Multi-sensor data fusion using geometric transformations for the nondestructive evaluation of gas transmission pipelines

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by

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ABSTRACT

Nondestructive evaluation (NDE) plays a vital component in the operation and maintenance of large infrastructure such as gas transmission pipelines, nuclear power plants, aircraft, bridges and highways, etc. As this infrastructure continues to age it is essential that the inspection techniques reliably and accurately predict the integrity of these systems. No single NDE method is capable of inspecting all types of anomalies and extracting all required information – a combination of methods must be used and the resulting data fused. Moreover, newer systems that are developed are often made of composite materials that include metals and dielectrics. One interrogation modality cannot be used to inspect such components for reliability – multiple tests are always needed.

This thesis presents a technique that can be used to fuse data from multiple sensors that are employed in modern NDE applications, specifically in the in-line inspection of gas transmission pipelines. A radial basis function artificial neural network is used to perform geometric transformations on data obtained from multiple sources. The technique allows the user to define the redundant and complementary information present in the data sets. The efficacy of the algorithm is demonstrated using simulated canonical images and experimental images obtained from the NDE of a test specimen suite using magnetic flux leakage, ultrasonic and thermal imaging methods. The results presented in this thesis indicate that neural network based geometric transformation algorithms show considerable promise in multi-sensor data fusion applications.
CHAPTER 1: INTRODUCTION

The use of nondestructive evaluation (NDE) techniques in many real-world applications has become more apparent during recent years; significant federal and state funding has been appropriated to improve NDE techniques. The recent increase in the application of NDE methods to evaluate structures and mechanisms can be attributed to the fact that the nation’s large infrastructure is aging. For example, aircraft in the civilian fleet have an average age of approximately 25 years [1]. Likewise, bridges (40 years) [2], rail fleet vehicles (20 years) [3] and gas pipelines (60 years) [4] all have high average ages based on their expected lifetimes. Periodic, non-invasive, in-service inspection is vital for assuring the integrity of these structures and maintaining the strict flow of commerce.

Typically, NDE systems involve the use of one type of inspection modality. This concept is displayed in Figure 1. First, some specific type of energy $E_{1,\text{in}}$ is sent through the object under inspection and the energy output $E_{1,\text{out}}$ is measured. Then, the change between the input energy and the output energy is examined to determine specific internal and/or external characteristics of the object.

![Figure 1: Typical NDE system – single inspection modality](image)

The inspection of objects with one type of modality may be sufficient in certain controlled instances of inspection. However, for most real-world applications, NDE systems that rely on only one type of inspection modality are insufficient. Recent
material development has caused modern materials to become more complex (e.g. composites). Also, widely varying and/or inaccessible infrastructures have become increasingly relevant in modern NDE applications (e.g. the inspection of natural gas transmission pipelines). Therefore, the need exists for the development of an NDE system that relies on numerous inspection modalities. An example of this concept is displayed in Figure 2.

![Figure 2: Revised NDE system - various inspection modalities](image)

In this example system, three inspection modalities provide three different types of input energies to the object under inspection. The resulting output energies are measured and the changes between their respective input energies are determined. The result of this process is one set of object characteristics for each particular inspection modality.

The addition of multiple inspection modalities to the general NDE system model provides additional information on the characteristics describing the object of interest. However, the addition of heterogeneous modalities also generates many problems when attempts are made to comprehend the data set. The first problem encountered is the registration problem. The registration problem is defined in [5] as the process of “finding the correct mapping of one image onto another.” The determination of the optimum data fusion combination technique for a specific suite of inspection modalities is also a
relevant problem. Finally, once the gathered data sets have been combined successfully, the problem of devising measures of the efficacy of the technique arises.

1.1 Nondestructive Evaluation

The concept of nondestructive evaluation (NDE) was developed to serve as a cost-effective replacement for destructive evaluation methods [6]. In certain structures and mechanisms, specific flaws may not render the structure or mechanism inoperable. Therefore, NDE methods, provided they are considerably less expensive than the replacement of the particular structure or mechanism, are preferred over destructive methods of evaluation. This is provided that the NDE method is also reliable.

This thesis focuses on the development of NDE techniques for the inspection of natural gas transmission pipelines. Nondestructive testing methods are preferred over destructive testing methods for pipeline inspection since they do not compromise the normal operation of the pipeline structure. The nondestructive testing process aims to diagnose flaws present in the structure as well as to predict where future failure may occur. Specific flaws that may cause failure in a gas transmission pipeline are corrosion, pitting, stress corrosion cracks, seam weld cracks and dents [7].

Furthermore, all NDE methods can be separated into one of the following two categories:

1. **Active** – Methods which require that some energy is exerted from the testing setup towards the test specimen and detect flaws from changes in the expected energy.

2. **Passive** – Methods that monitor the test specimen under normal conditions and wait for a specific change in the monitored signal to detect flaws.
A few examples of active NDE methods are ultrasonic, magnetic flux leakage, and eddy current testing. Examples of passive NDE methods are acoustic emission and visual inspection.

The two leading methods for NDE of natural gas transmission pipelines are magnetic flux leakage (MFL) and ultrasonic testing (UT). In MFL testing, a test specimen is first magnetized by one of two methods. The first of the magnetization methods requires the placement of the test specimen within the propinquity of a magnetizing agent. The second method requires that an electrical current be passed through some conductive material. This conductive material can be the test specimen itself or some material placed within a certain proximity of the test specimen. Then, MFL sensors such as coils, C-core yokes and solid-state magnetic sensors are placed within a small distance of the test specimen to acquire an MFL reading.

Currently, MFL testing is the most widely used method for flaw detection in natural gas transmission pipelines. As mentioned previously, when the MFL method is applied to gas pipeline inspection, a magnetic field is induced inside of the pipe. This causes the magnetic flux lines to pass through the pipe wall. If flaws such as corrosion are present in a section of the pipe wall, the wall thickness will be smaller than normal causing a decrease in the amount of flux that passes through the pipe wall. Therefore, an MFL sensor that is placed inside the pipe wall can sense an increase in magnetic flux density when passing through a section of pipe with reduced wall thickness. The MFL testing method described creates magnetic flux lines parallel to the pipe’s axis and provides high-quality detection of corrosion and dents. However, axial SCC and seam weld cracks are imperceptible with this method.
An example of MFL testing of a pipe wall is shown in Figure 3. As the current traveling through the pipe wall reaches the defect, magnetic flux will begin to leak from the wall due to the defect. The dimensions and therefore the severity of the defect can be determined through the use of neural networks trained with known patterns of MFL behavior due to specific pipeline anomalies.

![Image of MFL testing of a pipe wall with a defect](image)

**Figure 3: MFL testing of a pipe wall with a defect**

In general, UT NDE techniques rely on the features of propagating energy pulses with frequencies higher than 20 kHz. These propagating pulses, created using a piezoelectric crystal, are sent towards the test specimen. When the pulses strike the specimen, they travel first through a coupling medium, and then through the specimen. This causes an echo to recoil off the back-wall of the specimen. This echo then returns back to and is measured by the source. The difference between the original pulse and its echo depends on the characteristics of the pulse and specimen as well as the distance between the source and specimen.

The UT method is also applied to the inspection of natural gas transmission pipelines. In this particular application, the high-frequency UT waves travel through the pipe wall and are distorted according to the different features they encounter within a specific area of the pipe wall. This method has been proven to work well in theory;
however, the coupling requirement produces a problem when using the UT method for pipeline inspection. The problem arises because it is very difficult to maintain a good, consistent contact between the pipe wall and UT testing device. It is because of this problem that most NDE measurements for natural gas pipelines have relied on the MFL method of testing.

Two examples of UT testing of a pipe wall are displayed in Figure 4. The first method of UT testing displayed is the through transmission. The through transmission technique of UT testing requires the use of a source and a receiver element. The source launches an ultrasonic pulse into the object under inspection. The receiver collects the pulse after it has moved through the object and the change between the original pulse and the received pulse is used to produce a UT image. Because of the environment in which gas pipelines are located, the through transmission technique of UT testing is not used in practice.

