Integrated NDE Methods Using Data Fusion For Bridge Condition Assessment

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ABSTRACT

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Bridge management system (BMS) is an effective mean for managing bridges throughout their design life. BMS requires accurate collection of data pertinent to bridge conditions. Non Destructive Evaluation methods (NDE) are automated accurate tools used in BMS to supplement visual inspection. This research provides overview of current practices in bridge inspection and in-depth study of thirteen NDE methods for condition assessment of concrete bridges and eleven for structural steel bridges. The unique characteristics, advantages and limitations of each method are identified along with feedback on their use in practice. Comparative study of current practices in bridge condition rating, with emphasis on the United States and Canada is also performed. The study includes 4 main criteria: inspection levels, inspection principles, inspection frequencies and numerical ratings for 4 provinces and states in North America and 5 countries outside North America. Considerable work has been carried out using a number of sensing technologies for condition assessment of civil infrastructure. Fewer efforts, however, have been directed for integrating the use of these technologies. This research presents a newly developed method for automated condition assessment and rating of concrete bridge decks. The method integrates the use of ground penetrating radar (GPR) and infrared thermography (IR) technologies. It utilizes data fusion at pixel and feature levels to improve the accuracy of detecting defects and, accordingly, that of condition assessment. Dynamic Bayesian Network

(DBN) is utilized at the decision level of data fusion to overcome cited limitations of Markov chain type models in predicting bridge conditions based on prior inspection results. Pixel level image fusion is applied to assess the condition of a bridge deck in Montreal, Canada using GPR and IR inspection results. GPR data are displayed as 3D from 24 scans equally spaced by 0.33m to interpret a section of the bridge deck surface. The GPR data is fused with IR images using wavelet transform technique. Four scenarios based on image processing are studied and their application before and after data fusion is assessed in relation to accuracy of the employed fusion process. Analysis of the results showed that bridge condition assessment can be improved with image fusion and, accordingly, support inspectors in interpretation of the results obtained. The results also indicate that predicted bridge deck condition using the developed method is very close to the actual condition assessment and rating reported by independent inspection.

The developed method was also applied and validated using three case studies of reinforced concrete bridge decks. Data and measurements of multiple NDE methods are extracted from Iowa, Highway research board project, 2011. The method utilizes data collected from ground penetrating radar (GPR), impact echo (IE), Half-cell potential (HCP) and electrical resistivity (ER). The analysis results of the three cases indicate that each level of data fusion has its unique advantage. The power of pixel level fusion lies in combining the location of bridge deck deterioration in one map as it appears in the fused image. While, feature fusion works in identification of specific types of defects, such as corrosion, delamination and deterioration. The main findings of this research recommend utilization of data fusion within two levels as a new method to facilitate and enhance the capabilities of inspectors in interpretation of the results obtained. To demonstrate the use of the developed method and its model at the decision level of data fusion an additional case study of a bridge deck in New Jersey, USA is selected.

Measurements of NDE methods for years 2008 and 2013 for that bridge deck are used as input to the developed method. The developed method is expected to improve current practice in forecasting bridge deck deterioration and in estimating the frequency of inspection. The results generated from the developed method demonstrate its comprehensive and relatively more accurate diagnostics of defects.

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CHAPTER 1

1. INTRODUCTION

1.1. PROBLEM STATEMENT

Bridges play a vital role in road infrastructure network. The United States (US) has 614,387 bridges and 9.1% of bridges are rated structurally deficient (ASCE 2017). Average age of bridges in the USA is 43 years and more than one in eight (13.6%) are functionally obsolete (ASCE 2017). According to Canada statistics, Bridges and overpasses accounted for 8% of total public assets in 2007. Bridges are the second highest of five assets; they account for 72% in Québec and 66% in Nova Scotia. Ontario ranked as the third among provinces in terms of having old bridges. In 2007, Bridges in Ontario accounted for 7% of its public infrastructure, while in Alberta, bridges are accounted for 9% of total public infrastructure (Statistics Canada 2009). Bridges are subjected to excessive deteriorations and corrosions due to harsh environment, heavy transport, increasing traffic and aging. It has been reported that the number and size of vehicles in constructed bridges have significantly increased than the forecasted design (Gattulli and Chiaramonte 2005, Amleh and Mirza 2004). Moreover, concrete Bridges are usually suffering from cracks due to concrete shrinkage and are subjected to chloride content. This deterioration can be increased with freezing and thawing cycles during the winter. The damage in bridge elements lead to a reduction in serviceability and load carrying capacity. As a result of bridges' deteriorations, the American Society of Civil Engineers infrastructure report card reported in June 2013 that one in nine nation's bridges are rated as structurally deficient, more than 66,000 in total. Moreover, bridges in Canada have a mean service life of 43 years, which means that

Canadian bridges have passed 57% of their design life (Statistics Canada 2009). However, the current funding used for rehabilitation and replacement of deteriorated bridges is not adequate to fulfill the target needs (Aboudabus and alkass 2010, Gattulli and Chiaramonte 2005, Gucunski and Nazarian 2010). The Federal Highway Administration (FHWA) estimates that they would need to invest $20.5 billion annually to eliminate bridges' deficiencies by 2028. However, only $12.8 billion is currently being spent. Therefore, the main Challenge for local governments is to increase investment in bridge maintenance by $8 billion (ASCE 2013).

Bridge management System (BMS) is the process of making decisions on structure needs and preparing a corrective action at a proper time; these include maintenance, repair, rehabilitation and replacement actions. All bridge management decisions require inspection data to identify current condition and needs. The decision makers can avoid the worst consequences of underestimating the degree of deterioration and avoid the costly consequences of overestimating the degree of deterioration. It also helps to select the appropriate solution. However, BMS often faces imbalance between the need for repairs or replacements and many challenges due to incorporating of multi objectives: structural safety, serviceability, optimum maintenance and economic considerations. The main goal of BMS is to gain the maximum performance with minimum cost and this can be achieved by efficient techniques and technologies that can be automatically updated. Consequently, the service life of bridges can be increased within effective cost (Rens et al. 2005, Steart et al. 2002, Wang et al. 2007). Thus, inspection process and condition assessment are considered main components of BMS.

Bridge condition assessment is conducted to determine load rating capacity for bridge components. The main components of bridges are deck, superstructure and substructure. Each component has different role in bridge structure with specified relative importance. Bridge condition assessment defines the structural importance of each bridge element. The identification of current condition of each element provides with early warning of necessary maintenance. Condition rating is performed using the inspection data; these collected data are converted to a rating to assess bridge condition (Xia and Brownjohn 2004, Yehia et al. 2007). The main difficulty in bridge condition assessment is the large number of bridges in the network, which requires regular inspection.

Non Destructive Evaluation (NDE) methods are inspection tools that do not affect the integrity of the member under evaluation. The member remains in service while being tested. (NDE) technologies are considered advanced methods as these methods usually use automated and speedy data acquisition systems. Also, the software used to process the NDE data is considered reliable and provides better accuracy. NDE methods are used to supplement visual inspection.

Research efforts were made using single NDE method to detect defects, crack, delamination and voids in concrete bridges such as impact echo. Ground Penetrating Radar (GPR) is capable of detecting deterioration, location of voids, mapping of reinforcement location and depth of cover of steel bars. Infrared thermography is used to detect delamination. Some research efforts have been made within the area of condition assessment using different technologies. Robotic systems were developed and used for inspection of bridges and tunnels, using multiple sensing technologies, including digital imaging and impact acoustics methods (Balaguer et al. 2014, Laa et al. 2014). Gucunski et al. (2010) studied the performance of NDT technologies in detection of reinforced concrete deck deterioration. They evaluated the performance of ground penetrating radar, galvanostatic pulse measurements, impact echo, infrared and ultrasonic surface waves. Recently, Laa et al. (2014) worked on developing robotics assisted bridge inspection tool (RABIT). The technologies used in RABIT system are: electrical resistivity, impact echo, ground penetrating radar and ultrasonic surface waves. RABIT integrates measurements from multiple technologies. The outputs from RABIT are deterioration maps for each individual technology for detecting locations and severity of damages in bridge deck. To the best of authors' knowledge, the algorithms and the methodology for integration and fusion of data captured by multiple technologies in the RABIT are briefly referred to in a conference paper (Laa et al. 2014) without any detailed description.

It is expected that using multiple sensing technologies can provide better condition assessment than that based on the use of one sensing technology. This can be attributed to the fact that each of such technologies has its capabilities and limitations. As well, when large amount of data of multiple sensors are fused, it can provide output that is more comprehensive and thus be of more help to decision makers. The simplest way to deal with a multi sensor problem is to combine all observations in a single group sensor. Data fusion can also be done by dealing with each sensor independently and then fuse all information together (Hoseini and Ashraf 2013).

Multi sensor data fusion is a technique used to combine features extracted from measurements taken from different sources to enrich the captured inspection. The main purpose of combining data from multiple sources is to improve the accuracy of diagnostics; in a manner that mimic medical diagnostic which utilizes the results of different tests.

Data fusion can be done within three levels: pixel level image fusion, feature level and decision level. Pixel level fusion is a form of integration of pixels from different images acquired from different sources. Feature level involves first the extraction of features from the images captured by multiple sensing technologies and then fusing these features into a single feature.

Decision level fusion involves fusion of information obtained from the feature level and done by many techniques such as Bayesian Networks (BNS) and Dynamic Bayesian Networks (DBNs) (Hall and Llinas 1997, Naidu and Roal 2008).

According to the literature review, there is no application of data fusion in bridge condition assessment. In this research, data fusion method is developed using pixel and feature levels. The main objective of using pixel image fusion is to assess bridge condition using multiple sensor data. The application of pixel image fusion and feature fusion in bridge condition assessment is considered a novel technique as, with the use of multiple sensors, it can interpret condition assessment results more accurately with less cost and interruption for traffic. However, there may be higher initial cost involved to acquire condition assessment using different technologies. The total cost is expected to be reduced in view of reduction of labor hours and reduction in time required to carry the scanning in compare to manual methods. However, no detailed cost comparison is fully conducted in this research. The main objective of using data fusion in this research is to improve the accuracy of condition assessment.

Currently, there is lack of tools that inspectors can use to fuse data. The current research is focusing on using pixel and feature levels of data fusion as a tool to assess the condition of reinforced concrete bridge decks. Wavelets transform and Bayesian Networks techniques have been utilized to apply data fusion method.

The developed method of this research has been validated using three case studies. Deterioration maps of NDE methods are extracted from Iowa, highway research project, 2011. Results analysis and recommendation with the main findings of this research are provided based on the three case studies of bridge decks located in Iowa, United States.

The current research is extended to incorporate the decision fusion level by integrating the fused measurements of NDE methods with Bridge Management System (BMS). Deterioration models are used in Bridge Management System (BMS) to predict the future conditions and performances of bridges. Therefore, the effective maintenance of bridge structure relies on the quality, accuracy of deterioration models that are used to predict bridge performance and service life (Agrawal et al. 2010, Cesare et al. 1992, Robelin et al. 2007).

Currently, there are two major types of deterioration models: Deterministic Models and stochastic models. Deterministic models describe relationships between factors affecting bridge deterioration. However, it ignores random errors in prediction. Stochastic models deal with deterioration process as random variables that incorporate uncertainty. Markov models are the most widely used deterioration models used to predict the condition of infrastructure facilities. It covers two limitations of deterministic models as it incorporates uncertainty and account for the current facility condition. Markov Chain Model forecasts bridge condition rating based on the concept of defining states of bridge condition from one to another during transition period. Markov approach is a discrete time stochastic process that takes number of possible discrete states. It has been suggested that integrating NDE methods into Markov model will reduce its limitation (Frangopol et al. 2004). Also, the accuracy of Transition Matrix increases the accuracy of Markov-deterioration model (Madanat et al. 1995, Roelfstra et al. 2004).

Another type of stochastic model available is Bayesian Networks (BNs). According to Weber et al. (2010), BN has the capability of modeling complex system. It makes prediction and diagnostics. It computes the probability of event occurrence. It updates beliefs based on new evidence. It integrates qualitative information and the quantitative ones. BN merges experience, past knowledge, impacting factors and measurements. So far, according to the literature review, BN has limited applications in maintenance and in bridge deterioration modeling. Dynamics Bayesian Network (DBN) is a class of BNs, which represent stochastic process. These DBNs are expected to alleviate the main limitations of current Markov model. To demonstrate the use of the developed method and its model at the decision level of data fusion an additional case study of a bridge deck in New Jersey, USA is used. The developed method is expected to improve current practice in forecasting bridge deck deterioration and in estimating the frequency of inspection.

1.2. RESEARCH OBJECTIVE

The main objectives of this research can be summarized as follows:

1- Identify and study NDE methods for concrete and steel bridges. This is done by conducting a comparative study of current practice in bridge condition assessment

2- Develop a generic methodology to assess Bridge condition based on integrated multiple sensing technologies.

3- Develop a generic deterioration model and integrate NDE methods with the developed deterioration model to predict remaining service life for concrete bridge decks and predict inspection frequency.

1.3. RESEARCH METHODOLOGY

This research provides a comparative study of current practices in bridge condition rating worldwide, with emphasis on the United States and Canada. The study includes 4 main criteria: inspection levels, inspection principles, inspection frequencies and numerical ratings for 4 provinces in North America: Alberta, Ontario, Quebec and state of Oregon and 5 countries outside North America: United Kingdom, Denmark, Portugal, Sweden and Australia. The limitations of current practices are discussed and recommendations for improved inspection are provided. In this research, NDE methods used for concrete bridges are studied and classified based on the physical principal of the method to Acoustic, Electrical, Electrochemical, Magnetic, Electromagnetic and Sonar methods. NDE methods used for steel bridges are classified as Acoustic, Imaging, Coating, Magnetic, and Laser. The limitations, advantages and applicability of each method are presented.

The developed data fusion method consists mainly of two main steps. At first, data from inspection of multiple NDE methods are processed based on the physical principal of each method. The second step is image processing techniques that are applied on the images of NDE methods. Image processing techniques are used to enhance contrast of images and to rescale these images. Data fusion method is applied within two levels: pixel level and feature level fusion.

In pixel level fusion, the method utilizes image fusion to generate new and improved image from those captured by multiple sensing technologies. These images can be observed with much better details when fused. So, the main objective of image fusion is to obtain a unique image with enhanced information and resolution that better represents the condition state of the scanned bridge deck. It is the technique of combining data using the advantages of image processing. Image fusion has been employed using wavelet transform technique. The captured images during the inspection are rescaled to ensure that all images have the same coordinate system to fuse pixels of these images. In order to apply wavelet transform decomposition fusion, the scaled images of NDE methods are decomposed. These decompositions are fused to develop the new fused image. This new image is then used to extract features that depict the conditions of the scanned bridge deck.

In the feature fusion level, the developed method utilizes captured inspection images from multiple sensing technologies along with image processing algorithms. The features extracted from the processed images are then fused using feature level data fusion; employing Bayesian Networks.

Data fusion method is applied utilizing measurements that are collected using Infrared thermography camera and ground penetrating Radar from previous study (Salam et al. 2014). These measurements were acquired during the inspection process on June, 2014 to assess the condition of a bridge deck in Montreal. Detailed description of these two technologies and data processing are included in the methodology.

The sensing technologies utilized and applied later to three case studies for bridge decks in Iowa, US are Ground Penetrating Radar (GPR), impact echo (IE), Half Cell Potential (HCP) and Electrical Resistivity (ER). A detailed description of these technologies and data processing is included in the highway research project report 2011, Iowa, US.

The research method is extended to incorporate the decision fusion level. Deterioration model for bridge deck is developed and integrated with inspection measurements of multiple sensing technologies using Dynamic Bayesian Networks (DBNs). The deterioration model incorporates deterioration factors extracted from the literature review.

1.4. THESIS PROPOSAL OVERVIEW

The first chapter introduces the problem statement, the main objective, and the research methodology. The second chapter contains a comprehensive literature review of current practice in bridge condition assessment in North America and outside North America, NDE evaluation methods for concrete and steel bridges, data fusion and current practice deterioration models. The proposed method is elaborated chapter three with its application on a case study of bridge deck in Montreal, QC. The fourth Chapter provides the impact of image processing technique on the accuracy of image fusion. It includes the analysis of the results for bridge deck in Montreal based on four scenarios. The fifth chapter includes three case studies for bridge deck in Iowa, US. The analysis of results is included with conclusion and recommendation of the use for data fusion within two levels. The sixth chapter includes the decision level of data fusion and the integration of the developed deterioration model with bridge management system. The seventh chapter presents the conclusion, along with the expected contributions, limitations and future work.

CHAPTER 2

2. LITERATURE REVIEW

2.1. OVERVIEW

The literature review consists of five sections, as shown in Figure 2.1. Section 2.2 contains a literature review of current practice in bridge condition assessment in North America and outside North America. Section 2.3 reviews the literature related to NDE methods for condition assessment for steel and concrete bridges. Section 2.4 reviews the literature related to data fusion. Section 2.5 reviews the literature related to deterioration modeling. Section 2.6 identifies the research gaps addressed in the current study.

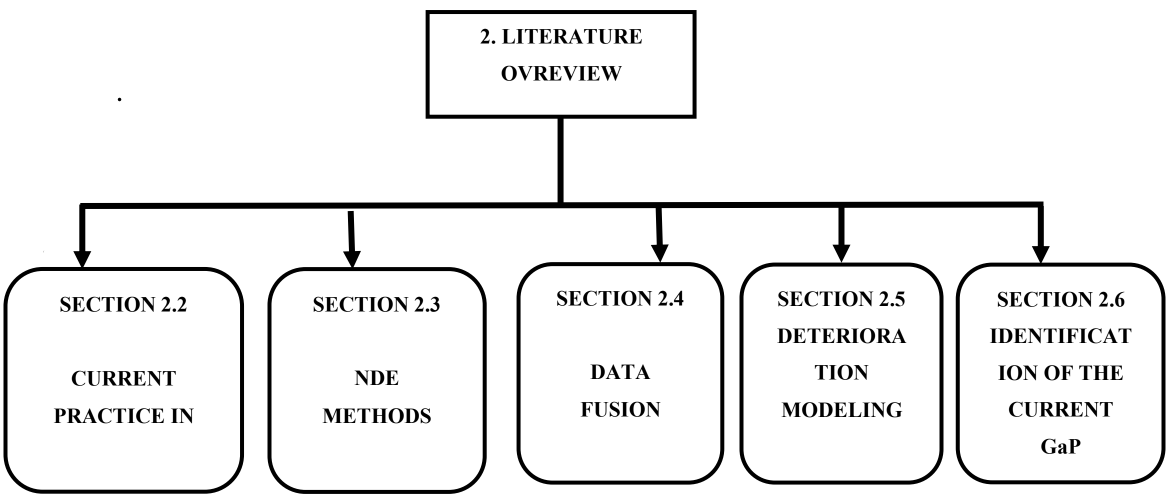


Figure 2.1: An overview of the literature review sections.

2.2. CURRENT PRACTICE IN BRIDGE CONDITION ASSESSMENT

Structural health monitoring, inspection process and condition assessment are considered main components of BMS. This section presents a detailed comparative study of current practices of bridge condition assessment in different countries.

2.2.1. Current Practice In Bridge Condition Assessment In North America

According to Federal Bridge Inspection Standard (FBIS), the levels of service deficiencies are based on comparisons of the actual load capacity of bridge with the level of service. The evaluation of bridge condition deficiency (BCD) includes an assessment of the condition of each of the three primary elements of the bridge: Super structure (SPD), Substructure (SBD) and bridge deck (BDD) as illustrated in Eq. (2.1)

After the total deficiency is established for all bridges, costs associated with replacement and rehabilitation should be determined (FHWA 2012, Branco and de Brito 2004).

$$BCD = SPD + SBD + BDD \qquad (2.1)$$

Condition ratings for each element of the bridge are assigned every two years and are then aggregated into overall condition ratings for super, sub structure and deck, the ratings are numerical values from 0 to 9. Bridges are considered structurally deficient if any of deck, substructure or superstructure is equal or less than 4 (poor). If the structural evaluation is equal or less than 2, then the bridge is having high priority for replacement (FHWA 2012, Branco and de Brito 2004). According to the manual for maintenance inspection, AASHTO describes two basic load rating procedures: (1) the allowable stress, (2) Load rating, LR. In the United States, bridges are periodically rated according to their structural capacity. The rating can actually increase with time in bridges inspected regularly with maintenance programs, where traffic police check the live load limits.

2.2.1.1. Bridge Condition Assessment In Alberta

According to Bridge Inspection Manual of Alberta Transportation, the condition rating system in Alberta consists of a numerical rating range of 1 to 9 (BIM 2004; Branco and de Brito 2004). This rating applies to all inspection elements as well as the general rating for each category. The rating is representative of the condition of the element and the ability of the element to function as originally designed. Bridge can be rated 9 if it is in excellent condition. Additionally, the rating of the element also reflects any safety concerns and maintenance priority. The rating of an element is determined by the rating of the worst item within the group. The inspector should describe, and explain the condition, why the post has a low rating and where it is located.

The rating of the element is visual inspection and based on what the inspector can see. The inspector should be able to see enough of the element to be comfortable assigning a rating. If the element is inaccessible or is not visible for the inspector to assign a rating, the element is rated 'N'. If a particular element does not apply to the structure being inspected, the element is rated 'X'. In situations where an element does not exist but is required in the judgment of the inspector, the element is rated 'X' with a comment provided in the 'Explanation of Condition' section, which illustrates within a maintenance recommendation (BIM 2004). The general rating for each category is determined by the ratings assigned to critical load carrying elements or members of the structure. The general rating must also reflect any safety concerns related to the function of the structure. The general rating is not an average of the element ratings as the general rating cannot be higher than the lowest critical element rating.

All bridges are to be inspected in accordance with the following intervals to ensure an appropriate level of safety: major Bridges, Standard Bridges, in highways with numbers less than

500 or greater than or equal to 900 are within 21 months interval. Major Bridges, Standard Bridges in highways with numbers equal to or greater than 500 but less than 900 are within 39 months interval. Major Bridges in parks that carry pedestrian traffic only are inspected within 57 months interval. All new bridge structures are to be inspected immediately after construction is complete and within 24 months after completion. All bridge structures are to be inspected immediately after any significant maintenance or rehabilitation is completed. The inspector may specify shorter intervals depending on the age, traffic characteristics and known deficiencies (BIM 2004; Branco and de Brito, 2004).

A certified bridge inspector on a routine basis, which is known as Level 1 inspection, inspects most major bridges, standard bridges. However, certain major bridges or components of standard bridges require inspection with specialized knowledge, tools and equipment. Almost all bridges will require specialized inspections, which are known as Level 2 inspections. Specialized inspection includes ultrasonic tests on steel bridges, CSE tests on deck concrete, coring test. Level 2 inspections are essential for high load and overload damage, or when critical or significant deficiencies are determined (BIM 2004; Branco and de Brito, 2004). Level 1 is a general inspection, which requires completion of the BIM report and use of basic tools and equipment. Certified bridge inspectors must undertake this level of inspection. Level 1 inspections are general visual inspections conducted using standard tools and equipment. This level must be performed at time intervals not exceeding those specified by department policy. Level 1 inspection rate the worst part of each element and do not take the overall element condition into account.

Level 2 inspection is an in-depth inspection, which requires completion of the BIM report, and use of specialized tools, techniques, and equipment. Level 2 inspections are quantitative inspections conducted using specialized tools. This level of inspection gathers detailed information on the condition of a particular bridge. In Alberta, concrete deck inspections are currently performed on approximately 120 bridge sites per year throughout Alberta on a 4 to 5 year inspection cycle. Additional Level 2 deck inspections might be completed as part of a bridge assessment that identified in a previous Level 1 inspection. The quantified condition data that are collected provide information on the element and this condition can be monitored over time. The condition rating for Level 2 inspections are grouped together into categories. Therefore, ratings from 9-7 are grouped as very good condition ratings, and then ratings 6 and 5 are grouped as adequate ratings. Ratings of 4 and 3 are grouped as ratings that are the most critical and give priority of the element. Ratings of 2 and 1 are grouped as these ratings are required immediate maintenance or repair. The inspector should rate the general condition and not only the worst case. The inspector should note that if the damage is significant to the structural capacity.

Level 1 rating should be used to reflect the worst damage to the element. A rating of 5 or higher is for elements that are functioning as designed. For a rating of 5, an element may have minor structural flaws, but these flaws should not impact the structural capacity of the member. A rating of 4 is a low maintenance priority, and these elements would generally be scheduled for repair in more than 3 years. A rating of 3 is a medium priority for maintenance, as repairs would typically be scheduled from 6 months to 3 years away. A rating of 2 is a high priority for maintenance and repairs would likely be less than 6 months away. A rating of 1 requires urgent and immediate action.

Chloride test is a field test to determine chloride content of concrete. It is most often performed on a deck because bridge deck is commonly exposed to the de-icing salt. This test is performed in level 2 inspection. Chloride testing is destructive because holes are drilled into the component that is being tested. This testing is also time-consuming as the samples must be extracted and tested. The destructive and time-consuming nature of the test means that only a limited number of samples can be gathered and tested. Copper Sulfate Electrode (CSE) test is a repeatable, non-destructive field test. Alberta Transportation remains one of the few agencies that use CSE testing as a predictive tool for preventative maintenance programs. CSE testing, also known as half-cell testing, is used to determine the potential of corrosion in reinforcing steel, but they do not indicate a corrosion rate. Test results from one year to another are compared to assess the advancement of corrosion and predict the future deck condition. The CSE data are used to develop prediction models and to determine the ideal time to rehabilitate a deck. CSE data is also used to evaluate the effectiveness of various rehabilitation methods. CSE testing is quick, and cost-effective. The limitation of CSE testing is that the readings can become higher, lower suddenly, as the ground connection may be broken, the voltmeter connections may have worked loose, or the grounding wire may be broken. In this case, inspector should stop and verify the validity of the ground connection or check if the deck is not wet enough for accurate results.

2.2.1.2. Bridge Condition Assessment in State of Oregon, USA

The Oregon department of transportation (ODOT) considers the routine inspection report to be the primary tool for reporting the condition of a structure. The routine inspection report is a summary of condition assessment data that is generated via a number of more detailed types of inspections. A routine Bridge Inspection is a regularly scheduled inspection that generally consists of visual observations that are needed to determine the functional condition of the bridge, and recommend any repairs or other services that may be needed. Standard routine inspection frequency is two years. However, the National Bridge Inspection System (NBIS) requires inspections be performed annually when conditions rating of bridge is 3 or less or the bridge has an operating load rating factor of less than 1.0 for any of the legal load types (ODOT 2012). In depth evaluation of bridge is needed to supplement the visual inspection. The bridge inspector may employ either nondestructive testing techniques or destructive techniques such as chipping, drilling and core drilling which are the most common in-depth exploratory methods. Nondestructive methods need expertise that is required to interpret the results in the field. The steps for in-depth evaluation of a concrete structure are as follows:

1. Visual inspection with the last inspection report in-hand.
2. Revision of engineering data, design, construction documentation, operation and maintenance records.
3. Revision of inspections reports and then, mapping of various deficiencies.
4. Monitoring and using nondestructive evaluation methods.

The steel location and depth of cover can be determined non-destructively using a device called a pachometer. This device measures variations in magnetic flux caused by the presence of steel. If the size of reinforcement is known, the amount of concrete cover can be determined. In general, these devices can measure cover to within ¼ inch at 0 to 3 inch from the surface. The accuracy of the devices is dependent on the amount of reinforcing steel that is present in the concrete. The more congested the reinforcing, the less accurate the device becomes. In some cases, when other bars interfere, the device cannot identify either location or depth of cover. Other techniques, such as ground-penetrating radar (GPR) or x-ray, can be used for locating steel rebar when the pachometer fails to provide the necessary information. By comparing GPR and x-ray, x-ray is more accurate in locating steel. The corrosion of steel rebar can be determined by using the CSE methods (ODOT 2012).

The state of Oregano uses destructive in depth testing such as chloride content test, depth of carbonation and core test to determine the compressive strength of concrete. Hammer sounding and chain dragging are used to determine delamination in concrete. While these methods are not expensive, they are time consuming to perform. Petrographic analysis is a detailed examination of concrete to determine the formation and composition of the concrete and to classify its type, condition, and serviceability. Petrographic examination helps determine some of the freeze-thaw, sulfate attack and alkali-aggregate reactivity. Petrographic examination is a highly specialized practice requiring skilled and well-trained technicians. The most common defects encountered in steel superstructures include corrosion, fatigue cracking, heat damage, and overload damage. One of the primary methods to mitigate corrosion is painting with an acceptable coating. Dye penetrate and ultrasonic are used as nondestructive evaluation methods for fracture critical members bridge inspection (ODOT 2012; FHWA 2012).

2.2.1.3. Bridge Condition Assessment in Quebec

Bridges in Quebec are managed by MTQ (Manuel d'entretien des structures). Bridge condition inspections in Quebec include visual examination, which can be used to document and record the severity and overall condition of bridges. A photographic record of this information is essential. Some testing can supplement observations and measurements. Some of the techniques that can be used during ordinary inspections are acoustic impact (hammer sounding, chain dragging) for detection of delamination, debonding, voids, and other defects underneath the surface; rebound hammer to evaluate the concrete strength and quality on a comparative basis. NDE methods are used for advanced inspection. However, these methods still need more development regarding data interpretation. Using combination of visual inspection, half-cell potential, acoustic methods and coring are the most widely used techniques in bridge inspection practice. There are currently three types of bridge inspection practice in Quebec. These are as follows:

- Routine inspection: It is a visual inspection and is done once a year where defects are observed and recorded. Routine inspection provide inspector with general knowledge about the condition of the bridge.
- General Inspection: This type of inspection is more accurate and is performed by an engineer or technician who has been trained by a regional bridge engineer. However, it remains a visual examination that is supplemented by hammer sounding, general dimension measurements and crack measurements. The frequency of this inspection varies from 3 to 6 years depending on the bridge type; concrete bridges are inspected every 5 years.
- Special inspection: This type of inspection usually follows the general inspection where significant deterioration is found and when the inspector has difficulties to assess the condition. This type of inspection is carried out as requested and can be done with the help of a structural engineer. The bridge condition-rating index in Quebec ranges from 1 to 6, where 1 is the lowest value and 6 is the highest: 1-critical, 2-defective, 3-mediocre, 4-acceptable, 5-good, 6-excellent and for elements that don’t exist, the index value is 0.

2.2.1.4. Bridge Condition Assessment in Ontario

Ontario Structure Inspection Management Systems (OSIMS) was developed to store and manage the inspection data that is collected during the detailed structure inspections. OSIM is capable of creating, updating and storing inspection-rating data for structures owned and maintained by the ministry of Transportation. The data are stored in database and then can be used to generate reports on condition rating. The general information for a structure is obtained from Ontario Structure Inventory System (OSIS). In the past, inspectors relied on their background and experience in reporting bridge condition.

OSIM sets standard for detailed routine inspection and condition rating for structures and their components (OSIM, 2000; Branco and de Brito, 2004). In order to classify defects, severity level should be illustrated. As an example, severity is considered light when delamination area measured is less than 150mm in any direction; medium when delamination area is between 150mm to 300mm; severe when delamination area is within 300 mm to 600 mm and very severe when area is more than 600mm. The defects are divided into material defects and performance defects. OSIM presents the material defects that are found in concrete and steel bridges and it is related to building materials regardless of any consequences to the structure. Performance defects are problem that may impact the structure as a whole.

The material and performance condition rating are numerical systems in which a number from 1 to 6 is assigned to each component of the structure. Number 0 is assigned to a component when it doesn't exist and number 9 is assigned to a component that is not visible at the time of inspection. In some cases, performance defect exists as a result of defects in design or construction. The lowest performance condition rating of primary component should be the performance condition rating of the structure (OSIM 2000; Branco and de Brito 2004).

The inspection system in Ontario is classified into general inspection, detailed inspection and condition survey. General inspections are based on visual inspections; routine general inspection can talk place daily, monthly or annually for bridges within span over 6 m. Non routine general inspection is performed when inspection is needed for specific problem. Detailed Inspection can be routine or non-routine inspection and should be done by using measurement tools, tabs, camera and thermometers. Inspectors should review all previous inspection reports, details and all records. The inspectors should take sketches and photographs. Condition Survey inspection requires measurements and documents of all areas of defects and deterioration. It requires access to all area of the structure. Routine condition survey can be done every 5 years on selected number of structure and it incorporates the load carrying capacity assessment. For bridge deck, condition assessment can be done using GPR and thermograph. A comparative study of current practice of bridge condition assessment in North America is illustrated in Table 2-1.

Table 2-1: Current Practice of Bridge Condition Assessment in North America

Current Practice	**Inspection Level**	**Inspection Type**	**Inspection Frequency**	**Numerical Rating**	**NDE Methods**	**Shortcoming**
Alberta	Level 1(Routine Inspection)	Visual Inspection	Set up by the department.	range of 1 to 9	-	Level 1 rating is subjective. Level2, the overall rating still not accurate, Chloride Test is time consuming, destructive test. The inspector should verify the reading.
	Level2 (Specialized Inspection)	In depth inspection		Grouped together into categories. ratings from 9-7, 6-5, 4-3, 2-1	Ultrasound for steel bridges, CSE for concrete deck.	
Ontario	-Routine General Inspection -Non	Visual Inspection	-Daily, monthly or annually		-	The detailed Condition survey still use destructive

	Routine General Inspection -Detailed Inspection - -Condition Survey	Visual Inspection Sketches and measurement tools In depth Inspection using load carrying capacity assessment	When needed for specific problem Two years 5 years		Camera, tab, thermometers GPR and thermograph for bridge deck assessment	methods. The use of NDT methods need high level training to interpret the results.
Oregano, USA	Routine Inspection In depth inspection	-Visual Inspection -use nondestructive methods and destructive test like core sampling, hammer and chain dragging	2 years 5 years	1-9	N/A Pachometer, X-ray and GPR Dye penetrate and ultrasound used for critical members in steel bridges Painting coating Used for corrosion in steel bridges. Petrograp	Rely on destructive methods chloride content test, and core test. Hammer sounding and chain dragging are time consuming. Pachometer sometimes fail to give accurate information. Petrographic examination is requiring skilled and well trained technicians.

					hic examination	
Quebec	-Routine Inspection -General Inspection -Special Inspection	Visual Inspection visual examination, that supplemented by hammer sounding, general dimension measurements, Coring	Once a year 3 to 5 years AS requested	range from 1 to 6, where 1 is the lowest value and 6 is the highest; 1-critical, 2-defective, 3-mediocre, 4-acceptable, 5-good, 6-excellent; for elements that don't exist, the index value is 0	N/A N/A Half Cell potential and Acoustic methods	The condition rating values cannot be used to evaluate the structural capacity of the element. These values are used for general condition of the structure. In addition, the special inspection is not clearly defined. Inspectors should be well trained; they should know the material behavior.

2.2.2. Current Practice In Bridge Condition Assessment Outside North America

2.2.2.1. Bridge Condition Assessment In United Kingdom

In United Kingdom, bridges are subjected to general inspection every 2 years and to more detailed inspection every 6-10 years. These inspections are visual inspection that record only damage or deterioration that are seen. Defects that have main concern are inspected within special inspection, such as half -cell potential and cores sampling are examined to check the presence of alkali reaction. Special inspection measures the depth of concrete cover, carbonation, chloride, sulfate contents. The condition of each element is given a rating on scale of 1 to 5 at the time of inspection. Each element is given a location factor based on its structural importance. The overall condition rating of bridge is given using the Eq. (2.2)

$$BCI = 100 - F1 \times \left[F2 \times \frac{(Efp \times Sf)}{Np} + F3 \times \frac{(Efs \times Sf)}{Ns} \right] \text{..} \quad (2.2)$$

where Efp is element factor from 1 to 10 of primary element, Efs is element factor of secondary elements, Sf = The extent of damage / Severity factor 1- 10, Np is the number of primary elements, Ns is the number of secondary elements and F1, F2 and F3 are the severity factors. Superstructure and substructure are both divided into a number of elements and receive score of 1 to 8. The element rating percentage can be calculated from Eq2. The overall condition rating for substructure and superstructure is taken as the lowest element rating. Bridge condition assessment in UK has some shortcoming as there is little use of nondestructive evaluation methods and there is no relationship between bridge age and maintenance cost. Current practice with countries outside North America are illustrated in Table 2-2.

Table 2-2 : Current Practice of Bridge Condition Assessment outside North America

Current Practice	**Inspection Levels**	**Inspection Principle**	**Inspection Frequency**	**Numerical Rating**
UK	General Inspection	Visual Inspection	2 years	range of 1 to 5, overall condition rating is taken as the lowest element
	Principal Inspection	In depth inspection	6-10years	Half-cell potential test

Denmark	-Routine superficial Inspection -Principal Inspection -Technical Inspection	Visual Inspection Visual Inspection More investigation In depth Inspection using load carrying capacity	- Annually -3 years	Final condition rating is based on bearing capacity and importance of each element.
Portugal	-Ordinary Inspection Principal inspection	-Visual Inspection -Visual inspection and simple use of nondestructive methods	3 to 6 years 3 years	1-7 defect rating 1-The defect degree doesn't increase. 2-doesnot require intervention 3-getting evolving 4-require not urgently intervention 5-doesnot influence structure 6-doesnot impair structural safety 7-it reduces safety coefficient
Sweden	-Regular Inspection -Superficial Inspection -General Inspection -Major Inspection	Visual Inspection Visual Inspection Done by well-trained inspector Complete examination	Quick monthly Each 1 year 3 years 6 years	-Degree of urgency 0 to 2 0-no action required 1-The same within 1 year 2-action require within 3 years -Defect Rating 0 to 3 0-gurantee for next 10 years,1-gurantee for next 3-10 years, 2-same before 3years,3-defective function found, Ultrasound and radiography.

Australia	-Level1 Inspection -Level2 Inspection -Level3 Inspection	-Visual Inspection -Visual Inspection In-depth Inspection		Ground Penetrating Radar and impact echo are used to determine voids .Ultrasonic Pulse Velocity is used to determine cracks, concrete strength, location of reinforcement can be measured using GPR. Half-cell potential used to detect steel corrosion and rebound hammer for concrete strength. Steel brides deterioration can be determined by using Eddy current, Dye penetrates Radiographic and ultrasonic testing. Concrete cover can be measured also using cover meter.

2.3. NON DESTRUCTIVE EVALUATION METHODS FOR BRIDGE CONDITION ASSESSMENT

All inspections are completed according to National Bridge Inspection Standard, (NBIS), All inspectors should be certified through (NBI). Bridges are inspected twice a year to detect damage at early stage and reduce the problem of costly maintenance and repair of existing bridges. Therefore, Bridge inspection is a critical role that provides safe highway system. Moreover, Periodic inspection is essential to prevent bridge failures, and then the current state of bridge components are reported with much detail. In addition, inspection process identifies and assesses bridge deficiencies and repair requirements with good estimates of deteriorated quantities. Therefore, it ensures an accurate bridge record with detailed reports describing specific details of damage. Hence, the main goal of inspection is to determine the degree of repair needed and decides whether more testing is required.

Visual inspection has limited capacity, damage can exist inside the structure and not visible. Although, signs of damage such as cracks, delamination, spalls, chemical deterioration and corrosion are sometimes visible, they do not indicate the correlation between actual bridge condition and the real structural reliability. Therefore, engineers and inspectors should know the actual condition of damage and its impact on structural reliability (Frangopol et al. 2008, Catbas and Aktan 2002). The bridge inspector is responsible to the public; the main responsibility of inspector is to maintain public confidence by reviewing and evaluating inspection reports. Moreover, Inspection team are responsible for critical basic tasks; planning inspection, performing inspection, preparing report, identifying items for repairs and following up the critical damage.

Planning inspection ensures safe and efficient inspection, it includes determination of inspection type, specify a qualified team leader, development of a schedule which specify the inspection duration. Planning achieves a successful preparation as bridge inspection should be well prepared by organizing the proper tools and equipment and reviewing the bridge files. Hence, reviewing the bridge structure file and records is the key factor of an efficient preparation. These revisions involve inspection history, specifications, rating records, permit loads and maintenance history.

Structural health monitoring is an effective part for maintenance, repair and replacement of bridges. Data extracted from monitoring is related to structural reliability, which should be used efficiently to detect damage by using the change of structure characteristics. Structural health monitoring helps to detect deterioration, damage and estimate the remaining service of life. Moreover, it provides the base of optimum maintenance; it ensures the structural integrity, safety and determines condition of structure. Also, structural health monitoring is used not only for damage detection but it ensures continuous reliability assessments. Nevertheless, structural health monitoring is complex due to different type of bridge material and surrounding environments. The integration of structural health monitoring data into condition assessment improves the accuracy of forecasting future condition of bridges.

2.3.1. Non Destructive Evaluation Methods For Concrete Bridges

Non Destructive Evaluation methods (NDE) are advanced inspections that do not affect the integrity of the member under evaluation. The member is still in service while being tested. Therefore, inspectors should understand and trained for various NDE methods. Advanced inspection methods are becoming more effective tool that supplement the visual inspection with more accurate data and detect bridge defects. These defects are resulted from Chloride attack that cause rebar to corrode rapidly and deicing salts are collected down from deck in any cracks or joints. Improper pouring, curing methods, water loss during curing, settlement, shrinkage and freeze-thaw damage are causing cracks (Ferraro 2003). Formation of large cracks impact the strength and durability of concrete. Chemical affects concrete and causes damage that are severe, Sulphate ions, Alkali-Aggregate Reaction, Alkali-Silica Reaction are the most common chemical attack. Shrinkage and honeycombing are resulted from improper vibration, poor formwork and poor mix. Honeycombing reduces concrete strength, increase porosity and reduce durability (Ferraro 2003). NDE methods assess the extent of rebar corrosion and predict the remaining service of life. NDE methods aid with crack detection, especially internal cracks that are not visible. Monitoring cracks is important for assessing the overall health of structure and determine maintenance needed. Currently, incorporating the results from NDE into bridge management system rating is considered a significant point that researcher should focus on. Bridge deck condition should be assessed at all stages. NDE methods are used to identify deterioration at specific time. Figure 2.2 is extracted from Iowa report for highway research project 2011. It shows bridge deck deterioration at different times versus NDE methods.

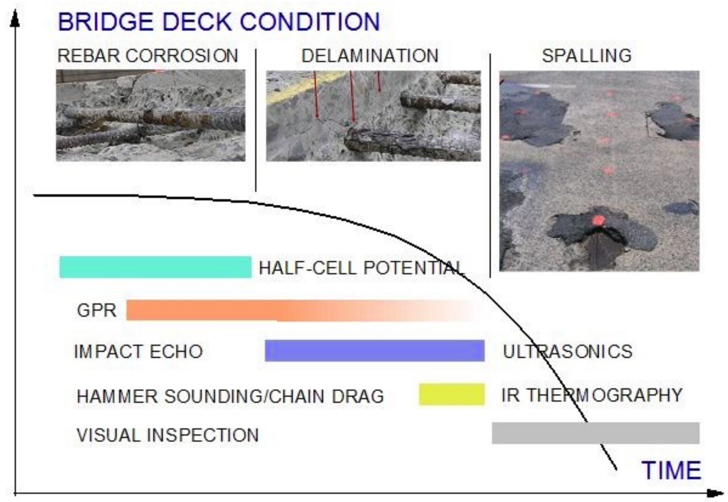


Figure 2.2: Bridge Deck Deterioration Vs NDE Methods (Iowa 2011)

As illustrated in Figure 2.3, NDE for concrete bridges are classified based on the physical principal of the method to Acoustic, Electrical, Electrochemical, Magnetic, Electromagnetic and sonar methods.

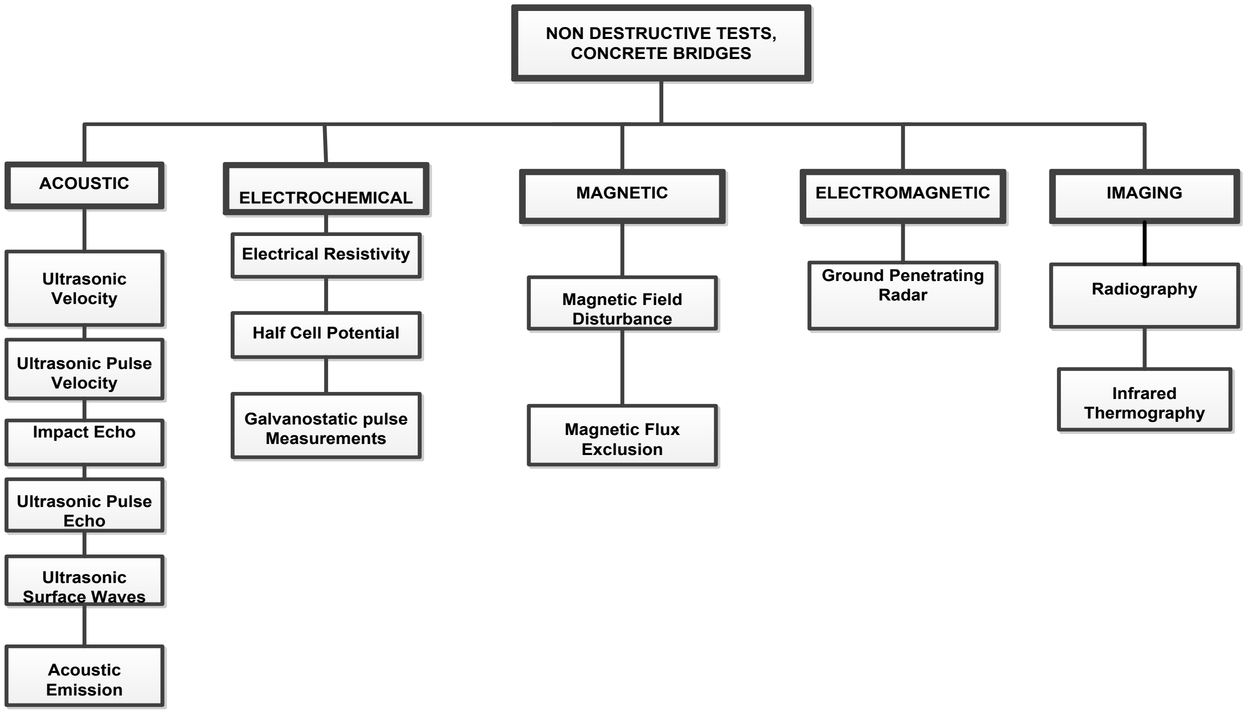


Figure 2.3: Non-Destructive Evaluation Methods for Concrete Bridges

2.3.1.1.Acoustic Methods

(I) Ultrasonic Velocity Measurements: The speed of ultrasonic pulses that travel in a solid medium depends on the density of the material. Ultrasonic testing is used to obtain the properties of materials by measuring the time of travel of stress waves through a solid medium. The time of travel of a stress wave can then be used to obtain the speed of sound of a given material (Boyd and Ferraro 2005, FHWA 2012). This method is used to evaluate concrete bridge deck. It detects areas with cracks, delamination and Concrete strength. Elastic waves are generated then detected by an array or pair of receiver and recorder. Bridge decks can be evaluated using computer based monitoring, using an automated mobile for data acquisition. This system works directly, and covering recording for large areas. Variation in the wave velocity is an indication of existence of delamination (FHWA 2012).

(II) Ultrasonic Pulse Echo: This method uses ultrasonic stress waves to detect objects. Waves are generated by piezoelectric material with high –amplitude pulse that has high voltage. The echo wave coming from the flaw is described by its transit time from the transmitter to the flaw and back to the receiver. The basic concern is on measuring the transit time of ultrasonic waves traveling through a material and being reflected to the surface of tested medium. This reflection is based on the transit time or velocity (SHRP2 2009, SHRP2 2013). This technique can be used to detect the presence of internal flaws; as when waves interface with defect, a small part of the released energy is reflected back to the surface. Regions with deterioration or cracking will have lower velocity.

(III) Impact Echo: This method produces low frequency stress waves into concrete structure. Hence these waves are reflected when it faces internal flaws. The reflected waves are received by a transducer; the piezoelectric material in the transducer converts stress waves into voltage time signal. Also, velocity of stress wave and the resulted displacement, can be measured (Carino 2001, Gassman and Tawhed 2004, Yehia et al. 2007, SHRP2 2009, FHWA 2012, SHRP2 2013, Boyd and Ferraro 2005). Impact echo can successfully be used to assess the distribution of damage by analyzing the vibration, monitoring the resulted stress waves and locate flaws, cracks, voids and delamination, wave velocity is an indication of concrete deterioration level. This method can detect concrete damage and thickness of a material such as concrete or asphalt pavement. The effective use of the impact-echo system requires that the user have a basic understanding of the properties of stress waves (Gassman and Tawhed 2004, Yehia et al. 2007, SHRP 2 2009, FHWA 2012, SHRP 2 2013, Ferraro 2003). Impact-echo testing can be performed within short duration of the testing procedure. This allows inspectors to accurately assess structures condition. The method is used most successfully to identify and quantify suspected problems within a structure, in quality control and in maintenance programs such as routine evaluation of bridge decks to detect delamination. Impact-echo may also be used to determine the location of steel reinforcing and can be applied to evaluate the corrosion of reinforcing bars. Concrete structures can be tested using impact echo at lower cost. With Impact echo test, no damage is done to the concrete and highway workers spend less time in temporary work zones, reducing the chance of injury and minimizing time for the traveling public (Ferraro 2003).

(IV) Ultrasonic Surface Waves: This test is part of spectral analysis of surface waves (SASW) used to evaluate material properties. It uses wave's dispersal. The propagation velocity is a function of frequency and wave length. Surface wave velocity is related to concrete modulus; when material is uniform and identical, the velocity of surface wave does not vary with frequency. Surface waves are elastic waves that travel along the free surface, waves of different wave length travel with different velocities. Therefore, information about subsurface can be obtained by measuring of phase velocity versus frequency relationship. Variation in wave velocity is an indication of presence of delamination (SHRP2 2009, SHRP2 2013).

(V) Acoustic Emission: This method is used to detect stress waves or sound energy that is released by the mechanical deformation of the material. The sound energy does not come from external sources. It comes from the material (Kaiser and Karbhari 2002). Portable AE sensors are available for the continuous monitoring of known flaws. Transducers are used to detect acoustic emissions, as they are not in the range of human hearing. There are two types of acoustic emission signals: continuous signals and burst signals. A continuous emission is produced by rapidly occurring emission events such as plastic deformation. A burst emission is a discrete signal related to an individual emission event occurring in a material, such as a crack in concrete. There are two types of sources: primary and secondary. Primary sources are released within the material as a result of cracks growth. The secondary sources are external from the material; including traffic noise and joint friction (Fu, G. 2005, Indot 2010). The emission is received by the sensor and transformed into a signal, then analyzed by acoustic emission instrumentation, resulting in information about the material that generated the emission (Ferraro, 2003).

