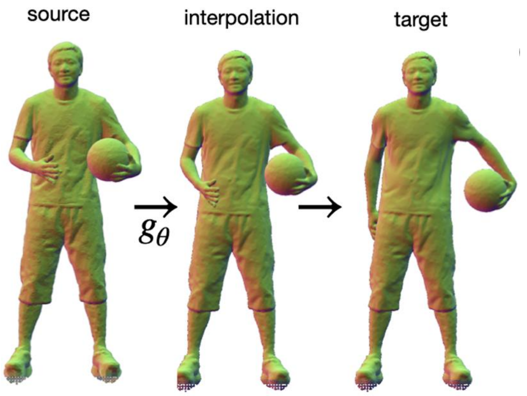
无监督聚类启发的非刚性点集配准

赵明阳
中国科学院香港创新研究院
2024年8月1日

非刚性配准的应用——几何

动态重建[1]

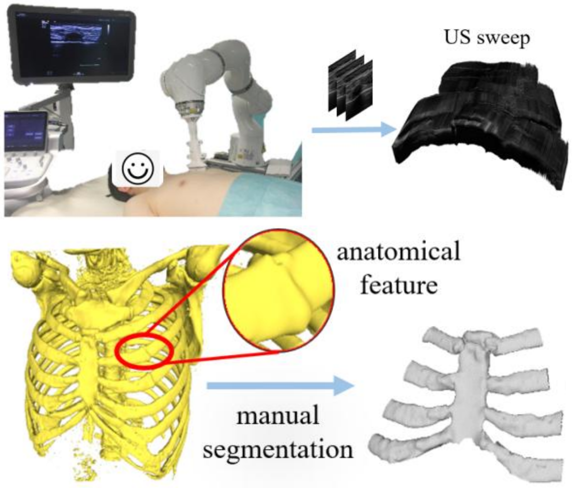
形状补全[2]



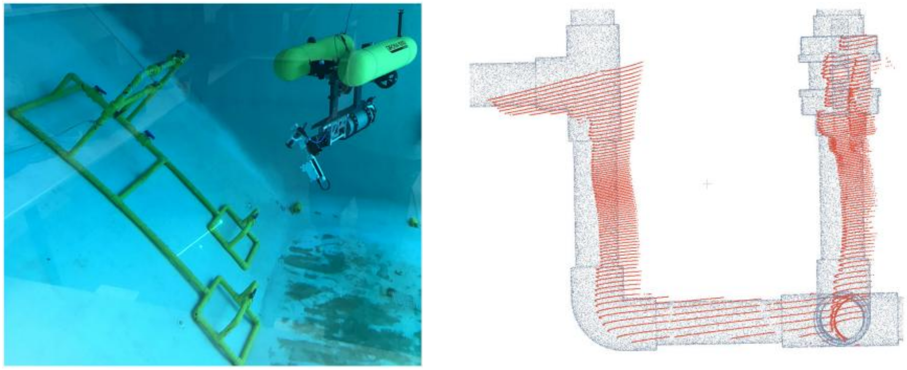
形状插值[3]

[1] Yao et al. DynoSurf: Neural Deformation-based Temporally Consistent Dynamic Surface Reconstruction, ECCV, 2024
[2] Halimi et al. Towards Precise Completion of Deformable Shapes, ECCV, 2020
[3] Prokudin et al. Towards Efficient and Scalable Dynamic Surface Representations, ICCV, 2023

非刚性配准的应用——机器人



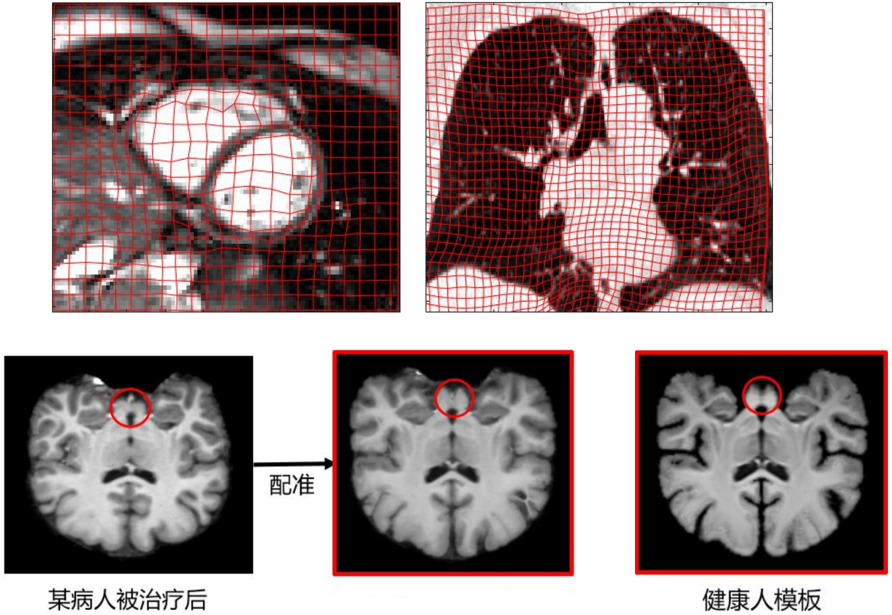
超声机器人 [1]



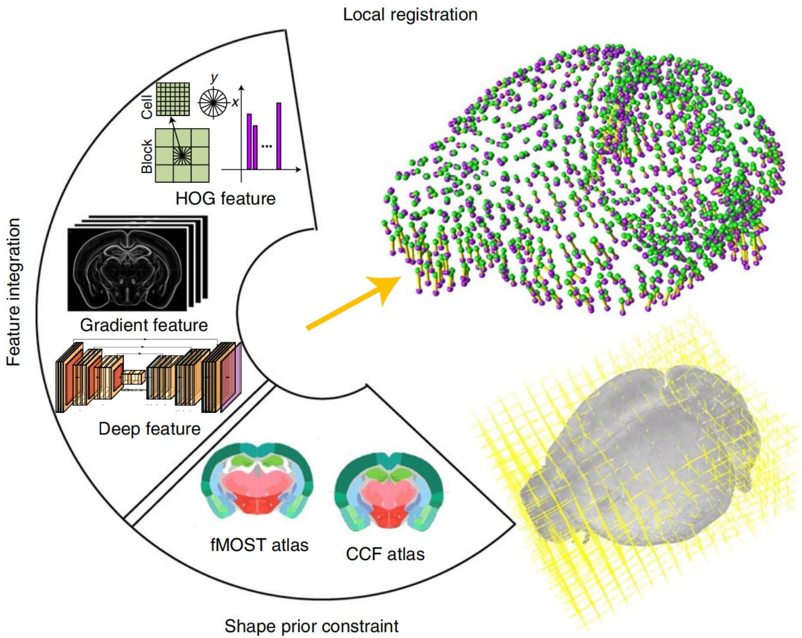
水下机器人 [2]

[1] Jiang et al. Skeleton Graph-based Ultrasound-CT Non-rigid Registration, RAL, 2023
[2] Castillón et al. Linewise Non-Rigid Point Cloud Registration, RAL, 2022

非刚性配准的应用——生物医学成像



医学诊断[1]



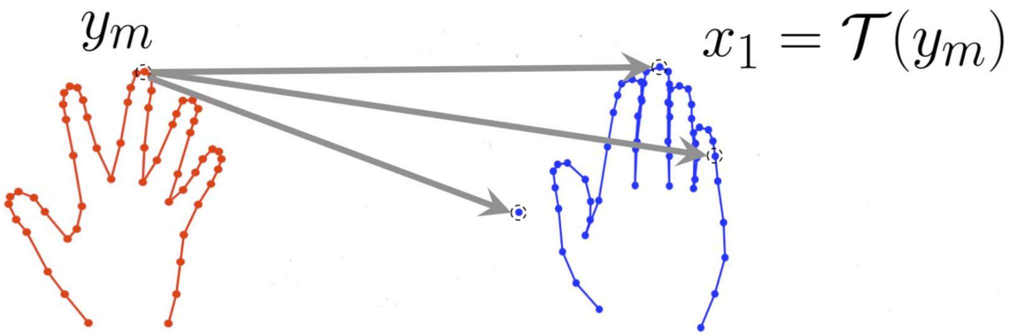
多模态鼠脑结构分析[2]

[1] https://bbs.huaweicloud.com/blogs/174612
[2] Qu et al. Cross-modal coherent registration of whole mouse brains, Nature Methods, 2021

非刚性配准的定义

Target: $\mathbf{X} = \{x_i \in \mathbb{R}^n\}_{i=1}^N$

Source: $\mathbf{Y} = \{y_m \in \mathbb{R}^n\}_{m=1}^M$



优化目标:

映射 $\mathcal{T}$
或形变场 ν

$$x_i = \mathcal{T}(y_m) = y_m + \nu(y_m)$$

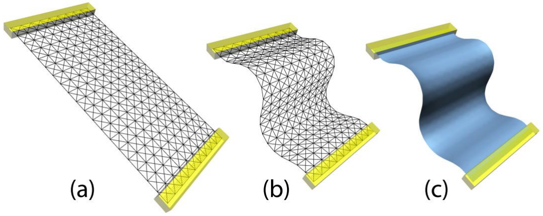
为每个点求其形变(位移)量

[1] Hirose et al. A Bayesian Formulation of Coherent Point Drift, TPAMI, 2020

非刚性配准的刻画

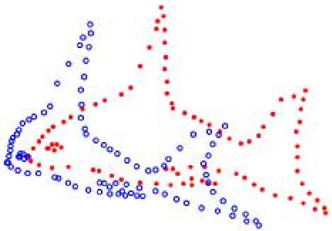
- 配准
  - 刚性配准
    - 线性变换：旋转、平移、缩放、仿射
    - 性质：全局变换
  - 非刚性配准
    - 非刚体变换（每个点位移）
      - 显式
        - 基函数: 薄板样条、核函数……
        - 形变图
        - ……
      - 隐式
        - 神经隐式表示
        - 符号距离场
        - ……
    - 性质：局部一致性变换（位移场）

