

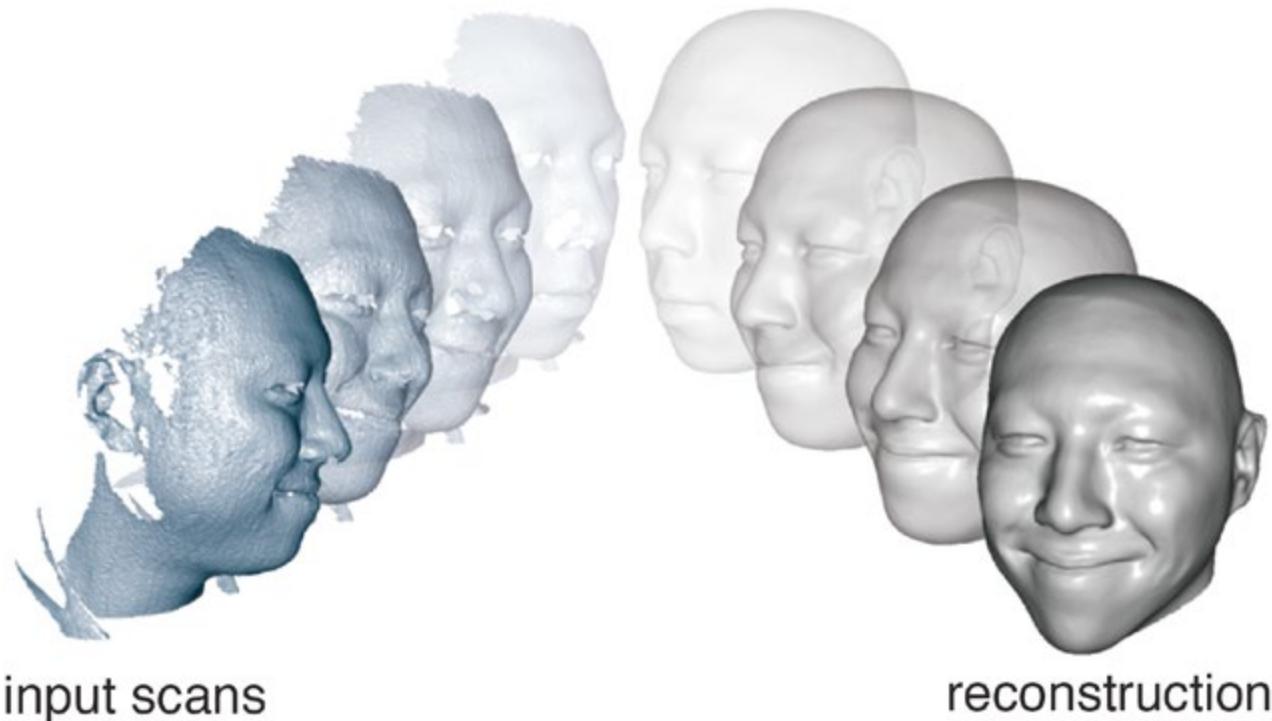
Improving Deformation Graph Based Non-Rigid Registration

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Goal of non-rigid registration

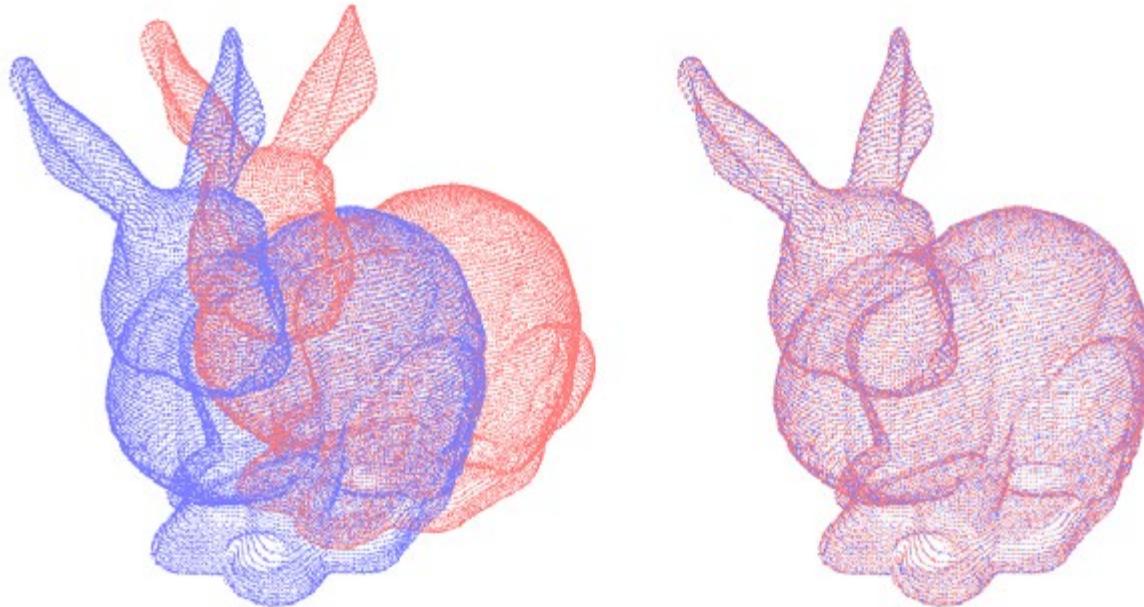
- Accurate 3D models from complex non-rigidly deforming objects
- Track deformations of an object over time



