DCPCR: Deep Compressed Point Cloud Registration in Large-Scale Outdoor Environments

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1 Introduction

Pointcloud registration is a common technique that aims to match multiple pointclouds captured at different time steps in order to perform map matching. However, pointcloud registration mainly causes two problems:

- A downgrade in term of matching performance especially when
  1. Pointcloud is noisy (presence of noisy objects in the scene, Sensor with high precision error ...)
  2. Huge gap between the initial guessed position of the pointclouds
- A huge computation cost due to the high number of data points per scan (thousands of points per scan).

1.1 Background

For pointcloud registration, two main methods are used:

1.1.1 Local Registration

The most common approach for aligning two point clouds is ICP [1] with its variants (Point-to-Point, Point-to-Plane...) (Figure 1). Here, the main challenge is to find the correct correspondences. Looking only at spatially close points often fails when the initial guess is too far from the correct transformation. Moreover, outdoor environments often change (moving objects, ...), and therefore assuming to have a lot of one-to-one correspondences does not necessarily hold.

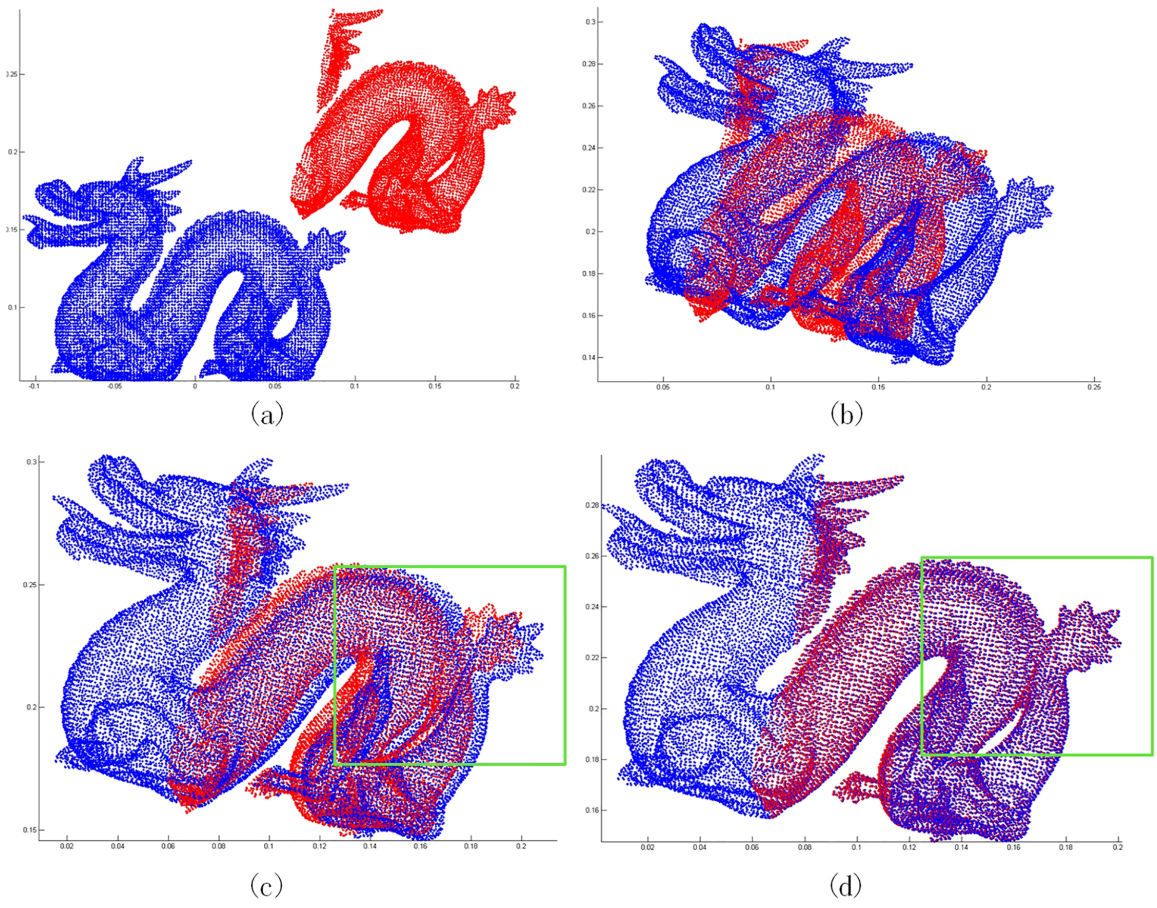

Figure 1: Registration results on a point cloud for different ICP variants

1.1.2 Global Registration

Global registration methods try to estimate the pose between the point clouds even when the initial guess is quite far away from the correct transformation. RANSAC (RANdom SAmple Consensus) [2] is one of these methods that provides the opportunity to deal with large transformations as well as outliers by sampling correspondences combined with a large number of repetitions. The biggest disadvantage of those methods is typically the high computation time.

2 DCPCR

2.1 Feature-Based Point Cloud Registration

For the alignment of two point clouds, DCPCR [3] follows the classical paradigm of first finding point correspondences, which are then used to estimate the relative transformation between a source and a target point cloud. While in the classical ICP, correspondences are determined via geometric neighborhood, DCPCR follows a feature-based approach. The transformation consisting of rotation and translation is estimated using a neural network described in figure 2.

