PROBLEMS OF SOFTWARE DETECTION OF PERIODIC FEATURES IN A TIME SERIES FOR DIAGNOSIS

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ABSTRACT
Problems arise when attempts are made to extract automatically, visually obvious periodic features indicative of defects in a vibration time series for diagnosis using computers. Such problems may be interpretational in nature arising either from insufficient knowledge of the mechanism, or the convolution of the source signal with the system structure effect. Some of the periodic structures may turn out to be interferences originating from the cyclic nature of events taking place in the mechanism. Such periodic interferences complicate considerably the selection of suitable parameter values to be used in the period extracting algorithms. There is also the problem of deciding which of the multiple peaks or nulls resulting from impact instabilities in the time series is the true peak or null to be used in estimating the impact period. These problems must be solved if the extracted period is to be used successfully for source identification of defective components. In this paper, we present the ways we have developed to addressing these problem

SYMBOLS
T_{UB} = Upper ball defect period
T_{LB} = Lower ball defect period
T_{BR} = Bottom race defect period
T_C = Cage defect period
L = summation length
M = delay index
K = maximum delay index
D(m) = mth value of the average magnitude difference function.

1. INTRODUCTION
The detection of periodic structures in a time series is of considerable importance in many practical applications. In the field of medicine, for example, cardiologists are trained to detect morphological changes of a physiological nature in the QRST complex of an ECG waveform [I]. Here, the trained eyes of a cardiologist act as a sophisticated pattern recogniser in extracting from the ECG waveform as normal or abnormal. One such feature is the periodicity of an R - R interval [2].

In the field of condition monitoring of rotating machines, the first signs of incipient defect usually manifest as a change in the vibration signature from random in the good case to quasi- periodic in the incipient defective case. By extracting the period of the periodic structure in the vibration time series, it is possible to identify the sources of defect in the machine non-invasively [3].

The advantages offered by software detection of periodic features in the time series of the two cases cited are immense. In both cases, the signal of interest exists side by side with noise. For example in the ECG case, the waveform may be corrupted by noise originating from the muscles (myopotentials), the electrode-skin interface, base line wander and the ever present 50Hz mains signal [4].

In the case of the vibration signature, the impacts due to defect maybe masked by the system structure effect. The system structure effect or transmission path effect refers to the changes induced in the source signal as it is transmitted from the site of defect through all the intervening internal machine elements on its path to an external sensor. These interferences may be suppressed using digital filtering. Digital filtering (linear or non-linear) is implemented relatively easily in software so as to enhance the singnal from the background noise. Another advantage of software detection of periodic structures in a time series for diagnosis is that various algorithms can be used to measure the periodicity of the enhance signal and a performance evaluation of different period extracting techniques implemented and ranked for diagnostic accuracy in order to choose the most appropriate algorithm or a small sub-set of algorithms. Manual measurement of the periodic structures requires considerable expertise and is prone to errors [5].

In this paper, some of the problems encountered in the software detection of periodic structures for diagnosis of rolling element incipient defect in a Seta mechanism [3] are discussed. Ways of handling these problems developed by the author are given to help researchers and practicing engineers apply the techniques effectively in their own situations.

2. DETECTION OF PERIODIC STRUCTURES

Periodic structures can be detected in the time domain or frequency domain. Algorithmic techniques used for such detection include the Average Magnitude Difference Function (AMDF) in the time domain, and the power cepstrum and power spectrum in the frequency domain. As reported in [3], problems of automatic extraction of periodic structures in the frequency domain result from the absence of the fundamental impact frequency (FIF) in the power spectrum. The FIF may be missing in the power spectrum as a result of two separate effects which may operate simultaneously:

(i) An average and shift effect which causes a slow migration of the fundamental impact frequency from its computed value.

(ii) An inter-modulation effect which translates defect related information to frequency.

In the time domain, problems of automatic extraction of periodic structures result from the following:

(i) the effective time series are quasi-periodic in nature.

(ii) periodic interference (noise) complicate considerably the selection of suitable parameter values to be used in the period extracting algorithm.

(iii) the difficulty of relating the periodic structures in the time series to events in the machine either due to insufficient knowledge of the mechanism; or due to the complexity of the acquired time series as a result of the convolution of the source signal with the system structure effect.

3. HANDLING THE SYSTEM STRUCTURE EFFECT IN THE TIME DOMAIN

The system structure effect can affect the acquired signal in the following ways:

(i) increase the dynamic range of the signal.