Overview

- Rigid Registration
- Non-Rigid Registration
- Variants of Non-Rigid Registration

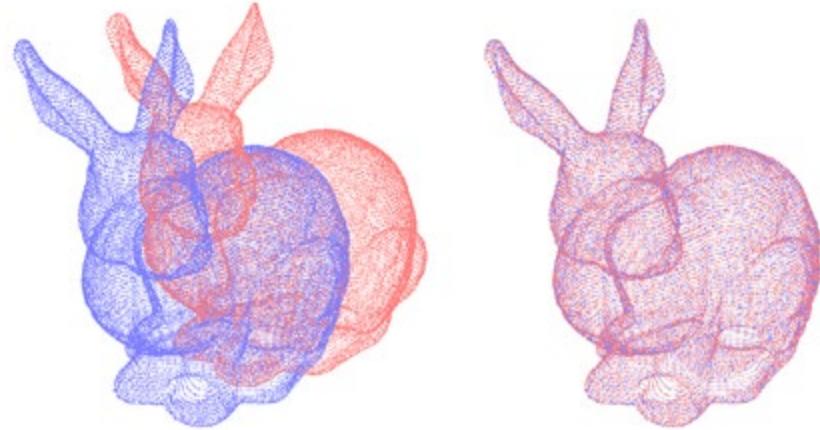
Iterative Closest Point (ICP)



- Given source and target point cloud
- Find best fitting rigid transformation RT

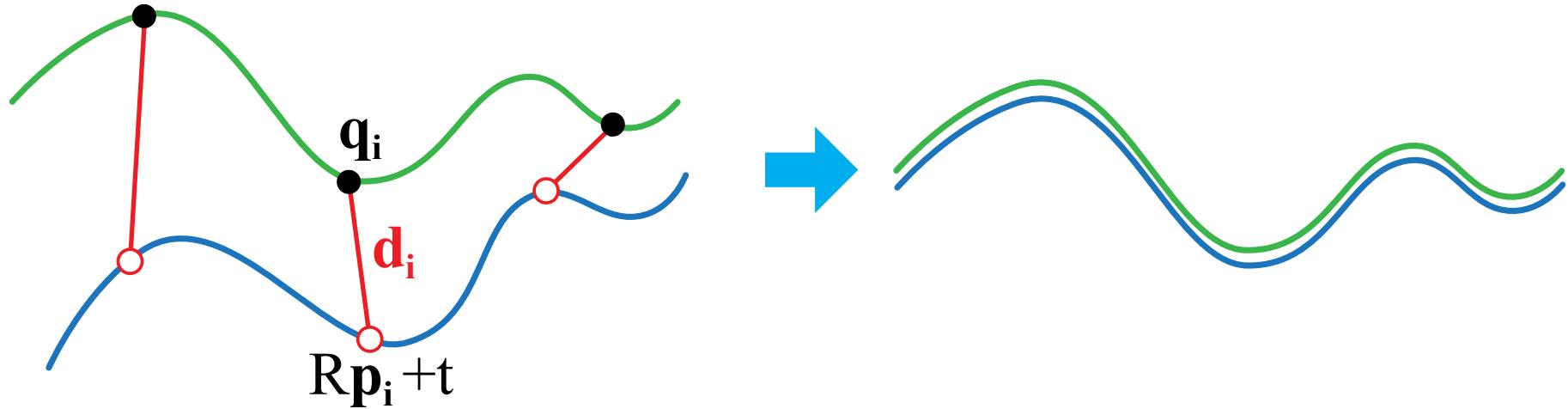
Besl and McKay „A method for registration of 3-D shapes“

