Unsupervised Learning of Global Registration of Temporal Sequence of Point Clouds

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Abstract—Global registration of point clouds aims to find an optimal alignment of a sequence of 2D or 3D point sets. In this paper, we present a novel method that takes advantage of current deep learning techniques for unsupervised learning of global registration from a temporal sequence of point clouds. Our key novelty is that we introduce a deep Spatio-Temporal REPresentation (STREP) feature, which describes the geometric essence of both temporal and spatial relationship of the sequence of point clouds acquired with sensors in an unknown environment. In contrast to the previous practice that treats each time step (pair-wise registration) individually, our unsupervised model starts with optimizing a sequence of latent STREP feature, which is then decoded to a temporally and spatially continuous sequence of geometric transformations to globally align multiple point clouds. We have evaluated our proposed approach over both simulated 2D and real 3D datasets and the experimental results demonstrate that our method can beat other techniques by taking into account the temporal information in deep feature learning.

Index Terms—Localization, Mapping, Point Cloud, Global Registration

I. INTRODUCTION

Registration on point sets is defined as finding the pointwise correspondence, either rigid or non-rigid transformation, that can optimally transform the source point set to the target one. Global registration of three-dimensional point cloud data is to find spatial geometric transformations between pairs in a sequence of local point cloud observations. All local observations can then be aligned into a single shape and brought into the same global coordinate. The applications of global registration are related to a wide range of industrial applications such as autonomous driving, medical imaging, and large-scale 3D reconstruction [1], [2], [3], [4], [5], [6]. Given practical sensors have a limitation on detection angle or solid obstacles, the acquisition of multiple partially-overlapped point cloud scans from different positions and camera poses is inevitable. A global registration process has to be performed to get an accurate global scene. The key challenge behind this task is the extraction and comparison of geometric information among a series of local scenes.

The classical methods such as Iterative closest point (ICP) [4] and its variants [7], [8] usually approach this problem in an optimization process to iteratively minimize a pre-defined alignment loss between the transformed source point sets and their corresponding target ones to reach the optimal set of parameters of a geometric transformation.

Deep learning models have recently achieved a great success in learning of point registrations [9], [10], [11]. However, there are some challenges for this specific learning task. Firstly, considering that the sequential registration task can be decomposed into a series of pairwise registration tasks, common questions such as how to extract features from 3D irregular non-grid point sets as well as how to explicitly model the geometric relationship between two point sets are still challenging for learning-based methods. Secondly, as a sequential registration problem, errors in registration of one pair may hurt the registration performance of the following pairs. Without an elegant solution to deal with this problem, the registration performance as a whole would be limited. For example, a recent learning-based research [12] suffers from those issues, their deep networks only extract spatial information which undermines the overall performance. Therefore, how to deal with the sequential impact during the optimization process is another main challenging obstacle here.

In this research, we propose an approach to consider both local spatial correlation and longer-term temporal sequential information sharing. Our method works in an unsupervised optimization manner where no extra training data and labels are required and the model focuses on aligning the given observations in series of local point sets that were scanned in different positions in a given scene. As shown in 2, each observation (i.e frame) has a corresponding learnable latent vector \( z \) as a temporal memory component with the purpose of conveying correlation information from its previous observations to the alignment process of other point sets. We
proposed an encoder-free (i.e. no need to define an explicit feature encoding model) learning architecture where the latent vectors are optimized to attached to point sets and then sent into decoders to regress camera poses. During the optimization process, the pre-defined loss can be back-propagated directly to all the latent vectors. Our network design avoids the design of an explicit encoder networks for extracting the latent feature representation vectors for 3D irregular non-grid point cloud. In addition, the new design of combination of the optimization and learning enables further fine-tuning on the unseen data with the guidance of a unsupervised alignment loss for model’s better generalization ability. In contrast, the conventional neural network based models do not have the flexibility in fine-tuning at testing phase. Furthermore, in order to control the depth of temporal memory, each latent vector is further defined as the recurrent weighted sum of previous latent vector controlled by a weight factor w, as shown in the left-hand side of Figure 2. This mechanism enables global temporal information sharing which mitigates the sequential impact of pair-wise error mentioned earlier.

