

## Appendix

This appendix presents a pseudo-code implementation of our Point Straight Flow (PSF), provides experimental training details on point cloud completion, and describes further experimental results on 3D point cloud applications.

### A. Method

#### A.1. Pseudo-code implementation of PSF

Our PSF has a simple formulation and is easy to implement with impressive performance on 3D point cloud generation. In Algorithm 2-4, we present a pseudo-code implementation for each stage of our proposed PSF.

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#### Algorithm 2 Train velocity flow model

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**Input:** Point cloud dataset  $\mathcal{D}$ .

**Input:** Neural velocity field  $v_\theta$  with parameter  $\theta$ .

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for  $K_{\text{train}}$  steps do
  # Construct Intermediate data
   $X_1 \sim \mathcal{D}$ 
   $X_0 \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$ 
   $t \sim \mathcal{U}(0, 1)$ 
   $X_t = tX_1 + (1 - t)X_0$ 
   $L_\theta = \|(v_\theta(X_t, t) - (X_1 - X_0))\|^2$ 
   $\theta \leftarrow \theta - \gamma_{\text{train}} \nabla_\theta L_\theta$ 
done

```

**Output:** Trained network  $v_\theta$  with parameter  $\theta$ .

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The hyperparameter  $\gamma$  in Algorithm 2 denotes the learning rate. For each stage in the experiment, described in Section 4, we provide the PyTorch implementation in the supplementary material.

#### A.2. Details of point cloud completion setup

Follow PVD [45], we extend the application of our model from unconditional generation to the conditional shape completion. The general setup of the shape completion is to complete the rest part of the shape with a given partial point cloud input. Let us take  $c \in \mathbb{R}^{M \times 3}$  to describe the partial point cloud input, and use neural network to predict the drift force with the conditional input. That means we are only required to change the drift force term into

$$v_\theta(X_t, t, c), \quad (10)$$

Prior to the *reflow* and distillation procedure, we additionally record the randomly sampled partial point cloud  $c$  together with random sampled  $X'_0$  and the corresponding generated  $X'_1$  as the finetuning data in  $(X'_0, X'_1, c)$ .

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#### Algorithm 3 Improving straightness via *reflow*