Iterative Closest Point



```
 $RT \leftarrow I$ 
while not converged do
    Select points from source point cloud
    for  $p$  in selected points do
         $p' \leftarrow RT(p)$ 
        Find corresponding closest target point  $q$  to  $p'$ .
        Remove outliers.
    end
     $RT \leftarrow$  minimize  $E_{fit}$  for corresponding points.
end
```

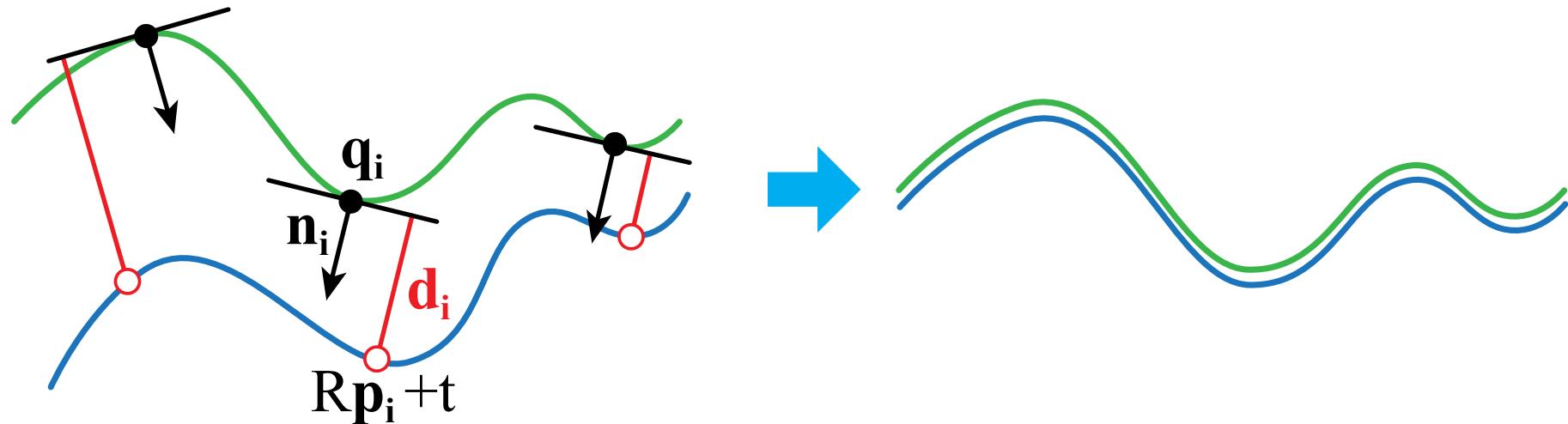
Point-to-Point Error



$$E_{point-to-point} = \sum_{(p_i, q_i) \in Q} (R\mathbf{p}_i + t - q_i)^2$$