非刚性配准的刻画



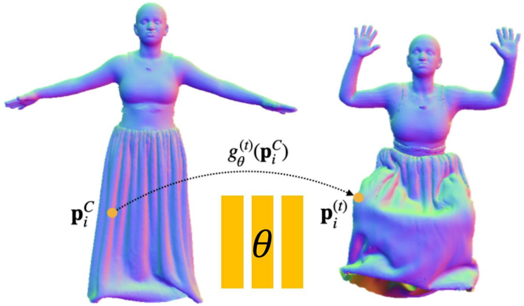
$$\hat{y}_m = \sum_{p_j \in \mathcal{I}(y_m)} \omega_{ij} \cdot \left(\mathbf{A}_j \left(y_m - p_j\right) + p_j + \mathbf{t}_j\right)$$

形变图[1]



$$\nu(y) = \sum_{m=1}^{M} w_m \mathcal{G}\left(y - y_m\right)$$

核函数[2]



$$\hat{y}_m = y_m + g_\theta(y_m)$$

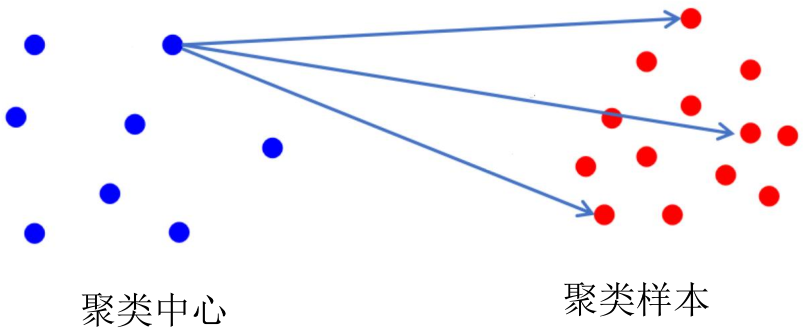
神经隐式表示[3]

[1] Sumner et al. Embedded Deformation for Shape Manipulation, Siggraph, 2007
[2] Hirose et al. A Bayesian Formulation of Coherent Point Drift, TPAMI, 2020
[3] Prokudin et al. Towards Efficient and Scalable Dynamic Surface Representations, ICCV, 2023

无监督聚类启发的非刚性配准

1. 将非刚性配准问题转化为无监督聚类过程

2. 尝试解决大形变问题



聚类过程：聚类中心位置更新

大形变

Zhao et al. Correspondence-Free Non-Rigid Point Set Registration Using Unsupervised Clustering Analysis, CVPR 2024

无监督聚类启发的非刚性配准

$$\min_{\mathbf{U},\mathbf{V}} J(\mathbf{U},\mathbf{V}) = \sum_{j=1}^{C}\sum_{i=1}^{M}(u_{ij})^r ||\boldsymbol{x}_i - \boldsymbol{v}_j||_2^2,$$

$$s.t. \quad \sum_{j=1}^{C} u_{ij} = 1, \quad u_{ij} \in (0,1]$$

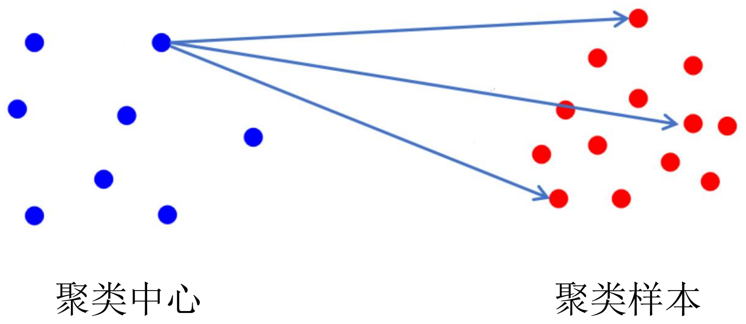
$$\min_{\mathbf{U},\mathbf{V},\boldsymbol{\alpha}} J(\mathbf{U},\mathbf{V},\boldsymbol{\alpha}) = \sum_{j=1}^{C}\sum_{i=1}^{M}(u_{ij})^r ||\boldsymbol{x}_i - \boldsymbol{v}_j||_2^2 + \lambda u_{ij}\log(\frac{u_{ij}}{\alpha_j}),$$

$$s.t. \quad \sum_{j=1}^{C} u_{ij} = 1, \quad \sum_{j=1}^{C}\alpha_j = 1, \quad u_{ij}, \alpha_j \in (0,1]$$

$$\min_{\mathbf{U},\mathbf{V},\boldsymbol{\Sigma},\boldsymbol{\alpha}} J(\mathbf{U},\mathbf{V},\boldsymbol{\Sigma},\boldsymbol{\alpha}) = \sum_{j=1}^{C}\sum_{i=1}^{M}(u_{ij})^r ||\boldsymbol{\Sigma}_j^{-\frac{1}{2}}(\boldsymbol{x}_i - \boldsymbol{v}_j)||_2^p$$

$$+ u_{ij}\log|\boldsymbol{\Sigma}_j| + \lambda u_{ij}\log\frac{u_{ij}}{\alpha_j},$$

$$s.t. \quad \sum_{j=1}^{C} u_{ij} = 1, \quad \sum_{j=1}^{C}\alpha_j = 1, \quad u_{ij}, \alpha_j \in (0,1].$$



模糊聚类

$$\mathbf{U} = [u_{ij}]_{M\times C} \in \mathbb{R}^{M\times C}$$

$$\boldsymbol{\Sigma}_j \in \mathbb{S}_{++}^n \triangleq \{\mathbf{A} \in \mathbb{R}^{n\times n} | \boldsymbol{x}^T\mathbf{A}\boldsymbol{x} > 0, \forall \boldsymbol{x} \in \mathbb{R}^n\}$$

无监督聚类启发的非刚性配准

非刚性配准

$$\min_{\mathbf{U},\boldsymbol{\alpha},\boldsymbol{\Sigma},\nu} J(\mathbf{U},\boldsymbol{\alpha},\boldsymbol{\Sigma},\nu)=\sum_{j=1}^{C}\sum_{i=1}^{M} u_{ij}||\boldsymbol{\Sigma}_j^{-\frac{1}{2}}(\boldsymbol{x}_i-(\boldsymbol{y}_j+\nu(\boldsymbol{y}_j)))||_2^2$$

$$+u_{ij}\log|\boldsymbol{\Sigma}_j|+\lambda u_{ij}\log\frac{u_{ij}}{\alpha_j},$$

$$s.t.\ |\boldsymbol{\Sigma}_j| = \theta_j, \sum_{j=1}^{C} u_{ij} = 1, \sum_{j=1}^{C} \alpha_j = 1, u_{ij}, \alpha_j \in (0,1].$$

Source: $\mathbf{Y} = \{\boldsymbol{y}_j \in \mathbb{R}^n\}_{j=1}^N$ ⇨ 聚类中心

Target: $\mathbf{X} = \{\boldsymbol{x}_i \in \mathbb{R}^n\}_{i=1}^M$ ⇨ 聚类样本

形变: $\mathcal{T}(\mathbf{Y}) \triangleq \mathbf{Y} + \nu(\mathbf{Y})$ ⇨ 更新聚类中心

Source 形变到 Target的配准问题等价为聚类中心更新过程

无监督聚类启发的非刚性配准

理论分析

1. 信息论角度：熵正则避免 $\mathbf{U}$ 过度稀疏

$$\min_{\mathbf{U},\boldsymbol{\alpha},\boldsymbol{\Sigma},\nu} J(\mathbf{U},\boldsymbol{\alpha},\boldsymbol{\Sigma},\nu)=\sum_{j=1}^{C}\sum_{i=1}^{M} u_{ij}||\boldsymbol{\Sigma}_j^{-\frac{1}{2}}(\boldsymbol{x}_i-(\boldsymbol{y}_j+\nu(\boldsymbol{y}_j)))||_2^2 + u_{ij}\log|\boldsymbol{\Sigma}_j| + \lambda u_{ij}\log\frac{u_{ij}}{\alpha_j},$$

$$H(\mathbf{U}) = -\sum_{j=1}^{C}\sum_{i=1}^{M} u_{ij}\log(u_{ij})$$

$$\sum_{j=1,i=1}^{C,M} u_{ij}||\boldsymbol{\Sigma}_j^{-\frac{1}{2}}(\boldsymbol{x}_i-(\boldsymbol{y}_j+\nu(\boldsymbol{y}_j)))||_2^2+u_{ij}\log(\frac{|\boldsymbol{\Sigma}_j|}{\alpha_j^{\lambda}})-\lambda H(\mathbf{U})$$

