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SIGNAL PROCESSING AND PATTERN RECOGNITION OF ULTRASONIC WAVEFOR--ETC(U)
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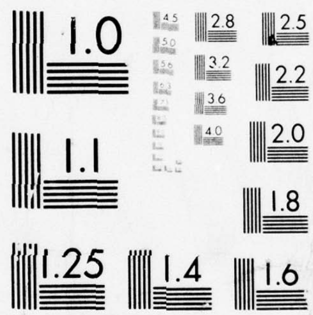

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SIGNAL PROCESSING AND PATTERN RECOGNITION OF ULTRASONIC WAVEFORMS FOR THE NONDESTRUCTIVE EVALUATION OF MATERIALS.

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PROJECT SUMMARY

The overall goal of this project has been to further investigate signal processing and pattern recognition techniques as to how they apply in the non-destructive evaluation of materials for classifying ultrasonic pulse echo waveforms. Computer programs were developed to implement algorithms to generate power spectrum, cepstrum, and auto-correlation waveforms from the ultrasonic pulse echo waveforms. These algorithms have a firm statistical foundation and also have properties associated with them that allow the Fast Fourier Transform to be utilized in an efficient manner. Also, statistical features were extracted from the waveforms. The features were then input to pattern recognition techniques in order to classify the data into appropriate material defects. The procedure outlined above was implemented with 49 ultrasonic pulse echo waveforms obtained from flat-bottom holes of eight different diameters.

A recognition accuracy of 98% has been attained when the flat-bottom holes are classified into two categories using only one feature from the original ultrasonic pulse echo waveforms reflected from the flat-bottom holes. The same results are achieved when the one feature is either the maximum amplitude, the root-mean-square value, or the variance of the waveform. An unexpected result was also observed when a time series method was applied to the portions of the ultrasonic pulse echo waveforms that were reflected from the backwalls instead of the flat-bottom holes. For this procedure an 88% recognition rate was achieved. This indicates that discriminatory information is also contained in the backwall echo.

SIGNAL PROCESSING ALGORITHMS

The signal processing algorithms considered are those used to generate the power spectrum, cepstrum, and auto-correlation. Justification for the algorithms suggested is based on statistical estimation theory. The Fast Fourier Transform (FFT) provides an efficient means of computing the power spectrum, cepstrum, and auto-correlation.

The periodogram, $I_N(\omega)$, is most often used in estimating the power spectrum. For a real finite-length sequence $x(n)$, $n = 0, 1, \ldots, N-1$, the Fourier transform is

$$X(j\omega) = \sum_{n=0}^{N-1} x(n)e^{-j\omega n}$$

and the periodogram is defined as

$$I_N(\omega) = \frac{1}{N}|X(j\omega)|^2 .$$

The periodogram is a biased estimator of the power spectrum. It is also a fact that the periodogram is not a consistent estimator and therefore can be expected to fluctuate about the true power spectrum [13].

Two smoothed spectrum estimators based on Bartlett's procedure [13] and Welch's method [21] are proposed. In the Welch method a data sequence $x(n)$, $n = 0, 1, \ldots, N-1$, is divided into K segments of M samples each so that $N = KM$. The K modified periodograms are defined as

$$J_i(\omega) = \frac{1}{MU}\left|\sum_{n=0}^{M-1} x_i(n)w(n)e^{-j\omega n}\right|^2, \quad i = 1, 2, \ldots, K$$

where

$$U = \frac{1}{M}\sum_{n=0}^{M-1} w^2(n)$$

and

$$x_i(n) = x(n + iM - M), \quad n = 0, 1, \ldots, M-1, \quad i = 1, 2, \ldots, K.$$

The spectral estimate is defined as the average of these modified periodograms,

$$P(\omega) = \frac{1}{K} \sum_{i=1}^{K} J_i(\omega).$$

Some of the commonly used windows are known as the Rectangular, Bartlett, Hanning, Hamming, and Blackman windows [13]. If the window $w(n)$ is chosen so that $w(n) = 1$, $n = 0, 1, \ldots, M-1$, (that is, the Rectangular window) the above spectral estimate $P(\omega)$ becomes the estimate based on Bartlett's procedure. Both Bartlett's procedure and Welch's method yield consistent estimators, although both are biased.

The FFT algorithm can be used to advantage in computing the power spectrum by any of the above methods.

The Discrete Fourier Transform (DFT) is defined to be [13]

$$X(k) = \sum_{n=0}^{N-1} x(n)e^{-j2\pi kn/N}, \quad k = 0, 1, \ldots, N-1,$$

for the sequence $x(n)$, $n = 0, 1, \ldots, N-1$, and the inverse Discrete Fourier Transform is given by

$$x(n) = \frac{1}{N} \sum_{k=0}^{N-1} X(k)e^{j2\pi kn/N}.$$

Computationally efficient algorithms that exploit both the symmetry and periodicity of the sequence $e^{-j2\pi kn/N}$ to compute the DFT are known as FFT algorithms [13,14,15].

The periodogram can be computed at equally spaced frequencies by first computing $X(k)$ using an FFT algorithm and then computing

$$I_N(k) = \frac{1}{N} |X(k)|^2, \quad k = 0, 1, \ldots, N-1.$$

The averaged periodograms used for Bartlett's procedure or Welch's method can be computed in the following way. First compute

$$X_i(k) = \sum_{n=0}^{M-1} x_i(n)w(n)e^{-j2\pi kn/M}, \quad k = 0, 1, . . . , M-1$$

for each section using an FFT algorithm. Next $|X(k)|^2$ is computed for each section. These terms may then be added together for the K segments and the results divided by KMU to yield $P(2\pi k/M)$, k = 0, 1, . . . , M-1.

The cepstrum [12] is defined as the inverse Fourier transform of the logarithm of the power spectrum. It is useful in detecting periodicities in the log spectrum.

The auto-correlation is usually found as the inverse FFT of the power spectrum. This procedure is fast, but the auto-correlation estimate can best be found by using the FFT in computing

$$c(m) = \frac{1}{N} \sum_{n=0}^{N-m-1} x(n)x(n+m), \quad m = 0, 1, . . . , M-1$$

where $M \leq N$ [13]. This estimator is asymptotically unbiased.

FEATURE EXTRACTION

Given a set of discrete time waveforms, the power spectrum, cepstrum, and auto-correlation waveforms can be obtained for each. In order to classify this set of waveforms into categories with common characteristics, discriminatory features must be extracted from these waveforms.

The features computed from the waveforms are statistical in nature. They are known as the mean, variance, maximum, root-mean-square, skewness, and kurtosis.

Suppose a waveform is denoted by $g(y)$ and the probability density function $f(y)$ is given by

$$f(y) = \frac{1}{N}\,\delta(y-y_1) + \frac{1}{N}\,\delta(y-y_2) + \ldots + \frac{1}{N}\,\delta(y-y_N).$$

With this information the features can be computed as

$$\mu = E[g(Y)] = \int g(y)f(y)dy = \frac{1}{N}\sum_{i=1}^{N} g(y_i),$$

$$\sigma^2 = E[\{g(Y)-\mu\}^2] = \frac{1}{N}\sum_{i=1}^{N} [g(y_i)-\mu]^2,$$

$$g(y)_{max} = \max_i\,[g(y_i)]$$

$$\text{r.m.s.} = \{E[g^2(Y)]\}^{\frac{1}{2}} = [\frac{1}{N}\sum_{i=1}^{N} g^2(y_i)]^{\frac{1}{2}},$$

$$SK = \frac{E[\{g(Y)-\mu\}^3]}{\sigma^3} = \frac{1}{N\sigma^3}\sum_{i=1}^{N} [g(y_i)-\mu]^3,$$

and

$$KR = \frac{E[\{g(Y)-\mu\}^4]}{\sigma^4} = \frac{1}{N\sigma^4}\sum_{i=1}^{N} [g(y_i)-\mu]^4,$$

where μ denotes the mean, σ^2 denotes the variance, $g(y)_{max}$ denotes the maximum, r.m.s. denotes the root-mean-square, SK denotes the skewness, and KR denotes the kurtosis [19].

The next section describes how these features may be used to classify the waveforms.

PATTERN RECOGNITION

Automated interpretation of ultrasonic pulse echo waveforms can be formulated as a classification problem in which it is desired to decide into which of T categories denoted by $C_1, \ldots, C_T$, each test block belongs. The numerical results from preprocessing time waveforms for each test block can be represented by a point in m-dimensional space assuming that results consist of m measurements or features.

A pattern is an m-tuple where each component represents a measurement or feature. A pattern is denoted by the vector Y where $Y = (y_1, \ldots, y_m)$. Let R^m denote the set of all m-tuples $(y_1, \ldots, y_m)$ whose components $y_1, \ldots y_m$ are real numbers. R^m is called m-space, and each m-tuple in R^m is said to be a point or vector in m-space.

The topic of classification is usually included under the more general topic of pattern recognition. Several good survey papers [5,7,10,20] and recently published books [1,3,18] have been written describing pattern recognition techniques.

