2016

A Novel Bridge Information Modeling (BrIM) Based Framework for Bridge Inspections

Abhimanu Fnu
Iowa State University

A novel bridge information modeling (BrIM) based framework for bridge inspections

by

Abhimanu

A thesis submitted to the graduate faculty

in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

Major: Civil Engineering (Construction Engineering and Management)

Program of Study Committee:
Yelda Turkan, Co-Major Professor
Simon Laflamme, Co-Major Professor
H. David Jeong

Iowa State University

Ames, Iowa

2016

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACKNOWLEDGMENTS

First and foremost, I would like to thank my advisor, Dr. Yelda Turkan, co-advisor, Dr. Simon Laflamme, and my committee member, Dr. David Jeong for their invaluable guidance and support throughout the course of my Master of Science degree. I would also like to thank all the professors and lecturers from whom I have learnt a lot at Iowa State University.

In addition, I would like to thank God and my parents for all their blessings and love that I have been blessed with. Also I would like to thank my colleagues and friends Firas A. Al Shalabi, Liangyu Tan, Deepanshi Jain, Rajat Sharma, Arko Basu, Rahul Singh, Bharat Raj Agarwal, and Vishal Mane for their support and cooperation in making my stay a memorable one here at Iowa State.

ABSTRACT

Bridges are critical components of civil infrastructure. According to the National Bridge Inventory (NBI), there are more than ten thousand structurally deficient bridges in the United States. It becomes critical for the authorities to maintain their serviceability and reliability in order to keep the transportation system operational. Current bridge condition assessment practices are mainly based on visual inspections carried out by technical experts, which is subjective as observations and opinions may vary from one individual to another, and is expensive and prone to human errors. The main focus of this study is to help improve current inspection practices by implementing image processing algorithms to detect concrete surface cracks and integrate the results into a bridge information modeling (BrIM) based framework. Integrating crack detection algorithm results with BrIM will allow users to view and explore cracks and their properties linked to a three dimensional (3D) model of the inspected bridge component. The proposed methodology processes 2D images by adjusting pixel parameters of gray scale images and detects cracks with their dimensional aspects. It implements existing crack detection algorithms, a scaling tool to automatically measure crack dimensions, and includes a framework to integrate crack detection results with BrIM for inspecting bridges in a more efficient manner. This will enable more effective repairs and maintenance operations, saving a considerable amount of effort, time, and money.

CHAPTER I

INTRODUCTION

Economic development of a country is governed by its transportation infrastructure to a large extent. In the United States, the total worth of civil structures is estimated to be $20 trillion and a major part of global assets is attributed to civil infrastructure systems (Jahanshahi *et al.*, 2011). Bridges serve as the most critical component of civil infrastructure and around 607,380 bridges are spread all over the United States (Report Card for America's Infrastructure, 2013).

According to the Report Card for America's infrastructure (2013), one in every nine bridges is considered as structurally deficient which amounts to one-third of the total decking area in the United States. In such a scenario, it becomes imperative for the authorities to maintain serviceability and reliability in order to keep the transportation system operational. Periodic assessment of these structures helps authorities to make sure that these structures are reliable and safe for public use. In particular, periodic health assessment of bridges is very important because of their cost and direct impact on public safety (Qader *et al.*, 2003).

Current practices for bridge inspection involve methods such as visual inspection for bridge conditional assessment. The assessment is carried out through a field inspection by a team of experts and technical support. This method of bridge inspection is subjective as observations and opinions may vary from one individual to another and is more prone to human error. Also, this approach seems to be less cost effective as the authorities have to account for costs incurred as a result of site travel and significantly long labor hours. Conventional methods are hampered by poor data reliability and the qualitative nature of the assessment. Nondestructive and structural health monitoring techniques have tremendous advantages over visual inspection method of carrying out bridge condition assessment because of their efficiency and ability to produce more accurate and on-time results, if properly applied.

The authorities are gradually implementing such processes which would save considerable amount of time, money and man power. Numerous computer vision and mathematical model based algorithms have been developed to enable fast interpretation of data and decision making. For example, in order to eliminate the data inconsistency and unreliability between bridge management systems and agencies due to limited historical data availability, Lee *et al.,* (2008) proposed Backward Prediction Model (BPM) that utilizes historical data such as climate, traffic volume etc. in order to generate historical bridge condition ratings. To automate the process of measuring bridge under clearance, Riveiro *et al*., (2012) proposed a technique that involves 3 dimensional (3D) reconstruction of a bridge and its components based on terrestrial convergent photogrammetric principles. This approach enabled remote and automated under-clearance measurements for bridges at low cost and in a safe working environment. Al-Shalabi *et al.,* (2015) proposed a BrIM based inspection framework for managing bridge condition data for inspection purposes. The study concluded that BrIM based bridge management systems can tremendously improve the overall bridge inspection process with significant cost reduction.

1.1 Proposed Approach

In order to improve the efficiency and accuracy of the bridge inspection process, a framework is proposed that integrates 3D bridge information models (BrIM) with crack detection results obtained using existing crack detection algorithms to automate the process of crack detection on concrete surfaces and improve efficiency and reliability of the process that would result in significant savings in terms of efforts, time, and cost.

Additionally, the proposed method will not disrupt moving traffic, as collected data and digital images could be processed offsite. Thus, field inspectors are not required to be physically present on-site for long hours, so that the safety of the inspection team is not compromised. The research methodology involves a literature review on current bridge inspection techniques and current crack detection algorithms followed by data collection and processing. First, in a laboratory setting, 2D digital images of cracked concrete specimens were captured and processed using gray scale image filtration and edge detection pixel approximation algorithms for identification of cracks and associated parameters (*i.e.*, length, width, location, etc.). The above-mentioned algorithms were then applied to data collected from a bridge located in the state of Iowa. Finally, the results from the crack detection algorithms were integrated in the proposed Bridge Information Modeling (BrIM) based inspection framework that enables automatic update and easy access to bridge inspection data associated with cracks and its various parameters within the same environment.

1.2 Goals and Objectives

The overarching goal of this study is to improve infrastructure safety and reduce inspection costs by developing a framework that integrates crack detection algorithm results into 3D BrIM environment, which can be accessed from a tablet computer on-site. This would enable inspectors enter inspection data and attach crack images directly to the BrIM database while on-site, and have access to historical inspection data real-time. The specific objectives of this study are detailed below:

1. *Test existing crack detection algorithms*: This research study aims to test existing crack detection algorithms to automatically detect concrete surface cracks from digital images, and to select the most robust and accurate algorithm to implement in the proposed BrIM

based inspection framework. The gray scale image filtration and edge detection pixel approximation algorithms were tested for their ability to rapidly and accurately process and analyze cracks on concrete surfaces.

2. *Test an existing scaling tool*: The second major objective of this study is to test an existing tool known as "Master" to scale the objects under inspection in order to calculate and convert crack dimensions from pixel length to SI units.
3. *Develop a framework to integrate crack detection algorithm results with 3D BrIM*: This study aims to develop a framework that integrates crack related information into a 3D BrIM model, which is an object-oriented database.

1.3 Implementation Benefits

The proposed BrIM based inspection framework would enable automated and remote crack assessment of bridge structures. The results would contribute to providing an improved means of accurately documenting the structural condition assessment data and eliminating errors resulting from data transcription. The proposed BrIM based inspection framework would facilitate easy and remote access to bridge inspection data and enable to automatically query, sort, and evaluate information associated with various bridge components, which ultimately improves the overall bridge inspection practice.

1.4 Organization of the Thesis

This thesis is organized in six chapters. Chapter 1 introduces the thesis topic and gives background information on it. Chapter 2 reviews pertinent literature on crack detection methods and bridge inspection. Chapter 3 describes the research methodology by documenting the step-by-step procedure followed to test and select the crack detection algorithms and the novel framework design for BrIM integration. Chapter 4 details the crack detection algorithms and presents results on various test samples. Chapter 5 introduces the novel framework that integrates the crack detection algorithm results with 3D BrIM model. Chapter 6 discusses the results, draw conclusions, and make recommendations for future research.

1.5 Contribution

Effective and accurate detection of concrete surface cracks requires fast, economical, and accurate methods. In the past years, several researchers have proposed image-based crack detection algorithms, however the pace of technology adoption and transfer to the commercial sector remains limited. This study implements an existing scaling tool that converts crack length from pixel units to SI units. The main contributions of this study are as follows:

- This study proposes a novel framework that integrates concrete crack data obtained from the image based crack detection algorithm into 3D BrIM model, which can be accessed in the field on a tablet computer. These images are processed in the office to detect and measure concrete cracks, and the results are attached to the 3D BrIM model as attribute data.
- A general workflow for an API which will query and manage data in an assigned database and will enable authorities to import/export, extract and analyze data based on unique component IDs.

CHAPTER II

LITERATURE REVIEW

Visual inspection is the most conventional and widely used method for crack detection procedure as part of bridge condition assessment. However, many researchers have proposed and developed several contact and non-contact techniques for crack detection on a variety of surfaces such as concrete, steel, etc. Contact techniques are referred to those techniques in which a physical contact is required between the instrument/tool and the entity of interest for the purpose of detecting a crack. On the other hand, non-contact techniques are those techniques that are independent of any physical contact. This chapter provides a review on previous studies on contact and non-contact inspection techniques, and it elaborates on the advantages of adopting a BrIM based framework and its importance in bridge condition assessment.

2.1 Non-Contact Techniques for Crack Detection

Several crack detection algorithms and techniques have been proposed and used in the last two decades. A study comparing traditional and neural-network classifiers was conducted by Kaseko *et al.*, (1994) for detecting defects on asphalt-concrete pavements. A remote visual (image based) inspection system of aircraft surfaces was developed by Siegel *et al.*, (1997). To be able to detect cracks, the proposed algorithm detected rivets as cracks propagate on rivet edges and then multi-scale edge detection was used to detect the edges of small defects at small scales and the edges of large defects at larger scales.

Dare *et al.*, (2002) proposed a technique for crack detection based on semi-automatic feature extraction. In this study, they used bilinear interpolation of pixel values to calculate the crack width. The measurements were made in pixels, not in unit length. A crack area quantification technique was proposed by Ito *et al.*, (2002), which involved an interpolation method based on the total brightness of gray scale images. A scale parameter was implemented to convert crack dimensions originally obtained in pixels into SI units. This approach was further improved by Yamaguchi and Hashimoto (2010), who proposed an edge information and percolation model based crack detection approach.

A system for monitoring crack growth was proposed by Sohn *et al*., (2005), which focused on detecting newly generated cracks with the help of spatio-temporal images. This study did not quantify crack width and orientation. Abdel-Qader *et al.*, (2003) compared and analyzed the efficiency of four different edge detection techniques for identification of cracks in concrete bridges. The study concluded that Fast Harr Transform (FHT) is the most effective edge detection method for crack detection on concrete surfaces compared to Fast Fourier Transform (FFT), Canny and Sobel methods.

