Point Cloud Registration Network Based on an Improved Edge Convolution

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Abstract: To address the limited capability of edge convolution in extracting neighborhood features under varying sampling densities, this paper proposes a point cloud registration network based on an improved edge convolution. First, a Progressive Interval Sampling (PIS) strategy is designed to enhance the spatial coverage of neighborhoods. Then, a Coordinated Attention-Pooling Module (CAPM) is incorporated into the PISEdgeConv to improve the edge feature extraction ability. Finally, a feature-weighted fusion module is employed to mine feature information extracted from multiple neighborhood scales. The network achieves root mean square errors (RMSE) of 0.893275 for rotation matrices and 0.002647 for translation vectors on the ModelNet40 dataset, demonstrating the effectiveness of the proposed method.

Keywords: deep learning; point cloud registration; pis sampling; feature extraction

1. INTRODUCTION

With the rapid development of 3D scanning devices and sensor technologies, the acquisition of 3D point cloud data has become more convenient and efficient. Point cloud registration, as a core task in point cloud processing, aims to align point clouds from different sources, viewpoints, or time instances into a unified coordinate system, enabling multi-source information fusion and complete model reconstruction. This process plays a critical role in applications such as 3D reconstruction[1], robot localization and navigation[2], and cultural heritage preservation[3].

Traditional point cloud registration methods have dominated early research in 3D data processing. Among them, the Iterative Closest Point (ICP) algorithm[4] optimizes rigid transformations by iteratively minimizing the mean squared error between source and target point clouds in Euclidean space. However, ICP is highly sensitive to initial poses and prone to convergence at local minima. To address these limitations, various improvements have been proposed, such as Go-ICP[5], which employs a branch-and-bound strategy to seek global optima. In terms of feature extraction, Rusu et al. initially proposed the Point Feature Histogram (PFH)[6] to describe the spatial geometric relationships between points and their neighborhoods. Subsequently, the Fast Point Feature Histogram (FPFH)[7] was introduced to significantly reduce computational cost by simplifying the feature relationship calculations.

In recent years, deep learning has brought new opportunities to point cloud registration. PointNetLK[8] first combined global features extracted by PointNet with the traditional Lucas-Kanade (LK) alignment algorithm, initiating research on learning-based registration models. Following this, Deep Closest Point (DCP)[9] utilized DGCNN to capture local geometric features and employed Transformer modules to achieve global soft matching between source and target point clouds. MFGNet[10] leveraged both shape features and spatial coordinates to guide correspondence search between point clouds. However, these networks face certain limitations when handling point clouds with uneven density and noise.

To tackle these challenges, this paper proposes a point cloud registration network based on an improved k-nearest neighbor (kNN) graph construction, which effectively enhances registration accuracy and robustness under varying sampling densities. Specifically, a Progressive Interval Sampling (PIS) module is designed to improve spatial neighborhood coverage, addressing the insufficient neighborhood construction problem of traditional kNN methods in density-varying scenarios and thereby stabilizing feature extraction. Additionally, a Coordinated Attention-Pooling Module (CAPM) is integrated into the PISEdgeConv to strengthen the model's representation of key structural features, enhancing its ability to perceive edges and geometric details. Finally, a feature fusion module is developed to achieve weighted integration of multi-scale features, establishing effective connections between local and global information and further boosting registration performance.

2. ALYZING NETWORK MODELS

The network consists of three key components: the PIS module, which enhances the spatial coverage of neighborhood construction and improves the representation capability of local graph structures for geometric features; the PISEdgeConv module, augmented with the CAPM to strengthen edge feature extraction; and a feature-weighted fusion module that mines feature information extracted from different neighborhood scales. The overall network architecture is illustrated in Figure 1.
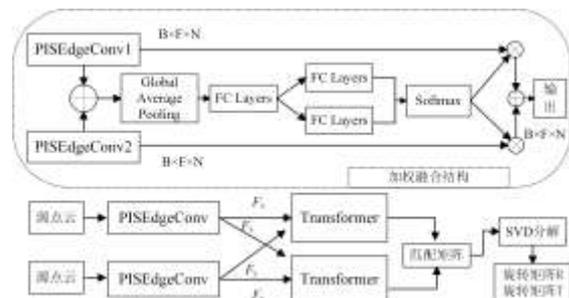

