Diagnostics and Prognostics Based on Adaptive Time-Frequency Feature Discrimination[1]

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This paper presents a novel diagnostic technique for monitoring the system conditions and detecting failure modes and precursors based on wavelet-packet analysis of external noise/vibration measurements. The capability is based on extracting relevant features of noise/vibration data that best discriminate systems with different noise/vibration signatures by analyzing external measurements of noise/vibration in the time-frequency domain. By virtue of their localized nature both in time and frequency, the identified features help to reveal faults at the level of components in a mechanical system in addition to the existence of certain faults. A prima-facie case is made via application of the proposed approach to fault detection in scroll and rotary compressors, although the methods and algorithms are very general in nature. The proposed technique has successfully identified the existence of specific faults in the scroll and rotary compressors. In addition, its capability of tracking the severity of specific faults in the rotary compressors indicates that the technique has a potential to be used as a prognostic tool.

Key Words: Diagnostic, Wavelet Packet, Time-Frequency Analysis, Noise and Vibration, Rotary Compressor, Scroll Compressor

1. Introduction

It has become an industry standard to provide parts and service warranty for durable products. It is not a surprising trend that a good warranty plan is not a market discriminator any longer but a market enabler. However, ever-increasing warranty or repair costs are directly reflected into the product price, which puts tremendous pressure on manufactures to develop efficient, reliable but still low-cost diagnostic/prognostic methodologies. To reflect on such a trend, the topic of diagnostic/prognostic has been extensively studied in recent years in several disciplines (Harrap and Wang, 1994 ; Cann, 1992 ; Meng and Qu, 1991 ; Thompson, 1983 ; Kim and Kim, 2000 ; Park and Lee, 1999 ; Park, 2000 ; Shim and Suh, 2002; Tahk and Shin, 2002). These diagnostic techniques have achieved remarkable successes in their specific applications. They can be classified based on the identification algorithms that unravel discriminating features.

Raw data from a mechanical system rarely exhibits discriminating feature (s) but buries the features. As a result, much identification work is focused on mapping relevant physical events to their signatures in the measured data. The data (signals) are measured in time-domain and are easily converted to frequency domain (FFT), where the analysis manifests some of the hidden features. However, certain physical events are not discernable in the classical approaches, since they are projecting essentially two-dimensional (time-frequency) information to one-dimensional (either time or frequency) subspace. Indeed,

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Meng and Qu (1991) used the celebrated Wigner distribution to detect a fault in rotating machinery. However, signal interference still deteriorates the resolution of the Wigner distribution, although alleviated by judicious selection of kernels. Wavelet analysis is the modern approach to time-frequency analysis that has drawn much attention in recent years. However, the commercially available tools for wavelet analysis (e.g., MATLAB toolbox, Wavelab, etc.) do not offer the resolution necessary for multiple feature identification in the frequency range necessary in certain diagnostic applications (Misti et al., 1996). Furthermore, while wavelet analysis can sometimes detect a specific, a priori known feature, it cannot be used in the general, multiple fault detection setting of realistic diagnostic/prognostic applications.

We propose a new feature identification methodology based on the more general wavelet-packet ideas, which can be subsequently combined with other classification techniques (e.g. neural network) to realize an efficient and reliable diagnostic tool. It provides fault classification algorithms with a qualitatively better tool that enables revelation of previously hidden features. The underlying key idea is to mass-produce alternate representations of a given signal, and then select the one that is best according to a certain metric (Euclidean distance or entropy). Using a dynamic programming approach, a best discriminating basis is obtained. Then we can rank the basis functions (waveforms) with respect to their contribution to the optimal (maximal) cost. By virtue of the time-and frequency-localized nature of wavelet-packets, the fault signatures can be identified at the physical component level. Considering that any practical diagnostic/prognostic technique has to rely on readily available measurements (e.g., external measurements obtained non-invasively) from which the component-level information is generally difficult to extract, such a capability provides the proposed technique with potential to complement the existing suite of diagnostic/prognostic techniques that yield fault or no fault information only.

The proposed technique is applied to discriminate between normal and different faulty components of scroll and rotary compressors. We achieve this aim by altering certain key components of a compressor and then measuring the external shell-vibrations (so-called seeded faults). The algorithms developed in this paper find the features that discriminate the modified compressor signal against the recorded baseline. They are related to physical components and behaviors in the compressor. In the demonstration we use compressor-shell vibrations and sound radiations (external measurements). These external measurements reveal faults at the physical component level by virtue of wavelet-packet analysis. Thus we have proven that our technique can be built around data collected with external accelerometers (noninvasive) and still can provide fault information at the internal component level, which is typically available only by disassembling the compressor (tear-down approach). The technique is also shown to track the severity of the faults, which indicates that it has potential to be used as a prognostic tool.

