AUSTRALIAN NETWORK OF STRUCTURAL HEALTH MONITORING

Newsletter

Issue 28, June 2021

Contents

President Message

Dear All,

On 10 May the Victorian government announced that it would invest $50 million to develop a new technology that will remotely monitor bridges to better manage their maintenance[1]. We are excited that the Victorian government appreciates so much the technologies of Structural Health Monitoring, quoting what the Minister for Transport Infrastructure, The Hon Jacinta Allan MP stated,

"This technology being rolled out on priority bridges enables remote real-time monitoring – meaning a small problem could be identified before it becomes a big costly problem that causes unnecessary delays to Victorians."

"This will help to detect problems earlier, reduce delays caused by road closures for manual inspections and repairs, and help to find problems more quickly and accurately in the case of bridge

[1] https://www.premier.vic.gov.au/new-tech-keep-our-bridges-open-and-strong

strikes or other unexpected events.”.

From what Jacinta stated, we can see that she understands what benefits that SHM could bring. We look forward to having more and more of SHM technologies to be implemented in Australia and no matter the Local, State and the Federal Governments could realise how important the technologies of SHM are to the country.

However, having said that, the objectives of ANSHM are to Implement, Promote, Apply and Develop SHM technologies which will help the asset owners understand the SHM technologies better. Many misconceive that SHM is just to install sensors on a structure to collect data and then such a system could provide information to detect damages. As I always say, SHM is more than installing sensors. We need to have the installed sensors to make sense, so we need to select the correct sensors to deploy them Correctly and transmit, store and retrieve them using a Correct system and use a Correct method to analyse them to provide Correct information for the decision makers and the relevant teams like maintenance teams. We need to develop some guidelines and standards to ensure what should be expected from such a system. The application of SHM could only grow healthily if we could help the potential users of SHM understand better what they will expect to get.

After some discussions among the Executive Committee members, it seems that we could not identify any open and transparent bidding process in awarding the contract to a particular SHM service provider, which becomes our concern. As an organisation advocating the SHM technologies, we are happy to provide advice to the government in such processes. In this regard, John Vazey, as our Industry Liaison Officer, coordinated with our EC and other local SHM related companies, prepared a letter to the relevant parties to voice out our concern. Jenny Wiggins, Infrastructure Report of the Financial Review wrote an article about this and it was published on 24 May 2021[2]. As mentioned above, we welcome more extensive application of SHM technologies in Australia, and what we are concerned is to ensure the potential users should have a correct expectation of their investment and it will be beneficial to all parties that if an open and transparent bidding process should be introduced for this kind of project. We should not be biased towards some companies and against others. We, ANSHM, with the experts and experienced engineers in SHM are happy and impartial to provide our

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[2] https://www.afr.com/companies/infrastructure/transparency-concerns-over-xerox-linked-bridge-contract-20210521-p57tyn

expert advice to help the potential users of SHM, including various, Local, State, and Federal governments to find the best solution and the best choice for their problems related to SHM.

The announcement[3] made by the Victorian Government did not state clearly what the new technology to be used to remotely monitor their bridges. It is most likely the technology would be optical fibre technologies and in particular using Fibre Bragg Grating sensor, which was first demonstrated by G. Meltz and his team more than three decades ago in 1989. Since then, many methods have been developed to increase the refractive index by improving both the ultra-violet exposure method, and the photosensitivity of the fibre core. The measurand versatility and the unique advantages offered by FBG sensors have resulted in their use in a wide range of sectors for a wide range of applications where quasi-distributed measurements of physical parameters such as strain, pressure, vibration, temperature, ultrasound, high magnetic field and high-g acceleration are required. The research works from 1989 to the end of the last millennium had shown that FBG sensors have several inherent advantages over conventional electrical sensors as follows:

- FBGs are extremely small and lightweight
- Non-conductivity
- Fast response
- Immunity to electro-magnetic interference (EMI)
- Many FBG sensors (>100) can be created on a single strand of optical fibre.
- Permit remote sensing (>50 km)
- Non-corrosive and very stable
- Encoded directly in terms of the wavelength, so being unaffected from disturbances of the light paths
- Serve as both the sensing element and the signal transmission medium

It is well known that the Highways Department of the Hong Kong Government is a pioneer in using SHM to monitor their landmark bridges connecting their new airport at that time located at Lantau

