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ULTRASONIC PROCEDURES FOR THE DETERMINATION OF BOND STRENGTH.(U)
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AFOSR Final Scientific Report

"Ultrasonic Procedures for the Determination of Bond Strength"

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Abstract

An ultrasonic inspection system for the prediction of adhesive bond strength for metal-to-metal applications is of great value to the U.S. Air Force, as well as many other agencies. The prediction of adhesive bond strength, assuming there are no delaminations, inclusions, or such cohesive type problem as curing, etc. is the goal of this study. Ultrasonically evaluating adhesive bonds that have partially delaminated, is easily accomplished using C-scan techniques, but a major problem arises when the defect in the bond is either adhesive or cohesive in nature. Our study involved primarily the adhesive aspect of the bond strength, which is related to the surface preparation problem. Test specimens were manufactured so that a deficient surface preparation occurred on either or both substrates in an aluminum-to-aluminum step-lap joint. The specimens with little or no surface preparation provided weak bonds, and the specimens with proper surface preparation, in general, produced strong bonds.

A completely automated ultrasonic inspection system has been developed at Drexel University for predicting bond strength in metal-to-metal adhesively bonded step-lap joints. Results to date provide a 91% reliability for solving this difficult problem of predicting adhesive bond performance.

A resource base developed in earlier years in experimental technology, theoretical ultrasonic wave interaction studies with adhesive bond models, manufacturing technology, and shear stress distribution analysis have all been incorporated into a pattern recognition program of study. Such topics as nearest neighbor philosophy, fuzzy logic analysis, probability density function analysis, and adaptive search and learning techniques for linear and non-linear models have been investigated. A Fisher Linear Discriminator algorithm has been developed which affords a 91% reliable prediction for adhesive bond strength. Unfortunately, results indicate that the prediction

algorithms depend strongly on the particular transducer being used. Data acquired with a different transducer, having different pulse form characteristics, created problems in predicting bond strength until a new algorithm was designed for that particular transducer. To compensate for the transducer differences, a deconvolution technique was implemented to expand the selection of useful transducers. Limited success on this technique has been obtained to date.

Background

Drexel University, as part of contract number 73-2480, has concluded a research program in the development of ultrasonic procedures for the determination of bond strength. Work tasks have been carried out to advance the state of the art in ultrasonic inspection for predicting adhesive bond performance in metal to metal structures. Emphasis in the program was directed towards the bond strength problem and not that of locating and classifying de-bonding within an adhesively bonded joint. Rather than study the mechanics of bonding and the relationship with many of the manufacturing and service variables outlined in Reference [1], it was proposed to examine the potential of various ultrasonic signal features and their ability for predicting performance of an adhesively bonded structure. A substantial resource base in bond model analysis and experimental data acquisition techniques, has been developed that allowed us to move into the more advanced problems in adhesive bond strength prediction.

The overall philosophy of employing ultrasonic analysis in the adhesive bond inspection problem is illustrated in Table 1. The path labelled 1-2-3, as an example, shows how the theoretical modelling analysis was used in the overall program of study, providing us with improvements in data acquisition and analysis. Our latest work was directed towards the path 4-5 in an attempt to obtain some correlation between ultrasonic signal feature and performance of the structure. Path 6 is avoided because of the difficulty in flaw characterization, as well as extensions by way of fracture mechanics into the ultimate goal of the project; that of performance prediction.

Early work in the project, as indicated in References [1 and 2], provides us with a substantial resource base in understanding manufacturing parameters, thickness measurement, and shear stress distribution in a step-lap joint. Modelling concepts for studying ultrasonic wave interaction with adhesive bonds is reported in References [3, 4, and 5]. Promise for solving the difficult performance prediction problem is illustrated in Reference [6], where acid etch surface preparation on both sides of an adhesive bond is eliminated, and performance and ultrasonic echoes are compared with a properly prepared adhesive bond specimen. In this particular case, the one feature of ultrasonic bond echo amplitude to upper surface reference amplitude provides us with a reasonable correlation for excellent and poor bonds. In this case, a 20 MHz transducer produced improved results compared to a 10 MHz transducer. Unfortunately, later results indicated that the amplitude feature was not reliable for predicting bond strength. As a result, additional work was carried out on other pulse shape features. This work is reported later.

Theoretical modelling of the effects of attenuation as a function of frequency on the physical modelling of adhesive bonds is reported in Reference [8], concepts of which may be extended to the metal-to-composite bonding problem in evaluating the masking effects of a composite material as an ultrasonic wave impinges on the interface from the metal side.

A fast data acquisition system, details of which are included in Reference [9], has been developed at Drexel University. A block diagram of the fast ultrasonic data acquisition and analysis system is illustrated in Fig. 1. Such work tasks as analog/digital converter interfacing, signal control interfacing, and specific software development programs have been carried out for the adhesive bond inspection program of study. A computer controlled scanning tank is illustrated in Fig. 2, followed by a photograph of our PDP 11/05 minicomputer system in Fig. 3.

Data acquisition and analysis principles are briefly outlined in a pattern recognition data analysis routine in Table 2. Although variations on the computation procedure presented in Table 2 are numerous, emphasis in the adhesive bond data analysis program was focused on fuzzy logic procedures, nearest neighbor rule techniques, and several advanced aspects of pattern recognition. Basic philosophy of the approach is outlined in Table 2 when considered with a probability density function estimator (PDF) for achieving threshold values in the fuzzy logic routine, prototype feature vectors required in the nearest neighbor rule algorithm development, and useful concepts of feature variation and interaction useful in many pattern recognition algorithms. The final prediction is based on a Fisher Linear Discriminator algorithm (see Appendix 1) which separates the data into two classes; good bonds and bad bonds.

Test Series Details

Seven series of metal-to-metal adhesively bonded specimens have recently been fabricated, data analysis results for the first three series being explained in Reference [10], and the last four series being presented in the following sections. Conditions for each test series, results, and also improvements for the last four series are included below.

Test Series IV

Test series IV consisted of 26 adhesively bonded specimens manufactured with a more recently available and popular adhesive, FM-73, which was chosen because of its current wide use in such Air Force applications as the PABST Program [11]. As before, application of the acid etch to one or more of the substrates was used to control the quality of the bond. In addition, specimen numbers 45 through 48 were exposed to contaminates before bonding. The contamination was accomplished using a silicon release agent, commonly used on fixtures ordinarily found in industrial bonding situations.

Due to the apparent failure of all of the pattern recognition based attempts at classification considered in Series III, in [10], the feature extraction approach was modified to yield more meaningful features and feature relationships as suggested by the initial PDF curves carried out in Series III, [10]. It was anticipated from both the computer modelling runs and the Series III test data that specific feature characteristics of the spectral depressions would be useful in a classification algorithm. However, none of the 13 features, many of which were associated with spectral depression depth and spacing, appeared to be sufficient for data separation. It was realized that due to minor thickness variations from specimen to specimen, the spectral depressions moved in the frequency domain to such an extent that depth measurements became meaningless in the extreme cases where the depressions occurred far away from that portion of the amplitude-frequency profile containing peak energy. A transducer compensation technique, where a normalization of the amplitude-frequency profiles is performed, was not considered in this program of study.

Three new features were therefore derived from seven of the existing amplitude-frequency features. The procedure is detailed in Fig. 4. The center frequency of the 6 dB down line was considered as a starting point in determining the peak energy area for each signal. Spectral depressions characterized by A_2 and A_4 occurred lower and higher, respectively, of the center frequency in the frequency domain. A preliminary calculation is made to determine which spectral depression, A_2 or A_4, occurs closest to the center frequency and, therefore, closest to the peak energy area in the signal. It is this depression that was chosen as the depression to be measured and correlated with bond strength. For every amplitude-time signal and its associated frequency profile, either A_2 or A_4 is chosen, and the frequency difference between the chosen spectral depression and the center frequency of the 6 dB down line is used as a first feature β_1. If the depression at A_4 is used, features β_2 and β_3 become A_3/A_4 and A_5/A_4, respectively. Although the frequency difference between the center frequency and the location of the spectral depression used is normally used as a feature indicating cohesive bond strength, it is used here as a compensating feature in combination with features β_2 and β_3 to treat the non-uniform energy distribution over the bandwidth considered.

