Active Neural Mapping

ICCV23 PARIS

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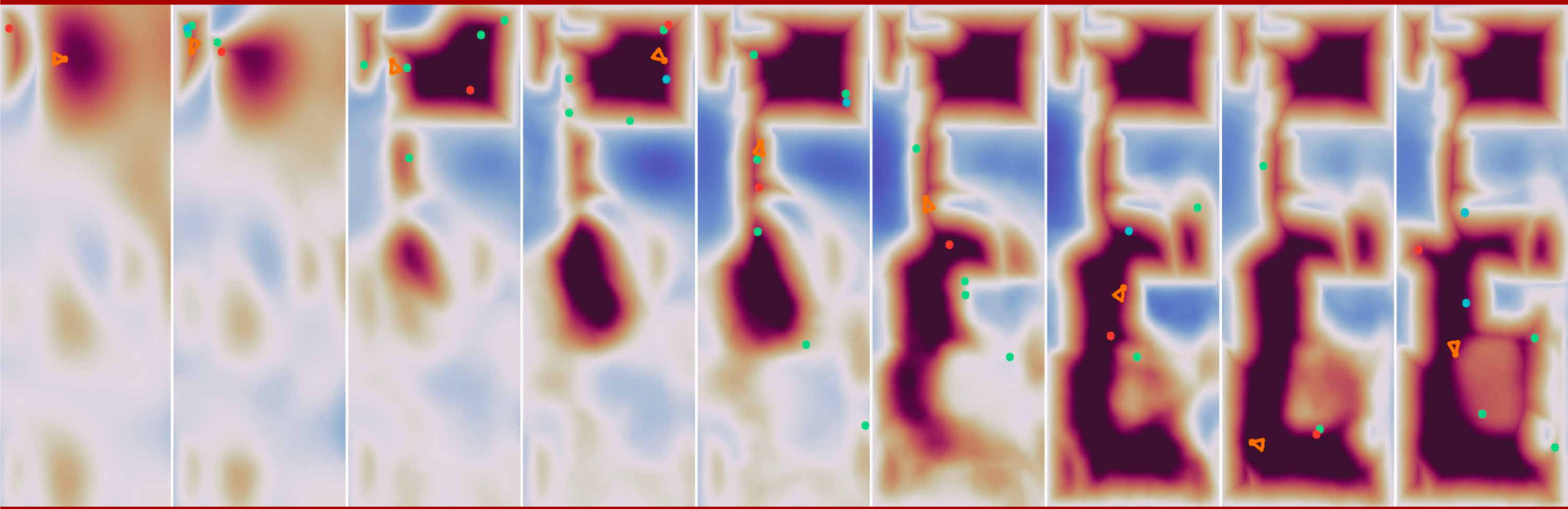
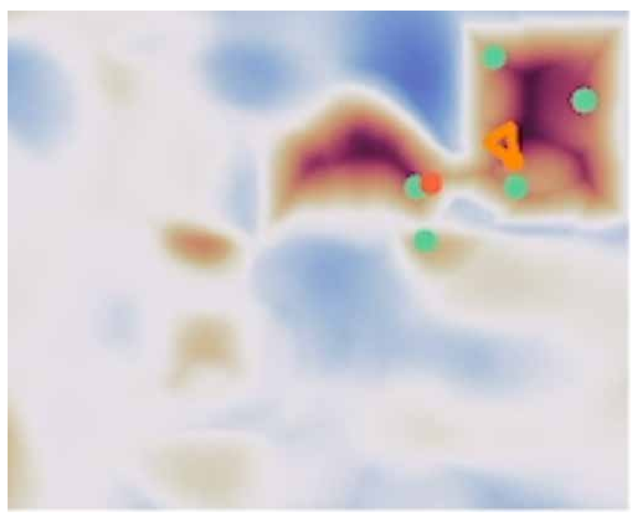