[3] https://www.premier.vic.gov.au/new-tech-keep-our-bridges-open-and-strong

Island with the Kowloon Peninsula and they called it Lautau Fixed Crossings which include one suspension bridge (Tsing Ma Bridge) and two cable-stayed bridges (Kap Shui Mun Bridge and Ting Kau Bridge) and a sophisticated SHM system known as Wind And Structural Health Monitoring System (WASHMS) was devised and implemented to monitor the structural health and conditions of the three cable-supported bridges[4]. I am fortunate to be involved in this development. This on-structure instrumentation WASHMS system consists of a total of about 800 sensors of different types permanently installed on the three bridges. However, the system was devised and implemented before 1997, so it had not benefited from the optical fibre sensor technology. In order to investigate the feasibility of using the developed FBG sensors for structural health monitoring, a field test was carried out in May 2003, in which a number of such FBG sensors were installed on the Tsing Ma Bridge to conduct real time and full-scale measurements. The results were assessed and compared with the conventional strain gauges obtained from the WASHMS. The application of FBG sensors and interrogation system to monitor the dynamic strain on Hong Kong's landmark Tsing Ma bridge was then demonstrated. It can clearly and correctly detect the dynamic strain responses of the bridge induced by the passage of trains on the bridge. The measurement results of the interrogation system were in excellent agreement with those obtained by resistive strain gauge measurements installed under WASHMS. There is a Youtube video describing the test[5]. It can be seen how to prepare the surfaces for installing the sensors and see how easy it is to join two parts of an optical fibre using a fusion splicer. One may note that in the video, the team members were wearing masks, signifying that the test was conducted in 2003 – eighteen years ago, when Hong Kong was being attacked by SARS. Now because of Covid-19, we are getting more used to wear masks in our different activities.

[4] Chan, T.H.T., Wong, K.Y., Li, Z.X. and Ni, Y.Q. (2011) "Structural Health Monitoring for Long Span Bridges – Hong Kong Experience & Continuing onto Australia" Chapter 1 in *Structural Health Monitoring in Australia*, edited by Chan, T.H.T. and Thambiratnam, D.P., Nova Publishers, New York.

[5] https://www.youtube.com/watch?v=VXWoLsOJ3tI

Photo 1 – Wearing Masks During the FBG Test

The test was reported in a paper published in Engineering Structures[6], which is a pioneer paper about using optical fibre sensors for SHM and it becomes Top 25 Articles in Engineering Structures for Academic Year 2009-2010. The test was very successful and after that the Hong Kong Government started to include optical fibre sensors for SHM purpose. Research on optical fibre sensors has been continued in Australia and further development in using optical fibre sensors include its application in vertical displacement in bridges[7] and developing accelerometers[8,9,10, & 11].

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[6] Chan, Tommy H.T. and Ashebo, Demeke B. and Tam, H.Y. and Yu, Y. and Chan, T.F. and Lee, P.C. and Gracia, Eduardo Perez (2009) "Vertical displacement measurements for bridges using optical fiber sensors and CCD cameras : a preliminary study" Structural Health Monitoring, 8(3). pp. 243-249

[7] Yau, M.H., Chan, T.H.T., Thambiratnam, D., & Tam, H.Y. (2013) "Methodology for measuring the vertical displacements of bridges using fibre bragg grating sensors" Australian Journal of Structural Engineering, 14(1), pp. 71-84.

[8] Li, K., Chan, T.H.T., Yau, M.H., Nguyen, T., Thambiratnam, D. P., & Tam, H.W. (2013) "Very sensitive fiber Bragg grating accelerometer using transverse forces with an easy over-range protection and low cross axial sensitivity" Applied Optics, 52(25), pp. 6401-6410.

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Below are the updates of the month.

ANSHM 13th Annual Workshop

As mentioned earlier, the 13th ANSHM Workshop will be held as a physical workshop in December 2021 in Sydney to be organised by Prof Jianchun Li of University of Technology Sydney and Prof Brian Uy of the University of Sydney. Since the situation is still not that clear at the moment, it adds some difficulties in planning the Workshop. There may be some sudden lockdowns due to Covid. I am preparing this update during the Melbourne 7-day lockdown since 27 May 2021. We hope the situation could be clearer in July and we try to have two hands ready for both real and virtual modes. More details will be provided in the coming months after the mode, venue, dates, etc. have been confirmed.

