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STEAP-MT-G 3 December 1976

SUBJECT: Final Letter Report of Phase I of Prediction of Equipment Failures by Acoustical Signature Analysis, TECOM Project No. 7-CO-MT5-AP1-001 Report No. APG-MT-4886

Commander
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1. References:

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h. Houser, Donald R. et al; Vibration Signal Analysis Techniques; Ohio State University and Army Air Mobility Research and Development Laboratory; AD-776 397; December 1973.

i. Curry, G. E. and Anderson, J. J.; Quality Evaluation of Automotive DC Motors, Using Real-Time Spectrum Analysis; a paper presented at the 14th meeting of the Mechanical Failures Prevention Group, Los Angeles,25-26 January 1971.

2. Background:

Diagnosis of the internal condition of equipment by analysis of sound and vibration has been done for many years. One of the most basic examples is a mechanic who listens to an engine with a screwdriver. More relevant examples are production quality control of DC motors by vibration analysis (reference i) evaluation of ball bearing faults by vibration analysis (discussed in reference g), and vibration monitoring of large, stationary machines to indicate when repair is necessary.

Major effort has been spent on diagnosis of automotive and aircraft engines through vibration analysis. Reference h provides a comprehensive listing of the various efforts to analyze helicopter turbine and transmission vibration. Several articles on diagnosis of turbine engines are also presented in reference g.

Efforts to automatically diagnose automotive engines through analysis of many parameters (pressures, temperatures, voltages, vibration, etc.) are described in references c, d, e, and f. Significant accomplishments in the area of multi-parameter diagnosis are the STE/ICE and ATE/ICE program, Depot MAIDS, and the PRD Diesel Engine Analyzer.

STE/ICE (Simplified Test Equipment/Internal Combustion Engine) is essentially a digital voltmeter, which is connected to various pressure, temperature, and voltage transducers on the engine. Each transducer value is read and compared with the acceptable limits provided in an accompanying table. ATE/ICE (Automatic Test Equipment/Internal Combustion Engine) is a micro-computer which tells the operator which transducers to attach, analyzes the output of those transducers, and tells the operator what malfunctions (if any) are present.

Depot MAIDS is a computerized test system used in instrumented dynamometer cells at Letterkenny Army Depot. Many pressure, temperature, air flow, speed, and vibration measurements are fed into the computer. The computer lists the malfunctions present as well as the corrective action, part number and TM required to correct the malfunctions. The PRD Diesel Engine Analyzer is similar to Depot MAIDS except that a smaller microprocessor and a portable dynamometer are used so that the unit is mobile.

These previous accomplishments are essentially electronic automation of the tasks presently done by mechanics. Compression, timing, oil pressure and other measurements are made and analyzed electronically rather than manually. This study involves the application of a new technique (pattern recognition) to a measurement not generally made (vibration).

Pattern recognition is a powerful, mathematic technique that determines how to distinguish one class of data (such as the vibration of faulty engines) from another class of data (the vibration of healthy engines). The pattern recognition system used in this study was a computer program which, when given data from two different classes, sequentially selects features (such as vibration level at a certain frequency) that best distinguish one class from the other. Inherent in the selection of features is the specification of what value of that feature is characteristic of class I (faulty engines) and what value is characteristic of class II (healthy engines).

The beauty of pattern recognition is that the computer does all the work. The features that distinguish one class of vibration data from another, while not immediately obvious, can be determined through rigorous mechanical analysis. The pattern recognition computer program finds these features empirically much faster and cheaper than a mechanical engineer toiling away with his handbook and calculator, or scrutinizing vibration records ever could.

3. Objective:

The general objective of this program is to develop a method of non-destructive assessment of the internal condition of equipment through analysis of the vibration emitted by that equipment. The specific objective of Phase I is development of the software necessary to distinguish between faulty and healthy engines.

4. Summary of Results:

Earlier work done by the Army, as well as work done by PRD in development of their Diesel Engine Analyzer attempted to use microphones to monitor internal combustion engines. Both attempts failed due to excessive variations of background noise. More successful results, such as the GE study referenced (reference b) have been obtained with vibration (accelerometer) signals. Because of these earlier failures of microphones and the success of accelerometers, it was determined that vibration (accelerometer) signals alone would be used in this phase rather than microphones.

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Data tapes of accelerometers mounted on 12-cylinder, air-cooled, AV-1790-7 engines before and after repair that were made for the GE study were obtained. These tapes were provided to a contractor (Scope Electronics) who did the pattern recognition work. The report from Scope is inclosed.

Several problems with the data (physical deterioration, missing channels, timing sensor improperly set, no defects in the engine before repair, etc.) resulted in only six engines with usable vibration data both before and after repair. The computer was able to distinguish between faulty engines and healthy engines with 100% success on the data available.

5. Conclusions:

MTD concurs with the conclusions of the Scope report (i.e., that this type of automatic vibration analysis is feasible). The success of the computer program in distinguishing between faulty and healthy engines is impressive but only a qualified success. The small sample size of data was not a rigorous test of the program. More data is needed to properly prove that the method works and implement a productive system.

6. Recommendations:

Section 1.3.2 of the Scope report recommends that a real time engine vibration analysis system be created. MTD concurs with the intent of this recommendation, but does not concur on the implementation. It is recommended that this idea be implemented by either purchasing or renting the pattern recognition program (OP-SEEKER). Using existing APG mini-computers, data can be gathered from a new type of engine that allows convenient access for instrumentation (perhaps an engine used in an engine-generator set). This plan will permit the engine vibration analysis system to become productive and pay for itself in a minimum amount of time.

FOR THE COMMANDER:

Billy D. Sissom

BILLY D. SISSOM
Associate Director
Materiel Testing Directorate

3 Incl
1. Engine Vibration Analysis Final Technical Report (Draft)
2. DD-1473
3. Test Directive

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ENGINE VIBRATION ANALYSIS

Final Technical Report

SEI Reference 5030 ● 10 November 1976

Submitted to

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20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

A feasibility study was conducted to investigate pattern recognition methods for automatic malfunction diagnosis in internal combustion engines using vibration signatures. A method for automatically and inexpensively generating the signal processor design best matched to an engine type was demonstrated. The data used were derived from air-cooled 12-cylinder tank engines. Accurate classification of good versus defective engines was

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20. ABSTRACT (continued)

attained using a small number of processed time domain data features. Data from only one engine speed and one sensor were required to achieve this level of classification. Improved methods for measurement, time and power normalization, and averaging were demonstrated, and studies were made of sensor placement, synchronization rectification and phase coherency of signatures. Tests indicated that successful classifiers can probably be developed using a single sensor rather than multiple sensors distributed over the engine.

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LIST OF TABLES

I. INTRODUCTION

1.1 METHOD

This final report describes a feasibility study investigating pattern recognition methods for automatic malfunction diagnosis in internal combustion engines using vibration signatures.

In the past five years, a number of approaches have been suggested for solving this problem and, in fact, it is apparent that vibration signals contain much information about engine condition. Successful engine analyzers have been built and demonstrated. However, the analysis problem in adapting to a new engine is a complex one. At this time, the major barrier standing in the way of progress in this field is the analytical cost of designing signal processors matched to individual engine types. The signal processing hardware itself is not expensive and can be built with a modular approach using off-the-shelf equipment. Classifier algorithms may be implemented on minicomputers which also gather engine data, add it to the data base, and diagnose it, all in real time.

The purpose of this effort was to demonstrate a method for automatically and inexpensively generating the signal processor algorithm design best matched to an engine type. Success at this endeavor eliminates the major cost now involved in the automatic diagnosis of engine problems from vibration signals.

The approach taken in this study begins with definition of a class of decision functions, called quadratic decision trees. Selected features of the measured data are available to all nodes of the tree. Each node is a quadratic classifier which is required to make a classification decision about the subject engine using the measured features available to it.

Each decision points to a node at a lower level of the tree, where the next decision is to be made, further defining the diagnosis. Thus, a sequence of decisions progresses from the top to the bottom of the three by a path which fully defines the diagnosis.

There are several important points to be made regarding this procedure:

a) The algorithm is fixed for all engines; only the node parameters change with changing engines.

b) The node decision criteria are the most powerful available (quadratic).

c) The system "learns" from an expanding data base since the decision functions are designed automatically from an empirical data base by an algorithm called OPSEEKER. Thus, performance can be improved constantly as more engines are tested and added to the data base.

d) The individual nodes are designed separately by the algorithm, so that problem areas are easily isolated and addressed.

e) A minimum number of features are automatically selected in the node design process. It is this factor which reduces the problem to the point that the powerful quadratic decision function may be used at each node of the decision tree and still run on-line, in real time on a minicomputer.

1.2 RESULTS

The work performed in this effort used data which have been analyzed before in earlier studies. The data were derived from air-cooled 12 cylinder tank engines. Feasibility of classification was demonstrated in earlier studies (Ref. 1).

The current effort demonstrated further the feasibility of automatic "learning" design of the classifier from an empirical data base. With the limited number of engine samples available, accurate classification of good versus defective engines was readily attained using a small number of processed time domain data features. Data from only one engine speed and one sensor were required to achieve this level of classification.

The major limitation of this study was the amount of data, as had been anticipated. A general solution to a decision theoretic problem having multiple sensors and a large number of classes demands an immense amount of raw data — a resource not currently available.

Improved methods for measurement, time and power normalization, and averaging were demonstrated, and studies were made of sensor placement, synchronization rectification and phase coherency of signatures.

Classifier tests indicated that successful classifiers can probably be developed using a single sensor rather than multiple sensors distributed over the engine, although some information is definitely lost in reduction of the number of sensors. This loss is a result of masking of components further away by components very close to the sensor.

Tests indicated that the feature sets selected by the OPSEEKER for classification using different sensors contained the same or similar features. This indicates a physical consistency in the results and emphasizes the likelihood of success with the single-sensor approach to engine classification.

1.3 CONCLUSIONS AND RECOMMENDATIONS

1.3.1 Conclusions

Automatic analysis of engines from vibration signals is feasible, and generation of classifiers for this purpose should be done automatically using statistics derived from empirical data rather than by study of induced failures or models.

The design of classifier algorithms can be performed automatically and in such a way that the classifier "learns," improving its performance each time a new engine is tested and analyzed.

Measurement should ideally be conducted under computer control at the source to assure good data. A possible scenario might have the computer 1) monitor signal level from each sensor and provide an alarm if any sensor is not connected or is not in the proper range; 2) monitor the timing channel for the presence and regularity of the timing mark pulse; and 3) monitor and display engine speed and trigger data intake only when the rpm is within a specified tolerance range. Stable signature estimates are achieved by averaging approximately 100 engine cycles. Thus, under this arrangement, the actual measurement time during which the sensors must be connected might be only a few seconds.

Both time and power normalization are required to remove effects of uncontrollable variables in the measurement process.

Averaging of many engine cycles is necessary because a wide variance exists between signatures of individual cycles. This must be preceded by time normalization to maintain coherence, or averaging will deteriorate the signature quality because of wave interference. This interference effect is increasingly more pronounced as distance from the timing marker increases.

The major concern in sensor placement is the masking of signature components by the signal strength of engine elements which are very close to the sensor. Results in this study were based upon using one sensor only in any one test. If a single sensor is to be used, it should be placed in the most central location possible relative to cylinder locations. If more sensors are used, they should be distributed symmetrically relative to the cylinders.

The need for rectification (which was pointed out in Ref. 1) is greatly reduced by time normalization, which was not possible with the instrumentation used in the referenced study. Time normalization, software fine-tuning of synchronization, and averaging of unrectified signals yields a surprisingly stable and structured signature.

1.3.2 Recommendations

The next step toward economical implementation of this concept is to install a real time engine Vibration Analysis System with the prototype software for data base, OPSEEKER, analysis, and classification. The software components must provide for creation and maintenance of an ever increasing data base, including engine signatures tagged with the results of analysis and repair by mechanics. The OPSEEKER will be resident to redesign problem nodes in the classifier as the data base becomes larger and includes representative samples of more specific failure types. The classifier will be a modular quadratic decision tree, and will output its diagnosis in real time while the engine is still connected to it.

This system should be installed where engines are actually repaired, so that they can be routinely tested and added to the data base, and so that vibration data can be tagged with results from repair reports.

System performance should be evaluated on a quarterly basis. When performance against the selected engine attains a satisfactory level, smaller less expensive microcomputer-based analyzers may be implemented using the same algorithm, but not requiring the data base or OPSEEKER capabilities. These inexpensive analyzers may be placed in all maintenance depots. In the meantime, the pilot system may be extended to develop an algorithm and data base for other engine types and continue to generate analyzer algorithms for new engines.

II. STATEMENT OF THE PROBLEM

2.1 PROBLEM

The problem is to diagnose engine condition instantly from external measurements of its vibration signature. The first level of decision to be made is "good" versus "bad." The second level is the classification of the individual failure modes which may be present.

There are many possible failure modes which may occur, and their symptoms are distributed broadly in time over the engine signature. Therefore, no static data base is likely to contain enough samples to allow design and evaluation for all possible engine failures. This constrains any analyzer designed automatically to perform well only for those failure modes which it has seen in its design data base.

2.2 APPROACH

2.2.1 Dynamic Data Base

The more common failure modes will quickly become represented as the size of the data base grows. As the capability of the analyzer to locate these faults improves, new data need not be added for these faults. However, the data base manager should continue to search for examples of the less common failures, and to analyze data for those engines which may be misclassified by the algorithm. So, the data base must be dynamic and capable of growing selectively throughout the engine life cycle.

2.2.2 How Many Classes of Engines

For a given engine type, the diagnosis problem is a many class decision theory problem. It is possible at the outset to define it as a 2-class problem - good and bad, as shown in Figure 1.

Here the signature is input to a single node, at which a statistical test is applied, resulting in the decision that the engine is good or bad.

As the system is applied to a growing data base, enough data will be accumulated on the most frequent failure modes to permit isolation of individual failures. Figure 2 shows two possible ways of adding decision modules to Figure 1 for isolation of sticking valves. Figure 2 introduces the architectural concepts of modular decision node functions and of decision trees.

Algorithmically, the decision functions at all nodes are identical, for simplicity of design and maintenance. Each node selects from the same array of signature data. The definition of a node includes the parameters which define its level, which nodes point into it, how many subclasses it must select from, and the statistical class descriptions which it uses to make these decisions.

