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Pattern Recognition Methods for Acoustic Emission Analysis

P. G. Doctor
T. P. Harrington
P. H. Hutton

July 1979

Prepared for
the U.S. Nuclear Regulatory Commission

Pacific Northwest Laboratory
Operated for the U.S. Department of Energy
by Battelle Memorial Institute

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PATTERN RECOGNITION METHODS FOR
ACOUSTIC EMISSION ANALYSIS

P. G. Doctor
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PALEONTOLOGICAL METHODS FOR
ACQUISITION OF EVIDENCE

R. H. Wilson
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1979

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ABSTRACT

Acoustic emissions are a type of nondestructive evaluation data that have received increasing attention, particularly as a method of monitoring the condition of inservice structures. Models have been developed that relate the rate of acoustic emissions to structural integrity. The implementation of these techniques in the field has been hindered by the noisy environment in which the data must be taken. Acoustic emissions from noncritical sources are recorded in addition to those produced by critical sources, such as flaws. This can lead to incorrect interpretation of the models.

The purpose of this report is to discuss a technique for prescreening acoustic events and filtering out those that are produced by noncritical sources. The methodology that we investigated is "pattern recognition." We applied three different pattern recognition techniques to a data set that consisted of acoustic emissions caused by crack growth and acoustic signals caused by extraneous noise sources.

Our examination of the acoustic emission data presented in this report has uncovered several features of the data that can provide a reasonable filter. Two of the most valuable features are the frequency of maximum response and the autocorrelation coefficient at Lag 13. When these two features and several others were combined with a least squares decision algorithm, we were able to correctly classify 90% of the acoustic emissions in the data set. Although these results must be verified on additional data sets, it appears possible to design filters that eliminate extraneous noise sources from flaw-growth acoustic emissions using pattern recognition techniques.

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Acoustic emissions are a type of nondestructive evaluation data that have received increasing attention, particularly as a method of monitoring the condition of inservice structures. Models have been developed that relate the rate of acoustic emissions to structural integrity. The implementation of these techniques in the field has been hindered by the noisy environment in which the data must be taken. Acoustic emissions from nonstructural sources are removed in addition to those produced by critical sources, such as flaws. This can lead to incorrect interpretation of the results.

The purpose of this report is to discuss a technique for preprocessing acoustic signals and filtering out those that are produced by noncritical sources. The methodology that we investigated is "pattern recognition." We applied three different pattern recognition techniques to a data set that consisted of acoustic emissions caused by crack growth and acoustic signals caused by extraneous noise sources.

Our examination of the acoustic emission data presented in this report has uncovered several features of the data that can provide a reasonable filter. Two of the most valuable features are the frequency of maximum response and the autocorrelation coefficient at lag 13. When these two features are used, others were compared with a least squares decision algorithm, we were able to correctly classify 90% of the acoustic emissions in the data set. Although these results may be verified on additional data sets, it appears possible to design filters that eliminate extraneous noise sources from flaw growth acoustic emissions using pattern recognition techniques.

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INTRODUCTION

Nondestructive evaluation (NDE) is used to assess the state of materials and structures from qualitative and quantitative measurements. The measurement data are utilized to describe the integrity, reliability, and serviceability of the items under evaluation. Most inspection techniques used in NDE rely on the interpretation of secondary effects; for instance, in ultrasonic testing, energy can be scattered by a variety of reflectors in the material. From the character of this scattered energy, the evaluator must decide whether or not the reflector is a critical flaw such as a crack or a void. The interpretation of these secondary effects presents a dilemma to the NDE engineer because, over the history of NDE, interpretation and inspection decisions have been highly operator-dependent. This method of examination presents two basic problems: 1) the interpretation of a particular signal will vary among any group of experts, and 2) the interpretation can be affected by various human factors, such as experience, concentration, and fatigue. The purpose of this paper is to discuss the application of computer-based pattern recognition techniques to flaw signal interpretation. These types of techniques produce results that are independent of most of the human factors connected with the operator. In addition, the results are accurate and, most importantly, repeatable.

There are several additional reasons why automatic data analysis methods, such as pattern recognition, need to be developed:

- Increasingly sophisticated NDE instrumentation produces too much data to be processed manually.
- Current and future applications demand greater accuracy than can be obtained from the visual interpretation of waveforms.
- Advances in microprocessor technology make the type of decision algorithms that are discussed hardware-implementable, thereby permitting real-time inspection decisions to be made in the field.

Ultrasonic testing is one area of NDE where pattern recognition techniques have already been applied. Mech and Michaels (1977) used pattern

recognition with ultrasonic testing to locate and to size flaws in pipe welds. They also used pattern recognition to discriminate between defects and the normal variations in the weld zone, which were due to the microstructure. Rose (1977) used several pattern recognition schemes to classify various types of flaws that were machined into steel test blocks. Mucciardi et al. (1975) used a pattern recognition technique referred to as adaptive learning to classify flat-bottom holes.

Pattern recognition techniques have also been applied to eddy-current inspections of steam generator tubing. Brown (1979) used pattern recognition to analyze eddy-current data from tube samples that contained both artificial defects and nondefects. (Nondefects are tube anomalies that affect eddy-current measurements but not the integrity of the tube.) The purpose of using pattern recognition was to develop criteria that can distinguish between defects and nondefects. Shankar et al. (1978) also applied adaptive learning pattern recognition techniques to eddy-current inspection.

In this paper, we discuss the application of pattern recognition techniques to a third area of NDE research: acoustic emissions. In this application, we are interested in classifying waveforms into two groups. One of the groups gives an indication of the failure rate of a particular specimen while the other consists of extraneous information that, if it were not filtered out, would combine with the first group and result in false indications of the specimen's failure potential.

The remainder of this paper is divided into five sections: Experiment, Feature Generation, Feature Analysis, Pattern Recognition, and the summary. In Experiment, we identify the source of acoustic emissions and discuss how they can be used to measure a specimen's structural integrity. We also discuss the data acquisition system and the types of acoustic emissions that were analyzed in this study.

Feature Generation begins with a discussion of the types of features that have been used in NDE applications of pattern recognition. These can be divided into two groups: time domain features and frequency domain features. We discuss the feature calculation procedure used in this study and present histograms of the features.

In Feature Analysis, we discuss several preprocessing steps that are necessary prior to the pattern recognition analysis. We also begin to examine the interrelationships between the chosen features. Several methods of performing this initial investigation are presented. Three of the methods discussed are interfeature correlations, cluster analysis, and multidimensional display techniques.

