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Ping Xiang
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Automatic multi-frequency rotating-probe eddy-current data analysis

by

Ping Xiang

A dissertation submitted to the graduate faculty
in partial fulfillment of the requirements for the degree of
DOCTOR OF PHILOSOPHY

Major: Electrical Engineering (Communications and Signal Processing)

Program of Study Committee:
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Iowa State University
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2005
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For the Major Program
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ABSTRACT

An automatic scheme for analyzing multi-frequency rotating-probe eddy-current data is proposed herein. This system integrates signal/image-processing algorithm with pattern recognition methods for accomplishing the objectives. The eddy-current signals are acquired from several kinds of frequency multiplexed eddy-current rotating-probes. The problem involves the detection of the flaw signals, classifying the defect format and sizing/characterizing the defect profile. The preprocessing steps include conversion of one-dimensional data to obtain a two-dimensional image, removing background noise, suppressing structure-masking signals, and calibration. Optimal thresholding of calibrated signal based on probability of detection (POD) concepts are discussed in detail. Feature extraction and signal classification steps are then implemented to discriminate signals produced by defects or non-defects, axial or circumferential defects, tight or volumetric defects. Finally, wavelet basis function neural networks are used for estimating defect profile.

Further analysis of the statistical properties of potential defect signals is needed to discriminate between different kinds of defects. A model for characterizing the amplitude and phase probability distributions is developed. The squared amplitudes and phases of the potential defect signals are modeled as independent, identically distributed (i.i.d.) random variables following gamma and von Mises distributions, respectively. A maximum likelihood (ML) method is employed for estimating the amplitude and phase distribution parameters from measurements corrupted by additive complex white Gaussian noise. Newton-Raphson iteration is utilized to compute the ML estimates of the
unknown parameters. Cramér-Rao bounds (CRBs) for the unknown parameters are computed. The obtained estimates can be utilized for maximum \textit{a posteriori} (MAP) signal phase and amplitude estimation as well as efficient feature extractors in a defect classification scheme. Numerical examples of both real and simulated data are presented to demonstrate the performance of the proposed method.
CHAPTER 1 INTRODUCTION

1.1 Problem Statement

It is a given that everything is fallible in this world. The most important thing is that failures can occur sometimes without any notice. This has motivated the search for techniques to locate and characterize flaws and prevent failures before they can result in serious consequences. If the methods employed for detecting and characterizing flaws are consistent, the practical benefits of using nondestructive methods are obvious. Nondestructive evaluation (NDE) techniques enable the detection of inhomogeneities in materials and characterizing their properties without impairing their ability to be useful. NDE has been used in a broad range of industrial applications such as transportation, petrochemical, nuclear and the semiconductor industry. Applications include the inspection of aircraft engines, nuclear reactors, railroads, gas pipelines and other components where failures can contribute to catastrophic disasters. NDE techniques can be employed to improve productivity, serviceability, reliability, and safety [1].

A variety of nondestructive testing (NDT) techniques including the use of electromagnetics, ultrasonics, radiography, and thermography, have evolved to cater to various applications. A typical NDT system consists of a specimen under test, an energy source interacting with the specimen, and a receiving transducer picking up the response of the interaction. A generic NDT signal is the response of energy-material interaction. Examples of electromagnetic NDT signals include potential drop, magnetic flux leakage (MFL), impedance change of an eddy-current (EC) coil, and impedance difference of
a pair of differential EC coils. NDT signals are further analyzed using signal/image processing techniques and inverse techniques to obtain the location, shape, depth, and other useful information about the defect.

1.2 NDE of Steam Generator in Nuclear Power Plant

A heat exchanger is a device that is used to transfer heat from a fluid flowing on one side of a barrier to another fluid flowing on the other side of the barrier. Heat exchangers are used in a variety of industries, including, power stations, petrochemical plants, oil refineries, air conditioning and refrigeration units. Heat exchanger used in nuclear power plants, as shown in Figure 1.1, are usually called steam generator (SG). Steam generators transfer heat from hot pressurized water in the tubes to the surrounding water that boils and produces steam. The tubes that are typically made from an alloy called Inconel serves as the boundary between the radioactive water circulating through the reactor, and the mixture of water and steam outside. The steam produced by the steam generator is used to run turbines. The steam generator tubes are approximately 7.5m high with an outer diameter of 22.225mm (0.875") and 1.27mm (0.05") wall thickness. The tubes are held in place using what are often referred as support plates. The tubes are forced through the ferromagnetic support plates, which are spaced about 150cm apart in the steam generator.

The crevice gap between the support plates is usually a hotbed of corrosive chemicals. It is critical that the primary coolant, which is radioactive, does not leak to the secondary side. However, steam generators are continuously exposed to high temperatures, pressures, fluid flow rates and material interactions. Because of these environmental effects, steam generators in nuclear power plants are subjected to mechanical wear between tube and tube support plates, outer diameter stress corrosion cracking (ODSCC), pitting, volumetric changes, primary water stress corrosion cracking (PWSCC), and inter
granular attack (IGA) resulting in tube thinning and multiple crack-like flaws. To prevent contamination of the secondary, the steam generator tubes have to be inspected periodically. Historically, steam generator tube inspection has been a difficult problem. There are numerous examples of unscheduled plant shutdowns. Since a plant outage in a utility can typically cost $500,000 a day, there are strong economic incentives to develop reliable NDE methods. Visual examination and ultrasonic techniques have limited use as they are very slow and only a small percentage of the tubes can be inspected. These problems have led to a widespread use of eddy-current techniques for the inspection of non-ferrous tubing, particularly in the nuclear power industry.

Eddy-current inspection has proven to be both fast and effective in detecting and sizing most of the degradation mechanisms that occurred in the early generators. However, as the nation’s generators have aged, newer and much more subtle forms of degradation have appeared that require more intelligent application of eddy-current tests. Conven-
tional eddy-current data analysis is carried out by human analysts. Normally, during the inspection signals from multiple channels of different frequency and probe types are recorded. Analysts combine their experience and information from shape of the signal, the shape of the Lissajous pattern of the signal and the phase of the signal in each channel to make a decision. Through the use of multi-frequency eddy-current systems, modern equipment is capable of acquiring the necessary data to correctly diagnose the indications. Applying consistent and reliable analysis techniques, however, is required to achieve improved test results. Human nature itself will cause some variance in analysis. Also, the combination of many different properties in the eddy-current signal makes it very difficult to analyze. Inspection results are often not consistent with prior inspection or are inconsistent among different analysts. To overcome these obstacles, an automatic analysis system is needed to improve test results.

1.3 Organization of the Dissertation

The development of automated technology for analyzing steam generator eddy-current data has the potential to provide utilities with significant cost savings associated with reduced analyst requirements and faster inspections. Additionally, the added consistency and accuracy that automated data analysis potentially affords may allow utilities to demonstrate higher tube degradation detection probability and improved sizing accuracy. These capabilities could provide the basis for longer inspection intervals and the use of alternate repair criteria. The rest of this Dissertation is organized as follows. Chapter 2 introduces the different types of NDE techniques currently in practice and then focuses on the principles of electromagnetic NDE techniques. Chapter 3 describes the eddy-current testing technique and its application to the inspection of steam generator tubes, focusing on the multi-frequency rotating-probe inspection methods. Signal preprocessing steps, which include one dimensional signal to two dimensional image
conversion, background removal and calibration, are discussed in Chapter 4. Signal classification techniques using multiplayer perceptrons (MLP) and defect characterization schemes employing wavelet basis function neural networks are presented in Chapter 5 and 6, respectively. A model for characterizing amplitude and phase probability distributions of the signals is developed in Chapter 7. Chapter 8 summarizes the research work and presents ideas for future work.
CHAPTER 2  PRINCIPLES OF NDE TECHNIQUES

2.1  Introduction

Rapid technological developments in the field of science and technology over the last couple of decades have resulted in a tremendous demand for new NDE techniques that are efficient, reliable and economical to use. Aviation, nuclear and many other industries utilize critical components requiring high reliability and structural integrity. The failure to detect defects that may lead to the structural failure of critical components could prove to be catastrophic. Thus accurate and reliable methods of NDE are needed in all these applications. In response to needs arising from various industries, a variety of NDE techniques have been developed such as radiography, magnetic particle, ultrasonic, liquid penetrant and electromagnetic testing methods. Eddy-current testing (ECT) is one of the most commonly used electromagnetic methods. It employs a time-varying electromagnetic field as a source of excitation to evaluate the properties of the test material, detect discontinuities and measure variations in the geometry and dimensions of the test materials.

Figure 2.1 shows a generic NDE system. The excitation transducer couples the energy source into the test specimen. The receiving transducer picks up the response of the field/flaw interaction and generates an output signal. The output signal is then processed, and passed through an inversion block. The inversion block performs defect characterization, which involves the estimation of defect dimensions, location, and shape.
2.2 Methods of Nondestructive Testing

A variety of nondestructive testing methods are used in practice. They are generally classified according to the form of probing energy source. Some of the most commonly used NDE techniques, ultrasonic, radiographic, and electromagnetic methods, are described briefly below. Electromagnetic methods will then be discussed in more detail in the next section.

2.2.1 Ultrasonic NDE

The ultrasonic method is probably one of the oldest NDE techniques. In this method, the probing source is ultrasound, whose frequency is above the audible frequency range (10 ~ 2000 Hz). The ultrasonic waves are coupled into the test specimen via a coupling medium. In the most common situation, this energy propagates as quasi-plane-wave beams traveling through the body of the material [2]. Whenever a material discontinuity is encountered, the wave is reflected and picked up by the transducer. Hence the received signal contains reflections due to front wall, the defect, and the back wall. The time
elapsed between the incident and the reflected signals is referred to as the time of flight (TOF). The amplitude of the signal provides information of the flaw size and the time of flight is a measure of the distance of the flaw from the specimen surface. The reliability of ultrasonic methods is dependent on many factors, such as probe type and excitation frequency, couplant method, scanning surface condition, and floor coating.

2.2.2 Radiographic NDE

Radiographic NDE is widely used for finding internal, non-planar defects. The radiation source emits energy traveling in straight lines and penetrating the test specimen. The energy pattern received on the opposite side is then analyzed to obtain useful information about the condition of the test sample. The radiation source can be gamma rays or X-rays. Both of them are in the high frequency end of the spectrum with wavelengths of the order of $10^{-9}$ to $10^{-13}$ meters. Gamma rays are generated by transition of radioactive nuclei from a high energy level to a more stable lower energy level. X-rays are produced when high-speed electrons strike a target wherein the kinetic energy of the electrons is converted to electromagnetic radiation [3]. Because of the high energy levels involved X-rays and gamma rays have high penetrating power and are capable of traveling through most materials. The intensity of the beam of energy transmitted through the object is reduced according to the thickness traversed by the beam and can be expressed as

$$I_t = I_0 e^{-\lambda t},$$

(2.1)

where $t$ is the thickness of the material, $I_0$ and $I_t$ are the incident and transmitted energies respectively, and $\lambda$ is the linear absorption coefficient that depends on the material properties. After passing through the test specimen, the radiation energy is recorded on a photographic film and analyzed to determine the condition of the specimen. The reliability of radiographic methods is dependent on a variety of parameters, such as
energy of the beam, size and shape of the beam source, source to film distance, type of film, and exposure time.

### 2.2.3 Electromagnetic NDE

Electromagnetic NDE methods are used widely for characterizing materials on the basis of their electric and magnetic properties (conductivity and permeability). The energy source in these methods is electric and magnetic fields. Eddy-current methods have both industrial and biomedical applications, such as evaluation of condition of artificial heart valve implants [4] and magnetic resonance imaging (MRI) [5, 6, 7]. The principles of these methods are discussed in the following section.

### 2.3 Principles of Electromagnetic NDE

#### 2.3.1 Magnetic Flux Leakage Methods

Magnetic flux leakage methods are widely used for testing ferromagnetic materials, which are capable of being magnetized very strongly by an external magnetic field. When removed from the field, they retain a considerable amount of their magnetization. The constitutive relation

$$B = \mu(B) H,$$  \hspace{1cm} (2.2)

relates the magnetic flux density $B$ and the magnetic field intensity $H$ via the magnetic permeability $\mu$. In the case of ferromagnetic materials $\mu$ is a nonlinear function of $B$.

The magnetic property of ferromagnetic material is characterized by the magnetization curve, as shown in Figure 2.2. At any point on the curve, $\mu$ is given by the ratio $B/H$. As $H$ is increased due to increase in current, from 0 to maximum applied field intensity $H_{\text{max}}$, curve OP is produced. This curve is referred to as the virgin or initial magnetization curve. Beyond P, further increase in the excitation current causes the
material to be saturated. If \( H \) is decreased, \( B \) does not follow the initial curve but lags behind \( H \). If \( H \) is reduced to zero, \( B \) is not reduced to zero but to \( B_r \), the remanent flux density. If \( H \) increases negatively, \( B \) becomes zero when \( H \) becomes \(-H_c\). \( H_c \) is known as the coercive field intensity. Further variation in \( H \) to reach \( P \) gives a closed curve named hysteresis loop.

The advantage of using magnetic flux leakage methods to detect localized inhomogeneities such as surface or near-surface cracks in ferritic steels and other ferromagnetic materials, is the high degree of certainty of detection when the magnetizing fields are properly applied. The technique offers a high sensitivity when testing for small surface cracks, even on rough surfaces, than any other conventional NDE techniques. With magnetic flux leakage methods, the object being tested is magnetized and a magnetic field is established inside the object. The distribution of the resultant lines of magnetic flux is determined by the values of magnetic permeability within the region of interest. The discontinuities of magnetic permeability, caused by the presence of a slot simulating a defect in a magnetized ferromagnetic bar, affect the distribution of the lines of induced magnetic flux in the manner as shown in Figure 2.3. North and south magnetic poles appear on the opposite sides of the slot. The lines of flux are highly distorted across the crack and “leak” out of the body. This is known as
the magnetic leakage field. It has been observed that flux leakage takes place not only at the surface containing the slot but also at the opposite surface, where the leaked flux densities have lower amplitude. Some of the fluxes pass through the slot. Flux leakage can be detected by magnetic particles, magnetic tape, or flux-sensitive coils and probes.