Besl and McKay „A method for registration of 3-D shapes“

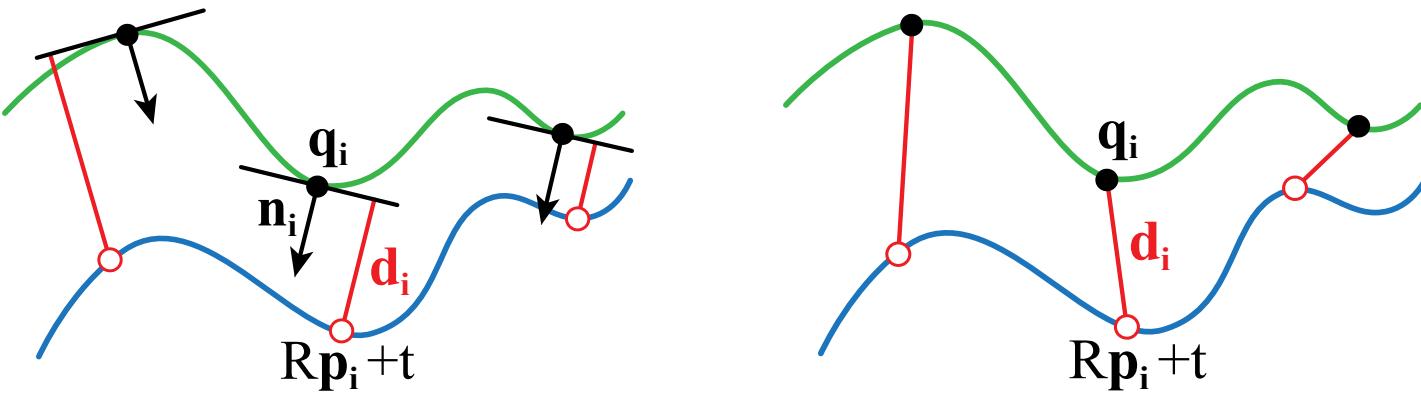
Point-to-Plane Error



$$E_{point-to-plane} = \sum_{(p_i, q_i) \in Q} ((R\mathbf{p}_i + t - q_i) \cdot n_i)^2$$

Chen and Medioni „Object Modeling by Registration of Multiple Range Images“

Iterative Closest Point

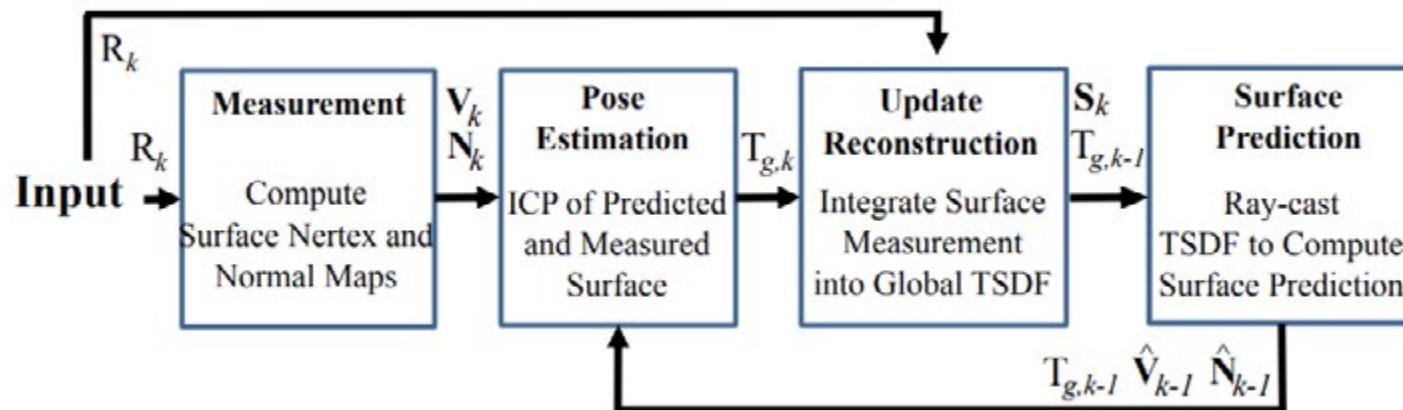


$$E_{fit} = \alpha_{plane} E_{point-to-plane} + \alpha_{point} E_{point-to-point}$$

