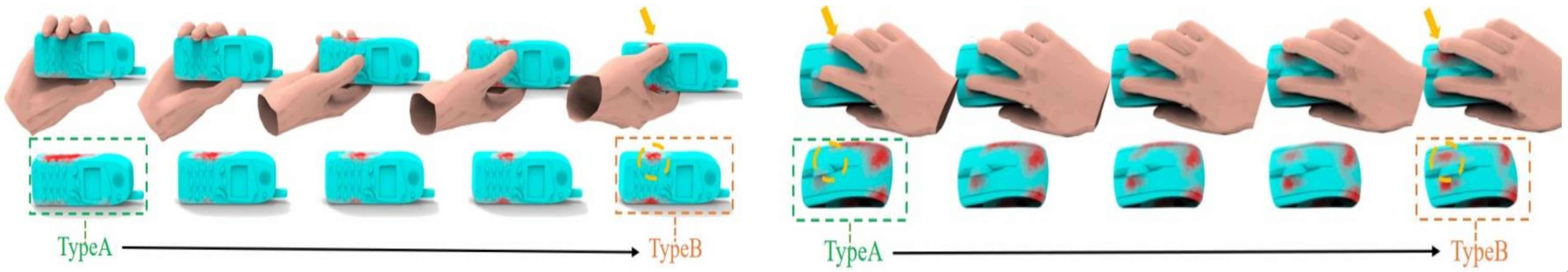
Contact2Grasp: 3D Grasp Synthesis via Hand-Object Contact Constraint

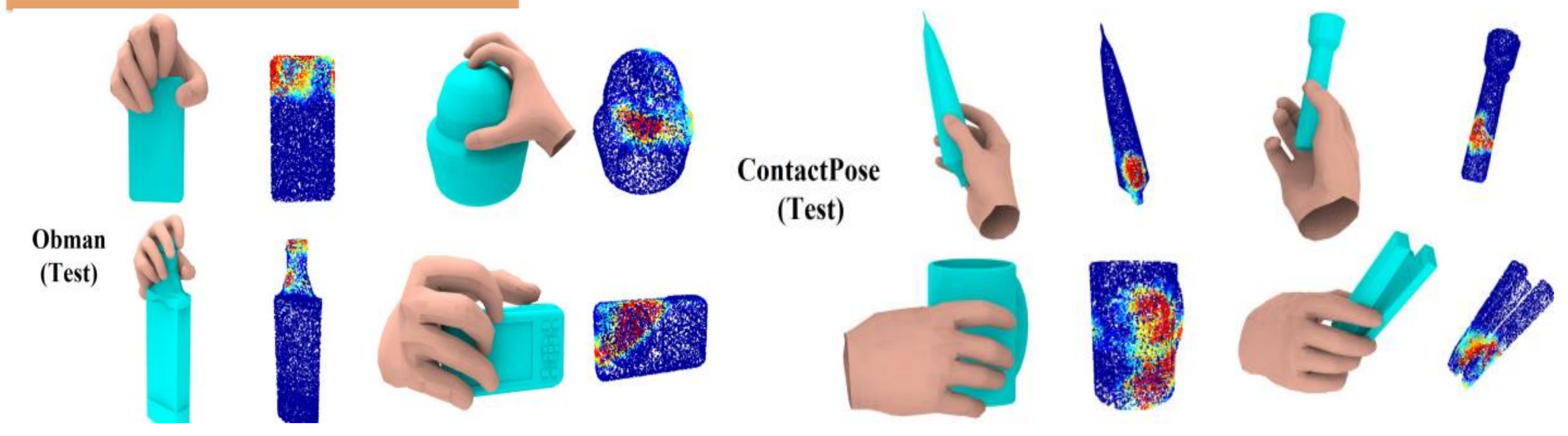
Haoming Li[1], Xinzhuo Lin[1], Yang Zhou[3], Xiang Li[3], Yuchi Huo[4,5], Jiming Chen[1,2] and Qi Ye[1,2*]
[1] College of Control Science and Engineering, Zhejiang University, China
[2] Key Lab of CS&AUS of Zhejiang Province, China [3] OPPO US Research Center
[4] State Key Lab of CAD&CG, Zhejiang University, China [5] Zhejiang Lab, China

Introduction

Objective:
To generate grasping poses given an input object.
Challenges:
- The physical contact is sensitive to small changes in pose.
- The mapping from the 3D object space to the pose space represented by rotations is highly non-linear.