A typical inspection would involve magnetizing the specimen either by passing a current or using a permanent magnet or electromagnet. The specimen surface is then scanned using a Hall element probe to detect leakage fields. Another approach that is commonly used in industry is to sprinkle iron filings on the specimen and observing the pattern on the surface. This method is called the magnetic particle inspection (MPI) [8]. Leakage field measurement performed when the magnetizing field is present, it is called active leakage field methods. When the magnetizing current is switched off, all the magnetic domains within the specimen do not revert back to their normal randomly oriented state. This causes the walls of the defect to acts as poles of a permanent magnet and a magnetic field is established across the defect. This field is referred to as the residual leakage field. Residual leakage field can also be used to detect defects in a material. Such methods tend to be highly sensitive to surface-breaking defects. A typical application of MFL methods is the inspection of natural gas transmission pipeline [9, 10].
2.3.2 Eddy-current Methods

An eddy-current is a local electric current induced in a conductive material by a time varying magnetic field that could be produced by the a coil that is excited by an alternating current source. Consider a simple coil excited by an alternating current. Since the coil is carrying an alternating current, an alternating magnetic field is set up in accordance with Maxwell-Ampere Law:

\[ \nabla \times \mathbf{H} = \mathbf{J}, \tag{2.3} \]

in the differential form or

\[ \oint_{C} \mathbf{H} \cdot d\mathbf{l} = \iint_{S} \mathbf{J} \cdot d\mathbf{S}, \tag{2.4} \]

in the integral form, where the displacement currents have been neglected. If the coil is taken close to a non-ferromagnetic test specimen, the time varying field causes an electromotive force (emf) to be induced in the specimen in accordance with Maxwell-Faraday Law:

\[ \nabla \times \mathbf{E} = -\frac{\partial \mathbf{B}}{\partial t}, \tag{2.5} \]

in the differential form or

\[ \oint_{C} \mathbf{E} \cdot d\mathbf{l} = -\frac{\partial}{\partial t} \iint_{S} \mathbf{B} \cdot d\mathbf{S}, \tag{2.6} \]

in the integral form. The emf causes currents to flow in the specimen. These currents are called eddy-currents since they follow closed circulatory patterns that are similar to eddy found in bodies of water. The induced current, in turn, generates a field (induced or secondary field), whose direction is opposite to that of the primary field established by the coil, according to the Lenz’s Law. This causes the net flux linking the coil to decrease. The inductance of a coil is defined as the net flux linkages per Ampere, i.e.,

\[ L = \frac{N\Phi}{I}, \tag{2.7} \]

where \( L \) is the inductance, \( N \) is the number of turns of the coil, \( \Phi \) is the flux going through the area encircled by the coil, and \( I \) is the source current. So the effective
inductance of the coil decreases. In addition, the $I^2R$ power loss incurred due to the flow of eddy-currents in the specimen manifests itself as a net increase in the terminal resistance of the coil. Figure 2.4 illustrates this phenomenon.

![Figure 2.4 Impedance plane trajectory of a coil over a non-ferromagnetic specimen.](image)

In the presence of a flaw in the test specimen, the distribution of the eddy-current is interrupted by the flaw. The eddy-current is reduced due to the material discontinuity. The reduction of the induced eddy-current leads to the reduction of the changes of the inductance and resistance of the excitation coil, as shown in Figure 2.4. The process is more complicated when the test specimen is ferromagnetic. Accompanying the decrease in inductance due to the influence of eddy-currents is an increase in inductance due to
the higher permeability of the material. The latter effect is more predominant and hence when the coil is taken close to a ferromagnetic specimen the overall inductance of the coil increases along with an increase in its resistance [11, 12]. Again, the presence of a flaw in the specimen reduces the changes in coil inductance and resistance, as shown in Figure 2.5. Systems that capable of monitoring the changes in impedance can, therefore, be used detect flaws in a specimen that is scanned by a coil.

The eddy-currents induced in the specimen decay rapidly as the depth increases. This is called skin depth (or skin effect [13]) phenomenon. The current density is a maximum at the material surface and decreases exponentially with depth. Thus, in the case of thick specimens, eddy-currents are largely confined to the outer “skin” of the test material and test sensitivity to subsurface defects decreases rapidly with depth. The term skin depth (δ), also called standard depth of penetration, is defined as the depth at which eddy-current density has decreased to 1/e of its surface value. The skin depth for the case where a sheet of current present at the surface of a half plane is given by:

\[ \delta = \frac{1}{\sqrt{\pi \mu f \sigma}} \]  

(2.8)

where \( f \) is the excitation frequency of the circuit, \( \mu \) is the magnetic permeability of the target material, and \( \sigma \) is the electrical conductivity of the target material. The skin depth is often used as a guideline to select the excitation frequency for a given test specimen.

2.3.3 Differential Coil Eddy-current Methods

Consider the situation as shown in Figure 2.6, where two coils A and B are located within a non-ferromagnetic tube containing a defect and connected in a differential mode, i.e., currents in the two coils have the same strength but opposite directions. When the coils are far away from the defect, the net impedance is zero (Point O is Figure 2.7). As the probe moves from right to left, the leading coil (Coil A in Figure 2.6) encounters
the defect first. Consequently the inductance of Coil A increases and the resistance decreases. Since the fields are very local, the impedance of the trailing coil (Coil B in Figure 2.6) remains unchanged. Hence the differential impedance traces the trajectory OP in Figure 2.7. When Coil A leaves the defect area, and Coil B moves close to the defect, the net differential inductance decreases and the net resistance increases. When the defect is exactly in the middle of the two coils, the differential impedance becomes zero since Coils A and B are affected equally. The trajectory PO in Figure 2.7 is thus traced. As Coil B moves closer to the defect, the trajectory OQ is traced. When Coil B leaves the defect area, the trajectory QO is traced. The shape and orientation of the impedance plane trajectory is determined by the defect profile, the host material electrical properties, excitation frequency, distance between the two coils, the size and shape of the coil, and the lift off, etc.
2.3.4 Swept Frequency Methods

Swept frequency eddy-current techniques involve collecting eddy-current data at a wide range of frequencies. This usually involves the use of a specialized piece of equipment such as an impedance analyzer, which can be configured to automatically make measurements over a range of frequencies. The swept-frequency technique can be implemented with commercial equipment but it is a difficult and time-consuming measurement. The advantage of a swept frequency measurement is that depth information can be obtained since eddy-current depth of penetration varies as a function of frequency.

Swept frequency measurements are useful in applications such as measuring the thickness of conductive coatings on conductive base metal, differentiating between flaws in surface coatings and flaws in the base metal, differentiating between flaws in various layers of built-up structure. An example application would be the lap spic of a commercial aircraft. Swept frequency measurements would make it possible to tell if cracking was occurring on the outer skin, the inner skin or a double layer.

2.3.5 Pulsed Eddy-current Methods

Conventional eddy-current inspection techniques use sinusoidal alternating electrical current of a particular frequency to excite the probe. The pulsed eddy-current (PEC) technique uses a step function voltage to excite the probe. The advantage of using a step function voltage is that it contains a continuum of frequencies. As a result, the electromagnetic response to several different frequencies can be measured with just a single step. Since the depth of penetration is dependent on the frequency of excitation, information from a range of depths can be obtained all at once. If measurements are made in the time domain (that is by looking at signal strength as a function of time), indications produced by flaws or other features near the inspection coil will be seen first and more distant features will be seen later in time.
To improve the strength and ease interpretation of the signal, a reference signal is usually collected to which all other signals are compared (just like nulling the probe in convention EC inspection). Flaws, conductivity, and dimensional changes produce a change in the signal and a difference between the reference signal and the measurement signal that is displayed. The distance of the flaw and other features relative to the probe will cause the signal to shift in time. Therefore, time gating techniques (like in ultrasonic inspection) can be used to gain information about the depth of a feature of interest.

2.3.6 Remote Field Eddy-current Methods

The remote field eddy-current (RFEC) techniques are characterized by their high sensitivity to material discontinuities at large depths. These methods gained popularity because they are equally sensitive to any discontinuity, irrespective of its location (inner or outer diameter in the tube wall) [14]. In detecting residual stress in infrastructures, which is becoming more and more of concern, the RFEC techniques are probably more useful than conventional EC techniques. The RFEC techniques were first introduced for tube inspection, as shown in Figure 2.8. A coil excited by an alternating current is placed in a pipe, the energy diffuses along two different paths: direct path and indirect path. It has been shown that the energy diffusing via the direct path attenuates very
rapidly, because it is restricted by eddy-current in the pipe wall. When a pickup coil is located at a certain distance away from the excitation coil, the received signal is primarily due to the energy diffusing via the indirect path. This portion of the energy passes the pipe wall twice before arriving at the pickup coil. So the received signal is closely related to the thickness, conductivity, permeability, and other wall conditions. And its phase is linearly proportional to the wall thickness. Recently, the RFEC technique has been successfully applied to detect compressive residual stress in carbon steel specimens of flat geometries [15].
CHAPTER 3 EDDY-CURRENT TESTING IN STEAM GENERATOR TUBE INSPECTION

3.1 Eddy-current Testing

Eddy-current techniques are widely used for inspecting heat exchanger tubes in steam generators used in nuclear power plants. Although there are several different eddy-current methods, they all rely on the principles of electromagnetic induction to ascertain the condition of a given test specimen. The basic principle underlying such methods can be illustrated with a simple arrangement shown in Figure 3.1.

When a flaw or inhomogeneity whose conductivity differs from that of the host specimen is present, the current distribution is altered, see Figure 3.2.

The variations in coil impedance caused by discontinuities in the test specimen are often very small in comparison with the quiescent value of the coil impedance. The de-
tection and measurement of the small changes is often accomplished using bridge circuits [16]. Factors that influence the eddy-current field, and therefore the coil impedance, are:

- The separation between the coil and specimen surface, called lift-off,
- The electrical conductivity of the specimen,
- The magnetic permeability of the specimen,
- The frequency of the AC inducing the eddy-current field,
- The design of the eddy-current probe,
- Geometric factors,
- Discontinuities, such as cracks, corrosion, pitting.

Successful detection and characterization of flaws requires a careful design of signal processing procedures to negate or compensate for these effects. It is this elimination of undesired response that forms the basis of much of the technology of eddy-current inspection.

3.2 Multi-frequency Techniques Employed for Steam Generator Tube Inspection

3.2.1 Need for Multi-frequency Testing

Single frequency eddy-current tests offer excellent sensitivity to a number of different types of steam generator tubing under normal conditions. However conditions are
often complicated by a number of factors and consequently inspection needs cannot be effectively solved by single frequency examinations. Some extraneous discontinuities, such as support structures, electrically conductive deposits, permeability variations and dents distort or mask defect signals that are located near them. This creates mistaken interpretation of the eddy-current signal resulting in unnecessary tube plugging. Lack of detection may also lead to unexpected leaks and costly shutdowns. The detection of other discontinuities such as wall thinning, sludge height, dents etc. need several successive probe passes at different frequencies and measurement mode. This increases the inspection time, which from safety as well as economic reason should be keeping to a minimum.

3.2.2 Multi-frequency Methodology

State of the art multi-frequency eddy-current testing overcomes most of the single frequency limitations. The multi-frequency technique consists of collecting data simultaneously using several excitation frequencies from just one probe pull. This provides data that are analyzed using multi-frequency mixing or multiparameter techniques. This technique allows the effect of extraneous discontinuities to be nullified [13, 17, 18, 19]. Alternating currents of different frequencies are either summed and sent simultaneously to the test coil, or multiplexed and sent successively. After frequency separation, using bandpass filters or the timing information in multiplexed method, the coil impedance is estimated and displayed for each frequency separately. Multiparameter or mixing techniques are then used to analyze the data to classify and characterize the defects. As mentioned early, each frequency is sensitive to a certain type of discontinuity. Low frequencies have a large skin depth and hence give clear signals from support structures that are located away from the coil. They are sometimes used to determine location of the probe along the tube. They can also be used to detect artifacts on the outside of the tubes such as magnetite deposits. At high frequencies, eddy-currents have a much
smaller skin depth and for defects on the outside of the tube, the depth can be estimated from the phase of the eddy-current signal. Because of the different skin depths at different frequencies, the relationship between signals from defects and support features changes with frequency. Consequently, it is possible to combine the signals from two different frequencies so as to subtract out a support feature but leave the signal from defect relatively intact [20]. In effect, this means that multi-frequency response signals contain more information that can be analyzed to extract relevant features. In summary, multi-frequency techniques have the following advantages [21]:

- Collects data at several test frequencies simultaneously (this decreases the in-service inspection time and human exposure to radiation),
- Allows separation of discontinuities that give similar signals at one frequency,
- Improve sensitivity to different types of discontinuities,
- Improve the detection, interpretation and sizing of defects even in the presence of artifacts that complicate the analysis procedure.

Two types of multi-frequency probes are used in practice. One is a bobbin coil probe which is a single coil excited with currents at multiple frequencies. Although the bobbin coil probe is the most widely used probe, it has limitations in its ability to detect degradation in all regions of the tube (e.g., expansion transitions). Other disadvantages include the limited ability to accurately size and characterize degradation as well as inability to provide any information concerning the location of the defect in the circumferential direction. As a result of these limitations, the bobbin coil probe is mainly used for the initial detection of possible degradation to quickly determine those areas of the tube requiring additional inspection with other types of probes that have improved ability to size and characterize degradation, e.g., rotating-probes.
3.3 Rotating-probe

The rotating-probe is a relatively new concept that is been used for the inspection of steam generator tubes [22]. The objective of this scheme is to increase the measurement resolution. Figure 3.3 shows a probe consisting of 3 different types of coils, rotating inside a tube at very high speeds (around 900 RPM) and moves forward in the axial direction (around 4 inches per second). By controlling the rotation rate, pull rate, and coil diameter, 100% coverage of the tube can be achieved for a most thorough inspection.

