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# An invariance transformation algorithm for defect characterization of ultrasonic signals for the nondestructive evaluation of concrete

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**An invariance transformation algorithm for defect characterization of ultrasonic signals for the nondestructive evaluation of concrete**

by

Michael Dominic Ciocco

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# ABSTRACT

Michael Dominic Ciocco

**An invariance transformation algorithm for defect characterization of ultrasonic signals for the nondestructive evaluation of concrete**

2002
Dr. Shreekanth Mandayam
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Nondestructive evaluation (NDE) techniques offer cost-effective strategies for monitoring the integrity of a variety of civil infrastructure, such as natural gas and sewer pipelines, without the need to take the system off-line. However, interpretation of NDE signals in terms of the location, size, and shape of underlying flaws in the material being inspected is fraught with difficulty. Typically, variations in the testing signal due to operational parameters have created a significant challenge for defect characterization. This thesis proposes, develops, and validates a defect characterization algorithm that compensates for operational variables and maps the test signal to a visual defect profile. This algorithm takes a two-step approach:

1. The raw NDT signal is processed via an invariance transformation feed forward artificial neural network that removes the effects of operational parameters and produces a signal containing defect related information only.
2. A second feed forward artificial neural network processes the defect signature developed by the invariance transformation network and predicts defect profiles representing the location, size, and shape of material flaws.

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# CHAPTER 1. INTRODUCTION

Nondestructive testing has played a major role in the maintenance and evaluation of a significant number of structures and technology including pipelines, bridges, buildings, pavement, ships, aircraft, and automobiles. As this infrastructure and machinery continue to age, it becomes more and more imperative that a safe and economical means of inspection is applied to extend service life. Various testing methods such as ultrasound, magnetic flux leakage (MFL), eddy current, microwave, etc., have been employed as non-intrusive inspection techniques over the years to assess the integrity of a variety of materials without the expense and damage typically incurred with past testing methods. This translates to a direct reduction in costs and labor, mainly by removing involved "guess work" such as that required when digging up an underground pipeline that has a suspected breach in a length of pipe. While the mentioned testing methods present viable solutions for many applications, and hold significant potential for many future applications, they are not without their inherent shortcomings.

For each nondestructive testing method and its application, there is a unique set of operational parameters that must be taken into consideration. Operational parameters are variables dependant upon the properties of the material being tested, the testing environment, and the test equipment – all of these affect the received NDE signals. Some examples of operational parameters are varying material composition, material thickness, magnetization level of the material (in the case of ferromagnetic materials), material permeability, and velocity of the probe or inspection device. In many cases, the operational parameters are very inconsistent or, in fact, unknown, and attempting to measure or quantify them becomes extremely difficult or impractical. Furthermore, defect characterization, also known as "the inverse problem" becomes a significant challenge. For this reason, we look to signal processing solutions to compensate for the effects of operational parameters in nondestructive evaluation (NDE) signals. By developing an algorithm that can remove or filter portions of an NDE signal that are caused by operational parameters from those portions of the signal that contain useful defect related information, the NDE signal is rendered "invariant" and defect characterization can be achieved with subsequent signal processing. The next section will briefly discuss the background of nondestructive testing in terms of MFL testing of metals and ultrasonic testing of concrete.

## 1.1 Nondestructive Testing

Nondestructive testing (NDT) plays an important role in the evaluation and maintenance of underground structures. Industries in the United States such as the natural gas industry and the water and sewer industry must provide their utilities in a safe, uninterrupted manner via underground pipelines. In the case of metal gas pipelines and concrete sewer pipelines, there is a definite degradation in pipeline integrity over the years. Maintenance and repair of these pipelines is vital to prevent the leakage of the substance they transport. Dealing with underground infrastructure maintenance can be extremely costly in time, resources, and money. Therefore, nondestructive testing provides a means of cost effective evaluation without affecting the quality of a pipeline or its surrounding environment.

While MFL and ultrasound testing are certainly not newcomers to the field of NDT, there has been a major roadblock in the form of operational parameters (mentioned in the previous section) that has hindered their application in the real world. In the field, and even in a laboratory setting, operational parameters vary vastly from place to place and setup to setup. To ensure accurate results, each testing instance would require that all operational parameters having an affect on the NDE signals received are quantified and accounted for. While this seems like a possible, but not probable, task, there are specific operational parameters that not only vary with every testing instance, but also are completely unknown and cannot be measured. These result in significant inaccuracies in defect characterization. In the following subsections, the background of MFL testing for metal gas pipelines and ultrasound testing for concrete sewer pipelines are presented.

*NDT of Natural Gas Pipelines*

The natural gas industry services the United States supplying natural gas energy via underground pipelines. Natural gas accounts for approximately thirty percent of US energy consumption and remains one of the most economical forms of energy. Considering the US's dependence on natural gas, it is imperative that the natural gas industry assures the integrity of the 280,000 miles of pipeline that supplies this utility. The natural gas industry currently employs an inline inspection system to obtain MFL scans of their underground pipeline network.

The inline inspection vehicle used to scan the inner pipe wall of a natural gas pipeline is called a "pig." The pig contains a permanent magnet that induces a magnetic field as it travels inside the metal pipe. When a crack or break occurs in the pipe wall, some of the magnetic flux "leaks" out of defect in the pipe. This phenomenon is known as magnetic flux leakage and measured by a set of flux sensitive devices on-board the pig. The pig travels hundreds of miles of gas pipeline and collects MFL data that is later recovered and analyzed.

The MFL inspection process is illustrated in Figure 1.1. A sample of pipe wall of a known metal grade and known thickness has several known defects scored into its surface. By sending a high direct current of varying amplitude through the section of pipe, a magnetic field is generated over the surface of the pipe. Where the defects occur in the pipe wall, the magnetic field is no longer contained by the pipe. The hall effect sensor and gaussmeter measures the magnetic flux leakage over the length of pipe being scanned. The result can be rendered into a magnetic image that is representative of the location, shape, and size of the defect.

There is a variety of operational parameters that can have an effect on MFL line scan signals of metal pipe walls. These include local variations in pipe wall thickness, different grades of steel, permeability of the steel, and the magnetization level of the pipe. While it can be a time-consuming task to measure pipe wall thickness, measuring the magnetization level of any section of pipe remains impossible without knowning the exact history of the magnetization of the pipe. The effects of the velocity of the

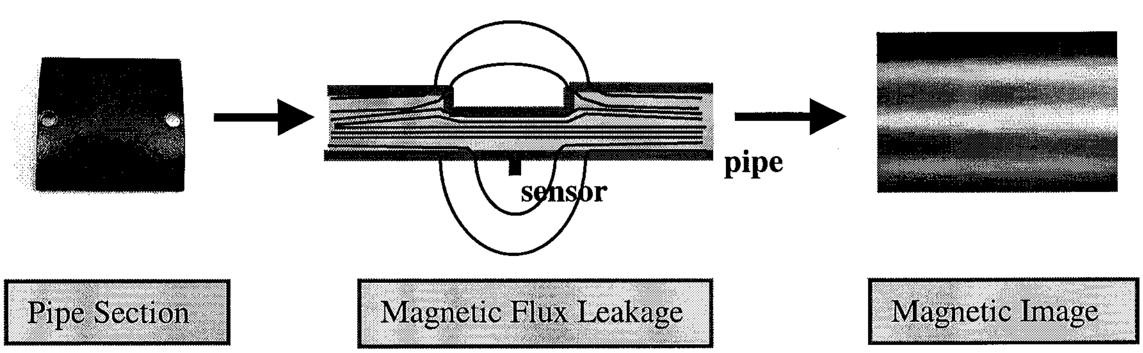


**Figure 1.1.** MFL testing process.

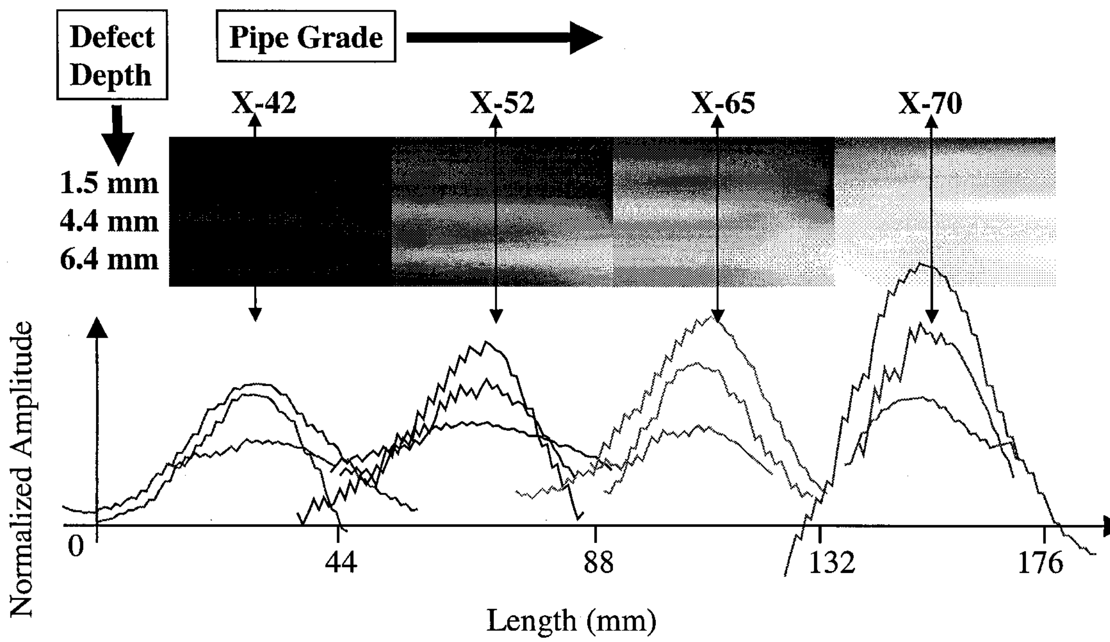


**Figure 1.2.** MFL line scans for various X-grades of metal gas pipe wall and various slot defect depths.

inspection vehicle is yet another operational variable that must be dealt with.

Figure 1.2 shows scans of pipe wall specimens, each of a different grade of steel, X-42, X-52, X-65, and X-70. Each specimen contained three different slot shaped defects of depths 0.06”, 0.17”, and 0.25”. Note that the signal amplitude for each defect depth varies as the pipe grade varies.

The laboratory setup for the MFL experiment involved the used of a standard Gaussmeter with a Hall effect probe affixed to a set of linear actuators and stepper motors. Each specimen was magnetized using a direct current with an amplitude of 200 A. Specimens were designed to represent a section of pipe wall for each grade of pipe, and three 1/32" key-cutter slots, one for each given defect depth, were cut into the specimen. Figure 1.3 shows the laboratory setup and a sample specimen.

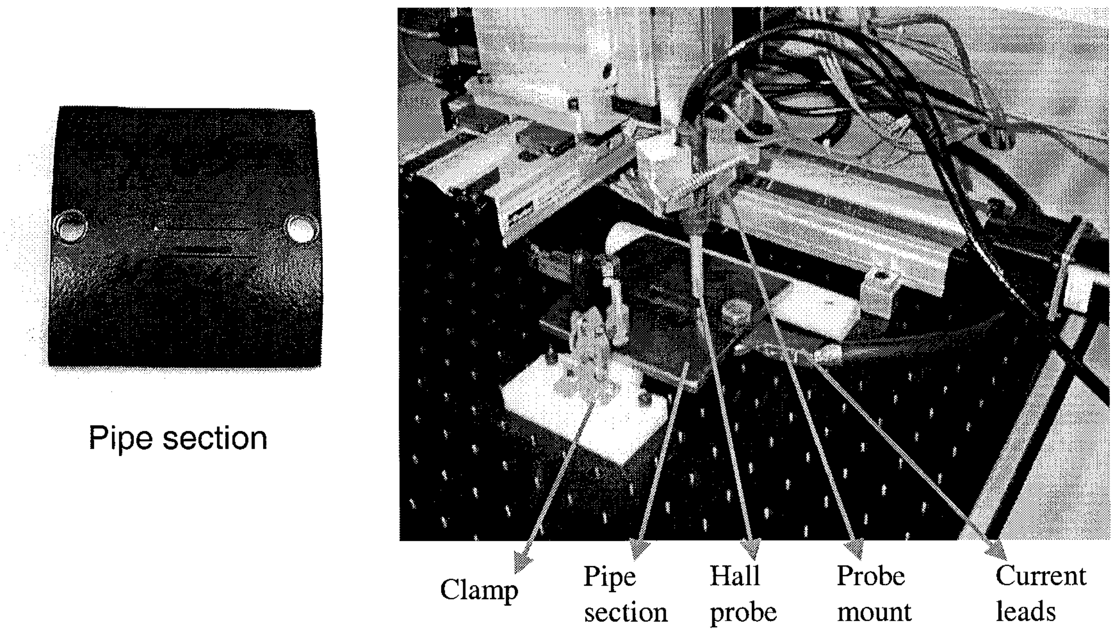


**Figure 1.3.** Laboratory setup and sample specimen for MFL experiment.

*NDT of Sewer Pipelines*

The wastewater industry in the United States is currently reaching a critical position where maintenance and repair is imperative to extend the service life of their pipeline network. Wastewater is transported by concrete sewer pipelines which are affected by corrosion over a long period of time due to the sulfuric acid present in the sewage water. This type of corrosion typically affects the crown of the pipe leading to defects and eventually collapse of the pipe wall. Currently, there is no NDE inspection method in place for concrete wastewater pipelines. The research pertaining to the NDE of concrete presented in this thesis is part of a long-term project to develop an inline inspection vehicle for the ultrasonic inspection of concrete sewer pipelines.

Ultrasound testing proves viable for a variety of materials including metals, non-metallic materials, and many composites. In the case of concrete, UT is the preferred testing method, but provides limited results. The major operational parameter concerning concrete is the concrete composition. Given any length of underground concrete sewer pipe, the composition of the concrete is generally unknown and may contain any combination of cement, sand, and different size aggregate. Another concern is couplant composition if any part of the wastewater will be present as a couplant in the inspection process. Since sewerage pipes transport wastewater, the composition of the wastewater varies from a typical tap water couplant in chemical composition. These operational variables have a tendency to attenuate and disperse the sound waves in ultrasonic testing, causing inaccuracies in the resulting test signal.

Figure 1.4 shows experimental ultrasound C-scan images of concrete specimens obtained in the laboratory. Two sets of four specimens were molded for testing to represent the concrete pipe wall – one set of a cement, sand, and ¾" aggregate mixture, and the second set of a cement and sand mixture. Both sets of disk shaped specimens contain 1" square shaped defects with depths varying between 0.0" and 1". The author of this thesis was instrumental in configuring the ultrasound equipment for the laboratory and performing the experimental scans for this research. Note that at the same frequency

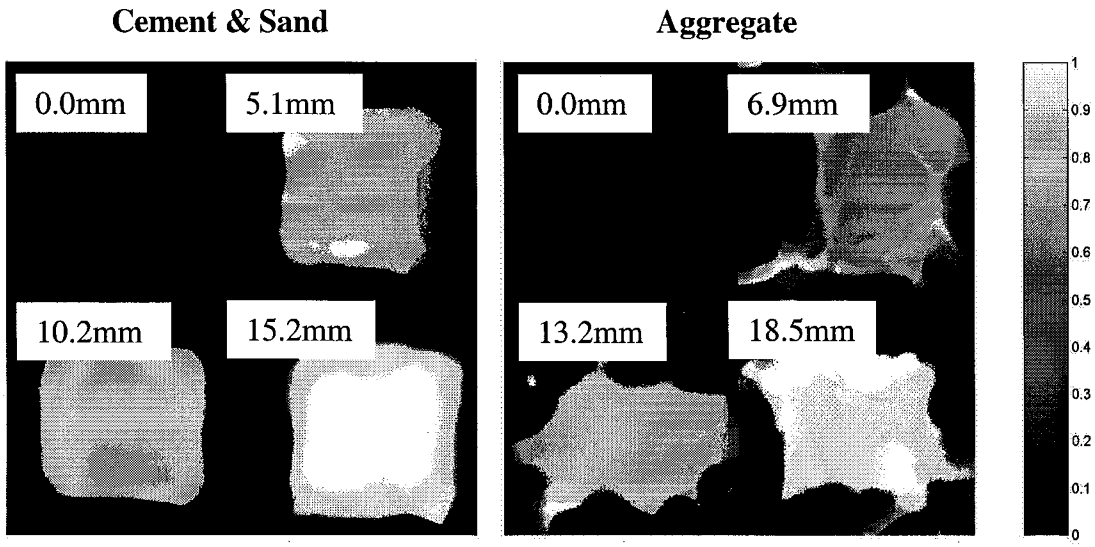


**Figure 1.4.** Experimental C-scans imaged from concrete specimens at 1 MHz frequency – all scans have been color normalized.