2.2 Contact Techniques for Crack Detection

A number of contact techniques have been proposed by several researchers to detect and monitor crack development on conductive concrete surfaces. Pour-Ghaz and Weiss (2011) introduced a technique to monitor cracks based on electrical resistance of a conductive thin film applied to the surface of cement material. In this method, the time and location of the crack are measured by monitoring abrupt increases in the resistance of the conductive surface coating. However, separate data acquisition channels are required for each component while using conductive surface components. Pour-Ghaz and Weiss (2011) solved this problem by developing frequency selective circuit (FSC) in which numerical methods were used in order to analyze the response of FSC for fast and synchronized interrogation of the multiple conductive surface elements.

In order to automate the process of structural assessment especially for concrete, a number of sensor based approaches have been proposed by several researchers. Ouyang *et al.*, (1991) and Shah and Choi (1999) developed a crack detection method by capturing stress waves generated by cracks in concrete elements. This technique was based on acoustic emission employing piezoelectric sensors, which can be categorized under passive stress wave methods. Carino (2004) developed pulse-echo and pitch-catch methods, which required using one and two transducers to categorize cracks on actual concrete elements. This technique can be sub-categorized under active stress wave methods, which are more accurate for crack detection purposes. Overall, contact techniques for crack detection are fairly accurate, however they require employing different sensing tools that increases overall life cycle costs of the structure under inspection. Moreover, these techniques require a great deal of experience and expertise in order to be able to interpret the produced results. The utilization of smart materials has also been proposed for crack detection. In particular, a sensing skin has been proposed for crack detection and localization in concrete (Kollosche et al. 2011), wood (Laflamme et al. 2013), and steel specimens (Kharroub et al. 2015).

2.3 Bridge Information Modeling (BrIM)

The construction industry has been relying on 2D drawings for years for designing and constructing civil infrastructure (Lee *et al.*, 2012). The 2D drawings and documents of respective structural systems are also kept in records for asset management and operations. Accordingly, bridge design, construction and maintenance process typically utilize 2D drawings. This is due to the fact that drafting 2D drawings after a satisfactory design evaluation by engineers is considered a safe and widely accepted practice (Lee *et al.*, 2012). The conventional 2D drawings and documents for planning and execution of the construction projects is slowly being replaced by 3D information modelling implementation. 3D information models are different from conventional 2D drawings as they are associated with object-oriented databases (Sacks *et al.*, 2010). 3D information modeling is based on parametric objects that are associated with attribute data such as material type, previous inspection date, crack dimensions etc. about the object. Building Information Modeling (BIM) has become a standard tool for building construction projects, and that knowledge is now being transferred to horizontal projects such as highways and bridges. Although the principles, methods, and software are very similar, different acronyms such as Virtual Design and Construction (VDC), 3D Engineered Models, Civil Integrated Management (CIM), BrIM, etc. are used to define BIM that is applied to horizontal projects. 3D bridge information models help improve the management of information in a 3D environment providing easy and remote access to various users (Eastman *et al.*, 2008). This study proposes a novel BrIM based inspection framework that integrates image based concrete crack detection algorithm results with a 3D bridge model database. 3D management of information (Eastman *et al.*, 2008) will enable users to download/view/update 3D models of concrete members and crack/inspection information associated with each member, which will eliminate the need for rewriting the field notes after going back to the office. Thus, it will help reduce overall asset life-cycle costs associated with bridge inspections.

2.4 Current Bridge Inspection Practices

As a part of this study, structural engineers and bridge inspectors from Iowa and Nebraska department of transportation were contacted in order to document the current bridge inspection practices followed by the respective DOTs. A semi-structured survey was specifically designed in order to document the visual inspection method carried out for bridge inspection. The result of the survey is as follows:

2.4.1 Nebraska Department of Roads (NDOR)

Nebraska Department of Roads (NDOR) Bridge Division follows their bridge evaluation manual for bridge inspections. Bridge inspection procedure is initiated by carrying out visual inspection and some non-destructive testing protocols such as ultrasonic testing methods to evaluate the condition of bridges. In case of concrete bridges, they use visual inspection method for detection of cracks and chain dragging and hammers to locate spalled concrete on decks. One of the NBIS inspector/load rating engineer of NDOR who was interviewed as part of this study stated that visual inspection method is relatively easy and quick. After visually inspecting all the elements of a bridge, the quantities of the area of cracks and severity are measured and documented. However, they have acknowledged that visual inspection method has its own limitations, as it becomes a challenging task to detect small hairline cracks. Also, due to weather conditions some small cracks may close up, which make it almost impossible to detect them through naked eyes. NDOR carries out bridge inspection in every 24 months; however, bridges that meet certain criteria may need to be inspected more frequently.

2.4.2 Iowa Department of Transportation

In order to maintain its bridge inventory, Iowa DOT uses Structure Inventory and Inspection Management System (SIIMS) (IOWA DOT, Bridge Inspection Manual, 2014). For the purpose of detecting cracks on various elements of a bridge, Iowa DOT uses field inspection including visual inspection and other non-destructive means of evaluation such as dye penetrant test, magnetic particle testing methods, ultrasonic testing methods etc. When implementing visual inspection method, critical areas are cleaned prior to inspection and additional lightning source and magnification techniques are employed if required. The inspectors capture photographs of the cracked elements and exact crack conditions are sketched and documented.

The process of visual inspection for crack detection is typically carried out in 24 months period (IOWA DOT, Bridge Inspection Manual, 2014).

2.5 Research Gaps and Needs

As mentioned in the literature review, significant attempts have been made in previous studies, both in terms of contact and non-contact techniques for crack detection on various surfaces/elements of different infrastructural systems. However, no attempts have been made so far in terms of integrating crack detection algorithms with 3D information models. This study proposes a novel framework that integrates crack detection algorithm results with 3D BrIM to enable easy and quick access to concrete crack/inspection related data associated with bridge elements included in 3D BrIM model.

CHAPTER III
RESEARCH METHODOLOGY

In this research study, a novel framework that integrates results obtained using existing crack detection algorithms to detect cracks on reinforced concrete bridges with 3D BrIM is proposed to improve bridge inspection process. Several structural engineers and bridge inspectors from Iowa and Nebraska DOTs were contacted to document the current bridge inspection techniques and the time and cost involved with it. First, data in the form of digital images (2D) was collected from various concrete test specimens as well as from a bridge located in the state of Iowa. Gray-scale image filtration and edge detection that uses pixel approximation algorithms were applied and their accuracy was tested on concrete test specimens. These algorithms were then demonstrated and validated with real-life data set collected from a bridge in the state of Iowa. Each research task is detailed below.

Task 1: Document Current Bridge Inspection Practices

A number of structural engineers and bridge inspectors from Nebraska and Iowa DOTs were contacted in order to document their current bridge inspection practices. Semi-structured interviews that were conducted with these authorities helped in pinpointing the needs and requirements for improving current inspection methods. The main idea was to document major problems and issues faced by the authorities in their bridge maintenance and repair operations such as field observation, bridge inspection, and bridge data management. The authorities were asked about the general protocol and methodology followed for bridge inspection practices (see Appendix A). Moreover, the survey was specifically designed for documenting the visual inspection methodologies carried out by Iowa and Nebraska DOTs for detection of cracks on reinforced concrete bridges as well as their advantages and limitations.

Task 2: Literature Review

A review of recent research that implements digital images and other non-contact methods for crack detection was carried out. The main focus of the literature review was to document different existing crack detection algorithms and to choose the best one and integrate the results with BrIM.

Task 3: Collect and Analyze 2D Digital Image Data in Laboratory Setting

A test-bed consisting of concrete cylinders with different dimensions was set up in the structures laboratory in the Department of Civil Engineering at Iowa State University. Cracked concrete cylinders of various sizes ranging from 100-200 mm diameter and 100-300 mm height, with different crack widths, orientation and depths were obtained from the laboratory so that the crack detection algorithms could be tested to detect cracks of different sizes. The digital image data was collected using a standard DSLR camera. The images were captured from variable distances from the object of interest to ensure the accuracy of the results obtained. The data was processed using Matlab, a proprietary programming language.

Task 4: Test Existing Crack Detection Algorithms

Image data was analyzed using classification metrics and computer vision algorithms to detect cracks on concrete surfaces. First, two crack detection algorithms, namely gray-scale image filtration and edge detection, were tested in Matlab environment. The image data appears as a matrix in Matlab, each component of the matrix corresponding to the intensity value of a pixel and organized based on their position in the image. The images are true/indexed or RGB

(Red, Green and Blue) in their raw format. It was necessary to convert them into gray scale for further analysis. Aforementioned crack detection algorithms were tested for their accuracy on cylindrical concrete samples of different sizes ranging from 100-200 mm diameter and 100-300 mm height, with cracks of various dimensions, depth, and orientation.

Task 5: Test Existing Scaling Tool for Crack Length Calculations

Cylindrical concrete samples with different crack sizes were tested and the measured crack length in pixels was converted into SI units using Matlab and compared with its length measured using a tape to test the accuracy of the tool.

Task 6: Validate and Demonstrate the Algorithm with Real Life Dataset

The proposed methodology for crack detection and scaling was tested on images collected from US-30 Bridge in the State of Iowa. Iowa DOT provided the research team with access to US-30 Bridge crossing the South Skunk River in Ames, IA. Images of cracks appearing on the piers of the US-30 Bridge were captured and tested using the proposed methodology.

Task 7: Framework Design for Data Integration into BrIM

This study proposes a novel framework that integrates the results of the proposed crack detection and scaling methodology with BrIM database. The framework is designed to incorporate attributes such as crack properties, their location and other parameters that are used to define concrete cracks and their severity. It defines a logical relationship between these attributes and the corresponding bridge component. The findings obtained from the proposed crack detection and scaling methodology is then integrated with the BrIM database, which should enable better access to inspection data.

CHAPTER IV

CRACK DETECTION ALGORITHMS

The Matlab environment was used to test the crack detection algorithms. The image data that was collected from concrete samples with various crack length, width, depth, and orientation and the ones that was collected from the US-30 bridge were used.

4.1 Method I: Gray Scale Image Filtration Algorithm

The data input in its original form is a true colored/index or RGB image (Figure 1), and in Matlab is presented in the form of a matrix (MXN). The original digital image data used here is an indexed image in .JPG converted to .PNG. The conversion can be done using any standard image viewing software supporting the required image format. After acquiring the image data in the required file format, the data was defined as a variable in Matlab. The crack detection algorithms require image data to be converted into gray scale. The indexed/RGB image data is converted into gray scale by calculating weighted sum of RGB values and the gray scale image is further adjusted in terms of its intensity. The conversion process enables retaining the luminance while eliminating the presence of hue and saturation information of the image (Thompson and Shure, 1995). The gray scale image and the image obtained after intensity adjustment are provided in Figures 2 and 3 respectively. The images obtained as shown in Figures 2 and 3 are subtracted from each other in order to remove irregularity in illumination conditions (Moon and Kim, 2011) (Figure 4). The results obtained from subtraction process may lead to noise in data, which affects crack detection considerably. The crack is not visible in the subtracted image as it is made of pixels with intensity values close to zero that result in an almost black image.