Figure. 1 The overall structure of the network

2.1 PIS diagram construction

EdgeConv[11] constructs edge graphs using the k-nearest neighbor (KNN) algorithm to enhance the network's ability to extract local features. However, it suffers from a limitation: when the sampling density is high, KNN may fail to adequately cover the object since all kkk nearest neighbors might be very close to each other and fall within the same local subregion of the object. For instance, assuming k=5, the traditional KNN method selects the five nearest points {q1,q2,q3,q4,q5}, which are clustered in a local neighborhood, hindering subsequent feature learning. To improve spatial coverage during neighborhood construction, this paper proposes a Progressive Interval Sampling (PIS) strategy.

Candidate Pool Expansion: Preselect the first s×k nearest neighbors from the original point cloud (where sss is the interval coefficient) to ensure a broader spatial coverage.

Uniform Interval Sampling: Select k points from the candidate pool at fixed intervals s, forming the neighborhood set {q1,q1+s,q1+2s,...,q1+(k−1)s}.

2.2 PISEdgeConv multi-scale feature extraction

The source and target point clouds are first separately fed into the PISEdgeConv layers, whose architecture is illustrated in Figure 2. Initially, the point clouds establish adjacency relations through the PIS module, forming multiple local clustered feature graphs. Subsequently, the point features are sequentially processed by EdgeConv modules to extract multi-scale geometric features with dimensions of 64, 64, 128, and 256, respectively. These four feature maps then pass through the CAPM modules to further enhance feature representation and emphasize critical structural information. The processed feature maps are concatenated along the channel dimension to form a 512-dimensional fused feature map. This fused representation not only encodes global shape semantics but also preserves local neighborhood geometric structures, providing a stable and rich representation for subsequent point cloud alignment.
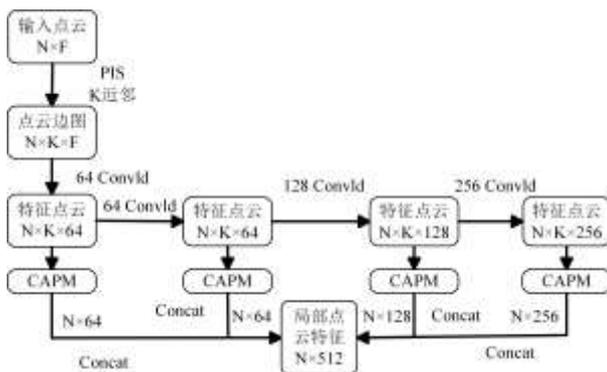

Figure. 2 PISEdgeConv

2.3 CAPM Module

The CAPM is designed to enhance the feature representation capability by capturing spatial and channel-wise interdependencies within the point cloud features. It employs a coordinated attention mechanism that simultaneously models cross-dimensional interactions, enabling the network to focus on key structural and geometric details. The module integrates attention pooling operations that aggregate informative features while suppressing irrelevant ones,

thereby improving the discriminative power of edge features extracted by PISEdgeConv.

3. EXPERIMENTAL RESULTS

3.1 Experimental Setup and Evaluation Metrics

The experiments were conducted in an environment comprising Python 3.8, PyTorch 1.10.1, an NVIDIA RTX 3090 GPU, and the Ubuntu 20.04 operating system. The proposed network was evaluated on the ModelNet40 dataset for unknown shape point cloud registration. ModelNet40 is a comprehensive dataset containing 12,311 CAD models from 40 different categories. In this study, 9,843 models were randomly selected as the training set, and 2,468 models as the test set.

