Single view 3D object reconstruction

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Summary

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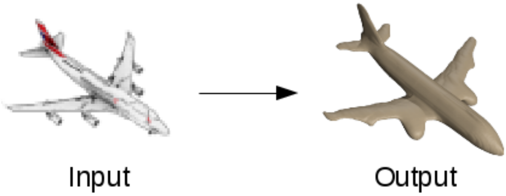
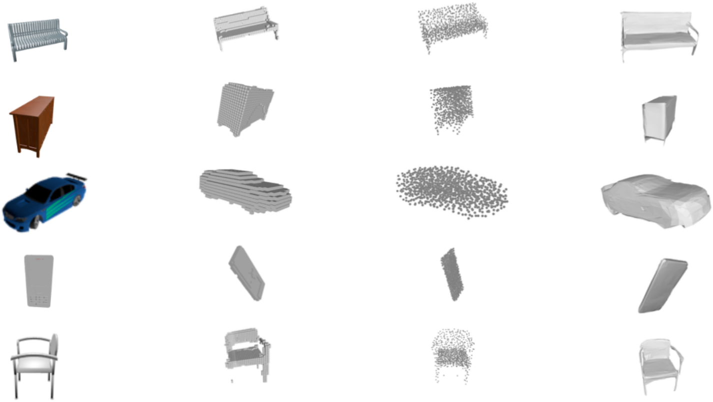


Figure – Source : bair.berkeley.edu

- Ill-posed, it requires to assume regularities, patterns and symmetries
- Still a very challenging vision task

Mesh representation

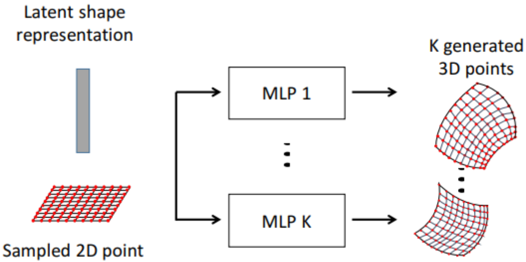


We focus on recent **deep learning** methods outputing **meshes**.

Objectives

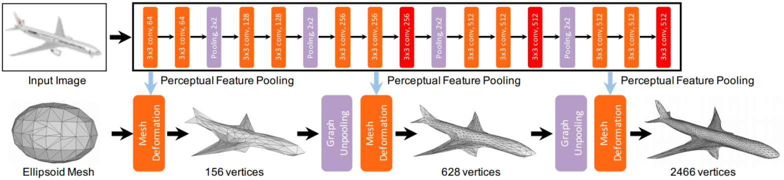
- ✓ **Compare** AtlasNet [2] and Pixel2Mesh [5] as fairly as possible
- ✓ Experiment **regularization** schemes proposed by Pixel2Mesh

Summary



Key points :

- A ResNet [3] encodes the input image
- Multiple templates are deformed **pointwisely** by MLPs to learn 2-manifolds in 3D



Key points :

- A **GNN** deforms a **template** in a coarse-to-fine fashion
- It uses **projected features** extracted by VGG-16 [4] from the image

For S_1, S_2 two point clouds :

Chamfer distance

$$d(S_1, S_2) = \sum_{x \in S_1} \min_{y \in S_2} \|x - y\|_2^2 + \sum_{y \in S_2} \min_{x \in S_1} \|x - y\|_2^2$$

- Not a distance on meshes, but on point clouds $\rightarrow$ Does not directly reflect mesh quality
- Depends on data normalization, number of points, ...
- Still a very popular metric.

Mesh regularizers

Laplacian regularization

$$\mathcal{L}_{\text{lap}} = \sum_{p} \|\delta'_p - \delta_p\|_2^2$$

where $\delta_p = p - \frac{1}{|\mathcal{N}(p)|} \sum_{k \in \mathcal{N}(p)} k$ and δ'_p is the same quantity after deformation.