Fast results of acoustic emission testing requires massive data calculations due to the extensive output from acoustic emission signals. Acoustic emission testing can provide indication of crack formation and propagation. Early use of acoustic emission testing is very useful. However, the first acoustic emission signals acquired contains large amounts of noise signals. This made it difficult, as researchers are unable to develop AE as a quantitative technique. The measurement of the acoustic emission count rate is one of the easiest and most applicable methods of analyzing acoustic emission data. Acoustic emission count indicates the occurrence of acoustic emission and gives a rough estimate of the rate and amount of emission.

The most common application of acoustic emission is detection of the presence of discontinuities or cracks, and their location, in concrete specimens and structures (Nair and Cai 2010). The applied load test is one of the application of acoustic emission where known force or stress is applied to an object under test and then analyzing the object's reaction by means of acoustic emission monitoring. Damaged area due to cracking can be identified by the acoustic emission source location. Most highway bridge inspection is performed via visual inspection. When deficiencies are observed, the action taken usually involves increased inspection of the defective area. Given that the rate of deterioration is usually unknown, the frequency of inspection is increased without a reasonable forecast of the behavior of the defect. Acoustic emission testing utilizes the induced stress waves that are released when microstructural damage occurs. Portable AE sensors are available for the continuous monitoring of known flaws.

Research to date has provided a reasonable scientific base upon which to build an application of acoustic emission as part of a bridge management program. This technique could be best utilized by implementing a continuous monitoring system with an array of sensors on newly constructed bridges. The technology is available for instrumentation configured with portable data acquisition and transfer systems, making it possible for engineers to continuously monitor bridge condition. Engineers could use the information gained via AE systems to decrease the frequency of inspection on sound structures and monitor profound AE events to determine the need for essential inspections (Ferraro 2003, Nair and Cai 2010).

2.3.1.2.Electrochemical Methods

(I) Electrical Resistivity: Low resistivity indicates high water content. The level of water content of a structure determines the resistivity of an element to the flow of electrons; low resistivity indicates high water content. The resistivity can be measured using electrodes placed into the deck, then passing current through outer electrodes and measuring voltage between inner electrodes (McCann and Forde 2001). This method is used to describe corrosion of concrete, chloride contents, water and salts. High moisture decreases the concrete electrical resistivity, which consequently increases corrosion rate of concrete. Chlorides influence concrete resistivity, as it occurs ionic current flow between anode and cathode, consequently concrete permeability increases and concrete resistivity decreases. Corrosion rate is correlated with concrete resistivity. So, the calculated resistivity is an indication of corrosion rate (Amleh and Mirza 2004, SHRP2 2009, FHWA 2012, SHRP2 2013).

(II) Half- Cell Potential: Half-cell potential is a widely used method, commonly known as CSE Copper Sulfate Electrode, to identify active corrosion in steel reinforced and pre-stressed concrete structures. Half-cell potentials of reinforcing bars are calculated by contacting CSE to the concrete surface, and then voltage is registered. High values of potentials are indication of corrosion activity. The test should be done on free concrete surface to make the measurements more realistic. The basic principal is based on when a metal is submerged into an electrolyte; the positive ions will resolve oxidation leads to surplus of negative charges. The positive metal ion will accumulate at metal liquid. Anions from electrolytic solution in concrete are attracted to the positive charge side. So, if two different metals are submerged into an electrolyte and connected electrically by a wire, galvanic element can be created. The more negative values are indication of corrosion activity (Amleh and Mirza 2004, SHRP2 2009, FHWA 2012, SHRP2 2013).

(III) Galvanostatic Pulse Measurements (GPM): GPM is electrochemical method used for rapid assessment of corrosion in concrete bridges. Measurements can be done when concrete is wet. The test is based on polarization of rebar using small current pulse (SHRP2 2009, SHRP2 2013).

2.3.1.3.Magnetic Methods

(I) Magnetic Field Disturbance (MFD): MFD is used to evaluate fatigue damage in steel reinforcement inside reinforced or prestressed concrete. The system of MFD monitors the magnetic field across bottom and sides of the beam. Therefore, any fracture produces a distinguished magnetic signal (FHWA 2012).

(II) Magnetic Flux Exclusion: This method can be used to identify bar location and concrete depth. It has many application in bridge deck, where magnetic field sensors are attached. The presence of any magnetic field is an indication of defects or corrosion.

2.3.1.4. Electromagnetic Methods

Ground Penetrating Radar (GPR): It is a rapid method. It produces electromagnetic waves from transmitting antenna into the structure at a velocity can be determined from structure properties. These waves spread out, reflected back to a receiving antenna if they face objects that have different properties. The signal responses are different for various interfaces due to the changing of two electrical properties. Therefore, the reflection of these waves at objects with the material is analyzed to determine the location and depth of this interface. When pulses reflect back, the time delay is related to location of these interfaces that determine the properties of materials. It has the ability to obtain subsurface information and rapidly covering large area with minimum interruption to traffic. Experimental results indicate that there is an agreement between GPR results and other method like chain dragging and core samples test. GPR measures signal responses caused by variations in electrical properties of materials (Maser and Roddis 1990, Maser 1996, Yehia et al. 2007, SHRP2 2009, Gucunski et al. 2006; FHWA 2012, SHRP2 2013).

2.3.1.5. Imaging Methods

(I) Radiography: It is performed with the use of radiographs, where concrete is subjected to radiation. Images are generated with X-Ray or Gamma Ray radiographic (FHWA 2012). Radiography is the NDE technique that employs the use of radiographs for material inspection. X-rays are a form of electromagnetic radiation with a relatively short wavelength. This extremely short wavelength enables X-rays or gamma rays to penetrate through most materials. Structural radiography is very similar to the X-ray technique. The limitation of radiography as an NDE technique is that both sides of the material to be tested must be accessible for inspection. Therefore, structural elements like slabs and foundation walls are not typically accessible for testing with radiography (Ferraro 2003). Radiation testing is the most powerful methods used in nondestructive testing today; however, it has several limitations that prevent it from becoming the most widely used NDE technique. Radiation testing techniques are the most expensive NDE methods. Radiation testing presents many safety concerns that are not easily addressed in the field and it is not always practical to use radiographic testing due to public safety (Ferraro 2003)

(II) Infrared Thermography: In this method, image of surface temperature can be determined to detect the delamination based on the uniformity of heat flow. This technique assesses the material defects by monitoring its reaction to thermal loading. The heat conduction of material is influenced by delamination existence (Maser and Roddis 1990, Yehia et al. 2007, SHRP2 2009, FHWA 2012, SHRP2 2013). In this method, image of surface temperature can be determined to detect the defect and delamination based on the uniformity of heat flow. This technique assesses the material defects by monitoring its reaction to thermal loading. Therefore, with no internal defect, heat flow through concrete is uniform. Surface with internal defects appears in the image with higher temperature and other parts are cooler; the change in heat flow creates a temperature difference between areas with defect and areas without defects (Maser and Roddis 1990, Yehia et al. 2007, SHRP 2 2009, FHWA 2012; SHRP 2 2013). This method characterizes the properties of a material by monitoring its response to thermal loading, which is commonly used to describe the transfer of energy from a heat source to a solid object. This technique is currently being used on an array of structures and materials. Recently, IR has been used for the nondestructive examination of concrete structures and structural repairs (Ferraro 2003, Andrew et al. 2005). Current applications of IRT include the evaluation of concrete and composite structures for delamination, coating thickness. IRT was proven to be effective NDE technique for the inspection.

The advantages, limitations and application of each method are illustrated in

Table **2-3**. This research identifies the limitations and advantages of each method based on the integration of information from current practice and previous research work. Infrared thermography, digital imaging, GPR, IE and acoustic emission are defined in the literature.

Electrical resistivity, HCP, ultrasonic velocity, ultrasonic pulse velocity, pulse echo and ultrasonic surface waves are defined and utilized based on the current practice.

Table 2-3: Benefits and Limitation of NDE Methods, Concrete Bridges

	TEST	CURRENT PRACTICE	ADVANTAGES	LIMITATION
ACOUSTIC	**Ultrasonic Velocity Measurements**	Evaluation of material damage from various causes: Freeze -thaw, alkali silica. Measurements of vertical cracks depth and determine concrete quality control.	Bridge decks can be evaluated using computer based monitoring, using an automated mobile for data acquisition. This system works directly, and covering recording for large areas	Complicated for layered systems; decks with overlay. Experience is required to understand results and used as supplemented tool to detect concrete deterioration such as delamination (FHWA, 2012).
	Pulse Velocity	Evaluates relative quality and uniformity, internal abnormalities of concrete. Provides information about the interior member of concrete.	Provides a digital output that can be used by a computer to characterize defects and material properties. It is nonhazardous operation with volumetric scanning ability. Electronic operation with high sensitivity.	Just can be used as supplemented tool. Access for both sides is needed. Does not provide information about depth of defects (Amleh and Mirza 2004, Rens and Kim 2007, FHWA 2012).
	Impact Echo	Used to detect defects, cracks, delamination, voids, distribution of damage, concrete compressive strength, debonding in plain, reinforced and post-tensioned concrete. Can be used for quality control and in	Can detect delaminated area in bridge deck with high accuracy, measurements are reliable. Moderate expensive. It needs access to one side of an element and detects depth of defect with high accuracy. It is not affected by steel presence and requires minimum surface preparation (Yehia et al. 2007).	For decks with asphalt concrete overlay, detection is possible when asphalt concrete temperature is low, the material is not viscous. The method does not provide deep penetration into bridge deck. Acoustic Knowledge is required in its use. Boundary effects should be taken into consideration, this boundary produces reflections, and this is common when used IE for other element than bridge deck surface such as girders and piers (Gassman and Tawhed 2004, Yehia et

		maintenance programs such as routine evaluation of bridge decks. Impact-echo may also be used to determine the location of steel reinforcing and evaluate the corrosion of reinforcing bars.	There is no damage is done to the concrete and highway workers as it spend less time in temporary work zones, reducing the chance of injury and minimizing time for the traveling public.	al. 2007, SHRP2 2009, FHWA 2012, SHRP2 2013). Interpretation of results needs training with specialized program. Expensive for large areas as many points have to be tested (Gucunski 2006).
	Ultrasonic Pulse Echo	Thickness measurements, assessing defects in concrete elements, deboning of reinforcement bars, shallow cracking and delamination. It can detect also material interfaces between steel and concrete.	It permits the detection of small flaws. High accuracy to determine the position of internal flaws, estimating their size and shape. Operation is automated.	It requires very close spacing between test points to develop images of the tested medium which making it time consuming. Data quality depends on coupling of sensor units which is difficult for rough surfaces. Very shallow flaws cannot be detected because it works under low frequency (SHRP2 2009, SHRP2 2013).
	Ultrasonic Surface Waves	It evaluates concrete damage from freeze-thaw cause. It is used for material quality control, concrete strength and indirect assessment of delamination.	It detects vertical cracks with a good accuracy, can be considered moderate expensive and repeatable test.	Cannot provide reliable values. Considered a supplemental tool for deterioration detection. Experience is required for interpreting results. It is more complicated with asphalt concrete overlay (SHRP2 2009, SHRP 2, 2013)

	Acoustic Emission	Detecting the presence of discontinuities or cracks, and their location with Continuous monitoring (Nair and Cai, 2010).	Proved to be a highly sensitive indicator of crack formation and propagation. Early use of AE proved to be valuable.	The first results require massive data calculations due to the extensive output from test signals with more noise signals. Difficult to be used as quantitative technique.
ELECTROCHEMICAL	**Half-Cell Potential**	Used to identify the probability of active corrosion in steel of reinforcement concrete structure	Economical test, fast, equipment set up and data analysis can be done quickly, don't require experience and easy to use	Measurements are not reliable when concrete is wet (Amleh and Mirza 2004, SHRP2 2009, FHWA 2012, SHRP2 2013).
	Galvan static Pulse Measurements	Used for rapid assessment, determines corrosion.	It covers the limitation of electrical resistivity. Measurements are reliable and it is economic test.	Pre-wetting is essential, a high electrical resistivity of concrete cover leads to unstable measurement and first reading should be taken after few moments (SHRP2 2009, SHRP2 2013).
MAGNETIC	**Magnetic Field Disturbance**	Determine discontinuity and fatigue damage in steel, such as fracture in a rebar. Produces a unique magnetic field (FHWA 2012).	-It is a quick method and accurate. Interpretation of results requires moderate skills	-Water with chloride leads to inaccurate reading -Cannot detect rebar corrosion.
	Radiography	It evaluates hidden flaws. Images for concrete are generated with radiation. Used to map defects in bridge deck, corrosion and flaws.	It can be installed in a van. Very good for inspection. Radiation testing is the most powerful methods that used in nondestructive testing	Penetration depth is only about 8 inch, training should be needed (FHWA 2012). Both sides of the material to be tested and must be accessible for inspection. Expensive and it is not practical to use in the field due to public safety.

	Infrared Thermography	Used to detect concrete defects such as cracks, delamination, subsurface voids in concrete structure - It has been applied to asphalt decks to characterizes the properties of a material by monitoring its response to thermal loading This technique is currently being used on an array of structures and materials	It produces an image for concrete and covers greater area. It is fully developed with a camera technique, can detect delamination directly with medium cost technique. Minimum traffic disruption, so it can be used in high-traffic volume areas. Results are easy to interpret with colour coded image. It is a fast method carried on a vehicle with real-time results possible. IRT was proven to be effective as a qualitative NDT (Maser and Roddis 1990, Yehia et al. 2007).	Various bridge conditions influence thermo graphic readings and complicate the identifications of delamination affected by atmospheric conditions of wind speed, moisture, season of year and time of day (Maser and Roddis 1990, Yehia et al. 2007). Deep flaws are difficult to be detected. The method is complicated by many issues; shadow and other factors, snow, ice and sensitive to any defects. It provides only good location accuracy with no information about depth layer , so other test should be done for depth details.
ELECTROMAGNETIC	**Ground Penetrating Radar(GPR)**	It is capable of detecting moisture and chlorides associated with deterioration, location of voids. Mapping of reinforcement location and depth of cover. locating of steel bars. Cracks detection, delamination are still qualitative comparisons	It has ability to obtain subsurface information rapidly and covering large areas with minimum interface to traffic. It has sensitivity and can be done anywhere then provide records hence signals can be processed immediately. Possess high capabilities in detections of different flaws (Maser and Roddis 1990, Maser 1996, Yehia et al. 2007, Gucunski et al. 2010). Can be used as quality assurance tool. Can produce contour maps for subsurface features. Equipment is light and portable.	Produces a complex signal which is not straight forward. GPR defect resolution is dependent on the antenna size and coupling (ground or air). Data analysis depends on experience and may be subjective. Claims about the capability have sometimes stated because of unrealistic expectations and disappointment in results. (Maser and Roddis 1990, Maser 1996, Yehia et al. 2007, Gucunski et al. 2010) Data can be negatively influenced by cold and de-icing conditions. It cannot provide information about compressive strength of concrete and presence of corrosion. It is not cost effective; results should be validated by other NDE methods, interpretation of images needs training.

2.3.2. Non Destructive Evaluation Methods For Steel Bridges

Advanced inspection method help inspectors to evaluate member that are not accessible in steel bridges. Figure 2.4 illustrates the NDE methods used for steel bridges. The methods are classified as Acoustic, Imaging, Coating, Magnetic, and Laser. The advantages, limitations and application of various methods used in steel ridges are illustrated in Table 2-4

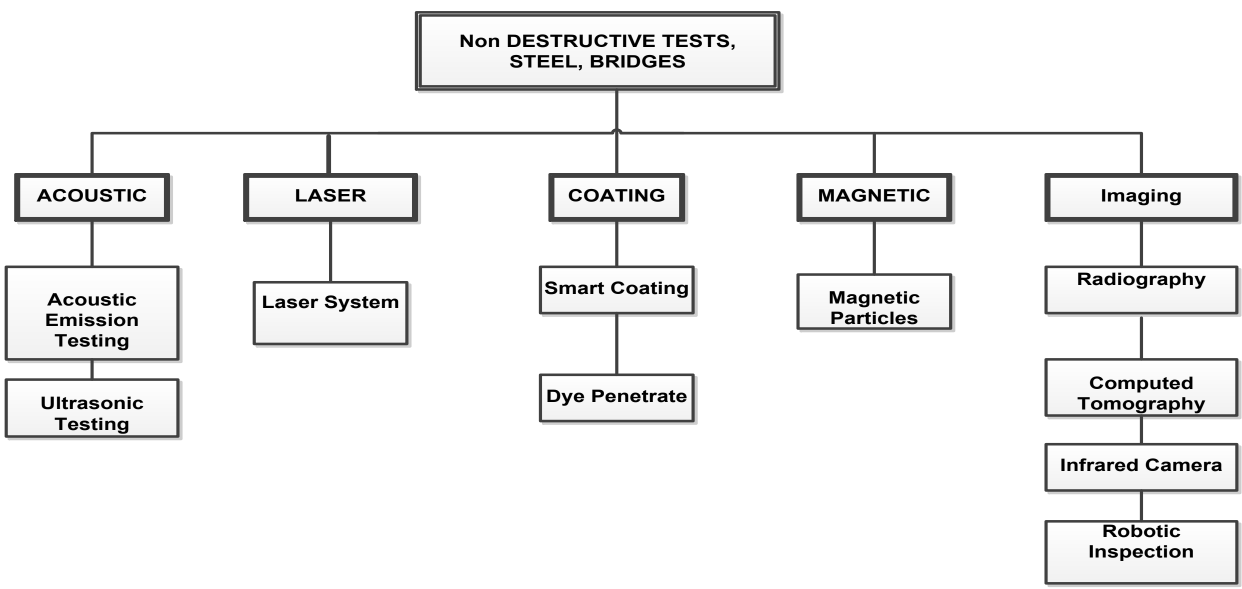


Figure 2.4 : NDE Methods for Steel Bridges

2.3.2.1. Acoustic

(I) Acoustic Emission:

In this method, areas with delamination generate mechanical waves motion, structure produces an acoustic sound range between 20kHZ and 1MHZ when it is subjected to certain load; velocity of propagating cracks can be monitored with monitoring system. Ultrasonic microphone is used to be sensitive to the sound comes from parts with defects. Therefore, flaws, cracks, deformation, corrosion and friction can be detected (SHRP 2 2009, Shiotani et al. 2009; FHWA 2012) .

(II) Ultrasonic Testing:

This method uses high frequency sound into the material to produce images. It helps inspector to measure steel thickness and provides more information about cross sections (SHRP 2 2009, Shiotani et al. 2009, FHWA 2012).

2.3.2.2.Laser

Laser System:

The test is non-contact laser scanner; the scanner directs a laser to areas to be measured in bridges and record the travel time from to reach the structure surface; then a full three-dimensional coordinates for measurements are obtained. The measured areas are taken from laser measurements and another two positions from mechanical scanners. The system is capable of obtaining large measurements with high accuracy and provides 3D modeling of bridge structure (SHRP 2 2009, FHWA 2012).

2.3.2.3.Coating

(I) Smart Coating:

The National Science Foundation for advanced technology has developed this method. Special paints are used to outline the fatigue on steel structure. Scientist in Japan has developed special kind of paint that send electrical signals that are associated with any vibration in the bridge; the higher the vibration, the greater the electrical signals, giving an alert of fatigue existence. Thus, with this method engineers have the ability to monitor fatigue in a much easier way (SHRP 2 2009, FHWA 2012).

(II) Dye Penetrant:

Special penetrant is sprayed over steel bridge; the surface should be cleaned and dye penetrant can be applied; the dye is drawn into the defects or opening. When penetrant is dried, the developer draws the dye out and determines the surface with flaw. In this method, inspector should pay attention to dwell time, which is the amount of time that the penetrant is allowed to be on the surface. This time is influenced by many factors, such as, temperature of member, humidity, size and shape of surface flaws (SHRP 2 2009, FHWA 2012).

2.3.2.4.Magnetic

Magnetic Particles:

This test is useful for detecting holes, crakes, voids and surface flaws. The member under evaluation is magnetized, and then filled with iron, which is attracted by the magnetized member forming a pattern; any cracks or defects in the member cause irregularities in the magnetic field (SHRP 2 2009, FHWA 2012).

2.3.2.5. Imaging

(I) Radiography Testing:

This test is used to locate subsurface cracks, voids. Inspector should have access for both sides; one for radiation with X ray or gamma and the other side for film. These rays are passed through the member and absorbed by different flaws; consequently, the deficiencies appear as shadow on the film (SHRP 2 2009, FHWA 2012, SHRP 2 2013)

(II) Computed Tomography:

This test uses X ray and gamma radiation to produce 2-D and 3-D cross sectional image of internal defects in steel member. This image is processed and reconstructed by a computer (Rens and Kim 2007, SHRP 2 2009, FHWA 2012).

(III) Infrared Camera:

This test is used to detect delaminated areas; it is designed for steel deck overlays. Heat flow is different in defected areas; so, the system uses thermal camera to take images for bridge deck. It automatically captures full video data, where data can be stored in system database (SHRP 2 2009).

(IV) Robotic Inspection:

Advanced system with high-resolution video camera attached to the bridge. This system allows inspector to visually monitor the bridge by remote tele scanning. This method has been applied successfully in California department of transportation. Moreover, In 2008, Texas transportation institute and Texas department of transportation gave permission for Robot assisted search for bridge inspection to use robots in the process of inspection. This method can be extended to be used for concrete bridges as well (FHWA 2012).

This research identifies the limitations and advantages of each method based on the integration of information from current practice and previous research work. Imaging methods such as Radiography, computed tomography and acoustic emission are methods identified in the previous research. Smart coating, dye penetrate and ultrasonic testing are methods that are identified and utilized by the current practice.

Table 2-4 : Benefits and Limitation of NDE Method, Steel Bridges:

	TEST	CURRENT BRACTICE	ADVANTAGES	LIMITATION
ACOUSTIC	**Acoustic Emission Testing**	It detects flaws and fatigue growth rate. It is used for detection of fatigue cracks in fracture critical members, corrosion and weld defects. Ultrasonic microphone is used to be sensitive to the sound comes from parts with defects	Recording, real time analysis of waves allowing automatic acquisition unit. The system can be directly connected to computer with low/ medium cost. Portable devices can be used to monitor areas with cracks (SHRP 2 2009, Shiotani et al. 2009, FHWA 2012). The whole structure can be monitored from a few locations. Test can be done while bridge is in service.	Test cannot be repeated once it is completed. Expensive, need additional cost for an operator. Other test should be used to determine the exact nature of defects. Background noise is similar to sound from flaws. Emissions can be very weak signals and difficult to detects due to noise. Difficulty in estimating structural integrity (SHRP 2 2009, Shiotani et al. 2009, FHWA 2012).
	Ultrasonic Testing	Many applications in inspection; detect cracks, voids, corrosion; identify fatigue and porosity (SHRP 2 2009, Shiotani et al. 2009, FHWA 2012).	- It is more accurate method with reasonable results; this method uses high frequency sound into the material to produce images. . It helps inspector to measure steel thickness and provides more information about cross sections (SHRP 2 2009, Shiotani et al. 2009, FHWA 2012).	It provides inaccurate reading for complicated geometry member. Flaws that are parallel to sound waves cannot be detected. The method needs skilled operator. Portable ultrasonic associated with many uncertainties as the method still new (SHRP 2 2009, Shiotani et al. 2009, FHWA 2012).

LASER	**Laser System**	It measures the deflection of bridge girders in the field. It is capable of measuring complicated movements and deformation in bridges in structural lab. Used for bridge load testing (SHRP2 2009, FHWA 2012).	It is a mobile system with high resolution and large volume measurements (SHRP 2 2009, FHWA 2012). It allows for data collection to enable accurate measurements. Minimum disruption for traffic. The measured areas are taken from laser measurements and another two positions from mechanical scanners. The system is capable of obtaining large measurements with high accuracy and provides 3D modeling of bridge structure (SHRP2 2009, FHWA 2012).	-Equipment is costly, some instrumental errors, influence of weather conditions. Collecting and interpreting data require trained persons. Should be used with other technique to increase the accuracy.
COATING	**Smart Coating**	It allows inspector to determine vibration and future fatigue (SHRP 2 2009, FHWA 2012).	-Easier to measure vibration than strain gauges (SHRP 2 2009, FHWA 2012). The higher the vibration, the greater the electrical signals, giving an alert of fatigue crack existence. In this way, engineers have the ability to monitor fatigue cracks initiation in a much easier way	Surface should be cleaned before the test for more accurate results
	Dye Penetrant	It defines the extent and size of surface law (SHRP 2 2009, FHWA 2012).	-Cost effective and it doesn't require extensive training from inspector (SHRP 2 2009, FHWA 2012). It is simple with no special equipment. Sensitive, can detect very small discontinuities. When penetrant has dried, the developer draws the dye out and determines the surface with flaw	It doesn't detect depth of cracks and the subsurface flaws. Many factors affecting on dwell time such as, temperature of member, Humidity, material type, penetrant removal, size and shape of discontinuity (SHRP2 2009, FHWA 2012). A temperature is required to get an acceptable results,(40 degree Fahrenheit).

MAGNETIC	**Magnetic Field Disturbance**	It determines subsurface cracks and holes. It Identifies corrosion rate in bridge components (SHRP2 2009, FHWA 2012).	-It is an effective method, with high sensitivity, small and not expensive (SHRP2 2009, FHWA 2012).	-Applicable only for member composed of aeromagnetic material. Small deficiencies are hard to be detected. -Unpainted surface should be clean to maximize the sensitivity of testing unit (SHRP2 2009, FHWA 2012).
IMAGING	**Radiography**	It locates subsurface cracks, voids and for full penetration groove welds during fabrication and construction (SHRP2 2009, FHWA 2012, SHRP2 2013).	It can be used successfully in bridge assessment. It can be integrated with other techniques. These rays are passed through the member and absorbed by different flaws. Consequently, the deficiencies appear as shadow on the film (SHRP2 2009, FHWA 2012, SHRP2 2013).	Strict safety with using the equipment is required. Requires access from both sides of tested member. It faces transportation difficulties. Inspector should have high skills to interpret results. Expensive, It cannot be used to detect corrosion(SHRP2 2009, FHWA 2012, SHRP2 2013).
	Computed Tomography	It locates deficiencies for steel member and concrete (Rens and Kim 2007, SHRP2 2009).	- Very effective method (Rens and Kim 2007, SHRP 2 2009, FHWA 2012). This test uses X ray and gamma radiation to produce 2-D and 3-D cross sectional image of internal defects in steel member. This image is processed and reconstructed by a computer (Rens and Kim 2007, SHRP 2 2009, FHWA 2012).	- Expensive, Public Safety issues . .
	Robotic Inspection	Condition assessment and inspection process in general (FHWA 2012).	It allows inspector to see elevated bridge from the ground. The system is controlled by remote control. It reduces traffic delay, increase safety of inspector. and also used for concrete bridge.	Sensitive to environmental conditions. This method need to be extended for concrete bridges as well (FHWA 2012).
	Infrared Camera	It detects delamination for steel deck and bar concrete(SHRP2 2009)	The system has automated data collection and storage. It has a system data base. Presentation of data is easy (SHRP 2 2009).	For thin material surface. It depends on the environment condition. Measurements are near surface (SHRP 2 2009).

2.4. DATA FUSION

Multi sensor data fusion is a technique to combine images taken from different imaging system and thus increase the acquired data. The main purpose of combining data from multiple sources is to improve the accuracy of information acquired and the measurements. It includes data processing and statistical estimation. There are many statistical advantages gained by combining data, as the quantity of data can be collected, observed and measured.

Data fusion can be done within three levels: pixel level image fusion, feature level and decision level. Pixel level is the integration of pixels from different images; images that will be fused acquired from different sources. These images must be matched into same coordinate system to compute pixel between two images (Wang et al. 2010). Naidu and Roal 2008 introduced pixel level image fusion by generating a combined image that contains additional information than the single image. The authors concluded that performance of image fusion could be estimated more precisely when the true image is available.

Feature level involves extraction of features from sensor. These features can be extracted from different sensors, combined into single feature. Feature level uses different algorithms to recognize objects for extraction from all data sources. Decision level involves fusion of sensor information and can be done by many techniques such as Bayesian inference or Bayesian Networks (BNs) (Hall and Llinas 1997, Naidu and Roal 2008).

The observations from multiple technologies can achieve better estimation performance than a single sensor. When large amount of data are fused, it can help in the decision-making. The simplest way to deal with a multi sensor estimation problem is to combine all observations in a single group sensor. Data fusion can be done also by dealing with each sensor independently and then combine all information from each one (Hoseni and Ashraf 2013). The main purpose of data fusion technique is to reduce the probabilities of errors when collecting and using data for specific assessment (Casstanedo 2013). Data fusion levels reviewed and defined by Casstanedo (2013) are as follows:

Level 0: fusion at the signal and pixel levels of raw data

Level 1: It deals with processed data, features, correlations and clustering.

Level 2: Setting relationships between objects and gives assessment for the situation.

Level 3: It is an assessment level, it gives decisions about future prediction. It includes risk prediction

Level 4: improves previous levels and achieves resource management.

Shahandashti et al. (2011) showed that experimental results with fusion method improve detection of construction material location. It also improves the reliability of information. Data fusion techniques need to be integrated in many applications in construction engineering field. However, different fusion assessment levels are not well defined and understood. Shahi et al. (2014) developed a frame work for multi sensor data fusion to track the progress of construction activity. The authors used 3D imaging with ultra wideband positioning.

Some researchers made efforts in condition assessment using single method to detect defects, crack, delamination and voids in concrete bridges such as impact echo (Gucunski et al. 2011, Chong et al. 2003, Olson et al. 2011, Tawhed and Gassman 2002). Ground Penetrating Radar (GPR) is capable of detecting moisture and chlorides associated with deterioration, location of voids, mapping of reinforcement location, depth of cover and locating of steel bars (Maser 1996, Dinh and Zayed 2014, Shin and Grivas 2003, Barnes et al. 2008, Parrillo et al. 2006). Infrared thermography is used to detect delamination (Abdel-Qader et al. 2008, Clark et al. 2003). Digital imaging can detect cracks (Adhikari et al. 2013, Ahikari et al. 2012, Abdel-Qader et al. 2006). Some research efforts have been made within the area of condition assessment using different technologies (Yaghi and Moselhi 2014). Yaghi 2014 integrated the deterioration maps of GPR and IR for bridge deck in Montreal, Qc, Canada. The author approximately utilized superimposing to combine total defected areas extracted from the two technologies. There are many robotic systems developed for inspection purposes; these systems are designed for bridge inspection purposes and tunnel as well. Balaguer et al. (2014) focused on the advantages of using robotic platforms for construction. The authors used robot to perform inspection for tunnel and data is processed after images are collected. The system uses an impact acoustics method for the inspection procedure called ROBINSPECT; it is an integrated robotic system consists of three subsystems: a mobile report, an automated crane arm and an industrial quality robot manipulator. Robot improves and overcomes the problems of manual inspection procedures (Balaguer et al. 2014).

Helmerich et al. (2006) illustrated results of bridge deck assessment using combination of NDE methods such as radar and ultrasound. The authors used data fusion to merge different images taken by single NDE using the sum of maximum amplitude without enough details about the methodology followed for data fusion. Utilizing NDE method in bridge condition assessment is still not common in many countries (Helmerich et al. 2006). So, the authors developed NDE methods tool box that can be used for all types of bridges.

Czarnecki et al. (2010) worked on a case study for bridge deck assessment. The inspection data was collected using radar and HCP combined with petrographic examination. The authors confirmed that corrosion is the major cause of deterioration. They defined the service life for bridge deck by the time it takes to reach to corrosion threshold. Radar results detect small defects that cannot be seen by traditional methods such as chain drag. So, integration of radar and HCP data and then verified by core results is more reliable assessment.

Kurz et al. (2012) reviewed the methods of data fusion; they emphasized on the efficiency of data fusion if it is performed with less cost. The authors believed that combination of different NDE results is reliable for more accurate condition assessment for reinforced concrete structures. The authors developed BetoScan inspection system to integrate NDE data for accurate bridge deck assessment. The system includes different sensors that generate condition maps. Moreover, the authors developed a multi sensors robot called OSSCAR. It integrates sensors information, such as eddy current, ultrasound and radar. However, the authors did not provide the reader any details of the method followed to perform this integration.

Manh La et al. (2014) focused on automated multi-sensor non-destructive evaluation techniques (NDE). NDE technologies provide high efficiency inspection and evaluation. The authors analyzed a bridge deck data, which is collected by a novel robotic system with NDE technologies. The authors applied image stitching algorithm and bridge deck viewer software. Impact echo and ultrasonic surface waves are integrated within Robot system. However, authors did not provide a technique for NDE sensors fusion. Kenh oh et al. (2009) developed bridge inspection robot system which is not fully automated; it is semi-automated type. The robot system developed is composed of a specially designed car. This robotic system is developed for automatic and manual inspection.

Gucunski et al. (2010) studied the performance of NDT technologies in detection of reinforced concrete deck deterioration. They evaluated the performance of ground penetrating radar, galvanostatic pulse measurements, impact echo, infrared and ultrasonic surface waves. Currently, Laa et al. (2014) are working on program of developing robotics assisted bridge inspection tool (RABIT). The technologies used in RABIT system are: electrical resistivity, impact echo, ground penetrating radar and ultrasonic surface waves. RABIT integrates measurements from multiple technologies. The outputs from RABIT are deterioration maps for each individual technology for detecting locations and severity of damages in bridge deck. To the best of the author knowledge, the algorithms and the methodology for integration and fusion of data captured by multiple technologies in the RABIT are briefly referred to in a conference paper (Laa et al. 2014) without any detailed description.

Since measurements from different sensors are often with degree of uncertainties, there is a need to better interpret results from sensors. The most important is to fuse large amount of data. The determination of the most informative data sources can achieve an efficient and timely decision. Zhag and Ji (2006) fused information into Dynamic Bayesian Networks; the fusion system is able to select sensors and produce decisions with reasonable time. The authors concluded that uncertainty of sensors reading can measure the degree of belief (Zhag and Ji 2006).

To obtain data from different sensors, multiple sensors can be arranged and configured. There are many types of sensors fusion: complementary type, competitive type, and cooperative sensor type. In complementary type, sensors don't depend on each other; one sensor views one part of region and another sensor views different part of another region. Therefore, sensors can be combined to establish a complete picture, as they are independent. In the competitive type, each sensor deliver measurements for the same feature or fusion of measurements from a single sensor obtained at different instants. In the cooperative sensor type, data provided by two independent sensors are used to derive information with more than one type. The actual fusion of data can be based on statistical or probabilistic models such as Bayesian-Networks (Mitani and

Matsumoto 2006). Data fusion technique can be applied to more areas to achieve large-scale knowledge bases. It helps to solve the conflicting variables extracted from different sources and trying to find the accurate values (Dong et al. 2014, Carvalho et al. 2009).

Knowledge fusion identifies subject based on information that extracted from different sources. Knowledge fusion involves three steps:1- identify the part of data that indicate a value, 2-linking any entity that depends on knowledge base, 3- linking any relation that is related to knowledge base. Dong et al. (2014) identified and solved the problem of knowledge fusion by using data fusion techniques.

Figure 2.5 illustrates the main three levels of data fusion technique.

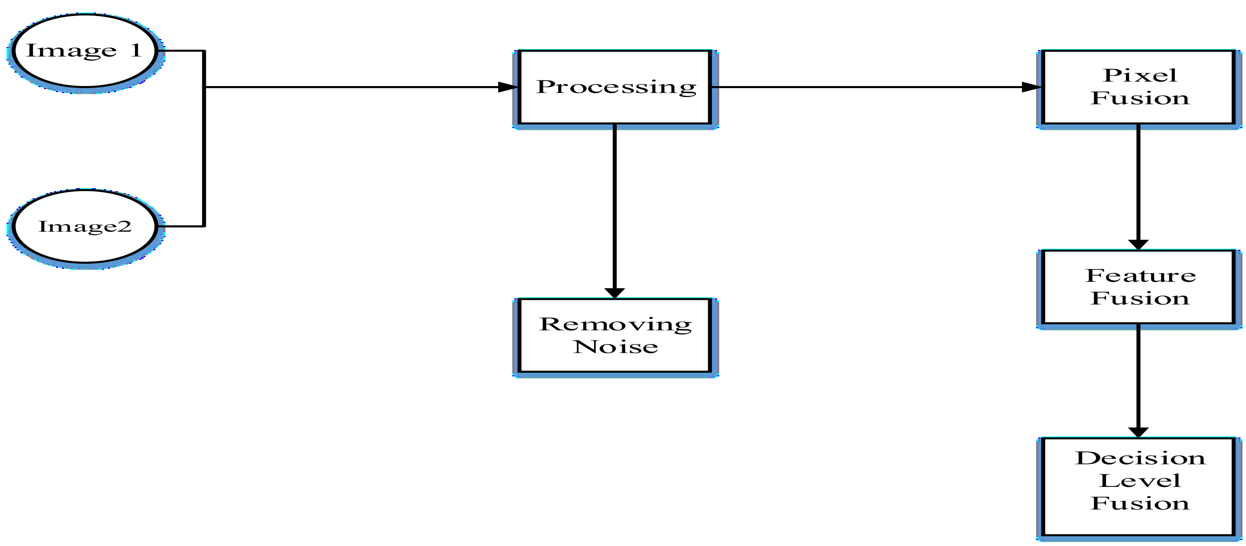


Figure 2.5 : Data Fusion Levels (Pajares and Manuel de la Cruz 2004, Naidu and Raol 2008, Simone et al. 2002, Wang et al. 2010, Matsumoto et al. 2012).

Research on data fusion is limited. Shahandashti et al. (2010) focused on the benefit of data fusion as it improves the confidence and reliability of measurements. The authors confirmed that the main challenge in the data fusion is not associated with the cost, but it is related to the algorithms used to process such captured data. The authors concluded that a gap exists between research and industry practice because the level of fusion are not well defined. Thus, there is a need to apply data fusion in different areas in civil engineering. Shahi et al. (2014) developed framework focusing on the highest level of data fusion for automated progress tracking of construction activity. Although the authors implemented data fusion framework at the highest level to help in decision making, they had to utilize specific design code.

Simone et al. (2002) applied data fusion using different methods through different case studies. The application of data fusion was done using: 1-multi sensors by using data from different sensors, 2-multi temporal using data from same sensors but recorded at different time, 3-multi frequency using data of the same sensor with different spectral bands, 4- multi resolution image fusion using data recorded by the same sensor at different heights.

Hoseini and Ashraf (2013) made a comparison of the computational complexity of different methods of data fusion. Naidu and Raol (2008) evaluated image fusion using three methods: wavelet transform, principal component analysis (PCA), and simple average method. The authors demonstrated that wavelets provide better performance with high level of decomposition. Wang et al. (2010) applied image fusion using weight fusion based on high-pass filter and Hue Intensity Saturation (HIS) transformation implemented in MATLAB with ease. Dong et al. (2014) studied data fusion and showed how to get knowledge fusion from data fusion.

Aside from the work cited above, there is limited research available that focuses on the application of image fusion for bridge condition assessment. Huang et al. (2010) applied data fusion in freeway infrastructure safety assessment including pavements, bridges and tunnels. They emphasized on the advantages of fusion methods, but did not provide detailed description of the method used in data fusion and, even the numerical example they presented lacked many details.

Some researchers applied data fusion for testing reinforced concrete structures. Zhang et al. (2012) used impact echo to detect delamination. They applied data fusion to increase the results accuracy by using multiple source receiver arrays. The experiment was done on reinforced concrete slab. The authors focused their observations on the spatial variations of Impact Echo (IE) signals for different source location. The ratio between spectral amplitude at the delamination echo Frequency and the bottom echo frequency was considered an important parameter for data fusion in that application. They confirmed that fusing the data of multiple NDE methods improve and enhance results interpretation. Maierhofer et al. (2004) also applied data fusion to accurately identify the location of concrete cover of tendon ducts by fusing measurements of radar, ultrasonic and impact echo. Their study recommended that future research should investigate different algorithm of fusion for different applications.

Su et al. (2009) used feature level of data fusion to detect delamination in composite structure. The authors studied three basic data fusion scheme: disjunctive, conjunctive and compromise fusion for two sensors. Their study evaluated the capability of these methods to identify delamination. Sun et al. (2016) proposed framework to compute the composite structure health index using data collected by sensors. The authors focused on the decision level data fusion for maintenance planning.

This research suggests use of two levels of data fusion, Pixel level fusion and Feature level fusion, for bridge deck condition assessment. Two levels are considered to gain benefits of both levels and to increase the confidence when presenting the assessment results. Pixel level fusion provides one single fused image that incorporates inspection data captured by multiple technologies, and results from the fusion node an overall assessment of the condition in the form of % good, % poor and/or % serious areas. Feature fusion is used to fuse features extracted from multiple images. In addition, decision level data fusion can be used for forecasting future condition which add more complexity to the proposed method

2.5. DETERIORATION MODELS

Deterioration models are used in Bridge Management System (BMS) to predict the future conditions and performances of bridges. Large number of historical data is required for deterioration modeling. The deterioration models are influenced by: 1-Bridge age, 2-Bridge type, 3-Bridge environment, 4-Material properties, 5-Bridge design, 6-Bridge loading and 7-Bridge Capacity. Bridge deterioration rate is a decrease in condition rating per year. Bridge age and daily traffic load are the most critical factors that cause bridge deterioration. Bridge service life can be determined by defining the correlation between bridge age and condition rating. Therefore, the effective maintenance of bridge structure relies on the quality, accuracy of deterioration models that are used to predict bridge performance and service life (Agrawal et al. 2010, Cesare et al. 1992, Robelin et al. 2007).

Currently, there are two major types of deterioration models:

(i) Deterministic Models:

Deterministic models describe relationships between factors affecting bridge deterioration. However, it ignores random errors in prediction. Some of the limitations of deterministic deterioration models are as follows:

1- Deterministic models neglect uncertainty

2- They predict the average condition of a group (of bridges) without focusing on individual facility. These models provide less focus on current condition and the history of the facility.
3- It is always difficult to estimate the impact of maintenance actions on deterioration when deterministic deterioration models are used.
4- These models neglect the interaction between bridge components.

(ii) Stochastic Models:

Stochastic models deal with deterioration process as random variables that incorporate uncertainty. Markov models are the most widely used deterioration models used to predict the condition of infrastructure facilities. It covers two limitations of deterministic models as it incorporates uncertainty and account for the current facility condition. Markov model has the following limitations:

1- Markov models assume discrete transition time intervals.
2- Future condition of a facility depends only on current facility condition and not on a history of the facility, which is unrealistic.
3- Markov models assume that the condition of a bridge can stay the same or reduced to avoid the complexity to consider the treatment process and its impact.
4- Markov models cannot determine the interaction between different components of bridges.
5- In these models, transition probabilities require update when new information is available.

Markov Chain Model is the most widely stochastic model. It forecasts bridge condition rating based on the concept of defining states of bridge condition from one to another during transition period. Markov approach is a discrete time stochastic process that takes number of possible discrete states. This can be presented as transition between certain states. The conditional probability that means an element can transfer from one condition, i, to condition, j, through a period of time is defined as Pij in Eq. (2.3)

$$P_{ij}= P\{ X_{t+1} = J \backslash X(t)= i\} \quad (2.3)$$

These probabilities are presented in a matrix called the transition probability matrix (TPM). As an example, if bridge has five condition states, this yields 5*5 matrix in Eq. (2.4)

$$P= \begin{bmatrix} P11 & P12 & P13 & P14 & P15 \\ P21 & P22 & P23 & P24 & P25 \\ P31 & P32 & P33 & P34 & P35 \\ P41 & P42 & P43 & P44 & P45 \\ P51 & P52 & P53 & P54 & P55 \end{bmatrix} = \begin{bmatrix} P11 & P12 & P13 & P14 & P15 \\ 0 & P22 & P23 & P24 & P25 \\ 0 & 0 & P33 & P34 & P35 \\ 0 & 0 & 0 & P44 & P45 \\ 0 & 0 & 0 & 0 & P55 \end{bmatrix} \quad (2.4)$$

Each element in TPM represents the probability of transition from one state to another for one inspection period. The sum of each raw of the TPM is equal to 1 based on the probability theory.

With no repair work, bridge components will be deteriorated. So, condition rating is increasing to higher numbers or remain with no change during one inspection period. Pij is null if I >j

Markov approach assumes that bridge condition rating would not be increased by more than one state within one year. Probability of increasing to more than one state within one year is assumed zero.

Then, the condition state vector, Ct =[C1(t) C2(t) C3(t) C4(t) C5(t)]……… (2.5)

where Ct is the percentage of bridge components in condition rating i where i= 1, 2, 3, 4, 5 after t years. The condition state matrix after zero years is known as C0, the initial condition.

C0 = [1 0 0 0 0]………………………………………………………………… (2.6)

Determine condition state matrix after t time with multiplication of initial condition state matrix by t power of TPM and using Chapman- Kolmogorov formula

C(t) = C(0) * TPM power t ……………………………………………………………(2.7)

Markov Model assumes that future condition depends mainly on current condition. Markov model can be defined by assessing the transition probabilities between all possible condition states. Transition probability does not depend on the state history (Frangopol et al. 2004).

Frangopol et al. (2004) has the following concerns regarding Markov-Model:

- Condition state in Markov model is discrete which makes it suitable for visual inspection.
- Researchers should focus on how to integrate Markov-Model to NDE, then to BMS.
- Markov assumption has no memory.
- Great concerns should be focused on the accuracy of transition matrix.
- Network level optimization can be enhanced by using a finite state Markov Model.

Frangopol et al. (2004) has the following guidelines and recommendations for a future concerns:

-Life cycle performance and reliability index is concerned with the physical condition of a structure.

- Markov-Model cannot be used to assess reliability of structure such as stress and strength, it is highly recommended to integrate structural assessment with deterioration models.

- Deterioration Models should address condition and reliability.

- Deterioration model is developed to achieve balance between three objectives; reliability, condition and cost.

Madanat et al. (1995) used data of condition that obtained from facility inspection. These data used to develop facility deterioration model. Discrete condition rating is commonly used for simplicity. Authors focused on the utilization of condition rating to predict deterioration models. The authors in their research, integrated incremental models that predict changes in condition that were added to previous condition to estimate the new condition. In this way, deterioration models incorporate different variables (Madanat et al. 1995).

The authors focused on Markov model because it is the most widely deterioration model incorporated to BMS. Transition probability specifies the probability of condition change of a facility from one state to another state in a unit time. Therefore, authors incorporated Ordered probit model to be used to construct an incremental discrete deterioration model. Incremental deterioration model predict deterioration of facility over period of time. The advantage of this method is that it provides specific and accurate transition probability.

The incremental data model is equal to the difference between condition states observed in two inspections. Drop in condition rating is an indication of deterioration process. So, the transition probability from state i to state j is the probability of changing the condition state i to be equal to j (Madanat et al. 1995).

Roelfstra, et al. (2004) incorporated various parameters in Markov-model. The model uses quantitative parameters related to concrete deterioration. The authors used condition state vector as follows:

- Condition state 1: defined as having free chloride ion less than 0.2%
- Conditions 2, 3, 4 and 5 are defined in terms of reinforcement section loss.
- *(i)* Condition 2: in term of section loss that lead to corrosion crack
- *(ii)* Condition 3: in terms of less between 50 mm and 10% of total cross section
- *(iii)* Condition 4: more than 10% section loss
- *(iV)* Condition 5:more than 25% section loss (Roelfstra et al. 2004)

The authors determined condition evolution in three steps:

1- Chloride penetration is simulated for each concrete cover.
2- Probabilities of corrosion initiation were determines as a function of time
3- Results of condition evolution used to set as quality for bridge element

The results of condition evolution can be incorporated to enhance the prediction of transition matrix (Roelfstra et al. 2004).

Morcous et al. (2000) provided a model that has the ability to consider incorporating various factors affecting deterioration process, account for bridge maintenance history, and take into consideration the effect of past conditions. The authors introduced a generic Case Based Reasoning (CBR) framework. The design of this framework includes the four main aspects:

1- Case representation

2- Case accumulation

3- Case retrieval

4- Case adaption

The framework is built on top of Object-Oriented Data Base-Management system. The module performs the followings:

1- This module stores time dependent defined for each domain along with their relationship

2- The retrieval knowledge base module stores the attributes that belong to each domain.

3- The adaption knowledge base stores the domain knowledge from domain experts.

4- Case template module stores the structures of some cases that are common and can be used as templates for new cases.

5- Module to store data and describe case contents.

Case description incorporates all factors that affect bridge deterioration process. There are two types of knowledge in the developed framework; retrieval knowledge and adaptation knowledge. Retrieval knowledge stands for the knowledge about attributes; name, groups and types. It describes different techniques used to measure similarity among attribute values. These techniques are different according to attribute type. The four attributes are continuous, grouped, enumerated and hierarchical. Adaption knowledge stands for the knowledge acquired from experts to be used for the retrieval case solution. The authors provided cases from transportation agencies (MTO and MTQ) to validate their approach.

Another type of stochastic models available are Bayesian Networks (BNs). These models consist of a graphs that includes nodes and arcs. The arcs connecting two nodes represent the dependences relationships between random variables nodes. BNs has many application in medicine diagnostics and in engineering predictions (Murphy 2002, Jha 2006, Straub 2009). Few researchers have applied BNs in deterioration modeling. By using BN, dependencies among variables is easy to interpret. Variables are considered independent if there is no edge connecting those variables.

According to Weber et al. (2012), BN has the capability of modeling complex system. It makes prediction and diagnostics. It computes the probability of event occurrence. It updates beliefs based on new evidence. It integrates qualitative information and the quantitative ones. BN merges experience, past knowledge, impacting factors and measurements. So far, according to the literature review, BN has limited applications in maintenance and in bridge deterioration modeling.

Dynamics Bayesian Network (DBN) is a class of BNs which represent stochastic process. DBN consists of sequence of slices. Each slice consists of BN nodes. These slices are connected by direct arc from slice at time T1 to slice at time T2. DBN provides computational framework that allows accurate and efficient prediction of deterioration based on observations and deterioration parameters (Faddoul et al. 2013, Straub 2009). Modeling bridge deterioration as DBNs is expected to cover the main limitations of current Markov model.

2.6. BAYESIAN NETWORK THEORY

The main advantage of BN is the graphical presentation and presenting joint probability distribution between random variables. BN includes table of conditional probabilities for each variables relating to its parents, each node represents probability distribution of a variable that can be continuous or discrete state. The conditional probability table represents the dependence relationships.

For two events A and B, according to Bayes theory in Eq. (2.8):

$P(A|B) = P(A)^* P(B|A)/P(B)$…………………………………………………………(2.8)

P(A) is the prior probability of A. P(A|B) is the posterior probability, it is the conditional probability of A given B, so it depends on the value of variable B. P(B|A) is the conditional probability of B given A. The component P(B|A)/P(B) is defined as the Bayes factor.