During training, a point cloud X was randomly sampled from the training set, and a target point cloud Y was generated by applying rigid transformations. Specifically, rotations and translations were applied along the X, Y, and Z axes. The rotation angles were uniformly sampled within the range [0∘,45∘], and translation distances within [−0.5,0.5].

The network was optimized using the Adam optimizer with an initial learning rate of 0.01. The Progressive Interval Sampling (PIS) intervals were set to 1 and 2, with k=1. The model was trained for a total of 200 epochs with a batch size of 32.

For the evaluation of point cloud registration, two metrics were employed: Root Mean Square Error (RMSE) and Mean Absolute Error (MAE).

3.2 Experimental Results

Table 1 presents a performance comparison between the proposed method and several classical point cloud registration algorithms under unknown shape conditions. The experimental results demonstrate that our method achieves the best performance across all metrics, with a rotation RMSE of only 0.893 and a translation RMSE of 0.0026, significantly outperforming mainstream approaches such as DCP, PointNetLK, and GSDCP.

The key to this performance improvement lies in the graph construction mechanism based on the Progressive Interval Sampling (PIS) strategy, which effectively alleviates the spatial coverage deficiency of traditional k-NN methods on non-uniformly sampled point clouds, thereby capturing local geometric information more comprehensively. Moreover, the integration of the multi-scale feature extraction module PISEdgeConv with the CAPM spatial structure modeling module enhances the representation capability of structural features. Finally, global feature fusion is accomplished through a Transformer, enabling high-precision registration in scenarios with unknown target shapes.

Table 1. Registration results of different methods on the ModelNet40 dataset

Moudle	RMSE(R)	MAE(R)	RMSE(t)	MAE(t)
ICP[4]	29.914 835	23.544 817	0.290 935	0.248 755
PointNetLK[5]	15.095 374	4.225 304	0.022 065	0.005 404
DCP[9]	1.826 415	1.580 438	0.004 737	0.003 235
GSDCP[12]	1.394 505	0.981 491	0.010 864	0.001 986
Our	**0.893 275**	**0.685 248**	**0.002 647**	**0.001 853**

3.3 Ablation experimental analysis

In this section, the ablation experiment of PISDCP network is carried out, the influence of each module of the network on the registration performance is studied, and the performance is tested on the ModelNet40 dataset, and the performance comparison analysis is carried out by eliminating each key module one by one, and its influence on the final registration accuracy is evaluated, and the ablation experiment results are shown in Table 2. The ablation experimental results fully verify the effectiveness and necessity of each module in the registration task.

Table 2. Results of ablation experiments

Remove Moudle	RMSE(R)	MAE(R)	RMSE(t)	MAE(t)
PIS	1.068263	0.813574	0.003605	0.002475
CAPM	1.031768	0.772903	0.004358	0.003147
Feature fusion	1.005390	0.739461	0.003321	0.002287
Full model	**0.893 275**	**0.685 248**	**0.002 647**	**0.001 853**

4. Conclusion

This paper proposes a point cloud registration network based on improved edge convolution, which aims to improve the accuracy and robustness of point cloud registration tasks. The network as a whole is composed of a progressive interval sampling module (PIS), a coordinate attention mechanism module (CAPM) and a feature fusion module. The PIS module effectively alleviates the problem of insufficient neighborhood coverage in the traditional kNN composition in the scene of uneven density, thereby enhancing the stability of feature extraction. The CAPM module adds an improved coordinate attention mechanism to improve the model's ability to express key structural features. The feature fusion module realizes the effective fusion of local and global information through the weighted integration of multi-scale features. In the clean and noisy ModelNet40 point cloud registration experiment, the proposed method is systematically validated and compared with the mainstream registration algorithms. Experimental results show that the proposed method is better than the existing algorithms in terms of registration accuracy and robbery, showing good application potential and research value. Future work will further explore the adaptability and generalization ability of the method in complex outdoor environments to promote its wide application in real scenarios.

5. REFERENCES

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