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**NORTH RIVER BRIDGE DECK: CONDITION ASSESSMENT USING FEATURE LEVEL DATA FUSION**

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**Abstract:** Integrated NDE methods in Bridge condition assessment is essential for more comprehensive and accurate diagnostics of defects. This research introduces a new method; designed to integrate inspection data captured by multiple inspection technologies. The method utilizes data collected from Ground Penetrating Radar (GPR) and Half Cell Potential (HCP). GPR data was collected from 12 scans to represent 66.43 m2 of North River bridge deck in County of Peterborough, Ontario, Canada. Feature level data fusion using Bayesian Networks (BNs) was applied in this research to classify and diagnose the intensity of different types of defects. BNS interprets the bridge condition as % serious deterioration, % high corrosion, % moderate corrosion and % good areas. The results from the developed feature level fusion are verified by the results of core samples, which were extracted from the inspection report of the bridge deck considered in the analysis. The analysis results indicate that the developed method provides better and accurate results interpretation for inspectors and project engineers in the field.

1. **INTRODUCTION**

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% of total asset 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 contamination. 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 2017 that one in ten nation’s bridges are 50 years or older. 9.1% of total bridges are rated as structurally deficient, around 56,007 in total. More than one in eight are functionally obsolete.

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 fast 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 have been made using single NDE method to detect defects, crack, delamination and voids in concrete bridges, such as impact echo (Gucunski et al. 2010). Ground Penetrating Radar (GPR) is capable of detecting deterioration, location of voids, mapping of reinforcement location and depth of cover of steel bars (Maser 1996, Dinh and Zayed 2014, Shin and Grivas 2003). Infrared thermography is used to detect delamination (Yaghi 2014). Some research efforts have been made within the area of condition assessment using different technologies (Yaghi 2014).

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 amounts 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 of sensors. 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 mimics 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 is the integration of pixels from different images; images that will be fused 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 Raol 2008). This research utilize the feature level of data fusion.

Currently, there is lack of tools that inspectors can use to fuse data (Moselhi et al., 2016). The main objective of this research is focusing on using feature level of data fusion as a tool to assess the condition of reinforced concrete bridge decks. Bayesian Networks technique has been utilized to apply feature level of data fusion.

1. **LITERATURE REVIEW**

Since measurements from different sensors often come with various degree of uncertainties, there is a need to better interpret results from sensors. The most important is to fuse large amounts of data. The determination of the most informative data sources can help reach an efficient and timely decision. Zhang 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 sensor readings can measure the degree of belief (Zhang and Ji 2006). To obtain data from different sensors, multiple sensors can be arranged and configured for different types. 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 a 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 times. 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. 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 was 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.

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 a 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. The authors did not illustrate a detailed methodology for the decision level data fusion.

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. The authors emphasized on the benefit and advantages of data fusion in terms of improving the accuracy through different case studies.

Hoseini and Ashraf (2013) made a comparison of the computational complexity of different four methods of data fusion. The authors evaluated and indicated that the inverse covariance method requires less computational complexity when numbers of sensors are increased to be twenty sensors. 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. 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 locations. 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 algorithms 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 a 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.

**2.1.** **Half Cell Potential (HCP)**

HCP uses a copper sulfate reference electrode (CSE) that is placed on the surface of concrete at the location of steel reinforcement. As illustrated in Figure 1, 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 CSE and the concrete to improve the electrical coupling between the deck and instrument during the survey. HCP measures the electric potential between the reinforcement and the reference electrode (CSE) where Corrosion potential are measured. Contour map is used to map area of corrosion (Gucunski et al. 2011). Measurements should be taken in a grid to facilitate the drawing of corrosion map.



Figure 1: Basics of HCP procedure

**2.2.** **GROUND PENETRATING RADAR (GPR)**

It is a rapid method. It produces electromagnetic waves from a 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 (Maser 1996, Yehia et al. 2007, SHRP2 2009, FHWA 2012, SHRP2 2013).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).

**RESEARCH METHODOLOGY**

The developed method of feature fusion utilizes captured inspection deterioration maps 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 2.

Figure 2: 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 types 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 et al. 2006), 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( Xi │ Pa( Xi)), where Pa(Xi) is the parent of node Xi. 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 Equation 1:

[1] P(X1, ……., Xn) =**Πi** ( Xi │Pa(Xi))

As an example, if we have three variables X1, X2 and X3. The joint probability distribution of the network connecting those variables are presented as in Equation 2.

[2] P{X1, X2, X3} = P{X1} P{X2│X1} P{X3│X1}

where P{X2│X1} and P{X3│X1} are conditional probabilities for X2 and X3 respectively given X1 and P{X1} is prior probability, as shown in Figure 3.

