Continual Neural Mapping: Learning an Implicit Scene Representation from Sequential Observations

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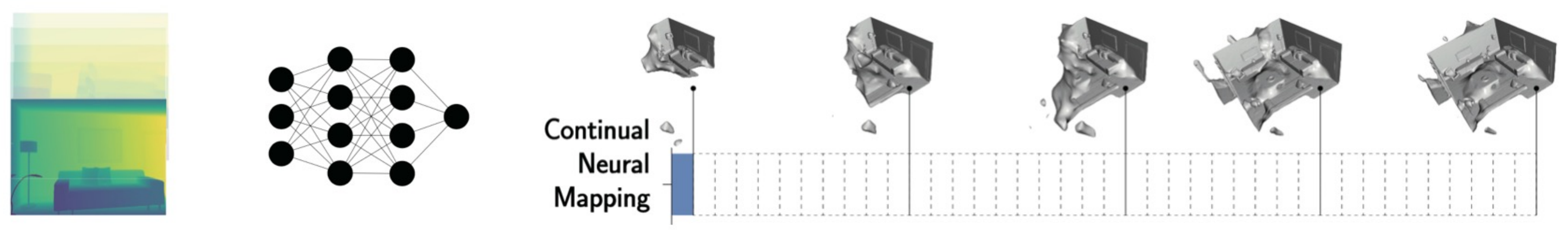
Highlights

- A novel problem setting namely ***Continual Neural Mapping***;
- An experience replay method for sequential SDF regression;
- State-of-the-art accuracy with promising memory efficiency.

Overview

The objective of the continual neural mapping is to learn a mapping function f(·) parameterized by a neural network θ^t continually from the observed data D^t to depict the connections between the spatial coordinates and the scene properties as:

$$\boldsymbol{y} = f(\boldsymbol{x}; \theta^t), \forall \boldsymbol{x} \in \mathcal{W}$$



A single MLP serves as:

- The compact **memory** of past observations (backward transfer)
- A **predictor** for unseen areas (forward transfer)

Future potentials (See supplementary materials)

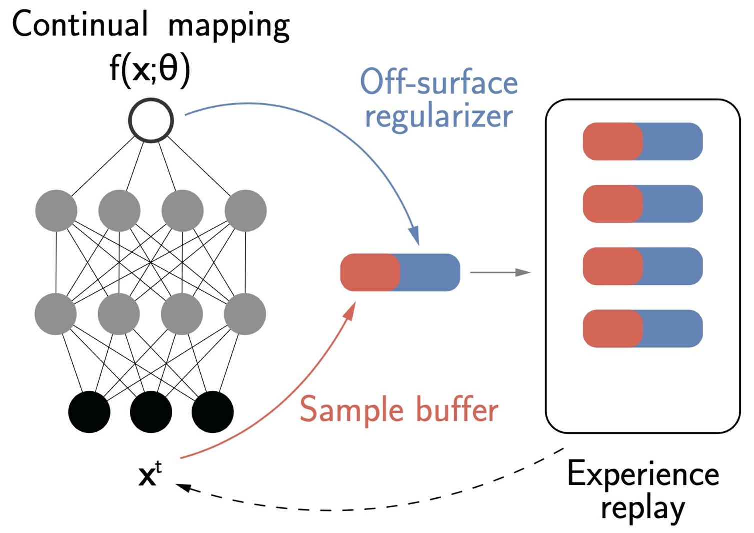
- *Online learning*: faster convergence for real-time applications;
- *Continual representation learning*: encoding multiple scene properties within a single network continually;
- *Generalization ability*: enhance the prediction quality.

SDF Regression from Sequential Observations

We instantiate the proposed continual neural mapping on the task of scene geometry approximation.

The SDF is parameterized by a single MLP, representing the 3D surface as a zero level-set:

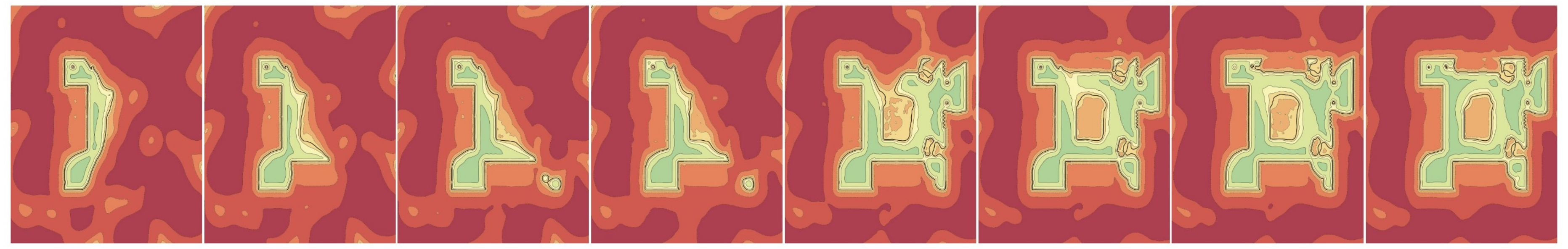
$$\mathcal{M} = \{\boldsymbol{x} \in \mathbb{R}^3 | f(\boldsymbol{x}; \theta^t) = 0\}, f(\cdot): \mathbb{R}^3 \mapsto \mathbb{R}$$