Figure 1 Original Cracked Concrete Block Image (DSLR Camera)

Figure 2 Gray Scale Image

Figure 3 Adjusted Gray Scale Image

Figure 4 The Result of Image Subtraction

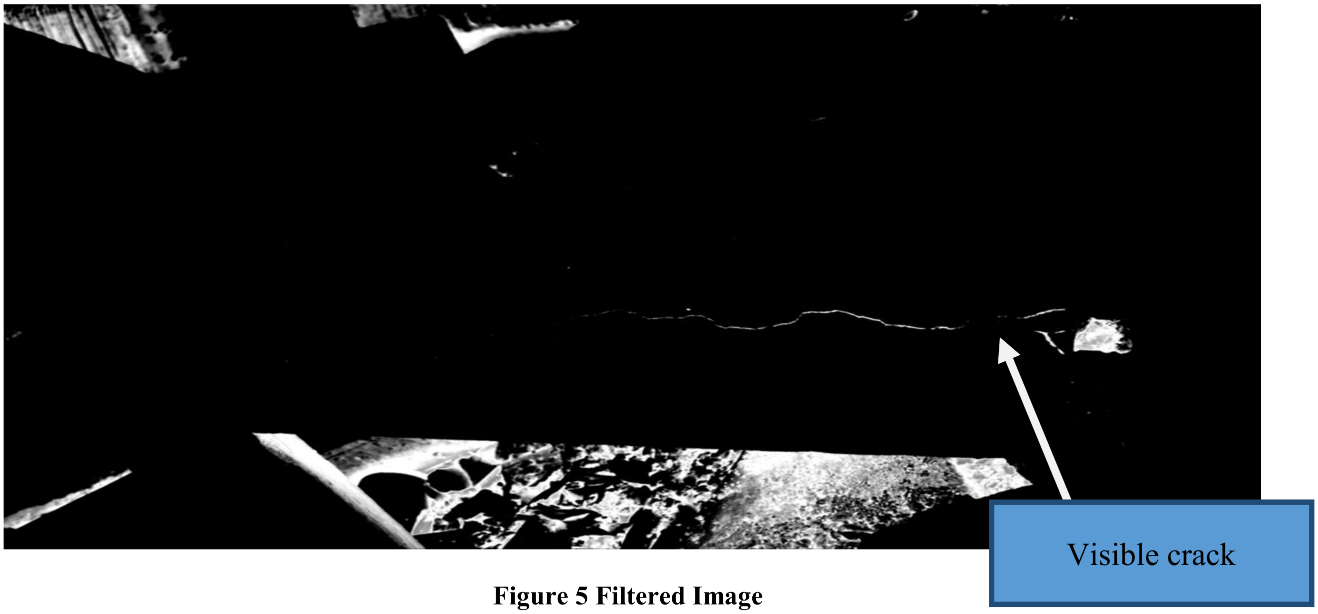

Figure 5 Filtered Image

In order to detect a surface crack, a predefined filter, often referred to as averaging filter, was applied to the subtracted image seen in Figure 4. This multi-dimensional filter filters the multi-dimensional array of an image that can be of any class or dimension. The predefined averaging filter ‘h’ is in the form of 8X8 matrix containing equal weights with the value of each cell as 1/64. The filter offers flexibility in boundary padding options. The filter ‘h’ does not double the input, it uses double precision floating for computing each element of the output. The filtered image shows the presence of a crack in the concrete member (Figure 5). For extracting image components such as cracks and for calculating crack dimensions, it is necessary to obtain the skeleton of the crack. Morphological operations enable skeleton extraction from the filtered image (Figure 5). The morphological operations can be applied several times until obtaining the desired result. In order to extract the crack skeleton, the ‘skel’ morphological operation is applied and repeated until the image has no changes. The morphological operation helps with pixel removal on the boundaries of the feature of interest by not allowing the object to break apart. The crack skeleton obtained (Figure 6) was then used for length and width calculations. Pseudo code for this method is provided below.

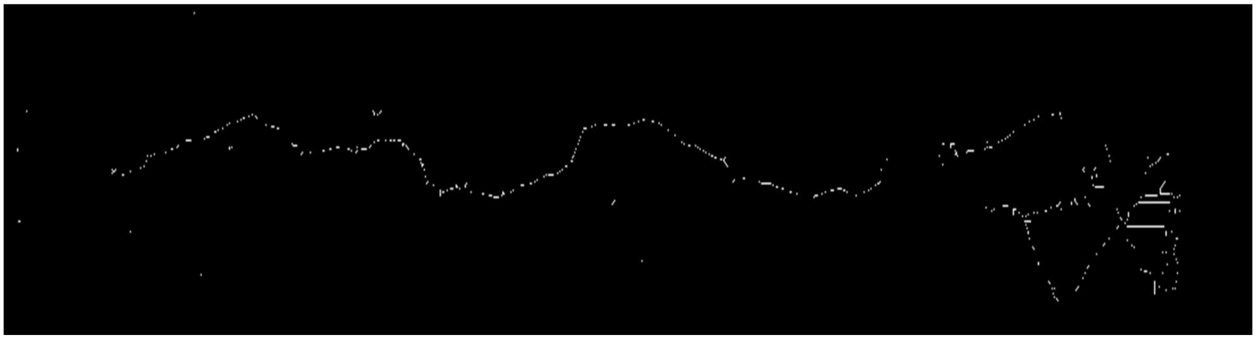

Figure 6 Crack Skeleton

Pseudo Code of Method-I

0. *Defining the variable "Image= a"*
1. *a = imread('image.png')*
2. *RGB values of variable 'a = [R,G,B]'*
3. ***for** i = 1:R, j = 1:G, k = 1:B*
4. *gray scale image [X,Y]* = $\sum_{i,j,k=1}^{R,G,B}(0.2989 * R + 0.5870 * G + 0.1140 * K)$
5. ***endfor***
6. *imshow [X,Y]*
7. *[X1,Y1]= imadjust[X,Y]*
8. ***for** i = 1:X, j = 1:Y*
9. *subplot (1,2,1)*
10. ***endfor***
11. ***for** i = 1:X1, j= 1:Y1*
12. *subplot (1,2,2)*
13. ***endfor***
14. *[M,N] = [X,Y]-[X1,Y1]*
15. *Apply filter '$h_{(8X8)}$' where every value is 1/64 = filtered image [C,D]*
16. *Apply morphological operation for n = ∞*
17. *bwmorph([C,D], 'skel', inf')*

4.2 Method II: Edge Detection Pixel Approximation Algorithm

Gradient of an image changes considerably around the edges of an object. This principle was kept in mind when selecting the second method for crack detection. The gradient of the image in the required format was calculated for each pixel and intensity/gradient value trend was observed. The maximum and minimum gradient values are then established.