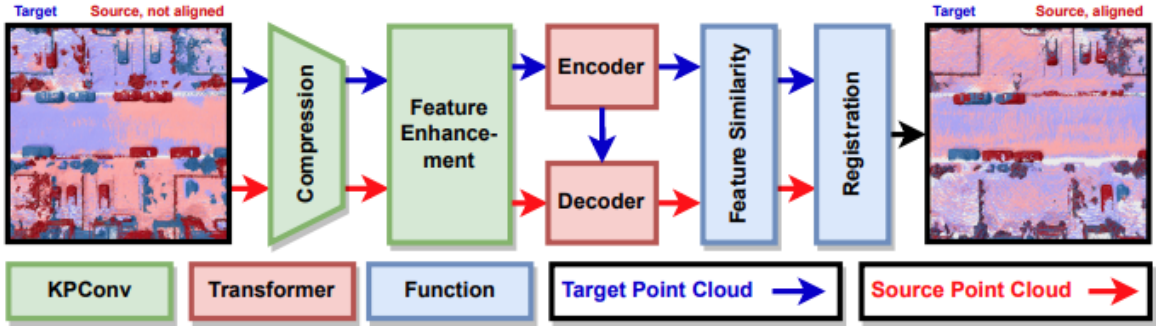

Figure 2: Network architecture

This network architecture consists of three parts, namely a compression encoder for memory and compute efficiency, a convolutional block to increase the receptive field, and a transformer head for global feature aggregation. The network can work on raw or compressed pointcloud. In DCPCR work, the compression of the pointcloud was done using a neural network [4] which substantially reduces the number of points and provides locally-aware features.

1. **Compression Network** PointNet [5] is used to transform the compressed point representation to a localization-specific feature space, which is better suited for matching than for reconstruction.

2. **Feature Enhancement Network** Since the features from the compression network contain only local information, KPConv , which is a sparse convolution, was used to aggregate the information from the points within a radius r.

3. **Transformer** Transformers are used for the multihead self-attention mechanism for global feature aggregation.

2.2 Results

We train DCPCR network on Apollo Dataset for 30 epochs on RTX 3060 GPU. We test the performance of the neural network on the test set and we compare it a to a pretrained model trained for 1000 epochs.

Test metric (mean)	dr_degrees	dt_meters
Our model	2.2	0.38
Pretrained model	**0.36**	**0.12**

Table 1: Metric comparison: **dr_degrees** is the angle between ground truth and prediction in degrees. **dt_meters** is the euclidean distance between the ground truth and the estimated translation vectors.

Since we would like to test the model's performance on newly seen dataset, we also report inference results on our local data. We split inference into 3 main categories.

1. **Easy tests**: During which we test our model's performance on the most non complex cases. One of these tests is introducing the same source and target input pointcloud to the model. We do not apply any rotation, translation or noise. For these experiments, the models performs perfectly by predicting the identity matrix as the estimated pose. The figure 3 below shows how the predicted position (blue) and the target/ground truth position (in green) are perfectly aligned.