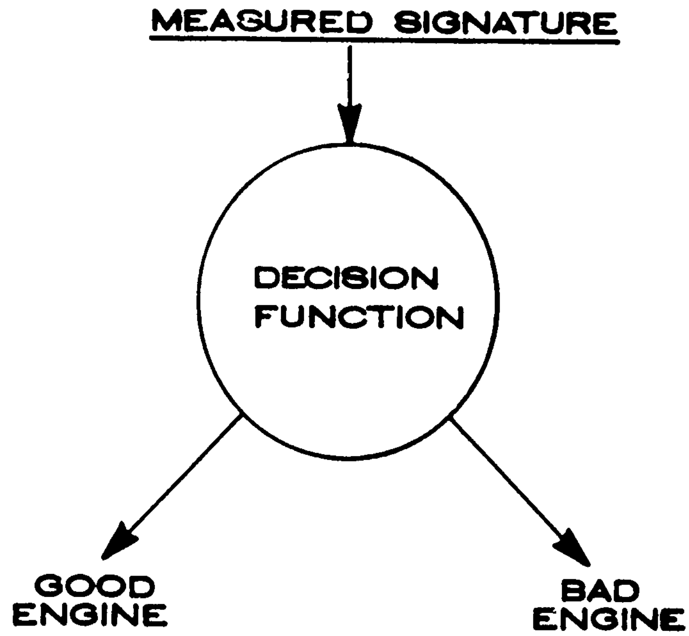
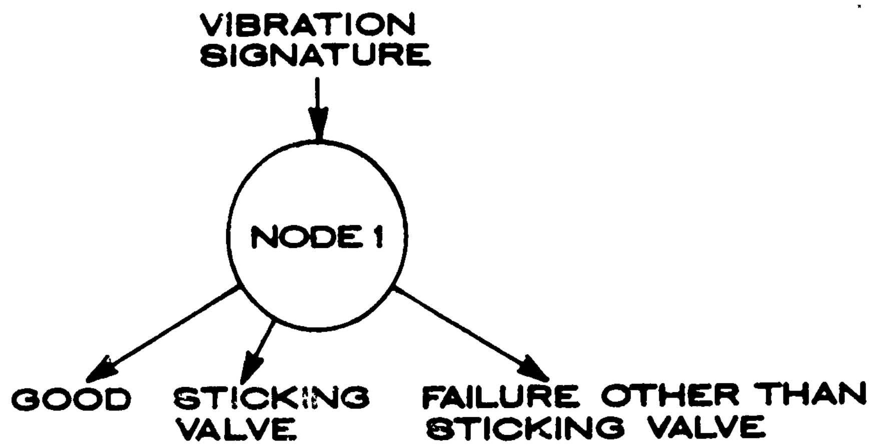


Figure 1. Decision Tree for a 2-Class Problem



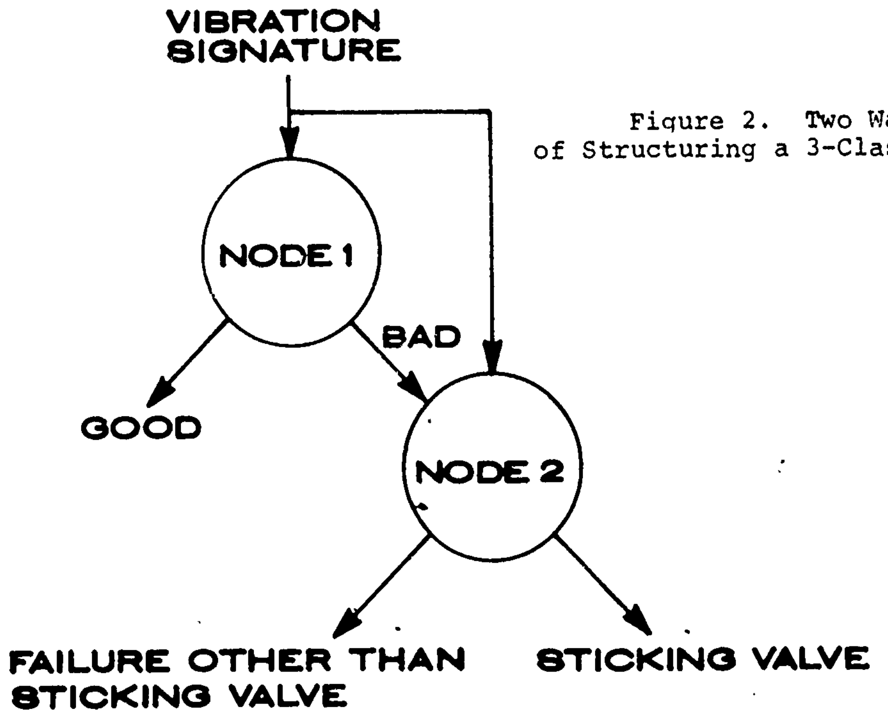


Figure 2. Two Ways of Structuring a 3-Class Problem

The tree structure is defined by levels and branches, generally shaped as shown in Figure 3. The definition of nodes and their arrangement into a tree can have significant effect on the performance of the system. The general methodology to be applied in defining tree structure is that of clustering.

It is desirable to define the smaller subclasses (e.g. sticking valves and loose wrist pins) to be grouped together into a larger subclass in a high level node (e.g. good and bad) so that the subclasses which are grouped together have signature statistics which are somewhat similar (or clustered in some proximity to each other in the signature space). Further, the clusters of bad signatures must not so surround the cluster of good signatures as to make a decision boundary between the two sets impossible to draw.

It seems reasonable to assume that the good engine signature samples will be clustered and separable from bad ones, which may be ideally thought of as deviations from the good signature model. For separating specific failure modes, as a beginning strategy, consider the following. Failure mode M_i, as a matter of course is classified at the top node as bad (or good), and therefore channeled to the appropriate Level 2 node, N_j. When enough data samples are available for failure mode M_i, the node N_j is retrained so that, in addition to its past function, it now isolates failure M_i. In a multi-level tree, each new failure mode should be isolated at the highest node at which its sample signatures remain grouped together.

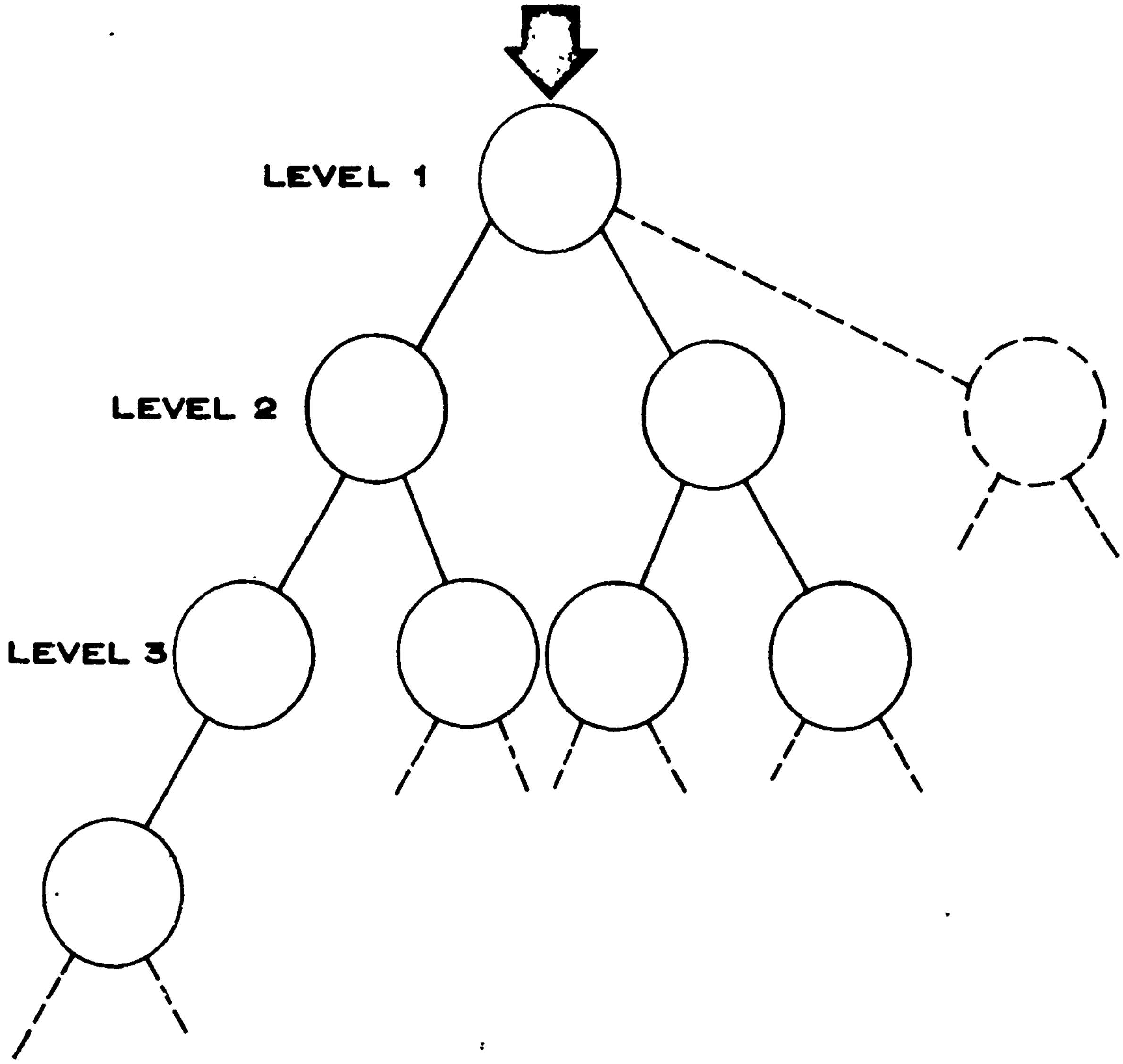


Figure 3. General Decision Tree Structure

III. DESCRIPTION OF WORK

This program paralleled the GE effort (Ref. 1) and used the same data base. Major improvements were made in the measurement and processing techniques. Emphasis is on automatic design of the classifier algorithm. Both time domain signatures and frequency spectrum signatures were used in classification experiments. Although performance was comparable, the time domain should prove to be the most useful because of physical considerations. The data did not support a three dimensional time versus frequency versus amplitude signature study.

3.1 DATA

The original GE study demonstrated the detection of the following kinds of faults:

a) Improperly adjusted and sticking valves
b) Bent connecting rods
c) Loose wrist pins
d) Defective piston rings
e) Damaged cylinder walls
f) Worn or loose connecting rod bearings
g) Poor combustion
h) Improper timing

This was done in two phases. Phase I used magnetic tapes of data from ten engines and detailed inspectors' reports of the engine condition. These tapes were found to be unusable in the SEI study, because of their physically deteriorated condition.

The GE Phase II study used vibration data from a lot of forty Continental Engine AV 1790-7s, instrumented with five high frequency accelerometers mounted in the engine blocks. The Phase II data were in good condition and were used in the SEI study. Not all of the forty engines were represented in the available data, as shown in Table 1. These data were labeled as to whether they were taken before or after repair, and repair reports indicated whether the measurements were made before or after repair and the magnitude of the repair. Sensors number 1 and number 5 were found to have good data for all runs in the data base, according to the tabulation in the GE test report, whereas the other sensors didn't. Sensors 1 and 5 were used for most of the SEI work. Some data from sensors 3 and 4 were used to check on the effects of using multiple sensor data and the effects of sensor placement. Some data runs were discarded because of error in the Rotan placement.

Available data existed at 1600 rpm full load power, 2800 rpm full load power, and an acceleration run at no load. Only 1600 rpm data were used in design and evaluation of classifiers.

Table 1. Summary of Data Base

ENGINE	SENSORS				NO. SAMPLES	GOOD	MAJOR REPAIR	ROTAN ERROR
	1	3	4	5				
11B	x			x	65		x	
11A	x			x	67			
12B	x			x	66		x	
12A	x			x	62			
13B	x			x	68	x		x
13A	x			x	70			x
14B	x			x	70	x		
14A	x			x	67			x
15B	x			x	56	x		
15A	x			x	72			
16B	x			x	69	x		
16A	x			x	58			
17B	x			x	62		x	
17A	x			x	67			
18B	x			x	51	x		
21B	x			x	69		x	
21A	x			x	68			
22B	x			x	60		x	x
42B	x	x	x	x	73		x	x
42A	x	x	x	x	57			
45B	x	x	x	x	62	x		
46B	x	x	x	x	69	x		
47B	x	x	x	x	63	x		
48B	x	x	x	x	62		x	
48A	x			x	71			
49B	x	x	x	x	56	x		
50B	x			x	64		x	
50A	x			x	63			

The recordings were narrow-band FM. Some d-c offset was encountered in playback because of variations in center frequency between record and playback equipment, but this was not enough to cause a problem in analysis.

A Visicorder was used monitoring the timing reference track to locate data on the tapes. Zero markers were placed on the tapes and run locations were measured and logged in a directory.

3.2 MEASUREMENT

Figure 4 is a block diagram of the measurement system.

The analog tapes are those from the Phase II data. They were recorded at 30 ips and played back at 15 ips, one half signal time (real time in the recording operation). The playback bandwidth at this speed is 2-1/2 kHz, which translates to 5 kHz in real signal time. The signals had been bandpassed in recording also to a 5 kHz bandwidth.

Data channels 1 and 2 consisted of buffer switch amplification of 20 to 1 and a 3 dB corner frequency at 3 kHz or 6 kHz in real signal time. This is implemented on Newport Model 70A differential amplifiers. The output signal levels are ±10 volts. The time channel is unity gain for buffering the timing data track.

The multiplexer and analog-to-digital converter is a Phoenix Data Inc. Model 2218. Each channel is converted with 10 bits resolution and input range of ±10 volts. The sampling rate is 5 kHz for each channel, which translates to 10 kHz in real signal time. This rate is the Nyquist rate for the band limitation imposed by record and playback.

The sampling scheme in the multiplexer and A/D converter was as follows. The time channel was monitored continuously (sampled every 200 microseconds) since the timing sync reference triggered sampling of the data channels. The leading edge of the timing sync pulse was arbitrarily used as the 0° reference in the engine cycle (0° to 720° for a complete cycle). When the timing sync pulse came up, the two data channels were sampled, approximately synchronously as shown in Figure 5. The delay between samples in channels 1 and 2 is approximately 80 microseconds. There was some variation in the duration of engine cycles from cycle to cycle and run to run, but the nominal rpm was 1600, and 2 revolutions (720°) are required per engine cycle. This results in 800 engine cycles per minute, or a nominal engine cycle duration of 75 milliseconds in real signal time. This translates to 150 milliseconds played back at one half speed. Therefore, there are nominally 750 samples per engine cycle per data channel. Data for any engine cycle which had a much larger or much smaller number of samples than 750 in a cycle was rejected since this implied a spurious or missed timing pulse.