However, the pulse-echo method of UT testing is used in practice for the inspection of gas pipelines. As discussed earlier, the pulse-echo technique of UT testing requires the use of one transducer. This transducer serves both as the source and the receiver. The transducer launches an ultrasonic pulse towards the pipe wall and the back-wall echo of the pulse is measured and compared with the original pulse to produce a UT image of the specimen.
Through transmission  |  Pulse-echo

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<tr>
<td>Received Signal/Image</td>
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Figure 4: UT testing technique

Figure 5: The "pig" - a pipeline inspection tool
Thermal imaging is another technique that uses the transfer of energy to evaluate an object non-destructively. The technique, which has not yet become prevalent for the inspection of gas pipelines, is illustrated in Figure 6. As shown, the thermal imaging technique sends energy in the form of heat into one side of the test specimen and the change in energy emitted is measured using an infrared camera. Finally, various heating techniques and image processing methods may be used in order to produce a proper thermal image containing relevant information on the condition of the object under inspection.

![Figure 6: Thermal imaging technique](image)

1.2 Data Fusion

Data fusion has become a widely used method for combining data to interpret the results in many applications. The development of data fusion techniques began with the military. However, many fields of science and engineering currently incorporate data fusion into a portion of their applications. While the concept of data fusion was being developed, the U.S. Joint Directors of Laboratories (JDL) Data Fusion Group defined a data fusion model in 1985. However, this model's definition of data fusion was too restrictive because of its strong relation to military applications. The model was revised in 1998.
The revision defined data fusion as "the process of combining data or information to estimate or predict entity states." These entity states are typically physical. For instance, the physical attributes of a structure or the location of a moving object or being. It is not uncommon, however, that the entity state is the informational or perceptual state of an individual or a group of individuals [5]. Even though the JDL Data Fusion Group has redefined their original definition, new definitions are continuously being proposed. Often times, however, these definitions are not accompanied with an in-depth model such as the one devised by JDL.

Although the JDL definition of data fusion is useful in all data fusion processes, a real-world example of data fusion is also helpful. A human brain provides a natural example of when data fusion occurs. The brain acquires data from the five senses: sight, hearing, smell, touch and taste. This data is then fused within the brain to make a decision. The brain uses its memory and reasoning capabilities to make the decision.

In the NDE world, data fusion methods seek to synergistically combine multiple non-commensurate NDE signals such that vital and useful information from each signal can be combined to improve defect characterization. In Figure 7, a general representation of the data fusion process after data signals have been collected from two inspection modalities is illustrated. The two independent NDE signals are assumed to have originated from the same scene or test specimen and are combined through the data fusion process. These NDE signals may come from any combination of inspection methods, for example: UT, MFL, x-rays, microwaves, thermal imaging, eddy current, etc.
The fused data signal displayed in Figure 7 relays two main types of information: redundant and complementary information. Redundant information is the common information present within each NDE signal. For instance, given three possible defect parameters $l$, $w$, and $d$, representing length, width and depth, respectively, perhaps source one contains the parameters $l$ and $d$ while source two contains the parameters $w$ and $d$. The resulting redundant information from the data fusion of the two sources will be the parameter $d$. Redundant information increases the accuracy and reliability of the result produced by the combination of more than one signal.

Complementary information is the novel information that is different between the NDE signals obtained from each source. In the previously discussed example, the resulting complementary information from the data fusion of the two sources would be the parameters $l$ and $w$, where the length $l$ comes from source one and the width $w$ comes from source two. Complementary information reveals features that are unique to each source and can be used to further characterize a defect. Figure 8 illustrates the resulting redundant and complementary information from the data fusion process.
1.3 Objectives of Thesis

This thesis aims to develop data fusion techniques for the extraction of redundant and complementary information. These techniques will be validated through the use of two data sets. The first of the data set is comprised of simulated canonical images. The second data set consists of experimental NDE signal images obtained from various test specimens. Finally, recommendations for effective data fusion will be made from the results achieved by these redundant and complementary information extraction techniques.

1.4 Expected Contributions

This thesis proposes to demonstrate that geometric transformations are capable of extracting redundant and complementary information from heterogeneous sensors that are evaluating the same object/specimen. Results illustrating the validity of the techniques for the application to gas pipeline inspection are presented.
1.5 Scope and Organization of Thesis

The focus of this research is on the development of data fusion techniques for the non-destructive evaluation of natural gas transmission pipelines. The experimental NDE signals (i.e. UT, MFL and thermal images) were collected at the Rowan University NDE Laboratory. This thesis is organized as follows:

- Chapter 1 provides an introduction to NDE and the use of the data fusion concept in NDE.
- Chapter 2 provides background material on image data fusion techniques and geometrical transformations.
- Chapter 3 discusses the approach taken to produce the results set forth in the objectives of the thesis.
- Chapter 4 discusses the implementation of the methods proposed in the approach and provides a presentation of the results produced from this implementation.
- Chapter 5 provides a discussion and interpretation of the results, draws conclusions, and makes recommendations for further research in the area.
CHAPTER 2: BACKGROUND

In this chapter, a background on image data fusion techniques is presented. This includes a description of various fusion levels and combination theories. Two main concepts of the geometric transformation process, spatial transformation and gray-level interpolation, are also described. Finally, a discussion of the previous image data fusion work that has been done in the field of NDE is provided.

2.1 Image Data Fusion

This section describes three main data fusion levels: pixel-level, feature-level and decision-level fusion. A description of the mathematical models of probability, possibility and belief combination theory is also contained in this section.

2.1.1 Fusion Levels

The development of new data fusion methods has been increasing in recent years. However, if the method is specifically designed for image fusion, it most likely is based on one or more of the following three image fusion levels [5]:

- Pixel-Level Fusion
- Feature-Level Fusion
- Decision-Level Fusion

Pixel-level fusion is also referred to as data-level-fusion. It requires that the images are first registered in pixel form so that both pixels in the pixel pairs correspond to the same position. After pixel registration, the images are combined pixel-by-pixel through the use of the fusion method. Finally, decisions are made from the result of the combination.
The second level of fusion is feature-level fusion. The first step in feature-level fusion is to extract specific features from each image. For each image, the extracted features are combined into a feature vector. The registration is then performed on the feature vectors. After the feature vectors are registered, they are combined using a data fusion technique and a classification is made based on the result.

Finally, images may be combined at the decision level. This is known as decision-level fusion. When images are combined at the decision level, a classification
result is determined for each image. These results are then combined to produce an improved classification.

![Diagram of decision-level fusion process](image)

**Figure 11: Diagram of the decision-level fusion process [5]**

Within most image fusion techniques, there are three major functions that are generally performed. The first function is registration. The registration function is used to properly align the images so that they are not shifted in time and/or space with respect to each other. Registration must be performed before the two latter functions, combination and reasoning. Combination uses mathematical models to fuse the registered images. These models range from simple probability theory to artificial neural network based models. Finally, the reasoning function processes the combined image data to produce a final result or decision.

As mentioned previously, many researchers are currently developing image fusion combination techniques based on one or more of the previous three fusion levels. These combination techniques also perform mathematical transformations on image pixels, features, or decisions. Some of these combination techniques use mathematical transforms such as the Discrete Fourier Transform (DFT), Discrete Cosine Transform...
(DCT), and wavelet based transformations to extract features and combine image data. For instance, the authors of [8] developed a technique for the combination of two-dimensional eddy current images produced by experiments conducted at multiple frequencies. This combination technique decomposes each image into multiple sub-band images through the use of the DFT and DCT. The fusion of an arbitrary number of images is performed based on the spectra of sub blocks of the sub-band images.

2.1.2 Combination Theory

Data fusion techniques may also be based on combinational theories such as probability, possibility, and belief theories. Summaries of the all three theories are presented below, more detailed descriptions can be found in [5].

2.1.2.1 Probability Theory

The main concept of probability theory used in data fusion techniques is Bayes’ theorem. Bayes’ theorem is used to compute the probability of each cause depending on the event observed. For example, an item recognition system used in a grocery store’s self-checkout counter may use Bayes’ theorem to identify if the item scanned by the customer is truly the item placed on the conveyer belt before allowing the customer to pay for the item and leave the store. In Bayes’ theorem, the list of items carried by the store will be defined as the sample space, $S$. Then, $A_1, A_2, \ldots, A_n$ can be defined as subsets of the sample space, $S$, and they represent all possible causes (i.e. subsets of the possible items given that a specific item has produced a certain event or feature to occur). Therefore, for an observed event, $B$, the following is true according to Bayes’ theorem:

$$P(A_i | B) = \frac{P(B | A_i)P(A_i)}{P(B)}$$  \hspace{1cm} (2.1.1)

where,
The variables $P(B|A_i)$ and $P(A_i)$ are available before the feature $B$ is observed. Thus, they are known as a priori probabilities. The probabilities calculated from Equation 2.1.1 and Equation 2.1.2 can be used along with the a priori probabilities to define interval probabilities for specific causes (or items), when the confidence of one or more events occurring is given.