KinectFusion

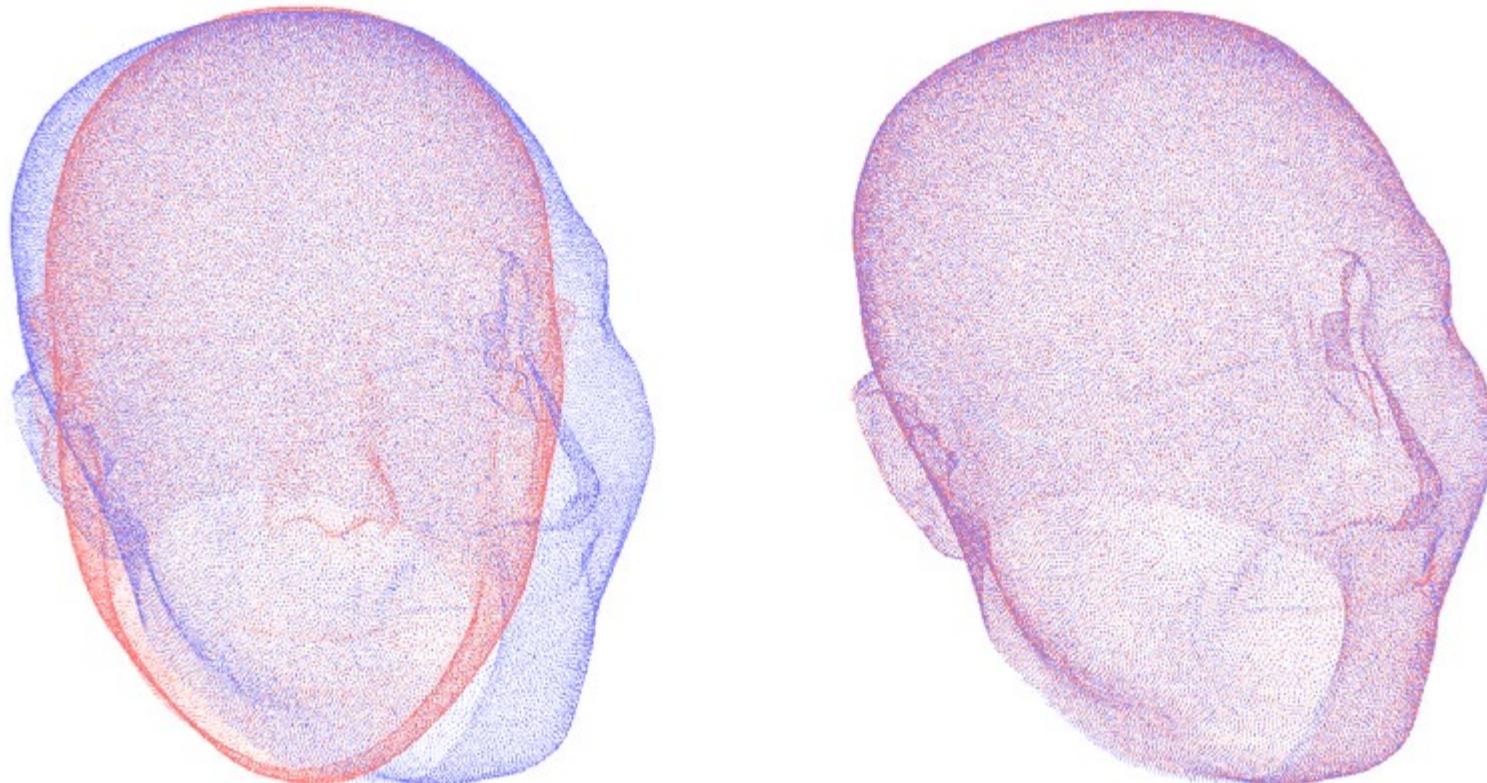


- Real Time mapping and tracking of static scene
- Implicit surface representation based on TSDF