(ii) emphasises or de-emphasises the signal excitation due to the filtering effects of the excited structural resonances of the system.

A major problem in detecting periodic structures in a time series in the time domain, is that the high frequency system structure peaks may be mistaken for the low frequency peaks due to defect. This interference of the system structure peaks in the defect period measurement results in measurement errors and therefore must be suppressed [5].

Pre-processing may be effected using linear filtering, for example by using time domain signal averaging technique; or by using non-linear filtering techniques. In non-linear filtering using non-linear functions, like the compressed centre clipper, the system structure effect is eliminated by setting signal values below an experimentally determined clipping threshold to zero and offsetting signal values above the threshold by the clipping level.

As a result of the wide variability in impact amplitude due to defect in the time series, the clipping level selected must satisfy the criteria that its use ensures that low level peaks due to defect are not lost in the process of removing the system structure effects. A more detailed treatment or signal pre-processing using the compressed centre clipper with illustrative examples has been reported [5].

4. HANDLING THE PARAMETER VALUE SELECTION PROBLEM

4.1 Understanding the Waveform Structure

It is vital to understand the detailed waveform structure and how this structure is related to events in the machine. This knowledge is essential in selecting appropriate parameter values for the period extracting algorithm. This concept is illustrated using a Seta 6 incipient defective time series shown in Fig. I and repeated in Fig. 2 to show the different time structures and their interrelationship. Table 1 shows the computed impact periods for defects in a Seta 6 and Seta 8 data.

Table I: Computed Impact Periods of Seta Components

Impact periods in milliseconds					
Dater name	Shaft speed in rpm	T_{UB}	T_{LB}	T_{BR}	T_C
Seta 6	1920	13.88	20.83	41.66	125
Steta8	3000	8.88	13.3	26.66	80

From Fig. 2 it can be seen that three periodic structures exist in the defective time series; they are:

(i) the quasi-periodic impacts due to defect with a period varying from 13.82 msec to 14.4 msec.

(ii) the periodic impact sequence spaced an impact cycle period of 41.6 msec and corresponding to the time interval between any four impacts within a cage period.

(iii) the period structure labelled A-A which corresponds to the cage period of 125 msec.

From table I the three periodic structures in the times series would suggest that

i. an upper ball defect
ii. a bottom race defect
iii. a cage defect

exist in the Seta 6 mechanism simultaneously

The periodicities due to defect can be extracted using the AMDF. The application of the AMDF technique to signature analysis has been reported in the literature [6]. It seems attractive to search for these defect periodicities in parallel using a single AMDF waveform. This can be done using a summation length L, and maximum delay index K greater than one cage period.

The AMDF is defined by the relation

$$D(m) = \frac{1}{L}\sum_{i=1}^{L} |X_i - X_{i-m}|, \qquad (1)$$

$m = 0,1, \ldots \ldots K$

For a perfectly periodic signal, the AMDF is zero for values of delay mT corresponding to the period of the input signal and its multiples. For the Seta data, the signal is expected to exhibit deep nulls at

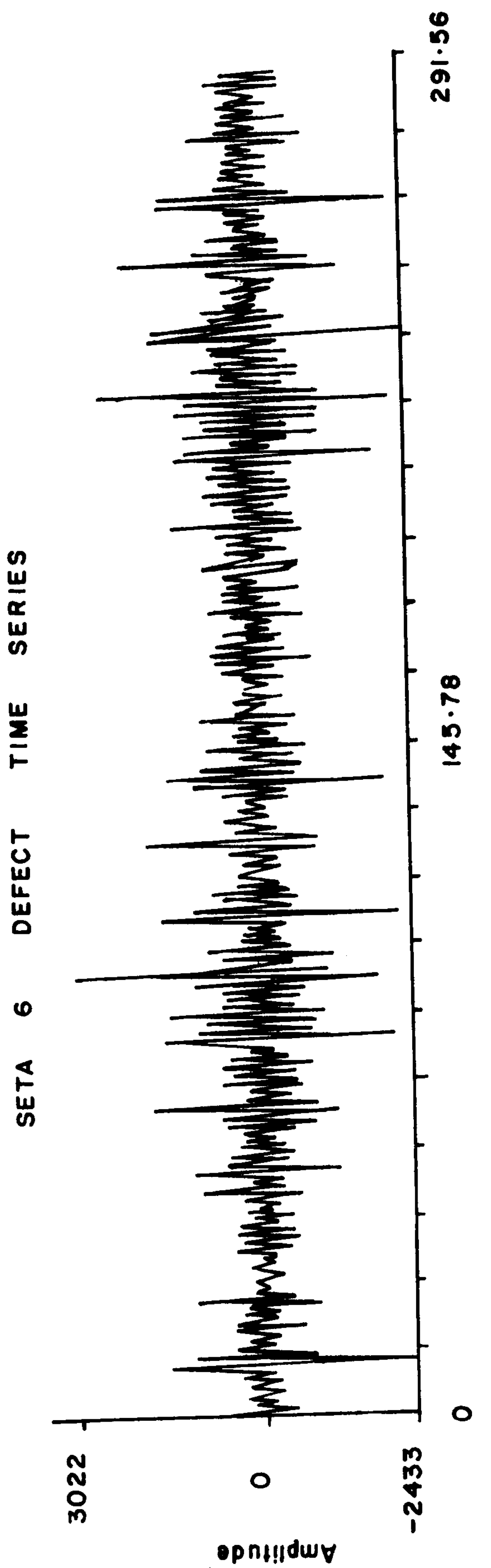
SETA 6 DEFECT TIME SERIES
Amplitude
3022
0
-2433
0
145·78
291·56