If Bayes’ theorem is used for data fusion purposes, the term Bayes-optimal is used to describe the data fusion process. Bayes-optimal refers to minimizing risk or the expected cost of making a decision. For every possible cause, two costs must be defined for choosing a specific cause: the cost if the choice is correct and the cost if the choice is incorrect. The resulting group of costs defines the cost structure.

For example, if it is assumed that there are only two possible items in the item recognition system example, C1 and C2, for a set of observations, the following represent all elements of the cost structure:

- $C_{11}$ – cost of choosing C1 when the correct cause is C1
- $C_{22}$ – cost of choosing C2 when the correct cause is C2
- $C_{21}$ – cost of choosing C2 when the correct cause is C1
- $C_{12}$ – cost of choosing C1 when the correct cause is C2

Using this cost structure, the risk or expected cost is defined as:

$$Risk = E\{cost\} = C_{11}P_{11} + C_{22}P_{22} + C_{21}P_{21} + C_{12}P_{12} \quad (2.1.3)$$

If numerous features have been produced from images taken at different angles of the item sent through the recognition system, the risk factor can be used to measure the effectiveness of the Bayes’ technique used to combine the various features.
It has been assumed that a feature vector $X$ is produced after an event is observed, therefore two regions can be defined in the vector space: $R_1 = \{X|\text{decide } C1\}$ and $R_2 = \{X|\text{decide } C2\}$. The terms $p(X|C1)$ and $p(X|C2)$ are defined as the conditional probability density functions of a specific vector value given C1 and C2, respectively. Also, $p(X)$ represents the marginal probability density function of the vector, $X$. The conditional probability functions defined are used to form a likelihood ratio. This ratio is then compared to a threshold determined by the expected cost in Equation 2.1.3. The cause, C1, is chosen if

$$I(X) = \frac{p(X|C1)}{p(X|C2)} \geq \frac{(C_{12} - C_{22})P(C2)}{(C_{21} - C_{11})P(C1)}$$

(2.1.4)

Otherwise, the cause, C2, is chosen. Alternative expressions can be produced using the concepts in Equation 2.1.4. One specific expression is the discriminant function in Equation 2.1.5.

$$d(X) = (C_{21} - C_{22})P(C2)p(X|C2) - (C_{12} - C_{11})P(C1)p(X|C1)$$

(2.1.5)

Using the discriminant function, C1 is chosen if $d(X) < 0$, and C2 is chosen otherwise. The discriminant function is used along with nonparametric estimators such as potential functions or Parzen estimators. They estimate the conditional probabilities and are used as a basis for many pattern recognition systems such as neural networks.

### 2.1.2.2 Possibility Theory

As mentioned previously, possibility theory, otherwise known as fuzzy logic, is another common theory employed in image fusion combination functions. Possibility theory begins with a reference set, $S$. Referring to the item recognition example in the probability theory section, this reference set is the same as the sample space. The collection of all subsets of $S$ is defined as $\Omega = 2^S$. This collection includes the reference
set $S$ itself as well as the empty set. Next, a confidence function is developed to map all elements of $\Omega$ to an interval from 0 to 1. The empty set, $\emptyset$, and the set $S$ are used to define the major requirements of the confidence function. The requirements are $C(\emptyset) = 0$ and $C(S) = 1$.

Another requirement of the confidence function is that $C(A) \leq C(B)$ if $A \subseteq B$. In the item recognition example, the variables $A$ and $B$ are subsets of $\Omega$ (i.e. \{item 1, item 5\}, \{item 1, item 2, item 3\}, \{item 11\}, etc.). The values $C(A)$ and $C(B)$ represent the respective confidences for $A$ and $B$ given a certain feature or feature set. It can be determined from this requirement that $C(A \cup B) \geq \max[C(A), C(B)]$ and $C(A \cap B) \leq \min[C(A), C(B)]$. The limiting case caused by the first inequality is $C(A \cup B) = \max[C(A), C(B)]$ and it is known as the possibility measure. Likewise, the second inequality results in the limiting case $C(A \cap B) = \min[C(A), C(B)]$ which is termed the necessity measure. Finally, the possibility and necessity measures are manipulated to form combination rules depending on the data fusion technique developed. The results of these combination techniques can be used as measures of the effectiveness of the techniques when compared to each other or various other techniques.

2.1.2.3 Belief Theory

Belief theory, also known as Dempster-Shafer theory, begins with a set of mutually exclusive results, $S$. Then, as in probability and possibility theory, the collection of all subsets is defined as $\Omega = 2^S$. A belief, $B(A)$, can now be defined for any $A$ included in $\Omega$. The next important concept introduced at this point in the theory is the mass of evidence. The mass of evidence, otherwise known as the basic probability assignment, is bounded by the following three basic rules:
• $m(\emptyset) = 0$

• $m(A) > 0$ for all $A \in \Omega$

• $\sum m(A) = 1$ for all $A \in \Omega$

Using the evidence masses that have been determined, the support and plausibility functions can be defined. The support function is

$$Su(A) = \sum m(B) \quad (2.1.6)$$

for all subsets $B$ in set $A$ as long as both sets are in $\Omega$. It is formally defined as the total belief assigned to the set. The support function alone does not distinguish Dempster-Shafer theory from probability theory. The support function alone is just a mere generalization of probability theory. However, the plausibility function differentiates Dempster-Shafer theory from probability theory. The plausibility function is

$$Pl(A) = 1 - Su(not - A) \quad (2.1.7)$$

which can be simplified to

$$Pl(A) = 1 - \sum m(B) \quad (2.1.8)$$

where the summation only requires that the subsets of $\Omega$ that produce an empty intersection with $A$ are added. The plausibility function is defined as the mass of evidence already assigned to the set or that is free for assignment to the set. The support and plausibility functions result in the definition of an interval which covers the belief available to the set to the belief that has a possibility of becoming available from the given information. The support and belief functions can be used to represent measures of data fusion.
Probability and possibility theory were developed much earlier than belief theory. Therefore, most data fusion researchers use the Dempster-Shafer theory as a basis in the development of new combination techniques. In [9], the authors performed pixel-level fusion using eddy current inspection and infrared thermographic inspection images of a damaged panel of carbon fiber reinforced plastic (CFRP). The images were combined using a variety of methods including probability theory, Dempster-Shafer theory, and a few trivial methods.

The development of new belief combination theories is also on the rise in the world of data fusion. Since the inception of the Dempster-Shafer theory, the Transferable Belief Model has been developed. More recently, the pignistic probability transform has been developed [10].

2.2 Geometric Transformations

The main objective for the use of a geometric transformation is to alter the spatial relationship between the pixels in an image. For instance, if an image has become distorted, a geometric transformation may be used to restore the image to its original form. In digital image processing, the geometric transformation procedure consists of two functions: spatial transformation and gray-level interpolation [11].

2.2.1 Spatial Transformations

The first step in the spatial transformation process is to define an image $f$ with pixel coordinates $(x, y)$. If geometric distortion affects $f$, an image $g$ can be defined with coordinates $(\hat{x}, \hat{y})$. Therefore, the spatial transformation can be represented by the following two equations:

$$\hat{x} = r(x, y) \quad (2.2.1)$$
\[ \hat{y} = s(x, y) \] (2.2.2)

where \( r \) and \( s \) represent the spatial distortion for the \( x \) and \( y \) coordinates. For example, if

\[ r(x, y) = \frac{x}{2} \quad \text{and} \quad s(x, y) = \frac{y}{2}, \]

the transformation of the original image is equivalent to shrinking the image by one-half in the \( x \) and \( y \) directions.

It is considered impossible to analytically derive \( r(x, y) \) and \( s(x, y) \) in order to describe the geometric distortion process. However, methods have been developed to estimate the equations. Specifically, the method of tiepoints has been developed. The "tiepoints" required for this method are a group of pixels whose image locations are known for both the distorted and corrected images [11].