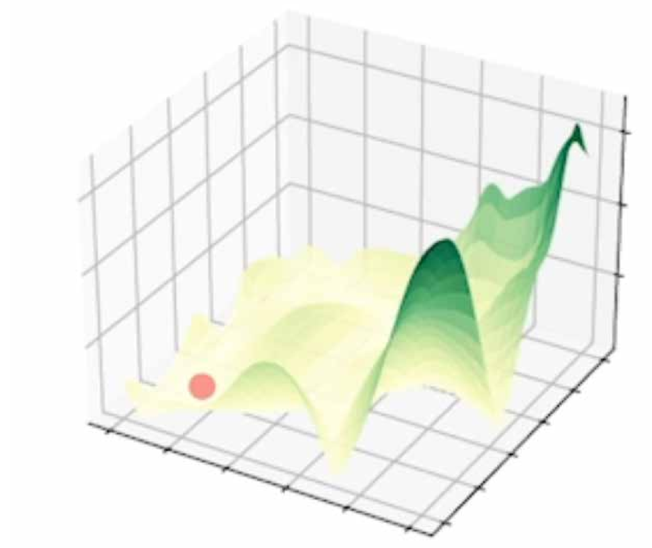
TARGET: Reconstructing a **3D neural field on-the-fly** with an **actively-exploring** mobile agent to best represent the scene

FORMULATION — A continual learning perspective of the neural field optimization

$$\theta^t = \arg\min \sum_{\tau=t}^{t+k} \lambda^\tau \mathbb{E}_{(\mathbf{x}^t,\mathbf{y}^t)\sim \mathbf{z}^{1:\tau}}(\mathcal{L}(\mathbf{x}^t,\mathbf{y}^t;\theta^t)) \longrightarrow H(\delta\mathbf{z},\theta^t) \approx \beta L(\theta^t,\mathbf{z}^{1:t}) + \sum_{\tau=t}^{t+k}(L(\theta^\tau,\mathbf{z}^{1:\tau}\cap\delta\mathbf{z}) - L(\theta^\tau,\mathbf{z}^{1:\tau})) + \sum_{\tau=t}^{t+k}(L(\theta^\tau+\delta\theta,\mathbf{z}^{1:\tau}) - L(\theta^\tau,\mathbf{z}^{1:\tau}))$$

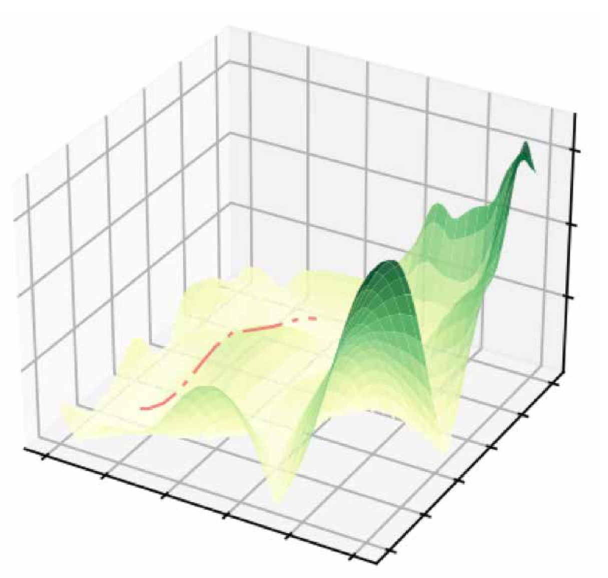
$$H(\delta\mathbf{z},\theta^*) \le H(\delta\mathbf{z}^*,\theta^*) \le H(\delta\mathbf{z}^*,\theta)$$



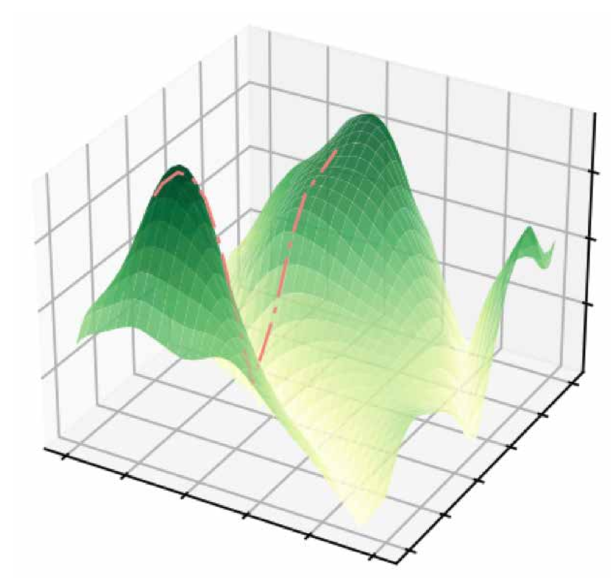


Local equilibrium point can be achieved by first maximizing the generalization, and then minimizing the forgetting [51] → Finding the next-best-view with the most distribution shifts and then optimizing the neural field given new data