In Bayesian network, the dependencies between variables are quantified by conditional probability table CPT for each variable node given its parents. Therefore, the arrows in the network represent causal connection. Using BNs enable determining the joint probability distribution of variables (JPD) as illustrated below:

If x_i is some values of variables X_i and Pa_i is the values of parents of x_i, then JPD can be determined using the product rule as in Eq. (2.9)

$P(x_i,\ldots\ldots,x_n) = \prod_i P(x_i| Pa_i)$………..……………………………………………………. (2.9)

BN automate Bayesian updating based on observation of each node. Once an observation of one node is available, the whole network will be automatically updated. In order to calculate the conditional probabilities, it is preferred to use discrete nodes to make calculation much easier.

BNs are developed in 3 stages:

1- Define the random variables and the relationship between them.
2- Determine the conditional probability distribution of each child node given its parents.
3- Define joint distribution of the variables.

BN includes qualitative parts which are graphs and nodes connected through linking the variables. The variables that are preceding the link are the parents' nodes; variables following the links are the childs nodes. So, parents for node Xi can be presented as Pa (Xi).

BN also includes quantitative parts that include estimating the conditional probabilities between parents and child nodes. BN estimates all the possible hypotheses, the Bayes rule is employed to calculate the hypotheses. Conditional probability is the probability of variable's state given some combination of parents' states (Najardardottir et al. 2005). BNs are usually used because it helps to integrate theory and expert knowledge. It allows reasoning with uncertainty. Najardardottir et al. (2005) developed a model to define the probability of deterioration mechanism of bridge deck. So, the user can define which mechanism is most likely causing deterioration. The authors used BNs to model their frame work, the model was tested on two case studies. The authors recommended the use of BNs for the assessment of bridges.

Discrete random variables are the most widely used applications to determine the conditional probabilities. For each child variable, a conditional probability table needs to be defined by linking condition states of child node to the parent. Conditional probabilities define the strength of the link between child and its parents. It presents the importance and the contribution of each parent variable in developing the condition of their child variable.

2.6.1 Dynamic Bayesian Networks

Dynamic Bayesian networks are a special class of BNs to analyze problems of bridge deterioration with time variation. It consists of a sequence of time slices (T_1, T_{+1}, ……….., T_{+n}). In each slice, there are one or more BN nodes. Time slices are connected with direct link, these links present probabilistic dependences.

In DBNs, bridge deterioration can be predicted from past experience. The knowledge from experts are used to build CPT directly. According to Wang et al. (2012), this task is performed through 5 steps as follows:

1- Experts Selection

2- Experts Training

3- Questions preparation

4- Expert Judgement

5- Results Verification

CPT can be determined directly from visual inspection or from NDE methods. In DBN discrete units of time is modeled. Each unit is defined as time slice. These time slices are connected through links. The probabilities associated with links connecting the time slices are defined as transition probabilities. In DBN, the basic network is repeated over time.

DBNs utilize the advantages of Markov model process and allow taking into consideration the prior probability distribution of random variables that do not have a direct impact on the deterioration process such as deterioration factors.

According to Rafiq et al. (2014), deterioration of bridge element leads to reducing level of service and bridge safety level. In current practice, deterioration models are presented by Markov stochastic process. For simplicity in existing BMS, discrete time stochastic process is employed to model bridge deterioration at T_{+1} by prior knowledge about deterioration at T_1. Rafiq et al. (2014) applied DBN model for modeling the deterioration of masonry arch bridge. The authors utilized DBN to address the interdependent between main element and sub element.

Wang et al. (2012) focused and studied BN. Wang et al. (2012) used dynamic Bayesian Networks for prediction of structural reliability of steel bridge element. The authors developed an approach that is able to update information from the observed measurements, and then corrosion process is modeled. Straub (2009) proposed DBN to model deterioration. The model proposed by the author updates variables based on information from inspection. Faddoul et al. (2013) presented DBN for maintenance action of roads. The authors extended Markov decision process to take into account the available information and improve the existing inspection, maintenance and rehabilitations action for roads using DBNs.

2.7. FINDINGS OF LITERATURE REVIEW AND IDENTIFICATION OF THE CURRENT RESEARCH GAPS

The current practice for bridge condition assessment and inspection in Alberta has some limitations. For example, their Level 1 inspection is visual and the rating is subjective, it depends on the inspector's experience. In Level 2 inspection, the overall rating might not be accurate as the areas that are not visible cannot be accurately assessed. In Level 2 inspection, chloride test is used to determine the chloride content in concrete. This test is time consuming and destructive test. When CSE test is used in level 2, the inspector should stop when reading is getting so high or low and verify the validity of the ground connection or check if the deck is not wet enough for accurate results. CSE test can determine the presence of corrosion but cannot determine the corrosion rate.

The state of Oregon still rely on destructive methods where samples should be taken in specific positions from the bridge to perform in depth inspection, such as chloride content test, depth of carbonation and core test. Hammer sounding and chain dragging are time consuming. Pachometer that used for depth of cover measurements sometimes fail to give accurate information. Petrographic examination is a highly specialized practice requiring skilled and well trained technicians.

The current practice in Quebec has some shortcomings. The condition rating values cannot be used to evaluate the structural capacity of the element. These values are used for general condition of the structure and for evaluation of deterioration. Also, the special inspection is not clearly defined and the system that is followed for reporting is not provided. Inspectors and engineer should be well trained; they should increase their knowledge regarding the material behaviour. General inspection is still visual inspection without condition evaluation for specific elements. Special inspections should include in-depth condition evaluation. Inspection system outside North America is based on number of visits to the bridge at fixed time interval, which is called periodic; the other type of inspection that is not based on interval is called non periodic inspection. The general system of inspection is classified as superficial inspection that is usually done every one year; it is visual inspection with portable support measurements. Thorough inspection, which is called detailed inspection, is usually done within period equal to a multiple of the superficial inspection; it is checkup of the structure with detailed visual inspection and is usually done by inspector with more experience. Special inspection is usually not periodic inspection; it is done based on specific defects that was detected; this inspection is usually done using specialized equipment and test with the use of NDE methods. Bridge condition assessment in other countries is almost the same. Bridge inspection levels are classified according to inspection interval where the inspection intensity varies with inspection interval. There are three levels of inspection that are defined based on the interval: Short interval check of safety, medium interval of maintenance needs and long intervals, in depth assessment. Identifications of repairs needed are identified during the inspection within medium interval. There is less use on non-destructive evaluation methods in the special inspection. However, MRWA Australian manual is incorporating the use of many NDE methods.

Subjective condition assessment reduces the accuracy of forecasting bridge condition. Integration of NDE technologies for evaluating and tracking condition of bridges over their life cycle is essential. So, this research identified and analyzed advantages, limitations and applications of each NDE method for concrete and steel bridges. These methods are illustrated based on current practice and their applicability to bridge condition assessment.

This research highlights the currently used NDE methods for bridge condition assessments in Canada and the USA. In Alberta, Ultrasonic testing is used to detect cracks, voids, corrosion, and to identify fatigue crack in steel bridges. For reinforced concrete bridges, half-cell potential is used to identify steel corrosion. In Ontario, digital imaging is used for general inspection of steel and concrete bridges. The use of imaging reduces traffic delay and enhances safety of inspector. For concrete bridges, GPR and Infrared thermography are used. GPR has many applications for its high capabilities in detections of flaws, cracks and in locating steel bars. It provides rapid test with minimum interruption to traffic. Infrared thermography is used to detect concrete defects such as cracks, delamination, and subsurface voids. It is fast with medium cost and minimum traffic disruption. In Quebec, Half–Cell potential and acoustic methods are frequently used. In United States, X-ray is used to map defects in concrete bridge decks. Dye penetrate is sometimes used to detect small discontinuities in steel bridges. It is cost effective and simple to use.

The main challenge of using NDE methods is the integration of results from multiple sources. Therefore, integration of different methods is recommended to reduce the limitation of each technology. Based on the literature review performed, there is no detailed methods on application of data fusion in bridge condition assessment. There is little application of data fusion in different areas. The application of pixel image fusion and feature levels in bridge condition assessment is considered a novel technique as, with the use of multiple sensors, it can interpret condition assessment results more accurately with less cost and interruption for traffic. However, there may be higher initial cost involved to acquire condition assessment using different technologies. The total cost is expected to be reduced in view of reduction of labor hours and reduction in time required to carry the scanning in compare to manual methods.

This research focuses on those gaps with the goal of allowing inspectors and engineers to assess bridge conditions based on fusing data from multiple technologies. This research, provide a generic method for data fusion within pixel level image fusion and feature level fusion.

In addition, the literature review highlights researchers' efforts to determine an accurate transition probability matrix in current practice deterioration models. Researchers agree that incorporating different variables is a key point to increase the accuracy of Markov-deterioration model. Moreover, integrating NDE assessment into Markov model will reduce its limitation and hence can be more accurate. DBN provides computational framework that allows accurate and efficient prediction of deterioration based on observations and deterioration parameters (Faddoul et al 2013, Straub 2009). Modeling bridge deterioration as DBNs is expected to cover the main limitations of currently used Markov deterioration model.

CHAPTER 3

3. RESEARCH METHODOLOGY AND IMPLEMENTATION

3.1. OVERVIEW

The research method provides a comparative study of NDE methods for fourteen methods for concrete and ten methods for steel bridges. Figure 3.1 illustrates the steps undertaken in this research to assess bridge condition based on fusing data from multiple technologies. Wavelet Transform technique is utilized to fuse images from multiple NDE methods within pixel fusion level. Bayesian network is utilized to fuse features from different sources. Image processing technique was implemented on images before and after fusion. The deteriorated areas are measured from the resulted fused image. Moreover, the research method assesses the impact of image processing techniques on image fusion accuracy.

In addition, the proposed research method incorporates decision level of data fusion and integrates NDE methods with deterioration modeling. This integration will reduce the limitation of current practice Markov deterioration model by incorporating different variables. In this chapter, the proposed research method will be explained in detail.

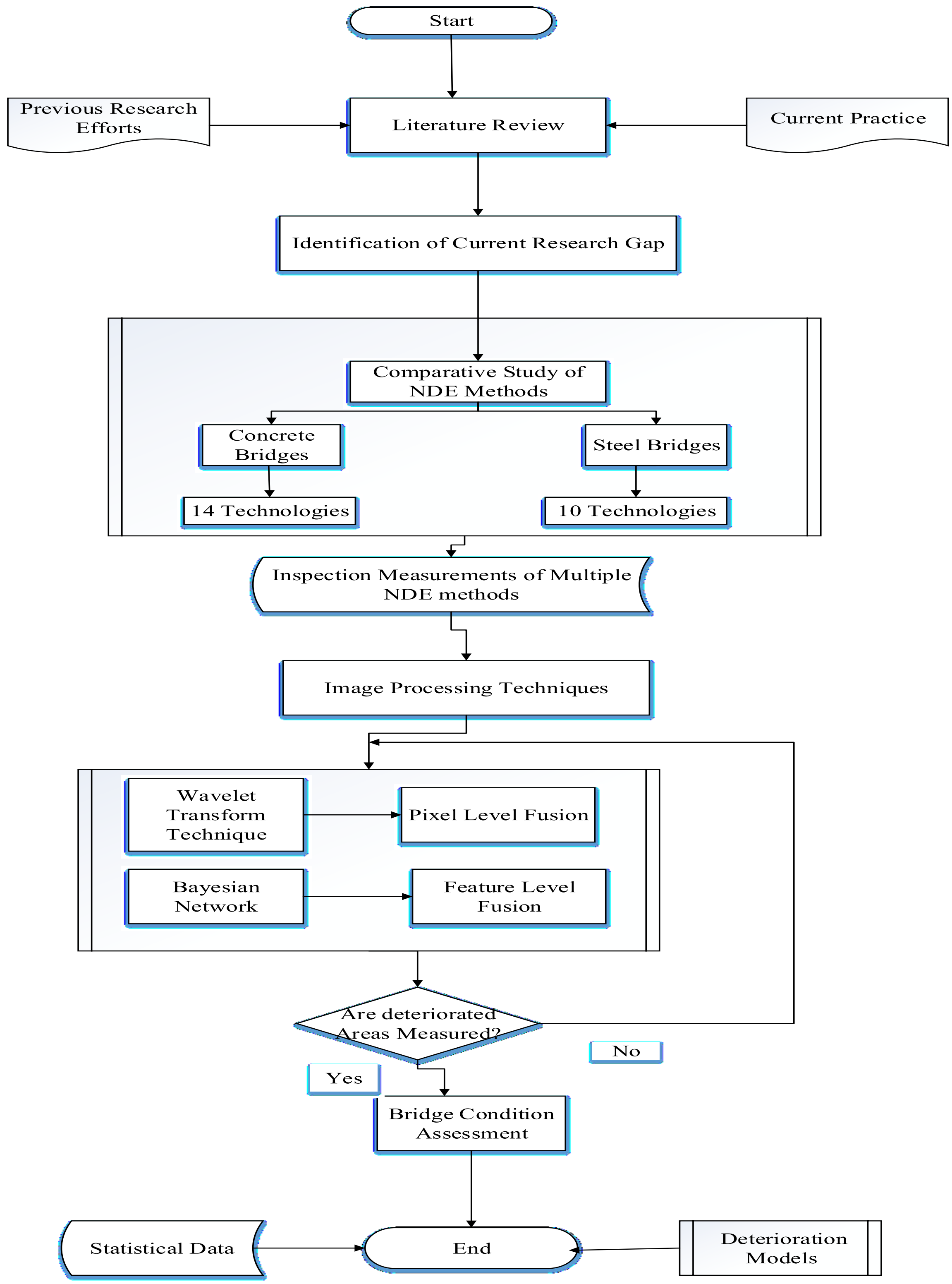


Figure 3.1 : Basic Flow Chart of Research Method

3.2. PIXEL LEVEL FUSION

Image fusion is used as a method to generate new and improved image from those captured by multiple technologies. In remote sensing fields, images from sensors have low resolution which makes small objects difficult to be detected. These images can be observed with much better details when fused. So, the main objective of image fusion is to obtain a unique image with enhanced information and resolution that better represents the condition state of the scanned bridge deck. It is the technique of combining data using the advantages of image processing (Pajares and Manuel de la Cruz 2004; Matsumoto et al. 2012; Simone et al. 2002; Naidu and Raol 2008; Wang et al. 2010). Figure 3.2 illustrates the basic components and data processing of the developed pixel fusion method. The developed method consists mainly of two main steps. In the first, images captured from multiple technologies are processed based on the physical principal of each NDE method. The second step is the image fusion, which includes image registration and wavelet, transform technique; the processed captured images from multiple technologies are registered and rescaled within same size and type to ensure that both have the same coordinate system to fuse pixels of these images. In order to apply wavelet transform decomposition fusion, the scaled images of multiple technologies are decomposed. These decompositions are fused to develop the new fused image. This new image is then used to extract features that depict the conditions of the scanned bridge deck.

Pixel level fusion is focusing on information integration in pixels of different images to enrich the data that can be extracted from the fused image. Images from both technologies are processed to reduce the influence of noises and enhance the contrast using imaging processing techniques. The traditional and simple way for pixel fusion is to take the average of image pixel by pixel as illustrated in Eq. (3.1).

$$\mathbf{IF(X,Y)} = \frac{\boldsymbol{I1(x,y) + I2(x,y)}}{2} \qquad (\mathbf{3.1})$$

where $I1(x,y)$ and $I2(x,y)$ indicate image 1 and 2 respectively.

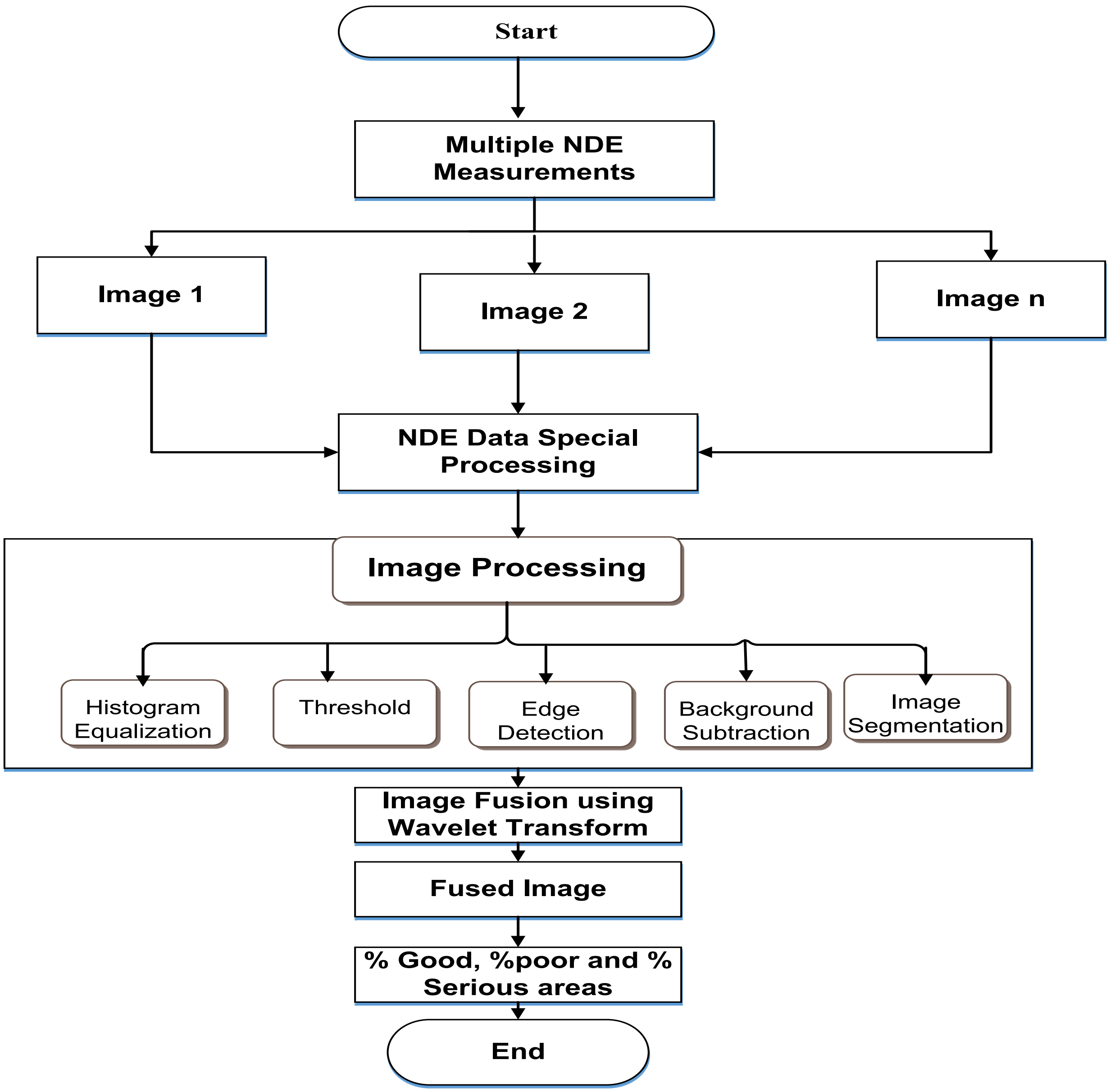


Figure 3.2 : Basic Flow Chart of Pixel Image Fusion

3.2.1. Image Fusion Using Wavelet Transform

Wavelet transform is a good tool to know the location of the low and high frequency areas. Wavelet transform is based on small waves called wavelets. It deals with images as matrix, Wavelet transform (WT) in two dimensions $\Phi(x,y)$. As illustrated in Figure 3.3, the original image matrix is decomposed into four sub images: $\boldsymbol{\Phi_{LL}(x,y)}$, $\boldsymbol{\psi_{LH}(x,y)}$, $\boldsymbol{\psi_{HL}(x,y)}$ and $\boldsymbol{\psi_{HH}(x,y)}$ (Pajares and Manuel de la Cruz 2004; Ryan 2004; Walker 2006; Toufik and Mokhtar 2012). The four sub images are determined using Eqs. (3.2) to (3.5). $\Phi_{LL}(x,y)$ is a sub image from the original image with low path filter to rows and low path filter to colums. $\psi_{LH}(x,y)$ is a sub image from the original image with low path filter to rows and high path filter to columns. $\psi_{HL}(x,y)$ is a sub image with high path filter to rows and low path filter to columns. $\psi_{HH}(x,y)$ is a sub image with high path filter to rows and high path filter to columns

$$\boldsymbol{\Phi_{LL}(x,y) = \Phi(x)\,\Phi(y)} \tag{3.2}$$

$$\boldsymbol{\psi_{LH}(x,y) = \Phi(x)\,\psi(y)} \tag{3.3}$$

$$\boldsymbol{\psi_{HL}(x,y) = \psi(x)\,\Phi(y)} \tag{3.4}$$

$$\boldsymbol{\psi_{HH}(x,y) = \psi(x)\,\psi(y)} \tag{3.5}$$

Wavelet fusion manages images with different resolutions and allows for image decomposition (Pajares and Manuel de la Cruz 2004). The main task of this method is to generate new coefficient for fused image based on to the decomposed coefficients of multiple images. As stated earlier, images are scaled before fusion to ensure that both have the same coordinate system to fuse pixels of these images. Fusing data at pixel level requires that images be within the same scale (Simone et al. 2002), this step will ensure alignment of two images taken from different sources. This is considered very important preprocessing step to ensure that information from each image refers to the same location. Since images from different sensors have different resolution and scale, image resampling should be achieved before fusion. According to the literature, images are resampled to a commonly used size of pixel spacing 512 pixels X 512 pixels (Pajares and Manuel de la Cruz 2004) .

The Wavelet approach is used for image fusion because it manages images having different resolutions (Pajares and Manuel de la Cruz 2004). It decomposes images to coefficients, which are then combined in the fusion process based on the maximum coefficient of the decomposed images. The Wavelet approach for image processing provides a multi resolution decomposition of an image which results in improved quality image representation (Naidu and Raol 2008; Simone et al. 2002; Wang et al. 2010). An example of the image decomposition and fusion is included in the Appendix II.

As illustrated in Figure 3.3, the important step in image fusion based on wavelet technique is the coefficient combination. This combination is achieved by processing the image. This processing includes decomposing the image from one level into four frequency band Low-Low (L-L), Low-High (L-H), High-Low (H-L), High-High (H-H).

So, for N decomposition levels, the number of frequency bands M can be calculated from the equation M=3N+1 (Pajares and Manuel de la Cruz 2004).

As illustrated in Figure 3.4 , wavelet filters the 2D image in vertical and horizontal directions. The input image I(X,Y) is first filtered by low path filter L and a high path filter H in the horizontal direction and then down sampled by a factor of two to create the coefficient matrices $I_L(X,Y)$, $I_H(X,Y)$. The low path and high path filters are then employed in the vertical direction on images $I_L(X,Y)$ and $I_H(X,Y)$ to create sub images I_{LL} (X,Y), I_{LH} (X,Y), I_{HL} (X,Y), and $I_{HH}(X,Y)$ (Pajares and Manuel de la Cruz 2004).

Accordingly, the I_{LL} represents the smoothed version of the original fused image and I_{HL}, I_{LH} are detailed sub images. Summation of all matrices is carried out to construct image I(x,y) (Naidu and Raol 2008; Simone et al. 2002; Wang et al. 2010). In wavelet, images $I_1(x,y)$, $I_2(x,y)$ are decomposed using wavelet. Max coefficients from both images are combined using fusion rule Φ. In this process, the fused image is obtained using Eq. (3.6). This is illustrated in Figure 3.5, where DWT is termed to Discrete Wavelet Transform. An example is illustrated in Appendix II.

$$\mathbf{IF(x,y)=[\Phi\{WT(I1(x,y)),WT(I2(x,y)\}]} \tag{3.6}$$

The described Wavelet transform is applied within MATLAB. MATLAB has great computing power for matrix and it has image processing toolbox (Wang et al. 2010). This toolbox improves the efficiency of final outputs. Pixel image fusion method was developed by using the wavelet transform techniques for image fusion and image processing techniques before and after the fusion process. The final fused image is obtained through the inverse discrete wavelet transform process IDWT.

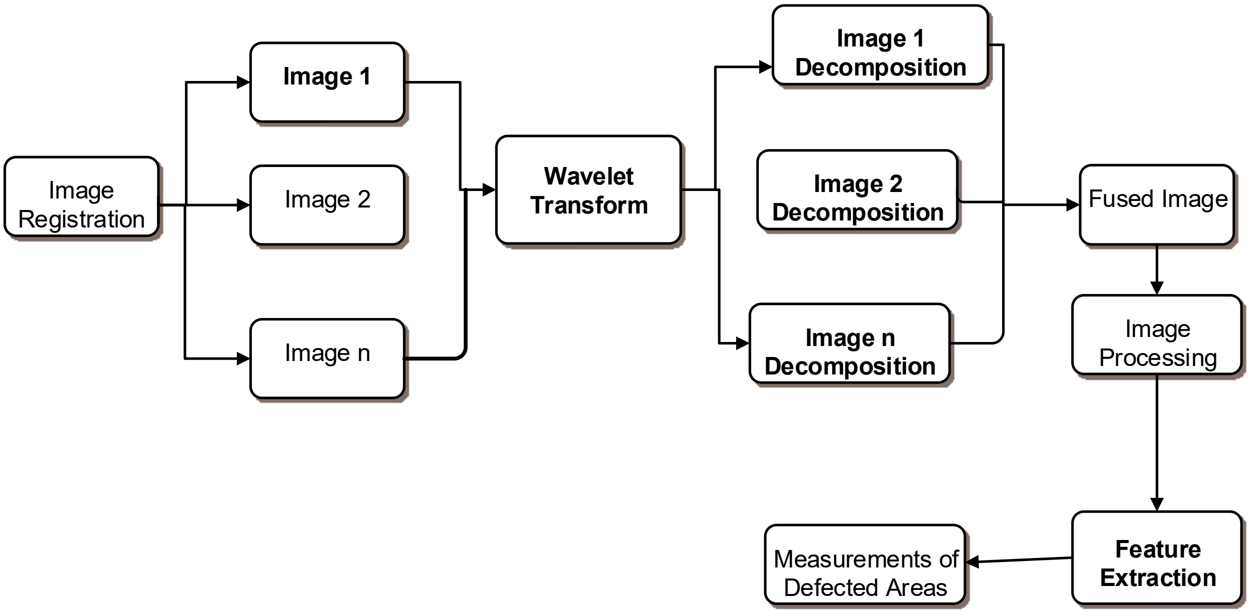


Figure 3.3: Flow Chart of Pixel Image Fusion Using Wavelet Transform

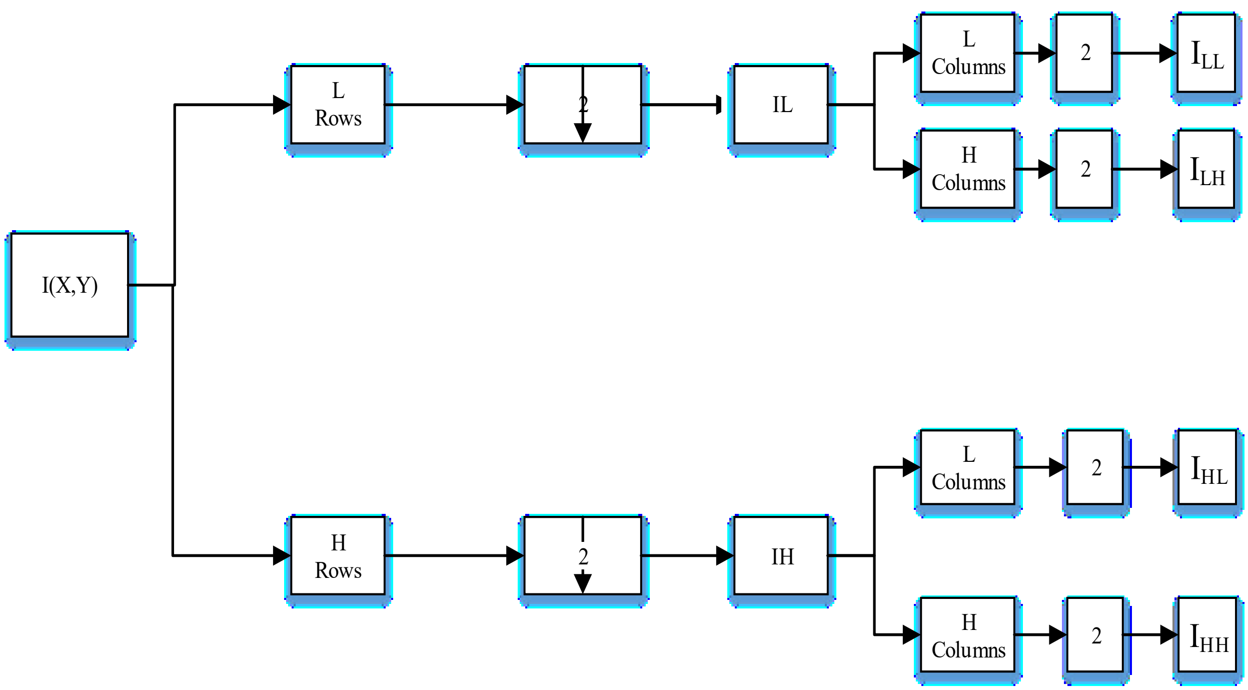


Figure 3.4 : The Basic Steps of Wavelet Transform Based on (Mallat, 1989; Pajares, and J. Manuel de la Cruz , 2004).

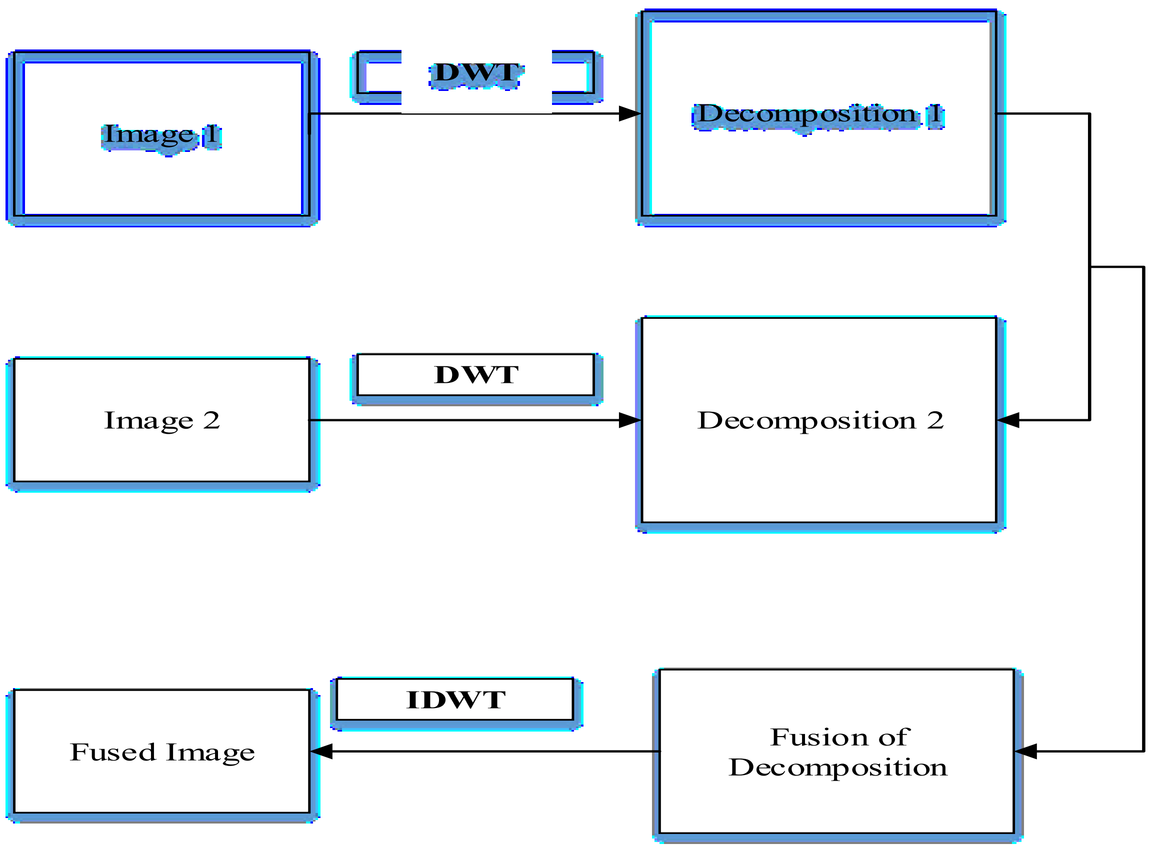


Figure 3.5: The main Steps of Applying Discrete Wavelet Transform Using MATLAB

3.2.2. Feature Extraction From Fused Images

Image processing refers to different techniques that are applied to an image. The most effective image processing techniques are threshold, edge detection, background subtraction and image segmentation (Moselhi and Shehab-Eldeen 2000; Moselhi and Shehab-Eldeen 1999; Adhikari et al. 2014; Adhikari et al. 2013). Figure 3.6 illustrates the main techniques used for feature extraction

Histogram Equalization is a technique to enhance the contrast of images. It is a method to stretch the histogram of an image.

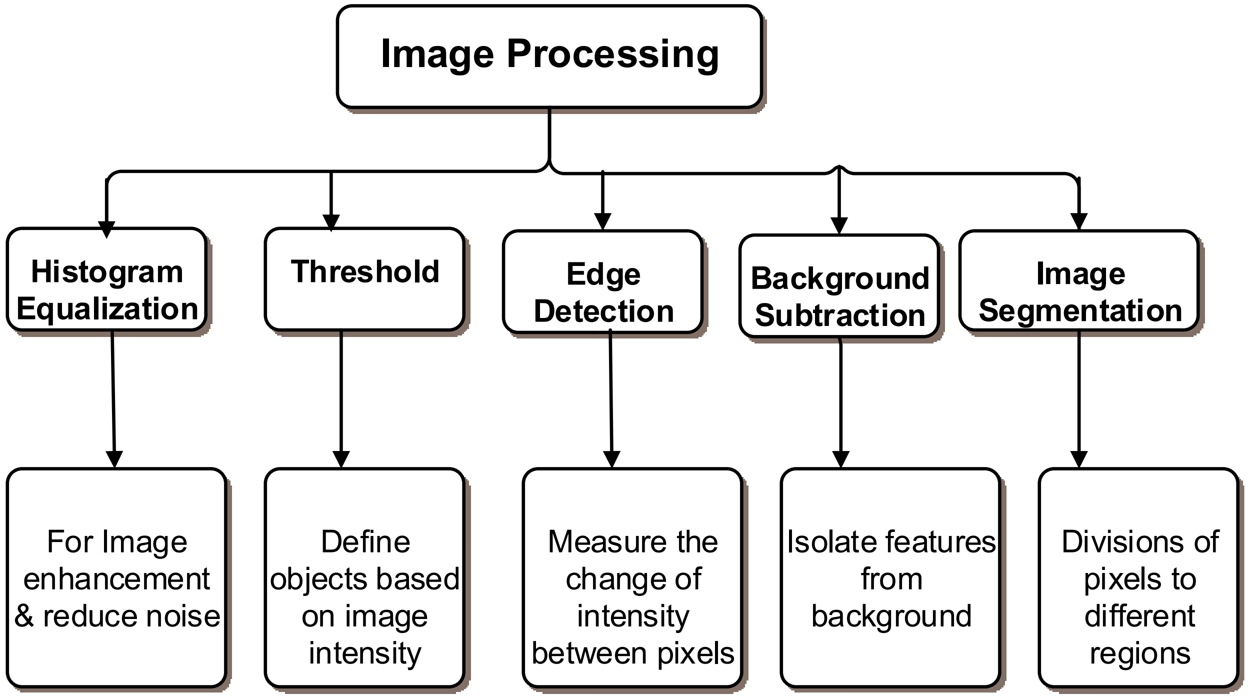


Figure 3.6: Image processing techniques Used For Feature Extraction

(i) Threshold Technique

The threshold technique is used to separate objects from the background of the image based on the differences in the image intensity. The intensity threshold is determined using the Eqs. (3.7) and (3.8).

$$\text{Threshold} = \alpha \, I_{mean} + \beta \, I_{max} \tag{3.7}$$

$$\alpha + \beta = 1 \tag{3.8}$$

α and β represent weight assigned to the mean intensity (Imean) and the max intensity (Imax) of the original image. Threshold help to make image segmentation where the different parameters of objects can be identified, analyzed and measured.

(ii) Edge Detection

Edge detection is performed by measuring the change in the intensity between pixels. It characterizes the edge of features to be extracted. This operation is based on detecting the boundary points that appear when there is a change in the image intensity

(iii) Back Ground Subtraction

Background subtraction helps to isolate objects from background of an image; it takes off the background noises. This method helps to show the region of interest

(iv) Image Segmentation

Segmentation, on the other hand, refers to the division of an image into a number of regions that are uniform in some characteristics. The simple method of segmenting an image is to threshold it and then considers each connected region as an object. Once the image is segmented, the different parameters of the identified objects can be measured and analyzed including areas, width, length and diameter (Adhikari et al. 2014; Adhikari et al. 2013).

3.3. FEATURE FUSION LEVEL

The developed method of feature fusion utilizes captured inspection images from multiple sensing technologies along with image processing algorithms. The features extracted from the processed images are then fused using feature level data fusion; employing Bayesian Networks. The main components of the developed method are shown in Figure 3.7.

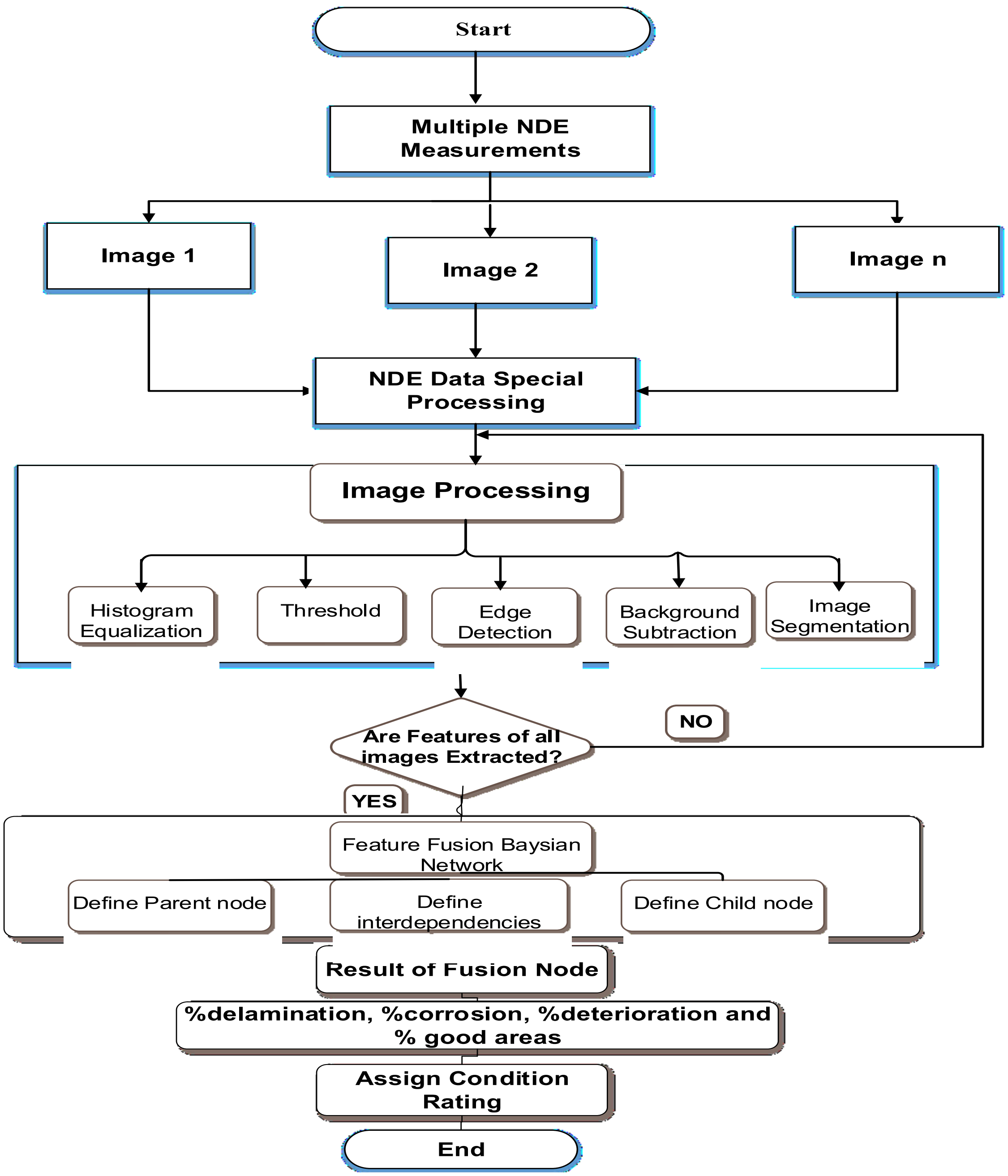


Figure 3.7: Feature fusion method with Bayesian Networks (BNs)

Bayesian network (BN) is an origin of classical Bayesian inference theory. Bayesian Network can update and integrate new data directly. It handles different type of data from different sources. The main advantage of BN is its ability to calculate probabilities of events based on new observed evidence. These probabilities are updated with observations. According to the literature review, Bayesian Networks are considered suitable techniques for performing multi sensor data fusion (Zhang and Ji 2006).

When building BNs, the prior probability of parent nodes should be specified and defined first.

Nodes that represent variables are connected through link between them. These links represent probabilistic dependence. The conditional probabilities between nodes can be estimated to define the strong relationship between child and the parent nodes.

According to the literature (Cowell and Dawid 2006; Mihajlovic and Petkovic 2001; Cowell and Dawid 1999), the Bayesian Networks are formulated mathematically as follows:

G = (V, E), where V= set of nodes and E are arrows connecting those nodes. The probability distribution of any child node is defined as $P(X_i \mid Pa(X_i))$, where $Pa(X_i)$ is the parent of node X_i. So, for a set of variables, the joint probability distribution of the nodes' values is the product of the distribution of each node given its parents as illustrated in Eq (3.9)

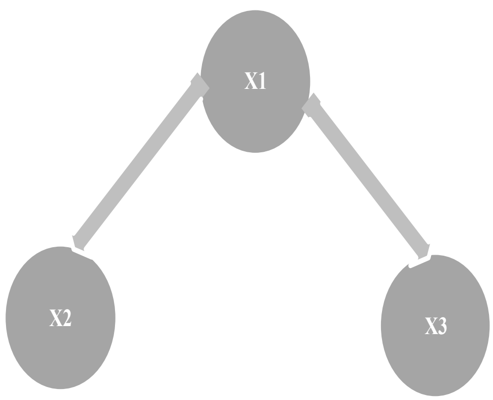
$$\mathbf{P(X_1, \ldots\ldots, X_n) = \Pi_i \; (X_i| \; Pa(X_i))} \qquad \mathbf{(3.9)}$$

As an example, if we have three variables X_1, X_2 and X_3. The joint probability distribution of the network connecting those variables are presented as in Eq (3.10).

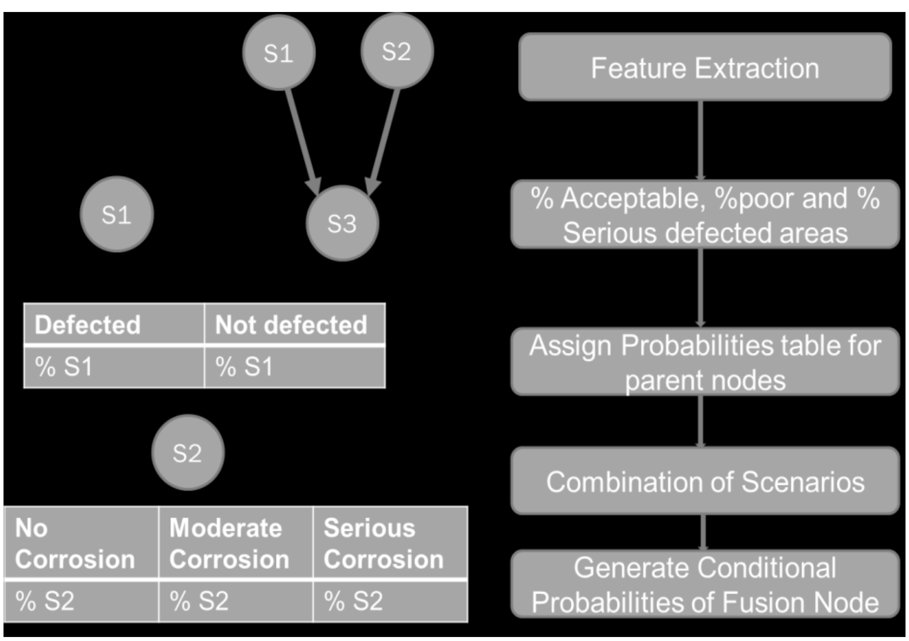
$$\mathbf{P\{X_1, X_2, X_3\} = P\{X_1\} \; P\{X_2|X_1\} \; P\{X_3|X_1\}} \qquad \mathbf{(3.10)}$$

where $P\{X_2|X_1\}$ and $P\{X_3|X_1\}$ are conditional probabilities for X_2 and X_3 respectively given X_1 and $P\{X_1\}$ is prior probability, as shown in Figure 3.8.

An example of simple Bayesian Network is illustrated in Figure 3.8. S1 and S2 are measurements of NDE1 and NDE 2 respectively. The states of node S1 are defined as defected and non-defected. The states of node S2 are defined as no corrosion, moderate corrosion and serious corrosion. The states of the fusion node are defined as non-defected, moderate defected and serious defected. The states of the parent nodes S1 and S2 are combined through combination of different scenarios. These scenarios are organized in conditional probability table (CPT) of the fusion node S3 as shown in Figure 3.8. For example, if S1 contributed defected %areas and S2 contributed serious % corrosion areas, then the %serious defected areas for the fusion node are the summation of %S1 + %S2 assigned in the CPT of the fusion node.



a) Bayesian Networks (BNs) for Three Variables X1, X2 and X3



b) Conditional Probability Table For Parent Nodes S1 and S2

		S3		
S1	**S2**	**Not defected**	**Moderate Defected**	**Serious Defected**
Defected	**No Corrosion**	% S2(No)	0	% S1(defected)
	Moderate	0	% S2 (Moderate)	% S1(defected)
	Serious	0	0	%S1(defected)+ %S2(Serious)
Not Defected	**No Corrosion**	%S1(no defect)+%S2(No corrosion)	0	0
	Moderate	%S1(not defected)	%S2(Moderate)	0
	Serious	% S1 (no defect)	0	%S2(Serious)

c) Conditional Probability Table For Fusion Node

Figure 3.8: Building Conditional Probability Table Using Bayesian Network

In this method, Bayesian network is utilized for feature fusions. These features are measurements of defected areas in a bridge deck inspected using multiple technologies. Each image is processed individually and then defected areas are extracted from images. The features extracted from each technology are fused. Condition rating for bridge deck is assigned based on the total defected areas calculated from each image and calculated for the total bridge deck section.

In the developed method, Bayesian network is modeled by applying the following steps:

1- Preprocessing for several numbers of images acquired from multiple NDE methods.

2- Images from each sensor are processed using edge detection and threshold so that images can be segmented and defected areas can be measured for each image.

3- Observations from multiple technologies are defined as parent nodes. Prior probability distribution of observations should be estimated and calculated from images.

4- Fusion node is the child node given the observation of parents' nodes. Conditional probability distribution of fusion node should be estimated.

5- The fusion of observation node is a parent of bridge condition ratings. The probability of the 5 condition ratings are the outcomes. These 5 condition ratings are child nodes of the parent node, the fusion node.

6- Conditional probabilities distribution of condition rating nodes, given the values of fusion nodes, should be estimated based on the current practice bridge condition rating. These five condition ratings are defined based on Minnesota department of transportation.

7- Results are interpreted based on the probability distribution of the resulted condition rating

The data fusion method is extended to incorporate the decision level of data fusion. A model is developed for bridge deterioration using integrated multiple NDE methods to improve the accuracy of forecasting bridge condition. The method covers the limitation of current practice deterioration models. It utilizes Dynamic Bayesian Networks (DBNs) technique and incorporate deterioration factors.

3.4. DECISION LEVEL: BRIDGE DECK DETERIORATION WITH DBNs AND NDE METHODS

The bridge deterioration model utilizes the inspection measurements acquired during bridge inspection. It includes the measurements from multiple NDE methods that usually used in the advanced inspection. These measurements are combined and their outputs are used to determine bridge deck condition rating. NDE measurements are used to detect bridge deck defected area. Bridge deck condition rating is assigned based on the percentage of the defected area. According to Minnesota department of transportation (2013), there are five condition states used to assign bridge deck condition rating. These five condition states are defined as follows:

Condition state 1: deck shows little or no deterioration

Condition State 2: combined deterioration of deck areas are less than 2%.

Condition State 3: combined deterioration of deck areas are between 2% and 10%.

Condition State 4: combined deterioration of deck areas are between 10% and 25%.

Condition state 5: combined deterioration of deck area are more than 25%.

Many attributes are impacting bridge deck deterioration. These factors are; bridge age, bridge design, environmental factors and excessive loading. The impact of these factors are stochastic. This impact is incorporated in the developed deterioration model.

The basic Bayesian network is modeled as illustrated in Figure 6.1. F1, F2,…… Fn are the deterioration factors impacting the bridge deck. Factors nodes are parents' variables contributing their impact to the condition states of the bridge deck. The bridge deck condition contributes the information to impact and cause the inspection measurements using NDE methods. Accordingly, the multiple measurements from NDE methods that are collected after the bridge deck inspection are child nodes of the bridge deck condition. These NDE measurements are considered parents nodes contributing and causing the information to their child node, which is the bridge deck condition rating. Bridge deck condition is assigned based on the combined defected area. The qualitative part of the basic Bayesian network is illustrated Figure 3.9. The quantitative part is defined using conditional probability table (CPT) between each parent node and its child node. CPT measures the strength of the relationship between them. In this research, the CPT is defined by varying the impact and occurrence of factors on bridge deck condition. CPT between bridge deck condition rating and NDE measurements is defined by varying the measured areas through five states, each state has specific range of % of the measured defected area.