The quadrilateral regions displayed in Figure 12 represent distorted and corrected image segments. There is a total of eight tiepoints between the two image segments represented by the vertices of the quadrilaterals. For this example, the assumption was made that distortion process can be modeled by the following pair of bilinear equations.

\[ r(x, y) = c_1 x + c_2 y + c_3 xy + c_4 \] (2.2.3)
\[ s(x, y) = c_5 x + c_6 y + c_7 xy + c_8 \] (2.2.4)

Through the combination of Equations 2.2.1 - 2.2.4, the following two equations are produced.

\[ \hat{x} = c_1 x + c_2 y + c_3 xy + c_4 \] (2.2.5)
\[ \hat{y} = c_5 x + c_6 y + c_7 xy + c_8 \] (2.2.6)

The eight coefficients, \( c_1 \) through \( c_8 \), can be solved using the eight known tiepoints. Finally, using these coefficients, a transformed coordinate \((\hat{x}, \hat{y})\) can be determined for each original \((x, y)\) coordinate [7].
2.2.2 Gray-Level Interpolation

The spatial transformation method requires that the distorted and corrected images have integer coordinate values. However, it is possible that Equations 2.2.5 and 2.2.6 will produce non-integer \((\hat{x}, \hat{y})\) coordinates given certain coefficient values. The distorted image is only defined on integer pixel values. Therefore, for every non-integer \((\hat{x}, \hat{y})\) coordinate calculated, there will be an absence of a gray-level value. This requires the need for an interpolation process that exploits the gray-level values of the integer coordinate pixels to calculate gray-level values for the non-integer coordinate pixels. This interpolation process is known as gray-level interpolation [11].

The most trivial gray-level interpolation technique employs the nearest neighbor technique. This technique is known as zero-order interpolation and is displayed in Figure 13. The figure illustrates the spatial transformation process in which the integer \((x, y)\) coordinates of the original image \(f(x, y)\) are transformed to the non-integer \((\hat{x}, \hat{y})\) coordinates of \(g(\hat{x}, \hat{y})\) through the geometric distortion process. After the original image has undergone the spatial transformation, the "nearest neighbor" integer coordinate to the
non-integer transformed coordinate is selected. Then, the nearest neighbor to the non-integer \((\hat{x}, \hat{y})\) coordinate is assigned the gray-level value of the \((x, y)\) coordinate of the original image \(f(x, y)\).

Various other interpolation techniques have been developed as well. These techniques include cubic convolution interpolation and bilinear interpolation.

2.3 Previous Work in Data Fusion for NDE

As mentioned previously, the use of data fusion for NDE purposes has been steadily increasing in recent times. In [8], a data fusion technique was developed to combine multi-frequency (50 kHz and 250 kHz excitation) eddy current images of the same test specimen. The test specimen was machined from aluminum and contained a total of four defects: two surface breaking and two embedded. The authors used 6, 7, 8, and 12-block Discrete Cosine Transforms (DCT) to fuse the two images in the transform domain.

The authors of [9] used several data fusion techniques to combine an eddy current image and an infrared thermographic image of the same test specimen. The specimen was a panel of carbon fiber reinforced plastic (CFRP) that had been subject to low energy impact damage. A total of six pixel-level data fusion techniques were employed to combine the eddy current and infrared thermographic images: maximum amplitude,
integration, averaging, weighted averaging, Bayesian analysis and Dempster-Shafer theory. The maximum amplitude technique is simply the selection of the pixel with the maximum amplitude between the two images. The integration technique used the AND operator between the pixels of each image to produce a fused image. The averaging technique is used the average of each corresponding pixel to produce a resultant image. In the weighted averaging technique, different NDE sensors were given assigned values in order to "weight" one type of sensors performance when compared to the other. The Bayesian analysis and Dempster-Shafer theory techniques were similar to the probability and belief combination theories discussed earlier. The authors used an ultrasonic C-scan image to quantify each data fusion technique result. The area of impact damage was calculated for the C-scan image of the specimen and used as a reference value. This area was also calculated for each fused image. The maximum amplitude and Dempster-Shafer theory techniques produced the closest values to the C-scan image value for the area of impact damage.

In [12], the authors used many of the same techniques as those in [9], including Bayesian analysis and Dempster-Shafer theory, to combine ultrasonic and eddy-current testing data from a database containing 108 artificial flaws. The specimens used to obtain the data were Zr-Nb pressure-tube billets with either notched or drilled defects. The results of the techniques were simply classification of a notched defect, drilled defect or no defect. Several techniques such as probability density functions, probability of detection and relative operating characteristics were used to provide a measure of how well each data fusion technique classified the flaws. The authors determined that the combination of ultrasonic and eddy-current data collected from a realistic specimen suite
showed significant reliability when compared to the use of either ultrasonic or eddy-current data alone.

The authors of [13] related their data fusion techniques to three types of processing architectures: decentralized, cascade and centralized. For each of the three fusion architectures, Bayesian inference and Dempster-Shafer processing theories were employed on the data collected. The data consisted of X-ray images and ultrasonic images of a steel block test specimen with a known anomaly. The test setups for each nondestructive testing method were carefully chosen so that complementary forms of data would be present in the data. The final results of the paper showed the potential of the three data fusion architectures for use in the field of NDE. The centralized architecture produced better results than the first two architectures. However, it has a higher complexity as well as a longer run-time.

Image data fusion is also possible through the use of artificial neural networks. This is proven in [14] where the authors used multi-layer perceptron (MLP) and radial basis function (RBF) neural networks for two applications: combination of eddy current and ultrasonic images and combination of multi-frequency eddy current images. The eddy current and ultrasonic images were collected for two test specimens. The first specimen, a block of aluminum with a thickness of 6 mm, had a \( \frac{1}{32} \) inch diameter hole through it and was covered with a 0.005" copper foil. The second specimen, also a block of aluminum with a thickness of 6 mm, had a simulated defect with a depth of 5.5 mm and a \( \frac{1}{32} \) inch diameter. Results are displayed for the fusion of eddy current and ultrasonic images of the first test specimen using an MLP network with two hidden layer nodes, an RBF network with two hidden layer nodes and an RBF network with 5 hidden
layer nodes and a K-means algorithm for center identification. For the fusion of multi-frequency eddy current images of the second test specimen, the result of the fusion of a 6 kHz and a 20 kHz eddy current image using an RBF network with 5 hidden layer nodes and a K-means algorithm for center identification is displayed. The fusion of eddy current and ultrasonic images using multi-resolution decomposition techniques to implement a linear minimum mean square error (LMMSE) filter was also presented in [14] and the continuation of this work in [15].
CHAPTER 3: APPROACH

The problem, as stated earlier, is to develop data fusion techniques for the extraction of redundant and complementary information between two non-commensurate signals. An illustration of the concept of redundant and complementary data extraction was shown in Figure 8 from Chapter 1. Redundant information is defined as information that is the same in both of the non-commensurate signals. It increases the accuracy and reliability of the result of the fusion more than one signal when compared to the use of a single signal. Complementary information is defined as information that is different between the non-commensurate signals. It has the ability to reveal features that are unique to each source and these features help to further characterize the specific object under inspection.

The proposed data fusion techniques will be based upon the geometrical transformation concept. As mentioned previously, geometrical transformations are generally used in the image processing field to reconstruct images that have undergone some type of distortion. This concept can be viewed as morphing one image to look like another image. There are two techniques performed when applying a geometric transformation to an image. The first of the two techniques is spatial transformation. The spatial transformation process employs a pair of equations to transform the distorted image pixels to their corresponding corrected image pixels. It is required that a subset of distorted image pixels and their corresponding corrected image pixels are known prior to the transformation so that the equation coefficients can be approximated.

The second technique involved in the geometric transformation process is gray-level interpolation. The gray-level interpolation process is used if the spatial transformation equations fail to produce integer pixel index values. If non-integer values
are produced by the spatial transformation equations, a nearest neighbor approach is employed to determine nearest integer pixel values and the appropriate gray-level value is assigned to the corrected image.

Two data fusion techniques were developed for this approach: a redundant data extraction technique and a complementary data extraction technique. Both techniques rely on the same transformation method to extract the relevant information. The basis of this transformation method is its use of universal approximation theory to perform the appropriate geometric transformation. The use of universal approximation can result in the approximation of a function that is invariant of certain features of an object under inspection. This is made possible by the ability of universal approximation methods to interpolate between two signals that have resulted from the inspection of the same exact object [16].

