Bridge Point Cloud Completion Using Deep Learning Obtained in Actual Bridge Structures

GEN MATONO and MAYUKO NISHIO

ABSTRACT

Point cloud, which can be obtained by optical measurement, is recently recognized to be useful in SHM for the maintenance and management of existing civil structures. However, there are some issues in measuring point cloud of large structures such as bridges. First, multiple measurements from different locations are required to reconstruct the point cloud of a whole structure. Second, the parts, where are interrupted by trees or other objects cannot be measured well even in uses of cameras or 3D scanners. Therefore, the point clouds acquired in actual structures cannot prevent missing parts or lack of details of structural configurations. This study aims to show applicability of deep learning for reproducing the partial point cloud obtained from measurements in actual structures into a completed point cloud. The experiment results show that even with limited data, transfer of training weight and component-wise completion can yield greater accuracy compared to completion of the entire bridge.

INTRODUCTION

Bridges are critical infrastructure that require periodic inspections to detect deterioration damage caused by ageing leading to major accidents. To detect deterioration damage caused at an early stage, periodic visual inspections are carried out in accordance with national standards. However, visual inspections are time-consuming, expensive, and hazardous for workers. To address these challenges, 3D models have been increasingly used for bridge maintenance and management, including the application of Building Information Modelling (BIM) [1,2]. On the other hand, in many cases, drawings are not available for existing bridges and modelling is not easy. Therefore, point clouds, which are a type of 3D data that can be obtained by optical measurements such as cameras and laser measurements, is expected to be used. Pang et al. [3] showed that the use of point clouds acquired by UAVs for 3D modelling of heritage bridges can be used to semi-automatically create structural surface models; Morgenstern et al. [4] performed BIM of existing bridges using point clouds acquired by laser scanners and showed that damage conditions obtained from the point clouds

Gen Matono, Department of Engineering Mechanics and Energy, University of Tsukuba, 1-1-1 Tennoudai, Ibaraki Prefecture, 305-0006, Japan

can be reflected in the BIM model to enable efficient maintenance management. Thus, the use of point clouds is expected to make modelling more efficient and solve problems in conventional periodic inspections. However, there are two problems with the measurement of point cloud for large structures such as bridges. First, it is essential to take photographs from several hundred locations and to take laser measurements from multiple locations. The second is that occlusions caused by other structures, trees and other obstructions can prevent measurement during the measurement.

In recent years, deep learning has emerged as a successful technique in various fields. Among its many applications, point cloud completion by deep learning has received significant attention and its accuracy is improving continuously[5–7]. However, most of these methods have been evaluated using artificially created datasets, and there is a need for validation experiments in real-world scenarios. Cheng et al.[8] developed a deep learning-based point cloud completion method for handling sparse data, which was evaluated on the KITTI dataset comprising real-world point clouds obtained using a Velodyne laser scanner. Although point cloud completion by deep learning has also been extensively studied, there are no examples of its application to bridge point cloud data obtained from real measurements. Therefore, it is essential to evaluate the ability of point cloud completion by deep learning for bridge data acquired in real-word measurement.

This study aims to shown ability for complete a partial point cloud of a bridge into a complete point cloud using point cloud shape completion with deep learning. First, the paper evaluates the performance of existing deep learning models on real measured data of bridges by applying three deep learning models and assessing the current issues qualitatively and quantitatively. Based on the issues obtained, the study shows that the performance can be improved by transfer of learning weights and component-wise completion. The results of this study contribute to the efficient maintenance and management of bridges, which is essential for ensuring their safe operation.

EXPERIMENT SETTING

Dataset Preparation

Deep learning requires multiple pairs of partial and complete point clouds for missing completion. However, obtaining real bridge measurements is challenging. To address this issue, we used point cloud data from both actual measurements and 3D models for experiment. We obtained a point cloud of the entire circumference by measuring several points on the real bridge. From this, we selected a few measurement points to obtain a partial point cloud. Additionally, we converted the 3D model into a complete point cloud by scattering points on the surface, then manually deleted points based on the partial point cloud from the real measurement to create a partial point cloud.

