



中国科学技术大学
University of Science and Technology of China

三维重建中的配准算法研究

张举勇

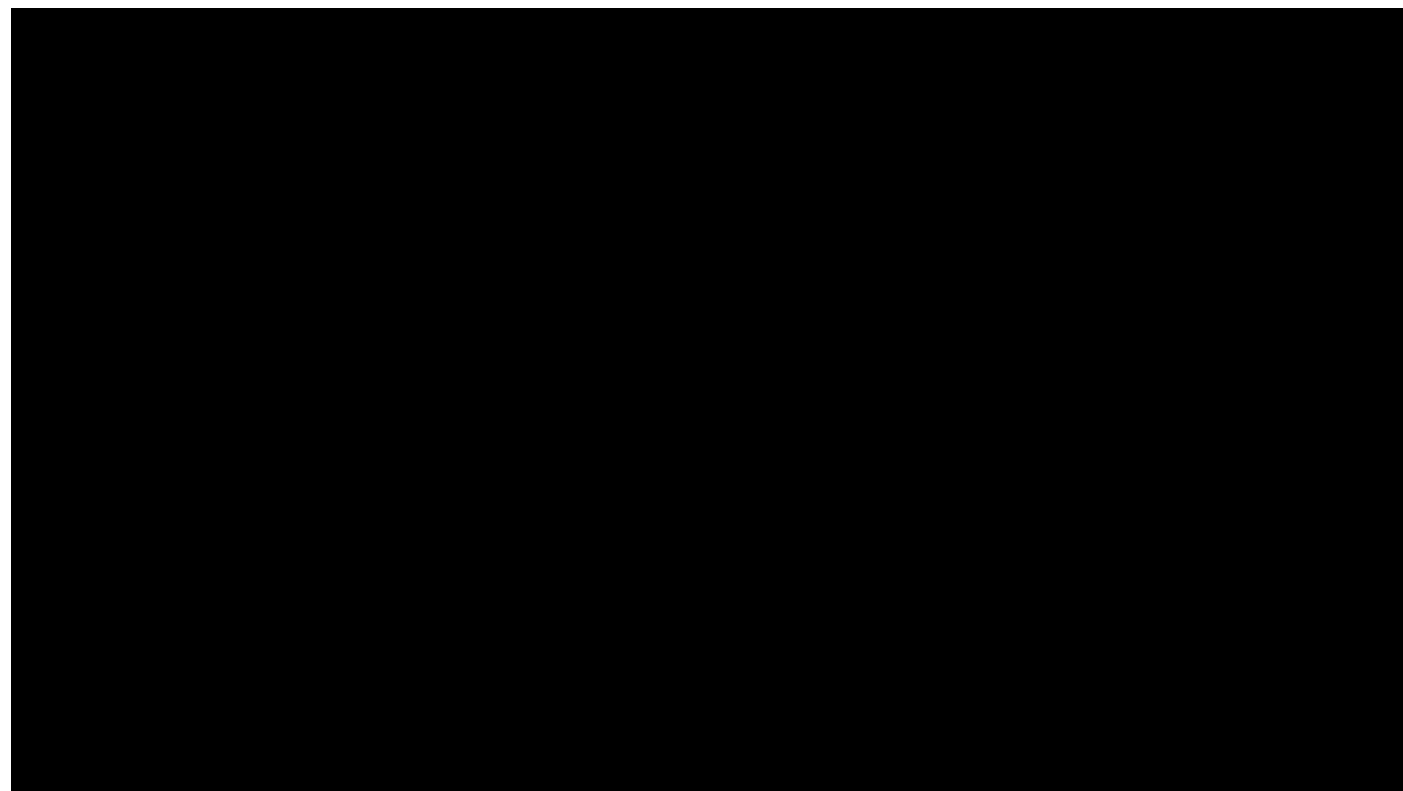
中国科学技术大学



- 多媒体世界正逐渐从2D时代走向3D时代

沉浸式视频会议

虚拟数字人



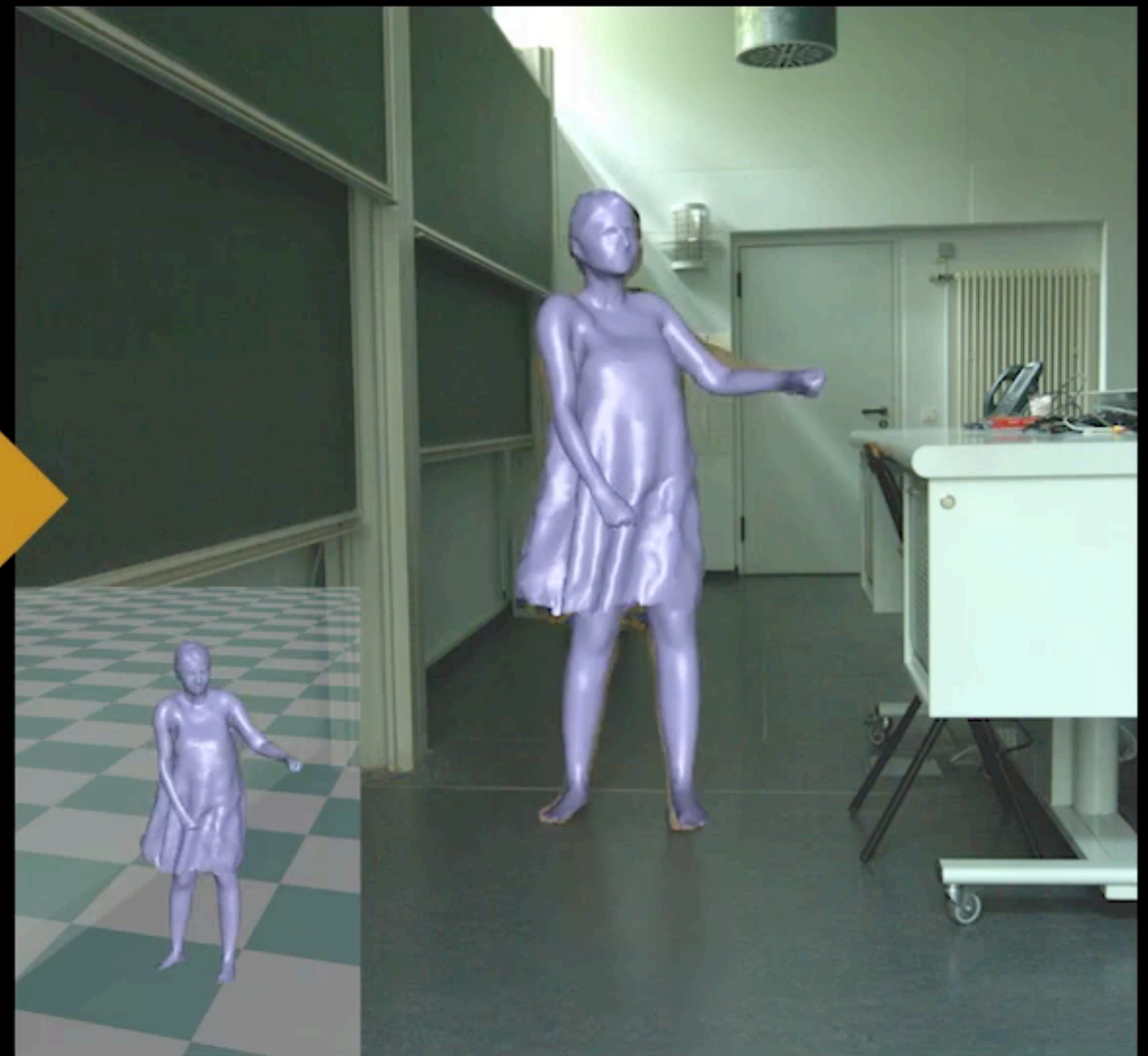


Newcombe, Izadi, Hilliges, Molyneaux, Kim, Davison, Kohli, Shotton, Hodges, Fitzgibbon
KinectFusion: Real-Time Dense Surface Mapping and Tracking, ISMAR 2011

Our Results



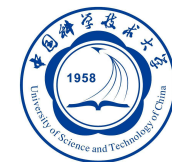
Input Image



Our Results

Marc Habermann, Weipeng Xu, Michael Zollhoefer, Gerard Pons-Moll, Christian Theobalt
DeepCap: Monocular Human Performance Capture Using Weak Supervision, CVPR 2020

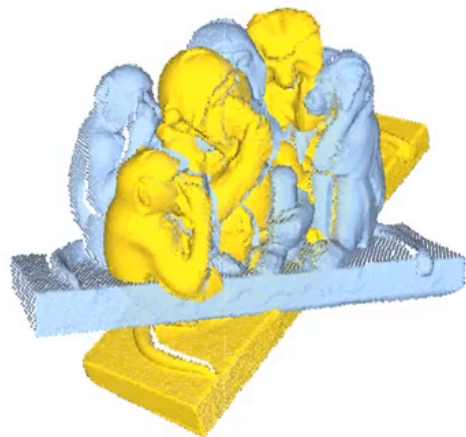
谷歌 - 沉浸式视频会议技术“ Starline项目”



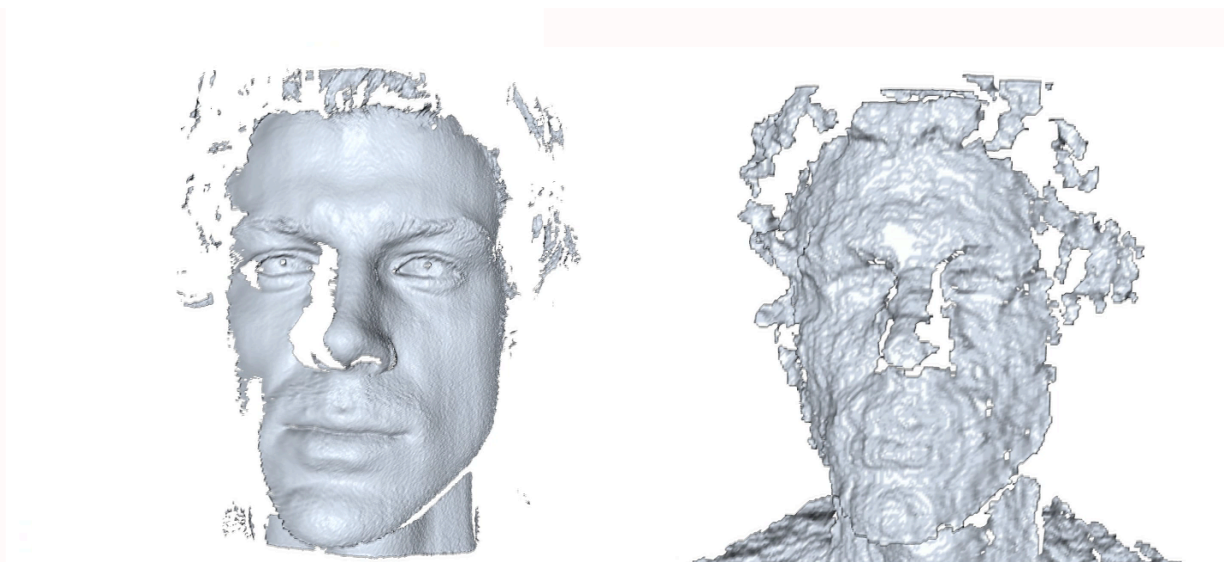
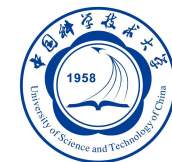
由数十个景深扫描传感器以及 65 英寸「光场显示器」实时生成 3D 模型

什么是几何配准?

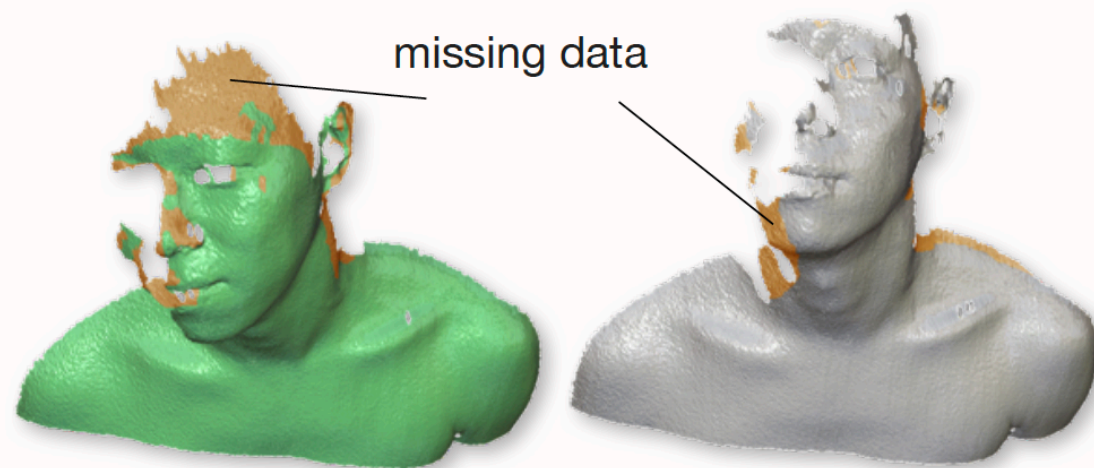
- 将源模型 P 配准到目标模型 Q
 - 寻找变换 $T(\cdot)$, 使得 $T(P)$ 与 Q 尽可能接近
- 两个主要问题:
 - 如何衡量配准结果的质量?
 - 变换的类型与表示方式?