The contributions of our work are three-fold: 1) We introduce an encoder-free temporal-spatial correlation latent vector that enforces a better alignment of sequential observations. Our design does not require a specific encoder model to extract the feature that represents the relationship between a pair of irregular non-grid point clouds. 2) Based on our proposed temporal latent vector, we introduce a latent fusion mechanism for accessing information of past frames in the sequence using our aggregated latent vectors. 3) We achieved a state-of-the-art experiment results on registration of both 2D and 3D datasets in which our model outperforms other approaches on solving scenes with complicated details.

II. RELATED WORKS

A. Pairwise registration

Iterative methods. The development of optimization algorithms to estimate the rigid or non-rigid geometric transformations in an iterative routine has been attracting attention in decades. The Iterative Closest Point (ICP) algorithm [4] is one successful solution for rigid registration. It initializes an estimation of a rigid function and then iteratively chooses corresponding points to refine the transformation. However, the ICP algorithm is reported to be vulnerable to the selection of corresponding points for initial transformation estimation. Go-ICP [7] was further proposed by Yang et al. to leverage BnB scheme for searching the entire 3D motion space to solve the local initialization problem brought by ICP. Zhou et al. proposed Fast Global Registration [8] for registration of partially overlapping 3D surfaces. TPS-RSM algorithm was proposed by Chui and Rangarajan [13] to estimate parameters of non-rigid transformation with a penalization on second-order derivatives. As a classical non-parametric method, coherence point drift (CPD) was proposed by Myronenko et al. [14], which successfully introduced a process of fitting Gaussian mixture likelihood to align the source point set with the target one. With the penalization term on the velocity field, the algorithm enforces the motion of the source point set to be coherent during the registration process. The existing classical algorithms achieved great success for the registration task. Even though all these methods state the registration task as an independent
optimization process for every single pair of source and
target point sets, they greatly inspire us for designing our
learning-based system.

Learning-based methods. In recent years, learning-based
methods achieved great success in many fields of computer
vision [15], [16], [17], [18], [19], [20]. Especially recent works
started a trend of directly learning geometric features from
cloud points (especially 3D points), which motivates us to
approach the point set registration problem using deep neural
networks [21], [22], [17], [15], [16], [23], [24], [25], [26].
PointNetLK [27] is proposed by Aoki et al to leverage the
newly proposed PointNet algorithm for directly extracting
features from Point cloud with the classical Lucas & Kanade
algorithm for rigid registration of 3D point sets. Liu et al.
proposed FlowNet3D [28] to treat 3D point cloud registration
as a motion process between points. Similarly, FlowNet3D
leverages PointNet structure to extract the correlation rela-
tionship between source and target point sets firstly to further
regress on the sense flow. [29][30] proposes removing fused
frames when they are gravelly inconsistent during dealing
with sequence data. Recently Wang et al. proposed Deep
Closest Point [31] which firstly leverages DGCNN structure
to extract the features from point sets and then regress the
desired transformation based on it. All these methods have
achieved outstanding registration performance. Moreover, in
related fields, Balakrishnan et al. [22] proposed a voxelMorph
CNN architecture to learn the registration field to align two
volumetric medical images. For registration of 2D images [32],
[21], an outstanding registration model was proposed by Rocco
et al. [21]. This work mainly focuses on a parametric approach
for 2D image registration. The parameters of both rigid and
non-rigid function (TPS) can be predicted by a CNN-based
structure from learning the correlation relationship between a
pair of source and target 2D images. For learning-based regis-
tration solutions listed above, there is a major challenge about
how to effectively model the relationship between the source
and target object in a learning-based approach. For example,
[21] proposed a correlation tensor between the feature maps
of source and target images. [22] leverages a U-Net based
structure to concatenate features of source and target voxels.
[28] [27] uses PointNet based structure and [31] uses DGCNN
structure to learn the features from a point set for further
registration. However, designing a model to extract the features
from point sets is troublesome and it is even more challenging
to define pair-wise correlation relationship. In this paper, we
propose an encoder-free structure to skip this encoding step. We
initialize a random latent vector without pre-defining a model,
which is to be optimized with the weights of network from
the loss back-propagation process.

B. Global registration

In comparison to pairwise registration, sequential/global
point clouds registration is much less explored. There are
several previous research [33], [34], [35] tried to solve related
tasks. For example, one of them tried to register a sequence of
point clouds one by one into a global frame. This framework
does not change the existing registration result after adding a
new point cloud, which accumulates errors during the process.
A global cost function over a graph of sensor poses was
proposed by [34], [36] for predicting the drifts. The most
recent research [12] is one of the most successful DNN based
approaches for sequential point set registration tasks. It pro-
posed an elegant two-step approach, solving the transformation
matrix and then estimating the global mapping. The whole
optimization process is unsupervised and each camera pose is
regressed from the input local captured point sets.

