UNIVERSITY OF CINCINNATI

June 1, 19 92

I hereby recommend that the thesis prepared under my supervision by Paul J. Grabill

entitled An Investigation of Signal Processing Techniques Used for Rotor Dynamic Fault Detection

be accepted as fulfilling this part of the requirements for the degree of Master of Science

Approved by:

Robert W. Rost

Randall J. Allemang

David L. Brown

An Investigation Of Signal Processing Techniques Used For Rotor Dynamic Fault Detection

a thesis submitted to the

Department of Mechanical Industrial and Nuclear Engineering

College of Engineering

UNIVERSITY OF CINCINNATI

in partial fulfillment of the

requirements for the degree of

MASTER OF SCIENCE

1992

by

Paul John Grabill

BSME University of Cincinnati 1986

Committee Chair: Dr. R. Rost

ABSTRACT

Several signal processing techniques were evaluated for their ability to detect rotor dynamic faults. A rotor rig was constructed to test several typical rotor dynamic faults. These faults included: a bearing inner race defect, a bearing outer race defect, a bearing rolling element defect, rotor unbalance, and shaft misalignment. Vibration data was acquired from a baseline (no-fault) condition, as well as from each of the known fault conditions. The vibration data was processed with the following signal analysis algorithms:

- Narrow band spectrum analysis
- Shock pulse analysis
- Cepstrum analysis
- Signal demodulation
- Singular value decomposition

Some of the methods were tested using analytical fault data to demonstrate the different features of the algorithms. The algorithms were then used to process the rotor rig fault data. Each of the different methods were evaluated for the ability to detect the faulty condition, as well as identify the location of the fault. A relative comparison was made of each of these methods for the application to health monitoring and fault detection.

It is shown in this thesis how the cepstrum and signal demodulation techniques were effective in locating the fault, while the shock pulse method and singular value decomposition were used to identify the start of a unhealthy condition.

ACKNOWLEDGMENTS

The author wishes to express his gratitude and appreciation to Dr. Robert Rost, Dr. Randy Allemang, and Dr. Dave Brown for their help and guidance at U.C.'s Structural Dynamics Research Lab.

The author is grateful for the support given by NASA's Health Monitoring Technology Center for Space Propulsion Systems, which sponsored this research, and for the encouragement and support from GE Aircraft Engines, especially Larry Bach.

Special thanks go to the Bently Nevada corporation for their help in constructing the rotor rig, and for the health monitoring training.

The author wishes to thank the Barden Corporation for the help with providing bearings with known faults installed.

The author would like to express his deep gratitude to his mother and father for their ever present encouragement throughout all stages of his education.

Finally the biggest thanks go to my wife, Barbara. Without her patience, sacrifices and encouragement, this work would have been impossible. To her, my most sincere gratitude for her help with the graphic design of this thesis.

Table of Contents

Page

List of Figures

Page

List of Tables

Page

Nomenclature

f_{sh}	fundamental shaft frequency
BPFI	ball pass frequency of the inner race
BFFO	ball pass frequency of the outer race
BSF	ball spin frequency
FTF	fundamental train frequency (bearing cage)
Nb	number of balls or rollers
Bd	ball or roller diameter
Pd	pitch diameter
Ø	contact angle
FFT	Fast Fourier Transform
x(t)	time history
x(f)	frequency spectrum
$C_x(t)$	power cepstrum
X(s)	Laplace transform of input function
F(s)	Laplace transform of forcing function
$[A]_r$	finite sequence of coefficient matrices
$[B]_r$	finite sequence of coefficient matrices
s^r	temporal operator in the Laplace domain
α_r	r^{th} autoregressive coefficient
2N	order of ARMA model
[Co]	coefficient matrix
SVD	singular value decomposition
[A]	matrix of time shifted response points
[U]	unitary matrix of left singular vectors
[V]	unitary matrix of right singular vectors
[S]	diagonal singular value matrix
f_s	sampling frequency

1.0 INTRODUCTION

This thesis summarizes a work effort to evaluate several signal processing algorithms that could be sensitive to various rotor dynamic faults. The methods were evaluated for their ability to detect the presence of the fault as well as identify the location of the fault. The faults included: an inner race bearing fault, an outer race bearing fault, a rolling element bearing fault, rotor unbalance, and shaft misalignment. Spectrum analysis, which has been in use for many years for fault detection, was used as a baseline technique. Newer techniques, such as signal demodulation and singular value decomposition, were compared for their sensitivity to detect the rotor dynamic faults. All the signal processing algorithms were evaluated by processing the same vibration data acquired on a controlled rotor rig that had known faults induced into the system.