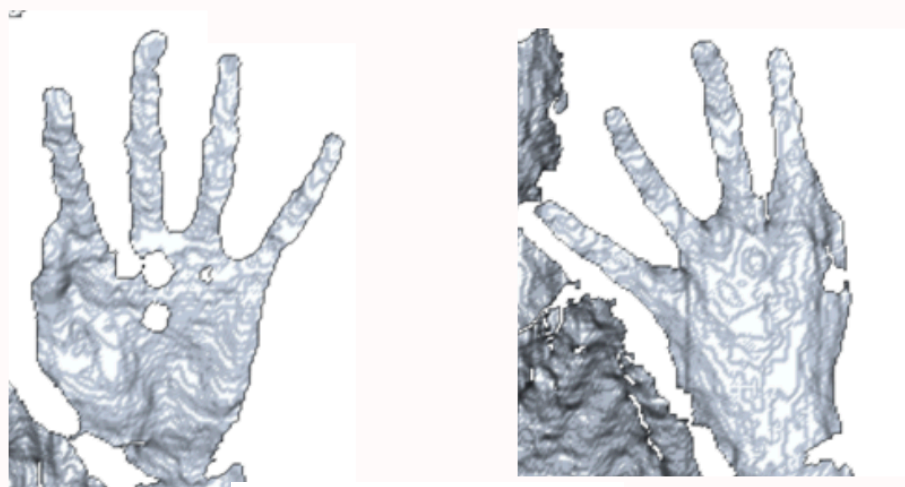
配准问题中的一些挑战



Noise



Partial matching



Ambiguity



Illumination changes

- 将配准问题表达为能量最小化问题：

$$\arg \max_T E_{reg}(T, P, Q)$$

$$E_{reg}(T, P, Q) = E_{match}(T, P, Q) + E_{prior}(T)$$

配准误差

如何衡量配准结果的质量？

变换误差

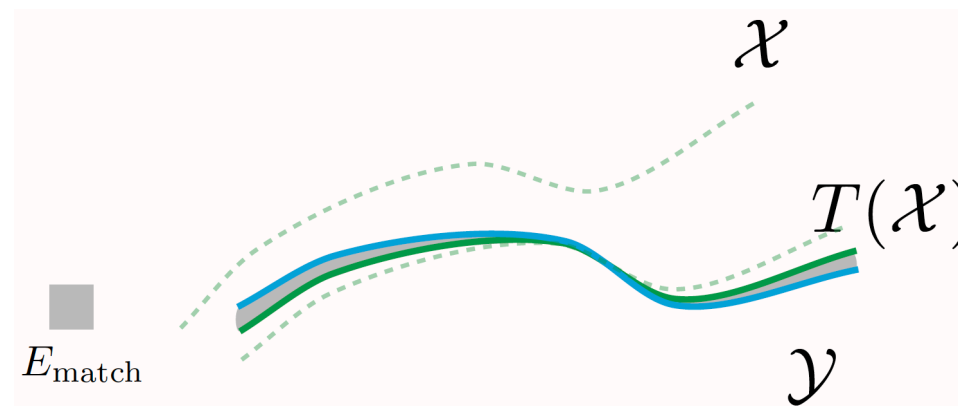
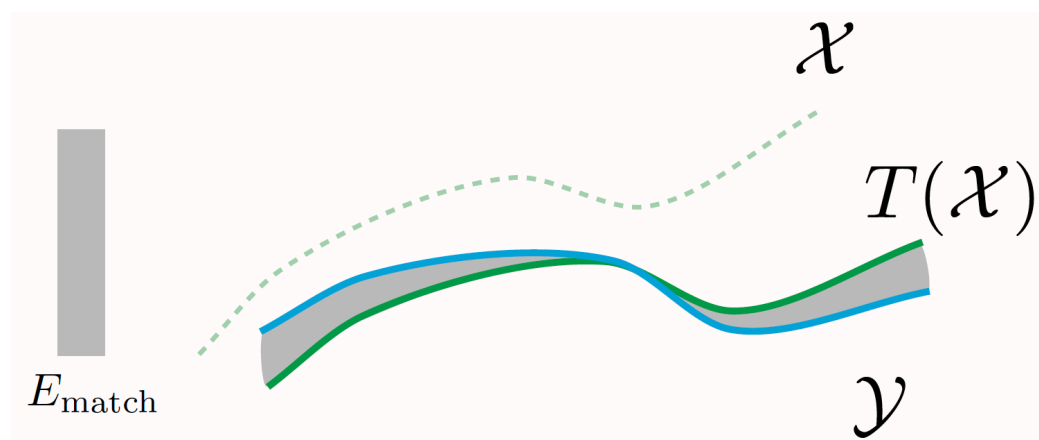
变换的类型与表示方式？

- 配准误差

$$E_{reg}(T, P, Q) = E_{match}(T, P, Q) + E_{prior}(T)$$

$$E_{match}(T, P, Q) = \int_X \phi(T(p), Q) dx$$

距离度量函数

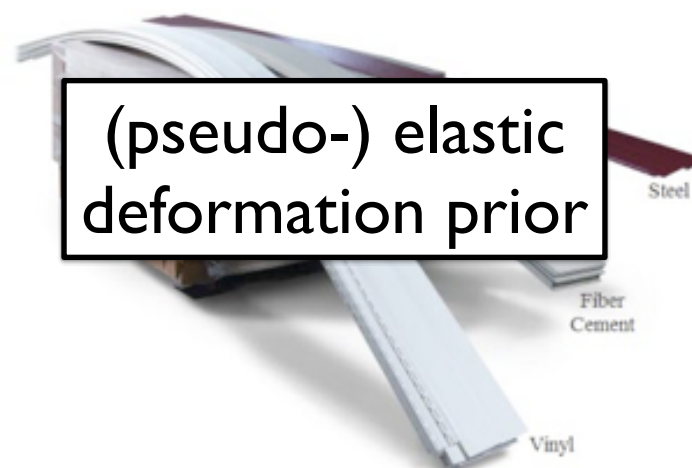


- 变换误差

$$E_{reg}(T, P, Q) = E_{match}(T, P, Q) + E_{prior}(T)$$



Rigid



Elastic



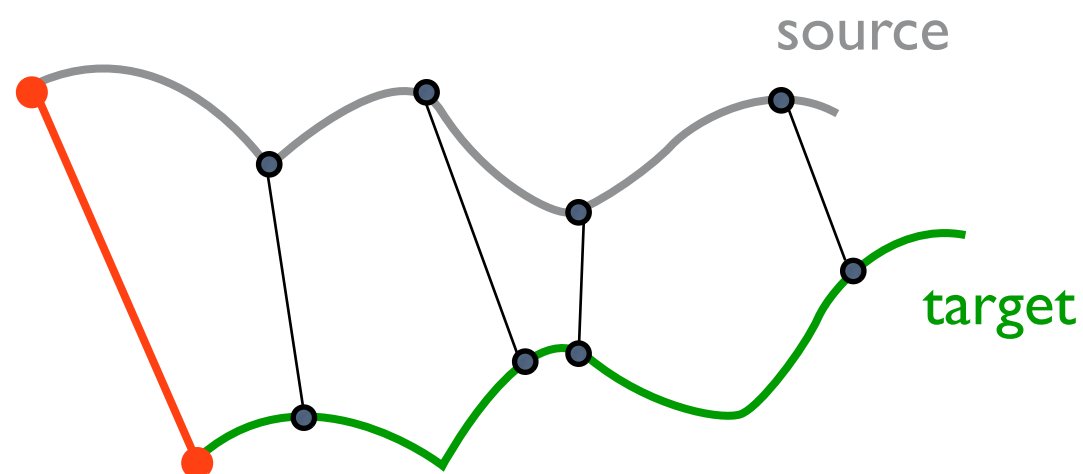
Articulated



Composite

iterate until convergence:

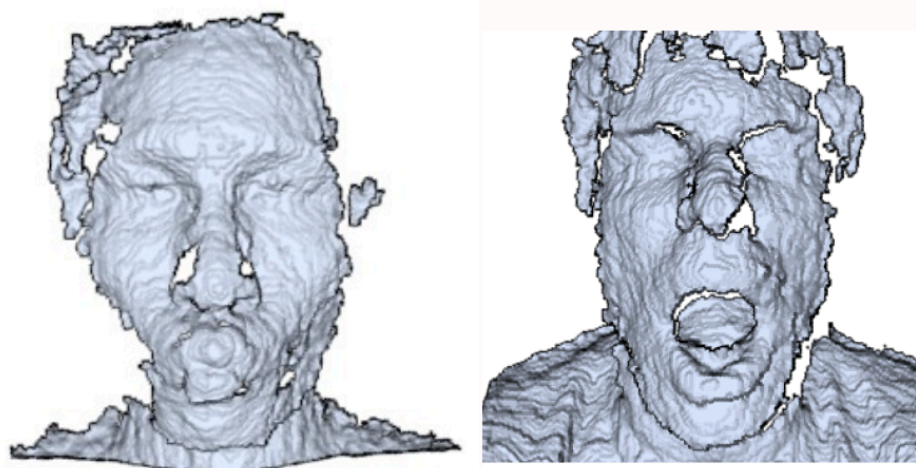
1. sample points p_i
2. find closest points q_i
3. reject bad pairs (p_i, q_i)
4. find optimal transformation \mathbf{R} \mathbf{t}
5. update scan alignment



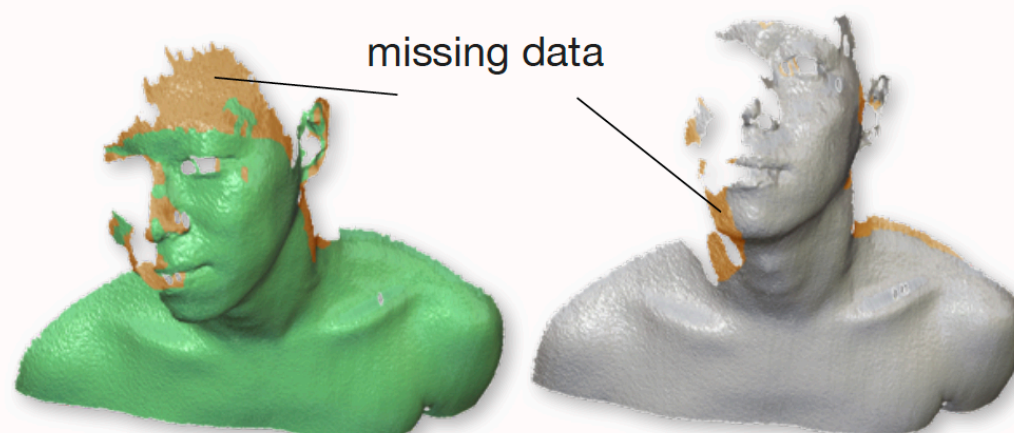
刚性配准 - 配准误差度量

◆ 刚性配准阶段所优化的能量

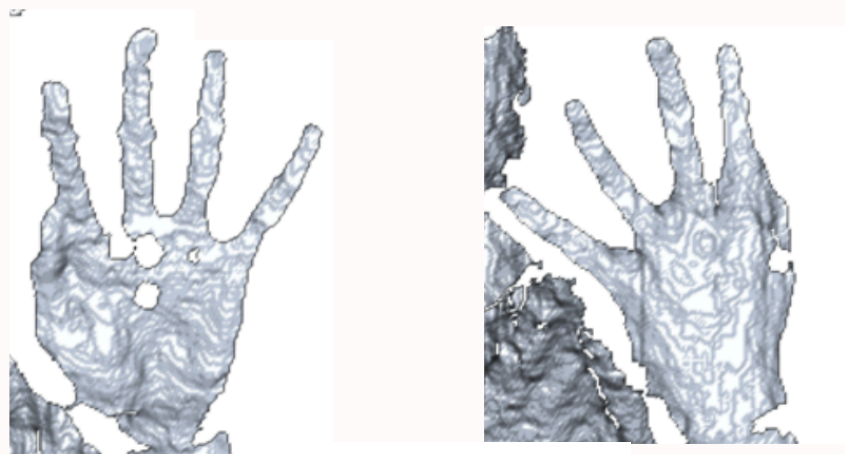
$$\min_{\mathbf{R}, \mathbf{t}} \sum_{i=1}^m \|\mathbf{R}\mathbf{p}_i + \mathbf{t} - \hat{\mathbf{q}}_i\|_2^2 + \mathbf{I}_{SO}(d)$$