ANSHM Mini-Symposium (MS26) in SHMII-10

For the SHIMII-10, so far there are 243 papers accepted for the presentations. As mentioned in the last updates, the conference will be fully on-line. It will then follow the local time of the organiser in Portugal (UTC+1), so the corresponding time in Australia will be outside our working hours. We noted that to Prof Álvaro Cunha, the Conference Chair and made a request to have our Mini-Symposium (MS26) to be scheduled in a morning of their 3-day programme. Although the final version of the Program depends on many different factors, but Álvaro replied that he would try his best to schedule us to the morning of the third day (2 July 2021), i.e.

i. ~6:00 PM – 10:00 PM (Brisbane, Sydney, Melbourne)
ii. ~5:30 PM – 9:30 PM (Adelaide)
iii. ~4:00 PM – 8:00 PM (Perth)

Regarding selecting the most relevant paper accepted at our Mini-Symposium (MS-26) for the consideration of the Best Paper Award for SHMII-10, it is really not easy as all the papers are of very

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[10] Li, Kuo, Chan, Tommy H.T., Yau, Man Hong, Thambiratnam, David P., & Tam, Hwa Yaw (2014) "Biaxial fiber Bragg grating accelerometer using axial and transverse forces", Photonics Technology Letters, IEEE, 26(15), pp. 1549-1552.

[11] Li, Kuo, Chan, Tommy H.T., Yau, Man Hong, Thambiratnam, David, & Tam, Hwa Yaw (2014) Experimental verification of the modified spring-mass theory of fiber Bragg grating accelerometers using transverse forces. Applied Optics, 53(6), pp. 1200-1211.

high quality. Finally, Andy, Alex and myself have identified a paper which all three of us considered to be well deserved for the nomination for the best paper award. We really look forward to having this paper to be appraised for the award.

Publication generated from the 11th ANSHM Workshop

As mentioned earlier, the publication will be published as a monograph by Nova Science Publishers Inc. The chapter coordinators are aiming to have their chapter ready for review by **30th July 2021**, allowing two months for internal review and submit the ready-to-print version to the publisher by **30th Sept 2021**. There will be 11 chapters in the book covering different important aspects of SHM, to help both academia and industry to learn more about SHM, from basic to advanced development in the last 10 years of SHM research in Australia.

Publication generated from the 12th ANSHM Workshop

This will be in a form of a special issue in a journal. We are still considering the special issue to be included in which journal and more information will be provided in due course.

ANSHM Who's Who

In our last EC meeting, we all agreed the importance of preparing ANSHM Who's Who. Some discussions have been made on the format, e.g., a Card, and whether those from the industry should be included or just academic. It was decided Prof Jianchun Li of UTS will first formulate a template for collecting information and distribute among all ANSHM members, and then the next step will be determining the format and how to present the information and who (academic and from the industry depending on experience and expertise) and which organization will be included. However, it is also agreed that it would be good to have the ANSHM Who's Who in certain form first and it could be helpful for us to be ready any time when opportunities come. Jianchun will send us message requesting the relevant information and give us more details in due course.

SHM Standard and Specification

As mentioned above, it is important to have SHM Standards/Specifications for us to know what are expected from various SHM systems. A/Prof Colin Caprani is taking the lead on this task. He is working on drafting 4-5 pages of goals and it will be shared amongst the EC members and John Vazey, our Industry Liaison Office for comments and then their input.

ANSHM WebForum

Dr Lei Hou is to organise an ANSHM WebForum later this year, which may include an industry talk followed by a panel discussion. More information will be provided in due course.

The ANSHM Newsletter

After implementing the strategic plan mentioned in the last updates, the ANSHM Newsletter Editorial Team find it much easier to collect articles for this issue of the ANSHM Newsletter and the articles could be received well in advance before mid-May. Well done to the Editorial Team! They will continue to follow the strategic plan for article collection for the articles for forthcoming issues and observe if any improvement and fine tuning is needed.

In the next sections, we will have two articles from our members. The first article is from Western Sydney University about the application of Terrestrial Laser Scanning (TLS) in bridge engineering and asset management. The other article is from the University of Melbourne about using autonomous and intelligent inspection systems, equipped with a visual camera for taking high resolution images for crack detection and assessment of concrete structures. Both papers are using contactless and vision-based methods, which are a new trend of SHM.

With kind regards,

Tommy Chan
President, ANSHM
www.ANSHM.org.au

Utilising Terrestrial Laser Scanning (TLS) for Health Monitoring of Bridges

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Over the last decade, particular interest in using state-of-the-art emerging technologies for asset management of civil infrastructure has remarkably increased. Advanced technologies such as drones and laser scanners have become a suitable alternative for laborious, expensive, and unsafe traditional inspection and maintenance methods, which encourage the increasing use of this technology for health monitoring of civil infrastructure. In this paper, the application of TLS in bridge engineering and asset management in the following categories has been reviewed: (1) generation of 3D model, (2) quality inspection, (3) structural assessment, and (4) Bridge Information Modelling (BrIM).