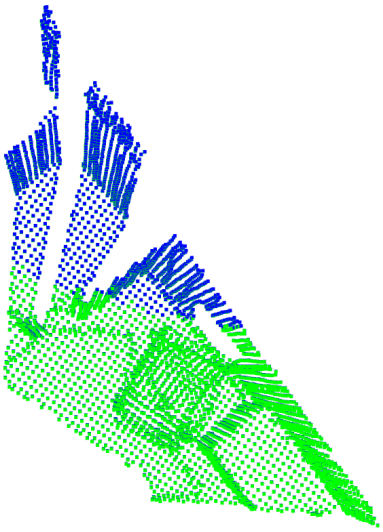

Figure 3: Registration: Identity matrix

2. **Medium tests** During which we test our model's performance on slightly challenging cases. We introduce some modifications to the source pointcloud including rotation, translation, random noise, interpolation of points, subsampling, ... We than try to match it with the unmodified target pointcloud. For these kind of experiments, we notice that, for small errors: translation offset $\widetilde{=}$[-1, 1], rotation $\widetilde{=}$[-35°, 35°], and few hundreds of interpolated or jittered points, the performance of the model is still high and precise enough. The figure 4 below shows how for slightly modified source pointcloud (green), the predicted position (blue) and the target/ground truth position (in red) are well aligned.

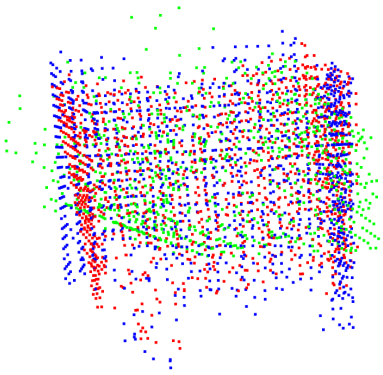

Figure 4: Registration: Low offset between source and target

3. **Hard tests**: During which we test our model's performance on challenging cases. We introduce many modifications to the source pointcloud at the same time including rotation, translation, random noise, interpolation of points, subsampling, ... We than try to match it with the unmodified target pointcloud. For these kind of experiments, we notice that, for big errors: translation offset $\|dt\| \geq 1, rotation \|rt\| \geq 35°$, and few hundreds of interpolated or jittered points, the performance of the model is very low. The figure 5 below shows how for highly modified source pointcloud (red), the predicted position (blue) and the target/ground truth position (green) are not well aligned.

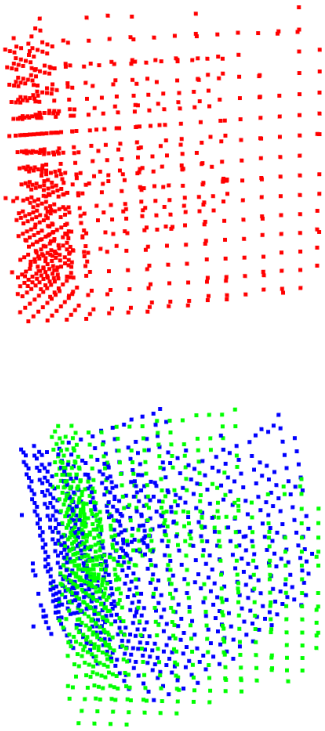

Figure 5: Registration: High offset between source and target

2.3 Generalized-ICP

Since the model's performance is highly effected by how challenging the data is, we follow DCPCR authors and we introduce Generalized-ICP (GICP) [6]. GICP is used on top of our network. It takes as input the estimated pose predicted by DCPCR. This input will be the initial guess for GICP algorithm making it more accurate. We confirm that the best results can only be achieved

when enabling all parts of the network and finetuning the results using GICP. The figure below shows the estimated position with and without enabling GICP.