Noise



Partial matching



Ambiguity



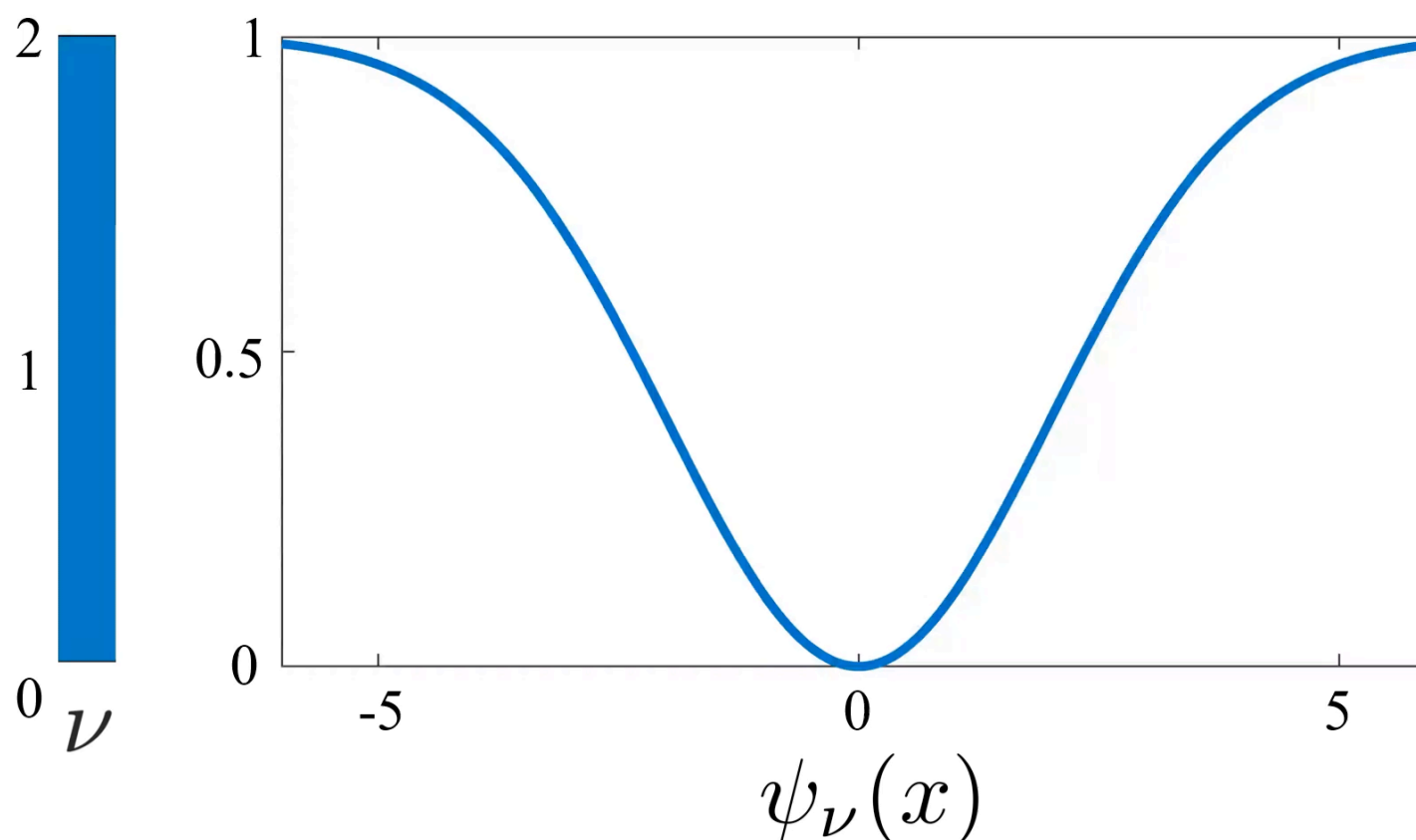
Illumination changes

刚性配准 - 优化模型的改进

◆ 刚性配准阶段所优化的能量

$$\min_{\mathbf{R}, \mathbf{t}} \sum_{i=1}^m \|\mathbf{R}\mathbf{p}_i + \mathbf{t} - \hat{\mathbf{q}}_i\|_2^2 + \mathbf{I}_{SO(d)}$$

$$\varphi_\nu(\|\mathbf{R}\mathbf{p}_i + \mathbf{t} - \hat{\mathbf{q}}_i\|) \quad \varphi_\nu(x) = 1 - \exp\left(-\frac{x^2}{2\nu^2}\right)$$



Juyong Zhang, Yuxin Yao, Bailin Deng

Fast and Robust Iterative Closest Point, IEEE TPAMI 2021

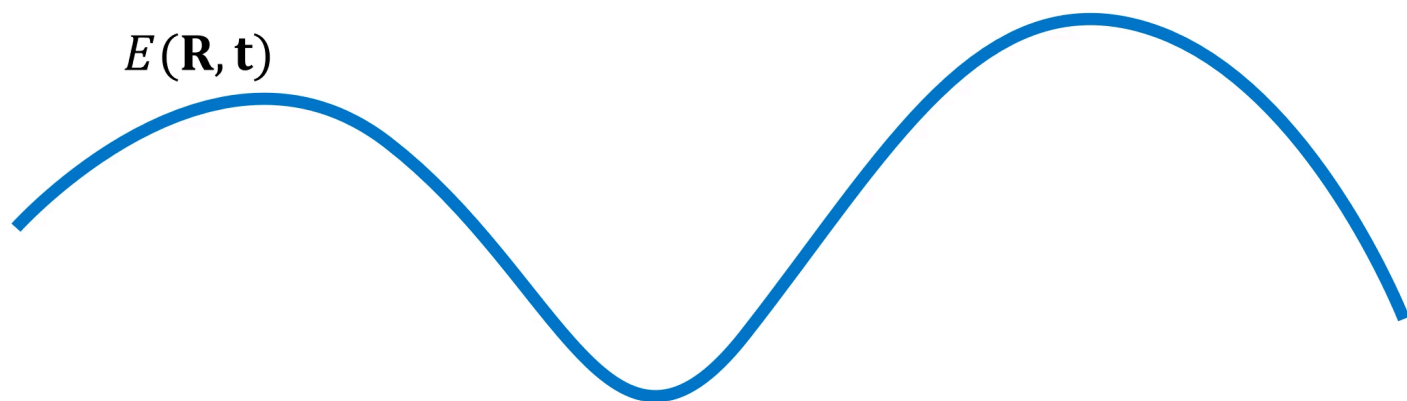
Majorization-minimization (MM)

◆ 构造代理函数

$$\bar{E}^{(k)}(\mathbf{R}, \mathbf{t}) = \begin{cases} > E(\mathbf{R}, \mathbf{t}), & (\mathbf{R}, \mathbf{t}) \neq (\mathbf{R}^{(k)}, \mathbf{t}^{(k)}) \\ = E(\mathbf{R}, \mathbf{t}), & (\mathbf{R}, \mathbf{t}) = (\mathbf{R}^{(k)}, \mathbf{t}^{(k)}) \end{cases}$$

◆ 下一步迭代

$$\left(\mathbf{R}^{(k+1)}, \mathbf{t}^{(k+1)}\right) = \arg \min_{\mathbf{R}, \mathbf{t}} \bar{E}^{(k)}(\mathbf{R}, \mathbf{t})$$



ICP算法 - 固定点迭代形式

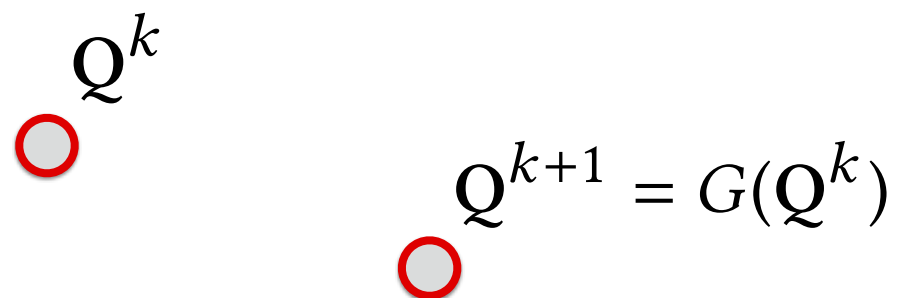
◆ Lloyd算法

□ 寻找对应 $\hat{\mathbf{q}}_i^k = \arg \min_{\mathbf{q} \in Q} \|\mathbf{R}^k \mathbf{p}_i + \mathbf{t}^k - \mathbf{q}\|$

□ 配准 $(\mathbf{R}^{(k+1)}, \mathbf{t}^{(k+1)}) = \arg \min_{\mathbf{R}, \mathbf{t}} \sum_{i=1}^m \|\mathbf{R} \mathbf{p}_i + \mathbf{t} - \hat{\mathbf{q}}_i^k\|_2^2 + \mathbf{I}_{SO(d)}$

◆ 结合两步骤 $(\mathbf{R}^{(k+1)}, \mathbf{t}^{(k+1)}) = G(\mathbf{R}^k, \mathbf{t}^k)$

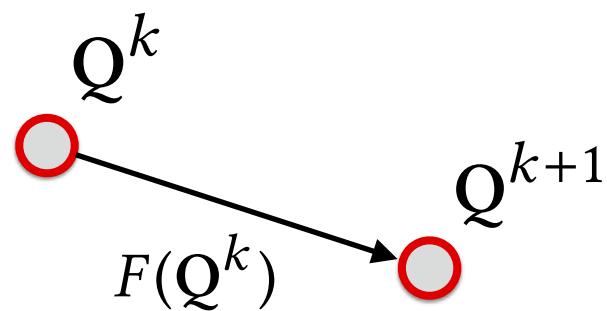
◆ 终止条件 $(\mathbf{R}^{(k+1)}, \mathbf{t}^{(k+1)}) - G(\mathbf{R}^k, \mathbf{t}^k) = 0$



Q^k

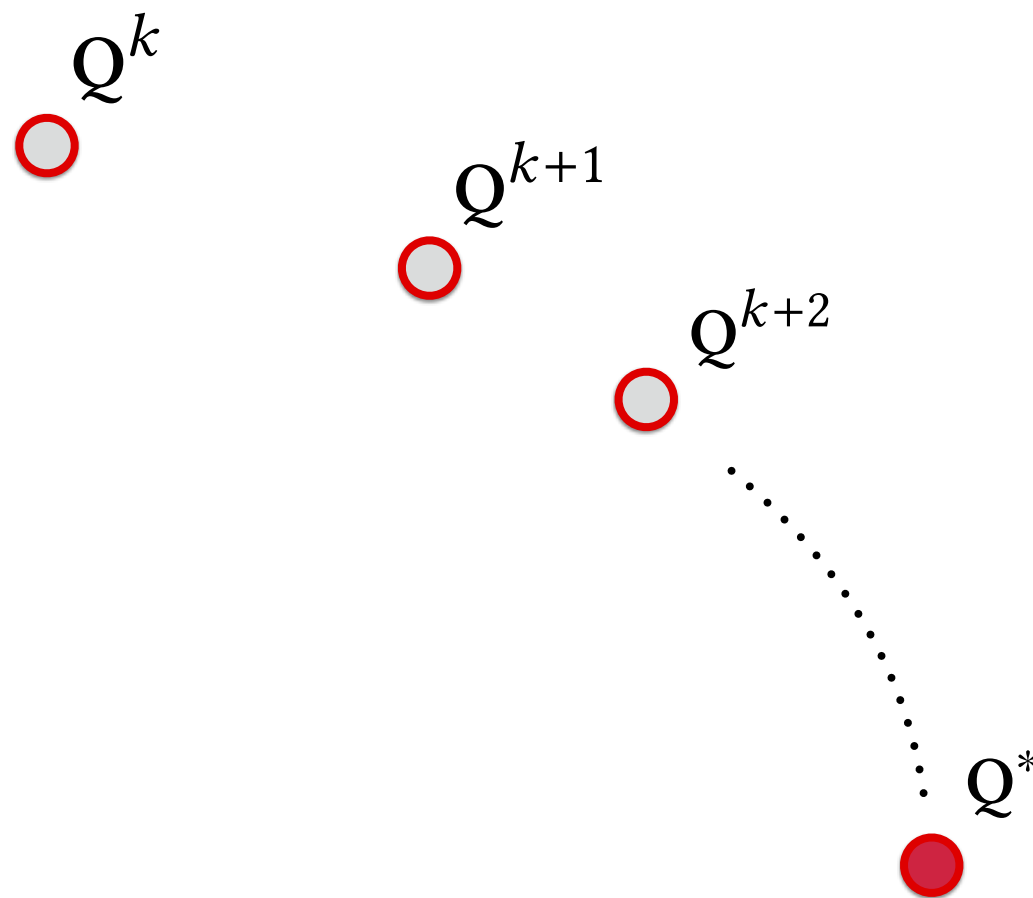
$Q^{k+1} = G(Q^k)$

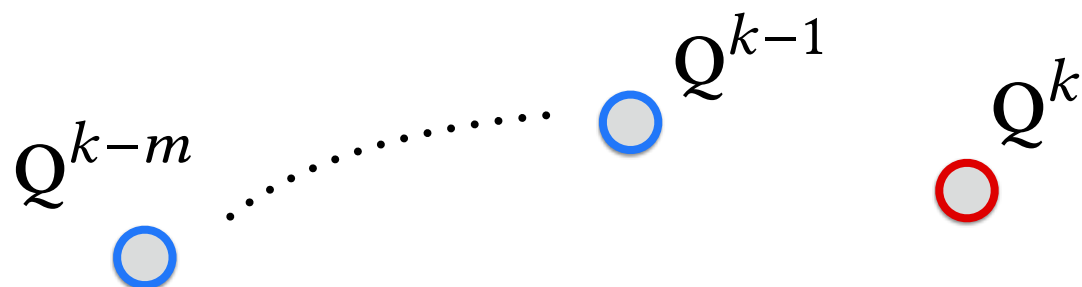
- **Residual** $F(Q) = G(Q) - Q$



- For fixed point Q^* :