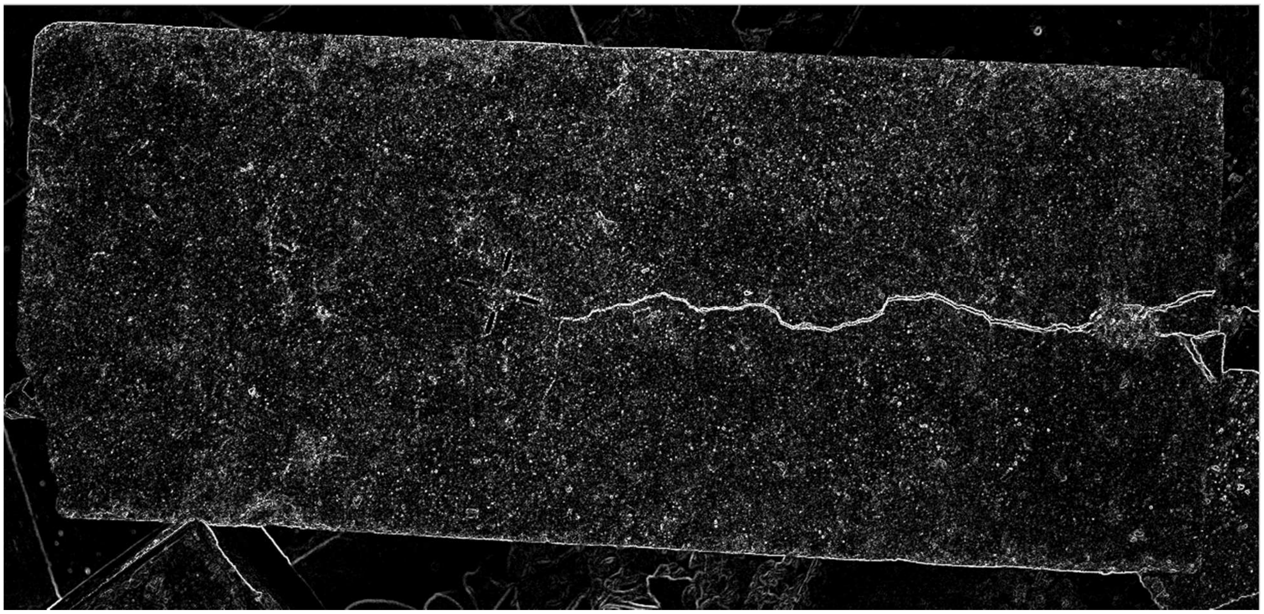

Figure 7 Edge Detection Applied Image

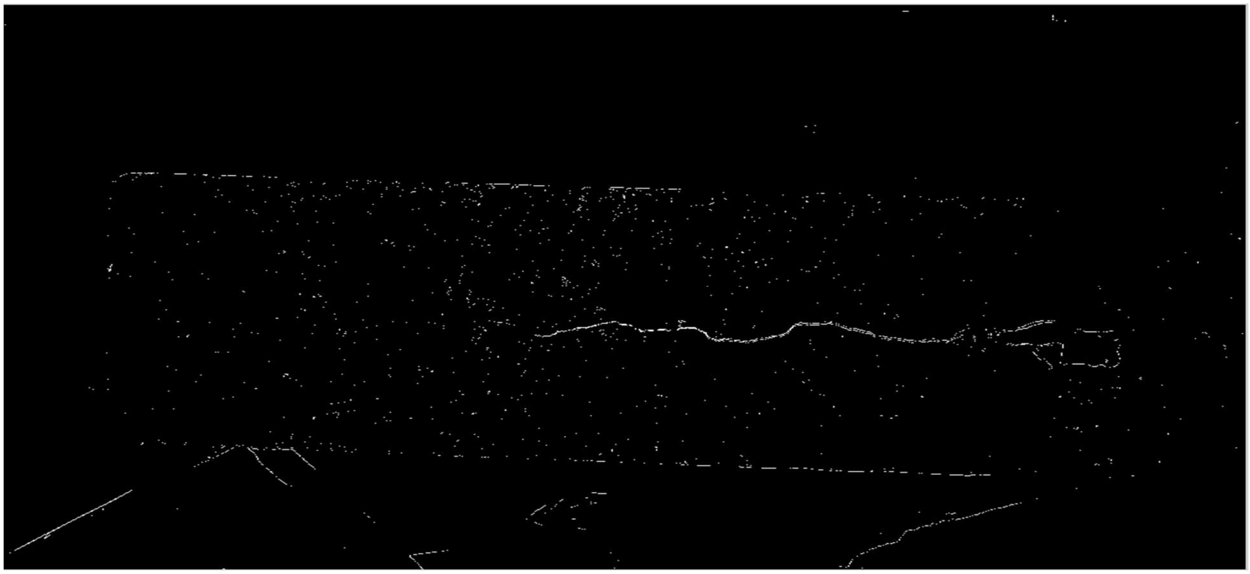

Figure 8 Binary Image

Figure 9 Noise Reduction Applied Image

After the conversion of the index image into gray scale, the trend in the pattern of gradient of the image was recorded and values corresponding to minimum and maximum gradient of the image were determined. In order to detect the edges of the object, the image gradient was adjusted according to the previously defined boundaries. The matrix obtained after adjusting the image gradient was then plotted in the form of an image as seen in (Figure 7). After detecting the edges of the object of interest, the trend in the intensity of the pixels was recorded and it was found that the intensity of the pixels forming the crack had a value of 1. Therefore, in order to highlight pixels corresponding to an intensity value of 1, a function known as pixel value approximation was used for the purpose of improving results obtained using the edge detection algorithm. This function checks intensity values of each and every pixel in the image and converts intensity value of a pixel to 0 only if the actual intensity value of that particular pixel is less than 1. The new image consists of pixels with intensity values 0 and 1, which are represented with black and white pixels respectively. The image obtained (Figure 8) contains some noise along the detected crack (pixels with intensity values of 1, but not corresponding to the crack itself). To remove noise from the image (Figure 8), a noise reduction function was used. This function checks intensity value of each pixel using a defined boundary condition for (x, y) coordinates surrounding the pixel under inspection. It then increments the counter only if the intensity value of the pixel under inspection and its adjacent pixels is 1 (Figure 9). This particular noise reduction function can be applied multiple times by defining new boundaries for (x, y) coordinates. The pseudo code for Method-II is provided below.

Pseudo Code of Method-II

Defining the variable "Image = a"
RGB values of variable 'a = [R,G,B]'
***for** i = 1:R, j = 1:G, k = 1:B*
    gray scale image [X,Y] = $\sum_{i,j,k=1}^{R,G,B}(0.2989 * R + 0.5870 * G + 0.1140 * K)$
endfor
I = imgradient[X,Y]
    Returns the gradient magnitude, measure maximum & minimum gradient values
I = mat2gray(gr,4,100])
Define crack = I = [X1,Y1]
***for** i = 1:X1, j = 1:Y1*
    ***if** (crack(i,j) <1)*
        crack(i,j) = 0.0
        else
            crack(i,j) = 1
endfor
crack_new = [C,D]
***for** i = 1:C, j = 1:D*
    count = 0
***for** L = 1:10, M = 1:5*
    ***if** (crack(i+L, j+M) == 1)*
        new count = count + 1
endfor
        ***if** (count >20)*
            Crack_new(i,j) = 1
            else
                crack_new(i,j) = 0

26. ***endfor***

4.3 Crack Detection Algorithm Results on Various Concrete Specimens

The crack detection algorithms described in 4.1 and 4.2 were tested on three concrete cylinder samples of different sizes with different crack width, length, and orientation, as well as on the data obtained from the US-30 Bridge. In Figures 10, 11, 12 and 13, the image labeled as 1 shows the original image of the concrete sample whereas images labeled as 2 and 3 shows the results obtained after applying method-I and method-II respectively. The images were captured using standard DSLR cameras. This section presents the crack detection results obtained for three different specimens and the U.S. 30 Bridge.

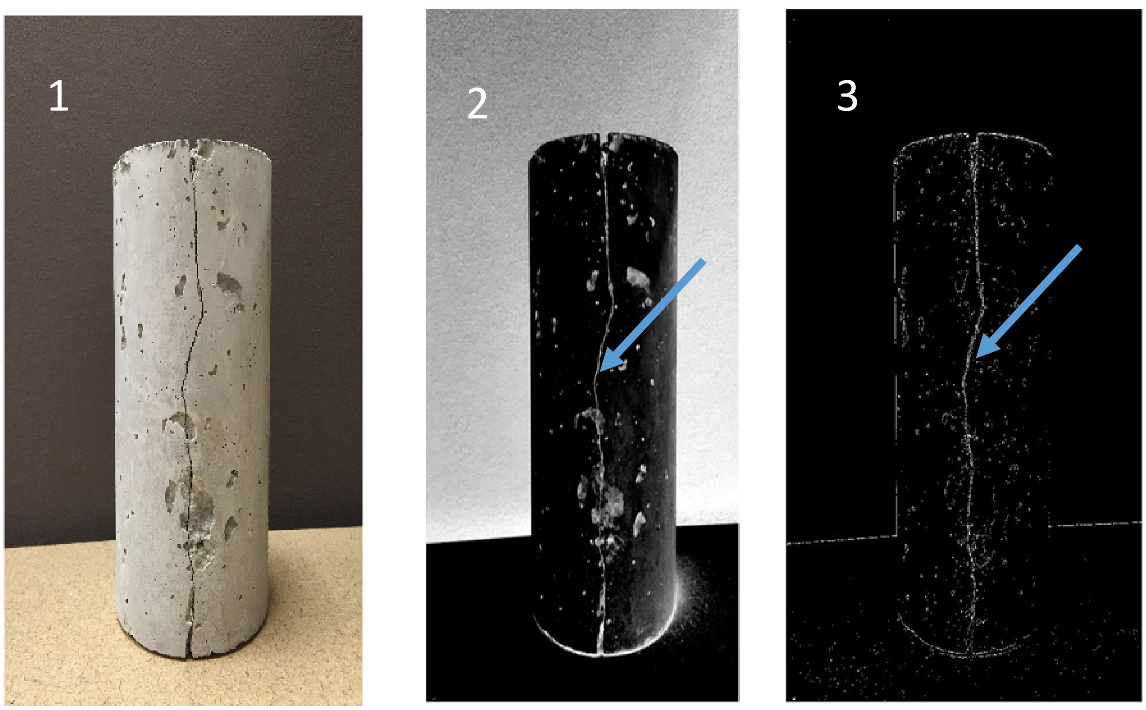

Figure 10 Results for Sample 1

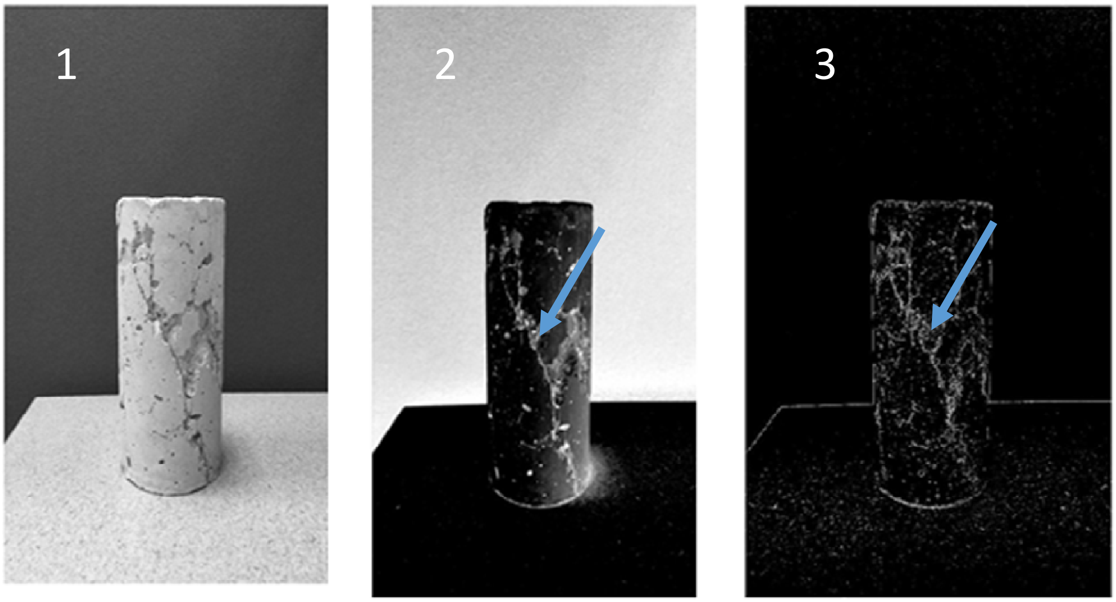

Figure 11 Results of Sample 2

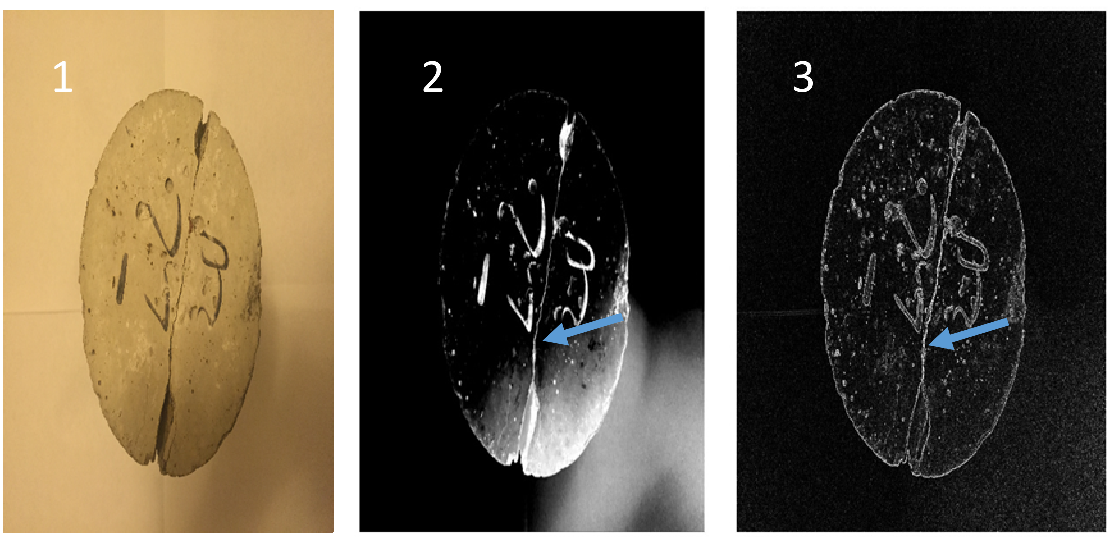

Figure 12 Results of Sample 3

Figure 13 Results of US-30 Bridge

4.3.1 Crack Dimension Calculations

In order to calculate the length and width of the crack, two techniques were used; namely, two-point and multi-point techniques. Both techniques are adaptations of the fly-fisher algorithm developed by Dare *et al*. (2002), where the user can define a start and an endpoint of a crack, and a series of short profiles are casted by the algorithm beginning at the starting point of the crack. This study adopted the concept of the fly-fisher algorithm in two separate ways to provide users with ease of categorizing cracks. Concrete surfaces develop cracks due to a number of reasons. These cracks do not necessarily require immediate attention at the time of inspection, however keeping records of developed cracks irrespective of their size and severity is considered as a safe practice. Multi-point technique can be used for severe/moderate cracks or cracks that need immediate attention and remedial measures in order to determine the exact crack dimensions. When implementing multi-point technique, the user can define closely spaced geometrical coordinates on the crack. The dimensions of the crack are then calculated using these coordinate values. On the other hand, two-point technique can be used for cracks with low severity. In this technique, the user defines the starting and end point of a crack, and uses these coordinate values for calculations. Snapshots of the results obtained using multi-point and two-point techniques can be seen in Figure 14 and Figure 15, respectively.

