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   An Automatic Deep Learning-based Crack Identification Methodology for Bridges Using UAV Images
2. Author(s)
   Chao Sun, Ph.D., Assistant Professor
   Zhiming Zhang, Ph.D. student
3. Performing Organization Name and Address
   Department of Civil and Environmental Engineering
   Louisiana State University
   Baton Rouge, LA 70803
4. Sponsoring Agency Name and Address
   Louisiana Department of Transportation and Development
   P.O. Box 94245
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Many bridges in the State of Louisiana and the United States are working under serious degradation conditions where cracks on bridges threaten the structural integrity and public security. To ensure the structural integrity and public security, it is required that bridges in the US be inspected and rated every two years. Currently, this biannual assessment is largely implemented using manual visual inspection methods, which is slow and costly. As unmanned aerial vehicles (UAVs) become more and more popular, researchers started to resort to mages and videos for damage detection. Hence, it is promising to integrate the deep learning method with UAV images to develop an automatic crack damage identification method. This research develops an efficient low-cost deep learning-based framework to detect and quantify cracks on bridges using computer vision-based technique and deep learning. The Convolutional Neural Networks (CNN) deep learning method which is powerful in extracting and learning image features will be used to identify cracks from images. Specific research activities include: (1) collection of a large volume of images online; (2) collection of images of target structures using a UAV camera; (3) development of a deep CNN model using collected images and their augmentation; and (4) identification of cracks using the learned

deep learning model. The research outcomes of this project will enable automatic crack damage detection and quantification of bridge key components in a cost-effective manner. The methodology to be developed is expected to facilitate crack damage identification for other transportation infrastructures, e.g. pavement and traffic sign structures.

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An Automatic Deep Learning-based Crack Identification Methodology for Bridges Using UAV Images

By
Chao Sun
Co-principal Investigator

Department of Civil and Environmental Engineering
3240K Patrick F. Taylor Hall
Louisiana State University
Baton Rouge, LA 70803

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Abstract

Many bridges in the State of Louisiana and the United States are working under serious degradation conditions where cracks on bridges threaten the structural integrity and public security. To ensure the structural integrity and public security, it is required that bridges in the US be inspected and rated every two years. Currently, this biannual assessment is largely implemented using manual visual inspection methods, which is slow and costly. As unmanned aerial vehicles (UAVs) become more and more popular, researchers started to resort to mages and videos for damage detection. Hence, it is promising to integrate the deep learning method with UAV images to develop an automatic crack damage identification method videos for damage detection. Hence, it is promising to integrate the deep learning method with UAV images to develop an automatic crack damage identification This research develops an efficient low-cost deep learning-based framework to detect and quantify cracks on bridges using computer vision-based technique and deep learning. The Convolutional Neural Networks (CNN) deep learning method which is powerful in extracting and learning image features will be used to identify cracks from images. Specific research activities include: (1) collection of a large volume of images online; (2) collection of images of target structures using a UAV camera; (3) development of a deep CNN model using collected images and their augmentation; and (4) identification of cracks using the learned deep learning model. The research outcomes of this project will enable automatic crack damage detection and quantification of bridge key components in a cost-effective manner. The methodology to be developed is expected to facilitate crack damage identification for other transportation infrastructures, e.g. pavement and traffic sign structures.

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Implementation Statement

The research conducted in this project is exploratory in nature. The PI's idea to establish an automatic bridge crack identification methodology using machine learning and unmanned aerial vehicle images. In the first 6 months, the PI has taken roughly 100 cracked and intact images using a UAV camera. In addition, another over 2000 pictures (both cracked and intact) have been collected online. It is mentioned that due to the impact of COVID-19, the PI couldn't take additional crack images (which was planned initially in the project) from real local structures. The collected images have been de-noised, reconstructed and labelled for learning. As a result, more than 2,000 sub-images were generated via augmenting and segmenting the raw images. MATLAB code has been developed to implement the image processing. Python code has been developed to detect crack damage using CNN based deep learning methods. Results indicate that the selected methods can process the image efficiently and the crack damage can be detected accurately.