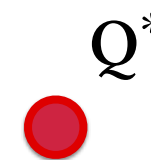
$$F(Q^*) = G(Q^*) - Q^* = 0$$

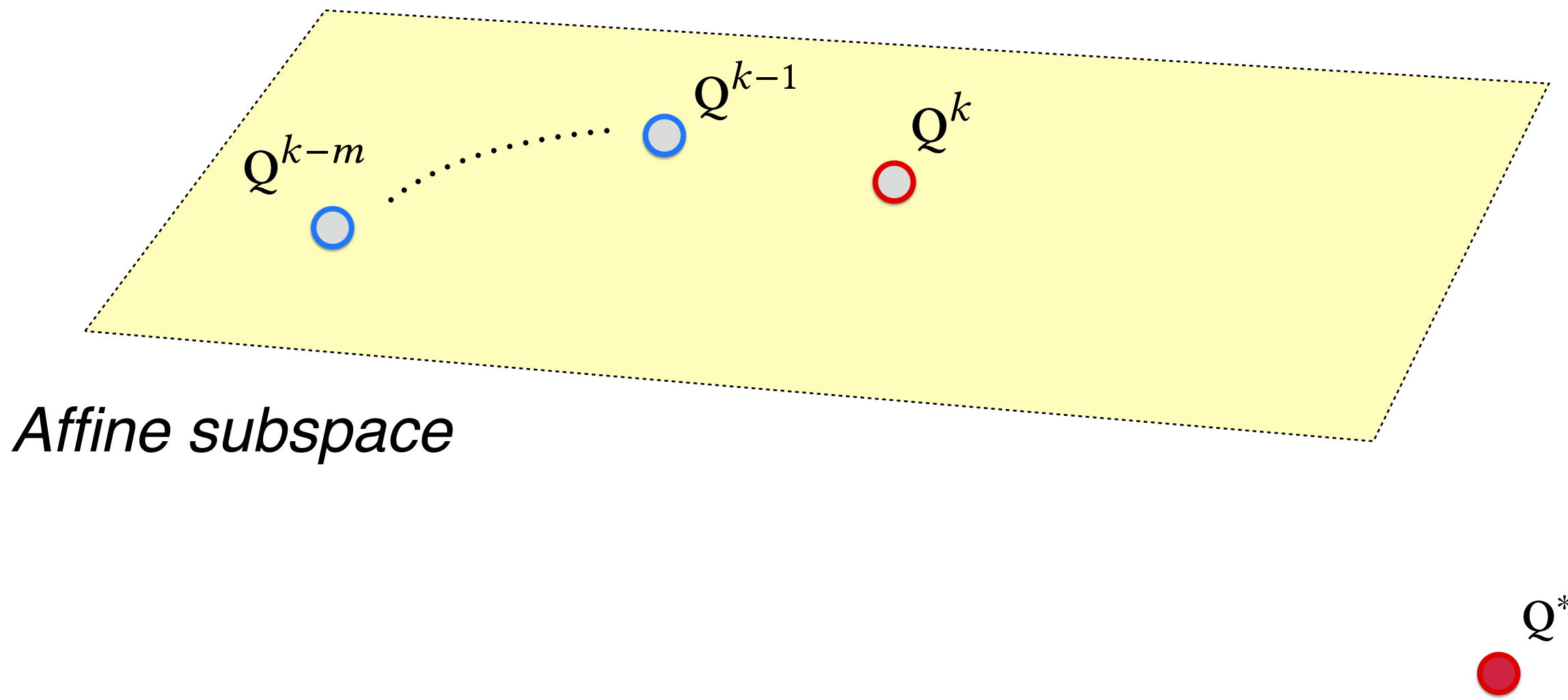




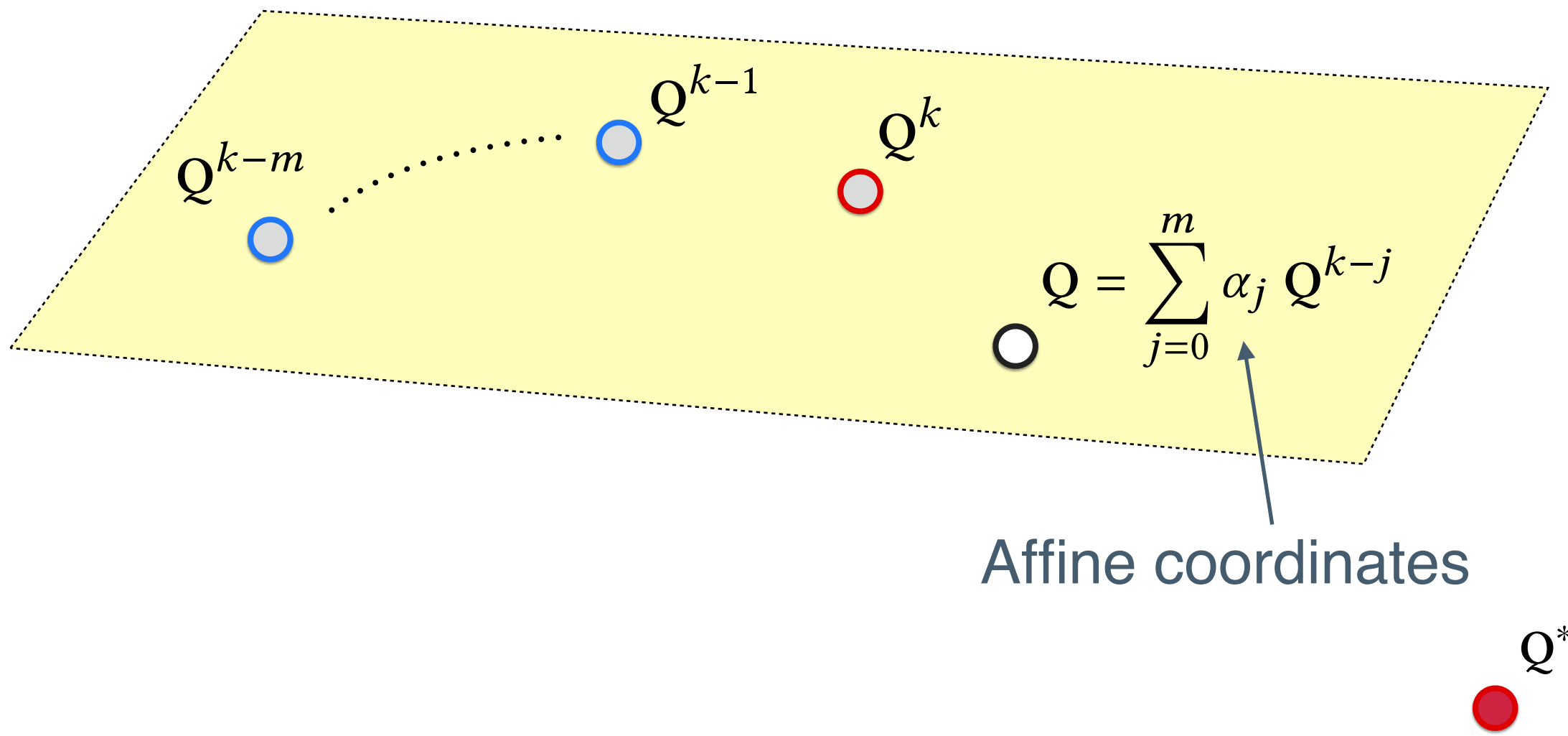
- Key idea:

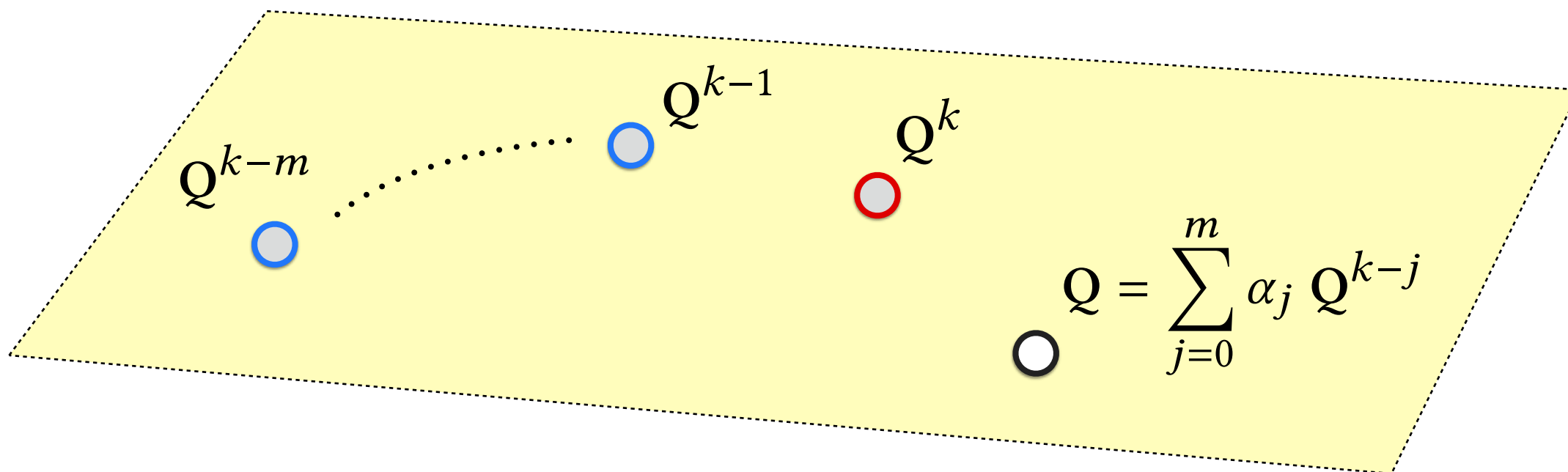
- Use $Q^k, Q^{k-1}, \dots, Q^{k-m}$ to approximate residual F





Affine subspace

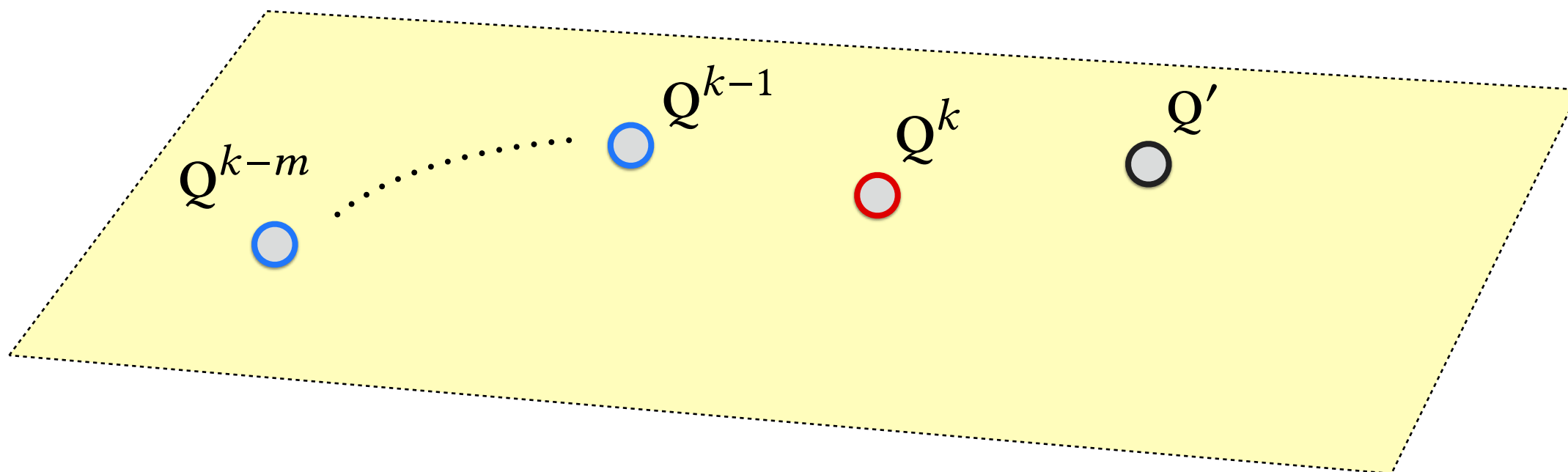




- Linear approximation of F :

$$\tilde{F}\left(\sum_{j=0}^m \alpha_j Q^{k-j}\right) = \sum_{j=0}^m \alpha_j F(Q^{k-j})$$