Newcombe et al. „KinectFusion: Real-time dense surface mapping and tracking“

Non-Rigid Registration



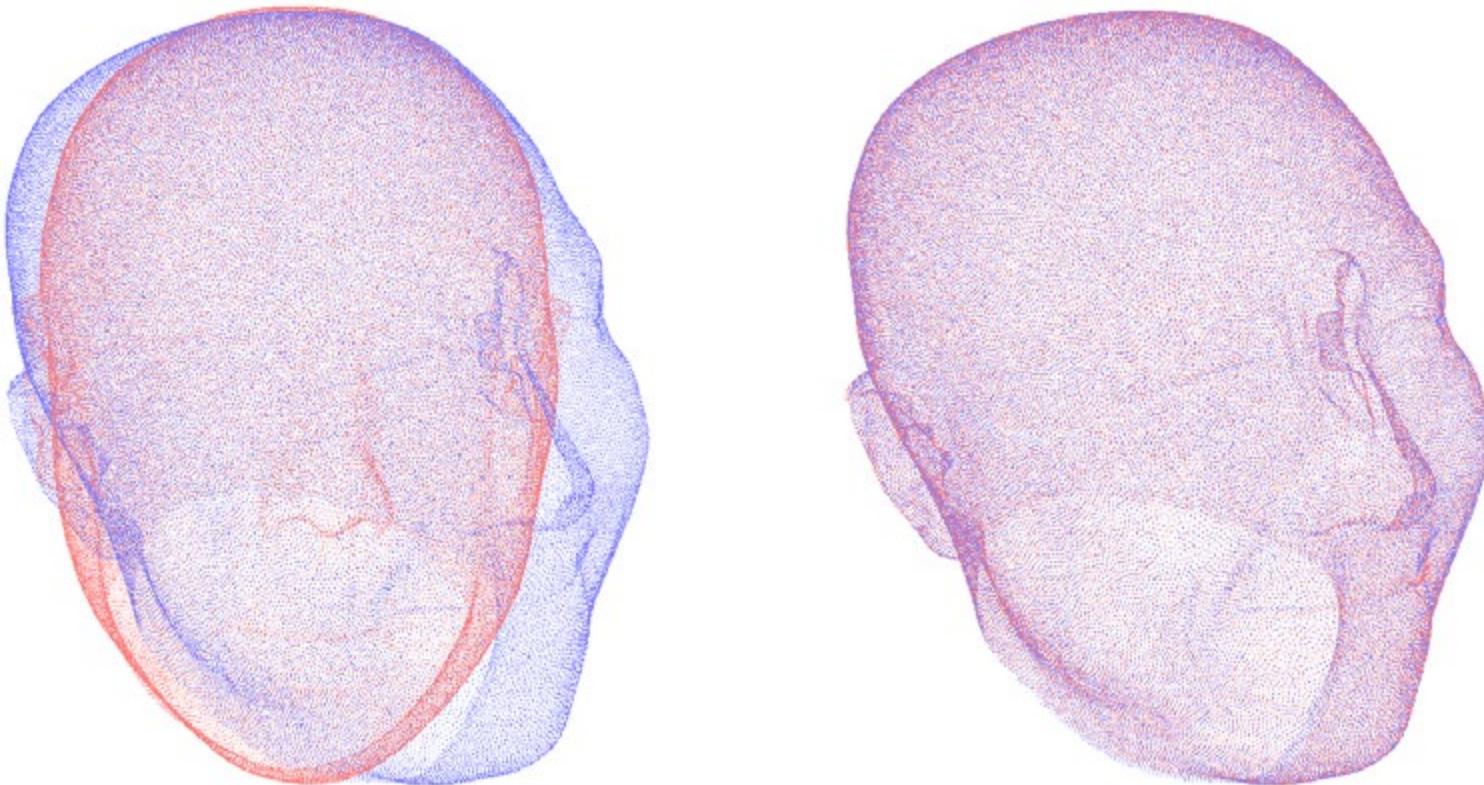
As-Rigid-As-Possible



$$E_{arap} = \sum_i \sum_{j \in \mathcal{N}(i)} ||R_i(v_i - v_j) - (v'_i - v'_j)||^2$$