Keywords: Terrestrial Laser Scanner (TLS); Bridge; 3D Model Reconstruction; Quality Inspection; Structural Assessment; Bridge Information Modelling (BrIM)

Introduction

Three-dimensional (3D) laser scanning is an efficient innovation for rapid and precise monitoring of an object without direct contact. This remotely high-precision method acquire a massive amount of topographic data points from the visible surfaces of an observed object based on laser measurements. The developed data points are generally defined based on x, y, z coordinates associated with attributions such as intensity of the laser beam reflected from the observed object. Laser scanning can classify based on a position of the laser sensors during the data capture, which are aerial, mobile and terrestrial laser scanning corresponding from air (e.g. helicopter, plane, or drone), mobile equipment (e.g. vehicle, train or boat) and the ground. Although each of these classifications has their own advantages, using Terrestrial Laser scanners (TLS) are more common and popular. Recently, Terrestrial Laser scanners (TLS) offers widely application in construction industry and maintenance strategies. TLS has also great potential to be utilized for inspection processes due to its ability to capture objects in high speed with accuracy up to sub-millimetre and low cost in comparison to other traditional inspection methods.

Generation of 3D model

A raw topographic point cloud data generally appears in a form of x-, y-, z-coordinates associated with attribution such as intensity value and colour range, which cannot interpret information of the objects' surfaces. As the primary and most challenging task, this raw data needs to be converted as a meaningful information for subsequent applications. Therefore, the current task includes data acquisition processes and 3D model development from the captured raw data points. The output of this task as a solid 3D representation is often the preferred form of embodiment for engineers. The generated 3D model in this task for an infrastructure such as a bridge not only could provide a better understanding of as-is conditions but also could benefit engineers in making better decisions either in bridge management or in assessment.

Based on the aforementioned information to investigate the common approaches/projects in application of a point cloud for bridge engineering, the process can be roughly classified into two phases: (1) data acquisition and (2) creation of 3D model. The first phase refers to the onsite data acquisition strategies to maximize the data coverage and optimize the number of scan stations while the second phase implies the process and methods of obtaining a 3D geometric model from the raw captured points. Bridges often facing major challenges due to the shape and orientation of the structure in the data acquisition phase and containing complex structural components that make difficulties for the second phase. The generated virtual 3D model could be used throughout the bridge's lifespan, from the design stage which is generally known as-design to practical purposes of the existing structure which is often called as-built or as-is.

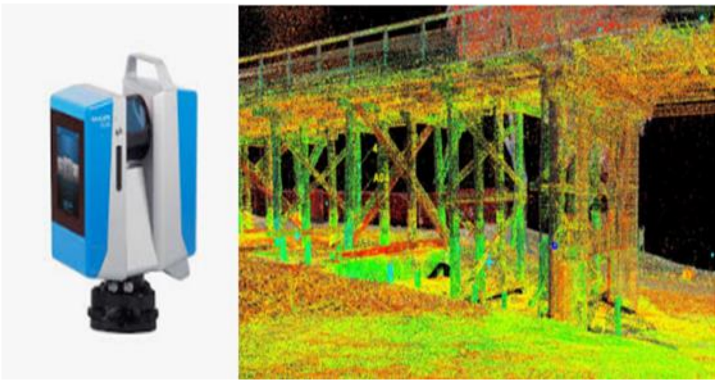

Figure 1. Generation of point cloud data for John Foord bridge using Z+F laser scanner

Quality Inspection

In the last few years, TLS has proven its potential benefits in conducting geometry quality inspection of damaged infrastructures such as bridges. Although various types of damages can be detected by TLS, this section summarizes the research efforts on most probable bridge surface damages such as cracks, mass loss and corrosion in structural members.

Structural Assessment

The successful application of laser scanning technology in providing precise and efficient information about the state of the health of structures in a short time has significantly impressed and drawn civil engineer's attention. The possibility of extracting detailed geometric information as the basis of creating a precise computer model has made TLS a high-potential instrument for structural mappings. Extracting a precise computer model not only provides a detailed vision of the existing structure but also benefits engineers to get better results in their simulations. In recent years, structural engineers generally have taken advantage of the constructed geometric models as a basis for assessing structural performance [1,2]. This experience allows enginners to make better decisions for possible actions of the maintenance, especially for large-scale complex structures such as bridges [3,4]. On some occasions, extracted 3D models were also used as a basis to obtain a calibration for unknown parameters of the structure or components known as inverse engineering [5,6].