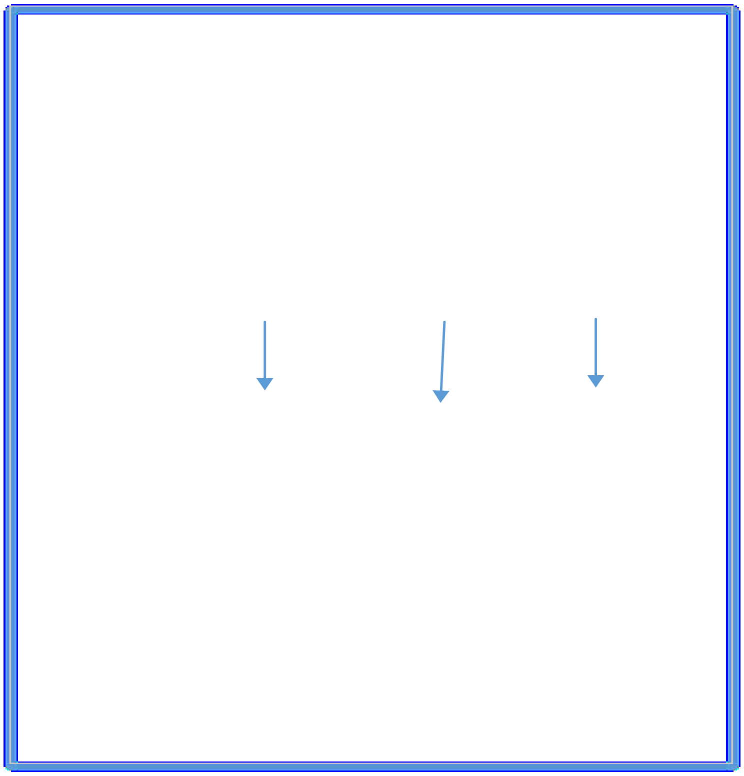


Figure 3.9**:** Bayesian Network for bridge deck deterioration modeling

The bridge deck condition state and the bridge deck condition rating are variables changing over the time. So, the basic Bayesian network is modeled as dynamic Bayesian network (DBN) through time slices. Each time slice includes the basic Bayesian network at specific time. Direct arrow is linking nodes of bridge deck condition at different times. The probabilities associated with links connecting the nodes of bridge deck condition at different time slices are defined as transition probabilities. As illustrated in Figure 3.10. The basic Bayesian network is repeated over the time. The bridge deck condition and condition rating are variables changing over the time T1, T2,….Tn. Temporary arc is used to link the change of bridge condition rating over the time to build the transition probabilities of the bridge condition.

The arc linking bridge deck condition at different times ensures that current bridge condition T2 depends on previous history of bride deck condition at T1. Modeling bridge deck deterioration in this way incorporates the maintenance action and deterioration factors in previous time units. Incorporating the stochastic impact of deterioration factors at each time unit helps accurately forecast bridge deck condition. In the developed model, the experience, past knowledge, measurements from different sources of NDE and deterioration factors are combined. The model can be updated with new information from NDE measurements. It will be updated, if more NDE methods are incorporated and their results are fused. More extra factors can be incorporated as well.

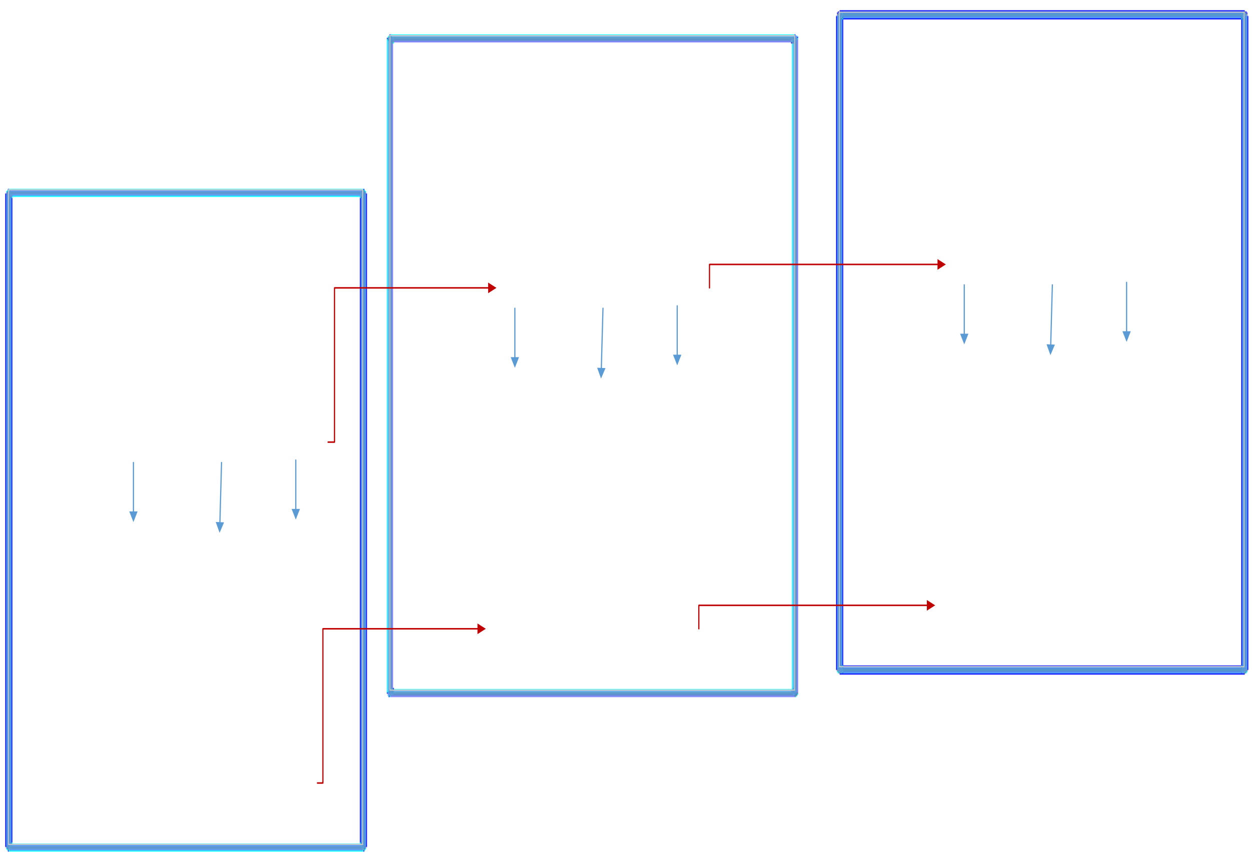


Figure 3.10: DBNs Model for bridge deterioration

3.5. APPLICATION OF PIXEL IMAGE FUSION WITHIN CASE STUDY

3.5.1. GROUND PENETRATING RADAR (GPR)

Ground penetration radar (GPR) uses electromagnetic waves that penetrate into the surface through different layers. These layers are with different dielectric material properties. The velocity of waves penetrating these different layers varies based on the material properties. When electromagnetic waves faces an interface between layers of materials with different properties, part of the waves reflect back and the remaining waves continues to the next layer. GPR measures the time that the waves take to travel through deck material and reflect back (Shin and Grivas 2003). From a given velocity and measured time that waves take to penetrate layers, distances of different layers can be measured.

The amplitude of the reflected waves is considered a basic principle to assess bridge deck condition using GPR (Shin and Grivas 2003). The amplitude of the reflected waves indicates changes in the material of the bridge deck and presences of two different materials located within bridge deck such as voids, cracks and rebar corrosion (Maser 1996; Shin and Grivas 2003). Therefore, GPR evaluates the reflection of electromagnetic waves at the interface between two materials with different dielectric constant. The penetration of waves into the subsurface is a function of the deck material properties (Dinh and Zayed 2014; Gucunski et al. 2010).

GPR data can be displayed in B scan (2D) or C scan (3D) format. Each 2D scan contains series of reflected waves that vary in amplitude. The vertical axis in B scans display the depth and the horizontal axis display the distance that is scanned by radar antenna. Series or parallel

2D scan image of GPR spaced within equal constant distance can be converted to C scan or 3D Image to map the condition of the bridge deck.

For simplicity of GPR data processing and results interpretation, amplitude color range is assigned to the amplitude variation on the bridge deck.

3.5.2. INFRARED-THERMOGRAGHY (IR)

A thermal imaging records the intensity of radiation in the infrared part of the electromagnetic spectrum and converts it into visible image temperature of colors increase from the violet to red part. So, it is the way to convert pixel to a temperature measure. IR is used to locate possible delamination of concrete through the monitoring of temperature variation on a concrete surface using infrared camera. The results of IR images provide inspectors images of concrete defects instead of sounding tests. Areas with high temperature present delaminated area of concrete. Areas with low temperature present areas with good conditions.

3.5.3. FUSING IR IMAGES AND GPR SCANS

Measurements are taken using Infrared thermography camera and ground penetrating Radar (Yaghi 2014). These measurements were acquired during the inspection process on June, 2014 to assess the condition of a concrete bridge deck in Montreal. The section of the deck, which is considered in this study, is of 7 m width and 11 m length. 77 infrared camera images were taken for this section and 24 paths within GPR scan.

The asphalt layer was removed from the inspected area. The inspected area was divided into grid with 77 square areas of dimension of 1m X 1m each. Regular images were taken to cover the same inspected area. Captured inspection images from IR is processed based on the physical principal of IR. The IR camera used in the inspection was Therma CAM S60 from

FLIR. Images are processed using software FLIR. Figure 3.11 illustrates the grid and locations of 77 IR images. Figure 3.12 illustrates the GPR scans acquired in the same bridge deck surface.

Bridge deck was mapped by 24 scans equally spaced by 0.3048 m as illustrated in Figure 3.12. GPR with pushing cart provided from GSSI with antenna of 1.5 GHZ was used to do the scan of the bridge deck. Scans are made starting from 0.4572 m from each side. The electromagnetic waves are generated by the control unit and transferred to the GPR antenna and finally to the bridge deck. The waves are reflected back to the antenna when facing different material in the bridge deck or facing deterioration and defects, then transferred back to the control unit to be processed and results of scans are interpreted.

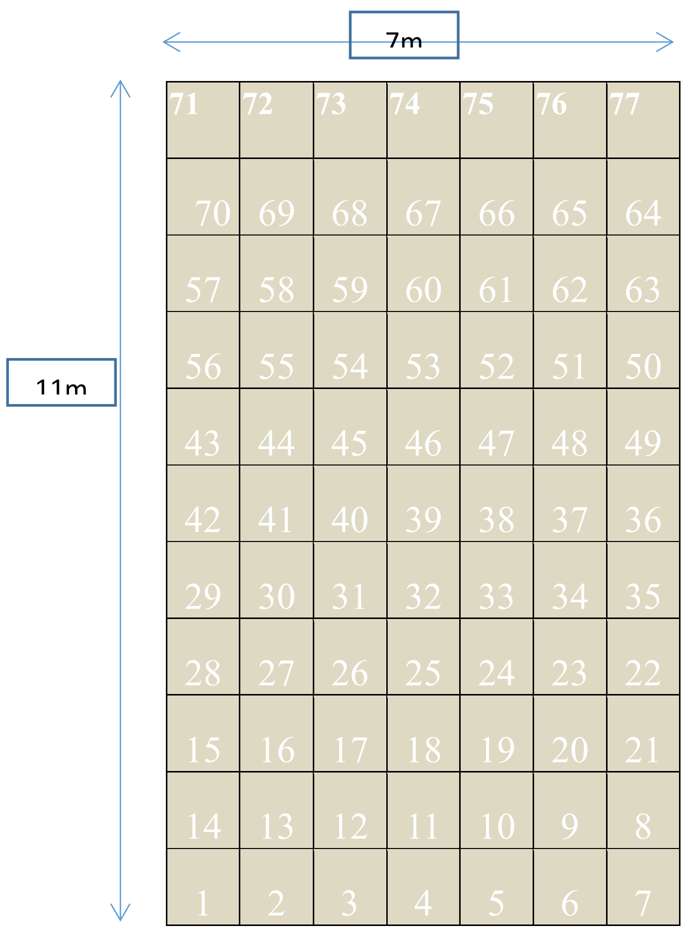


Figure 3.11 : IR images on the grid

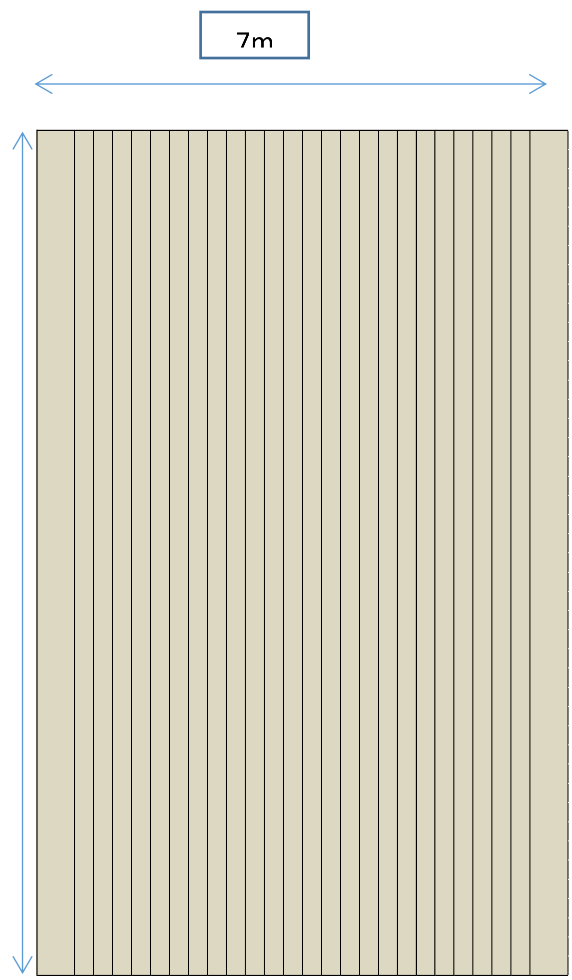


Figure 3.12: GPR 24 Passes

The proposed method can be applied for each image individually or for the total bridge deck. Each IR image is processed thermally to highlight the deteriorated areas with the high temperature. Image processing techniques such as histogram equalization is applied to enhance the contrast of the image. Edge detection and segmentation are applied to define objects in the image and then deteriorated areas are measured from the total area of the image. Image registration has been applied for both images from GPR and IR to ensure that both images are having the same coordinates when applied. Therefore, image registration is performed when images of GPR and IR are rescaled to be within same scale and size to fuse pixel of these images. The data fusion method applied to fuse IR and GPR are illustrated in Figure 3.13 and Figure 3.14.

For more illustration, IR image # 28 from total number of 77 images is used as an example; the deteriorated area is calculated as 0.12 m square in a total of 1 m square area. For IR image #28 location, there are three GPR passes. GPR B scans are processed to map deterioration of concrete bridge deck by converting B scan to C scan. Figure 3.15 shows the 3D GPR image implemented using RADAN7 software which, after processing, represents the GPR deck condition at the surface of same location of IR image. The 3D image of GPR was developed from 3 paths of GPR B scans spaced with 0.33 m. Image processing techniques are applied as well on the GPR 3D image. This image was processed by applying colors table # 28 to amplitudes variations. The dark red color represents the deteriorated area and blue represents the good area with less deterioration as illustrated in Figure 3.16. When utilizing image processing techniques such as edge detection, threshold and image segmentation, the deteriorated areas are measured from the total image area. The deteriorated area from GPR data is calculated as 0.16 m square from 1 m square. This deteriorated area was measured from the processed image as shown in Figure 3.16. Figure 3.17 illustrates the processed IR image; the light area presents the deteriorated area with high temperature where the dark area presents areas with less deterioration. Wavelet transform technique is applied to fuse IR image and GPR scan using MATLAB software. Figure 3.18 shows the fused image of IR#28 and GPR processed surface image. The output of image fusion is one image that includes all the deteriorated areas from both sensors, GPR and IR. The location of defected area on the fused image can be the same location for the both technologies. If the defected areas that captured by the two sensors in the fused image are not within same location, total defected areas will be calculated as sum of both IR and GPR areas. So, fusing the defected areas from IR and GPR is complementary. The calculated total defective area for IR and GPR in the fused image is 0.15 m square. As illustrated in Figure 3.18, the deteriorated area is measured as sum of the high temperature area which appears as white from IR and red area from GPR.

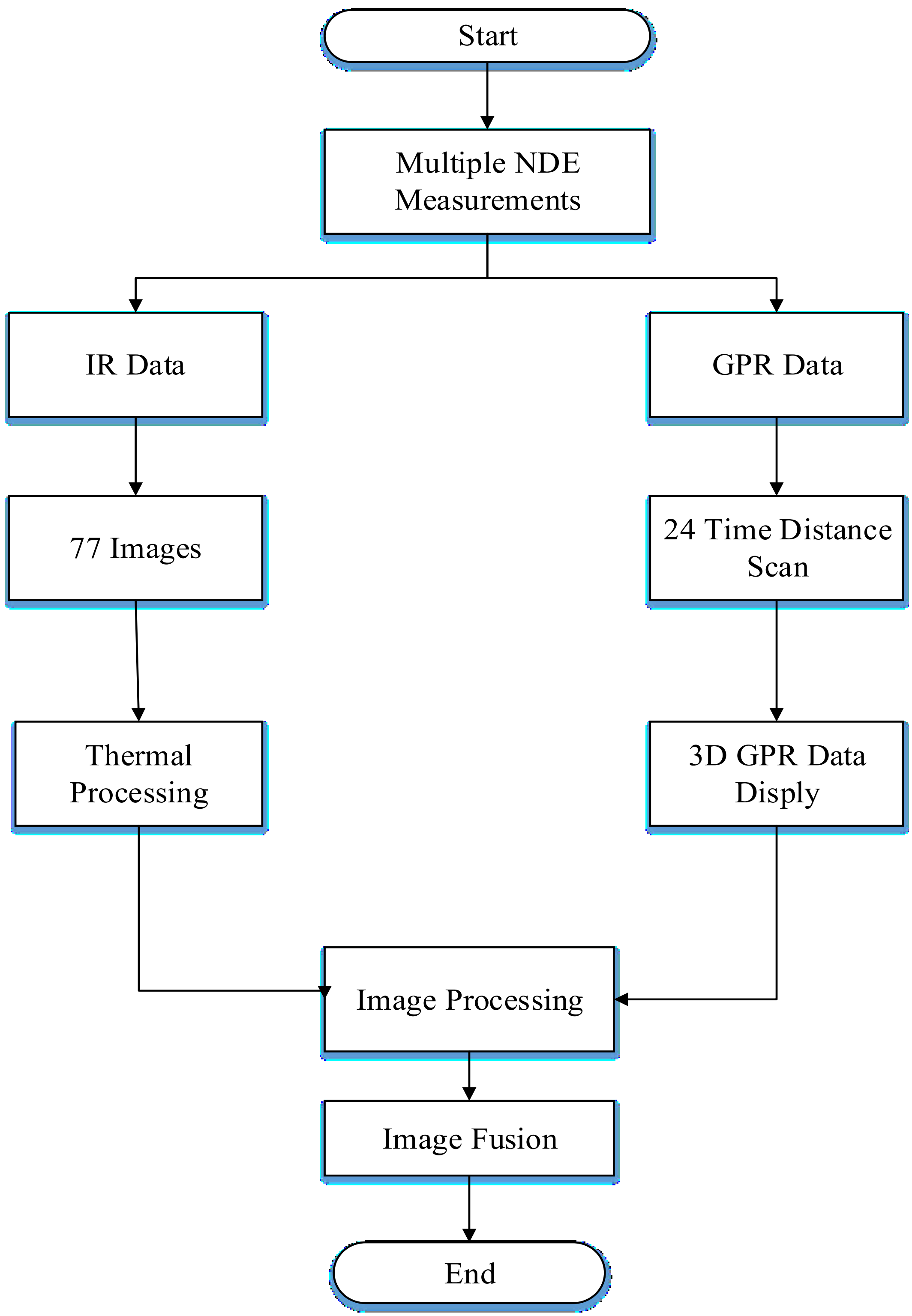


Figure 3.13 : Basic Flow Chart of fusing GPR and IR

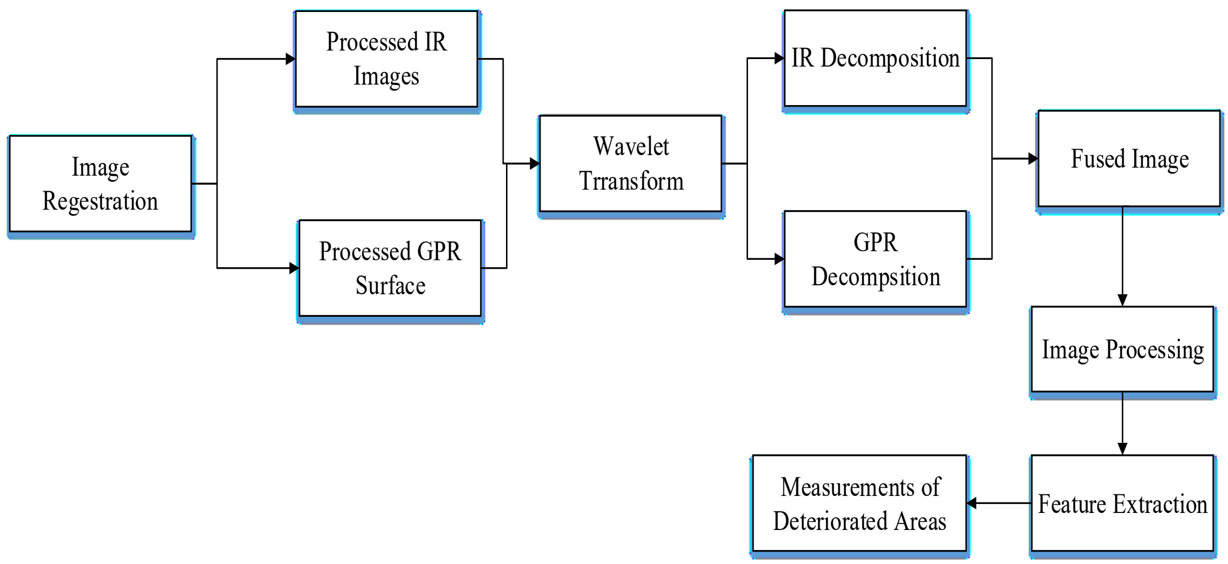


Figure 3.14: The main steps of IR and GPR Decomposition

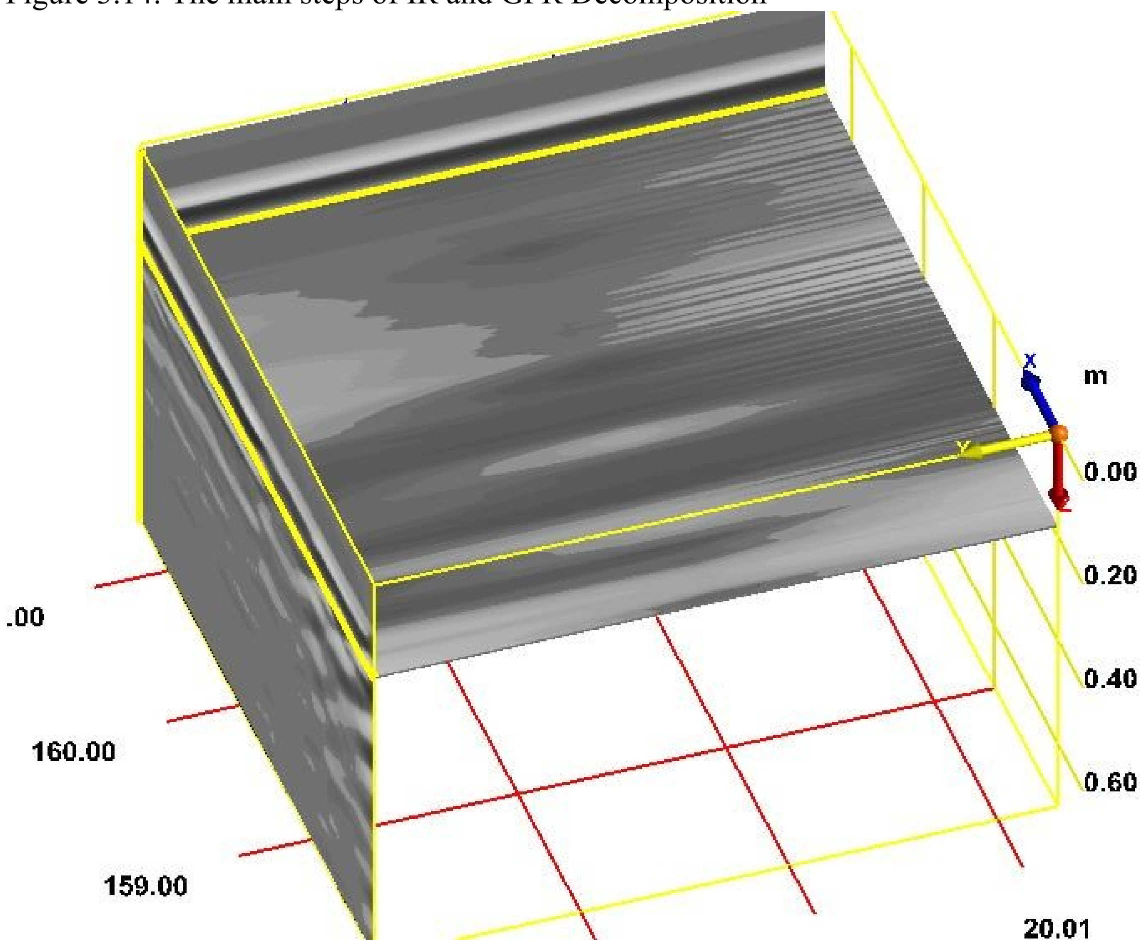


Figure 3.15: GPR 3D Image in the location of image # 28

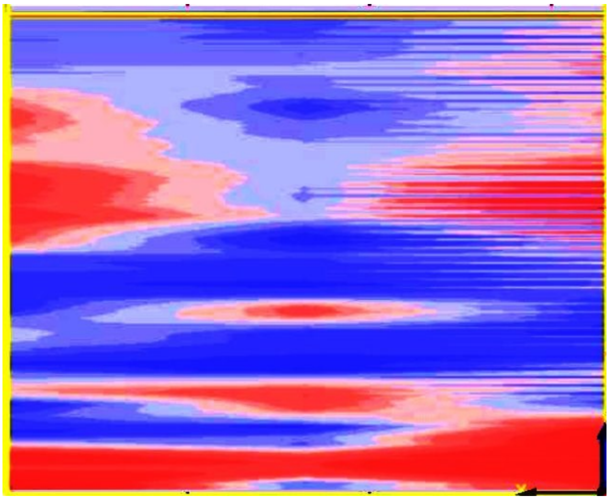


Figure 3.16: Processing GPR 2D surface in location of Image 28

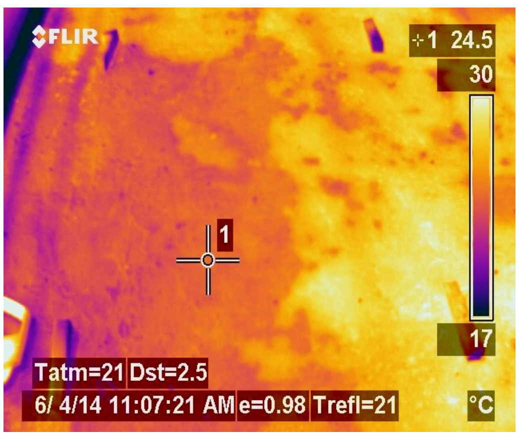


Figure 3.17: IR 28 (Yaghi 2014) Figure 3.18 : Fused Image IR+GPR

3.5.4. IMAGE FUSION FOR INSPECTED BRIDGE DECK

As stated earlier, a 77 square meter section of the concrete bridge located in Laval, Montreal was inspected with IR and GPR. GPR images were collected from 24 GPR 2D scans, and were preprocessed, before fusion. Figures 3.19 and 3.20 illustrate the total bridge surface for IR and GPR respectively before fusion. It was observed that total deteriorated areas in the bridge are 13 meter square with IR and 15.3 meter square from GPR. In this research, Image fusion was done using wavelet decomposition in MATLAB software. The deteriorated areas were calculated after highlighting the defective areas, as it is the combination of the area with the high temperature from IR images and the more light areas from the colors that was assigned to the GPR amplitude. As explained earlier, there are 30 color tables that can be assigned to the GPR amplitude. For the total section surface, grey level color was assigned to GPR amplitude to represent the more defective areas. The very dark grey is an indication of good areas; the more light grey is an indication of the areas with more deterioration. In Figure 3.19, the discontinuities that appear at the edge of the Infrared images are a result of stitching the individual 77 images each of 1m*1m to represent the entire inspected area, 7m*11m. These discontinuities are neglected while measuring the defected areas.

The fused image is presented in Figure 3.21. In this research, the contrast of images can be enhanced using image normalization or histogram equalization techniques. The fused image is normalized in Figure 3.22. It is observed that the total deteriorated areas were 21 meter square, which represents around 25 percent from the total tested deck area (77meter square). The deteriorated areas are measured from Figure 3.23 using image segmentation technique. These deteriorated areas are shown as the lighter areas in the bridge deck surface. Light areas are the combination of the deteriorated areas from IR and GPR. The repeated features in the upper left hand corner for IR images in the fused image are information about the temperature of the image. These features are included in the fused image, but have not been considered as defected areas.

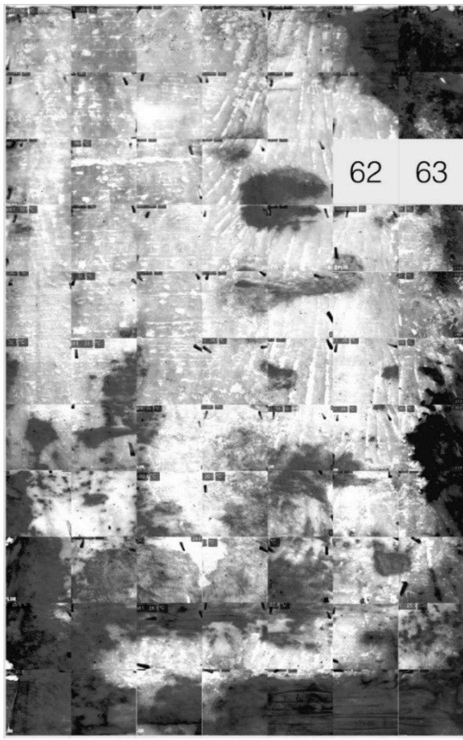


Figure 3.19: IR surface before fusion

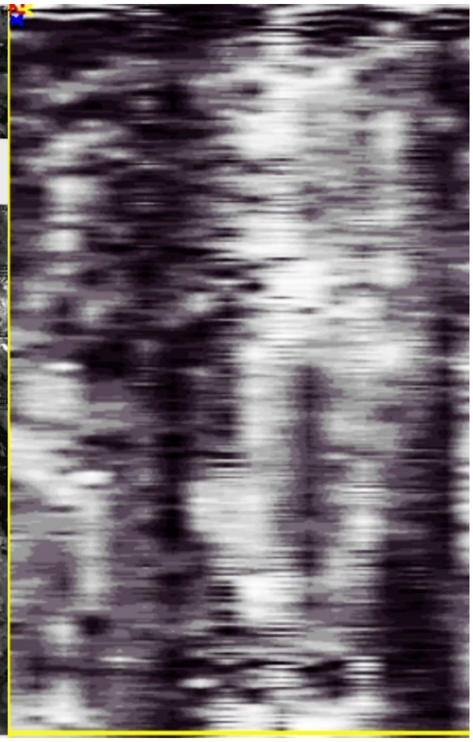


Figure 3.20: GPR surface before fusion

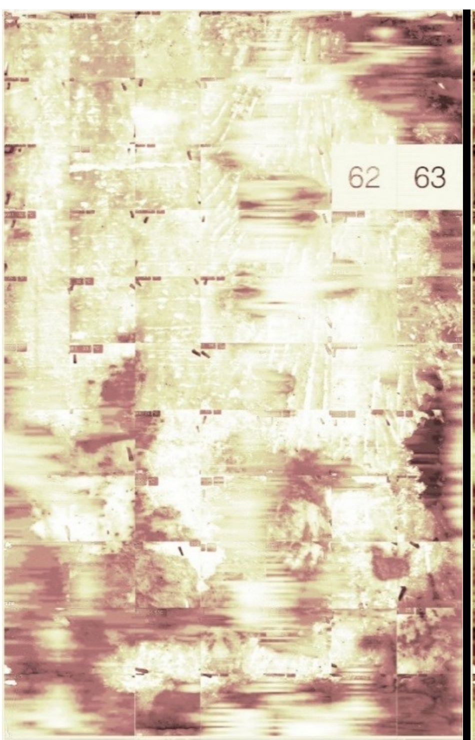


Figure 3.21 : The fused image

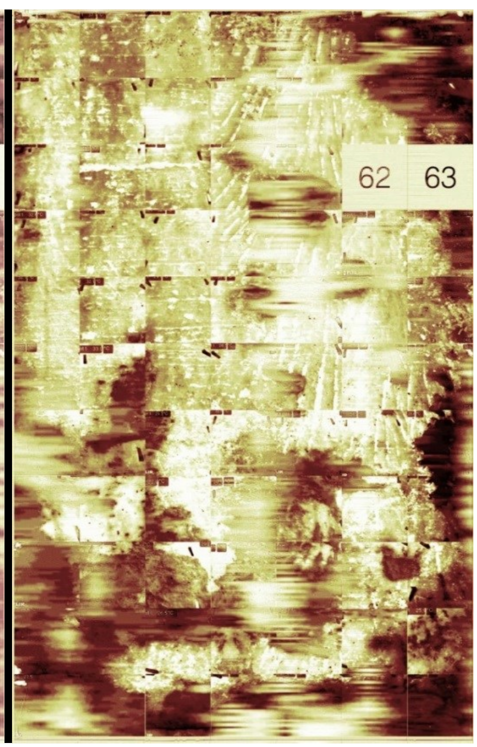


Figure 3.22: The normalized fused image

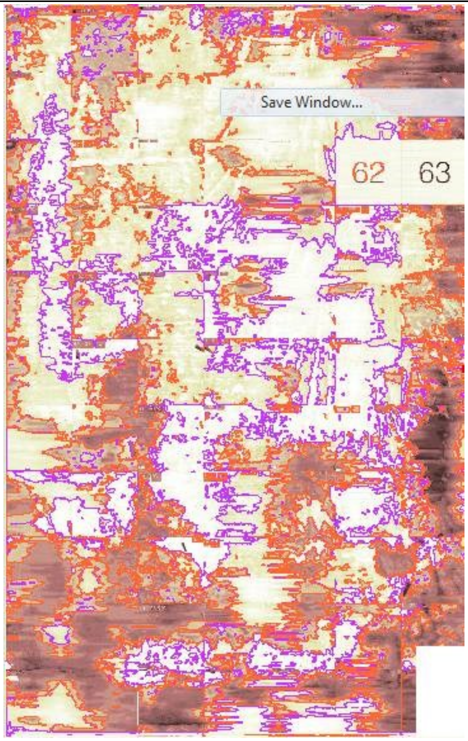


Figure 3.23: Extraction of defected areas from the fused image

3.6. APPLICATION Of FEATURE FUSION WITHIN THE CASE STUDY

Measurements were taken using Infrared thermography camera and Ground Penetrating Radar (Yaghi 2014). These measurements were acquired during the inspection process on June 2014 to assess the condition of a bridge deck in Montreal, Quebec, Canada. The section that assessed is 7 m width and 11 m length. 77 infrared camera images were taken for this section, The asphalt layer was removed from the inspected area. The inspected area was divided into grid with 77 square areas of dimension of 1m X 1m each. Regular images were taken to cover the same inspected area. The IR camera used in the inspection was Therma CAM S60 from FLIR. Pieces from wood were used to define the edges of 77 squares areas. Images were processed using software FLIR.

Bridge deck was scanned by 24 scans equally spaced by one foot. GPR with pushing cart provided from GSSI with antenna 1.5 GHZ was used to do the scan on bridge deck. Scans were made starting from 1.5 feet from each side. Figure 3.24 illustrates the basic steps for feature fusion using two sensing technologies GPR and IR.

Deterioration areas were mapped from both GPR images and IR images. It was observed that total deteriorated areas in the bridge are 13 meter square with using only IR images and 15.3 meter square from GPR scans. The deteriorated areas were extracted and measured for each image individually. Accordingly, 77 measurements values from IR are fused with 77 measurements values from GPR. Measurements of features that extracted from each image data of IR and GPR can be modeled to fuse data within feature level. Bayesian network is used to model two networks: network1 and network2. Table 3.1 illustrates the defected areas extracted from GPR and IR. Condition rating is assigned to each individual image based on the defected area measured from each image. These defected areas are extracted after applying image processing techniques that help to extract the defected areas in the bridge deck.

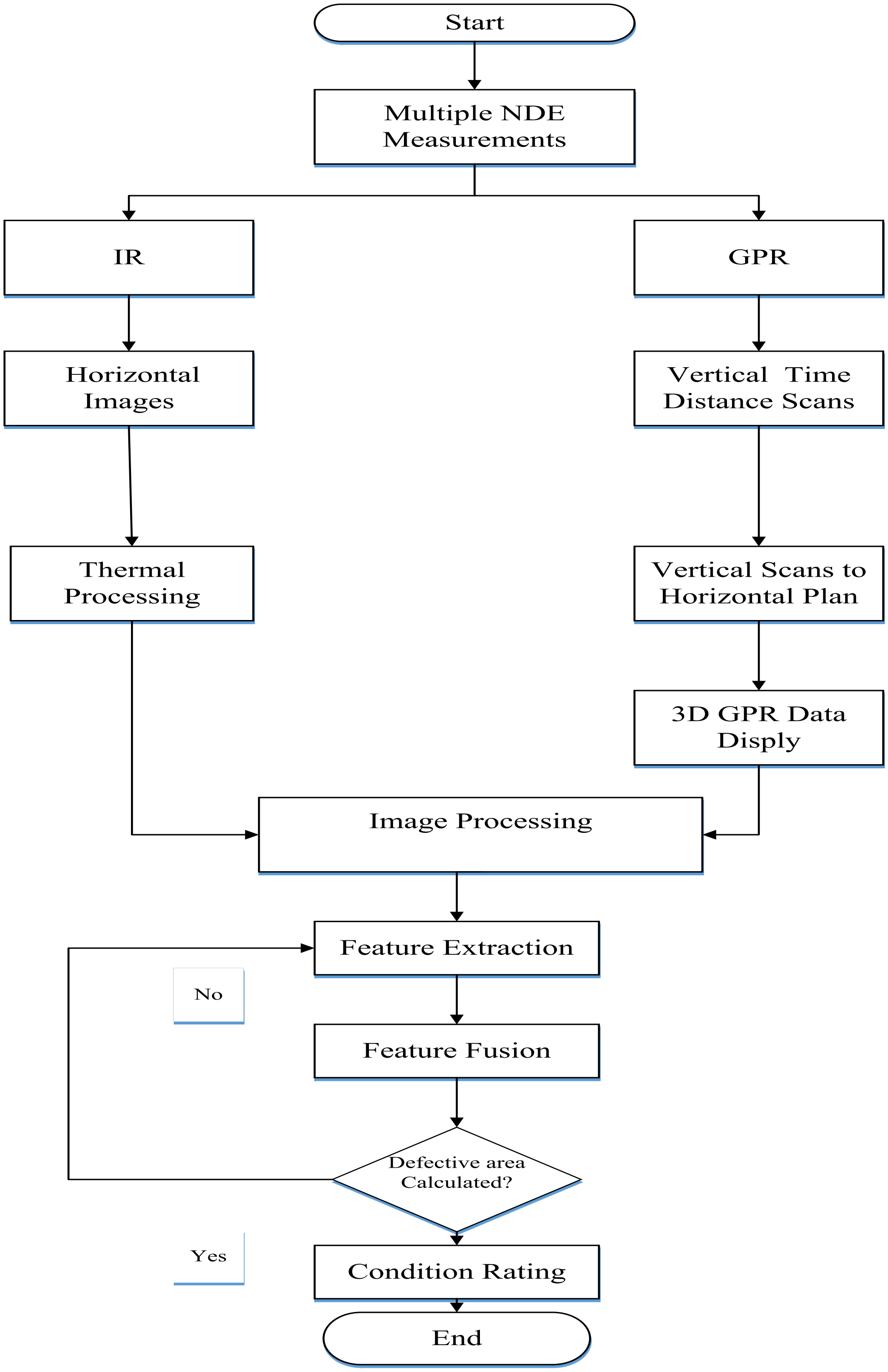


Figure 3.24: The basic steps of feature fusion using IR and GPR

Table 3-1: Deteriorated areas extracted from GPR Scans located with 77 IR Images

IR	Area	Calibration	% Defected Area	GPR	Area	Calibration	% Defected Area	IR(X1)	Condition Rating	GPR	Condition Rating
IR1	0	0	0	GPR1	25057	0.225789592	22.57895923	IR1	1	GPR1	4
IR2	7428	0.0967188	9.671875	GPR2	40458	0.364568597	36.45685965	IR2	3	GPR2	5
IR3	8309	0.1081901	10.81901042	GPR3	27258	0.245622888	24.5622888	IR3	4	GPR3	4
IR4	11610	0.1511719	15.1171875	GPR4	27687	0.249488624	24.94886236	IR4	4	GPR4	5
IR5	7234	0.0941927	9.419270833	GPR5	20297	0.182897049	18.28970489	IR5	3	GPR5	4
IR6	5033	0.0655339	6.553385417	GPR6	29751	0.268087407	26.80874071	IR6	3	GPR6	5
IR7	11540	0.1502604	15.02604167	GPR7	36620	0.329984231	32.99842307	IR7	4	GPR7	5
IR8	4859	0.0632682	6.326822917	GPR8	38889	0.350430277	35.04302771	IR8	3	GPR8	5
IR9	6566	0.0854948	8.549479167	GPR9	37632	0.339103402	33.91034017	IR9	3	GPR9	5
IR10	8149	0.1061068	10.61067708	GPR10	22842	0.205830142	20.58301419	IR10	4	GPR10	4
IR11	8310	0.1082031	10.8203125	GPR11	34858	0.314106781	31.41067808	IR11	4	GPR11	5
IR12	3421	0.0445443	4.454427083	GPR12	41897	0.377535481	37.7535481	IR12	3	GPR12	5
IR13	15094	0.1965365	19.65364583	GPR13	37310	0.336201847	33.62018473	IR13	4	GPR13	5
IR14	0	0	0	GPR14	25195	0.227033116	22.70331156	IR14	1	GPR14	4
IR15	11087	0.144362	14.43619792	GPR15	25195	0.227033116	22.70331156	IR15	4	GPR15	4
IR16	3554	0.046276	4.627604167	GPR16	39139	0.352683037	35.26830367	IR16	3	GPR16	5
IR17	16558	0.215599	21.55989583	GPR17	44759	0.403325073	40.33250732	IR17	4	GPR17	5
IR18	9818	0.1278385	12.78385417	GPR18	32506	0.292912818	29.29128182	IR18	4	GPR18	5
IR19	16842	0.2192969	21.9296875	GPR19	23490	0.211669295	21.16692949	IR19	4	GPR19	4
IR20	9335	0.1215495	12.15494792	GPR20	28174	0.253876999	25.38769993	IR20	4	GPR20	5
IR21	13955	0.1817057	18.17057292	GPR21	36123	0.325505745	32.55057445	IR21	4	GPR21	5
IR22	14513	0.1889714	18.89713542	GPR22	37562	0.338472629	33.8472629	IR22	4	GPR22	5
IR23	22471	0.2925911	29.25911458	GPR23	25844	0.23288128	23.28812796	IR23	5	GPR23	4
IR24	6338	0.082526	8.252604167	GPR24	23101	0.208164001	20.81640009	IR24	3	GPR24	4
IR25	30139	0.3924349	39.24348958	GPR25	31199	0.281135391	28.11353909	IR25	5	GPR25	5
IR26	19742	0.2570573	25.70572917	GPR26	45317	0.408353233	40.83532327	IR26	5	GPR26	5
IR27	1562	0.0203385	2.033854167	GPR27	40015	0.360576706	36.05767065	IR27	2	GPR27	5
IR28	14380	0.1872396	18.72395833	GPR28	25195	0.227033116	22.70331156	IR28	4	GPR28	4
IR29	10277	0.1338151	13.38151042	GPR29	26601	0.239702636	23.97026357	IR29	4	GPR29	4
IR30	9465	0.1232422	12.32421875	GPR30	41281	0.371984681	37.19846812	IR30	4	GPR30	5
IR31	12932	0.1683854	16.83854167	GPR31	44569	0.401612976	40.16129759	IR31	4	GPR31	5
IR32	13539	0.1762891	17.62890625	GPR32	31850	0.287001577	28.70015769	IR32	4	GPR32	5
IR33	11094	0.1444531	14.4453125	GPR33	19832	0.178706916	17.8706916	IR33	4	GPR33	4
IR34	11466	0.1492969	14.9296875	GPR34	27451	0.247362018	24.73620185	IR34	4	GPR34	4
IR35	5066	0.0659635	6.596354167	GPR35	35338	0.318432079	31.84320793	IR35	3	GPR35	5
IR36	11263	0.1466536	14.66536458	GPR36	38738	0.34906961	34.90696103	IR36	4	GPR36	5
IR37	12046	0.156849	15.68489583	GPR37	25879	0.233196666	23.31966659	IR37	4	GPR37	4
IR38	19580	0.2549479	25.49479167	GPR38	22450	0.202297815	20.22978148	IR38	5	GPR38	4
IR39	14952	0.1946875	19.46875	GPR39	29049	0.261761658	26.1761658	IR39	4	GPR39	5
IR40	19806	0.2578906	25.7890625	GPR40	41281	0.371984681	37.19846812	IR40	5	GPR40	5
IR41	3682	0.0479427	4.794270833	GPR41	40408	0.364118045	36.41180446	IR41	3	GPR41	5
IR42	3313	0.043138	4.313802083	GPR42	25137	0.226510475	22.65104753	IR42	3	GPR42	4
IR43	33566	0.4370573	43.70572917	GPR43	25195	0.227033116	22.70331156	IR43	5	GPR43	4
IR44	3359	0.043737	4.373697917	GPR44	38988	0.35132237	35.13223699	IR44	3	GPR44	5
IR45	14588	0.1899479	18.99479167	GPR45	33459	0.301500338	30.15003379	IR45	4	GPR45	5
IR46	7095	0.0923828	9.23828125	GPR46	29312	0.264131561	26.41315612	IR46	3	GPR46	5
IR47	6992	0.0910417	9.104166667	GPR47	22180	0.199864834	19.98648344	IR47	3	GPR47	4
IR48	3713	0.0483464	4.834635417	GPR48	28965	0.261004731	26.10047308	IR48	3	GPR48	5
IR49	9017	0.1174089	11.74088542	GPR49	38109	0.343401667	34.3401667	IR49	4	GPR49	5
IR50	10906	0.1420052	14.20052083	GPR50	39370	0.354764587	35.47645866	IR50	4	GPR50	5
IR51	6444	0.0839063	8.390625	GPR51	28805	0.259562965	25.95629646	IR51	3	GPR51	5
IR52	5037	0.0655859	6.55859375	GPR52	23908	0.215435909	21.5435909	IR52	3	GPR52	4
IR53	7057	0.091888	9.188802083	GPR53	26947	0.242820455	24.28204551	IR53	3	GPR53	4
IR54	5201	0.0677214	6.772135417	GPR54	38281	0.344951566	34.49515657	IR54	3	GPR54	5
IR55	4424	0.0576042	5.760416667	GPR55	40846	0.368064879	36.80648795	IR55	3	GPR55	5
IR56	8906	0.1159635	11.59635417	GPR56	25195	0.227033116	22.70331156	IR56	4	GPR56	4
IR57	10697	0.1392839	13.92838542	GPR57	25195	0.227033116	22.70331156	IR57	4	GPR57	4
IR58	6646	0.0865365	8.653645833	GPR58	38517	0.347078171	34.70781708	IR58	3	GPR58	5
IR59	11064	0.1440625	14.40625	GPR59	44160	0.397927461	39.79274611	IR59	4	GPR59	5
IR60	8553	0.1113672	11.13671875	GPR60	31309	0.282126605	28.21266051	IR60	4	GPR60	5
IR61	4459	0.0580599	5.805989583	GPR61	20262	0.182581663	18.25816625	IR61	3	GPR61	4
IR62	314360	0.1573714	15.73713636	GPR62	25771	0.232223474	23.22234738	IR62	4	GPR62	4
IR63	672618	0.3367184	33.67184496	GPR63	38317	0.345275963	34.52759631	IR63	5	GPR63	5
IR64	7205	0.0938151	9.381510417	GPR64	36071	0.325037171	32.50371705	IR64	3	GPR64	5
IR65	6863	0.089362	8.936197917	GPR65	29450	0.265375084	26.53750845	IR65	3	GPR65	5
IR66	8222	0.1070573	10.70572917	GPR66	20262	0.182581663	18.25816625	IR66	4	GPR66	4
IR67	10752	0.14	14	GPR67	24024	0.216481189	21.64811895	IR67	4	GPR67	4
IR68	7626	0.0992969	9.9296875	GPR68	40328	0.363397162	36.33971615	IR68	3	GPR68	5
IR69	6838	0.0890365	8.903645833	GPR69	38718	0.34888939	34.88893895	IR69	3	GPR69	5
IR70	16571	0.2157682	21.57682292	GPR70	25195	0.227033116	22.70331156	IR70	4	GPR70	4
IR71	7493	0.0975651	9.756510417	GPR71	25195	0.227033116	22.70331156	IR71	3	GPR71	4
IR72	6272	0.0816667	8.166666667	GPR72	38718	0.34888939	34.88893895	IR72	3	GPR72	5
IR73	7329	0.0954297	9.54296875	GPR73	46549	0.419454832	41.94548322	IR73	3	GPR73	5
IR74	23287	0.3032161	30.32161458	GPR74	28467	0.256517234	25.65172336	IR74	5	GPR74	5
IR75	14879	0.193737	19.37369792	GPR75	23101	0.208164001	20.81640009	IR75	4	GPR75	4
IR76	9982	0.129974	12.99739583	GPR76	29371	0.264663212	26.46632124	IR76	4	GPR76	4
IR77	275550	0.1379427	13.79427384	GPR77	38406	0.346077945	34.60779455	IR77	4	GPR77	5
		10.363426	13.45899452	2460180		22.16877675	0.287906192				

3.6.1. FEATURE FUSION NETWORK 1

As stated earlier, Bayesian network is employed for feature fusion. Two networks are considered in this research. Bayesian network 1 is shown in Figure 3.25 and is modeled by applying the following steps:

1- Pre-processing of IR observations from the 77 images. These images are equalized to enhance the image contrast.

2- IR images are processed using edge detection and threshold techniques so that images can be segmented and defected areas can be measured for each image.

3- GPR 2D scans are interpreted as 3D to present the plan view and map deterioration of the bridge deck.

4- The mapped bridge deterioration is processed using image processing techniques to calculate the defected areas based on the variation of the amplitude of the reflected waves.

5- The defected areas for each IR images and GPR maps are measured. 77 measurements values of the defected areas for each sensor are obtained.

