# Appendix A Graph Neural Network

In this section, we describe the details of the graph neural network (GNN) we use in our IDAM+GNN model.

Suppose we have a point cloud $\mathcal{P}$. Let $\mathcal{N}_i$ denote the set of indices of $K$ points closest to the point $\mathbf{p}_i$ in $\mathcal{P}$. In the $n$th layer of GNN, let $\mathbf{u}_i^{(n)}$ be the feature vector for $\mathbf{p}_i$. Then the features for the next layer is computed as

$$\mathbf{u}_i^{(n+1)} = f(\bigoplus_{j \in \mathcal{N}_i} g(\mathbf{u}_i^{(n)} - \mathbf{u}_j^{(n)})) \tag{1}$$

where $f$ and $g$ are multi-layer perceptrons (MLP), $\bigoplus$ is the element-wise max operation. We use a 2-hidden-layer MLP with output dimensions (64, 64) for $g$, and a single-layer MLP with output dimension 64 for $f$. Batch normalization [3] and ReLU [2] are used in each layer in the MLPs.

The initial features $\mathbf{u}_i^{(0)}$ are just the 3D coordinates of the points in $\mathcal{P}$. We stack 5 layers of Eq. 1 to hierarchically extract high-level features. The dimension of the output features is 64.

# Appendix B Visualization

In this section, we show some visualization results. Appendix B.1 shows the visualization of IDAM+GNN registering two partially overlapping point clouds in ModelNet40. Appendix B.2 shows the results of the same model on the Stanford 3D Scan dataset [1]. Appendix B.3 shows the visualization of the preserved points by hard point elimination. Appendix B.4 visualizes how the hybrid point elimination works.

## Appendix B.1 ModelNet40

In this section, We show the visualization of IDAM+GNN registering two partially overlapping point clouds in ModelNet40. The model is trained on the whole training set of ModelNet40 with Gaussian noise of standard deviation 0.01. The visualization shows the results of the model on the shapes in the test set of ModelNet40. This corresponds to the “Gaussian Noise” experiment in the paper. The results are shown in Fig. 1.

## Appendix B.2 Stanford 3D Scan

We also test the same model (Appendix B.1) on the Stanford 3D Scan dataset [1]. We use the same method described in the paper to generate partially overlapping point clouds. Note that we only train on the ModelNet40 dataset. This shows the generalization ability of our model. The results are shown in Fig. 2.