In Pattern Recognition, we compare three types of classification algorithms. The three techniques are an empirical Bayes procedure, the K-nearest neighbor algorithm, and a least squares procedure. In the summary, we briefly recap our results, discuss future plans, and indicate several of the obstacles that must be overcome before these techniques can be applied in the field.

In feature analysis, we discuss several preprocessing steps that are necessary prior to the feature reduction analysis. We also begin to examine the relationships between the various features. Several methods of forming this initial investigation are presented. Some of the methods discussed are interfeature correlations, cluster analysis, and multidimensional display techniques.

In feature reduction, we compare three types of classification algorithms. The three techniques are an empirical based procedure, the nearest neighbor algorithm, and a least squares procedure. In the summary, we briefly recap our results, discuss future plans, and indicate several of the obstacles that must be overcome before this technology can be applied in the field.

EXPERIMENT

A relatively new nondestructive testing technique detects elastic waves (acoustic emissions) produced by deformation and cracking in a solid material. As a solid material deforms and cracks, energy is released, part of which produces elastic waves that propagate through the material. (For additional information on the nature of acoustic emissions, see Spanner 1974.) These waves can be detected at the material surface through the use of piezoelectric transducers. The resulting electrical signal, which is produced by the sensor, can be processed in various ways to indicate crack locations and to estimate crack growth rates. Acoustic emission techniques are currently being investigated for inservice monitoring of nuclear pressure vessels (Hutton et al. 1978). These techniques have also been used to detect flaws in steel highway bridges (Hutton and Skorpik 1977).

The relationship between the rate of acoustic emissions and crack growth is the focus of current acoustic emission research. However, one of the problems faced in this work is determining whether data are acoustic emissions from crack growth or generally similar acoustic signals from innocuous sources. The rubbing of supports, electrical transients, and slag inclusions are examples of these noncritical sources.

The purpose of this pattern recognition investigation is to develop methods that discriminate between acoustic emissions due to crack growth and acoustic signals from the noncritical noise sources. If such a discrimination function could be developed, an instrument could be built that would screen data to eliminate the extraneous noise sources. A by-product of developing this discrimination function would be a characterization of the acoustic emission energy at the source, which, in turn, could contribute to a better understanding of the process of crack growth.

As an initial feasibility study of the pattern recognition technique, we recorded acoustic emissions during an experiment that was designed to study the effects of fatigue cycle rate on acoustic emissions (Hutton et al. 1978).

During this experiment, a specimen with a prestarted crack was sinusoidally stressed between fixed maximum and minimum loads at cycle rates between 0.1 Hz and 2 Hz. A spatial filtering technique was employed that restricted the acoustic events to an acceptance zone of about 0.5 in. on either side of the known crack location.

The acoustic emission waveforms were digitized with a Biomation 8100 at a sampling rate of 20 MHz. Each digitized waveform consisted of 2048 8-bit data words. The Biomation was operated in the pretrigger mode; in this mode, the analog signal, which appears at the input of the instrument, is digitized continuously. This information is shifted through the 2048-word digital memory at the data digitization rate. When the system was triggered, which happened in our case if the spatial filter determined that the analog signal was from the crack area, the recording function ceased after a prespecified trigger delay. The advantage of this mode of operation is that it allows the signal prior to the trigger to be recorded. After the Biomation had recorded the acoustic event, the digitized waveform was transferred from the Biomation memory to a mass storage device attached to a small minicomputer. Following the transfer, the Biomation was rearmed to await the next acoustic event. In addition to recording the waveform, the minicomputer also appended a sequence number (and several additional pieces of information) to the waveform so that it could be easily identified during the subsequent analyses.

The fatigue cycling rate used in this experiment can be represented by the load curve shown in Figure 1. The load ranges from a minimum of 8 kips (1 kip is equal to a 1000 lb load) to a maximum of 80 kips. This means that the specimen was under tensile stress during the entire test. The period of the load cycle was arbitrarily divided into 100 parts, as shown in Figure 1. The load position at the instant that an acoustic event occurred was determined and recorded by available instrumentation. Because we felt that the valid acoustic emission (valid AE) waveforms might have different characteristics in the rising and the falling portions of the load curve (LC), we divided them into two groups. One group corresponded to an increasing load ($LC \leq 25$ or $LC \geq 75$) and the other corresponded to a decreasing load

FIGURE 1. Fatigue Cycle Test Load Curve

($25 < LC < 75$). When we chose a data set for the pattern recognition investigation, we selected enough representatives from each group so that their different characteristics would not hamper the noise versus valid AE discrimination.

Figure 2(a through d) shows two waveforms from each of the valid AE groups. The notation in the upper right corner of each plot gives the waveform sequence number (ID) and the point on the load curve (LC) at which it was recorded. The source notation (TY: Actual) indicates that the waveform was produced by valid AE.

For the feasibility study, we chose noise waveforms that were easy to generate in the laboratory but, at the same time, similar to those that might be encountered in actual field inspections. The noise data were generated in the area of the crack and recorded using the same equipment that was used to

FIGURE 2a. A Valid AE Waveform Digitized During the Falling Portion of the Load Curve

FIGURE 2b. A Valid AE Waveform Digitized During the Falling Portion of the Load Curve

FIGURE 2c. A Valid AE Waveform Digitized During the Rising Portion of the Load Curve

FIGURE 2d. A Valid AE Waveform Digitized During the Rising Portion of the Load Curve

monitor the acoustic emissions during crack growth. While the noise measurements were taken, the fatigue cycling was halted and the specimen was placed under zero load. The sources of noise included:

- 1) tapping the specimen with the blade and handle of a screwdriver;
- 2) rubbing the specimen with various objects;
- 3) tightening a C-clamp on the specimen to simulate noises from pipe hangers, pipe brackets, or other friction-coupled devices; and
- 4) breaking a Pentel pencil lead (0.5 mm by 0.25 in.) on the surface of the specimen at an angle of 30° .

Figure 3(a through c) shows examples of the first three types of noise sources. The notation in the upper right corner gives the sequence number for the waveform (ID) and also the noise source from which it was generated (TY). The acoustic emissions produced by breaking the Pentel pencil lead saturated the recording system. Although we could have attenuated the input signals, we wanted to hold all the measurement system parameters constant, so we eliminated the Pentel noise source from this investigation. When the plots in Figures 2 and 3 are compared, it is obvious that visual inspection, alone, is insufficient to distinguish between valid AE and noise sources.

The data available for this study are summarized in Table 1.

