Automated prediction of condition state rating in bridge inspection

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Purpose This paper presents a new automated method to predict condition state rating in bridge inspection. The method is designed to identify proper risk-based inspection interval by neural networks and image processing techniques. **Method** The surface defect considered in this research work is the loss of surface portion (scaling) of concrete due to freeze-thaw action based on Ontario Structure Inspection Manual (OSIM). Earlier, digital camera has been effectively used for identification of cracks in concrete bridge inspection. The research presented in this paper uses digital camera and artificial neural networks (ANN) for defects identification and rating purposes. The problem associated with scale calibration while zooming of the camera to capture the details of defects is solved either by known dimension of existing nearby element s of the bridge or via artificial objects with known dimensions in the picture frame. Determination of depth of defects, however, poses another challenge when 2D picture frames are used in this process. Red, green and blue (RGB) color profile is used to estimate the depth of defects. Various image processing techniques are used to extract the feature vectors to characterise and quantify defects. Subsequently, an ANN model is developed to predict the depth of defects based on 7 attributes obtained from the image processing. Condition state rating of scaling defects is then modelled using a developed back propagation neural network model (BPNN). **Results & Discussion** The developed model is capable of predicting condition state (CS) rating of scaling defects as light, medium, and severe with correlation coefficient (CR) of 99%. The proposed method is aimed to identify the proper risk-based bridge inspection interval which can significantly shorten the inspection interval and can assist in planning and executing necessary maintenance and rehabilitation work.

Keywords: *bridge inspection, condition state rating, neural networks, image analysis*

INTRODUCTION

Bridges built during the boom period of infrastructure construction in the sixties and seventies are still in operation today. In Canada, more than 40% of the bridges currently in use were built over 50 years ago[1]. The situation is not different in rest of the world. In the the United States, there are 565 thousands bridges, and more than 70% of them were built prior to 1935[2]. The aging bridges are in need of immediate upgrade or renewal. In many cases, maintenance and rehabilitation actions are driven by crisis or disasters when funds are limited. This approach is not suitable for bridge management when most of the infrastructure has reached the design service life[3]. Therefore, Bridge Management System (BMS) is developed to help in planning maintenance and rehabilitation actions to avoid crisis based management[4,5]. For example, PONTIS has become a national standard for bridge management which has been adopted by the departments of transportation (DOT) in more than 40 jurisdictions in the United States[6]. However, the reliability of the predicted results of BMS is highly dependent of the quality of inspection data. Many of the bridges in U.S. are required to be inspected once in every two years[7]. Traditionally, inspections are based on visual observations which lack adequate quantitative data for bridge condition evaluation. Risk-based bridge maintenance strategies and optimal inspection intervals are needed for proper utilization of available fund to maintain proper safety level to bridge structures[8,9]. This method needs to proper identification and quantification of defects to assist risk-based BMS. The focus of this research is to support the risk-based BMS by developing an automated damage prediction method by analyzing the surface defects of bridges and of condition rating of concrete bridges surface defects.

BACKGROUND

The I-35 W Mississippi River Bridge was inspected one year before the collapse in August 2007[10]. The bridge was built in 1964 and rated 4 out of 9 which could be operated without load restrictions[10]. The investigations imply that the condition of such deficient bridges in the country may be worse than what officials have predicted[10]. This draws serious attention towards proper inspection strategies for efficient bridge management. In 1990 Hachem[11] had used the sufficiency ratio as one of the scheduling inspection parameter to determine the inspection interval. Wirsching and Torng (1989)[12] used reliability analysis to find the inspection intervals of marine structures. Liu and Frangopol[13] pointed that the BMS software does not consider environmental factors, material prices, geographical factors, and design parameters. This leads to uncertainty about the result of BMS to determine schedule for maintenance and rehabilitation. Liu in 2008[14] studied 69 collapsed bridges in the U.S. after 1967. The data showed that more than 50% bridges were collapsed due to collisions and natural disasters. These phenomenons are difficult to capture and to incorporate into BMS to get better results. In the past, a wide range of construction materials had been used for bridge construction. Therefore, it is difficult to establish a common inspection interval for bridges. One way to tackle this problem is to revise the inspection frequency based on risk-based management strategies. Since bridge monitoring and inspection are expensive, there is a need for developing automated bridge inspection systems.