Section II briefly reviews the technical huddles of the existing techniques when applied in feature identification. Section III describes adaptive time-frequency analysis on which our proposed feature identification algorithm is based. In Section IV, the proposed technique is shown to identify faults in scroll and rotary compressors.

2. Technical Challenges in Feature Identification

Classical methods of feature identification rely on either time-series or spectral analysis of the signal. These approaches have their own limitations since the time-series data in itself is incomprehensible and the spectral data lacks information about the time localization of important events. A compromise is the short time (or windowed) Fourier analysis, but this technique is very limited in time localization. The energy of a signal measured off a rotary compressor shell is represented in Figure 1.

An alternative is to know (guess) a parametric

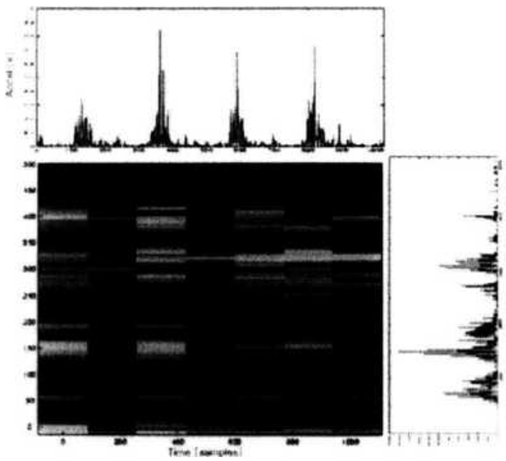

Fig. 1 Time (top), frequency (right) and time-frequency representations of the same signal. All plots represent energy. The time-frequency plot exhibits many more features than the other two

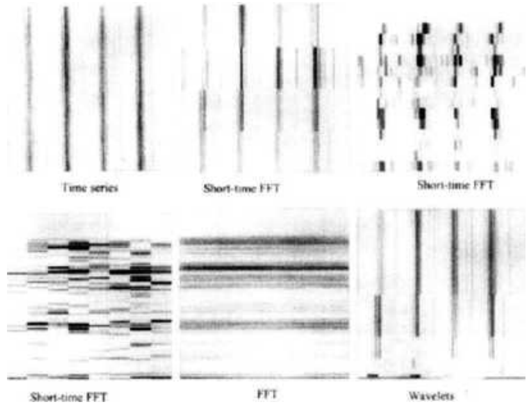

Fig. 2 Different possible time-frequency representations of the same signal. In this case there are $2^{1024} \approx 10^{300}$ distinct orthogonal representations using one generating shape function. Energy is plotted on in gray-scale using the software by Coifman and Wickrhauser (1992)

representation of the features one is looking for, and then to detect their presence and strength. However, it is unrealistic to assume that such a parametric representation is known a priori or can be guessed with acceptable accuracy in a wide variety of applications, where the features can have very different signatures.

Instead, we choose to perform the feature identification in the so-called time-frequency representation of the signals, which is the systematic setting for generic feature identification. Again, there is a choice: the classical approach is the scalogram, used, e.g., in the analysis of speech. Due to a fundamental result (akin to the Heissenberg uncertainty principle), such a representation contains so-called ghost features, which are artifacts of the numerical method (Choi and Williams, 1989). The chosen alternative is to build the representation from a basis of orthogonal waveforms, and the basis is chosen to "suit" the signals. If the available set of waveforms is rich enough, the chosen basis elements will recover information about the physical behavior of the generating components. The simplest example is the well-known Walsh system.

Such an approach is difficult because of two factors: First, there is no unique time-frequency representation, as seen in Figure 2. which makes it necessary to build selection criteria.

Second, the number of such representation is exponentially increasing as a function of the sample length, which makes brute-force search impossible. However, efficient numerical algorithms have been developed to overcome these difficulties.

As seen in Figure 2. the wavelet representation of the signal does not reveal more than its classical competitors. The salient point is the fact that there is an optimal representation of this sample signal, as illustrated in Figure 3.