无监督聚类启发的非刚性配准

理论分析

2. 优化角度：$u_{ij}\log(u_{ij})$ 凸化目标函数，尽量避免局部最优解

$$\min_{\mathbf{U},\boldsymbol{\alpha},\boldsymbol{\Sigma},\nu} J(\mathbf{U},\boldsymbol{\alpha},\boldsymbol{\Sigma},\nu)=\sum_{j=1}^{C}\sum_{i=1}^{M}u_{ij}||\boldsymbol{\Sigma}_j^{-\frac{1}{2}}(\boldsymbol{x}_i-(\boldsymbol{y}_j+\nu(\boldsymbol{y}_j)))||_2^2$$
$$+u_{ij}\log|\boldsymbol{\Sigma}_j|+\lambda u_{ij}\log\frac{u_{ij}}{\alpha_j},$$

$$\nabla^2 f(u_{ij}) = \nabla^2 u_{ij}\log(u_{ij}) = \frac{1}{u_{ij}} > 0$$

$u_{ij}\log(u_{ij})$ 罚函数，避免 $u_{ij} \notin (0,1]$

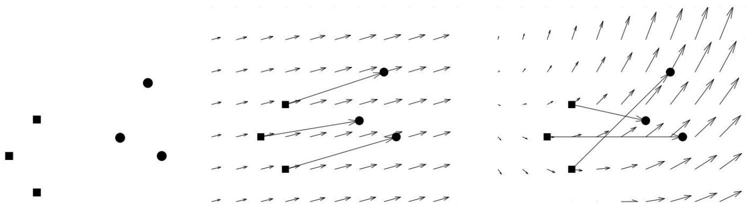
无监督聚类启发的非刚性配准

正则化

Tikhonov 正则化，使得形变场光滑

$$\min_{\mathbf{U},\boldsymbol{\alpha},\boldsymbol{\Sigma},\nu} J(\mathbf{U},\boldsymbol{\alpha},\boldsymbol{\Sigma},\nu)+\zeta\mathcal{R}(\nu)$$

$$\mathcal{R}(\nu)=\int_{\mathbf{R}^n} d\mathbf{s}\frac{||\tilde{\nu}(\mathbf{s})||_2^2}{\tilde{K}(\mathbf{s})}$$

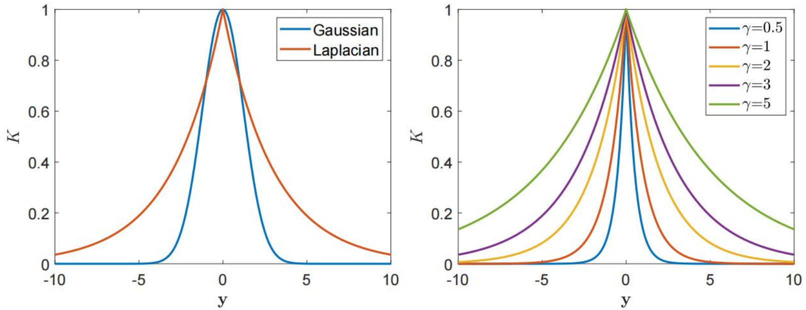


(a) (b) (c)

运动一致性[1]

Laplace 核函数

$$K(\boldsymbol{y}_i,\boldsymbol{y}_j)=\exp(-\gamma\|\boldsymbol{y}_i-\boldsymbol{y}_j\|_1),\quad \gamma>0$$



Laplace VS. Gauss

[1] Myronenko et al. Non-rigid point set registration: Coherent Point Drift, NeurIPS, 2006

无监督聚类启发的非刚性配准

解析解

$$\min_{\mathbf{U},\boldsymbol{\alpha},\boldsymbol{\Sigma},\nu} J(\mathbf{U},\boldsymbol{\alpha},\boldsymbol{\Sigma},\nu)+\zeta\mathcal{R}(\nu)$$

$$s.t.\ |\boldsymbol{\Sigma}_j|=\theta_j,\sum_{j=1}^{C}u_{ij}=1,\sum_{j=1}^{C}\alpha_j=1,u_{ij},\alpha_j\in(0,1]$$

$$J(\mathbf{U},\boldsymbol{\alpha},\boldsymbol{\Sigma},\nu)=\sum_{j=1}^{C}\sum_{i=1}^{M}u_{ij}||\boldsymbol{\Sigma}_j^{-\frac{1}{2}}(\boldsymbol{x}_i-(\boldsymbol{y}_j+\nu(\boldsymbol{y}_j)))||_2^2$$
$$+u_{ij}\log|\boldsymbol{\Sigma}_j|+\lambda u_{ij}\log\frac{u_{ij}}{\alpha_j}$$

⇩

虽然目标函数非凸，但对每个未知变量可导出其解析解

⇩

直接交替优化或坐标下降法即可

无监督聚类启发的非刚性配准

解析解--更新U

$$\min_{\mathbf{U},\boldsymbol{\alpha},\boldsymbol{\Sigma},\nu} J(\mathbf{U},\boldsymbol{\alpha},\boldsymbol{\Sigma},\nu)+\zeta\mathcal{R}(\nu)$$

$$s.t.\ |\boldsymbol{\Sigma}_j| = \theta_j, \sum_{j=1}^{C} u_{ij} = 1, \sum_{j=1}^{C}\alpha_j = 1, u_{ij}, \alpha_j \in (0,1]$$

$$J(\mathbf{U},\boldsymbol{\alpha},\boldsymbol{\Sigma},\nu)=\sum_{j=1}^{C}\sum_{i=1}^{M} u_{ij}\|\boldsymbol{\Sigma}_j^{-\frac{1}{2}}(\boldsymbol{x}_i-(\boldsymbol{y}_j+\nu(\boldsymbol{y}_j)))\|_2^2 + u_{ij}\log|\boldsymbol{\Sigma}_j| + \lambda u_{ij}\log\frac{u_{ij}}{\alpha_j}$$

$$\mathcal{L}(\mathbf{U},\boldsymbol{\beta},\boldsymbol{\gamma},\boldsymbol{\eta}) = \sum_{j=1}^{C}\sum_{i=1}^{M} u_{ij}\|\boldsymbol{\Sigma}_j^{-\frac{1}{2}}(\mathbf{x}_i-(\mathbf{y}_j+\nu(\mathbf{y}_j)))\|_2^2 + u_{ij}\log|\boldsymbol{\Sigma}_j| + \lambda u_{ij}\log\frac{u_{ij}}{\alpha_j} + \sum_{i=1}^{M}\beta_i\Big(\sum_{j=1}^{C} u_{ij}-1\Big) + \sum_{j=1}^{C}\sum_{i=1}^{M}\gamma_{ij}(u_{ij}-1) + \sum_{j=1}^{C}\sum_{i=1}^{M}\eta_{ij}(-u_{ij}),$$

$$\begin{cases}\sum_{i,j=1}^{M,C}\Big(\|\boldsymbol{\Sigma}_j^{-\frac{1}{2}}(\mathbf{x}_i-(\mathbf{y}_j+\nu(\mathbf{y}_j)))\|_2^2 + \log|\boldsymbol{\Sigma}_j| + \lambda\big(\log\frac{u_{ij}}{\alpha_j}+1\big) + \gamma_{ij} - \eta_{ij}\Big) + C\sum_{i=1}^{M}\beta_i = 0, \\ \sum_{j=1}^{C} u_{ij} - 1 = 0, \quad u_{ij-1} \le 0, \quad -u_{ij} < 0, \\ \gamma_{ij} \ge 0, \quad \eta_{ij} \ge 0, \quad \gamma_{ij}(u_{ij-1}) = 0, \quad \eta_{ij}(-u_{ij}) = 0.\end{cases}$$

$$\mathbf{U} = (\mathrm{diag}(\mathbf{A}\mathbf{1}_C))^{-1}\mathbf{A}$$

$$\mathbf{A} = \exp(-\mathbf{D}/\lambda)\mathrm{diag}(\boldsymbol{\alpha}\odot|\boldsymbol{\Sigma}|)$$

无监督聚类启发的非刚性配准

更新 $\boldsymbol{\alpha}$

$$\boldsymbol{\alpha} = \frac{1}{M}\mathbf{U}^T\mathbf{1}_M$$

更新$\boldsymbol{\Sigma}$

$$\sigma^2 = \frac{\mathrm{tr}(\mathbf{X}^\top \mathrm{diag}(\mathbf{U}^\top \mathbf{1}_M)\mathbf{X} - (2(\mathbf{U}\mathbf{X})^\top + \mathbf{T}^\top \mathrm{diag}(\mathbf{U}\mathbf{1}_C))\mathbf{T})}{n \times M}$$

无监督聚类启发的非刚性配准

更新 ν

$$\nu(\boldsymbol{y}) = \sum_{j=1}^{C} c_j K(\boldsymbol{y}, \boldsymbol{y}_j) + \sum_{\eta=1}^{N} d_\eta \psi_\eta(\nu)$$

$\{\psi_\eta\}_{\eta=1}^{N}$ 是 RKHS Null空间中的基函数

由于Laplace Kernel 正定，$\psi_\eta \equiv 0$

$$\mathbf{c} = (\mathbf{L} + \zeta\sigma^2 \mathrm{diag}(\mathbf{U}\mathbf{1}_C)^{-1})^{-1}(\mathrm{diag}(\mathbf{U}\mathbf{1}_C)^{-1}\mathbf{U}\mathbf{X} - \mathbf{Y})$$