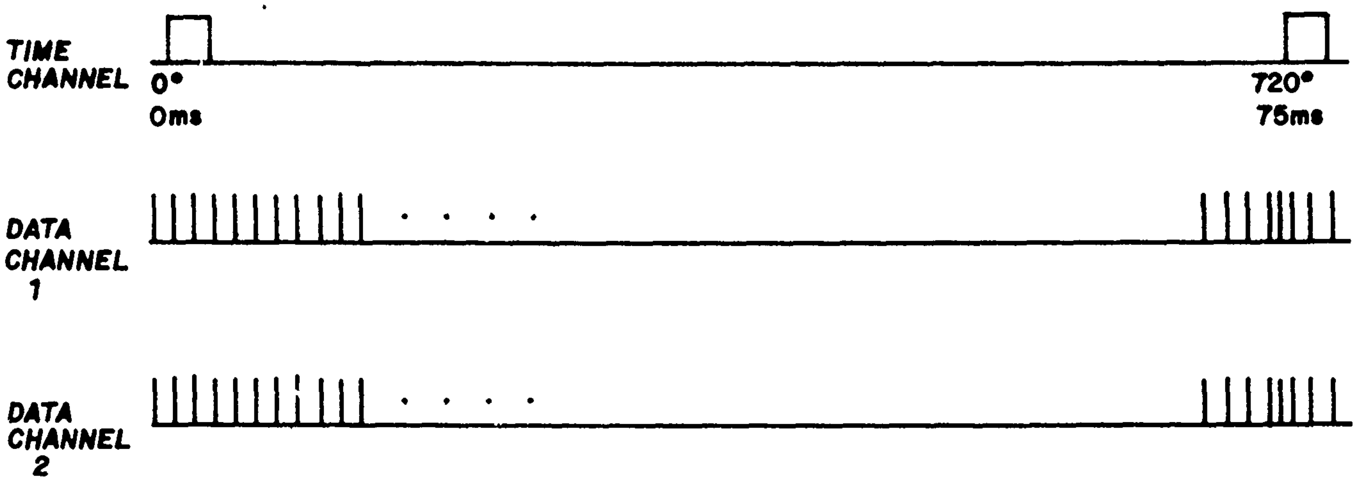


Figure 5. Sampling Scheme for Time Channel and Two Data Channels

A PDP-11 minicomputer was used to concentrate the data into blocks and transmit it to a PDP-10 timesharing computer in the SEI Computer Center. Algorithms were implemented on both the PDP-11 and the PDP-10 to assure error-free transmission in the time shared environment of the PDP-10. Algorithms were also developed for unpacking and demultiplexing the sampled data on the PDP-10 and formatting it into disk and magnetic tape files.

3.3 SIGNATURE PROCESSING

3.3.1 Summary

A variety of processing and display programs were used in this study. They include:

1) Graphics terminal display of individual raw data samples, averaged or processed samples
2) Hard copy plots of the above
3) Max and min values over a run for each point in the waveform
4) Variance over a run for each point
5) Zero mean waveform
6) Rectification of waveform
7) Peak normalization
8) Power normalization
9) Time normalization
10) Cycle averaging

3.3.2 Signature and Data Base Description

Figure 6 is a plot of a typical raw data signature. It is created from approximately 750 time samples of a single 720° engine cycle as measured at one of the sensors. The number of engine cycles measured for each engine ranged from 55 to 70, constituting a run. The plotted output labels are described in Table 2.

3.3.3 Display

For study and editing purposes, any engine cycle signature or any processed signature data can be instantly displayed on a GT-40 graphics data terminal or on a digital plotter.

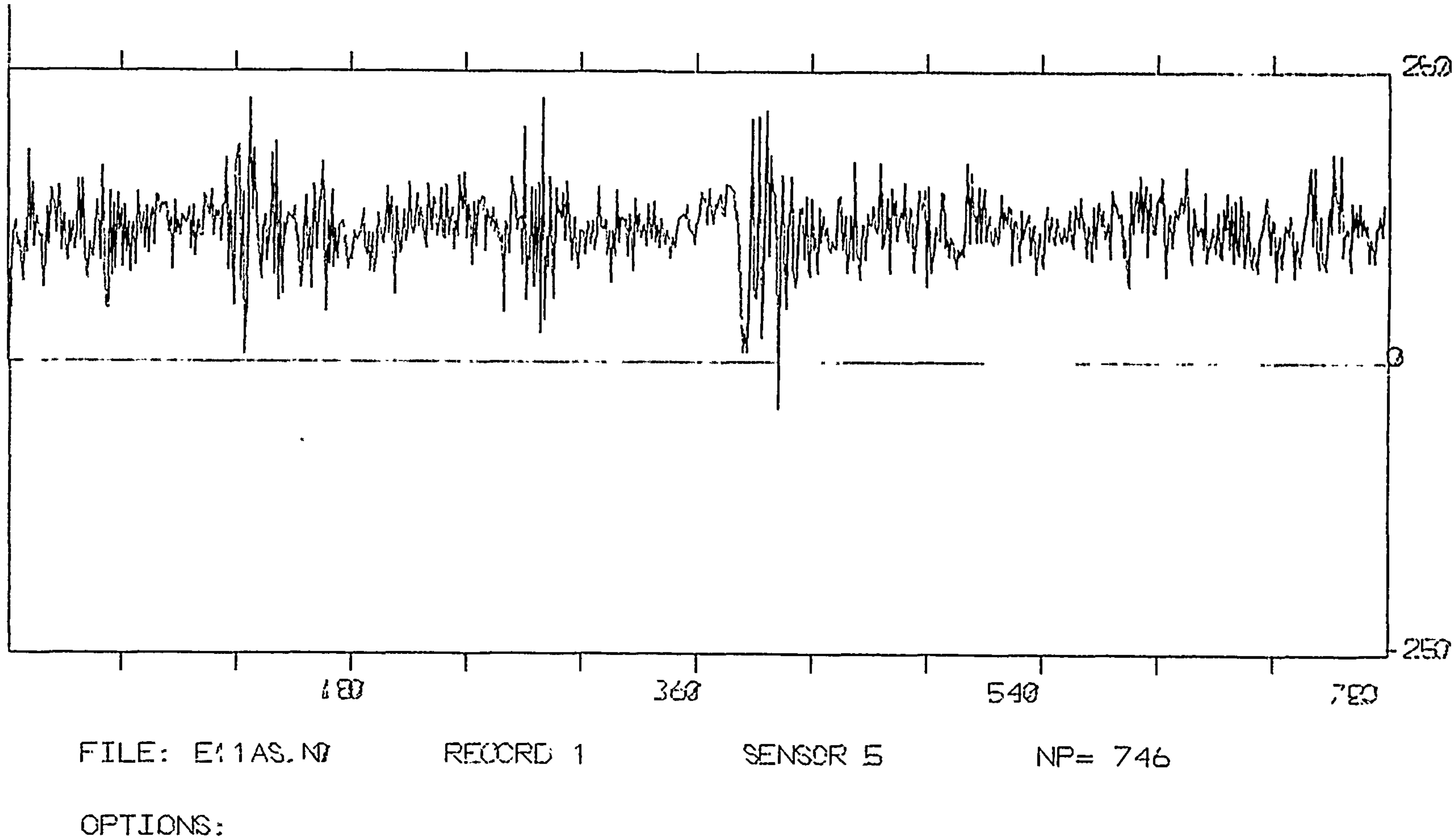


Figure 6. Raw Data Signature for a Single Engine Cycle

Table 2. Processing Options for Displayed Data

FILE NAME:

E X X Y Z

Engine number

Engine rpm
S = 1600 rpm
F = 2800 rpm
A = acceleration run

A or B for after repair, before repair

OPTIONS:

ZERO — input data were zero meaned

RCTFY — input data were rectified

T = n — input data time normalized to n points

A = n — amplitude normalized, peak = n

P = n — power (length) normalized, length = n

3.3.4 Max and Min Values Over Runs

A run is a series of consecutive engine cycles at 1600 rpm. There is relatively little variation from engine cycle to engine cycle in time (or phase) of individual signatures which have undergone time normalization. One interesting statistic is the relative stability of the amplitude values from cycle to cycle over a run. A measure of this is the maximum and minimum values of observations over a run for each sample interval.

3.3.5 Variance versus Sample Time

A measure similar to the preceding is the variance of observations for each time point over all engine cycles in the run.

3.3.6 Zero Mean

The recording, playback, conditioning and sampling processes result in a dc offset in the data signature waveforms. This is removed from the digital data base by subtracting the mean value over each individual cycle.

3.3.7 Waveform Rectification

In the GE report of Reference 1, it was decided to rectify waveforms prior to averaging. This was based on lack of phase coherence in the signature from cycle to cycle and run to run, so that averaging without rectification often resulted in cancellation rather than enhancement of high frequency portions of the signature. A rectification algorithm is included in the processing package.

3.3.8 Peak Normalization and Power Normalization

It is common practice to normalize amplitude in some fashion prior to applying pattern recognition algorithms prior to display of waveforms. This is helpful in reducing the channel gain effects on the appearance of the waveform, thereby making comparison of the actual shapes easier for the analyst.

The two methods used in this study were peak normalization and power normalization. In peak normalization, the highest peak value in the signature V_p, is scaled to a selected value, V_S, and all other points are scaled by the factor (V_S,V_P), so that the shape of the waveform is preserved while all signatures are constrained to have the same maximum.

Energy normalization is also a shape-preserving transformation, but in this case, the scale factor is $\sqrt{1/E}$,

Where $E = \sum_{t=1}^{N} S(t)^2$, $S(t)$ being the sample value at time t, N being the total number of samples taken in the engine cycle. This normalization is often preferable to peak normalization because it makes all transformed N-dimensional vectors have equal length and removes any amplitude (often channel-related rather than source-related) effects from the signal. The processor which performs classification on energy normalized signatures uses purely the shape of the signature (or vector direction) and not amplitude (vector length) in its classification.

In the data, energy was observed to be fairly constant from one cycle to another within a given run, but varied widely from one run to another.

3.3.9 Time Normalization

Time normalization is particularly important in this problem, since no two runs are performed at exactly the same rpm. For this reason, it is crucial to reconstruct the sampled data waveforms, which may consist of 700 to 800 samples in an engine cycle, and then to sample the reconstructed waveform with exactly 750 evenly spaced samples before processing. This preserves the phase coherence of the signature so that its shape may be compared or averaged directly with signatures from other runs and other cycles. The lack of this ability would appear to be a major shortcoming of the Enhancetron of Reference 1, since it depends on the engine speed to maintain a constant time reference, a condition which is not met in the data.

3.3.10 Cycle Averaging

Averaging waveforms which are rectified or which have timing coherence enhances the signal while reducing the random noise components. This is because the signal components add in amplitude, which increases signal energy as the square of the number of waveforms added together, while the random phase noise components add in energy so that their energy contribution only increases proportionally to the number of waveforms to the first power.

3.4 RELATIONSHIP BETWEEN TIME SIGNATURE AND ENGINE CYCLE

Key events and their locations in the engine cycle are described in Tables 3 and 4 and Figure 7. In Table 3, note that the Rotan device is the device which generates the timing marker used in the data base. Its occurrence is offset by 10° from the true 0° reference point in the engine cycle. Figure 7 maps key engine events onto the graphical scale used in all plots in this report.

3.5 SENSOR PLACEMENT STUDY

Figure 8 shows the locations of the accelerometers on the test engines. Figures 9 through 12 show averaged and normalized engine cycles for the same engine as observed at sensors 1, 3, 4 and 5 respectively.

Table 3. Engine Cycle Event Locations

ROTAN SIGNAL IMPOSES +10° SHIFT TO CALCULATIONS BELOW

	TDC	-360		
EXHAUST	CLOSE	-328		
	BDC	-180		
INTAKE	CLOSE	-56		
POWER	TDC	0	168	firing in here somewhere
EXHAUST	OPEN	+112		
	BDC	+180		
INTAKE	OPEN	+320		
	TDC	+360		