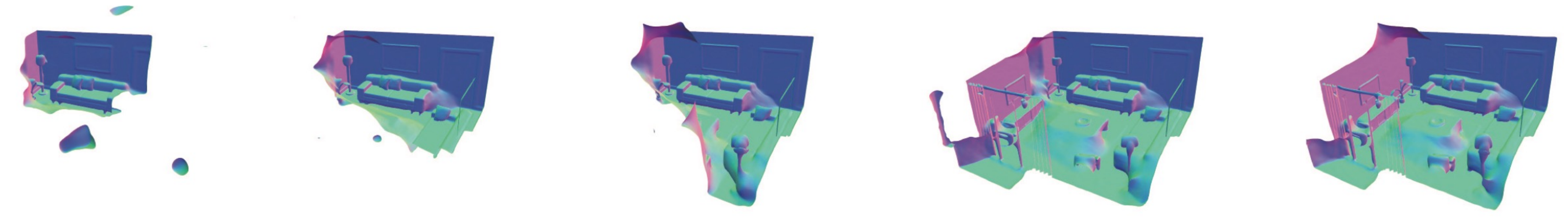
A continual learning method based on experience replay is introduced to alleviate catastrophic forgetting. Replayed samples guided by the last network are utilized:

- Off-surface samples to regularize the distance sign
- Zero level-set samples to regularize SDFs and the derivatives

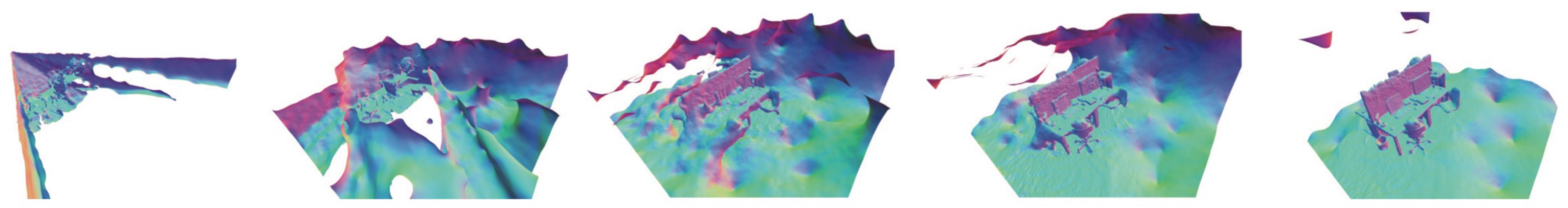
Incrementally-updated Geometry



2D visualization (top view on ICL-NUIM)



3D visualization (ICL-NUIM)



3D visualization (TUM RGB-D)

Continual Neural Mapping without Forgetting

The objective is to establish an accurate mapping between spatial coordinates and the corresponding SDF value in previously visited areas