- Minimize approximate residual:

$$Q' = \operatorname{argmin} \|\tilde{F}\|^2$$

- linear least squares with m variables



方法总结与结果

- ◆ 寻找对应：最近邻搜索
- ◆ 配准：基于鲁棒Welsch函数进行刚性变换
- ◆ 根据 $SE(d)$ 空间中前 m 步的信息进行加速



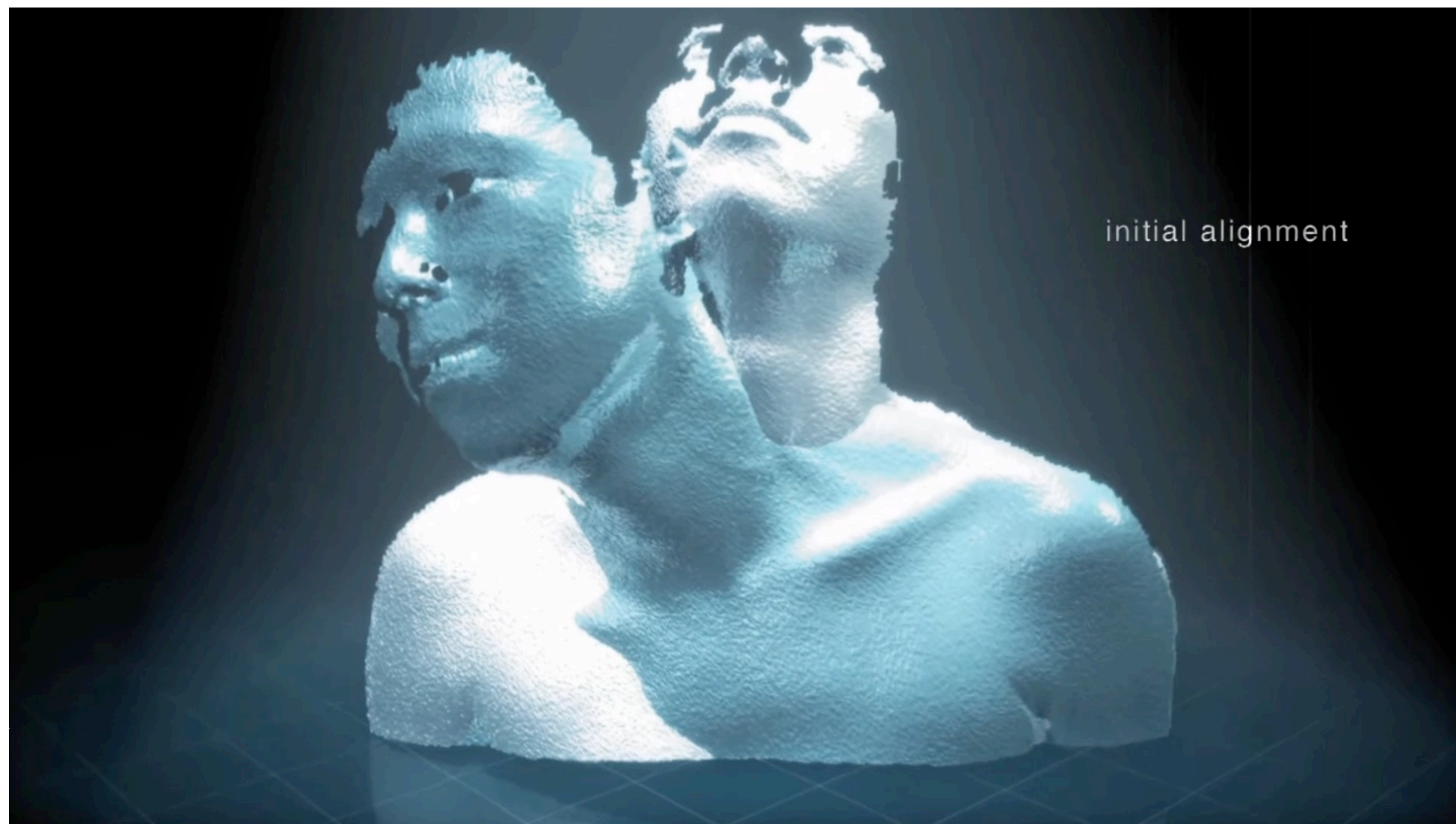
在公开数据集上的测试误差(单位:mm)：RGBD-SLAM datasets, ETH-laser datasets

RGBD-SLAM	xyz	360	Teddy	ETH-laser	Apartment	Stairs	Mountains
对比方法	78	220	146	对比方法	438	481	482
本方法	21	88	68	本方法	81	30	27

代码：<https://github.com/yaoyx689/Fast-Robust-ICP>

什么是非刚性注册及其挑战

- ◆ 目标：寻找非刚性变换 ϕ ，使得变形后模型 $\bar{P} = \phi(P)$ 与目标模型 Q 尽可能接近。
- ◆ 相比于刚性变换，非刚性变换自由度大、求解难度大



非刚性注册算法与模型

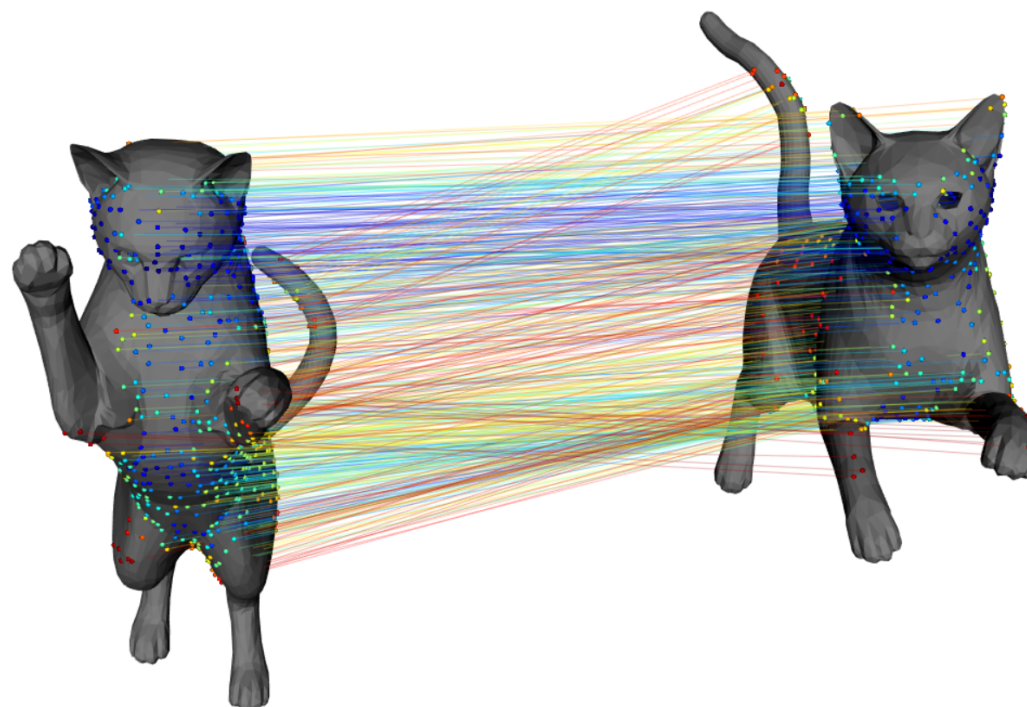
- 建立对应关系: 对源模型上的每个点, 获取其在目标模型上的对应点

$$\mathbf{u}_{\rho(i)} = \underset{\mathbf{u} \in \{\mathbf{u}_1, \dots, \mathbf{u}_t\}}{\operatorname{argmin}} \|\mathbf{v}_i - \mathbf{u}\|, \quad \text{for } i = 1, \dots, n$$

- 更新变换: 固定对应点, 优化求解变换

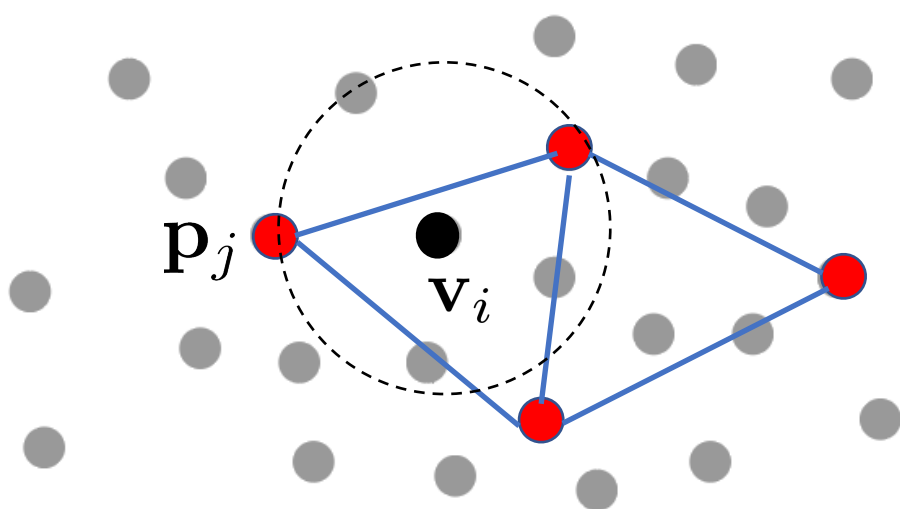
$$E(\mathbf{X}) = E_{\text{align}}(\mathbf{X}) + \alpha E_{\text{reg}}(\mathbf{X}) + \beta E_{\text{rot}}(\mathbf{X})$$