In this case, the redundant features extracted should be invariant to the complementary features and the complementary features extracted should be invariant to the redundant features for each extraction method, respectively. For example, assume that $x_1(r, c_1)$ and $x_2(r, c_2)$ are two different signals that are the results of the inspection of the same object using two different inspection modalities. The variable $r$ represents the redundant information features and is the same for both signals. Likewise, the variables $c_1$ and $c_2$ represent the complementary information features for each signal $x_1(r, c_1)$ and $x_2(r, c_2)$ respectively [16].

A specific process must be developed to obtain functions based on the signal features: $r$, $c_1$, and $c_2$. This function is defined as $h$. For the redundant data extraction
technique, \( h \) is a user-defined function of \( x_1 \) and \( x_2 \) that is invariant to \( c_1 \) and \( c_2 \). This function can be defined as the following:

\[
f^\{x_1(r,c_1),x_2(r,c_2)\} = h_1(r) \tag{3.1}
\]

If two arbitrary functions \( g_1 \) and \( g_2 \) are defined, \( h_1(r) \) can be obtained using the following equation:

\[
h_1(r) \odot g_1(x_1) = g_2(x_2) \tag{3.2}
\]

where \( \odot \) represents a homomorphic operator. For this case, the homomorphic operator was chosen to be the addition operator, \( + \). Therefore, Equation 3.2 becomes the following:

\[
h_1(r) + g_1(x_1) = g_2(x_2) \tag{3.3}
\]

In order to use the technique defined by Equation 3.3, the three arbitrary functions \( h, g_1 \), and \( g_2 \) must be determined. The first function \( h \) is chosen depending on the needs of the user. \( g_2 \) is defined as a conditioning function and is an application-dependant function that may be used to condition the data to better suit the application. An example of this is if the data values within \( x_2 \) have a wide spread, \( g_2 \) may be chosen to be a logarithmic function. If \( h \) and \( g_2 \) are known, a universal approximation technique may be used to determine the function that maps \( g_1 \) to the rest of the expression in Equation 3.4.

\[
g_1(x_1) = g_2(x_2) - h_1(r) \tag{3.4}
\]

Ideally, a radial basis function (RBF) neural network will produce the best function approximation of \( g_1 \) given the proper training data. The function \( g_1 \) can be modeled as the activation function of the RBF neural network, as shown in Eq 3.5.
\[ g_1 = \sum_{j=1}^{n} \lambda_j \phi_j \left( \| x_i - c_{y_j} \| \right) \]  \hspace{1cm} (3.5)

The variable \( \lambda_j \) represents the \( j \)th hidden layer node weight. The function \( \phi \) is the window function or basis function of the neural network. For this application, the basis function was chosen to be the Gaussian window function:

\[ \phi_j \left( \| x_i - c_{y_j} \| \right) = e^{-\frac{|x_i - c_{y_j}|^2}{2\sigma^2}} \]  \hspace{1cm} (3.6)

In Equation 3.6, \( \sigma \) is the variance of the Gaussian window function and \( c_{y_j} \) is the mean of the Gaussian window function.

If the conditioning function \( g_2 \) is assumed to be unity, Equation 3.4 can be simplified to the following equation:

\[ g_1(x_i) = x_2 - h_1(r) \]  \hspace{1cm} (3.7)

where \( x_i \) is the training input of the RBF and the expression \( x_2 - h_1(r) \) is the training output. The training process is displayed in Figure 14.

![Figure 14: Block diagram of the redundant data extraction RBF training process](image)

After the RBF neural network has been trained with an appropriate training data set, the network is ready to receive the testing data set. The testing procedure is illustrated in Figure 15 and displayed in equation form in Equation 3.8.

\[ h_1(r) = x_2 - g_1(x_1) \]  \hspace{1cm} (3.8)
The RBF neural network is fed the testing $x_1$ data as in the training sequence. However, the output of the network $x_2 - h_1(r)$ is inverted and $x_2$ is subtracted from the inverted output. Therefore, the redundant data is effectively extracted resulting in $h_1(r)$ as the final output.

![Block diagram of the redundant data extraction RBF testing process](image)

**Figure 15:** Block diagram of the redundant data extraction RBF testing process

The complementary data extraction technique follows a mathematical process that is almost identical to the redundant data extraction technique. The only exception is that the $h$ is a function of $x_1$ and $x_2$ that is invariant to $r$. Therefore, Equation 3.1 becomes

$$f(x_1(r,c_1), x_2(r,c_2)) = h_2(c_1,c_2)$$  \hspace{1cm} (3.9)

where $h_1(r)$ has been replaced with $h_2(c_1,c_2)$. Also, the RBF neural network whose output is denoted as $g_1$ is different for the complementary data extraction technique since the network has been trained with complementary, not redundant, data.

In the next chapter, implementation details and results obtained using the complementary and redundant data extraction algorithms described in this chapter, are presented. The algorithms are first exercised simulated canonical images and then on nondestructive evaluation signals obtained from MFL, UT and thermal interrogations of a suite of test specimens.
CHAPTER 4: IMPLEMENTATION RESULTS

In this chapter, results obtained by applying the proposed data fusion algorithms are presented. The complementary and redundant data fusion algorithms are exercised first on simulated canonical images and then on magnetic flux leakage (MFL), ultrasonic testing (UT) and thermal inspection images obtained from a suite of test specimens in the laboratory. Results obtained using canonical images are presented first to demonstrate the efficacy of the algorithm. The experimental set-up for obtaining the NDE images are then described; followed by a detailed description of the signal analysis procedure.

4.1 Canonical Images for Data Fusion

The redundant and complementary data extraction algorithms were tested using a series of canonical images before they were tested on experimental laboratory data. Figure 16 displays the parameters chosen for the three different canonical image simulations performed. All three of the simulations consisted of six 20-by-20 pixel images containing both redundant and complementary information as defined in Figures 16 through 18; 4 for training and 2 for testing. The simulation 1 input and output images are shown in Figure 16. The six images for simulation 1 contained only varying redundant data. This data varied only in size and kept the same basic position throughout the six images. In Figure 17, the simulation 2 input and output images are displayed. In simulation 2 the redundant and complementary data varied throughout the six-image data set. Once again, this variation was only in the size of the information, but not the location. Finally, in Figure 18, the simulation 3 redundant and complementary data both varied in size and in location. The input and output feature vectors to the redundant and complementary data extraction neural networks consisted of the Discrete Cosine
Transform (DCT) coefficients of the images. Training and test data results can be seen in Figures 19 through 24.

Figure 16: Simulation 1 block diagram

Figure 17: Simulation 2 block diagram
Figure 18: Simulation 3 block diagram

Figure 19: Simulation 1 training data results
Figure 20: Simulation 1 test data results

Figure 21: Simulation 2 training data results

Figure 22: Simulation 2 test data results
4.2 Experimental Setup

4.2.1 Test Specimen Suite

The first step in the development of the experimental setup was to design a test specimen suite that is representative of a sufficient number of real-world anomalies that are likely to occur in gas transmission pipelines. According to PII Pipeline Solutions, General Electric Power Systems' center dedicated to pipeline inspection and integrity, gas transmission pipeline anomalies can be categorized into four main groups [17]. The first
of these groups is manufacturing defects. Manufacturing defects are inconsistencies produced during the manufacturing of the pipeline materials. These defects may be harmless such as blister and sliver plate defects or serious seamless defects such as copper penetration that may open under stress. However, under the right conditions, "harmless" defects such as blister and sliver defects may lead to more harmful defects such as pitting corrosion.

The second group of gas transmission pipeline anomalies is construction defects. This group of defects can be broken down into two subgroups of defects: construction operation defects and girth weld defects. Construction operation defects may occur due to mistakes during the pipe laying process. For instance, cold bend kinks may occur if there is a lack of proper control during the field bending process. They may also occur due to improper repair procedure. For example, a fillet-welded patch may be used to cover an access hole in a pipeline when the area should be covered by a welded sleeve around the section of pipeline. Girth weld defects are anomalies that occur in or around a weld connecting two sections of pipeline. They can result in cracks that can be detrimental to the pipeline structure and are caused by improper welding procedure or inconsistencies in the welding process. Girth weld defects include hollow beads, lack of penetration, weld-metal cracking and lack of fusion.