$\mathbf{L}$ Gram 矩阵 $\quad l_{ij} = K(\boldsymbol{y}_i, \boldsymbol{y}_j)$

$$\mathbf{T} = \mathcal{T}(\mathbf{Y}) = \mathbf{Y} + \mathbf{L}\mathbf{c}$$

无监督聚类启发的非刚性配准

更新 ν

$$\mathbf{c} = (\mathbf{L} + \zeta\sigma^2 \mathrm{diag}(\mathbf{U1}_C)^{-1})^{-1}(\mathrm{diag}(\mathbf{U1}_C)^{-1}\mathbf{UX} - \mathbf{Y})$$

基于聚类的 Nyström 低秩矩阵逼近

对source 点集进行聚类 获取聚类中心

$$\{\boldsymbol{z}_i \in \mathbb{R}^n\}_{i=1}^{C'} \quad (C' \ll C)$$

$$O(C^3) \xrightarrow{C' = C^{1/3}} O(C)$$

$$\mathbf{L} \approx \mathbf{E}\mathbf{W}^{-1}\mathbf{E}^T$$

$$\mathbf{E} = [e_{ij}] \in \mathbb{R}^{C \times C'} \quad e_{ij} = K(\boldsymbol{y}_i, \boldsymbol{z}_j)$$

$$\mathbf{W} = [w_{ij}] \in \mathbb{R}^{C' \times C'} \quad w_{ij} = K(\boldsymbol{z}_i, \boldsymbol{z}_j)$$

[1] Zhang et al. Improved Nystr¨om low rank approximation and error analysis, ICML, 2008

无监督聚类启发的非刚性配准

基于聚类的 Nyström 低秩矩阵逼近

$$\mathbf{L} \approx \mathbf{E}\mathbf{W}^{-1}\mathbf{E}^T$$

$$\mathbf{E} = [e_{ij}] \in \mathbb{R}^{C \times C'} \qquad e_{ij} = K(\boldsymbol{y}_i, \boldsymbol{z}_j)$$

$$\mathbf{W} = [w_{ij}] \in \mathbb{R}^{C' \times C'} \quad w_{ij} = K(\boldsymbol{z}_i, \boldsymbol{z}_j)$$

低秩矩阵逼近误差界

Proposition 1. *The low-rank approximation error* $\epsilon = \|\mathbf{L} - \mathbf{E}\mathbf{W}^{-1}\mathbf{E}^T\|_F$ *in terms of the Laplacian kernel is bounded by*

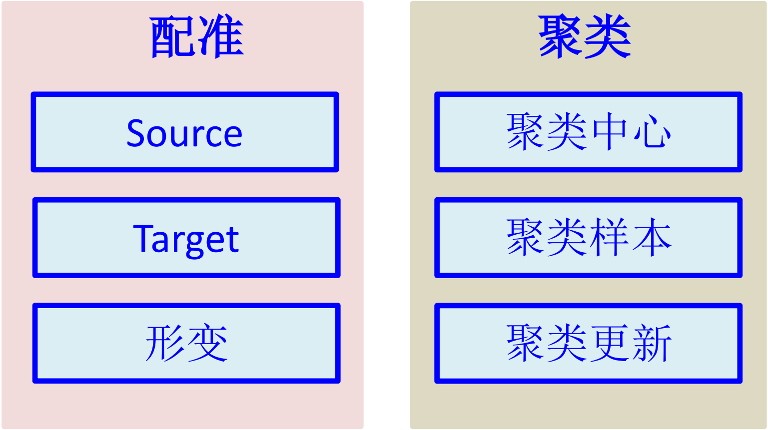
$$\epsilon \leq 4\sqrt{2}T^{3/2}\gamma\sqrt{C'q} + 2C'\gamma^2 Tq\|W^{-1}\|_F, \qquad (11)$$

where $\|\cdot\|_F$ *is the matrix Frobenious norm,* $T = \max_i |\mathbf{P}_i|$, $q = \sum_{j=1}^{C} \|\boldsymbol{y}_j - \boldsymbol{z}_{c'(j)}\|_2^2$ *is the clustering quantization error with* $c'(j) = \operatorname{argmin}_{i=1,\cdots,C'} \|\boldsymbol{y}_j - \boldsymbol{z}_i\|_2$, *and* γ *is the Laplacian kernel bandwidth defined in Eq. (8).*

无监督聚类启发的非刚性配准

算法总结

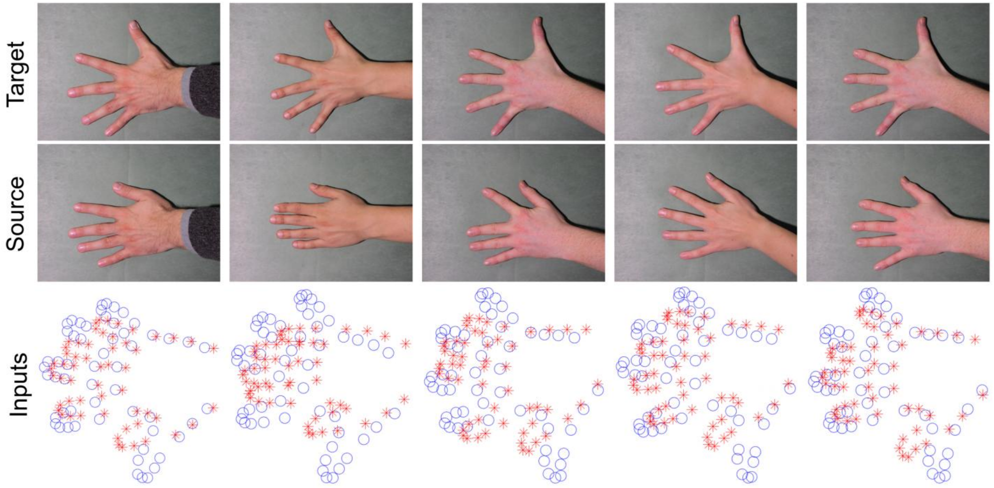
1. 将非刚性点集配准问题建模为聚类过程
2. 变量更新有闭形式解，可直接交替优化
3. 聚类低秩矩阵逼近，严格误差界
4. 和点集嵌入空间维度无关，适用 $\mathbb{R}^n$



实验

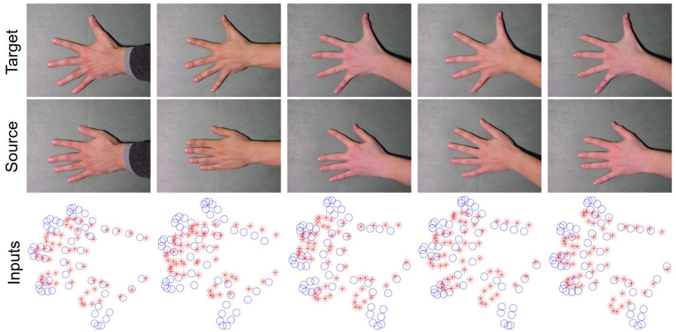
非刚性点集配准——2D

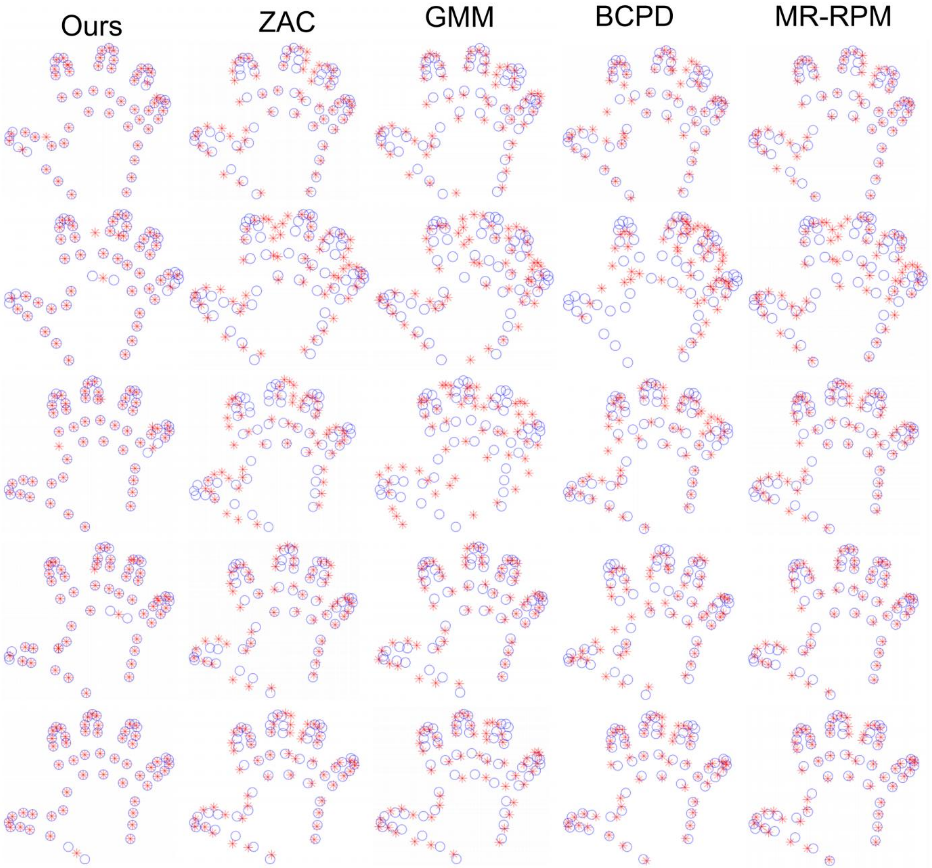
Method	Subject 1	Subject 2	Subject 3	Subject 4	Time (s)
MR-RPM [30]	0.0940	0.0834	0.1028	0.1388	0.2382
BCPD [20]	0.1027	0.1055	0.1080	0.1579	0.6890
GMM [23]	0.0571	0.0547	0.0734	0.0917	0.1140
ZAC [45]	0.4886	0.4566	0.4879	0.4935	0.4254
Ours	**0.0383**	**0.0481**	**0.0537**	**0.0879**	**0.1074**