POINT CLOUD DATA ACQUISITION OF ACTUAL BRIDGE

The target bridge for point cloud acquisition was a concrete bridge on the campus of the author’s university. The scanner is equipped with a Times of Flight (ToF) laser that measures the distance from the laser reflection time and has a resolution of 3 mm

(a) appearance (b) acquired point cloud from 25 measuring locations (c) acquired point cloud from 5 measuring locations

Figure 1. Appearance and point cloud of target bridge.

at a measurement distance of 10 m and a coordinate accuracy of ±1.9 mm (RTC360, Leica). The original point cloud data was configured by combining point clouds acquired in multiple locations, here, 25 locations. The partial point cloud data for experiments were then created from the original data, by reconfigure the point clouds using some data acquired in selected five or six measurement locations. Three patterns of the partial point cloud data were then prepared. Figure 1 shows (a) target bridge (b) acquired point cloud from 25 measuring locations (c) acquired point cloud from 5 measuring locations.

Deep Learning Construction

DEEP LEARNING MODEL

In this study, we used Point Completion Network (PCN) [5], Morphing and Sampling Network (MSN) [6] and Point Fractal Network (PF-Net) [7] as representative deep learning models. The data used were point clouds created from 3D models, 60 data for training, 8 data for validation and 3 data for evaluation. During input, normalization was added to transform the minimum and maximum values of each coordinate to 0-1 to align the scale of the bridge and eliminate extrapolation. The inputs are the position of each point, and the number of input/output points has been reduced to 16384 to reduce computational costs. The training epoch was 1000, the learning rate was 0.0001 and Adam was used as the optimization method.

EVALUATION METHOD

Evaluation of point cloud completion methods involves both qualitative and quantitative evaluations. Qualitative evaluation is based on visual inspections and assess the completion performance and surface distribution of the main components. Quantitative evaluations are based on numerical measurements and use the Chamfer Distance (CD) and Earth Mover's Distance (EMD) metrics[9]. Where S_1, S_2 are point cloud, x, y are point in each point cloud and ϕ is bijection. Each defining expression are shown in (1) and (2). By using both qualitative and quantitative values, this study aims to comprehensively evaluate the performance of point cloud completion methods and provide insights into their strengths and weaknesses.

$$d_{CD}(S_1, S_2) = \sum_{x \in S_1} \min_{x \in S_2} \| x - y \|_2^2 + \sum_{y \in S_2} \min_{x \in S_1} \| y - x \|_2^2 \quad (1)$$

$$d_{EMD}(S_1, S_2) = \min_{\phi : S_1 \to S_2} \sum_{x \in S_1} \| x - \phi(x) \|_2 \quad (2)$$

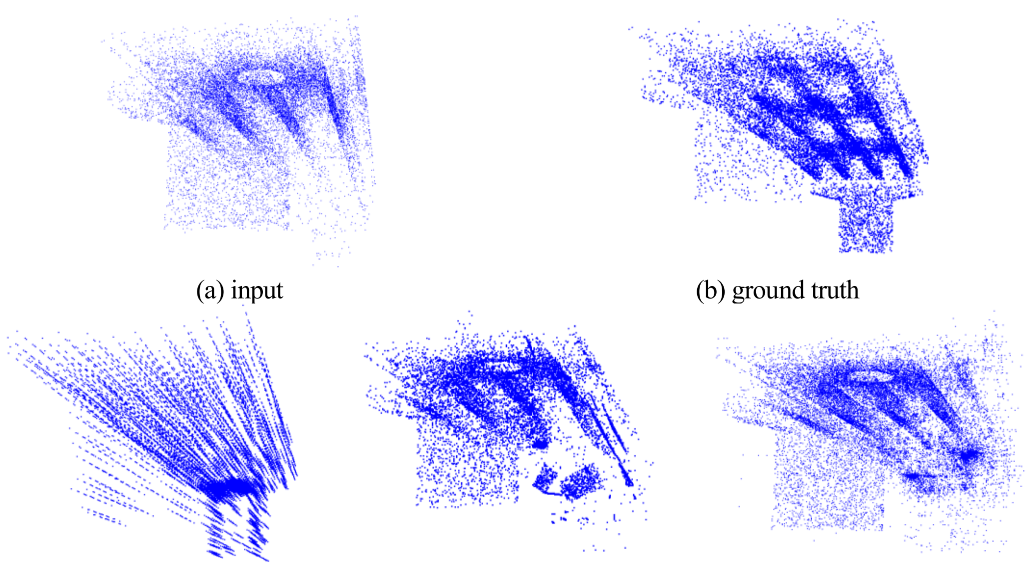
RESULTS

Normal Learning

First, the models were trained with randomly set initial weights. Figure 2 shows (a) input partial point cloud, (b) ground truth, (c) result of PCN, (d) result of MSN and (e) result of PF-Net. All models failed to achieve sufficient missing completion and had low reproducibility. This can be attributed to the small amount of training data, as deep learning models heavily rely on the amount and quality of data. Therefore, it was confirmed that achieving detailed completion with this small amount of training data is challenging.