Bridge Information Model, BrIM

In recent years, application of bridge information modelling has provided faster solutions and processes for integrated bridge information in a shared platform. BrIM pertains to the specific form of Building Information Modelling (BIM) application in terms of bridge engineering referring to the creation of 3D CAD model associated with integrated additional information of time and cost estimation, energy consumption, and etc [7]. In this regard, 3D CAD models are linked to other related tools that allow evaluation of time as the fourth dimension (4D), cost as the fifth dimension (5D), and energy as the sixth dimension (6D) during the different phase of bridge design, fabrication/construction, operation and maintenance. BrIM technology can improve, support, and facilitates simultaneous works by multiple process disciplines while reducing the time-consuming project controls and possible errors in terms of design, construction, and management [8]. The bridge model can provide a wide range of information includes the 3D graphic presentation and all used specifications in the bridge project such as previous analysis, equipment, control systems, and other related decisions provided in the different phase of the project. BrIM as an integrated platform can also support real-time monitoring/inspection of bridges by providing an interface for as-is conditions and remote operating management of the system.

Conclusion

This study investigated the application of laser scanning as an emerging technology in modern bridge health monitoring. The four major applications of TLS in bridge engineering have been reviewed and categorised. The first category is the generation of 3D model that refers to the data acquisition phase and reconstruction of the geometry model from the acquired point cloud data. The second is the quality inspection mainly focused on the most probable bridge surface damages. In addition, the application of TLS in structural assessment and bridge information model as two other categories were discussed. Further research is suggested on practical methodologies that allow the direct transformation of raw data points into a valid 3D model. Localizing, classifying, and quantifying the structural deficiencies are other aspects of using TLS can be further investigated with the aim of bridge quality inspection. Real-time inspection methods and potential integration with AI techniques are also considered as valuable topics for fundamental research.

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CRACK DETECTION AND ASSESSMENT OF CONCRETE STRUCTURES USING CONVOLUTIONAL NEURAL NETWORKS

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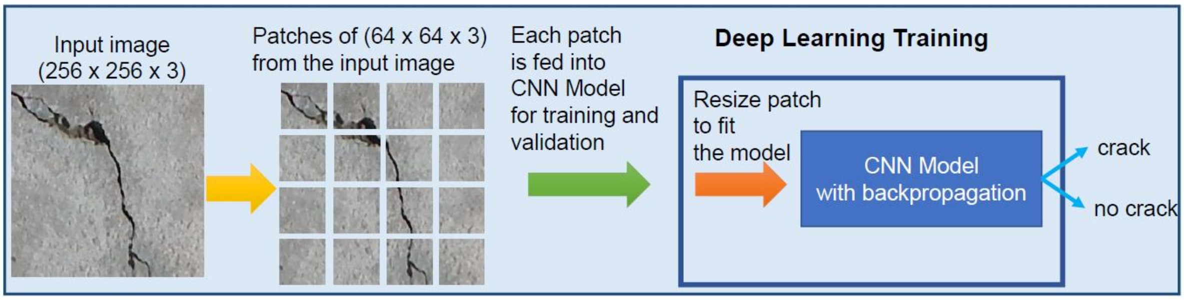
1 INTRODUCTION

With the growing number of ageing concrete structures (e.g. bridges, buildings) across the world, there is a high demand for a more effective inspection method to assess its conditions. Cracks in concrete structures are one of the most important indicators of structural damage, and the occurrence of concrete cracks indicates underlying structural damage and requires continuous monitoring and measurement. Current mainstream methods of concrete crack assessment involve performing visual inspection periodically to inform management agencies the current stage of structures. For example, as per the current inspection manual regulated by VicRoads, the current level-1 and level-2 inspection guidelines heavily rely on visual inspection carried out by qualified inspectors to detect visible cracks on the surface of structures [1]. The current manual inspection practice to detect cracks is prone to efficiency and cost concerns. Moreover, manual inspection of large infrastructure such as long-span bridges requires inspectors to enter hazardous areas or inaccessible to physical location limits, which not only affects the reliability and efficiency of the inspection but is also a safety concern for inspector [2].