III. METHODS

We introduce our approach in the following sections. First,
we define the learning-based global registration problem in
section 3.1. In section 3.2, we introduce the spatial-temporal
feature learning module. We also explain the purpose and
mechanism of temporal latent fusion. Section 3.3 illustrates
our loss components. In section 3.4, we detail the model
optimization process.

A. Problem Statement

For a given sequence of k input point sets \( S = \{ S_i \}_{i=1,...,k} \),
where \( S_i \subseteq \mathbb{R}^N \) (N=2 or N=3). We define the learning-based
optimization task for global registration in the following way.
We assume the existence of a parametric function \( g_\phi(S_i) = \phi_i \)
using a neural network structure, where \( \phi_i \) is a set of the
parameters of sensor pose including the location coordinates
and rotation angle \( \phi_i \) has a size of 4/6 depending on 2D/3D
data. \( \theta \) represents all of the parameters in the deep neural
networks. Each input local point set can be then transformed
by the calculated rotation and translation operations defined
by camera pose parameters \(\phi \) according to a global frame.
For a given training dataset \( D \), we can define a sequential
registration loss by comparing transformed neighboring local
input point sets. A global registration loss can be further
defined on the correctness of combined transformed local
frames and the global ground truth. Stochastic gradient descent
can be used for weights \( \theta \)’s optimization towards minimizing
our loss function:

\[
g_{optimal} = \arg\min_\theta,\gamma \mathbb{E}_{\{S_i\} \sim D}[L_\gamma(g_\theta(S_1), \ldots, g_\theta(S_k))],
\]

where \( L_\gamma \) represents a global registration loss. \( L_\gamma \) can be
an unsupervised learnable objective function with weights \( \gamma \).
After training, a trained model is able to perform an inference
to obtain the parameters \( \phi \) based on the optimized optimal
\( \theta_{optimal} \) in the neural network structure.

B. Spatial-Temporal feature learning.

For a sequence of input point sets \( S = \{ S_i \}_{i=1,2,...,k} \), learning
shape’s feature is our first task. A better feature learning
architecture directly has an impact on the performance of cam-
era pose regression for each local shape. Firstly, we discuss the
vanilla network without using a temporal latent component.
As the backbone of the model, a PointNet-based structure
is adopted for points’ features learning. More specifically,
assuming there are n points in each point set, a multi-layer
perceptron (MLP) is utilized for learning the spatial feature. The architecture includes multiple MLP layers with ReLu activation function: \( \{g_i\}_{i=1,2,\ldots,s} \), such that: \( g_i : \mathbb{R}^{v_i} \rightarrow \mathbb{R}^{v_{i+1}} \), where \( v_i \) and \( v_{i+1} \) are the dimension of input layer and output layer. A maxpool layer is used to extract the global spatial feature, defined as \( \mathbf{L}_k^{\text{spatial}} \). Therefore, \( \forall S_k \),

\[
\mathbf{L}_k^{\text{spatial}} = \text{Maxpool}\{g_sg_{s-1}\ldots g_1(\mathbf{x}_i)\}_{\mathbf{x}_i \in S_k} \quad (2)
\]

However, this only extracts the spatial information from each local observation. During our experiments, we discover that only utilizing spatial feature is rather inept at solving frames with complicated details where the effort made in aligning one pair of neighboring observations sometimes impact the alignment of others. Moreover, if a sequence of local point sets has to be broken up into several batches because of the restriction of computational resources, alignment between different batches is prone to failure for the lack of loss constraints. To address this issue, we introduce our solution to take shareable temporal information into account during the feature extraction phase. The following structure aims to learn the temporal-spatial feature, defined as \( \mathbf{L}_k^{\text{spatial-\text{temporal}}} \), for each local input point set.