By constructing PDF curves for these three features, it is then possible to determine thresholds on each feature when used on an interactive basis with the remaining two. Fig. 5 illustrates the technique of using PDF curves in separating the data into a three-class system. The classes chosen were low (0 to 2,000 lbs.), medium (2,000 to 3,500 lbs.), and high (over 3,500 lbs.). As may be seen from Fig. 5, thresholds for feature

β_1 may be chosen at 2.55 and 2.74 for a high class bond and between 2.05 and 2.50 for a medium class bond. Similar studies were made for the remaining classes and features considered with thresholds shown in Table 3. Exploring the possibility of feature interaction, features β_1, β_2, and β_3 were plotted against one another in the three possible combinations for each set of bond data in the series. Data not falling within the designated thresholds, may not be classified using this approach. If any data falls outside of the range of the existing data altogether, it is also considered not able to be classified. For all specimens considered in Series IV, an overall index of performance of 94% was obtained using this technique. Classifications and failure loads are shown in Table 4.

Test Series V

Series V data consisted of 29 specimens fabricated in a fashion similar to Series IV; a balance of properly prepared specimens expected to yield high failure loads, unetched on one or both substrates expected to yield medium failure loads, and contaminated specimens expected to yield low results were established. This balance, however, was not achieved due to quality control variations in the bonding procedure. Predictions and failure loads are shown in Table 5. Only a single specimen existed in the high failure load range, along with six specimens in the low range. It might be pointed out that specimens 118 through 124 were purposely contaminated in an attempt to provide representatives of the low load category. However, three of these - specimen numbers 120, 121, and 122 - all failed at medium loads and were correctly predicted.

A summary of the data spread for Series IV is shown in Table 6a, for Series V in Table 6b, and for the combined Series in Table 6c. It may be concluded that the performance of the classification algorithm is similar in both Series IV used as a training set, and Series V used as a test set.

Possibly, PDF curves could be made from combined data sets to yield better performing threshold levels for classification.

Test Series VI

Series VI data consisted of 29 specimens fabricated in a fashion similar to Series IV and Series V; a balance of: properly prepared specimens expected to yield high failure loads, unetched on one or both substrates expected to yield medium failure loads, and contaminated specimens expected to yield low results was established. A summary of the data spread for Series VI is presented in Table 7.

The Series VI data naturally separated into two groups at the 2500 pound failure load. Thus a two class problem, good bond and bad bond, was considered. The Fisher Linear Discriminant (see Appendix 1) is a technique which forces data separation into two classes, and thus the Fisher Linear Discriminant is ideally suited to the bond strength problem. To implement the Fisher scheme, a training set of data was arbitrarily selected from Series VI data, this data set was used to determine the good bond - bad bond separation threshold. Once the threshold was calculated, the entire Series VI data was fed into the Fisher algorithm to correlate predicted strength with actual load. Employing the Fisher Linear Discriminant algorithm, the bond strength class was predicted correctly for 95% of the bonds, using pulse shapes 2 and 3, and 89% of the bonds for pulse shape 4. (See Fig. 6).

Test Series VII

Series VII data consisted of 28 specimens fabricated in a fashion similar to the three previous series. The Series VII specimens were made up of four low bonds, which had both of the bonding surfaces contaminated, ten bonds with only one substrate improperly prepared, and fourteen good bonds with proper surface preparation on both bonding surfaces. The results of the Series VII test data are: for the transducer with pulse shape 2, the performance was 77%; for pulse shape 3, the performance was 87%; and for pulse shape 4, the performance was 60%. (See Fig. 6).

A loss function analysis of the Series VII test results with the good bond - bad bond threshold set at 2500 pounds, provides a bond strength prediction reliability of between 96% and 100%. The loss function analysis places the correct prediction of bad bonds as the goal of a bond strength prediction algorithm. This means that incorrectly predicting the strength of a good bond, though not desireable, is acceptable. Table 8 shows the reliabilities of the bond strength prediction algorithms using this loss function analysis.

Table 9 considers the combined reliability of both Series VI and Series VII test results. By combining these results, a realistic value of the bond strength prediction algorithm's reliability is presented, a value of 91% reliability is shown for the best transducer. Also an apparent need for transducer compensation is displayed in Table 9, and will be discussed in the next section.

Transducer Dependance

Table 10 displays all of the previous bond strength prediction algorithm's reliabilities plus the effect of using a transducer other than the design transducer in a particular algorithm. As indicated earlier, in addition to acquiring all of the Series VII data with one 10 MHz transducer, two other complete sets of data were taken using two different 10 MHz transducers. (See Fig. 6). Once a reliable bond strength prediction algorithm was developed for the first transducer, data obtained using the other two transducers was introduced into the first transducer's algorithm to determine if the reliability of the algorithm was dependant on the transducer. As shown in Table 10, the reliability of the algorithm is very much dependent on input pulse shape.

To compensate for the transducer, or at least to provide a go-no go criteria, a deconvolution technique must be implemented. (See Appendix 2). A go-no go criteria is a technique to decide if the transducer being used is within acceptable limits, which in turn are dependant on the test situation. As an example of how the go-no go criteria would be used, consider the following; if the significant feature for the bond strength prediction were a spectral depression at 5 MHz, for example, then only a transducer having energy in the 5 MHz range would be useable for that algorithm. The deconvolution theory [12] utilizes the frequency domain to perform algebraic manipulation of the input and output functions. The output function in the frequency domain of an adhesive bond system is the product of the input function and transfer function. This transfer function is representative of the entire system which includes the specimen and the electronics used to process the data. In theory, the transfer function should remain constant for a single bond, except for any instrument noise. By dividing the output by the input function, the systems transfer function can be calculated. Using the transfer function, a second input function from a second transducer can be compensated to produce results which resemble those from the first input function. Table 10 also shows the results of incorporating transducer compensation. As displayed in Table 10, application of a deconvolution algorithm certainly increases the reliability of a second transducer in a bond strength prediction algorithm.

Concluding Remarks

1. A computer controlled scanning system has been developed which can inspect an adhesively bonded specimen and predict the bond strength, all automatically. The value of such a system is that an accurate record of the adhesive bond strength can be acquired quickly and efficiently.

2. The reliability of this pattern recognition technique is certainly high enough for most bonding situations, 91% reliable. The predicting algorithm was designed to predict correctly all bad bonds, thus the incorrect predictions were mislabèling the good bonds, which is not as critical. Thus, as shown in Table 8, a loss function analysis of Series VII data produces 100% reliability for pulse shapes 2 and 3, and 96% reliability for pulse shape 4. (See Fig. 6).

3. The major problem encountered in using this inspection algorithm is its dependance on a particular transducer. To expand the transducer acceptance criteria, a deconvolution procedure was implemented. This procedure not only increases the range of the acceptable transducers but also provides a valuable go-no go criteria.

4. Transducer compensation by deconvolution does, in most cases, increase the reliability of the adhesive bond strength prediction algorithm as can be seen in Table 10. The pulse shape for transducers 2 and 3 were almost identical but the pulse shape of transducer 4 differed somewhat from transducers 2 and 3. The similarity of transducers 2 and 3 explain why their bond strength prediction reliability was exceptional for an algorithm designed on either transducer 2 or 3. On the other hand, their similarity to each other and their difference to transducer 4 explain why transducer 4 did not predict as well when using an algorithm designed on transducer 2 or 3. The reason that deconvolving transducer 2 with transducer 3 produced poorer results than without deconvolution is that our

deconvolution technique is somewhat succeptable to noise. The noise in our ultrasonic signals hampered the effectiveness of our deconvolution scheme and caused several incorrect bond strength predictions. Part of a transducer go-no go criteria should be a method to decide if deconvolution is needed. If the second transducer is similar to the transducer used to design the prediction algorithm, a deconvolution compensation routine may only add noise to the results. Yet if the second transducer is considerably different from the first transducer, then a deconvolution compensation routine will help. Thus a criteria must be established to first decide if the transducer is acceptable without compensation, and if this transducer is not acceptable, then use deconvolution to enhance the signal and then recheck the transducer's acceptability.