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Introduction

A large number of bridges in Louisiana and the United States are working under serious degradation conditions where the crack damage of the bridges threatens the structural integrity and security. To preserve the structural integrity and security, it is required that bridges in the United States be inspected and rated every two years. Currently, this is implemented using manual visual inspection techniques largely. The procedure however is slow and not quantifiable. In addition, it is challenging for workers to inspect the crack information of regions that are hard to reach, e.g., top part of bridge tower, mid-span of the bridge girders and decks. Hence, it is possible that there will be crack damage going undetected during an inspection, which might cause bridge to collapse when the undetected damage on load-carrying members is beyond the critical level. A well-known catastrophic example is the I-35 Bridge that collapsed in Minneapolis during the summer of 2007. As unmanned aerial vehicles (UAVs) become more and more popular, researchers started to resort to UAVs to obtain images and videos from places which are hard to reach. Especially for bridges, UAVs can quickly fly to the desired location to take images and videos. Hence, it is promising to integrate the deep learning method with UAV images of bridges to implement automatic crack damage detection and quantification.

Image-based crack identification has been investigated in civil engineering recently. Although computer vision and image processing techniques have been proposed for crack identification, complicated background information from a real bridge structure is always involved in the images, such as handwriting scripts during human inspection, electrical wires of sensors for health monitoring, and desultory edges of welding joints. All these image background noises will result in errors in the identification of cracks. Therefore, advanced algorithms are required for crack identification based on images with complicated background information.

Literature Review

Recent advances in computer vision and image processing techniques have provided an automatic visual monitoring system that can capture structural damage via processing the images or videos. This method doesn't require the incorporation of expensive sensors and is less dependent on labor work and experts' experience in comparison with traditional manual inspection methods. Various image processing techniques have been proposed for machine vision purposes including the generative adversarial network [1], convolutional neural network (CNN) [2], seeded region growing algorithm [3] and edge detection [4]. Recently, vision-based crack identification has been investigated and received more and more research effort. A literature review of vision-based crack detection techniques for bridge structure local damage detection has been presented in [4], including noise removal, edge detection, line detection, morphological functions, color analysis, texture detection, wavelet transform, segmentation, clustering, and pattern recognition.

Digital image correlation (DIC) technique compares changes of digital images at different deformation stages to measure deformation and strain and to detect cracks. However, DIC requires precise camera alignment and reference points of a target surface, which is suitable for lab testing and might not be practical for real life structures. In comparison with to DIC, vision-based crack identification method is more practical and widely accepted due to its advantages of simplicity, noncontact, cost effectiveness, and intuitive interpretation of data [5, 6]. In recent years, computer vision-based technique is emerging as an effective tool for structural damage identification of a wide range of civil, mechanical and aerospace structures. Although computer vision and image processing techniques have been proposed for crack identification, complicated background information from a real bridge structure is always involved in the images, such as handwriting scripts during human inspection, electrical wires of sensors for health monitoring, and desultory edges of welding joints. All these image background noises will result in errors in the identification of cracks. Therefore, advanced algorithms are required for crack identification based on images with complicated information.

Application of vision-based inspection and monitoring includes deflection measurement [7-9], detection of concrete spalling [10-11] and steel corrosion [12]. Existing methods to detect cracks from images include the image binarization method [13], the stereo-vision method [14] and sequential image processing [15]. Abdel et al. [16] evaluated the performance of four methods for crack detection of bridges: fast Haar transform (FHT), fast Fourier transform, Sobel and Canny. The authors found that the FHT is the most effective technique in identifying bridge cracks. Prasanna et al. [17] developed an automatic crack detection algorithm STRUM (spatially tuned robust multifeature) classifier to detect cracks on concrete structures. It was found that the proposed STRUM can provide accurate crack detection of concrete structures.

To detect cracks in inaccessible areas, robotics and unmanned aerial vehicles (UAVs) were used. Ho et al. [18] used cameras mounted on cable climbing robotics, image processing and pattern recognition techniques to detect damage of bridge cables. It was found that the proposed method could be used to detect damage of bridge cables. Zhong et al. [19] used a UAV camera to detect cracks on concrete surfaces. Ellenberg et al. [20] used UVA camera images to quantify bridge related damaging including deflection, corrosion and cracks. The results indicated that the developed post-processing algorithms were able to extract quantitative information from UAV captured imagery.

Although the combination of UAV cameras and vision-based technique can provide damage information via graphing of inaccessible areas and extensive structures, it is still limited and time consuming to process thousands of target images to extract accurate damage information. Images directly taken using UAV cameras need to be de-noised, standardized and reconstructed for extraction of damage information. To improve image processing efficiency, machine learning techniques have been used and shown effective. In recent years, as an emerging technique, deep learning, which refers to artificial neural networks with many hidden layers for enhanced performance, is spotlighted and shown promising for efficient image processing and damage identification.