Table 4. Power Top Dead Center Timing

CYLINDER	POWER TDC*
1L	0
6R	90
5L	120
2R	210
3L	240
4R	330
6L	360
1R	450
2L	480
5R	570
4L	600
3R	690

* +10° for Rotan

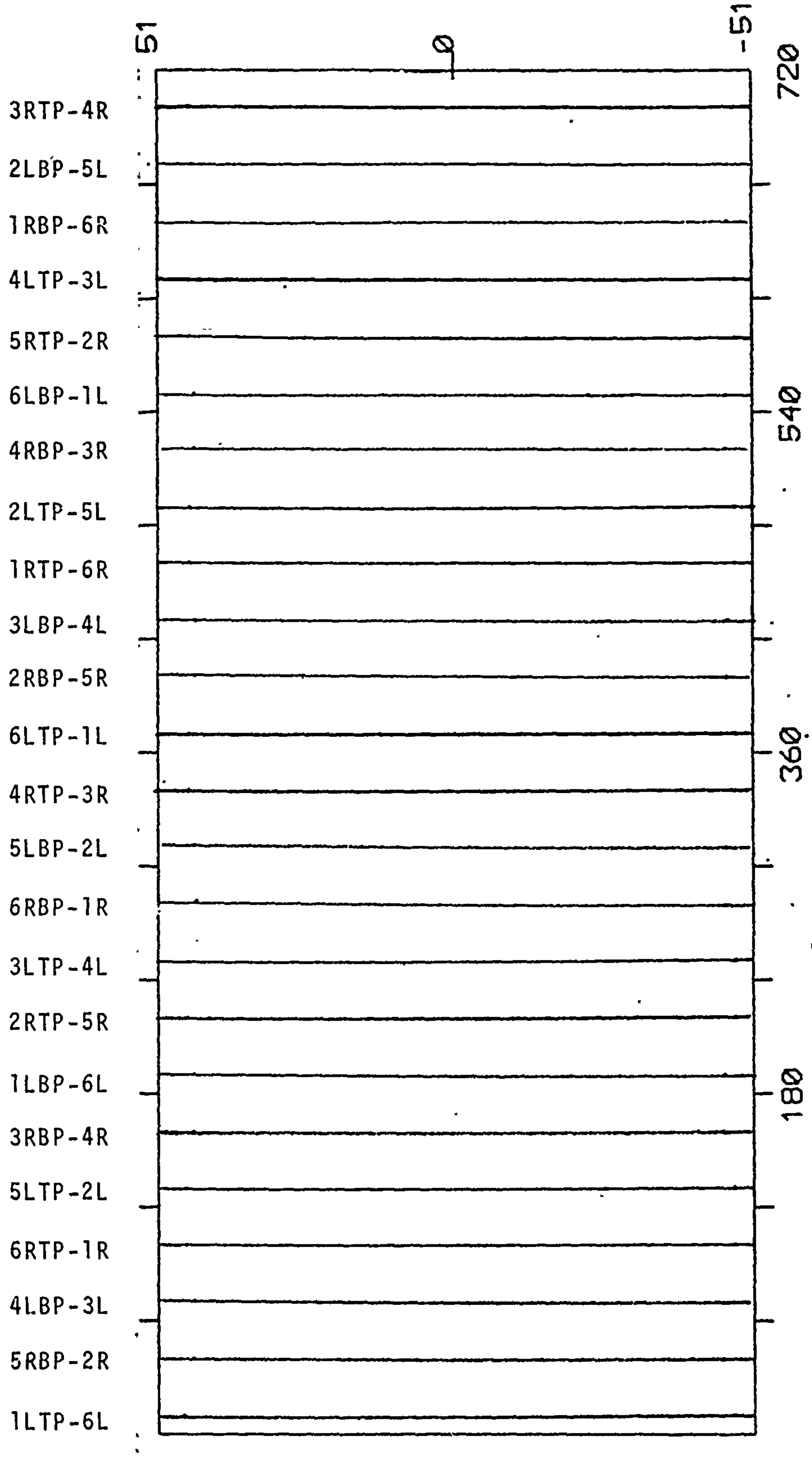
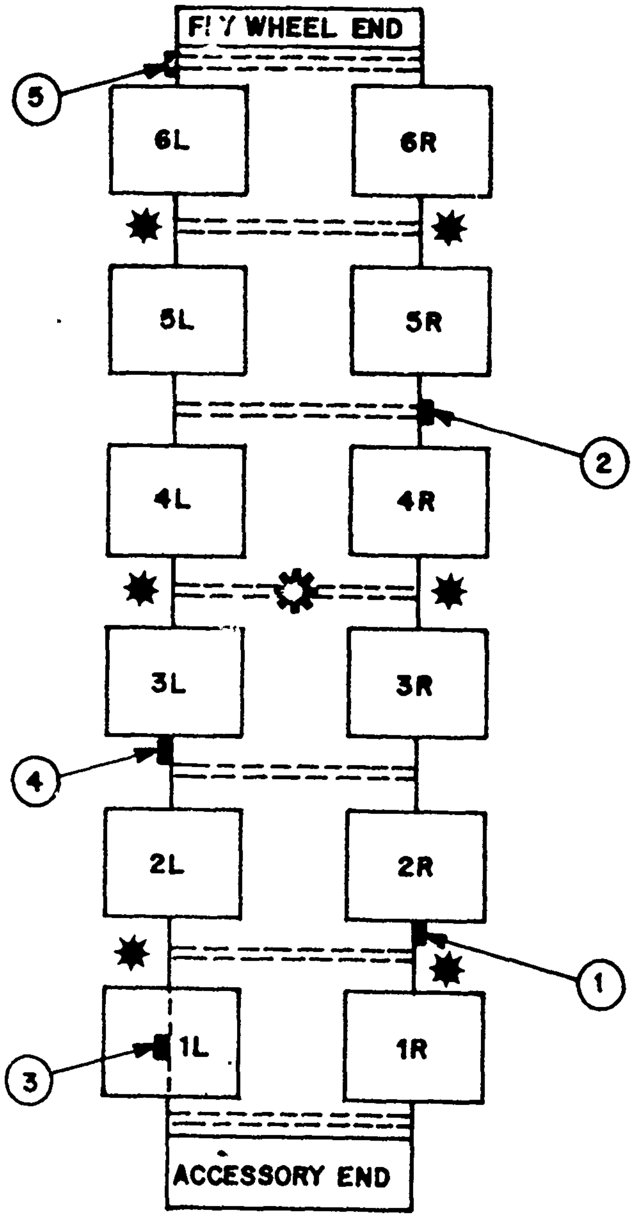


Figure 7. Key Engine Events versus Angle



Accelerometers are attached to the outer surface of the crank case at a height corresponding to the level of the upper main bearing.

Symmetrical placement using one sensor for every two cylinders.

Central placement for a single sensor.

Figure 8. Location of Pickups

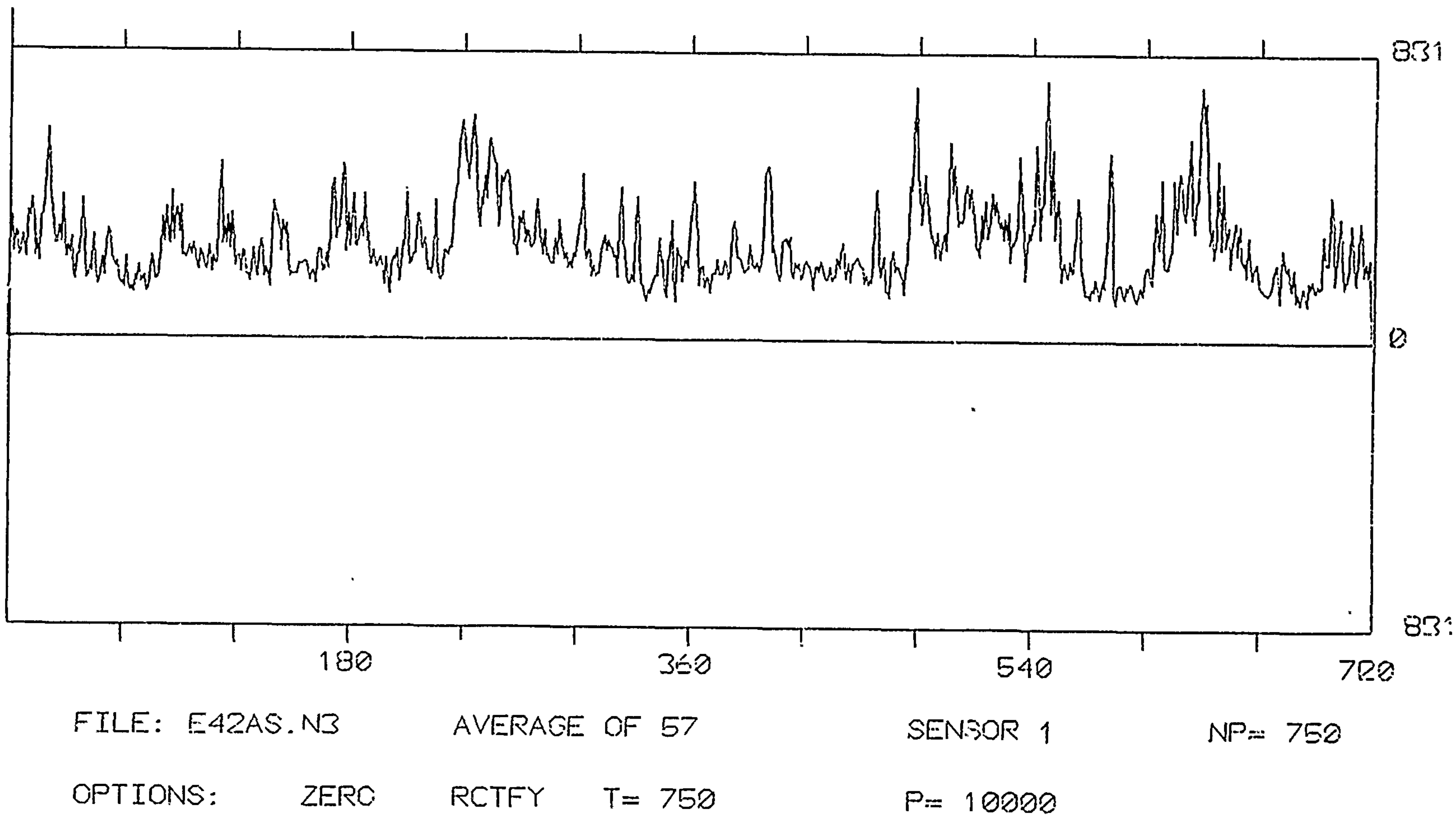


Figure 9. Engine 42 after Repair, Average of Rectified Signatures Observed at Sensor 1

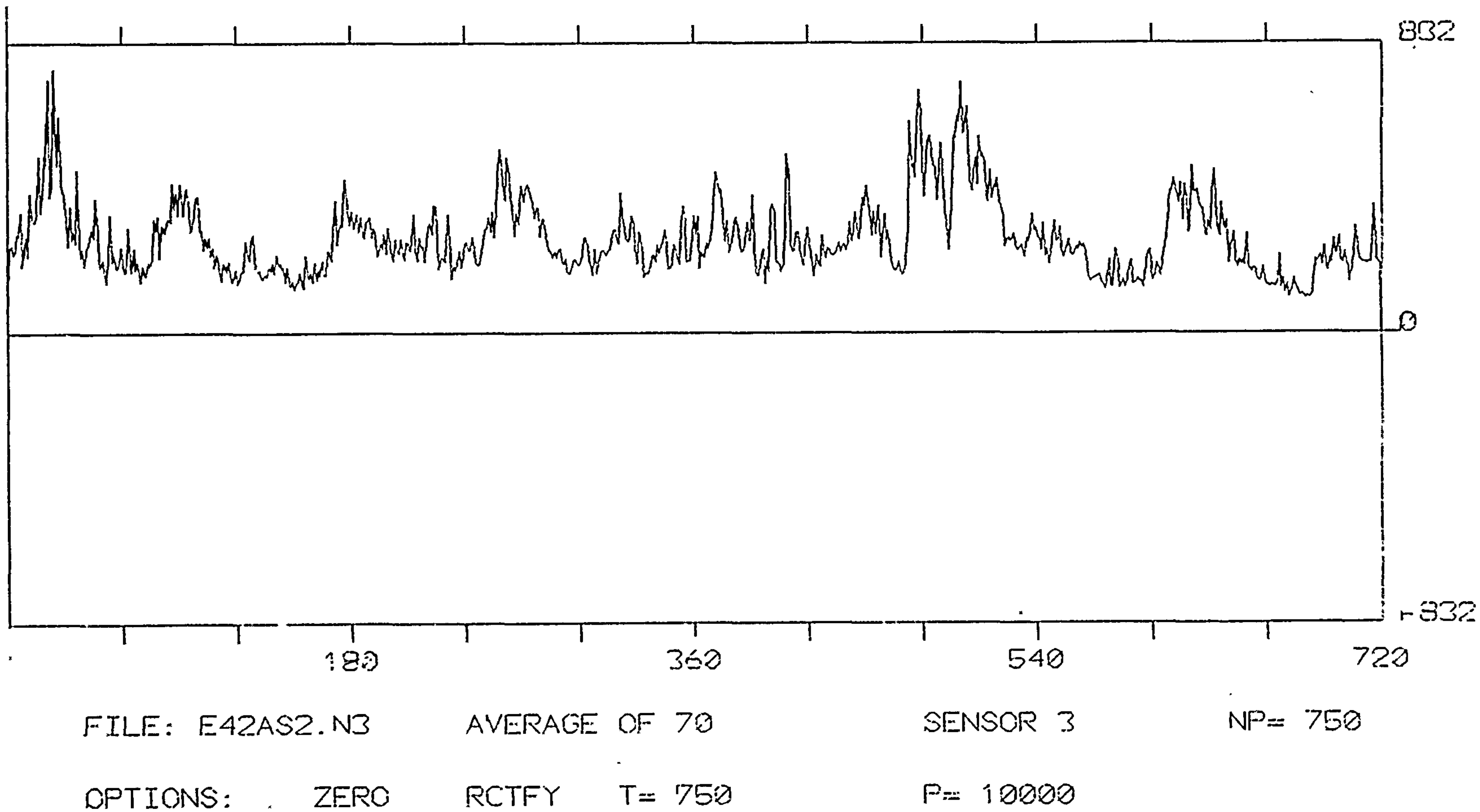


Figure 10. Engine 42 After Repair, Average of the Rectified Waveforms Observed at Sensor 3

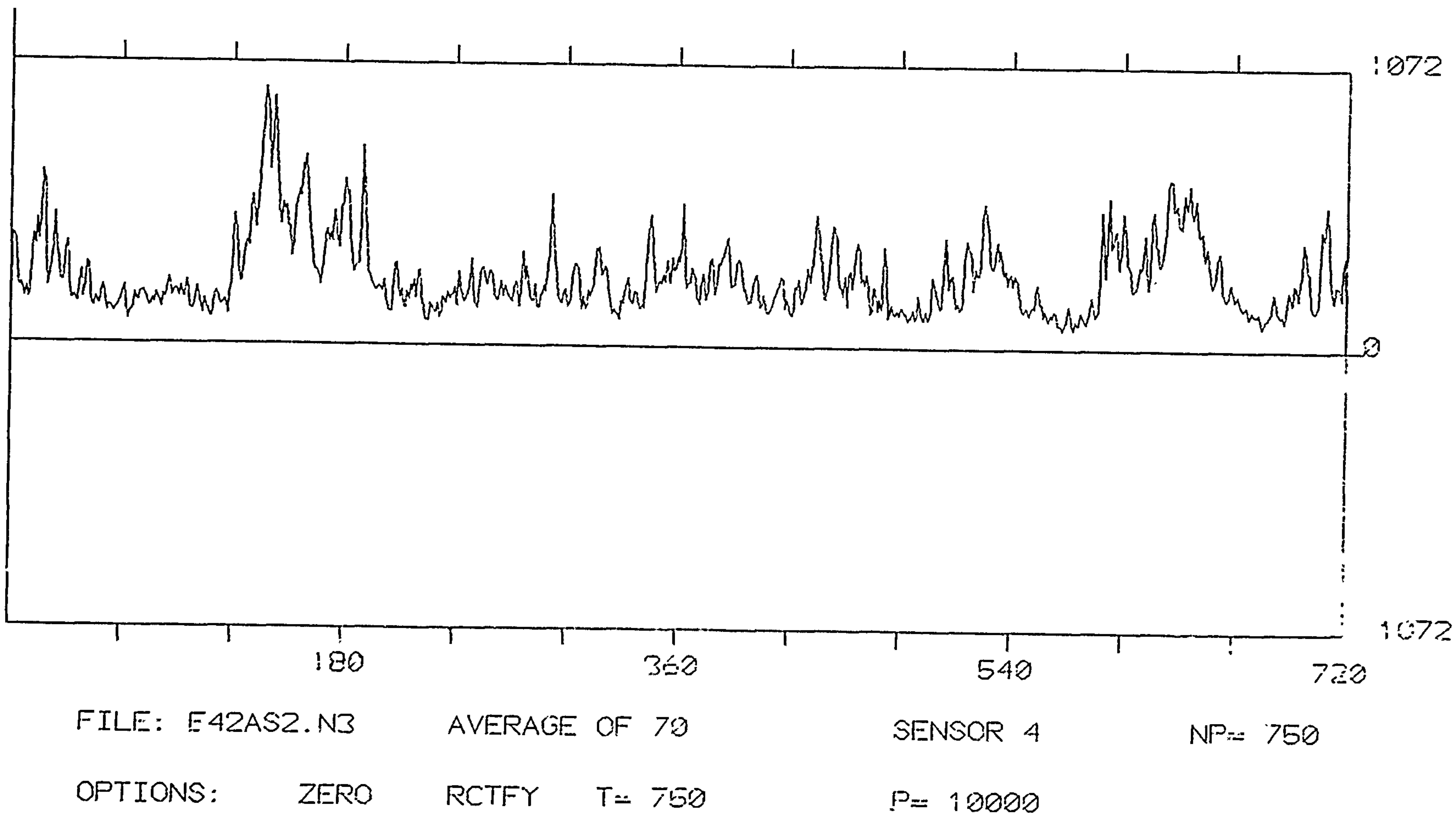


Figure 11. Engine 42 After Repair, Average of 70 Rectified Waveforms Observed at Sensor 4

