Beyond Dense Grids: Sparse SDF Diffusion for Efficient 3D Shape Completion

Bc. Tomáš Rajsigl
Supervisor: doc. Ing. Michal Španěl, Ph.D.

BRNO UNIVERSITY OF TECHNOLOGY
FACULTY OF INFORMATION TECHNOLOGY
Excel@FIT 2026

From Partial Scans to Complete Shapes

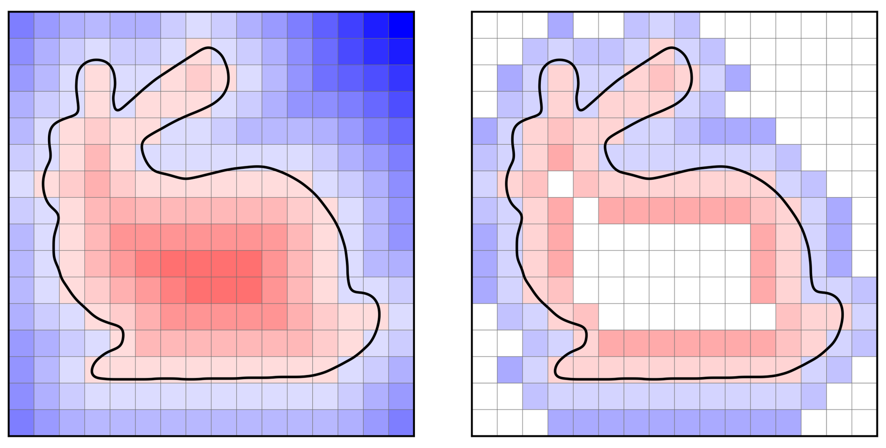
- **Motivation:** Real-world 3D scans frequently suffer from missing geometry due to **occlusions**, **noise**, or **sensor errors**.
- **Shape Representation:** We utilize a **Sparse SDF Representation** to process 3D models with a greatly reduced memory footprint.
- **Neural Architecture:** A **Dual-Branch Diffusion Model** utilizing **sparse convolutions** reconstructs the missing geometry.

Surface-Centric SDF Representation

Utilizing a *Signed Distance Function* (SDF), defined as:

$$f(p) = \begin{cases} -d(p, \mathcal{S}) & \text{if } p \text{ is inside } \mathcal{S}, \\ 0 & \text{if } p \in \mathcal{S}, \\ d(p, \mathcal{S}) & \text{if } p \text{ is outside } \mathcal{S}. \end{cases}$$

Equation 1.



(a) Dense Grid (b) Sparse

Figure 1.

Instead of wasting compute on empty space, the grid is sparsified within an **adjustable narrow band** around the target surface. This allocates memory **strictly where geometric detail is required**.

