a gammatone filter bank ($f_s = 20$ kHz, $f_0 = 300$ Hz, $N = 20$) is shown in Fig. 2.

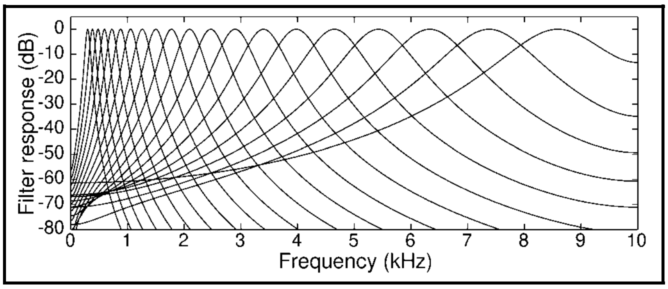

Figure 2. Gammatone filter bank ($f_s = 20$ kHz, $f_0 = 300$ Hz, $N = 20$).

After band-pass filtering, the filtered signals are half-wave rectified and low-pass filtered at 1 kHz. Low-pass filtered envelopes are defined by:

$$\varepsilon_n = \Phi_L(R(\Phi_B(x,n))); \quad n = 1,\ldots,N. \tag{1}$$

Operators denote the band-pass filter as Φ_B, the half-wave rectifier as R, and the low-pass filter as Φ_L, while they denote x as the acoustic input signal. This stage roughly simulates the transformation of mechanical oscillations of the basilar membrane into receptor potentials in the inner hair cells. Low-pass filtering, essentially, preserves an envelope of a signal for high carrier frequencies. Low-pass filtered envelopes are a final product of psychoacoustic processing and are then fed into feature-extraction and feature-evaluation modules.

Further stages of psychoacoustic models are not included in our analysis, although they could potentially improve the fault diagnosis ability for dynamic events. An example of a potentially interesting stage is a chain of feedback loops that form a non-linear adaptation that compresses stationary signals and reinforces rapid acoustic fluctuations.[19]

4. EXTRACTION OF FEATURES

The input of the feature-extraction module is low-pass filtered envelopes for each frequency band (ε_n; $n = 1,\ldots,N$). The objective of this module is to generate a vector of informative features (z_n; $n = 1,\ldots,N$) of a reduced dimension compared to the original signals. Such features are more convenient for the evaluation of possible machine faults. We propose feature-extraction methods for stationary and dynamic acoustic phenomena and define simple scalar features for each frequency band.

4.1. Detection of Stationary Phenomena

Stationary diagnosis of machine defects is suitable for machines that emit continuous sounds, − defects occur as slight alterations for a base sound pattern. In such a case, the averaging of low-pass filtered envelopes will result in an average contribution of each frequency band to the overall sound power. Features for the detection of stationary phenomena are defined as mean values of low-pass filtered envelopes:

$$z_n = \overline{\varepsilon_n}; \quad n = 1,\ldots,N. \tag{2}$$

In this case, dynamic components of the envelopes are neglected and features z_n resemble a spectral analysis. The main differences are in the considerable overlapping of frequency bands and the non-uniform frequency scale, as in the case of extracted stationary features.

4.2. Detection of Dynamic Phenomena

Often, dynamic acoustic phenomena cannot be detected either in a basic acoustic signal or by spectral analysis. In contrast, filtered envelopes ε_n can reveal such events due to increased time-frequency resolution. An example is shown in Fig. 3, where a collision event occurs at time $t = 2.45$ s. The event is still audible but is masked in the environmental noise of the acquired acoustic signal. An envelope of the 19-th filter band (ε_{19}) clearly reveals the event.

Dynamic acoustic events can be detected by the maximum value of the particular signal envelope. A relative comparison of maximum value vs. median value is preferable due to an appropriate normalisation and adaptation to various signal levels. Consequently, we propose the following features for the detection of dynamic transient phenomena:

$$z_n = \log\left(\frac{\max(\varepsilon_n)}{\mathrm{median}(\varepsilon_n)}\right); \quad n = 1,\ldots,N. \tag{3}$$

Features, defined for the detection of dynamic events capture the transient signal peaks but are invariant to time information and to specific signal characteristics, such as shape of the transient, etc. Therefore, the proposed features are only a basic choice for an automated acoustic machine diagnosis application. Optionally, if higher detection accuracy is required, more complex features based on psychoacoustic signal preprocessing can be derived.