- 数据点匹配项
- 正则项
- 旋转项

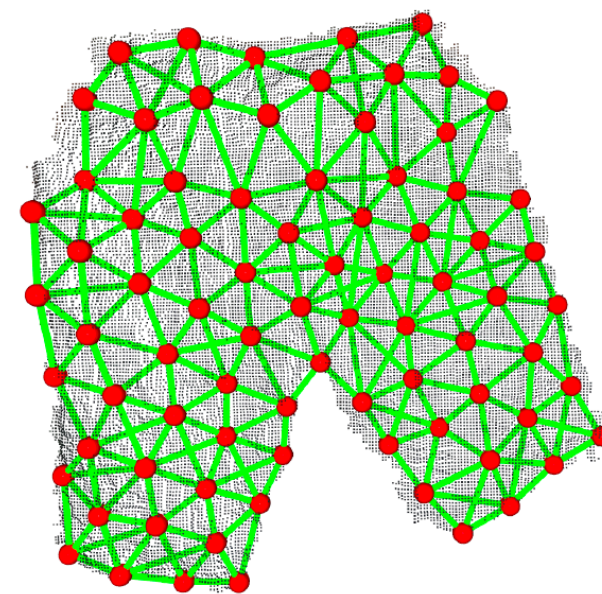


非刚性变形表示形式

- 方式一：将变换定义在源几何模型的每个数据点上
- 方式二：建立节点图, 变换定义在节点图的每个节点上

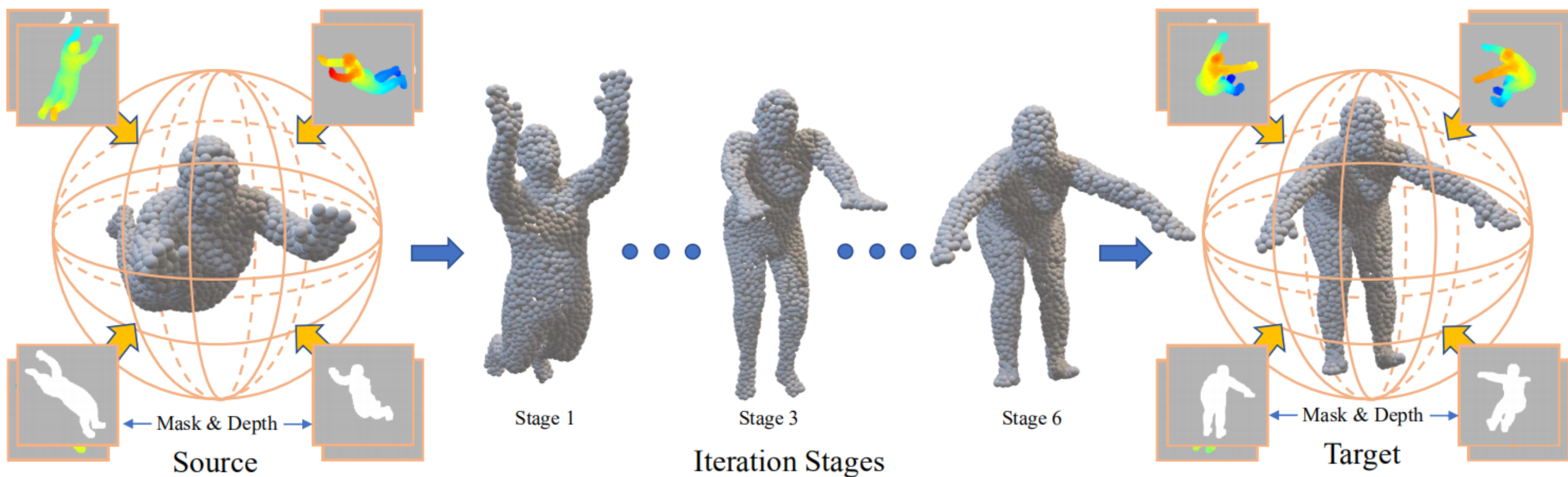


Points on source surface



基于深度学习的非刚性注册

- ◆ 一种适合深度学习的非刚性注册表示方式
- ◆ 一种可微loss函数，以驱动几何曲面之间的注册



Wanquan Feng, Juyong Zhang, Hongrui Cai, Haoifei Xu, Junhui Hou, Hujun Bao

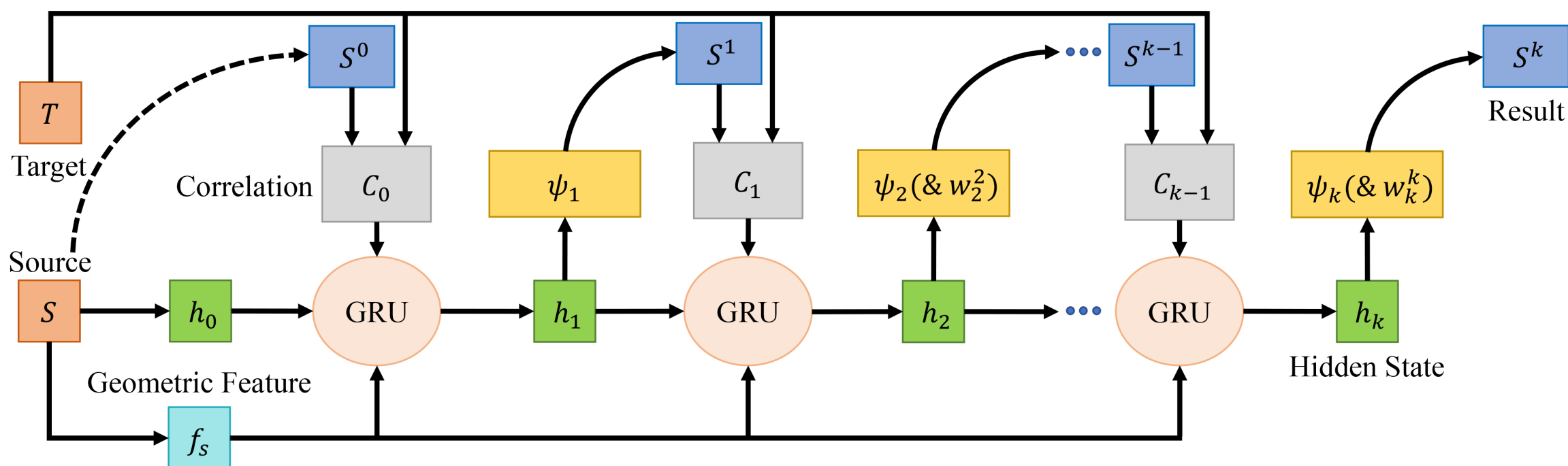
Recurrent Multi-view Alignment Network for Unsupervised Surface Registration, CVPR 2021

非刚性变形表示

所提出表示:
$$\phi(P) = \sum_{r=1}^K \mathbf{w}_r \cdot \psi_r(P)$$

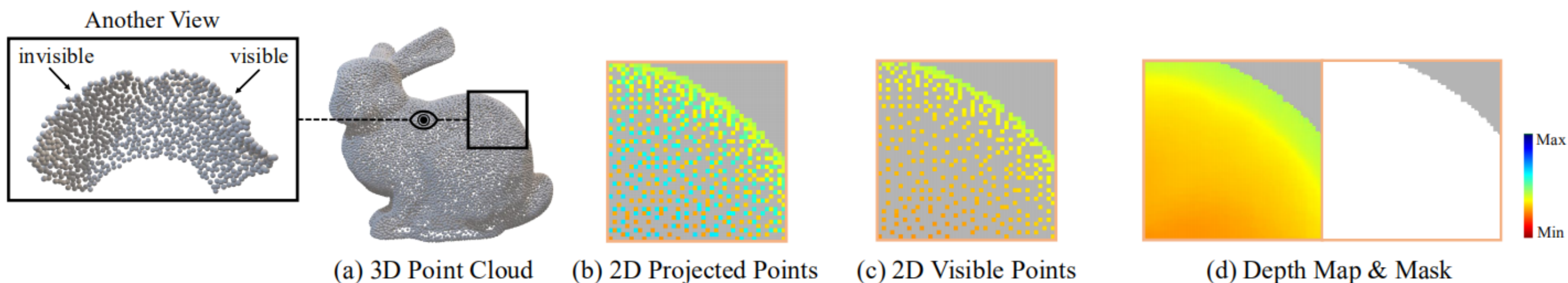
约束:
$$\sum_{r=1}^K \mathbf{w}_r(i) = 1, \quad \forall i = 1, 2, \dots, M.$$

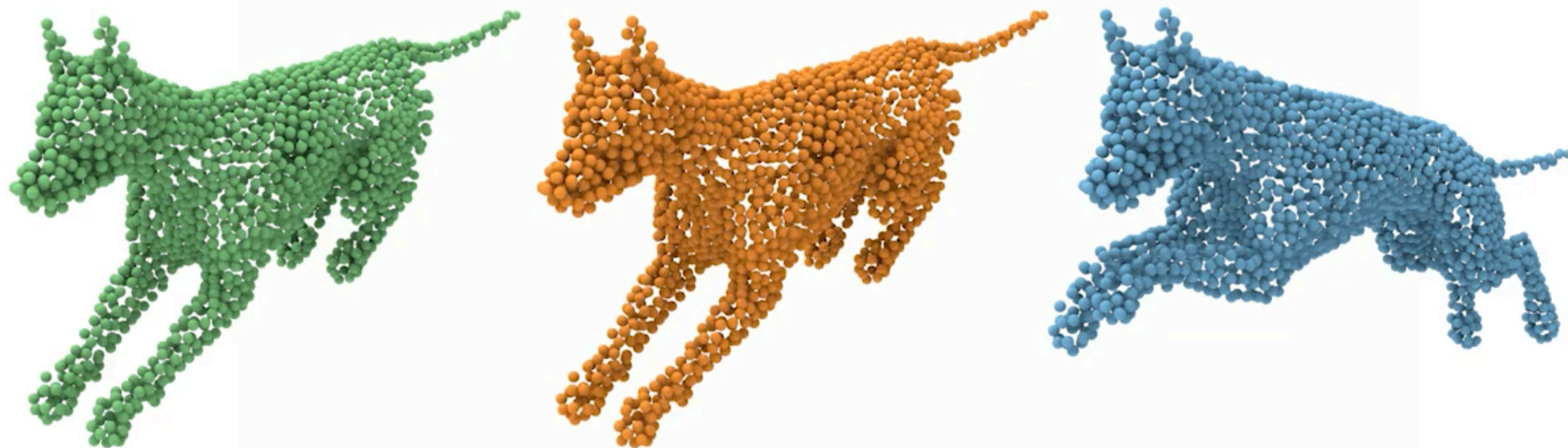
- $\phi(P)$: 非刚性变换; $\{\psi_r\}_{r=1}^K$: 一系列刚性变换; $\mathbf{w}_r \in \mathbb{R}^{M \times 1}$: 逐点蒙皮权重
- 蒙皮权重逐点可学习, 可根据目标曲面自适应变化



基于可微渲染的多视角loss函数

- 将三维物体投影到二维平面上并通过从初始点云、目标点云分别渲染得到的深度图、Mask图构造损失函数





Source

Stage 1

Target

代码：<https://github.com/WanquanF/RMA-Net>

Dataset	Metric	Input	CPD	BCPD	CPD-Net	PR-Net	Ours
Deform	CD	37.246	4.126	2.375	14.678	29.457	0.599
	EMD	25.952	7.853	5.478	21.696	25.192	0.386
Face	EMD	1.230	1.168	0.979	1.054	1.304	0.578
	MSE	21.469	9.568	8.013	13.752	14.575	5.245

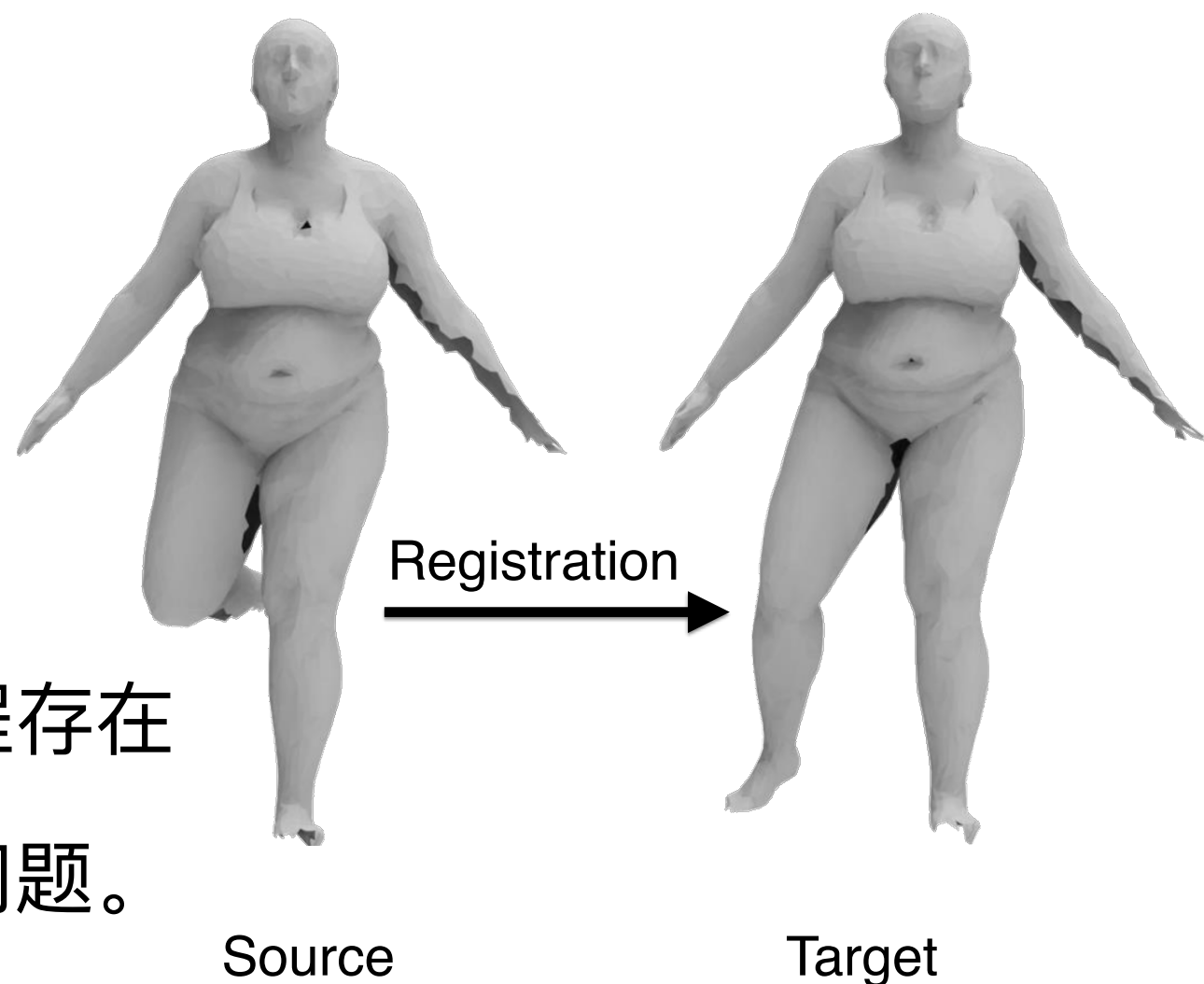
Table 2. Results on the deformable objects dataset (denoted as Deform for short, with metrics $CD(\times 10^{-4})$ and $EMD(\times 10^{-3})$) and the FaceWareHouse dataset (denoted as Face for short, with metrics $EMD(\times 10^{-2})$ and $MSE(\times 10^{-4})$).