Recommendations for Future Work

1. The combined cohesive-adhesive test situation should certainly be considered even though problems associated with each, on an individual basis, seem promising for obtaining a solution.

2. Implementation potential of this pattern recognition algorithm and automated data acquisition analysis procedure should be considered, perhaps using microprocessor technology. Both computational speed and storage requirements should be investigated in detail.

3 Additional tests should be conducted using similar techniques on various practical adhesive-substrate systems. Possibly the treatment of the critical composite-to-metal bond problem could be considered.

4. Additional work should be done to establish a two part acceptance criteria for transducers. First check the transducer for acceptability before using a compensation routine on the transducer, and then recheck for acceptance after using the compensation routine.

5. Improving the data acquisition techniques, that is using as pure a signal as possible, will greatly increase the effectiveness of transducer compensation by deconvolution. Noise generated by the ultrasonic nondestructive test system can be alleviated by incorporating many different signal processing techniques. Random noise can be eliminated with signal averaging and correlation routines. Other noise may be lessened by using more sophisticated analog to digital converters and by filtering the ultrasonic signal, for example by incorporating a Wiener filter in the software.

6. A tremendous data base has been acquired for the adhesive bond strength prediction problem. See Table 11. This data includes the ultrasonic reference and echo signals from numerous bonds with various degrees of bond strength. Over one hundred bond situations have been inspected with each of the three different 10 MHz transducers. Additionally,

approximately a quarter of these bonds have been inspected with both a 15 MHz and 25 MHz transducer. This data reflects the state of the art in data acquisition and signal processing using real time analog to digital conversion and computer aided signal enhancement. An extensive, sophisticated data base such as this, is necessary to develop any improved bond strength prediction techniques, which might include predicting adhesive strength in a more reliable fashion.

7. Such other problems as delaminations, cohesive strength prediction, and bond thickness measurement should be studied in combination with the adhesive type problem studied in this work.

References

1. Rose, J.L. and Meyer, P.A., "Ultrasonic Procedures for Predicting Adhesive Bond Strength", Materials Evaluation, June 1973.

2. Rose, J.L. and Meyer, P.A., "Ultrasonic Signal-Processing Concepts for Measuring the Thickness of Thin Layers", Materials Evaluation, November 1973.

3. Rose, J.L. and Meyer, P.A., "AFOSR Interim Scientific Report - Ultrasonic Procedures for the Determination of Bond Strength", AFOSR-73-2480, (AFOSR TR-74-0779).

4. Rose, J.L. and Meyer, P.A., "AFOSR Interim Scientific Report - Ultrasonic Procedures for the Determination of Bond Strength", AFOSR-73-2480A, (AFOSR TR-75-0672).

5. Rose, J.L. and Meyer, P.A., "Modeling Concepts for Studying Ultrasonic Wave Interaction with Adhesive Bonds", Journal of Adhesion, Vol. 8, pp. 107-120.

6. Meyer, P.A. and Rose, J.L., "Ultrasonic Determination of Bond Strength Due to Surface Preparation Variations in an Aluminum-To-Aluminum Adhesive Bond System", Journal of Adhesion, Vol. 8, pp. 145-153.

7. Rose, J.L. and Shelton, W., "Damage Analysis in Composite Materials", American Society for Testing and Materials, 1975.

8. Meyer, P.A. and Rose, J.L., "Ultrasonic Attenuation Effects Associated with The Physical Modeling of Adhesive Bonds", Journal of Applied Physics, March 1977.

9. Rose, J.L., "AFOSR Interim Scientific Report - Ultrasonic Procedures for the Determination of Bond Strength", AFOSR-73-2480B.

10. Rose, J.L. and Meyer P.A., "AFOSR Interim Scientific Report - Ultrasonic Procedures for the Determination of Bond Strength, AFOSR-73-2480C.

11. "Primary Adhesively Bonded Structures Technology (PABST) Air Force Executive Review", Department of the Air Force, September 22-23, 1976.

12. Rose, J. L., Avioli, M. J., "Transducer Compensation Concepts in Flaw Classification," presented at the Spring meeting of ASNT, New Orleans, LA, 1978.