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**Input:** Pretrained neural velocity field  $v_\theta$  in Algorithm 2.

# Sample pairs set  $\mathcal{S} = \{(X'_0, X'_1)\}$

**for**  $K_{\text{sample}}$  steps **do**

$X'_0 \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$

**for**  $\hat{t}$  in  $\{0, 1, \dots, N - 1\}$  **do**

$X'_{(\hat{t}+1)/N} \leftarrow X'_{\hat{t}/N} + \frac{1}{N} v_\theta(X'_{\hat{t}}, \frac{\hat{t}}{N})$

**done**

$X'_1 := X'_{(N-1+1)/N}$

Add pair  $(X_0, X_1)$  into  $\mathcal{S}$

**done**

# *reflow* procedure

**for**  $K_{\text{reflow}}$  steps **do**

$(X'_0, X'_1) \sim \mathcal{S}$

$t \sim \mathcal{U}(0, 1)$

$X'_t = tX'_1 + (1 - t)X'_0$

$L_\theta = \|(v_\theta(X_t, t) - (X_1 - X_0))\|^2$

$\theta \leftarrow \theta - \gamma_{\text{reflow}} \nabla_\theta L_\theta$

**done**

**Output:** Finetuned network  $v_\theta$  with parameter  $\theta$ .

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#### Algorithm 4 Flow distillation

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**Input:** Finetuned neural velocity field  $v_\theta$  in Algorithm 3.

**Input:** Sampled data pairs set  $\mathcal{S}$ .

# Distill for a one-step model

**for**  $K_{\text{distill}}$  steps **do**

$(X'_0, X'_1) \sim \mathcal{S}$

$L_\theta = \text{CD}(v_\theta(X_0, 0) + X_0, X_1)$

$\theta \leftarrow \theta - \gamma_{\text{distill}} \nabla_\theta L_\theta$

**done**

**Output:** Distilled network  $v_\theta$  with parameter  $\theta$  as the final PSF.

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## B. Further Experimental Results

### B.1. Unconditional 3d point cloud generation

**MMD and COV metrics** We report the MMD and COV score in CD and EMD distance for three classes, e.g., Airplane, Chair and Car. We show that PSF with one step can perform comparably or even better in some categories than 1-NNA when comparing to PVD. The impressive performance is attributed to the ODE fashion transport style as well as the desired distillation properties in PSF.

**Reflow result before distillation** We show that the PSF after reflow without distillation can provide smooth shape in a few-step setup. We denoted the PSF before the distillation as PSF-reflow and PSF after distillation as PSF-distill. Figure 10 shows that PSF-reflow can obtain similar results as PSF-distill when iterating up to 20 steps, which indicates

Class	Airplane				Chair				Car			