[1] Stegmann et al. A brief introduction to statistical shape analysis

非刚性点集配准——2D

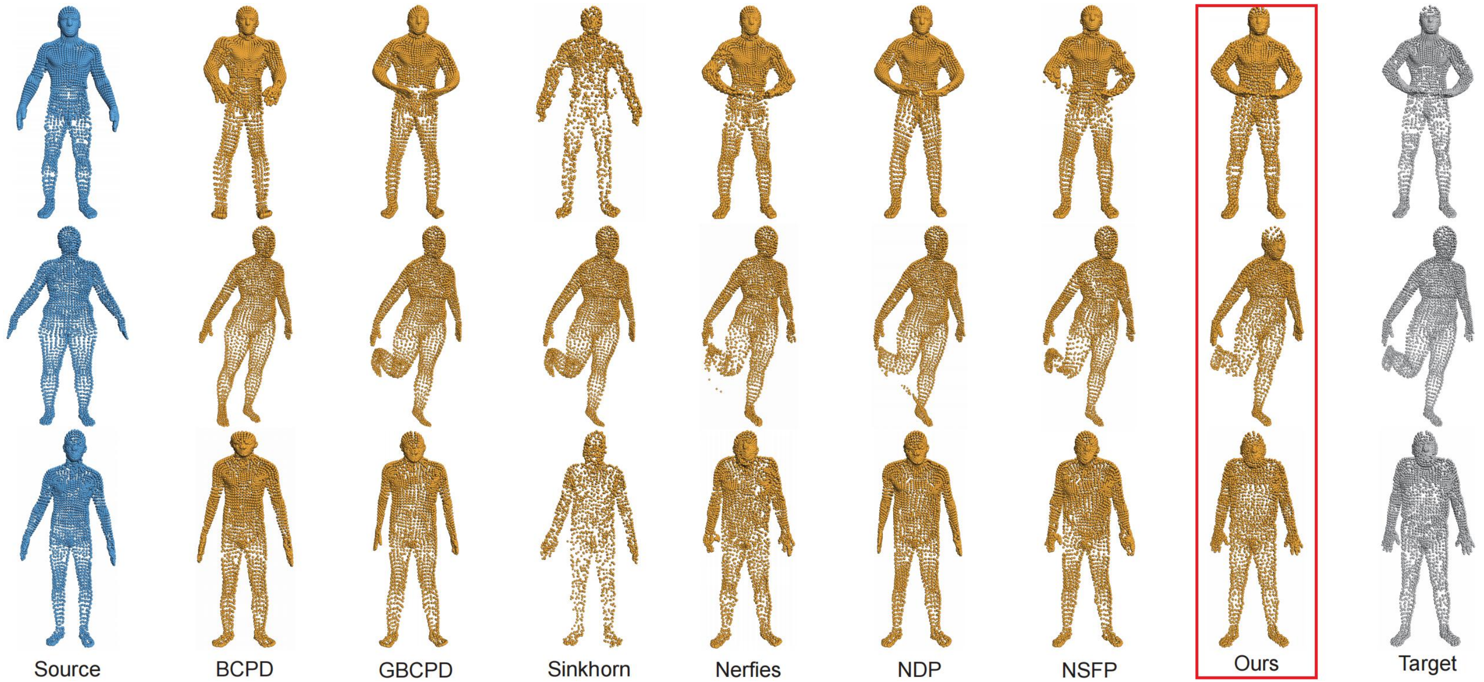




非刚性点集配准——3D

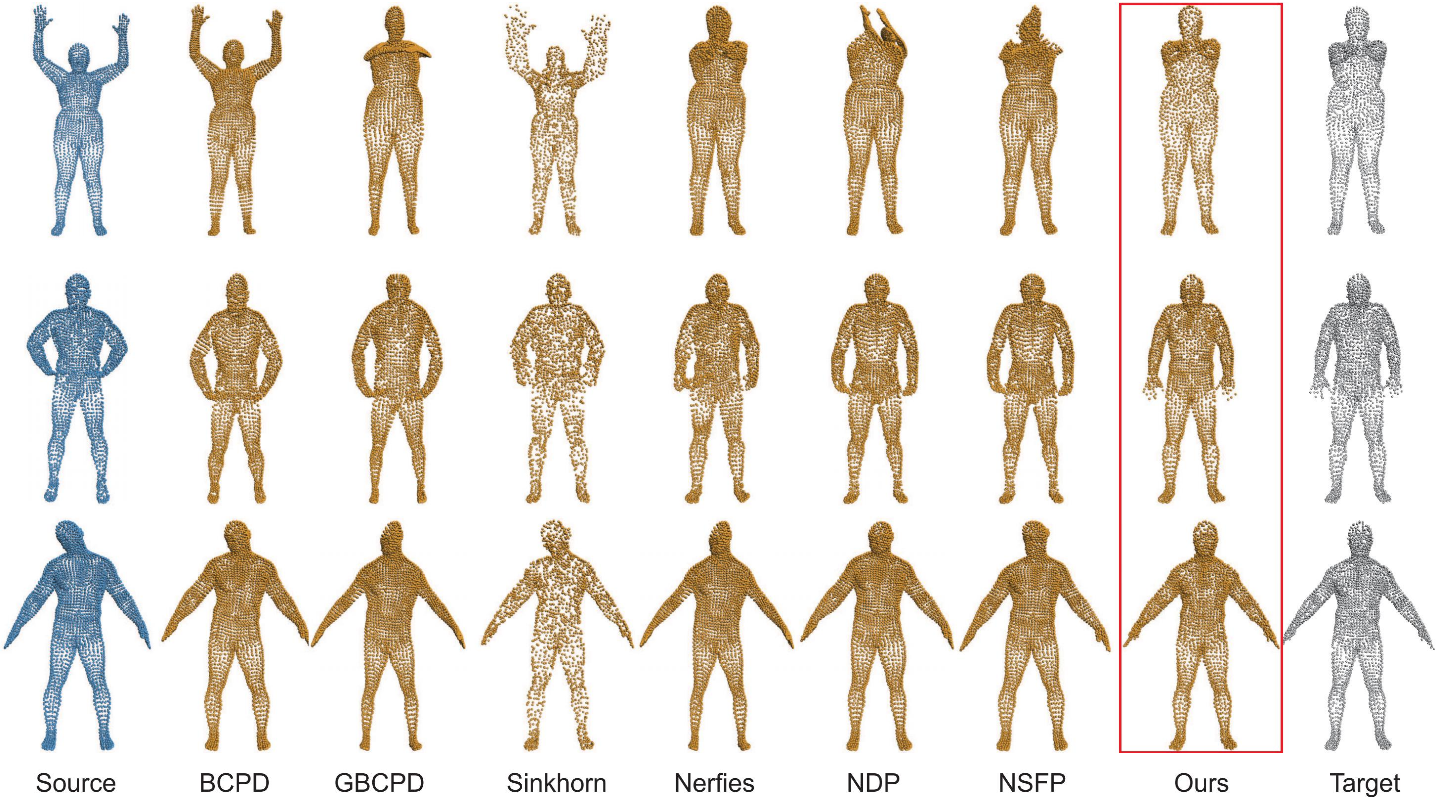
Method \ Settings	Intra-1	Intra-2	Intra-3	Intra-4	Intra-5	Intra-6	Inter-1	Inter-2	Inter-3	Inter-4	Average
BCPD [20]	0.0913	0.1011	0.0872	0.0577	0.1004	0.0746	0.1196	0.0705	0.0935	0.0923	0.0888
GBCPD [21]	0.0285	0.0212	0.0211	0.0260	0.0244	0.0339	0.0359	0.0340	0.0212	0.0190	0.0265
Fast_RNRR [47]	0.0430	0.0487	0.0397	0.0504	0.0429	0.0391	0.1358	0.0743	0.0477	0.0358	0.0557
AMM_NRR [48]	0.0544	0.0486	0.0400	0.0539	0.0405	0.0393	0.0838	0.0686	0.0422	0.0399	0.0511
Sinkhorn [16]	0.0654	0.0638	0.1372	0.1096	0.0749	0.0821	0.2467	0.0781	0.1400	0.1720	0.1170
Nerfies [35]	0.0120	0.0107	0.0138	0.0129	0.0135	0.0118	0.0121	0.0144	0.0140	0.0140	0.0129
NDP [26]	0.0183	0.0199	0.0192	0.0152	0.0170	0.0149	0.0181	0.0198	0.0164	0.0155	0.0174
NSFP [24]	0.0126	0.0134	0.0132	0.0118	0.0137	0.0142	0.0167	0.0162	0.0148	0.0166	0.0143
Ours	**0.0086**	**0.0089**	**0.0103**	**0.0096**	**0.0089**	**0.0081**	**0.0097**	**0.0099**	**0.0094**	**0.0081**	**0.0092**