![Diagram of Rotating-probe eddy-current system](image)

**Figure 3.3 Rotating-probe eddy-current system.**

Typical signals generated by a multi-frequency-rotating-probe testing system are shown in Figure 3.4. The x-axis is length (or time) along the axial direction and the y-axis is magnitude in volts (after sampling and quantization). The trigger signals, which are generated by a commutator to localize the probe circumferential position, can be used to transform the one-dimensional signals to two-dimensional images. The low frequency channel is usually designed to locate structure signals such as those generated by tube support plated (TSP), tube sheet (TSH), etc.
3.4 Research Objectives

Although it is relatively easy to understand the basic eddy-current probe-flaw interaction phenomenon, the analysis of real-world inspection data is difficult because noise and other artifacts cause significant distortion of the flaw signal. Automatic flaw detection schemes involving the analysis of bobbin coil eddy-current data have been well studied by many researchers [20, 23]. These studies mainly focus on the relationship between the flaw characteristics and the shape and orientation of the corresponding Lissajous pattern. These methods very often in effect mimic the decision making process of a human expert. Compare to one-dimensional bobbin coil data, two-dimensional rotating-probe eddy-current signals are more complex, contain more information and are more difficult to analyze. Research work associated with rotating-probe eddy-current
signal analysis is relatively new. M. Hayakawa, et al [24], evaluate the characteristics of rotating eddy-current probe using 3-D edge-based FEM. Upadhyaya, et al [25], propose an automatic diagnostics system to analyze rotating-probe eddy-current data using artificial intelligence techniques. Although this was among the first complete systems which attempted to analyze rotating-probe data, its algorithms were limited to one-dimensional signal features, such as impedance signatures. This effects its ability to identify defect types and to estimate defect parameters. The objective of developing an automatic flaw detection system is to reduce the workload of human analysts and improve the speed, accuracy and reliability of eddy-current data analysis results. This dissertation presents an automatic multi-frequency rotating-probe eddy-current data analysis system whose main components are shown in Figure 3.5.

Figure 3.5 Proposed eddy data analysis system.
The three major steps in the analysis procedure are signal preprocessing, signal classification and defect characterization. Each of these steps is explained in detail in the following chapters.

To get better understand of the eddy-current signals, further analysis of the statistical properties of potential defect signal is necessary. A statistical model is developed to characterize the amplitude and phase probability distributions of potential defects. To estimate the unknown parameters from noisy measurements, a maximum likelihood (ML) method is derived. The results of this estimating can be used as an effective feature extractor for classification as shown in Figure 3.5.
CHAPTER 4 SIGNAL PREPROCESSING

4.1 Introduction

The objective of data preprocessing is to extract “meaningful” information from the data to be used subsequently for data analysis. This is implemented with several steps as shown in Figure 4.1. First, one dimensional raw data was synchronized and converted to two dimensional images. Then, a segmentation algorithm was applied to the low frequency signals to locate the support structures. To provide accurate defect analysis, signals obtained from a piece of tube of the same material and dimensions as the tubes to be inspected can be used as calibration standard.

![Data preprocessing scheme](image)

Figure 4.1 Data preprocessing scheme.
4.2 Data Synchronization

4.2.1 Trigger Channel Signal

The rotational speed of an RPC probe during inspection is not always uniform and the number of samples per pitch changes with axial motion of the probe. This synchronization information is present in the trigger channel. The trigger channel provides synchronization points for each cycle (the local sync is generated for 72°, 144°, 216° and 288°, while the main sync is produced at 360° points) as shown in Figure 4.2.

![Trigger information](image1)

Figure 4.2 Trigger information.

![Typical trigger signal](image2)

Figure 4.3 Typical trigger signal.
A typical output of the trigger signal is shown in Figure 4.3. One of the problems with the trigger channel is that it does not always give as clear signals as shown in Figure 4.3. Oftentimes, simple thresholding can be quite inadequate in distinguishing the main sync pulses from the local sync pulses, and therefore a preprocessing scheme is necessary to separate the main sync pulses from local ones. Furthermore, the exact beginning and end points of these pulses are not always obvious due to noise. Figure 4.4 illustrates such a case.

Consequently, the preprocessing algorithm must be sufficiently robust to accommodate noisy readings, and be able to distinguish between the main and local sync pulses.

4.2.2 Synchronization Algorithm

By checking the polar plot of the trigger signals, as shown in Figure 4.5, a simple preprocessing scheme can be employed. Firstly, the three centers of impedance plot are estimated with $K$-means clustering algorithm or maximum likelihood clustering.

$K$-means clustering [26]
The objective is to partition \( N \) patterns, \( x_1, x_2, \ldots, x_N \), into \( K \) mutually exclusive regions. Denote by \( N_k \) the number of patterns in the \( k \)th class. The partitioning is performed in a manner that minimizes the cost function equal to the sum of squared distances between the cluster centers and all points with in the clusters:

(i) Assign any \( K \) (first, randomly selected, or user-assigned) patterns to the \( K \) clusters;

(ii) Assign each of the remaining \( N - K \) patterns at the \( j \)th iteration to one of the \( K \) clusters whose center is the closest (using the Euclidian norm), i.e.

\[
x \in C^{(j)}_m \quad if \quad \| x - z^{(j)}_m \| < \| x - z^{(j)}_n \| \quad for \quad 1 \leq m, n \leq K,
\]

where \( C^{(j)}_m \) is class \( m \) at \( j \)th iteration and \( z^{(j)}_m \) is a cluster center of class \( m \) at \( j \)th iteration;

(iii) Update the cluster centers \( z^{(j+1)}_k \), \( k = 1, 2, \ldots, K \) in a manner that minimize the performance index

\[
P^{(j)}_k = \sum_{x \in N^{(j)}_k} \| x - z^{(j+1)}_k \|^2.
\]

It can be shown that the centers \( z^{(j+1)}_k \), \( k = 1, 2, \ldots, K \), which minimize the above performance index is the sample mean of all points within the cluster, i.e.

\[
z^{(j+1)}_k = \frac{1}{N^{(j)}_k} \sum_{x \in C^{(j)}_k} x;
\]

(iv) If \( z^{(j+1)}_k = z^{(j)}_k \) for all \( k = 1, 2, \ldots, K \), the algorithm has converged and the process can be terminated. Otherwise go to step (ii).

The \( K \)-means algorithm converges if the classes are linearly separable and the performance generally improves if the initial cluster centers are chosen from the \( K \) classes.

Maximum Likelihood Clustering
Here, our objective is to partition \( N \) measurements or patterns, \( x_1, x_2, \ldots, x_N \), into \( K \) regions. If the statistical distribution of the observed patterns can be modeled as a mixture of several distributions whose parametric form is known, then we can perform clustering using the ML method. Figure 4.5 illustrates the mixture-distribution concept.

![Figure 4.5](image)

**Figure 4.5** Mixture Gaussian distribution.

Typically, the mixture components are assumed to follow a (multivariate) Gaussian distribution; the Gaussian model was adopted here. In the case of complex patterns, the mixture components can be modeled using the complex multivariate Gaussian distribution:

\[
p(x; \mathbf{m}, \Sigma) = \frac{1}{|\pi \Sigma|} \exp\left[-(x - \mathbf{m})^H \Sigma^{-1} (x - \mathbf{m})\right],
\]

where "\( H \)" denotes the Hermitian (conjugate) transpose. Assume that the mixture distribution \( p(x) \) consists of \( K \) components, i.e.

\[
p_{\text{mixture}}(x) = \sum_{k=1}^{K} P(C_k)p(x; \mathbf{m}_k, \Sigma_k),
\]
where \( p(x; m_k, \Sigma_k) \) is modeled as a (complex) multivariate normal with expectation \( m_k \) and covariance matrix \( \Sigma_k \). Under this assumption, the goal is to estimate \( P(C_k), m_k \) and \( \Sigma_k \) from \( N \) available samples, \( x_1, x_2, \ldots, x_N \), draw from \( p(x) \). The inference on each sample \( x \) will be based on the posterior distribution of \( C_k \) given \( x \), denoted as \( q_k(x) \).

Under the complex-Gaussian model for the mixture components [27], the ML clustering algorithms is described as follows:

(i) Choose the initial estimates \( P^{(0)}(C_k), m_k^{(0)}, \Sigma_k^{(0)} \) for \( k = 1, 2, \ldots, K \);

(ii) Having calculated \( P^{(i)}(C_k), m_k^{(i)}, \Sigma_k^{(i)} \) and \( q_k^{(i)}(x_n) \), compute the new estimates as:

\[
P^{(i+1)}(C_k) = \frac{1}{N} \sum_{n=1}^{N} q_k^{(i)}(x_n),
\]

\[
m_k^{(i+1)} = \frac{1}{P^{(i+1)}(C_k)} \sum_{n=1}^{N} q_k^{(i)}(x_n)x_n,
\]

\[
\Sigma_k^{(i+1)} = \frac{1}{P^{(i+1)}(C_k)} \sum_{n=1}^{N} q_k^{(i)}(x_n)(x_n - m_k^{(i+1)})(x_n - m_k^{(i+1)})^H,
\]

\[
q_k^{(i+1)}(x_n) = \frac{P^{(i+1)}(C_k) \cdot p(x_n; m_k^{(i+1)}, \Sigma_k^{(i+1)})}{\sum_{i=1}^{K} P^{(i+1)}(C_i) \cdot p(x_n; m_i^{(i+1)}, \Sigma_i^{(i+1)})},
\]

for \( k = 1, 2, \ldots, K, n = 1, 2, \ldots, N; \)

(iii) When \( q_k^{(i+1)}(x_n) = q_k^{(i)}(x_n) \) for all \( k = 1, 2, \ldots, K \) and \( n = 1, 2, \ldots, N \), then stop.

Otherwise increase the iteration number by 1 and go to step (ii).

Unlike the \( K \)-means clustering algorithm, which makes a "hard" decision by assigning each sample to a single class, the above algorithm assigns \( K \) posterior probabilities \( q_1(x), q_2(x), \ldots, q_K(x) \) to each sample \( bx \), which allows us to make a decision (by choosing the cluster with the largest posterior probability) as well as to make inference about the reliability of our decision. The \( K \)-means clustering algorithm could be used to obtain the initial estimates in step (i).

After the three centers of the impedance plot was found, the corner of the plot is shifted to the origin, and the plot is rotated such that the horizontal component of the
data lines up with the horizontal axis. The polar plot is then converted back to line plots of vertical and horizontal readings.

Initial results have been promising, as shown in a typical signal shown in Figure 4.6. Note that the main sync pulses are completely isolated from the local sync pulses in the vertical component after processing. A simple scaling and subtraction of the vertical component from the horizontal component subsequently isolates the local sync pulses.
4.2.3 Synchronization Results

Once the local and main sync pulses are separated, we can use these pulses to convert one dimensional eddy-current data into two-dimensional images. This is achieved by adjusting the length of each reading between the local pulses, such that each reading is of equal length. Typical data from a single channel before and after synchronization is shown in Fig. 4.7.

4.3 Segmentation

Flaws are more likely to develop in regions with support structures. With skin depth phenomena, low frequency signal, 10kHz or 20kHz typically, are obtained to locate the support structures, such as TSPs or TSHs. After all the TSPs and TSHs are located, the signal from the entire tube is segmented and each segment is analyzed separately. The location of each defect is reported relative to the position of these support structures.

An edge enhancement operation using a Sobel edge detector [28] is used to identify the ends of the support plate. Figure 4.8 shows a typical image with low frequency
Sobel edge detector

The source image can be represented by \( f(x, y) \) where \((x, y)\) denote the pixel locations of the image. The Sobel edge magnitude image \(|\nabla f(x, y)|\) is given by

\[
|\nabla f(x, y)| = \sqrt{\left(\frac{\partial f(x, y)}{\partial x}\right)^2 + \left(\frac{\partial f(x, y)}{\partial y}\right)^2}.
\]  

\(|\nabla f(x, y)|\) is then compared with a threshold \( T \) to determine candidate boundary points. The threshold \( T \) is set at [29]

\[
T = \sqrt{\beta(\mu^2 + \sigma^2)},
\]  

where \( \beta \) is a constant, \( \mu \) is the mean, and \( \sigma \) is the variance of the image defined by

\[
\mu = \frac{1}{MN} \sum_{x=1}^{M} \sum_{y=1}^{N} f(x, y), \tag{4.9a}
\]

\[
\sigma = \frac{1}{MN} \sqrt{\sum_{x=1}^{M} \sum_{y=1}^{N} (f(x, y) - \mu)^2}. \tag{4.9b}
\]

This step provides the two edges of the tube support plate. The center of the TSP is marked midway between the two edges. Since the width of the TSP is 3/4 inch, the
information is also used as an axial scale standard to establish the relationship between the image pixels and real distance (inches or millimeters).

4.4 Calibration

In order to provide accurate defect analysis, it is necessary to obtain a piece of tube of the same material and dimensions as the tubes to be inspected and use it for calibrating the instrument. Defects that are well characterized are machined on the calibration tube. One example of such standard tube with specifications is shown on Figure 4.9. This is essential to optimize the frequency and sensitivity setting required in order that actual defects can be classified relative to the reference defects. The calibration procedure consists of three steps: normalization, phase rotation, and voltage scaling.

Figure 4.9 One example of calibration standard tube.
4.4.1 Normalization

Normalization consists of two steps. The first step was to suppress signals from structural discontinuities, such as tube support plates or tube sheets. This is obtained by subtracting the median value along each column. Here, the median value is treated as the defect-free reference signal. The second step is to remove low frequency noise, such as lift-off noise. The median along each row is subtracted to accomplish this objective.

4.4.2 Phase Rotation

Defect analysis of eddy-current testing mainly relies on the depth dependence of the phase of a defect signal. Phase lag is very important in ECT since it permits defect characterization as well as reliable estimation of depth. Many signal sources are possible during ECT since anything that affects sample resistance or permeability will be detected as a change in probe coil impedance. Only some of these changes are caused by defects. Phase analysis allows one to decide which signals represent defects and which are irrelevant indications, such as support plates. Figure 4.10 illustrates the impedance plane representation of a tube support plate signal, signals from throughwall, 79% OD and 81% ID flaw.

As can be seen in the figure, the three signals have distinctive phase characteristics. So the phase of eddy-current signal can be used to determine the indication type and estimate the depth of the flaw. To correct for possible phase offset due to different probe response and instrumentation setup, a phase calibration process is applied in industrial practice. In eddy-current tube inspection, the major sources of noises include those due to probe motion caused by the vibration of the probe when it was pulled through the tube. To reduce the effect of this noise, eddy-current signals were usually rotated to make the probe motion signal horizontal in the impedance plane. When the phase of a 100% throughwall (TW) hole is rotated to around 140° the probe motion signal
becomes horizontally in the impedance plane. The rotation procedure is followed in eddy-current phase analysis in industry routinely. The phase rotation step ensures that all raw data have the same reference standard so that the phase analysis of all the data set is consistent. To provide the same phase analysis standard, a 100%TW hole in the calibration standard tube is used as a reference and the phase angle of the flaw is defined to be 40° (with respect to the negative x-axis for MIZ30 data, it is 140° with reference to the standard coordinate system). The phase angle of the 100%TW hole is first calculated and the phase is then adjusted by subtracting the original phase from 140° as shown Figure 4.11. Finally, these phase adjustments are applied to the normalized raw data, channel by channel.