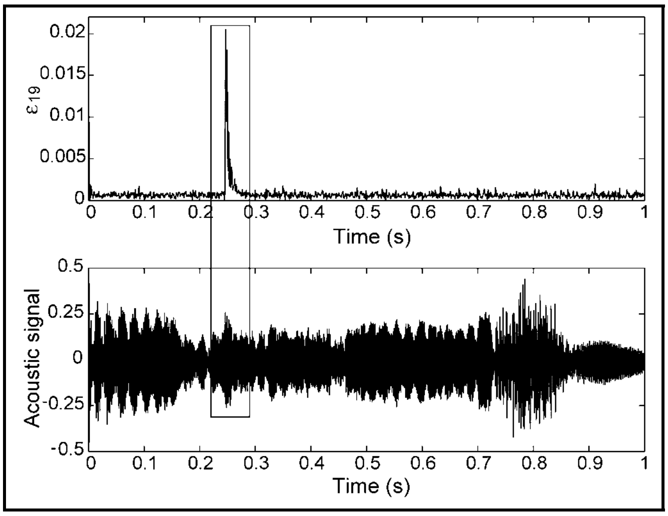

Figure 3. Example of an audible collision event that is hidden in the raw acoustic signal. The envelope of the 19-th filter band (ε_{19}) clearly reveals the event.

5. STATISTICAL EVALUATION OF FEATURES

Extracted features must be properly evaluated because thresholds of features have an essential influence on the diagnostic accuracy and sensitivity of the system.[20] A feature-evaluation module is responsible for statistical comparison of extracted features with a database of recorded features. A 1-class classifier case is discussed, in which a database consists only of features extracted from a regular machine operation. In this case, a statistical evaluation procedure must determine if novel extracted features differ considerably from the database and, if so, must indicate a possible machine fault.

Each extracted feature from a set $\{z_n;\ n=1,\ldots,N\}$ is evaluated separately by statistical comparison with the corresponding feature database. Statistical margins are defined in order to denote the range of regular machine operation. Values outside of this range indicate the presence of a machine fault.

If the distribution of features is normal, symmetrical $\pm 3\sigma$ margins can be applied, with σ indicating the standard deviation. In many practical applications, extracted features are not normally distributed, and, therefore, asymmetrical margins of permissible operation range are preferable. Some features extracted by the proposed method (Eqs. (2) and (3)) are often not informative and mainly represent noise. Such features can disturb the diagnosing process by indicating false alarms, which should be prevented by properly setting the margins. This can be accomplished by substituting the second moment in the calculation of the standard deviation by a generalised higher moment. This results in broadening the margins for very noisy features.

Consequently, we define the permissible operation range based on separate asymmetrical calculations of high (σ_+) and low (σ_-) margins that are calculated by generalised higher moments of features. The margins are defined for each feature separately by the following equations:

$$\sigma_+ = m + s\left(\overline{(z_+ - m)^p}\right)^{1/p}; \tag{4}$$

$$\sigma_- = m - s\left(\overline{(m - z_-)^p}\right)^{1/p}. \tag{5}$$

Symbols denote: median value m, features above median z_+, and features below median z_-. The calculation of margins is controlled by parameters s and p which denote the stretching factor and the generalised higher moment of the feature. For a normal distribution, values $s = 3$ and $p = 2$ correspond to $\pm 3\sigma$ margins. We propose to keep the default value $s = 3$ and to increase the p value to $p = 4$ which increases the robustness of the feature evaluation with respect to outliers in the feature space.