There are many reasons to be interested in fault detection of rotor dynamic systems. If a fault can be detected in the early stages, corrective action may be taken before any further secondary damage or catastrophic failure will occur. The benefits from health monitoring of machinery also include the following:

- Production losses are reduced.
- Machinery efficiency, reliability, availability, and longevity are improved.
- Maintenance costs are reduced (overtime payments for labor are reduced, spare parts and stocked inventory costs are decreased, fuel costs are reduced).
- Work load planning is improved.
- Safety and environmental standards are improved.

Investigating the health of the rotating system can be divided into three categories. The first level of monitoring is detecting the difference between a healthy system and an unhealthy system. The second level attempts to identify the type and location of the fault. The third level of fault detection is involved in determining the time to catastrophic failure. For example, a rocket engine might start to exhibit a unique vibration, which can be identified as the start of an unhealthy condition. The next critical task is to determine the source of vibration, for example the High Pressure Oxygen Turbo Pump, No 3 Bearing, outer race. The last and the hardest part of fault detection is determining how far the fault has progressed, and when failure will occur. Many times, the vibration environment can provide information on the properties of the fault. The key is extracting the fault information from a very complex and information rich vibration signal.

1.1 Types of Faults

An important property of fault detection is the identification of the fault as early as possible. The longer the time span over which a developing fault can be observed, the greater the accuracy of the predicted failure time. For this reason it is important to understand the fault mechanisms. A complete literature search was made on rotor dymanic faults, health monitoring, and signal processing [1-28].

Unbalance is a common malfunction in rotating machines. When a rotor is unbalanced, the rotor mass centerline does not coincide with the axis of rotation. During rotation the unbalance will generate an inertial centrifugal force which rotates at the rotor rotational frequency. The unbalance excitation force is determined from the response measured at the rotational speed [9].

Misalignment faults will cause a constant radial force that will push the rotor to one side. The joint where the misalignment is concentrated can generate a 2X rotational frequency reaction force. This is because of non uniform stiffness to bending at the misaligned joint. For one complete shaft rotation, each segment of the misaligned joint will undergo both compression and tension. The non uniform segment will generate a reaction force for both the compression and tension parts of the cycle, thus introducing the 2X force [1].

Rolling element bearings generate characteristic vibration signatures in several ways. It is important to note that even a healthy fault-free bearing can introduce vibration components at the characteristic fault frequencies. There can be variable flexural compliance of the bearing components. This means that the bearing components will deform non-uniformly and will produce the fault frequencies. Also there can exist geometrical imperfections that will generate fault frequencies from a new "good" bearing. The key to determining the start of a faulty condition is to identify the changes in the vibration signal that the faults will produce.

A rolling element bearing has a finite life and will eventually fail due to fatigue, even if operated under ideal conditions. The life limits can be calculated and are known for most bearings [20]. Unfortunately, many bearings will fail before reaching their design life. Most premature bearing failures can be attributed to one or more of the following causes:

1. Excessive loading.
2. Insufficient lubrication.
3. External contamination.
4. Improper installation.
5. Incorrect design or load rating.
6. Exposure to vibration while not rotating (false brinelling).

The rolling element bearing failure progression can be classified into three stages. In the pre-failure stage hairline cracks or microscopic spalls are formed that are not visible to the human eye. The bearing usually has a significant amount of operating life remaining, and it is not economical to replace the bearing at this time. In the second stage, the failure stage, the bearing develops spalls that are visible to the human eye. The bearing can produce an audible sound. This is the bearing fault stage that was investigated with the rotor rig. At this time it is very important that a health monitoring system detects the fault before it progresses to the third fault stage, the catastrophic failure stage. When the bearing enters the catastrophic stage, rapid failure is imminent. Audible noise produced from the bearing significantly increases. The bearing temperature will increase until the bearing overheats. Loss of bearing support and rotor to stator rubs could lead to extensive secondary damage [2].

If a roller or a ball has a defect such as a pit, each revolution will result in a impact which is transmitted to the bearing housing. The fundamental frequency of these impacts is called the ball spin frequency (BSF). If the bearing inner race has a defect, then each ball will produce a shock as it passes giving rise to a fundamental vibration frequency called the ballpass frequency, inner race (BPFI). Likewise a fault on the bearing outer race will produce a frequency at the ballpass frequency, outer race (BPFO). A fault in the bearing cage will produce a frequency at the fundamental train frequency (FTF) [20].

