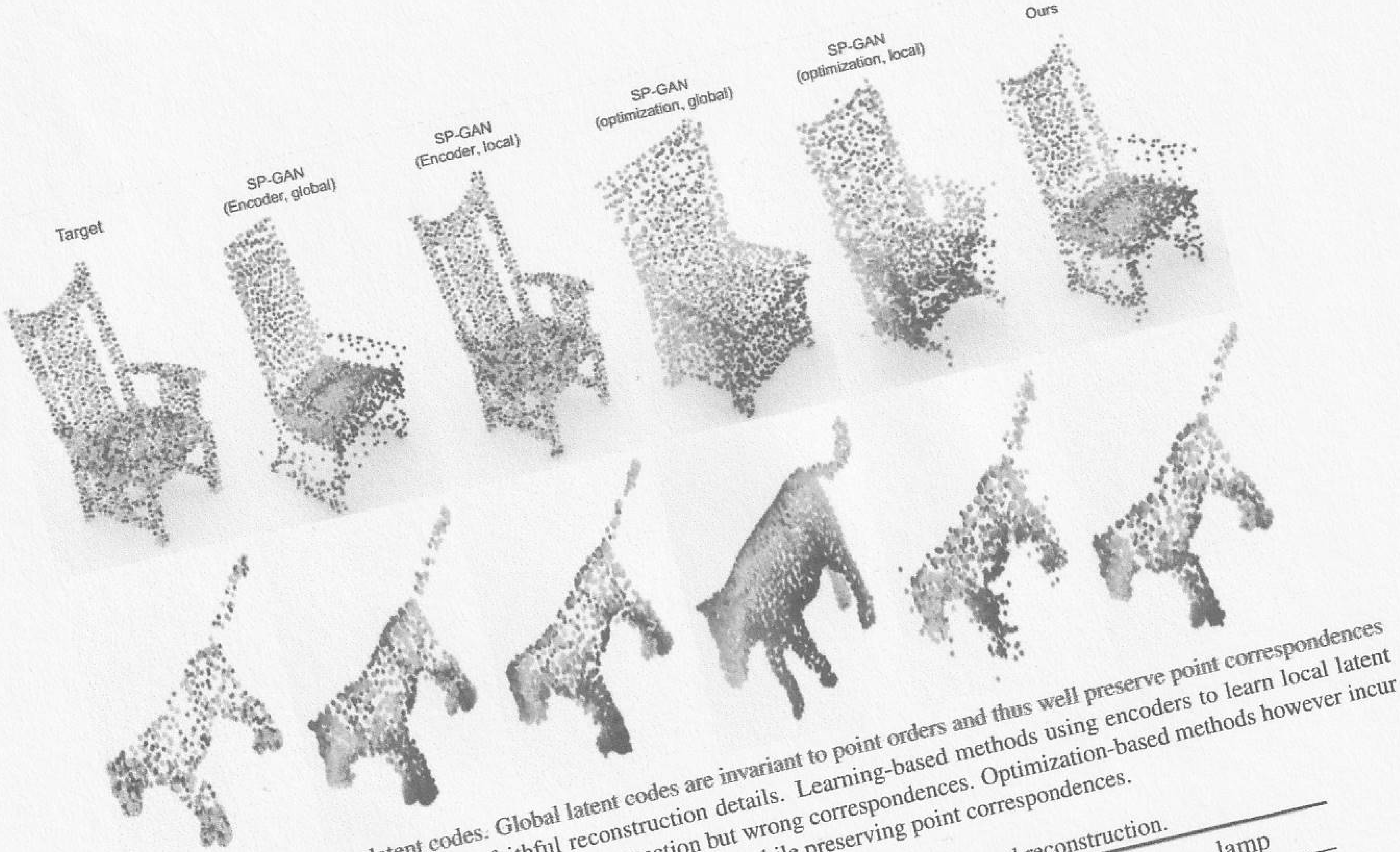

Figure 3. Design choices of the latent codes. Global latent codes are invariant to point orders and thus well preserve point correspondences given in the shape prior, but produce less faithful reconstruction details. Learning-based methods using encoders to learn local latent codes tend to over-fit, resulting accurate geometry reconstruction but wrong correspondences. Optimization-based methods however incur inaccurate reconstruction. Our inversion achieves accurate geometry while preserving point correspondences.

Table 1. Comparison of our method with existing works in point cloud reconstruction.

	avg.	chair	airplane	car	lamp
Achlioptas et al. [1]	3.46×10^{-3}	3.61×10^{-3}	1.15×10^{-3}	1.14×10^{-3}	7.95×10^{-3}
Zhang et al. [40]	2.50×10^{-3}	2.09×10^{-3}	3.59×10^{-3}	1.95×10^{-3}	2.38×10^{-3}
Ours	$\mathbf{0.54 \times 10^{-3}}$	$\mathbf{0.66 \times 10^{-3}}$	$\mathbf{0.49 \times 10^{-3}}$	$\mathbf{0.55 \times 10^{-3}}$	$\mathbf{0.49 \times 10^{-3}}$

point cloud by Achlioptas et al. [1] is not editable. Compared with the results of Zhang et al. [40], our reconstruction results are also more accurate by a large margin.

Qualitative results. We visually assess the quality of reconstructed point clouds by our method in Figure 4. As can be seen, our inversion algorithm can reconstruct target point clouds reasonably while preserving shape details better than other methods. For example, patterns on the back of chairs can be well recognized in our reconstructions.

5.3. Ablation studies

Global vs local latent codes. To further understand the effectiveness of our method, we provide an ablation study in Table 2 and Figure 3. Specifically, we built different baselines including learning-based (i.e., using learned encoders) and optimization-based baselines. For each baseline, we output global or local latent codes, which are then used by the SP-GAN for point cloud reconstruction. Table 2 shows that the learning-based baselines are generally better than the optimization-based ones. Additionally, optimizing local latent codes increases the precision of reconstruction. However, it is worth noting that this could lead to overfitting, as shown in the case of using encoders to output local codes. In this case, reconstruction achieves the best accuracy but point correspondences are significantly corrupted in reconstructed shapes (see Figure 3), making subsequent shape manipulation impossible. Our method instead has slightly lower reconstruction accuracy compared with the overfitting case, but it can keep the correspondences intact. We found that dense correspondence problem is not shown in the animal dataset. This is probably because the number of static shapes in the animal dataset is small while the shapes has diverge. The encoder can avoid overfitting, but reconstruction results are not as good as those from the ShapeNet. Note that our method guarantees the reconstruction performance and dense correspondence regardless of the datasets.

Table 2 also shows the results on the Animal dataset. As