Initial Weight Transfer

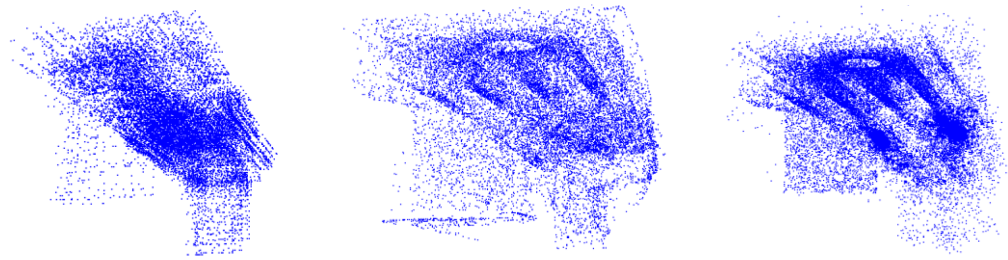
To enable completion with less training data, the initial weights of a pre-trained model on an existing dataset were transferred. ShapeNet[10] dataset was used for pre-training. The results obtained are shown in Figure 3. It was confirmed that by transferring the initial weights, the models were able to reconstruct the piers and the floorboards greater detail compared to the normal learning method. This trend was consistent for all models. Although all models were able to approximately reconstruct large members, the smaller members such as girders and bearings could not be reconstructed as accurately as the piers and floor plates.



(a) input (b) ground truth

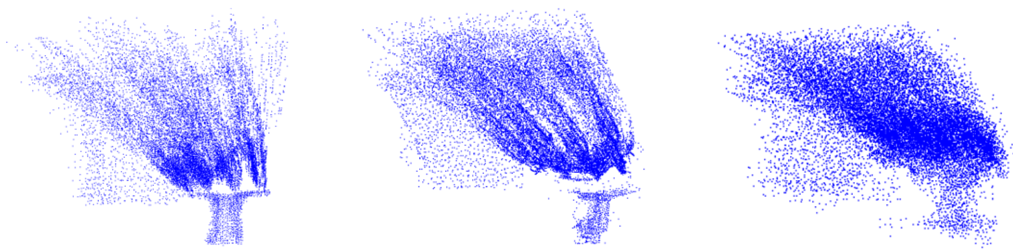
(c) PCN (d) MSN (e) PF-Net

Figure 2. Result of normal learning



(c) PCN (d) MSN (e) PF-Net

Figure 3. Result of initial weight transfer



(c) PCN (d) MSN (e) PF-Net

Figure 4. Result of initial weight transfer and component-wise completion

Component-Wise Completion

Although the transfer of initial weights made it possible to complete the piers and deck plates, the girder could not be completed using this method alone. Therefore, in addition to the transfer of initial weights, the bridge was segmented into piers, main girders, and other members, and each member was completed separately. The segmentation of the training and test data was performed manually. Figure 4 shows the results of component-wise completion. By component-wise completion, it was possible to achieve more detailed completion of the girder. This is since the geometry of component is simpler than that of the entire bridge and learning for component resulted in increased learning data. However, the input data becomes sparser towards the back, and in the case of component-wise completion, the span length of the completed girder cannot be maintained and is shortened because the global shape of the bridge cannot be captured. Therefore, better results were obtained when the entire bridge was used as input, capturing the external shape of the bridge.

Quantitative Evaluation

Finally, a quantitative evaluation was conducted to compare the performance of the normal learning results, the results with initial weight transfers, and the results with initial weight transfers and component-wise completion.