FIGURE 3a. An Acoustic Signal Generated by a C-Clamp

FIGURE 3b. An Acoustic Signal Caused by Tapping

FIGURE 3c. An Acoustic Signal Caused by Rubbing

TABLE 1. The Data Available for Pattern Recognition Investigations

<u>Data</u>	<u>Number</u>
Valid AE	148
$LC \leq 25, LC \geq 75$	100
$25 < LC < 75$	48
Noise	75
Tapping	31
Rubbing	28
Clamp	16

FEATURE GENERATION

Feature generation is essential to the successful utilization of pattern recognition techniques in any application. It is especially important in the field of NDE because only one measurement is normally available. This measurement, however, is usually a waveform digitized over some interval of time. The set of features that we use, therefore, must be functions of this waveform. In the past, NDE features from both the time domain and the frequency domain have been used to describe the waveform. Features from the time domain include:

- peak amplitude
- rise time
- moments
- autocorrelations

In the frequency domain, via the fast Fourier transform (FFT), these are possible features:

- maximum frequency response
- energy in selected bandwidths
- power spectrum parameters

The cepstrum, which is the fast Fourier transform (FFT) of the complex logarithm of the FFT of the original waveform, has also been found to contain valuable features in several NDE applications (Mucciardi et al. 1975).

The time domain features used in this study were divided into two categories. The first category consisted of several statistical parameters that are related to the shape of the frequency density function of the digitized waveform. The second category contained autocorrelation coefficients that were computed at various lags.

The shape parameters were the mean, standard deviation, skewness, and kurtosis of the original time domain waveform. To compute these parameters, we calculated the mean, V , and the first three moments, m_2 , m_3 , and m_4 , about the mean using the following formulas:

$$\bar{V} = \frac{1}{2048} \sum_{i=1}^{2048} V_i$$

$$m_2 = \frac{1}{2048} \sum_{i=1}^{2048} (V_i - \bar{V})^2$$

$$m_3 = \frac{1}{2048} \sum_{i=1}^{2048} (V_i - \bar{V})^3$$

$$m_4 = \frac{1}{2048} \sum_{i=1}^{2048} (V_i - \bar{V})^4$$

where V_i is the value of the digitized waveform.

Using the moments calculated above, the shape features: mean, $\bar{V}$; standard deviation, s ; skewness, α_3 ; and kurtosis, α_4 , are defined as follows:

$$s = \sqrt{\left(\frac{2048}{2048 - 1}\right) m_2}$$

$$\alpha_3 = \frac{m_3}{(m_2)^{3/2}}$$

$$\alpha_4 = \frac{m_4}{(m_2)^2}$$

Histograms of these four features are shown in Figure 4(a through d). The horizontally shaded region corresponds to the values for the valid acoustic emission (valid AE) waveforms, and the vertically shaded region corresponds to the values for the noise waveforms.

The second type of time domain feature that we investigated was the autocorrelation function. It is defined as

$$C_k = \frac{\sum_{\ell=1}^{2048} (v_{k+\ell} - \bar{v})(v_{\ell} - \bar{v})}{\sum_{\ell=1}^{2048} (v_{\ell} - \bar{v})^2}$$

$$k = 0, 1, \dots$$

where k (called the lag) is the separation between two points of the digitized waveform. In this experiment, the lag can be related to the time interval between the digitization of the two points. For instance, at a sampling rate of 20 MHz, a lag of $k = 1$ is equivalent to a time separation of 0.05 microseconds (μsec). The feature C_k is simply the correlation between all of the values of the waveform that are k units apart. The mathematical properties of C_k are $C_0 = 1$ and $-1 \leq C_k \leq 1$.

Figure 5 shows a plot of the average autocorrelation functions for the 148 valid AE waveforms and for the 75 noise waveforms. A very distinct difference is apparent between these two averages as the lag parameter (k) increases. We chose lag parameters that produced the best separation between valid AE and noise by computing the t statistic for the difference between the means of the two categories. The lags with the two largest t values were selected. Figure 6(a and b) shows plots of the histograms for valid AE and noise waveforms for the lags with the two largest t values, Lags 13 and 37.

In order to search for features in the frequency domain, we computed the average spectra for both the valid AE waveforms and for the noise waveforms. The average power spectrum for the valid AE waveforms is shown in Figure 7.

FIGURE 4a. Histogram for the Mean

FIGURE 4b. Histogram for Standard Deviation

FIGURE 4c. Histogram for Skewness

FIGURE 4d. Histogram for Kurtosis

FIGURE 5. Average Autocorrelations of Valid AE and Noise Waveforms for Lags 0 Through 100

The spectrum of each waveform was obtained using the FFT algorithm. Prior to computing the FFT, the mean of the waveform was removed by subtraction, and the Hanning window was applied. Two characteristics of this average power spectrum are worth mentioning: 1) the maximum frequency response occurred at about 425 KHz, and 2) the build up to this maximum was interrupted by a jagged plateau 10 db below the maximum. This jagged plateau suggests that some of the 148 valid AE waveforms had maximum frequency responses that were less than 425 KHz. The average power spectrum for all of the noise waveforms is shown in Figure 8. For this power spectrum, the maximum occurred at approximately 260 KHz, and the rise to this maximum was smooth. A jagged region followed the maximum; this indicated that some of the noise waveforms had maxima that were greater than 260 KHz.

FIGURE 6a. Histogram for Autocorrelation at Lag 13

FIGURE 6b. Histogram for Autocorrelation at Lag 37

FIGURE 7. The Average Power Spectrum for All Valid AE Waveforms

FIGURE 8. The Average Power Spectrum for All Noise Waveforms

After examining Figures 7 and 8, we chose five frequency domain features for this study. The features chosen were: the maximum frequency response, the frequency of the maximum response, and the first three moments of the frequency distribution.

Histograms for the maximum frequency response and the frequency of maximum response are shown in Figure 9(a and b). Of the two features, the frequency of the maximum response appears to be the most valuable in terms of separation ability. In fact, if we were to use just this single feature to classify the waveforms, we could correctly classify 78%. Classification could be accomplished by selecting the frequency that results in the lowest number of misclassifications. In practice, we would determine the frequency of maximum response for each incoming waveform. If this maximum were greater than the preset frequency, the new waveform would be classified as valid; otherwise, it would be placed in the noise category. A successful classification rate of 78% from the use of this single feature was encouraging because the pattern recognition algorithms improve the success rate.