(1 MHz) ultrasound, the results vary greatly between the two types of concrete mixtures. For the cement and sand concrete specimens, the resolution of the defect image is clear. However, for the cement, sand, and aggregate specimens, the resolution of the defect image is relatively poor and the geometry of the defect is not clear. This is the result of attenuation and scattering of the ultrasound. Here the difficulty of UT of concrete becomes obvious and the affects of operational parameters on NDE signals are apparent.

The laboratory setup for the ultrasound experiment consisted of a typical immersion ultrasound test station that allows for through transmission tests with a pair of piezoelectric transducers operating in the pitch-catch mode. A set of precision linear actuators and controlled stepper motors were interfaced via custom hardware to a PC. The PC was fitted with data acquisition and stepper motor control cards and used for data collection and signal/image processing. The PC provided real-time control and display of

A-scan, C-scan and time-of-flight ultrasound data that can be utilized for defect characterization.

Concrete specimens were prepared to represent a thickness of 2" of a 24" internal diameter ASTM C14 Class 2 non-reinforced concrete pipe. The specimens were embedded with 1"x 1" rectangular shaped defects ranging in depth from 0.0" to 1.0". All specimens were disk shaped with a 2" radius. The composition of the concrete varied between a pure water-cement mixture and a 1.93:1.51:1 ratio of coarse aggregate ( 3/4" top size gray granite), sand, and cement. Figure 1.5 shows the laboratory setup and a sample specimen.

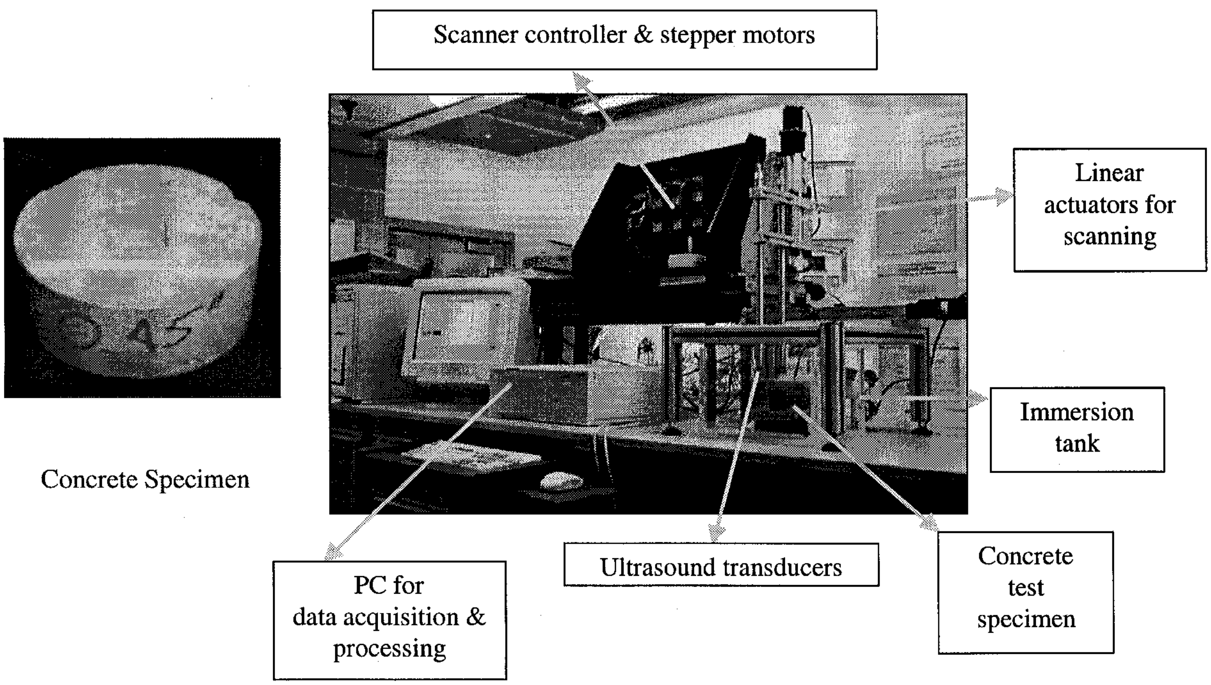


**Figure 1.5.** Laboratory setup and sample specimen for ultrasound testing experiment.

## 1.2 Research Contribution

The research work presented in this thesis demonstrates a technique that will eliminate the need for measurement of operational parameters in the field or a laboratory setup. An invariance technique will not only minimize the need to quantify operational

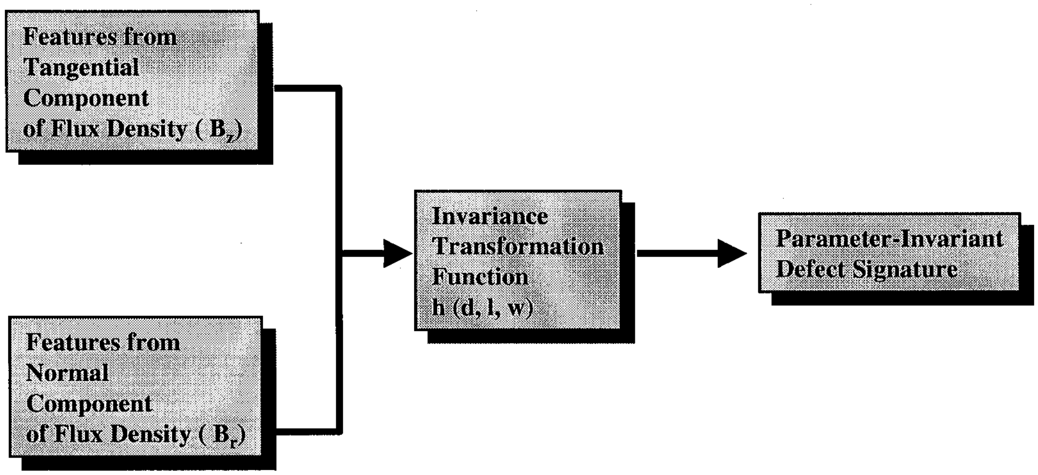


**Figure 1.6.** Block diagram of invariance transformation process.

parameters, but it will also remove the need to qualify, or recognize, the operational parameters involved in the testing. The only step required in testing to implement this invariance technique is to make two separate measurements of the same test specimen. For instance, one can use orthogonal MFL probes to measure separate components of the magnetic field vector – the tangential and normal components (See Figure 1.6). The invariance algorithm then synergistically combines the two signals and generates a parameter-invariant defect signature. The next step is to map this defect signature to a defect profile. Similarly, two separate signals are received from UT of concrete by testing the same section of pipe wall with two different ultrasound frequencies. For the experimental results in this thesis, the frequencies of 1 MHz and 500 kHz were used. The frequency of 500 kHz was chosen as a "low" ultrasound frequency, or a frequency between 20 kHz and approximately 500 kHz. A low frequency is used to provide better penetration of the test specimen by the acoustic waves; lower frequencies with longer wavelengths can achieve this objective. The 1 MHz frequency was chosen as a "high" ultrasound frequency, or a frequency greater than 500 kHz. A high frequency is used to obtain better resolution in the C-scan image; higher frequencies have shorter wavelengths allowing more acoustic waves to fit in a smaller depth defect; the result is better imaging of the geometry of the defect. There is a trade off, however, where low frequencies provide better penetration, but poor resolution, due to the longer wavelengths, and high frequencies provide better resolution, but tend to attenuate in the test specimen quickly, reducing the penetration of the signal. The same invariance process used for the MFL testing is then performed with these two UT signals. These two NDE methods, MFL testing and UT, were chosen to show that the same invariance algorithm can be employed for a multitude of raw NDT signals.

## 1.3 Objectives and Scope of Thesis

The invariance technique explored in this thesis has been developed using NDE signals simulated with finite element models. The objectives of this thesis are to (1) implement the invariance algorithm with experimental data to demonstrate that it holds valid for real world NDE signals, and (2) implement the invariance algorithm with two separate NDT techniques, MFL testing and UT, to illustrate the versatility of the algorithm and its ability to be applied to a variety of experimental NDE signals. This thesis is intended as a stepping-stone towards the practical application of the presented invariance algorithm in the field of NDE. Ideally, the invariance technique will aid in industry utilizing a multitude of efficient, cost effective NDE methods.

### 1.4 Thesis Organization

This thesis is organized as a compilation of three papers. The first paper entitled "An invariance algorithm for defect characterization," pp. 13-38, was submitted to the *Nondestructive Testing and Evaluation International* (NDT & E) *Journal* in March 2002. The second paper entitled "Ultrasonic imaging of defects in concrete pipelines," pp. 39-49, was presented at the 2001 *Review of Progress in Quantative Nondestructive Evaluation* (QNDE) conference at Bodin, Maine. The third paper entitled "A defect characterization technique for experimental NDE signals," pp. 50-64, was submitted to *Materials Evaluation* in March 2002. A conclusion chapter follows the three papers where a summary of the results presented is given as well as recommendations for future work.

# AN INVARIANCE ALGORITHM FOR DEFECT CHARACTERIZATION

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**Abstract** - Nondestructive evaluation methods offer cost-effective approaches for examining the integrity of a variety of civil infrastructure such as natural gas and sewer pipelines. However, extracting defect related information, such as location, size, and shape of a flaw, from NDE signals remains a considerable challenge as a result of variations in the signal due to material properties and the testing environment. This paper presents a defect characterization technique that renders NDE signals invariant to operational parameters and predicts a defect profile from the flaw information in the signal.

**Keywords:** characterization, ultrasound, magnetic flux leakage, neural networks

## Introduction

The main objective in nondestructive evaluation (NDE) is the characterization of materials based on information gathered in the response from interactions of energy and these materials. The inherent problem in methods employed to reach this objective is that there typically are no tractable, full analytic solutions to such problems. Approaches for solving them utilize techniques by limiting the number of parameters and variations in the problem, yet these solutions are still dependent on certain operational variables for proper results. Such methods can be simplified by using the received signal for characterizing defects in objects in terms of the location, size and shape. However, the raw NDE signal received by the sensors is influenced not only by the defect, but also by the operational parameters associated with the experiment. Optimally, excluding dependence upon any operational parameters would provide invariant results that contain only defect specific information [1, 2, 3]. This paper deals with the subject of invariant pattern recognition techniques that render NDE signals insensitive to operational variables. As a result, the information relaying the defect location and geometry is preserved. The application of a feed forward neural network as an invariance transformation is explored. Invariance transformations are studied in the context of the magnetostatic flux leakage (MFL) inspection technique and the ultrasonic testing (UT) technique, which are typical nondestructive testing methods for inspecting natural gas transmission pipelines and concrete sewer pipelines, respectively.

An NDE signal received by a scanning device is very sensitive to a number of operational parameters. Some factors that have a major impact on a magnetic flux leakage signal include those caused by variations in the permeability of the pipe-wall material, pipe-wall thickness, and the velocity of the inspection tool. Operational parameters that influence the ultrasonic signal received in ultrasound testing include concrete composition and coupling medium. This study describes novel approaches to compensate for the effects of these variables.

This paper is organized as follows. First, the background to this research is presented. Then the approach taken in this study is presented where invariance theory is introduced and described mathematically. Implementation examples for the invariance algorithm are then provided for both the MFL and UT testing scenarios where a brief background, laboratory setup, implementation procedure, and results are discussed for each. Finally, the paper concludes with a summarization of this study and a discussion of the results.

## Background

Providing routine maintenance to extend the service life of existing infrastructure plays a critical role in non-destructive testing, specifically in the areas of underground pipelines such as metal gas and concrete sewer pipelines. The natural gas industry has used an automated, inline inspection system to scan for pipe wall defects for over forty years. A similar inspection system for testing the integrity of concrete sewer pipes does not exist. This type of inspection system is crucial for the inspection of aging pipelines if companies plan to avoid the danger of a break down or collapse of an underground pipeline.

Using raw MFL scans to determine if defects are present in the pipe wall of a gas line is difficult because of the various material properties of metal pipelines. A broad range of test parameters affect MFL scans in gas pipelines including the pipe material, pipe wall thickness, axial and hoop stresses in the pipe, the velocity of the inspection vehicle, remnant magnetization in the pipe, etc. While it is possible to control or monitor some of these parameters, such as the vehicle velocity, others, such as remnant magnetization in the pipe, remain a virtual mystery since there is no way to calculate the hysteresis of the pipe [2]. In the case of obtaining UT scans to determine defects in concrete pipes, operational parameters include concrete composition and coupling medium. The porous nature of concrete adversely affects UT scans since mixtures may contain cement, sand, and even aggregate causing scatter and attenuation of sound waves [4]. Furthermore, any given length of pipe may vary in concrete composition. The viscosity of the couplant may have adverse effects on the signal as well [3, 5].

All of these parameters alter signal levels and distort the shape of the signal. A signal that has been rendered invariant to such parameters can be analyzed to predict a three dimensional geometry of a defect showing its shape and depth. With such an invariance technique in place, NDE signals can be obtained from any portion of pipe and evaluated without prior knowledge of the operational variables involved in the testing.

## Approach

The approach taken in defect characterization is two-fold. First, experimental NDE signals are processed in an invariance transformation feed forward neural network, the result of which is a signal that is an invariant defect signature. Next, the invariant signal is processed by a defect characterization network that predicts a defect profile displaying the defect's estimated size and shape. This process is outlined in the block diagram in Figure 1.

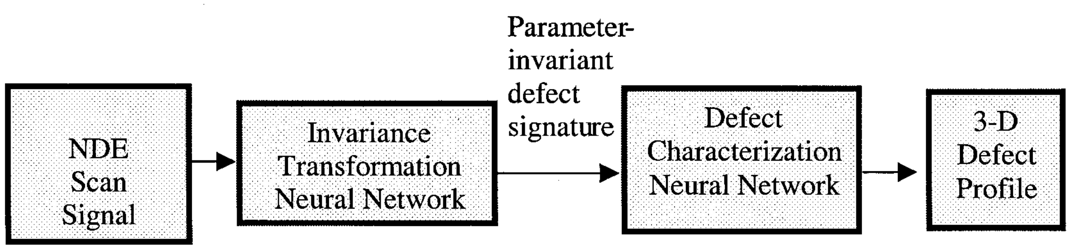



**Figure 1.** Block diagram of defect characterization process.

Developing a defect characterization algorithm that is dependent upon any number of testing parameters can prove impractical and perhaps impossible. The challenge in defect characterization is developing a technique that can render an NDE signal invariant to the operational parameters that affect the raw signal. Raw signals relay defect information that is distorted by parameters in the testing environment, be it either from the natural properties of the test material or even an effect of the measurement device. The objective of an invariance algorithm is to isolate a defect signature from those parts of the signal that are dependent on operational parameters. Having processed a raw signal such that information revealing a defect's size, shape, and location is invariant to experimental factors makes defect characterization a simple, general procedure. The general theory behind the invariance algorithm and defect characterization is described below and followed by a description of the implementation of the algorithm using experimental data.