TABLE I shows the CD and EMD values for each of these methods. In the CD evaluation, PCN and MSN outperformed the other methods in terms of component-wise completion. However, PF-Net had a higher CD value than the other methods, which could be attributed to the fact that PF-Net is a relatively difficult method to learn and

TABLE I QUANTITATIVE EVALUATION OF EACH SETTING

Method	Normal learning		Initial weight transfer		Initial weight transfer + component-wise	
	CD	EMD	CD	EMD	CD	EMD
PCN[5]	54499.1	708.2	874.4	616.0	365.8	653.7
MSN[6]	642.0	658.6	1021.6	644.9	273.5	650.7
PF-Net[7]	470.8	667.8	421.6	626.2	751.62	676.0

did not perform well in this study. On the other hand, the evaluation using EMD did not agree with the qualitative evaluation. While these metrics are useful for assessing geometric similarity, they may not be suitable as the primary metrics when verifying the ability to complete the main components, as in this study.

CONCLUSIONS

The presented study demonstrates the effectiveness of using deep learning for point cloud completion of bridges. We performed a three-step approach to improve the accuracy of completing partial point clouds. First, we conducted an initial validation by training deep learning models with random initial values. Then, we improved the accuracy by transferring the initial weights of a pre-trained model to models, enabling us to achieve better results with a small amount of training data. Finally, we developed a component-wise completion method to enhance the accuracy of individual components, such as piers, deck plates, and girders, which resulted in more detailed and precise completions. Through the experiments, it was found that transfer learning with pre-trained models can improve the accuracy of point cloud completion with a small amount of data. Additionally, performing a component-wise completion was shown to further improve the completion accuracy of individual bridge components. However, component-wise completion was not able to keep overall shape of bridge. Based on the quantitative evaluation using CD and EMD, different results were obtained compared to the qualitative evaluation. As a result, it was concluded that an alternative index should be used when the focus is on complementing the primary structural component of the bridge.

In the future, we aim to develop a model that can recognize both the components and the outer shape of the bridge by incorporating a mechanism to recognize the overall shape. This will help to complement each component and outer shape more accurately. Additionally, we plan to validate the end-to-end system by implementing deep learning to segment component, which is currently done manually.

REFERENCES

1. Li, S., Z. Zhang, D. Lin, T. Zhang and L. Han. 2023. "Development of a BIM-Based Bridge Maintenance System (BMS) for Managing Defect Data," *Sci. Rep.*, 13(1): p. 846.
2. Wan, C., Z. Zhou, S. Li, Y. Ding, Z. Xu, Z. Yang, Y. Xia, and F. Yin. 2019. "Development of a Bridge Management System Based on the Building Information Modeling Technology," *Sustainability*, 11(17):4583.

3. Pan, Y., Y. Dong, D. Wang, A. Chen, and Z. Ye. 2019. “Three-Dimensional Reconstruction of Structural Surface Model of Heritage Bridges Using UAV-Based Photogrammetric Point Clouds,” *Remote Sens.*, 11(10):1204.
4. Morgenstern, H., and M. Raupach. 2022. “Quantified Point Clouds and Enriched BIM-Models for Digitalised Maintenance Planning,” *MATEC Web Conf.*, 364, p. 05001.
5. Yuan, W., T. Khot, D. Held, C. Mertz, and M. Hebert. 2019. “PCN: Point Completion Network.”
6. Liu, M., L. Sheng, S. Yang, J. Shao, and S.-M. Hu. 2020. “Morphing and Sampling Network for Dense Point Cloud Completion,” *Proc. AAAI Conf. Artif. Intell.*, 34(07), pp. 11596–11603.
7. Huang, Z., Y. Yu, J. Xu, F. Ni, and X. Le. 2020. “PF-Net: Point Fractal Network for 3D Point Cloud Completion,” *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, IEEE, Seattle, WA, USA, pp. 7659–7667.
8. Cheng, R., C. Agia, Y. Ren, X. Li, and L. Bingbing. 2020. “S3CNet: A Sparse Semantic Scene Completion Network for LiDAR Point Clouds.”
9. Fan, H., H. Su, and L. J. Guibas. 2017. “A Point Set Generation Network for 3D Object Reconstruction From a Single Image,” pp. 605–613.
10. Chang, A. X., T. Funkhouser, L. Guibas, P. Hanrahan, Q. Huang, Z. Li, S. Savarese, M. Savva, S. Song, H. Su, J. Xiao, L. Yi, and F. Yu. 2015. “ShapeNet: An Information-Rich 3D Model Repository.”