SRPCN: Structure Retrieval based Point Completion Network

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Abstract

Given partial objects and some complete ones as references, point cloud completion aims to recover authentic shapes. However, existing methods pay little attention to general shapes, which leads to the poor authenticity of completion results. Besides, the missing patterns are diverse in reality, but existing methods can only handle fixed ones, which means a poor generalization ability. Considering that a partial point cloud is a subset of the corresponding complete one, we regard them as different samples of the same distribution and propose Structure Retrieval based Point Completion Network (SRPCN). It first uses k-means clustering to extract structure points and disperses them into distributions, and then KL Divergence is used as a metric to find the complete structure point cloud that best matches the input in a database. Finally, a PCN-like decoder network is adopted to generate the final results based on the retrieved structure point clouds. As structure plays an important role in describing the general shape of an object and the proposed structure retrieval method is robust to missing patterns, experiments show that our method can generate more authentic results and has a stronger generalization ability.

1. Introduction

Point cloud completion aims to complete authentic point clouds when given inputs with various missing patterns. It can contribute to a series of downstream applications, like robotics operations[27], scene understanding[4], and virtual operations of complete shapes[5].

Most of the recent point cloud completion methods are related with deep learning and achieve promising results. However, they have two problems. First, the authenticity of the completion results is poor. As shown in Figure 1, we can find that the results in existing methods are fuzzy and unreasonable. This may be caused by two reasons: the fuzzy structure and the usage of Chamfer Distance[5]. Structure plays an important role in describing the general shape of an object and helps to understand the object itself, but existing methods[14, 24, 28, 30, 31, 34, 38, 39] do not explicitly consider this low-frequency information. Besides, many methods[24, 28, 31, 38, 39] use Chamfer Distance as a loss function or an evaluation metric, but as mentioned by [1, 14], Chamfer Distance might be blind to some visual inferiority.

Second, existing methods[14, 24, 28, 30, 31, 34, 38, 39] fix missing patterns in advance, such as, back-projecting 2.5D depth images into 3D, removing some points within a certain radius from complete point clouds in a view-point. This leads to the poor generalization ability of their models. Although PF-Net[9] tries to tackle this situation, the new missing parts for testing are close to what in the training set and are only experimented in the airplane category. What’s more, PF-Net makes a dataset based on ShapeNet-Part dataset[36] with a fixed missing rate, which rarely happens in real scenarios.

To address these issues, we propose Structure Retrieval based Point Completion Network. It mainly includes two steps: structure retrieval and retrieval recovery. Specifically, we first use k-means clustering to extract structure points and disperses them into distributions. Then KL Divergence is used as a metric to find the complete structure point cloud that best matches the input in a database. Finally, through adopting a PCN-like decoder network, we upsample the retrieved structure point clouds to obtain final results. Because of the reasonable structure point clouds obtained

Figure 1. The completion results of a cabinet and a chair in PCN[38], TopNet[24] and GRNet[34], which have fuzzy structures and poor authenticity.
by structure retrieval, which represent general shapes, our
method can achieve more authentic completion results. Be-
sides, as the structure retrieval is robust to missing patterns,
our method has a stronger generalization ability.
Our main contributions are the following:

• We propose a new representation of the point cloud, structure
distribution, which well preserves the general shape with a smaller number of points.

• We continuous the structure point clouds into distrib-
utions and propose a fast structure retrieval method
based on KL Divergence.

• Our proposed method achieves more authentic com-
pletion results and shows stronger generalization abil-
ity on the Completion3D dataset.

2. Related work

2.1. Alignment-based 3D Shape Completion

Alignment is a commonly used method in 3D shape comple-
tion [12] [16] [17] [21] [22] [23]. It usually includes two
steps: The first step is retrieving some similar template
shapes, which can be complete or part of shapes from a
large shape database. The second step is deforming and as-
sembling the matched shapes to finish the completion. For
example, Shen et al. [22] assemble reasonably labeled parts
to complete the low-quality scanned point cloud data, from
a small-scale shape repository. Sung et al. [23] associate the
local coordinate system with existing shape parts and learn
the position and orientation distribution of all other parts
from the database. This method uses shape databases for
completion and contributes a lot to the 3D reconstruction
task.