Analogy: Human Vision

The theory behind parameter invariant defect characterization can be described through the human vision in the analogy of monoscopic vs. stereoscopic vision (see Figure 2). Consider an instance where there are two similar objects in one's field of view. One object is smaller and relatively closer to the individual while the second object

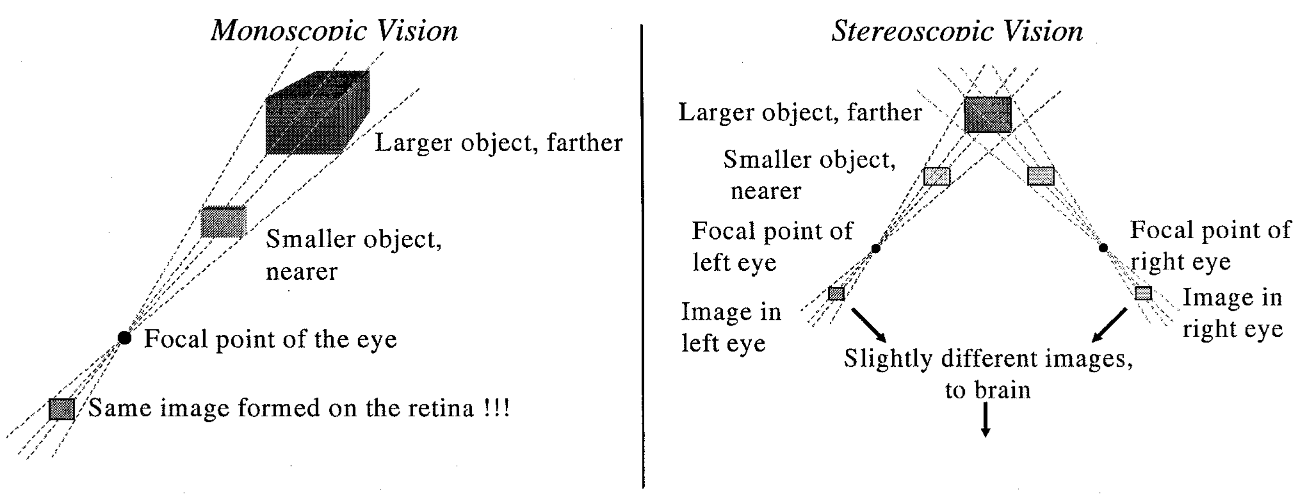



**Figure 2.** Model of human vision system - monoscopic vs. stereoscopic vision.

is situated a distance behind the first object, farther from the individual, and is larger than the first object. If one were to view this scenario given the use of only one eye, or monoscopic vision, the image perceived on the retina of the eye would be that of two objects of identical size. Monoscopic vision drastically reduces the capabilities of size and depth perception and somewhat reduces human vision to two dimensions. Given stereoscopic vision, viewing the scenario with both eyes, a separate and unique image is developed from each eye with respect to the angle of the individual eye to the objects.

With two separate, dissimilar images of the same scene, the brain can then interpolate the images to synthesize a composite three-dimensional view of the objects and develop fairly accurate estimates of the size and distance of the objects. Thus stereoscopic vision provides significantly more accurate size and depth perception. This analogy is related to invariance algorithms in that two separate signals of the same phenomenon that are dissimilar in one or more parameters can be used to interpolate a signal that is invariant to such parameters [6]. Here, the invariance algorithm acts as the brain and, in a sense, filters out the unwanted operational parameters and interpolates desired defect related features of the signal. This procedure can be modeled mathematically in a general form such that it can be implemented for a variety of NDE test signals.

## Classical Invariance Transformation

At the root, defect characterization is a signal classification problem that can be achieved using pattern recognition techniques. The concept of developing invariance methods for signal processing to compensate for or "correct" anomalies or variations in

NDE signals has been exercised for years; the results of which have yielded a number of mathematical theories for invariance. For many applications, algebraic invariant methods are used to determine a one-to-one correspondence between the coordinate transformations and the variation of a physical parameter. It follows that invariant functions under coordinate transformations become invariant features to the variation of the physical parameter. Several classical invariant pattern recognition methods are Euclidean, Affine, Projective, and Moment invariants and Fourier descriptors.

Euclidean invariants involve the use of Euclidean distances and contain transformations of the form

$$\begin{aligned} x' &= x\cos\omega - \varepsilon y\sin\omega + h \\ y' &= x\sin\omega + \varepsilon y\cos\omega + h \\ \varepsilon &= \pm 1 \end{aligned} \tag{1}$$

These invariants include the distance between two points, the ratio in which an interval is divided by a point, the length of a vector, angle between two straight lines, etc. They are of a group called metric invariants (also known as the group of motions and reflections) and are the basis of Euclidean geometry. Such invariants are typically applied in elementary pattern recognition systems.

Affine invariants contain transforms that map a point **p** = (x,y) into **p'** = (x',y') by the following relation

$$p \rightarrow p' = Ap + v \tag{2}$$

where **A** is a general nonsingular 2x2 matrix and **v** = $[v_1,v_2]^T$ is any vector in $\mathbf{R}^2$ [7]. Affine transformations can be used to map straight lines into straight lines, intersecting lines into intersecting lines, and parallel lines into parallel lines. The shared locations of any two lines are not affected by the transformation. This can by shown in the following example. Consider the affine transformation given by

$$x' = px + qy + h$$
$$y' = rx + sy + k$$

It can be shown that given three points ($x_1$,$y_1$), ($x_2$,$y_2$), ($x_3$,$y_3$), the equations

$$x_3 = \frac{x_1 + \lambda x_2}{1 + \lambda}$$
$$y_3 = \frac{y_1 + \lambda y_2}{1 + \lambda}$$

are invariant with respect to the affine transformation. Often affine invariants are employed in computer vision applications in the task of identifying an object from different perspective views [7].

Projective invariants concern a general case affine transformation with the mapping given by

$$p \rightarrow p' = \frac{1}{\omega_1 x + \omega_2 y + 1} Ap + v \tag{3}$$

where all quantities are identical to the quantities in equation (2). Projective transformations map points onto points and preserve the sum and intersection of subspaces and the independence of points. From equation (3), it can be seen that the formula reduces to the affine transformation for $\omega_1 = \omega_2 = 0$. A significant projective invariant is the cross-ratio, also known as the double or anharmonic ratio [8]. The cross-ratio relates an ordered set of four points on a single line ($x_1$,$y_1$), ($x_2$,$y_2$), ($x_3$,$y_3$), and ($x_4$,$y_4$) and is given as

$$\frac{(x_3 - x_1)(x_2 - x_4)}{(x_2 - x_1)(x_3 - x_4)} = \frac{(y_3 - y_1)(y_2 - y_4)}{(y_2 - y_1)(y_3 - y_4)} \tag{4}$$

The projective invariant cross-ratio is typically used in image analysis and object recognition for applications involving perspective projections and partial obscurations. A common application is the identification of aircraft images [9].

Moment invariants can be applied as a set of seven equations that can characterize a signal regardless of coordinate translation, rotation, and scaling. The moments of order $(p+q)$ of a two-dimensional function $f(x,y)$ are given by

$$m_{pq} = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} x^p y^q f(x,y)dxdy; \quad p,q = 0,1,2,.... \tag{5}$$

The central moments $\mu_{pq}$ are given by

$$\mu_{pq} = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} (x-\overline{x})^p (y-\overline{y})^q f(x,y)d(x-\overline{x})d(y-\overline{y}) \tag{6}$$

where $\overline{x} = m_{10}/m_{00}$ and $\overline{y} = m_{01}/m_{00}$. Typical applications for moment invariants involve image processing, such as character recognition [10].

Fourier descriptors are used to parameterize the shape of a signal for closed contours. Derived from the Fourier series, the approach taken for Fourier descriptors is based on the fact that any closed curve can be represented by a cumulative angular function or a complex contour that repeats every $2\pi$ radians, which can then be represented by a Fourier series. Appropriate functions of the Fourier series can be used as invariants as their coefficients remain unaffected by translation, rotation, or scaling of the original signal. Fourier descriptors are often applied in the fields of handwriting recognition, character analysis, and characterization of impedance plane trajectories in eddy current systems [11, 12].

Classical invariant pattern recognition techniques, such as those listed above, involve the algebraic theory of invariants which primarily deal with deriving functions that are invariant to coordinate transformations. In order to use these techniques, it is intrinsic that a one-to-one correspondence exists between the operational parameters and the coordinate transformation function. If the variation in the undesired operational parameter and the defect related parameter is represented by the same coordinate transformation, the result of the invariant function will be the destruction of any defect related information in the signal [13]. Unfortunately, this latter situation is the case for MFL and ultrasound NDE signals taken from metal and concrete pipe walls, respectively. Thus, a novel invariant pattern recognition approach is required to remove the effects of operational parameters and maintain defect related information in such NDE signals. The algorithm presented in this paper provides accurate approximations of invariant defect signatures in cases where classical invariance methods have failed.

## The Invariance Transformation Algorithm

The basis for the invariance algorithm presented in this paper lies within the universal approximation theory. Universal Approximation allows the interpolation between independent signals that characterize the same instance such that a function, $f$, is approximated which is invariant to specified parameters [13]. For example, given two separate signals, $x_1(d,l,t)$ and $x_2(d,l,t)$, that characterize the same phenomenon and are based on the defect related parameters $d$ and $l$, the depth and length of the defect, and $t$, an operational parameter (such as permeability of the material or concrete composition), $x_1$ and $x_2$ are chosen such that they have dissimilar variations with $t$. From this, a process can be developed to obtain a feature, $h$, which is a function of $x_1$ and $x_2$ and invariant to the parameter $t$. Thus we can determine a function, $f$, such that

$$f\{x_1(d,l,t), x_2(d,l,t)\} = h(d,l) \tag{7}$$

Given two arbitrary functions $g_1$ and $g_2$, a signal invariant to the parameter t can be obtained by the following condition

$$h(d,l) \lozenge g_1(x_1) = g_2(x_2) \tag{8}$$

where $\lozenge$ is a homomorphic operator. The desired $t$-invariant response can then by obtained by

$$f(x_1, x_2) = g_2(x_2) \lozenge g_1^{-1}(x_1) = h(d,l) \tag{9}$$

The functions $h$, $g_1$, and $g_2$ must be determined to implement this procedure. The function $h$ is user defined and can be chosen conveniently; for example, a linear combination of $d$ and $l$. The function $g_2$ can serve as a "conditioning" function and can be chosen such that it will better condition the data. For example, if the values of the data contained in $x_2$ are widely spread, a logarithmic function can be chosen for $g_2$. Having chosen $h$ and $g_2$, the coefficients of the function $g_1$ can be determined by solving a set of simultaneous equations at discrete points, $(d_i, l_j, t_k)$; $i$: 1 to $m$; $j$: 1 to $n$; $k$: 1 to $p$, in the data space. From this, the set of equations given as

$$h(d_i, l_i) \lozenge g_1\{x_1(d_i, l_j, t_k)\} = g_2\{x_2(d_i, l_j, t_k)\} \tag{10}$$

and must be solved exhaustively. This method for invariance can only be implemented if a unique solution exists for equation (10). Such a solution is dependent upon the choice of the function $g_1$. Interpolation methods can be employed here where $g_1$ would act as a "warping function" and, in effect, warps the defect dependent parameters, $d$ and $l$, of $g_1$ to those of $g_2$ such that the solution $h(d,l)$ to the ratio given as

$$h(d,l) = \frac{g_2\{x_2(d,l,t)\}}{g_1\{x_1(d,l,t), x_2(d,l,t)\}} \tag{11}$$

is rendered invariant to the parameter $t$ [1, 2, 5]. Feed-forward neural networks provide an ideal solution to $g_1$ [13].

With the presence of experimental training data, the radial basis function (RBF) neural network provides the best function approximation for $g_1$. The activation function, or the function approximator for $g_1$, for a RBF network is given as:

$$g_1 = \sum_{j=1}^{m} \lambda_j \phi(\| x_i - c_{ij} \|) \tag{12}$$

where $\lambda$ denotes the weights of the hidden layer nodes in the network and $\phi$ is a "basis," or window function. In this case, the radial basis or Gaussian basis function is substituted for $\phi$, given as:

$$\phi_{ij}(\| x_i - c_{ij} \|) = e^{-\frac{|xi - c_{ij}|^2}{2\sigma^2}} \tag{13}$$

where $c_{ij}$ is the basis center (mean) and $\sigma$ is the radius (variance) of the Gaussian kernel [14]. Given the nature of the RBF network, this method of universal approximation can be used to estimate the g function for any NDE signal [13]. Therefore, this invariance algorithm can be applied to a multitude of test signals for any application given that there is initial training data present in the form of two distinct signals $x_1$ and $x_2$ to characterize the same test specimen.

The resulting signal from the RBF network is invariant to operational parameters and contains only defect geometry related information in $h(d,l)$. This defect signature signal can then be processed by a second defect characterization algorithm to predict a profile of the defect. The defect characterization is performed again by using a RBF network and a set of target profiles based on the known training data.

Prior development of an invariance algorithm has been completed and tested using simulated data obtained using finite element models. The next step in the development is to apply the algorithm to experimental data to prove its viability in the field. Specimens were developed and scanned in a laboratory to obtain experimental data for implementation of the invariance algorithm.

## Implementation Examples

Presented in this section are two application examples: one involving experimental magnetic images of gas pipeline defects and one involving experimental ultrasonic C-scan images of concrete sewer pipeline defects. Each application utilizes a typical non-destructive testing method, magnetic flux leakage (MFL) line scans for the metal gas pipelines and ultrasound imaging for the concrete sewer pipelines. With experimental data from test specimens, the invariance algorithm has been implemented and the defects have been characterized with defect profiles in each case. Each application is further explained concerning background and experimental procedure in the sections below.

## Gas Pipeline Inspection

The United States natural gas industry provides a safe, uninterrupted supply of natural gas to its consumers via a network of underground pipelines that span some 280,000 miles. Since natural gas is responsible for approximately 30% of the US energy supply, it is imperative that this pipeline delivery system is well maintained [15,16]. Since the 1960s, the natural gas industry has employed a method of pipeline inspection using a device known as a "pig" that travels through the pipe under the pressure of natural gas (see Figure 3). The pig is comprised of a permanent magnet that magnetizes the metal pipe wall as it moves through the pipe and induces magnetic flux. At the occurrence of a defect in the pipe wall, some of the magnetic flux "leaks" out of defect in the pipe [17,18]. This phenomenon is referred to as magnetic flux leakage and can be measured with flux sensitive devices on-board the pig. The pig may travel hundreds of miles of gas pipeline, during which time it collects and stores MFL data that can later be retrieved and analyzed [1].

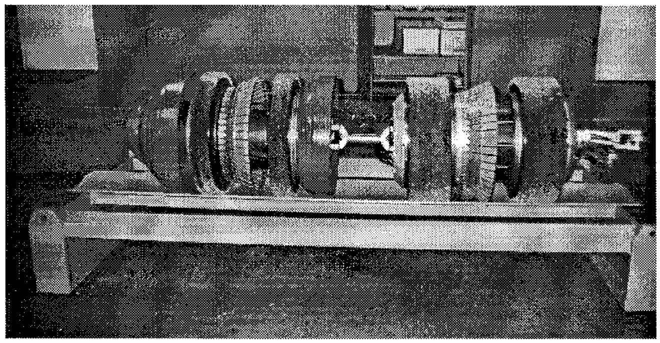


**Figure 3.** The “pig” or inline inspection vehicle used for MFL testing of natural gas pipelines.

There are a variety of operational parameters that affect MFL scans of metal gas pipelines. Along any length of pipe, the magnetization level, thickness, and permeability of the pipe wall may vary. These variations affect images developed with MFL line scans and can make defect characterization difficult. For this application example it was desired to remove the effects of the magnetization level on the MFL line scans since insufficient knowledge or control exists to determine a pipe’s magnetization history. Two unique MFL scans of the same section of pipe can be acquired from a set of orthogonal sensors that will read different components of the magnetic flux density vector; thus providing us with the necessary dissimilarity between scans to employ our invariance algorithm [6, 19].

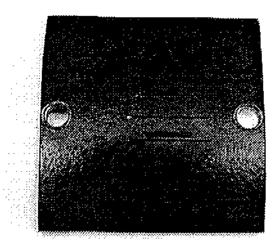


**Figure 4.** Sample metal gas pipeline wall experimental specimen.

For our application, we experimented with different grades of metal pipe wall with specimens of ASTM 836 steel stock and X-grade pipe: X-42, X-52, X-65, X-70. Defects varying in depth from 1.5 mm to 6.4 mm and all exactly 0.8 mm wide were cut into the specimens as key cutter slots (see Figure 4). The specimens were scanned under an induced 200Amp direct current. Scans received for the depths of 1.5 mm, 4.4 mm, and 6.4 mm for the X-42, X-52, and X-65 grade specimens were used as the training data for the invariant RBF neural network. The X-70 grade scans, with identical depths as the previously mentioned grades, were used as the test data.