非刚性点集配准——3D



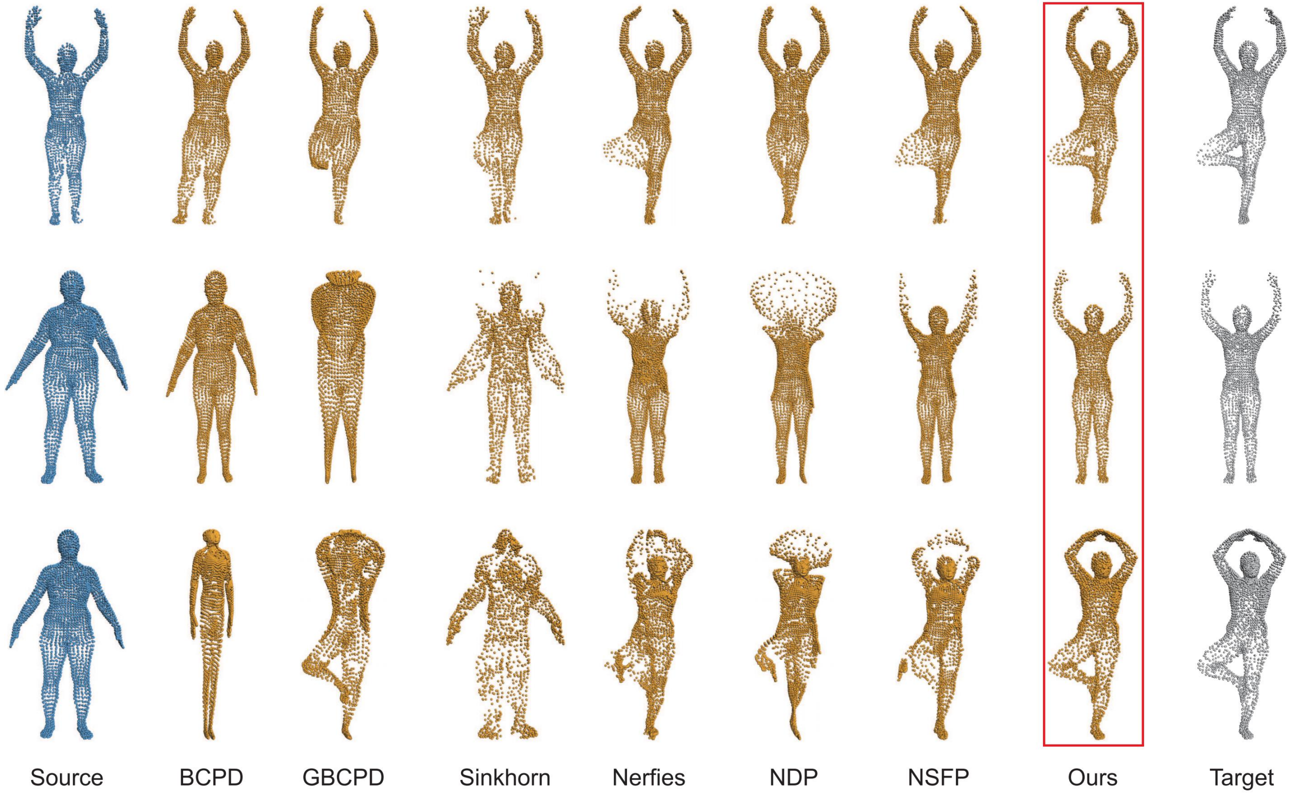
[1] Bogo et al. FAUST: Dataset and evaluation for 3D mesh registration, CVPR, 2014

非刚性点集配准——3D



[1] Bogo et al. FAUST: Dataset and evaluation for 3D mesh registration, CVPR, 2014

非刚性点集配准——3D

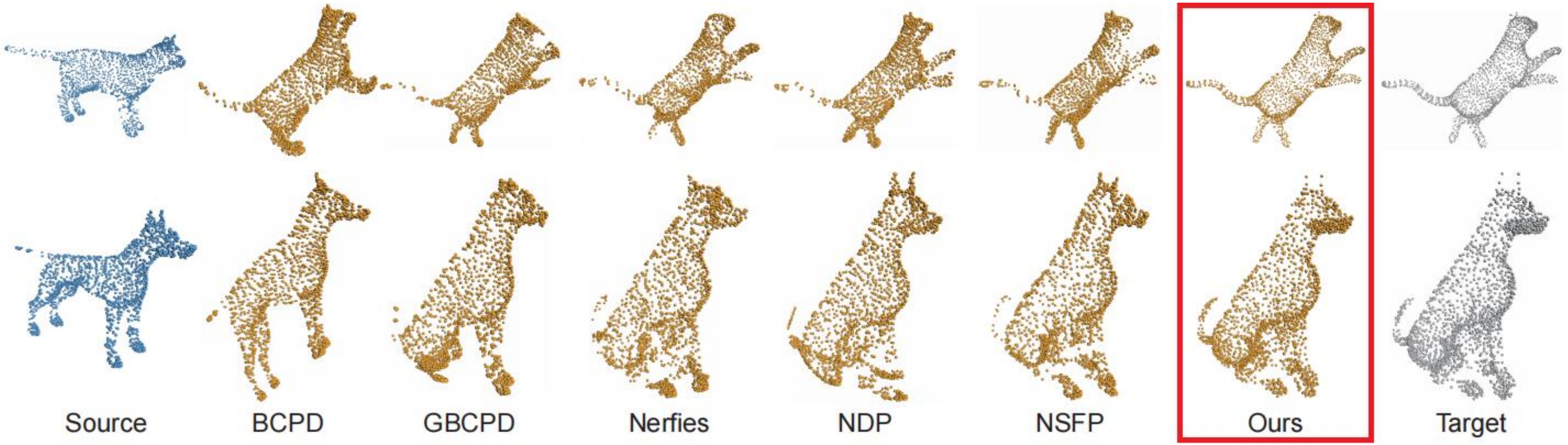


[1] Bogo et al. FAUST: Dataset and evaluation for 3D mesh registration, CVPR, 2014

非刚性点集配准——3D

Method	Cat	Centaur	Dog	Gorilla	Average
BCPD [20]	3.9884	8.1017	7.2800	5.6253	5.9935
GBCPD [21]	1.5631	2.9480	1.5300	3.5751	2.6523
Nerfies [35]	3.2704	2.8826	1.3612	2.2809	2.3211
NDP [26]	4.3639	3.4373	3.1285	2.8312	3.2560
NSFP [24]	1.8774	2.6425	1.6734	2.2044	2.0710
Ours	**1.3496**	**1.8125**	**1.2088**	**1.6807**	**1.5247**