SOLUTION — Through the lens of loss landscape



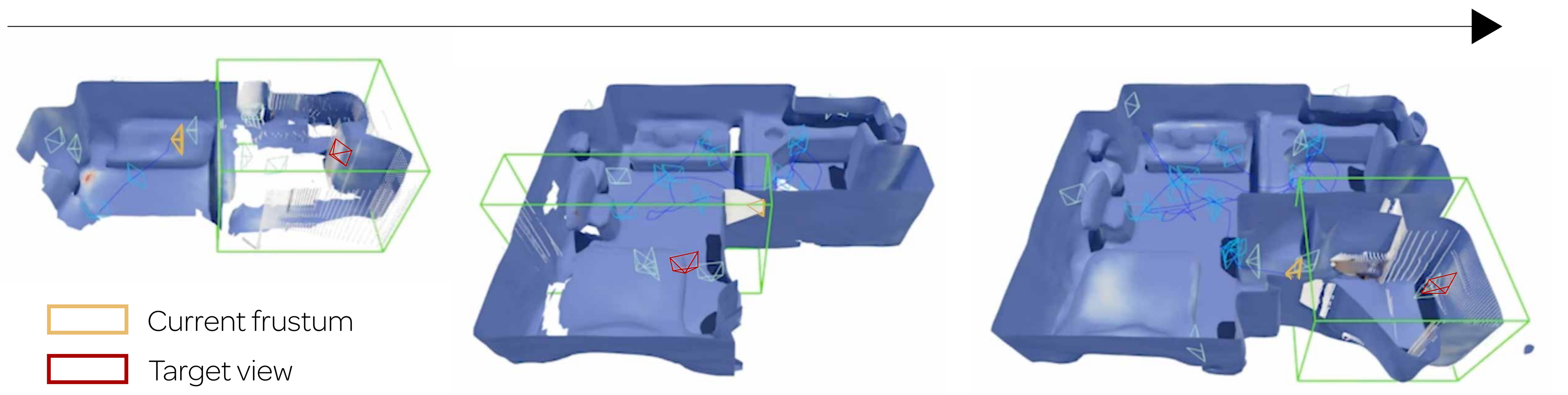
True zero-crossing point: flat basin



False-positive zero-crossing point: sharp ridge

Exploration: pushing the agent toward the unstable minima

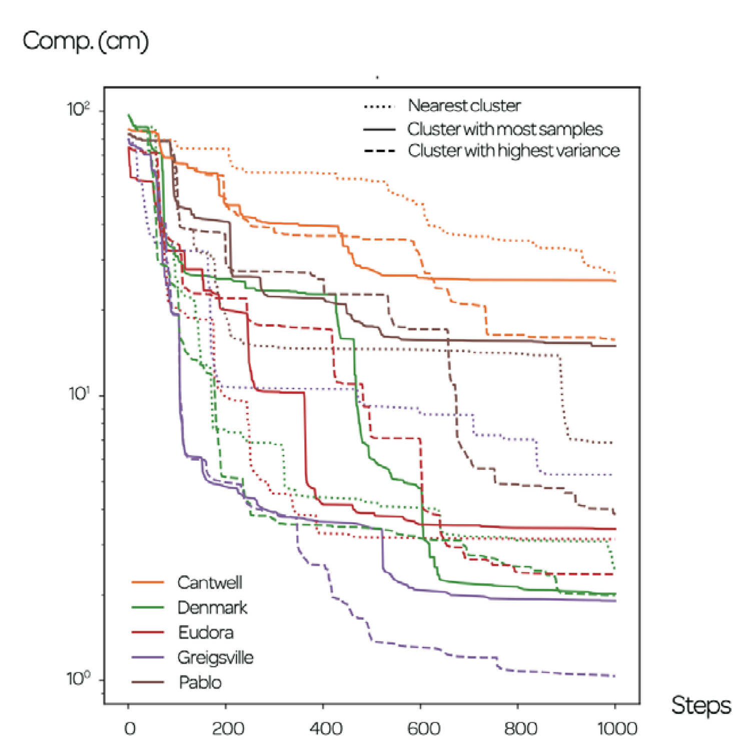
Goal location: $\mathbf{x} = \arg\max \mathbb{V}_{\hat{\theta}\sim N(\theta,b^2 I)}[f(\mathbf{x};\hat{\theta})]$