Simulate Holes to Repair Them

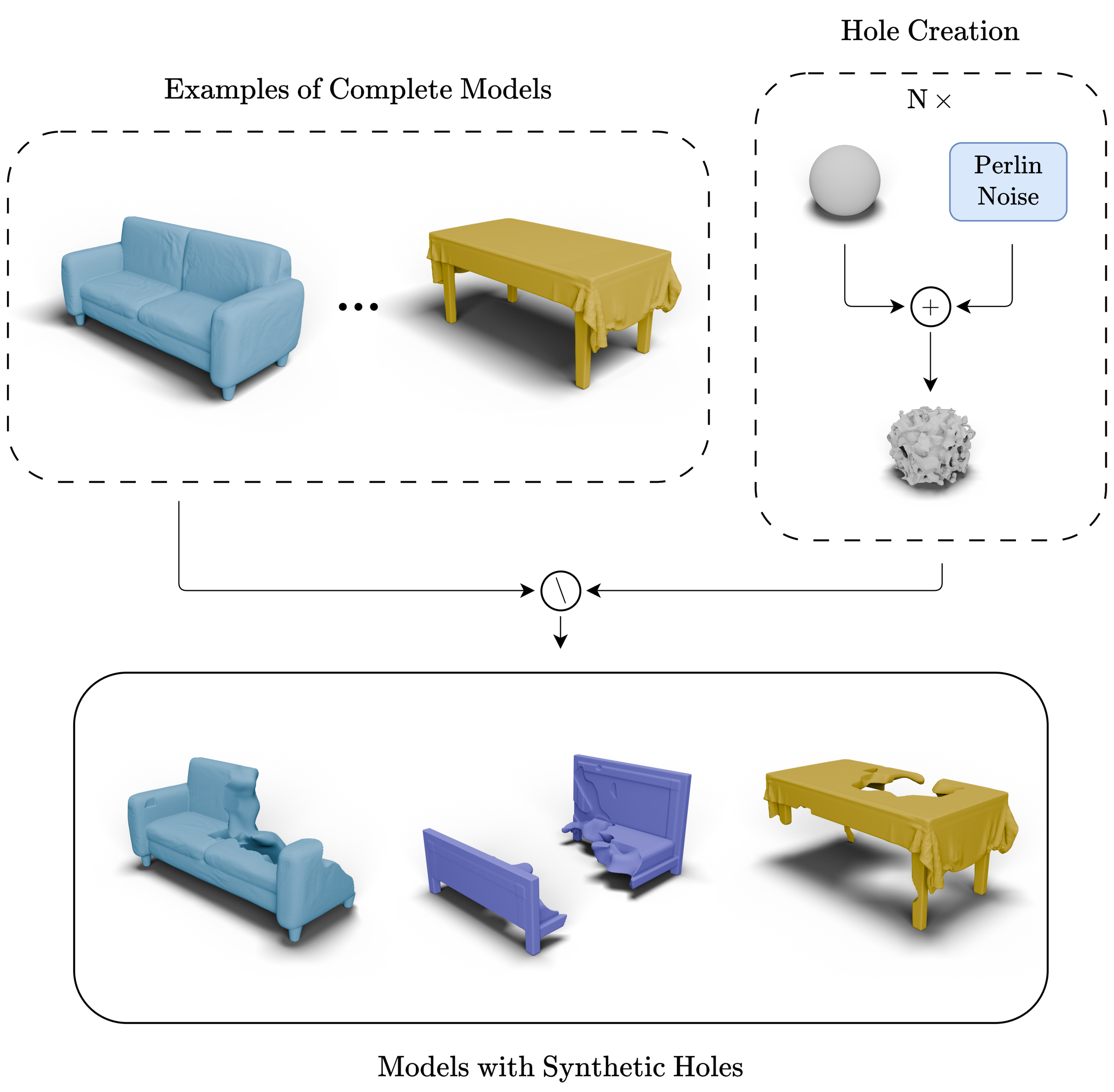


Figure 2.

By simulating occlusions on roughly **6,000** complete 3D models of furniture composed of **6 classes** in total, we generate **infinite synthetic pairs** to train the network in a **self-supervised manner.**