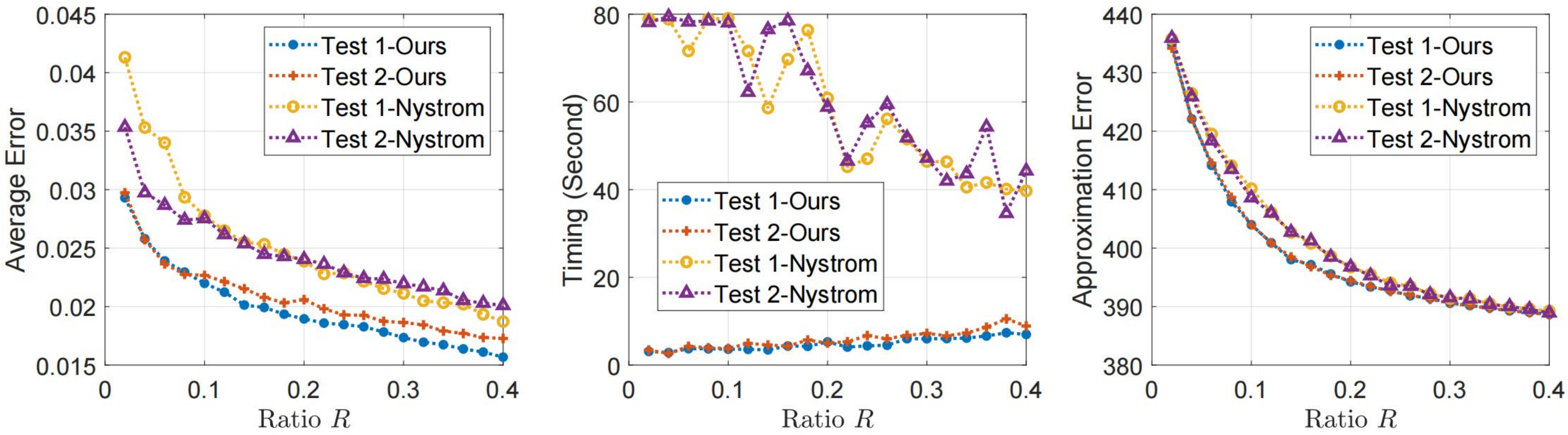
非刚性点集配准——3D



[1] Bronstein et al. Numerical geometry of non-rigid shapes. 2008

非刚性点集配准——消融实验

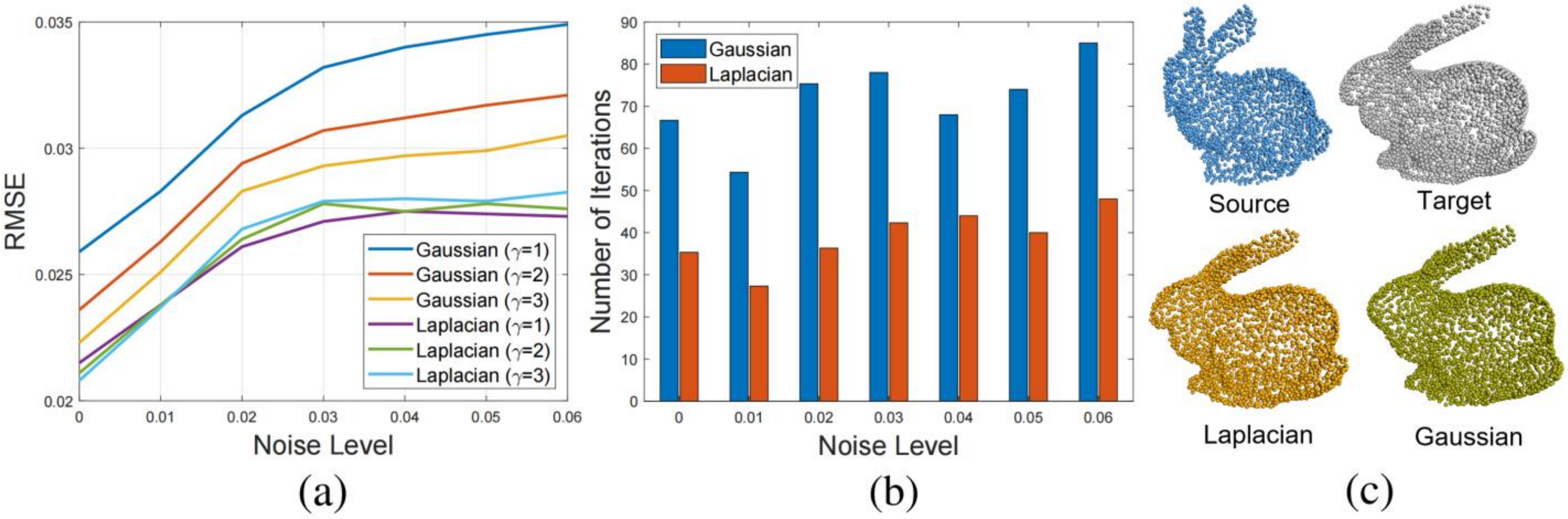
聚类 Nyström VS. 非聚类



基于聚类的 Nyström 低秩矩阵逼近的配准精度和速度都显著优于非聚类的

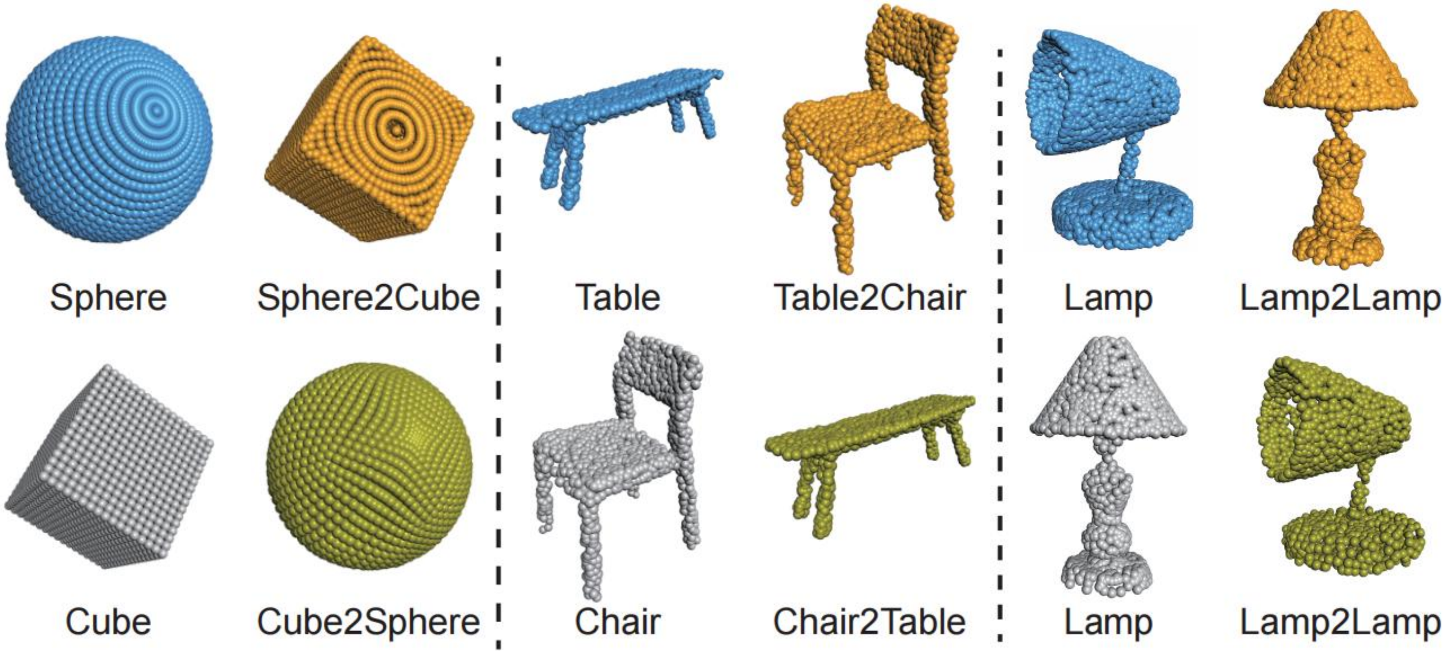
非刚性点集配准——消融实验

Laplacian VS. Gaussian kernel



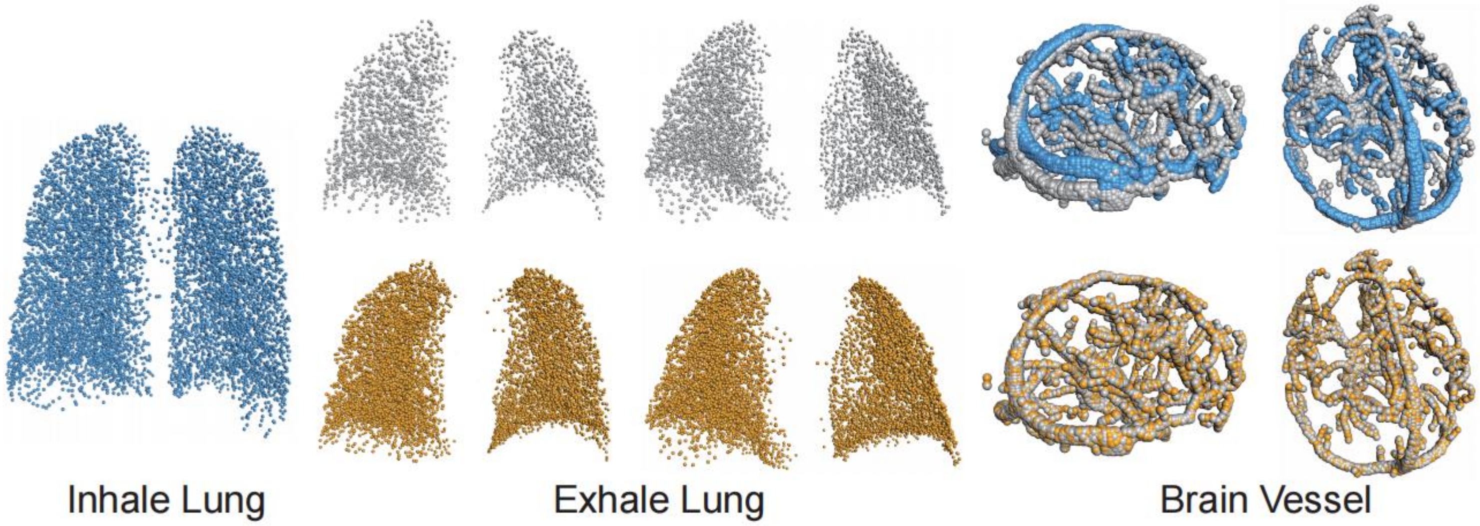
基于Laplacian kernel的配准精度和收敛速度均显著优于Gaussian kernel