The third group of defects is operational defects. Operational defects occur during the normal operation of pipelines and are usually caused by the environment in which pipelines operate. Over long periods of continuous operation, pipelines can begin to corrode internally and externally, buckle, erode and/or fall victim to mechanical damage.
Finally, the last group of defects that may occur in gas transmission pipelines is *coating defects*. Depending on the type of pipeline coating used, different variables may compromise the integrity of the pipeline’s coating in the affected area. There are various types of pipeline coating materials that are susceptible to anomalies. The most commonly used coatings that are susceptible to the occurrence of anomalies are hot enamels, fusion bonded epoxy powders, heat shrink materials, multi-component liquids, polyolefins and tapes.

Using this information, the test specimens shown in Figure 16 were fabricated to mimic a subset of a few common anomalies that occur in gas transmission pipelines. All of the specimens were machined from ASTM-836 steel and have length and width dimensions of 6” x 4”. However, three separate specimen thicknesses, $\frac{5}{16}$, $\frac{3}{8}$ and $\frac{1}{2}$ inch, have been incorporated into the test specimen suite to account varying pipe-wall thicknesses. Three specimens, one of each thickness, have been fabricated without any defect as shown in Figure 25(a). Figure 25(b) displays one of the specimens developed to mimic pitting corrosion defects. A total of nine slotted-defect specimens were produced in a milling machine with 0.1, 0.2 and 0.3-inch deep defects for all three specimen thicknesses discussed earlier. The specimen nomenclature is indicated in Table 1.
4.2.2 Magnetic Flux Leakage Scanning Test Setup

The first set of experimental data collected for the test specimen suite was produced using the Rowan University NDE laboratory magnetic flux leakage scanning test setup, shown in Figure 26. The setup's hardware consists of an HP 6571A DC power supply, an F. W.
Bell 9900 series Gaussmeter, and 3-axis Parker Automation scanning system. The setup’s software was created by researchers in the Rowan University NDE lab.

For the test specimen suite developed, the HP 6571A DC power supply output current was set at a constant 200 Amps for each specimen. In the software, the x, y, and z components of the magnetic flux were collected for each specimen.

The tangential (x-) component of MFL NDE images obtained by scanning the test specimens are shown in Figure 27. The images are scaled and registered to reflect the actual scanning resolution of 100 pixels/inch.

Figure 26: Magnetic flux leakage scanning test setup
4.2.3 Ultrasound Scanning Test Setup

The second set of experimental data was collected at the ultrasonic testing facilities at Physical Acoustics Corporation (PAC) Princeton, NJ. The facilities consisted of a 4-axis immersion tank scanning system equipped with a 10 MHz flat pulsing transducer. The software was also developed by PAC and was used to collect amplitude and a time of flight ultrasound images for each specimen using the pulse-echo technique. The UT scanning setup is shown in Figure 28.
The time-of-flight (TOF) UT images obtained by scanning the test specimens are shown in Figure 29. These images are scaled and registered to reflect the actual scanning resolution of 100 pixels/inch.

Figure 28: Ultrasound scanning test setup
4.2.4 Thermal Imaging Test Setup

The thermal imaging test set-up is shown in Figure 30. The heat source consists of a high-power 110 W Halogen lamp that is sinusoidally excited at a rate of 8-10 seconds/cycle. The specimen is placed on an optical table and is thermally insulated with an Aluminum honeycomb panel. The thermal images of the test specimens are captured using a FLIR Systems Microbolometer camera. The images were obtained at 1 second intervals over the excitation cycle. Five images at equally spaced time intervals over each
cycle were processed to extract the phase images – these are shown in Figure 31. The images are scaled and registered to reflect a resolution of 100 pixels/inch. It can be noticed that the defect related information in the thermal phase images is less than that contained in the UT and MFL images presented in previous monthly reports.

Figure 30: Thermal imaging test setup
Figure 31: Registered thermal phase image data
4.3 Results

4.3.1 Training and Test Datasets

The complementary and redundant data extraction algorithms were exercised on the NDE images obtained from the test specimens. The data was parsed into training and test data sets for the data fusion neural network in 3 distinct combinations. These data analysis trials are shown in Tables 2 through 4. For each trial, NDE images from two different modalities of the three (MFL, UT and thermal) were fused using the complementary and redundant data extraction neural networks. A total of three data fusion combinations were conducted for each trial.

Table 2: Training and test data assignments for Trial 1

<table>
<thead>
<tr>
<th>Specimen #</th>
<th>Plate thickness (in)</th>
<th>Defect Type</th>
<th>Defect Depth (in)</th>
</tr>
</thead>
<tbody>
<tr>
<td>00</td>
<td>0.5</td>
<td>None</td>
<td>N/A</td>
</tr>
<tr>
<td>01</td>
<td>0.5</td>
<td>Pitting</td>
<td>0.3005</td>
</tr>
<tr>
<td>02</td>
<td>0.5</td>
<td>Pitting</td>
<td>0.198</td>
</tr>
<tr>
<td>03</td>
<td>0.5</td>
<td>Pitting</td>
<td>0.0945</td>
</tr>
<tr>
<td>10</td>
<td>0.375</td>
<td>None</td>
<td>N/A</td>
</tr>
<tr>
<td>11</td>
<td>0.375</td>
<td>Pitting</td>
<td>0.298</td>
</tr>
<tr>
<td>12</td>
<td>0.375</td>
<td>Pitting</td>
<td>0.199</td>
</tr>
<tr>
<td>13</td>
<td>0.375</td>
<td>Pitting</td>
<td>0.1105</td>
</tr>
<tr>
<td>20</td>
<td>0.3125</td>
<td>None</td>
<td>N/A</td>
</tr>
<tr>
<td>21</td>
<td>0.3125</td>
<td>Pitting</td>
<td>0.303</td>
</tr>
<tr>
<td>22</td>
<td>0.3125</td>
<td>Pitting</td>
<td>0.1955</td>
</tr>
<tr>
<td>23</td>
<td>0.3125</td>
<td>Pitting</td>
<td>0.0995</td>
</tr>
</tbody>
</table>

Note: All specimens have a length of 6 inches and a width of 4 inches.
### Table 3: Training and test data assignments for Trial 2

<table>
<thead>
<tr>
<th>Specimen #</th>
<th>Plate thickness (in)</th>
<th>Defect Type</th>
<th>Defect Depth (in)</th>
</tr>
</thead>
<tbody>
<tr>
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<td>0.5</td>
<td>None</td>
<td>N/A</td>
</tr>
<tr>
<td>01</td>
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<td>Pitting</td>
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</tr>
<tr>
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<td>Pitting</td>
<td>0.198</td>
</tr>
<tr>
<td>03</td>
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<td>Pitting</td>
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<tr>
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<td>Pitting</td>
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</tr>
<tr>
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<tr>
<td>21</td>
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<td>Pitting</td>
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<tr>
<td>22</td>
<td>0.3125</td>
<td>Pitting</td>
<td>0.1955</td>
</tr>
<tr>
<td>23</td>
<td>0.3125</td>
<td>Pitting</td>
<td>0.0995</td>
</tr>
</tbody>
</table>

Note: All specimens have a length of 6 inches and a width of 4 inches.

### Table 4: Training and test data assignments for Trial 3

<table>
<thead>
<tr>
<th>Specimen #</th>
<th>Plate thickness (in)</th>
<th>Defect Type</th>
<th>Defect Depth (in)</th>
</tr>
</thead>
<tbody>
<tr>
<td>00</td>
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<td>None</td>
<td>N/A</td>
</tr>
<tr>
<td>01</td>
<td>0.5</td>
<td>Pitting</td>
<td>0.3005</td>
</tr>
<tr>
<td>02</td>
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<td>Pitting</td>
<td>0.198</td>
</tr>
<tr>
<td>03</td>
<td>0.5</td>
<td>Pitting</td>
<td>0.0945</td>
</tr>
<tr>
<td>10</td>
<td>0.375</td>
<td>None</td>
<td>N/A</td>
</tr>
<tr>
<td>11</td>
<td>0.375</td>
<td>Pitting</td>
<td>0.298</td>
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<tr>
<td>12</td>
<td>0.375</td>
<td>Pitting</td>
<td>0.199</td>
</tr>
<tr>
<td>13</td>
<td>0.375</td>
<td>Pitting</td>
<td>0.1105</td>
</tr>
<tr>
<td>20</td>
<td>0.3125</td>
<td>None</td>
<td>N/A</td>
</tr>
<tr>
<td>21</td>
<td>0.3125</td>
<td>Pitting</td>
<td>0.303</td>
</tr>
<tr>
<td>22</td>
<td>0.3125</td>
<td>Pitting</td>
<td>0.1955</td>
</tr>
<tr>
<td>23</td>
<td>0.3125</td>
<td>Pitting</td>
<td>0.0995</td>
</tr>
</tbody>
</table>

Note: All specimens have a length of 6 inches and a width of 4 inches.
4.3.2 Definition of Redundant and Complementary Information

In order to train the artificial neural network for each of the trials, it is necessary to indicate the desired complementary and redundant information between the two NDE inspection methods. In this thesis, since the actual defect size, shape, depth and location is known for the specimen suite, these definitions can be made by comparing the NDE signature for each of the inspection methods with the size, shape, depth and location of the defect. Figure 32 illustrates this definition process.