An example of setting the regular operation range margins for a database of extracted features is shown below. Figure 4 shows the standard statistical $\pm 3\sigma$ margins, and Fig. 5 shows the asymmetrical margins obtained by Eqs. (4) and (5). In the first case (Fig. 4), several false alarms are indicated, therefore the $\pm 3\sigma$ margins are not an appropriate choice. The selection of margins is considerably improved in the second case (Fig. 5).

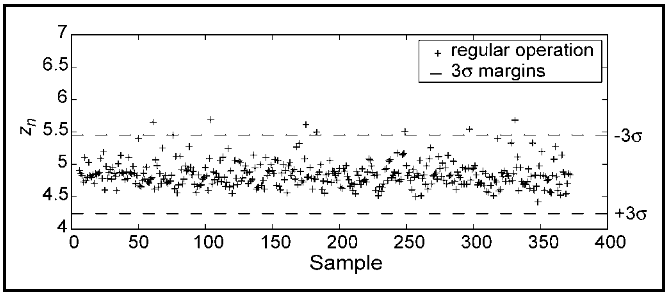

Figure 4. Population of extracted features with standard statistical $\pm 3\sigma$ margins.

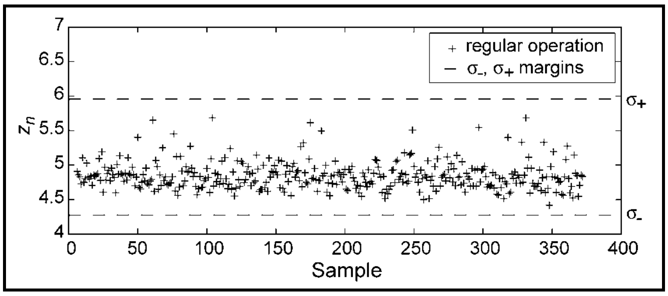

Figure 5. Population of extracted features with asymmetrical σ_+ and σ_- margins defined by parameters $s = 3$ and $p = 4$.

This article discusses a calculation of asymmetrical margins based on a complete database of regular samples. However, an online adaptation of margins based on recent machine states, is preferable in a case of frequent fluctuations due to process drift in a changing industrial environment.[21] In such a case, the most recent samples from the database have more impact on the calculation of margins.

The last step of the feature-evaluation module depends on the statistical evaluation result. An alarm is triggered in the case of a recognised machine fault. If the evaluation result indicates a regular faultless state, a database is updated with the most recent features. Thus, the calculation of asymmetrical margins in the next evaluation step will be based on the refreshed database.

6. INDUSTRIAL APPLICATIONS

An application of the proposed machine-diagnosis method to commercially produced compressors is presented. The industrial production of compressors at the company Danfoss Compressors, d.o.o., Slovenia, requires an accurate fault-detection system at the end of the production line. Completed compressors can only be inspected by non-destructive methods. At present, skilled human operators perform this by aural monitoring. Various neural-network-based approaches to automatic compressor fault diagnosis can be found in the literature.[22-25] This section describes the possibility of automatic aural diagnosis based on the proposed method.

6.1. Stationary Fault Detection in Compressors

Several defects that occur during the production process result in a modified sound pattern emitted by a running compressor. Such defects can be analysed through a stationary approach. Two types of stationary defects are considered:

1) Noxious space defect: caused by mechanical micro-particles on the piston surface.
2) Lubrication defect: caused by an abnormal amount of lubricating oil.

Both defects can deteriorate the performance of a compressor and shorten its lifespan. The experiments were performed on the production line at the company Danfoss Compressors, d.o.o. A set of compressors with built-in defects was prepared and inserted into the normal production line. Acoustic signals were recorded on a set of 332 normal compressors, 20 compressors with a noxious space defect, and 20 compressors with a lubrication defect. Signals were acquired at the top of the operating compressors with the sampling frequency $f_s = 20$ kHz in the time interval $[0.3 - 1.3]$ seconds after the compressors were switched on.