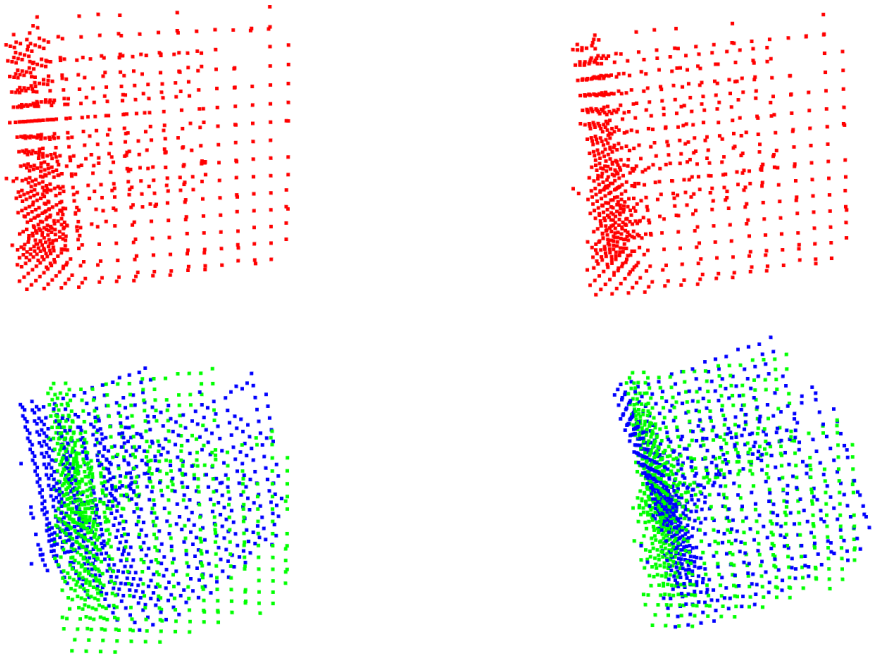

Figure 6: An example of the network estimated pose with (right) and without (left) GICP

3 Local Experiments

To better understand the potential of this method, we applied the algorithm in our current project for building classification. The image below 7 represent a map describing the position and status (ground truth category) of each building that we are interested in. Different colors represent different categories.

Figure 7: Ground truth: Building categories

The aim of this task is to be able to automatically classify a set of {source, target} building pointclouds into one of these categories:

1. **Modified** (blue)
2. **Reconstructed** (green)
3. **Newly constructed** (yellow)
4. **Destructed** (red)

3.1 Data

Our dataset is composed of source and target pointclouds

1. **Source:** The source pointcloud are scans captured via LiDAR of different buildings in Sendai city. These scans have different sparsities, number of points, view angles of the buildings, ... We also note that the source pointcloud captures only the visible portion of the scanned building. Our goal is to use that portion and match it with the target. Source can be found under **PointCloud** folder in the structure below.
2. **target:** The target pointcloud is generated for our LOD2 database. Each LOD2 building is converted into a single dense pointcloud. Unlike the source scan, our LOD2 to pointcloud transformation will cover the whole building. Target can be found under **LOD2** folder in the structure below.

```
Datafolder
├── LOD2
│   ├── BLUE
│   │   ├── buildingID1.las
│   │   └── ...
│   ├── GREEN
│   │   ├── buildingID20.las
│   │   └── ...
│   └── RED
│       ├── buildingID40.las
│       └── ...
└── Pointcloud
    ├── BLUE
    │   ├── buildingID1.las
    │   └── ...
    ├── GREEN
    │   ├── buildingID20.las
    │   └── ...
    ├── RED
    │   ├── buildingID40.las
    │   └── ...
    └── YELLOW
        ├── buildingID60.las
        └── ...
```

3.2 Algorithm

The algorithm works as below:

1. The scipts takes as input a set of source (scans) and target LOD2 pointclouds.
2. For each Source, Target we perform a preprocessing phase which includes: normalization and subsampling using voxelization.
3. For each Source, Target we perform parallarily GICP and DCPCR + GICP combined together.
4. For each technique mentioned in step 3, we allign the source to target and we calculate the similarity. The similarity is the ratio (%) of points from the source that are within a threshold euclidean distance from points from the target pointcloud.
5. We get the transformation matrix that results in higher similarity between the two techniques in step 3
6. We classify the Source, Target set accordingly:
   (a) If the LOD2 doesn't exist = Category 3: Building is newly constructed
   (b) If the source scan is empty (or too sparse) = Category 4: Building destructed
   (c) If similarity ratio between source and target is above 50% = Category 1: Building modified
   (d) If similarity ratio between source and target is below 50% = Category 2: Building reconstructed