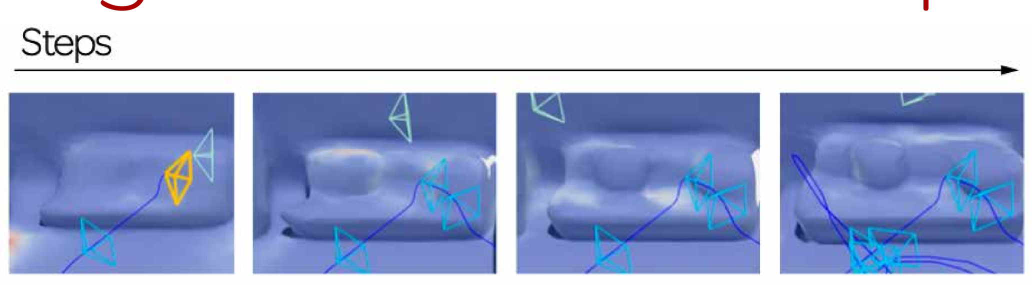
RESULTS — Scene geometry recovery through autonomous exploration

	Gibson		MP3D	
	Comp. ↑ (%)	Comp. ↓ (cm)	Comp. ↑ (%)	Comp. ↓ (cm)
Random	45.80	34.48	45.67	26.53
FBE	68.30	15.42	68.53	9.78
UPEN	63.30	19.13	69.09	10.60
OccAnt	61.88	32.25	71.72	9.40
Ours	**80.48**	**7.44**	**73.15**	**9.11**

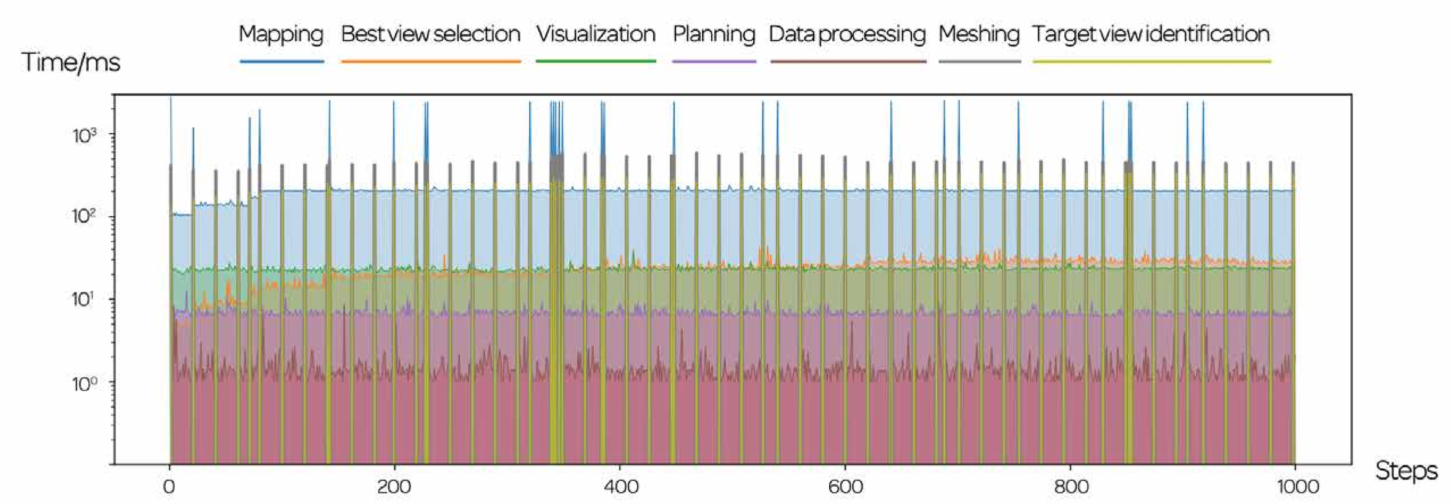
The coverage of the actively-captured data



The coverage of the actively-captured data



Continually-optimized scene geometry



The runtime of each module