The objective of this task is to automatically recognise a faulty compressor based on its acoustic signature. The acoustic signals of each compressor are analysed by the proposed solution. The features are extracted by psychoacoustic filtering ($f_s = 20$ kHz, $f_0 = 300$ Hz, $N = 10$) and the results are shown in Fig. 6 together with asymmetrical fault-detection margins ($s = 3$, $p = 4$).

Figure 6 shows that a noxious space defect is automatically detected by features z_7 and z_{10}. A lubrication defect is best detected by features z_1 and z_5. All defective compressors are successfully recognised without triggering false alarms. Extracted features z_3 and z_4 are noisy and do not contribute toward fault detection. For noisy features, it is important not

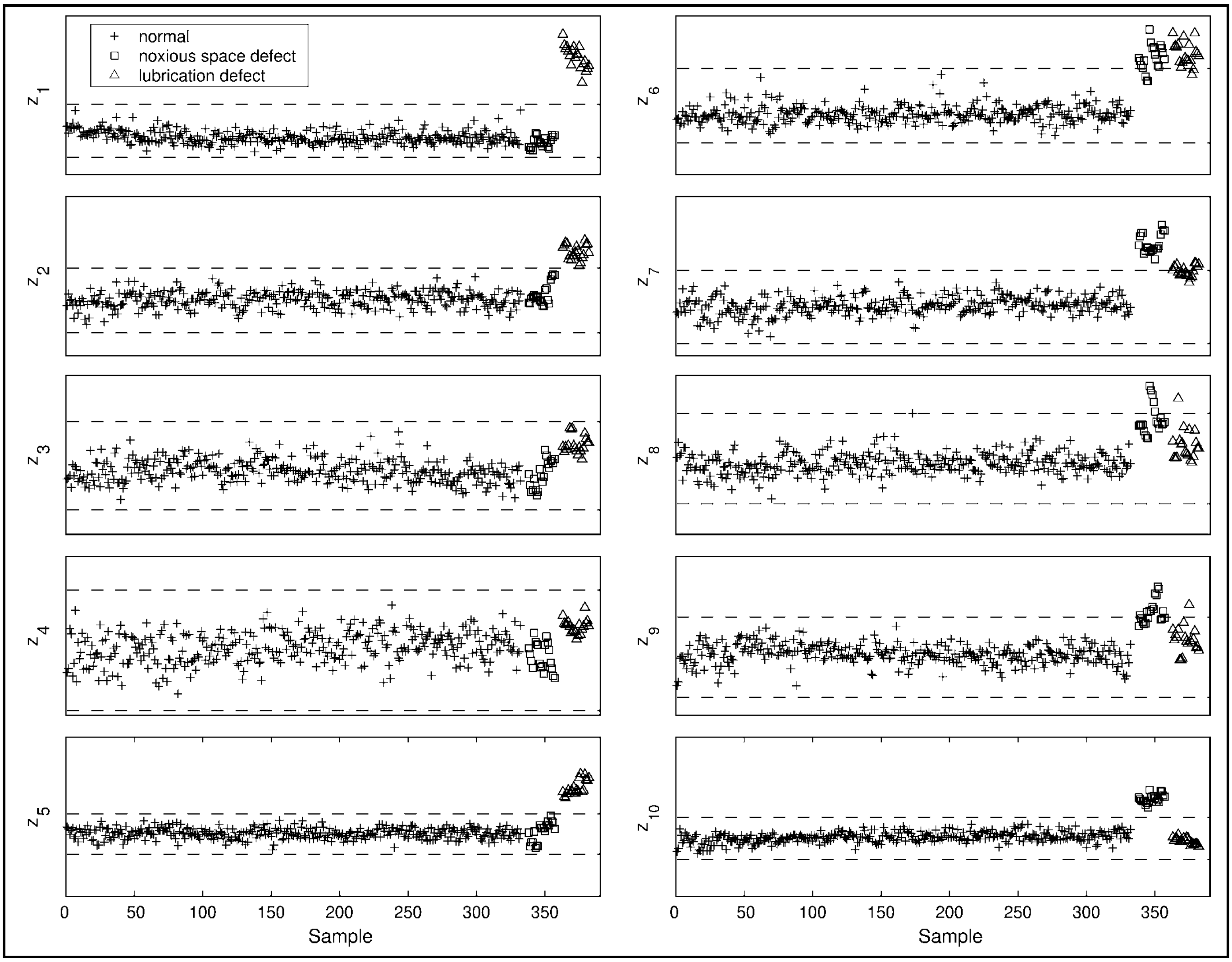

Figure 6. Extracted features ($f_s = 20$ kHz, $f_0 = 300$ Hz, $N = 10$) with asymmetrical evaluation margins ($s = 3$, $p = 4$) for the set of normal compressors, of compressors with a noxious space defect, and of compressors with a lubrication defect.

to trigger false alarms, and this is accomplished by applying the proposed feature evaluation procedure. It is evident from Fig. 6 that the activity of various features not only indicates a normal or defective condition but also the type of defect.

6.2. Dynamic Detection of Mechanical Defects in Compressors

Various mechanical defects cannot be detected during the normal operation of compressors. Mechanical defects considered here include displacements of supporting springs at the base of a compressor, as shown in Fig. 7.

There are four supporting springs (A, B, C, D), with possible displacements in various directions (1, 2, 3) or even a missing spring (4). A photo of a complete compressor group is also shown in Fig. 7. Because such defects are critical but not audible during the normal operation of a compressor, the additional dynamical inclination of a compressor is required. Industrial operators are checking for such defects by simple aural detection of collisions during the manual shaking of a compressor.