Currently, some bridges use electronic sensors to constantly monitor bridges condition. Bagchi et al. (2007)[15] developed a model for damage detection based on vibration of structures. Close-range photogrammetric and Non-Destructive Test (NDT) are widely being used in bridge monitoring and evaluation. In 1849, Laussedat first utilized terrestrial photographs to compile maps and later was recognized as the "father of photogrammetry"[16]. Photogrammetry has been successfully used in identification of bridge length, width, lateral and vertical clearance and also documentation of historical monuments[17]. An automatic bridge condition evaluation system based on LiDAR (Light Detection and Ranging) is developed by Liu[14]. The above methods use advance tools and sensors and may be applicable for major rehabilitation works. There is a need to develop a procedure which can accelerate the primary inspection process and enhance the output of existing BMS. Existing BMS uses experts for condition rating based on inspection report. Abudayyeh et at. 2004[3] have proposed a framework for automated bridge imaging system which stores different surface defects, but the condition rating is assigned by expert through viewing the defects on monitors. Hence, an automation condition rating system needs to be developed that can be connected with any BMS database. In this paper, for automation, ANN has been used for prediction of condition rating of defects based on analysis of digital photographs. Moselhi and Shehab-Eldeen (2000)[18] used image processing and neural networks to automatically detect and classify defects in sewer pipes. As reported by authors, the accuracy rate of proposed algorithm is 98.2%. Khan et al. (2010)[19] also used neural networks to analyze structural behavior of sewer pipes in terms of variation of condition rating. The reported success rate was 92.3%.

METHODOLOGY

In the 2011 Annual report of the office of the Auditor General of Ontario, a risk-based approach for monitoring the inspection for infrastructure has been recommended[20]. The approach requires following up any unusual changes in a bridge's condition since the previous inspection and identification of high-risk bridges. Once maintenance is performed, then risk and age associated with the bridge also change[11]. This paper does not discuss the risk-based ranking of bridges, but recognizes that the risk of bridges depends on unit cost of repair which is evaluated form quantity measurement of defects. An automated procedure is proposed for quantification of scaling the defects based on Ontario Structure Inspection Manual (OSIM) and condition state rating of bridge elements as shown in Fig. 1. This approach assumes no prior database information about bridge surface defects. The methodology consists of three major components: data acquisition, attributes extraction (image processing), and neural networks models. The following paragraphs describe each component in detail.

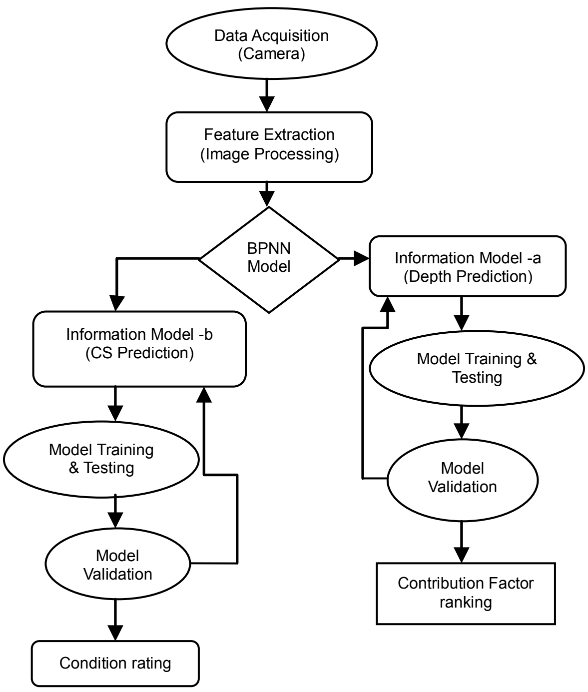

Fig.1. Research Methodology

Data Acquisition

A commercially available SONY-DSC T5 digital camera of 5.1 mega pixels with optical zoom 3x has been used here for data collection of bridge surface defects. For surface defect identification, close-range photographs are required with proper focus on details of defects. However, just taking random photographs are not much of our interests. So, each photograph frames must include either natural or artificial targets for calibrating the scale. In general, natural targets can include structural details of beams, columns, parapet walls and railings, patches on concrete and steel surfaces, and nuts or bolts on girders. When there is insufficient natural targets, artificial targets are to be used. The artificial target used in the present research consists 5 cents coin placed in the vicinity of defects. Fig. 2 shows an example of artificial target placed in the picture frame.

Fig.2. Use of Artificial Target for Scale Calibration

Image Processing

ImageJ[22], commercial software for image analysis, was used to extract feature vectors of defects attributes. The general methodology for feature extraction is shown in Fig. 3. Images are loaded to imageJ software and preprocessed using a a series of steps to enhance the image for further processing. These enhancements include image smoothing, image sharpening, contrast modification, and histogram modification. The attributes of a feature vector considered in this work are area, perimeter, and the lengths of the major and axes, aspect ratio, roundness, and depth as shown in Fig. 3. The first six attributes are obtained by selecting the defects, and setting the scale in software to convert pixel value to actual measurement. But for the estimation of depth, a different approach that uses the RGB color profiles is required.