In most pattern recognition problems the only information available consists of a "training" set of L patterns whose true classifications are known. The L patterns denoted by $Y_1, \ldots, Y_L$ are called training samples. The training samples from each category are assumed to be independent and identically distributed according to some unknown density function. The training samples are used to construct decision rules which are implemented by discriminant functions. These functions are defined to be real-valued functions of the pattern Y used in classifying pattern Y as a member of one of the T categories. The discriminant functions yield a decision rule which specifies that pattern Y is classified as being a member of that class which has the largest discriminant function value.

Sample and Feature Size

In most pattern recognition problems little is known about the underlying probability distributions of the T categories or classes. Therefore, the discriminant functions must be determined on the basis of the L training samples.

The classification results obtained from the training samples should be related to the performance of the decision rule on future samples. Quite often the error rate obtained is lower than the true error rate of the classifier.

One method quite often used to estimate the true error rate of a classifier is to divide the original L samples into a design set and a test set. The design set is then used as the training set and the resulting discriminant functions are then tested on the test set. One problem with this approach is that the value of L may be small and a better classifier could be designed by using all of the samples.

Based on a fixed sample size Kanal and Chandrasekaran [6] recommend using the "leaving-one-out" method in designing a classification system and evaluating its performance. In the leaving-one-out method a classifier is designed based on L-1 samples and then tested on the one removed sample. This procedure is repeated for each of the L training samples. A problem associated with this approach is that it may be too time consuming.

Foley [2] using both experimental and theoretical results, indicates that the ratio of the number of samples per class to the number of features should be at least three to obtain good estimates of the optimum error rate. That is,

$$\frac{L_c}{m} \geq 3, \qquad (1)$$

where L_c represents the number of samples per class.

Meisel [8] points out that the m used in equation (1) should in some sense be the "intrinsic dimensionality". This means that the set of m features should contain only relevant information. Feature selection schemes [7,8,18] might be used in reducing m-space to one that contains only useful discriminatory information. Kanal [7] discusses other investigations into dimensionality, sample size, and error estimation.

When a classifier's performance cannot be generalized to future unknown samples the classifier is said to be overtrained or overfitted. This situation occurs most frequently when the number of samples per class is small compared to the number of features.

Perceptron Algorithm

A class of machines developed as a model of machine learning and decision making has been called a perceptron and has played an important role in the development of pattern recognition theory [1,16,17].

The basic perceptron algorithm is a simple scheme for the iterative determination of the weight vector W used to define the hyperplane $d(Y) = W \cdot Y = 0$, which is a linear discriminant function. An outline of the perceptron algorithm can be stated as follows.

Given two sets of training samples belonging to pattern classes C_1 and C_2, respectively, let the initial weight vector W_1 be chosen arbitrarily. Then, the (k+1)st approximation is given by:

1. If the kth member of the training sequence Y_k is classified correctly leave the weight vector W_k unchanged. That is,

$$W_{k+1} = W_k \quad \text{if} \quad W_k \cdot Y_k > 0 \text{ and } Y_k \varepsilon C_1$$

$$W_{k+1} = W_k \quad \text{if} \quad W_k \cdot Y_k < 0 \text{ and } Y_k \varepsilon C_2$$

2. Otherwise, the weight vector is changed by

$$W_{k+1} = W_k + cY_k \quad \text{if} \quad W_k \cdot Y_k \leq 0 \text{ and } Y_k \varepsilon C_1$$

or

$$W_{k+1} = W_k - cY_k \quad \text{if} \quad W_k \cdot Y_k \geq 0 \text{ and } Y_k \varepsilon C_2$$

where c is a positive correction increment, possibly depending upon k.

The algorithm is said to have converged when all of the training samples are classified correctly. It can be shown that if the two classes are linearly separable then the perceptron algorithm converges in a finite number of iterations [1,11,18]. The correction increment c may be selected in several ways although in practice a value of $c = 1$ works quite well.

Linear Prediction

Linear prediction is becoming increasingly important in signal processing because of the accuracy with which it forecasts time series data and the speed of computation of its coefficients. The linear predictor coefficients and the auto-correlation values can be used as features in classifying waveforms. This technique has been particularly successful in speech recognition [4].

Linear prediction requires the waveform to be stationary. By dividing the waveform into a sufficient number of windows, each window can be assumed to be stationary. Over each window the waveform can be modeled as an autoregressive process of order p (AR(p) process); that is, it is assumed that each sampled value Z_t can be represented by the past p values, plus a zero-mean noise term a_t:

$$Z_t = \phi_1 Z_{t-1} + \phi_2 Z_{t-2} + \cdots + \phi_p Z_{t-p} + a_t.$$

The waveform is thus described over each window by the parameters $\phi_1, \phi_2, \ldots, \phi_p$. The least squares estimate of these terms can be obtained by solving the Yule-Walker equations

$$\rho_k = \sum_{i=1}^{p} \phi_i \rho_{|i-k|} \qquad k = 1, 2, \ldots, p$$

by replacing the true auto-correlation coefficients ρ_k by c_k, their calculated estimates [4]. The least squares estimate $\hat{\phi}$ of $\phi = (\phi_1, \phi_2, \ldots, \phi_p)$ is a maximum log likelihood estimate of the parameter ϕ and a distance measure of the form

$$\log \left(\sum_{k=1}^{p} \left| \sum_{i=1}^{p} \hat{\phi}_i c_{|i-k|} - c_k \right| \right) \qquad (2)$$

was considered, since this distance measure gave excellent results in speech recognition [4]. (This expression does not represent a true metric, and thus it is actually a similarity measure instead of a distance measure). The $\hat{\phi}_i$ are the estimated linear predictor coefficients of the reference or training sample while the c_k are the auto-correlation coefficients of the unknown or test sample. The total distance between a test sample and a training sample is the sum of (2) over all windows of the sample. The test sample is then classified as being a member of the same class as the training sample which gives the minimum distance to the unknown test sample. Hence the classification technique used for this procedure is the Nearest Neighbor decision rule [1].

RESULTS

The Air Force Materials Laboratory initiated a program to determine if an advanced signal processing system could classify the ultrasonic pulse echo waveforms from flat-bottom holes. This study examined forty-nine samples obtained from aluminum area-amplitude test blocks and three different transducers [9].

Sixteen test blocks were fabricated from two different sets of 7075-T6 aluminum alloy. Each of the two sets contained eight test blocks which had flat-bottom hole sizes ranging in diameter from 1/64 to 8/64 inches in increments of 1/64-inch.

The three transducers used in this study were all 5 MHz transducers with diameters of 0.5, 0.75, and 1.0 inch.

The received ultrasonic pulse echo waveforms were sampled at 100 MHz and the resulting digitized time waveforms were obtained. The forty-nine samples for the eight categories were divided into a training set and a testing set consisting of 31 and 18 samples, respectively. The class distribution of each class is given in Table I.

TABLE I

DISTRIBUTION OF THE TRAINING AND TESTING SET FOR

THE FLAT-BOTTOM HOLE DATA

Class (Hole Sizes in 64th's)	Number of Training Samples	Number of Testing Samples
1	4	2
2	4	2
3	2	2
4	4	2
5	4	2
6	4	2
7	4	3
8	5	3
TOTAL	31	18

Before applying the signal processing algorithms and feature extraction techniques it is of interest to consider the relationship between the number of samples available for processing and the number of features used for classification.

The basic perceptron algorithm described earlier is based on the two class problem, although it is easily extended to the multiclass situation [18]. For the T class problem the idea is to determine T linear discriminant functions $d_1(Y), \ldots \ldots, d_T(Y)$, with the property that if $Y \in C_i$, then

$$d_i(Y) > d_k(Y) \text{ for all } k \neq i. \quad (3)$$

When all of the training samples are classified correctly by (3) the T classes are said to be linearly separable.

It is well known [11] that if $L \leq m + 1$ then there exists a linear discriminant function which effects the same dichotomization as specified by the two class assignment of the L points. This situation demonstrates that overtraining may occur when $L \leq m + 1$ since a separator does exist that will dichotomize the samples correctly, although it may not be the optimal classifier. This fact may also be demonstrated by the use of the perceptron algorithm [18].

From Table I it can be seen that the two smallest classes contain a total of 4 and 6 samples, respectively. This implies that L has a value of 10. The argument above indicates that m must have a value less than 9 to be sure that these two classes are not forced to be linearly separable. When the same argument is applied to only the training samples, it is seen that m must have a value less than 5 in order to avoid the forced linear separability. Hence, the number of features extracted from the waveforms that are to be used for classification must be less than 5. This number is still marginal since the ratio of the number of training samples per class, which varies from 2 to 5, to the number of features is less than 1.25 for each class when m is equal to 4. This ratio should be much higher as indicated earlier of the performance of a classifier is to be generalized to unknown samples.

The overall problem can be reformulated into a more satisfactory problem in terms of the relationship between the number of samples and the number of features. In order to accomplish this two separate cases were considered to reduce this to a two-class problem. First, classes 1, 2, 3, and 4 can be grouped together as a single category and classes 5, 6, 7, and 8 can also be grouped together as a single category. Second, classes 1, 2, and 3 can be considered as one category and classes 4, 5, 6, 7, and 8 can be considered as a second category.