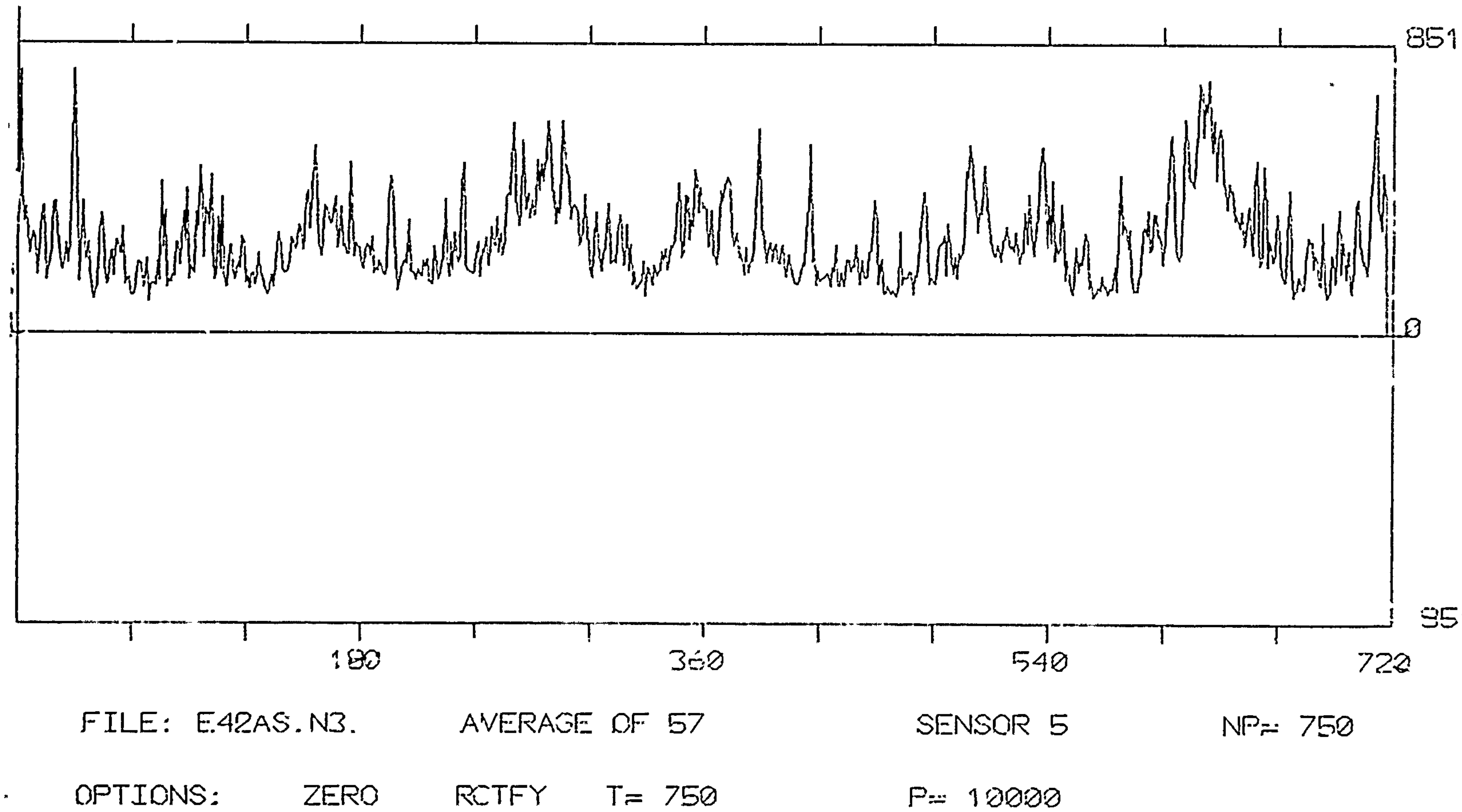


Figure 12. Engine 42 After Repair, Average of the Rectified Waveforms Observed at Sensor 5

Therefore obvious differences are apparent in the amplitude characteristics of the signatures from sensors in different locations. It has been verified that the largest signal regions from a given sensor relate to the firing time of the cylinder nearest to it.

Several conclusions may be drawn from this study regarding sensor placement.

First, the engine classification experiments which were done used single sensor data and it seems possible that satisfactory performance might be achieved operationally using a timing sensor and a single accelerometer, if the accelerometer were centrally located on the engine. This would offer significant advantage in the connection and disconnection aspects of testing, and also in the volume of data to be stored and processed.

At the other extreme, one sensor might be used for every two cylinders, with the sensor placed halfway between the two. Intermediate numbers of sensors could also be used.

Whatever the number of sensors used, the placement should strive for symmetry in the matrix of cylinders, since the information is lost from the signatures by masking. When a sensor is much closer to cylinder A than to cylinder B, the activity of cylinder A tends to dominate the sensor's dynamic range in certain time segments of the engine cycle. The result that problems in the remote cylinder during those intervals may be difficult to discern.

3.6 SIGNAL TO NOISE ENHANCEMENT BY AVERAGING

Figures 13 and 14 are signatures for engine number 42 after repair, as measured on sensor 5. The plots are time normalized to 750 points and power normalized to 10,000.

Figure 13 is a single engine cycle, rectified, while Figure 14 is the average of 57 engine cycles. Under close comparison, it may be seen that much of the apparent fine structure in the single-cycle signature is misleading and not statistically significant, since it washes out in the averaging process. It is clear that a single engine cycle signature does not provide a good estimate either of the average amplitude at a given time in the signature or of the location of those amplitude peaks which will emerge as significant in the averaged signature.

3.7 TIME NORMALIZATION STUDY

Time normalization is vital to success in engine signature analysis. Results indicate that the engine rpm is not sufficiently stable even within the same run for clean averaging. This can be seen in Figures 15 and 16. Figure 15 shows the result of averaging without time normalization of 69 engine cycles from the same run at nominally the same rpm. Figure 16 is an average of the same runs, but time normalized prior to averaging. Generally, it is apparent that the

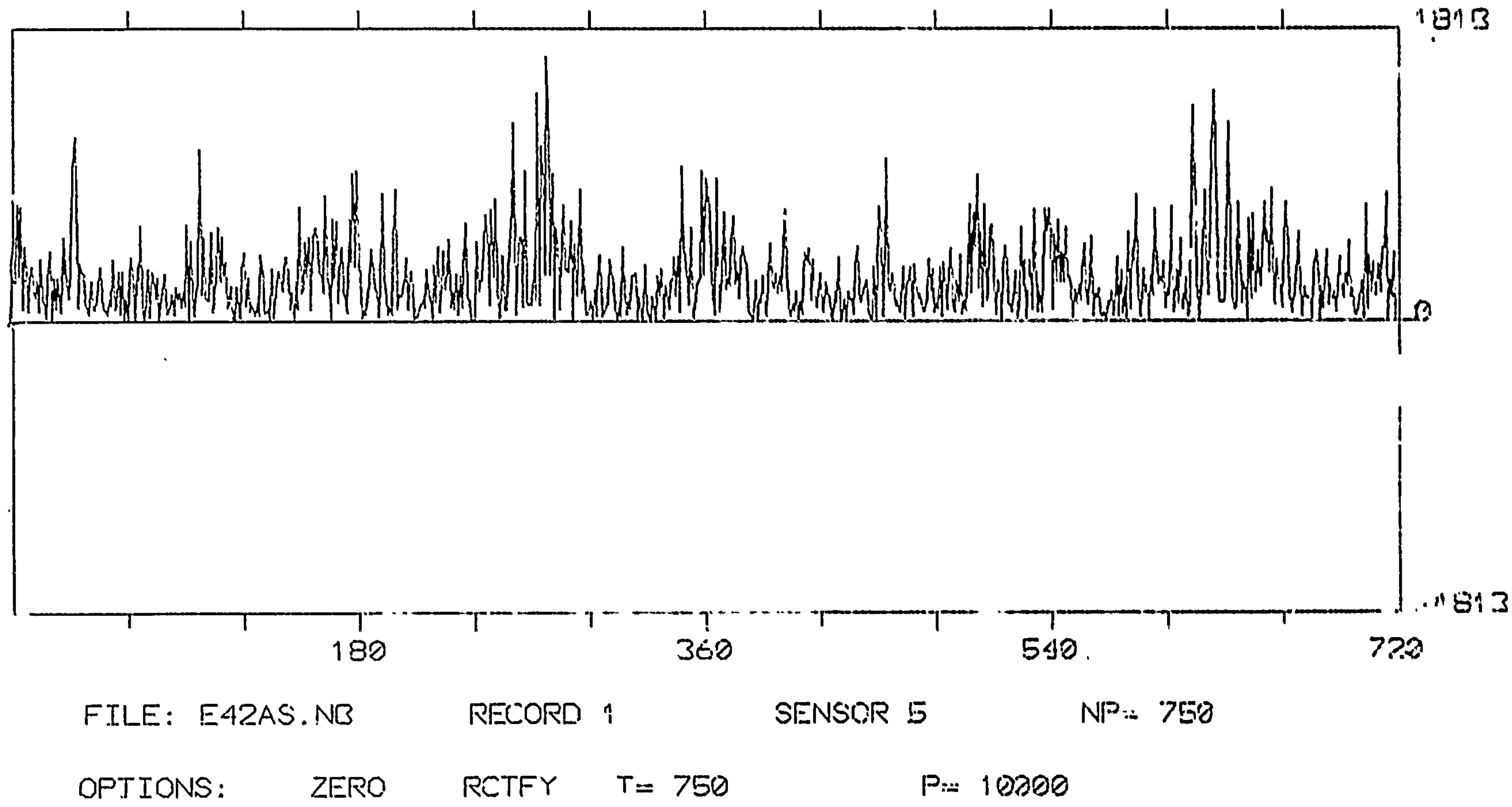


Figure 13. Signature for Engine 42 After Repair,
Single Cycle, Rectified Without Averaging

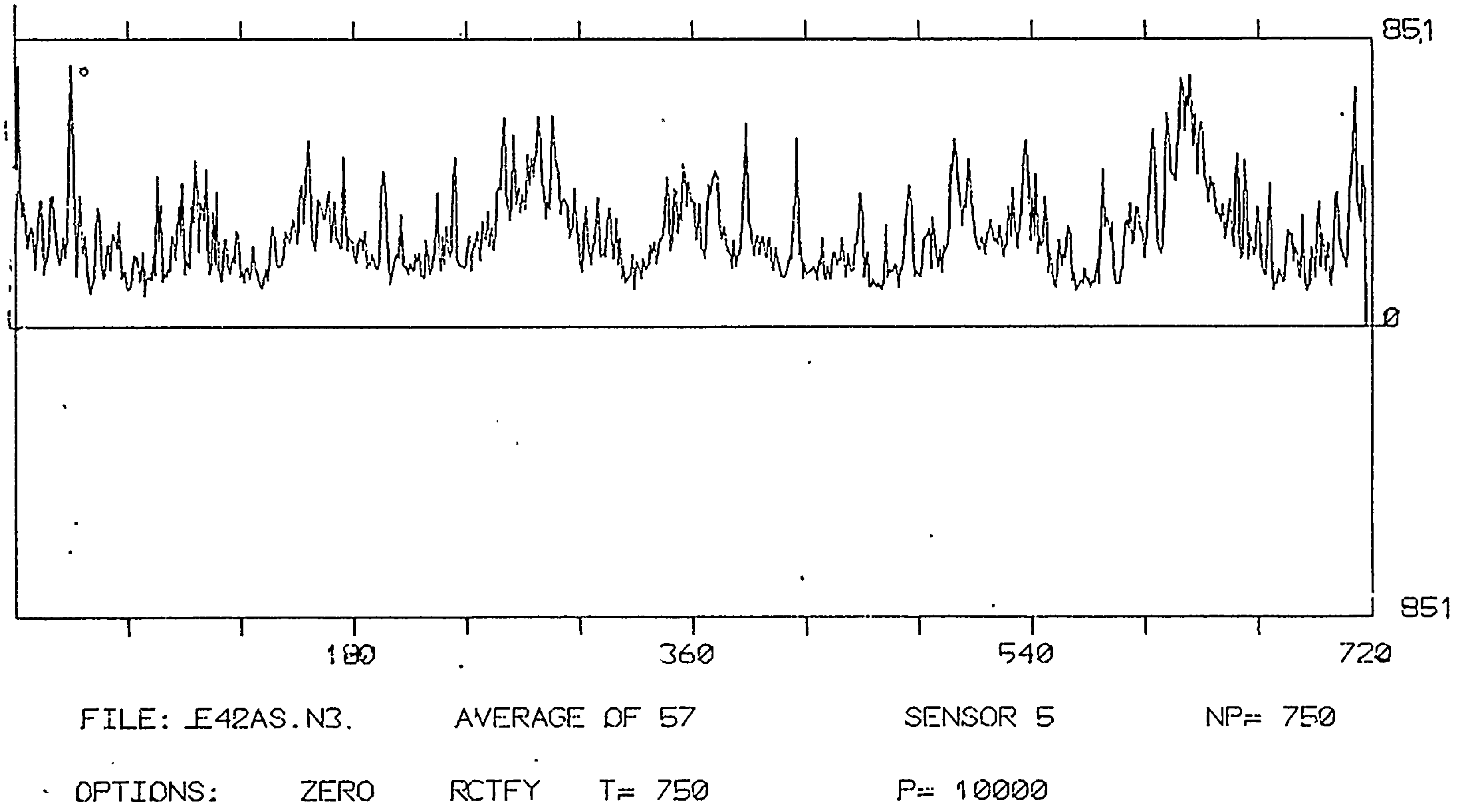


Figure 14. Signature for Engine 42 After Repair, Average of 57 Engine Cycles, Rectified