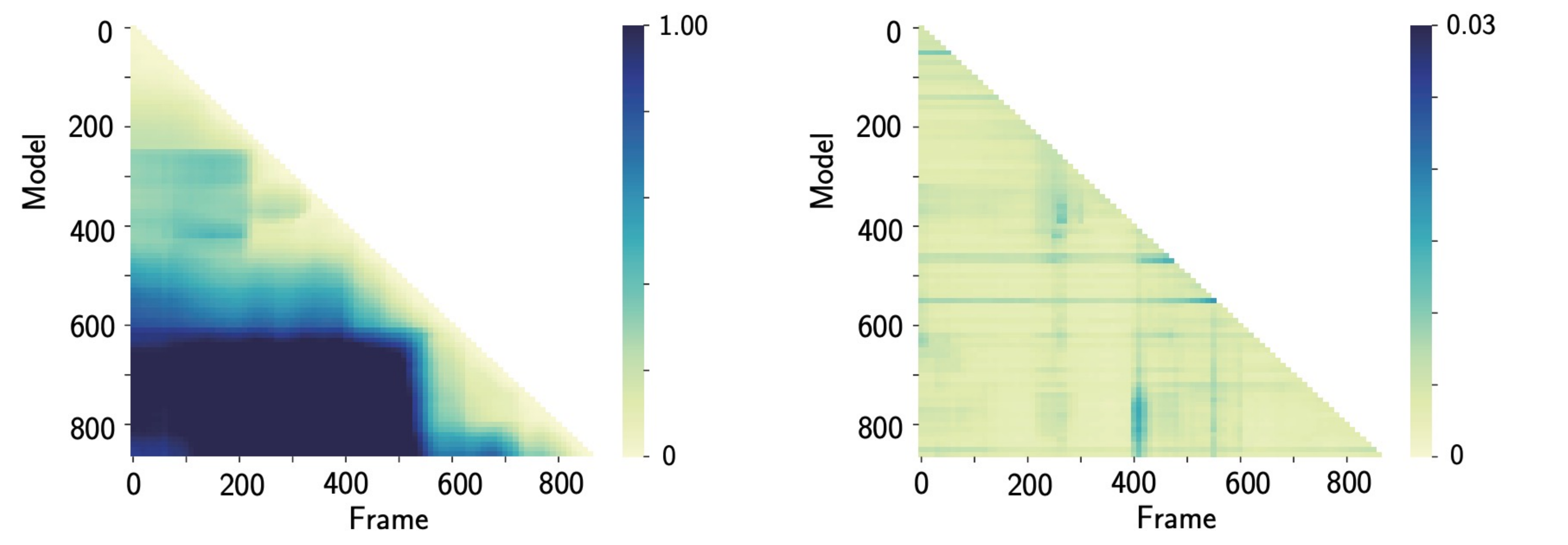


Figure: The accuracy heatmap with overall mean/std. (m) of each method on the ICL dataset.

Light-weight and Accurate

Method	Mean	Std.	Parameters
RoutedFusion [64]	0.0403	0.0687	512^3
LIG [21]	0.0106	0.0146	69,795×32
Ours	0.0584	0.2115	198,657
Ours (masked)	**0.0044**	**0.0010**	198,657

Table: Comparisons in terms of representation parameters and the generated mesh accuracy.

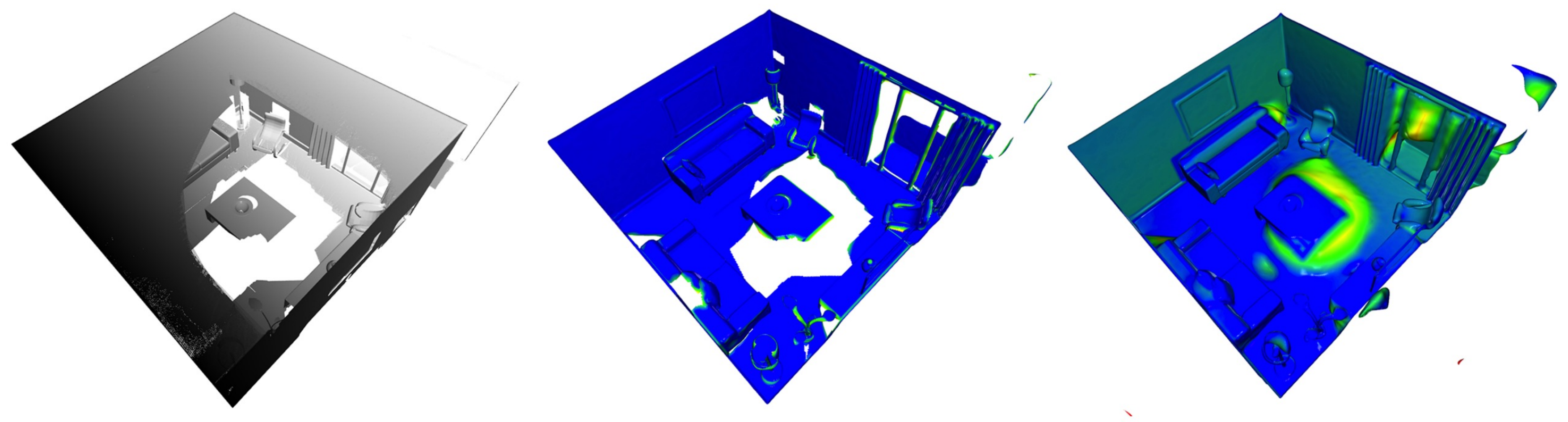


Figure: Error map of the extracted mesh model using the proposed method.