In applying the signal processing algorithms to the reflected ultrasonic pulse echo waveforms and classifying the samples based on the extracted features, it was found that the cepstrum and the auto-correlation waveforms contained little discriminatory information. Therefore, the following discussion will center on the original waveforms and the power spectrum waveforms.

Figure 1 shows one of the reflected ultrasonic pulse echo waveforms from a test block with a hole diameter of 8/64 inches. A plot of the pertinent pulse echo defect data is shown in Figure 2. This is actually a magnified picture of the first portion of the waveform shown in Figure 1. Figures 3-7 show the power spectrum of Figure 2 based on the different algorithms discussed earlier. It should be apparent from Figures 3 and 4 that Bartlett's procedure with one window yields the periodogram. Figure 8 exhibits a plot of the pulse echo data that traveled past the defect and was reflected by the surrounding backwall. Actually, this is a magnified picture of the second portion of the waveform shown in Figure 1. Figures 9-12 show the power spectrum of Figure 8 based on Bartlett's procedure and Welch's method.

It should be noted that each of the 49 pulse echo waveforms were corrected, before any processing was performed, for the three instruments settings of sensitivity, attenuation, and damping. These settings were varied as the data were recorded [9]. The corrected waveforms will be referred to as the original waveforms in the following discussion.

Table II shows the distribution of training samples and testing samples for case 1 in which classes 1, 2, 3, and 4 are grouped together as one category and classes 5, 6, 7, and 8 are grouped together as a second category. Table III exhibits the same information for case 2 in which category one is composed of classes 1, 2, and 3 and category two is composed of classes 4, 5, 6, 7, and 8.

The classification problem for both of these cases appears to be more realistic in terms of the earlier discussions on the relationships between the number of samples and the number of features. Both cases can be thought of as

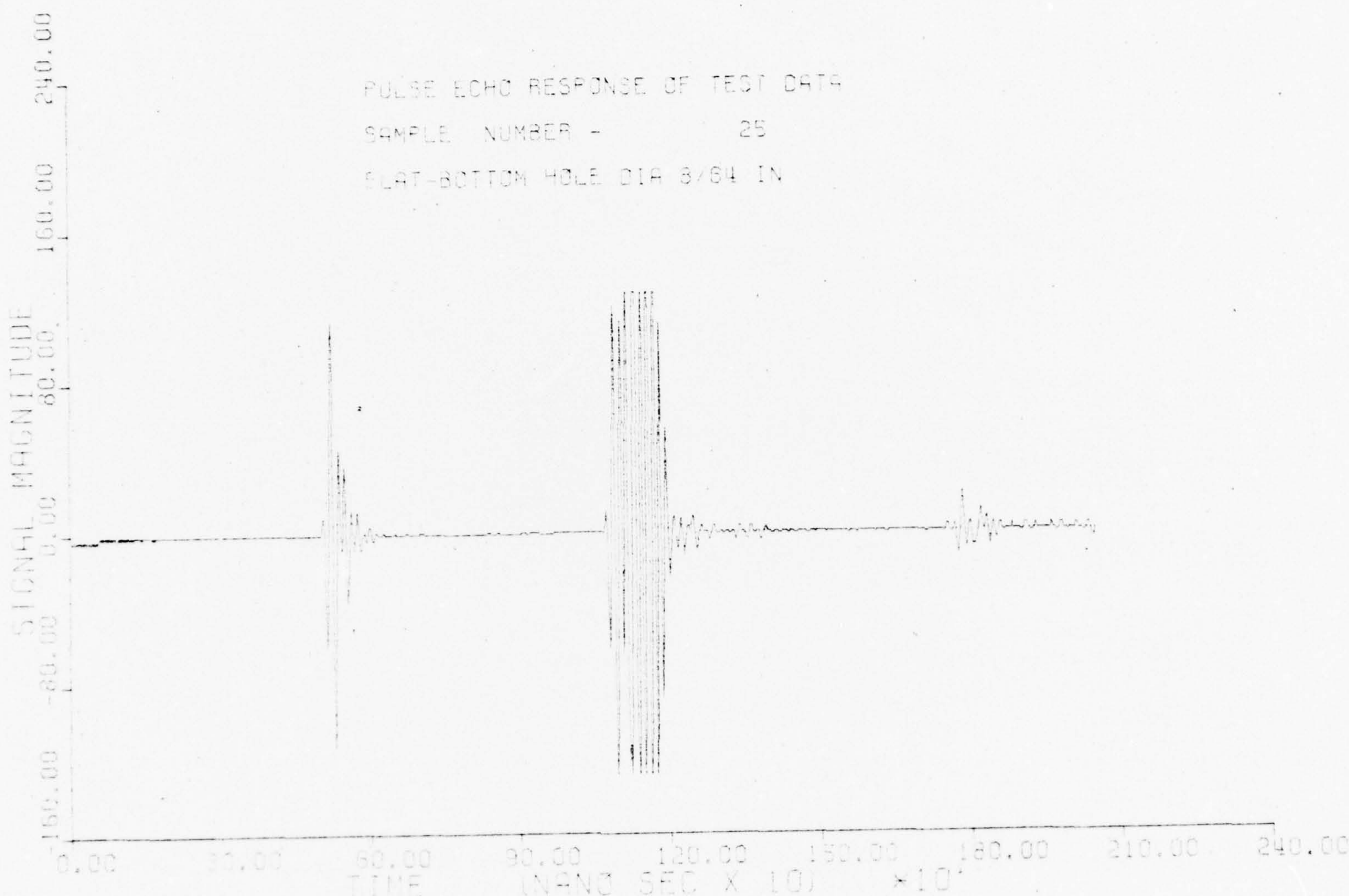

FIGURE 1. REFLECTED ULTRASONIC PULSE ECHO WAVEFORM.

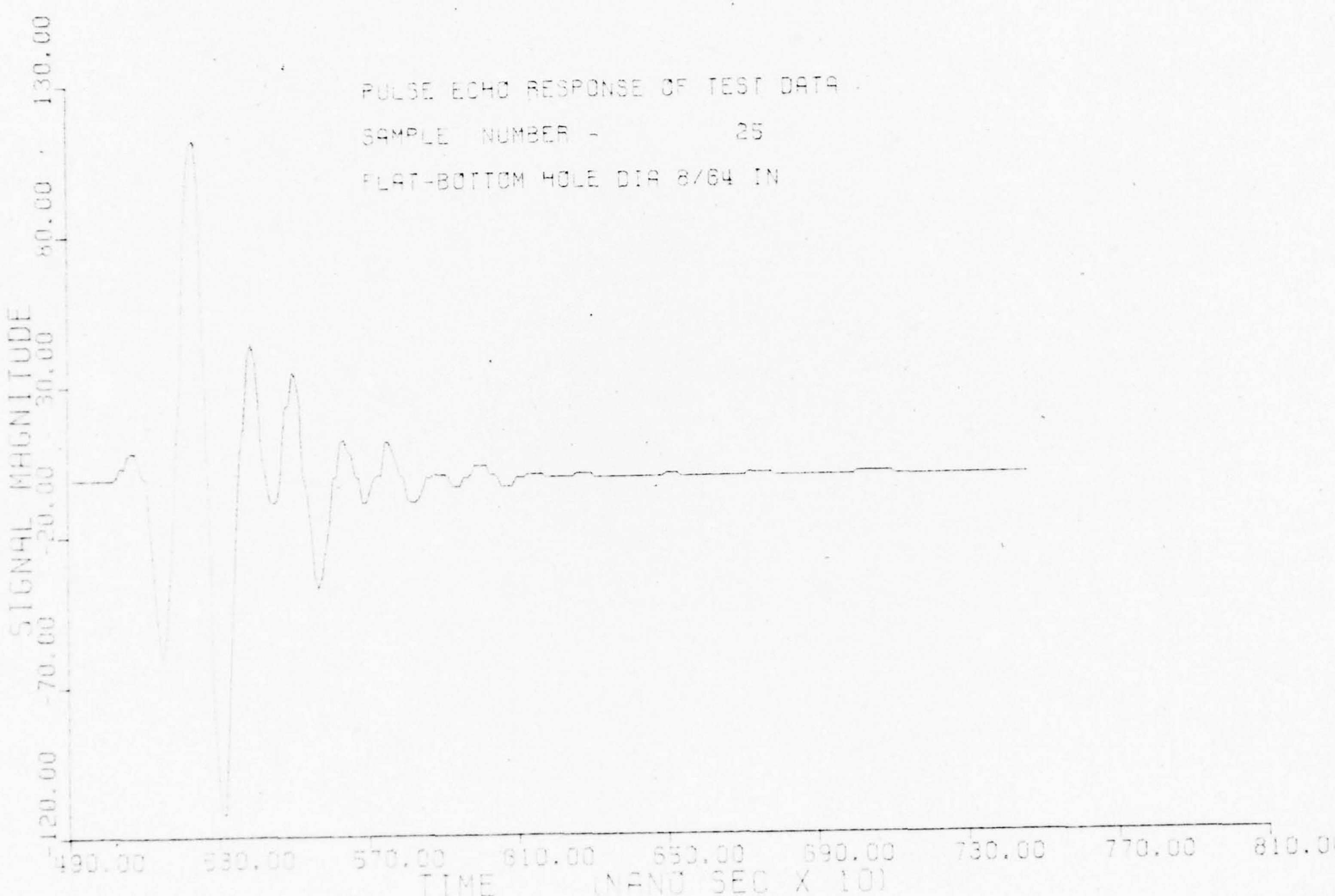

FIGURE 2. PLOT OF SIGNIFICANT PULSE ECHO DEFECT DATA.