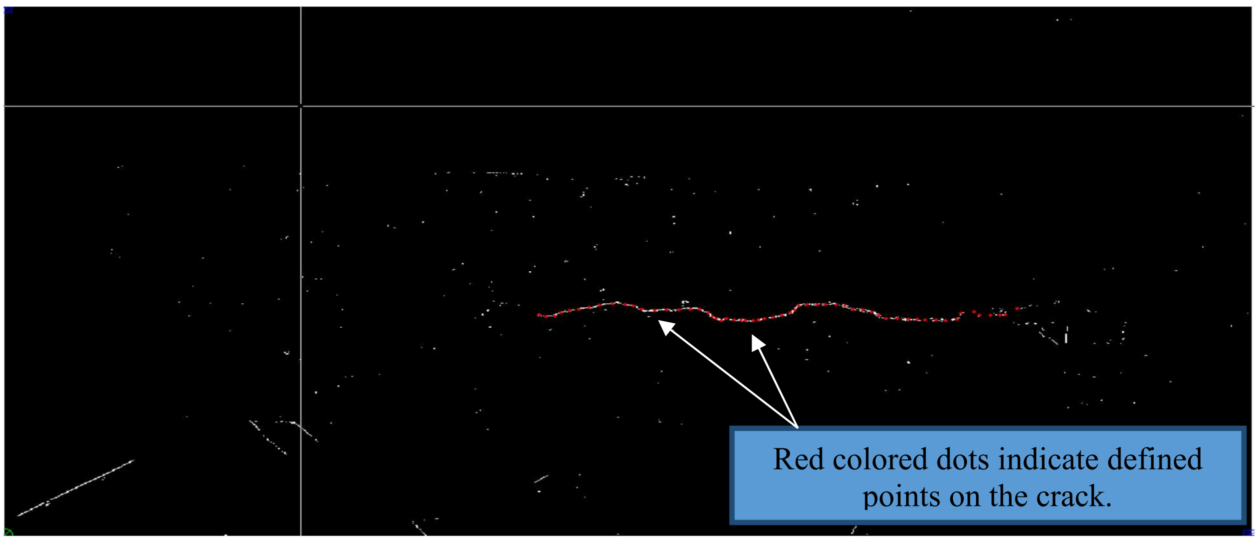

Figure 14 Crack Dimension Calculation using Multi-point Technique

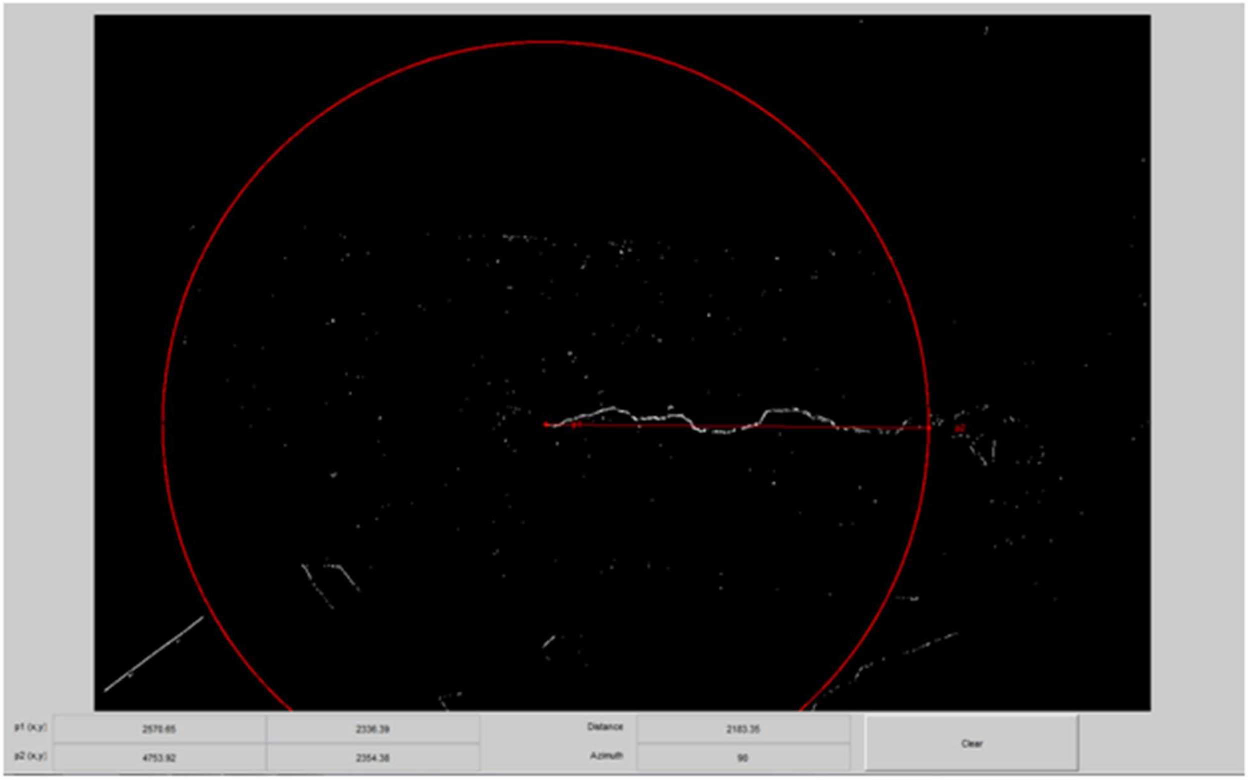

Figure 15 Crack Dimension Calculation using Two-Point Technique

4.3.2 Crack Length Conversion (pixels to SI units)

In order to convert pixel lengths of cracks, which are calculated using two-point and multi-point technique, into SI units, it is essential to scale the input image with respect to the size of the test object. For this purpose, the scaling tool included in Matlab was modified to automatically scale the input image with reference to the given object size. This tool enables user to select the object in the input image and measures the object size in pixels. Once the object size in pixels is obtained, the user can calculate the crack length in pixels using either of the two techniques (two-point or multi-point). In the next step, the original object size (SI units) is entered in the system for the purpose of scaling the input image in SI units. The tool then converts the crack length that was calculated in Pixels to SI units (mm) (Figure 16). Pseudo code of the scaling tool is provided below.

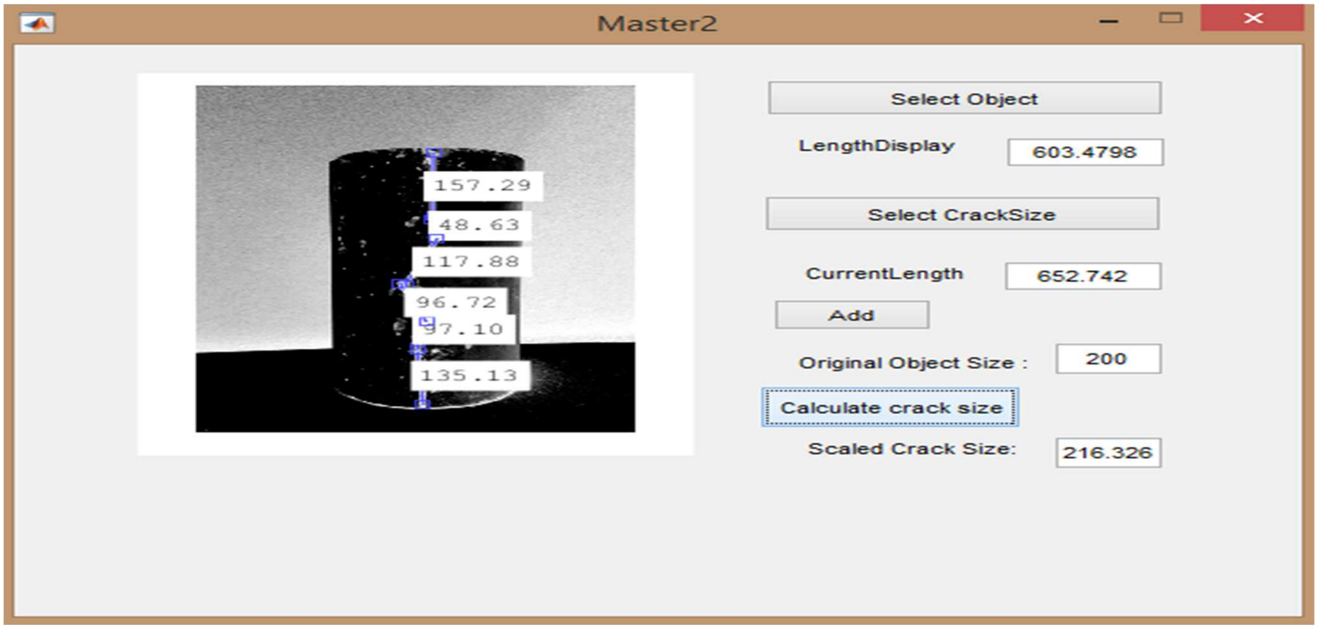

Figure 16 Length Conversion Tool in Matlab

Pseudo Code of the Scaling Tool

Input: (I, OriginalSize, DimensionMeasure), where I = Grayscale Image of object with crack, OriginalSize = the original size of the object in real life, and DimensionMeasure is the boundaries of the object in the input Image.