We initialize a set of trainable latent vectors \( \tilde{Z} = \{\tilde{z}_i\}_{i=1,2,\ldots,k} \). For each \( S_i \), we have \( \tilde{z}_i \sim \mathcal{N}(0,1) \) and \( \tilde{z}_i \in \mathbb{R}^p \). The latent vectors represent a frame-wise shareable sequential memory. By conditioning model loss on the latent vectors in an optimization manner, it allows more concrete information sharing between nearby observations after several iterations. Furthermore, we propose a latent fusion method where the past latent information helps the alignment of the present pair of observations. A memory decay weight \( w \in \mathbb{R} \) is also defined so that past frame information can be utilized for the alignment task at hand. Empirically, it is designed as a learnable vector.

The latent vectors \( \mathbf{Z} \) can be expressed as:

\[
\left\{\begin{array}{l}
\tilde{z}_1 = \tilde{z}_1 \\
\tilde{z}_k = \tilde{z}_k + wz_{k-1} \text{ for } k > 1
\end{array}\right.
\]

By leveraging the same structure of formula (2), with the extra help of the extra temporal feature, the model is guided to view multiple pair-wise tasks in a more global manner that greatly improves the performance. \( \mathbf{L}_k^{\text{spatial-temporal}} \) is defined as:

\[
\mathbf{L}_k^{\text{spatial-temporal}} = \text{Maxpool}\{g_sg_{s-1}\ldots g_1([\mathbf{x}_i; \tilde{z}_k])\}_{\mathbf{x}_i \in S_k} \quad (3)
\]

where the notation \([*,*]\) represents the concatenation of vectors in the same domain. Using the learned feature from previous part as the input, \( \forall L_k \), a encoding network \( f \) composed with MLP and ReLU layers is proposed.

\[
\phi_k = f(L_k) \quad (4)
\]

\( \phi_k \) is the desired camera pose for shape \( S_k \).

After the pose is obtained through optimization, we can transform the local point sets \( S_k \) into a global version \( G_k \). The multiple point set frames can then be stacked together and get the final global scene \( G_m \).

C. Loss Components.

Our loss components are composed of two parts: pair-wise registration loss and global registration loss.

For pair-wise registration, a typical loss component used in researches[9] is variations of squared Euclidean Distance that measures the distance between points in the target (ground truth) observation and points in the transformed source observation. It can be expressed by:

\[
\mathcal{L}(A, B) = \sum_{i=0}^{N} ||a_i - b_i||^2 \quad (5)
\]

The Chamfer Distance is a less strict criterion that measures the average distance between points in one observation and their closest neighbors located in the other point set observation. This criterion describes how similar a pair of observations are without the constraint of knowing the point-wise matching. Since we do not presume the direct point correspondence, it is chosen for further experiment. The Chamfer distance between point sets \( A \) and \( B \) can be defined as:

\[
d_{\text{Chamfer}}(A, B) = \sum_{a \in A} \min_{b \in B} ||a - b||^2 + \sum_{b \in B} \min_{a \in A} ||a - b||^2 \quad (6)
\]

The total registration loss \( \mathcal{L}_{\text{ch}} \) can be defined on point set \( S_i \) with its neighbors \( G_j \) as:

\[
\mathcal{L}_{\text{local}} = \sum_{i=1}^{K} \sum_{j \in N(i)} d(S_i, S_j) \quad (7)
\]

In [12], a global loss component is utilized for their mapping task so that a smoother and more accurate global scene can be generated. In essence, it is a binary cross entropy loss for evaluating global frame accuracy. It estimates the occupancy status of the coordinates in the aligned global frame. For the coordinate of any actual point belong to the ground truth global frame, it should be marked as occupied. Any point between the scanning sensor and any ground truth point should be labeled as unoccupied. A sampling process will be performed to gather coordinates of unoccupied points. For a aligned local observation \( F_j \subset F_m \); \( BE[*] \) as binary cross entropy loss and \( S \) \([*]\) as unoccupied point sampling procedure.

\[
\mathcal{L}_{\text{global}} = \frac{1}{K} \sum_{j=1}^{K} BE[F_j, 1] + BE[S(F_j), 0] \quad (8)
\]

As mentioned, in scenes with complicated yet isometric details, an alignment of pair-wise observations sometimes leads to local optimums with regard to our global registration task. The error it caused will have a sequential impact on the registration of later pairs. Therefore, we consider \( 8 \) as a global registration loss to be experimented further.

Experimented with multiple loss function settings, the summation of a pair-wise Chamfer Loss and a global registration loss described by \( 8 \) yields the best results.
D. Optimization process.

