

Application of 3D point cloud completion for underwater structures

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ABSTRACT

The point cloud completion network has been widely used in point cloud measurement projects. However, underwater structure detection often cannot obtain detailed 3D point cloud data in advance, resulting in the inability to train point cloud completion networks. This study proposes a 3D point cloud completion technique for underwater structures. Based on the 2.5D point cloud's geometric characteristics of underwater structures, the RANSAC algorithm is applied to estimate the reference 3D model of underwater structures. Furthermore, train the PCN network with the characteristics of the reference 3D model. Finally, utilize PCN network to generate a comprehensive 3D point clouds of underwater structures. The effectiveness of the proposed method is verified through actual underwater experiments in harbor. The proposed method realizes the application of 3D point cloud completion for underwater structures without a reference ground truth.

Keywords: point cloud completion, RANSAC, PCN, underwater structures

1. INTRODUCTION

Three-dimensional LiDAR, through point cloud format, can scan spatial geometric shapes and become an important remote sensing device. However, due to the discontinuity or occlusion of the sensing environment surface, the generated point cloud may appear locally sparse or a missing dataset. Point Cloud Completion is a technique that produces the complete 3D shape of an object by inputting a partial point cloud of the object. Early point cloud completion technology mainly relied on prior geometric features of objects, such as symmetry and repetitive structures, for completion. The current research is dominated by deep learning based methods. Although various point cloud completion techniques are becoming increasingly diverse, the core challenges of point cloud completion still include sparse raw data, network generalization ability, and improving computational efficiency [1, 2].

The point cloud completion technology based on deep learning can be divided into three kinds of methods. The point-based method adopts the classic encoder-decoder architecture and can run directly on point clouds. However, these methods do not fully consider the geometric relationships between 3D point clouds. On the other hand, Convolutional neural networks (CNN) can learn local spatial correlations to represent the geometric relationships of a 3D point cloud set. Because point clouds have both discreteness and unstructured features, CNN find it difficult to represent fine-grained details of complete shapes. Transformer is a model that utilizes attention mechanisms to improve training efficiency. By utilizing attention mechanisms, the robustness of point cloud matching can be enhanced [3].

Point Completion Network (PCN) is an encoder-decoder network. PCN can directly access the point cloud completion process without making any structural assumptions or data annotations. Firstly, the encoder outputs a k-dimensional feature vector based on the input point cloud data. Through using the feature vector, the decoder generates a coarse output point cluster and a detailed output point cluster in sequence. The advantage of PCN is that it can generate fine-grained completion and has a smaller number of model parameters [4].

To avoid the loss of local details caused by focusing on a global feature, Zhang et al. proposed the Point Shift Network (PS-Net) [5]. The author designed a shift network and a multi-resolution encoder to achieve more accurate point cloud completion prediction. The strategy for point cloud completion is to create a skeleton with a small number of points to roughly describe the shape of the point cloud. Finally, generate new points around the skeleton and repeat the combination with the original skeleton to form a new skeleton. On the other hand, regarding the use of recursive coarse to fine restrictions for PS-Net, the joint skeleton and surface point cloud completion network (S^2 -PCN) is proposed. The network

includes multi-scale feature encoders and geometry disentanglement modules, which can simultaneously complete point cloud completion of skeleton structure and surface details [6].

The traditional point cloud completion method is based on symmetrical structural features. Although the symmetrical object does not require any external reference annotation data, it can only be applied to objects with obvious structural geometrical features [7]. As for the current mainstream deep learning network methods, reference annotated samples need to be provided in advance as training samples [8]. However, the reference training samples (i.e., ground truth) often cannot be obtained in advance before practical underwater engineering measurements. The 3D underwater sonar usually only scans the underwater scene at fixed positions and obtains 2.5D point cloud data. How to apply point cloud completion technology in underwater environment measurement without ground truth has become an important research topic.

This study proposes a 3D point cloud completion technique for underwater structures. By using underwater 3D sonar, the 2.5D point cloud of underwater structures can be directly obtained. Secondly, based on the 2.5D point cloud geometric features, the Random Sample Consensus (RANSAC) algorithm is used to model the shape of reference sample of underwater targets. Then, train the PCN network based on the geometric features of the reference model. Finally, the PCN network is used to generate a whole 3D point cloud of underwater structures. The proposed method realizes the application of 3D point cloud completion for underwater structures without a reference ground truth. The main contribution of this study is as follows:

- A new 3D point cloud completion technique is proposed, which can be applied to underwater projects without reference 3D object models.
- A quality improvement algorithm for 2.5D point cloud is proposed to serve as training samples for 3D point cloud completion networks.