4.4.3 Voltage Scaling

In voltage scaling, the magnitude of the signal corresponding to a TW hole is first scaled and set to a fixed value. The raw data is then scaled, channel by channel. Figure 4.12 shows the calibration result. The defects were rotated to the right position in the
4.5 Thresholding and Phase Gating

After calibration, the potential defect signals should lie in the first and second quadrant in the impedance plane as explained earlier. The signals can be thresholded to minimize noise in a fairly straightforward manner if the noise is additive and the mean of the noise component is different from the mean of the signal component. The phase information is also important when it is necessary to discriminate between inner diameter (ID) defects and outer diameter (OD) defects. Although the calibration procedure improves the visibility of the defect, additional artifacts are introduced due to phase wrapping as shown in Figure 4 (a). The amplitude and phase components of the signal need to be filtered and thresholded before the features are extracted for signal classification.
4.5.1 POD Concepts

The interpretation of NDT data involves taking a decision as to whether the observed signal response is a flaw signal or noise (no flaw signal). The simplest approach to making this decision is to choose a threshold signal level \( T \) such that all signals above the level are classified as flaw signals and all signals below the level are interpreted as noise. If the signal and noise probability density functions overlap, as shown in Figure 1, the data interpretation process based on threshold detection will inevitably involve two types of errors which are of significance: false alarm and false acceptance [30]. Given the signal and noise PDFs, one can determine how the probability of flaw detection (a signal is correctly interpreted as a flaw indication) and the probability of false alarm (a signal is incorrectly interpreted as a flaw indication) depend on the choice of the threshold signal. This is illustrated schematically in Figure 4.13, which shows the detection probability (POD) is the area to the right of the threshold under the signal PDF, while the false alarm probability (PFA) is the corresponding area under the noise PDF. By choosing
a number of different threshold values, one can generate a set of ordered pairs of POD and PFA values, which comprise the so-called receiver operating characteristic (ROC) associated with the inspection. The significance of the ROC is that it defines the tradeoff one must make between the efficiency of flaw detection, as measured by the POD, and the chance of rejecting a part that has no flaw, as measured by the PFA.

4.5.2 Vertical Component Thresholding

The amplitude of the eddy-current signals can vary greatly from one tube to another. These variations limit the use of a single (or global) threshold level to produce a detection process that both maximizes the POD and minimizes the PFA. For example, a threshold level selected to provide high POD and low PFA in an area of high lift-off noise would lead to an artificially low POD in the low noise areas. Conversely a threshold set to work in a low noise area would provide an unacceptably high PFA in a high noise area. A dynamic thresholding algorithm is therefore necessary. Such an algorithm would automatically estimate the local noise statistics in each data segment, and compute a threshold value to discriminate defect signals from noise. Here we can treat our defect detection problem as that in radar or sonar systems, where the well-known Neyman-Pearson (NP) criterion...
is generally used. This criterion can be phrased as: “Maximize $P_d$ while maintaining the false alarm probability at most at the specified level $P_f$.” Here $P_d$ is the probability of detection. This is usually implemented as a likelihood ratio test:

$$\lambda(y) = \frac{f(y|H_1)}{f(y|H_0)} > \lambda_0,$$  \hspace{1cm} (4.10)

where $f(y|H_0)$ and $f(y|H_1)$ are the densities of $y$ conditioned on two hypotheses, $H_0$ (without target) and $H_1$ (with target). For our defect detection problem, targets mean defects. This NP procedure was applied to the vertical component of the signal. Two hypotheses of measured signal $y$ are:

$H0$: signal from non-defect, $F(y_i)$ is Gaussian with $\mu_i = 0$ and $\sigma_i^2 = \sigma^2$,

$H1$: signal from a defect, $F(y_i)$ is Gaussian with $\mu_i = s_i$ and $\sigma_i^2 = \sigma^2$.

The measured signal $y$ could be assumed to be $K$ independent and identically distributed (i.i.d.) random variables, $y_i$, $i = 1, 2, \ldots, K$. The density function of the $y_i$ under the hypothesis $H_0$ is therefore given by

$$f(y|H_0) = (2\pi\sigma)^{-K/2} \exp \left[-\sum_{j=1}^{K} \frac{y_j^2}{2\sigma^2}\right],$$  \hspace{1cm} (4.11)

and similarly the joint density of the $y_i$ under $H_1$ can be written as

$$f(y|H_1) = (2\pi\sigma)^{-K/2} \exp \left[-\sum_{j=1}^{K} \frac{(y_j - s_j)^2}{2\sigma^2}\right].$$  \hspace{1cm} (4.12)

Using the Neyman-Pearson fundamental lemma, the likelihood ratio can now be formed

$$L(y) = \frac{f(y|H_1)}{f(y|H_0)} = \exp \left[-\sum_{j=1}^{K} \frac{(2s_j y_j - s_j)^2}{2\sigma^2}\right].$$  \hspace{1cm} (4.13)

$L(x)$ is then compared to a threshold $T$. After simplifying [31], the optimum detector using the Neyman-Pearson lemma is

$$\sum_{j=1}^{K} s_j y_j \begin{cases} < T_0 & \Rightarrow H_0 \\ > T_0 & \Rightarrow H_1 \end{cases},$$  \hspace{1cm} (4.14)

where the threshold $T_0$ is determined by setting the false alarm probability $\alpha$.
When all of the \( s_j \) are assumed to be equal to some unknown positive constant \( C \), the detection problem can be simplified as a linear detector

\[
\sum_{j=1}^{K} y_j \begin{cases} < T_1 \Rightarrow H_0 \\ > T_1 \Rightarrow H_1 \end{cases}, \tag{4.15}
\]

The threshold \( T_1 \) can be determined under the NP criterion by fixing the false alarm probability \( \alpha_0 \) \[31\]

\[
T_1 = \sqrt{K} \sigma \Phi^{-1}(1 - \alpha_0), \tag{4.16}
\]

where \( \Phi(\cdot) \) is the cumulative distribution function of a zero mean Gaussian random variable with unit variance.

**Vertical component thresholding results** In order to capture the test statistics of a defect signal more accurately, a sliding window of size \( M \times M \) is used. The threshold procedure introduced above was implemented on the data within the window. Signals before and after thresholding with two different PFAs, 5% and 10%, are shown in Figure 4.14.

### 4.5.3 Phase Thresholding

#### 4.5.3.1 Distribution of Phase Signal

Following a strategy similar to the one used in amplitude thresholding, we need to derive the distribution of the phase signal. We assume both the vertical and horizontal components are normally distributed, i.e.

\[
p_{x_1}(x_1) = \frac{1}{\sqrt{2\pi}\sigma_1} \exp \left( -\frac{(x_1 - \mu_1)^2}{2\sigma_1^2} \right), \tag{4.17a}
\]

\[
p_{x_2}(x_2) = \frac{1}{\sqrt{2\pi}\sigma_2} \exp \left( -\frac{(x_2 - \mu_2)^2}{2\sigma_2^2} \right), \tag{4.17b}
\]

where \( x_1 \) and \( x_2 \) are horizontal (real) and vertical (imaginary) components of eddy-current signal respectively. To calculate the distribution of the phase signal, we need to
normalize these two components

$$
\begin{bmatrix}
  y_1 \\
  y_2
\end{bmatrix}
= \begin{bmatrix}
  \frac{1}{\sigma_1} & 0 \\
  0 & \frac{1}{\sigma_2}
\end{bmatrix}
\begin{bmatrix}
  x_1 \\
  x_2
\end{bmatrix}
+ \begin{bmatrix}
  \frac{-\mu_1}{\sigma_1} \\
  \frac{-\mu_2}{\sigma_2}
\end{bmatrix}.
$$

To find the distribution of amplitude and phase, we use the transformation

$$
r = \sqrt{y_1^2 + y_2^2} > 0, \\
\phi = \tan^{-1}\left(\frac{y_1}{y_2}\right),
$$

where \(\tan^{-1}\) operation returns the principal value: \(-\pi < \phi < \pi\). The Jacobian is

$$
\frac{\partial(r, \phi)}{\partial(y_1, y_2)} = \begin{vmatrix}
  \frac{y_1}{r} & \frac{y_2}{r} \\
  -\frac{y_2}{r^2} & \frac{y_1}{r^2}
\end{vmatrix} = \frac{1}{r},
$$

and the inverse transformations are \(y_1 = r \cos \phi, \ y_2 = r \sin \phi\). For two independent normalized Gaussian variables, \(Y_1\) and \(Y_2\), we have

$$
p_{Rs}(r, \phi) = \frac{r}{2\pi} \exp\left(-\frac{r^2}{2}\right) = \frac{1}{2\pi} \left[r \exp\left(-\frac{r^2}{2}\right)\right].
$$

The marginal density of \(\Phi\) is

$$
p_{\Phi}(\phi) = \int_0^\infty p_{Rs}(r, \phi)dr = \frac{1}{2\pi}.
$$

This implies that \(\Phi\) follows a uniform density.

The marginal density of \(R\) is

$$
p_R(r) = r \exp\left(-\frac{r^2}{2}\right),
$$

which is a Rayleigh distribution.

**4.5.3.2 Thresholding Algorithm**

The calibration procedure results in signals from all defects lying between \(0^\circ\) and \(180^\circ\) in the impedance plane in the absence of measurement noise. So we have two hypotheses:
• \( p_{\phi}(\phi|H_1) = \frac{1}{\pi}, \quad \phi \in (0, \pi) \), for signals from specimens with a defect,

• \( p_{\phi}(\phi|H_0) = \frac{1}{\pi}, \quad \phi \in (0, 2\pi) \), for signals from specimens without defects.

The phase signals were thresholded with two thresholds, \( T_1 \) and \( T_2 \) as shown in Figure 4.13. Based on POD concepts, we get

\[
PFA = \int_T^\pi p_{\phi}(\phi|H_0)d\phi = \int_T^\pi \frac{1}{2\pi}d\phi = \frac{T_2 - T_1}{2\pi}, \tag{4.24a}
\]

\[
PFA = \int_T^\pi p_{\phi}(\phi|H_1)d\phi = \int_T^\pi \frac{1}{\pi}d\phi = \frac{T_2 - T_1}{\pi}, \tag{4.24b}
\]

where \(-\pi < T_1 < T_2 \leq \pi\).

In this case, it appears that it is not possible to establish a threshold \( T \) using POD/POFA concept. Further discussion for characterizing amplitude and phase probability distributions are given in Chapter 7.

### 4.5.3.3 Phase Thresholding Results

For a given POD = \( \delta \), we set the two thresholds, \( T_1 \) and \( T_2 \) equally apart, i.e.

\[
T_1 = \frac{\pi(1 - \delta)}{2} = \pi - T_2 \tag{4.25}
\]

We retain signals whose phase lie between \( T_1 \) and \( T_2 \). Phase images before and after the application of the thresholding scheme with two different PODs are shown in Figure 4.15. As shown in the figures, many artifacts remain after the phase thresholding. New scheme was introduced in next section.

### 4.5.4 Phase Gating

In the previous phase thresholding algorithm, the POD is always set at twice the PFA. An additional step is necessary to reduce the PFA for a given POD. The artifacts introduced in the phase signal due to phase wrapping is mainly applicable to signals whose magnitude is small. So we employ a two-step thresholding approach, called phase
gating, to highlight the defect indication more clearly. It includes two thresholding procedures; one for magnitude and the other for phase. In magnitude thresholding, signals whose magnitude are less than some threshold level are treated as noise and replaced with zeros. The zero levels are assigned to the horizontal as well as vertical components of the eddy-current signal. The phase thresholding scheme involves the application of the algorithm described earlier. The phase image obtained after phase gating is shown in Figure 6.5. With this two-step thresholding algorithm, most of the artifacts arising from phase wrapping phenomena are filtered out.

4.5.5 Discussions

Optimal thresholding algorithms based on POD concepts are applied both to the vertical component and phase signal. Thresholds for signals within a sliding window are determined according to Neyman-Pearson criterion and applied to the vertical component. This procedure has been successfully implemented and initial results looks promising.

However, things are different for the phase signal. Since the phase signal has a uniform distribution after normalizing the horizontal and vertical component there is no straightforward basis for establishing a threshold. We can only determine threshold levels for a given POD (or PFA). Furthermore, a simple phase thresholding scheme cannot eliminate artifacts that are attributable to phase wrapping. Phase gating, a two-step thresholding procedure, was applied to the phase signal. Preliminary results demonstrate the effectiveness of the scheme.

4.6 Feature Extraction

The task of this operation is to extract features that are relevant for detection and/or classification of the preprocessed signals. The extracted features should be relevant, in
that they should enable detection of different types of degradations. Various features considered for classification include the area of the region of interest (ROI), the maximum, minimum and mean phase angles in the indication, the phase spread and the volume of the ROI. The features are computed for both the real and imaginary components of the signals from all coils at all frequencies. In Figure 4.16, the preprocessed vertical component and phase signal are depicted. In practice, the following quantities were calculated as candidate features:

- **Area\_vert**: area of indication, number of pixels in vertical component,
- **Max\_vert**: maximum value of the indication in vertical component,
- **Volume\_vert**: volume of indication, summation of values in vertical component,
- **Mean\_phase**: mean of values in phase after phase gating,
- **Maximum, and minimum phase value**,
- **Parameters of defect boundary in vertical component (perimeter, vertical range and horizontal range),**
- **Number of distinct indications.**

A well-known decision tree algorithm, named *iterative dichotimizer 3 (ID3)* [32], is employed to identify key features that have the maximum amount of discriminatory information. The algorithm uses concepts from information theory to select the feature that maximizes the classification performance at each stage of the decision tree. By performing this operation iteratively at each level of the decision tree, the algorithm obtains the best possible subset of features for optimal classification. This subset of features is saved and applied to our neural network classifier to discriminate between defect and nondefect signals, and different degradation types.
Figure 4.14 Vertical component thresholding: (a) after calibration, (b) results with PFA=5% and (c) results with PFA=10%.
Figure 4.15 Phase thresholding: (a) after calibration, (b) results with POD=80% and (c) results with POD=90%.