The second set of features from the frequency domain were the moments of the frequency spectra. The moments are defined by the following formulas:

$$M_0 = \int_0^{\infty} p(w) dw \quad (1)$$

$$M_1 = \int_0^{\infty} wp(w) dw \quad (2)$$

$$M_2 = \int_0^{\infty} w^2 p(w) dw \quad (3)$$

where $p(w)$ is the power spectral density.

The zeroth moment, M_0 is equivalent to the total power. From Fourier transform theory, it is easy to show that the first and second moments

FIGURE 9a. Histogram for Maximum Frequency Response

FIGURE 9b. Histogram for Frequency of Maximum Response

are related to the total power of the first and second derivatives (with respect to time) of the original time domain waveform.

For this study, we computed the moments in the frequency band from 0 Hz to 1 MHz by integrating Equations 1, 2, and 3. The integration method used was the trapezoidal rule defined as

$$\int_{w_0}^{w_n} w^i p(w) dw = \frac{\Delta w}{2} \left[w_0^i p(w_0) + 2w_1^i p(w_1) + \dots + 2w_{n-1}^i p(w_{n-1}) + w_n^i p(w_n) \right]$$

where

$$w_0 = 0 \text{ Hz}$$

$$w_n = 1 \text{ MHz}$$

$$w_j = j\Delta w$$

$$\Delta w = \text{fundamental Fourier frequency}$$

Histograms for the valid AE waveforms and the noise waveforms are given in Figure 10(a through c). For all three moments, the histograms show considerable overlap between the valid AE waveforms and the noise waveforms.

Together, the set of features just discussed form the pattern used to describe each waveform. A complete list of the features chosen for this study is given in Table 2.

A statistical measure of a feature's ability to separate noise waveforms from valid AE waveforms is given by the biserial correlation between the feature and the factor of interest, such as the presence of a flaw. The factor is called the property of the waveform in pattern recognition terminology. The correlation between Feature i and the property is given by

$$r_i' = \frac{(\bar{x}_{1i} - \bar{x}_{2i}) p_q}{z_i s_i}$$

FIGURE 10a. Histogram for Total Power

FIGURE 10b. Histogram for the First Moment

FIGURE 10c. Histogram for the Second Moment

TABLE 2. Features for a Pattern Recognition Study

Time domain features:

1. mean
2. standard deviation
3. skewness
4. kurtosis
5. autocorrelation at Lag 13
6. autocorrelation at Lag 37

Frequency domain features:

7. maximum frequency response
8. frequency of maximum response
9. total power (0 Hz to 1 MHz)
10. first moment of the power spectrum (0 Hz to 1 MHz)
11. second moment of the power spectrum (0 Hz to 1 MHz)

$\bar{X}_{1i}$ and $\bar{X}_{2i}$ are the means of the feature for the data in the smaller and larger categories, respectively; p is the proportion of patterns in the larger category, and $q = 1 - p$. The term z_i is the value of the normal deviate such that $P(Z > z_i) = q$; s_i is the standard deviation of Feature i . The value of the biserial correlation for each of the 11 features is given in Table 3. Features 5, 6, and 8 had the highest correlations to the property, and Features 2, 3, and 7 had the lowest correlations.

The goal of feature generation is to produce features that contain enough information for us to perform an adequate categorization. In the histograms shown earlier, it is clear that several features, such as the frequency of the maximum response, contain sufficient information to perform a fair discrimination by themselves. Other features visually do not appear to have good separation capabilities. However, when several different features are combined, their resolving power improves.

TABLE 3. Biserial Correlation Coefficients

<u>Feature</u>	<u>Correlation Coefficient</u>
1. mean	-0.454
2. standard deviation	0.164
3. skewness	-0.023
4. kurtosis	-0.203
5. autocorrelation, Lag 13	-0.793
6. autocorrelation, Lag 37	0.763
7. maximum frequency response	0.187
8. frequency of maximum response	0.653
9. total power	0.243
10. first moment of power spectrum	0.370
11. second moment of power spectrum	0.445

FEATURE ANALYSIS

Once an initial set of features has been defined, several preliminary feature analysis steps should be performed before the pattern recognition techniques are applied. In the previous section, Feature Generation, we discussed the ability of each feature to separate noise from valid AE waveforms. In this section, we analyze the interrelationships among the features and how these interrelationships influence predictions of the property. Our approach to this preliminary analysis has emphasized visual display methods in conjunction with analytic methods as a means of examining these interrelationships. Since man has the best pattern recognition capabilities known today, the graphical techniques allow us to interact with the data in order to guide the pattern recognition process. Later in this section, we illustrate the use of two display techniques that we have applied to the acoustic emission data. They are feature-by-feature plots and two-dimensional projections. A non-display technique known as clustering will also be discussed.

Since the goal of a pattern recognition analysis is to predict the property of interest solely on the basis of the features, a necessary first step in the analysis is to divide the data into two sets: a training set and a test set. As the name implies, the training set is used to produce the best prediction for the property. Since this prediction must hold for future data as well, it is validated on the test set. For this procedure to be reasonable, the test and the training sets should be as similar as possible; that is, they should differ only randomly.

There were a total of 223 usable waveforms in our data set. They were randomly assigned to the training and test sets under the condition that each set should contain approximately an equal number of each type of waveform listed in Table 1. There were 112 waveforms in the training set and 111 in the test set. Several analyses of the training and test sets showed that they were basically similar.

The second step in feature analysis is to scale the features. The original features frequently have different physical units and may be vastly different in magnitude. The goal of scaling is to obtain a transformed set of

features that are all of approximately the same magnitude. The method used to scale the acoustic emission data resulted in features with zero mean and unit variance. The transform is defined by

$$X_{ij} = \frac{(X'_{ij} - \bar{X}_i)}{s_i}$$

where

X_{ij} = the transform value of the i^{th} feature of the j^{th} pattern,

X'_{ij} = the unscaled value of the i^{th} feature value of the j^{th} pattern,

$\bar{X}_i$ = the average of the X'_{ij} values over all of the patterns in the training set, and

s_i = the standard deviation of the X'_{ij} values over all the patterns in the training set.

After the features have been transformed, pairs can be plotted and then examined for their ability to separate the patterns into the categories of valid AE and noise. Where earlier we examined the separation ability of a single feature by examining its histogram, we can now examine two or more features simultaneously. For a single feature, the dichotomy is produced by a single point. For two features it is defined by a line, for three features a plane, and so on. Figure 11 is an example with two features; it shows the frequency of maximum response plotted against the autocorrelation coefficient at Lag 13. In this figure, the valid AE patterns are indicated by the triangles and the noise patterns are indicated by the squares. The line superimposed on this plot separates the data into the two categories with the fewest misclassifications. The resulting success rate was 84%; this exceeds the 78% success rate that was obtained using the frequency of maximum response feature.