Zhao et al. [21] developed a traffic surveillance system using deep learning and speeded-up robust features (SURF) to track vehicles and their movements. Zhang et al. [22] used convolutional neural network (CNN) deep learning method for road crack detection. To overcome the challenges from real-engineering structures, e.g., lightening and shadow changes, Cha et al. [23] developed a CNN-based method for concrete crack detection. It was found that the proposed CNN using Canny and Sobel edge detection methods can find concrete cracks in real structures. Tong et al. [24] proposed a CNN-based method for crack length measurement. The authors used k-means clustering analysis to calculate the pre-extract cracks' properties which were used for training and testing. It was found that the accurate crack length recognition can be achieved. Till now, most existing literature on crack identification using vision- and machine learning-based techniques have been validated via laboratory testing. However, the images (crack and intact) used in most existing literature don't include various challenging conditions that widely exist in real-life structures (e.g., human-made markings). In addition, there will be image distortion, lightening, edges and shadow issues when using an UAV camera. All these deficiencies in existing methodologies need to be addressed. In other words, there is a lack of a framework that can implement UAV image sensing and automatic image processing for accurate damage identification of both laboratory and real-engineering structures.

Therefore, an automatic vision- and deep learning-based crack detection method will be developed in this research to detect cracks among a large dataset of images recorded under field conditions. One of the key contributions of this project is the development of multiple classes including non-crack objects using training data collected online, which makes the trained deep learning model capable to cover a wide range of field environment. The proposed methodology is envisioned to facilitate the regular inspection of concrete bridges and other aging civil structures and accelerate the assessment of detailed crack distribution without losing accuracy using various cameras and vision devices, such as drones. Specific research activities include: (1) collection of a large volume of images from the Internet with subsequent categorization into five classes (intact surfaces, cracks, multiple joints and edges, single joint or edge, etc.); (2) collection of images of target structures using a UAV camera; (3) development of an image processing method and a deep CNN model using collected images and their augmentation; and (4) identification of cracks using the learned deep learning model.

Objective

The main objectives of this research are: (1) to collect a large volume of images with and without cracks using UAV cameras and from the Internet; (2) to develop a novel methodology that includes image processing and reconstruction, feature extraction and deep learning to implement automatic crack identification for bridges and other transportation infrastructures, e.g., pavement and traffic sign structures. The overall research objective is to develop a computer vision-based framework using deep learning for automatic cracking damage detection and quantification. The research methodology and specific activities and approaches are elaborated as follows.

Scope

The proposed image-based approach for crack damage detection of bridges has the potential to be applied to a large range of critical civil infrastructures. Examples of such applications include high rise buildings, energy infrastructures, and pavement condition sensing.

Methodology

Figure 1 illustrates the proposed procedure for crack damage detection and quantification. As shown in Figure 1, in the first step, many images with and without cracks have been collected from the Internet and using a UAV camera. Figure 2 shows the structure of a typical CNN for crack image recognition. From Research Rask 3, the original images will be processed and cropped into smaller images, e.g., 128 x 128 pixel resolutions. The crack features of the smaller images will be extracted and used as input of the CNN classifier for training and validation.