13. Duda and Hart, Pattern Classification and Scene Analysis, John Wiley & Sons Inc., New York, 1973, pp. 114-118.

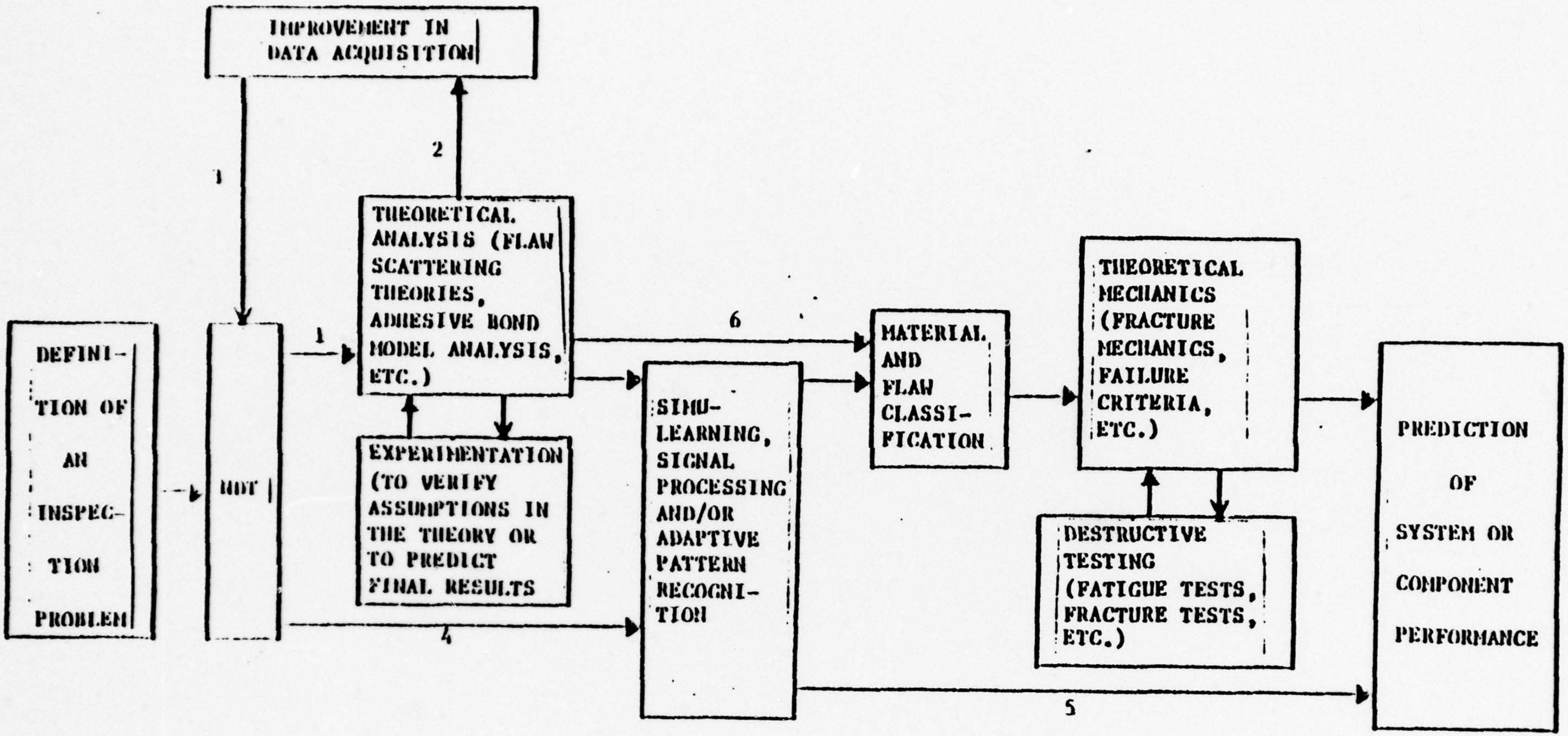
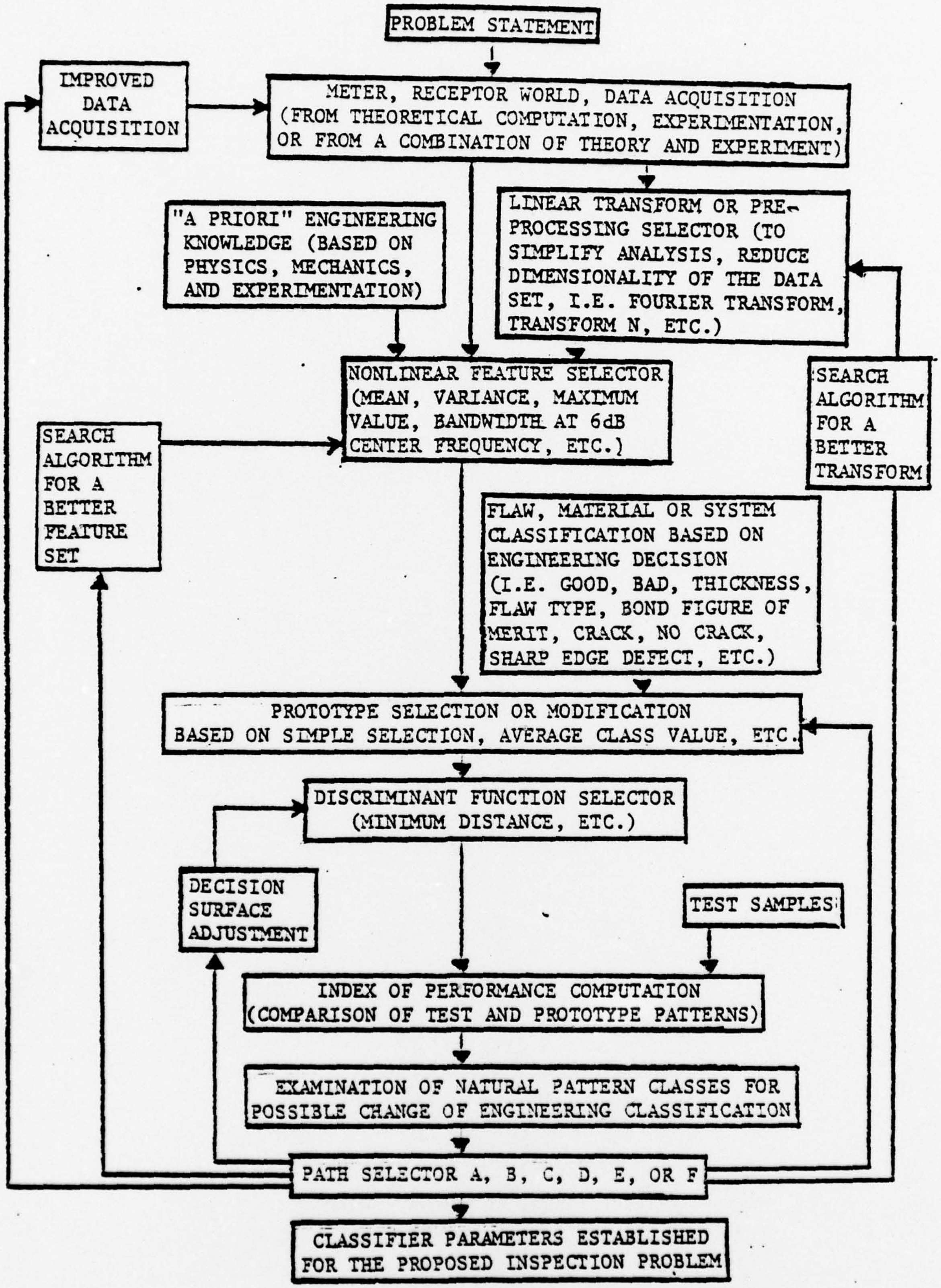


TABLE 1 - NDT VALUES IN THE MATERIAL AND FLAW CLASSIFICATION SYSTEM PERFORMANCE POTENTIAL PREDICTION PROBLEM

TABLE 2 - A PROPOSED PATTERN RECOGNITION COMPUTATION PROCEDURE



β_1		β_2		β_3		
$\geq$	$\leq$	$\geq$	$\leq$	$\geq$	$\leq$	DECISION
2.05	2.50	1.10	1.355	*	*	Medium
2.05	2.80	1.355	1.7	*	*	Medium
2.50	3.05	1.10	1.355	*	*	High
2.50	2.875	1.75	2.05	*	*	High
2.50	2.60	2.05	2.45	*	*	High
2.60	2.95	2.05	2.45	*	*	Medium
2.95	3.05	2.40	2.55	*	*	High
2.90	3.05	1.1	2.55	*	*	Low
3.05	*	2.55	*	*	*	Out of Range
2.05	2.55	*	*	2.10	3.05	Medium
2.50	2.60	*	*	1.30	1.56	High
2.55	3.05	*	*	1.56	2.85	High
2.60	2.95	*	*	1.30	1.56	Medium
2.555	3.05	*	*	1.56	2.85	Low
3.05	*	*	*	3.05	*	Out of Range
*	*	1.10	1.70	2.10	2.97	Medium
*	*	1.75	2.55	1.56	2.80	High
*	*	1.90	2.07	1.20	1.56	High
*	*	2.07	2.55	1.20	1.40	High
*	*	2.07	2.55	1.40	1.56	Medium
*	*	2.55	*	3.05	*	Out of Range

* Data not Required

TABLE 3 - SEQUENTIAL THRESHOLD SELECTION FOR THREE CLASS PROBLEM ON FEATURES β_1, β_2, AND β_3

Specimen No.	Failure Load (pounds)	Actual Classification	Classification from Pattern Recognition Solution	
			Top	Bottom
37	4350	H	H	H
38	3600	H	H	H
39	2100	M	M	M
40	2450	M	M	M
41	4300	H	H	H
42	4050	H	H	H
43	2300	M	M	M
44	2750	M	M	M
45	400	L	L	L
46	500	L	L	L
47	300	L	L	L
48	400	L	L	L
49	4300	H	H	H
50	3100	M	M	M
51	2750	M	M	M
52	2650	M	M	M
53	2300	M	M	M
54	1850	L	H	H

L: 0 - 2000 lb.

M: 2000 - 3500 lb.

H: over 3500 lb.

TABLE 4 - SUMMARY OF SERIES IV FAILURE LOADS AND BOND CLASSIFICATION

Specimen No.	Pattern Recognition Prediction		Failure Load (pounds)
	Top	Bottom	
67	H	L	3170
68	M	M	2950
70	M	H	2560
72	L	L	2110
73	OR	OR	3300
74	M	OR	2900
76	M	H	2390
77	OR	OR	1920
78	L	L	1940
93	H	H	3950
95	M	M	2700
96	M	M	2750
98	M	M	2400
101	M	OR	2860
102	M	M	2930
103	M	OR	2850
104	L	M	2520
105	M	M	3200
107	M	M	2620
108	M	M	2750
109	M	OR	3050

continued on next page

TABLE 5 - SUMMARY OF SERIES V BOND CLASSIFICATION PREDICTIONS AND FAILURE LOADS

Specimen No.	Pattern Recognition Prediction		Failure Load (pounds)
	Top	Bottom	
110	M	M	2870
118	L	L	1290
119	L	L	1340
120	M	M	3150
121	M	M	2310
122	M	M	2680
123	L	M	1020
124	L	L	1260

L: 0 - 2000 lb.

M: 2000 - 3500 lb.

H: over 3500 lb.