6- IR and GPR measurements are defined as parent nodes. Conditional probability table for each sensor is estimated based on the 77 values for each.

7- Fusion node is the child node for IR and GPR observation parents' nodes. Conditional probability table is defined based on the parents' nodes values. Each parent is contributing information to the fusion child node.

8- Fusion observation node is a parent of five condition rating states. The probability of the five condition ratings is the outcomes of the fusion node. The conditional probability tables of the condition rating are defined based on the current practice (Minnesota department of transportation 2013) that considers the total defected areas of the bridge deck.

Condition rating is calculated according to Minnesota department of transportation (2013). This condition rating is calculated based on the calculated defective area as follows:

- Condition rating 1: There is no defective area
- Condition rating 2: The combined defective area is less than 2% from total inspected area
- Condition rating 3: The combined defective area is less than 10% from total inspected area
- Condition rating 4: The combined defective area is more than 10% and less than 25%
- Condition rating 5: The combined defective area is more than 25%

9- The final results are interpreted based on the probability of the percentage for the resulted condition rating.

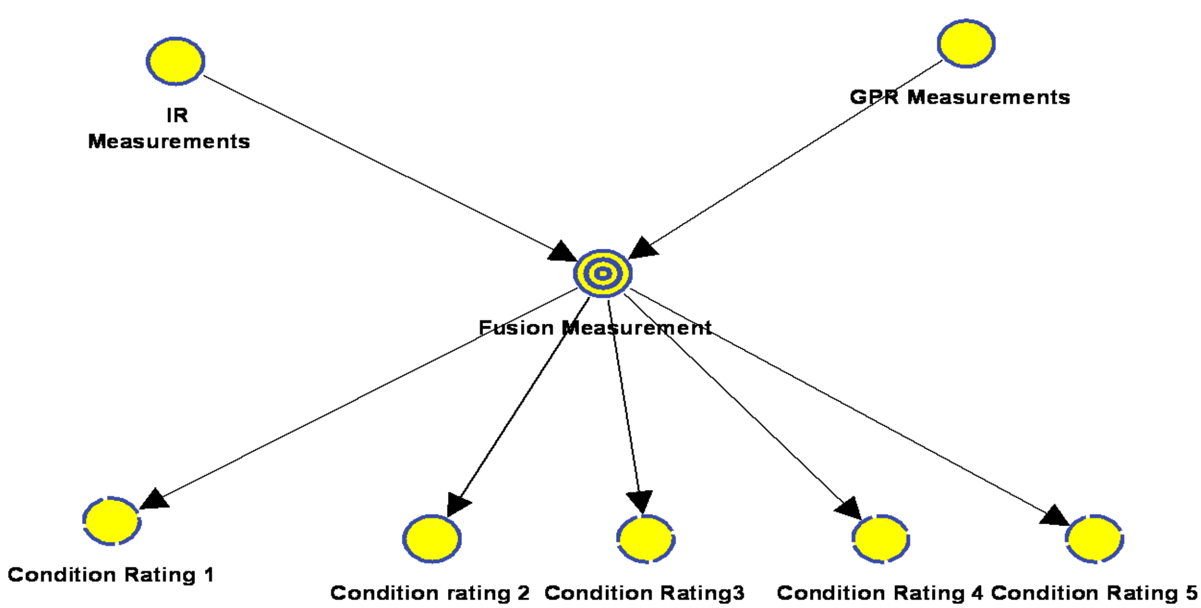


Figure 3.25: Bayesian Network1 for case1

The results in Network1 illustrated in Figure 3.26 indicate the probability of the assigned condition rating for bridge deck. These final results are interpreted based on the 77 observations values from IR and GPR. Condition rating 4 has a false percentage of 60.30% and true percentage of 39.7%. These false and true percentages represent the probability of not occurrence and occurrence respectively for condition rating 4. Condition rating 5 has a true value of 56.56% and false value of 43.44%. These results show that bridge deck condition is between condition rating 4 and condition rating 5 with higher true probability to be within condition rating 5. Condition ratings 1, 2 and 3 have high probabilities of false values as 97.40%, 98.70% and 62.34% respectively, which means that condition ratings 1, 2 and 3 are not representing the condition of the tested bridge deck section. The condition probability of the fusion measurements node has 26.57% defected areas and 73.43% not defected areas from the total tested area.

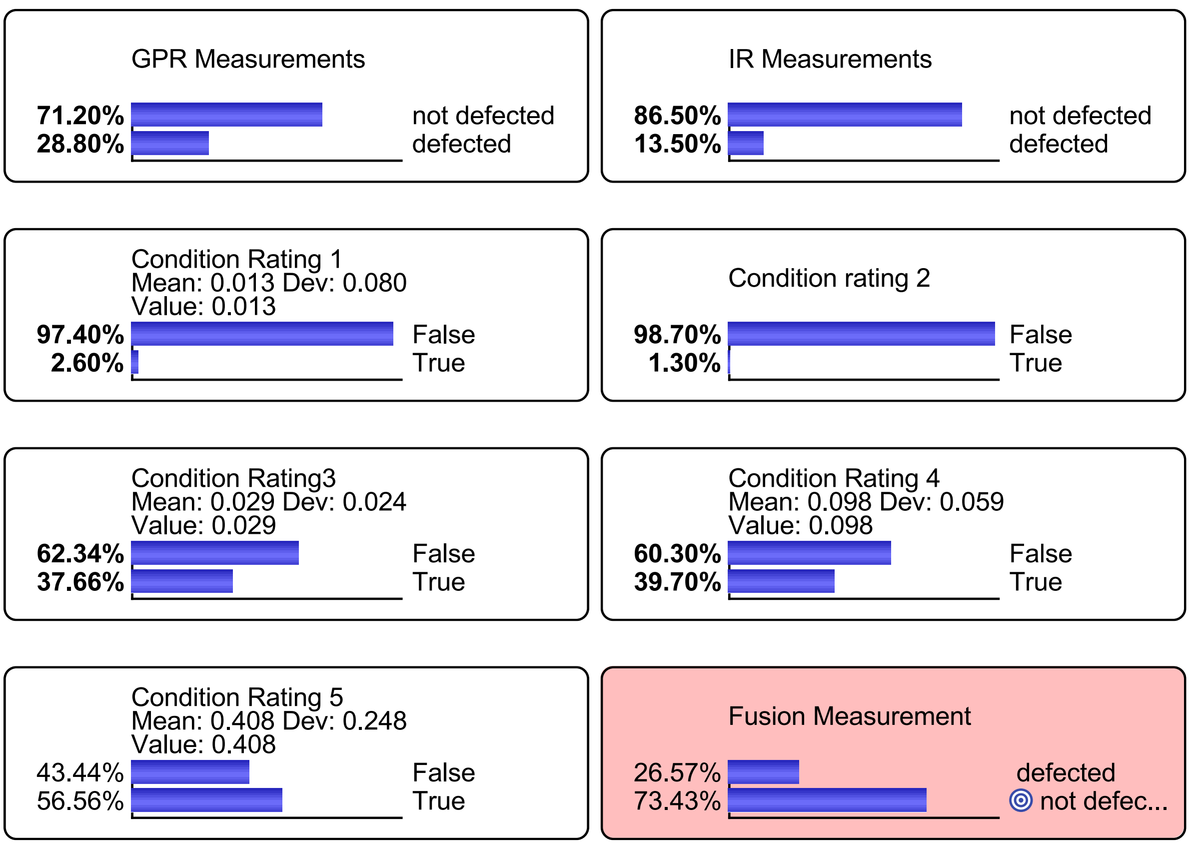


Figure 3.26: Feature Fusion results Network 1

3.6.2. FEATURE FUSION NETWORK 2

Network 2 is modeled as shown in Figure 3.27 and by applying the following steps:

Steps 1,2,3,4 and 5 are the same as Network 1

6- Condition ratings 1, 2, 3, 4 and 5 for IR are modeled as parents' nodes for IR observations node. From the analysis of the 77 individual images of IR only, the condition rating of bridge deck has a probability to be in condition 1, 2, 3, 4 and 5.

7- Only condition ratings of 4 and 5 for GPR are modeled as parents' nodes for GPR observations node for this fusion network. This is because, from the analysis of the 77 individual maps of GPR only, it is observed that the condition rating of bridge deck has a higher probability to be in between condition rating 4 and 5. The parents' nodes for GPR observation node are condition rating 4 and 5, assumed only for this case. However, for the general cases, condition rating 1, 2, 3, 4 and 5 are modeled as parents' nodes.

8- Fusion observation node is the child of GPR and IR measurements.

9-Final condition rating is assigned based on the total fused defected area.

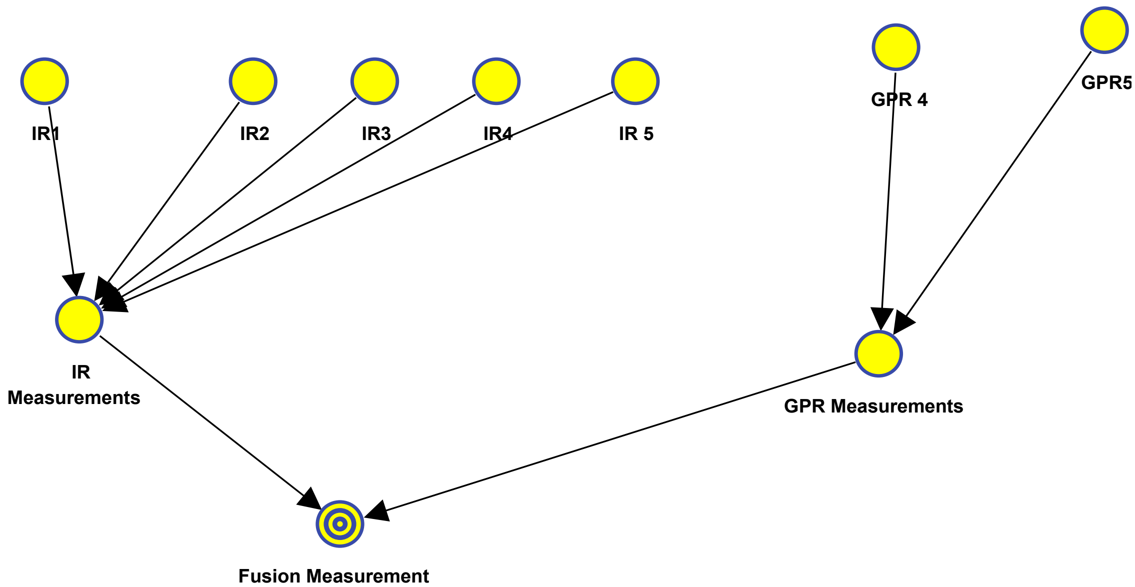


Figure 3.27: Feature Fusion Bayesian Network 2

The final results in network 2, as shown in Figure 3.28, indicate probability of total defected area for the bridge deck, presented as fusion measurements node, is 26.72%. Condition rating 4 that is based on GPR only has a false percentage of 70 % and true percentage of 30%. Condition rating 5 that is based on GPR only has a true value of 61% and false value of 39%. Thus, results show that bridge condition based on GPR only has high probability to be condition rating 5. Condition ratings 1, 2, 3 and 5 based on IR have high probabilities false values as 97.40%, 98.70%, 62.34% and 91.00% respectively, which means that condition ratings 1, 2, 3 and 5 based only on IR (single sensor) are not representing the condition of the tested bridge deck section. So, for the selected bridge, bridge condition rating based on IR only has high probability to be condition rating 4. The condition probability of the fusion measurements node has 26.57 % defected areas and 73.43% not defected areas from the total tested area. So, condition rating 5 is the most probable for the fusion measurements.

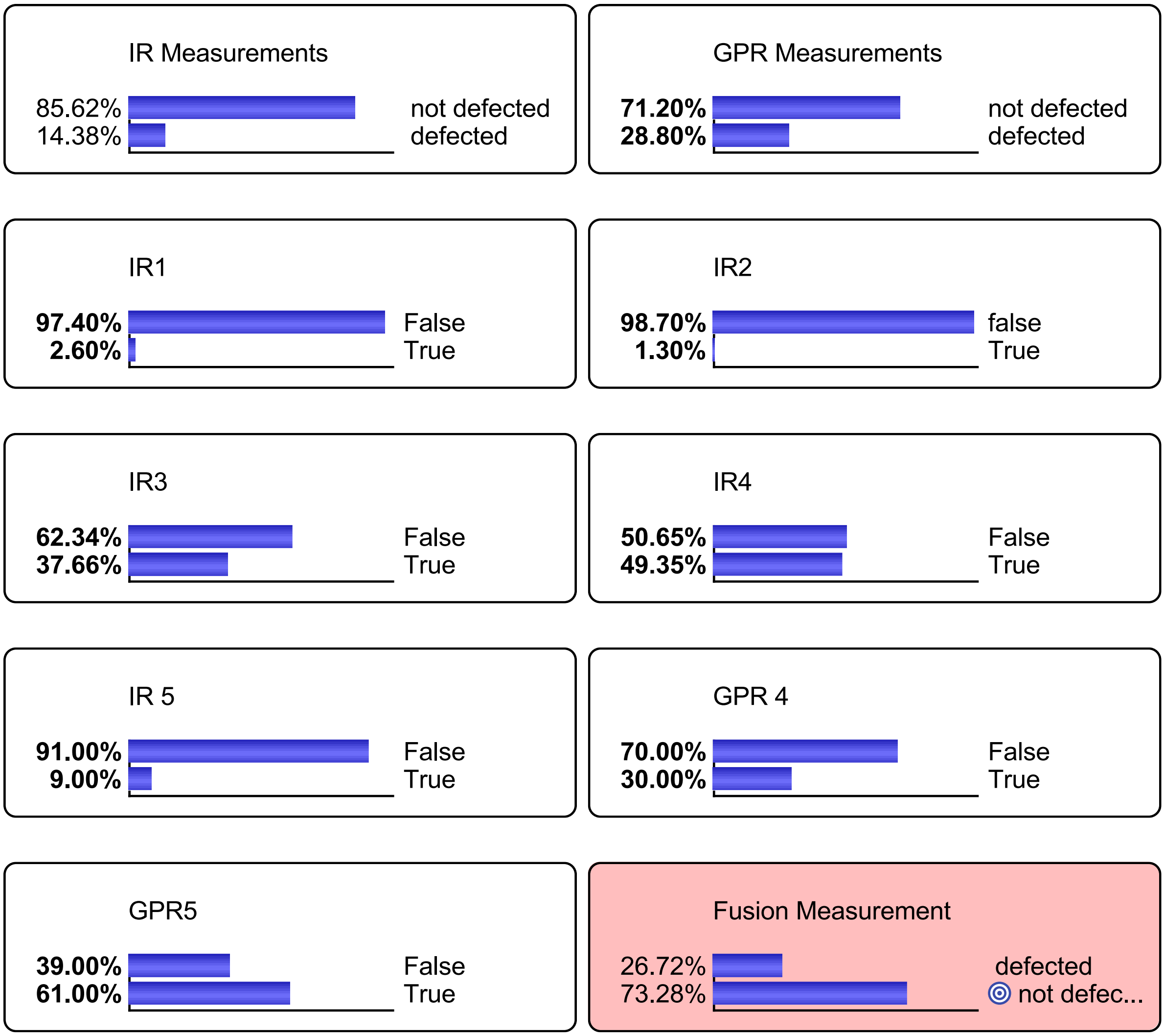


Figure 3.28: Feature Fusion Results Network 2

3.7. ANALYSIS OF RESULTS

The results show that image fusion of GPR and IR can be used to improve the accuracy of condition assessment and rating of concrete bridge decks. The final results present the defected areas generated by the developed fusion-based method. The same area with the dimension of 7 m X 11 m was inspected using the hammer sound test and visual inspection during June 2014 inspection. The defected area from hammer sound test and visual inspection is presented in Figure 3.29.

With the two networks considered in this study, feature fusion was done to assess bridge deck condition. Network 1 presents the probability of occurrence of bridge deck condition rating. All the probabilities of occurrence and not occurrence of condition ratings will help the inspectors to assign bridge condition based on fusing the measurements from two technologies (GPR and IR measurements). Network 2 fuses the condition rating resulted from each technology. The outcome is the percentage of the defected area from the total tested bridge deck. This final percentage helps to assign the final condition rating

The results show that image fusion of GPR and IR can be used to improve the accuracy of condition assessment and rating of concrete bridge decks. Table 3-2 compares results obtained from five assessments: 1- IR results, 2- GPR results, 3-pixel fusion of IR and GPR results, 4- feature fusion of IR and GPR results and 5- Hammer sound results with visual inspection, which is referred to as actual. Table 3-2 also presents the percentage of the defected area to the inspected area. The results are analyzed to illustrate the difference between fusing multiple technologies and using traditional methods such as hammer sound and visual inspection. Hammer sound is a simple technique for detecting delamination of concrete bridge deck. It is based on the sound effect when a hammer or chain is dragged over the surface of concrete bridge deck. The area with no delamination, the sound will be clear. The area with delamination, the sound will be hollow because of voids. During the inspection, the delaminated areas on this section were obtained as 8.54 meter square and 13.6 meter square for hammer sound and visual inspection respectively. As illustrated in Figure 3.29, green and grey colors are for hammer sound and visual inspection respectively. In Table 3-2, condition rating is calculated according to Minnesota department of transportation (p2013).

This condition rating is calculated based on the calculated defective area as follows:

- Condition rating 1: There is no defective area
- Condition rating 2: The combined defective area is less than 2% from total inspected area
- Condition rating 3: The combined defective area is less than 10% from total inspected area
- Condition rating 4: The combined defective area is more than 10% and less than 25%
- Condition rating 5: The combined defective area is more than 25%

The percentage errors are calculated as difference between actual inspections, which represents the visual inspection plus hammer sound, and the other methods used: IR as single sensor, GPR as single sensor and the fusion of GPR and IR as multiple sensors. The results as shown in Table 3-2 illustrates that fusion method is very close to the actual case. Thus, method 4, which is the actual condition using hammer sound and visual inspection at the inspected area, is assigned condition rating of 5.

The scope of this research is to address the condition rating based on the measured defected area on the bridge deck as per the state of Minnesota. This does not specifically address deck strength against different types of loads applied on the bridge.

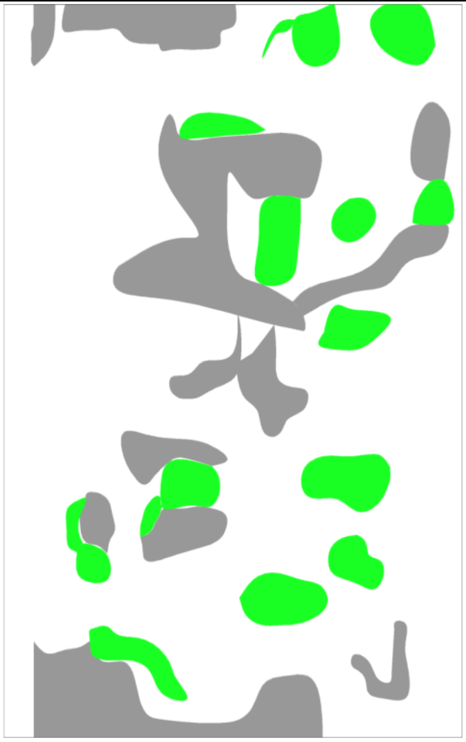


Figure 3.29: Defected areas from visual inspection and hammer sound test

Table 3-2: Comparison of Fusion result with other Assessment results

Assessment	Deteriorated Area	Percentage of Defective area from total	Condition Rating	Error Percentage
1- IR results	13 m^2	17 %	4 (more than 10%)	40%
2- GPR results	16 m^2	20.7 %	4 (less than 25%)	27%
3- Feature IR+GPR	20.57 m^2	26.72 %	5 (more than 25%)	5%
4- Pixel Fusion	21 m^2	27.27%	5	
5- Hammer Sound +Visual Inspection	8.5 m^2 + 13.6 m^2 = **22 m^2**	11.1 % +	4(more than 10%)	**Actual condition**
		17.6 % = **28.6 m^2**	4 (more than 10%)	

CHAPTER 4

4. THE IMPACT OF IMAGE PROCESSING TECHNIQUES ON THE FUSION ACCURACY

4.1. OVERVIEW

This chapter presents the analysis undertaken to assess the impact of image processing techniques such as normalization or histogram equalization, background subtraction, edge detection and image segmentation on the image fusion accuracy. These techniques are utilized in the developed data fusion-based method to enhance the contrast of images and extract the feature. These features are the deteriorated areas. Histogram equalization technique enhances the contrast of images. Background subtraction, edge detection and image segmentation are utilized to extract features from images. The capability of these techniques are experimented within four scenarios to study their impact. These four scenarios are defined based on applying image processing whether after or before image fusion. Scenario 1, does not apply image processing before or after fusion, Scenario 2 applies image processing before fusion and not after fusion. Scenario 3 applies image processing before and after fusion, scenario 4 applies image processing after fusion and not before. The results were analyzed based on these four scenarios. Deteriorated areas are measured from the fused images for all four scenarios.

4.2. SCENARIOS

In this chapter, background subtraction and equalization are experimented to study their impact on the accuracy of the developed data fusion technique as described in the following four scenarios. The actual condition results from the inspection using hammer sound and visual inspection are used as a reference to make the comparison between different scenarios and, accordingly, select the most accurate scenario.

4.2.1. SCENARIO I

In this scenario, no image processing techniques are applied to IR and GPR images before fusion or after fusion as illustrated in Figure 4.1. The deteriorated areas are extracted from the fused image and calculated as 14 meter square, which represents 19% of the total surface area. The deteriorated areas are extracted and interpreted based on IR and GPR as shown in the fused image in Figure 4.2. The resulted fused image in this scenario is having the major deteriorated areas that appears from IR results and with little appearance of GPR results. This is because of the lack of processing for GPR scans that are with low resolution and few numbers of pixels.

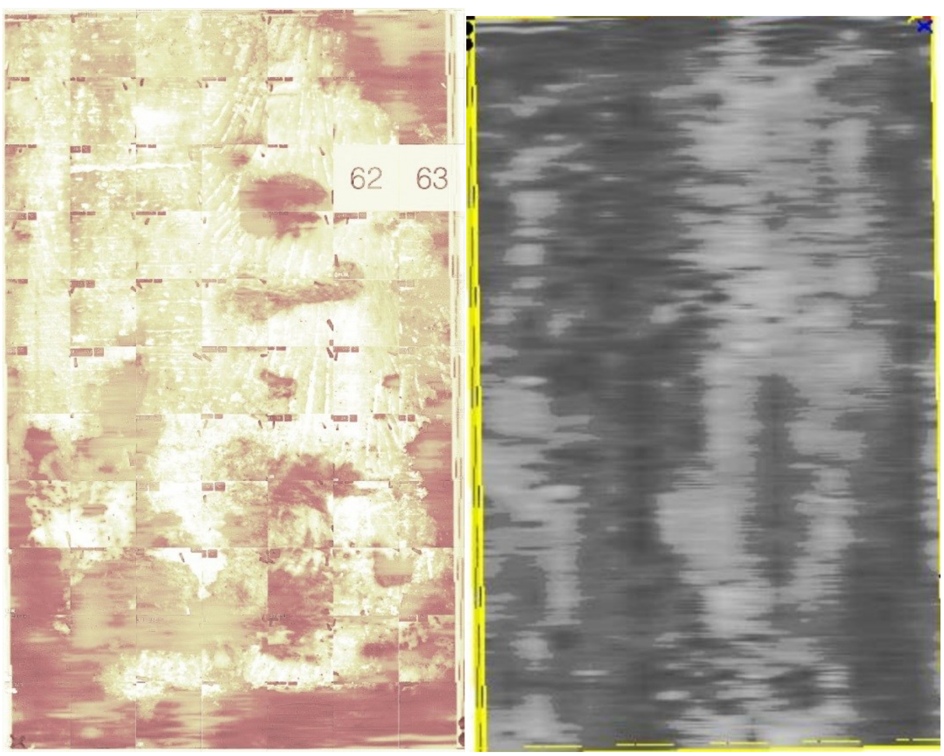
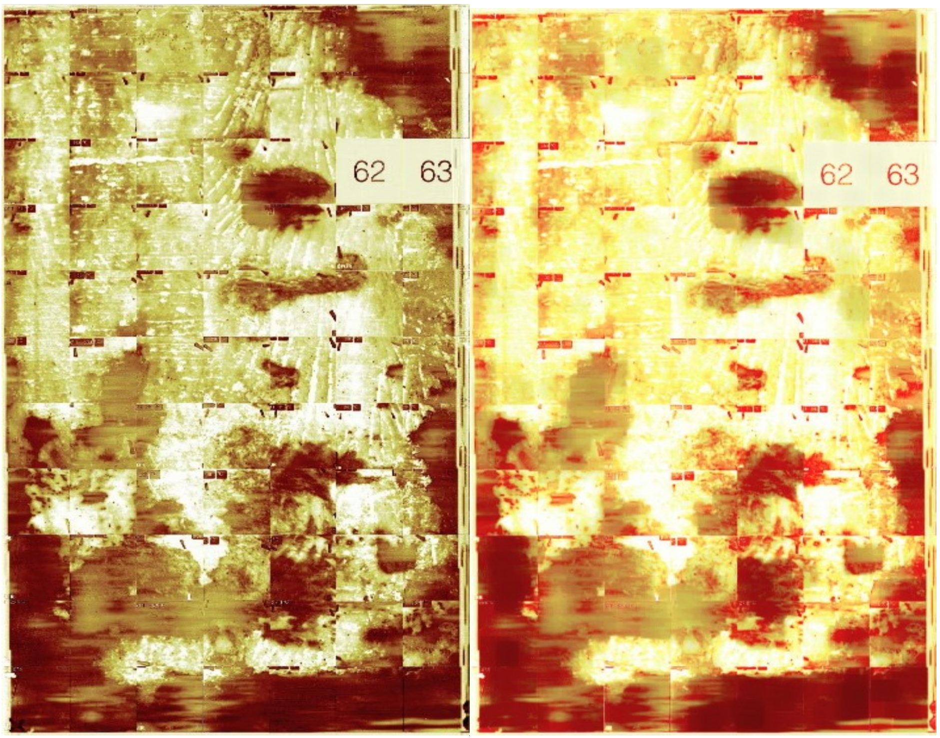


Figure 4.1: IR images and GPR surface before fusion with no image processing

Figure 4.2: The defective areas in the fused image without image processing

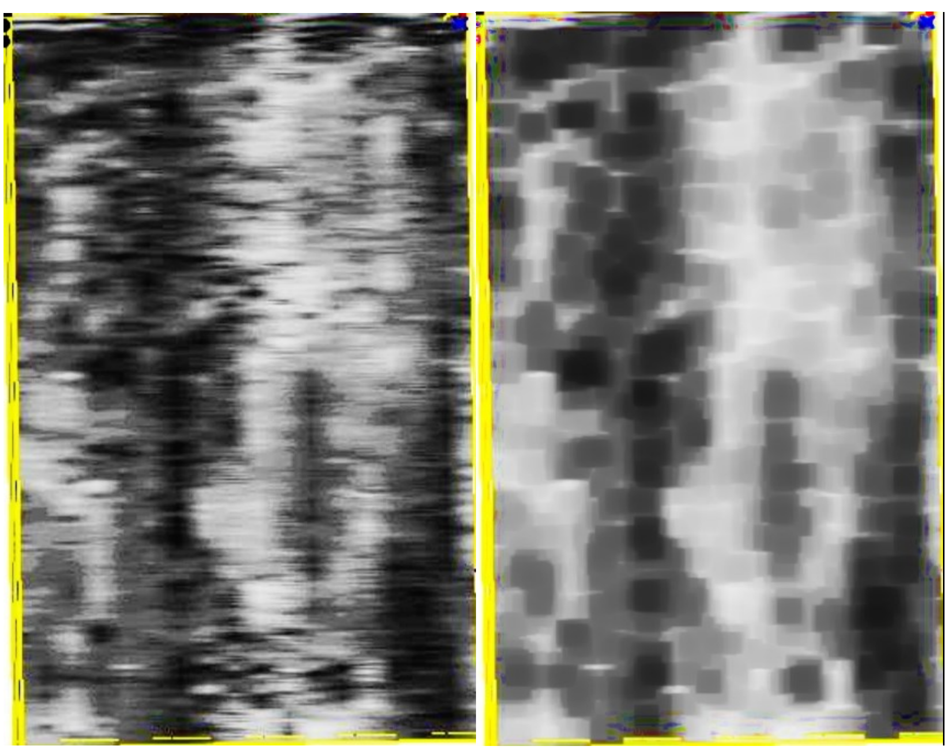
4.2.2. SCENARIO 2

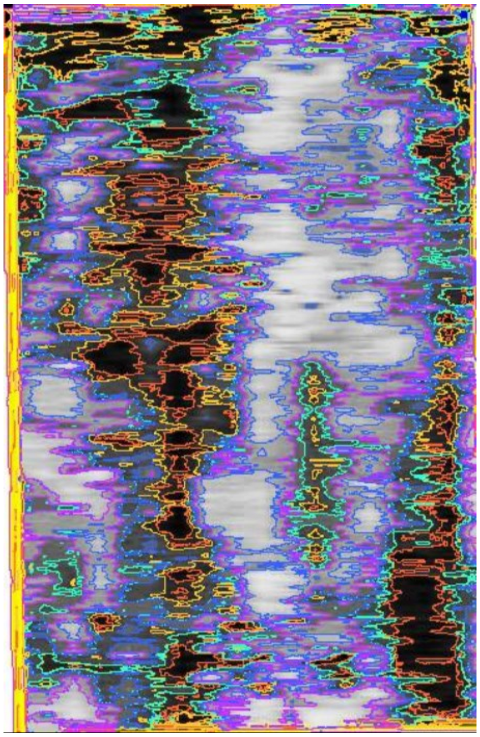
In this scenario, image-processing techniques such as equalization and background subtraction are applied on IR images and GPR surface before fusion. These are shown in Figures 4.3 and 4.4. The image processing techniques have not been applied after fusion on the resulted fused image. The deteriorated areas are extracted from the fused image and calculated as 16.5 meter square, which represents 22% of the total surface area. The deteriorated areas are extracted and interpreted based on IR and GPR as shown in the fused image in Figure 4.5. The resulted fused image in this scenario is having the major deteriorated areas that appears from IR results and the appearance of GPR results are increasing in this scenario than scenario 1. In the fused image, some new areas are illustrated with deterioration. However, these areas were dark when single IR sensor was used to assess bridge condition.



(a) Equalized IR Images (b) IR Images with Background Subtraction

Figure 4.3: IR images before image fusion with image processing techniques


(a) Equalized GPR (b) Background Subtraction



(c) GPR Segmentation

Figure 4.4: GPR images before image fusion with image processing techniques

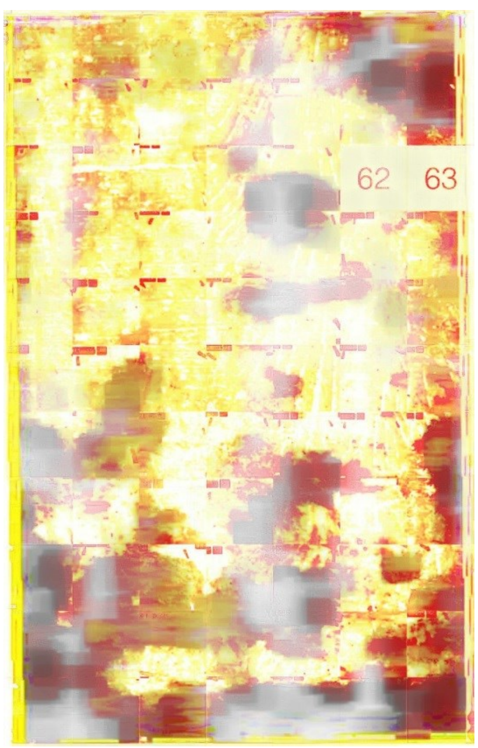


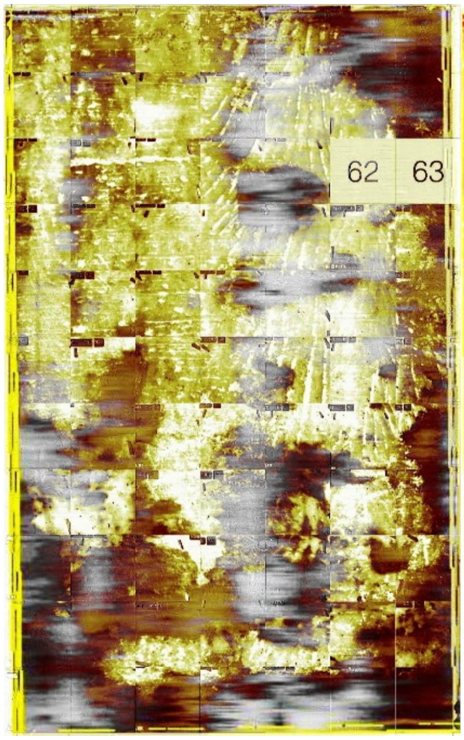
Figure 4.5: The fused image without image processing in Scenario 2

4.2.3. SCENARIO 3

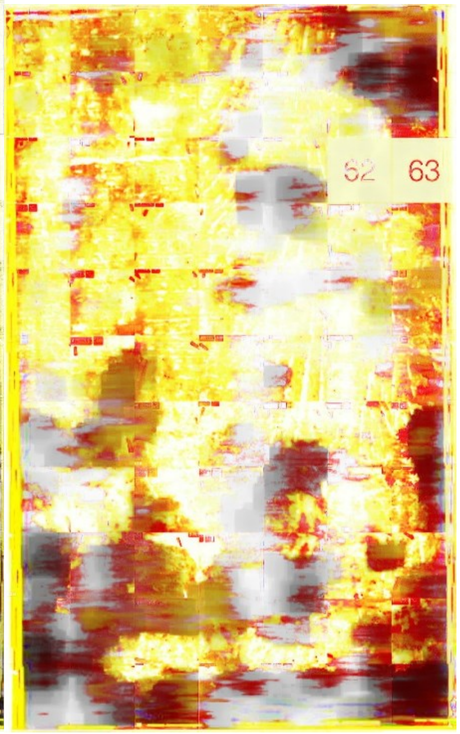
In this scenario, image processing techniques such as equalization and background subtraction are applied on IR images and GPR plane view scans before and after fusion as shown in Figure 4.6. The deteriorated areas are extracted from the fused image and calculated as 21 meter square, which represents 27% of the total surface area. The deteriorated areas are extracted and interpreted based on IR and GPR as shown in the fused image. The resulted fused image in this scenario lead to much higher accuracy in predicting the deteriorated areas and accordingly the condition rating of the inspected concrete deck as shown in Table 4-1. In this scenario, it is very clear to determine the impact of applying image processing techniques before and after fusion. These techniques detect the boundaries of objects to be measured which facilitate and add more enhancements to interpretation of results for image fusion than in scenarios 1 and 2. Image processing techniques are used till the image can be enhanced and features can be detected and measured.

4.2.4. SCENARIO 4

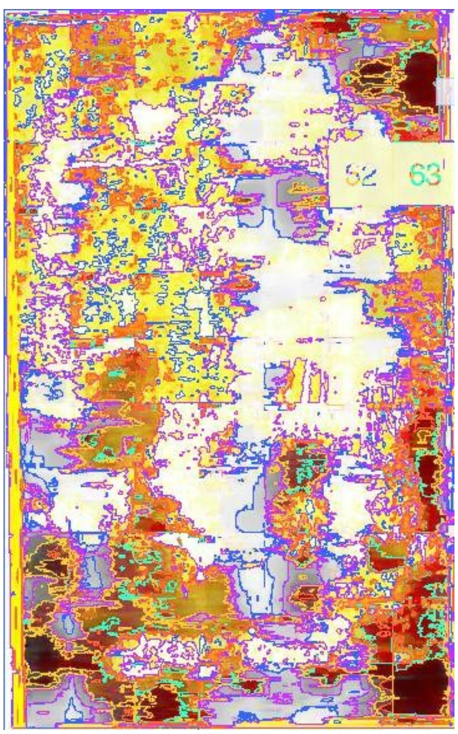
In this scenario, no image processing techniques are applied on IR images and GPR surface before fusion. These techniques have been applied after fusion on the resulted fused image as shown in Figure 4.7. The deteriorated areas are extracted from the fused image and calculated as 17 meter square, which represents 22% of the total surface area. The deteriorated areas are extracted and interpreted based on IR and GPR as shown in the fused image in Figure 4.7. The resulted fused image is processed using equalization, background subtraction and segmentation. The resulted deteriorated areas from this scenario are almost the same of scenario 2.



(a) Equalized Image

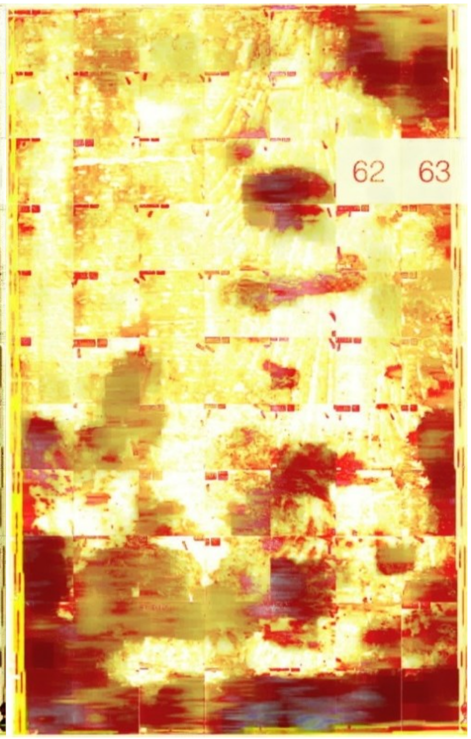


(b) Background Subtraction

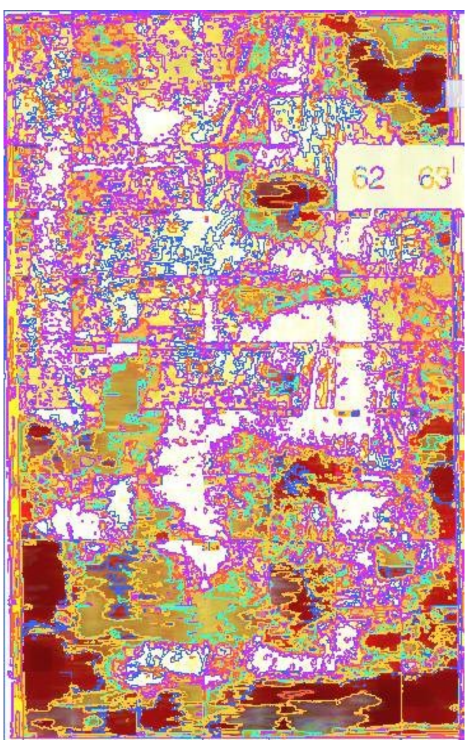


(c) Segmented Image

Figure 4.6: The fused Image in Scenario 3



(a) Equalized Image (b) Back ground Subtraction



(c) Segmented Image

Figure 4.7: The fused image with image processing techniques, Scenario 4

The results generated from the four scenarios are summarized in Table 4-1. It is observed that scenario 3 where the fused image of IR and GPR are obtained by applying image processing techniques before and after fusion, yielded the best estimate of defected areas, i.e. the closest to actual condition defined by visual inspection combined with the field tests referred to earlier in the chapter 3.

Table 4-1: The Impact of Image Processing Techniques on Image Fusion Accuracy

Scenarios	**Deteriorated Area**	**Percentage of Defective area from total**	**Image Processing**		**Condition Rating**
			Before Fusion	**After Fusion**	
1-	14 meter square	19%	**No**	**No**	**4** (more than 10%)
2-	16.5 meter square	22%	**Yes**	**No**	**4** (less than 25%)
3-	21 meter square	27%	**Yes**	**Yes**	**5** (more than 25%)
4-	17 meter square	22%	**No**	**Yes**	**4**(more than 10%)

CHAPTER 5

5. TWO-LEVELS DATA FUSION METHOD FOR BRIDGE CONDITION ASSESSMENT

5.1. OVERVIEW

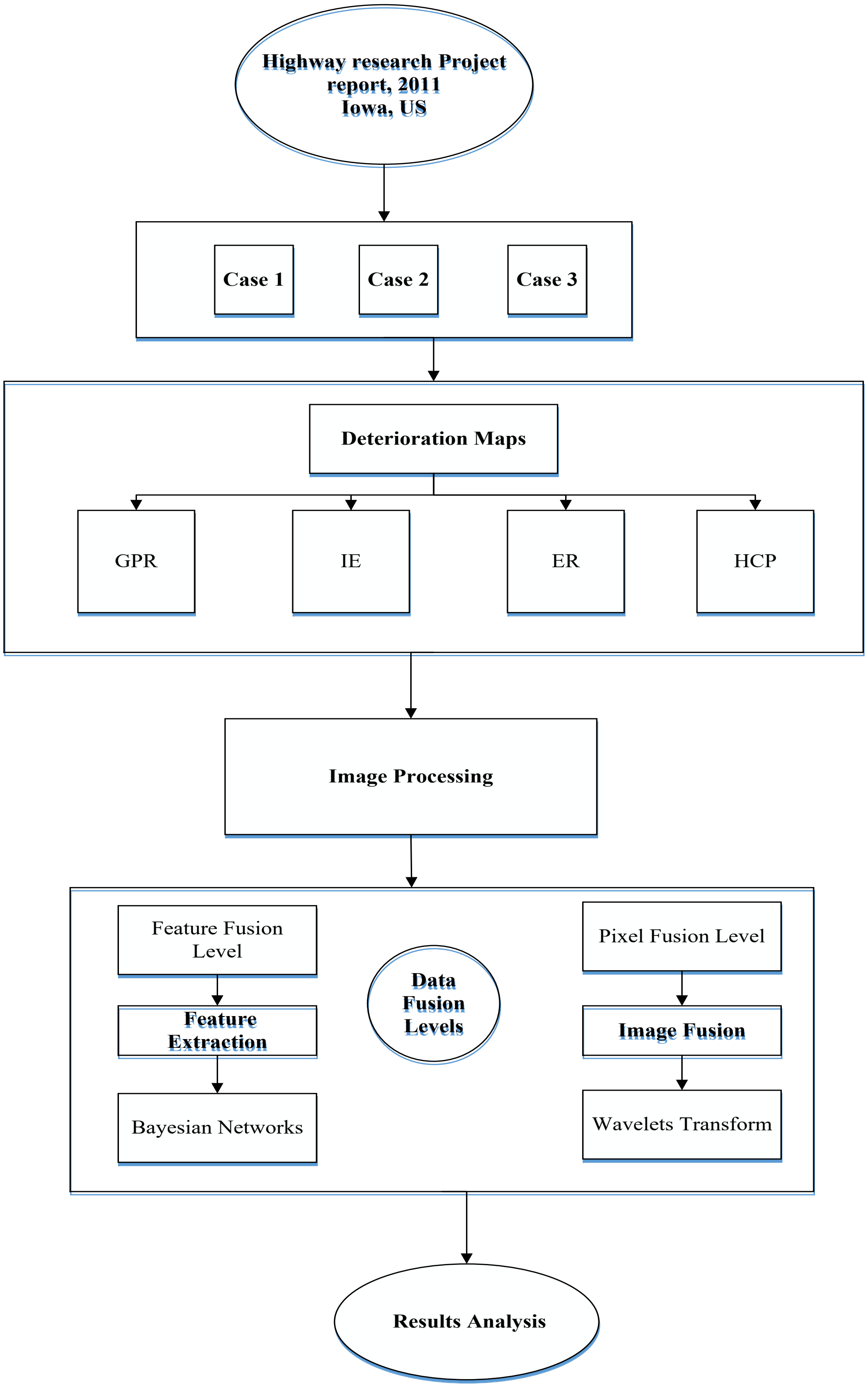
This chapter presents a new two-tier method that utilizes the pixel and feature levels data fusion of multiple NDE methods for bridge condition assessment of reinforced concrete bridge decks. Wavelets transform and Bayesian networks techniques have been employed to apply pixel level and feature level respectively. Data and measurements of NDE methods are extracted from Iowa, Highway research project 2011 report for three case studies. The method utilizes data collected from ground penetrating radar (GPR), impact echo (IE), Half-cell potential (HCP) and electrical resistivity (ER) for the three bridge decks in Iowa, united states. First, the method is proposed and then, it is applied in this chapter for bridge deck condition assessment. The method can be used for the whole bridge assessment as well.

5.2.THE USE OF DATA FUSION IN BRIDGE CONDITION ASSESSMENT

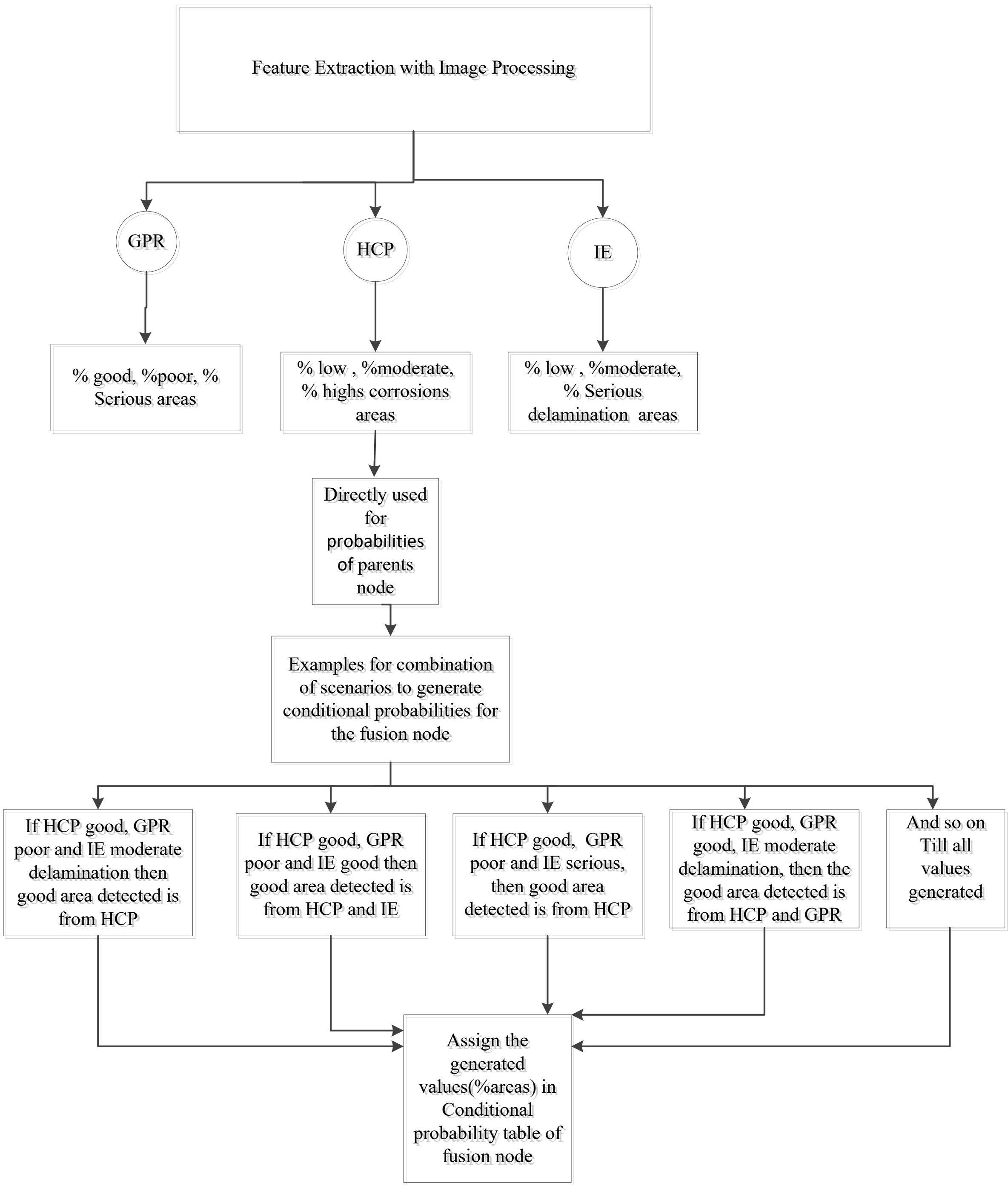
As stated earlier, the developed data fusion method consists mainly of two main steps as illustrated in Figure 5.1. In the first, data from inspection of multiple NDE methods are processed based on the physical principal of each method. Then, deterioration maps of each NDE methods are developed for each method. In the current chapter, data processing step and deterioration maps of bridge decks are extracted from Iowa highway research project report 2011. The second step is the use of image processing techniques that are applied on the deterioration maps of NDE methods. Image processing techniques are used to enhance contrast of deterioration maps and to rescale these maps. Data fusion method is applied within two levels: pixel level fusion and feature level fusion.

In pixel level fusion, the method utilizes image fusion to generate new and improved image from those captured by multiple sensing technologies. These images can be observed with much better details when fused. So, the main objective of image fusion is to obtain a unique image with enhanced information and resolution that better represents the condition state of the scanned bridge deck. Pixel level image fusion has been employed using wavelet transform technique as illustrated in Figure 5.1; the extracted deterioration maps are rescaled to ensure that all maps have the same coordinate system to fuse pixels of these maps. In order to apply wavelet transform decomposition fusion, the scaled maps of NDE methods are decomposed. These decompositions are fused to develop the new fused image of new map. This new image is then used to extract features that depict the conditions of the scanned bridge deck.

In the feature fusion level, the developed method utilizes deterioration maps of bridge decks in Iowa, United States high way research project report from multiple sensing technologies along with image processing algorithms. The features extracted from the maps are then fused using feature level data fusion; employing Bayesian Networks. The sensing technologies utilized in this research and applied later to three case studies are Ground Penetrating Radar (GPR), impact echo (IE), Half Cell Potential (HCP) and Electrical Resistivity (ER). A detailed description of these technologies and data processing is included in the highway research project report (2011), Iowa, US. A brief description of these technologies is included subsequently to provide continuity.



a) Two Levels of Data Fusion



b) Conditional probability table using Feature Fusion

Figure 5.1: Basic chart for data fusion method with case studies from Iowa, US, (2011) Report

5.2.1. Half Cell Potential (HCP)

It is defined as coper sulfate reference electrode (CSE) that is placed on the surface of concrete at the location of steel reinforcement. As illustrated in Figure 5.2, the CSE is connected to the end of high input impedance voltmeter connected to the data device. The negative end of voltmeter is connected to reinforced steel. A hole should be drilled into the concrete to expose the steel. A moist sponge should be placed between HCP and the concrete to improve the electrical coupling between the deck and instrument during the survey. Corrosion potential are measured. Contour map is used to map area of corrosion. Measurements should be taken in a grid to facilitate the drawing of corrosion map.