FIGURE 11. Frequency of Maximum Response Plotted
Against Autocorrelation at Lag 13

The Pearson product moment correlation coefficient is an analytic measure of the relationship between two features. This correlation between Features i and j is defined as

$$r_{ij} = \frac{\sum_l (x_{il} - \bar{x}_i) (x_{jl} - \bar{x}_j)}{\sqrt{\sum_l (x_{il} - \bar{x}_i)^2 \sum_l (x_{jl} - \bar{x}_j)^2}} \quad (4)$$

For n features there are $n(n - 1)$ correlations; r_{ij} measures the linear association between Features i and j in the presence of the other $n - 2$ features. The correlation matrix for the training set is given in Table 4.

TABLE 4. Feature Correlation Matrix for the Training Set

	Feature										
	1	2	3	4	5	6	7	8	9	10	11
1		-0.730	-0.369	0.484	0.092	-0.065	-0.691	-0.087	-0.752	-0.754	-0.730
2			0.456	-0.241	-0.050	0.071	0.919	0.096	0.972	0.934	0.872
3				-0.169	0.012	0.030	0.449	-0.037	0.411	0.396	0.368
4					-0.117	0.156	-0.347	0.130	-0.269	-0.265	-0.256
5						-0.934	-0.072	-0.715	-0.082	-0.228	-0.312
6							0.117	0.692	0.075	-0.189	-0.242
7								0.103	0.876	0.842	0.779
8									0.103	0.182	0.212
9										0.980	0.936
10											0.986

An examination of Table 4 reveals two basic groups of features (based on an absolute value of the correlation that is larger than 0.15). The first group contains Features 1, 2, 3, 4, 7, 9, 10, and 11 and the second group consists of Features 5, 6, and 8. These correlations are not sufficient to explain the interrelationships among the features and, particularly, which of the features contain the most relevant information. Partial correlation techniques provide a means of assessing the relationship between two features, independent of the other features. The partial correlation for three features is

$$r_{ij \cdot l} = \frac{r_{ij} - r_{il} r_{jl}}{(1 - r_{il})^2 (1 - r_{jl})^2} \quad (5)$$

If more than three features are used, Equation (5) is defined recursively.

An example of how the presence of other features can affect the correlation coefficient is illustrated by Features 5, 6, and 8. The three are very highly correlated:

$$r_{56} = -0.934$$

$$r_{58} = -0.715$$

$$r_{68} = 0.692$$

However, when the third feature is controlled for, the relationships change dramatically:

$$r_{56 \cdot 8} = -0.870$$

$$r_{58 \cdot 6} = -0.266$$

$$r_{68 \cdot 5} = 0.097$$

The apparently high correlations between Features 5 and 8 and Features 6 and 8 are mainly the result of the very strong relationship between Features 5 and 6.

In the remainder of this paper, it will be convenient to consider the features as coordinates in an n-dimensional feature space. The patterns of individual waveforms become points in this space. In thinking of the features as coordinates in feature space, the redundant information contained in the

features is equivalent to having features that can be expressed as linear combinations of other features. Prior to the actual pattern recognition analysis, it is often necessary to reduce the feature space to include only the features or the functions of the features that contain the best separation information. This procedure is necessary to avoid numerical problems in the classification algorithms. Feature reduction can be performed in several ways; one way that it can be performed is to examine the feature correlation matrix and another is to use the partial correlation coefficients.

The feature reduction algorithm used on the training set is based on a partial correlation analysis that uses the Pearson product moment correlation to property. It is the same correlation coefficient given in Equation (4) except that the property is used instead of one of the features. On the basis of a stepwise regression, five features seemed to contain the pertinent information. The feature numbers of the five selected were

5. Lag 13
1. mean
2. standard deviation
9. total power
6. Lag 37

This reduced set of features was orthogonalized to avoid numeric problems in the pattern recognition or classification analyses.

Using the reduced set of features, we applied several techniques to verify their ability to predict the property. The methods included cluster analysis and two-dimensional projection. These methods are used, because, in general, even though the feature set has been reduced to include only the most valuable features, the feature space usually exceeds three dimensions and is impossible to visualize. The methods that we discuss are used in an attempt to determine the structure of the patterns in a high-dimension space. Cluster analysis preserves the local structure of the patterns while the projection methods preserve the global structure. Together they form a valuable tool for discovering the nature of the data.

Clustering consists of grouping patterns that are similar. An obvious measure of the similarity of two patterns, and hence of two waveforms, is the distance between them. Although this distance may be computed by a variety of metrics, the most appealing is probably the euclidean norm. This metric assumes that a good measure of the similarity between Patterns i and j is

$$d_{ij} = \sqrt{\left[\sum_{\ell} (x_{i\ell} - x_{j\ell})^2 \right]}$$

where the summation is over all features (ℓ). Ideally, for the acoustic emission data, we would like to obtain two clusters, one containing only the valid AE patterns and the other containing all the noise patterns. If this were the case, we could determine the characteristics of the two clusters and use them as templates for classifying unknown waveforms, or we could classify an unknown waveform on the basis of the category of its nearest neighbors. We will elaborate on the latter of these two techniques in the next section, Pattern Recognition.

The particular clustering technique that we will discuss in connection with the acoustic emission data is referred to as the K-means algorithm. Basically, this algorithm attempts to minimize a performance index, which is defined as the sum of the squared distances from each pattern associated with a cluster to the center of the cluster. The general procedure is to move a pattern from one cluster into another if this movement will reduce the performance index. After a pattern has been moved, new cluster centers must be computed for the cluster that loses the pattern and the cluster that gains the pattern. In this algorithm, the cluster center is computed as the mean of all the patterns that are assigned to the cluster, hence the name K-means. If a new cluster is to be added, the algorithm searches the existing clusters to locate the one with the maximum variance. This cluster is replaced by two new clusters; their centers are the average feature values for features greater than, and less than, the original cluster center. The algorithm that we used to perform the cluster analysis is one given by Hartigan (1975).

The results of applying the K-means algorithm to the combined training and test sets are shown in Table 5. To produce this table, the algorithm was instructed to cluster the patterns into eight groups. In this method, the algorithm first defines a single cluster consisting of all the patterns. This cluster is divided into two clusters using the procedure described above, and the patterns are moved to minimize the performance index. The algorithm continues to add clusters and to minimize the performance index until eight clusters have been defined. Table 5 shows the number of patterns that were grouped into each of the eight clusters at the completion of the run. The pattern counts for the intermediate clusters formed by the algorithm are also shown in Table 5.