Expectation : enforce a global movement and avoid self intersections

Edge Length regularization

$$\mathcal{L}_{\text{edge}} = \sum_{p} \sum_{k \in \mathcal{N}(p)} \|p - k\|_2^2$$

Expectation : prevents outliers

Summary

Dataset

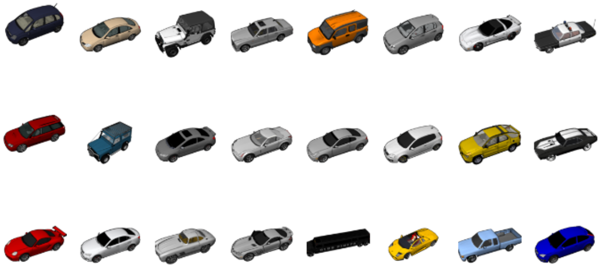


Figure – Sample of the dataset

- Compare both methods on the same data from ShapeNet [1]
- Training only on **cars**
- Same normalization before metrics computation

Quantitative comparison

	Chamfer	F1-score
Atlas (1 templ.)	5.11	0.41
Atlas (5 templ.)	4.93	0.43
Atlas (25 templ.)	4.95	0.42
P2M	**3.98**	**0.54**

Table – Performance of both methods (cars)

Qualitative comparison

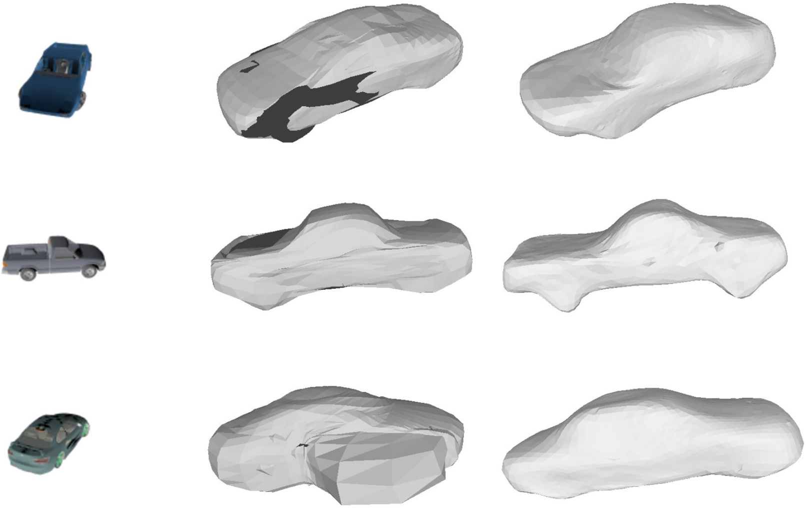
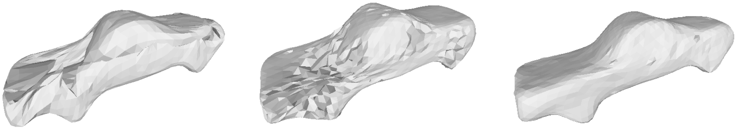


Figure – Meshes outputs by AtlasNet (middle) and Pixel2Mesh (right)

Pixel2Mesh regularization

	Chamfer	F1-score
P2M (base)	3.98	0.54
P2M (-edge)	**3.76**	**0.55**
P2M (-lapl.)	3.95	0.53

Table – Pixel2Mesh, ablation study (cars)



(a) wt. edge-length (b) wt. Laplacian (c) both reg.

AtlasNet regularization

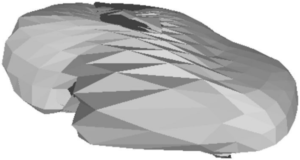
Edge-length regularization :

$$\mathcal{L} = \mathcal{L}_{\text{chamfer}} + \lambda \mathcal{L}_{\text{edge}}$$

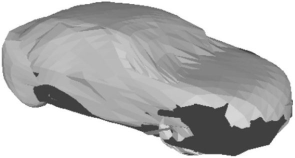
	Chamfer	F1-score
Atlas (5)	4.93	0.42
Atlas (5) + reg	**4.89**	**0.43**

Table – AtlasNet, regularization effect.

(a) input



(b) no regularization



(c) regularization

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