Figure 1 Procedure of CNN deep learning based crack detection and quantification

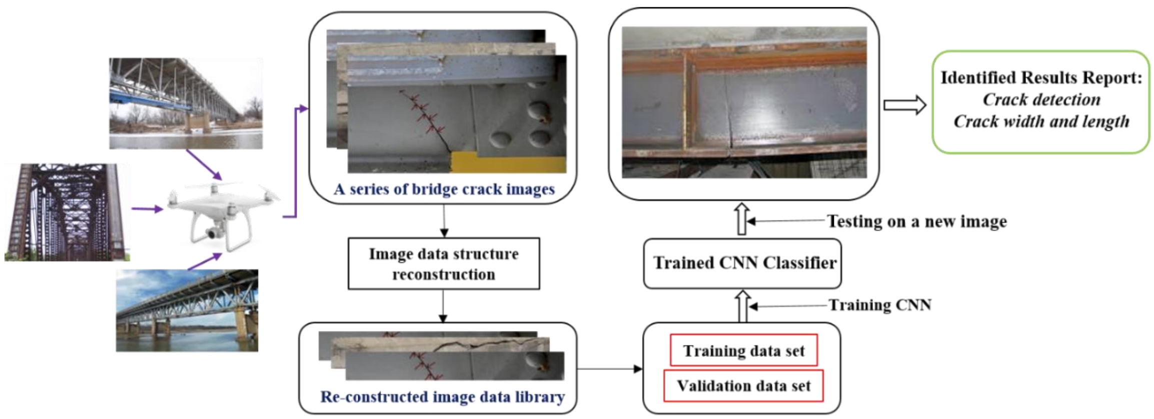
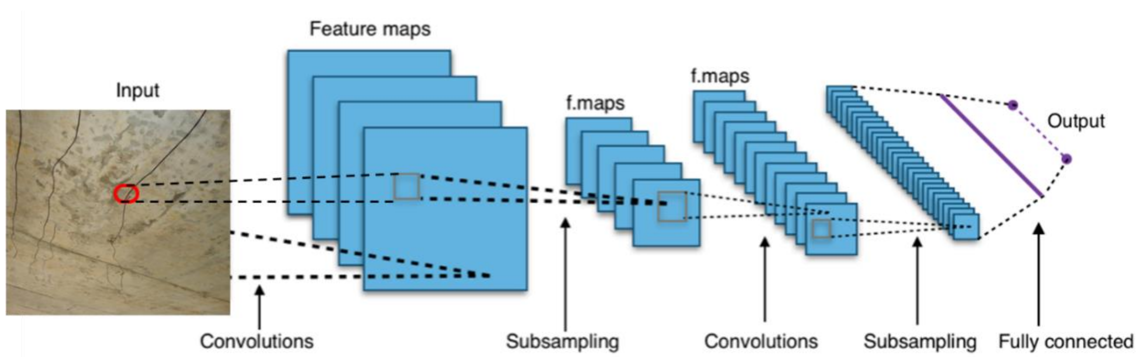


Figure 2 Training, validation and testing of a classifier for crack identification



The reason to use small cropping size is that a machine learning model trained through small images enables scanning of any images larger than the selected cropping size. Then the convolutional layers apply a convolution operation to the input and pass the result to the nest layer. This convolution emulates the response of an individual neural to visual stimuli. The convolutional layer is the core component of a CNN classifier. The layer's parameters consist of a set of learnable filters. During the training process, the convolutional layer performs the following two operations throughout an input array extracted from the image.

Calibration and Homography

Raw images directly taken from the camera are always distorted due to the wide angles of the camera lens. Therefore, distortion calibration will be implemented in the first step to get precise crack assessment. In this research task, the camera calibration algorithm developed by Zhang et al. [25] will be used. The basic idea is described here. Let $m = [u, v]^T$ denote a 2D point and $M = [X, Y, Z]^T$ denote a 3D point. Then define $\widetilde{m} = [u, v, 1]^T$ and $\widetilde{M} = [X, Y, Z, 1]^T$. The relationship between a 3D point M and its 2D projection is:

$$s\widetilde{m} = A[R,t]\widetilde{M}, \; A = \begin{matrix} \alpha & \gamma & u_0 \\ 0 & \beta & v_0 \\ 0 & 0 & 1 \end{matrix} \qquad [1]$$

where is a scale factor, A is the camera intrinsic matrix; $[R, t]$ is the rotation and translation parameters that relate the world coordinate system to the camera coordinate system; α, β, γ are the scale and skew factors; u_0, v_0 are the coordinates of the principal point. Without loss of generality, the model plane is assumed to be on $Z = 0$ of the world coordinate system. Equation (1) can be written as:

$$s \begin{Bmatrix} u \\ v \\ 1 \end{Bmatrix} = A[r_1, r_2, r_3, t] \begin{bmatrix} X \\ Y \\ 0 \\ 1 \end{bmatrix} = H \begin{bmatrix} X \\ Y \\ 1 \end{bmatrix}, \text{with } H = \; A[r_1, r_2, t] \qquad [2]$$