Fig: 1.

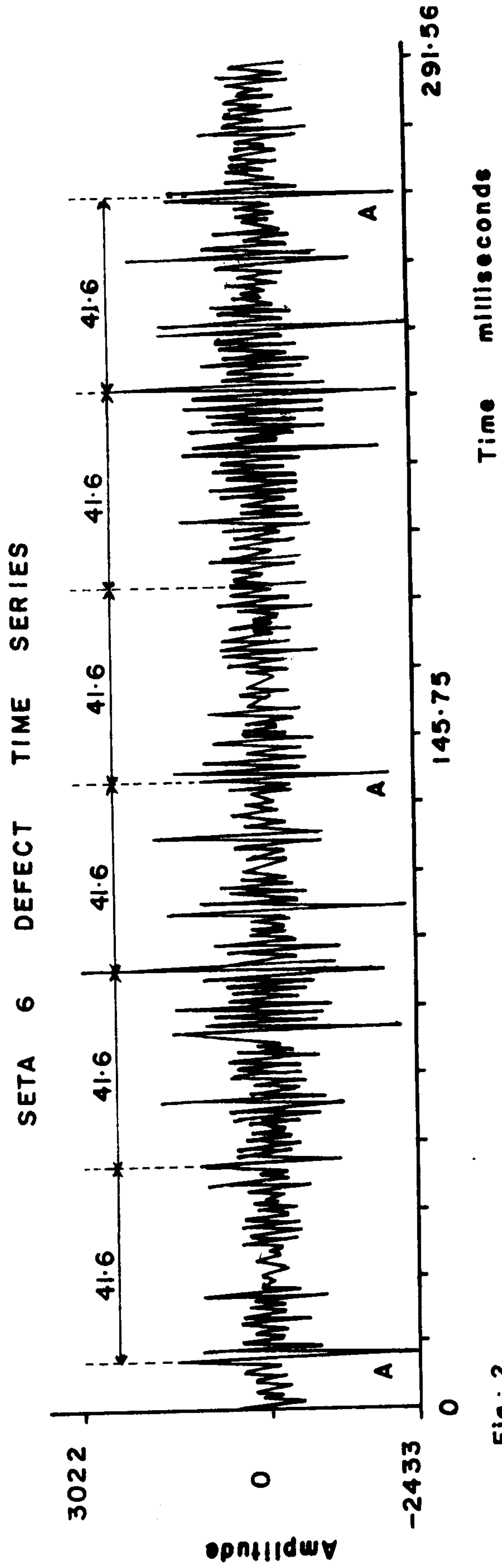
SETA 6 DEFECT TIME SERIES
Amplitude
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Fig: 2

the periods corresponding to the quasi-periodic impacts and its multiples.

4.2 Results

Fig. 3 shows the result of such an analysis. The data analysed (upper plot) is a 291 .56 msec Seta 6 signal, low pass filtered at 1KHz and sampled at 3.2KHz. Notice that there are nine deep nulls in the AMDF waveform (lower plot). The AMDF is 0 at the 9th null indicating that a perfectly periodic signal exists in the time series with a period of 125 msec. This will confirm the presence of a cage defect.