0. *Load the image file into the matlab program for processing the crack size.*
1. *Mark OriginalSize of the object in the picture, by dragging the utility tool of imdistline.*

   Length(OriginalSize) = x, where x ϵ N
2. *Mark CrackSize.*
3. *While(CrackSize segments all added and not marked complete)*
4. *Add the crackSize by dragging the imdistline till the entire crack is covered.*

   Length(CrackSize) = Length(CrackSize) + Length(CrackSegment)
5. *End-while*
6. *Mark the Length(DimensionMeasure) of the original object in the picture using utility tool imdistline. This is done to give a pixel ratio of the original dimension of the object to that of what is in the supplied input picture.*

7. *Calculate CrackLengthScale = CrackSize/DimensionMeasure*

8. *Calculate CrackLength = CrackLengthScale * OriginalSize*

9. *End Program*

4.4 Crack Detection Algorithm Performance Matrix

In order to test the accuracy of the crack detection and scaling methodology adopted in this study, actual lengths of cracks obtained from three concrete cylinder samples as well as US-30 Bridge in the state of Iowa were measured using a tape and compared to the crack lengths obtained using the proposed methodology. The accuracy was tested for both crack calculation techniques, namely two-point and multi-point technique, and percentage errors were calculated using Equation 1. The percentage error for Sample 1, Sample 2, and Sample 3 when using two-point technique was found to be 5.9%, 8.38%, and 2.43% respectively. On the other hand, percentage error when using multi-point technique for Sample 1, Sample 2 and Sample 3 was found to be 1.55%, 6.8%, and 3.5% respectively. In the case of US-30 Bridge, percentage error for two-point technique and multi-point were 23.23% and 1.2%, respectively.

$$\%\,Error = \frac{[Crack\ length\ obtained\ from\ scaling\ tool - original\ crack\ length]}{Original\ crack\ length} \qquad (1)$$

Table 1 Performance Matrix

Sample number	Actual Crack Length	Two-Point Technique		Multi-Point Technique		Error (%) Two-Point Technique	Error (%) Multi-Point Technique
		Pixel Length	Length in mm	Pixel Length	Length in mm		
1	208	609.9	199.0	640.8	211.2	5.90	1.6
2	126	317.6	115.4	364.6	134.6	8.38	6.8
3	102	1799	99.52	1791	98.38	2.43	3.5
US-30 Bridge	1979	636.8	1519	881.9	2005	23.2	1.2

4.5 Discussion

In order to test the accuracy of both crack length calculation techniques (two-point and multi-point technique), the crack lengths (mm) were compared to the actual crack length (measured using a tape), and percentage errors for both methods were calculated. As can be seen in Table 1, multi-point technique performs better overall. The percentage errors obtained when using multi-point technique is smaller than the error obtained using two-point technique for Sample 1 and Sample 2. However, multi-point error is larger than the one observed when using two-point technique for Sample 3, but the difference appears to be insignificant. The percentage error difference between multi-point and two-point techniques for Sample 1 and Sample 2 are 4.35% and 1.58% respectively. In the case of US-30 Bridge, this difference is 22.02%. The two-point technique performed less accurately as it measures the shortest straight line distance by selecting end points of the crack. The percentage error for the U.S. 30 Bridge case when using two-point technique is 23.23%. As the size of the crack becomes larger (as in the case of US-30 Bridge), more coordinate points get neglected, which affects the performance of this method considerably.

CHAPTER V

A NOVEL FRAMEWORK FOR BrIM BASED CRACK DETECTION SYSTEM

5.1 Overall Workflow

The overarching goal of this study is to develop a framework that integrates the image based crack detection results with BrIM database. Digital images of the object of interest can be acquired using a variety of devices such as mobile phones, digital cameras, tablets computers, etc. We propose a framework where tablet computers are used to take and attach images directly to the BrIM model that can be accessed from anywhere via cloud storage. These digital images would then be processed using crack detection algorithms in the office, and the output would be stored in the BrIM as attribute data of the corresponding model objects. BrIM is an object-oriented database that assigns specific ID numbers for each component. The proposed BrIM based framework for inspections would enable access to 3D BrIM of the inspected bridge on a tablet computer. 3D BrIM consist of 3D bridge components such as deck, slab, piers, etc., each associated with inspection data including original digital images and concrete surface crack information through attribute values, which can be accessed by clicking an individual 3D object in the BrIM. Once the 3D BrIM is uploaded to the tablet computer, the user can select any bridge component using the tablet computer, rotate the view, and attach pictures of the selected component, which can be used later for crack detection. Figure 17 presents the overall workflow of the proposed framework. Inspection data can be accessed using 3D models and the user can further explore, analyze, and update information stored in the BrIM database. The proposed framework can help evaluate, sort, and query crack related information in a more efficient manner than the conventional practices, thereby helps improve bridge management operations.

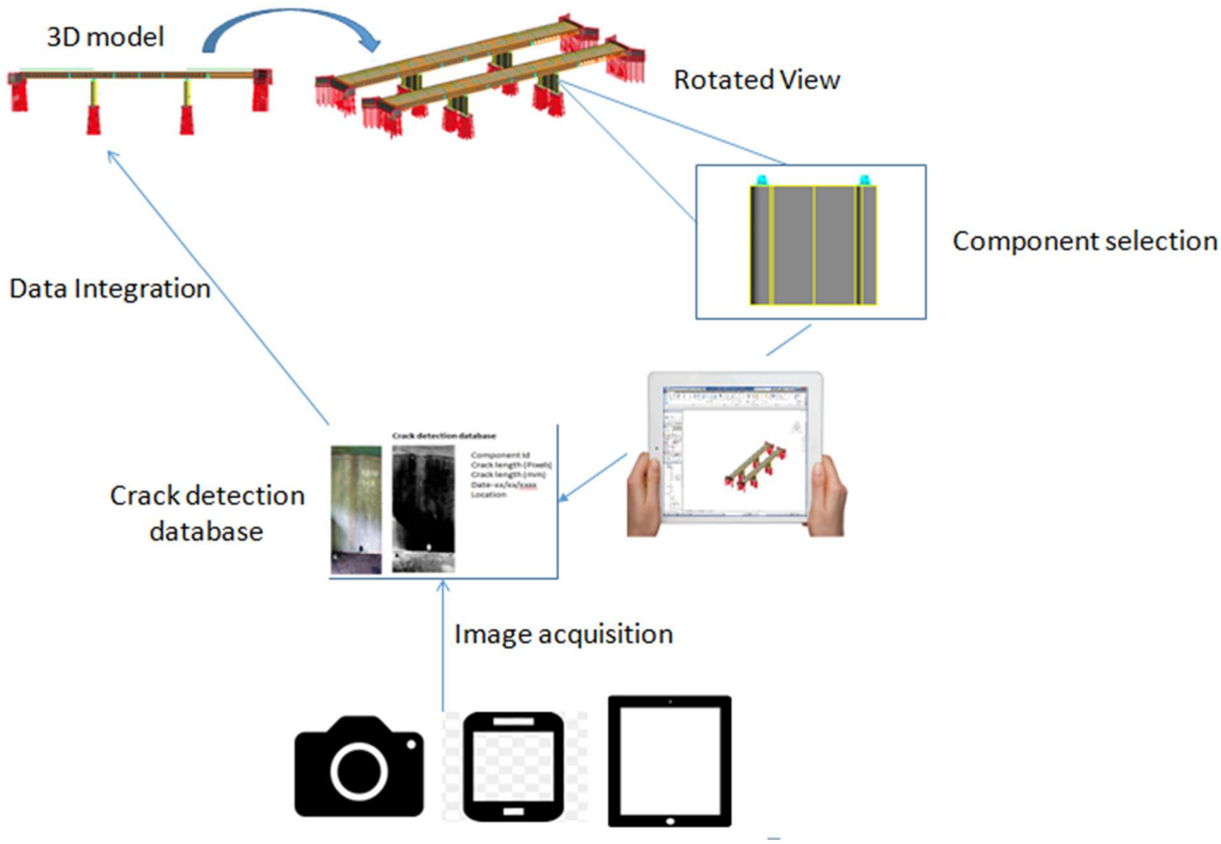

Figure 17 General Workflow Diagram

5.2 System Context Diagram

A system context diagram (Figure 18) explains the flow of information and basic functionality of the proposed framework. 2D drawings and other detailed specifications and condition data of a bridge were obtained and combined in 3D BrIM (spatial and attribute data) using Autodesk Revit software. In this framework, the crack detection and scaling tool inherits component IDs of the bridge component of interest from the 3D BrIM model. The crack detection and scaling tool checks its own database for the component IDs and enables to create a new component ID from the 3D BrIM model if the component ID does not exist. Upon creation of the new component ID, the users can upload the acquired crack data for a particular bridge component and the data can be stored and managed in the database based on the created component ID. On the other hand, if a component ID already exists in the database, the system will initiate a terminal for component's properties where various condition parameters (*e.g.*, cracks and its properties) can be explored, updated, and managed by the users. The crack detection tool will also enable users to rate the severity of the damage based on their own judgment, and share this information immediately through the cloud based capabilities of 3D BrIM to inform the responsible authorities to plan and execute adequate maintenance and risk mitigation measures.

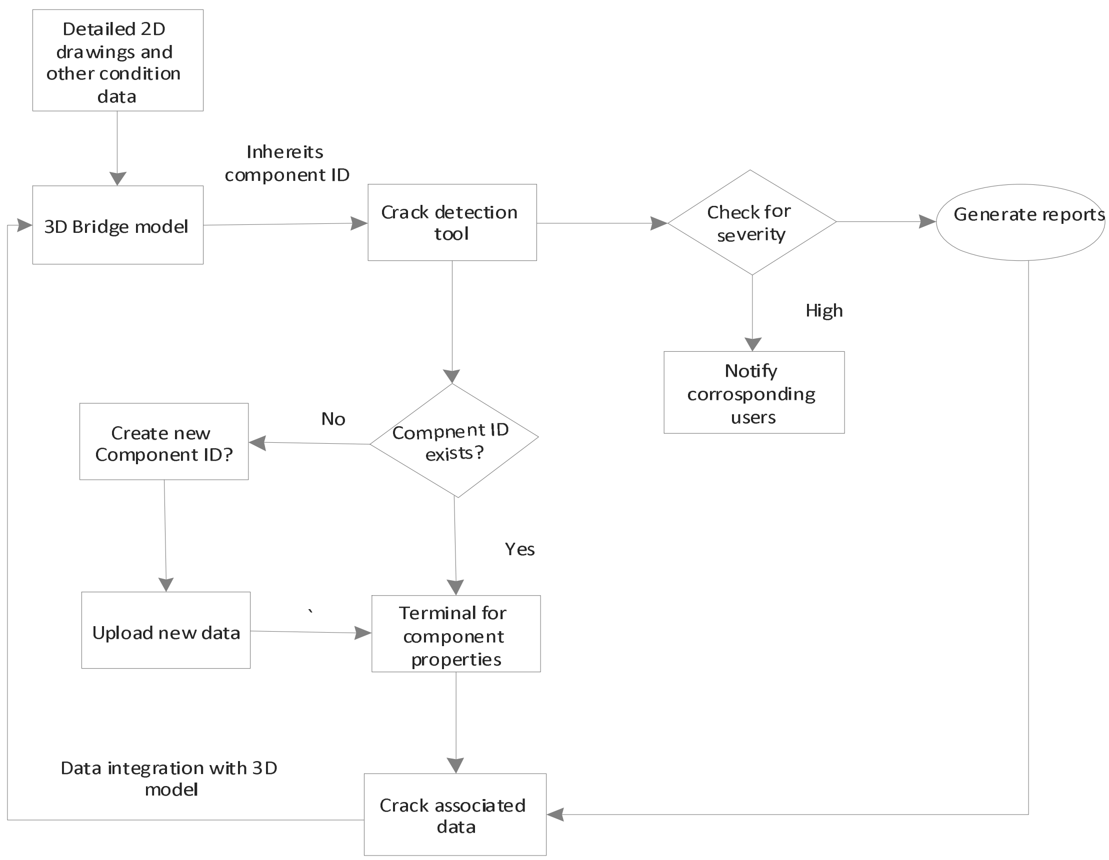

Figure 18 System Context Diagram

5.3 Data Query and Integration

Figure 19 shows the workflow of an API that links crack data into the BrIM model. In order to integrate crack data into the BrIM model, a new object parameter is created and defined in the appropriate family type. The parameter is defined based on different entities and it's attributes. Each element in a 3D model has its unique component ID. The crack data file can be imported in various file formats or even as an external link. Once, the system extracts the unique component IDs, the data can be assigned to a particular component in the model by searching and selecting either a particular element in the model or it's component ID. The data can be classified under two sub categories: Instance and Type data. Properties of an object similar for all the occurrences in a given data set is categorized under type data while on the other hand, the object properties unique to its installation in a given data set is categorized under instance data. The API is used as an add-in tool and upon initiation; the API will show a dialog box initiating the crack tool. Once crack tool is open, the inspector can select the element under inspection and the API will extract the assigned data based on the unique component ID. The API will also feature a search and data filter system, which will enable the authorities to search a particular type of data that they are specifically looking for within the database. The filtered data then can be exported and send out to designated authority for further analysis.