2. METHOD

The use of underwater 3D sonar can automatically generate underwater panoramic point clouds. However, due to occlusion and shadow effects, underwater structures can only be represented in 2.5D point cloud format. Point cloud completion can restore a comprehensive underwater scene. This study first utilizes the Statistical Outlier Removal (SOR) to denoise the raw data. Through using the RANSAC algorithm, the reference model of the underwater structure can be reconstructed. Then, the PCN network is trained using the reference model to output the missing areas of a 2.5D point cloud. Finally, complete the point cloud completion of underwater structures. The flowchart of point cloud completion process for underwater structures is shown in Figure 1.

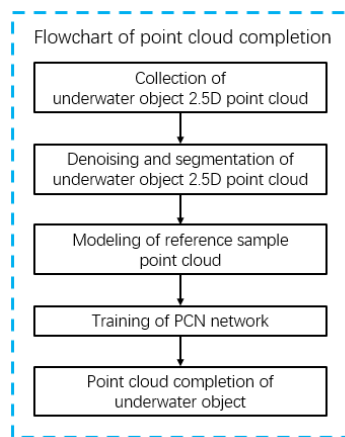


Figure 1. Flowchart of point cloud completion.

2.1. Denoising and segmentation of 2.5D point cloud

When using 3D underwater sonar scanning, the original point cloud is affected by the seabed environment, resulting in unnecessary noise. Noise point clouds can be removed using the classic Statistical outlier removal (SOR) algorithm. Due to significant differences in Gaussian distribution parameters between noise and underwater structures, SOR can set noise parameter thresholds based on the statistical values of Gaussian parameters of underwater structures.

For the practical measurement of underwater engineering in ports, the underwater structures are mainly the underwater pillars of the dock, and the seabed is the environmental background. The purpose of applying the RANSAC algorithm is to segment underwater structures from the background point clouds. The RANSAC algorithm can automatically detect the point clouds of the seabed plane and segment the corresponding point clouds of underwater structures.

RANSAC is an iterative robust estimation method and consists of two parts: 1. Assuming geometric models (such as linear or planar models); 2. Iterative evaluation: randomly select a sample set and evaluate it through model parameters. In iterative testing, based on the model threshold and the least squares cost function, RANSAC can find predefined models from the inner candidate set. The RANSAC algorithm processing procedure is as follows:

- 1) Assuming a geometric model. Randomly select a subset and evaluate the model parameters for all subsets.
- 2) Test all other data points and decide the internal candidates that meet the model parameters.
- 3) Evaluate the estimated model parameters based on the number of internal candidate data points.
- 4) Use all assumed internal candidate iterations to estimate model parameters.
- 5) Stop the evaluation loop based on the estimated internal candidates and model error rate.

2.2. Modeling of reference sample point cloud

At present, point cloud completion networks based on deep learning require a whole ground truth during the training phase. However, this is impractical in actual underwater measurement. Generally, the complete ground truth cannot be obtained before measurement. To address the limitation of ground truth training samples in PCN networks. This study used RANSAC to estimate the 2.5D point cloud of underwater pillars, thereby obtaining a 3D reference training sample. Further serve as training samples for PCN networks.

2.3. Point Completion Network (PCN)

The PCN network can complete unmeasured point clouds without assuming any geometric shape of the object. The PCN encoder is responsible for encoding the geometric information in the input point cloud data into a feature vector V . On the other hand, the PCN decoder generates coarse and detailed output point clouds from the feature vector V output by the encoder in a two-stage sequence. During the training section of PCN, Chamfer Distance (CD) and Earth Mover's Distance (EMD) are generally used as loss functions.

$$CD(s_1, s_2) = \frac{1}{|s_1|} \sum_{x \in s_1} \min_{y \in s_2} \|x - y\|_2 + \frac{1}{|s_2|} \sum_{y \in s_2} \min_{x \in s_1} \|y - x\|_2, \quad (1)$$

where s_1 and s_2 are the output point cloud and the ground truth point, respectively.

$$EMD(s_1, s_2) = \min_{\phi: s_1 \rightarrow s_2} \frac{1}{|s_1|} \sum_{x \in s_1} \|x - \phi(x)\|_2, \quad (2)$$

where ϕ represents a bijection that minimizes the average distance between corresponding points.