Since the shape databases are in mesh format, all the
methods above finally get the mesh shape, not only the
matching speed is slow but also the output data format is not
what we need. In contrast, we build a database in the format
of the point cloud. The database is based on the structure
point clouds, so the speed of retrieval in our method is fast.
Through combining deep learning methods for upsampling,
final shapes completed by our method have strong authen-
ticity.

2.2. Deep Learning on Point Cloud Completion

The method of deep learning for point cloud research is
first proposed by PointNet [18] and achieves great success
in 3D point cloud classification [11] [15] [19] [25] [26] [29] [33].
This causes the popularity of employing deep learning on
the point cloud. About 3D point cloud completion, existing
deep learning methods can be roughly divided into two
categories:

Directly output the complete shape. This method does
not need to know the missing parts and the missing rate of
shapes, instead, are obtained implicitly through deep learn-
ing. However, due to the lack of attention to reasonable
structures, the completion results are not very authentic.

PCN [38] provides an autoencoder to combine the global
and local shape information for point cloud completion.
TopNet [24] further designs a tree-structured decoder to re-
alize multi-scale completion. MSN [14] uses multi-MLPs
as patches to generate better local shapes and states that us-
ing the metric of Earth’s Mover Distance [5] is more reason-
able than Chamfer Distance [5]. GRNet [34] transfers point
cloud into a new voxel representation, which better retains
the spatial information of original partial point clouds. In
addition, [8] [20] [28] [30] [31] [35] [39] play an important role
in promoting the point cloud completion task.

Complete the missing parts and then merge. This
method well retains existing point clouds and only fills in
the missing parts of shapes. But existing work assumes that
the missing parts and the missing rate are known, which
greatly reduces the difficulty of completion. PF-Net [9] pro-
vides a multi-resolution encoder to get better feature em-
beddings and a point pyramid decoder to complete the miss-
ing parts progressively, which is a heuristic work.

In this paper, we combine deep-learning-based methods
with alignment-based methods. To make our method more
reliable, we first use a PCN-like network to predict the miss-
ing rate. Based on this, we further design a structure re-
trieval method based on KL Divergence to predict structure
point clouds of the missing parts. Finally, a PCN-like de-
coder is used for upsampling the retrieved complete struc-
ture point clouds. Even when the missing parts and the
missing rate are indeterminate, our method still can com-
plete reasonable point clouds.

3. Methods

In this section, we describe the architecture of our model
SRPCN. As shown in Figure 2, the input of SRPCN in-
cludes partial point clouds and a database generated from
complete point clouds in the trainset and the output of SR-
PCN is the completed 2048 point clouds. SRPCN first de-
termines the structure of point clouds through structure re-
trieval and then combines the PCN [38] network to achieve
completion. It includes three parts: Missing Rate Predic-
tion, Structure Retrieval, and Point Cloud Upsampling.
In the Missing Rate Prediction, we use the architecture of the
encoder in PCN to predict the missing rate of the input,
which determines the number of points in the partial struc-
ture point cloud. In the Structure Retrieval, we first use
k-means clustering to extract structure points and disperses
them into distributions, and then KL Divergence is used as
a metric to find the complete structure point cloud that best
matches the input in a database. In the Point Cloud Upsam-
pling, we use a PCN-like decoder to upsample the matched
structure point clouds. Next, we will describe the specific
Figure 2. The Architecture of SRPCN. The three-color blocks of yellow, green, and blue represent different parts. The most critical and novel part is Structure Retrieval and it can be divided into three steps: K-means clustering is adopted to get structure points; each structure point forms an ellipsoidal Gaussian distribution; these distributions are merged to form an overall distribution and KL Divergence is used to guide the retrieval.

The design of SRPCN from the three parts.

3.1. Missing Rate Prediction

In reality, the missing rates of partial point clouds are often uncertain. For example, the partial point clouds in the Completion3D dataset are generated by back-projecting 2.5D depth images into 3D and thus different views lead to different missing rates. Since the distribution matching in our structure retrieval also contains structure information, it is necessary to extract structure points from the input while keeping the missing rate basically unchanged. To this end, we adopt a neural network to predict the missing rate. We follow the architecture of the PCN Encoder while adding a fully connected layer ($1024 \rightarrow 256 \rightarrow 64 \rightarrow 1$) to design the network. This part requires pre-training and the L1 loss function is used for optimizing.