Algorithm 1 Building classification

```
PCD_path ← path_to_PointCloud_folder
LOD2_path ← path_to_LOD2_folder
for File in PCD_path do
    if FileID not in LOD2_path then                ▷ If BuildingID doen't exist in LOD2
        Return Newly constructed
    end if
    PCD ← Read_source(PCD_path + File)             ▷ Read pointcloud source scan
    PCD ← Preprocessing(PCD)                       ▷ Normalize and subsample using voxel grids
    if length(PCD) < threshold then                ▷ if scan is empty (or too sparse)
        Return Destructed
    end if
    LOD2 ← Read_target(LOD2_path + File)           ▷ Read LOD2 target pointcloud
    LOD2 ← Preprocessing(LOD2)                     ▷ Normalize and subsample using voxel grids
    GICP_align(PCD, LOD2)                          ▷ Align using GICP
    S1 ← GICP_similarity(PCD, LOD2)                ▷ Get the number of similar points L2 distance
    DCPCR_GICP_align(PCD, LOD2)                    ▷ Align using DCPCR and GICP
    S2 ← DCPCR_GICP_similarity(PCD, LOD2)          ▷ Get the number of similar points L2
    Sim_ratio ← Max(S1, S2)                        ▷ Get ratio of Similar points/total number of points
    if Sim_ratio > 50% then                        ▷ If more than 50% of the scan is similar to LOD2
        Return Modified
    else                                           ▷ If less than 50% of the scan is similar to LOD2
        Return Reconstructed
    end if
end for
```

3.3 Results

The table below summarizes our results on Sendai data for building classification:

Ground truth/Prediction	Modified	Reconstructed	Destructed	Newly constructed	Accuracy
Modified (16 scan)	11	4	1	0	68.75%
Reconstructed (39 scan)	0	36	3	0	92.3%
Destructed (65 scan)	4	54	7	0	10.8%
Newly constructed (30 scan)	0	0	0	30	100%

3.3.1 Results discussion

We notice that:

1. For high quality scans, our algorithm's performance is high 8.
2. For modified and reconstructed buildings, we notice that the quality of the pointcloud may be poor for a number of scans. These scans may be empty which explains the prediction of destructed category instead.
3. It is very hard to differentiate between fully reconstructed and under reconstruction buildings 9.
4. For destructed building, some constructions have already started when the scans were captured. For our algorithm, these constructions are enough to deceive the model to predict a reconstructed category instead.
5. Our DCPCR currently works well for predicting initial pose guess. It can work better if we can include r,g,b colors for each point. (This requires also LOD2 to have colors as well)
6. Currently GICP + DCPCR gives the best pose estimation. However, We need to explore what other ICP methods we can use in the future.

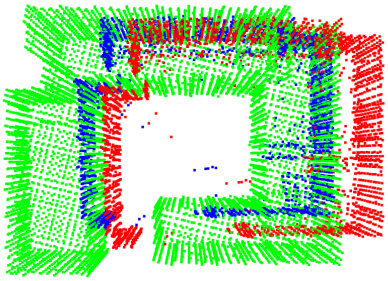

Figure 8: Data example: High quality scan

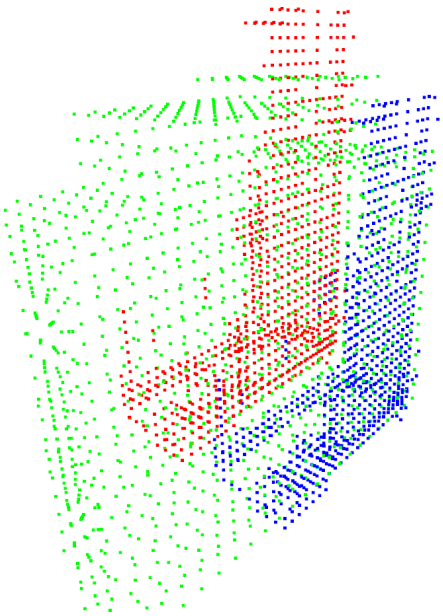

Figure 9: Data example: Destructed building (Under construction phase)

3.4 Visualizations

The user can easily turn on and off open3d visualization to easily track the alignment performance. Below 10 some of our results for modified, reconstructed and destructed buildings:

4 Conclusion

The performance of the model depends on how challenging the data is. It also depends on its quality. With the current pretrained model on Apollo-Southbay and finetuned with GICP, we can achieve good results. However, to improve the overall performance we can:

1. Train the DCPCR neural network on our private data instead of open source Apollo
2. Conduct research on other variants of ICP algorithm
3. Improve preprocessing phase
4. Rely on feature similarity instead of point to point similarities.
   (a) Point Feature Histograms (PFH) descriptors
   (b) Fast Point Feature Histograms (FPFH) descriptors
   (c) ...