The important point is what is understood by a "best" representation. In classical applications, called "best basis wavelet packets", developed by Coifman and Wickerhauser (1992), "best" refers to storage needed to reproduce (approximately) the signal. In this case, the objective is to find "crisp" features, which turns out to be related to the efficient information storage problem. However, finding crisp details of signals is not the goal of feature identification. Essentially, we want to find the distinguishing features between classes of signals, and thus we need to find crisp details of differences between those signals. This approach is used for both source identification and diagnostics. Saito (1994) adopted this idea and

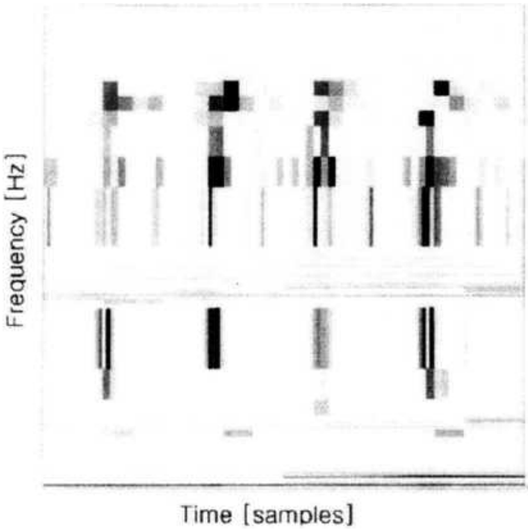

Fig. 3 Best time-frequency representation of the given signal. Note the trade-off between time- and frequency-resolution, not present in the representations of Figure 2

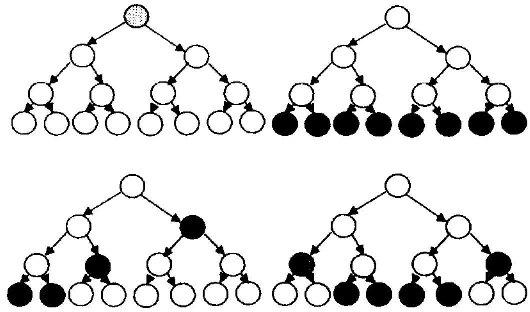

Fig. 4 Four wavelet packet decomposition trees. Upper left : standard time-series basis ; upper right : frequency only (Fourier-type) basis ; lower left : standard wavelet basis ; lower right : an arbitrary wavelet packet basis. Circles in each tree represent bases of waveforms, while the dark circles in each tree indicate the chosen basis waveforms of the specific tree. Each pair of arrows represents the 1-level wavelet decomposition

developed local feature classification and regression based on best basis wavelet packets and applied these to classify triangular waveforms in the presence of noise, which is further developed in this paper.

3. Adaptive Time-Frequency Analysis

We adopt the generic wavelet-packet analysis framework. The key idea behind this analysis is to "mass-produce" alternate representations of a given signal, and then to select the one that is best according to a certain metric.

3.1 Wavelet packets

The representations are obtained by hierarchically splitting the signal into a coarser version and a correction as shown in Figure 4. With the aid of one-level wavelet decomposition this can be done in a computationally efficient and stable manner. Mathematically, this is equivalent to replacing any given waveform by its coarser version and a correction. In fact, the correct statement is that each basis of waveforms can be substituted with two "smaller" bases, containing "coarse grain" and "higher frequency" waveforms respectively. In this process there is no information loss, since the signal can be represented in either the original basis, or the union of the two children-bases. Thus we obtain a binary tree of bases in which each node spans the same signals as its two children.

The selection of a particular basis is related to the cost of representing a specific signal. The signal $s(t)$ is represented in a basis $\Gamma=\{\psi_j^\Gamma(t)\}_{j\in B(\Gamma)}$ by the vector of inner products.

$$s_j^\Gamma=\int s(t)\,\overline{\psi_j^\Gamma}(t)\,dt,\ j\in B(\Gamma)$$

where $B(\Gamma)$ is the binary tree of the basis. The cost of the representation is any positive and additive functional, such as or $c(\Gamma)=\sum_{j\in B(\Gamma)}|s_j^\Gamma|^2$ or $c(\Gamma)=-\sum_{j\in B(\Gamma)}|s_j^\Gamma|\log|s_j^\Gamma|$. The latter expression uses normalized coefficients and it is usually called the entropy of the representation. Such cost functions permit the comparison of the parent and children bases at each node of the decomposition tree. Let Γ_1, Γ_2 be the children of a basis Γ. Due to orthogonality of the wavelet step, their union spans exactly the same space as their parent, and due to the additivity of the cost function, $c(\Gamma_1\cup\Gamma_2)=c(\Gamma_1)+c(\Gamma_2)$. This provides the possibility of comparing the parent basis to the children bases. A dynamic programming algorithm can efficiently select the basis that best represents the signal, sweeping bottom-top through the wavelet-packet decomposition tree in $O(N)$ operations (N is the length of the original signal). Due to the implementation of the wavelet transform computing the coefficients s_j^Γ for all bases in the decomposition tree (also called the time-frequency energy map) is also done in optimal complexity. These features are critical for efficient implementations of the algorithms.

Note that the notion of "best" depends on the choice of the wavelet decomposition and the additive cost function.