As predicted, the nulls in the AMDF waveform corresponding to the quasi-periodic impacts and its multiples are not zero but deep nulls. Note that the impact instabilities in the time series produce multiple nulls in the AMDF waveform at the impact instant resulting in different estimations of the impact period due to defect. In this case, null 1 at 13.39 msec confirms the presence of an upper ball defect while null 3 at 42.68 msec confirms the presence of a bottom race defect.

However, physical examination of the Seta components after the test showed that only an upper ball defect was present. Hence a faulty diagnosis has been made about the states of the bottom race and the cage. Therefore, the presence of deep nulls at these periodicities does not indicate bottom race and cage defects. But what do they indicate?

4.3 Explanation of the misdiagnosis of the states of the bottom race and the cage

For a feature to be used for fault detection and diagnosis it must be free from the following errors:

CLASS I ERROR: classifying a defective state as good. This type of error leads to catastrophic failures.

CLASS 2 ERROR: classifying a good state as defective (false alarms).

It is therefore important to explain the origin of the false alarm in the AMDF analysis. To do this, the power cepstrum of the Seta 6 data is obtained in the good and defective states. For comparative purposes, the Seta operating characteristics (in this case the speed), is altered from 1920 rpm to 3000 rpm to demonstrate that the information due to defect in the vibration time series is speed dependent. The resulting Seta data is called Seta 8 (see table 1). The power cepstrum of the Seta 8 data is also obtained in the good and defective states.

The use of the power cepstrum to identify the sources of defect in a vibration time series has been reported in the literature [3]. A good treatment of the theory and terminology of the power cepstrum technique is given in [7,8].

In this paper the technique is used to explain the classification error resulting from the AMDF analysis.

4.4 Analysis result

Figs. 4 and 5 show the results of the analysis. The upper plots show the power cepstrum of the Seta 6 and 8 time series in the good state, while the lower plots show the power cepstrum of the Seta 6 and 8 time series in the defective state. The results show that the bottom race period and the cage period (labelled 3R and 9R respectively in the lower plots) are present in both the good and defective Seta waveforms. The upper ball defect information is present only in the defective case showing that only an upper ball defect is present. Hence the cage periodicity and the impact cycle periodicity are interferences (noise) due to the cyclic nature of events that take place in the mechanism within a cage period. The period interference found every four impacts in the defective case (3rd null in fig. 3, 3R in figs 4 and 5) results from the fixed time it takes the upper ball to revolve round the lower balls in both the good and defective cases; the complicating factor in this example is that this interference occurs exactly at the bottom race defect period. The periodic interference at nine times the fundamental impact period in the defective case (9th null in