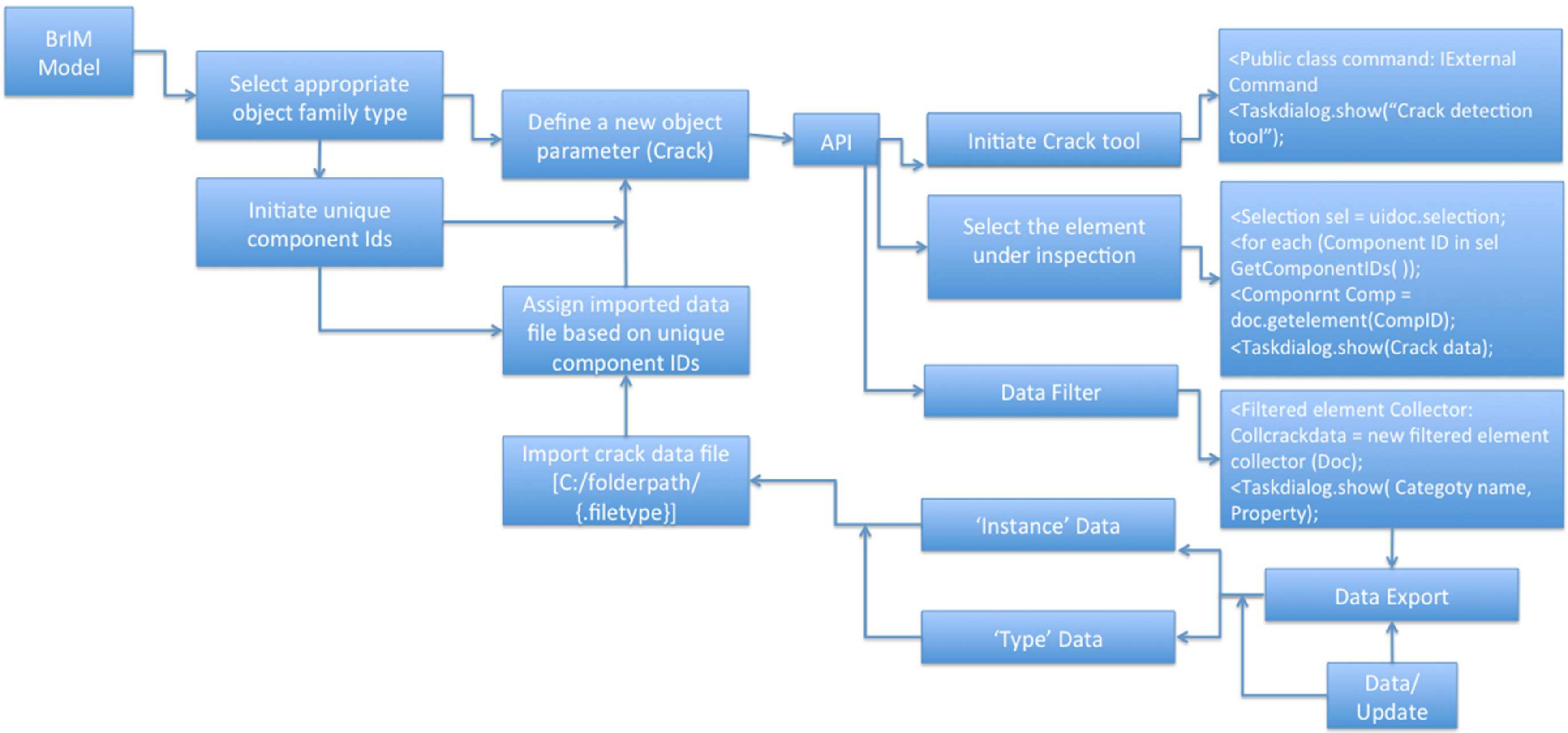

Figure 19 Data Query and Integration Workflow

5.4 US-30 Bridge Case Study

Figure 20 illustrates the example of US-30 Bridge undertaken this study. From the US-30 BrIM model, appropriate family type is selected and a new object parameter is defined. In this case, the appropriate family type is structural column as one of the concrete pier of the US-30 bridge is under inspection. Depending upon the location of the crack, the user can select different family types. For example- if the crack is present on one of the beams supporting the deck, then the user can select structural connections or structural beams as one of the family type. Once, the appropriate family type is selected, the new object parameter is defined and in this case it is crack. The parameter is defined keeping in mind, various entities and their attributes that are associated with the parameter. Crack dimensions, Images, severity etc. are few of the many entities that are associated with the crack parameter.

The data is broadly classified under two sub categories: Instance and Type data. In this study, location properties, user properties can be categorized under type data as these properties will be same for any number of occurrences within the model. However, crack properties such as crack length (SI/pixel length), images (Original/Matlab processed) are categorized under instance data, as these properties are unique and different for each element within the model. The type-based data can be edited if required. For example, if there is a new inspector who is now responsible for the bridge under inspection then the system will allow editing the user based information. Once the API is initiated in the 3D software, the authorities can select the element under inspection and rotate its view according to convenience. Using the data filter, the inspectors can extract a particular type of data based on unique component IDs based on which the crack data has been assigned to different elements within the given BrIM model. For example- if an inspector is looking for two-point crack length (SI units) of a specific component ID then the system will extract that particular data from the database. The authorities then can export the extracted data and can update the existing data by replacing it with a new data set.

