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Biography

I'm a master student at New York University and a research assistant in NYU Multimedia and Visual Computing Lab, advised by Professor Yi Fang. I am broadly interested in 3D Computer Vision, Pattern Recognition and Deep Learning.

Research Project: 3D Meta Registration: Learning to Learn Registration of 3D Point Clouds

1 Description

Deep learning-based point cloud registration models are often generalized from extensive training over a large volume of data to learn the ability to predict the desired geometric transformation to register 3D point clouds. In this paper, we propose a meta-learning based 3D registration model, named 3D Meta-Registration, that is capable of rapidly adapting and well generalizing to new 3D registration tasks for unseen 3D point clouds. Our 3D Meta-Registration gains a competitive advantage by training over a variety of 3D registration tasks, which leads to an optimized model for the best performance on the distribution of registration tasks including potentially unseen tasks. Specifically, the proposed 3D Meta-Registration model consists of two modules: 3D registration learner and 3D registration meta-learner. During the training, the 3D registration learner is trained to complete a specific registration task aiming to determine the desired geometric transformation that aligns the source point cloud with the target one. In the meantime, the 3D registration meta-learner is trained to provide the optimal parameters to update the 3D registration learner. After training, the 3D registration meta-learner, which is learned with the optimized coverage of distribution of 3D registration tasks, is able to dynamically update 3D registration learners with desired parameters to rapidly adapt to new registration tasks. We have evaluated the proposed 3D Meta-Registration model on two widely used datasets: FlyingThings3D and KITTI. Experimental results demonstrate that 3D Meta-Registration achieves superior performance over other previous techniques (e.g. FlowNet3D).

2 Method

This paper proposes a novel meta-learning-based approach to our research community for point cloud registrations. Previous learning-based methods treat the "registration problem" as a single task for any pair of source and target point clouds. In this way, the pre-trained "registration learner" is good at handling the

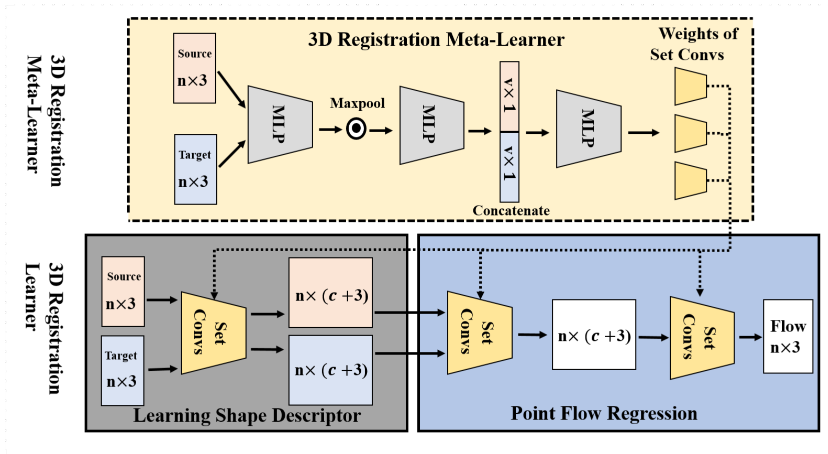

Figure 1: Main Pipeline. Our model includes two networks: Registration Learner and Registration Meta-Learner. The registration learner includes a module of learning shape descriptor and points flow regression. The weights in set convolution are predicted from the registration meta-learner.

pairs which have similar task distribution to the training pairs. However, in practice, the distribution of registration tasks can be different. Therefore, in comparison to previous learning-based methods, we propose a "meta-learner" to treat the registration of each pair of source and target point clouds as an individual registration task. Instead of learning the distribution over data, our meta-learner enables us to learn over the distribution of tasks. After training, the 3D registration "meta-learner" is capable of predicting the optimal registration learner to register each pair of source and target point clouds as an independent task. As displayed in Figure.1, our model includes two modules: 3D registration learner and 3D registration meta-learner. The 3D registration learner includes a module of learning shape descriptor and point flow regression. Other than previous methods, the weights of all the set convolutions in the 3D registration learner are predicted from the 3D registration meta-learner. Therefore, for a given pair of source and target point clouds, the registration learner's structure is updated by the registration meta-learner according to the new registration task.