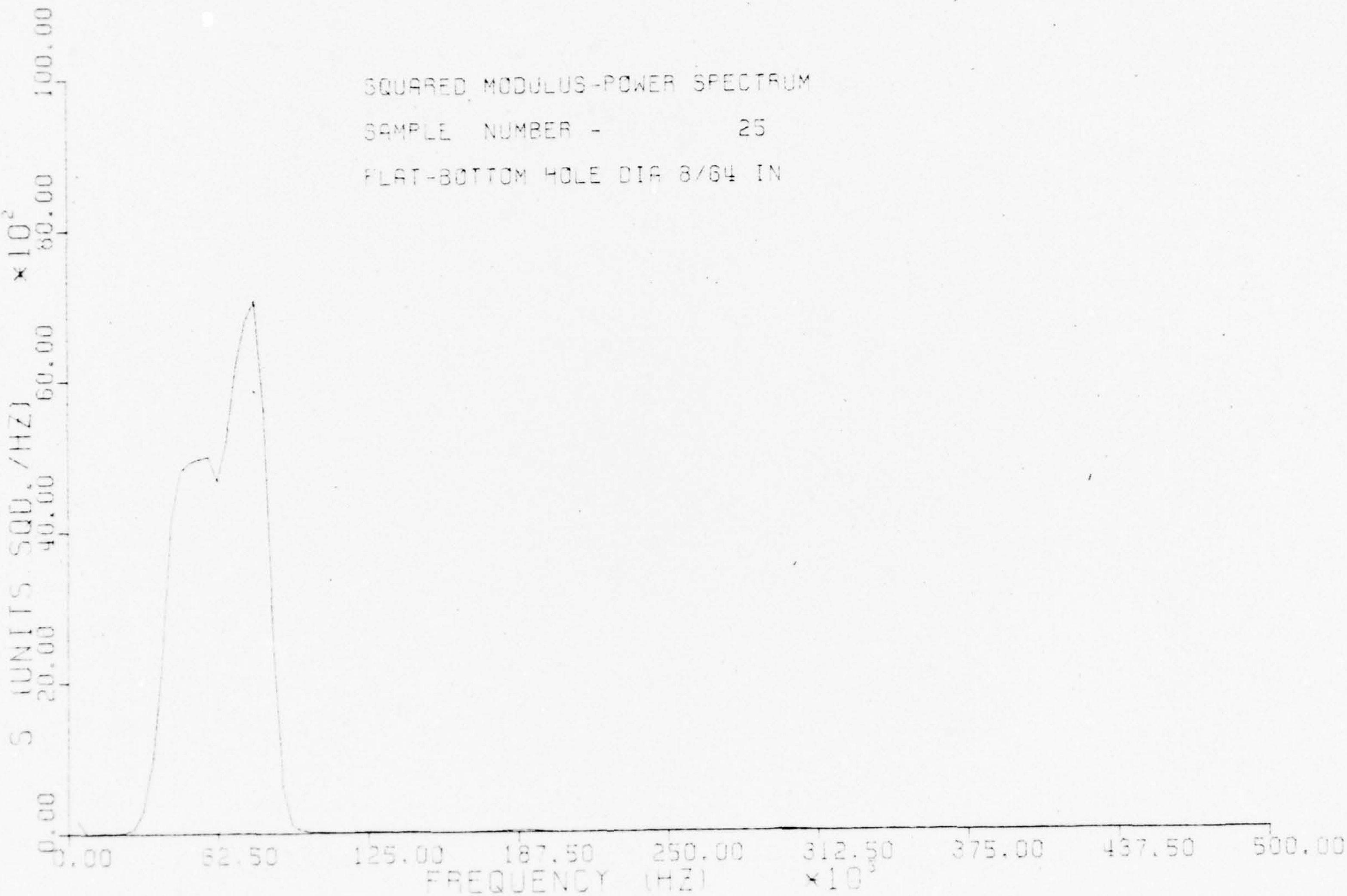

FIGURE 3. POWER SPECTRUM OF FIGURE 2 USING THE PERIODOGRAM.

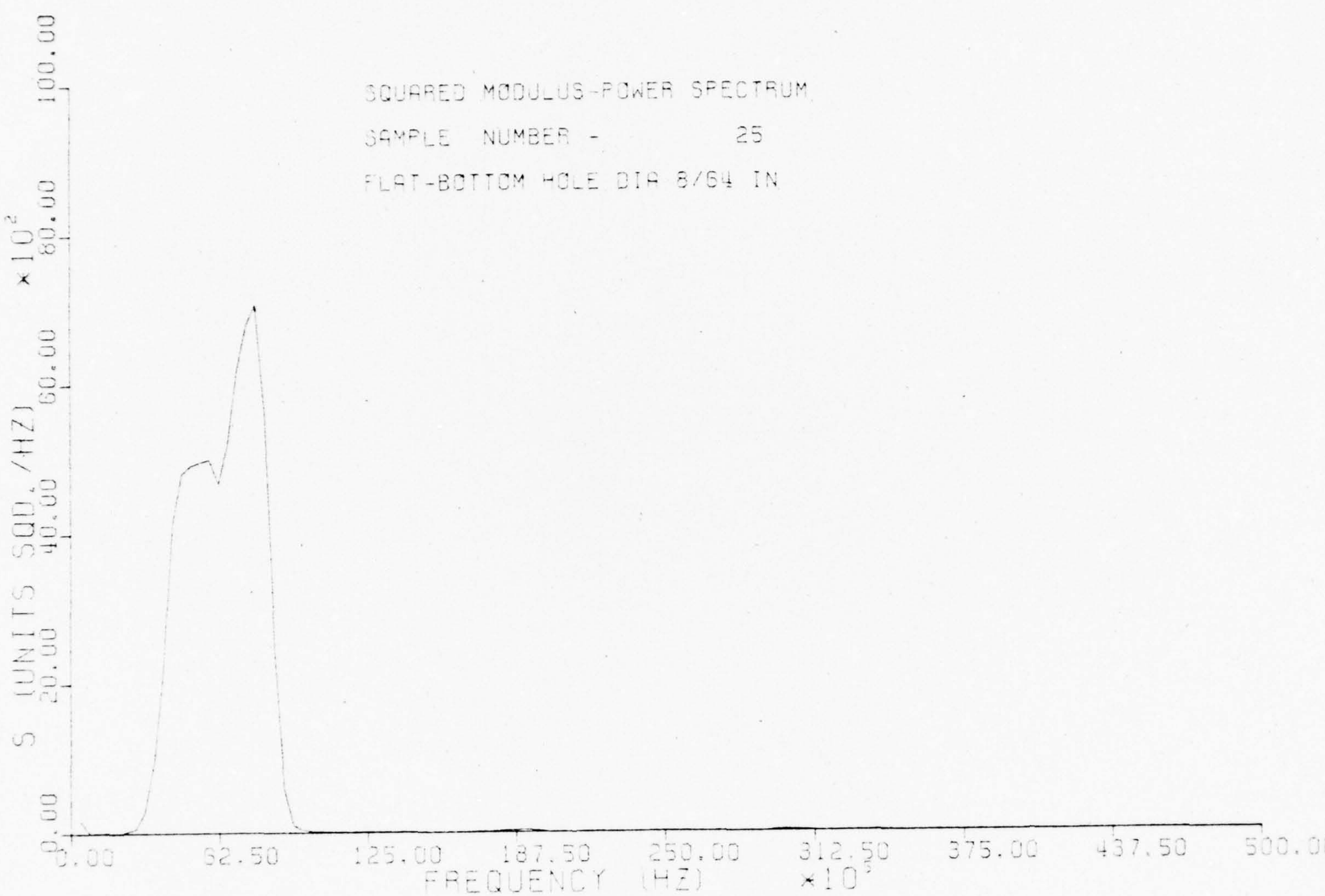

FIGURE 4. POWER SPECTRUM OF FIGURE 2 USING BARTLETT'S PROCEDURE WITH ONE WINDOW.