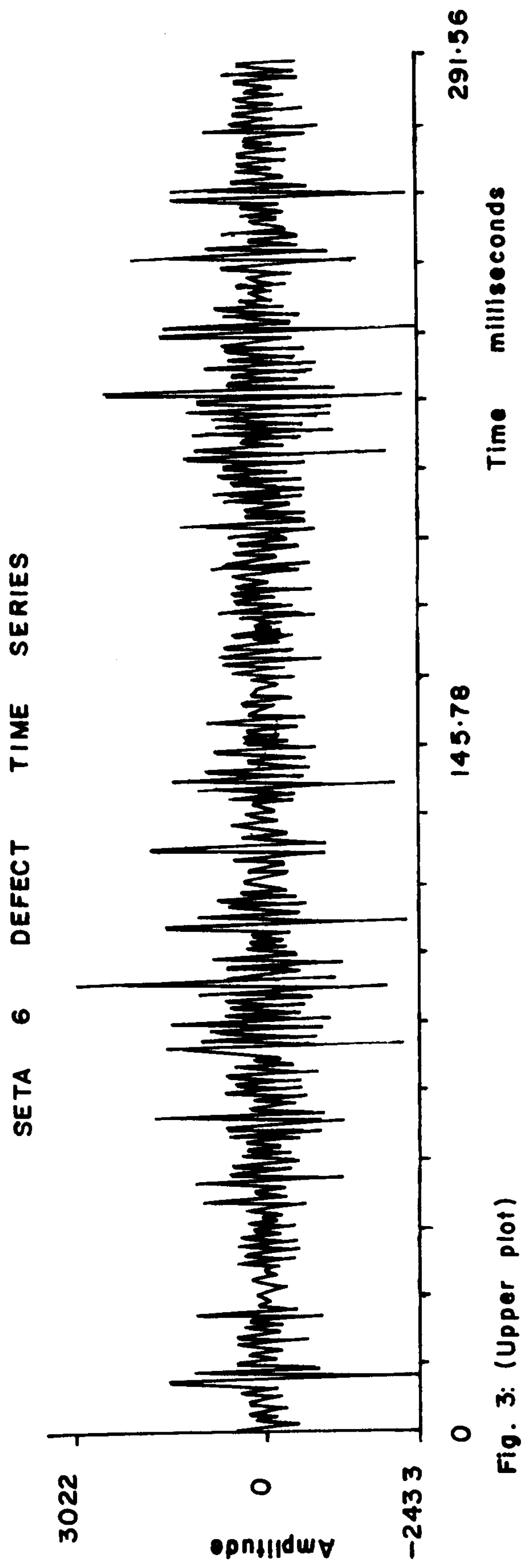

Fig. 3: (Upper plot)

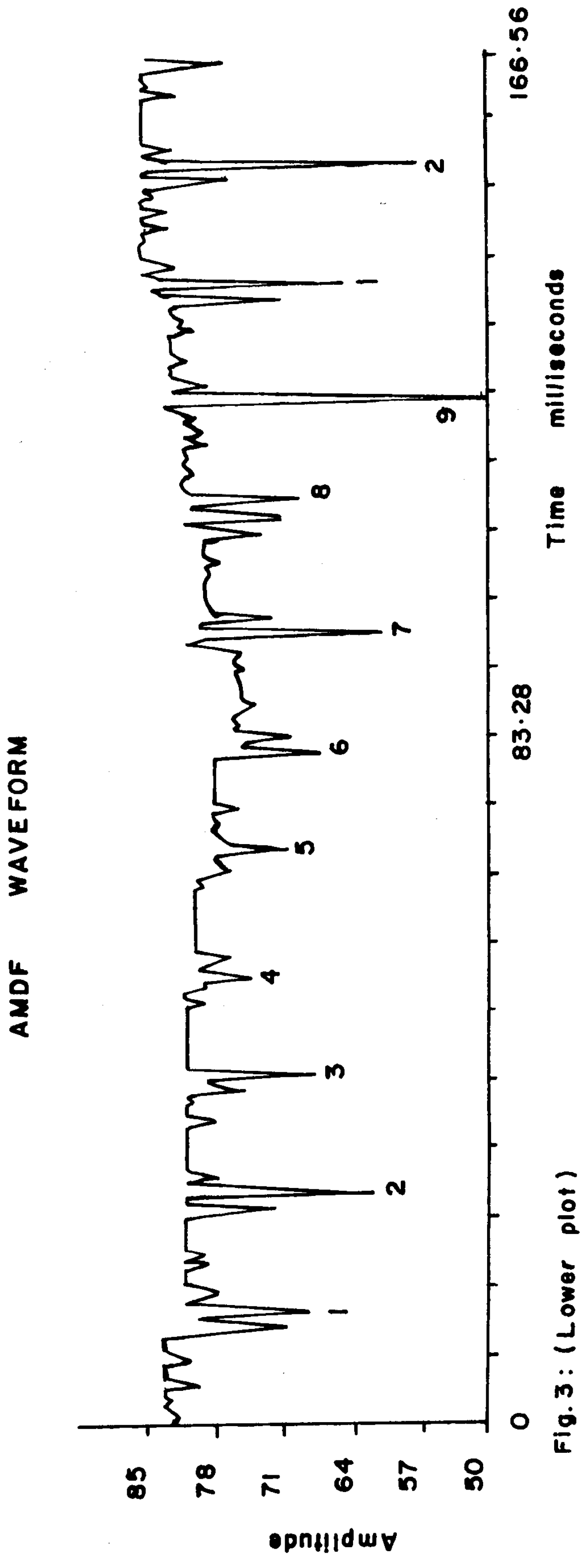

Fig. 3: (Lower plot)