OR: Data could not be obtained within range to make a performance prediction

TABLE 5 (continued) - SUMMARY OF SERIES V BOND CLASSIFICATION PREDICTIONS AND FAILURE LOADS

	Failure Load Range			
	Low 0 - 2000 lb.	Medium 2000 - 3500 lb.	High over 3500 lb.	Total
Number of Possible Decisions	10	16	10	36
Number of Feature Vectors Out of Range	0	0	0	0
Number of Decisions Made	10	16	10	36
Number of Correct Decisions	8	16	10	34
Number of Incorrect Decisions	2	0	0	2
Percent Correct (Index of Performance)	80	100	100	94.4
Percent of Specimens Classified				100

TABLE 6a - SUMMARY OF BOND CLASSIFICATION PERFORMANCE - SERIES IV

	Failure Load Range			
	Low 0 - 2000 lb.	Medium 2000 - 3500 lb.	High over 3500 lb.	Total
Number of Possible Decisions	12	44	2	58
Number of Feature Vectors Out of Range	2	6	0	8
Number of Decisions Made	10	38	2	50
Number of Correct Decisions	9	31	2	42
Number of Incorrect Decisions	1	7	0	8
Percent Correct (Index of Performance)	90	81.6	100	84
Percent of Specimens Classified				86.2

TABLE 6b - SUMMARY OF BOND CLASSIFICATION PERFORMANCE - SERIES V

	Failure Load Range			
	Low 0 - 2000 lb.	Medium 2000 - 3500 lb.	High over 3500 lb.	Total
Number of Possible Decisions	22	60	12	94
Number of Feature Vectors Out of Range	2	6	0	8
Number of Decisions Made	20	54	12	86
Number of Correct Decisions	17	47	12	76
Number of Incorrect Decisions	3	7	0	10
Percent Correct (Index of Performance)	85	87	100	88
Percent of Specimens Classified				91.4

TABLE 6c - SUMMARY OF BOND CLASSIFICATION PERFORMANCE SERIES IV AND V (COMBINED)

Bad Bonds		Good Bonds	
Specimen No.	Failure Load	Specimen No.	Failure Load
150	300	128	2600
		133	3000
152	400	129	3100
		130	3100
149	500	125	3200
		145	3200
151	770	126	3350
		143	3650
154	970	134	3700
		144	3800
146	1200	142	4000
		139	4200
147	1350	140	4200
		141	4200
153	1620	137	4250
		135	4250
148	1700	136	4250
		138	4500
127	2400	131	4750
		132	4750

TABLE 7 - SUMMARY OF SERIES VI FAILURE LOADS

	Pulse Shape 2	Pulse Shape 3	Pulse Shape 4
Algorithm 2	100%	100%	96%
Algorithm 3	100%	100%	100%
Algorithm 4	100%	100%	96%

TABLE 8 - LOSS FUNCTION ANALYSIS OF TEST SERIES VII DATA'S RELIABILITY

	Pulse Shape 2	Pulse Shape 3	Pulse Shape 4
Algorithm 2	86.3%	85%	61%
Algorithm 3	70%	91%	65%
Algorithm 4	71%	69%	74.5%

TABLE 9 - SUMMARY OF BOND STRENGTH PERFORMANCE SERIES VI AND SERIES VII (COMBINED)

Before Deconvolution / After Deconvolution	Pulse Shape 2	Pulse Shape 3	Pulse Shape 4
Algorithm 2	95.5%	86% / 82%	63% / 78%
Algorithm 3	95% / 88%	94.9%	68% / 78%
Algorithm 4	71% / 82%	71% / 79%	89%

TABLE 10 - COMPARISON OF BOND STRENGTH PREDICTION ALGORITHM'S RELIABILITY WITH AND WITHOUT DECONVOLUTION - SERIES VI

Bond No.	Failure Load	Bond No.	Failure Load
125	3200	150	300
126	3500	151	770
127	2400	152	400
128	2600	153	
129	3100	154	970
130	3100	155	4800
131	4750	156	4800
132	4750	157	4800
133	300	158	4400
134	3700	159	4400
135	4250	160	4400
136	4250	161	2900
137	4250	162	2900
138	4500	163	2950
139	4200	164	4100
140	4200	165	2800
141	4200	166	2800
142	4000	167	100
143	3650	168	600
144	3800	169	1150
145	3200	170	900
146	1200	171	1500
147	1350	172	2100
148	1700	173	1000
149	500		