Learning features from point clouds is a challenging task, but it would be more challenging if we need to model the temporal relationship among local patches in a neighborhood. We propose a model-free structure for learning the latent vector and thus skip all the subjective designs as in previous researches. As discussed in section 3.2, we leverage a trainable randomly initialized latent vectors $z$ to realize temporal-spatial feature learning. Instead of extracting the latent vector from inputs using an encoder structure, our latent vector $z$ is initialized from a random vector, which is sampled from a Gaussian Distribution $\mathcal{N}(0, 1)$. The whole training phase is an optimization process on the given observations where both the weights of the decoder and the latent vectors are updated. The model is capable of aligning given observations of a scene in an “unsupervised” optimization manner for this task, we do not use and additional information for our setting in comparison to other methods. It cannot perform any inference operation on new data.

For a given series of observations $D$, we use stochastic gradient descent-based algorithm to optimize not only parameter set $\theta$ as the weights of the model and the parameter set $\gamma$ in mapping loss, but also the set of latent vectors $z = \{z_1, ..., z_n\}$ and the temporal weights $w$ for minimizing the expected loss function:

$$\theta_{optimal}, z_{optimal}, w_{optimal}, \gamma_{optimal} = \arg\min_{\theta, z, w, \gamma} [\mathbb{E}_{(S_1) \sim D} \left(\mathcal{L}_\gamma(g_\theta([S_1, z_1]), ..., g_\theta([S_k, z_k]))\right)],$$  \hspace{1em} (9)

where $\mathcal{L}_\gamma$ represents a pre-defined loss. For the testing cases in dataset $T$, we fix the optimized parameters $\hat{\theta} = \theta_{optimal}$, $\hat{\gamma} = \gamma_{optimal}$ in the network and loss function and the temporal weights $\hat{w} = w_{optimal}$. We need to optimize the following function again:

$$z_{optimal} = \arg\min_{z} [\mathbb{E}_{(S_1) \sim T} \left(\mathcal{L}_\gamma(g_{\hat{\theta}}([S_1, z_1]), ..., g_{\hat{\theta}}([S_k, z_k]))\right)],$$  \hspace{1em} (10)

After this optimization process, the desired transformation is $\phi_i = g_{\hat{\theta}}(S_i, z_{optimal})$ and the transformed source shape $S_i' = \phi_i(S_i)$

IV. EXPERIMENTS

In this section, we implement the following experiments to validate the performance of our proposed model for global point set registration. For a fair comparison, we follow the experiment setting from the state-of-the-art learning-based method [12] on two datasets: a simulated 2D Lidar point cloud dataset and a real 3D dataset called Active Vision Dataset (AVD) [37]. In section 4.1, we test our model’s performance on synthesized 2D simulated point clouds. Experiments on real-world 3D active vision dataset and comparison with state-of-the-art methods are discussed in section 4.2. Moreover, Section 4.3 discusses the ablation study for our proposed method. Our method is implemented with PyTorch 1.0. Adam optimizer is our default optimization algorithm and we set a learning rate of 0.001 for network and 0.0001 for the temporal latent vector $\gamma$.

### A. Experiments on 2D Simulated Point Cloud

**Dataset:** We use 20 trajectories from three global environments that are provided by authors of [12]. More specifically, assuming that we have a large 2D binary image as the global ground truth environment, we need to sample the trajectory as a moving agent to obtain local frames. The trajectory includes a sequence of 2D coordinates which represents the pose location. Between consecutive scans, a rotation from -10 degree to 10 degree and a translation of 0-16 pixels are randomly generated. The sampled 2D translation vector and rotation angle is then our ground truth local camera pose.

**Baseline:** We use [12] as our baseline model since it is the current state-of-the-art result, which has significantly better performance than more traditional methods such as ICP, GoICP, PSO, Direct Optimization on the same task.
Implementation: Hereby we introduced our network architecture that was illustrated in Fig. 2. The temporal latent vectors are firstly attached to each point and sent into the MLP to calculate a camera pose. The series of points sets to be aligned are fed to the model together. This part of the network is composed of: C[64]-C[256]-C[1024]-M[1024]-F[512]-F[128]-F[3]. C[*] represents 1D convolution with kernel size 3. M[*] represents 1D max-pooling layer. F[*] denotes fully-connected layers. Then the poses can be utilized to transform local observations to a global one and further conditioned by the difference in combined local observations that have been aligned and the ground truth. The network for computing global registration is composed of: F[64]-F[256]-F[512]-F[256]-F[128]-F[1]. For our temporal latent vector z, we set its dimension to 16. During the training process, both latent vectors and weights in the network are optimized. We notice that the whole learning process is unsupervised. We set the batch size to 128.