The MFL line scans received from the experimental setup are shown in Figure 5. Orthogonal MFL sensors provide the two sets of dissimilar signals. One sensor measures the tangential component and the other sensor measures the radial component, which

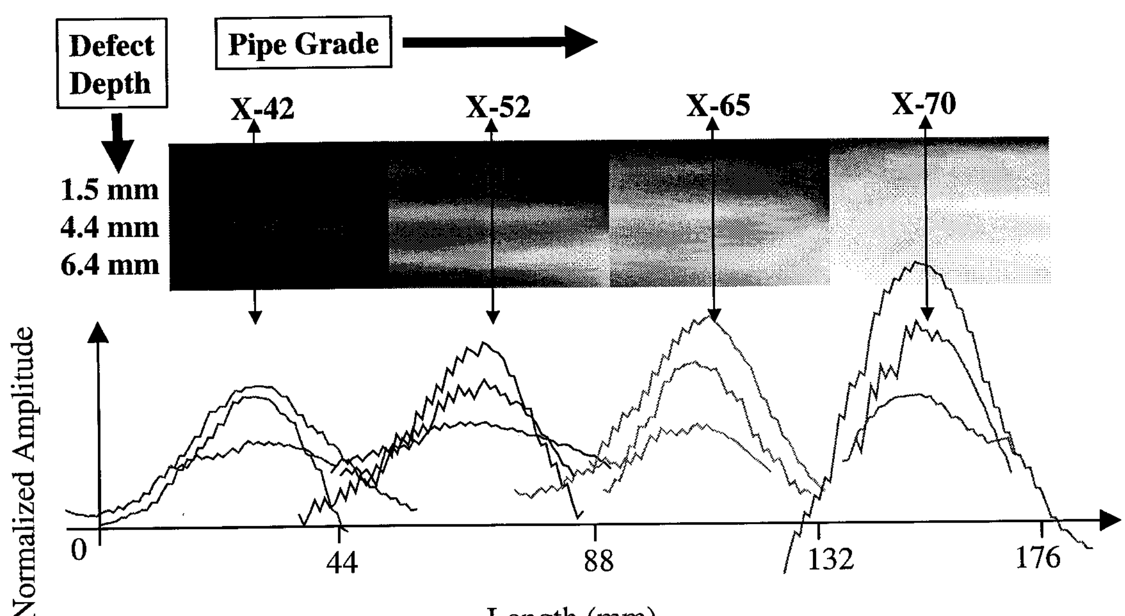



**Figure 5.** MFL line scans for various X-grades of metal gas pipe wall and various slot defect depths.

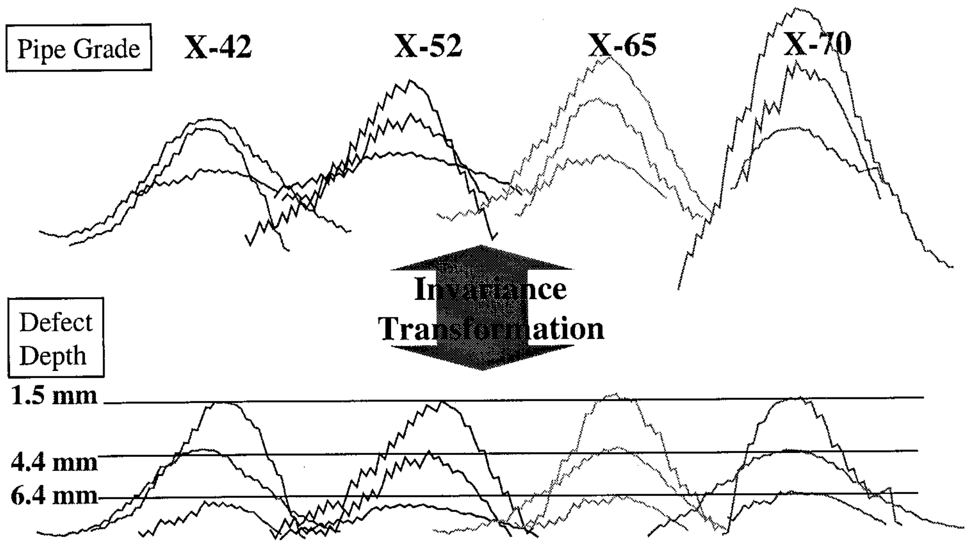



**Figure 6.** Results from the invariance transformation performed on the experimental MFL line scans.

serve as $x_1$ and $x_2$ for the invariance algorithm, respectively. From this figure, it is obvious that various amplitudes are obtained for the same size defect in different grades of pipe. The difficulty in defect characterization is evident when little noticeable difference between the line scan of a 1.5 mm defect of X-42 grade pipe and the line scan of a 4.4 mm defect of X-52 grade pipe. Once processed by the invariant RBF neural network, the defect signature is rendered invariant to operational parameters and relays defect geometry information only (See Figure 6). This defect signature can then be processed by a second RBF neural network that predicts a vector defect profile for the signal.

The results shown in Figure 7 present the defect profiles which give a visual representation of a line scan of the slot defects in the specimen. Set (a) was manually generated to represent the slotted 1.5 mm, 4.4 mm, and 6.4 mm defects of the X-42, X-52, and X-65 grade pipes and was used as target training data for the neural network. Set (b) was predicted by the RBF neural network for the three line scans of the 1.5 mm, 4.4 mm, and 6.4 mm defects in the X-70 grade of pipe. While the predictions are not precise, the 1.5 mm defect was predicted as 1.52 mm with an error of 1.3 percent, the 4.4 mm defect was predicted as 4.6 mm with an error of 4.5 percent, and the 6.4 mm defect was predicted as 6.6 mm with an error of 3.1 percent.

**(a)** Generated Defect Profiles (Training Data) **(b)** Predicted Defect Profiles (Test Data)

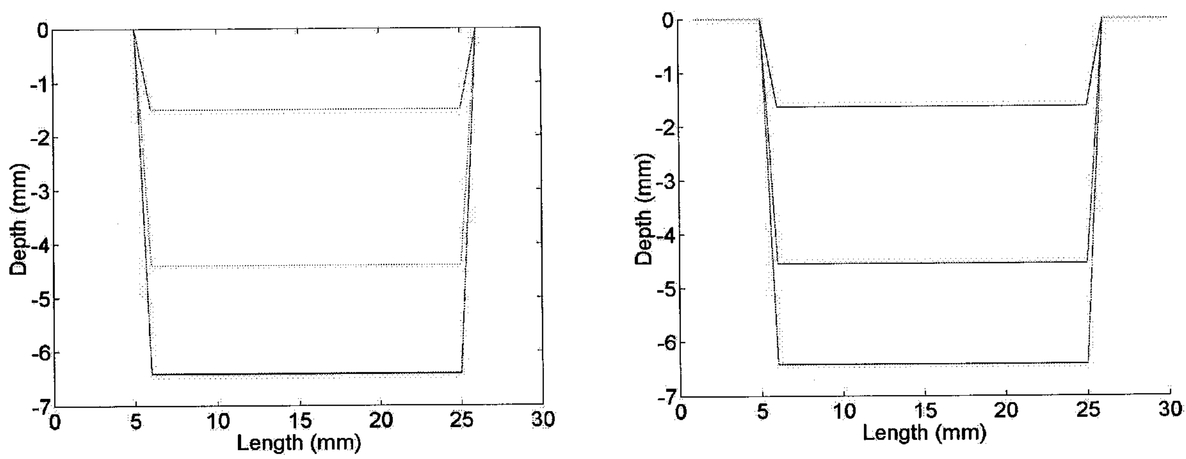



**Figure 7.** (a) Vector defect profiles generated from training data. (b) Vector defect profiles generated from test data.

<u>Concrete Pipeline Inspection</u>

Similar to the natural gas industry, the wastewater industry is reaching a vital point where the maintenance of sewer pipelines must be initiated to extend service life [20]. Currently, there is no existing non-destructive sewer pipeline inspection system. Concrete sewer pipelines are affected by the biological production of sulfuric acid from the wastewater they transport. Corrosion typically occurs in the crown area of the pipe when biological activity in the wastewater develops an anaerobic environment and produces hydrogen sulfide ($H_2S$). The hydrogen sulfide is contained within condensation which collects at the crown of the pipe, and it then reacts with oxygen ($O_2$) creating sulfuric acid which can weaken the concrete resulting in cracks and ultimately collapse of the pipe [21]. While a breach in a gas line requires immediate attention and is more severe than that of a sewer line, the long term environmental and ecological effects of a sewage spill can be devastating. Ultrasonic inspection is widely used for the evaluation of a variety of non-metallic materials, including composites and concrete [22]. A literature survey has shown that studies involving the deterioration of underground concrete pipelines consist primarily of laboratory investigations only [23]. For our experimental application involving defects in concrete sewer pipes, ultrasound imaging was performed on a variety of concrete specimens.

The concrete specimens used in laboratory testing are designed to represent the thickness of 24" (61 cm) internal diameter ASTM class 2 non-reinforced and 24" (61 cm) to 36" (91.4 cm) diameter ASTM C 76 reinforced concrete pipes. The specimens are disc shaped with a radius and thickness of 50.8 mm and contain rectangular shaped defects with a surface area of 25.4 mm long by 25.4 mm wide and depths varying from 0.0 mm to 19.1 mm. The specimens also vary in composition with one set comprised of a 1:1 cement-sand ratio, and another set of a 2.93:1.51:1 of coarse aggregate (19.1 mm top size gray, granite), sand, and cement. All specimens are non-air entrained with the only admixture being a water reducer. Figure 8 shows a typical test specimen.

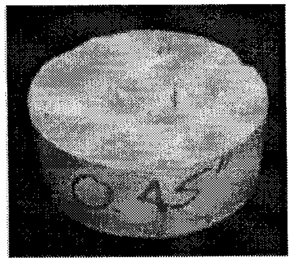


**Figure 8.** Sample concrete disk specimen.

For the results presented in this paper, two sets of four specimens are considered. One set of specimens is molded from a cement and sand mixture, and the second set is molded from a coarse aggregate, sand and cement mixture. For each specimen, two UT C-scans were taken - one at 1 MHz and one at 500 kHz providing the dissimilar signals necessary for the invariance algorithm [12]. For all scans, through transmission ultrasound was used. A 50.8 mm by 50.8 mm area centered about the specimen defect was scanned, and the C-scans were gated specifically for each individual scan such that the surface of the specimen is scanned as a depth of zero.

From this laboratory setup, two sets of C-scans, one set scanned at 1 MHz and one set scanned at 500 kHz were developed from each set of specimens (See Figure 9). The images generated at 500 kHz supply the data for $x_1$ of the invariance algorithm, and images generated at 1 MHz supply the data for $x_2$. From observing the sets of C-scans for each set of specimens, the difficulty inherent in the ultrasonic scanning of concrete is made clear. At 1 MHz, better resolution of the defect geometry is obtained yet the frequency is too high to effectively penetrate the depth of the specimen. On the other hand, at 500 kHz, the ultrasound has much better depth penetration of the specimen, but there is significant degradation in the resolution of the defect geometry.

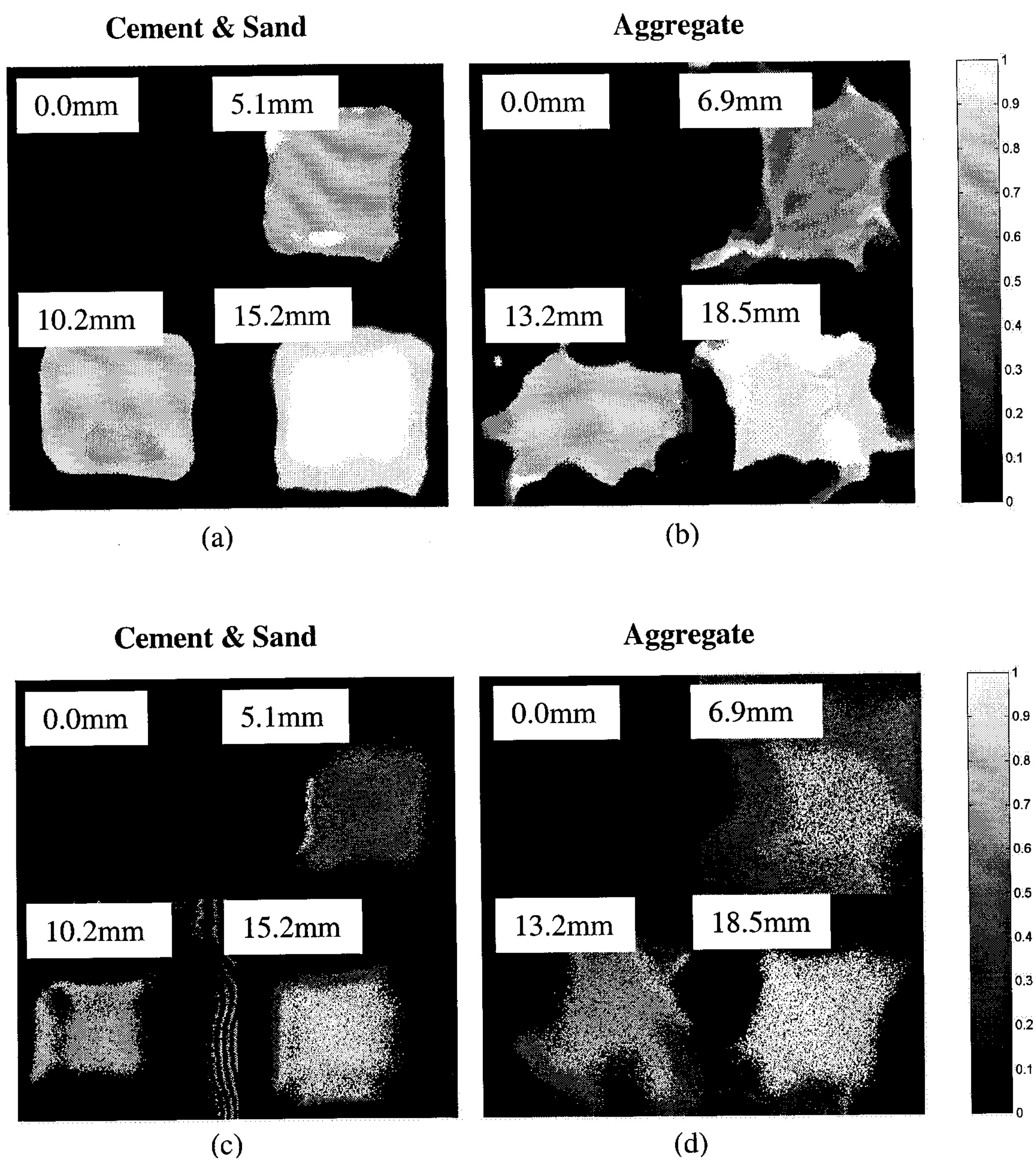



**Figure 9.** Experimental C-scans imaged from concrete specimens – all scans have been color normalized and are broken into four sets as follows: (a) 1MHz C-scans of cement and sand composition with various defect depths. (b) 1MHz C-scans of aggregate composition with various defect depths. (c) 500 kHz C-scans of cement and sand composition and various defect depths. (d) 500 kHz C-scans of aggregate composition and various defect depths.

Once processed by the feed-forward, invariant RBF neural network, the resulting data is a defect signature dependent on defect geometry only. These defect signatures are then processed by a second defect characterization neural network that predicts a three-dimensional defect profile representing the defect's length, width, and depth. Figure 10 shows the resulting defect profiles predicted by the defect characterization neural network.

From the UT C-scan images in Figure 9, the 1 MHz and 500 kHz images of the cement and sand specimens with depths of 0.0, 5.1, and 15.9 mm were used as the input training data for the invariance transformation and defect characterization network. The defect profiles corresponding to these depths were manually generated and used as target training data for the network. The C-scan image of the fourth defect with a depth of 10.2 mm was used as test data to test the network. The resulting output of the network is the three-dimensional 10.2 mm defect profile shown in Figure 10 under cement and sand. The network's predicted profile is actually 10.32 mm giving an error of approximately 1.18 percent. The 1 MHz and 500 kHz images of the aggregate specimens with depths of 0.0, 6.9, and 18.5 mm and defect profiles of corresponding depths were used as training data for the neural network. The image of the fourth depth of 13.2 mm was used as test data. The predicted defect profile for the 13.2 mm depth defect is shown in Figure 10 under aggregate. Again, the prediction of the network is not entirely accurate with an error of 2.27 percent.