基于节点图的非刚性配准

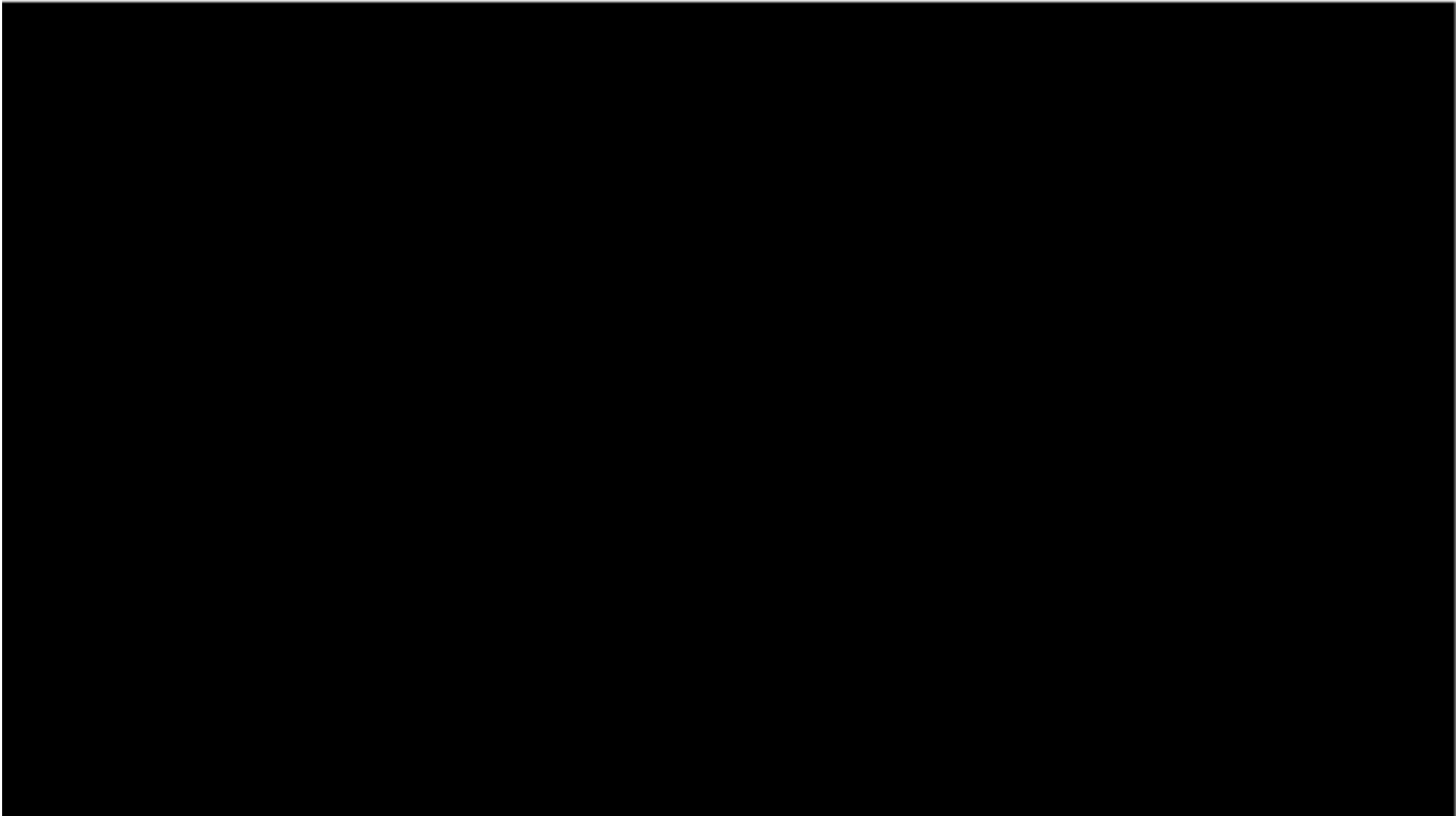
算法流程：采用迭代格式，交替更新对应关系与求解形变（通常通过求解优化问题），流程大致如下：

$$\begin{aligned} P^0 &= P, \\ (P_k, Q) &\xrightarrow{\text{Match}} C_k, \\ (P_k, Q, C_k) &\xrightarrow{\text{Deform}} P_{k+1}, \end{aligned}$$

最终使得 $\lim_{k \rightarrow \infty} P_k = Q$ 。该算法流程存在对初值、重叠区域、异常值敏感等问题。

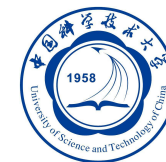


基于可微变形图的非刚性配准



- 整体上为 Course to Fine的模式：
 - 先基于节点图，求解Source模型structure level的形变
 - 再逐点求解displacement，从而实现vertex-level的refinement