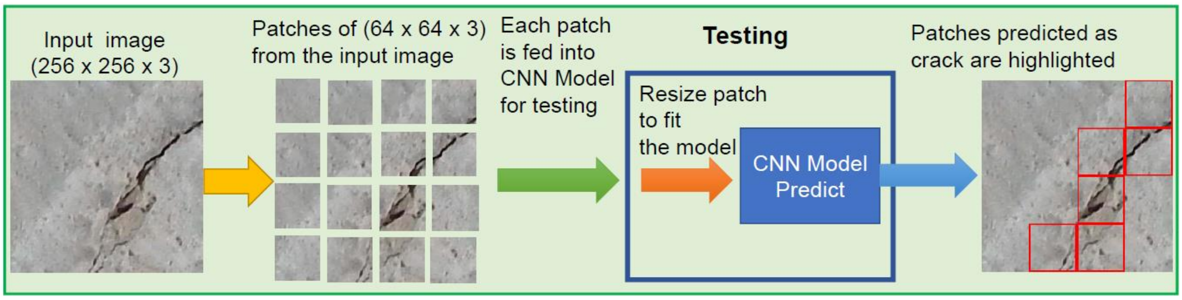
With rapid advancements in automation technologies, there is an increasing trend in inspecting concrete structures using autonomous and intelligent inspection systems, which is usually equipped with a visual camera for taking high resolution images. As a result, it requires an automated detection for cracks to maximise the benefits of the automated inspection system [3]. Recently vision-based systems appear to be a promising solution for an autonomous inspection system to analyse images and detect cracks on structures. Broadly, vision-based methods can be classified into four categories: (1) image processing methods use signal processing tools to detect cracks; (2) region-based classification methods aim to detect cracks by localizing the cracks in the image regions (using traditional machine learning-ML or the recent deep learning-DL approaches); (3) object-detection methods using generic objection schemes to detect cracks along with other objects; and (4) segmentation methods detect cracks by classifying whether each pixel belongs to a crack or any other object. In this study, we present an automated crack detection (ACD) framework based on the region-based classification method and convolutional neural networks (CNN).

2 DEVELOPMENT OF THE ACD FRAMEWORK

In this work, we employ the existing state-of-the-art CNN models to compare their effectiveness in detecting cracks in concrete structures. Then, we develop the ACD frameworks by creating a dataset of images and classifying whether a given image contains crack or otherwise. Figure 1 presents the overview of the crack detection approach used in this work, including the training phase (Figure 1a) and testing phase (Figure 1b). Input images (data) of size 256x256 pixels are divided into 16 patches (each patch of size 64x64 pixels) in both the training and testing phases. Then, the image patch in fed into to one of the CNN models for training. During training, we use image patches belonging to 'crack' and 'no crack' and test the model against validation image patches. During testing, the test image is first divided into patches, and then the trained model is used for inference (to predict) whether or not there is a crack in each patch.



(a) Training phase



(b) Testing phase

Figure 1: Overview of the ACD framework developed in this study.

In this study, we test the performance of 15 state-of-the-art CNN models, including AlexNet, Visual Geometry Group Networks (VGG-16, VGG-19), Residual Networks (ResNets-50, ResNets-101, ResNets-152), ResNet with Aggregated Residual Transformations (ResNeXt-50-32x4d, ResNeXt-101-32x8d), Wide Residual Networks (Wide-ResNet-50-2, Wide-ResNet-101-2), Inception Networks (Inception-v3, Inception-v4, Inception-ResNet-v2) and Dense Convolutional Networks (DenseNet-121, DenseNet-169). Readers are encouraged to refer to the publication of this work [4] for the details of each CNN model used in this study

3 DATASET AND CLASSIFIER PERFORMANCE METRICS

To develop the ACD framework, the dataset gathered consists of 2,173 training images (2044 train + 129 validation) and 377 test images of size 256x256. Cracks in the dataset were annotated manually using LabelImg software. Table 1 provides the details of number of patches used for training, validation and testing of models in this study. The dataset, codes and trained models are available publicly for further development in the publication of this study [].

Table 1: The dataset used in this work. Table shows the number of images (256x256) and the corresponding number of patches (64x64).

	Images	No crack (patches) – Class 0	Crack (patches) – Class 1	Total (patches)
Train	2,044	23,797	8,907	32,704
Validation	129	1,032	1,032	2,074
Test	377	4,358	1,674	6,032

Table 2: Confusion matrix for a binary classifier.