	MMD↓		COV↑		MMD↓		COV↑		MMD↓		COV↑	
	CD	EMD	CD	EMD	CD	EMD	CD	EMD	CD	EMD	CD	EMD
I-GAN (CD) [1]	0.3398	0.5832	38.52	21.23	2.589	2.007	41.99	29.31	1.532	1.226	38.92	23.58
PointFlow [39]	0.2243	0.3901	47.90	46.41	<b>2.409</b>	1.595	42.90	50.00	<b>0.9010</b>	0.8071	46.88	50.00
SoftFlow [12]	0.2309	0.3745	46.91	47.90	2.528	1.682	41.39	47.43	1.187	0.8594	42.90	44.60
DPF-Net [15]	0.2642	0.4086	46.17	48.89	2.536	1.632	44.71	48.79	1.129	0.8529	45.74	49.43
Shape-GF [5]	2.703	0.6592	40.74	40.49	2.889	1.702	46.67	48.03	9.232	<b>0.7558</b>	<b>49.43</b>	50.28
PVD	0.2243	0.3803	<b>48.88</b>	52.09	2.622	<b>1.556</b>	<b>49.84</b>	<b>50.60</b>	1.077	0.7938	41.19	50.56
PVD-DDIM (N=100)	0.2434	0.3991	44.23	49.75	2.758	1.703	46.32	48.19	1.202	0.8176	40.01	48.34
PSF (N=1) ( <i>ours</i> )	<b>0.2205</b>	<b>0.3661</b>	46.17	<b>52.59</b>	2.624	1.573	46.71	49.84	1.023	0.8020	42.89	<b>53.12</b>

Table 4. Further experimental results on unconditional 3d point cloud generation with MMD and COV scores. The scale is aligned with PVD [45].



Figure 9. Visualization results of PSF generated Airplane samples.

a very straight trajectory after applying reflow procedure. These results further suggest that the distillation is mainly useful in extreme small steps to help correct some inaccurate directions.

**More qualitative results** We show more qualitative results for visualizing generated Airplane, Chair, and Car shapes in Figure 9, 11 and 12 by randomly sampling 20 point clouds without any cherry-picking. These results indicate that PSF can consistently provide reasonable shapes.

## B.2. Point Completion

### Further experimental results on real-world application

We here show more experimental results on car point cloud

completion in Figure 13. Our preliminary work suggests that our fast PSF can eventually benefit many 3D perceptual tasks in the future.

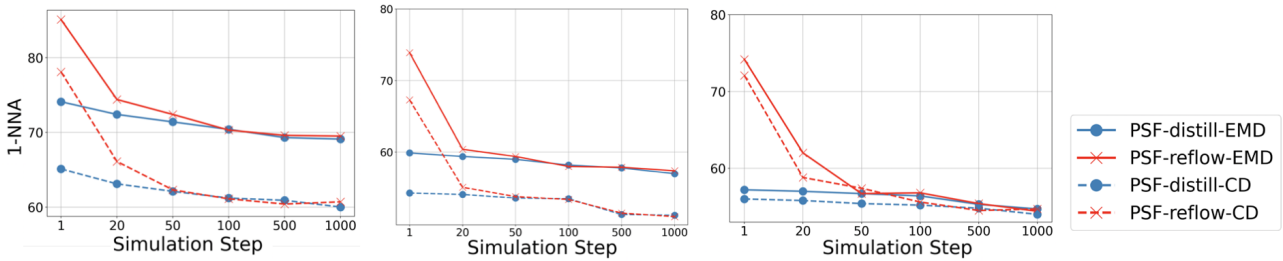


Figure 10. Results of PSF before distillation and after distillation. We show that PSF-reflow achieves similar results as PSF-distill. Distillation is mainly serve as a one-step generation.



Figure 11. Visualization results of PSF generated Chair samples.



Figure 12. Visualization results of PSF generated Car samples

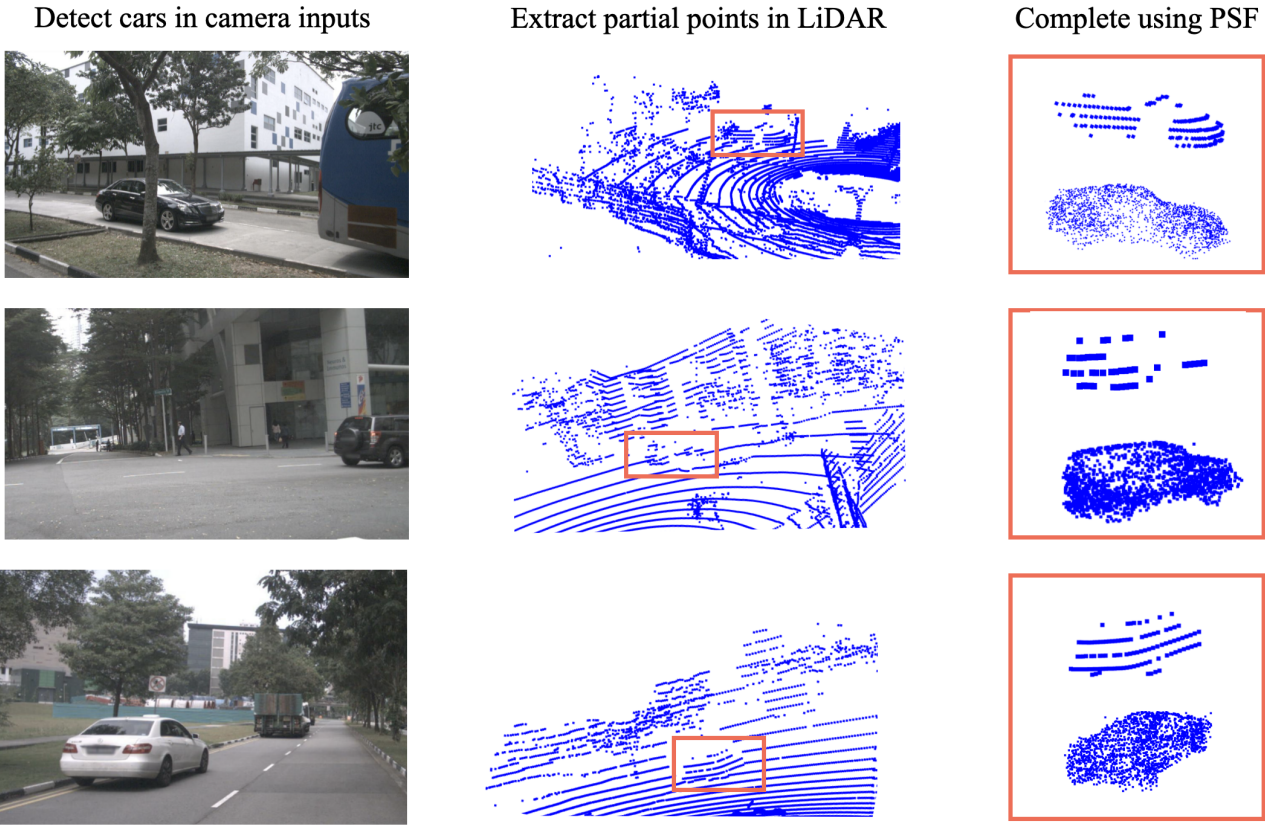


Figure 13. Further completion results on real-world application. Image data is from nuScene [4].