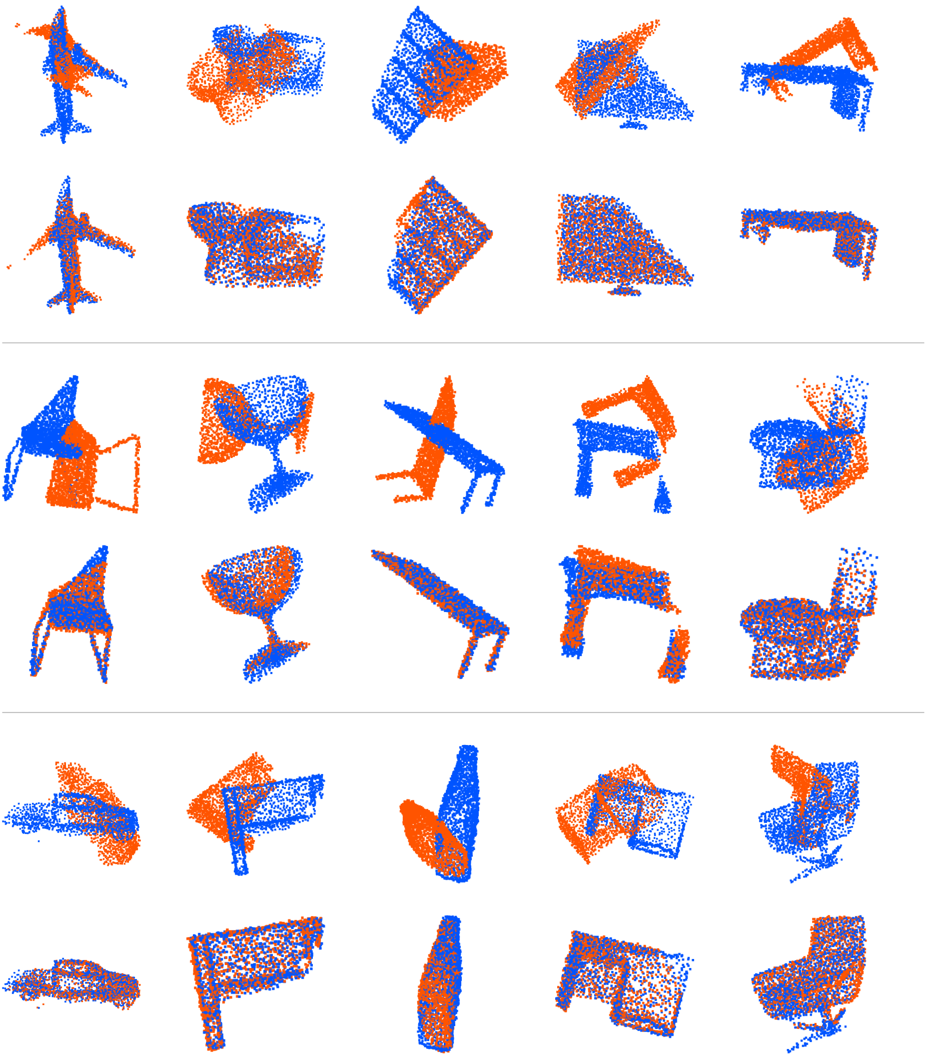

Fig. 1: The results of IDAM+GNN on ModelNet40. In each cell separated by the horizontal line, the top row shows the initial positions of the two point clouds, and the bottom row shows the results of registration.

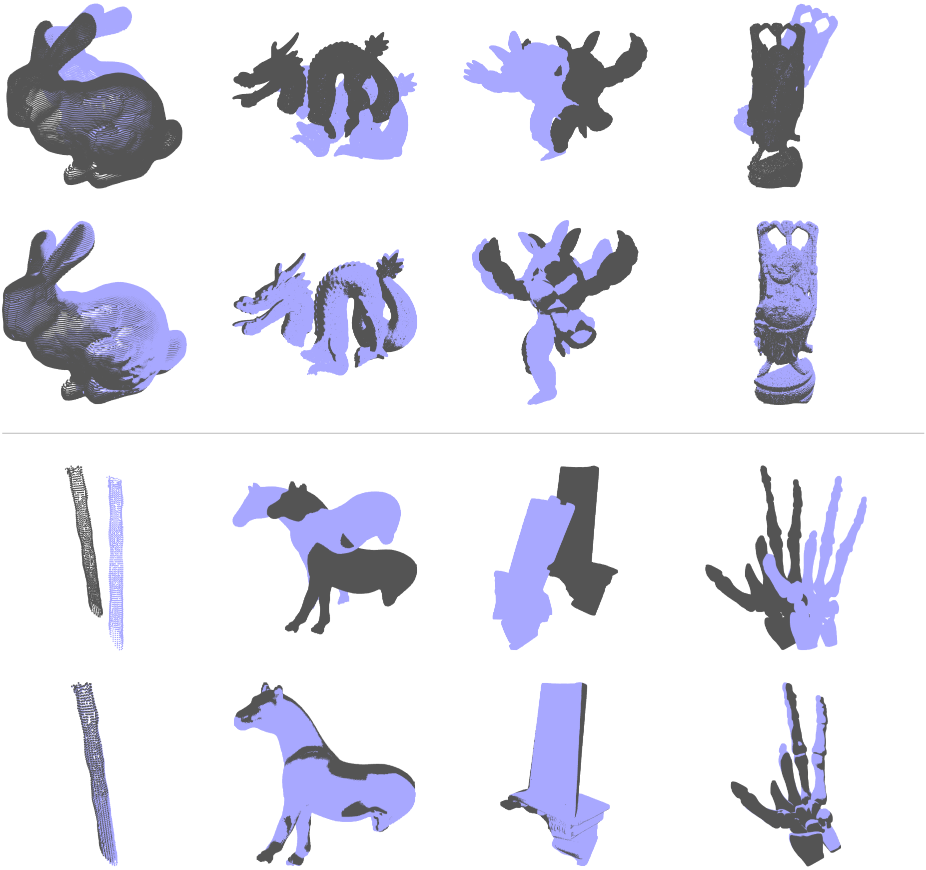

Fig. 2: The results of IDAM+GNN on the Stanford 3D Scan dataset. The model is trained on the training set on ModelNet40, and no fine-tuning is done on Stanford 3D Scan. In each cell separated by the horizontal line, the top row shows the initial positions of the two point clouds, and the bottom row shows the results of registration.

## Appendix B.3 Hard Point Elimination

This section shows the visualization results for the hard point elimination Fig. 3. In each point cloud of 1536 points, the top 128 points with the highest significance scores are highlighted.