The faults tested in this thesis are only used as a tool to evaluate the different signal processing techniques. The faults were chosen to be representative of common faults. There are a number of other rotor dynamic faults that were not tested, but still would be applicable to the fault detection algorithms. These other types of faults include rotor to stator rubbing, fluid induced instabilities, loose stationary and rotating parts, cracked shafts, gear faults, and bearing cage faults.

1.2 Signal Processing Techniques

The different fault detection techniques investigated in this thesis attempt to enhance the known vibration characteristics from the fault. The narrow band spectrum analysis is used to identify the fundamental fault frequencies previously outlined. The shock pulse method attempts to quantify the high frequency short impulse nature of the fault. The cepstrum analysis will evaluate the harmonic content created by the short duration of the fault impulses. The demodulation technique will translate down the fault frequencies that are present in the high frequency spectrum. And lastly the singular value decomposition will identify the added sources due to the fault frequencies.

Testing from the rotor rig showed that some of the signal processing methods were better at identifying the fault verses no fault condition, where other methods were found to be better at determining the location of the fault. However, for this test, no attempt was made to address the problem of determining the severity of the fault. The rotor rig had artificial faults introduced that were not at different stages in the fault. A baseline no fault condition was tested and compared to three different types of bearing faults and a misalignment fault. Therefore, the progression of one type of fault could not be tracked.

The vibration data was processed using MATLAB™ [28] on a personal computer. MATLAB is a powerful software package for engineering numeric computations. The "programs" or script files for each of the processes investigated in this thesis are found in Appendix A.

1.3 Test Rig

A rotor rig was constructed to acquire real vibration data from a controlled fault condition. Bearing faults were introduced into disassembled ball bearings. The faulty bearings were re-assembled by the bearing manufacturer. Each faulty bearing was tested individually and was compared to a no fault condition. The static axial load and unbalance level was varied for each fault condition. The rotor rig could be operated at speeds from 0 to 10,000 rpm. A misalignment could be introduced in the system by moving the motor relative to the main shaft.

The vibration data was measured by using accelerometers mounted at various positions on the rotor rig. There are many other methods to measure the vibration that were not investigated in this thesis. Some of the other methods include: placing a proximity transducer on the bearing outer race [21] and using a fiber optic bearing deflectometer [27].

1.4 Scope of Thesis

The objective of the thesis is to evaluate several different signal processing algorithms for the ability to detect typical rotor dynamic faults.

Chapter 2 describes the theory behind the different signal processing techniques that were investigated. Examples, using analytical data, are included to help show how some of the algorithms work.

A description of the test rig that was used to acquire data for the rotor faults is given in Chapter 3. This includes the details of the different faults, and a description of the data that was recorded.

Chapter 4 contains the results from processing the rotor rig test data with the fault detection algorithms.

In Chapter 5 a summary and conclusion of the results, which includes a comparison between the different signal analysis methods, takes place.

2.0 Signal Processing Techniques Theory

Five (5) different techniques were investigated in this thesis. The first two, spectrum analysis and shock pulse energy are the most common techniques currently used for fault detection. The last three methods: cepstrum analysis, signal demodulation, and singular value decomposition are newer methods that were evaluated.

2.1 Spectrum Analysis

Spectrum analysis of vibration data is simply the method where the time domain data is Fourier transformed into the frequency domain. Each fault is known to create a vibrational component at the fault impact frequency. The spectrum is plotted and inspected for the magnitude at the fault frequency. The fault frequencies are calculated from the kinematics of the bearing, which are determined by the geometry of the bearing [26]. The equations for the three bearing fault frequencies tested on the rotor rig are as follows:

$$\text{Inner Race Fault Frequency (BPFI)} = (Nb/2)(f_{sh})(1+(Bd/Pd)\cos\emptyset) \quad (1)$$

$$\text{Outer Race Fault Frequency (BPFO)} = (Nb/2)(f_{sh})(1-(Bd/Pd)\cos\emptyset) \quad (2)$$

$$\text{Ball Fault Frequency (BSF)} = ((Pd/2Bd)(f_{sh})(1-(Bd/Pd)^2\cos^2\emptyset) \quad (3)$$

where: Nb = Number of balls or rollers.

f_{sh} = Fundamental shaft frequency.

Bd = Ball or roller diameter.

Pd = Pitch diameter.

$\emptyset$ = Contact angle.