TABLE 11 - DATA BASE FOR FURTHER ANALYSIS

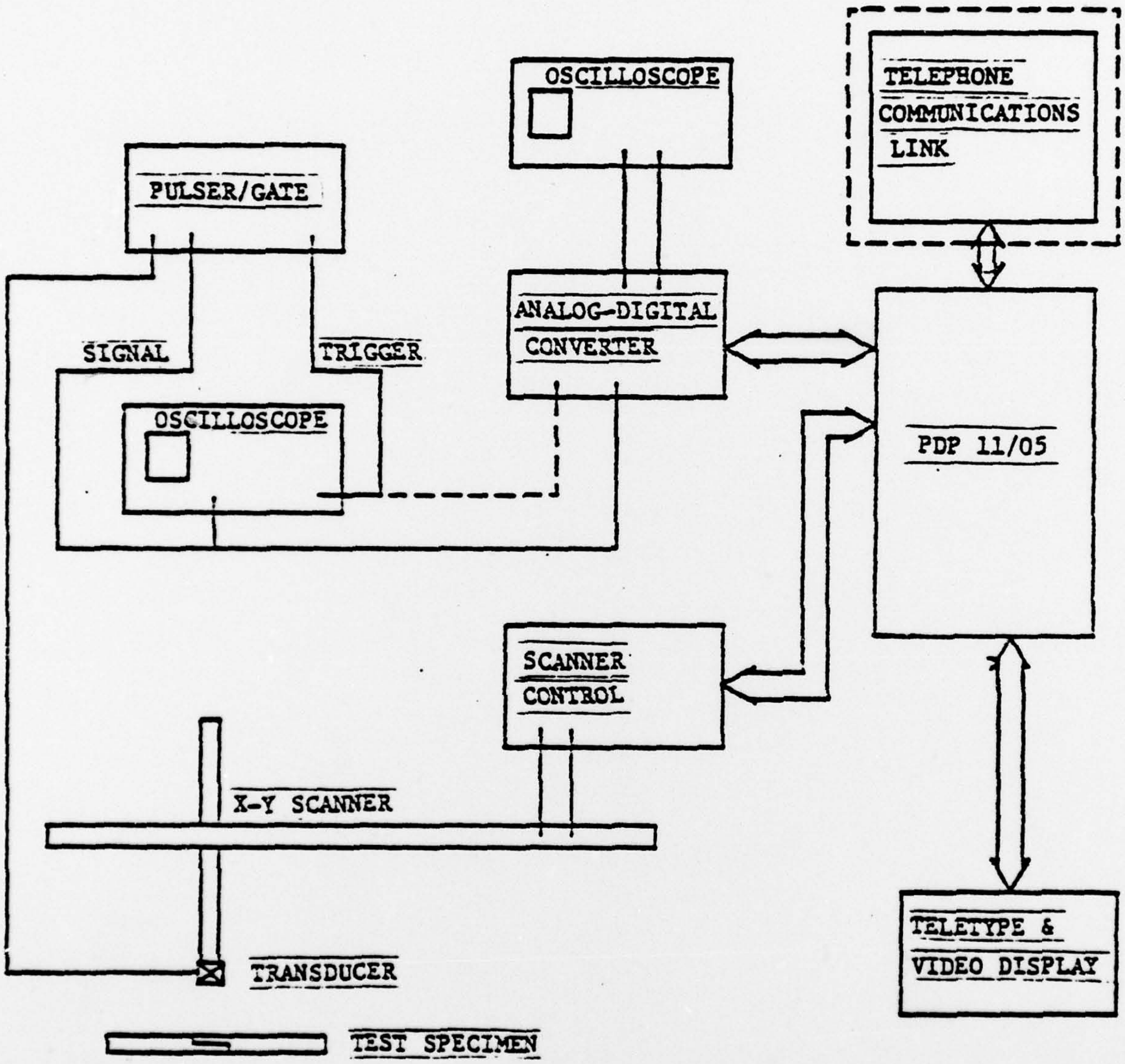


Fig. 1 - BLOCK DIAGRAM OF THE FAST ULTRASONIC DATA ACQUISITION AND ANALYSIS SYSTEM

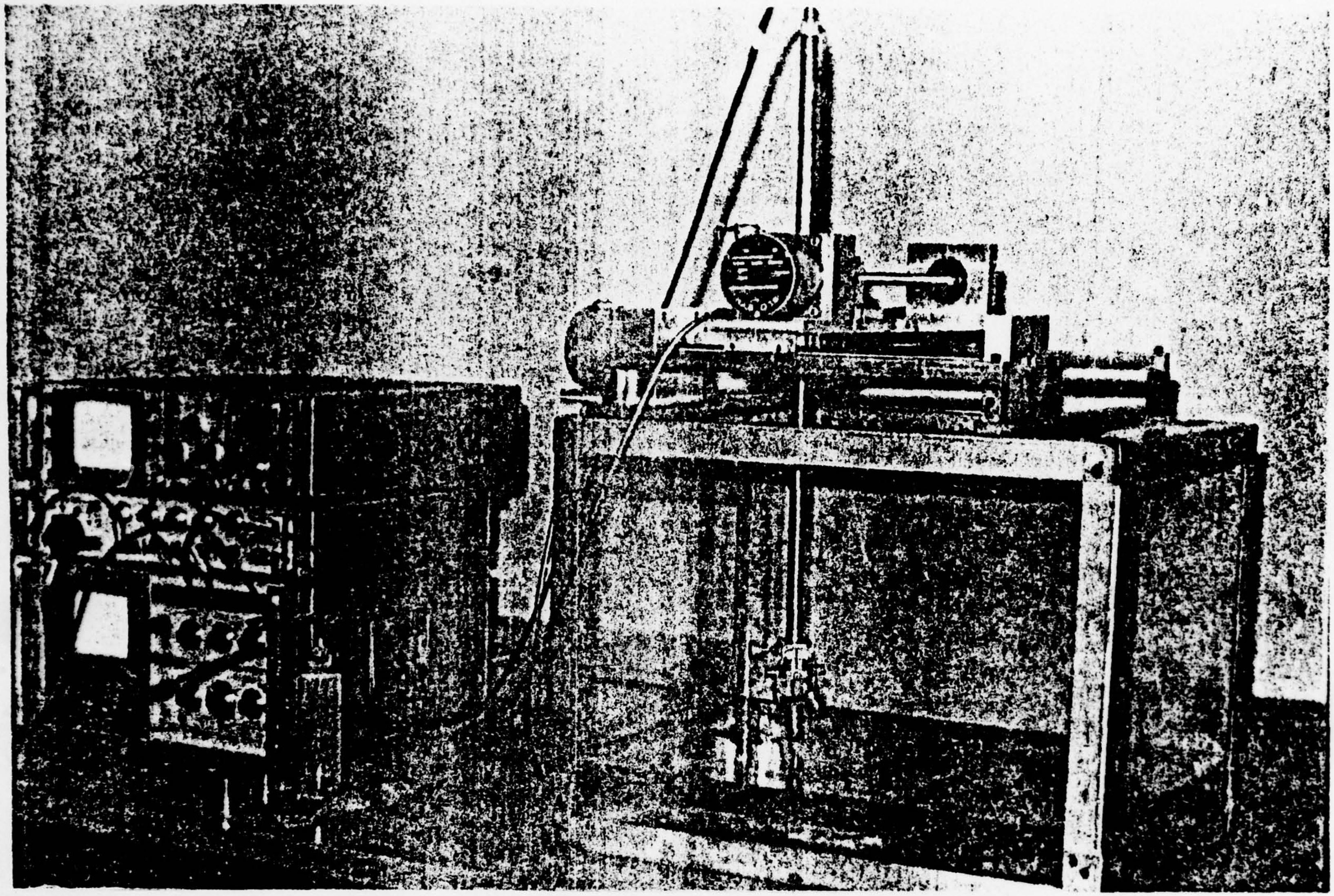


FIG. 2 - THE IMMERSION TANK, DRIVING STEP MOTORS, ULTRASONIC PULSER, AND SPECTRUM ANALYZER USED IN THE AUTOMATED ULTRASONIC SCANNING PROCEDURE

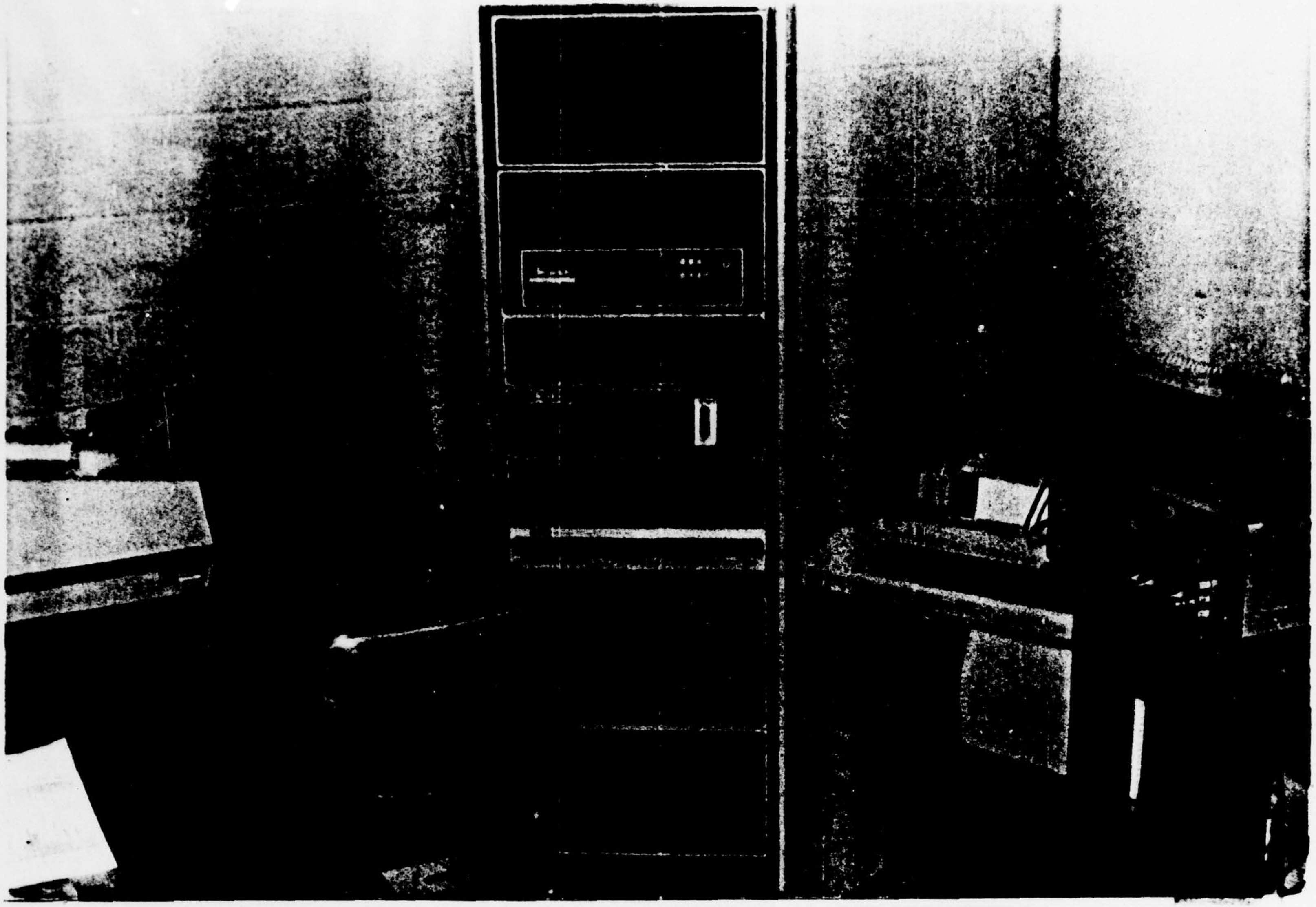
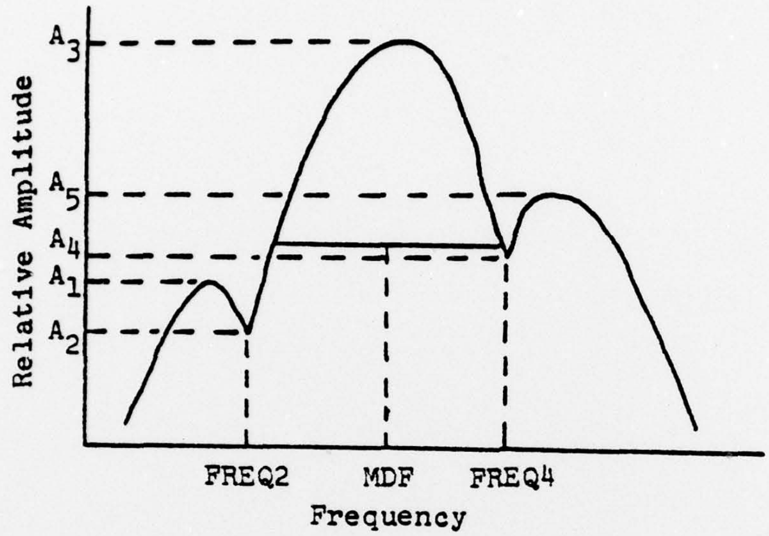