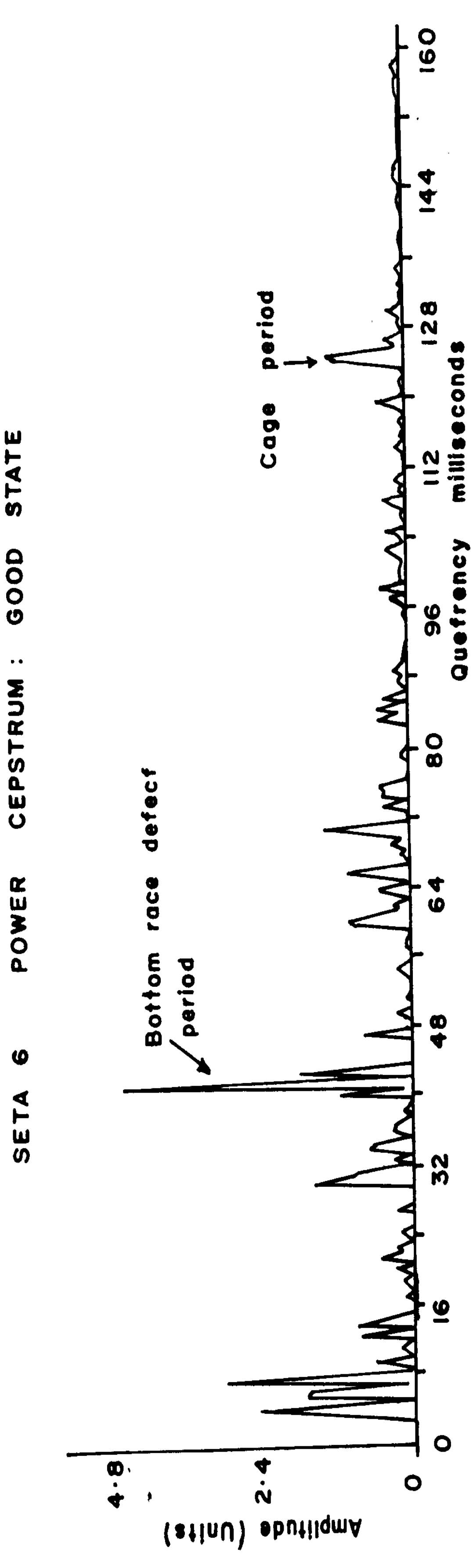

Fig. 4 (Upper plot)

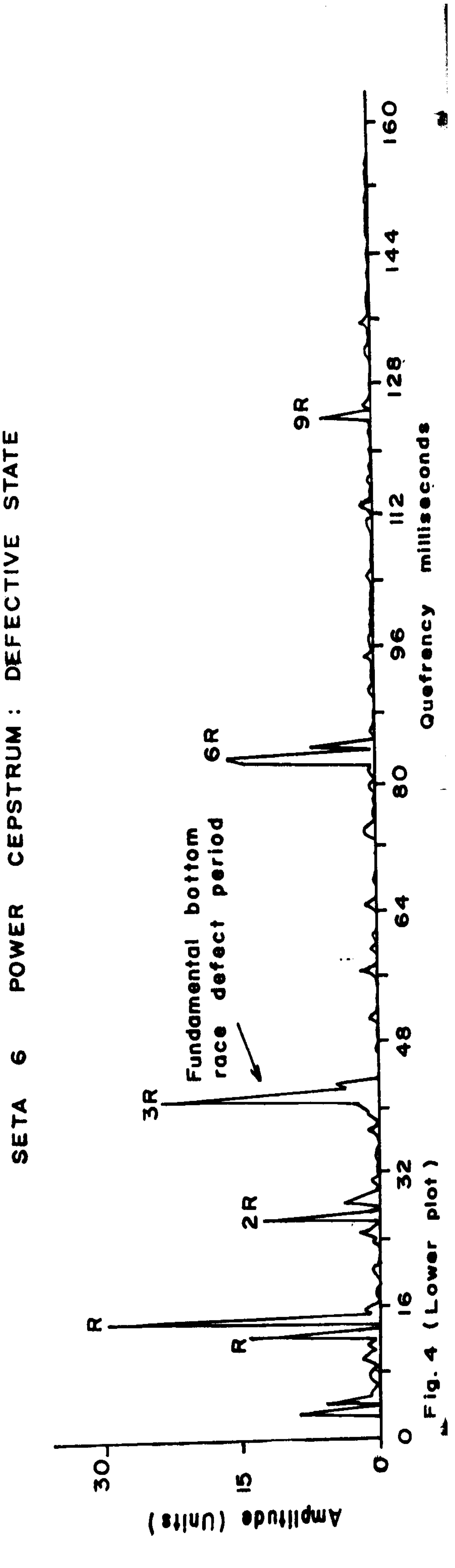

Fig. 4 (Lower plot)