3 Results

In this section, we test the performance of our model for 3D point cloud registration on the FlyingThings3D and the KITTI scene flow dataset. The FlyingThings3D dataset is an open-source collection, which consists of more than 39000 stereo RGB images with disparity and optical flow ground truth. By following the process procedures provided by FlowNet3D, we generate 3D point

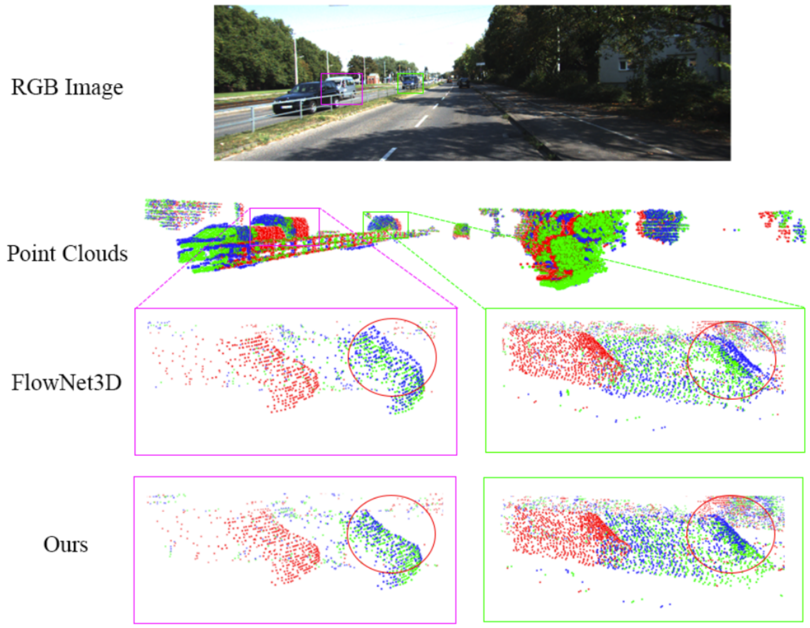

Figure 2: Qualitative results of point cloud registration on the KITTI dataset. Red points represent the source point cloud. Green points represent the target point cloud. Blue points represent the transformed source point cloud.

clouds and registration ground truth using the disparity map and optical map rather than using RGB images. Another dataset used in this paper is the KITTI scene flow dataset, which consists of 200 training scenes and 200 test scenes. Following previous work FlowNet3D, we use the pre-processed point clouds data which is generated using the original disparity map and ground truth flow. As shown in Table 1, our method achieves lower EPE (0.1453) compared to FlowNet3D (0.1694) and ICP (0.5019). As to the registration estimation accuracy (ACC), our method achieves significantly better result with 29.27% for the threshold 0.05 and 62.21% for the threshold 0.1, which is better than 26.67% for the threshold 0.05 and 59.65% for the threshold 0.1 achieved by FlowNet3D. Moreover, for the qualitative results shown in Figure 2, we can clearly see that our registration result for the two cars on the left side is clearly better since all the blue points are almost overlapped with the green points. In comparison, the result of FlowNet3D shows a gap between blue and green points.

Table 1: Results on the FlyingThings3D test dataset.

Method	EPE	ACC (0.05)	ACC (0.1)
ICP	0.5019	7.62%	7.62%
FlowNet3D (EM)	0.5807	2.64%	12.21%
FlowNet3D (LM)	0.7876	0.27%	1.83%
FlowNet3D	0.1694	25.37%	57.85%
Ours	**0.1453**	**29.27%**	**62.21%**