Sorkine and Alexa “As-rigid-as-possible Surface Modeling“

Non-Rigid Registration



$$E = \alpha_{fit} E_{fit} + \alpha_{smooth} E_{arap}$$

Surface Deformation Model

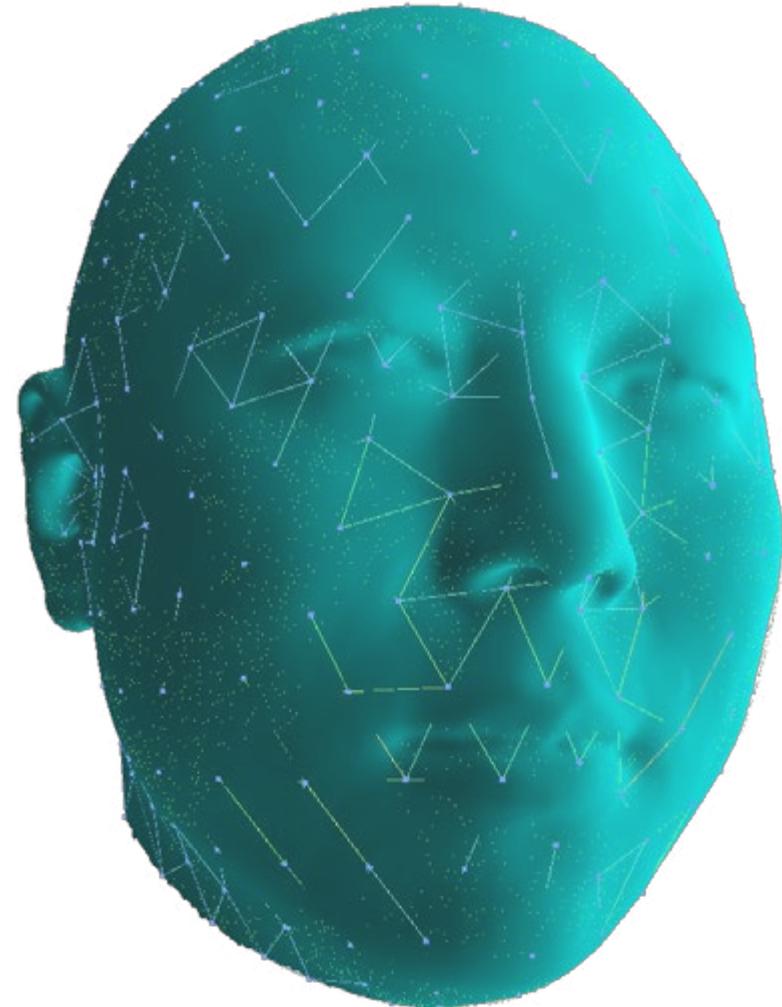
- Deformation Graph

$$G = \{x_j\}_1^n \quad x = \{g, r, t\}$$

$$x_{global} = \{g, r, t\}$$

- Deformation around Node

$$\phi_x(v) = R(v - g) + g + t$$



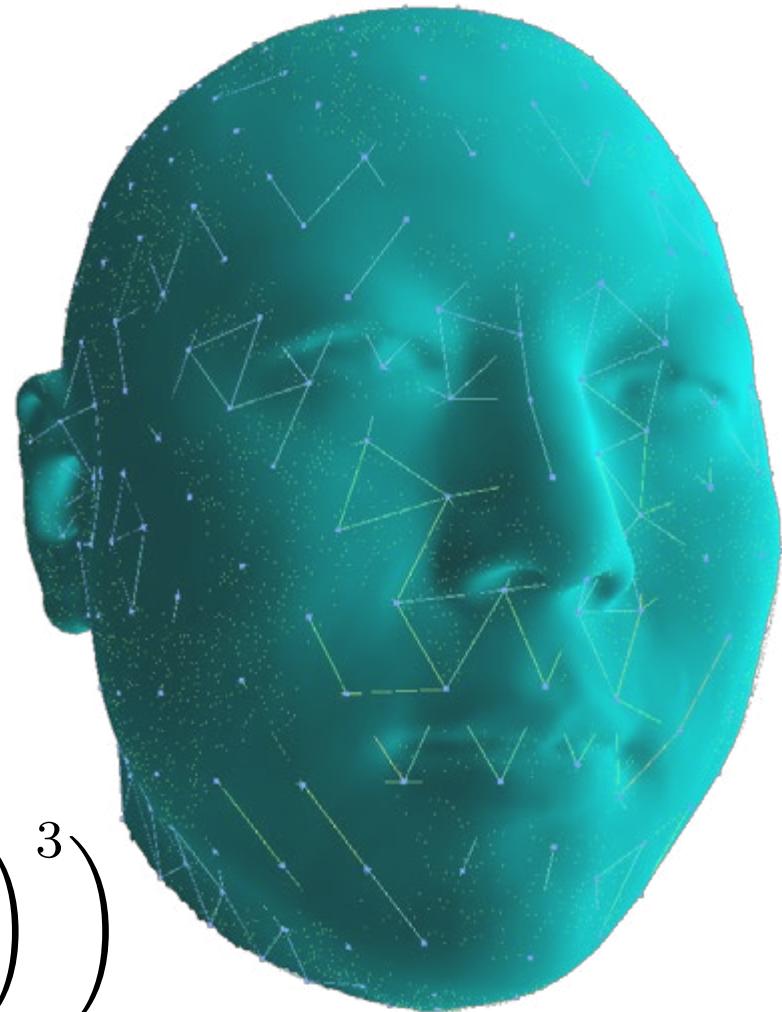
Sumner et al. "Embedded Deformation for Shape Manipulation"

Surface Deformation Model

$$v'_i = \phi_{global} \circ \phi_{local}(v_i)$$

$$\phi_{local}(v_i) = \sum_{j=1}^n w_j(v_i) \phi_{x_j}(v)$$

$$w_j(v_i) = \max \left(0, \left(1 - \frac{d(v_i, g_j)^2}{{r_j}^2} \right)^3 \right)$$



Non-Rigid Registration

$G, x_{global} \leftarrow I$

while *not converged* **do**

 Select points from template surface model.

for v *in selected points* **do**

$v' \leftarrow \phi_{global} \circ \phi_{local}(v)$

 Find corresponding closest *target* point q to v' .