Error in the test data is expected since the network must interpolate and predict a depth and profile based on its training data. Since the depths of the images used for test data were within the range of the network's training data, it is expected that the RBF

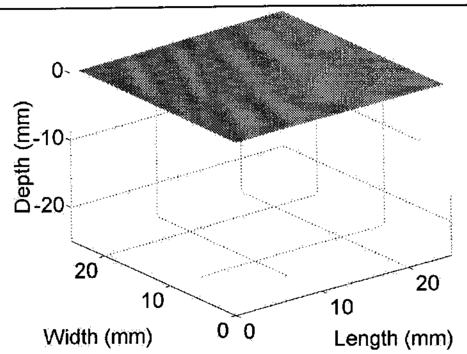
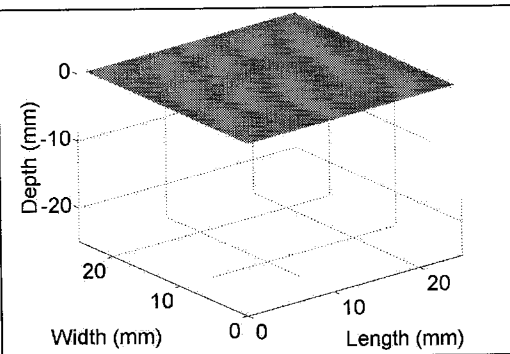
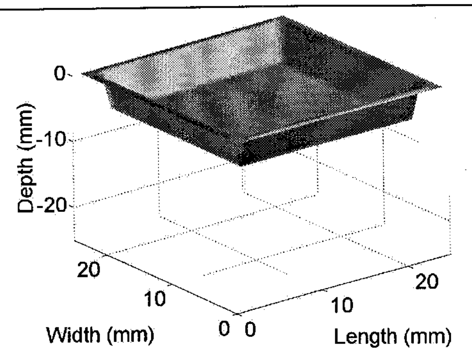
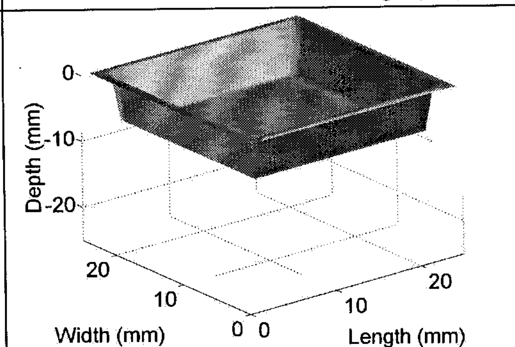
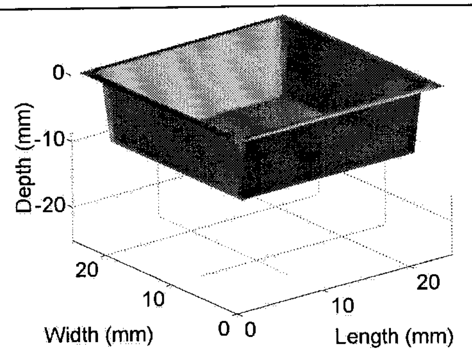
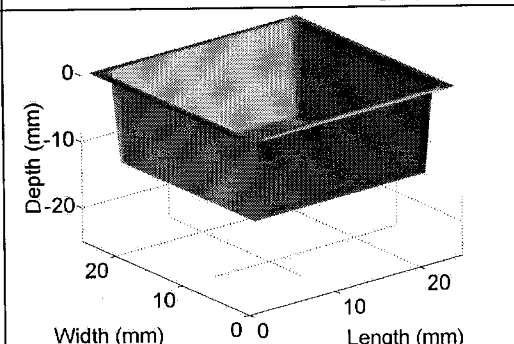
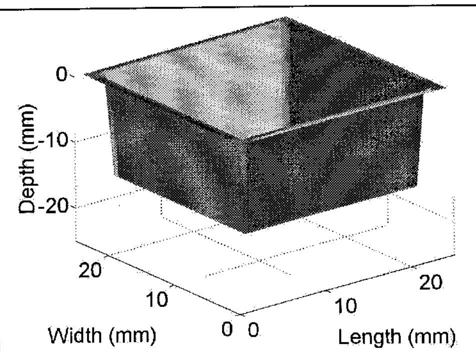
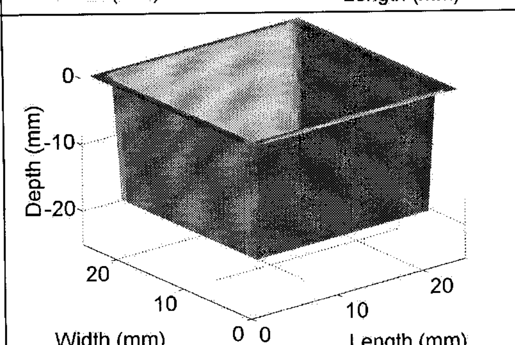
| Defect Depth | Cement and Sand | Defect Depth | Aggregate |
|---|---|---|---|
| **0.0 mm** |  | **0.0 mm** |  |
| **5.1 mm** |  | **6.9 mm** |  |
| **10.2 mm** |  | **13.2 mm** |  |
| **15.2 mm** |  | **18.5 mm** |  |

**Figure 10.** Three dimensional defect profiles generated using the invariance transformation algorithm and the defect characterization RBF neural network.

network should provide a good approximation of the actual depth of the defect. It is unlikely that the network will ever perfectly predict the depth of any given test data that was not part of the network's training data, and the network's reliability drastically reduces for any test data that falls outside of the range of the network's training data.

## Conclusions

This paper has presented a unique solution to the problems in NDT associated with operational parameters in the form of a robust and innovative invariance algorithm and defect characterization process. The results presented provide adequate proof of concept for the invariance technique and its potential for practical application to real world NDE signals. In the cases of MFL testing and UT, the raw signals are successfully rendered invariant to the operational parameters that typically have adverse affects on such signals, and the defect characterization process has provided clear and concise visual predictions of the geometric information retained in the invariant signals. This technique may prove beneficial for many other NDT fields such as eddy current, microwave, thermal imaging, and other methods. This research has laid the foundation for future work in realizing defect characterization for NDE signals that originally may have been considered ineffective due to difficulty in compensating for the effects of operational variables in the signals.

## Acknowledgements

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# ULTRASONIC IMAGING OF DEFECTS IN CONCRETE PIPELINES

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**Abstract.** This paper describes the first stage of a research project to develop an automated vehicle for inspecting the structural integrity of concrete sewer pipelines. We have developed an innovative interrogation and signal processing algorithm for detecting and sizing defects in concrete media, irrespective of the composition of the concrete - a crucial factor for realizing an in-line inspection process for concrete pipes. We have simulated concrete pipeline inspection by fabricating concrete specimens of diverse compositions embedded with rectangular defects of varying depths immersed in synthetic wastewater of varying density. We present ultrasonic C-scans and their corresponding defect characterization profiles.

## INTRODUCTION

In an effort to improve maintenance and extend the service life of concrete sewer pipelines, the wastewater industry must consider implementing a non-destructive method of pipeline inspection. The natural gas industry has employed an automated, inline inspection system to scan existing pipe infrastructure for possible pipe wall defects for over 60 years. A similar inspection system for testing the integrity of concrete sewer pipes currently does not exist. Concrete sewer pipelines are affected by sulfuric acid present in the wastewater they transport. Typically, corrosion from sulfuric acid affects the pipes in the crown area which can weaken the concrete leading to cracks and

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eventually collapse of the pipe. While the level of danger that is eminent with the breach of a gas line is more severe than that of a sewer line, the long term environmental and ecological effects of a sewage spill from a sewer line can be devastating. This paper explores techniques and the feasibility of developing an automated, inline inspection system for concrete sewer pipes.

For this study, the technique utilized for the non-destructive inspection of concrete is immersion ultrasound. There are many issues involved in the ultrasonic testing of concrete sewer pipelines. The inhomogeneous nature of concrete composition makes it a difficult medium to test. Also, there is the possibility that in any length of sewer pipe, the composition of concrete may vary (cement and sand, cement and aggregate, etc). Adding to this complexity is the fact that an inline inspection vehicle using water as its couplant may come into contact with wastewater as part of its coupling media, in which case the viscosity of the wastewater may affect ultrasonic signals. Furthermore, the difficulty of characterizing concrete with ultrasound has hindered progress in this field compared to the NDE of other materials [1] [2].

This paper presents the first step in the development of an automated, inline inspection system for concrete sewer pipelines. An innovative signal processing technique is developed for the characterization of defects found in the pipeline wall. This technique produces a defect signature that is invariant to varying material properties and operational parameters and can be processed such that a three dimensional profile of the defect can be viewed.

This paper is organized as follows. First, an introduction to the research problem is presented. Research objectives are stated and the expected results are indicated. The approach taken for this research is offered and broken down into the various sub-tasks involved where a technical description of each task is presented. The paper concludes with a section that presents the results achieved from this study and a summarization drawn from these results.

## RESEARCH OBJECTIVES

This research focuses on preliminary laboratory testing and signal processing that will form a basis for future work towards the development of an automated, in-line inspection system. The objectives for the research presented in this paper are given below:

1. Perform laboratory tests with concrete specimens using immersion ultrasound.
2. Study the effects of variations in the composition of the concrete and fluid medium.
3. Develop signal processing algorithms that generate defect-related signatures that are invariant to changes in concrete composition and fluid medium.
4. Predict three dimensional defect profiles.

Previously, the focus of this research was to develop a method for the collection of ultrasound C-scan data from concrete specimens under controlled laboratory conditions. Currently, the focus has shifted to the task of signal processing to obtain defect signatures that are invariant to various operational parameters. While these ideal laboratory conditions are not representative of the inside of an actual concrete sewer pipe or real world inline inspection system environment, it is necessary to take these preliminary steps in the laboratory before attempting to apply these techniques to an actual system.

The approach taken to complete these research objectives is described in the following section.

## APPROACH

### Specimen Preparation

The concrete specimens used in laboratory testing are designed to represent the thickness of 24" internal diameter ASTM class 2 non-reinforced and 24" to 36" diameter ASTM C 76 reinforced concrete pipes. The specimens are disc shaped with a radius and thickness of 2" and contain rectangular shaped defects with a surface area of 1" long by 1" wide and depths varying from 0.0" to 0.75". The specimens also vary in composition with one set comprised of a 1:1 cement-sand ratio, and another set of a 2.93: 1.51 : 1 of coarse aggregate (3/4" top size gray, granite), sand, and cement. All specimens are non-air entrained with the only admixture being a water reducer. Figure 1 shows a typical test specimen.

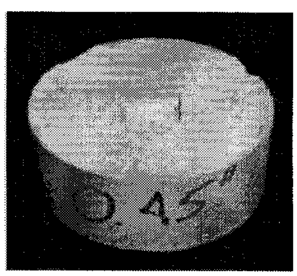



**FIGURE 1.** Example of specimens used for ultrasonic testing.

**TABLE 1.** Synthetic wastewater composition.

| CONSTITUENT | CONCENTRATION (mg/L) | | |
|---|---|---|---|
| | Weak | Medium | Strong |
| Biochemical Oxygen Demand | 110 | 220 | 400 |
| Total Nitrogen as N | 20 | 40 | 85 |
| Total Phosphorus as P | 4 | 8 | 15 |
| Chlorides | 30 | 50 | 100 |
| Sulfate | 20 | 30 | 50 |
| Alkalinity as $CaCO_3$ | 50 | 100 | 200 |

## Wastewater Preparation

Synthetic wastewater is used as one of two immersion media (the other being tap water). Since wastewater present in concrete sewer pipes is different from tap water in both chemical composition and viscosity, and wastewater may be present in the couplant during in-line inspection of concrete pipes, studying the affects wastewater on ultrasonic testing is essential. Its chemical composition is given below in Table 1.

## Ultrasound Testing

Through transmission is used in all concrete ultrasound tests. All specimens used for testing are scanned twice, once at 1MHz and then again at 500kHz. We chose these specific frequencies based on a preliminary investigation as to which frequencies provide the best results for the purposes of this study. The importance of scanning each specimen with two frequencies is discussed in the defect characterization portion of this paper.

## Defect Characterization

Defect characterization involves developing signal processing algorithms that will determine the geometry of a defect in concrete despite the composition of the concrete or wastewater couplant. The approach taken in the defect characterization process is shown in Figure 2. The defect characterization algorithm utilizes C-scan ultrasound data to determine the size and shape of the defect. This data is first processed through an

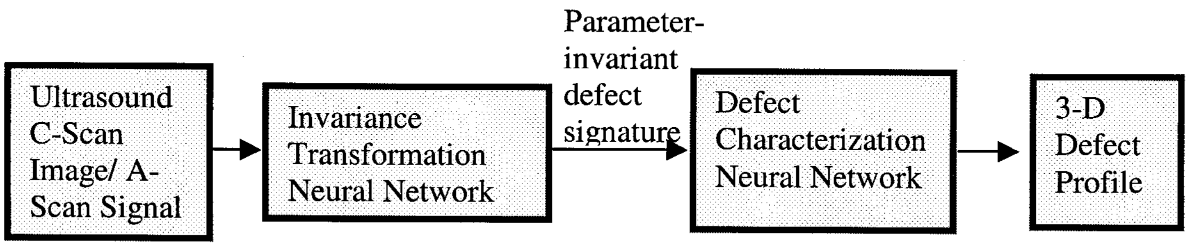



**FIGURE 2.** Defect characterization approach.

invariance transformation feed forward radial basis function (RBF) neural network that renders the ultrasound signals taken from the C-scan data invariant to operational parameters such as concrete and wastewater composition. Next, the invariant defect signature is processed by a defect characterization RBF neural network that predicts a 3-D profile of the defect. Details of the invariance algorithm can be found in previous publications [3] [4]. A brief description follows.

The objective of the invariance RBF neural network is to produce a signal that is representative of the defect geometry only. The process of transforming signals such that they are invariant to operational parameters involves multiple (at least two) signals that originate from the same process. In the case of this study, the 500kHz and 1MHz C-scans provide two different perspectives of the same specimen. Given multiple signals as the input, the invariance transform network synergistically combines these signals to isolate a unique defect signature. This process can be modeled mathematically through the invariance transformation algorithm.

The invariance transformation algorithm involves the input of two distinct test signals $x_1(d, l, t)$ and $x_2(d, l, t)$ where $d$ and $l$ represent the depth and length of the defect and $t$ represents an operational parameter such as concrete composition. The invariance network interpolates these two signals to eliminate the operational parameter t and produce a single output $h(d, l)$ that is characterized by the defect depth and length only. The basis for this procedure is the theory of universal approximation [5], where the invariance transformation can be represented mathematically as

$$h(d,l) = f(x_1, x_2) = \frac{x_1(d,l,t)}{g[x_1(d,l,t), x_2(d,l,t)]} \tag{1}$$

where the function $g$ is a function that is chosen arbitrarily. Since the experimental data is extremely diverse due to operational parameters, there is no unique solution for $g$. The goal in this case is to choose a general function that will provide the best possible solution for $h(d,l)$, that is, the output is the best approximation of $h(d,l)$. The radial basis function neural network provides the best approximation of $h(d,l)$ based on a set of experimental training data. The mathematical representation of a RBF network is given as

$$\phi_{ij} = e^{-\frac{\|x_i - c_j\|^2}{2\sigma^2}} \tag{2}$$

Two RBF networks are utilized in series to produce a final output of a 3-D defect profile.

## RESULTS

Two sets of C-scans obtained from ultrasonic inspection of our specimens are shown in Figures 3 and 4. The set of images in Figure 3 are of 1MHz scans of defects of various depths for both sets of specimens (cement & sand and the aggregate mixture). The second set of images is of the same specimens scanned at 500 kHz. Figure 5 shows a comparison of C-scan images obtained by scanning the same specimen at the same frequency immersed in two different media – water and synthetic wastewater. It is evident that the effect of synthetic wastewater as an immersion media is minimal. Therefore, all defect characterization algorithms used C-scan images from specimens immersed in a water media as input.