	True class	
Predicted class	True Positives (TP)	False Positives (FP)
	False Negatives (FN)	True Negatives (TN)

For the binary classification applications such as detecting crack/no crack in concrete structure, the confusion matrix presented in Table 2 is used. From Table 2, we can define the performance metrics, including True Positive Rate (TPR), False Positive Rate (FPR), Specificity, Accuracy and Precision, as follow:

$$\text{True Positive Rate} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{1}$$

$$\text{True Negative Rate} = \frac{\text{FP}}{\text{FP} + \text{TN}} \tag{2}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{FP} + \text{TN}} \tag{3}$$

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FN} + \text{TN} + \text{FP}} \tag{4}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (5)$$

4 RESULTS AND DISCUSSION

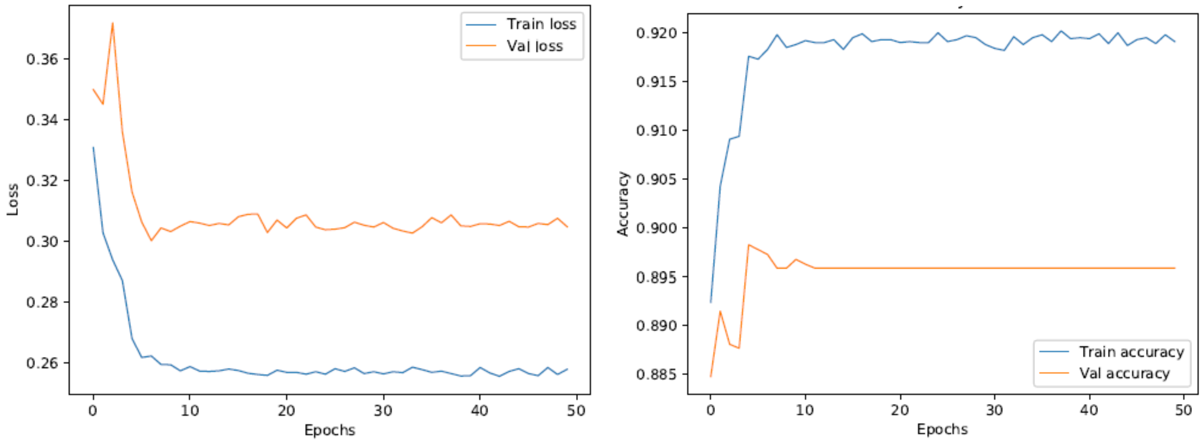


Figure 2: The loss and accuracy of AlexNet model during training and validation.

Figure 2 presents the training and validation loss and accuracy curves for the AlexNet. For the sake of simplicity, we do not present the loss and accuracy curves for the remaining 14 models, which can be obtained from the publication of this work. Figure 2 shows the learning process and improvement of the models with respect to training epochs. Figure 2 also shows that training loss is lower and validation accuracy is lower, indicating this slightly lower error is common in practical applications as expected. Figure 3 presents the sample of automated crack detection results using the VGG-16 model. In Figure 3, (a)-(h) represent the manually annotated ground truths (marked in purple color), and (i)-(p) show the corresponding predicted output (marked in red color).

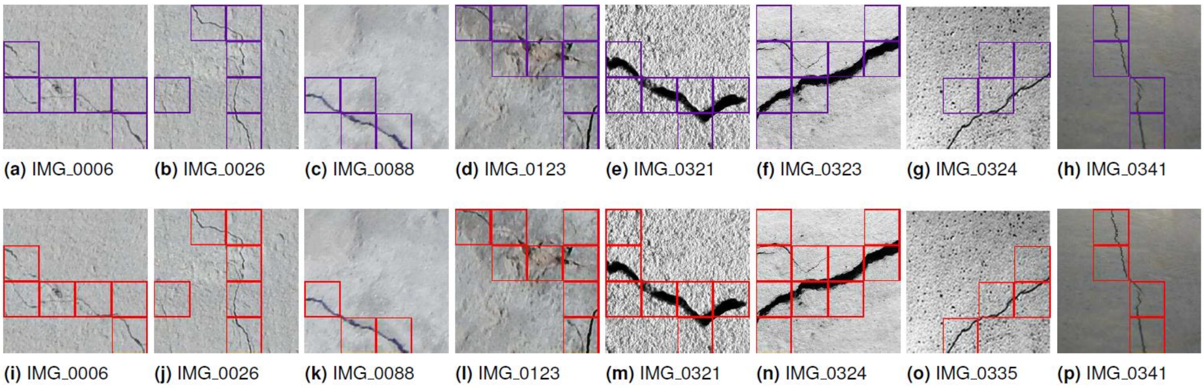


Figure 3: The sample results of VGG-16 model. In Figure 3, (a)-(h) represent the manually annotated ground truths (marked in purple color), and (i)-(p) show the corresponding predicted output (marked in red color).