The proposed PCN network architecture with reference training samples is shown in Figure 2.

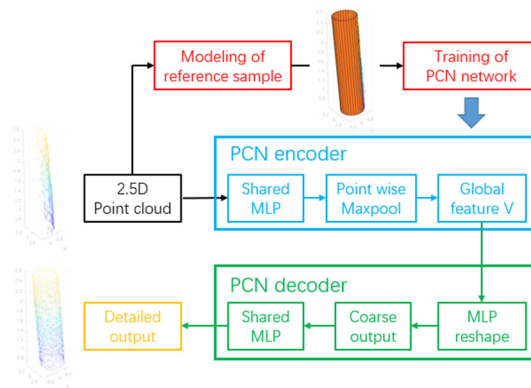


Figure 2. PCN network architecture with reference training samples.

3. UNDERWATER EXPERIMENT RESULT

An actual underwater experiment is designed to verify the feasibility of the proposed method. The underwater experimental scene is located at Keziliao Fishing Port in Kaohsiung City, Taiwan. The experiment uses BlueView BV5000 underwater 3D sonar to scan the raw data. The dock of Keziliao Fishing Port is supported by a series of pier pillars. The depth of the harbor is about 5 meters. BV5000 is mounted on a tripod and then placed at the bottom of the harbor to scan the underwater environment of the harbor. The specifications of BV5000 sonar are as follows:

- Maximum Scan Range: 30 m
- Spherical Scan Area: 360 °
- Number of Beams: 256
- Operation Frequency: 1.35 MHz
- Vertical Spatial Resolution: 16 mm at 10 m
- Horizontal Spatial Resolution: 30 mm at 10 m

By using SOR algorithm, the raw data has been denoised first. The RANSAC algorithm estimates the seafloor plane based on the normal direction of the seafloor datum. After removing the point clouds of seabed plane, the underwater scene objects are mainly composed of dock structures, a row of supporting pillars, and sloping silt. Figure 3 (a) demonstrates the underwater point cloud of the BV5000 measured harbor. However, due to the limitation of fixed-point measurements, BV5000 cannot scan the back side of underwater pillars. Underwater measurement data can only obtain 2.5D point clouds of dock pillars (Shown in Figure 3 (b)).

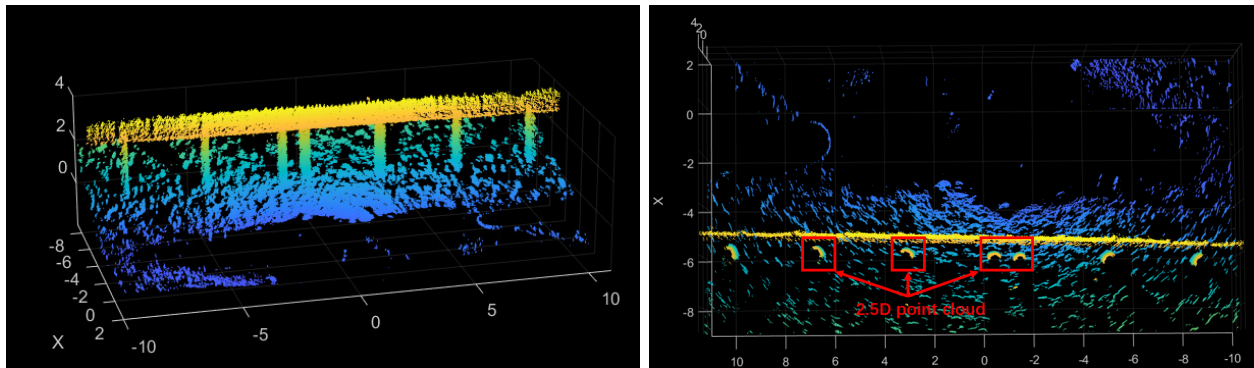


Figure 3. Underwater point clouds. (a) Underwater scene of harbor. (b) 2.5D point clouds of dock pillars.

Segmenting the 2.5D original point cloud of underwater structure's pillars. Remove the point clouds of the background seabed. Obtain the point clouds of the underwater structure. Figure 4 (a) shows that the sonar sound waves of BV5000 can only reflect the point clouds of the line of sight, and the 2.5D original point clouds have lost half of the point clouds of underwater pillars. Due to the lack of detailed 3D training samples for underwater structures, 2.5D point clouds cannot be used to train PCN networks.