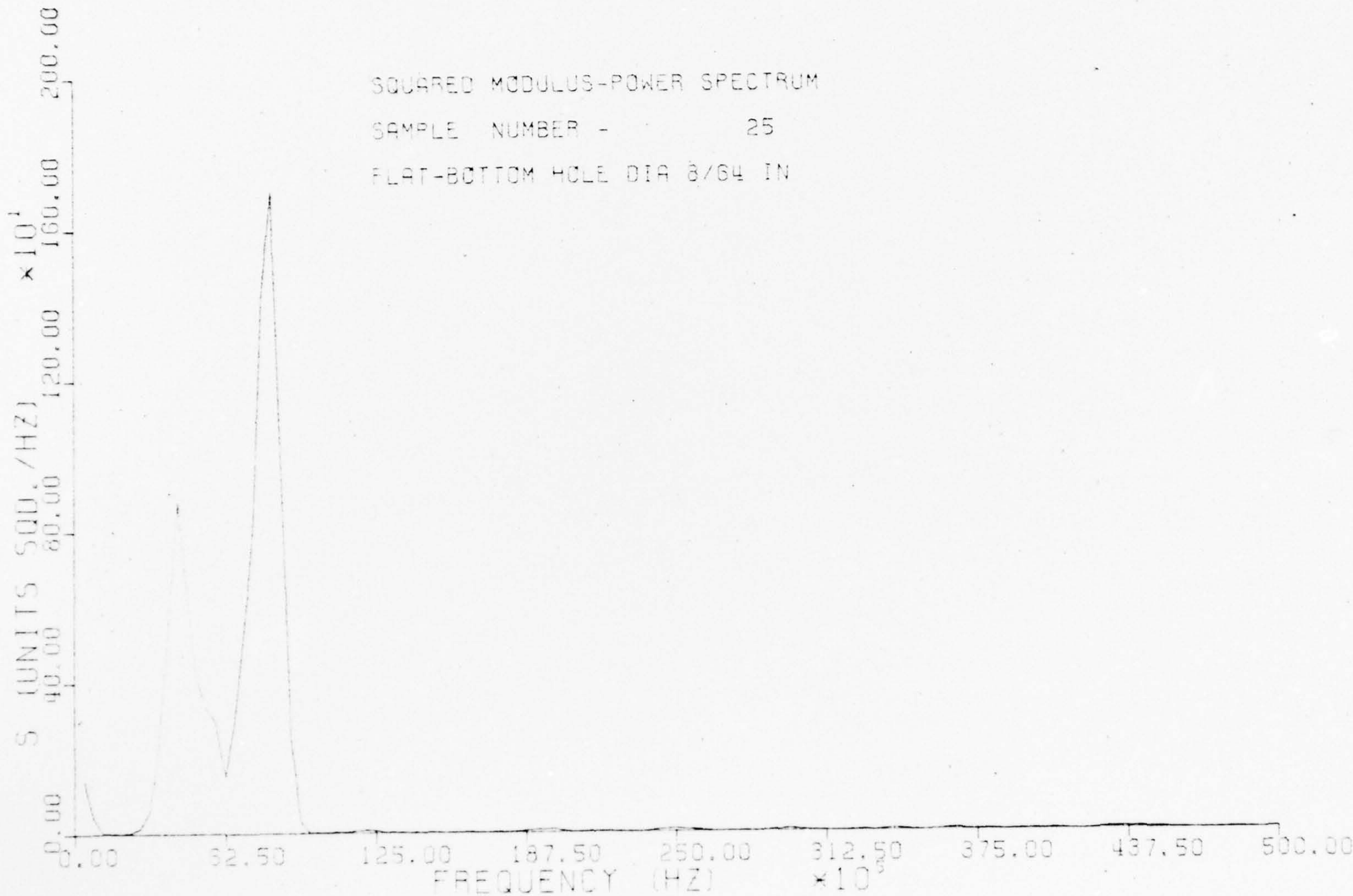

FIGURE 5. POWER SPECTRUM OF FIGURE 2 USING WELCH'S METHOD WITH ONE WINDOW.

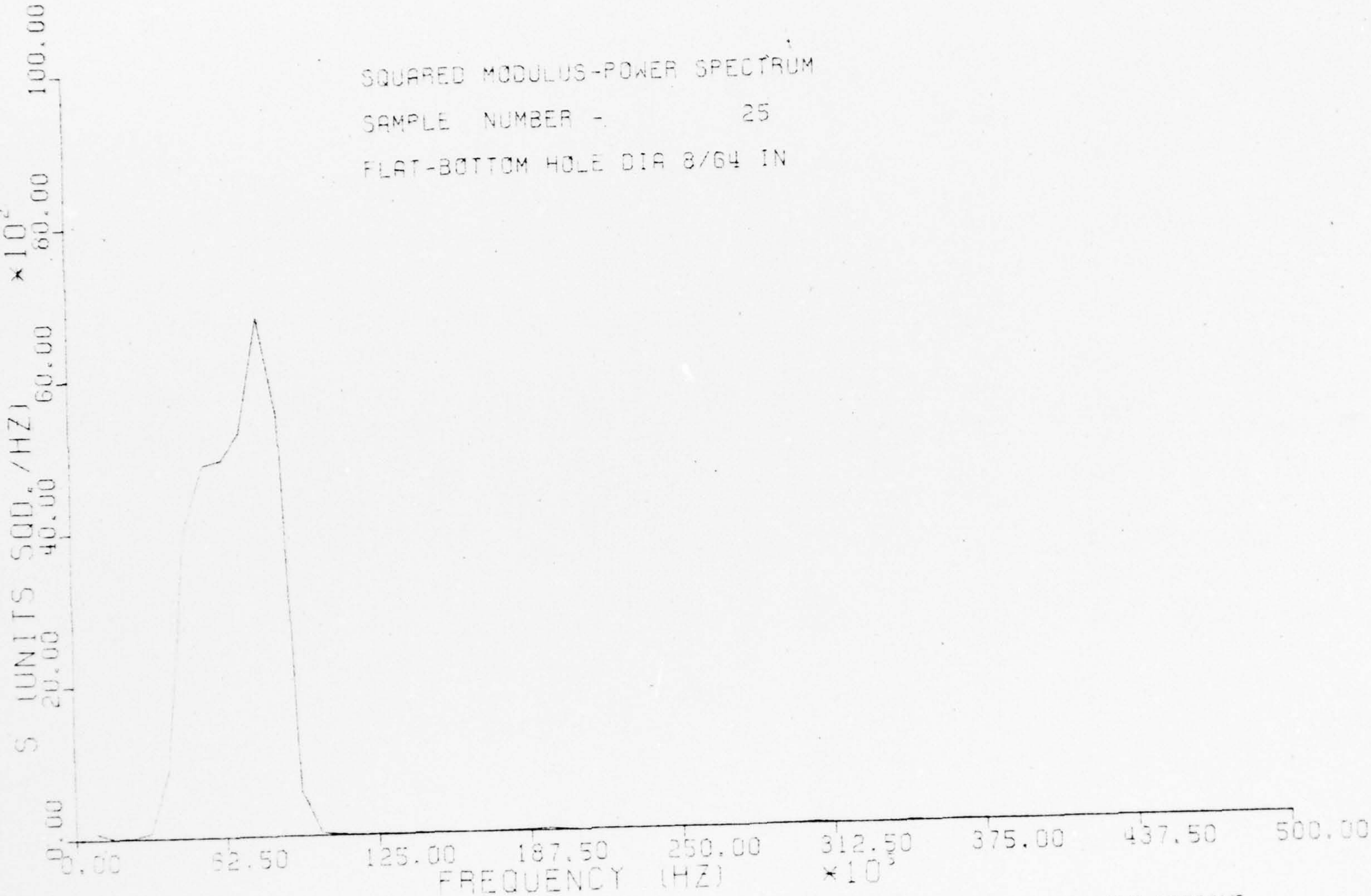

FIGURE 6. POWER SPECTRUM OF FIGURE 2 USING BARTLETT'S PROCEDURE WITH TWO WINDOWS.