3.2. Structure Retrieval

The main purpose of this part is to realize the prediction of the missing parts. Inspired by the retrieval methods used in traditional point cloud reconstruction, we try to borrow this method to point cloud completion. However, if we suppose the retrieval method is based on complete point cloud data, the time and space complexity will be very high. For this, we first downsample point clouds into structure point clouds and then do retrieval on this small scale, which greatly accelerates the efficiency of retrieval. Our proposed structure retrieval method can be divided into the following three steps: K-means clustering is adopted to get structure points; each structure point forms an ellipsoidal Gaussian distribution; these distributions are merged to form an overall distribution and KL Divergence is used to guide the retrieval. With the retrieved structures, the authenticity of final completion results is greatly improved.

3.2.1 Definition of KL Divergence

Kullback-Leibler Divergence (KLD), also called relative entropy in the information system, randomness in continuous time series, and information gain in statistical model inference, is proposed by Kullback et al. KL Divergence is a measure of the asymmetry of the difference between two probability distributions $P$ and $Q$. The KL Divergence is a measure of the average number of extra bits required to use the Q-based distribution to encode samples that follow the $P$ distribution. Typically, $P$ represents the true distribution of the data, and $Q$ represents the theoretical distribution of the data, the estimated model distribution, or the approximate distribution of $P$.

For discrete random variables, the KL Divergence of the probability distributions $P$ and $Q$ can be defined as:

$$D_{KL}(P||Q) = \sum_x P(x) \ln \frac{P(x)}{Q(x)}$$ (1)

For continuous random variables, the KL Divergence of
the probability distributions $P$ and $Q$ can be defined as:

$$D_{KL}(P||Q) = \int_{-\infty}^{\infty} p(x) \ln \frac{p(x)}{q(x)}$$  \hspace{1cm} (2)$$

Through the definition and formula of KL Divergence, we can find that it is unidirectional and asymmetric. If we regard distribution $P$ as a distribution of a partial point cloud and $Q$ as a distribution of the corresponding complete point cloud, $D_{KL}(P||Q)$ will measure the degree of matching between the partial point cloud and the complete point cloud, so the value of KL Divergence can be used to guide the structure retrieval.

### 3.2.2 Unilateral Discrete

Point cloud data is discrete and there is no good distribution to describe it currently. Besides, it is difficult for the computer to calculate the KL Divergence of the two distributions $P$ and $Q$ with complicated formulas. Therefore, the KL Divergence of continuous random variables may not be suitable for point cloud completion. Another idea is to match partial point clouds and complete point clouds without downsampling by using discrete KL Divergence, but we have stated before that the time and space complexity will be very high. Therefore, it is a reasonable solution to downsample the point clouds to structure points and then perform matching. Since the commonly used downsampling methods, such as farthest point sampling (FPS) and Poisson disk sampling (PDS), are unstable and cannot well represent the structure of point clouds, we finally use k-means clustering to extract structure point clouds. Because of the instability of k-means clustering, we diffuse complete structure point clouds into distributions to realize a unilateral discrete KL Divergence matching.

The distribution formation of complete structure point clouds in the database is shown in the Structure Retrieval part of Figure 2. There are three steps. First, we perform k-means clustering on partial point clouds and complete point clouds. Each partial point cloud forms $(1 - \text{missing rate}) \times K$ clusters, and each complete point cloud forms $K$ clusters. The center of each cluster is treated as a structure point. As shown by the Structure Partial or the Structure Database in Figure 2, different colors indicate different clusters, and the × means the center of a cluster. Second, we take the variance of each cluster in the three dimensions $(x, y, z)$ as the variance of the corresponding structure point. With the center point $\mu$ and the variance $\sigma^2$, each structure point can form a Gaussian distribution $\mathcal{N}(\mu, \sigma^2)$. As shown by the Cluster Distribution in Figure 2, each structure point is diffused to form an ellipsoidal Gaussian distribution. Finally, we accumulate these Gaussian distributions corresponding to all the structure points to form the overall distribution.