Dual-Branch Diffusion Framework

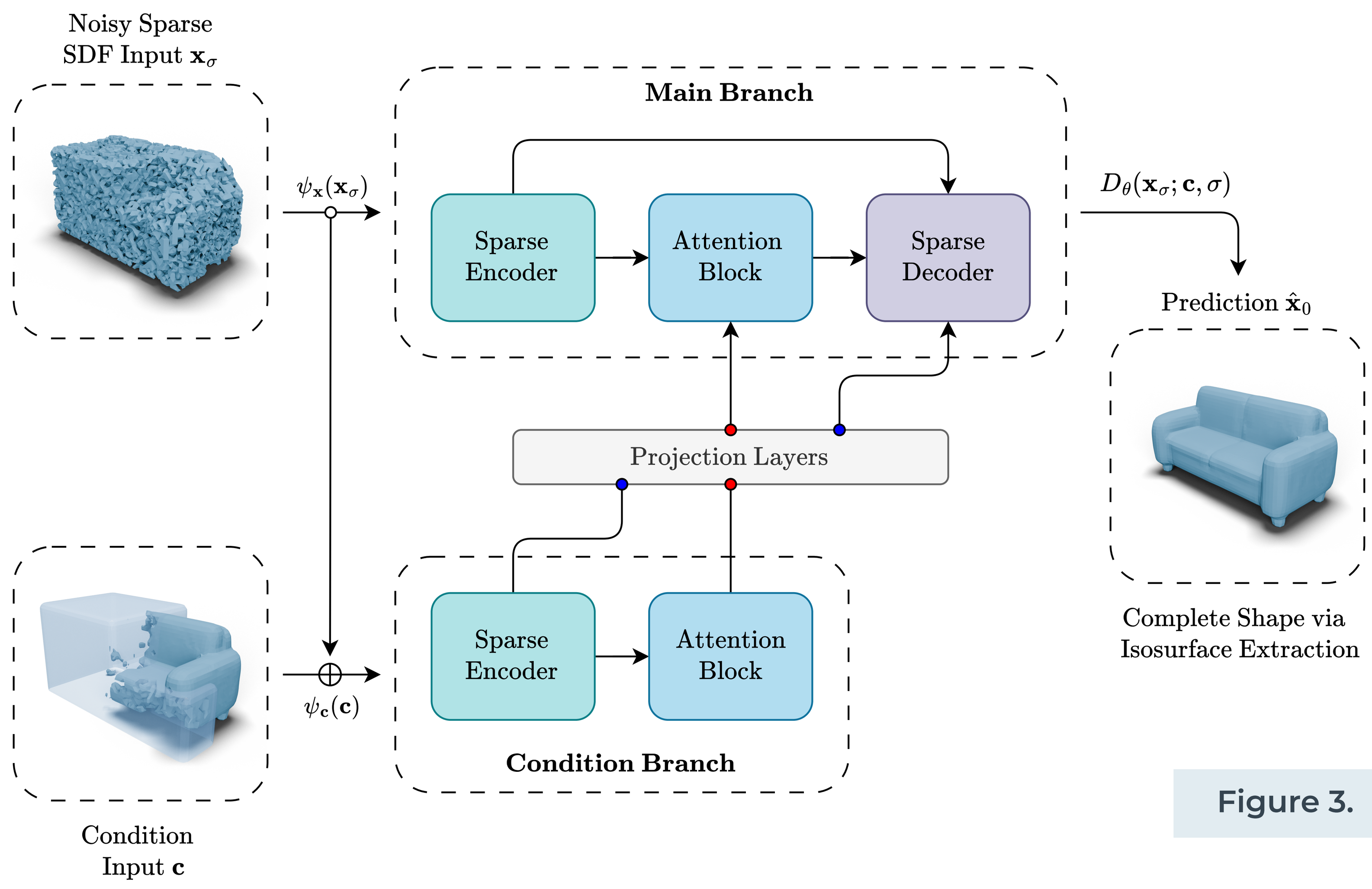


Figure 3.

1. Encode noisy SDF and partial shape conditions.
2. **Condition Branch** extracts multi-scale spatial features.
3. **Projection Layers** fuse guidance into the network.
4. **Main Branch** iteratively denoises the sparse representation.

Quantitative Results

	Grid Footprint		Reconstruction Quality (32^3)		
Variant	Cutoff d_c	Active Voxels	m-IoU ↑	CD-ℓ_1 ↓	F-Score@1% ↑
DiffComplete*	-	100%	83.58	**3.62**	**74.57**
Proposed (Efficient)	2	45.8%	78.53	4.18	71.11
Proposed (Balanced)	3	54.9%	81.71	3.87	72.18
Proposed (Accurate)	4	64.1%	**83.61**	3.71	73.85

Table 1.