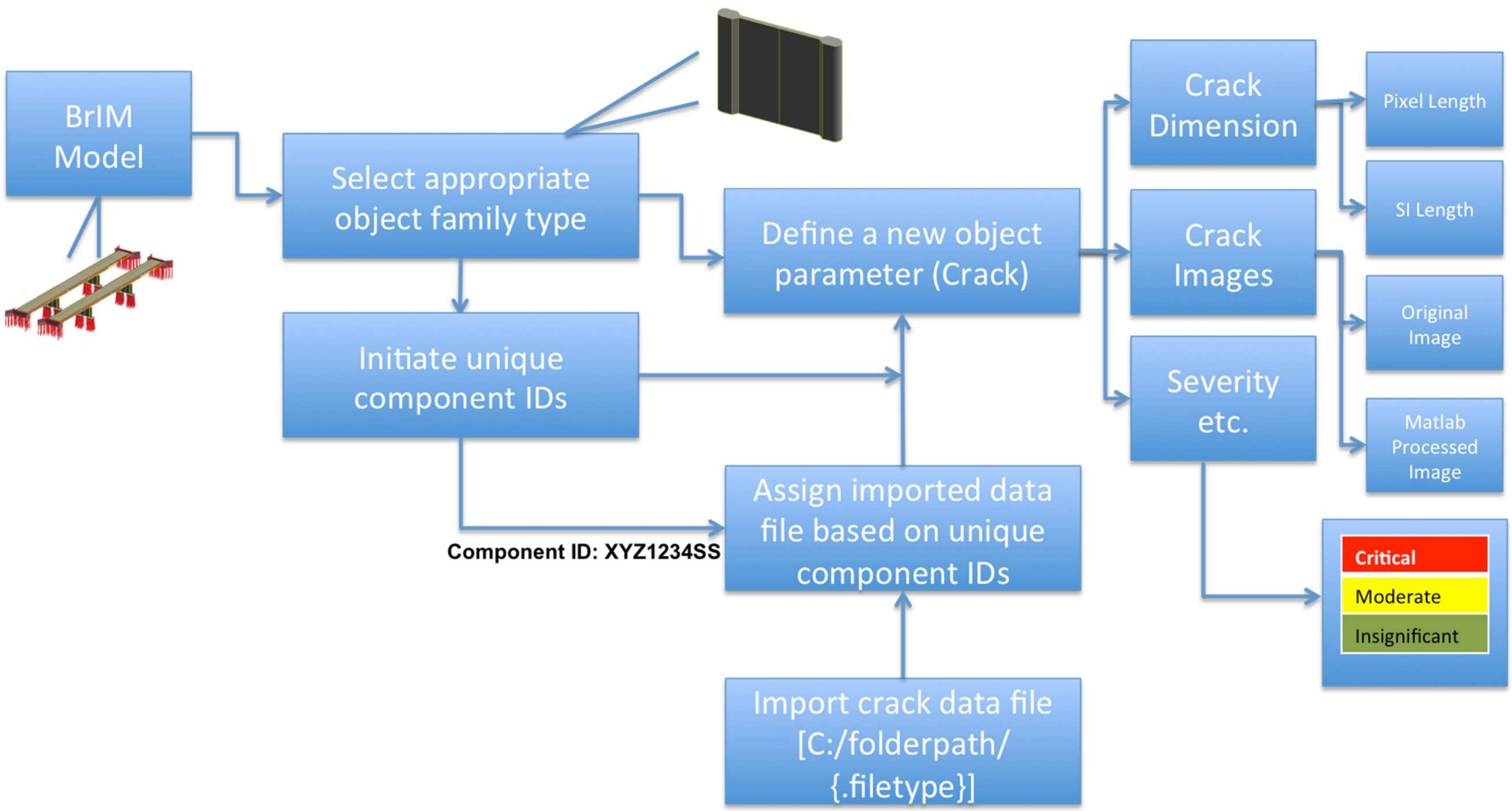

Figure 20 US-30 Bridge: Example 1

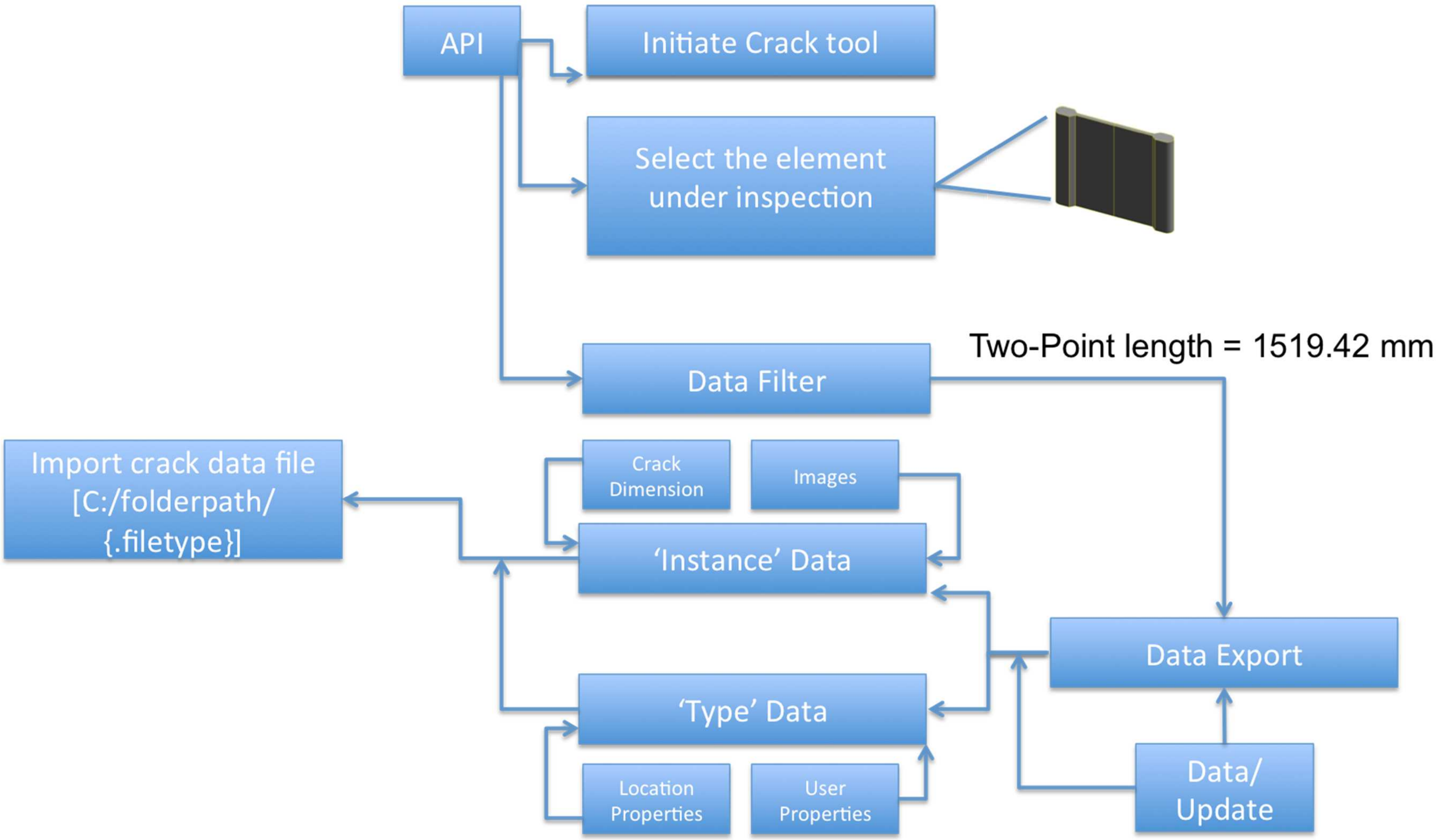

Figure 21 US-30 Bridge: Example 2

CHAPTER VI

SUMMARY AND CONCLUSIONS

This study focused on developing a BrIM based framework that implements an image based crack detection and scaling tool to improve current bridge inspection processes. As bridges are vital part of civil infrastructure, it is imperative to maintain their reliability, serviceability, and safety for public use by conducting condition assessments at regular intervals. The commonly used visual inspection method for bridges is prone to human error, subjective in nature, and requires expertise, more effort and resources. All these disadvantages along with the inability to produce accurate results indicates the need for a better and faster method to assess bridges.

The proposed BrIM based framework uses an image based crack detection and scaling tool, which employed two different crack detection algorithms, namely gray scale image filtration and edge detection pixel approximation algorithms. Once identified, crack lengths were calculated using two-point and multi-point techniques, and converted into SI units using the conversion tool in Matlab. To test the accuracy of the algorithms and the scale conversion tool, the length of cracks were compared with their actual lengths (measured using a tape). Percentage errors for each case were calculated and it is found that multi-point technique performs better overall. Finally, the results were integrated into 3D BrIM database to be used for bridge inspections.

The proposed framework provides a workflow, which can be used for advancement in collection, and use of crack data that is managed and sorted based on unique component IDs and incorporated in BrIM database. Implementing the proposed framework should result in less hours spent in the field and also it would not cause any traffic disruptions as digital images collected on field can be processed later in office. The future research should focus on developing algorithms that link BrIM database and image crack detection results.

REFERENCES

Abdel-Qader, I., Abudayyeh, O., & Kelly, M. E. (2003). Analysis of edge-detection techniques for crack identification in bridges. *Journal of Computing in Civil Engineering*, 17(4), 255-263.

Al-Shalabi, F. A., Turkan, Y., & Laflamme, S. (2015). BrIM implementation for documentation of bridge condition for inspection.

ASCE. (2013). Report Card for America's Infrastructure.

Carino, N. J. (2004). Stress wave propagation methods. *Handbook on Nondestructive Testing of Concrete*.

Dare, P., Hanley, H., Fraser, C., Riedel, B., & Niemeier, W. (2002). An operational application of automatic feature extraction: the measurement of cracks in concrete structures. *The Photogrammetric Record*, 17(99), 453-464.

Eastman, C. M., Teicholz, P., Sacks, R., Liston, K., & Handbook, B. I. M. (2008). A Guide to Building Information Modeling for Owners, Managers, Architects, Engineers, Contractors, and Fabricators.

Eastman, C., Teicholz, P., Sacks, R., & Liston, K. (2011). *BIM handbook: A guide to building information modeling for owners, managers, designers, engineers and contractors*. John Wiley & Sons.

Gunatilake, P., Siegel, M., Jordan, A. G., & Podnar, G. W. (1997, April). Image understanding algorithms for remote visual inspection of aircraft surfaces. In *Electronic Imaging'97* (pp. 2-13). International Society for Optics and Photonics.

Ito, A., Aoki, Y., & Hashimoto, S. (2002, November). Accurate extraction and measurement of fine cracks from concrete block surface image. In *IECON 02 [Industrial Electronics Society, IEEE 2002 28th Annual Conference of the]* (Vol. 3, pp. 2202-2207). IEEE.

IOWA DOT office of bridges and structures. "*Bridge Inspection Manual*", 2014.

Jahanshahi, M. R., & Masri, S. F. (2011, June). A novel crack detection approach for condition assessment of structures. In *ASCE International Workshop on Computing in Civil Engineering, Miami, Florida* (pp. 388-395).

Jahanshahi, M. R., & Masri, S. F. (2012). Adaptive vision-based crack detection using 3D scene reconstruction for condition assessment of structures. *Automation in Construction*, 22, 567-576.

Jahanshahi, M. R., & Masri, S. F. (2013). A new methodology for non-contact accurate crack width measurement through photogrammetry for automated structural safety evaluation. *Smart materials and structures*, 22(3), 035019.

Kaseko, M. S., Lo, Z. P., & Ritchie, S. G. (1994). Comparison of traditional and neural classifiers for pavement-crack detection. *Journal of transportation engineering*, 120(4), 552-569.

Kharroub, S., Laflamme, S., Song, C., Qiao, D., Phares, B., & Li, J. (2015). Smart sensing skin for detection and localization of fatigue cracks. *Smart Materials and Structures*, *24*(6), 065004.

Kollosche, M., Stoyanov, H., Laflamme, S., & Kofod, G. (2011). Strongly enhanced sensitivity in elastic capacitive strain sensors. *Journal of Materials Chemistry*, *21*(23), 8292-8294.

Laflamme, S., Kollosche, M., Connor, J. J., & Kofod, G. (2012). Robust flexible capacitive surface sensor for structural health monitoring applications. *Journal of Engineering Mechanics*, *139*(7), 879-885.

Lee, J., Sanmugarasa, K., Blumenstein, M., & Loo, Y. C. (2008). Improving the reliability of a Bridge Management System (BMS) using an ANN-based Backward Prediction Model (BPM). *Automation in Construction*, *17*(6), 758-772.

Lee, K. M., Lee, Y. B., Shim, C. S., & Park, K. L. (2012). Bridge information models for construction of a concrete box-girder bridge. *Structure and Infrastructure Engineering*, 8(7), 687-703.

Ouyang, C., Landis, E., & Shah, S. P. (1991). Damage assessment in concrete using quantitative acoustic emission. *Journal of Engineering Mechanics*,117(11), 2681-2698.

Pour-Ghaz, M., & Weiss, J. (2011). Application of frequency selective circuits for crack detection in concrete elements. *ASTM Int, 8,* 1-11.

Pour-Ghaz, M., & Weiss, J. (2011). Detecting the time and location of cracks using electrically conductive surfaces. *Cement and Concrete Composites*,33(1), 116-123.

Riveiro, B., Jauregui, D. V., Arias, P., Armesto, J., & Jiang, R. (2012). An innovative method for remote measurement of minimum vertical underclearance in routine bridge inspection. *Automation in Construction*, 25, 34-40.

Sacks, R., Radosavljevic, M., & Barak, R. (2010). Requirements for building information modeling based lean production management systems for construction. *Automation in construction*, 19(5), 641-655.

Shah, S. P., & Choi, S. (1999). Nondestructive techniques for studying fracture processes in concrete. *International Journal of Fracture*, 98(3-4), 351-359.

Sohn, H. G., Lim, Y. M., Yun, K. H., & Kim, G. H. (2005). Monitoring crack changes in concrete structures. *Computer-Aided Civil and Infrastructure Engineering*, 20(1), 52-61.

Tah, J. H. M., Carr, V., & Howes, R. (1999). Information modelling for case-based construction planning of highway bridge projects. *Advances in Engineering Software*, 30(7), 495-509.

Yamaguchi, T., & Hashimoto, S. (2010). Fast crack detection method for large-size concrete surface images using percolation-based image processing. *Machine Vision and Applications,* 21(5), 797-809._2

Yamaguchi, T., Nakamura, S., Saegusa, R., & Hashimoto, S. (2008). Image-Based Crack Detection for Real Concrete Surfaces. *IEEJ Transactions on Electrical and Electronic Engineering*, 3(1), 128-135.

APPENDIX A: SURVEY QUESTIONAIRE

QUESTIONNAIRE

1. What are the current bridge inspection practices followed and what parameters of a bridge are taken under inspection using these methods?

2. What method/s is/are used for detecting cracks on bridges?

3. What are the advantages and challenges for methods used for bridge inspection in terms of accuracy, time, cost and efficiency?

4. How the method of visual inspection of bridges is carried out specifically for crack detection on concrete surfaces? Explain briefly.

5. What are the advantages and limitations for visual inspection method in terms of accuracy, time, cost and efficiency?

6. How frequently bridge inspection practices are carried out in a year's time for a given bridge?