With the description of the distribution, we can measure the degree of matching between two structure point clouds. Here we set $DB$ as the database, $Y_X$ as the target of the retrieval, $X$ as the partial structure point cloud and the corresponding distribution is $P_X$, $Y$ as the complete structure point cloud in the database and the corresponding distribution is $Q_Y$. In the unilateral discrete, $P_X$ is a fixed discrete value, and thus the goal of structure retrieval is:

$$Y_X = \arg\min_{Y \in DB} D_{KL}(P_X || Q_Y)$$

$$\Leftrightarrow \arg\min_{Y \in DB} \sum_{x \in X} \ln \frac{1}{Q_Y(x)}$$

$$\Leftrightarrow \arg\max_{Y \in DB} \sum_{x \in X} Q_Y(x)$$

$$\Leftrightarrow \arg\max_{Y \in DB} \sum_{x \in X} \sum_{\mu \in Y} G(x; \mu, \sigma^2)$$  \hspace{1cm} (3)

Since the three dimensions $(x, y, z)$ are not related, Gaussian distribution can be written as:

$$G(x; \mu, \sigma^2) = \prod_{i=1}^{3} \frac{1}{\sqrt{2\pi} \sigma_i} \exp\left(-\frac{(x_i - \mu_i)^2}{2\sigma_i^2}\right)$$  \hspace{1cm} (4)

Considering that different objects have different structure point cloud densities (for example, the structure point cloud density of a lamp is usually greater than that of a car), the value range of the Gaussian distribution is different, which is very important for cross-category structure retrieval. Therefore, we first normalize the Gaussian distribution of each structure point to achieve the same value range of the final distributions in different objects. The normalization process is as follows:

$$\left\{ \begin{array}{l}
\sigma_1' \ : \ \sigma_2' \ : \ \sigma_3' = \left(\frac{\lambda}{\sqrt{2\pi}}\right)^3
\sigma_1' : \sigma_2' : \sigma_3' = \sqrt{\sigma_1} : \sqrt{\sigma_2} : \sigma_3
\end{array} \right. \Rightarrow \left\{ \begin{array}{l}
\sigma_1'^2 = \frac{\lambda^2}{2\pi^2} \left(\frac{\sigma_1}{\sigma_2 \sigma_3}\right)^2
\sigma_2'^2 = \frac{\lambda^2}{2\pi^2} \left(\frac{\sigma_2}{\sigma_1 \sigma_3}\right)^2
\sigma_3'^2 = \frac{\lambda^2}{2\pi^2} \left(\frac{\sigma_3}{\sigma_1 \sigma_2}\right)^2
\end{array} \right. \hspace{1cm} (5)$$

Here $\lambda$ is a scaling ratio suitable for the dataset. We have the final Gaussian distribution function for each structure point as follows:

$$G(x; \mu, \sigma^2) = \prod_{i=1}^{3} \frac{1}{\lambda \sqrt{2\pi} \sigma_i} \exp\left(-\frac{(x_i - \mu_i)^2}{2\sigma_i^2}\right)$$  \hspace{1cm} (6)

Through retrieving in a structure point cloud database, we will get the complete structure point cloud with the
smallest KL Divergence value. In order to enhance the rationality and accuracy of the retrieval, we further optimize the formula. We consider that the partial point cloud is a subset of the complete point cloud, so the partial structure point cloud should completely fall into the distribution formed by the complete structure point cloud. Therefore, we design a threshold $\gamma$. When a certain point of the partial structure point cloud, its calculated value in the distribution is less than the threshold, we believe that they are not a match. The improved formula is as follows:

$$Y_X = \arg\max_{Y \in DB} \begin{cases} 0, & \exists x \in X \sum_{\mu \in Y} G(x; \mu, \sigma^2) \leq \gamma \\ \sum_{x \in X} \sum_{\mu \in Y} G(x; \mu, \sigma^2), & \text{otherwise} \end{cases}$$

(7)

To preserve the original partial point cloud as perfectly as possible, we also need to calculate the KL Divergence backward to determine which points are the structure points of the missing parts. We merge these structure points with the structure points of the original partial point cloud to form the final output. In summary, we obtained a reasonable complete structure point corresponding to each partial point cloud through structure retrieval.