非刚性配准结果动态展示



Source



Stage 1



Target

Differentiable Deformation Graph based Neural Non-rigid Registration, Submitted

应用展示：基于神经渲染的完整人头重建

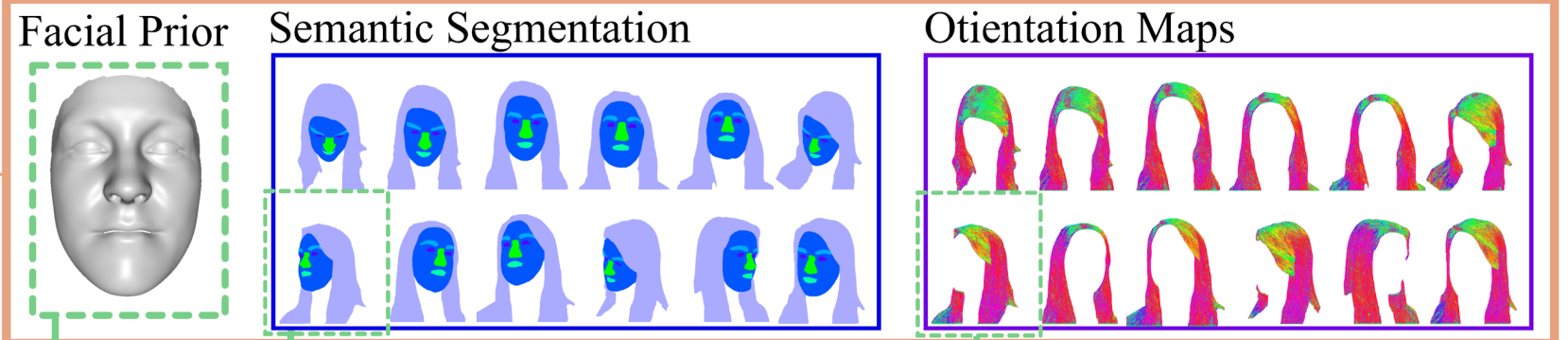


Input Images

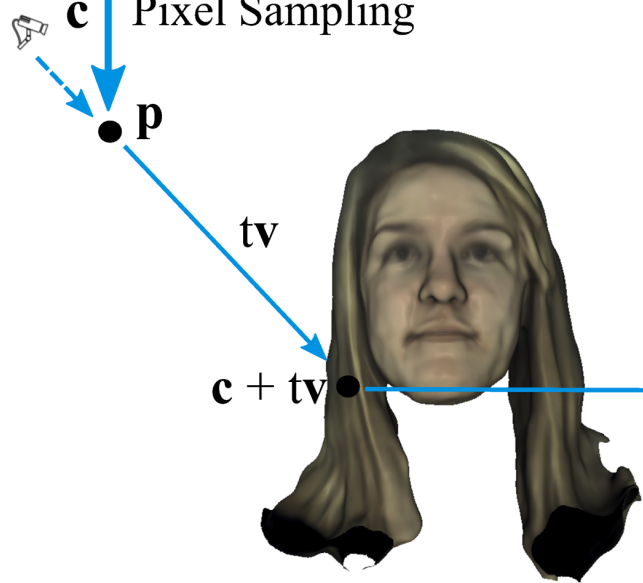


Prior Generation

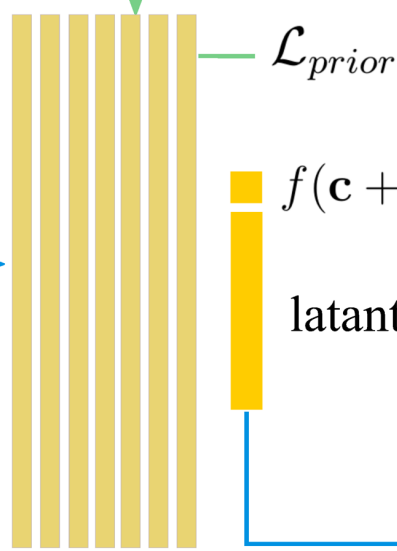
Head Priors



Pixel Sampling

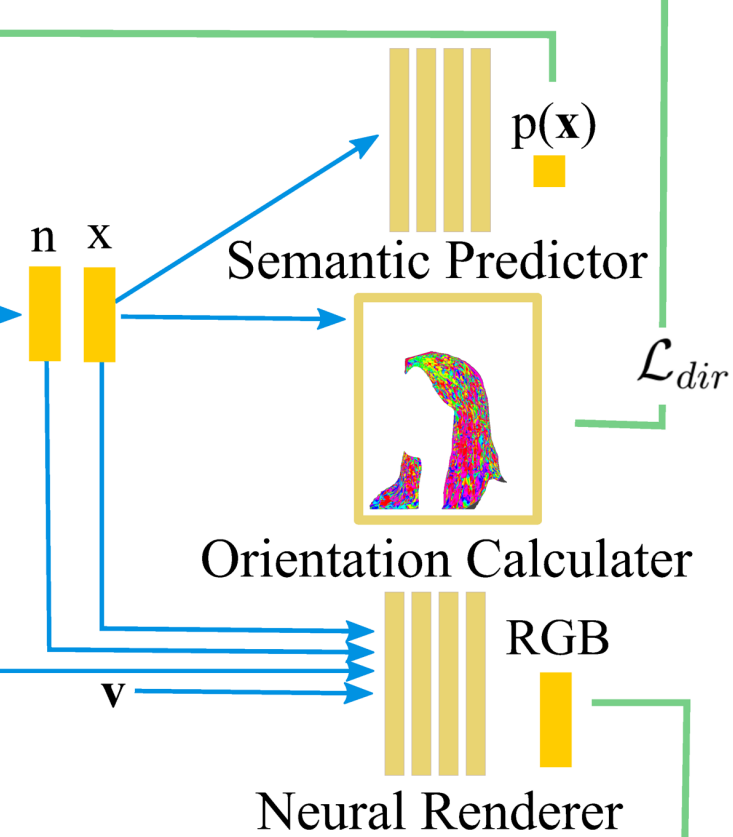


Vertex Sampling



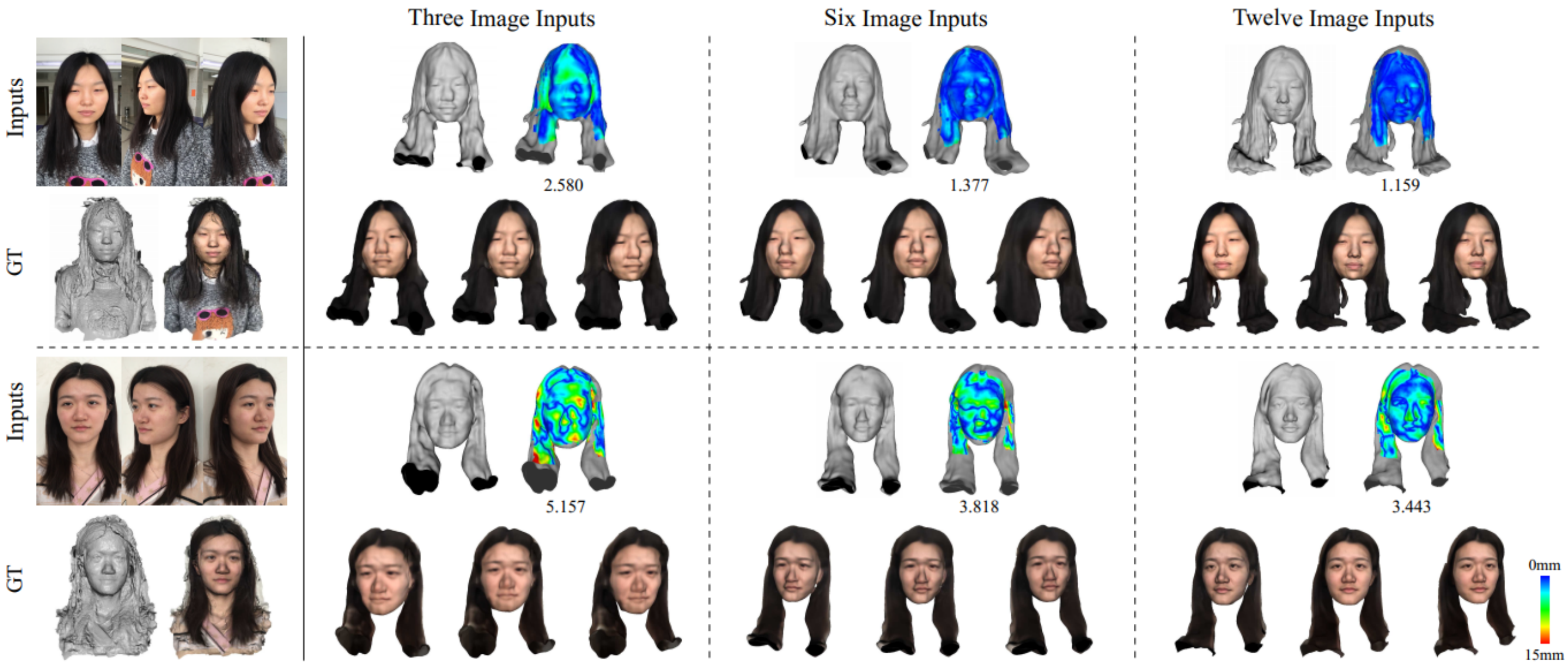
Implicit Neural Representation

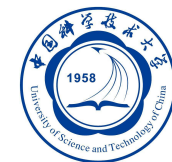
Differentiable Sampling



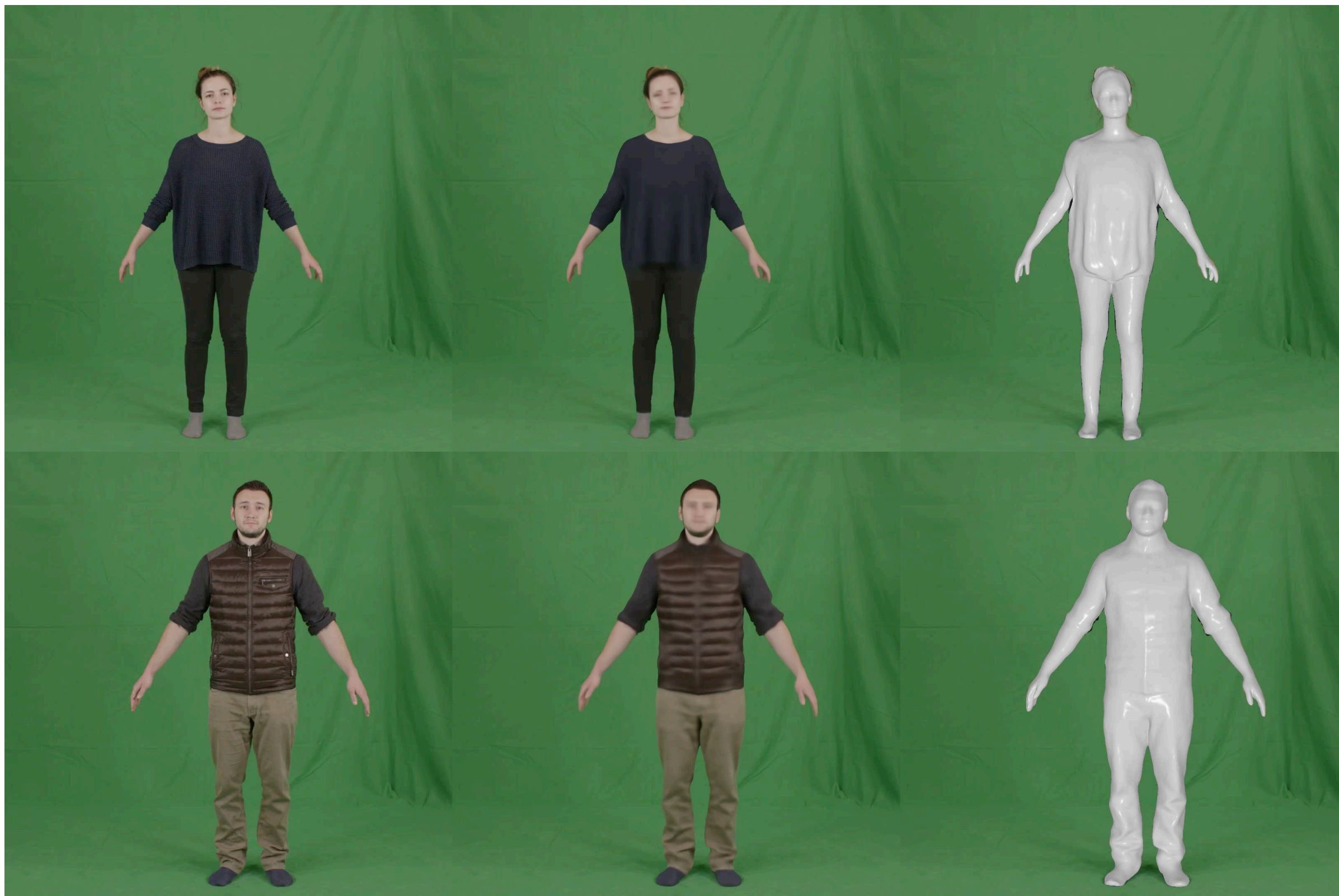
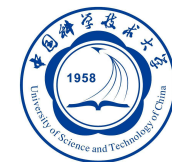
\mathcal{L}_{rgb}

结果展示

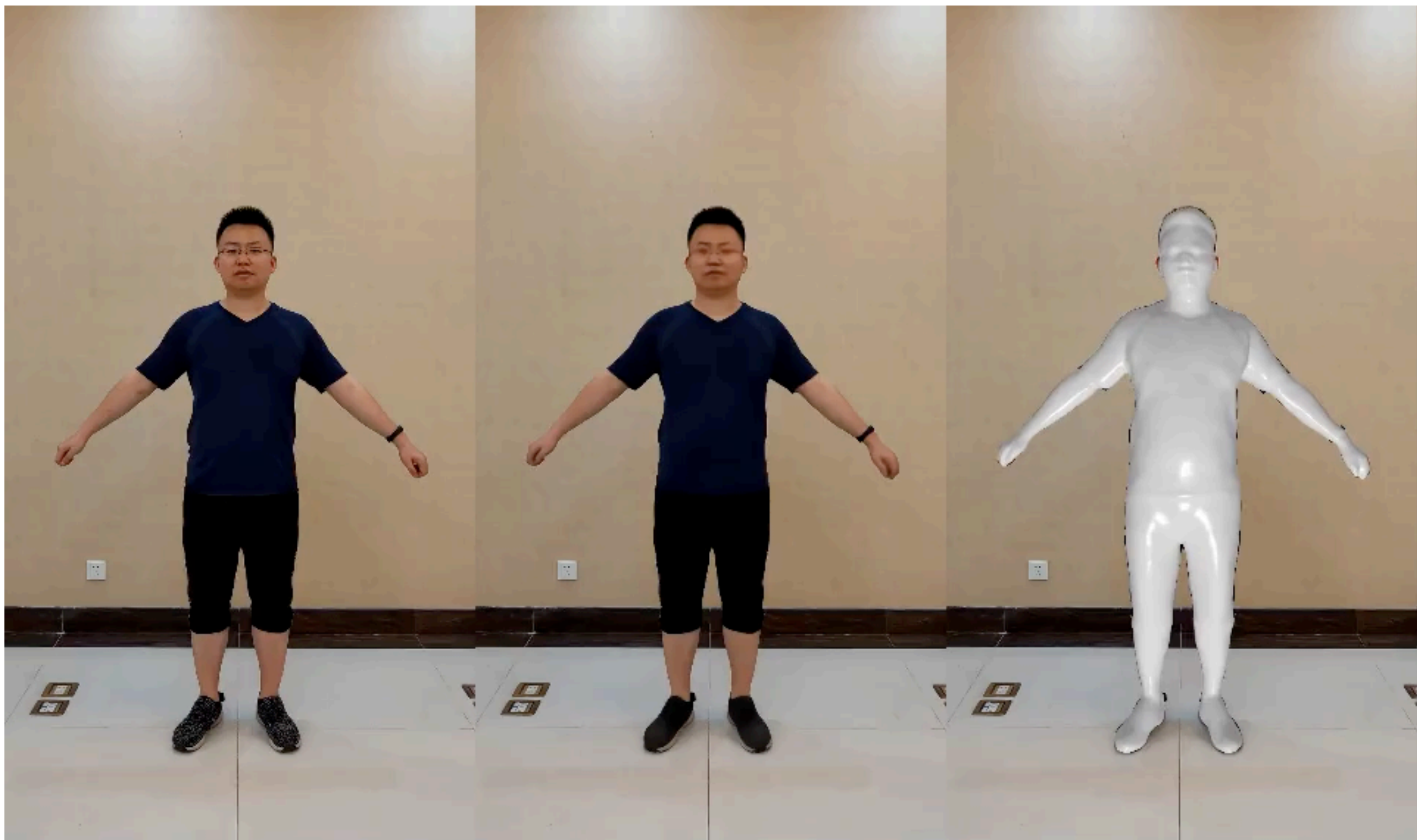
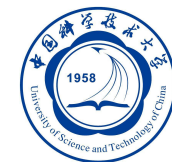




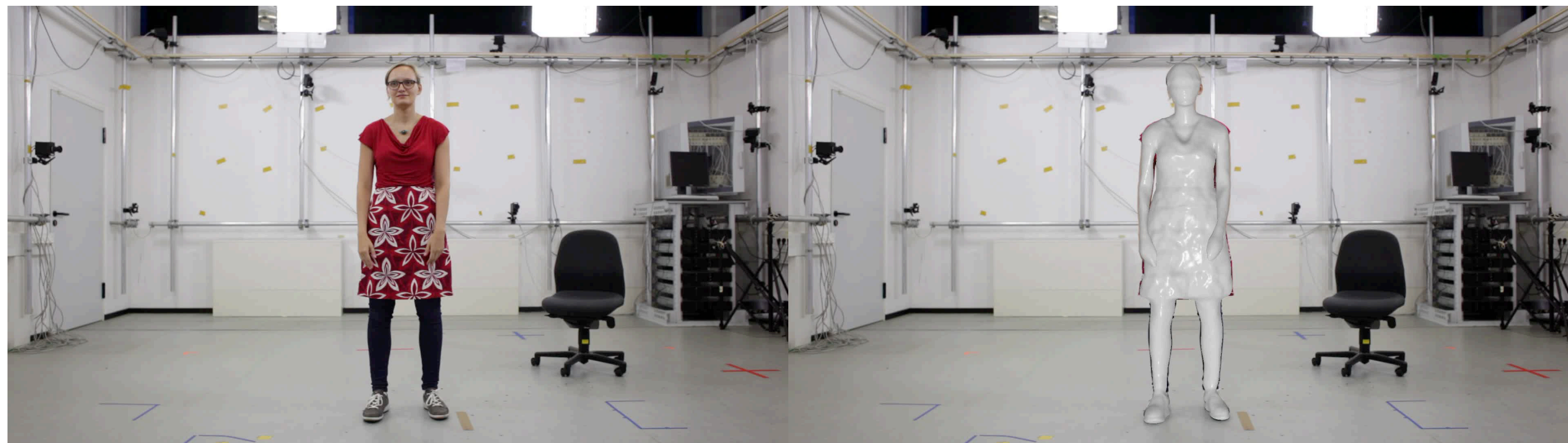
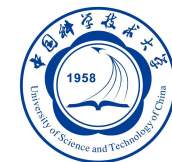
应用展示：单目自转下的动态人体重建



应用展示：单目自转下的动态人体重建



应用展示：单目任意动作下的动态人体重建



- 根据数据中噪音的实际分布自适应调整，提高算法鲁棒性
- 将配准迭代算法看作固定点迭代，从而设计加速算法来提高配准算法的收敛速度
- 设计不依赖于数据的非刚性变形表示方式，并借鉴可微渲染，提出基于深度学习的非刚性配准算法
- 将网络预测对应关系与基于节点图的非刚性变形在可微框架下进行端到端训练

报告完毕，谢谢！