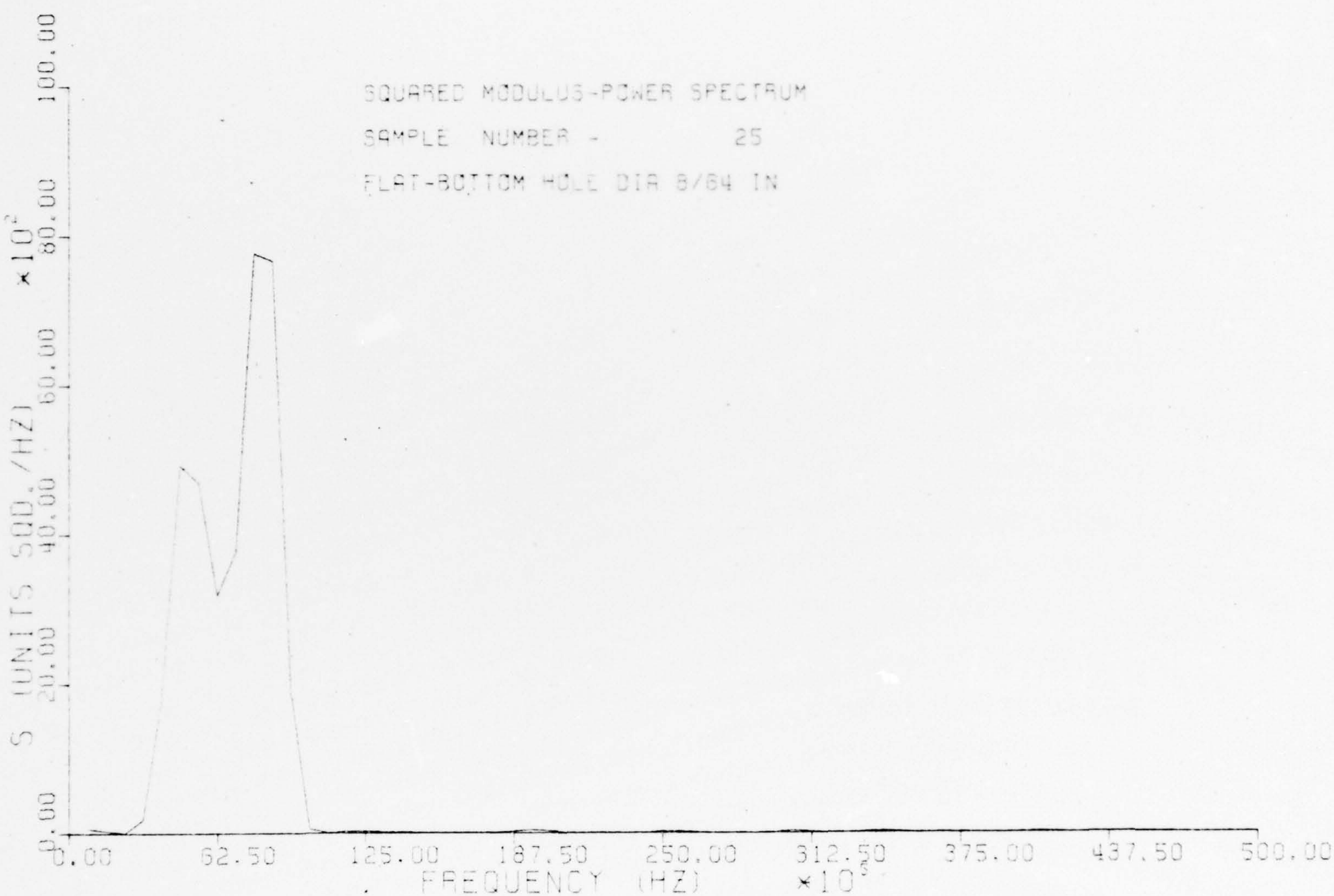

FIGURE 7. POWER SPECTRUM OF FIGURE 2 USING WELCH'S METHOD WITH TWO WINDOWS.

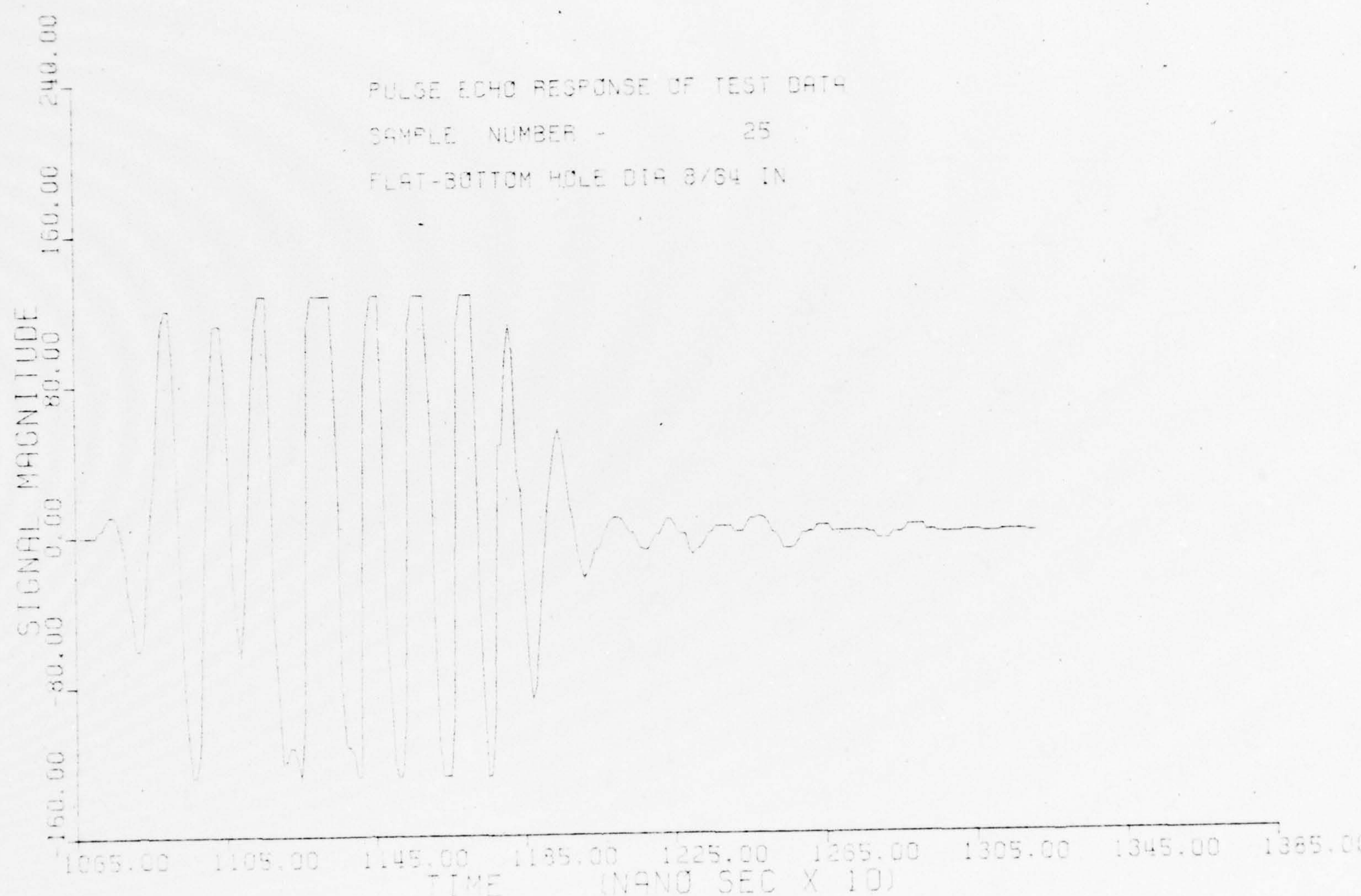

FIGURE 8. PLOT OF PULSE ECHO DATA REFLECTED BY SURROUNDING BACKWALL.