An examination of Table 5 shows that for six, seven, and eight clusters the patterns essentially fall into four groups. In Table 6, we have expanded Table 5 to show the breakdown of the patterns for the six-cluster case.

TABLE 5. The Sequential K-Means Clustering Results for One to Eight Clusters

Number of Clusters	Pattern Count							
	<u>1</u>	<u>2</u>	<u>3</u>	<u>4</u>	<u>5</u>	<u>6</u>	<u>7</u>	<u>8</u>
1	223							
2	146	77						
3	95	109	19					
4	75	85	55	8				
5	77	83	53	4	6			
6	39	87	40	48	6	3		
7	39	87	40	48	6	2	1	
8	39	86	40	47	3	2	1	5

TABLE 6. Cluster Structure for Six Clusters

Cluster No.	Pattern Count				
	Valid AE		Noise		
	$25 < LC < 75$	$LC \leq 25, LC \geq 75$	Clamp	Tapping	Rubbing
1	6	33	0	0	0
2	32	24	1	5	25
3	4	17	2	15	2
4	5	25	13	5	0
5	1	0	0	4	1
6	0	1	0	2	0

Several interesting characteristics of the structure of the patterns are shown in Table 6. Basically, each of the three types of noise waveforms fell into separate clusters. In comparing the two categories of valid AE, we found that 67% of the waveforms that were digitized during the falling portion of the load curve are grouped into Cluster 2. Most of the waveforms digitized during the rising portion of the load curve were distributed among the first four clusters. Clusters 5 and 6 contained a total of nine patterns, six of these were from tapping noises. Of these nine patterns, three were selected for the training set and six were selected for the test set. Rather than eliminate these waveforms as bad data, we chose to leave them in the data base during the pattern recognition analyses.

One of the problems with cluster analysis is that it is difficult to visualize the clusters if the feature space has more than two or three dimensions. In this case, a very useful technique is to project the patterns in some manner from n-dimensional feature space to two or three-dimensional space. An intuitively appealing way to accomplish the projection is to use a technique called nonlinear mapping. This technique seeks to preserve the interpattern distances in the projection. This is accomplished by first computing the interpattern distances in the feature space. Define the distance

from Pattern i to Pattern j to be d_{ij} . If the data base consists of N patterns, then $N(N - 1)/2$ distances must be computed. Next, define the distance in two-dimensional space $\hat{d}_{ij}$ as

$$\hat{d}_{ij} = \sqrt{[(x_i - x_j)^2 + (y_i - y_j)^2]}$$

Ideally, we would like $\hat{d}_{ij}$ to equal d_{ij} for each pair of patterns. Clearly, this is not always possible; however, we can define an error function, E , as

$$E = \sum_i \left[\frac{\sum_{i < j} (d_{ij} - \hat{d}_{ij})^2}{\sum_{i < j} d_{ij}} \right]$$

The procedure is then to search for the $2N$ unknowns, x_i and y_i , that minimize E . There are several disadvantages to this technique; primarily, the algorithms available to minimize E can be very time consuming on the computer, especially if N is large. Further, depending on the starting values for x_i and y_i , different local minima might be found.

A computationally more attractive approach for displaying the patterns is to first generate a minimal spanning tree and then to use one of several techniques to graphically represent the minimal spanning tree in two dimensions. Bentley and Friedman (1978) discussed minimal spanning trees and described several algorithms for constructing them. In general, a spanning tree is a network of line segments that join all of the patterns in the data base. Associated with each line segment is a cost, which in our case was the distance between the two patterns joined by the line segment. The total cost of the network is defined as the sum of all the costs that are associated with the line segments. The minimum spanning tree is the subset of the network

that has the minimum cost while connecting all the patterns. The output of a minimal spanning tree algorithm is a sequential list that identifies each pattern and its nearest neighbor.

Friedman and Rafsky (1978) gave a procedure for graphically representing a minimal spanning tree, which they refer to as MST planing. Their procedure produces a two-dimensional representation of the patterns in which all of the MST line-segment distances are preserved. They also attempt to preserve distances between sets that contain three patterns. The result of this mapping is that interpattern distances between MST neighbors are reproduced fairly well. In their algorithm, Friedman and Rafsky also took several steps to preserve the global structure of the pattern space.

The MST planing of the combined training and test sets is shown in Figure 12. To increase the clarity of this figure, we have drawn the MST line segments that connect nearest neighbor pairs when they are in different categories (valid AE and noise). Although this display of the patterns is somewhat cluttered, it is apparent that the valid AE patterns (indicated by the small triangles) are concentrated in two regions of the plane. In the area of overlap between these two regions, noise patterns are mingled (indicated by the small squares) with valid AE patterns. There are several widely separated noise patterns to the left of the plot. A comparison of these noise patterns with the clustering results discussed in Table 6 shows that they belong to either Cluster 3, 4, or 5. The three patterns that belong to Cluster 6 in Table 6 are the two noise patterns and the connected valid AE pattern in the upper portion of the figure. The lowest valid AE pattern in Figure 12 was grouped in Cluster 1 by the K-means algorithm. However, its distance from the center of Cluster 1 was over two times farther than that of any other pattern in Cluster 1.

This projection of the data using MST planing shows no distinct separation of the patterns into the two desired categories; however, the small number of connecting line segments indicates that the nearest neighbors of most patterns are patterns in the same category.

FIGURE 12. An MST Planing of Acoustic Emission Patterns

PATTERN RECOGNITION

In this section we discuss the statistical techniques that actually make the classification decision from the reduced set of features. There are many different classification techniques available; each one is based on a different set of mathematical assumptions. The best technique for a particular situation is not chosen solely on the basis of theoretical considerations: in many cases, information about the behavior of the phenomenon is insufficient to determine the best classification algorithm. For this reason, we compare the results of three different classification algorithms for the acoustic emission data. The three algorithms^(a) are an empirical Bayes procedure, a K-nearest neighbor algorithm, and a least squares procedure.

EMPIRICAL BAYES PROCEDURE

In terms of statistical theory, the empirical Bayes procedure is perhaps the most sophisticated of the three classification techniques that are discussed here. It is often used as the standard of comparison for other classification techniques.