The RANSAC algorithm calculates the corresponding Gaussian distribution parameters based on the geometric characteristics of the 2.5D point clouds of the underwater support pillar, and restores the reference 3D model of the underwater pillar (Shown in Figure 4 (b)). Furthermore, the reference 3D model can serve as the ground truth for PCN network training samples.

From Figure 3 (b), it can be observed that the 2.5D point clouds of the pillar structure at the left and right ends illustrate opposite directions. PCN network must perform point cloud completion for the missing parts of different pillars. This study sequentially inputs the segmented underwater pillar into the PCN network, and aligns the 3D point clouds output by the PCN network with the 2.5D point cloud position of the pillar to complete the point cloud completion of the underwater structural object. Figure 5 demonstrates the underwater scene after point cloud completion. Comparison with the top view of the underwater scene in Figure 3 (b), it can be observed that the completed point clouds of support pillars are 3D structures.

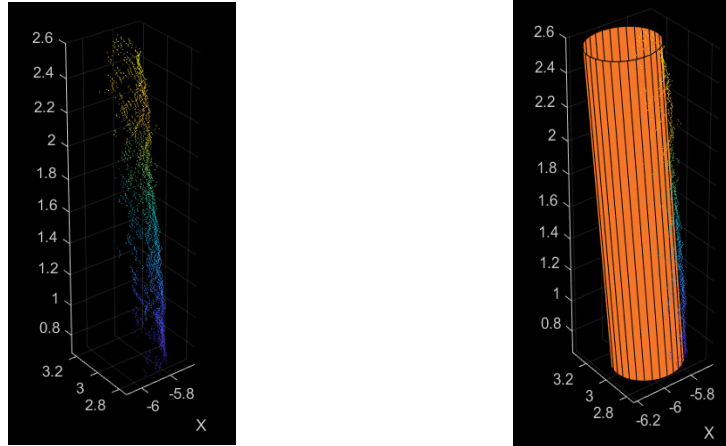


Figure 4. The geometric characteristics of the support pillar. (a) 2.5D point clouds. (b) The reference 3D model of the pillar.

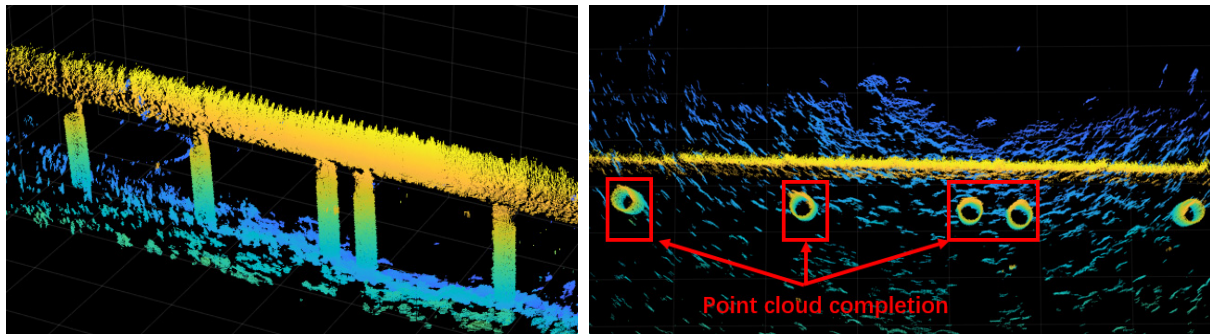


Figure 5. Underwater scene after point cloud completion.

The completion results of the proposed method are compared with the method proposed in [9], which is based on the 3D PatchMatch algorithm. The comparison results are shown in Figure 6. As shown on the left side of Figure 6, due to the lack of reference training point cloud information, the density distribution of the obscured area is inconsistent. By contrast, the proposed method effectively reconstructs the geometric features of underwater structures.