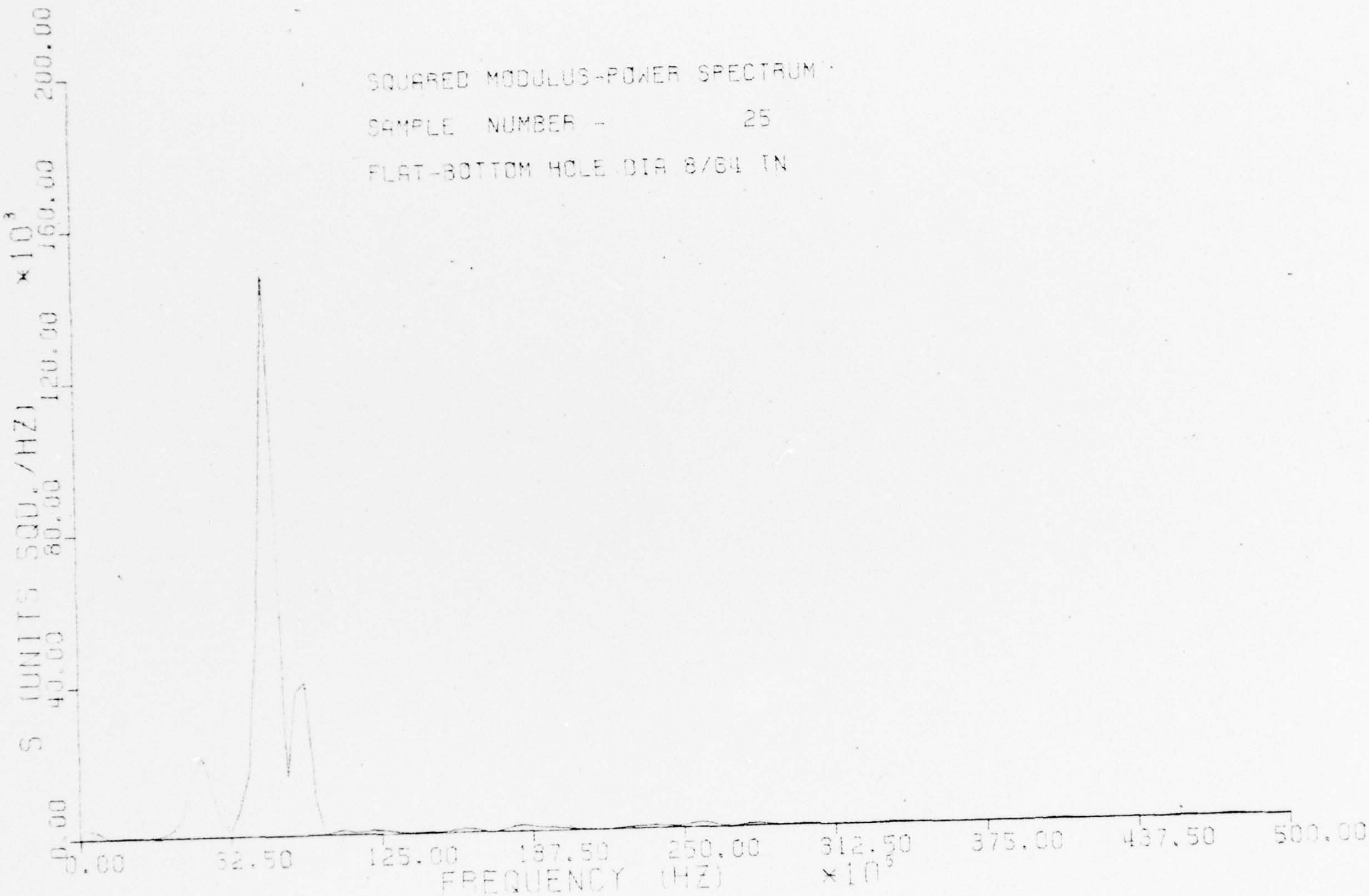

FIGURE 9. POWER SPECTRUM OF FIGURE 8 USING BARTLETT'S PROCEDURE WITH ONE WINDOW.

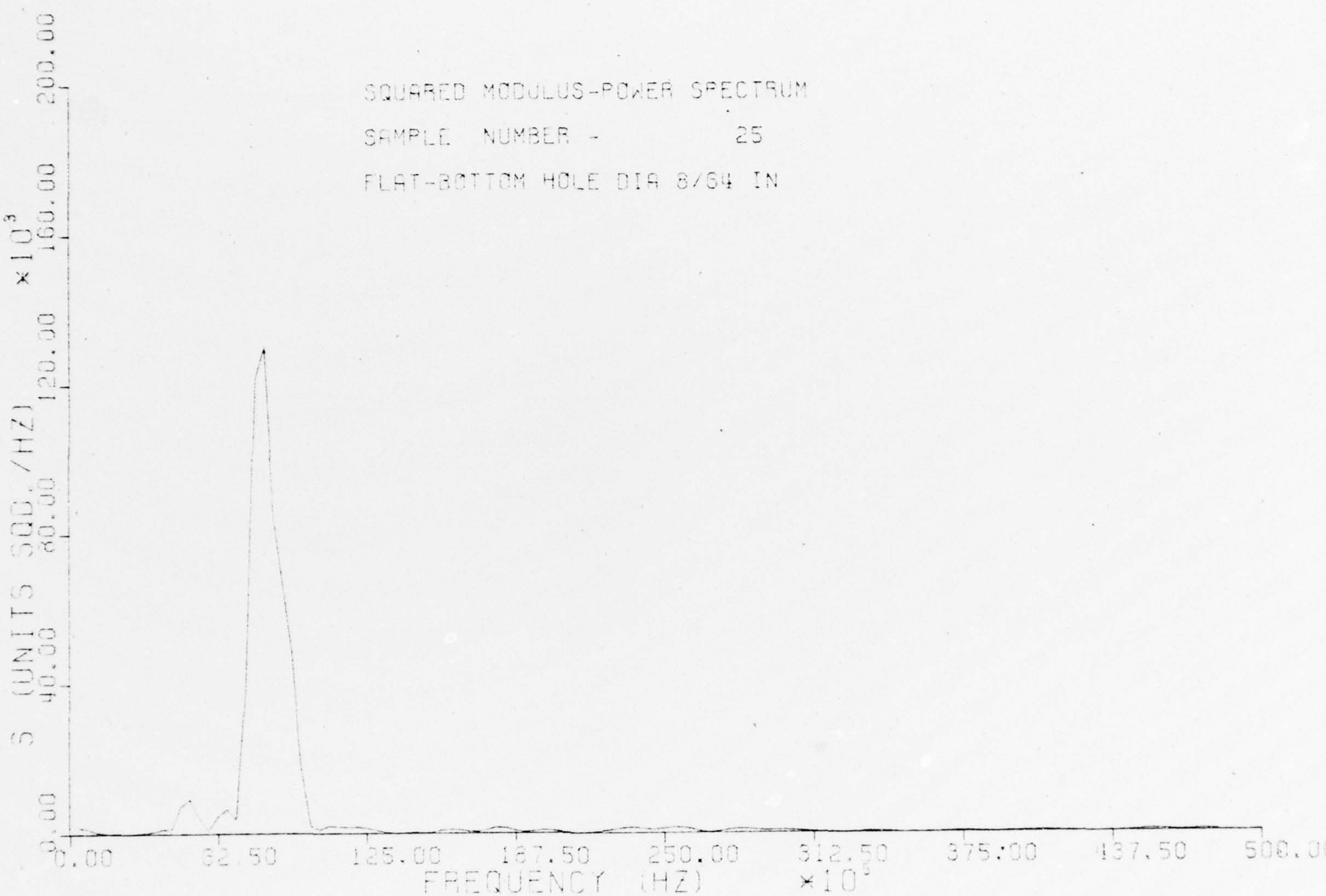

FIGURE 10. POWER SPECTRUM OF FIGURE 8 USING WELCH'S METHOD WITH ONE WINDOW.

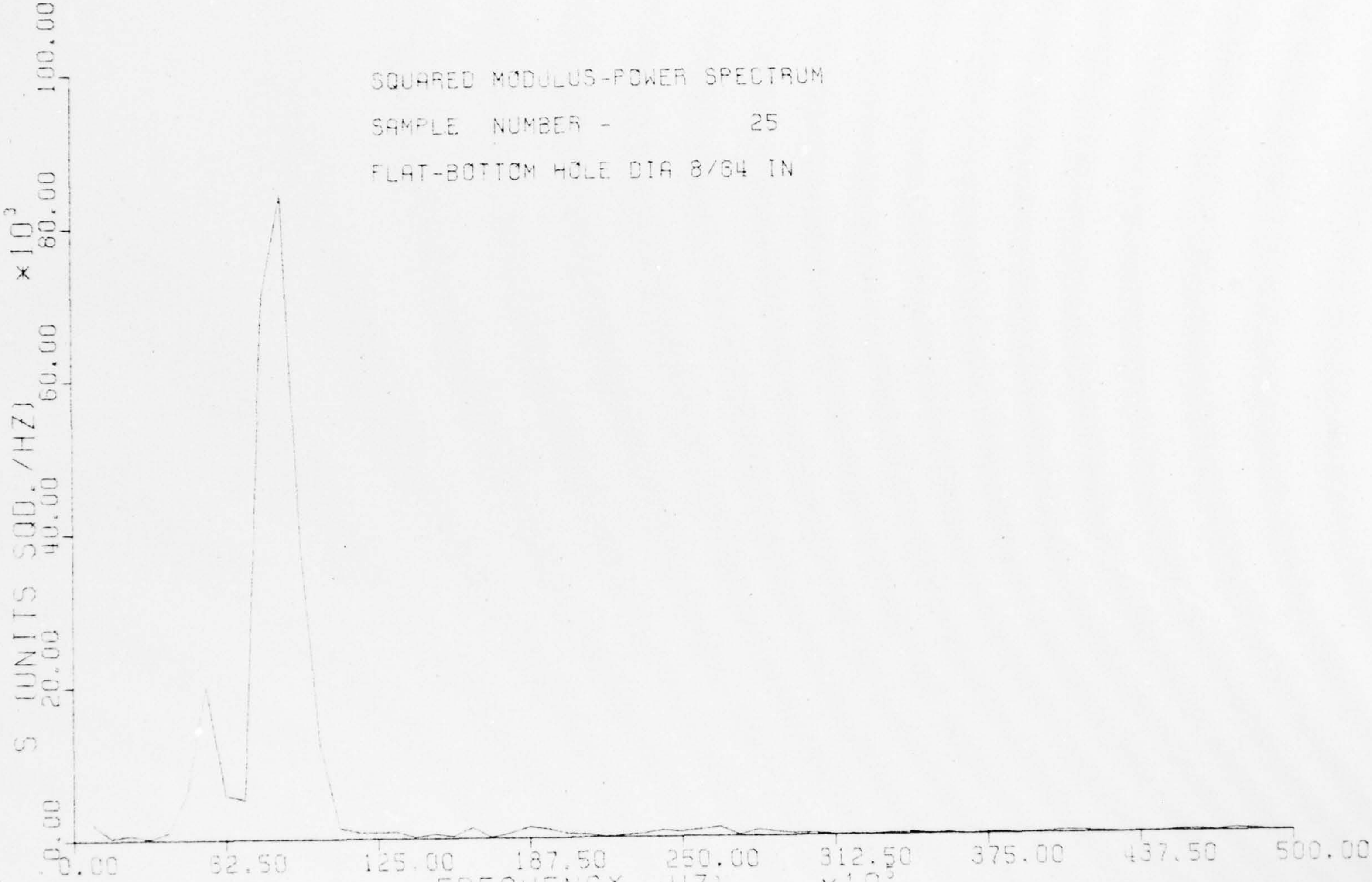

FIGURE 11. POWER SPECTRUM OF FIGURE 8 USING BARTLETT'S PROCEDURE WITH TWO WINDOWS.