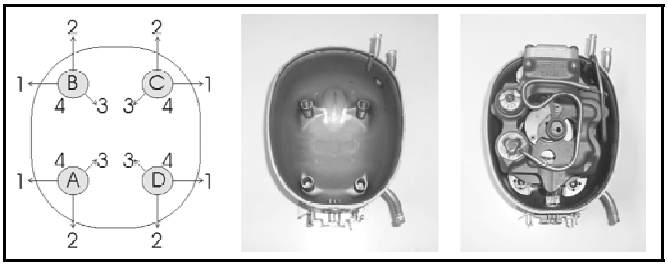

Figure 7. Mechanical defects in a compressor (top view). Possible defects are indicated for all four springs (A, B, C ,D); various displacement directions (1, 2, 3), or for a missing spring (4).

Experimental setup. For the purpose of automatic detection of spring displacements, an experimental rotary shaker was constructed, as shown in Fig. 8. The shaker is computer-controlled and driven by a step-motor. The experimental setting for the rotary part of the shaker was a rotation of 180 degrees in a time duration of 1 s. When a mechanical defect is present, the rotational swing of the compressor causes the collision of the compressor group into the housing. Audible collisions indicate the presence of a mechanical defect.

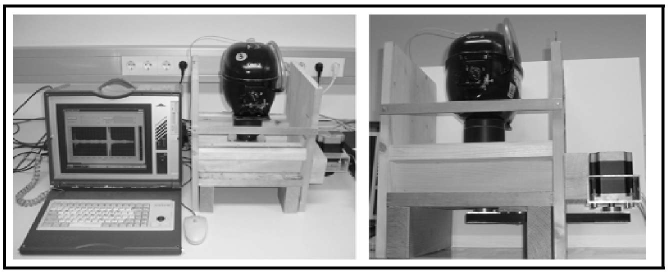

Figure 8. Computer-controlled rotary shaker for the detection of mechanical defects.

Experiments were performed with a set of normal compressors (denoted as G1, G2, …, G9) and with a set of compressors having spring dislocations (denoted as A1, …, A4, …, D1, …, D4). Compressors were switched off during the experiment. Sound emission was recorded by a magnetically attached microphone at the top of a compressor. Five measurements were recorded with every compressor defect. The compressor group with missing spring D4 did not collide with the housing due to the asymmetric positioning of the group in the housing and due to construction details of the rotary shaker. Consequently, we do not expect D4 compressors to indicate a defect and, therefore, exclude them from the evaluation.