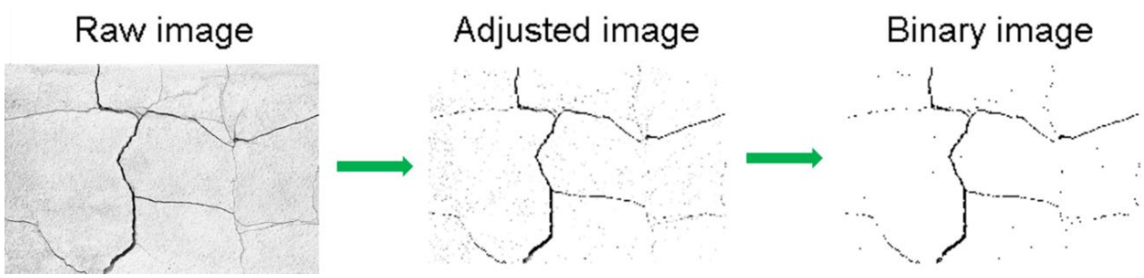
where $H_{3\times3}$ is the homography to be determined. For each image, we can have a linear transformation as shown in Equation (2). With the coordinates of n $(n \geq 3)$ images. The homography can be determined via solving the least squares problem. Then the calibration and homography is completed for the selected camera.

Crack Feature Extraction

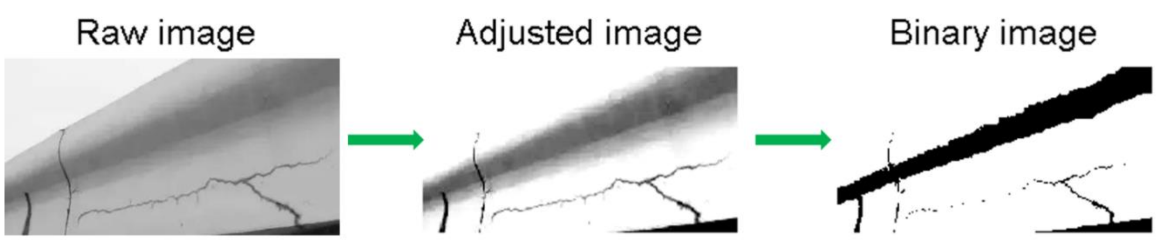
The collected raw images are RGB (red, green and blue) images in JPG/PNG format, including color information, which increases the difficulty of feature detection and recognition of crack characteristics. To facilitate crack feature extraction, the color information will be changed, and images will be converted to grey-scale binary figures in BMP format. Figure 3 shows the procedure converting the RGB crack images to gray-scale binary images. In this research, the raw image will be segmented into a number of unit sub-figures for the deep learning process. It is noted that the shadows in Figure 3(b) produces fake cracks in the binary image. This issue will be addressed in this research task by finely adjusting the parameters during image conversion.

Figure 3 Illustration of crack feature extraction

(a)



(b)



Collected Images

Around 400 raw images (with and without cracks) have been collected from the Internet. Some of the representative images are shown in Figures 4 and 5. As a preliminary study, these figures were processed and converted from RGB images to gray images. Figure 3 shows the conversion process of a raw crack image to a binary image. It can be observed that the binary image contains accurate and complete crack information of the raw image. Hence, the binary image can be segmented and directly used as input of a deep learning model. However, when there is shadow or edges, the binary image might contain false crack information as shown in Figure 6 where the large crack regions in the binary image were essentially caused by the shadow and the edge. These challenges commonly exist in real-life structures and will be addressed in the second phase of this research.

Figure 4 Illustration of representative concrete structure cracks from the Internet

Figure 5 Illustration of representative steel structure cracks from the Internet

Crack Identification Results

Based on the procedures described above, the concrete images collected online and from local structures using a UAV camera were processed and divided into a set of subfigures. Figures 7 (a) and (b) show some example images with and without cracks, respectively. The output sub figures are used as input into the CNN model. In this study, the used dataset contains 2255 images of resolution 128 by 128. Among the 2255 images, 991 are cracked with 958 set for training and 33 for testing; 1264 are not cracked with 1189 set for training and 75 for testing.

Figure 6 Example images used for training the CNN model

(a) with cracks

(b) without crack

Figure 8 shows the architecture of the CNN model used in this study, that is, the MatConvNet model. The input layer takes images with the resolution of 128 by 128 as input. Table 1 shows the dimensions of each layer of the MatConvNet model.