The original Bayes rule classification requires a functional form for the n-dimensional joint probability of features. It also requires a quantification of the risks and costs of misclassification. A waveform is assigned to the category to which it has the greatest probability of belonging. [See Mendel and Fu (1970) for a detailed derivation.] In practice, the n-dimensional probability distribution is usually not known, so a functional form must either be assumed or it must be estimated empirically. An empirical approach uses the histogram of each feature for each category and then combines the histograms to approximate the n-dimensional probability. Let the probability of an Observation j on Feature i, given that it belongs to Category 1, be denoted by

$$P(X_{ij} \mid \text{Category 1}) \tag{6}$$

(a) The algorithms used are contained in the pattern recognition computer package, ARTHUR (Duewer, Koskinen, and Kowalski 1975).

This probability can be estimated by the histogram. What we really want to know is the reverse of this probability: the probability of Category 1 for Feature i given Observation j . This probability is a function of Expression (6), the misclassification risk for Category ℓ (R_ℓ), and the a priori probability of the ℓ^{th} category (q_ℓ). It is given by the equation

$$P(\text{Category 1} \mid X_{ij}) = \frac{q_1 R_1 P(X_{ij} \mid \text{Category 1})}{\sum_{\ell} q_{\ell} R_{\ell} P(X_{ij} \mid \text{Category } \ell)}$$

Since these probabilities are for each feature separately, they must somehow be combined to approximate the joint probability distribution function for all of the features. Because the probability densities are estimated with histograms that can have empty cells, problems can occur if the probabilities are simply multiplied together; a strictly empirical approach is to add a function of the probabilities:

$$P(\text{Category 1} \mid \text{Observation } j) = \sum_i f [P(\text{Category 1} \mid X_{ij})]$$

where f is either a positive power or the natural logarithm. In practice, the choice of f is based on the function that best predicts the property for a particular data set.

For the acoustic emission data, we chose $q_1 = q_2$, since the number of noise and valid AE waveforms were chosen arbitrarily and do not necessarily reflect real-life experience. Also, in lieu of assessing and quantifying the relative consequences of the two types of misclassifications, R_1 was chosen equal to R_2 .

The function, f , that produced the highest successful classification for the training set was the power function with $\beta = 0.1$. The percent of correct classifications was 86% for both the valid AE and noise waveforms. For the test set, the success rates were 83% for noise and 79% for valid AE. The success rate for the test set is generally lower than that for the training set;

however, the similarity of these success rates provides reassuring evidence that the training and test sets were selected in a reasonable manner.

We analyzed the misclassifications to look for any systematic effects of noise type or load curve position. Of the five noise waveforms in the training set that were misclassified, one was caused by rubbing and four were caused by clamp noise. For the valid AE waveforms, 8 out of 10 of the misclassifications were recorded during an increasing load. For the test set, three rubbing waveforms were misclassified and three clamp waveforms were misclassified. Of the valid AE waveforms in the test set, 14 of the 15 misclassified waveforms were from the increasing portion of the load curve. We will comment on this point after the results of the other two classification techniques have been presented.

K-NEAREST NEIGHBOR

This classification algorithm assigns patterns in the test set to the category to which the majority of its K-nearest neighbors in the training set belong. "Nearest" is defined in terms of a measure in n-space; we used the euclidean distance measure described in Feature Analysis.

The K-nearest neighbor classification technique has several desirable statistical properties. First, it is a nonparametric technique; this means that no distributional assumptions are required on the feature space. Second, it can be shown to have the same asymptotic misclassification rate as Bayes procedure if K is chosen to be a certain function of sample size. [See Cover and Hart (1967) and Freidman (1977) for a more complete discussion of this classification rule.]

The percent of correct classifications for the test set with the five orthonormalized features, Features 5, 1, 2, 9, and 6, for K = 1, 3, ..., 10 is shown in Table 7.

TABLE 7. K-Nearest Neighbor Classification Results for the Test Set

	Correct Classifications (%)								
	K = 1	3	4	5	6	7	8	9	10
Noise	76	73	78	70	73	70	70	68	70
Valid AE	85	88	88	89	89	91	91	92	92

The misclassifications using the 10-nearest neighbor algorithm for the test set were examined. The examination revealed that a total of 11 noise waveforms were misclassified; of these waveforms, one was from tapping, five were from rubbing, and five were clamp noises. A total of six valid AE waveforms were misclassified, and all of these occurred during an increasing load.

LEAST SQUARES

The least squares procedure assumes that the property can be expressed as a linear function of the features. We let $Y = 1$ for noise and $Y = 2$ for valid AE. We searched for a linear function of the features that estimates Y as accurately as possible. This relationship can be expressed formally as a decision function:

$$Y = a_0 + a_1X_1 + a_2X_2 + \dots + a_mX_m$$

where m is the number of features and a_i , $i = 0, \dots, m$ are coefficients that are estimated from the training set data by least squares minimization. Using the estimated coefficients and the feature values, a decision function value, $\hat{Y}$, can be calculated for each pattern. This value is also called the predicted value of the property for the pattern. [See Draper and Smith (1966) for a general discussion of least squares regression analysis.]

The decision rule is defined as follows: a particular value of the decision function, Y^* , is chosen so that waveforms with $\hat{Y} > Y^*$ are classified as valid AE and waveforms with $\hat{Y} \leq Y^*$ are classified as noise. The value of Y^* is chosen to minimize the number of misclassifications.

The least squares classification has actually performed another feature reduction; the m features are combined into one feature that is the best predictor of the property under the least squares assumptions. The technique was applied to the training set. Using the five orthonormalized features, the estimated decision function is

$$\hat{Y} = 1.661 - 3.086X_5 - 1.492X_1 - 0.8859X_2 + 0.5526X_9 + 0.6759X_6$$

Because they lend themselves to graphic display, the decision function and the decision rule that were applied to the test set are plotted in Figure 13. The horizontal axis represents the waveform number; this number is arbitrary except that the noise waveforms are listed first. The vertical axis represents the value of the decision function, and the horizontal line represents the decision rule. The value of Y^* is 1.545; the success rate was 92% for the noise waveforms and 89% for the valid AE waveforms.

Of the noise waveforms, one tapping, and two clamp waveforms were misclassified. All of the eight misclassified valid AE waveforms were recorded during an increasing load.

The number of misclassifications for the five types of waveforms are summarized in Table 8 for each of the three classification techniques.