Results. Acoustic signals are analysed by the proposed method for the detection of dynamic acoustic phenomena. Features are extracted by psychoacoustic filtering ($f_s = 20$ kHz, $f_0 = 1$ kHz, $N = 20$). Results are summarised in Fig. 9, where a number of detected faults for each feature z_n is shown. The results for a subset of features $\{z_1, z_2, z_3, z_{16}, z_{17}, z_{18}\}$ are presented in Fig. 10 together with asymmetrical fault-detection margins ($s = 3$, $p = 4$). None of the particular defects (75 samples) are detected by a single feature only, but all of them are detected by the mutual contribution of several features. Features in a higher frequency range ($z_{16}, \ldots, z_{20}$) are more informative for the detection of dislocated springs.

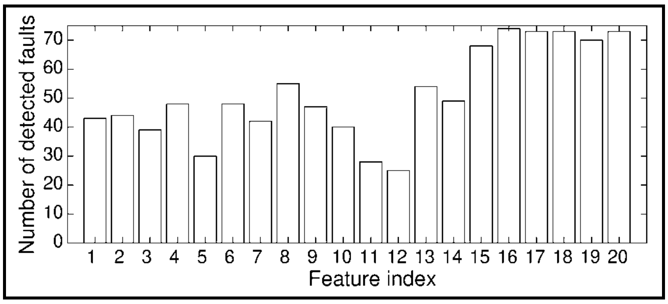

Figure 9. Number of detected faults for each extracted feature z_n, $n = 1, \ldots, N$.

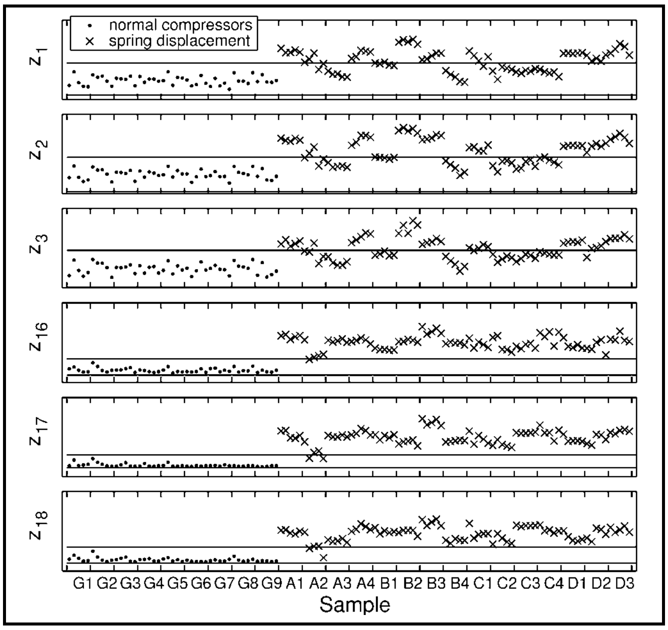

Figure 10. Subset of extracted features: $\{z_1, z_2, z_3, z_{16}, z_{17}, z_{18}\}$ with asymmetrical evaluation margins ($s = 3$, $p = 4$) for the set of normal compressors and compressors with spring displacement.

7. CONCLUSIONS

A system for automatic aural machine diagnosis is described. The system is based on psychoacoustic modelling that simulates human auditory perception. Acoustic signals are pre-processed by a gammatone filter bank, half-wave rectified, and low-pass filtered by 1 kHz. Stationary and dynamic features are extracted from signal envelopes by applying simple processing steps. Extracted features are evaluated in an evaluation module. Asymmetric fault-detection margins are proposed in order to prevent false alarms and to assure reliable diagnosing processes. The method is applied to the industrial production of compressors, where various mechanical defects in compressors are successfully diagnosed.

Psychoacoustic modelling is a promising tool for automatic machine diagnosis. Further research in this field is needed. Various stages of psychoacoustic models – for example, a chain of feedback loops for non-linear adaptation[19] – have not been analysed yet as a method for machine diagnosis. Such potentially interesting psychoacoustic steps could also contribute to the successful detection of machine defects.

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