### 3.2.3 Comparison with CD/EMD

In the previous section, we introduce a novel measurement of the matching degree by using KL Divergence, which well satisfies the two important properties required by structure retrieval: subset matching and discrete adaptation. In this section, based on these two properties, we will explain why Chamfer Distance (CD) and Earth Mover’s Distance (EMD) are not suitable for structure retrieval.

CD and EMD are first adopted by Fan et al. [5] in point cloud research and are widely used as loss functions or evaluation metrics for measuring the proximity of two point clouds. Their formulas are as follows, where $S_1$ and $S_2$ represent two point clouds respectively:

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

(8)

$$EMD(S_1, S_2) = \min_{\phi: S_1 \rightarrow S_2} \frac{1}{|S_1|} \sum_{x \in S_1} ||x - \phi(x)||_2$$

(9)

We can find that EMD requires the same number of points in $S_1$ and $S_2$, which obviously does not satisfy the property of the subset matching required by structure retrieval, so here we focus on the analysis of CD. A specific example is shown in the top three figures of Figure 3. The input is a letter $P$, and the letters to be matched are $E$ and $R$. We can clearly identify that $P$ is a subset of $R$. But through calculating the CD, we get:

$$CD(P, F) = \frac{25}{72} < CD(P, R) = \frac{1}{2}$$

(10)

It means that the actual matched result is $F$, rather than the correct result $R$, so CD does not satisfy the property of subset matching in structure retrieval.

Furthermore, we consider that if half CD, prediction to the ground truth (Pre_GT)[7][13], can well satisfy the property of subset matching. However, since the calculation of Pre_GT is discrete, it cannot satisfy the property of discrete adaptation. A specific example is shown in the bottom three figures of Figure 3. The input is a letter $E$, and the letters to be matched are $F$ and $R$. We can clearly identify that $E$ should match $E$. But through calculating the Pre_GT, we get:

$$Pre_{GT}(E, F) = \frac{5}{11} < Pre_{GT}(E, E') = \frac{1}{2}$$

(11)

It means the actual matched result is $F$, rather than the correct result the slightly shifted $E$, so Pre_GT does not satisfy the property of discrete adaptation in structure retrieval.

### 3.3. Point Cloud Upsampling

With the matched structure point clouds, we further modify the PCN Decoder and adapt it to point cloud upsampling. Specifically, the spatial coordinate of each structure point is concatenated with the feature embedding obtained by the PCN encoder and a shared-MLP is used to generate M offsets (M is the upsampling rate). Then we accumulate these offsets to the original structure points and get the complete point cloud. Finally, following MSN[13], we use EMD as the loss function. Due to the retrieved structure information, the upsampling method guarantees the authenticity of the completion results.
4. Experiments

4.1. Datasets and Implementation Details

We evaluate our experiments on the Completion3D dataset generated from the ShapeNet dataset. It includes 30974 models and 8 categories: airplane, cabinet, car, chair, lamp, couch, table, watercraft. We pre-train our missing rate prediction model for 200 epochs, and then execute k-means clustering in multiple processes to get the structure point clouds. We set the number of clusters $K$ to 64 in our experiments. The structure retrieval runs on an Nvidia GPU for about 0.04s per shape. With the retrieved structure, we train our upsampling model on an Nvidia GPU for 200 epochs with a batch size of 32. Adam is used as the optimizer and the initial learning rate is 1e-3.

4.2. Comparison with Existing Methods

We make quantitative and qualitative comparisons with PCN, TopNet and the current best method GRNet on the Completion3D dataset. Since our method relies on the intermediate representation of reasonable structure point clouds, inaccurate but reasonable retrieval results might cause the output to be different from the ground truth. As shown in Table 1, our method performs poorly on the metric of Chamfer Distance. The data of other methods in Table 1 are from Completion3D benchmark. But it needs to be pointed out that even if some retrieval results are inaccurate, the authenticity of the output will not be affected, in other words, reasonable objects different from the ground truth will output. As shown in Fig-

Figure 4. Qualitative completion results on the validation set of Completion3D dataset. Since the guarantee of reasonable structure point clouds in advance, we can find that the results of our method are more authentic.
Figure 5. The three views of structure distribution in each category. The star represents the structure point and the color from deep to shallow corresponds to the value of distribution from high to low. We can find that a small number of points combined with the distribution well represent the structure information.