FIG. 3 - THE PDP 11/05 DIGITAL COMPUTER AND BIOMATION 8100 A/D CONVERTER USED TO CONTROL AND ACQUIRE THE ULTRASONIC BOND ECHO SIGNAL



$\beta_1 = |MDF\text{-}FREQ2|$ or $|MDF\text{-}FREQ4|$, whichever is smaller

$\beta_2 = A_3/A_2$ if $\beta_1 = |MDF\text{-}FREQ2|$

$\beta_2 = A_3/A_4$ if $\beta_1 = |MDF\text{-}FREQ4|$

$\beta_3 = A_1/A_2$ if $\beta_1 = |MDF\text{-}FREQ2|$

$\beta_3 = A_5/A_4$ if $\beta_1 = |MDF\text{-}FREQ4|$

Fig. 4 - MODIFIED FEATURE EXTRACTIONS DETAILS FOR SERIES IV TEST SPECIMENS

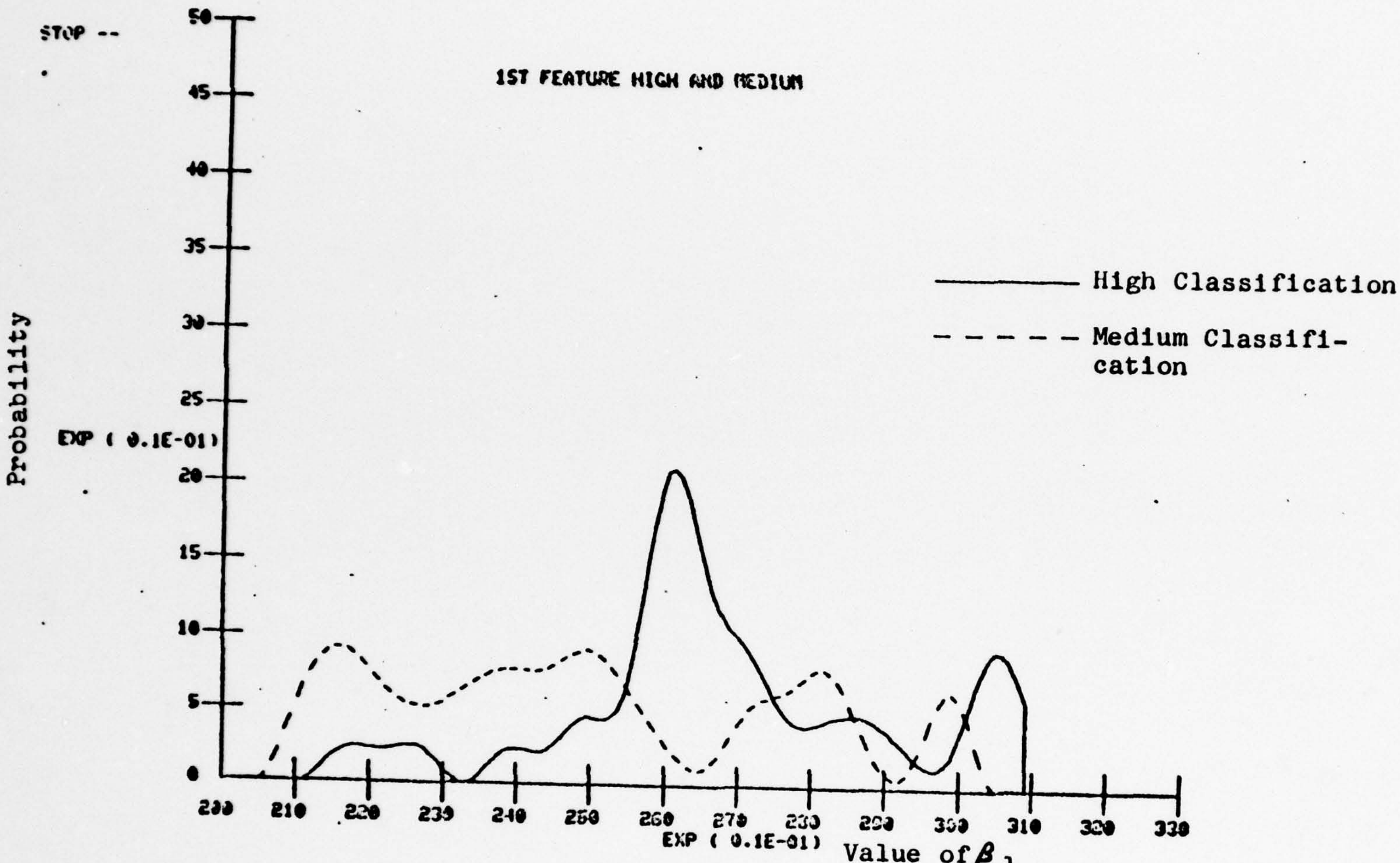


Fig. 5 - PROBABILITY DENSITY ESTIMATOR CURVES FOR β_1

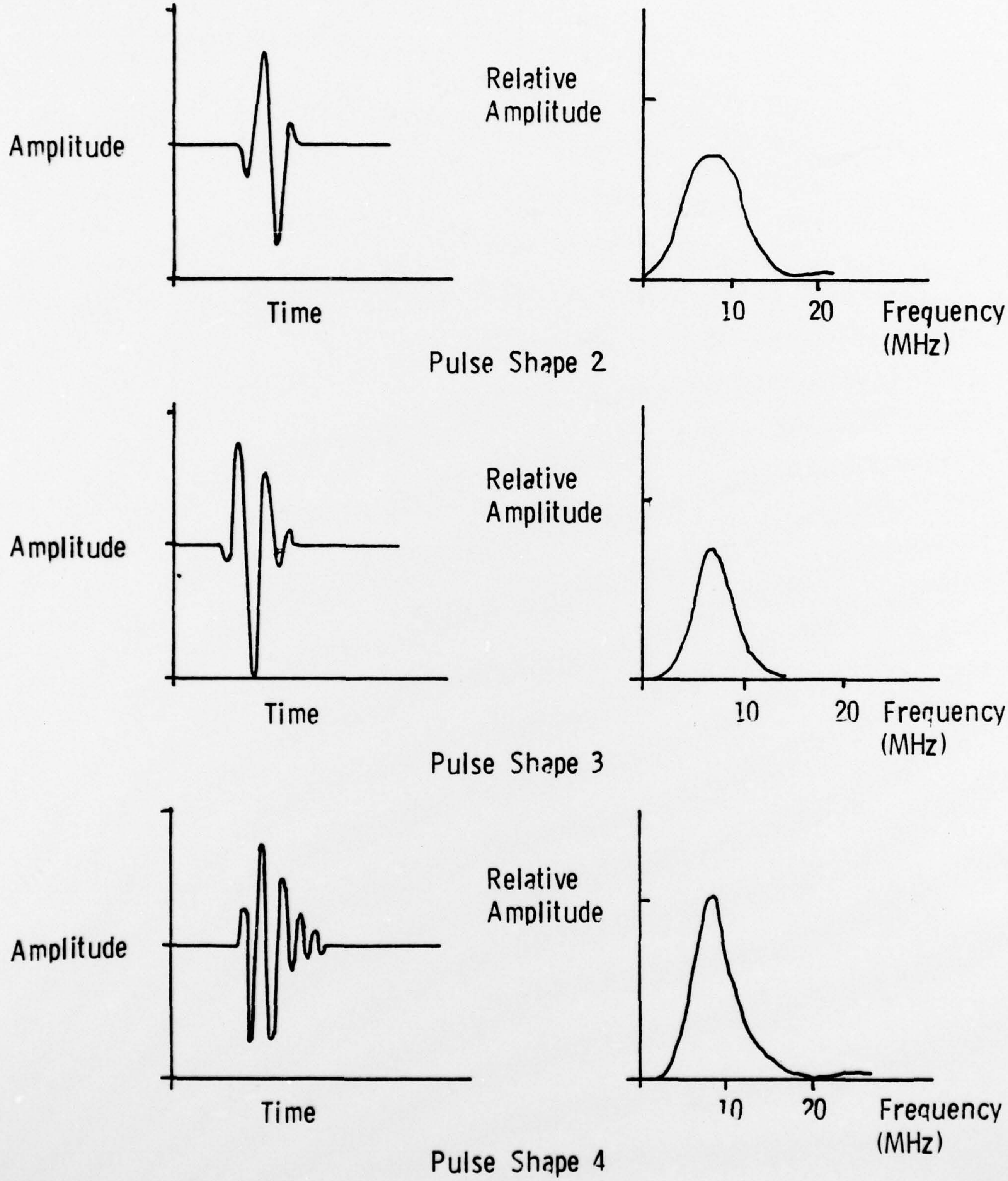


Fig 6 - AMPLITUDE-TIME AND FOURIER SPECTRUM GRAPHS FOR PULSE SHAPES 2, 3, AND 4

Fisher Linear Discriminant

One of the major problems encountered in pattern recognition work is the vastness of the feature space. Procedures that are analytically and computationally manageable in low-dimension spaces become impractical in higher-dimension space. An ideal dimensioned space is the one-dimension or a line. The advantage of a Fisher Linear Discriminant [13] is that it projects all the data from an x-dimension space on to the best line for separating the data. Once the data has been projected unto the line, a threshold value may be selected which will separate the data into two classes. Thus the Fisher Linear Discriminant is ideally suited to a two class problem.

The Fisher Linear Discriminant is defined as that linear function $w^t x$ for which the criterion function $J(w) = \dfrac{|\bar{m}_1 - \bar{m}_2|^2}{\bar{s}_1^{\,2} + \bar{s}_2^{\,2}}$ is maximum.

The linear function $w^t x$ is the product of a weighting constant, w, and the feature vector x. The weighting constants, w, are calculated by the criterion function, $J(w)$ at its maximum value. The criterion function, $J(w)$, will be at its maximum value when the distance between the mean values of the data clusters, $|m_1 - m_2|^2$, is the largest and also when the within-class scatter, $\bar{s}_1^{\,2} + \bar{s}_2^{\,2}$, is the smallest. Thus the equation of the criterion function $J(w) = \dfrac{|\bar{m}_1 - \bar{m}_2|^2}{\bar{s}_1^{\,2} + \bar{s}_2^{\,2}}$ is explained.

Deconvolution Concepts

a) Basic Concepts

Transducer compensation is essentially the removal of the effects of different transducers from a given test situation. Consider the procedure for determining the shape of a subsurface flaw by ultrasonic methods. Physically, a transducer is excited by a voltage spike ($G(\omega)$ $P(\omega)$) which distorts the crystal in the transducer ($T_1(\omega)$). This distortion is propagated as a pressure wave through the medium hosting the flaw. Upon incidence on the flaw, the wave is reflected distorting the transducer's crystal ($T_2(\omega)$), which generates a time-varying voltage. This voltage-time profile is amplified and is either displayed on a CRT, digitized and stored, or both.

The host medium and the flaw may be viewed as a physical system excited by the initial distortion of the transducer crystal and responding with another distortion of the crystal. When transducers are changed, crystals are changed, and therefore excitations and responses from the same physical system are changed.

The linear systems approach to this problem is to consider the responses of the system as the convolution of the excitation and impulse of the system. This greatly simplifies (conceptually) the analysis of the situation, since the frequency convolution theorem states that the convolution of two time functions is the product of their Fourier transforms in the frequency domain.

Mathematically,

$$\int_{-\infty}^{\infty} f(t)\, g(\tau - t)\, dt = F(\omega) \cdot G(\omega)$$

where $F(\omega)$ = Fourier Transform of $f(t)$

$G(\omega)$ = Fourier Transform of $G(t)$