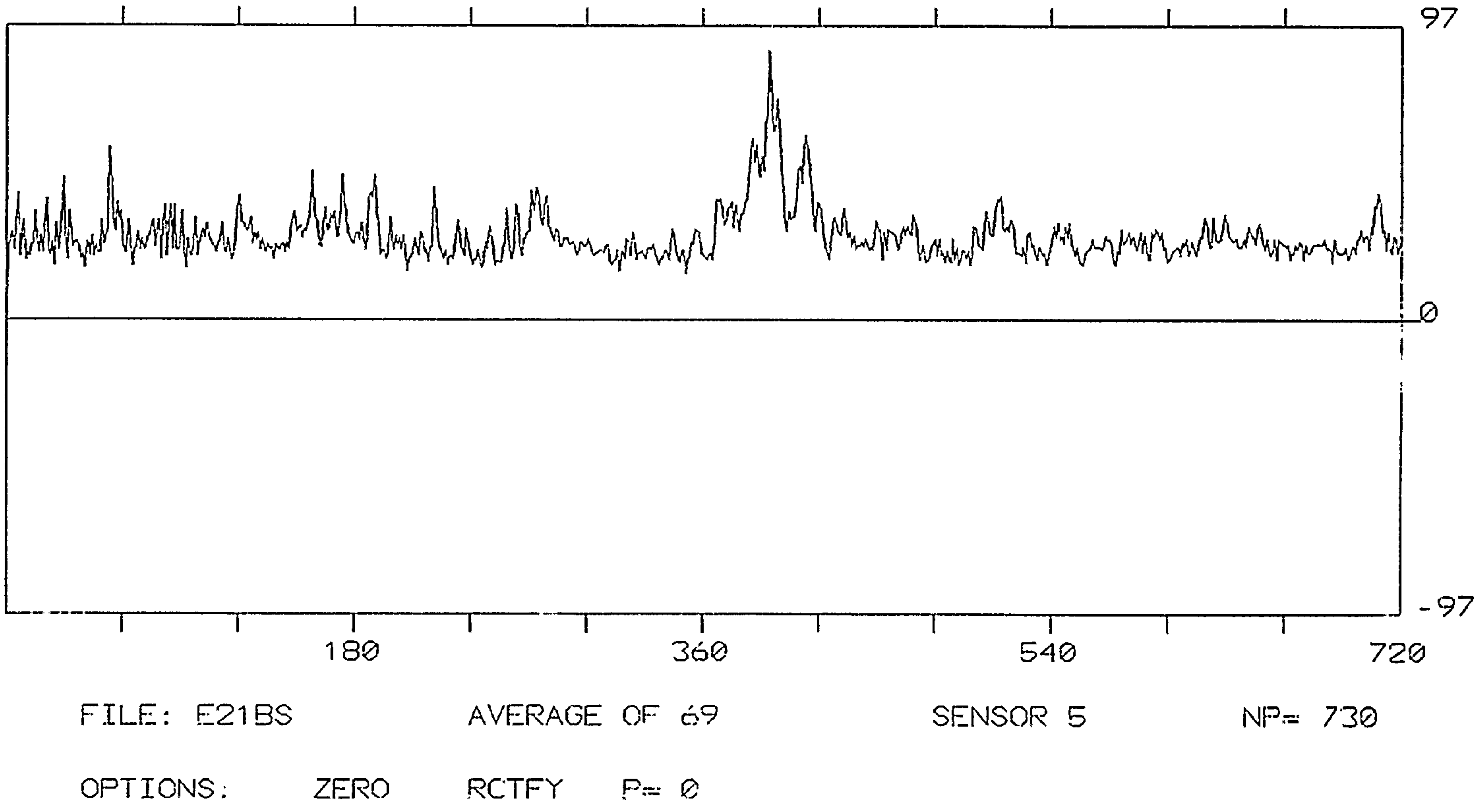


Figure 15. Averaging Without Prior Time Normalization, Engine 21 Before Repair, Average of 69 Engine Cycles

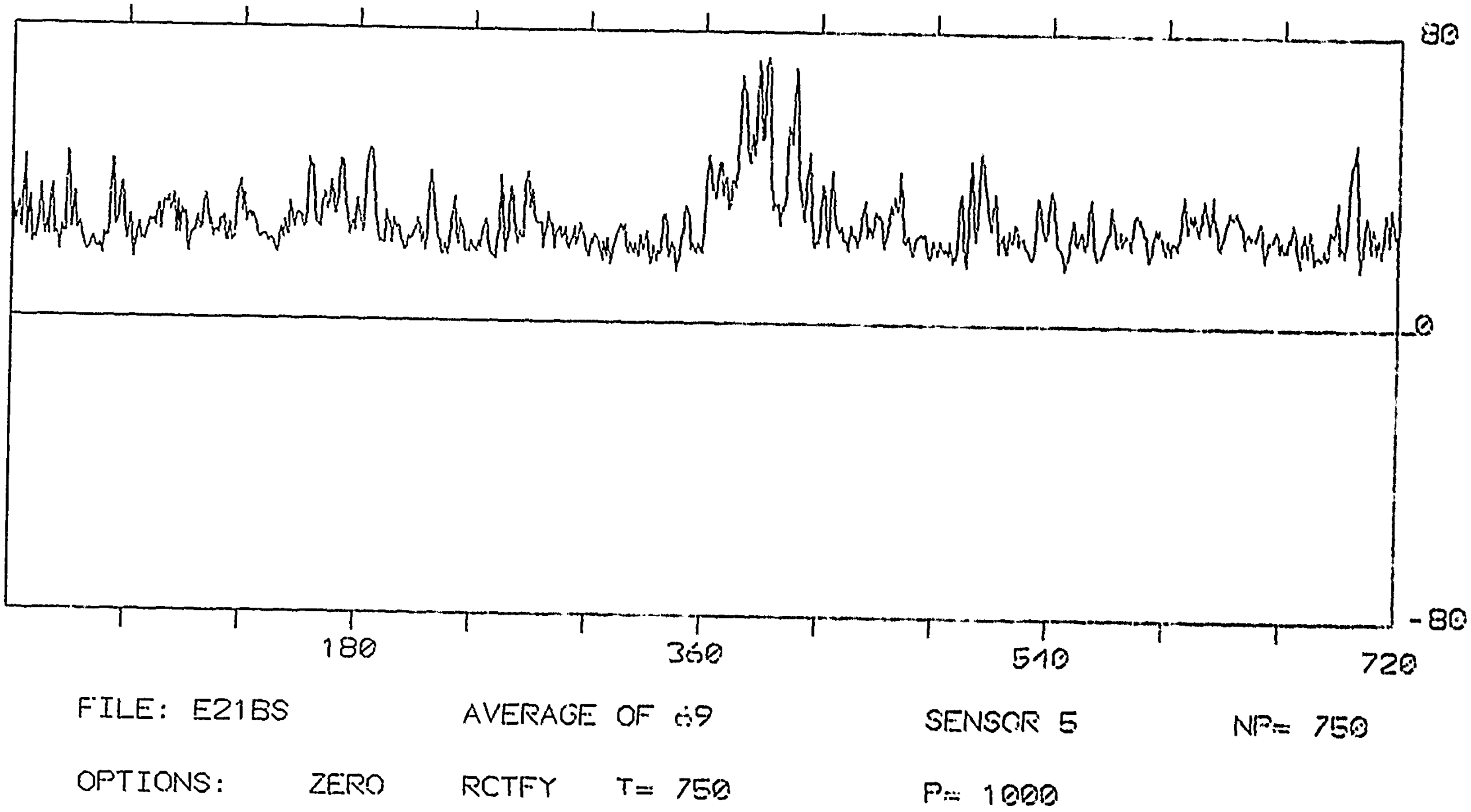


Figure 16. Averaging With Prior Time Normalization, Using the Same Raw Data as in Figure 15

peaks occurring nearest the timing marker (to the left of the plot) are sharp and clear in both cases. However, as you move further toward the right, the effects of small rpm variations within the run cause a blurring of the peaks in the unnormalized data of Figure 15. At the same time, the normalized data retain sharpness and focus throughout the 720° engine cycle.

The signal enhancement within a run is obvious from this comparison. The results of Reference 1, using the same data, depended upon the rpm regulation since the Enhancetron instrument had an independent fixed time base.

This enhancement effect is magnified when consideration is extended to data from two different runs, which must ultimately be compared in any automatic pattern recognition processor. Tests showed that rpm variation between different runs was considerably greater than variation within a run.

The use of software time normalization on a cycle-by-cycle basis relieves the demands on mechanical and human test specifications in an automatic data collection system because data may be recorded over a range of 5 to 10% from nominal rpm.

Time normalization was accomplished by reconstructing the waveform from the sample values, using linear interpolation, and then sampling the reconstructed waveform so that there were exactly 750 samples per engine cycle.

A further refinement may be appropriate to fine-tune the engine cycle synchronization. An error-prone step in measurement is the mounting of the Rotan device or other 0° synchronizing signal source, as witnessed by the fact that errors occurred in several runs in the data base used here. Given a good marker delineating each cycle, minor adjustments in timing may be provided by a digital matched filter. The measured signature should be correlated against the matched filter (or prototype signature) at various time shifts, and correlation measured as a function of the time shift. The time shift yielding maximum cross-correlation should then be used as the reference marker. This should yield timing accuracy within ±1° of rotation, probably better than can be done by mechanical means.

3.8 PHASE COHERENCY AND RECTIFICATION

In Reference 1, rectification of the signature was recommended on the basis of phase instability in the timing of major peaks. The result of Enhancetron averaging of successive wave forms was always some degree of cancellation, as shown graphically in the preceding section. Rectification provides a hedge against this problem. In the rectified signature, the peaks may be diminished, but the time regions of high energy are still apparent. In fact, the uncertainty resulting from phase instability in the signatures is translated from a cancellation of peaks to a smearing or time uncertainty in the averaged signature.

Experimentation here has shown that averaging of unrectified signatures can result in clear and well structured signatures, provided that cycle time is normalized prior to averaging. This is demonstrated by Figure 17, which is the average of 67 time normalized engine cycles for engine 11 after repair. Comparison of Figure 17 with the rectified average in Figure 18 shows the equivalency and hence the phase coherence of the time normalized signatures.

Another measure of phase coherence of the signature is shown in Figure 19, which is a histogram of the number of times that each time point was a local maximum or minimum, out of 67 samples. Note that certain points have a very high incidence of occurrence as extrema, while others very seldom occur as extrema.

One further perspective on the variation of engine signatures is given in Figure 20, in which the max, min and range of measurements are plotted for each time interval over 67 sample signatures from a single run.

Extremely wide variation occurs from cycle to cycle for engine signatures, emphasizing the fact that automatic classification would not be practical on these signatures without averaging.

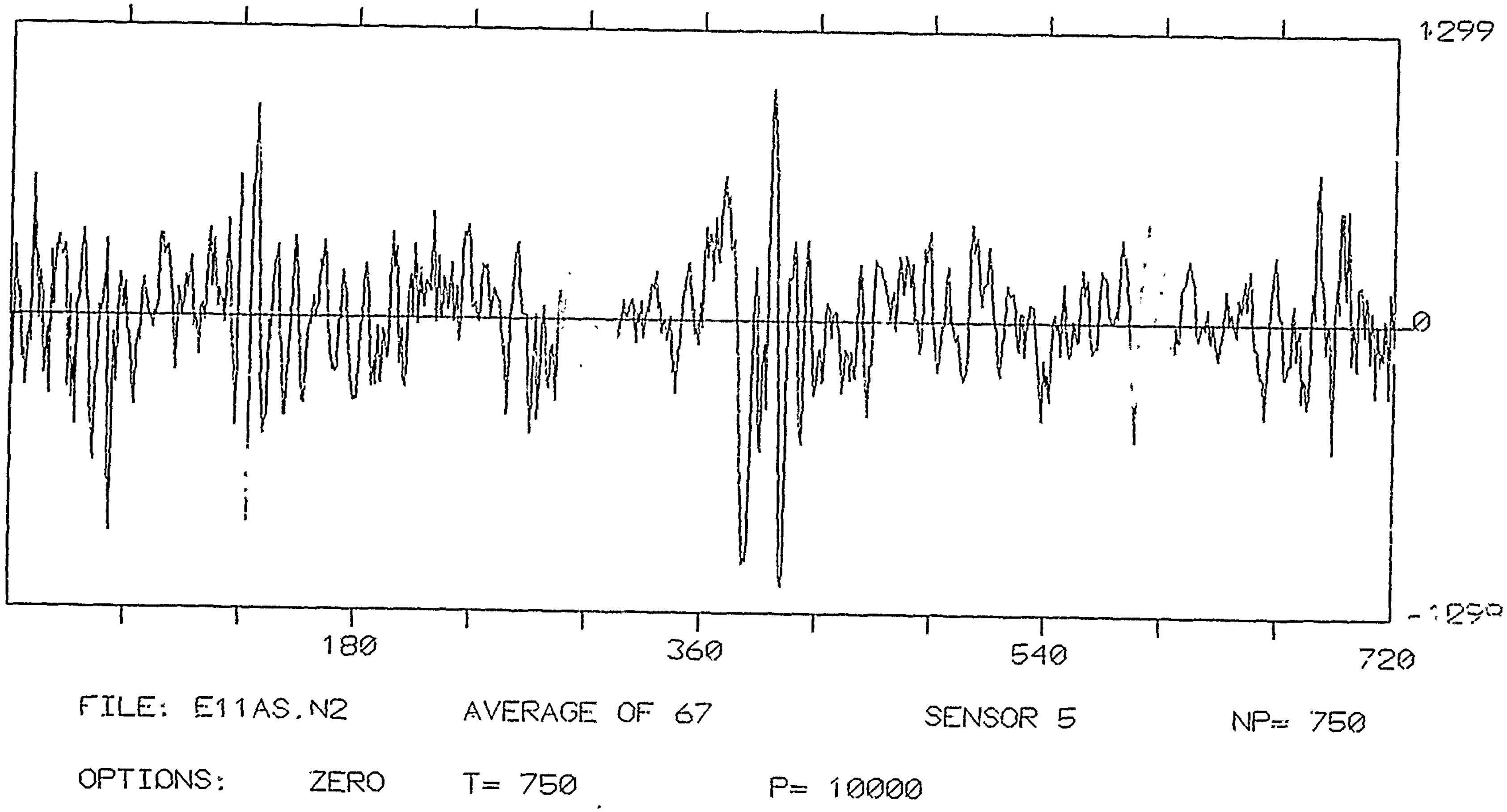


Figure 17. Unrectified Average of 67 Engine Cycles, for Engine 11 After Repair, Demonstrating Coherence of Time Normalized Signatures