![Diagram showing redundant and complementary information definitions between two NDE signatures.

Figure 32: Redundant and complementary information definitions between two NDE signatures

Complementary information in two NDE images are defined as those distinct pixels in each of the NDE signatures that are present in the defect region, but are not shared between them. Redundant information in two NDE images are defined as those common pixels that are present in both NDE signatures and are also present in the defect region.

The training and test data results for the 3 separate trials, using combinations of 2 NDE methods from the 3 total, employ these definitions for redundant and
complementary information for neural network training. The network inputs and outputs used were the spectral coefficients of the images using the Discrete Cosine Transform (DCT). The results for the various combinations and approaches can be seen in the following sections.
4.3.3 UT and MFL Combination Results

Trial 1: Test Results

(a) Redundant Complementary
(b) Redundant Complementary
(c) Redundant Complementary
(d) Redundant Complementary
Trial 1: Test Results (cont.)

(e) Redundant Complementary

(f) Redundant Complementary

(g) Redundant Complementary

(h) Redundant Complementary
Figure 33: UT and MFL results for Trial 1. (a) Specimen 00 (train); (b) Specimen 03 (train); (c) Specimen 02 (train); (d) Specimen 01 (train); (e) Specimen 10 (train); (f) Specimen 13 (train); (g) Specimen 11 (train); (h) Specimen 20 (train); (i) Specimen 23 (train); (j) Specimen 22 (train); (k) Specimen 21 (train); (l) Specimen 12 (test)
Trial 2: Test Results

(a) 

(b) 

(c) 

(d)
Trial 2: Test Results (cont.)

(e) Redundant Complementary

(f) Redundant Complementary

(g) Redundant Complementary

(h) Redundant Complementary
Figure 34: UT and MFL results for Trial 2. (a) Specimen 00 (train); (b) Specimen 03 (train); (c) Specimen 01 (train); (d) Specimen 10 (train); (e) Specimen 13 (train); (f) Specimen 11 (train); (g) Specimen 20 (train); (h) Specimen 23 (train); (i) Specimen 21 (train); (j) Specimen 02 (test); (k) Specimen 12 (test); (l) Specimen 22 (test)
Trial 3: Test Results

(a) Redundant Complementary
(b) Redundant Complementary
(c) Redundant Complementary
(d) Redundant Complementary
Trial 3: Test Results (cont.)
Figure 35: UT and MFL results for Trial 3. (a) Specimen 00 (train); (b) Specimen 03 (train); (c) Specimen 02 (train); (d) Specimen 01 (train); (e) Specimen 20 (train); (f) Specimen 23 (train); (g) Specimen 22 (train); (h) Specimen 21 (train); (i) Specimen 10 (test); (j) Specimen 13 (test); (k) Specimen 12 (test); (l) Specimen 11 (test)
4.3.4 UT and Thermal Combination Results

**Trial 1: Test Results**

(a) Redundant Complementary

(b) Redundant Complementary

(c) Redundant Complementary

(d) Redundant Complementary
Trial 1: Test Results (cont.)

- Inputs:
  - $x_1$, Thermal Data
  - $x_2$, UT Data

- Outputs:
  - Redundant
  - Complementary

- Desired Output:
  - Redundant
  - Complementary

(e) 

- Inputs:
  - $x_1$, Thermal Data
  - $x_2$, UT Data

- Outputs:
  - Redundant
  - Complementary

- Desired Output:
  - Redundant
  - Complementary

(f) 

- Inputs:
  - $x_1$, Thermal Data
  - $x_2$, UT Data

- Outputs:
  - Redundant
  - Complementary

(g) 

- Inputs:
  - $x_1$, Thermal Data
  - $x_2$, UT Data

- Outputs:
  - Redundant
  - Complementary

(h)
Figure 36: UT and thermal results for Trial 1. (a) Specimen 00 (train); (b) Specimen 03 (train); (c) Specimen 02 (train); (d) Specimen 01 (train); (e) Specimen 10 (train); (f) Specimen 13 (train); (g) Specimen 11 (train); (h) Specimen 20 (train); (i) Specimen 23 (train); (j) Specimen 22 (train); (k) Specimen 21 (train); (l) Specimen 12 (test)
Trial 2: Test Results

(a) [Diagram of Inputs and Outputs]

(b) [Diagram of Inputs and Outputs]

(c) [Diagram of Inputs and Outputs]

(d) [Diagram of Inputs and Outputs]
Trial 2: Test Results (cont.)

(e) (f)

(g) (h)
Trial 2: Test Results (cont.)

Figure 37: UT and thermal results for Trial 2. (a) Specimen 00 (train); (b) Specimen 03 (train); (c) Specimen 01 (train); (d) Specimen 10 (train); (e) Specimen 13 (train); (f) Specimen 11 (train); (g) Specimen 20 (train); (h) Specimen 23 (train); (i) Specimen 21 (train); (j) Specimen 02 (test); (k) Specimen 12 (test); (l) Specimen 22 (test)
Trial 3: Test Results

(a)  (b)  (c)  (d)
Trial 3: Test Results (cont.)

(e) 

(f) 

(g) 

(h)
Trial 3: Test Results (cont.)

Figure 38: UT and thermal results for Trial 3. (a) Specimen 00 (train); (b) Specimen 03 (train); (c) Specimen 02 (train); (d) Specimen 01 (train); (e) Specimen 20 (train); (f) Specimen 23 (train); (g) Specimen 22 (train); (h) Specimen 21 (train); (i) Specimen 10 (test); (j) Specimen 13 (test); (k) Specimen 12 (test); (l) Specimen 11 (test)
4.3.5 MFL and Thermal Combination Results

Trial 1: Test Results

(a)

(b)

(c)

(d)
Trial 1: Test Results (cont.)

Inputs: $x_1$, Thermal Data  $x_2$, MFL Data

Outputs: Redundant  Complementary

(continued)

Inputs: $x_1$, Thermal Data  $x_2$, MFL Data

Outputs: Redundant  Complementary

(continued)

Inputs: $x_1$, Thermal Data  $x_2$, MFL Data

Outputs: Redundant  Complementary

(continued)
Figure 39: MFL and thermal results for Trial 1. (a) Specimen 00 (train); (b) Specimen 03 (train); (c) Specimen 02 (train); (d) Specimen 01 (train); (e) Specimen 10 (train); (f) Specimen 13 (train); (g) Specimen 11 (train); (h) Specimen 20 (train); (i) Specimen 23 (train); (j) Specimen 22 (train); (k) Specimen 21 (train); (l) Specimen 12 (test)
Trial 2: Test Results

(a) x1, Thermal Data
   x2, MFL Data
   Redundant
   Complementary

(b) x1, Thermal Data
   x2, MFL Data
   Redundant
   Complementary

(c) x1, Thermal Data
   x2, MFL Data
   Redundant
   Complementary

(d) x1, Thermal Data
   x2, MFL Data
   Redundant
   Complementary
Trial 2: Test Results (cont.)
Trial 2: Test Results (cont.)

Figure 40: MFL and thermal results for Trial 2. (a) Specimen 00 (train); (b) Specimen 03 (train); (c) Specimen 01 (train); (d) Specimen 10 (train); (e) Specimen 13 (train); (f) Specimen 11 (train); (g) Specimen 20 (train); (h) Specimen 23 (train); (i) Specimen 21 (train); (j) Specimen 02 (test); (k) Specimen 12 (test); (l) Specimen 22 (test)
Trial 3: Test Results

(a) Redundant Complementary

(b) Redundant Complementary

(c) Redundant Complementary

(d) Redundant Complementary
Trial 3: Test Results (cont.)