Table 1. Results of Chamfer Distance ($10^{-4}$) on the test set of Completion3D dataset.

| Methods     | Airplane | Cabinet | Car  | Chair | Lamp  | Couch | Table | Watercraft | Overall |
|-------------|----------|---------|------|-------|-------|-------|-------|------------|---------|
| PCN[38]     | 9.79     | 22.70   | 12.43| 25.14 | 22.72 | 20.26 | 20.27 | 11.73      | 18.22   |
| TopNet[24]  | 7.32     | 18.77   | 12.88| 19.82 | 14.60 | 16.29 | 14.89 | 8.82       | 14.25   |
| GRNet[34]   | **6.13** | **16.90** | **8.27** | **12.23** | **10.22** | **14.93** | **10.08** | **5.86** | **10.64** |
| SRPCN(Ours) | 16.06    | 35.02   | 12.6 | 42.47 | 46.43 | 26.67 | 35.4  | 13.06      | 28.67   |

Our method performs well on most objects. Although we may match to a point cloud that is different from the ground truth, the result is actually quite reasonable for the input, such as the second example of the cabinet, the first example of the chair, and the first example of the watercraft in Figure 4. Compared with other methods that may complete ambiguous shapes, at least the results of our method are more authentic. Overall, the qualitative completion results confirm the necessity of reasonable structures, which contributes to the authenticity of final outputs.

4.3. Distribution Rationality

In this section, we visually show the rationality of the new proposed representation of point clouds: structure distribution. It includes two parts: structure points and distribution. As shown in Figure 5, we give three views of some objects. The color from deep to shallow corresponds to the value of distribution from high to low. We hope that the distribution will become an envelope of the object, which can reduce the instability of structure points and retrain more details of the original point cloud. It can be found that the distributions indeed meet our expectation in Figure 5.

4.4. Generalization Experiments

In this section, we prove that our method is robust to different missing patterns, i.e., it has a strong generalization ability. We conduct our experiments on two new missing patterns in the validation set of the Completion3D dataset: 1. We use missing parts in the original dataset as input. 2. The same as to what in PF-Net[9], i.e., we remove some points within a certain radius from complete point clouds in a viewpoint. For the first pattern, because it is similar to the original incompleteness caused by back-projecting 2.5D depth images into 3D, the differences in the completion results of each method are insignificant. But overall, as shown in (a) of Figure 6, the completed shape of our method is...
much better and more authentic. For the second pattern, since it is quite different from what in the original training set, the existing methods sometimes are not able to do completion, like the completion of the airplane, the cabinet, the car, and the watercraft in (b) of Figure 6.

5. Discussion

The prediction of the missing rate is a difficult problem. For example, when only the back of a chair is left, it is hard to accurately predict due to the various size of the chair surface and legs. The structure points used in our retrieval method might lead to the loss of some details in the input. For example, we may match a relatively large square table when giving the structure points of a round tabletop.

Some recent papers [3, 32] point out that shape completion does not necessarily have paired data in reality, and the irreversible incompleteness may lead to the diversity of results. Regardless of whether the completion results are diverse or not, authenticity must be guaranteed. Existing evaluation metrics are not suitable for evaluating authenticity, which can be studied in the future.

6. Conclusion

We propose a novel point cloud completion method based on structure retrieval. Based on the method of PCN, it adds an intermediate representation of reasonable structure point clouds to make the output more authentic. Considering the diversity of missing patterns, one input may correspond to multiple different reasonable outputs. We design a retrieval method to solve this problem. Specifically, it includes three steps: K-means clustering is adopted to get structure points; each structure point forms an ellipsoidal Gaussian distribution; these distributions are merged to form an overall distribution and KL Divergence is used to guide the retrieval. Our method does well on the situation of reversible incompleteness and can generate more reasonable results for the situation of irreversible incompleteness, while other methods may give ambiguous results. In addition, the generalization experiments also show that our method is more robust to different missing patterns.
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