Use of Low Pass Filter: To reduce the effect of high frequency components, low pass filter such as, Gaussian Blur can be used. In this work, the similar effect is produced from line selection tool of ImageJ. The width of selection line has been magnified 150 times the default mode until the edge can be detected clearly (Fig. 4). The digital data are extracted in MATLAB and processed further to find the difference in average color intensity at desired locations.

Relationship between the difference in intensity (DIB) and the depth of a crack: The relationship between DIB and depth of defects is developed by taking actual field measurements. The resultant approximation can be expressed by

$$t_d = K * DIB \qquad (1)$$

Where, t_d the depth of a defect in mm, and K is the slope of the line plotted in Fig. 5. The value of K is obtained by taking the first derivative of equation (1) which is found to be 1.0253. The result shows that depth prediction error varies from 5 to 15% as compared to actual measurement depending on the presence of dirt in defected area, wet surface or exposed reinforcements. In many cases, the estimated depth is highly dependent on the color intensity at the detected edge.

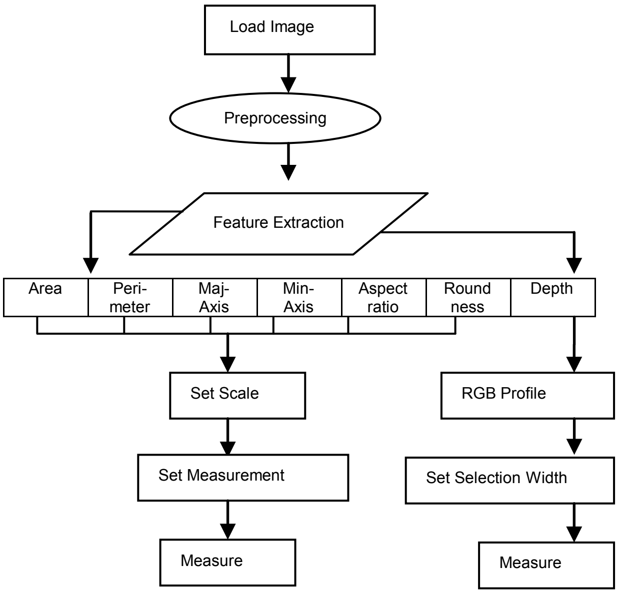

Fig.3. Attributes feature Extraction

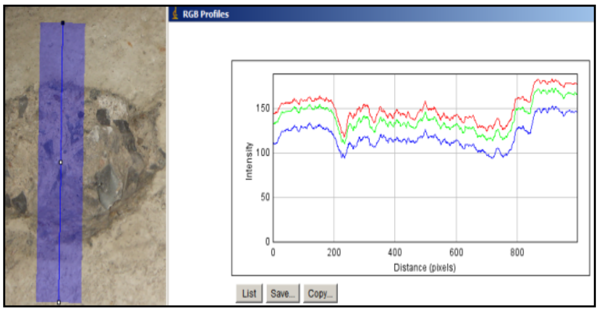

Fig.4. RGB Color Profiles for Depth Estimation

BPNN Models

A back propagation neural networks (BPNN) has been developed to model the relationship between the depth and condition rating of structural elements. The following two models have been constructed: Model ‘a’ to predict depth, and Model ‘b’ to predict condition rating, as discussed above. While both models are similar, Model ‘b’ contains an additional attribute of depth input variable in the data pattern to predict condition state (CS) rating of defects in bridge elements based on the severity of observed defects. The neural networks modeling process is shown in Fig. 6. The above models have been implemented using a commercial software namely Neuroshell 2[21].