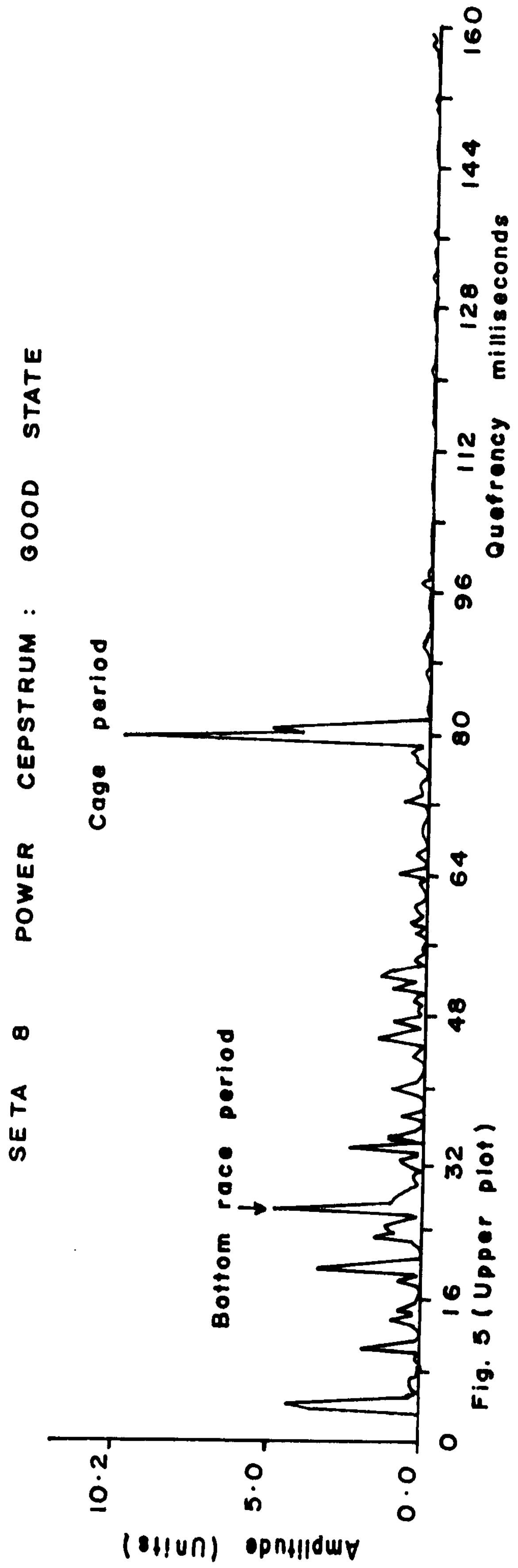

Fig. 5 (Upper plot)