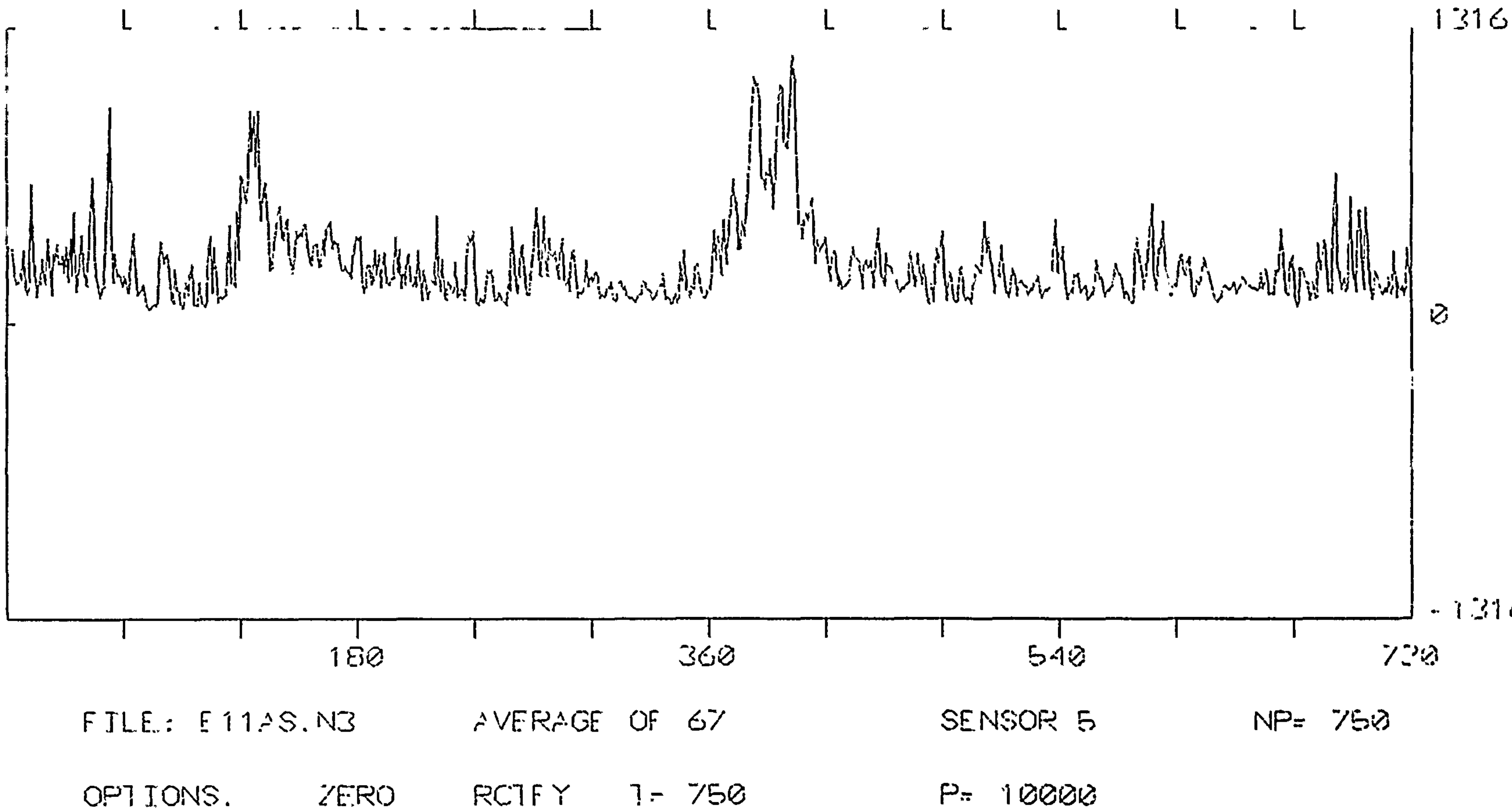


Figure 18. Rectified Average of 67 Engine Cycles for Engine 11 After Repair

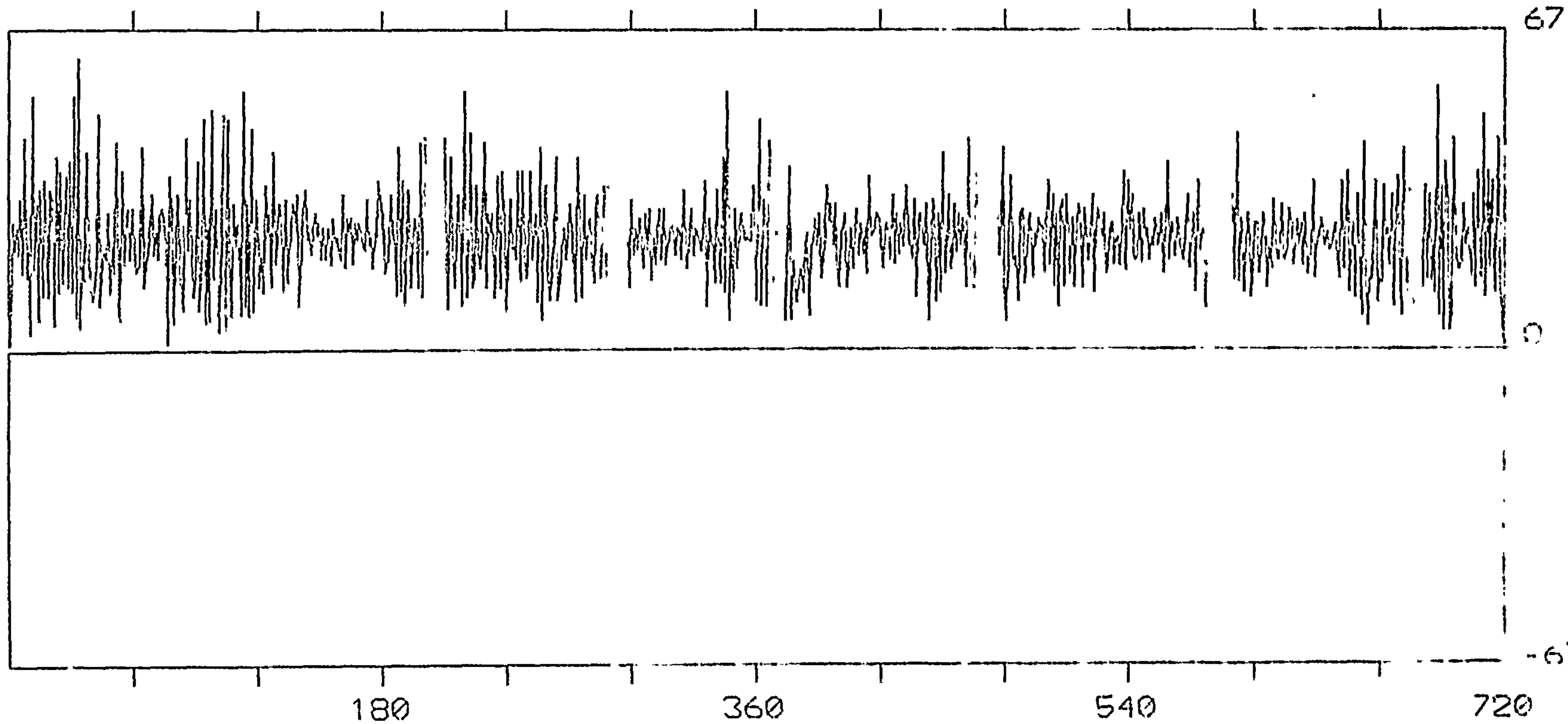


Figure 19. Histogram of Number of Times Each Point was a Local Maximum or Minimum, 67 is Number of Trials

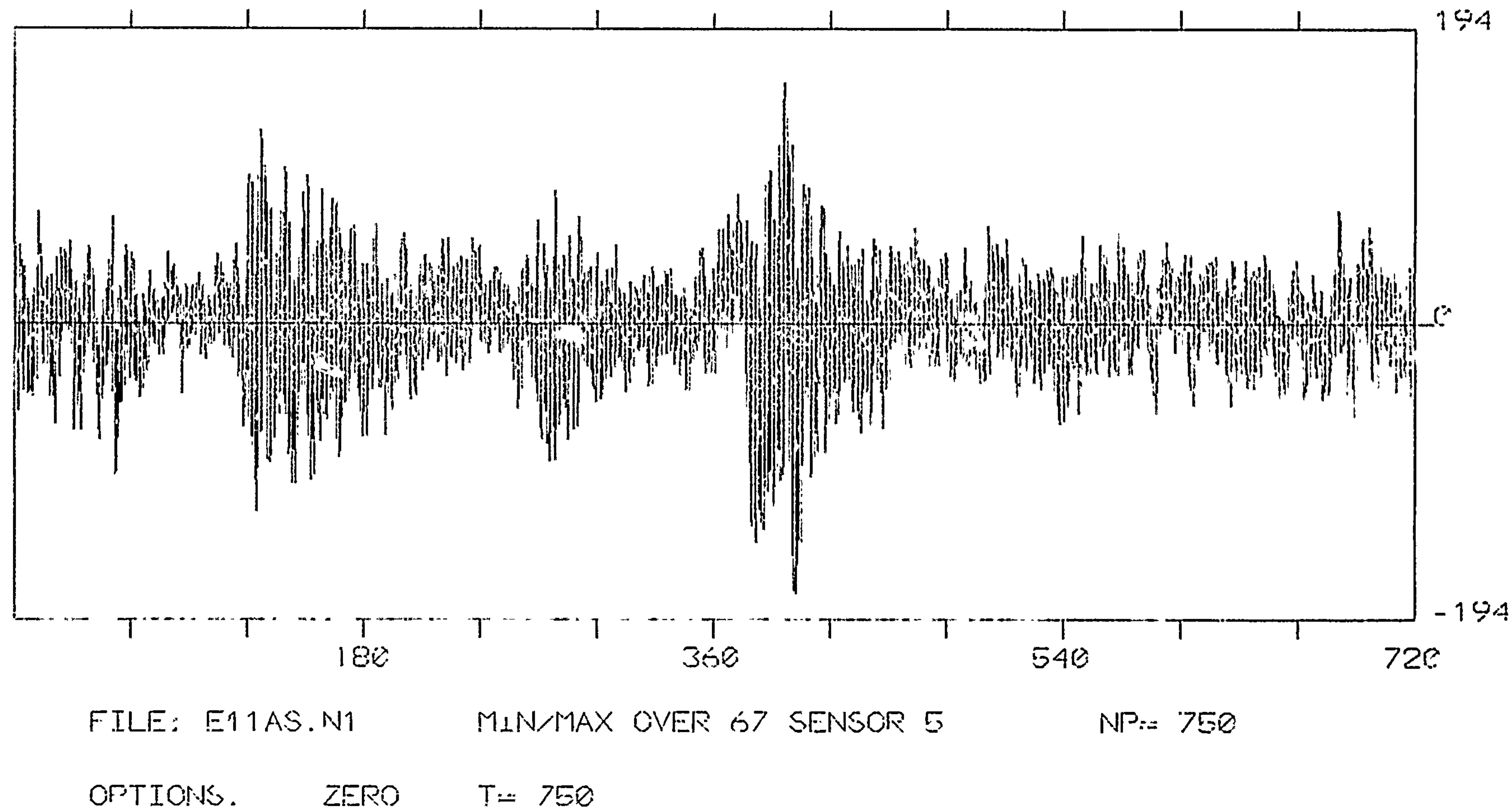


Figure 20. Minimum, Maximum, and Range of Measurements Occurring in 67 Signature Samples for Engine 11 After Repair

IV. CLASSIFICATION EXPERIMENTS

4.1 SUMMARY

An essential result of this study was good results in engine classification using the vibration data available. Successful classification demonstrates the feasibility of completely automatic design of engine classifiers from empirical data.

Past efforts have depended very heavily on human analysis for the design of classifiers and, while they have had some success, they were both expensive and heavily dependent on individuals for their success. By contrast, automatic design is relatively inexpensive, the major cost element being the empirical data base, so that it allows for easy extension to new engine types and additional failure modes for a given engine type. Automatic design also escapes from the subjective nature of human design. In a problem which has as many classes (possible failure modes) and as many dimensions in the signal space as this problem, human insight can be unreliable and easily misled.

The OPSEEKER algorithm developed by SEI provides a means by which classifiers can be automatically designed and their performance evaluated. The OPSEEKER requires as input an equal number of representative signatures for each class to be discriminated. The OPSEEKER works in an interactive manner in which it first selects a feature, then designs a classifier incorporating this feature along with those previously selected, and then uses this classifier on the data base to determine its performance. Each interaction of this process is referred to as a pass.

The following experiments demonstrate performance and stability of automatic classifier design, given the empirical data available, using data from a single sensor in either the time or frequency domain.

4.2 CLASSIFICATION WITH TIME DATA

4.2.1 Sensor 5, Zero Mean, Time and Power Normalized, Not Rectified

The first experiment used time signatures from sensor 1. These signatures were processed to have zero mean but were not rectified. They are time normalized and power normalized. The signature for each engine was on an average of 50 engine cycles.

Class 1 was defined as engines after major repairs, while Class 2 was engines which were definitely bad, prior to major repairs. The data base is described in Table 5.

The obvious problem with this data base is its small size, imposed by the source analog data base. Given that there were only six

Table 5

	CLASS 1	CLASS 2	
Engine	11	11	Training Data
	12	12	
	17	17	
	21	21	
	48	48	
	50	50	Independent Test

engines available with data from before and after major repair, the test strategy selected was to use five signatures for the design of the classifier (or training) and then use those five plus a sixth which the classifier had not seen before to test its performance.