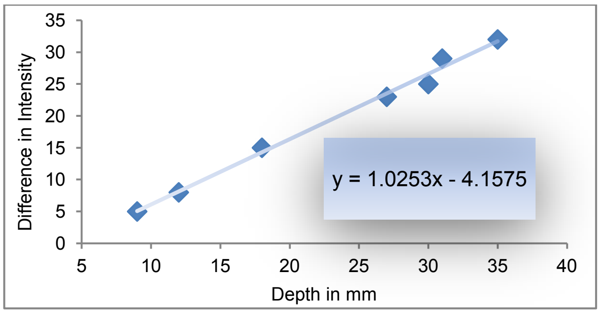

Fig.5: Relation between different in Intensity and Depth in mm

Table1. Description of Condition State Rating

Defects	Condition State Rating		
	Light (1)	Medium (2)	Severe (3)
Scaling	Local Flaking/Loss of Surface Portion of Concrete or Mortar due to Freeze or Thaw		
	Up to 5mm Depth	6-10 mm Depth	> 10mm Depth

Data Collection and pre-preprocessing

Data are collected from bridges located in Montreal, Quebec, Canada. Digital photographs are taken from close range so that the defects are magnified. Condition rating grades are adopted from Ontario Structure Inspection Manual (OSIM)[23] where condition state rating of 1 indicates light damage and 3 indicates severe damage. Table 1 summarizes the condition state rating grades mentioned in OSIM.

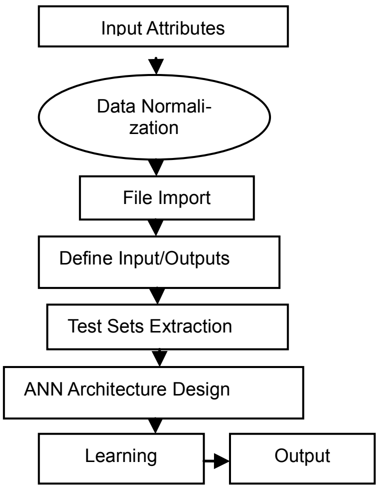

Fig.6. Neural Networks Modeling Process

The input data used in the BPNN models have been normalized (between 0 and 1) using the following equation (Eq. 2).

$$X_{ni} = (X_i - X_{min})/(X_{max} - X_{min}) \quad (2)$$

where X_{ni} is the normalized value of X_i; X_i is the i^{th} value of a data series X representing the raw data; X_{min} is the minimum value of X in the sample set; and X_{max} is the maximum value of X in the sample set.

Training of the BPNN

The network architecture is adopted from Neuroshell 2, 1996[21] online documentation manual shown in Fig. 7. The network consists of five layers of neurons with one input layer (the number of input neurons are equal to number of attributes in each pattern), 3 hidden layers, and one output layer (the number of output neuron is one). A total of 19 data patterns have been prepared using the image analysis process which consists of 60% training sets, 20% testing sets, and 20% validation sets. Validation data set is also called the production set. The production set of data, which is not presented to the network during training, is later used to validate the model.

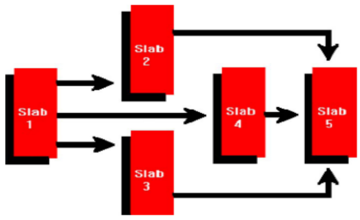

Fig.7. Architecture of BPNN (Source: Neuroshell 2)

Table.2. Performance of Model-a

Patterns processed	19
R squared	0.7024
r squared	.7990
Mean squared error	0.028
Mean absolute error	0.147
Min. absolute error	0
Max. Absolute error	0.278
Correlation coefficient r	0.8939

Table.3. Performance of Model-b

Patterns processed	19
R squared	0.9807
r squared	0.9839
Mean squared error	0.003
Mean absolute error	0.032
Min. absolute error	0.000
Max. Absolute error	0.167
Correlation coefficient r	0.9919

RESULTS

The accuracy of the developed models is evaluated by applying validation sets data to the models. The validation sets of data are not exposed to the models during the training and testing of the models. After applying these sets of data, various statistical parameters are obtained to measure the accuracy of prediction of CS rating. The statistical features of the trained BPNN models are shown in Tables 2 and 3. To measure the importance of an input variable in the neural networks output relative to the other input variables in the same network, a parameter called the contribution factor (CF) used in Neuroshell 2[21]. A large value of CF of a variable will indicate that it contributes more to the output than other input variables. However, a variable having a low value of CF does not mean that it shall be excluded from the model. The values of CF obtained for both the models are shown in Tables 4 and 5.

Table.4. Contribution Factors – (Model-a)

Ranking	Parameter	CF
1	Length of Major Axis	27.6%
2	Area	23.8%
3	Length of Minor Axis	19.6%
4	Aspect Ratio	12.2%
5	Perimeter	9.9%
6	Roundness	6.7%

Table.5. Contribution Factors – (Model-b)

Ranking	Parameter	CF
1	Depth	53%
2	Length of Minor Axis	9.6%
3	Aspect Ratio	8.8%
4	Roundness	7.6%
5	Length of Major Axis	7.2%
6	Perimeter	6.8%
7	Area	6.7%

A comparison of the estimated output given by the BPNN model and the actual one for all data points of both models is presented in Fig 8. In Fig.9, the actual condition state is first obtained after evaluating the depth information from the first model and plotted against all the 19 patterns. Then Model 'b' is used to predict the condition state rating and validated by using the production sets. The results are summarized in Table 3.