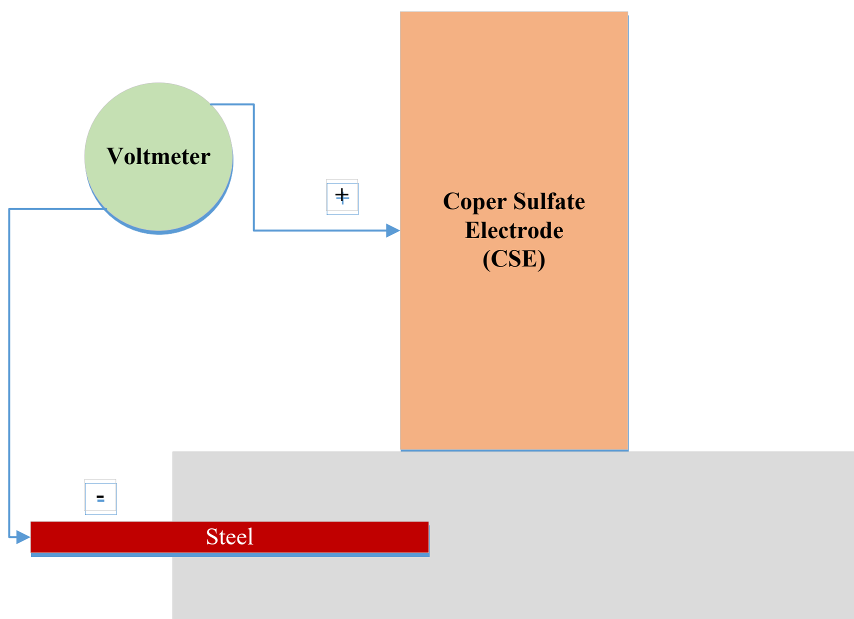


Figure 5.2: Basics of HCP procedures

According to highway research project report (2011) for Iowa bridges in United States, HCP measures the electrical potential between reinforcement and reference electrode CSE. As illustrated in Figure 5.3, the test is done by moving the electrode from one point to another or using a wheel. Potential map can be created with more negative potential indicating higher probability of corrosion. Data collected using a Proceq™ data logger and rolling, half-cell probe. A hammer drill used to prepare a hole in the concrete

Figure 5.3: HCP procedures (Iowa, 2011)

5.2.2. Impact Echo (IE)

It uses stress waves generated on the surface of concrete. The waves generated on the surface of concrete are reflected by internal defects or discontinuities in the material such as delamination, voids, and cracks. To detects these defects, the emitted waves are recorded by displacement or transducer placed near the impact point on the surface of structure. The depth of defect is determined by analyzing the recorded signal and its characteristics. So, the basic principle of impact echo involves impacting concrete structure with a mechanical impactor to measure the reflected wave energy with transducer. As illustrated in Figure 5.4 , the conventional impact echo method relies on the followings steps:

1- A hammer is used to generate an impact on the surface of concrete structure

2- Transducer is placed near the impact point to collect the stress waves which propagate inside the structure. Signal analysis is performed on echo signal to determine the structural condition of concrete.

3- Echo signal is performed through spectral analysis

4- For voids and delamination detection, a formula is proposed:

$$d = \frac{B * v}{2f} \quad \text{...(5.1)}$$

d is the depth of voids or defects, B is the shape factor, constant = 0.96 for plate structure wave, V is the wave velocity, f is the frequency of echo signal spectrum.

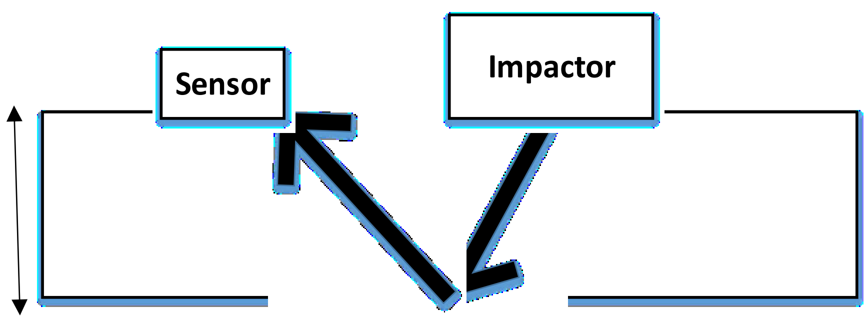


Figure 5.4: Basic principle of Impact Echo (IE)

According to Highway research project report (2011), IE determines delamination at different stages. It is based on generating stress waves on the deck surface. It detects the location of reflection of waves because of defects existence. The reflected waves are recorded by transducer. It detects the depth of defects by knowing the velocity of waves and frequency. As illustrated in Figure 5.5, the test was done on different points on a grid usually 2ft spacing. Device was mounted on a robotic stepper, for automated data acquisition.

Figure 5.5: Data Acquisition Procedures using IE (Iowa 2011)

Based on the equation, different grades are assigned to the tested section of the deck. In case of good condition, a peak corresponding to the full depth of the deck can be observed. In case of delaminated condition or poor condition, reflection of waves occurs at shallower depth than deck thickness. In case of severe condition, reflection of waves occurs at depth larger than deck thickness.

5.2.3. Electrical Resistivity (ER)

Electrical Resistivity (ER) measures concrete resistivity properties by Wenner method. It is commonly used because of low cost and ease of implementation. The method uses four points wenner resistivity apparatus developed to measure resistivity, the method uses four equally spaced probes. Corrosion rate depends on the electrical resistance of concrete that control movement of ions through concrete depending on Eq. (5.2):

$$\rho = 2\pi a R \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (5.2)$$

ρ is the resistivity in units, a is the spacing between probes, R is the actual measured resistance. High concrete resistivity decreases the current flow that causes corrosion. The results from ER are interpreted based on the following guidelines:

≥ 20 KΩ-Cm Low corrosion

10-20 KΩ-Cm Low to moderate corrosion

5-10 KΩ-Cm High corrosion rate

≤ 5 KΩ-Cm Very high corrosion rate.

5.3. CASE STUDY OF BRIDGE DECK O1

The bridge is located in Iowa, USA. All the information, data, and measurements were extracted from Iowa Highway research project report (Iowa report, 2011). The deck is 180 inch * 28inch, constructed in 1957. The bridge deck was repaired with dense low-slump concrete in 1983 and had some epoxy injection in 1999. Deterioration maps were extracted directly from Iowa report, 2011. The actual raw data collected is not provided in the report.

The following NDE Methods used for the bridge inspection:

a- GPR , ground coupled antenna and air coupled

b- Impact Echo, device mounted on a robotic stepper TM

c- Rolling half cell potential measurements device

d- A wenner resistivity probe for electrical measurements

e- Portable seismic property analyzer (PSPA) to conduct ultrasonic surface waves

GPR data is obtained from ground coupled (GC) 1.5 GH mounted in a cart. GPR scans are collected by GSSI SIR-20 acquisition system. Impact echo data collection is performed in longitudinal lines spaced 2 ft. GPR detects bridge deterioration resulted from indirect delamination and corrosion. Half Cell Potential (HCP) detects corrosion and IE detects delamination.

According to Iowa high way research project, (2011) deterioration map of GPR shows, as shown in Figure 5.6, good areas as green colors with little deterioration. Poor areas with moderate deterioration are illustrated with yellow color. Serious areas with high deterioration are illustrated with red color. As illustrated in Figure 5.7, deterioration map of HCP shows good areas with little corrosion as blue color. Serious areas with high corrosion are illustrated as red and yellow colors. Deterioration map of IE shows, as shown in Figure 5.8, good areas with no or little delamination as blue and green colors. Serious areas with high delamination are illustrated as red colors. Deterioration maps of GPR, Half Cell Potential and Impact Echo are fused using pixel level image fusion based on Wavelet Transform technique implemented on MATLAB explained earlier in the methodology section. Figure 5.9 shows the result of the fused image. Red areas indicate serious deterioration, Yellow indicates poor areas and green with blue indicates good areas.

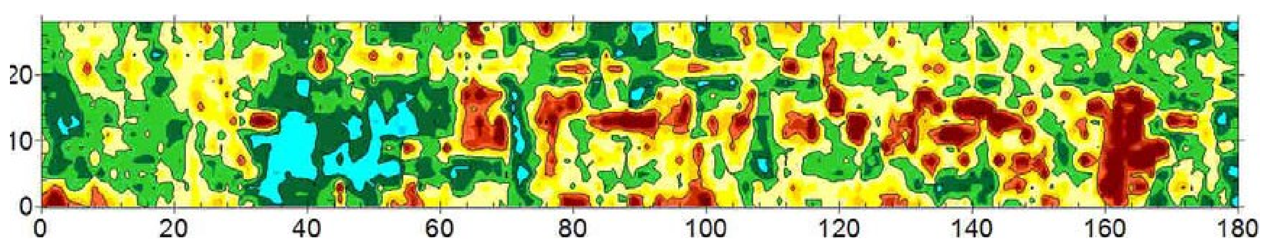


Figure 5.6: Deterioration map of GPR in Case 1 (Iowa report 2011)

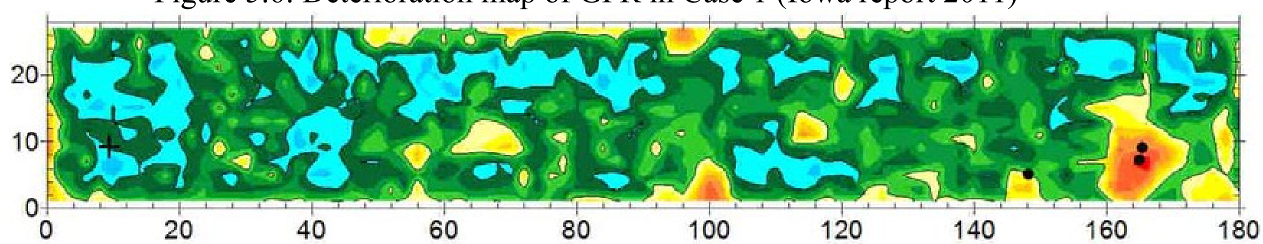


Figure 5.7: Deterioration map of HCP in Case 1 (Iowa report 2011)

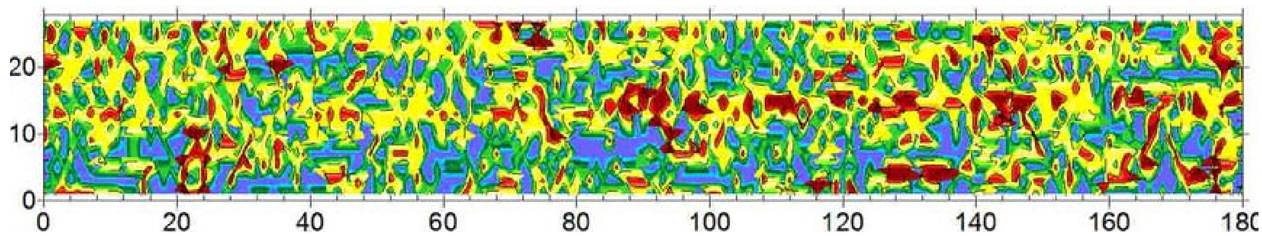


Figure 5.8: Deterioration map of IE in Case 1 (Iowa report 2011)

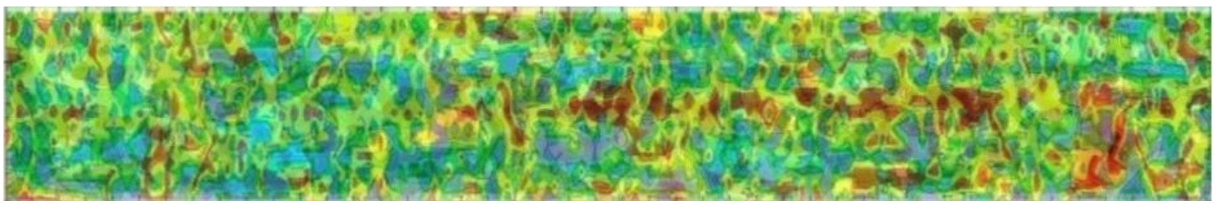


Figure 5.9: The Fused image of GPR, HCP and IE

Features are extracted from the fused image using image-processing techniques explained earlier. These features are the serious areas, poor areas and good areas with respect to the bridge deck condition. The extracted good areas illustrated in Table 5-1. Table 5-2 illustrates the results of the extracted good, poor and serious areas from the fused image.

Table 5-1: The extracted good areas from the fused image

Green_ Fused Image	Area Sq.(pixel)	Total Area Sq.(Pixel)	Width (pixel)	Length (Pixel)
1	286	134496	144	934
2	147	134496	144	934
3	1206	134496	144	934
4	1648	134496	144	934
5	815	134496	144	934
6	5810	134496	144	934
7	1091	134496	144	934
8	932	134496	144	934
9	6481	134496	144	934
10	6266	134496	144	934
11	4084	134496	144	934
12	8938	134496	144	934
13	891	134496	144	934
14	3274	134496	144	934

15	8984	134496	144	934
16	243	134496	144	934
17	630	134496	144	934
18	6002	134496	144	934
19	5224	134496	144	934
20	232	134496	144	934
21	299	134496	144	934
Total Green Area	63483	47.2006602	%of Good areas	

Table 5-2: The percentage of areas extracted from the fused image

Areas	Percentage
Good Areas	47.2%
Poor Areas	40.77%
Serious Areas	12.0263%

To apply feature level fusion, features are extracted from each deterioration map of GPR, Impact Echo (IE), Half Cell Potential (HCP). The extracted features from each method are the good, poor and serious areas. Table 5-3 illustrates the areas extracted from each individual technology. These features are fused using Bayesian Networks (BNs). Figure 5.10 shows the BNs of the three technologies as parent nodes to the fusion measurement node. Conditional probabilities tables are built for each parent node based on the measured good, poor and serious areas for each technology. Figure 5.11 shows the final results of the fusion measurement node which present the final result after the features extracted from each individual technology are fused. Table 5-4 shows comparison of the fusion results and areas extracted using single technologies.

Table 5-3: Features extracted from each individual technology

Areas	HCP	GPR	IE
Good Areas	16.94%	42.73%	36.23%
Poor Areas	72.807%	43.7%	50.41%
Serious Areas	10.253%	13.572%	13.3%

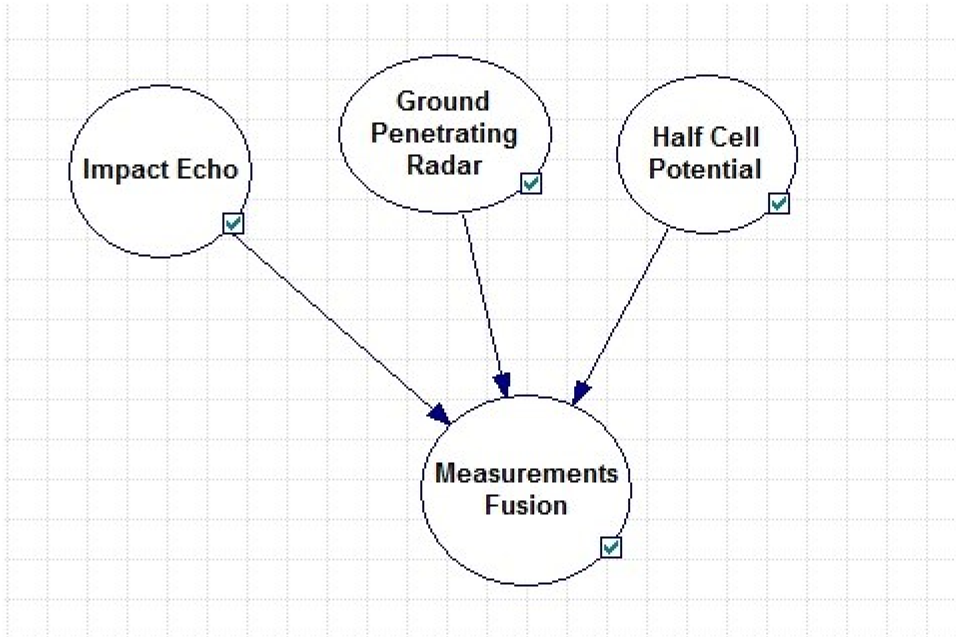


Figure 5.10: Bayesian Network (BN) for three technologies: GPR, IE and HCP

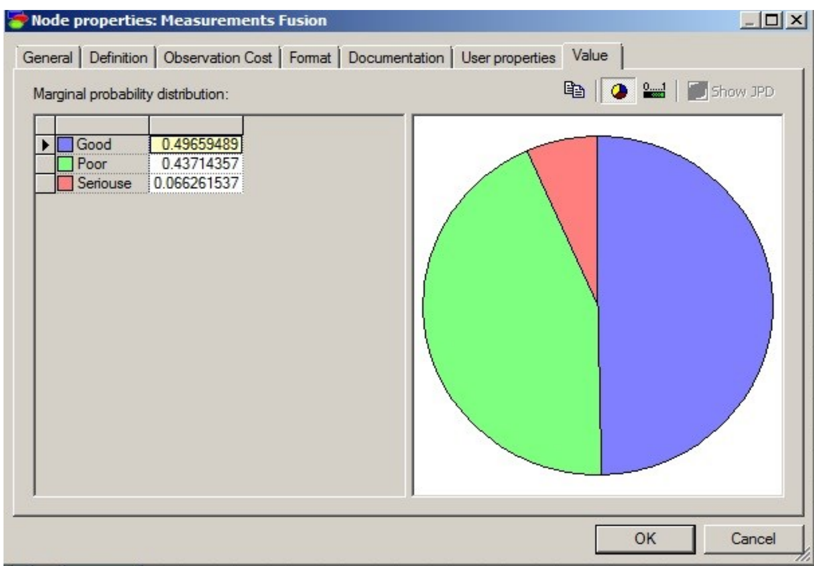


Figure 5.11: Final results of the feature fusion using BNs

Table 5-4: Summary of fusion results

Areas	HCP	GPR	IE	Pixel Fusion	Feature Fusion
Good Areas	16.94%	42.73%	36.23%	47.2%	49.65%
Poor Areas	72.807%	43.7%	50.41%	40.77%	43.71%
Serious Areas	10.253%	13.572%	13.3%	12.0263%	6.63%

As observed in Table 5-4, good areas are areas that are not defected. Poor areas are moderate defected areas. Serious areas are defected areas. Each technology detects specific type of defect. Therefore, results of HCP, GPR and IE are given equal weight when utilized in pixel or feature fusion. Serious areas predicted by GPR and IE are close to each other. IE detects more poor areas than GPR. IE is able to detect direct delamination than GPR. Consequently, GPR detects % good areas more than IE. HCP detects serious areas (10.25%) that are less than GPR and IE. HCP detects more poor areas with a possibility of corrosion existence. The good area that is detected by HCP is the area with no corrosion. So, it is less than GPR and IE.

Table 5-4 also presents the results from pixel fusion and feature fusion. Pixel Fusion fuses all areas in one image and captures the advantages of using the three technologies in one image. The interpretation of poor and serious areas from pixel fusion results provides more confident to the inspectors than using single technology.

The results of good and poor areas of feature fusion are close to the results of pixel fusion. However, the serious areas obtained from feature fusion are not close to the pixel fusion results and also lower than serious areas detected by single technologies. In this case, feature fusion level does not work properly because total serious and poor areas have not been merged for different types of defects. These types of defects are moderate and serious areas of deterioration, corrosion and delamination. This issue will be taken into consideration within the following two case studies. The pixel fusion provides one deterioration map combining all the good, poor and serious areas captured by the three technologies. It indicates the locations and % of good, poor and serious areas. Each technology has its own advantages and detects specific type of defect. In pixel fusion, the final fused image shows all captured defected areas. So, in pixel fusion information from different sources are complementary.

On the other hand, the feature fusion provides only the % of good, poor and serious areas. In feature fusion, the parents' nodes contribute their information, the percentages of good, poor and serious areas to the fusion node. The Conditional probabilities of the fusion node are built based on different scenarios that specify whether good, poor and serious areas coming from all technology or only some of them. Conditional probabilities are designed to incorporate uncertainties. For example, in case if GPR detects and contributed % serious deterioration areas to the fusion node, IE detects and contributed %moderate delamination to the fusion node and HCP detects and contributed % good areas to the fusion node, then the fusion node will interpret the percentage of good areas that comes only from HCP. All conditional probabilities are assigned this way in the conditional probability table of the fusion node. So, information from different sources in feature fusion are not complementary, it incorporates uncertainties. Thus, pixel fusion helps bridge engineers and inspectors better interpret the inspection results and identify the defected areas accurately. However, incorporating two levels of data fusion is recommended to increase the confident of engineers when interpreting the results of the bridge deck condition assessment.

5.4. CASE STUDY OF BRIDGE DECK O2

The deck on bridge O2 was originally constructed in 1936 with 63 ft. long and 24 ft wide. It was reconstructed in 1960 with 63 ft long and 48 ft wide. Similar to case study 1, all the information, data, and measurements for this bridge deck are obtained from Iowa, Highway research board project (2011).

The following NDE methods were used for the bridge inspection:

a- Ground Penetrating radar (GPR), ground coupled antenna and air coupled
b- Impact Echo (IE), device mounted on a robotic stepper TM
c- Rolling half-cell potential (HCP) measurements device
d- Electrical Resistivity (ER), a wenner resistivity probe for electrical measurements

The deteriorations map of GPR, IE, HCP and ER are extracted directly from Iowa, Highway research board project 2011 as illustrated in Figures 5.12, 5.13 and 5.14. To apply pixel level fusion**,** deterioration maps of GPR, IE, HCP and ER are fused using Wavelet transform technique. The result of pixel level fusion is one deterioration map. Good, poor and serious areas are measured from the fused image. Figure 5.15 illustrates the fused image with good areas shown in green and blue colors, red areas shown in serious areas and the other areas considered poor areas shown in yellow colors. According to Iowa report 2011, coring was taken outside the area indicated by the arrow in Figure 5.15. The area indicated by the arrow represents the repaired area. The locations of cores are done during the assessment of the bridge deck to verify the results of using single technologies. These locations were indicated on the original deterioration maps extracted from the report and accordingly appeared in the fused image.

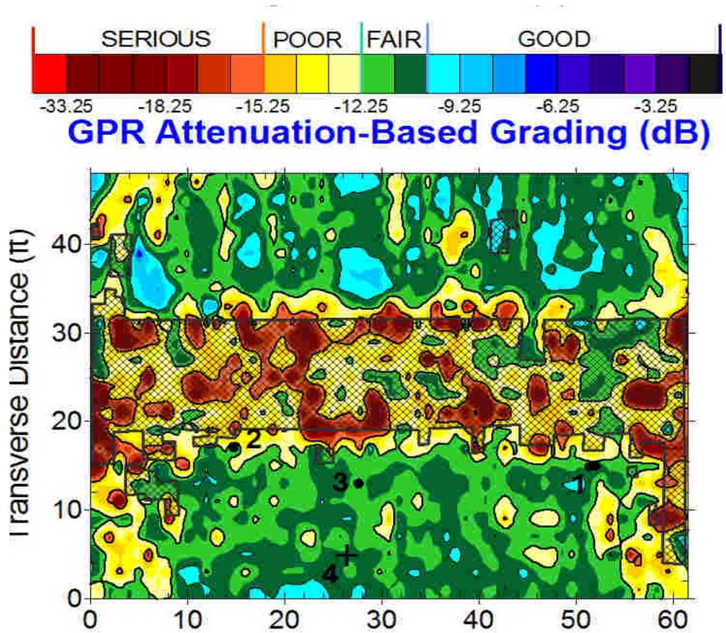


Figure 5.12: Deterioration map of GPR (Iowa report 2011)

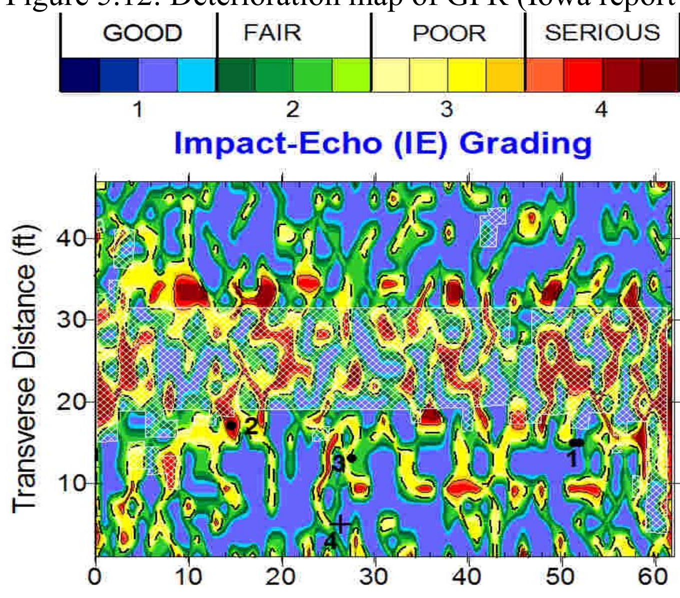


Figure 5.13: Deterioration map of IE (Iowa report 2011)

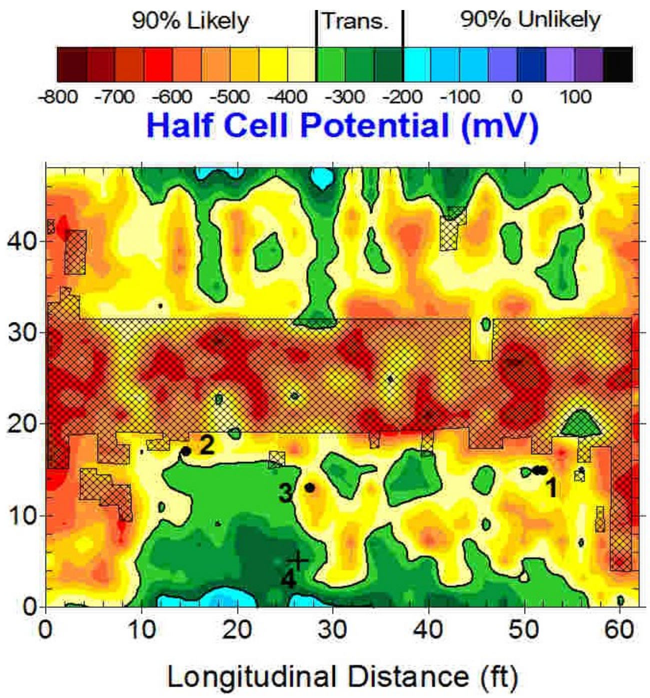


Figure 5.14: Deterioration map of HCP (Iowa report 2011)

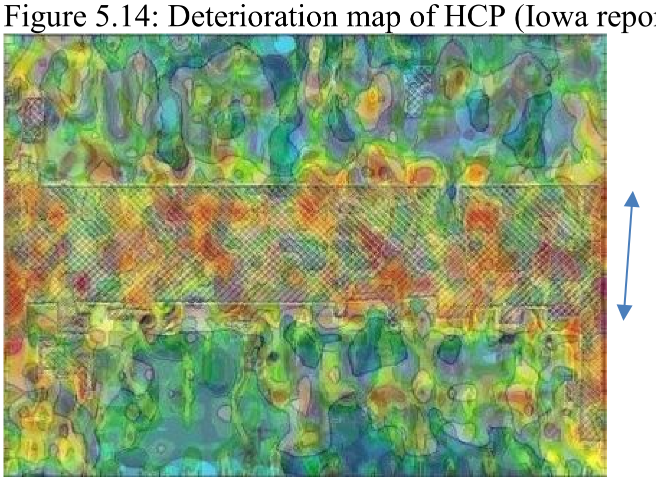


Figure 5.15: The Fused image of GPR, IE, HCP and ER

Table 5-5 illustrates presents the extracted poor areas from the fused image, the poor areas are shown with the yellow color in Fig. 5.15. The poor areas are extracted and measured using image processing techniques. Table 5-6 illustrates the final results of the measured good, poor and serious areas.

Table 5-5: The Extracted Poor Areas from the Fused Image

Yellow Area Sq.(pixel)	Area Sq. (pixel)	Width (pixel)	Height (pixel)	Total Area Sq.(pixel)
1	1133	419	319	133661
2	451	419	319	133661
3	646	419	319	133661
4	755	419	319	133661
5	115	419	319	133661
6	604	419	319	133661
7	515	419	319	133661
8	995	419	319	133661
9	1320	419	319	133661
10	2319	419	319	133661
11	712	419	319	133661
12	685	419	319	133661
13	60413	419	319	133661
Total Yellow Areas	70663	% Yellow		36.522329

Table 5-6: Final results of pixel level image fusion

Condition	Percentage	Area Color
Good Areas	47.1327%	Green
Poor Areas	36.5223%	Yellow
Serious Areas	16.345%	Red

For feature level fusion, deterioration maps from GPR, IE, HCP and ER are used. Areas from IE, ER and HCP are also extracted and measured. All the extracted features are fused with the use of Bayesian Networks (BNs) technique. Features extracted and measured from GPR deterioration map are good, poor and serious deteriorated areas. Good, moderate delamination and serious delamination areas are the features extracted from IE deterioration map. Low corrosion, moderate corrosion and high corrosion areas are the features extracted from HCP and ER deterioration maps. Features extracted from multiple technologies GPR, IE, HCP and ER are the information used to build the probabilities in the parents nodes of Bayesian Networks (BNs).

Figure 5.16 illustrates the developed Bayesian network to fuse features of GPR, IE, HCP and ER. In Figure 5.16, nodes of HCP, ER, GPR and IE are parents of fusion measurements node. Bridge condition rating is the child node of the fusion measurements node.

Figure 5.17 illustrates the feature network with the probability distribution of each node. The percentage of areas extracted from each technology is considered for the probability distribution of each parent node. Therefore, HCP node shows probability distributions for low corrosion of 20.32%, moderate corrosion of 54.246% and high corrosion of 25.427%. ER node shows probability distributions for no corrosion of 17.3%, low corrosion of 63.93% and high corrosion of 18.77%. For GPR node probability distributions are serious condition of 11.9%, poor condition of 27.2% and good area of 60.9%. Probability distributions of Impact Echo are serious delamination of 9.36%, moderate delamination of 14.07% and good condition of 76.57%. The result of the fusion measurement node, as illustrated in Figure 5.17, are 27.949% moderate corrosion, 9.477% high corrosion, 0.86% serious delamination, 1.918 % areas with moderate delamination, 1.377% serious deterioration, 7.197% poor and 51.221% good.

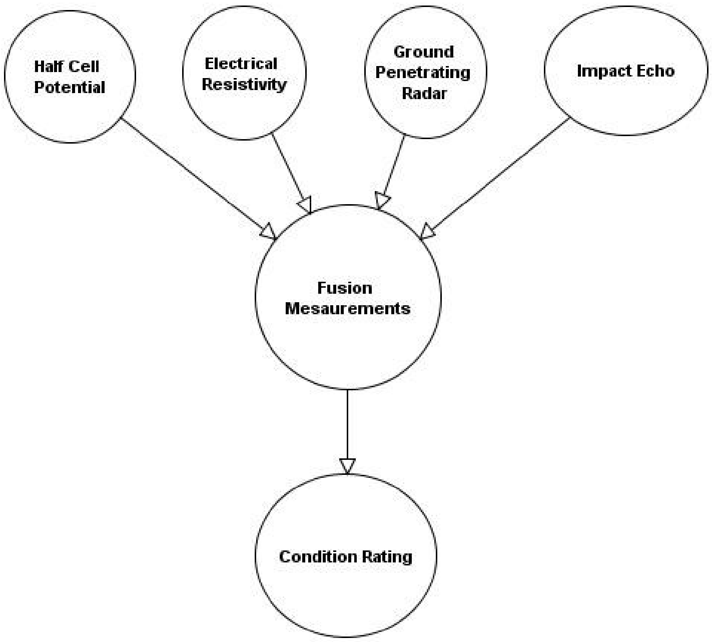


Figure 5.16: Feature Fusion Bayesian network of HCP, ER, GPR and IE

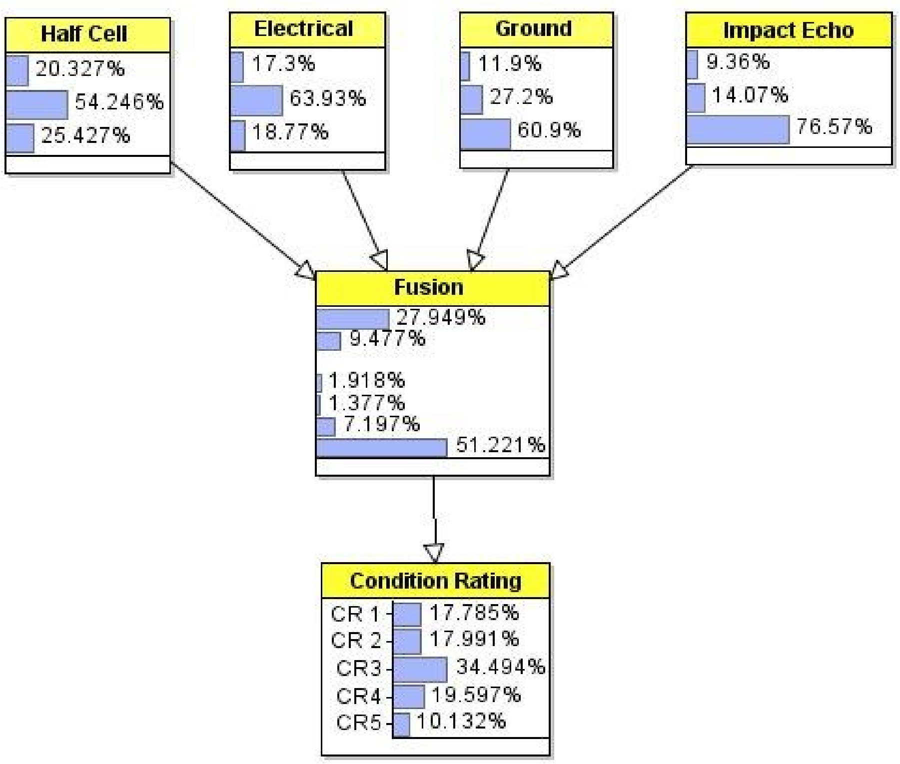


Figure 5.17: Feature Fusion Network with all nodes' distribution

This section provides more details on how the feature fusion works. The feature fusion node has 4 parents' nodes: HCP, ER, GPR and IE. The conditional probabilities tables of this node are built based on combination of different events and scenarios as it incorporates the uncertainties. From Table 5-7 to Table 5-11, the conditional probability tables (CPT) are generated based on combination of scenarios for parents' states. CPT values are generated and assigned based on occurrence and non-occurrence of parents' states. If one state of one parent occurred, then the state value of this parent will be assigned. If all states of parents HCP, ER, GPR and IE occur, then the states values from each parent will be added and assigned in the CPT. If non of the parents states occurred, then 0 value is assigned in CPT. States of HCP, ER, GPR and IE are extracted directly from the defected areas depicted in their respective deterioration maps.

Table 5-7 presents one of these scenarios; it shows the conditional probabilities of the fusion measurements node in the case when HCP measures low corrosion and ER node with no corrosion. As an example, shown in Table 5-7, if IE contributes information of the serious delamination only and GPR only contributes value of serious deterioration, then the value assigned for the serious delamination is 9.36%, contributed only from impact echo. The percentage 9.36% is the serious delamination area extracted from IE deterioration map. If GPR contributes serious deterioration and IE contributes delamination existence, then the value assigned for the delamination existence is 14.07% contributed only from IE. Another example in the table, when HCP and ER contribute low corrosion, GPR contributes serious deterioration and IE contributes serious delamination, the value assigned for good areas are coming only from HCP and ER equal to 78%. Therefore, conditional probabilities are the outcomes of information contributed from parent nodes, GPR, IE, HCP and ER. The other values of probabilities included in CPT are assigned in the same way.

Table 5-7: The probabilities of fusion with HCP low corrosion and ER with no corrosion

HCP	Low corrosion								
ER	Good/_no corrosion								
GPR	Serious			Poor			Good		
IE	Serious delamination (SD)	Delamination exist (DE)	Good (G)	S.D	D.E	G	S.D	D.E	G
Moderate corrosion	0	0	0	0	0	0	0	0	0
High corrosion	0	0	0	0	0	0	0	0	0
Serious delamination	0.0936	0	0	0.093	0	0	0.09	0	0
Delamination exist	0	0.1407	0	0	0.14	0	0	0.14	0
Serious deterioration	0.119	0.119	0.119	0	0	0	0	0	0
Poor	0	0	0	0.272	0.27	.27	0	0	0
Good	0.7874	0.7403	0.881	0.6344	0.58	0.7	0.9	0.8	1

Table 5-8 presents the conditional probabilities of the fusion measurements node with HCP measures low corrosion and ER detects low corrosion. As an example, if GPR contributes serious deterioration to the fusion node and IE only contributes good (no delamination) areas, then the assigned value to the serious deterioration defect is 0.119, comes from the GPR. Other values are assigned in the same way.

Table 5-8: The probabilities of fusion with HCP Low corrosion and ER with Low corrosion

HCP	Low corrosion								
ER	Low corrosion								
GPR	Serious			Poor			Good		
IE	Serious Delamination (S.D)	Delamination Exist (D.E)	Good (G)	S.D	D.E	G	S.D	D.E	G
Moderate corrosion	0	0	0	0	0	0	0	0	0
High corrosion	0	0	0	0	0	0	0	0	0
Serious delamination	0.09	0	0	0.09	0	0	0.09	0	0
Delamination exist	0	0.147	0	0	0.14	0	0	0.14	0
Serious deterioration	0.119	0.119	0.119	0	0	0	0	0	0
Poor	0	0	0	0.27	0.27	0.27	0	0	0
Good	0.7874	0.734	0.881	0.63	0.58	0.7	0.9	0.8	1

Table 5-9 presents these probabilities when HCP measures low corrosion and ER measures high corrosion. Table 5-9 shows that if IE considers serious delamination only and GPR only considers poor condition, then high corrosion value is assigned 0.1877, this value is the high corrosion contributed only from ER node, as shown in Figure 5.17, however no contribution comes from HCP as it is contributing by low corrosion.

Table 5-9: The probabilities of fusion with HCP Low corrosion and ER with High corrosion

HCP	Low corrosion								
ER	High corrosion								
GPR	Serious			Poor			Good		
IE	S.D	D.E	G	S.D	D.E	G	S.D	D.E	G
Moderate corrosion	0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
High corrosion	0.1877	0.1877	0.187	0.1877	0.187	0.1877	0.1877	0.1877	0.18 77
Serious delaminatio n	0.0936	0.1407	0.0	0.0936	0.0	0.0	0.0936	0.0	0.0
Delaminatio n exist	0.0	0.0	0.0	0.0	0.1407	0.0	0.0	0.1407	0.0
Serious deterioration	0.119	0.119	0.119	0.0	0.0	0.0	0.0	0.0	0.0
Poor	0.0	0.0	0.0	0.272	0.272	0.272	0.0	0.0	0.0
Good	0.5997	0.5526	0.693	0.4467	0.3996	0.5403	0.7187	0.6716	0.81 23

Table 5-10: The probabilities of fusion with HCP Moderate corrosion and ER with No corrosion

HCP	Moderate corrosion								
ER	Good_No corrosion								
GPR	Serious			Poor			Good		
IE	S.D	D.E	G	S.E	D.E	G	S.D	D.E	G
Moderate corrosion	0.5424	0.5424	0.542 46	0.542	0.54	0.54	0.5	0.54	0.54
High corrosion	0.0	0.0	0.0	0.0	0	0	0	0	0
Serious delaminatio	0.0936	0.0	0.0	0.0936	0	0	0.093	0	0

n									
Delamination exist	0.0	0.1407	0.0	0.0	0.14	0	0.0	0.14	0
Serious deterioration	0.119	0.119	0.119	0.0	0	0	0.0	0.	0.
Poor	0.0	0.0	0.0	0.272	0.27	0.2	0.0	0	0
Good	0.244	0.197	0.338	0.0919	0.04	0.18	0.363	0.31	0.45

Table 5-11: The probabilities of fusion with HCP Moderate corrosion and ER with Low corrosion

HCP	Moderate corrosion								
ER	Low corrosion								
GPR	Serious			Poor			Good		
IE	S.D	D.E	G	S.D	D.E	G	S.D	D.E	G
Moderate corrosion	0.397	0.3973	0.397	0.3973	0.39	0.39	0.397	0.39	0.39
High corrosion	0.137	0.1375	0.137	0.1375	0.137	0.13	0.137	0.137	0.137
Serious delamination	0.0685	0.0	0.0	0.0685	0.0	0.0	0.068	0.0	0.0
Delamination exist	0.0	0.1030	0.0	0.0	0.103	0.0	0.0	0.10	0.0
Serious deterioration	0.0871	0.0871	0.0871	0.0	0	0	0	0	0
Poor	0.0	0.0	0.0	0.199	0.19	0.19	0.0	0.0	0.0
Good	0.3093	0.2748	0.377	0.197	0.162	0.2	0.396	0.36	0.46

Table 5-12 presents final results of the measured deteriorated areas detected by single technologies of HCP, ER, GPR and IE. Each technology detects specific type of defects. Table 5-12 also shows the results from pixel level fusion and the feature level fusion.

Table 5-12: Final results of pixel level fusion and feature level for bridge deck O2

HCP	Low Corrosion	20.327%	Blue _Green
	Moderate Corrosion	54.246%	Yellow
	High corrosion	25.427%	Red
	Low or No corrosion	17.3%	Grey, purple
	Moderate corrosion	63.93%	Blue, green
	High corrosion	18.77%	Red, Yellow

ER			
GPR	Good	60.9%	Green
	Poor Deterioration	72.2%	Yellow
	Serious Deterioration	11.9%	Red
IE	No Delamination	76.57%	Blue Green
	Delamination Exist	14.07%	Yellow
	Serious Delamination	9.36%	Red
Pixel Level Fusion	Good areas	47.13%	Green
	Poor areas	36.52%	Yellow
	Serious	16.345%	Red
∑ Yellow $\boxed{37.057\%}$ Feature Level Fusion ∑ Red $\boxed{12.765\%}$	Good	51.221%	Green
	Moderate corrosion	27.949%	Yellow
	Delamination Exist	1.92%	Yellow
	Poor	7.197%	Yellow
	High corrosion	9.47%	Red
	Serious delamination	1.918%	Red
	Serious Deterioration	1.377%	Red

As observed from Table 5-12, HCP detects the percentages of low corrosion, moderate corrosion and high corrosion as 20.327%, 54.246% and 25.427% respectively. ER detects the percentage of low corrosion, moderate corrosion and high corrosion as 17.3%, 63.93%, and 18.77% respectively. IE detects the percentage of low delamination, moderate delamination and serious delamination as 76.57%, 14.07% and 9.36% respectively. GPR detects the percentage of low, moderate and serious deterioration as 60.9%, 27.2% and 11.9% respectively.

Pixel fusion combines all single deterioration maps in one map. It combines all common good, poor and serious areas as it appears on the fused single image. Pixel Fusion results indicate good, poor and serious areas as 47.1327%, 36.522% and 16.345% respectively.

Feature fusion combines all good areas in one, it takes the advantages of using all technologies to predict the results. It merges the different types of defects individually. To obtain moderate defected areas from the feature fusion, the moderate corrosion of 27.949% is added to poor areas of 7.197 % and delamination existence of 1.92%, which gives 37.05% poor/defected areas. For the serious defected areas, the high corrosion of 9.47% is added to serious delamination of 1.918% and serious deterioration of 1.377%, which gives a total of 12.77% area. In this case, the pixel fusion and feature fusion results are very close.

As shown in Figure 5.16, condition rating is a child node of the fusion measurements node. It represents the probability of the condition rating based on the combined defected areas. In this case, condition rating 3 is within higher probability to be assigned to the bridge deck.

5.5.CASE STUDY OF BRIDGE DECK O3

For case study 3, all the information, data, measurements are taken from Iowa, Highway research board project 2011. The deck is designed in November 1969 and constructed in 1971 with 123 ft long and 44 ft wide.

The NDE methods used for the bridge inspection are:

a- Ground Penetrating radar (GPR) , ground coupled antenna and air coupled

b- Impact Echo (IE), device mounted on a robotic stepper TM

c- Rolling Half Cell Potential (HCP) measurements device

Deterioration maps of GPR, IE and HCP are extracted directly from Iowa, Highway research board project 2011. The maps are presented in Figures 5.18, 5.19 and 5.20.

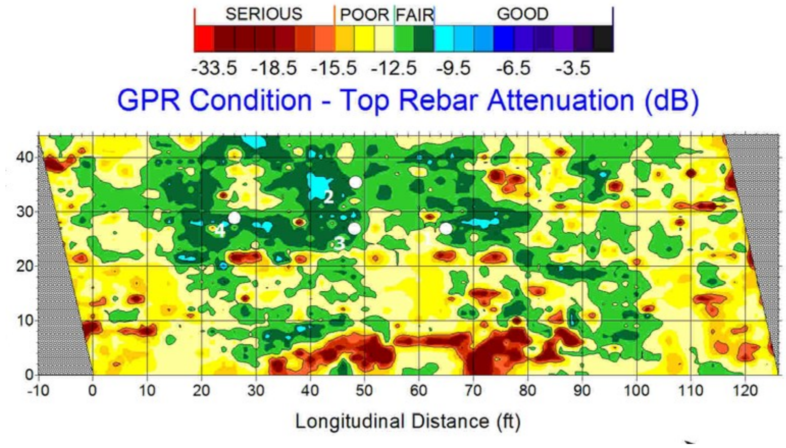


Figure 5.18: Deterioration map of GPR (Iowa report 2011)

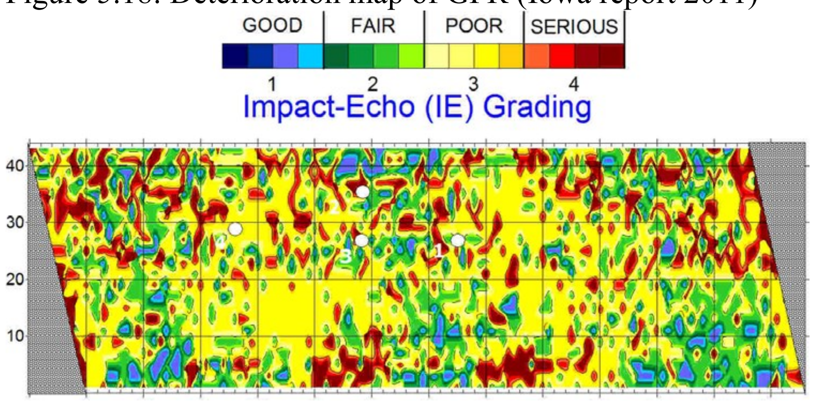


Figure 5.19: Deterioration map of IE (Iowa report 2011)

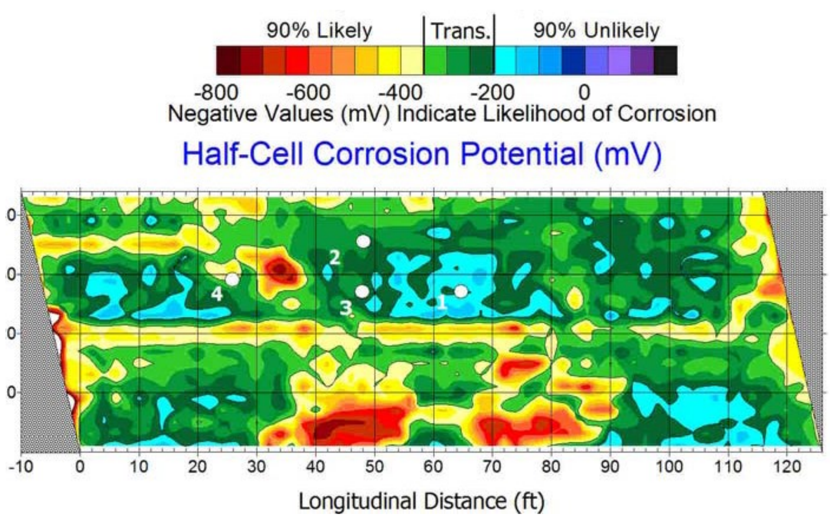


Figure 5.20: Deterioration map of HCP (Iowa report 2011)

As explained earlier, to apply pixel level fusion, deterioration maps of GPR, IE, and HCP are fused using Wavelet transform technique. Figure 5.21 illustrates the fused image. The numbers indicated in the fused image indicate the location of cores that are taken to verify the results of single technologies. The locations of these cores are illustrated in the original deterioration maps of GPR, HCP and IE, extracted from Iowa report. Table 5-13 presents the extracted good areas from the fused image; the good areas are shown with the green mixed with blue colors in Figure` 5.21. The good areas are extracted and measured using image processing techniques explained earlier. The extracted serious areas from the fused image are shown with the red color in Figure. 5.21. Table 5-13 presents the final results of the measured good, poor and serious areas.

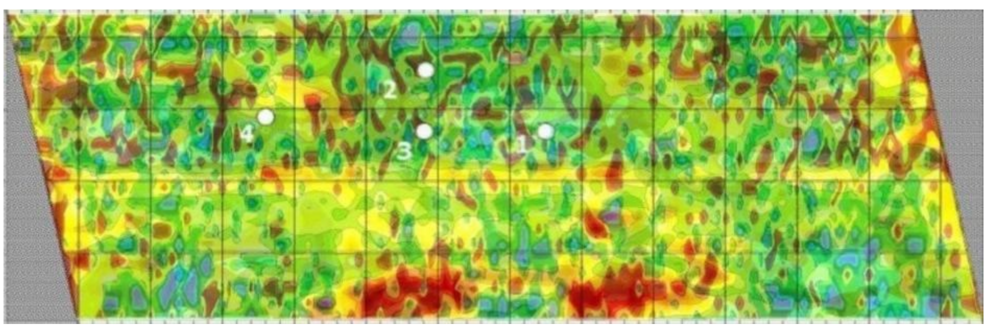


Figure 5.21: The Fused image of GPR, IE, and HCP

Table 5-13: Extracted Green Areas from the Fused Image

Green	Area (Sq.Pixel)	Width (Pixel)	Height (Pixel)	Total Area (Sq.Pixel)
1	308	939	301	282639
2	986	939	301	282639
3	436	939	301	282639
4	893	939	301	282639
5	245	939	301	282639
6	466	939	301	282639
7	507	939	301	282639

8	5491	939	301	282639
9	3659	939	301	282639
10	2202	939	301	282639
11	3788	939	301	282639
12	1200	939	301	282639
13	1631	939	301	282639
14	479	939	301	282639
15	552	939	301	282639
16	3710	939	301	282639
17	1210	939	301	282639
18	3266	939	301	282639
19	9462	939	301	282639
20	605	939	301	282639
21	697	939	301	282639
22	3967	939	301	282639
23	1358	939	301	282639
24	839	939	301	282639
25	19795	939	301	282639
Sum Green	67752	%green Fusion		23.97121

Table 5-14: Final results of pixel level image fusion

Condition	Percentage	Color
Good Areas	23.971%	Green
Poor Areas	60.61%	Yellow
Serious Areas	15.418%	Red

For feature level fusion, features are extracted from each deterioration maps of GPR, IE, GPR and ER. The good areas extracted from GPR deterioration map are mixed with some poor areas. These areas are extracted with the use of image processing techniques. The good, poor and serious areas in the GPR deterioration map are shown with green, yellow and red colors respectively.