Figure 7 Overall architecture of the MatConvNet model

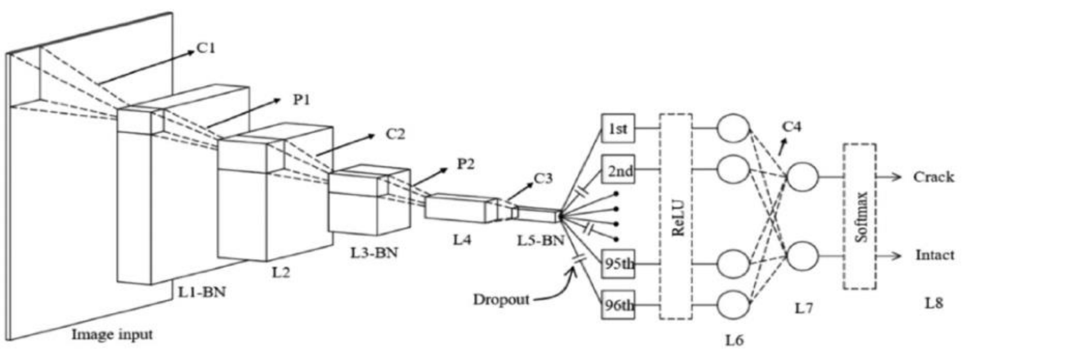


Table 1: Dimensions of the CNN layers

Layer	Height	Width	Depth	Operator	Height	Width	Depth	No	Stride
Input	128	128	3	C1	20	20	3	24	2
Layer 1	64	64	24	P1	7	7	-	-	2
Layer 2	32	32	24	C2	15	15	24	48-	2
Layer 3	16	16	48	P2	4	4	-	-	2
Layer 4	8	8	48	C3	10	10	48	96	2
Layer 5	1	1	96	ReLU	-	-	-	-	-
Layer 6	1	1	96	C4	1	1	96	2	1
Layer 7	1	1	2	Softmax	-	-	-	-	-

Layer 8	1	1	2	-	-	-	-	-	-

In this crack detection problem, each image in the dataset is labelled according to whether it contains crack or not. Hence, this classification problem has two labels, that is, “Crack” and “No-Crack”. In the model training, 10 percent of the images are used for validation. The output results show that the learned CNN model yields a 93% testing accuracy, which is confirmed through cross validation.

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Conclusions

A vision-based framework using deep learning technique for automatic crack identification of bridges and other structures has been developed in this research. In this bi-annual report, a complete literature review is completed and presented. Based on the literature review, detailed research activities are planned. A large volume of representative images with and without cracks have been collected online and using UAV cameras. Matlab based image processing codes have been developed for preprocessing the images to offer input to the DNN deep learning model. The image processing results shown that binary images can well indicate the crack information when there is no shadow, lightening or edge issues. An initial bank of concrete images (with >2000 images) is established, which can also be used for training deep learning models for concrete crack detection of other infrastructures. Research results show that the developed combined image processing and deep learning modules can efficiently and accurately (accuracy >90%) detect cracked concrete damage.

Recommendations

Computer vision and machine learning-based damage identification is a promising method for structural health monitoring of the aging critical civil infrastructure. Image collection and processing is the first essential step in which representative images with and without cracks need to be collected and processed. Then deep learning methods can be used to train, test, and validate the selected learning model. Based on the results presented in this project, recommendations stemming out of this research are summarized as follows:

(1) A computer-vision and deep learning-based methodology for crack damage detection can be used for bridges, especially those old bridges that are with noticeable cracks.

(2) A full research project needs to be conducted to generalize the established methodology for other transportation infrastructure, e.g., pavement and road surface quality sensing.

(3) Another full research project needs to be conducted to develop a complete computer-vision and machine learning based methodology for fatigue crack detection of steel structures.

Acronyms, Abbreviations, and Symbols

Term	Description
CNN	Convolutional Neural Network
UAV	unmanned aerial vehicle
DIC	Digital image correlation
RGB	red, green and blue
LADOTD	Louisiana Department of Transportation and Development
LTRC	Louisiana Transportation Research Center

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Appendix

Journal Publications produced

Three journal papers have been published under the support of this grant, which are listed as follows:

[1] Z. Zhang, **C Sun***. Structural Damage Localization via Physics-Guided Machine Learning: A Methodology Integrating Pattern Recognition and Finite Element Model Updating, *Structural Health Monitoring,* DOI: 10.1177/1475921720927488.

[2] Z. Zhang, **C. Sun***. Multi-site Structural Damage Identification Using a Machine Learning Method of Multi-label Classification. *Measurement* 2020, 154: 107473.

[3] Z. Zhang, **C. Sun***. A Numerical Study of Multi-Site Damage Identification: A Data-Driven Method via Constrained Independent Component Analysis, *Structural Control and Health Monitoring* https://doi.org/10.1002/stc.2583