Figure 4.16 Phase gating results: (a) after magnitude thresholding, (b) results with POD=80% and (c) results with POD=90%.
CHAPTER 5 SIGNAL CLASSIFICATION WITH MLP NEURAL NETWORK

5.1 Introduction

Classification with neural network is one of the most popular nonphenomenological approaches to addressing the NDE inverse problem. The inverse problem in this context involves reconstruction of defect profiles given a transducer response signal. Because the physical process associated with eddy-current phenomenon is diffusive in nature, inverse problem are, in general, ill-posed, lacking continuous dependence of the measured signals on defects. This has led to the development of a variety of approaches, from simple calibration method to complex neural networked based iterative algorithm, to address the issue [33].

Neural networks have been used with considerable success in the classification and characterization of eddy-current and ultrasonic NDE signals [34, 35, 36]. These networks are also capable of learning in an incremental mode and use prior knowledge for improving its performance with time. Here, a brief introduction of neural networks and its learning algorithm is given out in section 5.2. The classification procedure using a multilayer perceptron (MLP) neural network and results obtained to date are presented in section 5.3. Wavelet basis function neural network and its application for characterizing defects are discussed in Chapter 6.
5.2 Neural Networks

An artificial neural network is a massively parallel-distributed processor that is capable of storing and retrieving experiential knowledge [37]. It consists of simple processing elements that are densely interconnected. The characteristics of the network are determined by the nature of the processing elements, known as nodes, and by the strengths of the interconnections, known as synaptic weights, which are used to store the knowledge. The network acquires knowledge by a learning process, which modifies the synaptic weights in an orderly fashion to achieve a desired objective.

5.2.1 General

The basic neuron model proposed by Minsky and Papert [38] is the much discussed single layer perceptron. The input to the perceptron is an n-dimensional vector. It then performs a weighted sum, adds a bias and passes the result through a nonlinear element. The primary use of a perceptron is in pattern classification. Patterns are distinct features that are derived from signals of different classes. The perceptron can distinguish between two classes by separating them with linear decision boundary. The perceptron model cannot generate nonlinear decision boundaries and consequently cannot be used in a variety or real world pattern recognition problems, wherein classes are not linearly separable. This problem is overcome in the next generation of neural networks, the multilayer perceptron.

5.2.2 Multilayer Perceptron

The multilayer perceptron is constructed by cascading several layers of perceptrons. It has proved to be the mainstay of pattern recognition applications in the industry. The MLP overcomes the limitations of a single perceptron, in that, it can generate arbitrary complex, nonlinear decision boundaries for multi-class pattern recognition problems. A
four-layer MLP with two hidden layers is shown in Figure 5.1. Each perceptron is now referred to as a node.

The input signal (vector) is presented to the first layer of nodes, the output of which is fed to each node in the second layer, and so on. The intermediate layers of nodes, in between the input and output layers are known as the hidden layers.

**Learning algorithm for training an MLP**  As mentioned earlier, the knowledge gained by a neural network resides in the strength of the interconnection weights. A popular learning paradigm for determining these weights is to present the network with inputs and known (desired) outputs and then to adapt the weights to yield the desired objective. This operation of learning by examples is referred to as training the network. Once sufficient amount of data is obtained from a physical process, the design and development of a neural network proceeds as follows in two steps:

(i) Training — part of the data that is deemed most representative of the entire data set is used to determine the network weights,

(ii) Testing — the remaining data is passed through the network to see if the desired objective is attained.

A “properly trained” network has the ability to generalize, i.e., it can recognize patterns and/or make decisions on data that are not part of the training data set. The power of a neural network to generalize gives it the ability to interpret varied data types.

### 5.3 Signal Classification

#### 5.3.1 Types of Defects and Probes

Various kinds of defects appeared in tubes of the steam generator. Based on the orientation, defects can be categorized as axial defect and circumferential defect as shown
Based on the coils connection in the bridge circuit, eddy-current inspection probe can be categorized as absolute probe and differential probe. The details and pro-cons of them are beyond of the scope of this report. To detect cracks in different orientation along the tube, like axial and circumferential defect, coils in the probe are also mounted in different direction. The newly designed +Point [39] probe makes groundbreaking advances in the development of rotating-probe eddy-current testing. Its unique “+” coil configuration is actually two coils, one is wound longitudinal and the other is wound circumferential. Intersecting one another in the middle, these two coils are connected in differential opposition to form one bidirectional coil pair. This bidirectional coil pair is able to “sense” the orientation of an indication as either axial or circumferential. Working alongside the “+” coil are two pancake-type coils: the primary test coil and a high frequency shielded coil as shown in Figure 5.1. Today, probes used in industry are mainly this type. So our data analysis is focused on data collected with this +Point probe.

Compared with this +Point probe is the traditional 3-Coil rotating-probe (Delta probe), which consists of one pancake coil, one axial coil and one circumferential coil as
shown in Figure 5.2. The axial coil has greater sensitivity to axial cracks and circumferential coil is oriented for greater sensitivity to circumferential cracks. The pancake coil, commonly in both type of probes, are used to detect general discontinuities. Data collected from both of these two types of coils are analyzed and results are compared.

5.3.2 Classification Scheme

A hierarchical neural network classifier shown in Figure 5.5 is employed for signal classification. The data is first classified on a defect/non-defect basis. The defect signal, as classified in step 1, is applied to an Axial/Circ defect classifier. In the case of axial defect signals, a second classifier is employed to distinguish between multiple axial/circ indications and a single axial/circ indication. MLP neural networks are used for classification in each of the three cases.

5.3.3 Classification Results

The neural network classifier was evaluated with field data provided by the Electrical Power Research Institute (EPRI). Data collected from two types of inspection systems, Delta probe and +Point probe, were preprocessed and classified. For the Delta probe system, a total of 40 TSP data files were available. Twenty of them were reported to
contain defects by operators, the rest were reported as containing benign indications (non-defects). Ten of the signals representing defects were labeled as multiple axial indication (MAI) data, while the remaining 10 were single axial indication (SAI) data. Of the twenty defect and non-defect signals, twelve were employed to train the neural network, the remaining eight were used for testing. The results obtained are summarized in Table 1. With the 10 MAI and 10 SAI signals, we use 6 for training and 4 for testing. The results obtained are summarized in Table 2. Seventy-six +Point probe signals were made available by EPRI. Thirty-eight of them are labeled as defect signals while the remaining are non-defect signals. Among the thirty-eight defect signals, 26 were reported by analysts to be axial indications. The rest (12) were reported to circumferential indications. Among the 26 axial indication signals, analysts reported 19 of them, as MAI and 7 were SAI. The data set was partitioned into training and testing data set as indicated in Table 5.1.

The results presented for the two-step classification procedure indicates that the
Table 5.3 Axial/Circumferential classification result

<table>
<thead>
<tr>
<th>Test Database</th>
<th>Classifier Output</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Actual Class</td>
</tr>
<tr>
<td>Delta Probe</td>
<td>Axial</td>
</tr>
<tr>
<td></td>
<td>Circ</td>
</tr>
<tr>
<td>+Point Probe</td>
<td>Axial</td>
</tr>
<tr>
<td></td>
<td>Circ</td>
</tr>
</tbody>
</table>

Table 5.4 MAI/SAI classification result

<table>
<thead>
<tr>
<th>Test Database</th>
<th>Classifier Output</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Actual Class</td>
</tr>
<tr>
<td>Delta Probe</td>
<td>MAI</td>
</tr>
<tr>
<td></td>
<td>SAI</td>
</tr>
<tr>
<td>+Point Probe</td>
<td>MAI</td>
</tr>
<tr>
<td></td>
<td>SAI</td>
</tr>
</tbody>
</table>

The proposed preprocess algorithm is capable of extracting meaningful information from the eddy-current data and MLP was successfully used to classify signals between different degradation types. As we can see, there are no false alarms and misclassification in the results of +Point data. This is just as we expected, since +Point probe is more sensitive to defects and is more widely used in practice.

In order to determine the degree of the generalization of the trained classifier, additional data not used in the training of the neural networks were processed and applied to the classifier.

- +Point three coil probe: 60 data files from TSH regions (all NDD)
- Delta Probe: 28 data files from TSP regions

The results obtained are summarized in Table 5.5. From this table, the percentage of misclassification rates is rather high (10 of 28 for Delta probe data, 7 out of 60 for +Point probe data). Closer analysis of the data leads to the reason that the signals are obtained at different instrument parameters, especially the different excitation frequencies. This
Table 5.5  MLP classifier validation result

<table>
<thead>
<tr>
<th>Test Database</th>
<th>Classifier Output</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Actual Class</td>
<td>Degradation</td>
<td>NDD</td>
</tr>
<tr>
<td>Delta Probe</td>
<td>Degradation</td>
<td>14</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>NDD</td>
<td>8</td>
<td>4</td>
</tr>
<tr>
<td>+Point Probe</td>
<td>NDD</td>
<td>7</td>
<td>53</td>
</tr>
</tbody>
</table>

means that additional algorithms, like compensation or data fusion, need to be applied to make signals comparable, when the signals are obtained under different conditions or circumstances. This is part of our future work.
For each indication in the processed signal, which was classified as defect in previous step, a simple characterization scheme can be used to predict its mean length, depth and width, conveying little information about its actual shape. In most situations, defects caused by corrosion have complicated shapes. A complicated defect characterization algorithm is needed to predict the exact profile of the defect, indicating the variation in defect depth along the axial and circumferential directions, on the tube. One of the earliest and most widely used approaches is the calibration method, in which the phase of eddy-current signal was related to the depth of the defect. A calibration curve of depth of defects and phase was obtained from known defects signals from the calibration standard. For a given defect signal, its equivalent depth was predicted with simple interpolation algorithm. This method is currently used in industry to generate estimates of 1-D size of a defect. The limitation of calibration method is that it becomes invalid if the defect shapes are substantially different from the shapes of the calibration defects.

The other approach is using learning algorithm such as neural networks. This approach implements function approximation using multiresolution wavelets and neural network. Mathematically, this approach is a complex, highly nonlinear mapping from an input vector space on to an output vector space, as shown in Figure 6.1. Here the input vector is the phase image of eddy-current signal and the output vector is the 3-D defect depth profile. In this section, a brief introduction of wavelet basis function neu-
neural network was given in section 6.1. The implementation result and its comparison to calibration curve method was presented in section 6.2.

6.1 Wavelet Basis Function Neural Network

The wavelet basis network is based on the theory of multiresolution representation of a function by wavelet transforms [40]. It is known that function can be represented as a weighted sum of orthogonal basis functions. Typical orthogonal functions are sinusoids, Legendre polynomials etc. However such basis functions do not have a finite length of support and are therefore good global approximators. A special class of functions, called wavelets, can be constructed as a basis for all square-integrable functions. Such sets of basis functions are both local and orthogonal. The wavelet transform represents functions in terms of fixed building blocks, the wavelets, at different scales and translations. A flurry of research activity in recent years, especially in the field of data compression, has led to the construction of different types of wavelets, with varying properties. Characterizing defects using neural networks can be recast as a problem in multidimensional interpolation. The input space corresponds to the NDE signal generated by sensors and the output corresponds to the defect characteristics such as length, width, depth and profile. WBF neural networks allow functional approximation based on multiresolution...
where $L$ is the number of resolutions, $N_j$ is the number of translated basis functions at resolution $j$, $k$ is the translated point, $\psi^j_k$ is a dilated and translated version of a mother wavelet, and $c_k$ is the center of basis function at translation point $k$. The architecture of a typical WBF neural network implementing the above equation is similar to radial basis function (RBF) neural networks in that both neural networks have a single hidden layer. In contrast to RBF neural networks, a WBF neural network employs a family of wavelets as basis functions and has sets of wavelet function nodes depending on the number of resolutions. In this method, the number of resolutions is either increased or decreased to control the level of prediction accuracy. The number and location of the basis function centers $C$ is determined using the well-known ISODATA clustering scheme. $\sigma$ is the standard deviation that is used as a bias term, $R$ is the length of input eddy-current signal, $Q^1$ is the number of training data set, $Q^2$ is the length of defect profile, and $W$ is the weight matrix relating the input phase and the output defect profile.
6.1.1 Scaling and Wavelet Basis Functions

Scaling and wavelet functions are employed as basis functions so that the norm error of the function approximation is minimized using a minimum number of functions [34]. An intuitive procedure is used to select these functions. Wavelet bases functions with a high degree of smoothness are usually chosen for obtaining good generalization in the case of multidimensional problems with limited training data. In this paper, the Mexican hat function is employed as a wavelet:

\[
\psi(x) = (1 - x^2) \exp\left(-\frac{x^2}{2\sigma^2}\right),
\]

where \(\sigma\) is the standard deviation. This wavelet decays rapidly in the time and frequency domains and the frame constant is very near unity. A Gaussian radial basis function is used as a scaling function:

\[
\phi(x) = \left(-\frac{x^2}{2\sigma^2}\right).
\]

6.1.2 Centers Selection

The centers of the basis functions can be estimated using the k-means clustering algorithm or one of its several variants. The number of centers at each resolution can be determined heuristically. Previous studies have shown that the performance of the network is highly dependent on the location and number of centers. Therefore, an LMS algorithm is typically employed in order to obtain better performance instead of using the k-means clustering algorithm not only for determining the optimal locations, but also for determining the widths of the centers. However, such an algorithm is unsuitable for training a multiresolution network. In this research work, a dyadic center selection scheme was used to calculate the location and number of centers. Since the task at the lowest resolution is to coarsely approximate the function, the locations of basis functions are chosen using the ISODATA clustering algorithm. This corresponds to the first term in the approximation given by Equation (6-1). Subsequently, new centers,
which correspond to the second term in Equation (6-1), are calculated using the dyadic selection scheme to obtain finer approximations. The dyadic selection scheme is similar to the dyadic dilation scheme in wavelet theory. The centers at the next resolution are expanded by dividing the Euclidean distance between adjacent centers at the previous resolution. If too many basis functions are used and overfitting have occurred, a center pruning algorithm is used in order to eliminate unnecessary centers.

6.2 Characterization Results

The algorithms were evaluated with eddy-current data obtained from defects machined in tube samples. The data was collected using a three-coil rotating-probe (two pancake coils and a plus-point coil) at several excitation frequencies. In this paper, data from pancake coil rotating-probe was used. Figure 6.4 and Figure 6.5 show the outputs of the calibration and phase gating stages respectively. Figure 6.3 indicates the calibration curve obtained from calibration data.

![Calibration curve](image)

Figure 6.3 Calibration curve.
Figure 6.4 Calibration result.

