



Active Perception for Grasp Detection via Neural Graspness Field

Haoxiang Ma¹, Modi Shi¹, Boyang Gao² and Di Huang^{1*} ¹Beihang University ²Geometry Robotics

Problem

- **Observing from multi-view is crucial for grasp detection** •
- Moving the camera to scanning the whole scene can increase the time cost •



Multi-view Reconstruction

Active perception to achieve the trade-off between time cost and accuracy

Neural Graspness Field (NGF)



• Employ the NeRF-based mapping system to render the grasp distribution

Next-Best-View Planning



NBV Problem:

$$s^* = \underset{s \in S}{\operatorname{argmax}} \sum_{n=1}^{N} I(v_n)$$

View Uncertainty:

$$I(v) = \left|\sum_{r \in v} \hat{g}(r) - g(\hat{d})\right|$$

Next-Best-View Planning



Experiments

• Comparison on different NBV policies



Experiments

• Overall Performance

Mathada	Seen			Similar			Novel		
Wiethous	AP	$AP_{0.8}$	$\mathbf{AP}_{0.4}$	AP	$AP_{0.8}$	$\mathbf{AP}_{0.4}$	AP	$AP_{0.8}$	$\mathbf{AP}_{0.4}$
Close-loop [5]	43.84	53.95	34.18	42.17	51.51	34.02	19.54	23.96	9.49
ACE-NBV [32]	46.74	56.17	38.13	46.14	55.42	38.86	21.76	26.89	12.16
Ours	55.12	65.07	48.88	52.85	62.63	46.49	24.74	30.21	12.00
All views	63.75	73.30	58.38	61.54	71.17	55.94	24.89	30.18	13.95

Table: Overall results compared to the state-of-the-art active grasp detection methods.

• Runtime Analysis

Overall	NBV Planning	Mapping	Grasp Detection	Robot Execution
3.44s	1.00s (29.07%)	0.45s (13.08%)	0.23s (6.69%)	1.76s (51.16%)

Table: Runtime analysis of the proposed method.

Real-world Experiments

• Physical Setting



Model	Success Rate (%)
Close-loop [5]	70.67 (53/75)
ACE-NBV [32]	62.67 (47/75)
Ours	74.67 (56/75)



Visualization

• NGF from different steps



• Planned Camera Trajectories









Thanks!



GitHub: http://github.com/mahaoxiang822/ActiveNGF

Contact: mahaoxiang822@buaa.edu.cn