Similar to the other case studies, the feature fusion of all the extracted features is done with the use of Bayesian Networks (BNs) technique. Figure 5.22 shows the developed Bayesian network to fuse features of GPR, IE, and HCP. In Figure 5.22, nodes of HCP, GPR and IE are parents of fusion measurements node. Bridge condition rating is the child node of the fusion measurements node.

Figure 5.23 shows the feature network with the probability distribution of each node. It shows HCP node has probability distributions of low corrosion of 8.6%, moderate corrosion of 67.49% and high corrosion of 23.8247%. GPR node probability distributions are serious condition of 6.955%, poor condition of 57.098% and good area of 35.95%. Probability distributions of Impact Echo are serious delamination of 18.312%, area where delamination exist of 57.68825% and good condition of 23.999%. The result of the fusion measurement node, as illustrated in Figure 5.23, are 26.392% moderate corrosion, 6.235% high corrosion, 3.357% serious delamination, 23.93 % areas with moderate delamination, 5.069% serious deterioration, 18.911% poor and 16.107% good.

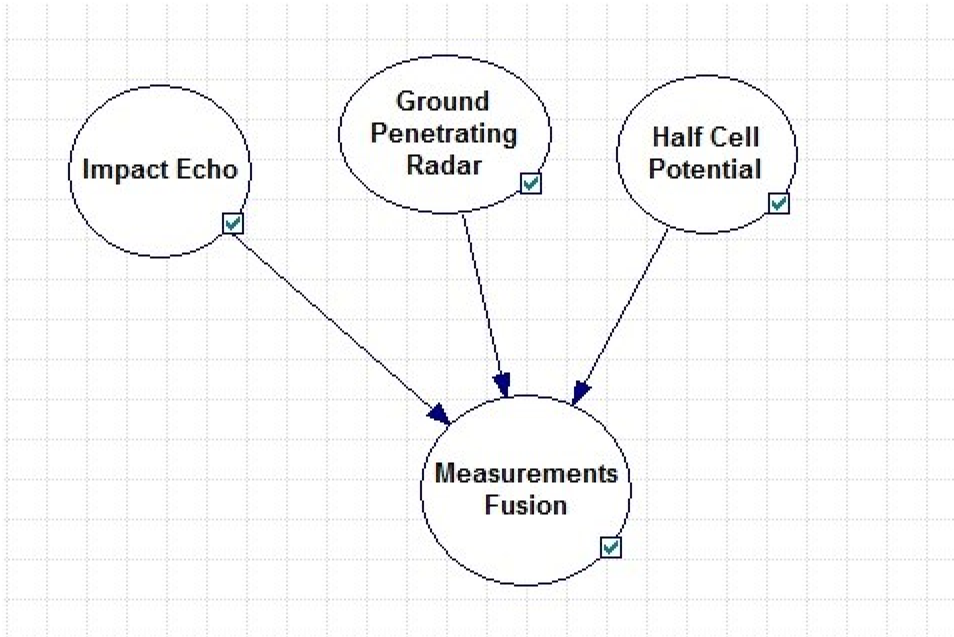


Figure 5.22: Feature Fusion Bayesian network of HCP, ER, GPR and IE

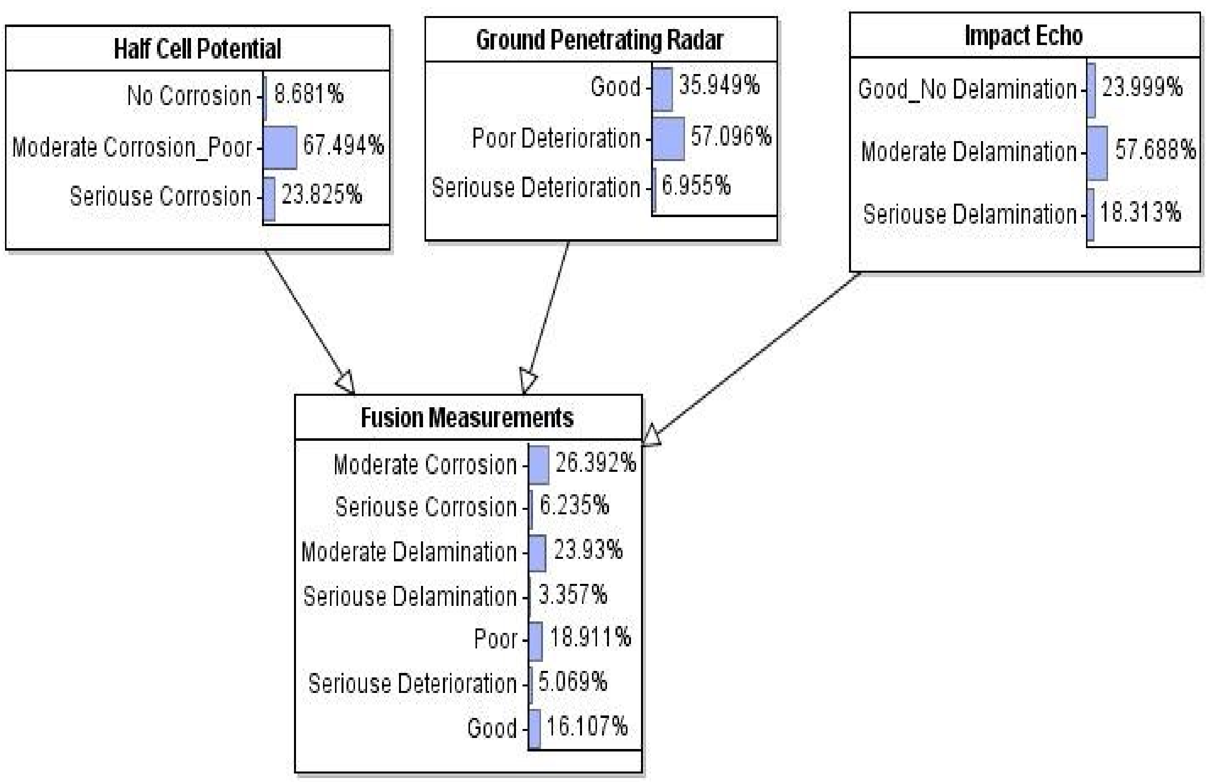


Figure 5.23: Feature Fusion Network with all nodes' Distribution

Table 5-15 recaps the results of the measured deteriorated areas detected by single technologies of HCP, GPR and IE. It shows the features extracted from pixel level fusion and the feature level fusion.

Table 5-15: The results of pixel level fusion and feature level

HCP	Low Corrosion	8.68%	Blue Green
	Moderate Corrosion	67.49%	Yellow
	High corrosion	23.825%	Red
GPR	Good	35.95%	Green
	Poor Deterioration	57.098%	Yellow
	Serious Deterioration	7%	Red
IE	No Delamination	23.99%	Blue Green
	Delamination Exist	57.688%	Yellow
	Serious Delamination	18.31%	Red
Pixel Level Fusion	Good	23.971%	Green
	Poor	60.61%	Yellow
	Serious	15.418%	Red
∑ Yellow %69.233	Good	16.107%	Green
	Moderate corrosion	26.392%	Yellow
	Moderate Delamination	29.93%	Yellow
Feature Level Fusion	Poor	18.911%	Yellow
	High corrosion	6.235%	Red
∑ Red % 14.662	Serious delamination	3.357%	Red
	Serious Deterioration	5.07%	Red

Table 5-15 presents the results of each individual technology. Each technology detects specific type of defects. HCP detects the percentages of low corrosion, moderate corrosion and high corrosion as 8.68%, 67.49% and 23.825% respectively. IE detects the percentage of low delamination, moderate delamination and serious delamination as 23.99%, 57.688% and 18.31% respectively. GPR detects the percentage of low, moderate and serious deterioration areas as

35.95%, 57.098% and 7% respectively. Pixel Fusion results indicate good, poor and serious areas as 23.971%, 60.61% and 15.418% respectively.

Feature fusion combines all good areas in one value. It takes the advantages of using all technologies to predict results. It merges different types of defects individually. From analysis the moderate defected areas resulted from the feature fusion is summation of moderate corrosion (26.39%), poor areas (18.911%), and moderate delamination (29.93%), which is equal to 69.233%. The serious defected areas are obtained by combining the high corrosion (6.235%) areas, serious delamination areas (3.357%) and serious deterioration (5.07%) areas, which is in total of 14.662%.

5.6.COMPARISON OF CORE SAMPLES RESULTS WITH THE PIXEL FUSION

5.6.1. Results From Core Samples For Bridge Deck O1:

Core samples have been taken from bride deck O1 to verify the results obtained from nondestructive evaluation methods. These samples have been taken at different locations during the assessment of the bridge deck (Iowa Highway research board project 2011.). Figure 5.24 shows the location of four core samples.

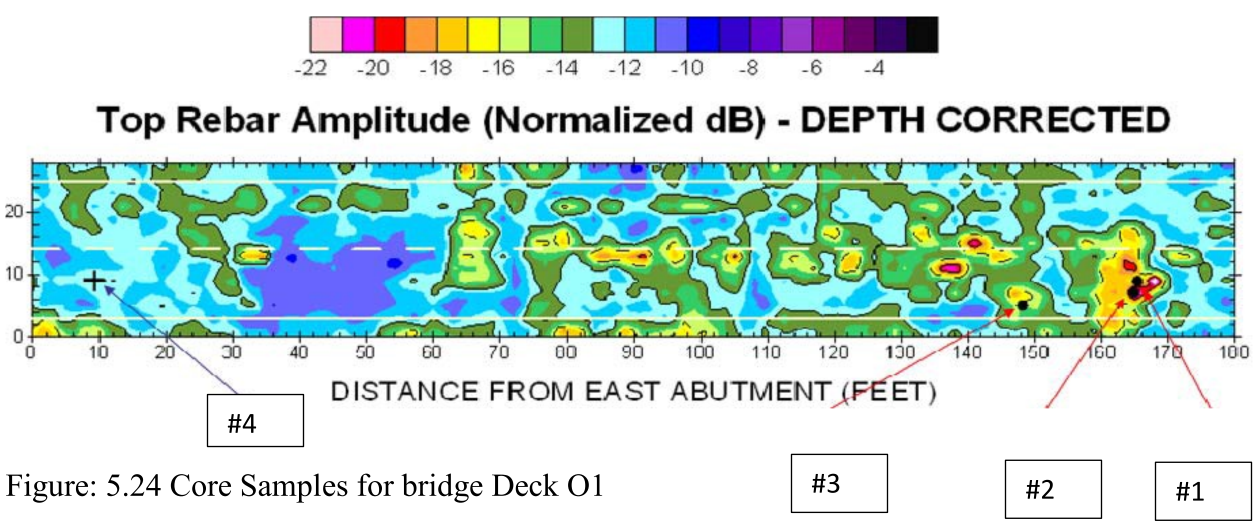


Figure: 5.24 Core Samples for bridge Deck O1

The developed fusion method has previously been shown to provide results that are in good agreement with results obtained from the traditional inspections. In this section, results from core samples' tests of the selected bridges are compared with the results from the developed fusion method.

The results from core sample #1 show a zone with significant deterioration. This zone has high moisture content and chloride content. Core sample #2 shows epoxy filled delamination. Core sample # 3 shows delamination and degradation. Core sample #4 shows sound concrete. The results obtained from core samples are qualitatively compared with the results of the fused image for bridge deck O1 in Figure 5.9. In the fused image of bridge deck O1, core samples #1 and #2 are located in the serious area. Core sample #3 is located in the poor area. Core sample #4 is located in the good area. The results of the fused image is in agreement with the core samples.

5.6.2. Results From Core Samples For Bridge Deck O2:

Core samples have been taken from bridge deck O2 to verify the results obtained from Nondestructive evaluation methods (Iowa Highway research board project 2011). These samples have been taken at different locations as illustrated in the fused image of bridge deck O2 in Figure 5.25.

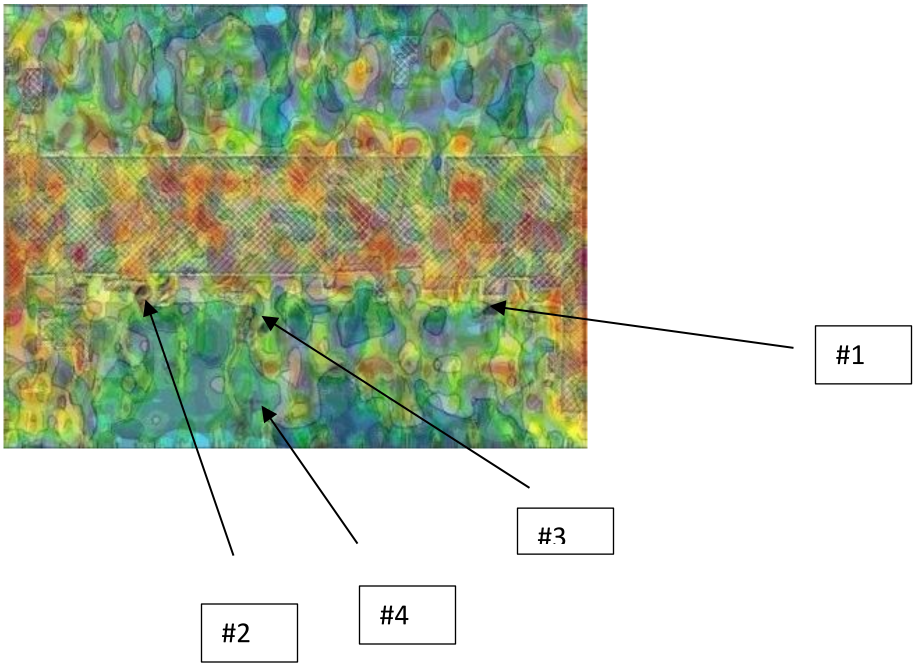


Figure 5.25 Core Samples Location in the fused image of Bridge Deck O2

According to Iowa Highway research board project 2011 report, the results of core sample #1 and #2 showed delamination and corroded steel. Core sample #3 showed high steel corrosion and is described as deteriorated in the Iowa report, 2011. Core sample #4 is sound concrete. As shown in Figure 5.25, the core sample #1 is located in poor areas in the fused image. Core Sample #2 is located in serious area. Core sample # 3 is located in between poor and serious areas. Core sample #4 is located in good areas. The result of the fused image is in agreement with the core samples.

5.6.3. Results From Core Samples For Bridge Deck O3:

Core samples have been taken from bridge deck O3 to verify the results obtained from nondestructive evaluation methods. These samples have been taken at different locations as illustrated in the fused image of bridge deck O3 in Figure 5.26.

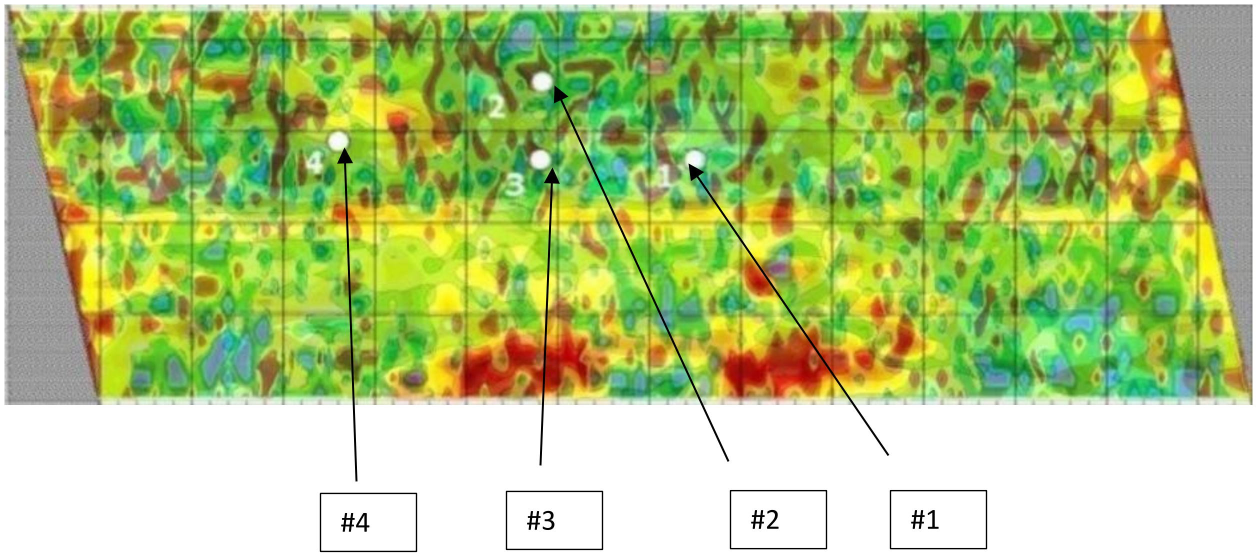


Figure 5.26: Core Samples Location in the fused image of Bridge Deck O3.

According to Iowa Highway research board project 2011 report, the results of core sample #1 is sound concrete. Core sample #2 showed big size of defects. Core sample #3 and #4 are fair but having some defects such as cavity and a hole filled with water. As shown in Figure 5.26, the core sample #1 is located in good areas in the fused image. Core Samples #2 and #3 are located between good and serious area. Core sample #4 is located between good and poor areas. The result of the fused image is in agreement with the core samples.

5.7. COMPARISON OF CORE SAMPLES RESULTS WITH THE FEATURE FUSION:

Feature level data fusion is mainly based on extracting features from single technologies and then fuses these features. Features extracted from HCP and ER maps are low, moderate and high corrosion. GPR map shows deterioration resulted from indirect delamination and corrosion. Features extracted from GPR are good, poor and serious deterioration areas. Deteriorated areas from features extracted from IE are good, moderate and serious delamination areas.

The results of core samples for bridge deck O2 have been compared with the results of the feature extracted from each individual technology and the results obtained from the feature level data fusion as shown in Table 5-16. The core samples information are extracted from Iowa, 2011 report. Core 1 shows moderate corrosion, poor deterioration and existence of delamination. Core 2 shows high corrosion and poor deterioration. Core 3 shows high steel corrosion and is described as deteriorated in the report. As per the feature fusion results related to corrosion, Core 3 includes serious steel corrosion. Also, after reviewing the deterioration maps of GPR and IE, it is found that core 3 is located in the fair areas of both technologies GPE and IE. However, it is located in serious areas of HCP map. As shown in Figure 5.25, the pixel fusion image, Core 3 is located between poor and serious areas.

Core 4 shows sound concrete. As illustrated in Table 5-16, the results obtained from core samples are focusing on specific locations. However, results extracted from each technology and results obtained from the feature level data fusion are for the whole deck surface. Table 5-16 shows that the feature fusion level interprets the % high, % moderate and % low of delamination, corrosion and deterioration. Feature fusion also represents the total serious areas as sum of % high delamination plus % high corrosion plus % high deterioration. It represents total poor area as sum of % moderate delamination plus % moderate corrosion plus % moderate deterioration.

Table 5-16 compares the results of feature fusion with the core samples results analysis. It shows that total serious defects are coming mainly from high corrosion, as indicated in core samples 3 and 4 tests. Poor areas are coming from moderate corrosion. Serious delamination value is low in feature fusion, the same as indicated in core sample 1 test.

Table 5-16: Comparing the results of feature extracted with the core samples for bridge deck O2

Diagnostic /Inspection Methods_ Single technologies/All Bridge Deck surface Core No											
IE_ Delamination			HCP_ Corrosion			GPR_ Deterioration			ER_ Corrosion		
Serious	Moderate	Good	High	Moderate	low	Serious	Poor	Good	High	Moderate	Low
9.36%	14.07%	76.57%	25.427%	54.246%	20.327%	11.9%	27.2 %	60.9%	18.77 %	63.93%	17.3%
Feature Fusion Results/ All Bridge Deck surface											
Feature Fusion_ Delamination			Feature Fusion_ Corrosion			Feature Fusion_ Deterioration			Total Feature Fusion		
High	Moderate	low	High	Moderate	Low	High	Moderate	Low	Serious	Poor	Good
0.86%	1.92%	51.22%	9.47%	27.949%	51.22%	1.377 %	7.2%	51.22 %	11.707 %	37.069 %	51.22%
Core Test Remarks											
Core Location # 1			Core Location #2			Core Location #3			Core Location #4		
Moderate Corrosion, Poor, Existence of delamination			High Corrosion, Moderate Deterioration			High Corrosion			Sound Concrete		

5.8. SUMARRY OF RESULTS INTERPRETATION FOR TWO LEVELS DATA FUSION

Tables 5-4, 5-12 and 5-15 present the advantages of each level of data fusion. It shows the capabilities of each level to interpret the final results. Tables 5-4, 5-12 and 5-15 are organized based on the three case studies of Iowa, US. As illustrated in Table 5-4, In case 1, the feature fusion level interprets the % of good, % poor and % serious areas extracted from multiple technologies. In Tables 5-12 and 5-15 for cases 2 and 3 respectively, the feature fusion level interprets the % of good, % moderate deterioration, % moderate corrosion, % high corrosion, % serious delamination and % serious deterioration extracted from multiple technologies.

In addition, the pixel level fusion shows and interprets the locations and % of good, poor and serious areas captured from multiple technologies. Pixel fusion is integration of pixels, the fused image combines all defected, moderate defected and good areas in one image. These areas are calculated after fusion. Image processing techniques are utilized to extract these features. Also, extracting these features depends on colors of different regions. In this research, pixel fusion level is used to identify location of defected areas without identifying specific types of defect. In this research, feature level fusion is used to identify specific type of defect such as corrosion, delamination and deterioration. Pixel and feature levels of data fusion are independent. Both levels are used to interpret the final results of bridge deck condition assessment. Two levels of data fusion complement one another; they can be considered by the bridge inspectors to assess bridge condition. It will increase their confidence. It provides engineers and inspectors by a new tool to interpret the result based on different technologies. Incorporating two levels of data fusion is recommended in bridge condition assessment to get the benefit from the two levels. Pixel and feature levels of data fusion are complementing one another. Each level has its own advantages; the pixel level indicates the locations and % of good, poor and serious areas. On the other hand, feature level assesses bridge deck conditions by providing only the % of good, poor and serious areas. However, the feature level fusion has the advantage to interpret the % of total poor areas to moderate deterioration, moderate delamination and moderate corrosion. It interprets the % of total serious areas as high corrosion, serious delamination and serious deterioration. Future condition of bridge decks can be predicted by developing deterioration model and assessing bridge condition in future by incorporating the third level of data fusion, the decision level.

5.9. NORTH RIVER BRIDGE DECK

This chapter include another case study is extracted from North River bridge deck report.

North River Bridge currently owned and maintained by the County of Peterborough. The bridge is located in the Township of Havelock-Belmont-Methuen, County of Peterborough, Ontario. The existing North River Bridge structure, built in 1966, it is a single span, rigid frame concrete bridge with a concrete deck and asphalt wearing surface width of 8.33 m, deck length of 10.36 m. Span length 9.1m and width of 7.3m from curb to curb.

The bridge deck Inspection in 2014 was prepared by G.D. Jewell Engineering Inc with lab test completed by Golder Associates Ltd. The detailed inspection was studied on September 2014. The concrete cover with average depth of 75mm. The concrete deck was in poor condition, it was delaminated with cracks.

The chloride content was evaluated using 4 core samples taken from the bridge deck. The results indicated that corrosion exists at different locations of the bridge deck. The chloride content was 0.311% exceeding the chloride limit threshold (0.05%). The Corrosion Potential

Survey conducted on the deck riding surface resulted in approximately 93% of the deck. Half-cell potential readings ranged with minimum -0.309V, average -0.438V and maximum -0.530V. On January 2015, Ainley Graham and Associates limited retained Multiview lnc to perform field test using Ground Penetrating Radar (GPR). They provided a comparison between half cell potential (HCP) and GPR. The road map was collected over 12 profiles distributed over the bridge deck. Data was acquired by 2 passes per lane with three ground coupled operating at 1000 MHz antennas. The data collected indicated GPR signal amplitude attenuation, the results showed % of deteriorated areas.

The report followed ASTM D6087-08 that is using threshold of 6-8db. Areas located within signal amplitude attenuation above of 6-8db are considered deteriorated. GPR report concluded that areas in HCP of -0.450V correlate with the areas in GPR of 6db signal attenuation. According to the North River bridge deck report 6db was taken as indication of deterioration threshold. Areas located above 6db is considered deteriorated. 70% of the bridge deck was deteriorated based on GPR.

In this research, feature network is built using measurements of GPR and HCP extracted from the report as indicated in Figure 5.27. Feature fusion is applied using the proposed data fusion method utilizing Bayesian Networks (BNs). The results from feature fusion is interpreted by two method. Feature fusion 1 shows % good, moderate defected and serious defected areas. Feature fusion 2 shows % no corrosion, % no deterioration, moderate corrosion, high corrosion and serious deterioration.

Table 5.17 provides a summary of results using feature fusion method and results from single technologies GPR and HCP. Table 5.17 shows the results from core samples.

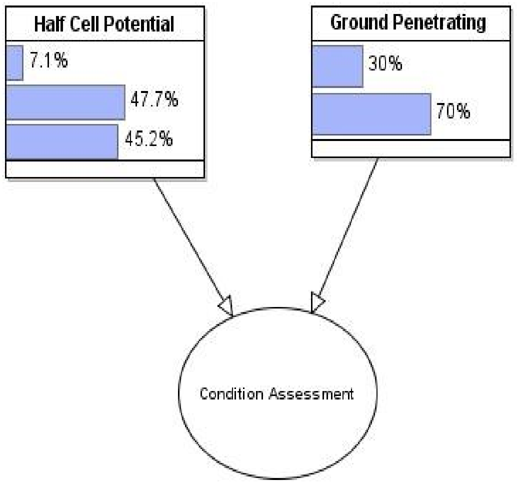


Figure 5.27: Feature Fusion Network for North River Bridge Deck

The results of core samples indicate high corrosion at different locations of bridge deck. The results of feature Fusion 1 and 2 are matching with the core sample results. It indicates serious areas (65%-70%). Feature fusion 1 and 2 utilize the advantages of both technologies. The final serious areas are three times of the moderate area and not equal to it as indicated by HCP. The final good area ranges between (3% to 9%) and not 30% as indicated from GPR.

Table 5-17: Summary of Results For North River Bridge Deck

<table>
<tr><td colspan="2" rowspan="3"><u>HCP</u></td><td colspan="2">No Corrosion</td><td colspan="2">7.1%</td></tr>
<tr><td colspan="2">Moderate Corrosion</td><td colspan="2">47.7%</td></tr>
<tr><td colspan="2">High corrosion</td><td colspan="2">45.2%</td></tr>
<tr><td colspan="2" rowspan="2"><u>GPR</u></td><td colspan="2">No deterioration</td><td colspan="2">30%</td></tr>
<tr><td colspan="2">Deterioration</td><td colspan="2">70%</td></tr>
<tr><td colspan="2" rowspan="3"><u>Feature Fusion 1</u></td><td colspan="2">Good</td><td colspan="2">2.85%</td></tr>
<tr><td colspan="2">Moderate Defected</td><td colspan="2">25.30%</td></tr>
<tr><td colspan="2">Serious Defected</td><td colspan="2">71.85%</td></tr>
<tr><td colspan="2" rowspan="5"><u>Feature Fusion 2</u></td><td colspan="2">No corrosion</td><td colspan="2">0.50%</td></tr>
<tr><td colspan="2">No Deterioration</td><td colspan="2">8.85%</td></tr>
<tr><td colspan="2">Moderate corrosion</td><td colspan="2">22.38%</td></tr>
<tr><td colspan="2">High Corrosion</td><td colspan="2">20.09%</td></tr>
<tr><td colspan="2">Serious Deterioration</td><td colspan="2">48.19%</td></tr>
<tr><td colspan="6">Core Tests</td></tr>
<tr><td>C1</td><td>C2</td><td>C3</td><td>C4</td><td>C5</td><td>C6</td></tr>
<tr><td>0.508V</td><td>0.465V</td><td>0.506V</td><td>0.511V</td><td>0.494V</td><td>0.399V</td></tr>
<tr><td>High</td><td>moderate</td><td>High</td><td>High</td><td>High</td><td>moderate</td></tr>
</table>

CHAPTER 6

6. DECISION LEVEL DATA FUSION

6.1. OVERVIEW

Deterioration models are required and used in Bridge Management System (BMS) to predict the condition and performance of bridges. Effective maintenance of bridge structure relies on the accuracy of deterioration models used to predict bridge performance. Markov Model is a deterioration forecasting model that is widely used in BMS. However, research showed that Markov Model has many shortcomings. This chapter provides a review of bridge deterioration modeling with emphasis on accuracy improvement of the generated transition probability matrix used in the model. Dynamic Bayesian Network (DBN) technique is utilized to predict the future conditions of bridge decks. Variables such as, factors affecting deterioration process and inspection measurements from Non-Destructive Evaluation (NDE) methods are incorporated to increase the accuracy of the developed deterioration model. The impact of these factors is extracted from the literature and the DBN model is developed. Measurements of NDE for years 2008 and 2013 for a case of a bridge deck are used to apply the model. The developed method is expected to improve current practice in forecasting bridge deck deterioration and in estimating the frequency of inspection. In this chapter, the fused measurements from multiple NDE methods are integrated with deterioration modeling. This integration extends data fusion method to the decision level. This chapter illustrates the computational framework for three levels of data fusion.

6.2. APPLICATION OF DBNs MODEL

Factors affecting bridge deterioration are incorporated in Dynamic Bayesian network model. The impact of these factors are extracted from the literature review. Huang (2010) identified 11 attributes that extracted from the inventory data of decks record from BMS. The author analyzed five factors that have great impact on transferring bridge deck condition from state 1 to state 2, A12. These factors are: District, Design Load, ADT (Vehicle/Day), Environment, and Degree of Skew. The author analyzed five factors that have great impact on transferring bridge deck condition from state 2 to state 3, A23. These five factors are: Design Load, Deck Length (m), Deck Area (m2), Environment, and Number of Spans. Huang (2010) listed the 11 factors that did impact the bridge deck deterioration. Table 6-1 illustrates the impact of factors on the transition of bridge deck condition from state 1 to state 2 (A12), from state 2 to state 3 (A23) and from state 3 to sate 4 (A34).

Table 6-1: The impact of factors on the transition of bridge deck condition (Huang 2010).

Factors(A12)	***P-value***	**Factors (A23)**	***P-value***	**Factors (A34)**	***P-value***	**Factors (A45)**
District	0.0014	Design Load	0.0211	Design Load	0.0211	Design Load
Design Load	0.0001	Deck Length	0.0158	Environment	0.0158	Environment
ADT	0.0158	Deck area	0.0019	Deck Length	0.0019	Deck Length
Environment	0.0005	Environment	0.0053	Deck area	0.0053	Deck area
Degree of Skew	0.05	Number of Spans	0.0149	Number of Spans	0.0149	Number of Spans
				Maintenance History		Maintenance History
				Age		Age
				Previous Condition		Previous Condition

Measurements for years 2008 and 2013 of GPR for a bridge deck are used in this study. This data were extracted from condition mapping of bridge deck in years 2008 and 2013 (Kien and Zayed 2014). The % of delamination for years 2008 and 2013 are calculated using generic model of Martin (2013). The amplitude values for years 2008 and 2013 of bridge deck are shown in Table 6-2. The amplitude values are extracted approximately from the deterioration mapping of previous research efforts for years 2008 and 2013 (Kien and Zayed 2014). Table 6-2 shows % of delaminated areas that are calculated using the generic model. Percentage (%) of delamination is calculated in the following steps because of lack of the raw data:

1- Dinh et al. (2014) plotted two deterioration mapping for years 2008 and 2013. These deterioration mapping were built based on GPR signal attenuation. Amplitude values for the bridge deck are obtained from the deterioration maps.

2- Dinh et al. (2014) plotted the results based on the rebar reflection amplitude and related the deterioration of bridge deck with this reflection.

3- The GPR amplitude ranges that appears as values of GPR in the literature (Dinh et al. 2014) are utilized to apply generic linear model (Martin 2013) to get % of delamination in the bridge deck for each year.

4- Martin (2013) indicated that the model can be used for bridge deck with moderate corrosion and with threshold -1.6dB) by using Eqs (6.1), (6.2) and (6.3)

$$Y = 7.051725 * \mathrm{X} + 1.78044 \qquad (6.1)$$

$$Y = \%\ Delamination \qquad (6.2)$$

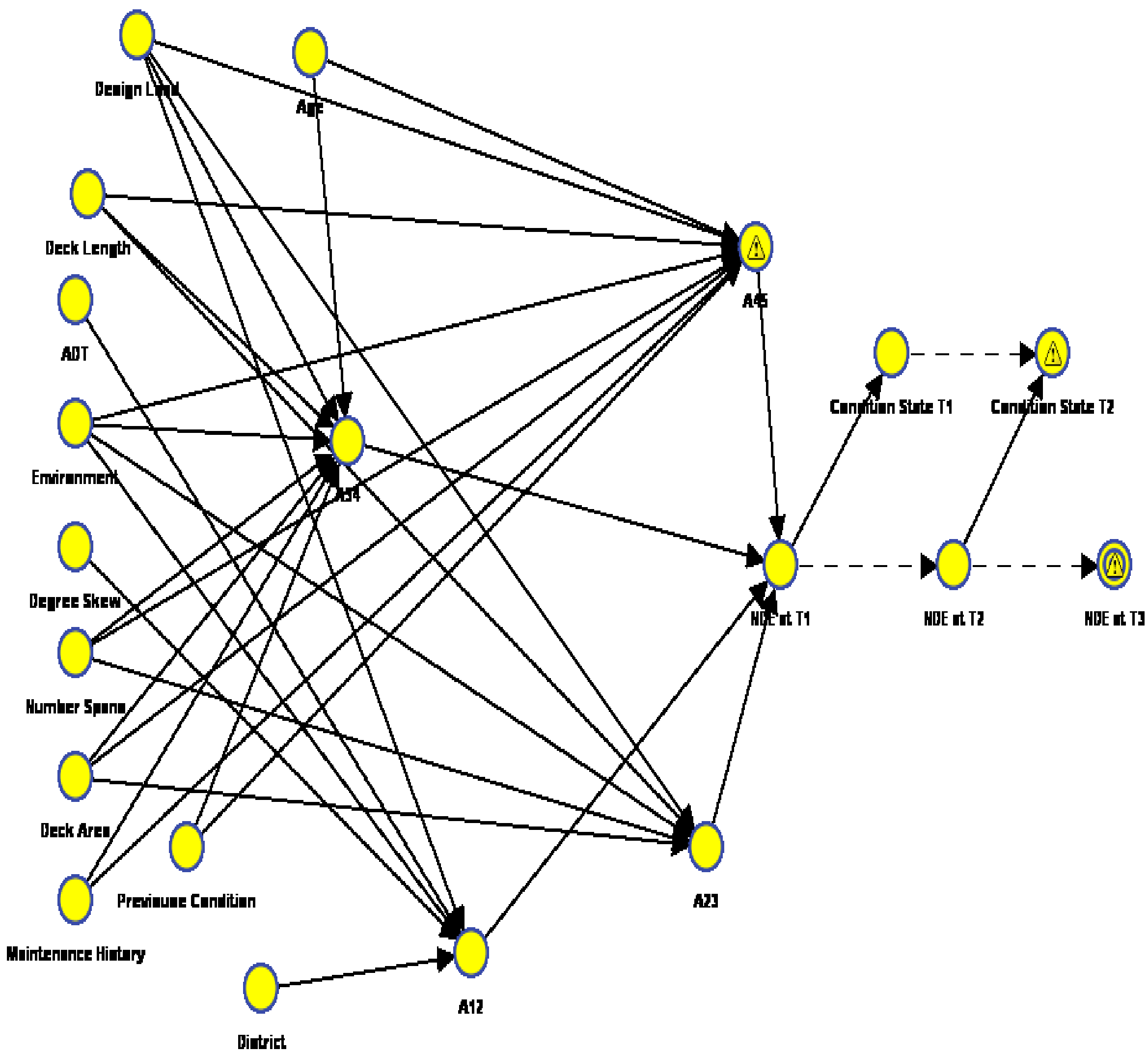
$$\mathrm{X} = \mathrm{Skew} * \mathrm{Mean\ GPR\ Amplitude} \qquad (6.3)$$

5- In this way, % delamination for each year (2008 and 20013 of the case study) are obtained.

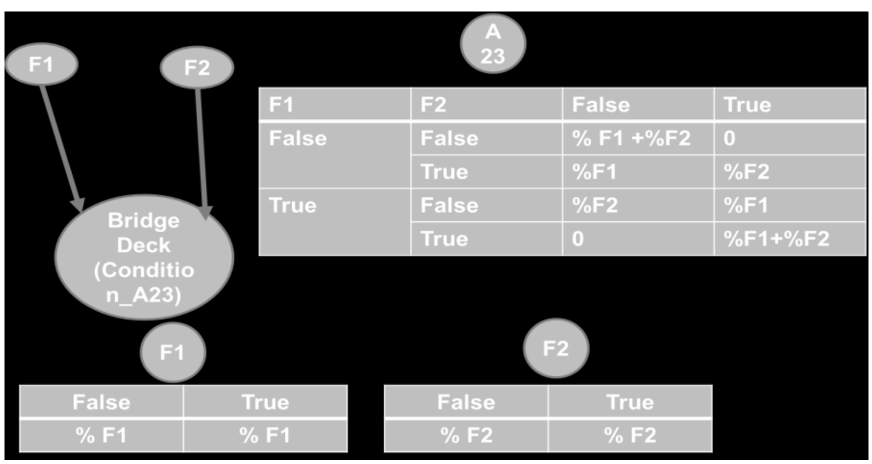
Table 6-2: Amplitude values of Bridge Deck

2008	2013	2008	2013
-9	-7	-7	-4
-7	-7	-6	-5
-10	-8	-9	-9
-11	-9	-12	-13
-16	-11	-14	-10
-16	-11	-17	-8
-17	-13	-18	-13
-18	-18	-16	-14
-10	-10	-7	-16
-11	-14		
-25.667	-22.222	**Mean**	
-0.0608	-0.1694	**SKEW**	
1.56151	3.7651	**Mean *SKEW**	
12.7105	**28.1357**	**%Delamination**	

Figure 6.1 illustrates the basic network that consists of factors impacting on the transition of bridge deck condition. NDE measurements are child node of A12, A23, A34 and A45. From NDE measurements at different times, condition assessment nodes are determined with different time. Figure 6.1 is considered the qualitative part of the network as it shows the relationship between different nodes. The relationship between nodes is quantified by defining the conditional probability table



a) Dynamic Bayesian Networks



b) An example of building CPT in BNs

Figure 6.1: Dynamic Bayesian Network of Bridge Deck Deterioration Model

The relationship between nodes is quantified by defining the conditional probability table. Factors that are impacting transition of bridge deck condition at different states are defined in BNs as illustrated in Figure 6.1. States of each factor are defined based on their respective P value. P values of each factor are extracted from previous study (Huang 2010). Table 6-3 defines false and true states for each factor. These states are defined in BN for each factor node. Figure 6.1 illustrates an example of values generated in CPT based on factors impact, in case if F1 contributed %trues occurrence and F2 contributed %true occurrence, then the true value of occurrence for the two factors are summation of true values from the two factors %F1+%F2 that assigned in the CPT of fusion node S3.

Table 6-3: The Defined Factors' States

Factors	**False**	**True**
District	14%	86%
Design Load	01%	99%
ADT	30%	70%
Environment	05%	95%
Degree of Skew	50%	50%
Deck Length	30%	70%
Deck area	19%	81%
Number of Spans	25%	75%
Maintenance History	15%	85%
Age	15%	85%
Previous Condition	10%	90%

Table 6-4 shows 32 conditional probabilities on node A12. Table 6-4 utilized to define the relationship between the factors and bridge state transition from state 1 to state 2 (A12). It measures the true and false percentage of A12 occurrence with high and the low impact of the factors. As shown in Table 6-4, the factors impacting A12 are District, Design Load, ADT, Environment and Degree of Skew. The 32 probabilities are generated based on varying the impact of the factors. For example, the first conditional probability is generated based on the low or false impact of factors District, Design Load, ADT, Environment and Degree of Skew. So, the first conditional probability is assigned true and false percentage values of 0% and 100% respectively. The second conditional probability is generated based on the false value of factors District, Design Load, ADT, Environment and the true value of the factor Degree of skew. The second conditional probability is assigned true and false percentage values of 50% and 50% respectively because Degree of skew factor is one of the significant factors with high impact comparing to the other factors. The other 30 conditional probabilities are assigned in the same way. Table 6-5 defines the conditional probability table of 32 conditional probabilities that measure the strength of the relationship between factors Deck Length, Deck area, Number of Spans, Environment, Design Load and node A23.

Table 6-4: Conditional probability table of transition from state 1 to state 2 (A12)

District	Design Load	ADT	Environment	Degree Skew	FALSE	TRUE
FALSE	FALSE	FALSE	FALSE	FALSE	100	0
				TRUE	50	50
			TRUE	FALSE	95	5
				TRUE	75	25
		TRUE	FALSE	FALSE	70	30
				TRUE	20	80
			TRUE	FALSE	65	35
				TRUE	15	85
	TRUE	FALSE	FALSE	FALSE	99	1
				TRUE	51	49
			TRUE	FALSE	94	6
				TRUE	44	56
		TRUE	FALSE	FALSE	49.286	50.714
				TRUE	19	81
			TRUE	FALSE	64	36
				TRUE	14.286	85.714
TRUE	FALSE	FALSE	FALSE	FALSE	86	14
				TRUE	64	36
			TRUE	FALSE	19	81
				TRUE	31	69
		TRUE	FALSE	FALSE	44	56
				TRUE	80	20
			TRUE	FALSE	51	49
				TRUE	1	99
	TRUE	FALSE	FALSE	FALSE	85	15
				TRUE	35	65
			TRUE	FALSE	80	20
				TRUE	30	70
		TRUE	FALSE	FALSE	55	45
				TRUE	5	95
			TRUE	FALSE	50	50
				TRUE	0	100

Table 6-5 shows the relationship between factors and A34 through different probabilities and varying of incorporating the impact of the factors. It measures the true and false percentage of A34 occurrence with the high and the low impact of the factors. For example, the first conditional probability is generated based on the low or false impact of factors Deck Length, Deck area, Number of Spans, Environment and Design Load. So, the first conditional probability is assigned true and false percentage values of 0% and 100% respectively. The second conditional probability is generated based on the false value of factors District, Design Load, ADT, Environment and the true value of the factor Design load. So, the second conditional probability is assigned true and false percentage values of 28% and 72% respectively.

Table 6-5: Conditional Probability table of transition from state 2 to state 3 (A23)

Deck Length	Deck Area	Number Spans	Environment	Design Load	FALSE	TRUE
FALSE	FALSE	FALSE	FALSE	FALSE	100	0
				TRUE	72	28
			TRUE	FALSE	86	14
				TRUE	58	42
		TRUE	FALSE	FALSE	77	23
				TRUE	49	51
			TRUE	FALSE	63	37
				TRUE	35	65
	TRUE	FALSE	FALSE	FALSE	90	10
				TRUE	37	63
			TRUE	FALSE	76	24
				TRUE	48	52
		TRUE	FALSE	FALSE	67	33
				TRUE	39	61
			TRUE	FALSE	53	47
				TRUE	25	75
TRUE	FALSE	FALSE	FALSE	FALSE	75	25
				TRUE	47	53
			TRUE	FALSE	61	39
				TRUE	33	67
		TRUE	FALSE	FALSE	52	48
				TRUE	24	76
			TRUE	FALSE	38	62
				TRUE	10	90
	TRUE	FALSE	FALSE	FALSE	65	35
				TRUE	37	63
			TRUE	FALSE	51	49
				TRUE	23	77
		TRUE	FALSE	FALSE	42	58
				TRUE	14	86
			TRUE	FALSE	28	72
				TRUE	0	100

Table 6-6 shows the conditional probabilities of GPR measurements at year 2008. Table 6-6 measures the strength of transition for condition states between A12, A23, A34 and A45 and the probability of existence of defected areas. For example, the first conditional probability is generated based on the true occurrence of A12, A23, A34 and A45. So, the first conditional probability is assigned 0 value if there is no area defected. The first conditional probability is assigned 0.25 if the defected area is less than 2%, less than 10%, more than 10% and more than 25 %. The second conditional probability is generated based on the true occurrence of A12, A23, A34 and the false occurrence of A45. So, the second conditional probability is assigned 0 value if there is no area defected or the area defected is more than 25%. It is assigned a value of 0.1 if the defected area is less than 2%. It is assigned a value of 0.45 when the defected area is less or more than 10%.

Table 6-6: Conditional Probabilities of node NDE measurements

A12	TRUE					
A23	TRUE					
A34	TRUE		FALSE		TRUE	
A45	TRUE	FALSE	TRUE	FALSE	TRUE	FALSE
No Area Defected	0	0	0	0	0	0
Area Defected Less 2%	0.25	0.1	0.1	0.5	0	0
Area Defected Less 10%	0.25	0.45	0.45	0.5	0.3333	0
Area Defected More 10%	0.25	0.45	0	0	0.3333	0.5
Area Defected More 25%	0.25	0	0.45	0	0.33333	0.5

A12						Fa
A23	se		True			
A34	False		True		False	
A45	True	False	True	False	True	False
No_Area_Defected	0	0	0	0	0	0
Area_Defected_Less_2	0	0.5	0	0	0	0
Area_Defected_Less_10	0.5	0.5	0.33333333	0.5	0.5	1
Area_Defected_More_10	0	0	0.33333333	0.5	0	0
Area_Defected_More_25	0.5	0	0.33333333	0	0.5	0

A12	False					
A23	ue		False			
A34	False		True		False	
A45	True	False	True	False	True	False
No_Area_Defected	0	0	0	0	0	1
Area_Defected_Less_2	0	0	0	0	0	0
Area_Defected_Less_10	0.5	1	0.33312226	0.5	0	0
Area_Defected_More_10	0	0	0.33342237	0.5	0.5	0
Area_Defected_More_25	0.5	0	0.33345538	0	0.5	0

As illustrated in Figure 6.2, the dynamic Bayesian network of the basic network at different times T0, T1 in 2008 and T2 in 2013 is built. The basic Bayesian network is repeated within the time and at each time slice the networks are connected thorough temporary arcs. Modeling deterioration this way ensures that future condition depends mainly on current condition, previous condition and related factors.

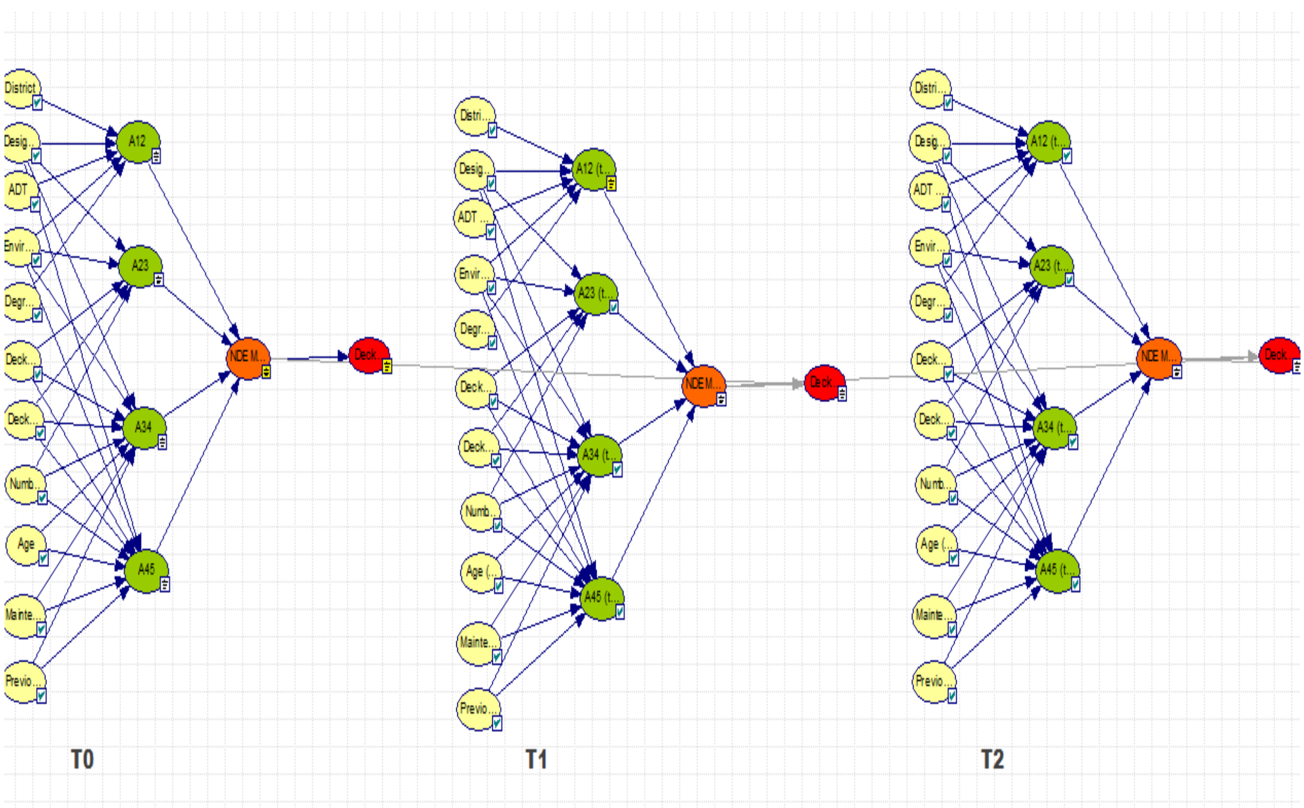


Figure 6.2: Dynamic Bayesian Network for Bridge Deck assessment

The results of the developed DBNs show the probability of condition states at different times. As illustrated in Figure 6.3, the vertical axis represents the probability of different condition states and the horizontal axis represents the time steps. The spacing between time steps is 5 years. From time t0 to time t1, the bridge deck falls under condition state 1. From time t1 to time t2 (year 2008) and from time t2 (year 2008) to t3 (year 2013), the bridge deck fall under condition state 3. After 5 years (year 2018), the bridge deck will fall under condition state 5.