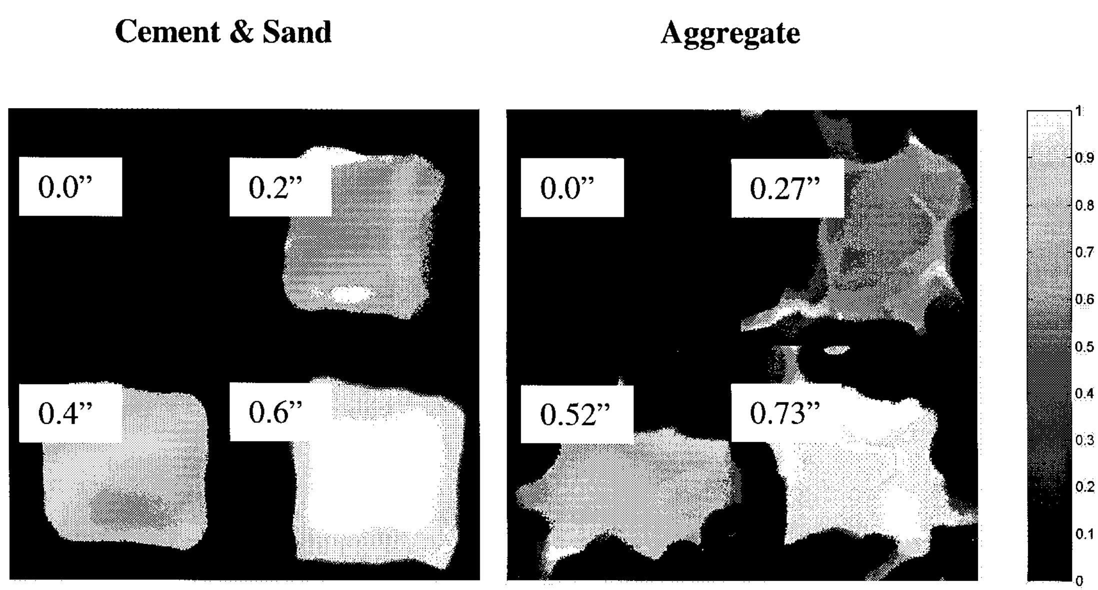



**FIGURE 3.** 1MHz C-scans of concrete specimens of various compositions and various defect depths.

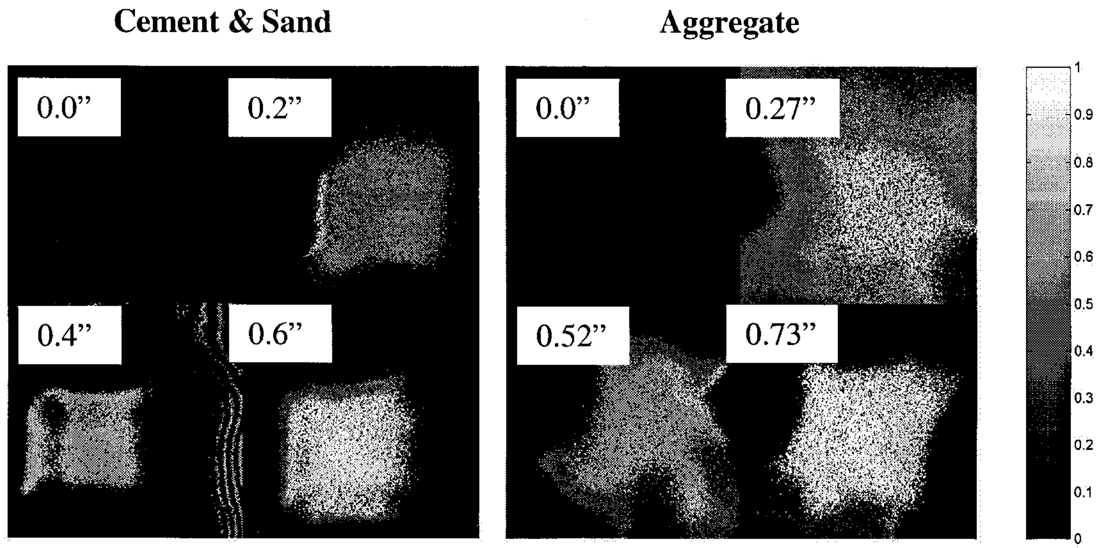



**FIGURE 4.** 500 kHz C-scans of concrete specimens of various compositions and various defect depths.

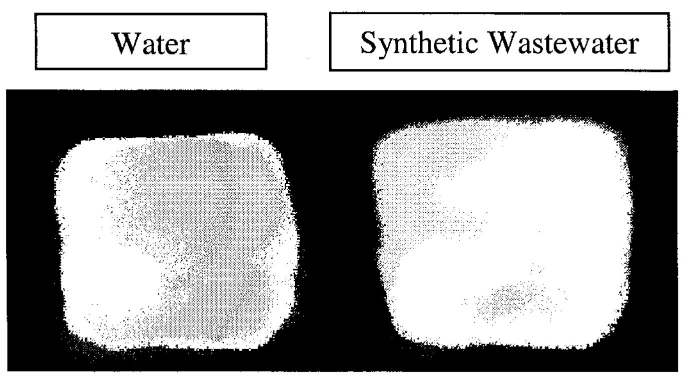



**FIGURE 5.** C-scan images of 0.6” rectangular defect in a cement and sand specimen showing tap water (left) vs. synthetic wastewater (right) as couplants.

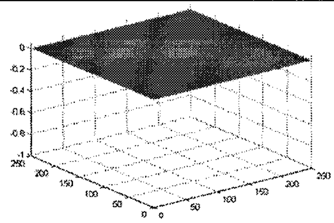
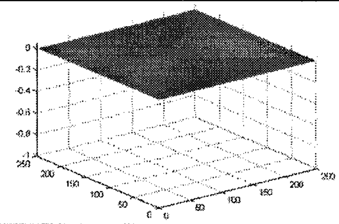
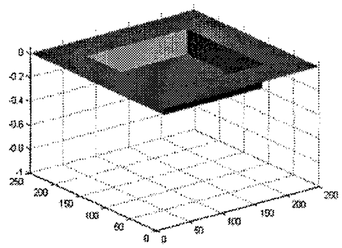
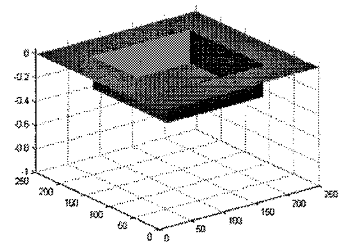
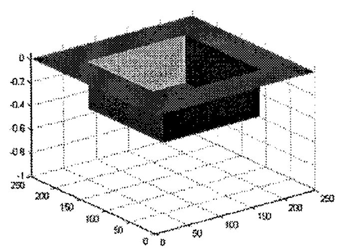
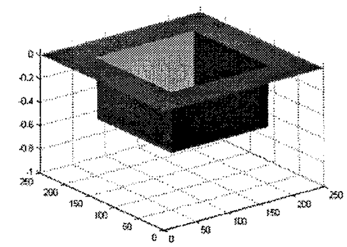
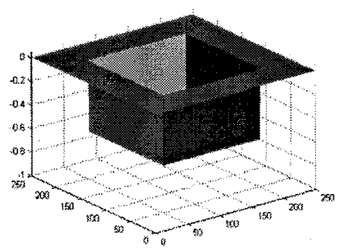
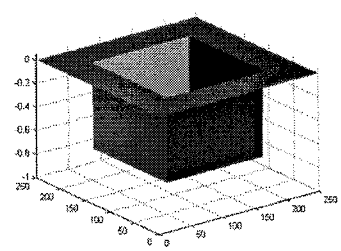
| Defect Depth | Cement and Sand | Aggregate |
|---|---|---|
| 0.0" |  |  |
| 0.2" |  |  |
| 0.4" |  |  |
| 0.6" |  |  |

**FIGURE 6.** Three dimensional defect profiles generated using the invariance transformation algorithm and the defect characterization RBF neural network.

Figure 6 shows a set of 3-D defect profiles generated from the invariance transformation algorithm and defect characterization neural network described in the previous section. It can be seen that the predicted 3-D defect profile is invariant to the composition of concrete and represents only the defect geometry.

## DISCUSSION

We have presented an innovative interrogation and signal processing algorithm for detecting and sizing defects in concrete media. The ultrasonic C-scans and corresponding defect characterization profiles demonstrate that this algorithm is robust and provides accurate results. This research work lays the foundation for realizing an inline inspection process for concrete sewer pipelines.

## ACKNOWLEDGEMENTS

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# A Defect Characterization Technique for Experimental NDE Signals

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**Abstract** – Defect characterization using actual NDE signals is hampered by the effects of operational parameters on testing signals. This paper presents a general signal processing technique can be employed with raw, experimental test signals to remove variations due to such parameters and produce a defect signature that can easily be mapped to a profile of the defect. This technique can be applied to a variety of nondestructive testing methods and has been validated with experimental data.

**Keywords:** characterization, ultrasound, magnetic flux leakage, neural networks

## Introduction

Operational parameters that are parts of a nondestructive evaluation signal place limitations on the ability to characterize defects in the material being tested since compensating for such parameters requires that the variables are accurately measured for each individual testing scenario. In some cases, this dependence of the test signal on operational parameters has made nondestructive testing (NDT) a less desirable choice for material inspection.

There is no simple or typical mathematical solution available for the compensation of many test parameters. For some testing variations, it is impossible to quantify, or sometime even qualify, various individual parameters. The algorithm presented in this paper provides an approach to defect characterization that involves an invariance transformation that removes the need to account for operational parameters interfering with a raw NDT signal. This invariance technique optimizes the raw NDT signal by canceling the effects of the operational parameters and producing an invariant defect signature that relays information about the defect's size, shape, and depth only [1, 2, 3]. The defect can then be characterized by a simple mapping process that provides a visual profile of the flaw. This technique is exercised using experimental magnetostatic flux leakage (MFL) and ultrasonic testing (UT) which are typical NDT methods for metal natural gas pipelines and concrete sewer pipelines, respectively.

This paper is organized as follows. First a background the NDT of natural gas pipelines and concrete wastewater pipelines is discussed. Next, the approach taken in this study is presented and the invariance transformation and defect characterization algorithms are described. Finally, the results of the experimental research performed to validate the algorithm are presented. A discussion of the results and potential for further applications follow in the conclusions section.

## Background

### *Natural Gas Pipeline NDT*

Natural gas is responsible for approximately thirty percent of the United States energy consumption and provides its natural gas supply via some 280,000 miles of underground pipelines [4,5]. Since the 1940s, a device known as a "pig" that travels through the pipe under the pressure of natural gas has been employed to evaluate this network of pipelines. The pig uses a permanent magnet to magnetize the metal pipe wall and induce magnetic flux as it travels through the pipe. Where there is a flaw in the pipe wall, the magnetic flux "leaks" out of the defect [6,7]. This event is known as magnetic flux leakage and can be measured with on-board flux sensors. The pig collects and stores MFL data that can later be retrieved and analyzed [1].

A wide range of test parameters effect MFL scans in gas pipelines including the pipe material, pipe wall thickness, axial and hoop stresses in the pipe, the velocity of the inspection vehicle, and the remnant magnetization in the pipe [8]. While it is possible to manage some of these parameters, such as the pipe wall thickness, others, such as remnant magnetization in the pipe, are impossible to measure without the full magnetization history of the pipe. Without a means to measure and compensate for certain parameters, defect characterization becomes an intractable challenge.

*Wastewater Pipeline NDT*

The wastewater industry is reaching a crucial point where the inspection of sewer pipelines is necessary to extend service life [9]. Currently, a non-destructive sewer pipeline inspection system, similar to that used by the natural gas industry, does not exist. Concrete sewer pipelines are affected by sulfuric acid present in the wastewater they transport. Corrosion occurs in the crown area where sulfuric acid and water vapor tends to collect, and can result in cracks leading to the possible collapse of the pipe. The long-term environmental and ecological effects of a sewage spill can be devastating and costly. For this reason, it is imperative that the wastewater industry seeks a means of pipeline inspection. Typically, ultrasonic inspection is applied for the evaluation of a variety of non-metallic materials, such as composites and concrete [10].

Concrete proves a very difficult medium to inspect with ultrasound. Operational parameters involved in the UT of concrete include concrete composition and viscosity of the coupling medium. The nature of concrete adversely affects UT scans since mixtures may contain cement, sand, and even aggregate causing scatter and distortion of sound waves that often results in poor C-scan images [11]. In addition, the composition of concrete may vary in any given length of pipe. Additionally, it is possible for the viscosity of the couplant to have undesirable effects on the signal as well, but this is not within the scope of this paper. [3]. Similar to MFL testing, defect characterization of concrete proves difficult due to the variations in the testing results.

## Approach

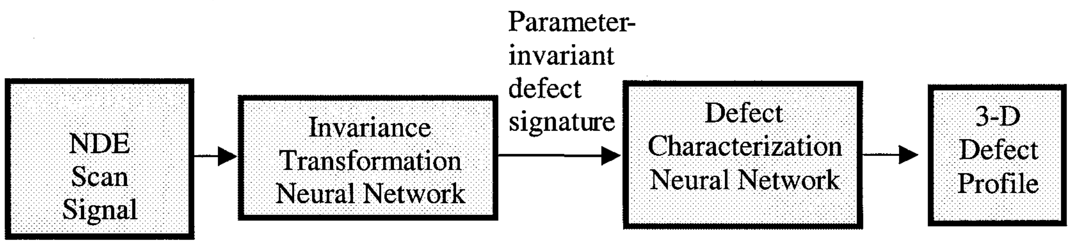



**Figure 1.** Block diagram of defect characterization process.

A two-step approach is taken in the defect characterization of NDE signals. Figure 1 provides a block diagram of this process. The first step processes raw NDE signals via the feed forward invariance neural network such that the resulting signal contains defect related information only. The second step processes the invariant defect signature through a defect characterization network that presents an estimated defect profile that visually depicts the defect size, shape, and depth. Each step in this approach is described in detail below.

For step one, the NDE signal must be rendered invariant to testing variables that affect the signal such that the defect related information is no longer distorted. Mentioned previously, each NDT method and its application involves a unique set of operational parameters that influence the testing signal such that signals from the operational parameters are mixed with the defect signature. Operational parameters are variables dependant upon the properties of the material being tested, the testing environment, and the test equipment. Typically, operational parameters must be measured and accounted for in each testing instance, whether in the field or the laboratory. The inherent problem with these variables is that they vary greatly between each testing setup and compensating for multiple operational parameters proves a nontrivial task which can often make defect characterization impossible or impractical. For this reason, a novel approach is necessary that does not require the measurement operational variables. Ideally, such an invariance technique should avoid the measurement, or even qualification, of operational parameters all together.

Operational parameters can be removed from a raw NDT signal by interpolating the defect signature from two dissimilar scans of the same test specimen. The invariance algorithm isolates the defect related information from those parts of the signal that are dependent on operational parameters. In the case of MFL testing of metal pipelines, two signals can be obtained by using a set of orthogonal probes, and for the UT of concrete pipelines, two different ultrasound frequencies can be used to obtain individual images of the same specimen. In general, these two signals are then processed by a radial basis function (RBF) neural network which, based on a set of training data, will return a signal that contains information describing a defect's size, shape, and depth without the interference of operational parameters. This invariance transformation process can be modeled mathematically.

The invariance transformation algorithm requires the input of two distinct test signals $x_1(d, l, t)$ and $x_2(d, l, t)$ where $d$ and $l$ represent the depth and length of the defect and $t$ represents an operational parameter. The RBF neural network interpolates these two signals to eliminate the operational variable $t$ and produce a single output $h(d, l)$ that is characterized by the defect depth and length only. This procedure is based on the universal approximation theory [12], and the invariance transformation can be represented mathematically as

$$h(d,l) = f(x_1, x_2) = \frac{x_1(d,l,t)}{g_1[x_1(d,l,t), x_2(d,l,t)]} \tag{1}$$

where the function $g_1$ is a function that is chosen arbitrarily. There is no unique solution for the function $g$ since the operational variables are attributed to arbitrary, real world signals. Therefore, $g_1$ is chosen as a general function that will provide the best possible solution for $h(d,l)$, that is, the output is the best approximation of $h(d,l)$. The RBF neural network provides the best estimation of the output, $h(d,l)$, based on a set of experimental training data. The radial basis function, or activation function, for the neural network is given as

$$g_1 = \sum_{j=1}^{m} \lambda_j \phi(\| x_i - c_{ij} \|) \tag{2}$$

where $\lambda$ denotes the weights of the hidden layer nodes in the network and $\phi$ is a "basis," or window function. Given the nature of the RBF network, this method of universal approximation can be used to estimate $g_1$, from Equation (1), for any NDE signal obtained in a variety of testing scenarios [8]. Therefore, this invariance algorithm can be applied to a multitude of test signals for any application given that there is initial training data present in the form of two distinct signals $x_1$ and $x_2$ to characterize the same test specimen.