Figure 6.6 describes the defect characterization result based on calibration curve and WBF neural network. The test data was a deep 59% ID axial defect. The result shows that WBF neural network shows considerable promise in predicting defect profiles. Additional improvement can be obtained using an adaptive boundary extraction algorithm to locate the defect area and using data fusion techniques to improve the characterization result.
Figure 6.5  Phasegating.

Figure 6.6  Defect characterization result based on calibration curve method and WBFNN.
CHAPTER 7 ESTIMATING STATISTICAL PROPERTIES

7.1 Introduction

As discussed in Chapter 4, there is no straightforward basis for establishing a threshold for phase information. Figure 7.1 shows impedance-plane plots of typical signals measured by the rotating-probe eddy-current system. Further analysis of the potential defects is needed to discriminate between defects and nondefects, as well as between different kinds of defects. In this chapter (see also [41], [42]), a statistical model for characterizing the amplitude and phase probability distributions of the potential defects is proposed. The squared amplitudes and phases of the potential defect signals are modeled as independent, identically distributed (i.i.d.) random variables following gamma and von Mises distributions (respectively) and derive a maximum likelihood (ML) method for estimating the unknown amplitude and phase distribution parameters from noisy measurements. A maximum a posteriori (MAP) estimator of the signal amplitudes and phases is also developed.

7.2 Signal and Noise Models

Characterizing the amplitude and phase probability distributions of eddy-current signals is important for flaw detection and classification. For example, after preprocessing and calibration of rotating-probe eddy-current data, the “true” defect signals should have sufficiently large amplitudes (compared with the noise level) and their phases should lie
in the first and second quadrants of the impedance plane (i.e. between 0 and \(\pi\) rad), see [43]. The phase information is also essential for discriminating between inner diameter (ID) and outer diameter (OD) defects, see [43] and Fig. 7.1. (Note that the defect signals in Fig. 7.1 were collected from machined defects in a low-noise environment.) Below, we describe a statistical model for characterizing the amplitude and phase probability distributions of the potential defects.

Assume that we have collected \(K\) complex measurements \(y_k, k = 1, 2, \ldots, K\) of an eddy-current signal from neighboring spatial locations. The measurements are modeled as follows:

\[
y_k = \sqrt{\alpha_k} \cdot e^{i\beta_k} + e_k, \quad k = 1, 2, \ldots, K, \tag{7.1}
\]

where

(i) \(\alpha_k, k = 1, 2, \ldots, K\) are i.i.d. squared signal amplitudes (powers) following a gamma distribution, described by the probability density function (pdf):

\[
p_\alpha(\alpha_k; a, b) = \frac{b^a}{\Gamma(a)} \cdot \alpha_k^{a-1} \exp(-b\alpha_k), \quad \alpha \geq 0, \tag{7.2}
\]
where \( a, b > 0 \). Fig. 7.2 (left) illustrates the gamma distribution and its versatility. (Interestingly, in the special case where \( a = 1 \), the amplitudes \( \sqrt{\alpha_k} \) follow a Rayleigh distribution.)

(ii) \( \beta_k, k = 1, 2, \ldots, K \) are i.i.d. signal phases, independent of the amplitudes, which follow a von Mises distribution [44, 45], described by the pdf:

\[
p_{\beta}(\beta_k; c, d) = \frac{1}{2\pi I_0(d)} \cdot \exp[d \cos(\beta_k - c)], \quad 0 < \beta_k \leq 2\pi, \tag{7.3}
\]

where \( c \) and \( d > 0 \) can be viewed as the mean and variance parameters (respectively), and \( I_0(\cdot) \) denotes the modified Bessel function of the first kind and order zero. The von Mises distribution is one of the most used distributions for modeling random phase and is analogous to the normal distributions on the real line. It is also known as the Tikhonov distribution in the communications literature, see e.g. [46], [47, eq. (3.37)], and [48, eq. (6.1)]. Von Mises distributions with different values of \( c \) and \( d \) are shown in Fig. 7.2 (right). Interestingly, in the special case where \( d = 1 \), it simplifies to the uniform distribution on interval \([0, 2\pi]\).

(iii) \( e_k, k = 1, 2, \ldots, K \) are i.i.d. zero-mean complex Gaussian noise samples independent of the signal amplitudes and phases, having known variance \( \sigma^2 \). [The noise variance \( \sigma^2 \) can be estimated from the neighboring measurement locations that contain only noise.]

Our goal is to find the ML estimates of the unknown model parameters \( a, b, c, \) and \( d \) using the observations \( y_k, k = 1, 2, \ldots, K \).

Define the unknown parameter vector

\[
\lambda = [a, b, c, d]^T \tag{7.4}
\]

and the vectors of signal amplitudes and phases

\[
\theta_k = [\alpha_k, \beta_k]^T, \quad k = 1, 2, \ldots, K, \tag{7.5}
\]
where $^{aT}$ denotes a transpose. From the assumptions (i)--(iii) and equations (7.1)--(7.3) it follows that the conditional pdf of $y_k$ given $\theta_k$ is complex Gaussian:

$$p_{\psi \theta}(y_k|\theta_k) = \frac{1}{\pi \sigma^2} \exp \left( - \frac{|y_k - \sqrt{\alpha_k} e^{i\beta_k}|^2}{\sigma^2} \right), \quad k = 1, 2, \ldots, K, \quad (7.6)$$

and the pdf of $\theta_k$ is

$$p_\theta(\theta_k; \lambda) = p_\alpha(\alpha_k; a, b) \cdot p_\beta(\beta_k; c, d), \quad k = 1, 2, \ldots, K. \quad (7.7)$$

The marginal distribution of $y_k$ is then

$$p_\psi(y_k; \lambda) = \int_\Theta p_{\psi \theta}(y_k|\theta)p_\theta(\theta; \lambda) \, d\theta$$

$$= \frac{1}{\pi \sigma^2} \int_0^{2\pi} d\beta \int_0^\infty \exp \left( - \frac{|y_k - \sqrt{\alpha} e^{i\beta}|^2}{\sigma^2} \right) p_\alpha(\alpha; a, b) p_\beta(\beta; c, d) \, d\alpha, \quad (7.8)$$

where $\Theta = \{(\alpha, \beta) : 0 < \alpha, 0 < \beta \leq 2\pi\}$. The ML estimate of $\lambda$ is obtained by maximizing the log-likelihood function of $\lambda$ for all available measurements $y = [y_1, y_2, \ldots, y_K]^T$:

$$L(\lambda, y) = \sum_{k=1}^K \ln p_\psi(y_k; \lambda). \quad (7.9)$$
The difficulty in estimating the unknown parameters in the above model arises due to the integral form of the density function (7.8). In the following, we present the Newton-Raphson method for finding the ML estimates of $\lambda$.

### 7.3 Maximum Likelihood Estimation

We derive the Newton-Raphson algorithm for maximizing (7.9). The gradient vector $\partial L(\lambda, y)/\partial \lambda$ and Hessian matrix $\partial^2 L(\lambda, y)/\partial \lambda \partial \lambda^T$ are

$$
\frac{\partial L(\lambda, y)}{\partial \lambda} = \sum_{k=1}^{K} \frac{\partial \ln p_v(y_k; \lambda)}{\partial \lambda}, \quad \frac{\partial^2 L(\lambda, y)}{\partial \lambda \partial \lambda^T} = \sum_{k=1}^{K} \frac{\partial^2 \ln p_v(y_k; \lambda)}{\partial \lambda \partial \lambda^T},
$$

where the terms in the above summations have been computed using the following formulas:

$$
\frac{\partial}{\partial \lambda_i} \{ \ln p_v(y_k; \lambda) \} = \frac{1}{p_v(y_k; \lambda)} \int_{\Theta} p_{\psi \theta}(y_k|\theta) \frac{\partial p_v(\theta; \lambda)}{\partial \lambda_i} d\theta
$$

$$
\frac{\partial^2}{\partial \lambda_i \partial \lambda_m} \{ \ln p_v(y_k; \lambda) \} = \frac{1}{p_v(y_k; \lambda)} \int_{\Theta} p_{\psi \theta}(y_k|\theta) \frac{\partial^2 p_v(\theta; \lambda)}{\partial \lambda_i \partial \lambda_m} d\theta
$$

$$
-\frac{1}{[p_v(y_k; \lambda)]^2} \cdot \int_{\Theta} p_{\psi \theta}(y_k|\theta) \frac{\partial p_v(\theta; \lambda)}{\partial \lambda_i} d\theta \cdot \int_{\Theta} p_{\psi \theta}(y_k|\theta) \frac{\partial p_v(\theta; \lambda)}{\partial \lambda_m} d\theta
$$

for $i, m = 1, 2, 3, 4$ and $k = 1, 2, \ldots, K$. Complete results of these first and second derivatives are given in Appendix A. After applying the change-of-variable transformation

$$u = b \alpha,$$

the above integral expressions can be easily computed using Gauss quadratures, see [49, Ch. 5.3]. We applied the Gauss-Chebyshev and generalized Gauss-Laguerre quadratures (of orders $N_c$ and $N_L$) to approximate integrals over $\beta$ and $u$ (respectively), yielding

$$
\int_0^{2\pi} d\beta \int_0^\infty f(u, \beta) u^{a-1} \exp(-u) du \approx \frac{2\pi}{N_c} \sum_{n=1}^{N_c} \sum_{i=1}^{N_L} w_i(a-1) f(u_i(a-1), \beta_n),
$$

where $f(u, \beta)$ is an arbitrary real function, $u_i(a-1)$ and $w_i(a-1)$ are the abscissas and weights of the generalized Gauss-Laguerre quadrature of order $N_L$ with parameter $a-1$, respectively.
and
\[ \beta_n = \frac{(2n - 1)\pi}{N_c}, \quad n = 1, 2, \ldots, N_c \] (7.14)
are the abscissas of the Gauss-Chebyshev quadrature. For example, applying (7.12) and
(7.13) to (7.8) yields

\[
p_{s}(y_k; \lambda) = \frac{1}{2\pi^{2}\sigma^{2} \Gamma(a) I_0(d)} \int_{0}^{2\pi} \exp[d \cos(\beta - c)] \, d\beta \
\times \int_{0}^{\infty} \exp \left[- \frac{|y_k - \sqrt{u/b \cdot e^{j\beta}}|^2}{\sigma^2} \right] u^{a-1} \exp(-u) \, du \\
\approx \frac{1}{\pi \sigma^{2} \Gamma(a) N_c I_0(d)} \sum_{n=1}^{N_c} \exp[d \cos(\beta_n - c)] \
\times \sum_{i=1}^{N_t} w_{n,i} (a - 1) \exp \left[- \frac{|y_k - \sqrt{u_{t,i}(a - 1)/b \cdot e^{j\beta_n}}|^2}{\sigma^2} \right]. \] (7.15)

To compute the derivatives in (7.11), we also utilized the following formulas (see [45, eqs. (A.7) and (A.9)]):

\[
\frac{d I_0(d)}{dd} = I_1(d), \quad \frac{d^2 I_0(d)}{dd^2} = I_2(d) = I_0(d) - I_1(d) \frac{d}{d}. \] (7.16)

The (damped) Newton-Raphson algorithm updates the estimates of \( \lambda \) as follows (see e.g. [49, eq. (13.25)], [51, Ch. 9.7], [52], and [53, Ch. 9.5]):

\[
\lambda^{(i+1)} = \lambda^{(i)} - \delta^{(i)} \cdot \left[ \frac{\partial L(\lambda^{(i)}, y)}{\partial \lambda} \right]^{-1} \frac{\partial L(\lambda^{(i)}, y)}{\partial \lambda}, \] (7.17)

where the damping factor \( 0 < \delta^{(i)} \leq 1 \) is chosen (at every step \( i \)) to ensure that the log-
likelihood function (7.9) increases and the parameter estimates remain in the allowable
parameter space \( (a, b, d > 0) \). Initialization of the above iteration is discussed below.

### 7.3.1 Initialization

The above Newton-Raphson iteration can be initialized by neglecting the noise effects
and utilizing the following simple moment estimators of \( a \) and \( b \):

\[
a^{(0)} = \frac{\bar{E}[|\alpha|^2]}{\text{var}(\alpha)}, \quad b^{(0)} = \frac{\bar{E}[|\alpha|]}{\text{var}(\alpha)}, \] (7.18a)
where

\[ \hat{\mathbf{E}}[\alpha] = \frac{1}{K} \sum_{k=1}^{K} |y_k|^2, \quad \text{var}(\alpha) = \frac{1}{K} \left[ \sum_{k=1}^{K} |y_k|^4 \right] - (\hat{\mathbf{E}}[\alpha])^2, \]

(7.18c)

and the following estimators of \( c \) and \( d \) (see [45, eqs. (2.2.4) and (5.3.11)]):

\[ c^{(0)} = \begin{cases} \tan^{-1}(S_y/C_y), & C_y \geq 0 \\ \tan^{-1}(S_y/C_y) + \pi, & C_y < 0 \end{cases}, \]

(7.19a)

\[ d^{(0)} = (1.28 - 0.53 \cdot \bar{R}_y^2) \cdot \tan(\pi \bar{R}_y/2). \]

(7.19b)

where

\[ \bar{C}_y = \frac{1}{K} \sum_{k=1}^{K} \cos(\angle y_k), \quad \bar{S}_y = \frac{1}{K} \sum_{k=1}^{K} \sin(\angle y_k), \quad \bar{R}_y = (\bar{C}_y^2 + \bar{S}_y^2)^{1/2}. \]

(7.19c)

### 7.3.2 Cramér-Rao Bounds

The CRB matrix for the unknown parameter vector \( \mathbf{\lambda} \) can be computed by inverting the expected negative Hessian matrix [see (7.10)], where the expectation is performed with respect to the distribution of \( y \) [54, Ch. 3.7]:

\[ \text{CRB}_\lambda(\lambda) = -\left\{ \mathbb{E}[y \left[ \frac{\partial^2 L(\lambda, y)}{\partial \lambda \partial \lambda^T} \right]] \right\}^{-1}. \]

(7.20)

The above expectation requires multidimensional integration, which can be performed using Monte Carlo integration, i.e. by averaging \( \partial^2 L(\lambda, y)/\partial \lambda \partial \lambda^T \) over many realizations of \( y \).