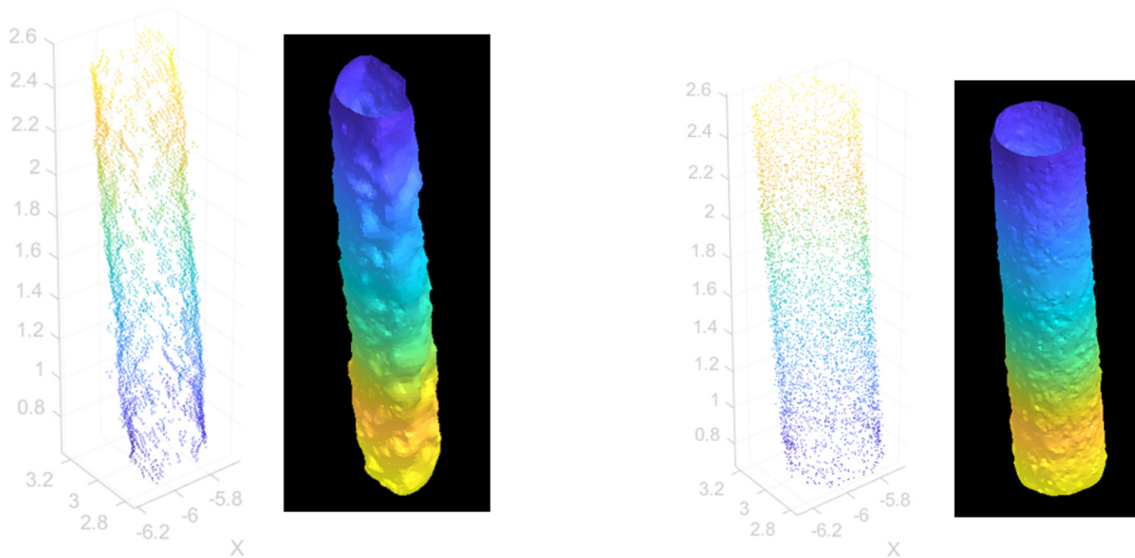


Figure 6. Comparison results. Left: Results of [9]. Right: Results of the proposed method.

4. CONCLUSION

This study proposes a 3D point cloud completion technique for underwater structures. By using underwater BV5000 3D sonar, 2.5D point clouds can be directly generated in underwater scenes. The noise and background point cloud in underwater scenes can be estimated and removed using SOR and RANSAC algorithms, respectively. Secondly, the proposed method utilizes the RANSAC algorithm to estimate the reference model of underwater structures based on their 2.5D point cloud geometric features. Train the PCN network with the reference model features. Finally, utilizes PCN network to generate a complete 3D point clouds of underwater structures. The proposed method realizes the application of 3D point cloud completion for underwater structures in the absence of a reference ground truth. The effectiveness of the proposed method has been verified through actual underwater experiments. Compared with traditional methods, the proposed method can quickly obtain high-precision and high-resolution 3D point clouds of underwater structures. Due to the limited information of single mode point clouds, the point cloud completion technology of multi-mode underwater objects is our future research direction.

ACKNOWLEDGEMENTS

This paper was supported by Xiamen University Tan Kah Kee College (Grant no. JGH 2025035). The author thanks the Systems Engineering Laboratory, National Sun Yat-Sen University for providing the sonar point cloud data.

REFERENCES

- [1] Tesema, K.W., et al., "Point Cloud Completion: A Survey. IEEE Transactions on Visualization and Computer Graphics," 30(10): p. 6880-6899, 2024.
- [2] Lai, Y.H., J.H. Yu, and Y. Gu. "Volume Estimation of Harbor Engineering Objects Using Underwater Three-Dimensional Sonar," in 2022 8th International Conference on Control, Automation and Robotics (ICCAR). 2022.
- [3] Zhang, K., et al., "Deep-learning-based point cloud completion methods: A review," Graphical Models, 136: p. 101233, 2024.
- [4] Yuan, W., et al. "PCN: Point Completion Network," International Conference on 3D Vision (3DV). 2018.
- [5] Zhang, Y., et al., "PS-Net: Point Shift Network for 3-D Point Cloud Completion," IEEE Transactions on Geoscience and Remote Sensing, 60: p. 1-13, 2022.
- [6] Zhang, Z. and F. Da, "S2-PCN: Joint skeleton and surface point cloud completion network via geometry disentangle," Expert Systems with Applications, 294: p. 128807, 2025.
- [7] Yan, J., et al., "High-fidelity 3D sonar point cloud data reconstruction of underwater bridge caisson foundation for scour inspection," Measurement, 244: p. 116480, 2025.
- [8] Han, S., et al., "Research and application on deep learning-based point cloud completion for marine structures with point coordinate fusion and coordinate-supervised point cloud generator," Measurement, 242: p. 116246, 2025.
- [9] Cai, Z., et al. "3D-PatchMatch: An optimization algorithm for point cloud completion,". 2nd IEEE International Conference on Spatial Data Mining and Geographical Knowledge Services (ICSDM). 2015.