The second step in the defect characterization process is to predict a visual profile that represents the dimensions of the defect being characterized. A set of profiles is generated for known defects that have been processed by the invariance transformation RBF neural network and used as training data for the RBF defect characterization network. The network can then interpolate test NDE signals that have been rendered invariant and predict a profile that will represent the geometry of the defect.

Experimental MFL scans of sample metal pipeline specimens and UT scans of sample concrete pipeline specimens were obtained to test the validity of this defect characterization technique. The next section discusses the experimental setup for obtaining the data and the results of processing the data through the defect characterization process.

**Implementation Examples**

This section presents two separate applications of the invariance transformation algorithm and defect characterization process. As previously mentioned, test specimens were designed to represent metal gas pipelines and concrete sewer pipelines. Experimental data was obtained from the metal pipeline specimens using MFL testing methods and from the concrete pipeline specimens using ultrasonic testing methods. The two sub sections below discuss the specimen design, scanning procedures, and results obtained from the algorithms.

*MFL Implementation*

For the MFL implementation example, we experimented with various grades of metal pipe wall with specimens of ASTM 836 steel stock and X-grade pipe: X-42, X-52, X-65, X-70. Defects varying in depth from 1.5 mm to 6.4 mm and all exactly 0.8 mm wide were cut into the specimens as key cutter slots, and each specimen was scanned under an induced 200Amp direct current. A sample specimen is pictured in the inset in Figure 2. For this example, the X-70 grade specimens are used as test data while the remaining specimens are used as training data for the RBF neural networks.

Orthogonal MFL sensors provide the two sets of dissimilar signals. One sensor measures the tangential component, or the $x_1$ signal, and the other sensor measures the radial component, or the $x_2$ signal. The invariant RBF rendered invariant to operational parameters and conveys defect geometry information neural network then processes the two signals $x_1$ and $x_2$, and the NDT signal is rendered invariant to operational parameters and conveys defect geometry information only. The outset of Figure 2 shows the raw

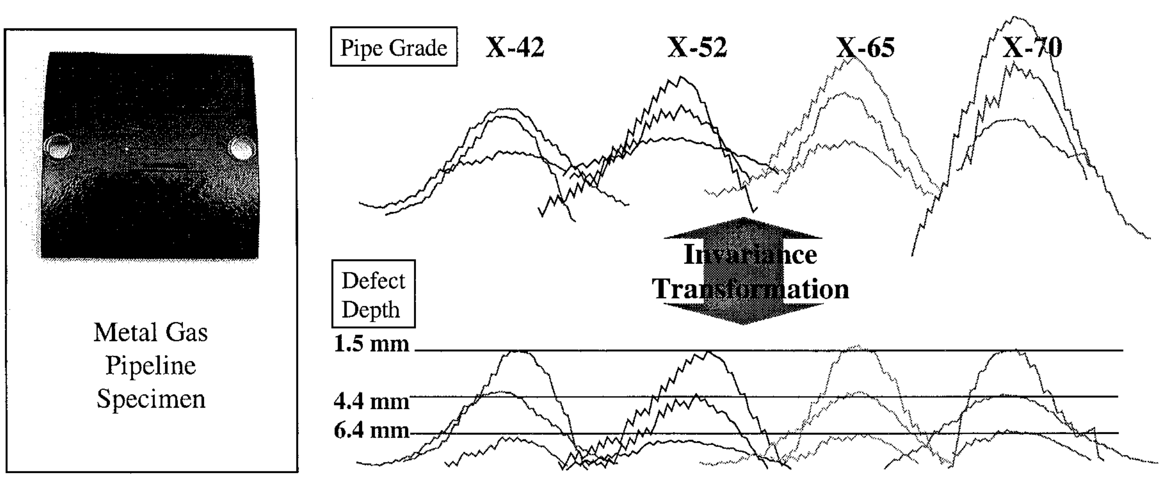



**Figure 2.** Inset: Sample metal gas pipeline wall experimental specimen. Outset: Raw

MFL line scans and the results from the invariance transformation performed on the experimental MFL line scans.

MFL scans of the specimens and the scans after having been processed by the invariance transformation algorithm. This defect signature is then processed by the defect characterization RBF network that predicts a vector defect profile for the signal.

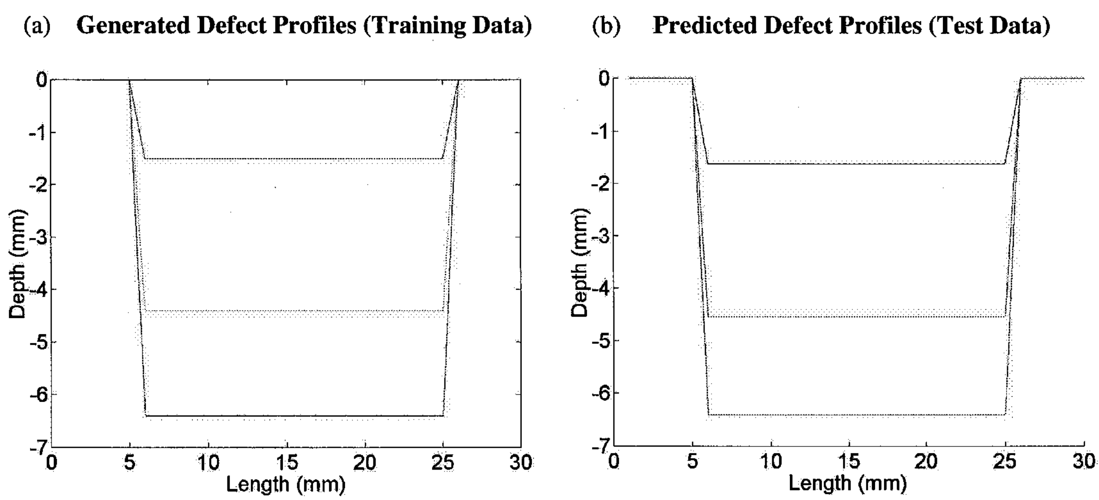



**Figure 3.** (a) Vector defect profiles generated from training data. (b) Vector defect profiles generated from test data.

The results of the defect characterization process are shown in Figure 3. The defect profiles in set (a) were generated manually to represent the 1.5, 4.4, and 6.4 mm defects for the line scans of the X-42, X-52, and X-65 grades of pipe and were used as input training data. The defect profiles in s`et (b) were predicted by the RBF neural network for the line scans of the defects in the X-70 grade of pipe which was used as test data. The average prediction error of the network was approximately 3 percent.

*UT Implementation*

Two sets of four concrete specimens were developed for experimental ultrasound C-scan imaging. The specimens were designed to represent the thickness of 24" (61 cm) internal diameter ASTM class 2 non-reinforced and 24" (61 cm) to 36" (91.4 cm) diameter ASTM C 76 reinforced concrete pipes. The specimens are disc shaped with a thickness and radius of 50.8 mm and include rectangular shaped defects with a surface area of 25.4 mm by 25.4 mm and depths varying between 0.0 mm and 18.5 mm. The specimens also vary in composition with one set mixed from a 1:1 cement-sand ratio, and another set of a 2.93:1.51:1 of coarse aggregate (19.1 mm top size gray, granite), sand, and cement. All specimens are non-air entrained with the only admixture being a water reducer. Figure 4 shows a typical concrete test specimen.

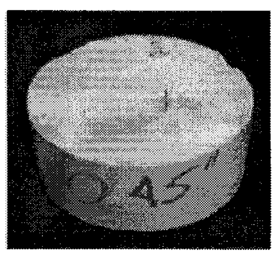


**Figure 4.** Sample concrete disk specimen.

For each specimen, two UT C-scans were obtained - one at a frequency of 1 MHz and one at a frequency of 500 kHz providing the dissimilar signals necessary for the invariance algorithm [12]. The data collected at 1MHz served as the signals for the $x_1$

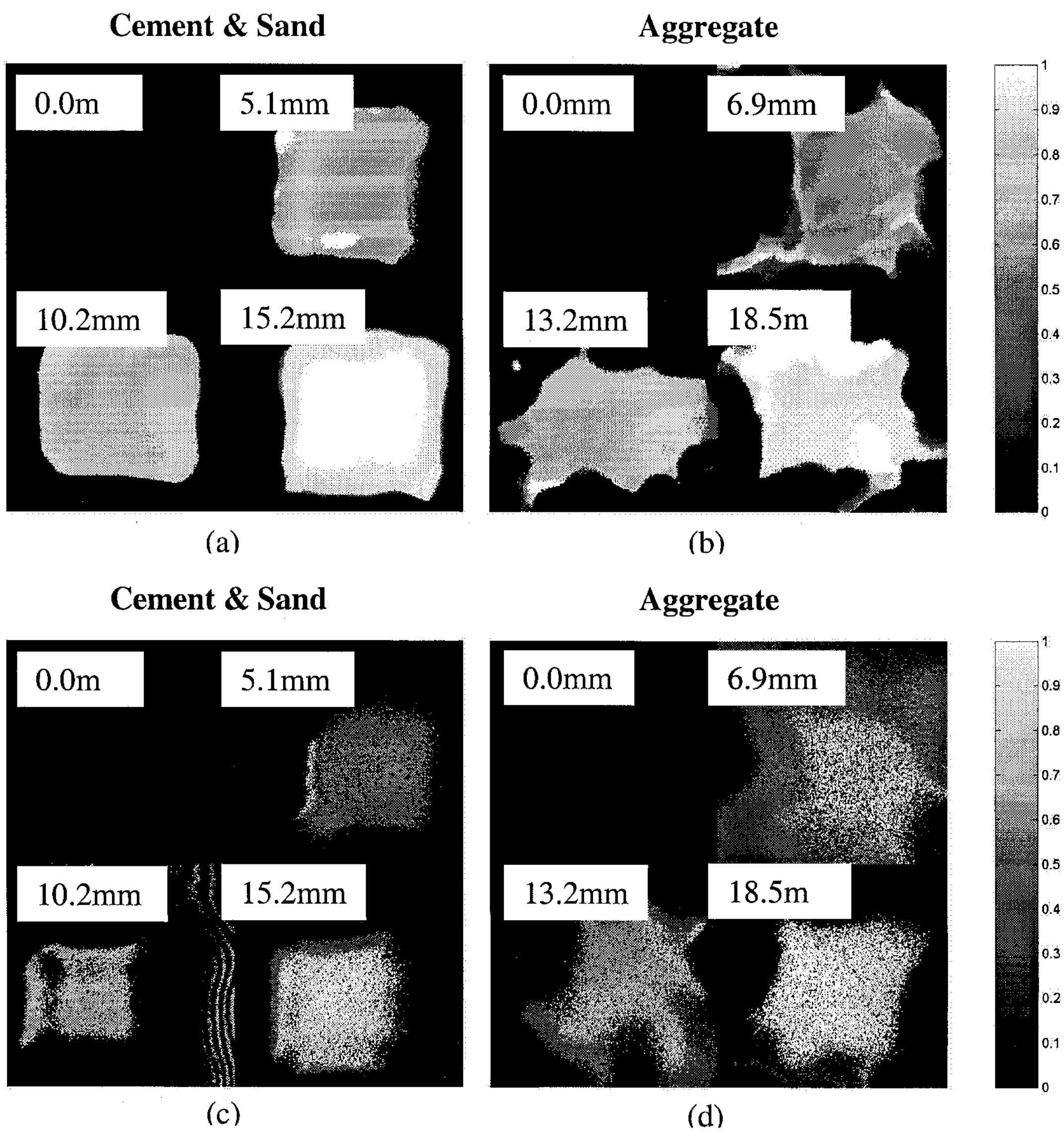



**Figure 5.** Experimental C-scans imaged from concrete specimens – all scans have been color normalized and are broken into four sets as follows: (a) 1MHz C-scans of cement and sand composition with various defect depths. (b) 1MHz C-scans of aggregate composition with various defect depths. (c) 500 kHz C-scans of cement and sand composition and various defect depths. (d) 500 kHz C-scans of aggregate composition and various defect depths.

component of the invariance transformation, and the data collected at 500 kHz served as the signals for the $x_2$ component. For all scans, through transmission ultrasound was used, and a 50.8 mm by 50.8 mm area centered about the specimen defect was scanned, and the C-scans were gated such that the surface of the specimens are scanned as a depth of zero.

By observing the four sets of scans in Figure 5, the difficulty inherent in the ultrasonic testing of concrete is made clear. The 1 MHz frequency was chosen to provide good quality resolution of the defect shape and size, yet higher frequencies such as this do not penetrate the concrete well and give poor depth perception. The 500 kHz frequency was chosen to provide better realization of the relative depth of the defect, but the resolution at this lower frequency is poor compared to 1 MHz. The four sets of C-scans shown in Figure 5 were used as the training data for the invariant neural network.

Once processed by the feed-forward, invariant RBF neural network, the resulting ultrasound signals are dependent on defect geometry only. These defect signatures are then processed via the defect characterization neural network that predicts a three-dimensional defect profile representing the defect's length, width, and depth. Figure 6 shows the resulting defect profiles predicted by the defect characterization neural network.

From the UT C-scan images in Figure 5, the 1 MHz and 500 kHz images of the cement and sand specimens with depths of 0.0, 5.1, and 15.9 mm were used as the input training data for the defect characterization network. The defect profiles corresponding to these depths were manually generated and used as target training data for the network (See Figure 6). The C-scan image of the fourth defect with a depth of 10.2 mm was used

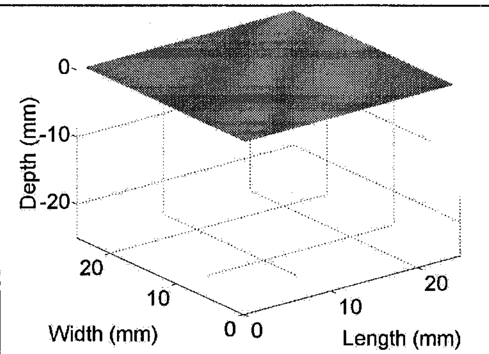
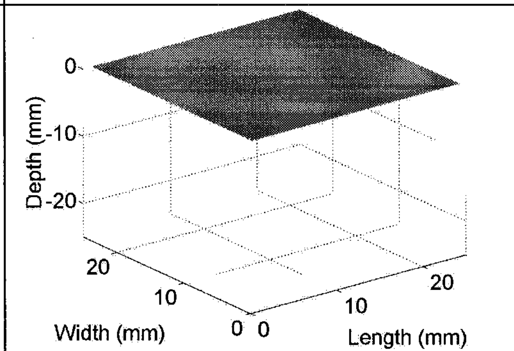
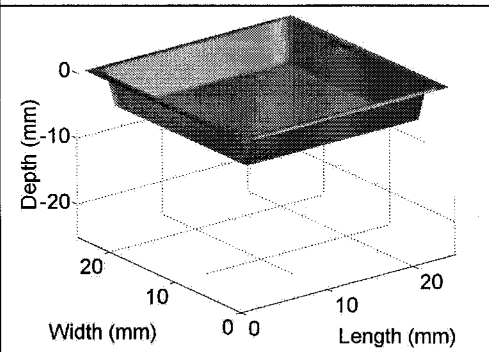
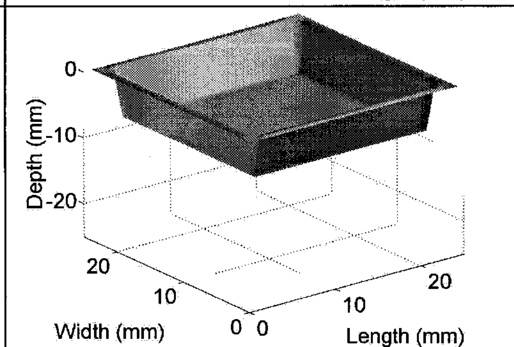
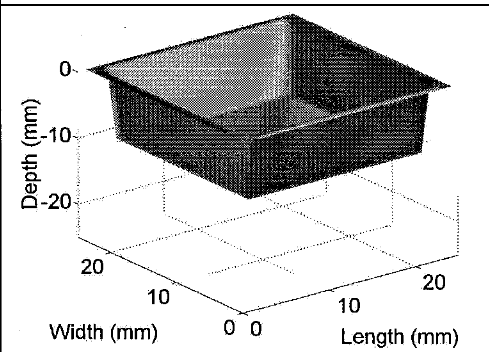
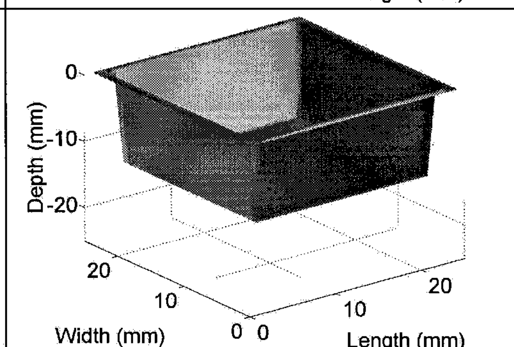
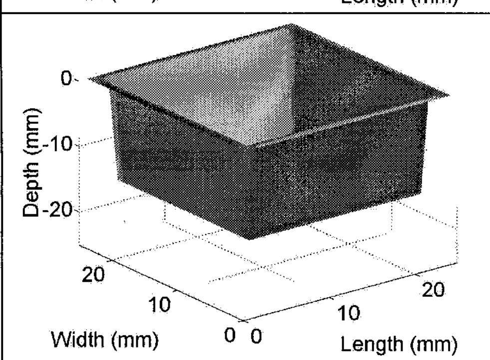
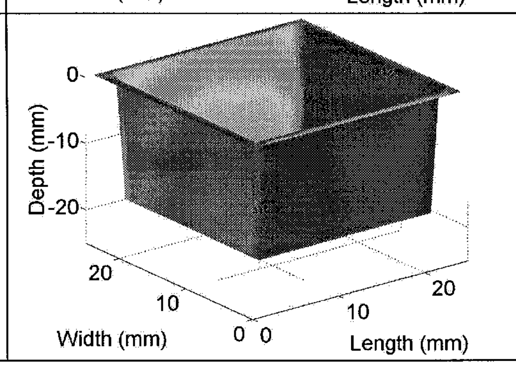
| Defect Depth | Cement and Sand | Defect Depth | Aggregate |
|---|---|---|---|
| **0.0 mm** |  | **0.0 mm** |  |
| **5.1 mm** |  | **6.9 mm** |  |
| **10.2 mm** |  | **13.2 mm** |  |
| **15.2 mm** |  | **18.5 mm** |  |