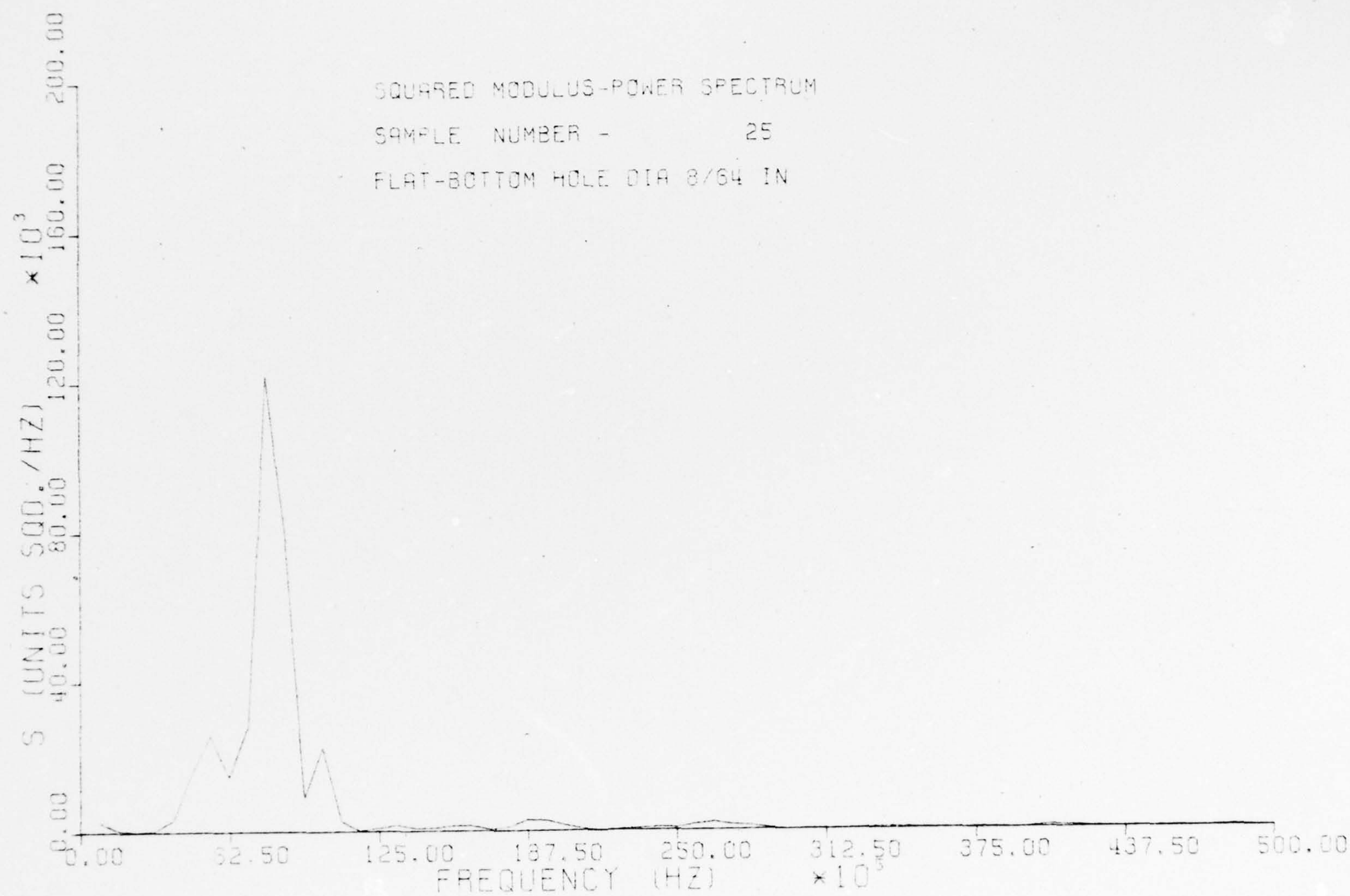

FIGURE 12. POWER SPECTRUM OF FIGURE 8 USING WELCH'S METHOD WITH TWO WINDOWS.

thresholding problems where the thresholds are equal to 4.5/64 and 3.5/64 inches for case 1 and case 2, respectively.

TABLE II

TWO CATEGORIES OF FLAT-BOTTOM HOLE DATA

(CASE 1)

Category	Number of Training Samples	Number of Testing Samples
1	14	8
2	17	10
TOTAL	31	18

TABLE III

TWO CATEGORIES OF FLAT-BOTTOM HOLE DATA

(CASE 2)

Category	Number of Training Samples	Number of Testing Samples
1	10	6
2	21	12
TOTAL	31	18

For Case 1, both the maximum amplitude and r.m.s. features of the original waveforms were found to correctly classify 46 of the 49 samples. The Nearest Neighbor decision rule yielded the same results using maximum amplitude, mean, variance, and r.m.s. as features. The mean of the power spectrum correctly classified 45 samples using Welch's method with two windows. When Bartlett's procedure with two windows was used to calculate the power spectrum, the r.m.s. correctly classified 45 samples.

For Case 2, the maximum amplitude, r.m.s. and variance of the original waveform were found to individually classify 48 of the 49 samples correctly. The same results were obtained when these three features were collectively used in 3-space. The Nearest Neighbor rule correctly classified 47 samples using maximum amplitude, mean, variance, and r.m.s as features. The mean of the power spectrum correctly classified 48 samples using two windows for both Bartlett's procedure and Welch's method.

The results above were based on the portion of the waveform that was reflected from the flat-bottom holes. Also, the perceptron algorithm was used to obtain linear discriminant functions when no classification procedure was mentioned. The features skewness and kurtosis were found to contain no discriminatory information when used for any of the waveforms.

For Case 2, another portion of the original waveforms was also analyzed. When the portions of the pulse echo waveforms that traveled past the defect and were reflected by the surrounding backwall were analyzed by the linear prediction technique, 43 samples were correctly classified. For this procedure p had a value of 10 and 6 windows were used. Also, the number of training samples was 24 and the number of testing samples was 25.

CONCLUSIONS

It has been shown that with a small sample size pattern recognition and signal processing techniques can be used effectively in classifying ultrasonic pulse echo waveforms for the nondestructive evaluation of materials. The sample size should be larger though in order to make the results statistically significant. One way that this could be achieved would be to shoot each test block several times with each transducer.

The techniques and procedures discussed in this report can be used to process other nondestructive evaluation data. The fatigue-crack data that was to be processed has never been received. The computer programs that were used have been delivered to the Nondestructive Evaluation Branch (AFML/LLP) at Wright-Patterson Air Force Base.

The author of this report and the project monitor took a trip to the Rome Air Development Center (RADC) at Griffiss Air Force Base to visit with personnel concerning the use of RADC's interactive pattern recognition facility OLPARS. This facility has excellent waveform processing, feature extraction, and pattern recognition techniques available. It allows the researcher who understands the physical problems to insert his knowledge into the solution by interaction at a CRT display. Another trip was taken to Wright-Patterson Air Force Base and the facilities at RADC were discussed with the personnel of AFML/LLP. It was pointed out to them that they could utilize the facility with a CRT via telephone lines.

This project has enabled the principal investigator to concentrate in an area in which he is very interested. It has also served as a research area for one M.S. report (in progress). A paper is being planned to be submitted to the 1978 IEEE SoutheastCon to be held in Atlanta, Georgia, in April 1978. Furthermore, it has inspired a general interest in the areas of pattern recognition and digital signal processing in numerous faculty and graduate students in the Electrical and Computer Engineering Department at Clemson University. For all of the above reasons, we are grateful to the Air Force Office of Scientific Research for making this project possible.

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The purpose of this project has been to further investigate signal processing and pattern recognition techniques as they apply to classifying ultrasonic pulse echo waveforms for the nondestructive evaluation of materials. Data analyzed was based on 49 ultrasonic pulse echo waveforms obtained from flat-bottom holes. Algorithms with firm statistical foundations were implemented to generate power spectrum, cepstrum, and auto-correlation waveforms from the pulse echo waveforms. These algorithms also have properties associated with them that allow the Fast Fourier Transform to be utilized in an efficient manner. In order

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20). Abstract - continued

to classify the data into appropriate material defects statistical features were extracted from the original and generated waveforms. The features were then used as input to pattern recognition techniques.

Using only one feature from the original ultrasonic pulse echo waveforms, 48 of 49 samples were dichotomized correctly for a recognition rate of 98%. The one feature can be either the maximum amplitude or the root-mean-square value or the variance of the waveform, since all yielded the same results. It was also discovered that 43 of the 49 samples were dichotomized correctly when a time series method was applied to the portions of the pulse echo waveforms that traveled past the defect and were reflected by the surrounding backwall. This indicates that the backwall echo also contains discriminatory information.