Figure 3: Bayesian Networks (BNs) for Three Variables X1, X2 and X3

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- 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.

2- Prior probability distribution of parent node should be estimated directly based on the observation of each NDE method.

3- Fusion node is the child node given the observation of parents’ nodes. Conditional probability distribution of fusion node should be estimated by generating combination of scenarios. These scenarios are built based on contributing the information from the parents node to the fusion node.

4- 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, which is the fusion node.

5- Conditional probabilities distribution of condition rating nodes, given the values of fusion nodes, should be estimated based on the current practice bridge condition rating.

1. **CASE STUDY: NORTH RIVER BRIDGE DECK**

All measurements for this case study are extracted from North River bridge deck report (MTO, 2015). GPR and HCP are utilized to scan the bridge deck. Deterioration maps for the utilized NDE methods are not available in the reports. Therefore, the image processing techniques have not been applied to extract features. HCP potential readings and signal amplitude of GPR are extracted directly from the 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.

The bridge deck Inspection in September 2014 was prepared by G.D. Jewell Engineering Inc with lab test completed by Golder Associates Ltd. 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 percentage of chloride by weight at the average depth of reinforcing steel in the bridge deck was 0.311% exceeding than chloride limit threshold (0.05%) by mass of concrete. This chloride limit is used and accepted by MTO current practice and reporting. The Corrosion Potential Survey conducted on the deck riding surface resulted in approximately 93% from the total area 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 Inc. 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 GPR report of North River Bridge Deck, 2015 followed ASTM D6087-08 standard that is utilizing 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 3. Feature fusion is applied using the proposed data fusion method utilizing Bayesian Networks (BNs). As illustrated in Figure 3, HCP and GPR are the parent’s node for the bridge condition assessment node. The states of the parents’ nodes are defined based on the measurements extracted from HCP and GPR. HCP detect corrosion; the node of HCP is defined as three states; no or low corrosion, moderate corrosion and high corrosion. GPR is capable to map deterioration in bridge deck; the node of GPR is defined as two states; no or low deterioration and deterioration. GPR states are defined based on GPR signal amplitudes that are given by the GPR report. The fusion node states are built based on conditional probabilities which are the probabilities of fusion node given the information of HCP and GPR. These probabilities are assigned based on combination of scenarios.

Figure 3: Feature Fusion Network for North River Bridge Deck

The results from feature fusion is interpreted by two methods; feature fusion 1 and 2. The difference between feature fusion 1 and 2 is the method followed to interpret the final result of the bridge deck assessment. Feature fusion 1 shows the condition of bridge deck as % good, %moderate and %serious areas. Feature fusion 2 shows % no corrosion, % no deterioration, %moderate corrosion, %high corrosion and % serious deterioration. Table 1 provides a summary of results using feature fusion method and results from single technologies GPR and HCP. Table 1 compares the results of individual technologies with the feature fusion method. The results of feature fusion are verified with the core samples results. The results of core samples indicate high corrosion at different locations of bridge deck. The results of feature fusion 2 indicates High and moderate corrosion as 20.09% and 22.38% respectively.

Table 1: Summary of Results For North River Bridge Deck

|  |  |  |
| --- | --- | --- |
| **HCP** | No Corrosion | 7.1% |
| Moderate Corrosion | 47.7% |
| High corrosion | 45.2% |
| **GPR** | No deterioration  | 30% |
| Deterioration | 70% |
| **Feature Fusion 1** | Good | 2.85% |
| Moderate  | 25.30% |
| Serious  | 71.85% |
| **Feature Fusion 2** | No corrosion | 0.50% |
| No Deterioration | 8.85% |
| Moderate corrosion | 22.38% |
| High Corrosion | 20.09% |
| Serious Deterioration | 48.19% |
| Core Tests |
| C1 | C2 | C3 | C4 | C5 | C6 |
| 0.508V | 0.465V | 0.506V |  0.511V |  0.494V | 0.399V |
| High | moderate | High |  High |  High | moderate |

1. **CONCLUSION**

This research utilizes feature level of data fusion. It provides engineers and inspectors by a new tool to interpret the result based on different technologies. Incorporating data fusion is recommended in bridge condition assessment to get the benefit advantages of each technology. 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. In the 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%). Table 1 provides a summary for the final results, it shows that 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 ranged from 3% to 9% and not 30% as indicated from GPR. Future condition of reinforced concrete bridge decks can be predicted by developing deterioration models and assessing bridge condition in future by incorporating the decision level of data fusion.

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