5

x, Thermal Data 1. MFL Data

0i

Redundant Complementary

0 or UJQ x, Thermal ... Complementary

(g)

Redundant Complementary

s a 0 0 w or wJ 0 Redundant Complementary

(h)
Trial 3: Test Results (cont.)

Figure 41: MFL and thermal results for Trial 3. (a) Specimen 00 (train); (b) Specimen 03 (train); (c) Specimen 02 (train); (d) Specimen 01 (train); (e) Specimen 20 (train); (f) Specimen 23 (train); (g) Specimen 22 (train); (h) Specimen 21 (train); (i) Specimen 10 (test); (j) Specimen 13 (test); (k) Specimen 12 (test); (l) Specimen 11 (test)
4.3.6 Observations and Discussion of Results

The following general observations can be drawn from the data fusion results shown in Figures 19 through 24 and Figures 33 through 41:

i. The training data results for the canonical images show no error between the predicted and desired network outputs; the test data, however, show some minimal error (false positives) for all simulations in Figures 20, 22 and 24.

ii. The training data results for all UT and MFL combination trials consistently show excellent performance – this indicates that information provided to the neural network is distinct and the resulting matrices are non-singular and is clearly visible in Figures 33(a)-(k), Figures 34(a)-(i) and Figures 35(a)-(h).

iii. The testing data results for all UT and MFL combination trials show considerable promise for both the redundant and the complementary information techniques. In Figure 33(l), the redundant information extraction neural network was capable of promoting a significant amount of the redundant data present within the two signatures and suppressing a fair amount of the complementary data present between the two signatures. Likewise, the complementary information extraction neural network performed just as well. In Trial 2, the networks had not seen as large an amount of training data as in Trial 1. Therefore, in Figures 34(j)-(l), the actual network outputs were satisfactory when compared with the desired outputs, however, they were not as good as those in Figure 33(l). A similar result was obtained for Trial 3 in Figures 35(i)-(l).

iv. The training results for all UT and thermal combinations as well as all MFL and thermal combinations performed well with the exception of one problem – all
training instances where the test specimen had a defect but the ability to extract a meaningful NDE signature from the thermal phase image was not possible had minimal error within the image output of the redundant data extraction algorithm. This error appeared because given the training data sets for Trials 1 through 3, the network had not seen enough data points and was therefore unable to suppress all of the complementary information within the redundant network. This is displayed in Figures 36(b), 36(c), 36(f), 36(i), 37(b), 37(e), 37(h), 38(b), 38(c), 38(f), 39(b), 39(c), 39(f), 39(i), 40(b), 40(e), 40(h), 41(b), 41(c), 41(f). The complementary extraction network for UT and thermal had a similar problem, but only for a minimal amount of training data – Figures 36(c) and 38(c).

v. The testing results for all UT and thermal combinations for redundant and complementary information extraction show a consistent effort to suppress and promote their respective information types. However, the results produced (Figure 36(l), Figures 37(j)-(l) and Figures 38(i)-(l)) are not as good as the UT and MFL combination results. Furthermore, some of the test results display the problem discussed in the above point as well. A similar result was obtained for the MFL and thermal combination results for all three trials – Figure 39(l), Figures 40(j)-(l) and Figures 41(i)-(l). However, it is difficult to compare the performance of UT and thermal combinations to the performance of the MFL and thermal combinations due the lack of a uniform edge detection for each method (UT, MFL and thermal).
CHAPTER 5: CONCLUSIONS

Research in multi-sensor data fusion has seen phenomenal growth in recent years, as the opportunities for sensor deployment have increased and the signal processing algorithms for managing the data have become more sophisticated. In this chapter, a listing of specific contributions made in this thesis related to multi-sensor data fusion is presented. Also, conclusions are drawn from implementing the data fusion algorithms designed and developed as part of this research work. Finally, recommendations are made for directions for future work in this area.

5.1 Summary of Accomplishments

The principal contributions of this thesis are:

1. The development of a generalized technique for fusing data from two distinct observations of the same object or phenomenon, using geometric transformations performed by a radial basis function artificial neural network.

2. The design and development of a data fusion algorithm that can extract redundant and complementary information present in two distinct observations of the same object or phenomenon.

3. The validation of the data fusion algorithms using both simulated canonical data and laboratory generated data that is representative of the nondestructive evaluation of gas transmission pipelines. In particular, combinations of MFL, UT and thermal imaging of metallic test specimens embedded with rectangular slot-shaped defects are chosen as candidates for data fusion.
5.2 Conclusions

The data fusion techniques presented in this thesis operate by extracting redundant and complementary information present in multiples sets of observations, specifically, NDE interrogations of defects in a test specimen suite. In order to extract such information it is essential that the artificial neural network that lies at the heart of the data fusion algorithm be trained with a sufficient diversity NDE signatures that is indicative of all typical anomalies encountered in the practice of in-line inspection of gas transmission pipelines. Furthermore, the data fusion algorithm is sufficiently general, in that it does not specify what features in the NDE signatures are redundant or complementary – that opportunity is left to the user of the algorithm. If this information is not predictable then the neural network based algorithms are inappropriate for characterizing NDE signals. In this thesis, the efficacy of the algorithm is demonstrated by defining complementarity and redundancy of two sets of NDE image data by correlating defect signature pixels with the location, size, and shape of the defect. Results presented in this thesis show that this definition and approach are extremely accurate in most instances of training data and sufficiently accurate in all instances of test data. The fact that the algorithm and this choice of definition result in no training error proves that the information presented to the artificial neural network is distinct; the matrices manipulated by the network algorithm are non-singular. The errors that occur during certain instances of testing the data fusion technique illustrate the need for a large, diverse and comprehensive training data set – efforts to address this issue are presently underway.

The approach and results presented in this thesis also serve to address a crucial requirement of all data fusion algorithms – when multiple sets of measurements are
available, the technique allows the user to choose subsets that are appropriate for extracting desired information. Separating the data fusion process into user-defined redundant and complementary information, allows us to identify those particular sets of data that are effective in extracting specified information contained within them, either singly or in combination.

5.3 Directions for Future Work

The task of combining data from multiple sources and extracting meaningful information as a result of this combination continues to be a challenging task. Although this thesis has made significant inroads in addressing this problem, there remains considerable work that needs to be done for arriving at a comprehensive technique for performing multi-sensor data fusion. The algorithm presented in this thesis shows considerable promise, as indicated by the implementation results; however, the following issues need to be addressed before the technique is ready for field-testing:

1. The size and diversity of the training and test data sets require enhancement, even though this requires an outlay of significant resources in time, personnel and supplies.

2. A variety of image preprocessing techniques need to be explored for information compaction and feature extraction.

3. Different ways of defining redundant complementary information present in multiple data sets must be investigated.

4. Although the data fusion algorithms described in this thesis have been exercised with experimental data, the robustness of the technique using noisy real-world NDE signals remains to be tested.
5. In this thesis, all of the data used to test the data fusion algorithms was homogeneous—i.e., it consisted of spatial domain 2-D images. In any real-word data fusion application, the information bearing data sets are heterogeneous—i.e., the data would consist of a combination of time-domain 1-D signals, spatial domain 2-D images, singular events describing time-history, anecdotal evidence and a priori knowledge. The data fusion algorithm proposed in this thesis must be augmented to handle such heterogeneous data sets.

Nondestructive evaluation plays a vital component in the operation and maintenance of large infrastructure such as gas transmission pipelines, nuclear power plants, aircraft, bridges and highways, etc. As this infrastructure continues to age and planned replacements are often significantly behind schedule due to cost overruns, it is essential that inspection techniques reliably and accurately predict the integrity of these systems that play crucial part in the conduct of the nation’s commercial operations. No single NDE method is capable of inspecting everything and extracting all required information—a combination of methods must be used and the resulting data must be fused. Moreover, the newer systems that are developed are often made of composite materials that include metals and dielectrics—the tail fin of a modern commercial aircraft is one example. One interrogation modality cannot be used to inspect such components for reliability—multiple tests are always needed. Multi-sensor data fusion techniques, such as the one presented in this thesis, will play a significant part in assuring the integrity and safety of infrastructure that will be used heavily in the near future.
BIBLIOGRAPHY


17. GE Power Systems, “PII Pipeline Solutions,”