The OPSEEKER algorithm was applied to these samples. Table 6 shows the scores attained after the first pass. The classifier output tables show the scores of the data signatures when played against the class discrimination functions. Scores with the lowest magnitudes are the nearest to the class membership criterion. Thus, in Table 6 under Class 1 data, it is seen that sample 1 is erroneously called a Class 2 while the others are correctly classified. Similarly, in the Class 2 data, the 6th sample was misclassified in the first training pass.

Table 7 shows that measurement number 294 was used (the 294th time sample in the averaged signatures) in the first pass classifier. This feature was selected as having the most information about class membership out of the 750 possible choices. The classification matrix shows that five Class 1 samples were called Class 1 and one was called Class 2 for a total percentage accuracy of 83.3%.

Table 8 shows the Pass 2 scores, and Table 9, the Pass 2 performance, which achieves 91.7%.

Tables 10 and 11 show the Pass 3 scores and features used. This was the final pass tested. The classification score remained 91.7%. The misclassified signal was the unknown Class 6 signature after repair.

4.2.2 Sensor 1 Time Signature Unrectified Classification

The engines and signal conditioning used here are the same as in the preceding section, except that sensor 1 is the signature source.

Classification results are shown in Table 12 for two passes with data from sensor 1, achieving 100% with two features.

OPDAT.P4	INPUT DATA FILE
OPDAT.STA	REORDERED DATA FILE
2	NUMBER OF CLASSES
6	NUMBER OF EXAMPLES PER CLASS
5	NUMBER OF EXAMPLES FOR TRAINING
750	NUMBER OF MEASUREMENTS PER EXAMPLE
1	NUMBER OF FIRST PASS TO DO
6	NUMBER OF LAST PASS TO DO
Ø	NUMBER OF LAST PASS DONE

PASS 1

CLASSIFIER OUTPUT CLASS 1 DATA

	Class 1 DF	Class 2 DF
1	-6.1246	-3.854Ø
2	-5.2566	-13.8532
3	-5.1123	-23.435Ø
4	-5.334Ø	-53.6Ø61
5	-6.1723	-93.85Ø3
6	-5.34Ø7	-11.3564

Scores of the Class 1 Signatures Measured Against Class 1 and Class 2 Discrimination Functions (DF)

CLASSIFIER OUTPUT CLASS 2 DATA

	Class 1 DF	Class 2 DF
1	-6.3739	-3.6187
2	-7.ØØØ8	-4.8885
3	-5.9Ø25	-4.6143
4	-6.1599	-3.786Ø
5	-6.4933	-3.6827
6	-5.5746	-7.262Ø

Scores of the Class 2 Signatures Measured Against Class 1 and Class 2 Discrimination Functions (DF)

Table 6. Scores of First OPSEEKER Pass on Sensor 5 Time Signatures, Unrectified Data

PASS 1 2 CLASSES 6 EXAMP/CLASS 750 MEAS/CLASS

MEASUREMENTS SELECTED

294

MEASUREMENTS REJECTED

750

STAT= 0.8134

CLASSIFYING MATRIX

5	1
1	5

PERCENT RIGHT= 83.3333

Table 7. Performance Matrix for Pass 1, Sensor 5, Time Signature Unrectified

CLASSIFIER OUTPUT CLASS 1

1	-12.9880	-72.1833
2	-9.9993	-487.4554
3	-13.5445	-811.7376
4	-10.9157	-1429.7120
5	-12.7495	-2567.0184
6	-21.4163	-222.4061

CLASSIFIER OUTPUT CLASS 2

1	-28.0110	-8.1303
2	-14.3972	-9.7823
3	-83.1974	-9.5575
4	-44.1840	-8.1012
5	-22.1199	-8.5184
6	-13.3623	-172.4542

Table 8. Pass 2 Scores, Sensor 5, Time Signature Unrectified

PASS 2 2 CLASSES 6 EXAMP/CLASS 750 MEAS/CLASS

MEASUREMENTS SELECTED

294 430

MEASUREMENTS REJECTED

750

STAT= 2.2463

CLASSIFYING MATRIX

5	0
1	5

PERCENT RIGHT= 91.6667

Table 9. Pass 2 Performance, Sensor 5, Time Signature Unrectified

CLASSIFIER OUTPUT CLASS 1

1	-13.3855	-334.9343
2	-13.1641	-494.9910
3	-14.0221	-853.3680
4	-13.5804	-1529.6897
5	-13.4714	-5096.8622
6	-530.5755	-237.5326

CLASSIFIER OUTPUT CLASS 2

1	-1192.2724	-11.0447
2	-915.3575	-12.3166
3	-2304.3245	-12.2699
4	-1479.3905	-11.2517
5	-1157.2715	-12.2873
6	-866.6089	-300.7449

Table 10. Pass 3 Scores, Sensor 1, Time Signature Unrectified

PASS 3 2 CLASSES 6 EXAMP/CLASS 750 MEAS/CLASS

MEASUREMENTS SELECTED

294 430 28

MEASUREMENTS REJECTED

750

STAT= 4.5527

CLASSIFYING MATRIX

5 1

0 6

PERCENT RIGHT= 91.6667

Table 11. Pass 3 Performance, Sensor, Time Signature Unrectified

PASS 3 2 CLASSES 6 EXAMP/CLASS 750 MEAS/CLASS

MEASUREMENTS SELECTED

398 674 644

MEASUREMENTS REJECTED

750

STAT= 4.6134

CLASSIFYING MATRIX

5	0
1	5

PERCENT RIGHT= 91.6667

Table 12. Results After Three OPSEEKER Passes Using Sensor 1 Time Signatures Unrectified.

4.2.3 Sensor 1 Rectified Time Signatures

Table 13 shows results for Sensor 1 data rectified, in the time domain. Accuracy is 100% after two passes.

4.2.4 Sensor 5 Rectified Time Signatures

See Table 14. Accuracy is 91.7% after four passes.

4.3 CLASSIFICATION IN THE FREQUENCY DOMAIN

Frequency domain signatures for each run were generated by computing the FFT for the time signature of each engine cycle sample in the run, typically 50 engine cycles per run. These individual samples were time and energy normalized prior to FFT. The time normalized engine cycle consisted of 750 sample points which were preceded by 137 zeroes and followed by 137 zeroes in a 1024 point waveform. submitted to the FFT. The result was a 512 filter spectrum for each engine cycle. These engine cycles were then averaged to produce a single spectrum representative of each engine.

The data used included those used for the time domain classifier experiments plus an additional engine, number 42 before and after, making a total of seven engines in each class. The classes were Class 1 - Before Major Repair, and Class 2 - After Major Repair, as before. It was possible to use engine 42 in this test and not in time domain tests because its Rotan timing reference device was installed incorrectly, destroying phase coherence with the other engines.

Linear and logarithmic amplitude displays were edited, and linear was chosen for the classifier tests.

The classifier was trained on six samples and tested on seven.

Results for Sensor 1 are given in Table 15 showing 100% correct classification after three passes. Sensor 5 results, in Table 16, show 92.9% accuracy after five passes.

4.4 INTERPRETING THE CLASSIFIER DESIGNS

Table 17 contains a summary of the classifiers designed for each experiment and their performance. The featured numbers selected can easily be translated into their actual physical meaning. For time domain studies, tests 1 to 4, each feature represents a sample taken at a particular crank angle. In all four tests time was normalized such that there were 750 samples taken across 720 degrees of crank rotation. Thus one need only multiply the feature number by 720/750 or 0.96 to determine what crank angle it represents. In the frequency domain studies, tests 5 and 6, each feature represents the power content at a particular frequency. The filter bandwidth in both tests is 5000 Hz/512 or 9.76 Hz; the center frequency for each of the selected features may be calculated by multiplying the feature number by the filter bandwidth.

```
PASS  1      2 CLASSES      6 EXAMP/CLASS      750 MEAS/CLASS

MEASUREMENTS SELECTED
 268
MEASUREMENTS REJECTED
 750

STAT=  0.9588
CLASSIFYING MATRIX

       5    1
       0    6
PERCENT RIGHT= 91.6667
```

```
PASS  2      2 CLASSES      6 EXAMP/CLASS      750 MEAS/CLASS

MEASUREMENTS SELECTED
 268  55
MEASUREMENTS REJECTED
 750

STAT=  2.4813
CLASSIFYING MATRIX

       6    0
       0    6
PERCENT RIGHT=100.0000
```

Table 13. Results with Two OPSEEKER Passes Using Sensor 1 Time Data Rectified

PASS 4 2 CLASSES 6 EXAMP/CLASS 750 MEAS/CLASS

MEASUREMENTS SELECTED

179 554 346 240

MEASUREMENTS REJECTED

750

STAT= 10.3175

CLASSIFYING MATRIX

6	0
1	5

PERCENT RIGHT= 91.6667

Table 14. Sensor 5 Rectified Time Signature Results

PASS 3 2 CLASSES 7 EXAMP/CLASS 512 MEAS/CLASS

MEASUREMENTS SELECTED

393 336 510

STAT= 3.5456

CLASSIFYING MATRIX

7	0
0	7

PERCENT RIGHT=100.000

Table 15. Classifier Results Using 512 Filter FFT Signatures, Sensor 1

```
PASS  5        2 CLASSES        7 EXAMP/CLASS      512 MEAS/CLASS

MEASUREMENTS SELECTED

 395   3 152 101 227

MEASUREMENTS REJECTED

 334

STAT= 11.2566

CLASSIFYING MATRIX

     6    1

     0    7

PERCENT RIGHT= 92.8571
```

Table 16. Classifier Results Using 512 Filter FFT Signatures, Sensor 5.

Table 17. Summary of Classifier Designs and Performance

TEST	INPUT DATA	CLASSIFIER DESIGN		CLASSIFIER PERFORMANCE
		NO. FEATURES	FEATURES SELECTED	% CORRECT
1	Sensor 5 Unrectified Time	3	294, 430, 28	91.66
2	Sensor 1 Unrectified Time	3	398, 674, 644	91.66
3	Sensor 1 Rectified Time	2	268, 55	100.00
4	Sensor 5 Rectified Time	4	179, 554, 346, 240	91.66
5	Sensor 1 Frequency	3	393, 306, 510	100.00
6	Sensor 5 Frequency	5	395, 3, 132, 101, 227	92.85

Table 18. Engine Repairs for Engines in Data Base (From Ref. 1)

ENGINE NO.	FAULT						REPAIR TIME (HOURS)	REMARKS
	BENT CON ROD	PISTONS	VALVES	JUGS	RINGS	OTHER		
11	x[1]	x[1]	All			Fan Tower Seal	40	
12				x[1]			42	
17				All			93	
21			All		All		82	
42	x[1]	x[1]		x[1]	x[1] set		43	
48			All	All	All		88	plus 36 hours cylinder rebuild
50			All	All	All		84	plus 36 hours cylinder rebuild

REFERENCE 1

J. E. Gibbons, "Engine Vibration Diagnostic Program for Automatic Checkout System for Combat Vehicles," Technical Report, Contract DA-36-038-AMC-1855(A) for United States Army Frankford Arsenal, General Electric Company, Schenectady, New York, June 1966.

REPORT DOCUMENTATION PAGE

READ INSTRUCTIONS BEFORE COMPLETING FORM

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Aberdeen Proving Ground, MD 21005
ATTN: STEAP-MT-G

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Aberdeen Proving Ground, MD 21005
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Watertown, MA 02172
ATTN: DRXMR-QA

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Distribution limited to US Government Agencies only; Test and Evaluation; November 1976. Other requests for this document must be referred to Commander, US Army Test and Evaluation Command, ATTN: DRSTE-ME.

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None

19. KEY WORDS (Continue on reverse side if necessary and identify by block number)
Vibration, Acceleration, Accelerometer, Internal Combustion Engine, Pattern Recognition, Vibration Analysis.

20. ABSTRACT (Continue on reverse side if necessary and identify by block number)
Magnetic tapes of vibration from 12 cylinder, AV-1790-7 engines before and after repair were analyzed. A computer program (OP-SEEKER) determined from the vibration which engines were faulty (needing repair) and which were not. Although only 6 different engines were examined (a larger sample size would have been a better test of OP-SEEKER), 100% success was obtained.

DEPARTMENT OF THE ARMY
HEADQUARTERS, U.S. ARMY TEST AND EVALUATION COMMAND
ABERDEEN PROVING GROUND, MARYLAND 21005

AMSTE-ME

23 AUG [illegible]

SUBJECT: Test Directive, Prediction of Equipment Failures by Acoustical Signature Analysis, TRMS No. 9-CO-MIP-AP5-001

Commander
US Army Aberdeen Proving Ground
ATTN: STEAP-MT-M
Aberdeen Proving Ground, MD 21005

1. Reference AMC Regulation 702-14, dated 27 December 1973.

2. This letter and attached STE Forms 1188 and 1189 (Incl 1) constitute a test directive for the subject investigation under the TECOM Materials Testing Technology (MTT) Program.

3. The proposal at Inclosure 2 and the additional guidance provided at Inclosure 3 are the bases for headquarters approval of the subject investigation. Any deviation from the approved scope, procedures, and authorized cost will require approval from this headquarters and the Army Materials and Mechanics Research Center prior to execution.

4. Special Instructions:

a. Reporting requirements are specified in the referenced regulation. The monthly reports will be submitted direct to the Army Materials and Mechanics Research Center with a copy furnished this office. The semi-annual and final report will be submitted through this headquarters.

b. Recommendations of new TOPs or revisions to existing TOPs will be stated in the letter transmitting the final report. Final decision on the scope of the TOP effort will be made based on both the recommendation and the final report.

23 AUG 1974

AMSTE-ME

SUBJECT: Test Directive, Prediction of Equipment Failures by Acoustical Signature Analysis, TRMS No. 9-CO-MIP-AP5-001

c. The addressee will determine whether any classified information is involved and will assure that proper security measures are taken when appropriate.

d. An Environmental Impact Assessment Statement (EIA) will be prepared for this investigation IAW AMCR 11-5 and TECOM Supplement 1 thereto, and submitted to this office for approval by 30 September 1974. Work in non-polluting areas may begin immediately upon receipt of this correspondence; however, work in areas that may involve pollution will be deferred until the approved EAP is received. The EAS will be coordinated with the local environmental coordinator.

e. The point of contact at this headquarters is Mr. B. F. Champion, extensions 2775/3286.

FOR THE COMMANDER:

3 Incl
as

SIDNEY WISE
Dir, Methodology Improvement

CF:
Dir, AMMRC, ATTN: AMXMR-M