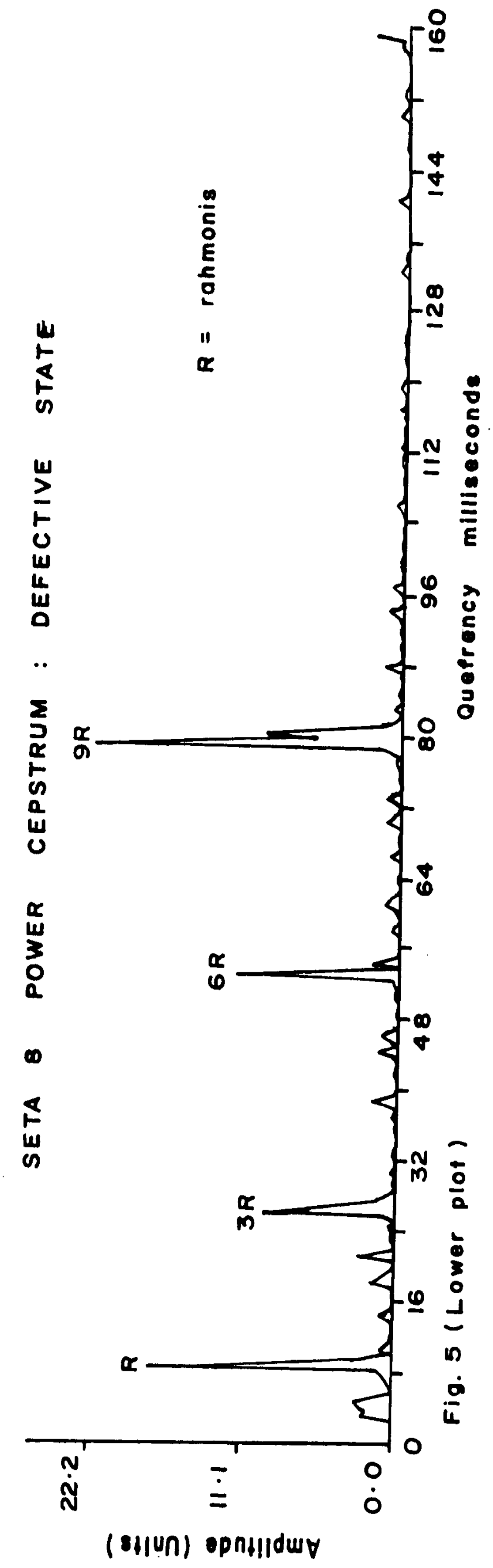

Fig. 5 (Lower plot)

Fig. 3: 9R in figs. 4 and 5) results from the fixed time it takes the cage to complete a revolution

Clearly then the 3rd and 9th nulls in the AMDF waveform result from these interferences and are not the result of defect in the mechanism. To avoid the misclassification error in the AMDF technique, it is necessary to use this knowledge of the origins of the detailed waveform structure in selecting appropriate parameter values L and m. Clearly, knowledge of the periodic interference resulting from the cyclic events in the mechanism imposes a constraint on the choice of the delay index if false alarms are to be avoided. This constraint is that a minimum and maximum delay index centred on the defect period of interest should be specified. The constraint ensures that the AMDF is not computed for delays extending into frequencies significantly different from the impact frequency. As a result, the summation length used depends on the defect condition investigated. Using this scheme, the component defects are diagnosed sequentially.

5. HANDLING THE QUASI-PERIODIC NATURE OF THE IMPACTS

The impact instabilities or quasi-periodic nature of the impacts in the defect waveform result in multiple estimates of the impact period in the AMDF waveform (see fig. 3, lower plot). This problem is also encountered when the power cepstrum is used for period extraction. Fig. 4 (lower plot) shows the power cepstrum of the Seta 6 defective data. Note the multiple peaks around the impact period labelled R and R' in the figure. These two peaks result in slightly different estimates of the impact period due to defect.

A problem in the development of an algorithm to extract the period corresponding to a defective component is to decide which of the multiple nulls or peaks corresponds to the impact period (null or peak selection). This problem is greatly complicated by the following observations

(i) the null with the smallest delay index in the AMDF waveform may be unrelated to the impact event.

(ii) in the power cepstrum, the largest peak may not occur at the impact period.

(iii) indistinct nulls may occur at the impact period in the AMDF waveform if there is a high variability in impact amplitude and impact periodicity in the time series segment length analysed. (Seta waveform segments of this sort occur when sections of the quiet zone, regions of no impacts or very low level impacts, separate two high level impact regions [6]).

Visually, it is easy to identify a clear and distinct null as opposed to an indistinct null at the impact period location in the AMDF waveform. Similarly, it is easy to distinguish significant peaks from insignificant peaks at the impact period times in the power cepstrum. For automatic extraction of impact periodicities such notions like 'significant', 'insignificant', 'distinct' and ‘indistinct’ have to be quantified.

Algorithms to solve these problems are usually developed heuristically and involve setting a time and an amplitude threshold. Essentially, the heuristics specify a narrow window width centred on the computed impact periods within which to search for the deepest null (highest peak) that satisfies a known experimentally determined amplitude threshold. Such a null (peak) is deep (significant) and the location of the null (peak) corresponds to the period of the defect.

6. CONCLUSION

Periodic structures in a vibration time series from a rotating machine may originate from sources of defect within the machine. These defective components may be identified non- invasively if only the characteristic periods can be extracted reliably.

It has been shown that for software based time domain techniques to be used reliably to extract the defect period for diagnosis, the signal must be suitably preprocessed. It has also been shown that a thorough understanding of the operation of the machine facilitates the isolation of machine specific constraints which may impose bounds on the parameter values to be used in the period extracting algorithms if a correct diagnosis is to result.

Finally, it was shown that the problem of multiple peaks or nulls which result in different estimation of the defect period can be handled by using time and amplitude thresholds embedded in a heuristically developed peak or null selection algorithm.

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