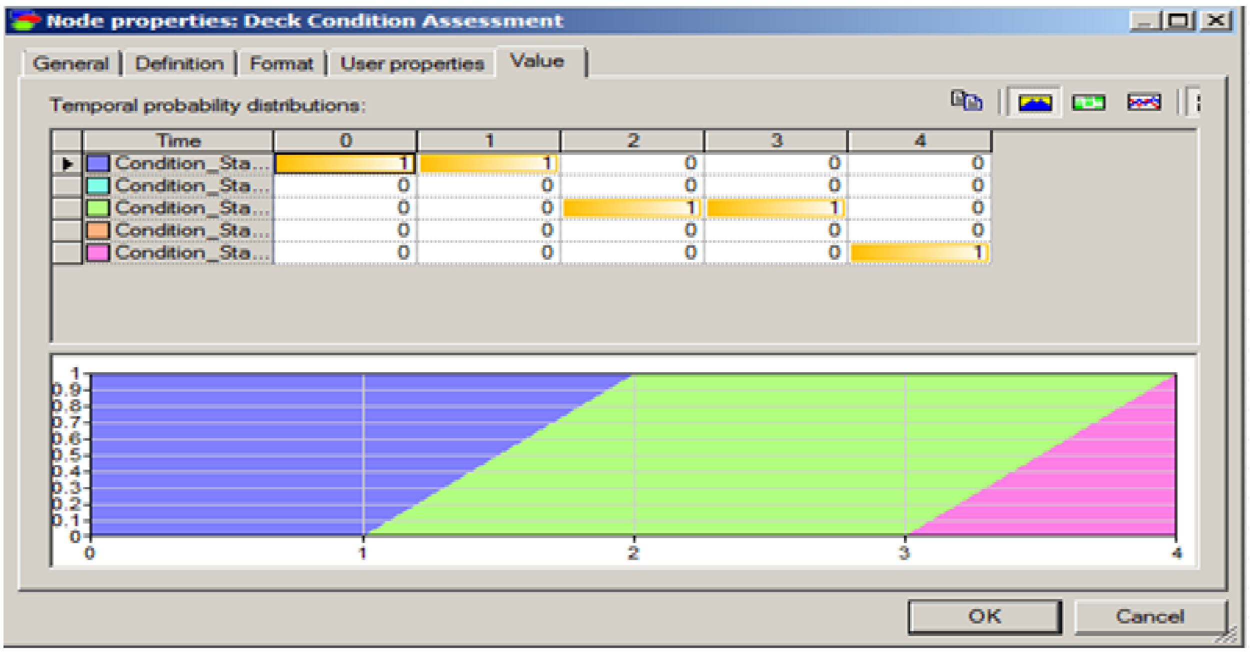


Figure 6.3: The results of bridge deck Condition

The results show also the probability of the existence of the defected areas measured by NDE at different time steps. As illustrated in Figure 6.4, from t0 to t1, the defected area is falling under the category of “no area defected”. From t0 to t2, the defected area is falling under the category of “area defected less more than zero and less than 2%”. From t1 to t4, the defected area is falling under the category of “area defected is more than 10% and less than 25%”. From t3 to t4, the defected area is falling under the category of “area defected is more than 25%”.

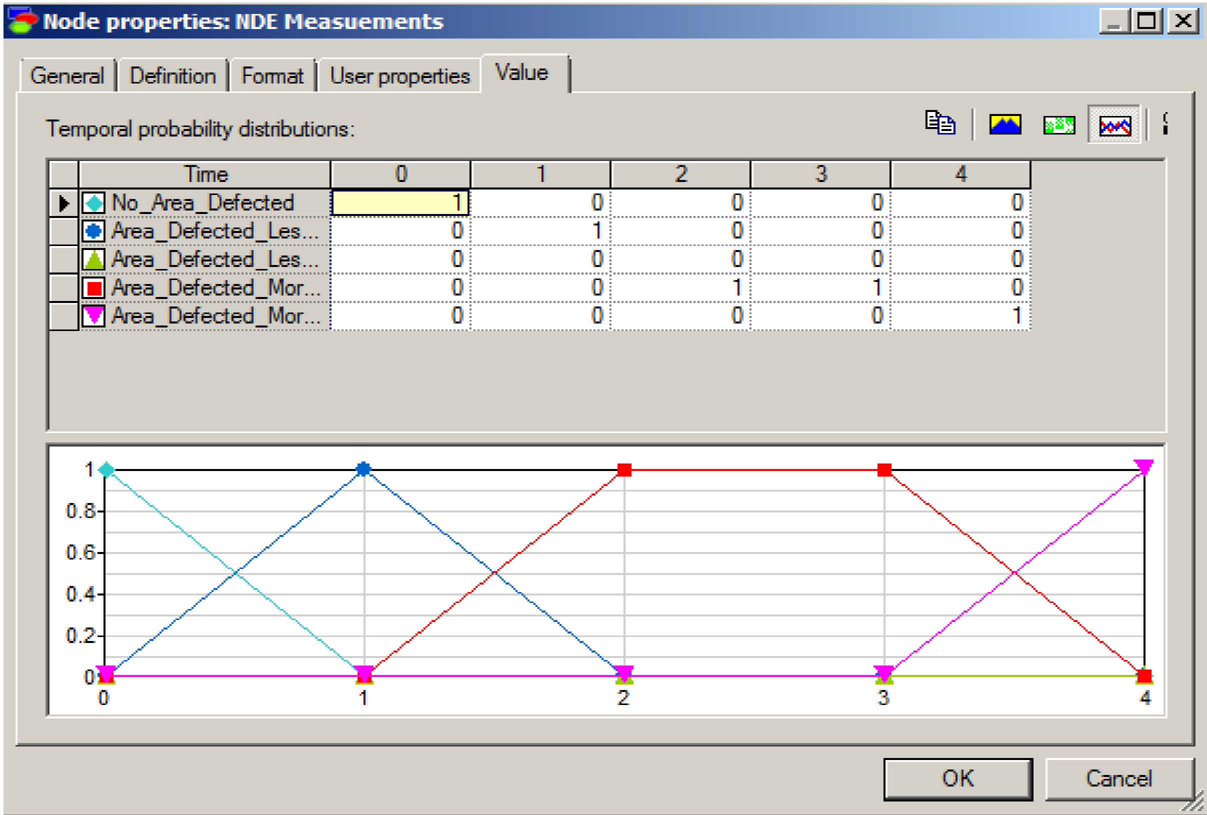


Figure 6.4: The NDE Measurements with 5 Time Steps

6.3. PREDICTION OF BRIDGE CONDITION USING MARKOV MODEL

Markov Model is used to predict the future condition of the bridge deck for the same case study. So, condition state C0 at time 0 is taken at year 1978. In order to predict the future condition of the deck at different times, every 5 years, Eq. (6.4) is applied, where t is the number of transactions:

C (t) = C (0) * TPM power t ……………………………………………………...(6.4)

The condition state vector C(t) = [C1(t) C2(t) C3(t) C4(t) C5(t)]…………(6.5)

C(0) = [1 0 0 0 0]

TPM: Transition Probability Matrix for five condition states:

P= [P11 P12 P13 P14 P15 P11 P12 P13 P14 P15

P21 P22 P23 P24 P25 0 P22 P23 P24 P25

$$\begin{matrix} P31 & P32 & P33 & P34 & P35 \\ P41 & P42 & P43 & P44 & P45 \\ P51 & P52 & P53 & P54 & P55 \end{matrix} = \begin{matrix} 0 & 0 & P33 & P34 & P35 \\ 0 & 0 & 0 & P44 & P45 \\ 0 & 0 & 0 & 0 & P55 \end{matrix} \quad \ldots\ldots\ \ldots(6.6)$$

$$= \begin{matrix} p11 & 1\text{-}p11 & 0 & 0 & 0 \\ 0 & p22 & 1\text{-}p22 & 0 & 0 \\ 0 & 0 & p33 & 1\text{-}p33 & 0 \\ 0 & 0 & 0 & p44 & 1\text{-}p44 \\ 0 & 0 & 0 & 0 & p55 \end{matrix} = \begin{matrix} 0.513 & 0.487 & 0 & 0 & 0 \\ 0 & 0.492 & 0.507 & 0 & 0 \\ 0 & 0 & 0.5 & 0.5 & 0 \\ 0 & 0 & 0 & 0.513 & 0.487 \\ 0 & 0 & 0 & 0 & 1 \end{matrix}$$

TPM in Markov model is calculated based on the true values of nodes A12, A23, A34 and A45. The summation of probabilities in each row equals 1. P12 is the probability of transition between condition state 1 and condition state 2. P12 is calculated as the average of the 32 true values of node A12, which is equal to 48.7 as presented in Table 6-4. P11 is calculated as 1- P12. P23 is calculated as the average of the 32 true values of node A23 which is equal to 0.507. P22 is calculated as 1-P23.

Year 1993 means 15 years after the initial condition and the time interval between inspection measurements are 5 years. So, the number of transactions are 3. Condition states at year 1993 are:

Condition States = [0.135005697 0.368965323 0.274562808 0.220489737 0]

At year 2008, 30 years after the initial condition and the number of transactions are 6, condition states are:

Condition States = [0.018227 0.093755 0.23468386 0.3171046 0.3345]

At year 2023, 45 years after the initial condition with time interval between inspection measurements of 5 years and thus the number of transactions are 9, condition states are:

Condition States= [0.0024607 0.01756 0.0698756 0.16798167 0.708455]

The results of the probabilities of the five condition states at different years are summarized in Table 6-7.

Table 6-7: Probability of bridge condition states at different transactions

Years	1978	1993	2008	2023
Condition 1	**1**	0.135	0.01823	0.0024
Condition 2	0	**0.3689**	0.09375	0.0175
Condition 3	0	0.27456	0.2347	0.06988
Condition 4	0	0.22049	**0.3171**	0.1679
Condition 5	0	0	0.3345	**0.70846**

6.4. COMPARING THE RESULTS OF DBNs AND MARKOV MODEL

Table 6-8 compares the final results of modeling bridge deterioration using Dynamic Bayesian Networks and Markov model techniques. Although, transition probabilities matrices for Markov model were built using some of the information from Bayesian networks, it doesn't consider the impact of the deterioration factors. Also, it doesn't take into consideration the previous condition of the structure. It is very clear from the result of Markov model that it doesn't consider the impact of maintenance action. So, at years 1993 and 1998, the bridge was deteriorated faster to reach condition 2. Starting from year 2008, the bridge deteriorated faster to reach condition 5. In the DBNs model, factors impacting bridge deterioration are incorporated. It is very clear from the results that bridge deck will start to deteriorate and reach condition state 5 at year 2018.

Table 6-8**:** The Results Comparison between Markov and DBNs models

Years	Markov Model	DBNs Model
1993	2	1
1998	2	1
2003	3	3
2008	5	3
2013	5	3
2018	5	5
2023	5	5

As a summary, this chapter provides a method to predict bridge deck condition states using Dynamic Bayesian Networks. The model is built using limited inspection records for two years at 2008 and 2013. The model incorporates the impact of deterioration factors extracted from the literature. Modeling bridge deck deterioration this way ensures that future condition depends mainly on current condition, previous condition and factors impacting bridge deck deterioration. The model circumvents the limitations of current practice which is based on traditional Markov model. The final results of Dynamic Bayesian Networks are compared with the results of Markov model. These results show that incorporating deterioration factors improve the forecasting accuracy and its impact on forecasting inspection frequency and maintenance action required. The main contribution of the developed model lies in building an advanced deterioration modeling for bridge deck by using measurements of NDE methods and incorporating related factors. The model is generic and it can be updated when new observations are incorporated.

6.5. COMPUTATIONAL FRAMEWORK FOR THREE LEVELS DATA FUSION

This section presents the computational framework for pixel, feature and decision levels of data fusion. It shows the computer software that are utilized to perform each level. As illustrated in Figure 6.5, multiple NDE measurements are main inputs of framework. These inputs are raw data processed based on the physical principal of each technology such as RADAN®7 Geophysical Survey Systems, Inc. (GSSI) for GPR and FLIR Tool, ThermaCam S60, FLIR System Inc for IR. After that, these inputs are processed also using image processing techniques, which are implemented using ImageJ 1.45s and MATLAB version R2012a software. Image fusion is implemented using Wavelet transform technique in MATLAB. Features are extracted from the fused image to calculate percentages of good, poor and serious areas. The second level of data fusion is the feature fusion utilizing Bayesian Networks (BNs) that is implemented using AgenaRisk7 and BayesiaLab5 software. The main output from pixel level is % of total defected areas. The % of total defected areas is used to assign bridge deck condition rating in accordance with condition rating of Minnesota department of transportation. This step is done manually in pixel level. However, in feature levels of data fusion, condition rating for bridge deck is assigned based on the % of defected measured areas. This step is performed automatically by incorporating condition rating node in BNs. Both levels are used to interpret the final results of bridge deck condition.

Figure 6.6 illustrates the computational framework for decision level data fusion implemented using Dynamic Bayesian Networks (DBNs). Condition rating at different times T1 and T2 are considered the main inputs for the framework using BayesiaLab5 and GeNIe 2. Software. The main output from the decision level of data fusion is the deterioration curve to forecast the future condition of bridge deck.

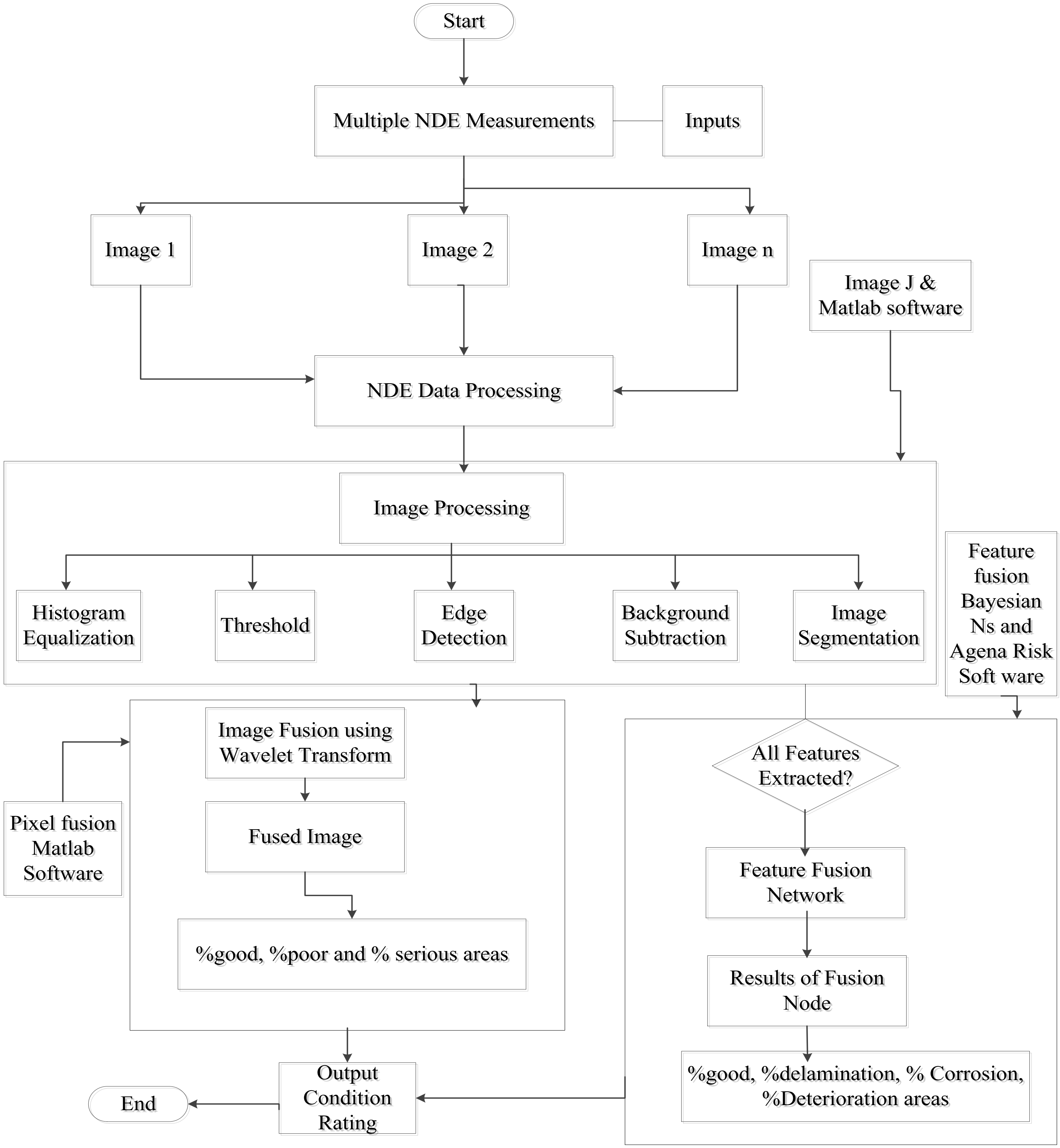


Figure 6.5: Computational Framework for Pixel and Feature Levels Data Fusion

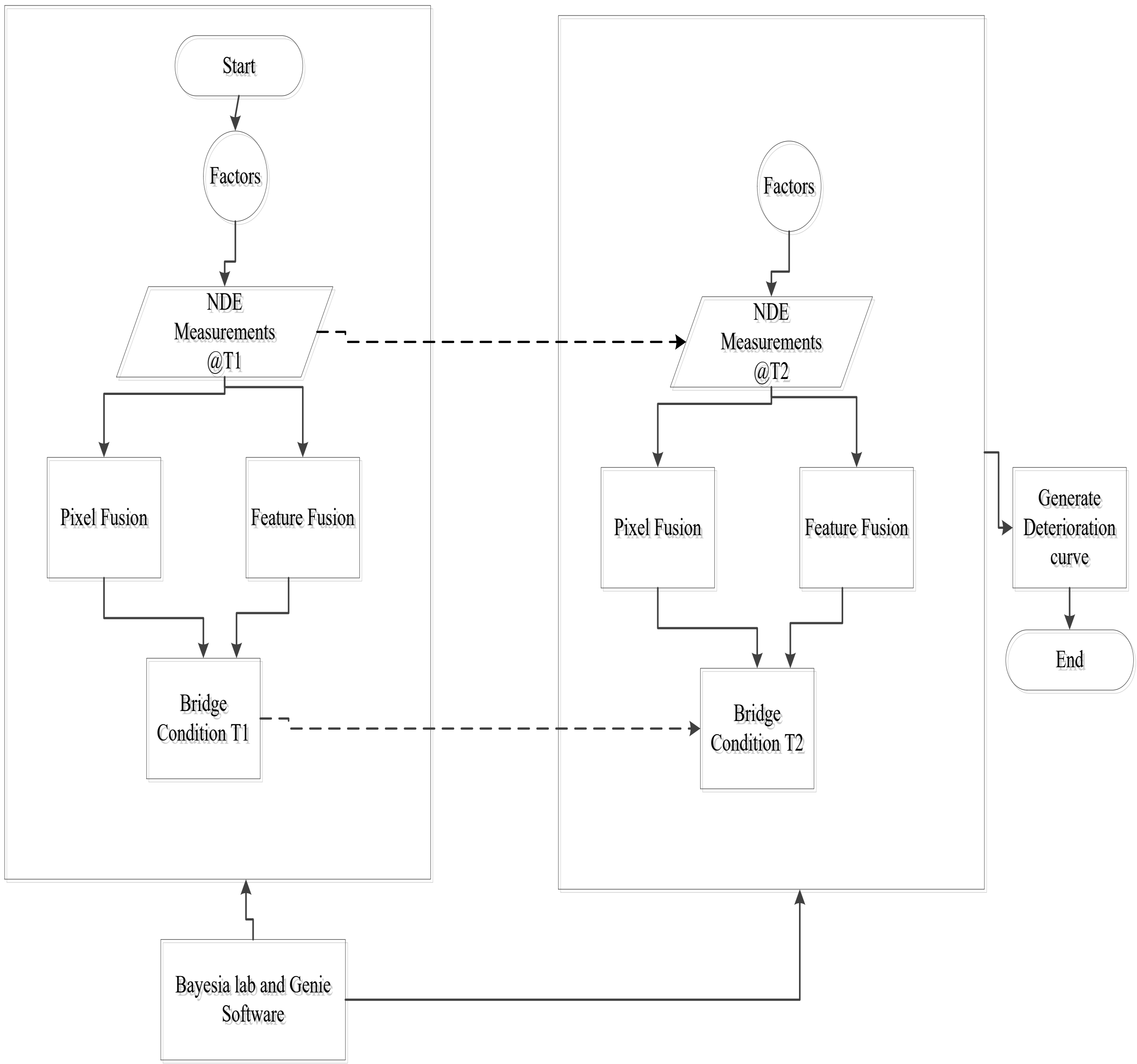


Figure 6.6: Computational Framework for Decision Level Data Fusion

CHAPTER 7

7. SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

7.1. SUMARRY AND CONCLUSIONS

Subjective condition assessment reduces the accuracy of forecasting bridge condition. Integration of NDE technologies for evaluating and tracking condition of bridges over their life cycle is essential. This research identified and analyzed advantages, limitations and applications of NDE methods used in Canada and the USA for condition assessment of concrete and steel bridges. These methods are selected based on current practice and their applicability to bridge condition assessment. The main challenge of using NDE methods is the interpretation and integration of results. Therefore, integration of different methods is recommended to reduce the limitation of each technology.

The purpose of this research is to assess bridge condition based on fusing data from NDE evaluation methods. A comprehensive literature review was undertaken. Based on the literature review, the gap of current research is identified. The literature review confirmed that incorporating multiple technologies would lead to better results interpretation and quantitative condition assessment.

Data fusion method is developed for condition assessment of concrete decks of bridges. The method is used to assign bridge condition rating more accurately. The application of the data fusion method developed in this study is considered new in the problem of bridge condition assessment. The method utilizes data fusion of processed images captured by multiple technologies in order to improve the accuracy of the generated assessment and rating of these concrete bridge decks.

This study reveals that image processing using techniques such as image segmentation, edge detection of captured GPR and IR images, prior to fusion, can improve the accuracy of condition assessment and rating of bridge decks. The method is applied on a case bridge deck in Montreal. GPR data was interpreted by determining the surface from 24 scans spaced by 0.33m. These 2D scans are converted to 3D GPR data. The results of GPR surface was interpreted by the amplitude reflections. Areas of low amplitude waves usually indicate uniform material while those of high amplitude indicate important changes and deterioration of concrete.

Pixel level image fusion was performed using wavelet transform technique. In wavelet transform, images of IR and GPR surface data are decomposed. In this research, the impact of image processing techniques on the accuracy of the developed method is analyzed through four scenarios. In scenario1, no image processing was used before or after fusion. In scenario 2, image processing was applied before fusion and in scenario 3, image processing was applied before and after fusion. In scenario 4, image processing was applied only after fusion. The results show that image processing has effective impact on the accuracy of image fusion as it enhances feature extraction. It is observed that scenario 3 improves the prediction of condition rating of bridge deck as it accurately detects the percentage of the defected areas. Finally, the fusion results are compared with the results from 1-IR single sensor, 2-GPR single sensor, Hammer sound results and visual inspection as used in current practice. The results show that combining deteriorated areas from both sensors are more accurate and close to the actual condition and it helps engineers and inspectors with better identification of the health of the structure.

Thus, the developed method based on data fusion can be used for condition assessment and rating of concrete bridge decks. The method utilizes data fusion of processed images captured by GPR and IR in order to improve the accuracy of the generated assessment and rating of concrete bridge decks. This study also reveals that image processing techniques such as image segmentation, edge detection of captured GPR and IR images, prior to fusion, improves feature extraction of the defective areas. Feature level fusion was employed using Bayesian Network. Deteriorated areas were extracted from 77 maps for GPR and IR images. Two networks were modeled to assign bridge condition rating based on the fused measurements. The fusion results were compared with results from single sensors (IR and GPR) and with Hammer sound and visual inspection results, as used in current practice.

The results show that using multiple sensing technologies can provide better condition assessment than that based on the use of one sensing technology. This can be attributed to the fact that each of such technologies has its capabilities and limitations. As well, when large amount of data of multiple sensors are fused, it can provide more comprehensive output and thus be of more help to decision makers.

The proposed method is further applied in three case studies. For all three cases, all deterioration maps of NDE methods are extracted from Highway research project of Iowa, US, 2011. The data fusion method has been applied within pixel and features level fusion using these three case studies. The final results show that the developed method can enhance the result interpretation and thus provides accurate decision regarding bridge deck condition. The major findings of the results' analysis can be summarized as follows:

1- Each single technology detects specific type of defects based on its physical principal.
2- Percentage of defected areas for the same bridge deck detected by each single technology varies from one technology to another based on the type of the detected defects.

3- Pixel fusion combines and fuse all deterioration in one single image. Its power lies in combining the location of bridge deck deterioration in one map as it appears in the fused image. As this image is the results of using multiple technologies, it can help inspectors and engineers in this field to assess condition of bridge deck by more ease.

4- Feature Fusion has the power to fuse the % of good, poor and serious areas extracted from multiple technologies. However, the results from feature fusion related to serious areas extracted from the different technologies did not match with the pixel fusion in case of one bridge deck. Feature fusion works better when it is used to detect and assess specific types of defects; corrosion, delamination and deterioration.

5- Pixel and feature fusion are completing one another. So, it is recommended to use data fusion method for bridge condition assessment within its two levels.

6- Condition rating is assigned based on the combined serious defected areas extracted from the pixel fusion or feature fusion. Condition rating can be determined also by stochastic value if it is incorporated as child node of the fusion measurements in the feature fusion network.

Finally, a method to predict bridge deck condition states using Dynamic Bayesian Networks is provided in this research and is considered to be the decision level of data fusion method. The method used limited inspection records for two years: 2008 and 2013. The method incorporates the impact of deterioration factors. The bridge deck deterioration model developed ensures that future condition depends mainly on current condition, previous condition and factors causing bridge deck deterioration. The method circumvents the limitations of current practice which is based on traditional Markov model. The final results of Dynamic Bayesian Networks are compared with the results of Markov model. It is observed that incorporating deterioration factors improve the forecasting accuracy and it can help with forecasting inspection frequency and maintenance action required. The main contribution of the decision level data fusion method lies in building an advanced deterioration modeling for bridge deck by using measurements of NDE methods and incorporating related factors. The model is generic and thus, it can be updated when new observations are incorporated.

7.2. EXPECTED CONTRIBUTIONS

1- Conduct in-depth study of NDE methods for steel and concrete bridges.

2- Apply data fusion to assess bridge condition

- Apply pixel and feature levels fusion
- Assess the impact of image processing techniques on data fusion accuracy.
- Interpret GPR 2D scan as 3D

3- Integrate NDE measurements with current practice deterioration model.

- Increase the accuracy of deterioration model with incorporating variables
- Building generic advanced deterioration model for bridge deck

4- Provide guidelines with the use of data fusion methodology

- Main findings from case studies

7.3. LIMITATIONS AND RECOMMENDATIONS FOR FUTURE RESEARCH

1- Deterioration model is tested using only one case study. It is recommended for future research to apply the model using different case studies.

2- Captured inspection images for Iowa case studies and North river bridge deck are not available. It is recommended for future research to apply the method using the captured inspection images.

3- No detailed cost comparison provided with the method. Future research can expand the method by conducting cost comparison between data fusion method and other assessment methods.
4- Factors considered to develop the deterioration model are extracted from the literature review. Future research can extend the decision level by studying the impact of deterioration factors of bridges.

5- The data fusion method in this research focus mainly on concrete bridge deck. It is recommended for future research to apply the developed method on steel bridges.

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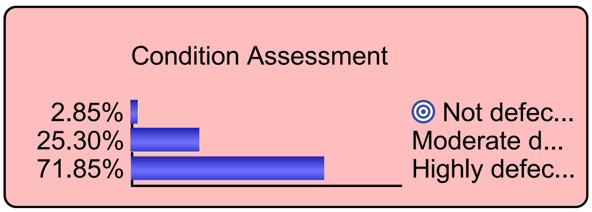
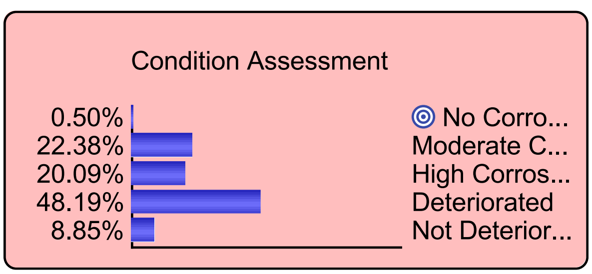
APPENDIX I

North River Bridge Deck

GPR	HCP	Not defected	Moderate d...	Highly defe...
No Deterior...	No Corrosion	100.000	0.000	0.000
	Moderate C...	0.300	47.700	0.000
	High Corros...	0.300	0.000	45.200
Deterioration	No Corrosion	7.100	0.000	70.000
	Moderate C...	0.000	47.700	70.000
	High Corros...	0.000	0.000	100.000



GPR	HCP	No Corrosion	Moderate C...	High Corros...	Deteriorated	Not Deterio...
No Deterior...	No Corrosion	7.100	0.000	0.000	0.000	30.000
	Moderate C...	0.000	47.700	0.000	0.000	30.000
	High Corros...	0.000	0.000	45.200	0.000	30.000
Deterioration	No Corrosion	7.100	0.000	0.000	70.000	0.000
	Moderate C...	0.000	47.700	0.000	70.000	0.000
	High Corros...	0.000	0.000	45.200	70.000	0.000



APPENDIX II

Fusion Measurements Node_Case O1

Half Cell Potential	Blue						
Ground Penetr...	Yellow_Poor			Green_Good			
Impact Echo	Yellow_Poor	Green_Good	Red_Seriouse	Yellow_Poor	Green_Good	Red_Seriouse	Yellow_Poo
Good	0.1525439	0.54887994	0.22910468	0.54206032	1	0.81773332	0.2093373
Poor	0.8474561	0.45112006	0.59101975	0.45793968	0	0	0.6229455
Seriouse	0	0	0.17987557	0	0	0.18226668	0.1677170

Half Cell Potential							
Ground Penetr...	Red_Seriouse			Yellow_Poor			
Impact Echo	Yellow_Poor	Green_Good	Red_Seriouse	Yellow_Poor	Green_Good	Red_Seriouse	Yellow_Poo
Good	0.20933739	0.79664979	0.38665206	0	0.40173869	0	0.4132774
Poor	0.62294555	0	0	0.90175637	0.48457026	0.64978514	0.4875571
Seriouse	0.16771706	0.20335021	0.61334794	0.09824363	0.11369105	0.35021486	0.09916532

Half Cell Potential	Red						
Ground Penetr...	Green_Good			Red_Seriouse			
Impact Echo	Yellow_Poor	Green_Good	Red_Seriouse	Yellow_Poor	Green_Good	Red_Seriouse	Yellow_Poo
Good	0.41327749	0.8850728	0.64466002	0	0.60328033	0	0.152543
Poor	0.48755718	0	0	0.67905974	0	0	0.847456
Seriouse	0.099165321	0.1149272	0.35533998	0.32094026	0.39671967	1	

Half Cell Potential	Red						
Ground Penetr...	Green_Good		Red_Seriouse			Yellow_Poo	
Impact Echo	Green_Good	Red_Seriouse	Yellow_Poor	Green_Good	Red_Seriouse	Yellow_Poor	Green_Goo
Good	0.8850728	0.64466002	0	0.60328033	0	0.1525439	0.5488799
Poor	0	0	0.67905974	0	0	0.8474561	0.4511200
Seriouse	0.1149272	0.35533998	0.32094026	0.39671967	1	0	

Half Cell Potential	Green						
Ground Penetr...	Yellow_Poor			Green_Good			
Impact Echo	Yellow_Poor	Green_Good	Red_Seriouse	Yellow_Poor	Green_Good	Red_Seriouse	Yellow_Poo
Good	0.1525439	0.54887994	0.22910468	0.54206032	1	0.81773332	0.2093373
Poor	0.8474561	0.45112006	0.59101975	0.45793968	0	0	0.6229455
Seriouse	0	0	0.17987557	0	0	0.18226668	0.1677170

Half Cell Potential	Green					
Ground Penetr...	Green_Good			Red_Seriouse		
Impact Echo	Yellow_Poor	Green_Good	Red_Seriouse	Yellow_Poor	Green_Good	Red_Seriouse
Good	0.54206032	1	0.81773332	0.20933739	0.79671984	0.38665206
Poor	0.45793968	0	0	0.62294555	0	0
Seriouse	0	0	0.18226668	0.16771706	0.20328016	0.61334794

Fusion Measurements Node_Case O2

Half Cell Po...				
Electrical R...				
Ground Pen...	Good			
Impact Echo	Seriouse Delamin...	Delamination Exi...	Good	Serio
Moderate C...	0.0	0.0	0.0	
High Corrosion	0.0	0.0	0.0	
Seriouse Del...	0.0936	0.0	0.0	
Delamination...	0.0	0.1407	0.0	
Seriouse Det...	0.0	0.0	0.0	
Poor	0.0	0.0	0.0	
Good	0.9064	0.8593	1.0	

Half Cell Po...				
Electrical R...				
Ground Pen...	Seriouse			
Impact Echo	Seriouse Del...	Delamination Exi...	Good	Seriouse
Moderate C...	0.0	0.0	0.0	
High Corrosion	0.0	0.0	0.0	
Seriouse Del...	0.0936	0.0	0.0	
Delamination...	0.0	0.1407	0.0	
Seriouse Det...	0.119	0.119	0.119	
Poor	0.0	0.0	0.0	
Good	0.7874	0.7403	0.881	

Half Cell Po...				
Electrical R...	Good_No Corrosion			
Ground Pen...	Poor			
Impact Echo	Seriouse Delamin...	Delamination Exi...	Good	Serio
Moderate C...	0.0	0.0	0.0	
High Corrosion	0.0	0.0	0.0	
Seriouse Del...	0.0936	0.0	0.0	
Delamination...	0.0	0.1407	0.0	
Seriouse Det...	0.0	0.0	0.0	
Poor	0.272	0.272	0.272	
Good	0.6344	0.5873	0.728	

Half Cell Po...				
Electrical R...				
Ground Pen...	Seriouse			
Impact Echo	Seriouse Delamin...	Delamination Exi...	Good	Serio
Moderate C...	0.0	0.0	0.0	
High Corrosion	0.0	0.0	0.0	
Seriouse Del...	0.0936	0.0	0.0	
Delamination...	0.0	0.147	0.0	
Seriouse Det...	0.119	0.119	0.119	
Poor	0.0	0.0	0.0	
Good	0.7874	0.734	0.881	

Half Cell Po...	**Low Corrosion**			
Electrical R...	**Low Corrosion**			
Ground Pen...	**Poor**			
Impact Echo	Seriouse Delamin...	Delamination Exi...	Good	Serio
Moderate C...	0.0	0.0	0.0	
High Corrosion	0.0	0.0	0.0	
Seriouse Del...	0.0936	0.0	0.0	
Delamination...	0.0	0.1407	0.0	
Seriouse Det...	0.0	0.0	0.0	
Poor	0.272	0.272	0.272	
Good	0.6344	0.5873	0.728	

Half Cell Po...				
Electrical R...				
Ground Pen...	**Good**			
Impact Echo	Seriouse Delamin...	Delamination Exi...	Good	Serio
Moderate C...	0.0	0.0	0.0	
High Corrosion	0.0	0.0	0.0	
Seriouse Del...	0.0936	0.0	0.0	
Delamination...	0.0	0.1407	0.0	
Seriouse Det...	0.0	0.0	0.0	
Poor	0.0	0.0	0.0	
Good	0.9064	0.8593	1.0	

Half Cell Po...				
Electrical R...				
Ground Pen...	**Seriouse**			
Impact Echo	Seriouse Delamin...	Delamination Exi...	Good	Serio
Moderate C...	0.0	0.0	0.0	
High Corrosion	0.1877	0.1877	0.1877	
Seriouse Del...	0.0936	0.1407	0.0	
Delamination...	0.0	0.0	0.0	
Seriouse Det...	0.119	0.119	0.119	
Poor	0.0	0.0	0.0	
Good	0.5997	0.5526	0.6933	

Half Cell Po...				
Electrical R...	**High Corrosion**			
Ground Pen...	**Poor**			
Impact Echo	Seriouse Delamin...	Delamination Exi...	Good	Serio
Moderate C...	0.0	0.0	0.0	
High Corrosion	0.1877	0.1877	0.1877	
Seriouse Del...	0.0936	0.0	0.0	
Delamination...	0.0	0.1407	0.0	
Seriouse Det...	0.0	0.0	0.0	
Poor	0.272	0.272	0.272	
Good	0.4467	0.3996	0.5403	

Half Cell Po...				
Electrical R...				
Ground Pen...	Good			
Impact Echo	Seriouse Delamin...	Delamination Exi...	Good	Serio
Moderate C...	0.0	0.0	0.0	
High Corrosion	0.1877	0.1877	0.1877	
Seriouse Del...	0.0936	0.0	0.0	
Delamination...	0.0	0.1407	0.0	
Seriouse Det...	0.0	0.0	0.0	
Poor	0.0	0.0	0.0	
Good	0.7187	0.6716	0.8123	

Half Cell Po...				
Electrical R...				
Ground Pen...	Seriouse			
Impact Echo	Seriouse Delamin...	Delamination Exi...	Good	Serio
Moderate C...	0.54246	0.54246	0.54246	
High Corrosion	0.0	0.0	0.0	
Seriouse Del...	0.0936	0.0	0.0	
Delamination...	0.0	0.1407	0.0	
Seriouse Det...	0.119	0.119	0.119	
Poor	0.0	0.0	0.0	
Good	0.24494	0.19784	0.33854	

Half Cell Po...				
Electrical R...				
Ground Pen...	Good			
Impact Echo	Seriouse Delamin...	Delamination Exi...	Good	Serio
Moderate C...	0.54246	0.54246	0.54246	
High Corrosion	0.0	0.0	0.0	
Seriouse Del...	0.0936	0.0	0.0	
Delamination...	0.0	0.1407	0.0	
Seriouse Det...	0.0	0.0	0.0	
Poor	0.0	0.0	0.0	
Good	0.36394	0.31684	0.45754	

Half Cell Po...				
Electrical R...				
Ground Pen...	Seriouse			
Impact Echo	Seriouse Delamin...	Delamination Exi...	Good	Serio
Moderate C...	0.54246	0.54246	0.54246	
High Corrosion	0.0	0.0	0.0	
Seriouse Del...	0.0936	0.0	0.0	
Delamination...	0.0	0.1407	0.0	
Seriouse Det...	0.119	0.119	0.119	
Poor	0.0	0.0	0.0	
Good	0.24494	0.19784	0.33854	

Half Cell Po…	Moderate Corrosion			
Electrical R…	Low Corrosion			
Ground Pen…	Poor			
Impact Echo	Seriouse Delamin…	Delamination Exi…	Good	Serio
Moderate C…	0.54246	0.54246	0.54246	
High Corrosion	0.0	0.0	0.0	
Seriouse Del…	0.0936	0.0	0.0	
Delamination…	0.0	0.1407	0.0	
Seriouse Det…	0.0	0.0	0.0	
Poor	0.272	0.272	0.272	
Good	0.09194	0.04484	0.18553999	

Half Cell Po…				
Electrical R…				
Ground Pen…	Good			
Impact Echo	Seriouse Delamin…	Delamination Exi…	Good	Serio
Moderate C…	0.54246	0.54246	0.54246	
High Corrosion	0.0	0.0	0.0	
Seriouse Del…	0.0936	0.0	0.0	
Delamination…	0.0	0.1407	0.0	
Seriouse Det…	0.0	0.0	0.0	
Poor	0.0	0.0	0.0	
Good	0.36394	0.31684	0.45754	

Half Cell Po…				
Electrical R…				
Ground Pen…	Seriouse			
Impact Echo	Seriouse Delamin…	Delamination Exi…	Good	Serio
Moderate C…	0.3973833	0.3973833	0.3973833	
High Corrosion	0.13750109	0.1375011	0.1375011	
Seriouse Del…	0.0685674	0.0	0.0	
Delamination…	0.0	0.10307088	0.0	
Seriouse Det…	0.08717438	0.08717438	0.08717438	
Poor	0.0	0.0	0.0	
Good	0.3093738	0.27487034	0.3779412	

Half Cell Po…				
Electrical R…	High Corrosion			
Ground Pen…	Poor			
Impact Echo	Seriouse Delamin…	Delamination Exi…	Good	Serio
Moderate C…	0.3973833	0.3973833	0.3973833	
High Corrosion	0.13750109	0.13750109	0.1375011	
Seriouse Del…	0.0685674	0.0	0.0	
Delamination…	0.0	0.10307088	0.0	
Seriouse Det…	0.0	0.0	0.0	
Poor	0.19925572	0.19925572	0.19925573	
Good	0.19729246	0.16278899	0.26585987	

Half Cell Po...				
Electrical R...				
Ground Pen...	Good			
Impact Echo	Seriouse Delamin...	Delamination Exi...	Good	Serio
Moderate C...	0.3973833	0.3973833	0.3973833	
High Corrosion	0.13750109	0.1375011	0.1375011	
Seriouse Del...	0.0685674	0.0	0.0	
Delamination...	0.0	0.10307088	0.0	
Seriouse Det...	0.0	0.0	0.0	
Poor	0.0	0.0	0.0	
Good	0.39654818	0.3620447	0.46511558	

Half Cell Po...				
Electrical R...				
Ground Pen...	Seriouse			
Impact Echo	Seriouse Delamin...	Delamination Exi...	Good	Serio
Moderate C...	0.0	0.0	0.0	
High Corrosion	0.25427762	0.24735878	0.25427	
Seriouse Del...	0.09360281	0.0	0.0	
Delamination...	0.0	0.13687569	0.0	
Seriouse Det...	0.11900357	0.11576551	0.119	
Poor	0.0	0.0	0.0	
Good	0.533116	0.5	0.62673	

Half Cell Po...				
Electrical R...	Good_No Corrosion			
Ground Pen...	Poor			
Impact Echo	Seriouse Delamin...	Delamination Exi...	Good	Serio
Moderate C...	0.0	0.0	0.0	
High Corrosion	0.25427	0.25427	0.25427	
Seriouse Del...	0.0936	0.0	0.0	
Delamination...	0.0	0.1407	0.0	
Seriouse Det...	0.0	0.0	0.0	
Poor	0.272	0.272	0.272	
Good	0.38013	0.33303	0.47373	

Half Cell Po...				
Electrical R...				
Ground Pen...	Good			
Impact Echo	Seriouse Delamin...	Delamination Exi...	Good	Serio
Moderate C...	0.0	0.0	0.0	
High Corrosion	0.25427	0.25427	0.25427	
Seriouse Del...	0.0936	0.0	0.0	
Delamination...	0.0	0.1407	0.0	
Seriouse Det...	0.0	0.0	0.0	
Poor	0.0	0.0	0.0	
Good	0.65213	0.60503	0.74573	

Half Cell Po...				
Electrical R...				
Ground Pen...	Seriouse			
Impact Echo	Seriouse Delamin...	Delamination Exi...	Good	Serio
Moderate C...	0.0	0.0	0.0	
High Corrosion	0.25427	0.25427	0.25427	
Seriouse Del...	0.0936	0.0	0.0	
Delamination...	0.0	0.1407	0.0	
Seriouse Det...	0.119	0.119	0.119	
Poor	0.0	0.0	0.0	
Good	0.53313	0.48603	0.62673	

Half Cell Po...	High Corrosion			
Electrical R...	Low Corrosion			
Ground Pen...	Poor			
Impact Echo	Seriouse Delamin...	Delamination Exi...	Good	Serio
Moderate C...	0.0	0.0	0.0	
High Corrosion	0.25427	0.25427	0.25427	
Seriouse Del...	0.0936	0.0	0.0	
Delamination...	0.0	0.1407	0.0	
Seriouse Det...	0.0	0.0	0.0	
Poor	0.272	0.272	0.272	
Good	0.38013	0.33303	0.47373	

Half Cell Po...				
Electrical R...				
Ground Pen...	Good			
Impact Echo	Seriouse Delamin...	Delamination Exi...	Good	Serio
Moderate C...	0.0	0.0	0.0	
High Corrosion	0.25427	0.25427	0.25427	
Seriouse Del...	0.0936	0.0	0.0	
Delamination...	0.0	0.1407	0.0	
Seriouse Det...	0.0	0.0	0.0	
Poor	0.0	0.0	0.0	
Good	0.65213	0.60503	0.74573	

Half Cell Po...				
Electrical R...				
Ground Pen...	Seriouse			
Impact Echo	Seriouse Delamin...	Delamination Exi...	Good	Serio
Moderate C...	0.0	0.0	0.0	
High Corrosion	0.44197	0.44197	0.44197	
Seriouse Del...	0.0936	0.0	0.0	
Delamination...	0.0	0.1407	0.0	
Seriouse Det...	0.119	0.119	0.119	
Poor	0.0	0.0	0.0	
Good	0.34543	0.29833	0.43903	

Half Cell Po...				
Electrical R...	High Corrosion			
Ground Pen...	Poor			
Impact Echo	Seriouse Delamin...	Delamination Exi...	Good	Serio
Moderate C...	0.0	0.0	0.0	
High Corrosion	0.44197	0.44197	0.44197	
Seriouse Del...	0.0936	0.0	0.0	
Delamination...	0.0	0.1407	0.0	
Seriouse Det...	0.0	0.0	0.0	
Poor	0.272	0.272	0.272	
Good	0.19243	0.14533	0.28603	

Half Cell Po...				
Electrical R...				
Ground Pen...		Good		
Impact Echo		Seriouse Delamin...	Delamination Exi...	Good
Moderate C...	0.0	0.0	0.0	0.0
High Corrosion	4197	0.44197	0.44197	0.44197
Seriouse Del...	0.0	0.0936	0.0	0.0
Delamination...	0.0	0.0	0.1407	0.0
Seriouse Det...	0.0	0.0	0.0	0.0
Poor	.272	0.0	0.0	0.0
Good	8603	0.46443	0.41733	0.55803

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Half Cell Po...				
Ground Pen...	Good			
Impact Echo	Good_No Delami...	Moderate Delami...	Seriouse Delamin...	Gooc
Moderate C...	0.0	0.0	0.0	
Seriouse Cor...	0.0	0.0	0.0	
Moderate D...	0.0	0.5768825	0.0	
Seriouse Del...	0.0	0.0	0.1831275	
Poor	0.0	0.0	0.0	
Seriouse Det...	0.0	0.0	0.0	
Good	1.0	0.4231175	0.8168725	

Half Cell Po...	No Corrosion			
Ground Pen...	Poor Deterioration			
Impact Echo	Good_No Delami...	Moderate Delami...	Seriouse Delamin...	Gooc
Moderate C...	0.0	0.0	0.0	
Seriouse Cor...	0.0	0.0	0.0	
Moderate D...	0.0	0.5768825	0.0	
Seriouse Del...	0.0	0.0	0.1831275	
Poor	0.57098	0.4231175	0.57098	
Seriouse Det...	0.0	0.0	0.0	
Good	0.42902	0.0	0.2458925	

Half Cell Po...				
Ground Pen...	Seriouse Deterioration			
Impact Echo	Good_No Delami...	Moderate Delami...	Seriouse Delamin...	Gooc
Moderate C...	0.0	0.0	0.0	
Seriouse Cor...	0.0	0.0	0.0	
Moderate D...	0.0	0.5768825	0.0	
Seriouse Del...	0.0	0.0	0.1831275	
Poor	0.0	0.0	0.0	
Seriouse Det...	0.06955	0.06955	0.06955	
Good	0.93045	0.3535675	0.7473225	

Half Cell Po...				
Ground Pen...	Good			
Impact Echo	Good_No Delami...	Moderate Delami...	Seriouse Delamin...	Gooc
Moderate C...	0.6749	0.33745	0.6749	
Seriouse Cor...	0.0	0.0	0.0	
Moderate D...	0.0	0.33	0.0	
Seriouse Del...	0.0	0.0	0.1831275	
Poor	0.0	0.0	0.0	
Seriouse Det...	0.0	0.0	0.0	
Good	0.3251	0.33255	0.1419725	

Half Cell Po...	Moderate Corrosion_Poor			
Ground Pen...	Poor Deterioration			
Impact Echo	Good_No Delami...	Moderate Delami...	Seriouse Delamin...	Gooc
Moderate C...	0.1900095	0.33333334	0.45	
Seriouse Cor...	0.0	0.0	0.0	
Moderate D...	0.0	0.33333334	0.0	
Seriouse Del...	0.0	0.0	0.18312	
Poor	0.1900095	0.33333334	0.36688	
Seriouse Det...	0.50002503	0.0	0.0	
Good	0.119955994	0.0	0.0	

Half Cell Po...				
Ground Pen...	Seriouse Deterioration			
Impact Echo	Good_No Delami...	Moderate Delami...	Seriouse Delamin...	Gooc
Moderate C...	0.33745	0.53045	0.6749	
Seriouse Cor...	0.5	0.0	0.0	
Moderate D...	0.0	0.4	0.0	
Seriouse Del...	0.0	0.0	0.1831275	
Poor	0.0	0.0	0.0	
Seriouse Det...	0.034775	0.06955	0.06955	
Good	0.127775	0.0	0.0724225	

Half Cell Po…				
Ground Pen…	Good			
Impact Echo	Good_No Delami…	Moderate Delami…	Seriouse Delamin…	Gooc
Moderate C…	0.0	0.0	0.0	
Seriouse Cor…	0.238247	0.238247	0.23247	
Moderate D…	0.0	0.57688	0.0	
Seriouse Del…	0.0	0.0	0.1831275	
Poor	0.0	0.0	0.0	
Seriouse Det…	0.0	0.0	0.0	
Good	0.761753	0.184873	0.5844025	

Half Cell Po…	Seriouse Corrosion			
Ground Pen…	Poor Deterioration			
Impact Echo	Good_No Delami…	Moderate Delami…	Seriouse Delamin…	Gooc
Moderate C…	0.0	0.0	0.0	
Seriouse Cor…	0.238247	0.23824713	0.23984087	
Moderate D…	0.0	0.5768828	0.0	
Seriouse Del…	0.0	0.0	0.1843526	
Poor	0.57098	0.1848701	0.57479984	
Seriouse Det…	0.0	0.0	0.0	
Good	0.190773	0.0	0.00100669	

Half Cell Po…				
Ground Pen…		Seriouse Deterioration		
Impact Echo	nin…	Good_No Delami…	Moderate Delami…	Seriouse Delamin…
Moderate C…	0.0	0.0	0.0	0.0
Seriouse Cor…	4087	0.238247	0.23824713	0.238247
Moderate D…	0.0	0.0	0.5768828	0.0
Seriouse Del…	3526	0.0	0.0	0.1831275
Poor	9984	0.0	0.0	0.0
Seriouse Det…	0.0	0.06955	0.06955004	0.06955
Good	0669	0.692203	0.11532006	0.5090755

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