The entropy cost function is particularly useful because it chooses representations in which a few waveforms (basis functions) concentrate most of the signal's energy. These waveforms match the dominating features of the signal (or provide a best orthogonal match): the waveforms with highest energy content correspond to the top orthogonal features of the signal. A pertinent analogy is the Singular Value Decomposition (SVD) of a matrix of column vectors, where the top singular values signal out the most important features (singular vectors) (Golub and Van Loan, 1996).

3.2 Discriminating features

Next we show how the best wavelet packet technology is used to find discriminating features among classes of signals. For simplicity, imagine two signals, $s_1(t)$, $s_2(t)$. The best basis for one of them is not necessarily a good basis for the other. However, the best basis for the difference $s_1(t)-s_2(t)$ highlights the features that discriminate between the signals. A second intuition is that white noise, which is expected to perturb any measured signal, is not well represented in any wavelet-packet basis, i.e., white-noise features will have a relatively low energy content.

Discriminating feature extraction is performed in the following setting: Assume that we are given classes of signals $\{x_i^c(t)\}_{i=1,\cdots,I(c)}$ where $c=1, \ldots, C$ represent the class index and $I(c)$ is the number of training signals used to extract discriminating features. For each class c and basis Γ in the decomposition tree, we compute the average time-frequency energy map:

$$s_j^\Gamma(c)=\frac{1}{I(c)}\sum_{i=1,\cdots,I(c)}\int x_i^c(t)\,\bar{\psi}_j^\Gamma(t)\,dt$$

For any two classes, we compute a distance between the time-frequency energy maps:

$$D^\Gamma(c_1, c_2)=\sum_{j\in B(\Gamma)}d(s_j^\Gamma(c_1), s_j^\Gamma(c_2))$$

where $d(x, y)$ is an additive scalar cost function, such as $|x^2-y^2|$ or $\left|x\log\frac{x}{y}\right|+\left|y\log\frac{y}{x}\right|$. Finally, the cost (discriminant power) of the basis is given by summing over all classes:

$$\Delta(\Gamma)=\sum_{1\le c_1<c_2\le C}D^\Gamma(c_1, c_2)$$

Using the additive cost function Δ, we employ the same dynamic programming technique to select the best discriminating basis, preferably with respect to the symmetric entropy cost. Note that we want waveforms that maximize the differences between the classes, thus we need to maximize the cost function.

Once a best discriminating basis is obtained, we can rank the basis functions (waveforms) with respect to their contribution to the optimal (maximal) cost. Because we optimize over a very large number of waveforms, we hope that those that are most discriminating ones contain information at physical level, i.e. are illustrations of the discriminant physical mechanisms responsible for the different classes. Since the waveforms are localized in both time and frequency, and do not contain ghost features or artifacts, the information about the nature and timing of the discriminating events should isolate the event.

Of course, there is no guarantee that a one-to-one matching between discriminating waveforms and physical events exists; e.g., the discriminating physical features may not be orthogonal, while all the waveforms have this property. In such a case, the most discriminating features will be combinations of the most discriminating waveforms. However, the algorithm still has value because it drastically reduces the dimensionality of the identification problem. However, tests on

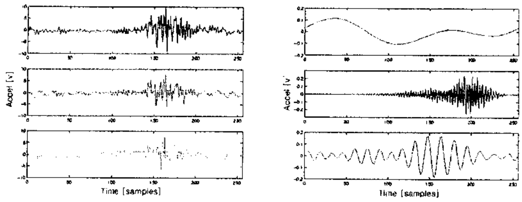

Fig. 5 Averages of three classes of signals (left) and the top three discriminating waveforms (right). The wavelet-packets are based on the 18 vanishing moments Daubechies wavelets. Other wavelets have been tested and, although the quality of the physical features varies, all of them display the same essential characteristics

the demonstration signals produced excellent results. Figure 5 shows the averages of raw signals from three different classes of rotary compressors (about which more will said in Section IV). Although the signals look quite similar (the same dominant behavior) in time domain, the discriminating waveforms are very different, which give precise indication about the distinguishing characteristics of the signals, as described in Section IV.

3.3 Classification

Once we have a set of discriminating waveforms, we can also attempt to classify new signals. Classification is the basis of passive diagnostics. Furthermore, the classification procedure can be adapted to include the normal, gradual wear-and-tear changes in the baseline behavior. The discriminating waveforms are associated with the presence or absence of discriminating features. Projecting an unclassified signal onto a waveform will give a measure of the existence of the corresponding feature. In fact, for classification purposes, it is not necessary to understand the relationship between the discriminating waveforms and physical events.