**Figure 6.** Three dimensional defect profiles generated using the invariance transformation algorithm and the defect characterization RBF neural network.

as test data. The error of the predicted 10.2 mm defect was approximately 1.2 percent. The 1 MHz and 500 kHz images of the aggregate specimens with depths of 0.0, 6.9, and 18.5 mm and defect profiles of corresponding depths were used as training data for the neural network. The image of the fourth depth of 13.2 mm was used as test data. The error of the predicted 13.2 mm defect was approximately 2.3 percent. All three-dimensional defect profiles used for training data and the resulting predicted defect profiles from the test data are shown in Figure 6.

## Conclusions

This paper presents a novel approach to defect characterization through the application of an invariance algorithm that can be implemented for a multitude of NDE signals. The results presented show that the general technique is successful in the implementation of two separate experimental NDT examples. This defect characterization method holds considerable potential for industries that seek a means of nondestructive evaluation for inspection of various infrastructures. In the future, this method can be applied to not only underground pipelines, but also other structures and machinery such as bridges, pavement, buildings, aircraft, and naval vessels.

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# CHAPTER 5. CONCLUSIONS

## 5.1 Summary

The three papers presented in this thesis describe a novel approach for defect characterization and provide substantial experimental results proving that the algorithm is viable for use in the field. While the mathematical theory behind the algorithm remains the same for each paper, the results presented and the ideals for the potential of the defect characterization technique progress over the course of the papers. Each paper will be briefly summarized in the following paragraphs.

The first paper entitled "An invariance algorithm for defect characterization," on pp 13-38, expands on the research presented in the previous paper. This paper presents classical mathematical invariance methods to compensate for operational parameters as well as the full mathematical theory behind the proposed defect characterization algorithm. The paper then presents two implementation examples from experimental data collected in the laboratory. The defect characterization algorithm is applied to magnetic flux leakage testing of metal pipeline specimens and ultrasonic testing of concrete pipeline specimens, which was taken from the previous paper. For each type of testing, results are presented to show the validity of the algorithm and the potential for the algorithm to be applied to data collected in the field. This paper also suggests that this algorithm can be applied to a large variety of NDE methods other than those that have been presented.

The second paper entitled "Ultrasonic imaging of defects in concrete pipelines," on pp 39-49, focuses on the application of the invariance algorithm to the ultrasonic testing of concrete pipelines. This paper is a follow up paper from previous research presented in a QNDE Conference paper by S. Mandayam in 2000 [11]. The main objective of this paper is to show the first experimental results achieved with the algorithm using concrete specimens designed in the laboratory. This study was part of a larger project funded by the Water Environmental Research Foundation (WERF) to investigate the possibility of an inline inspection system for concrete sewer pipelines. This research proposed an inspection vehicle that would employ the defect characterization technique presented in this thesis.

The third paper entitled "A defect characterization technique for experimental NDE signals," on pp 50-64, condenses the information presented in the previous paper and focuses more on the results presented. The mathematical theory behind the algorithm is briefly mentioned and the applications of the algorithm to the NDE of metal gas pipelines and concrete sewer pipelines are expanded upon. Similar to the last paper, this paper suggests that the algorithm holds the potential to serve a multitude of nondestructive testing methods.

## 5.2 Impact of Research Contribution

The research presented in this thesis provides the experimental proof for a robust and unique and powerful interrogation and signal-processing algorithm for detecting and sizing defects in a multitude of materials. The results prove that NDT signals obtained in a real world setting, in this case a laboratory environment, may be processed via the given invariance algorithm which is capable of extracting essential defect related information that was previously influenced by the effects of operational parameters. Having laid this experimental foundation, the future potential of this invariance and defect characterization technique lies in its application to the nondestructive inspection of a broad variety of materials. While MFL inspection of metal gas pipelines and ultrasonic inspection of concrete sewer pipelines has been investigated in this research, the invariance technique presented is a general purpose algorithm and can easily be applied to the inspection of materials such as plastics, laminates, composites, and even biological materials. The versatility of this invariance technique may open the door for further research in fields of NDT where defect characterization of raw NDT signals has hitherto proved to be complex.

The long-term impact of this research will benefit industries such as the US natural gas and wastewater companies that can effectively employ such invariance techniques to provide safe, cost effective inspection and maintenance of their pipeline infrastructure via NDT methods. Industries in many other areas may benefit from this work as well, such as the military and civilian aircraft industries that require inspection methods of many composite materials used in airplane construction. It is often found that there is no inspection method available for the parts and materials involved in an airline disaster. This fact is sometimes accredited to the difficulty of inspection due to the interference of operational parameters or the lack of a means of compensating for said variables.

## 5.3 Future Directions

Aside from the immediate impact that the use of this defect characterization technique may have, there is significant long-term potential for applying the algorithm in other venues. A recent Newsletter published by the Nondestructive Testing Information Analysis Center (NTIAC) lists the four "Holy Grails" of NDE to be (1) multi-materials,

(2) multi-layer structures, (3) limited access areas, and (4) materials with limited information [12]. All four of these topics are certain inspection problems that have no clear or simple solution. In many cases, there is currently no feasible method of NDE to apply to materials and structures falling in the above categories.

The invariance technique presented in this thesis may have the potential to aid in overcoming some of these inspection obstacles. As stated in the introduction of this thesis, operational parameters are a result of the material properties, testing environment, and the test equipment. A closer look at the NTIAC list reveals that these problem areas are, in general, due to the interference of operational parameters. Some of the problem areas of NDE, such as scanning composites and other multi-materials, contain a unique set of operational parameters that hinder the defect characterization process. Using the invariance technique to remove the effects of variables, such as multiple material properties and multiple layers, may potentially render a defect signature where obtaining information about a flaw in such materials was previously an issue. Limited access may also be treated as an operational parameter where two separate scans of the same flaw from different positions of the testing device may provide the necessary data for the invariance algorithm. It has been shown that unknown material properties can be surmounted with the invariance technique in the gas pipeline results provided in this thesis. The magnetization levels of a gas pipelines are almost certainly unknown in all cases and can be ignored in the defect characterization process. Similarly, other unknown parameters can be overlooked using the same process.

This defect characterization technique may also prove viable in the area of data fusion. Data fusion integrates two different types of NDE signals, such as eddy current and x-rays, of the same specimen to characterize a defect. The idea behind data fusion is that data with similar characteristics in each type of NDE signal can be related. The resulting "fused data" provides a perspective of information that cannot be inferred by looking at the data from the individual sources. From the fused data, redundant information from each source can be used to determine accuracy. Similarly, complementary information can be collected and combined to reveal a total picture of information that cannot be collected by a single sensor [13, 14].

The invariance transformation neural network can be modified to act as a data fusion neural network. Two different forms of data can be substituted for the NDE signals that serve as $x_1$ and $x_2$ in the invariance algorithm. The RBF neural network can then synergistically combine the two NDE signals to produce a fused image of the data. From the fused image, redundant and complementary data can be received through digital image processing, and the defect information can be mapped to a defect profile with a defect characterization neural network. Some preliminary results have been achieved as the first step in data fusion research concerning this defect characterization algorithm.

A defect characterization algorithm has been developed for ultrasound c-scans of a metal specimen as the first stage in developing a data fusion algorithm. Ultrasound C-scans were obtained from a stainless steel metal specimen. The specimen contained four holes of 6.35 mm diameter and depths varying from 13 mm to 61 mm. The C-scan images of the 13, 28, and 61 mm holes were used as input training data for the defect characterization algorithm and the image of the 45 mm hole was used as test data. Three-dimensional defect profiles were designed as target training data. The UT C-scans obtained in testing are displayed in Figure 5.1, and the defect profiles used for training are shown in figure 5.2.

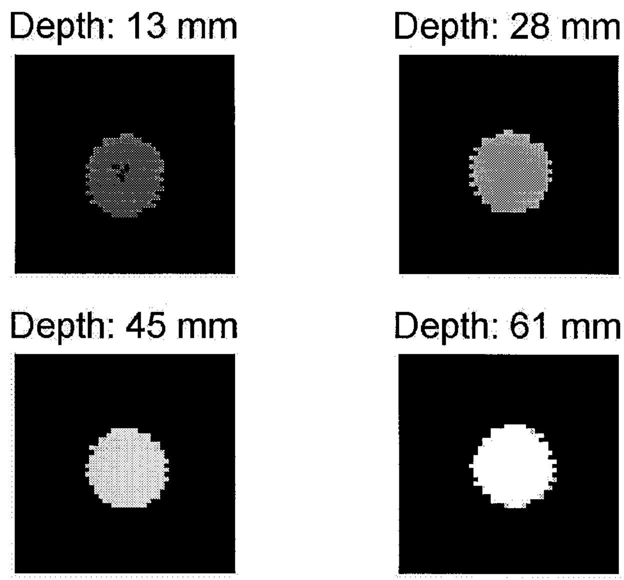



**Figure 5.1.** Ultrasound C-scans of the four holes used as data for the data fusion defect characterization algorithm.

The preliminary results provide the defect characterization mapping process for the ultrasound C-scan signals to a set of three dimensional defect profiles. The defect profile predicted by the network from the test data is presented in Figure 5.3. The defect characterization network predicted the depth of the test hole to be 45.7 mm, a difference of 7 mm with an error of approximately 1.56 percent. The network's prediction is expected to be accurate since the test data was within the range of the network's training data.

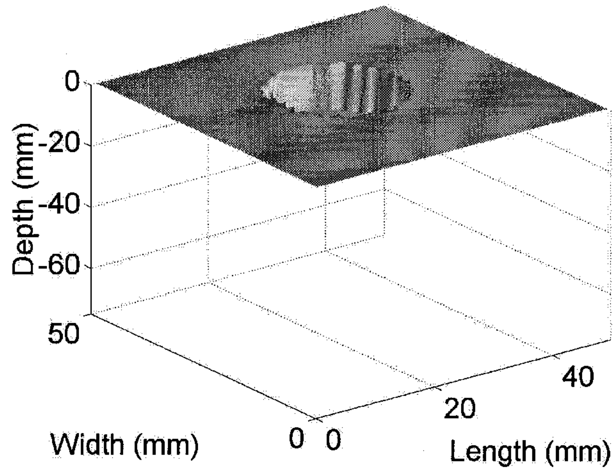
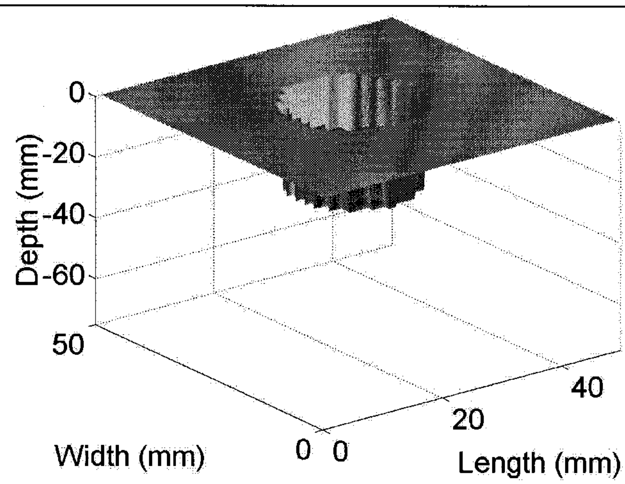
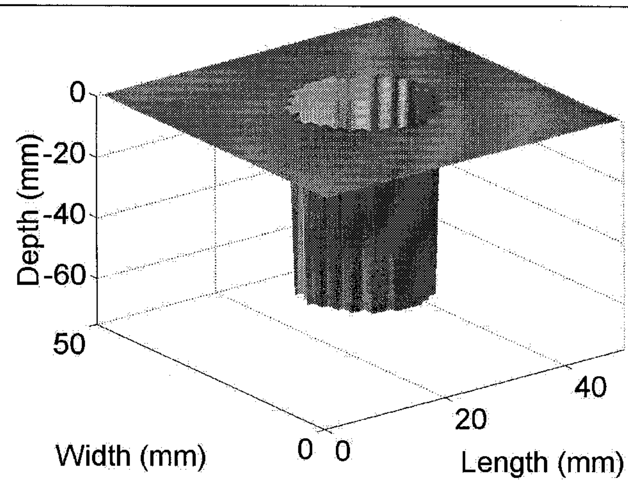
| Depth | Defect Profiles |
|---|---|
| 13 mm |  |
| 28 mm |  |
| 61 mm |  |

**Figure 5.2.** Defect profiles generated for the training data for the data fusion defect characterization algorithm.

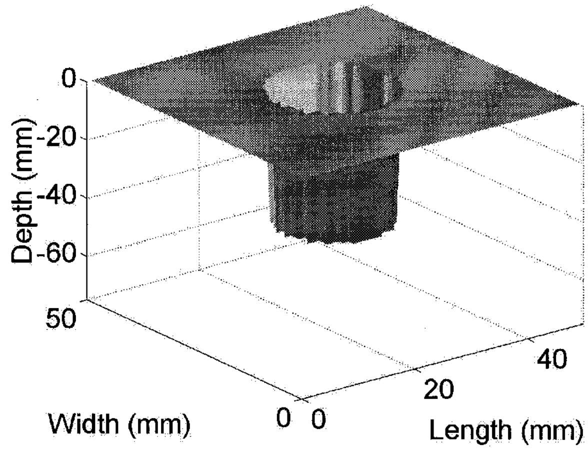



**Figure 5.3.** Defect profile generated from data fusion defect characterization algorithm from test data.

The next step in developing a data fusion algorithm is to obtain images from a second source. Preferably, since the media of the specimen is stainless steel, thermal scans of the specimen can be used as the second NDE signal source. Like the invariance transformation algorithm, the data fusion algorithm has the potential to be applied to a multitude of sources, and the algorithm can be expanded to accept several sources instead of just two at a time. This method may prove extremely cost effective in the future where a data fusion algorithm combining several sensors can be an alternative to an expensive, complex testing setup that will achieve the same goal.

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