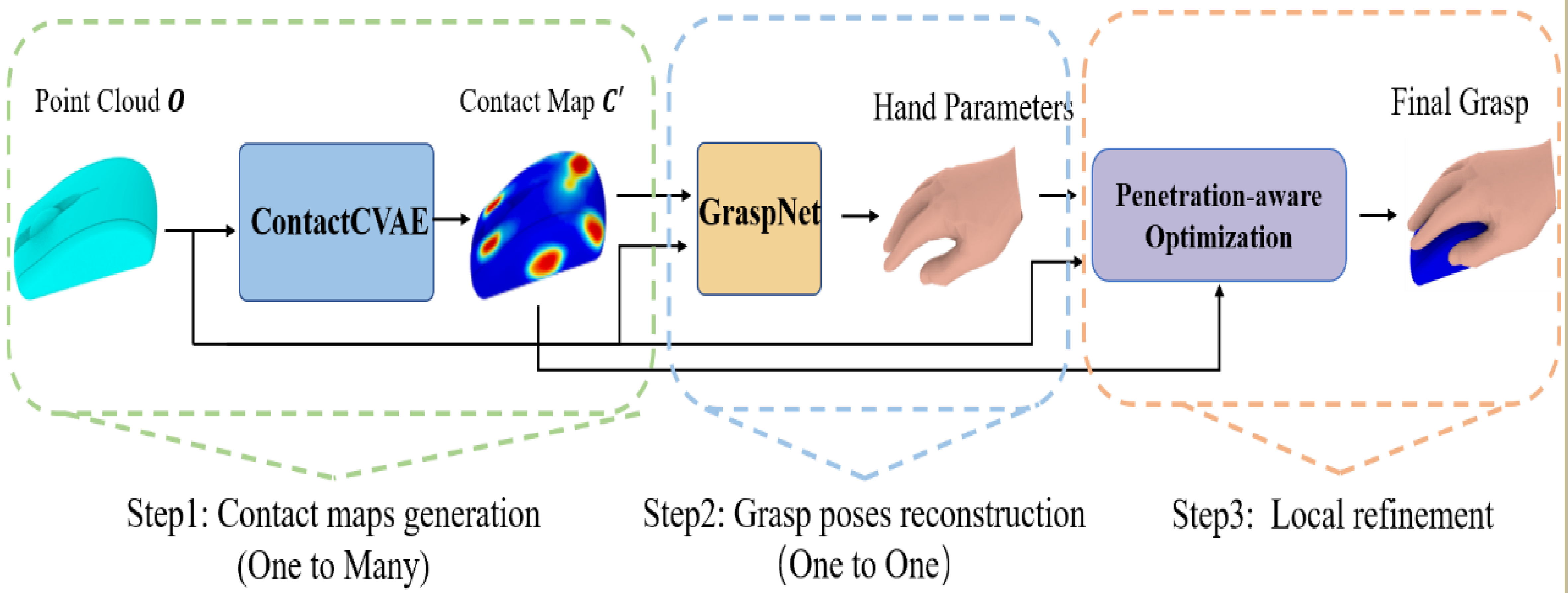


Qualitative Result



The visualization of generated contact maps and grasps for objects from the Obman and ContactPose. We present both the predicted grasp (left) and the corresponding contact map (right).

Methods



- **ContactCVAE**

A generative model based on CVAE, taking an object point cloud as input and generating a contact map.

- **GraspNet**

Aiming estimates a grasp pose parameter from the generated contact map.

- **Penetration-aware Optimization**

refining the pose parameters to get the final grasp.

Quantitative Result

Ptr Dep(cm): Penetration measured by the depth.
Ptr Vol(cm³): Penetration measured by the volume.
CR(%): Contact Rate.
SD Mean(cm): The average of the simulation displacement.
SD Var(cm): The variance of the simulation displacement.
Div(cm): Diversity of generation. **GSR(%):** Grasp Success Rate.

Dataset	Methods	Ptr (↓)		SD (↓)		CR (↑)	Div (↑)	GSR (↑)
		Dep	Vol	Mean	Var			
Obman	GrabNet [Taheri *et al.*, 2020]	0.61	8.31	1.78	±2.71	98.25	7.93	27.60
	GraspField [Karunratanakul *et al.*, 2020]	0.56	6.05	2.07	±2.81	89.40	-	-
	GraspTTA [Jiang *et al.*, 2021]	0.45	5.14	1.62	**±2.18**	99.05	8.07	47.88
	Ours	**0.44**	**3.94**	**1.60**	±2.28	**100.00**	**10.14**	**61.37**
	GT	0.01	1.70	1.66	±2.44	100.00	7.86	87.12
ContactPose	GrabNet [Taheri *et al.*, 2020]	0.92	16.74	**1.04**	±1.60	97.42	5.92	16.89
	GraspTTA [Jiang *et al.*, 2021]	0.79	6.01	1.52	±1.41	97.67	7.32	42.31
	Ours	**0.36**	**4.15**	1.40	±1.98	**98.85**	**7.91**	**58.97**
	GT	0.51	5.91	1.06	±1.13	99.65	7.03	41.78

Conclusion

We propose a novel framework for human grasps generation, which holds the potential for different deep architectures. The highlight of this work is exploiting the object affordance represented by the contact map, to formulate a functionality-oriented grasp pose and using penetration-aware partial optimization to refine partial-penetrated poses without hurting good-quality ones. The proposed method is extensively validated on two public datasets. In terms of diversity and stability, both quantitative and qualitative evaluations support that, our method has clear advantages over other strong competitors in generating high-quality human grasps.