Let A be the $N\times k$ matrix whose columns are the coefficients of the top k discriminating waveforms. If we want to separate C classes, we need $k\leq C-1$ such waveforms. The columns of A span the feature-space and the signals used for building the best discriminant basis are used

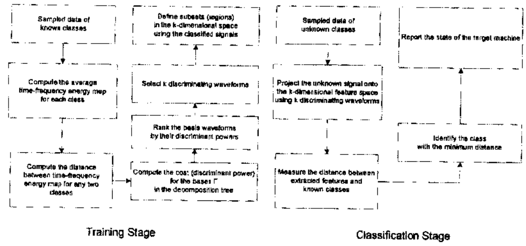

Fig. 6 A flowchart for training stage (left) and classification stage (right) using adaptive time frequency feature discrimination

to define subsets (regions) in this k dimensional space. The region associated with the class c is defined by the set $R(c)=\{A^T x_j^c\}_{j=1,\cdots,I(c)}$.

Note that the component-wise $(A^T x_j^c)_i=\int x_j^c(t)\,\bar{\psi}_j^T(t)\,dt$, which eliminates the need to use the wavelet transform and the decomposition tree for projection onto the best basis. Building A and the sets $R(c)$, $c=1, \ldots, C$ is the learning or training phase of the classification algorithm.

The classification of an unknown signal $x(t)$ is done by projecting it onto the feature space and assigning it the class to which it lies closest. Again, projection is a simple matrix multiplication $f=A^T x$, and classification is

$$c(x)=\arg\min_{c} d(f, R(c))$$

where d is any "distance" algorithm that ranges from the simple Euclidean norm (between two vectors) to the distance computed from neural networks.

Finally, Figure 6 summarizes the overall procedure for training and classification using the proposed technique.

3.4 Pilot implementation

A pilot program that implements the best discriminating basis algorithm was coded in MATLAB. It was used to produce the experimental results described in Section IV.

The pilot implementations demonstrates the following:

- The numerical algorithms can be efficiently implemented
- There is no need for specialized library func-

tions, thus it is feasible to embed the algorithms on dedicated chips

• The memory requirement for the training phases is $O(kN)$, where k is the maximal number of training signals in any class. The requirement for the simple classification rules actually needed in the demonstrations is $O(N)$. In the demonstrations we used $N=256$, ..., 1024 and $k=10$, ..., 45

Such low computational complexities of the proposed technique are extremely important when it is necessary to apply the technique on-line, e.g., in the factory production line.

4. Experimental Results on Rotary and Scroll Compressors

The newly developed feature identification technique based on adaptive time-frequency feature discrimination has potential to identify faults without explicit information on internal measurements. The feasibility of the technique is demonstrated with scroll and rotary compressors. Various faults commonly encountered in the field are seeded to the compressors, whose externally accessible noise, vibration, and pressure signals are recorded to examine whether the (seeded) faults can be identified based on the external measurements alone. For this purpose, two sets of measurements are required :

1. The first set of signals is used as a template for training and is pre-identified with different faults.
2. The second set of signals is used to examine whether the algorithm can match the signals with the corresponding faults (validation).

4.1 Scroll compressors

Dozen welded-shell scroll compressors with or without seeded faults were constructed in an effort to develop a diagnostic/prognostic technique. The seeded faults were chosen to represent typical faults in the field and consist of:

1. Back chamber pressurization flaw
2. Thermal valve failure
3. Scroll machining defect
4. Orbiting scroll bearing defect
5. Contamination (weld spatter)

For each fault, two compressors were constructed to examine repeatability and robustness. In addition, two baseline compressors without any apparent fault were constructed. Since our eventual goal was to perform factory diagnostic, the instrumentation was selected in such a way that they might be readily installed in the factory. In addition, the test was designed in such a way that it might be performed in the factory without any serious problem. An air test was performed with each compressor, which was monitored with the following sensor readings :

1. 1/rev
2. Radial accelerometer #1 (ms^{-2})
3. Radial accelerometer #2 (ms^{-2})
4. Axial accelerometer (ms^{-2})
5. Acoustic emission (V)
6. Pressure pulsation (psi)
7. Microphone (V)

The data was sampled at 24 kHz over 40 compressor cycles. The first task is to synchronize the data from different compressors that are not necessarily aligned. This is necessary since the proposed approach relies on both time and frequency information. The 1/rev signal measures the crank angle that indicates which state in the cycle a compressor is operating. For each measurement, 40 synchronized cycles are obtained using the 1/rev signals. Since the cycle length varies over time, the corresponding measurements are decimated or interpolated accordingly to obtain measurements with the equal cycle length.

Once the measurements are synchronized, the next step is to detect existence of any fault and furthermore to identify the type of the fault if there exists, based on the above measurements. We have experimented with various sensor readings to examine which of the sensor readings result in the best discrimination of faults. The pressure pulsation turns out to be the best one and is first described in the following.