FIGURE 13. Results of the Least Squares Decision Rule on the Test Set

TABLE 8. Number of Misclassifications by Waveform Type

Technique	Valid AE		Noise		
	25 < LC < 75	LC ≤ 25, LC ≥ 75	Tapping	Rubbing	Clamp
Empirical Bayes Procedure	1	14	0	3	3
10-Nearest Neighbor	0	6	1	5	5
Least Squares	0	6	1	0	2

In Table 8, only one of the decreasing-load valid AE and only one of the tapping waveforms were misclassified (both the 10-nearest neighbor and least squares algorithms misclassified the same tapping waveform). Nearly all of the misclassified valid AE waveforms occurred during a rising load. One possible explanation is that increasing stress may cause different types of waves to propagate from the area of the crack; perhaps what we are seeing is a composite waveform produced from many sources. The majority of the misclassified noise waveforms were caused by rubbing and clamp tightening; this suggests that the valid AE waveforms in the increasing part of the load cycle may contain characteristics of these particular types of noise waveforms.

The success rates for the three classification techniques are summarized in Table 9.

TABLE 9. Classification Success Rates

Technique	Success Rate (%)		
	Noise	Valid AE	Overall
Empirical Bayes Procedure	84	80	81
10-Nearest Neighbor	70	92	85
Least Squares	92	89	90

All three of the classification techniques produced high overall success rates (80% to 90%), although the individual success rates differed for noise and valid AE. It was somewhat surprising that the least squares technique produced the best overall classification. From a theoretical standpoint, we had expected the Bayes procedure to perform better; perhaps the technique is sensitive to differences between the histograms of the training and the test sets. The 10-nearest neighbor technique was less successful for noise waveforms than for the valid AE waveforms; this is not consistent with the performance of the other two techniques. Of the three, eleven, and six noise waveforms that were misclassified by, respectively, least squares, 10-nearest neighbor, and Bayes procedure, only two were consistently misclassified by all three techniques. We will need to perform additional studies using these techniques on acoustic emission data if we are to explain these differences.

For the set of data used in this study, the least squares technique produced the best numerical results. Of the three techniques, least squares is the most appealing because it would be the easiest to implement in hardware. The evaluation of the decision function for a waveform requires only the storage of $m + 1$ coefficients, a_i and Y^* ; the computation of the decision function would require very few multiplications and additions. In hardware, the Bayes rule would require storage capacity for a number of histograms that equals the number of categories times the number of features. If these histograms are given, the probabilities for each category can be computed rapidly. The amount of computation time required makes the K-nearest neighbor technique less feasible for hardware implementation because distances have to be computed from the new pattern to all of the patterns in the training set.

A comparison of the clustering and MST planing results with the classification results shows a basic consistency. The classification results are, however, better than one would expect from the feature analyses since the data did not break up into two separate groups as we had hoped. This suggests that the data is capable of a finer discrimination than a noise/valid AE dichotomy. This is evidenced by the four good clusters (Table 6); Clusters 5 and 6 probably contain mostly outliers. Of the nine patterns in these two clusters,

five were misclassified by one of the classification algorithms. Most of the outliers in Figure 12 were classified correctly.

There were 35 patterns whose nearest neighbor in the combined test and training sets were of the opposite category. The results for the 1-nearest neighbor classification algorithm are similar, despite the fact that the patterns in the test set are matched to the nearest neighbor in only the training set. There were 36 patterns in the test and training sets whose nearest neighbors in the training set were of the opposite category. The patterns in the set of the 35 with their nearest neighbor in the opposite category were misclassified at a higher rate than the full data set. The misclassification percentages were 37% for Bayes procedure, 31% for least squares, and 57% for 10-nearest neighbor; this is not as high as one would have expected. A higher percent of the nearest neighbors for these 35 patterns were misclassified: 57% for Bayes, and 49% for both least squares and 10-nearest neighbor. The significance of this is not clear.

More experience with the techniques and with acoustic emission data will resolve some of the questions on the relative performance of the statistical techniques discussed here. The resolution of these questions will result in improved classification algorithms and their implementation in field inspection instruments.

SUMMARY

The work reported in this paper represents an initial attempt to apply pattern recognition techniques to acoustic emission data. The results we obtained were surprisingly good. The majority of the noise waveforms used in this study cannot be distinguished from valid acoustic emissions (valid AE) by visual examination; however, we were able to correctly classify 90%^(a) of the waveforms as either valid AE or noise using the least squares decision rule. Since the current applications of acoustic emission information in NDE rely primarily on counting acoustic events, it is very important to be able to filter out the waveforms caused by noise in the environment. Otherwise, serious mistakes could be made in evaluating the results. The results of this investigation have convinced us that pattern recognition concepts can be used to design such a filter.

In this study, we were dealing with a small data set obtained in a laboratory setting under controlled conditions. The entire data set was gathered in a two-day period during which the recording equipment (transducer, receiver, etc.) were known to be stable. The crack being monitored grew little during such a short data-gathering period. The assumption that the waveforms are generated by a stationary process is implicit in several of the features generated for this study. This assumption may not be valid as the crack grows. For these and several additional reasons, our enthusiasm for this approach must be restrained until it has been verified on additional data sets. Some of these objections should be answered by several steps that are planned or currently underway.

A second experiment is in progress that will increase the data base by including additional types of noise and valid AE from the growth of a different type of crack. Although this new set of data will also be obtained under laboratory conditions, the experimental design is closer to conditions

(a) In Hutton et al. (1979), we reported a successful classification rate of 96% using the least squares decision rule. In this earlier work, we used all of the data to generate the decision rule. In this report, we employed separate training and test sets, as discussed in Feature Analysis.

in the field. One of the primary objectives of the new study will be to determine if the features used in the current experiment will prove valuable in partitioning the new data. In this study, we made no attempt to quantify the effect that the data acquisition system had on the waveforms. This system, consisting of the transducer, receiver, and amplifiers, has a system transfer function that will modify the waveforms being recorded. This was not a problem in the current study since all of the data were recorded with the same system. However, if we were to attempt to apply decision functions trained on data from one acquisition system to data gathered on another, the results would be unpredictable. One purpose of the new study will be to determine the influence of the equipment on the features.

Much additional research will be required to verify the results reported in this paper. Additional laboratory experiments will be needed to obtain the broad spectrum of noise waveforms that can be expected in a field environment. If the results of this work are to be applied in a nuclear reactor environment, the types of noise that are inherent in an operating reactor must be captured and analyzed. This type of data probably cannot be authentically reproduced in the laboratory and must be gathered in the reactor itself. Finally, if several of the features that were useful in this study prove to have broad applications in flaw identification and classification, then it is up to the materials scientists to explain why. This work will lead to additional insights into the mechanisms of crack growth and provide more reliable inspection techniques.

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