The performance metrics of the 15 CNN models is presented in Table 3. It can be observed from Table 4 that VGG-16 and VGG-19 both have higher sensitivity (0.95) and specificity (0.95). In addition, VGG-19 has higher precision (0.90) along with ResNet-152, Inception-v3, Inception-v4 and Wide-ResNet-50-2 and VGG-19 achieved the highest accuracy (of 0.96). From the literature, Feng et al. [5] used ResNet model and achieved about 87.5% accuracy. Our results show that we could reach over 95% accuracy with ResNet model in Table 3. Another study conducted by Jang et al [6] used GoogLeNet model and reported the precision value of 59.84%, which is far below when compared to our patch-based approach as can be seen in Table 3 – our approach achieves higher precision for the two GoogLeNet models (0.90 for Inception-v3 and 0.89 for Inception-v4).

Table 3: The performance metrics of each CNN model.

Model	Sensitivity	Specificity	Accuracy	Precision
AlexNet	0.94	0.95	0.94	0.88
VGG-16	**0.95**	**0.96**	0.95	0.89
VGG-19	**0.95**	**0.96**	**0.96**	**0.90**
ResNet-50	0.93	0.95	0.95	0.89
ResNet-101	0.94	0.95	0.95	0.88

ResNet-152	0.92	**0.96**	0.95	**0.90**
Inception-v3	0.93	**0.96**	0.95	**0.90**
Inception-v4	0.92	0.95	0.95	0.89
Inception-ResNet-v2	0.92	0.95	0.94	0.87
DenseNet-121	0.94	0.95	0.95	0.89
DenseNet-169	0.94	0.95	0.95	0.88
ResNeXt-50-32x4d	0.93	0.95	0.95	0.88
ResNeXt-101-32x8d	0.93	0.95	0.94	0.87
Wide-ResNet-50-2	**0.94**	**0.96**	0.95	0.90
Wide-ResNet-101-2	**0.95**	0.95	0.95	0.89

In this work, we also investigate the inference time of each CNN model, which is also important factor for choosing the models for real-time inspection application in addition to accuracy. For example, Kim et al. [7] reported that automated crack-detection using UAVs took 1.6 seconds to detect cracks in an image of concrete structures. In this work, we found that our AlexNet-based approach requires 0.0205 seconds to process a patch or 0.328 seconds for a 256 x 256 image. The results also indicate that although AlexNet was not the best in terms of accuracy (see Table 3), it requires the least inference time (about 20 ms) per patch. This is followed by DenseNet-121 and ResNet-50 with 86ms add 90ms, respectively. VGG-19, which had the highest accuracy, requires 278 ms per patch. Therefore, for practical applications, we have to choose models that fit the applications in hand not only based on accuracy, but also considering the inference time. If the inference time is too high, then those models may not be suited for real-time crack detection of concrete structures, but they can be used for offline assessments.

5 CONCLUSIONS

In this work, we present the development of an automated crack detection (ACD) framework for concrete structures based on the region-based approach and convolutional neural network (CNN). For this purpose, we constructed a publicly available dataset of crack/non-crack concrete images, consisting of 32,704 training patches, 2,074 validation patches and 6,032 test patches. We also employed and tested the performance of 15 state-of-the-art CNN models. The performance of these models was evaluated based on the several performance metrics, including accuracy and precision, and inference time. The results showed that our approach outperformed existing models in literature for both accuracy and efficiency. Our evaluation also shows that deeper models have higher detection accuracies, however, they also require more parameters and have higher inference time. Therefore, for real-time applications, one must choose models that provides a balance between accuracy and inference time. From this work, we also found that it is not only important to detect cracks in concrete structures but also obtain the crack features such as crack width and extent, which can be an interesting topic for future development.

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- The Fifth Australasian Conference on Computational Mechanics (ACCM2021), Sydney, Australia, 13th - 15th December 2021, organised by Assoc. Prof. Sarah Zhang, Prof Yang Xiang, and Prof Richard Yang.

  Webpage: https://westernsydney.edu.au/accm2021

  Extended Abstract submissions open: 15th April 2021

  Extended abstract submission due: 1st September 2021

- Mini Symposium "Advances in Bridge Monitoring Strategies: Novel Technologies and Information Fusion" in the 11th International Conference on Bridge Maintenance, Safety and Management (IABMAS2022), Barcelona, Spain, from 11 July to 15 July 2022. Organised by Prof. Kim, Dr Makki Alamdari, Dr. Zhang and Dr. McGetrick.

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