The exact CRB in (7.20) does not have a closed-form expression and it is hence difficult to predict how it behaves as a function of the unknown parameters. Under the complete-data model, i.e. assuming that the signal amplitudes \( \alpha \) and phases \( \beta \) are known, we can easily compute the complete-data CRB (see Appendix B):
CRB\text{c,}\lambda(\lambda) = \frac{1}{K} \begin{bmatrix}
\frac{\Gamma(\alpha)\Gamma''(\alpha) - \Gamma'(\alpha)^2}{[\Gamma(\alpha)]^2} & -\frac{1}{b} & 0 & 0 \\
-\frac{1}{b} & \frac{a}{b^2} & 0 & 0 \\
0 & 0 & \frac{d I_1(d)}{I_0(d)} & 0 \\
0 & 0 & 0 & \left[1 - \left(\frac{I_1(d)}{I_0(d)}\right)^2 \right]^{-1}
\end{bmatrix}, \quad (7.21a)

implying that

\text{CRB}_{c, e} = \frac{I_0(d)}{K \cdot d I_1(d)}, \quad \text{CRB}_{c, d} = \frac{1}{K} \cdot \left[1 - \left(\frac{I_1(d)}{I_0(d)}\right)^2 \right]^{-1}. \quad (7.21b)

Clearly, the complete-data CRB is a lower bound on the exact CRB, i.e. CRB(\lambda) > CRB_{c}(\lambda) is a positive semidefinite matrix.

**Wald Confidence Region:** Denote by \(\lambda^{(\infty)}\) the ML estimate of \(\lambda\) obtained using the iteration (7.17). Then, a linearized 100(1 - \alpha)\% confidence region (in the form of an ellipsoid) for testing the null hypothesis \(H_0: \lambda = \lambda^{(\infty)}\) versus the alternative \(H_1: \lambda \neq \lambda^{(\infty)}\) can be computed as (see [55], [56, Ch. 4.4], [57, Ch. 6e.3], [58, Ch. 7.3.3]):

\[\left\{ \lambda : (\lambda - \lambda^{(\infty)})^T \text{CRB}(\lambda^{(\infty)})^{-1}(\lambda - \lambda^{(\infty)}) \leq \chi^2_{4,1-\alpha} \right\}, \quad (7.22)\]

where the threshold \(\chi^2_{4,1-\alpha}\) is equal to the value at which the cumulative distribution function of a \(\chi^2\) random variable with \text{dim}(\lambda) = 4\ degrees of freedom is equal to \(1 - \alpha\).

Once the ML estimates of \(\lambda\) have been computed, we can utilize them to obtain maximum a posteriori (MAP) estimates of the amplitudes and phases of the eddy-current signal, as shown in the following section.

### 7.4 MAP Estimation of Signal Amplitudes and Phases

Assume that the model parameters \(\lambda\) are known. We compute the MAP estimates of the signal amplitudes \(\alpha = [\alpha_1, \alpha_2, \ldots, \alpha_K]^T\) and phases \(\beta = [\beta_1, \beta_2, \ldots, \beta_K]^T\) by
maximizing
\[ L_{\text{MAP}}(\alpha, \beta; y, \lambda) = \sum_{k=1}^{K} \ln[p_{y_k}(y_k|\theta_k) \cdot p_\alpha(\alpha_k; a, b) \cdot p_\beta(\beta_k; c, d)] \]

\[ = -K \ln(2\pi^2 \sigma^2) - \left( \sum_{k=1}^{K} \left| y_k - \frac{\alpha_k \cdot e^{j\beta_k}}{\sigma^2} \right|^2 \right) + K a \ln b - K \ln \Gamma(a) \\
+ (a - 1) \cdot \left( \sum_{k=1}^{K} \ln \alpha_k \right) - b \left( \sum_{k=1}^{K} \alpha_k \right) - K \ln I_0(d) \\
+ d \cdot \left[ \sum_{k=1}^{K} \cos(\beta_k - c) \right]. \tag{7.23} \]

For fixed \( \beta \), we can easily find the signal powers \( \alpha \) that maximize (7.23):
\[ \hat{\alpha}_k = \arg \max_{\alpha_k} \left[ \sqrt{\alpha_k} \cdot y_k e^{-j\beta_k} + \sqrt{\alpha_k} \cdot y_k^* e^{j\beta_k} - (1 + b \sigma^2) \cdot \alpha_k + (a - 1) \sigma^2 \ln \alpha_k \right], \quad k = 1, 2, \ldots, K, \]

where "*" denotes complex conjugation. Differentiating the above expression with respect to \( \alpha_k \) and solving for \( \alpha_k \) yields:
\[ \hat{\alpha}_k = \begin{cases} 
\left[ \frac{R_k + \sqrt{R_k^2 + 4(a - 1) \cdot \sigma^2(1 + b \sigma^2)}}{2(1 + b \sigma^2)} \right]^2, & R_k^2 + 4(a - 1) \cdot \sigma^2(1 + b \sigma^2) > 0 \\
0, & R_k^2 + 4(a - 1) \cdot \sigma^2(1 + b \sigma^2) < 0 \end{cases} \tag{7.24a} \]

for \( k = 1, 2, \ldots, K \). Here \( R_k = \text{Re}\{y_k \exp(-j\beta_k)\} \) for equation simplifying. Similarly, for fixed \( \alpha \), the signal phases \( \beta \) that maximize (7.23) can be obtained as follows:
\[ \hat{\beta}_k = \angle\{\sqrt{\alpha_k} \cdot y_k + \frac{1}{2} \cdot d \sigma^2 \exp(jc)\}, \quad k = 1, 2, \ldots, K. \tag{7.24b} \]

To obtain the MAP estimates of both \( \alpha \) and \( \beta \), we need to iterate between (7.24a) and (7.24b) until convergence.

### 7.5 Experimental and Simulation Results

We first apply the proposed ML estimation method to steam-generator inspection data containing two real defects. The tubes were made of Inconel 600 with outer diameter 0.875" and wall thickness 0.050". We selected \( K \) measurements \( y_k, \ k = 1, 2, \ldots, K \) from potential defect regions and estimated the noise variance \( \sigma^2 \) from neighboring regions.
Figure 7.3  Impedance and imaginary-component plots (left) and estimated amplitude and phase distributions (right) of two potential defects.
that contain only noise. The quadrature orders of the Gauss-Chebyshev and generalized Gauss-Laguerre approximation were $N_C = 120$ and $N_L = 80$, respectively. The proposed algorithms converged within 10 iterations. In Fig. 7.3, we show the estimated pdfs of the signal amplitudes $\sqrt{\alpha_k}$ and phases $\beta_k$. Here, the amplitudes $\rho_k = \sqrt{\alpha_k}$ follow the Nakagami-$m$ pdf (see [47, eq. (2.20)]):

$$p_\rho(\rho_k; a, b) = \frac{2b^a}{\Gamma(a)} \cdot \rho_k^{2a-1} \exp(-b\rho_k^2), \quad \rho_k \geq 0.$$ \hspace{1cm} (7.25)

For the first test signal, the noise variance was $\sigma^2 = 1.9$ and the potential defect region contained $K = 154$ measurements. The ML estimate $\lambda^{(\infty)}$ of the unknown parameter vector and the estimated covariance matrix of $\lambda^{(\infty)}$ are

$$\lambda^{(\infty)} = [0.548 \quad 0.0366 \quad 2.281 \quad 94.34]^T,$$

$$\text{CRB}(\lambda^{(\infty)}) = \begin{bmatrix}
6.29 \cdot 10^{-3} & 4.00 \cdot 10^{-4} & -8.01 \cdot 10^{-6} & -9.78 \cdot 10^{-2} \\
4.00 \cdot 10^{-4} & 4.32 \cdot 10^{-5} & -1.42 \cdot 10^{-6} & 8.02 \cdot 10^{-3} \\
-8.02 \cdot 10^{-6} & -1.42 \cdot 10^{-6} & 6.22 \cdot 10^{-4} & -4.60 \cdot 10^{-2} \\
-9.78 \cdot 10^{-2} & 8.02 \cdot 10^{-3} & -4.60 \cdot 10^{-2} & 4.31 \cdot 10^3
\end{bmatrix}.$$ \hspace{1cm} (7.26)

For the second signal, $\sigma^2 = 1.9$ and $K = 525$, and $\lambda^{(\infty)}$ and the estimated covariance matrix of $\lambda^{(\infty)}$ are

$$\lambda^{(\infty)} = [0.4765 \quad 0.0083 \quad 0.9676 \quad 14.65]^T,$$

$$\text{CRB}(\lambda^{(\infty)}) = \begin{bmatrix}
3.85 \cdot 10^{-3} & 6.48 \cdot 10^{-5} & -2.50 \cdot 10^{-5} & -5.93 \cdot 10^{-3} \\
6.48 \cdot 10^{-5} & 2.09 \cdot 10^{-6} & -1.07 \cdot 10^{-7} & 2.94 \cdot 10^{-5} \\
-2.50 \cdot 10^{-5} & -1.07 \cdot 10^{-7} & 8.99 \cdot 10^{-4} & -4.07 \cdot 10^{-3} \\
-5.93 \cdot 10^{-3} & 2.94 \cdot 10^{-5} & -4.07 \cdot 10^{-3} & 7.9538
\end{bmatrix}.$$ \hspace{1cm} (7.27)

We have used (7.20) to compute the CRB matrix where the expectation with respect to the distribution of $y$ was performed using Monte Carlo integration with 100 trials.

We now present a simulation example showing the estimation performance of the proposed method. Our performance metric is the mean-square error (MSE), calculated
using 400 independent trials. The simulated data was generated using the measurement model in Section 7.2 with $\lambda = [0.8, 0.14, 1.93, 13.2]$ and $\sigma^2 = 1.2$. In Figs. 7.4 and 7.5, we show the MSEs of

- the ML estimates of $a, b$ and $c, d$ computed using the Newton-Raphson iteration (7.17) in Section 7.3 and

- the initial estimates (7.18) and (7.19) in Section 7.3.1,

as well as corresponding exact and complete-data CRBs. The ML estimates performed well, achieving MSEs close to the exact CRBs. The initial estimates $a^{(0)}, b^{(0)}$, and $c^{(0)}$ performed fairly well, whereas $d^{(0)}$ performed poorly. The poor performance of $d^{(0)}$ can be explained by the fact that, being obtained by ignoring the noise effects, it cannot separate the phase variability of $y_k, k = 1, 2, \ldots, K$ due to the signal from that due to noise.

7.5.1 Empirical MAP Estimation of Signal Amplitudes and Phases

We apply the MAP estimator of signal amplitudes and phases (described in Section 7.4) to experimental eddy-current data whose impedance-plane and magnitude plots are
Figure 7.5  MSEs and corresponding CRBs for phase distribution parameters $c$ and $d$.

Figure 7.6  Impedance-plane and magnitude plots of original eddy-current data (left) and corresponding empirical MAP estimates (right).
shown in parts (a) and (c) of Fig. 7.6. This data set was collected from the Electric Power Research Institute’s laboratory sample 3 made of Inconel 600. The sample contained two machined defects: a 49% throughwall circumferential OD defect and a 59% throughwall axial OD defect. We first estimate the model parameters $\lambda$ from a training region containing defects of the type that we wish to detect, and then apply the proposed MAP method to the whole image. In this example, we selected the training region containing the 49% circumferential OD defect. In the MAP algorithm, we replaced $\lambda$ with its ML estimate obtained from the training region (in the spirit of empirical Bayesian estimation). The impedance-plane and magnitude plots of the resulting empirical MAP estimates are shown in parts (b) and (d) of Fig. 7.6. The empirical MAP estimator enhances potential defect signals having similar amplitude and phase distributions to those estimated from the training region and suppresses other signals. To show this effect, we have rotated the phases of the 59% throughwall axial defect signals by $-70^\circ$, yielding the impedance-plane and magnitude plots in parts (a) and (c) of Fig. 7.7. Clearly, Figures 7.6 (c) and 7.7 (c) are identical because phase rotation does not affect the signal magnitudes. After applying the proposed empirical MAP estimator, the rotated defect signals are completely suppressed, as shown in parts (b) and (d) of Fig. 7.7.

Finally, we apply the empirical MAP estimator to a data set containing real defect signals and show the obtained results in Fig. 7.8.
Figure 7.7  Impedance-plane and magnitude plots of eddy-current data with the axial defect signal's phases rotated by $-70^\circ$ (left) and corresponding empirical MAP estimates (right).
Figure 7.8  Impedance-plane and magnitude plots of original eddy-current data (left) and corresponding empirical MAP estimates (right).
CHAPTER 8 SUMMARY AND FUTURE WORK

8.1 Summary of the Research

A new approach, involving the use of image processing techniques, neural networks and statistical estimation is proposed for analyzing multi-frequency rotating-probe eddy-current data for automatic defect identification and characterization. In contrast to previous work which focused on one-dimensional signal features (such as impedance signatures or Lissajous pattern) a preprocessing step which explores the two-dimensional image features is developed. Two-dimensional processing can then take advantage of the spatial dependence in the potential defect signals.

In the first part of this research work, we developed an automatic data analysis system which consists of three stages: signal preprocessing, degradation type classification and defect profile characterization. To provide consistent and reliable analysis results, a signal preprocessing procedure was developed. It includes three steps: synchronization, segmentation and calibration. The synchronization step converts one-dimensional data to two-dimensional images. The segmentation procedure locates support structure signals and aligns data sets to provide a basis for localizing defects. The calibration step removes structure support signals and background variation first, and then calibrates the phase and amplitude based on standard calibration signals. In stage 2, a three-step hierarchical neural network classifier is used to classify different types of data. The first step classifies degradation signals from benign signals. The second step classifies the signals into two major categories: axial and circumferential indications. The last stage
differentiates between multiple indication defects and single indication defects. One issue that needs to be considered is how to render signals invariants such parameters as instrument settings. In stage 3, a wavelet basis function neural network is used to estimate the profile of each defect indication. A calibration curve method is also used for a comparative study of results obtained with the WBF neural network. Automation is emphasized in all stages of the data analysis system to reduce the workload of human analysts and improve the speed, accuracy and reliability of analysis results.

The second part of this research work is estimation of the statistical properties of potential defect signals. We developed a statistical model for characterizing the amplitude and phase probability distributions of potential defects in eddy-current systems and derived a maximum likelihood method for estimating the unknown parameters from noisy measurements. We also discussed initializing the proposed algorithm and computed exact and complete-data Cramér-Rao bounds for the unknown parameters. We showed how the estimated amplitude and phase distribution parameters can be utilized for maximum a posteriori signal phase and amplitude estimation. The proposed methods were applied to simulated and real data from steam generator tube inspection in nuclear power plants.