Result: For most 2D cases, during our experiments, we notice that our method and the baseline method can achieve similar results. Since the 2D synthesized cases are simple and only contain horizontal and vertical lines, we pick some failed cases obtained by the baseline method caused by their lack of temporal information sharing for comparison. We do not notice any case that the baseline method succeeds in registration while our model fails. The qualitative results are presented in Figure 3 and for each case, we demonstrate the ATE below the qualitative result. As shown in Figure 3, our method can succeed in the registration of all these five cases when the baseline method fails. The average ATE of our model for such cases is around 10 but the average ATE of the baseline method for these cases is more than 100.

B. Experiments on Active Vision Dataset

Dataset: we further test our method on a real 3D indoor dataset: Active Vision Dataset [37]. This dataset provides indoor scans with RGB-D datasets. AVD dataset has a set of discrete visiting points on a rectangular grid with a fixed width of 300mm. 12 views of images are taken at the position of each point by rotating the camera 30 degrees. We only use depth images and transform them into point clouds. 100 trajectories are randomly collected from the dataset using our custom script. Each trajectory contains 16 frames. During the generation of our custom trajectories and sequential point cloud observations, we emphasize the variety of the indoor scenes where all types of scenes (bedroom, office, living room) are presented and the trajectories are sampled evenly on each scene. We will provide our script and generated trajectories online.
Baseline: We do not use scores reported in any previous research since they did not publish their generated trajectories or any relative generation code. Both models are evaluated on our own generated trajectories for a fair comparison. The results are thus different from the original paper.

Implementation: For our temporal latent vectors \( z \), we increase its dimension to 24 in hope of caring more information. During the training process, both latent vectors and weights in the network are optimized. We decrease the batch size to 8 for the great memory consumption caused by a large 3D scene.

Result: The selected qualitative results are presented in Figure 4 and the quantitative results are presented in Figure 5. For quantitative result shown in Figure 5, we notice that both our average registration performance and the lower bound for the 100 trajectories are lower than the baseline. Bar charts are provided to illustrate that the comparison in Figure 4 is not handpicked. Our method is better at dealing with frames with complicated details as shown in Figure 4. The RGB images are captured at the location marked by a small black cross as the viewport. In Row A, we notice that the baseline model mistakenly registers the door area and the left wall in comparison to our result in the first case. In the second case, due to the complexity of the furniture’s arrangement in the right lower corner, the baseline model failed to align them correctly while ours achieves much better performance. In Row B, both our model and the baseline model failed to perfectly align each local frame. Our model failed to align the window area but the mismatching area achieved by the baseline model is much broader than ours.

C. Ablation study

Dataset: We sample extra trajectories of 20 from AVD dataset as explained in previous section.

Baseline: For verifying the advantages of temporal latent vector space. We remove the links between latent vectors for each scene but we still concatenate a latent vector \( z \) on each point of the input shape as our baseline model. We compare it with ours to further verify our temporal structure’s efficiency.

Implementation: For the baseline model, there is no additional initialized weight to link neighbor latent vectors. We further verify that the temporal setting of our model mainly contributes to the final result instead of purely searching for the latent vector space.

Result: One selected qualitative result is presented in Figure 6 and the quantitative statistics are presented in Figure 7. As shown in Figure 6, we can clearly see the baseline model failed to register the case but our method can achieve much better performance. For the quantitative result presented in Figure 7, our model achieves better results than the baseline model for both metrics, which further confirms the contributions of our temporal settings with regard to the performance enhancement.

V. Conclusion and Discussion

A Spatial-Temporal latent learning mechanism is introduced for sequential point set registration problems. It provides three unique advantages for global registration: 1) the features that represent irregular non-grid point clouds can be learned without the design of specific 3D feature encoders, 2) it improves global registration by considering the spatial smoothness and temporal consistency in point sets, and 3) it enhances the...
learning of global registration for point clouds acquired in unseen scenes which empowers our unsupervised optimization framework. Through a great number of experiments on 2D/3D point cloud data, our method is proved to be more effective when compared to the current state-of-the-art method.

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