$$I_1(\omega) \cdot S(\omega) = O_1(\omega)$$

where $I_i(\omega)$ = Fourier Transform of input i

$O_i(\omega)$ = Fourier Transform of output i

$S(\omega)$ = Fourier Transform of Medium and Flaw (known as the system transfer function)

This model admits a different definition of transducer compensation. Transducer compensation is the determination of the system transfer function (which is considered fixed).

Frequency domain analysis shows that for two different transducers, the following

$$I_1 \cdot S = O_1 \qquad S = \frac{O_1}{I_1}$$

$$I_2 \cdot S = O_2 \qquad S = \frac{O_2}{I_2}$$

Implying that the system transfer function is independent of transducer.

b) Deconvolution

Deconvolution is the process by which the transfer function of a physical system is determined. Analytically, this is a point by point division in the frequency domain, O/I.

The output O is usually taken as the return echo from the test piece. The input is determined by looking at the return echo from the back wall of a test block made of the same material as the system under test.

The Fourier Transforms of O and I are taken and complex division implemented. The result of this division is the system transfer function.

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COMPOSITES

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An ultrasonic inspection system for the prediction of adhesive bond strength for metal-to-metal applications is of great value to the U.S. Air Force, as well as many other agencies. The prediction of adhesive bond strength, assuming there are no delaminations, inclusions, or such cohesive type problem as curing, etc. is the goal of this study. Ultrasonically evaluating adhesive bonds that have partially delaminated, is easily accomplished using C-scan techniques, but a major problem arises when the defect in the bond is either adhesive or coheisve in nature. ~~Our~~ This study involved primarily

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the adhesive aspect of the bond strength, which is related to the surface preparation problem. Test specimens were manufactured so that a deficient surface preparation occurred on either or both substrates in an aluminum-to-aluminum step-lap joint. The specimens with little or no surface preparation provided weak bonds, and the specimens with proper surface preparation, in general, produced strong bonds.

A completely automated ultrasonic inspection system has been developed at Drexel University for predicting bond strength in metal-to-metal adhesively bonded step-lap joints. Results to date provide a 91% reliability for solving this difficult problem of predicting adhesive bond performance.

A resource base developed in earlier years in experimental technology, theoretical ultrasonic wave interaction studies with adhesive bond models, manufacturing technology, and shear stress distribution analysis have all been incorporated into a pattern recognition program of study. Such topics as nearest neighbor philosophy, fuzzy logic analysis, probability density function analysis, and adaptive search and learning techniques for linear and non-linear models have been investigated. A Fisher Linear Discriminator algorithm has been developed which affords 91% reliable prediction for adhesive bond strength. Unfortunately, results indicate that the prediction algorithms depend strongly on the particular transducer being used. Data acquired with a different transducer, having different pulse form characteristics, created problems in predicting bond strength until a new algorithm was designed for that particular transducer. To compensate for the transducer differences, a deconvolution technique was implemented to expand the selection of useful transducers. Limited success on this technique has been obtained to date.