As shown in figure 3.5, results of the estimation in the second part can be applied to the data analysis system. In Chapter 7.5, we show some results of utilizing the empirical MAP estimation algorithm as denoising filter to enhance the defect signals that have similar amplitude and phase distributions to the “training” defect and suppresses other signals. The estimated phase and amplitude distribution parameters can be used as feature extractors in defect classification schemes. This will be part of the future research work.
8.2 Future Work

The general problem of automatic eddy-current data analysis for steam generator tube inspection is a very complex problem due to the variability of the noise and interference signals under different inspection conditions. The diffusive nature of the eddy-current technique brings additional difficulties to the data analysis task. In addition, noise and artifacts from support structures, probe wobbles and dents complicate the task significantly. Test results show that the automatic defect identification and characterization system described herein has significant potential. In order to make this system more complete, practical and reliable, additional work needs to be carried out. Future work can be summarized as follows:

- Advanced signal preprocessing techniques to further reduce noise and unwanted signals. In the work reported, the local reference signal was used to suppress the support structure signals and lift-off noise. More sophisticated signal/image processing techniques, such as multi-parameter mixing, spline smoothing [59] and wavelet de-noising could be investigated. For signals obtained at different circumstance, such as excitation frequency or tube materials, additional algorithm need to be applied to make them comparable.

- Another goal of future research is to upgrade/optimize the classification algorithms. Features of each individual indication in each data file can be extracted and classified.

- Efforts may be directed towards using other techniques to optimize center selection and the architecture of the WBF neural network.

- In the estimation of statistical properties, further research will concentrate on utilizing the estimated parameters as feature extractors in defect classification schemes.
APPENDIX A  First and second order derivatives

In this appendix, we give explicit expressions of the first and second derivatives in equation (7.11).

The first derivatives are:

\[
\frac{\partial}{\partial a} \{ \ln p_y(y; \lambda) \} = \frac{1}{p_y(y; \lambda)} \cdot \frac{1}{\pi \sigma^2} \int_0^{2\pi} d\beta \int_0^\infty p_y(y|\theta) \frac{\partial p_\alpha(\alpha; a, b)}{\partial a} p_\beta(\beta; c, d) d\alpha, \quad (A.1a)
\]

\[
\frac{\partial}{\partial b} \{ \ln p_y(y; \lambda) \} = \frac{1}{p_y(y; \lambda)} \cdot \frac{1}{\pi \sigma^2} \int_0^{2\pi} d\beta \int_0^\infty p_y(y|\theta) \frac{\partial p_\alpha(\alpha; a, b)}{\partial b} p_\beta(\beta; c, d) d\alpha, \quad (A.1b)
\]

\[
\frac{\partial}{\partial c} \{ \ln p_y(y; \lambda) \} = \frac{1}{p_y(y; \lambda)} \cdot \frac{1}{\pi \sigma^2} \int_0^{2\pi} d\beta \int_0^\infty p_y(y|\theta) p_\alpha(\alpha; a, b) \frac{\partial p_\beta(\beta; c, d)}{\partial c} d\alpha, \quad (A.1c)
\]

\[
\frac{\partial}{\partial d} \{ \ln p_y(y; \lambda) \} = \frac{1}{p_y(y; \lambda)} \cdot \frac{1}{\pi \sigma^2} \int_0^{2\pi} d\beta \int_0^\infty p_y(y|\theta) p_\alpha(\alpha; a, b) \frac{\partial p_\beta(\beta; c, d)}{\partial d} d\alpha. \quad (A.1d)
\]

where

\[
\frac{\partial p_\alpha(\alpha; a, b)}{\partial a} = \left[ \ln b - \psi(a) + \ln \alpha \right] \cdot p_\alpha(\alpha; a, b),
\]

\[
\frac{\partial p_\alpha(\alpha; a, b)}{\partial b} = \left[ \frac{a}{b} - \alpha \right] \cdot p_\alpha(\alpha; a, b),
\]

\[
\frac{\partial p_\beta(\beta; c, d)}{\partial c} = d \sin(\beta - c) \cdot p_\beta(\beta; c, d),
\]

\[
\frac{\partial p_\beta(\beta; c, d)}{\partial d} = \left[ \cos(\beta - c) - \frac{I_1(d)}{I_0(d)} \right] \cdot p_\beta(\beta; c, d).
\]

The second derivatives are:

\[
\frac{\partial^2}{\partial a^2} \{ \ln p_y(y; \lambda) \} = \frac{1}{p_y(y; \lambda)} \cdot \frac{1}{\pi \sigma^2} \int_0^{2\pi} d\beta \int_0^\infty p_y(y|\theta) \frac{\partial^2 p_\alpha(\alpha; a, b)}{\partial a^2} p_\beta(\beta; c, d) d\alpha
\]

\[
- \left[ \frac{1}{p_y(y; \lambda)} \cdot \frac{1}{\pi \sigma^2} \int_0^{2\pi} d\beta \int_0^\infty p_y(y|\theta) \frac{\partial p_\alpha(\alpha; a, b)}{\partial a} p_\beta(\beta; c, d) d\alpha \right]^2 \quad (A.2a)
\]

\[
\frac{\partial^2}{\partial a \partial b} \{ \ln p_y(y; \lambda) \} = \frac{1}{p_y(y; \lambda)} \cdot \frac{1}{\pi \sigma^2} \int_0^{2\pi} d\beta \int_0^\infty p_y(y|\theta) \frac{\partial^2 p_\alpha(\alpha; a, b)}{\partial a \partial b} p_\beta(\beta; c, d) d\alpha
\]
\[
\frac{\partial^2}{\partial a \partial d} \{ \ln p_y(y; \lambda) \} = \frac{1}{p_y(y; \lambda)} \cdot \frac{1}{\pi \sigma^2} \int_0^{2\pi} d\beta \int_0^\infty p_{y|\theta}(y|\theta) \frac{\partial p_\alpha(\alpha; a, b)}{\partial c} \frac{\partial p_\beta(\beta; c, d)}{\partial d} d\alpha
\]  
(A.2b)

\[
\frac{\partial^2}{\partial a \partial d} \{ \ln p_y(y; \lambda) \} = \frac{1}{p_y(y; \lambda)} \cdot \frac{1}{\pi \sigma^2} \int_0^{2\pi} d\beta \int_0^\infty p_{y|\theta}(y|\theta) \frac{\partial p_\alpha(\alpha; a, b)}{\partial a} \frac{\partial p_\beta(\beta; c, d)}{\partial b} d\alpha
\]  
(A.2c)

\[
\frac{\partial^2}{\partial a \partial d} \{ \ln p_y(y; \lambda) \} = \frac{1}{p_y(y; \lambda)} \cdot \frac{1}{\pi \sigma^2} \int_0^{2\pi} d\beta \int_0^\infty p_{y|\theta}(y|\theta) \frac{\partial p_\alpha(\alpha; a, b)}{\partial b} \frac{\partial p_\beta(\beta; c, d)}{\partial c} d\alpha
\]  
(A.2d)

\[
\frac{\partial^2}{\partial b^2} \{ \ln p_y(y; \lambda) \} = \frac{1}{p_y(y; \lambda)} \cdot \frac{1}{\pi \sigma^2} \int_0^{2\pi} d\beta \int_0^\infty p_{y|\theta}(y|\theta) \frac{\partial^2 p_\alpha(\alpha; a, b)}{\partial b^2} \frac{\partial p_\beta(\beta; c, d)}{\partial d} d\alpha
\]  
(A.2e)

\[
\frac{\partial^2}{\partial b \partial d} \{ \ln p_y(y; \lambda) \} = \frac{1}{p_y(y; \lambda)} \cdot \frac{1}{\pi \sigma^2} \int_0^{2\pi} d\beta \int_0^\infty p_{y|\theta}(y|\theta) \frac{\partial p_\alpha(\alpha; a, b)}{\partial b} \frac{\partial p_\beta(\beta; c, d)}{\partial c} d\alpha
\]  
(A.2f)

\[
\frac{\partial^2}{\partial b \partial d} \{ \ln p_y(y; \lambda) \} = \frac{1}{p_y(y; \lambda)} \cdot \frac{1}{\pi \sigma^2} \int_0^{2\pi} d\beta \int_0^\infty p_{y|\theta}(y|\theta) \frac{\partial p_\alpha(\alpha; a, b)}{\partial c} \frac{\partial p_\beta(\beta; c, d)}{\partial d} d\alpha
\]  
(A.2g)

\[
\frac{\partial^2}{\partial c^2} \{ \ln p_y(y; \lambda) \} = \frac{1}{p_y(y; \lambda)} \cdot \frac{1}{\pi \sigma^2} \int_0^{2\pi} d\beta \int_0^\infty p_{y|\theta}(y|\theta) \frac{\partial^2 p_\alpha(\alpha; a, b)}{\partial c^2} \frac{\partial p_\beta(\beta; c, d)}{\partial d} d\alpha
\]  
(A.2h)

\[
\frac{\partial^2}{\partial c \partial d} \{ \ln p_y(y; \lambda) \} = \frac{1}{p_y(y; \lambda)} \cdot \frac{1}{\pi \sigma^2} \int_0^{2\pi} d\beta \int_0^\infty p_{y|\theta}(y|\theta) \frac{\partial p_\alpha(\alpha; a, b)}{\partial c} \frac{\partial^2 p_\beta(\beta; c, d)}{\partial c \partial d} d\alpha
\]
$$\frac{\partial^2}{\partial d^2} \{ \ln p_y(y; \lambda) \} = \frac{1}{p_y(y; \lambda)} \cdot \frac{1}{\pi \sigma^2} \int_0^{2\pi} d\beta \int_0^\infty p_y(y|\theta)p_\alpha(\alpha; a, b) \frac{\partial^2 p_\beta(\beta; c, d)}{\partial d^2} d\alpha$$

where

$$\frac{\partial^2 p_\alpha(\alpha; a, b)}{\partial \alpha^2} = \left[ (\ln b - \psi(a) + \ln \alpha)^2 - \psi(1, a) \right] \cdot p_\alpha(\alpha; a, b),$$

$$\frac{\partial^2 p_\alpha(\alpha; a, b)}{\partial b^2} = \left[ \left( \frac{a}{b} - \alpha \right)^2 - \frac{a}{b^2} \right] \cdot p_\alpha(\alpha; a, b),$$

$$\frac{\partial^2 p_\alpha(\alpha; a, b)}{\partial a \partial b} = \left[ \frac{1}{b} + \left( \frac{a}{b} - \alpha \right)(\ln b - \psi(a) + \ln \alpha) \right] \cdot p_\alpha(\alpha; a, b),$$

$$\frac{\partial^2 p_\beta(\beta; c, d)}{\partial c^2} = \left[ d^2 \sin^2(\beta - c) - d \cos(\beta - c) \right] \cdot p_\beta(\beta; c, d),$$

$$\frac{\partial^2 p_\beta(\beta; c, d)}{\partial d^2} = \left[ \cos(\beta - c) - \frac{I_1(d)}{I_0(d)} \right]^2 + \frac{I_3(d) - J_0(d) + I_1(d)I_0(d)/d}{I_1(d)} \cdot p_\beta(\beta; c, d),$$

$$\frac{\partial^2 p_\beta(\beta; c, d)}{\partial c \partial d} = \left[ \sin(\beta - c) + d \sin(\beta - c)[\cos(\beta - c) - \frac{I_1(d)}{I_0(d)}] \right] \cdot p_\beta(\beta; c, d).$$
APPENDIX B Derivation of the Complete-data CRB

We derive the complete-data CRB in (7.21a). Differentiating the complete-data log-likelihood function

\[ L_{DML}(\lambda; \alpha, \beta) = \sum_{k=1}^{K} \ln[p_{\alpha}(\alpha_k; a, b) \cdot p_{\beta}(\beta_k; c, d)] \]

\[ = Ka \ln b - K \ln \Gamma(a) + (a - 1) \cdot \left( \sum_{k=1}^{K} \ln \alpha_k \right) - b \left( \sum_{k=1}^{K} \alpha_k \right) - K \ln I_0(d) + d \cdot \left[ \sum_{k=1}^{K} \cos(\beta_k - c) \right] \quad (B.1) \]

with respect to \( \lambda \) yields:

\[ \frac{\partial L_{DML}(\lambda; \alpha, \beta)}{\partial a} = K \ln b - K \frac{\Gamma'(a)}{\Gamma(a)} + \sum_{k=1}^{K} \ln \alpha_k, \quad (B.2a) \]

\[ \frac{\partial L_{DML}(\lambda; \alpha, \beta)}{\partial b} = K \cdot \frac{a}{b} - \sum_{k=1}^{K} \alpha_k, \quad (B.2b) \]

\[ \frac{\partial L_{DML}(\lambda; \alpha, \beta)}{\partial c} = d \cdot \sum_{k=1}^{K} \sin(\beta_k - c), \quad (B.2c) \]

\[ \frac{\partial L_{DML}(\lambda; \alpha, \beta)}{\partial d} = -K \cdot \frac{I_1(d)}{I_0(d)} + \sum_{k=1}^{K} \cos(\beta_k - c). \quad (B.2d) \]

Now

\[ -E \left[ \frac{\partial^2 L_{DML}(\lambda; \alpha, \beta)}{\partial a^2} \right] = K \cdot \frac{\Gamma(a) \Gamma''(a) - \Gamma'(a)^2}{[\Gamma(a)]^2}, \quad (B.3a) \]

\[ -E \left[ \frac{\partial^2 L_{DML}(\lambda; \alpha, \beta)}{\partial a \partial b} \right] = -K \cdot \frac{1}{b}, \quad (B.3b) \]

\[ -E \left[ \frac{\partial^2 L_{DML}(\lambda; \alpha, \beta)}{\partial a \partial c} \right] = 0, \quad (B.3c) \]

\[ -E \left[ \frac{\partial^2 L_{DML}(\lambda; \alpha, \beta)}{\partial a \partial d} \right] = 0, \quad (B.3d) \]
\[(p)_{1}^{0}\cdot p \cdot \mathbf{Y} = \left(\sigma - \gamma\right)\text{sec} \mathbf{\Phi} \cdot \mathbf{p} \cdot \mathbf{Y} = \left[\frac{e^0}{(\mathbf{g}^0 \cdot \mathbf{Y})^{\text{dga}, t_0}}\right] \mathbf{\Xi} \]
BIBLIOGRAPHY


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