Pressure pulsation readings were taken from four compressors with different faults or no fault : baseline, back chamber pressurization flaw, thermal valve failure and scroll machining defect. The 40 cycles of the pressure readings from three compressors (baseline, back chamber pressurization flaw, and thermal valve failure) were used to train the algorithm, which in turn automatically extract the best discriminating features. Then, the components of the two best discriminating features are computed in each cycle of the pressure readings and plotted inside circles (each mark inside a circle indicates the component of a discriminating feature for a cycle of pressure reading) along x- and y-axis in Figure 7. The clear separation among three groups of marks in circles shows that the algorithm is capable of identifying discriminating features. It should be noted that the small scatter among the same mark indicates that the algorithm is robust to cycle-to-cycle variation, e.g. sensor noise.

Then, the pressure readings from three new compressors with the same three faults were fed to the algorithm in order to examine whether it is able to classify which type of faults each compressor displays. The results are plotted with marks in diamonds, which show that the components of each discriminating feature from the compressors with the same type of faults are very similar. Consequently, the corresponding marks in a circle and a diamond cluster together, far from others, which indicates that the algorithm is capable of classifying compressors with different faults. Note that the discriminating features are from the training sets of pressure readings.

When the diagnostic/prognostic tool is used in the field, it is unrealistic to assume that all the faults are known a priori. It is interesting to see how the proposed algorithm classifies unknown faults. It would be ideal if the algorithm classifies the unknown faults as unknown. In other words, the components of the unknown faults along x- and y-axis should be different from the known faults so that the marks from the unknown faults would not cluster together with those of known faults. For this purpose, the pressure readings from a compressor with scroll machining defect were fed to the algorithm (without re-training the algorithm for scroll machine defect). The marks in a square with a label "scroll machine defect" in Figure 7 show that the algorithm indeed detects the existence of an "unknown fault" (scroll machine defect).

The full discriminating power of the two features is illustrated in Figure 8. Note that while bearing faults are also well discriminated, the weld-splatter contamination is not. We are now probing the limits of the algorithm, asking to distinguish 6 classes of compressors with only two waveforms that were obtained from training the

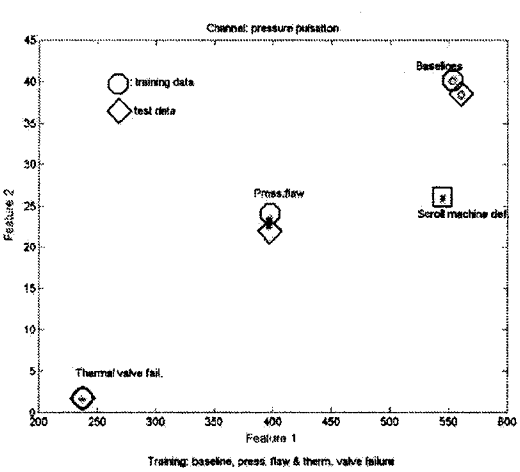

Fig. 7 Components of two discriminating features in the pressure readings of compressors with different faults

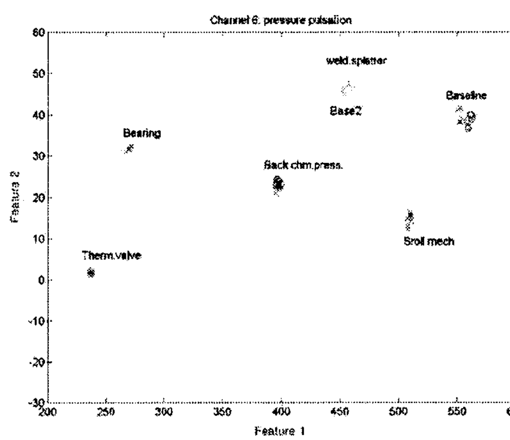

Fig. 8 Scattering of all the scroll compressor seeded fault data. The values along x- and y-axis indicate the components of the compressor data along the two discriminating features

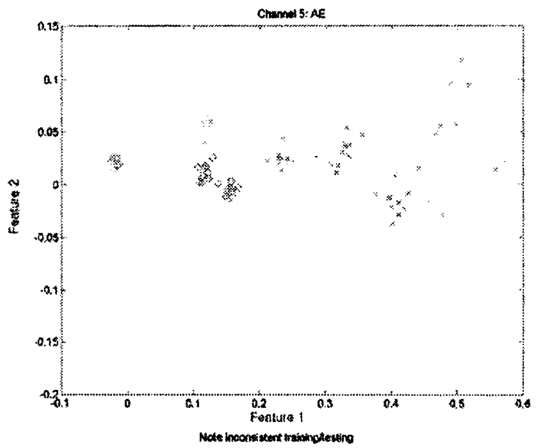

Fig. 9 Discrimination and classification with AE readings

algorithm on three classes.