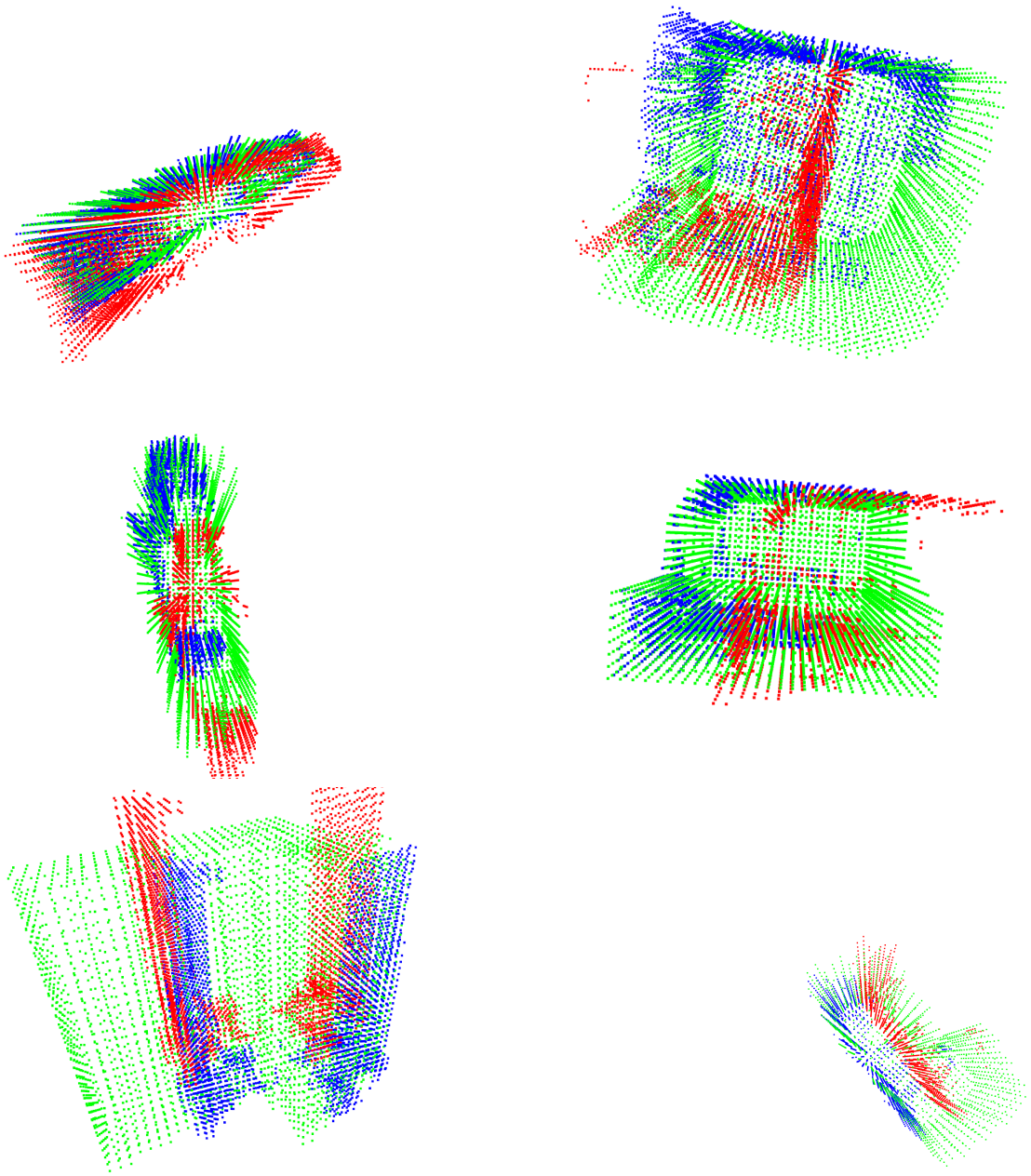

Figure 10: Other results. Green: target LOD2. Red: source scan. Blue: aligned source

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