APPLICATION AND LIMITATION OF THE DEVELOPED MODELS

The BPNN models developed here have designed by using Neuroshell 2 software. The trained model can be used to predict (a) the depth of cracks or defects on concrete bridge surfaces, and trained (b) the condition state rating of concrete bridge members. The trained models work in same way as experts classify and predict the attributes of defects based on their experience. The procedure can reduce the inspection time as the inspector needs only to take appropriate photographs, and analyze them using the proposed methods. With this application, the frequency of inspection can be increased without additional burden to client and hence could be possible to capture risk associated with environments and extreme loadings. Additionally, the efficiency of existing BMSs can be improved after integrating this model with any BMS like PONTIS. The risk associated with the changes in the condition of various elements or members in a bridge can be potentially assessed using the proposed methods which may help in making appropriate decisions for maintenance and rehabilitation actions. The proposed method will be helpful to track and record these events in proper time with less cost.

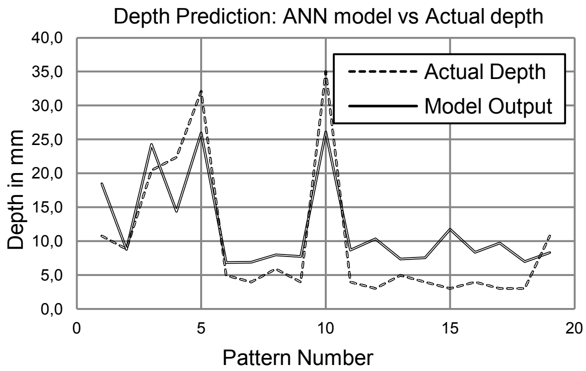

Fig.8. Prediction of Actual Depth Vs Model Output

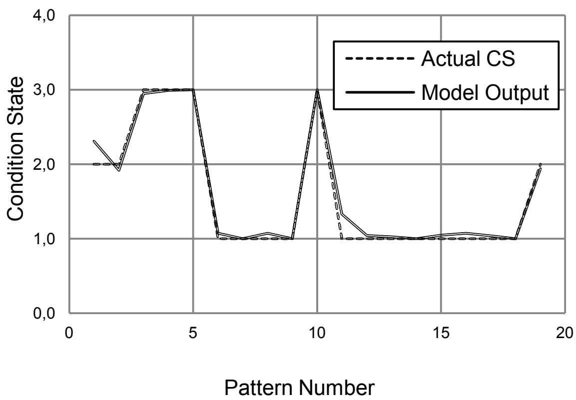

Fig.9. Prediction of Actual Condition State Rating Vs Model Output

However, the developed models have their limitations. A close range digital photographs are required for defect identification which needs zooming capability of cameras. This method also requires a reference object of known dimension such as known dimension in the picture frame for calibrating the scale. The changes in an attribute of a defect attribute depend upon location and weather conditions such as, temperature, moisture and lighting, and the developed models need corresponding reference conditions for calibration. More importantly, sufficient numbers of input data patterns are necessary to have better training and prediction capabilities. For better prediction capability, a robust database is required.

CONCLUSION

Inspection report is the major source of data for input to any BMS for maintenance and rehabilitation activities. Traditionally visual inspection, which is the primary method in use, is slow and expensive. In this research, machine vision techniques are used for automated prediction of condition rating and depth of defects. This approach utilizes digital photographs and neural networks to build data models which have many advantages as compared to traditional inspection. It uses non-contact techniques which is applicable to inspection in the areas which are not readily inaccessible. Also, it can quantify a large amount of geometric information in a short time with the help of digital image processing. Hence, it can be used as a tool for routine bridge inspection. There are several examples of photogrammetric identification and deformation measurement in bridge elements. Model 'a' demonstrates the prediction capability of depth of scaling defects where as Model 'b' shows the prediction capability of condition state rating of bridge surface defects. The results show that the length of major axis has the highest contribution factor for depth prediction and the depth of defects has the highest CF for prediction of condition rating of bridge elements. The success rate in the first case is 89% and that in the second case is 99%. Since the proposed method is fast and less expensive, the frequency of inspection can be significantly increased to provide additional safety to bridges by recognizing the effect of extreme loadings. Hence, it can be used as a tool for determination of risk-based inspection interval which requires proper quantification of bridge defects.

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