So far, the results from the pressure readings were explicitly shown in evaluating the performance of the proposed algorithm. However, it is easily imaginable that the results would be quite different with different sensor readings. In order to support such an observation, the same training and testing procedure used for pressure readings is applied with acoustic emission (AE) readings. Figure 9 shows how the discrimination and classification with AE readings fail. Of course, this does not imply that the AE readings are generally inadequate in diagnostics. It simply indicates that the careful design of instrumentation is crucial to the success of diagnostic/prognostic even with the same algorithm since it directly impacts the information contents of the sensor readings.

4.2 Rotary compressors

A bolted-shell rotary compressor was constructed to measure internal acceleration and pressure by placing sensors both internally and externally. Although we utilize only external measurements for feature identification, the internal measurements were also taken for the purpose of verification. Figure 10 shows sensors for external measurements.

Once all the internal and external transducers were in place, the bolted-shell compressor was

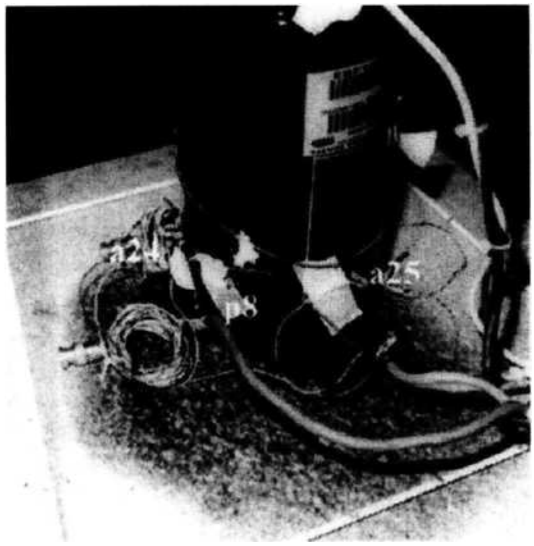

Fig. 10 Instrumentation for external measurements a24, a25, and p8 in a rotary compressor

run at the ARI condition for data collection. A 24-channel HP data acquisition system was used to collect the internal and external time data from 18 transducers simultaneously for 1 second at a 32768 Hz sampling rate. The signals from the 24-channel test were decimated in MATLAB to obtain the sample rate of 16384 Hz. The data serve as the baseline for a methodology validation. Two more data sets were successively collected under the same condition after modifying one internal component of the compressor at a time:

1. Muffler: one hole muffler to two hole muffler (modification I)
2. Valve stop without curvature to the one with curvature (modification II).

Then the criterion for validation is whether the proposed technique is capable of identifying the modification (s) made to the compressor from the external measurements (e.g. shell vibration).

The accelerometer a24 attached to the compressor as shown in Figure 10 was used to measure the shell vibration at the midpoint of the widest span between the crankcase welds. From a24 readings collected from three different bolted-shell rotary compressors (baseline, muffler-modified, valve stop modified), the features are identified in the time-frequency domain that best discriminate the different compressors. Since the features discriminate three compressors best, they can be used to trace back the root causes of the differences and thereby to identify the modifications (faults in the context of diagnostics).

Again, the data from different compressors are synchronized first. One of the internal measurements, magnetic pick-up at the crankcase, measures the crank angle that indicates which state in the cycle a compressor is operating. The magnetic pick-up is used to define a cycle. For each a24 measurement, 40 synchronized cycles are obtained, which are used to train the algorithm. The discriminating waveforms are obtained together with their contributions to a24 measurements. Figure 5 shows the averages of raw signals from three different classes of rotary compressors and the corresponding best discriminating waveforms.

Figure 11 shows the three best discriminating waveforms and their contributions. Judging from the relative contributions, it is clear from the figure that the baseline and the modification I compressors are best discriminated by the feature #3. The feature #2 discriminates the baseline and the modification II compressors best. These two features are further examined since they are the clues to the root causes of differences in shell vibration. The feature #3 turned out to be representative of pressure pulsation (centered around 600 Hz) while the feature #2 resembles the waveform of the valve stop ringing (centered around 2000 Hz). These matches could be found relatively easily in our case, since the internal measurements were available including the pressure pulsation and valve stop ringing. The root causes of the differences in shell vibration are traced back to muffler and valve stop since they are responsible for pressure pulsation and valve stop ringing. The diagnostic technique based on the proposed approach indeed identified the modifications to the compressor, which is surprising in that only external measurements (a24) were used in the analysis. Also it should be noted that the information on the internal measurements is not crucial to the success of the proposed approach although they were used to identify the discriminating waveforms. Since the discriminating waveforms are well localized both in time and frequency, the root causes can be identified by simultaneously examining 1) the crank angle when the discriminating waveforms are active and 2) the frequency content of the discriminating waveforms.