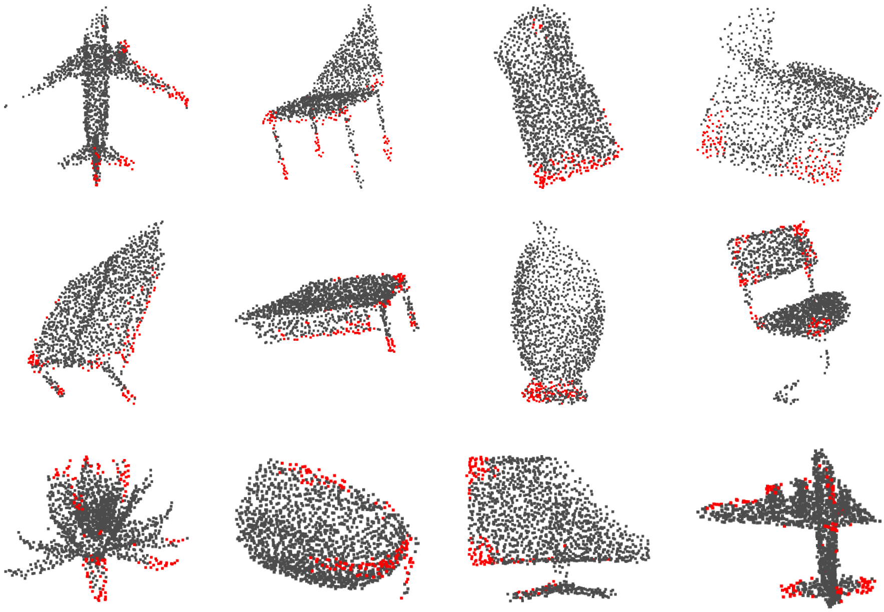

Fig. 3: Visualization of the points preserved by hard point elimination. Each point cloud contains 1536 points, and the top 128 points with the highest significance scores are highlighted.

## Appendix B.4 Hybrid Point Elimination

Fig. 4 shows the visualization of hybrid point elimination. For each point cloud pair, the correspondence pairs with non-zero weights are highlighted in green and those with zero weights are highlighted in red. We can see that most of the false positive correspondences are connected by red lines, and are thus filtered out by hybrid point elimination. This shows the effectiveness of hybrid point elimination in eliminating low-quality point pairs.

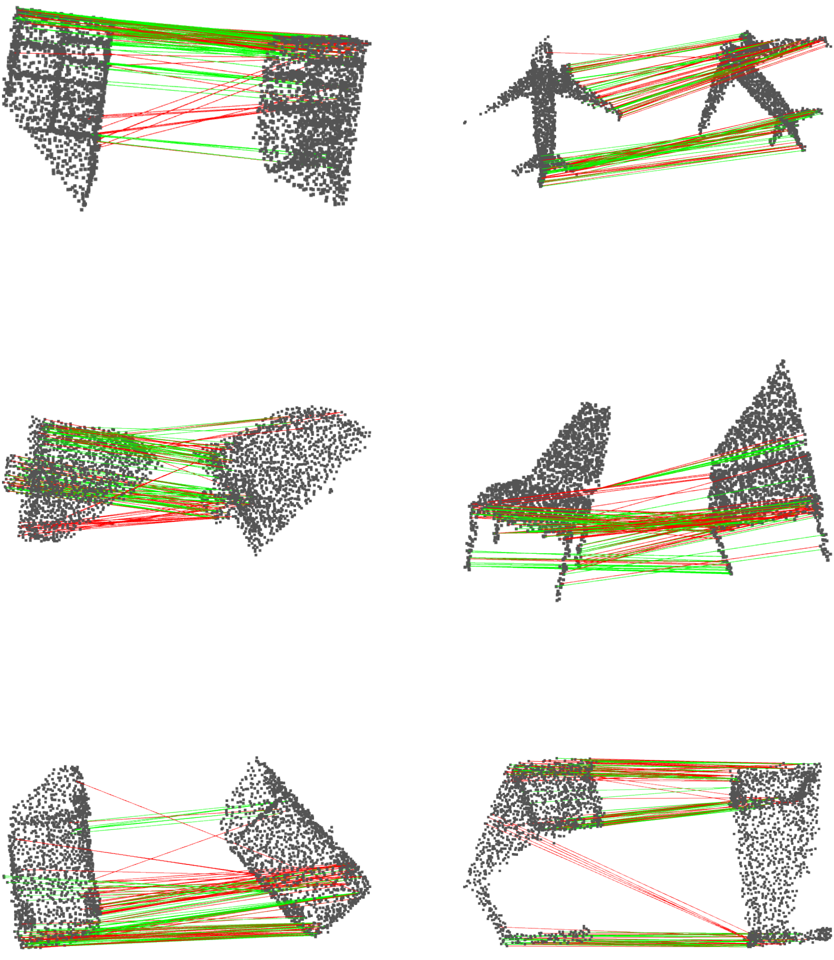

Fig. 4: Visualization of hybrid point elimination. The correspondence pairs with non-zero weights are highlighted in green and those with zero weights are highlighted in red.

## References

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