非刚性点集配准——形状迁移



[1] Chang et al. Shapenet: An information rich 3d model repository, arxiv, 2015

非刚性点集配准——医学数据

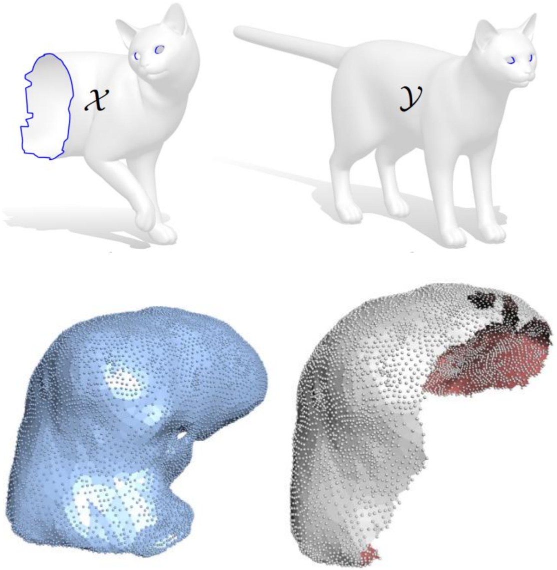


展望

非刚性配准——难点

非刚性配准

- 形状遮挡
- 显著形变
- 多视角
- 其他几何表示
- ……



术前　　术中

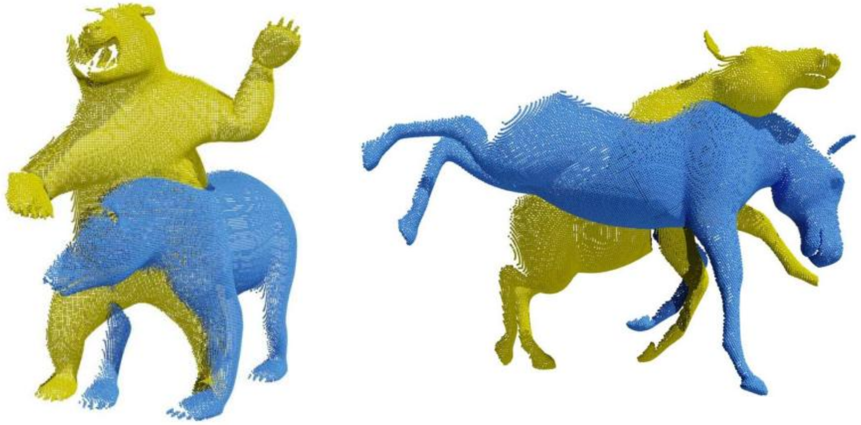
遮挡程度增加无对应部分的形变如何确定？
先验形状补全？

[1] Rampini et al., Correspondence-Free Region Localization for Partial Shape Similarity via Hamiltonian Spectrum Alignment, 3DV, 2019

非刚性配准——难点

非刚性配准

- 形状遮挡
- 显著形变
- 多视角
- 其他几何表示
- ……

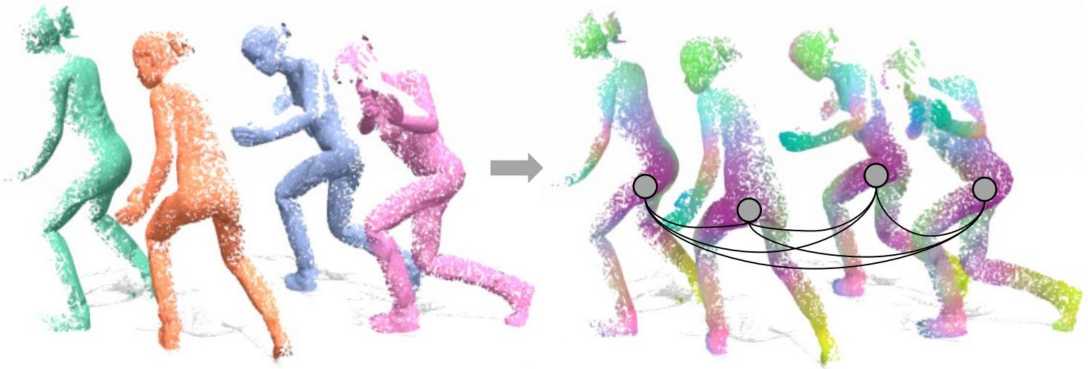


通过特征匹配提供初始化

[1] Li et al., Lepard: Learning partial point cloud matching in rigid and deformable scenes, CVPR, 2022

非刚性配准——难点

非刚性配准
- 形状遮挡
- 显著形变
- 多视角
- 其他几何表示
- ……



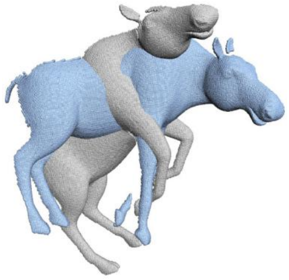
如何缓解累积误差

[1] Huang et al., Multiway Non-rigid Point Cloud Registration via Learned Functional Map Synchronization, TPAMI, 2022

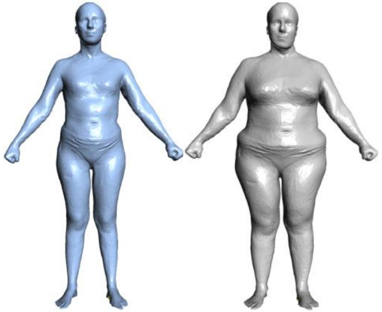
非刚性配准——难点

非刚性配准

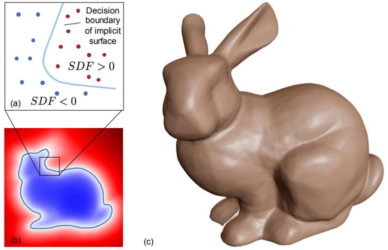
- 形状遮挡
- 显著形变
- 多视角
- 其他几何表示
- ……



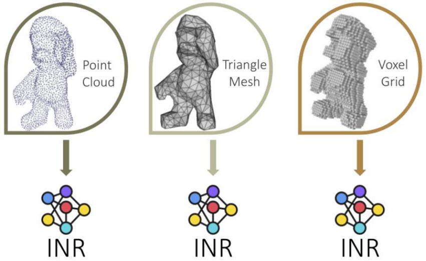
Point cloud



Mesh



SDF



INR

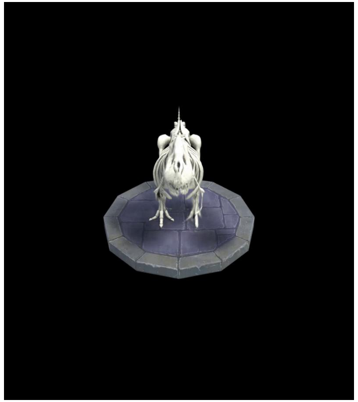
[1] Park et al., DeepSDF: Learning Continuous Signed Distance Functions for Shape Representation, CVPR, 2019
[2] Luigi et al., Deep Learning on Implicit Neural Representations of Shapes, ICLR, 2023

非刚性配准——应用

非刚性配准

- **NeRF**
- **Gaussian splatting**
- **Image morphing**
- ……

(a) Capture Process (b) Input (c) Nerfie (d) Nerfie Depth



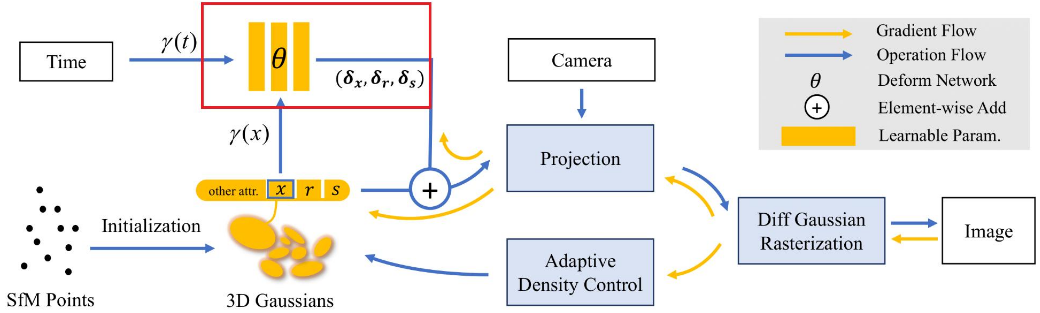
[1] Park et al., Nerfies: Deformable Neural Radiance Fields, ICCV, 2021
[2] Yang et al., Deformable 3D Gaussians for High-Fidelity Monocular Dynamic Scene Reconstruction, CVPR, 2024

非刚性配准——应用

非刚性配准

- **NeRF**
- **Gaussian splatting**
- **Image morphing**
- ……

Pipeline of Deformable 3D Gaussians



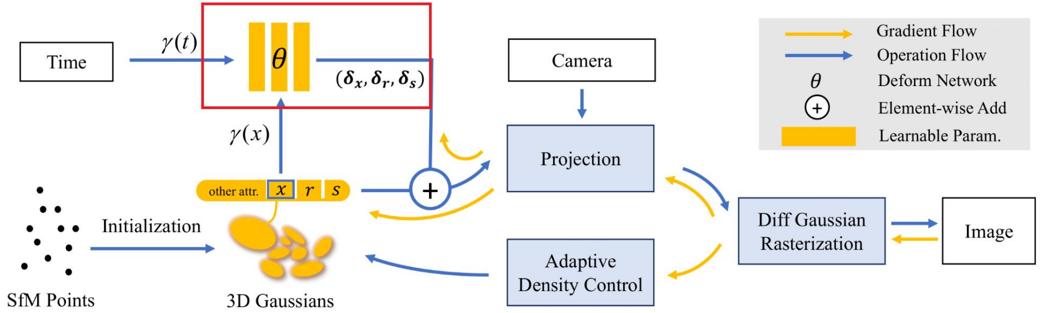
[1] Yang et al., Deformable 3D Gaussians for High-Fidelity Monocular Dynamic Scene Reconstruction, CVPR, 2024

非刚性配准——应用

非刚性配准

- NeRF
- Gaussian splatting
- Image morphing
- ……

Pipeline of Deformable 3D Gaussians



[1] Yang et al., Deformable 3D Gaussians for High-Fidelity Monocular Dynamic Scene Reconstruction, CVPR, 2024

THANK YOU FOR YOUR ATTENTION!

Code & Project