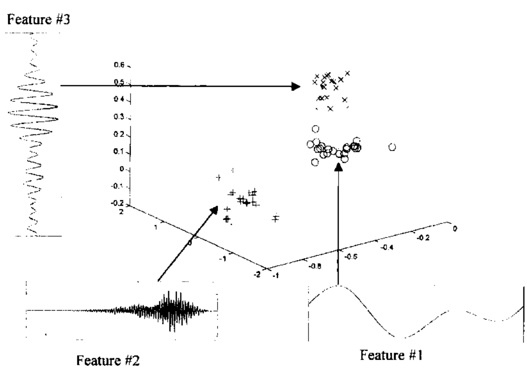

Fig. 11 Contribution of features in a 3-dimensional feature space. The values along the x-(Feature #1), y-(Feature #2) and z-axis (Feature #3) indicate the components of the compressor data along the three discriminating features

The successes with the scroll and rotary compressors have led us to examine whether the proposed technique has potential to be used in prognostics. In other words, it is interesting to test its capability of tracking the faults or discriminating the severity of faults. Eight rotary compressors were built en route to answering this question :

1. 2 baseline compressors built in the laboratory
2. 2 baseline compressors built in the factory line
3. 4 compressors with roller faults : 2 scratched and 2 scored

The scored roller is more severely damaged than the scratched one. The roller fault is one of the most frequently encountered faults in the field. Four baseline compressors were built in two different locations at two different instants in order to establish the level of lot-to-lot variations. If the lot-to-lot variations are more pronounced than the differences between baseline and faulty compressors when evaluated with the identified discriminating features, the proposed technique cannot be deemed very practical. An air test was performed with each compressor and only external measurements were taken from each of the eight compressors: accelerations, pressure, and electric power. The same data-processing procedure used earlier in scroll and rotary compressors were adopted to generate 40 synchronized cycles of acceleration signal for each of the eight compressors. Then, the acceleration signals from one lab-built baseline compressor and one scored-roller compressor were used to train the algorithm and to identify discriminating features.

Figure 12 shows contributions of two discriminating features in acceleration readings of the eight compressors. Clearly, the proposed algorithm is capable of distinguishing the two compressors with severe faults (score on roller) from the baseline compressors. In addition, the cluster of the scratched-roller compressors is well separated from those of the scored-roller compressors and the baseline compressors. In fact, it lies between the clusters of the scored-roller compressors and the baseline compressors. Such observations have very important practical implications: the proposed technique can identify the degree of severity of same fault and can map the degradation path (the contributions of the two features reveal the state of the compressor in the

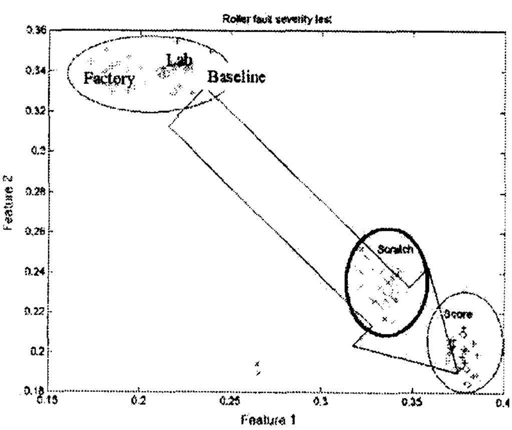

Fig. 12 Contributions of two discriminating features in the acceleration readings of the eight compressors

degradation map). Finally, it should be noted that the contributions of the baseline compressors from different production lots cluster together, which shows that classification is robust to lot-to-lot variations. Although not a statistically meaningful proof, these observations indicate that the proposed technique has potential to be used in predicting faults (prognostics). In this case, the discriminating features would be failure precursors.

5. Concluding Remarks

In this paper, a new feature identification methodology has been proposed based on the general wavelet-packet ideas. The best discriminating features are computed in a numerically efficient manner via dynamic programming, which tremendously reduces computational burden. The resulting features bear information not only for fault classification but also for root-causes of faults at the component level by virtue of their time-frequency localized nature. Due to the rather stringent constraint that any practical diagnostic/prognostic technique has to rely on readily available measurements (often external vibration or sound), the proposed technique has potential to complement the existing diagnostic/prognostic techniques that provide fault or no fault information only. Applications of the proposed technique to scroll and rotary compressors show its viability in a real-world application. It is currently being applied to Carrier compressor factory line in an effort to reduce warranty cost.

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