 Remove outliers.

end

$G, x_{global} \leftarrow$ minimize E for corresponding points.

end

$$E = \alpha_{fit} E_{fit} + \alpha_{smooth} E_{arap}$$

Non-Rigid Registration of Sequences

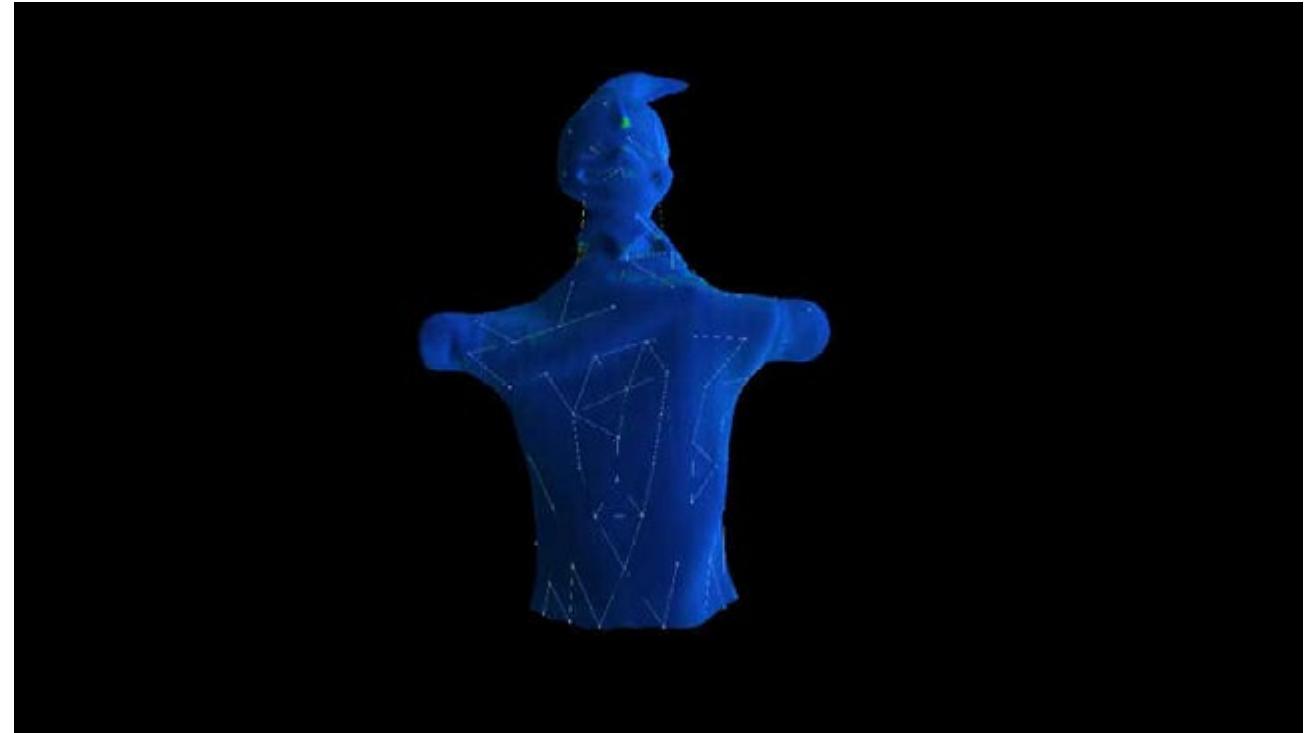
$G, x_{global} \leftarrow I$

for each frame in sequence of frames **do**

$x_{global} \leftarrow$ optimize using iterative closest point.

$x_{global}, G \leftarrow$ optimize using non-rigid iterative closest point

end



DynamicFusion

- Estimate warp field to deform canonical model
- Fuse frames into TSDF reconstruction



(a) Initial Frame at $t = 0s$



(b) Raw (noisy) depth maps for frames at $t = 1s, 10s, 15s, 20s$



(c) Node Distance



(d) Canonical Model



(e) Canonical model warped into its live frame

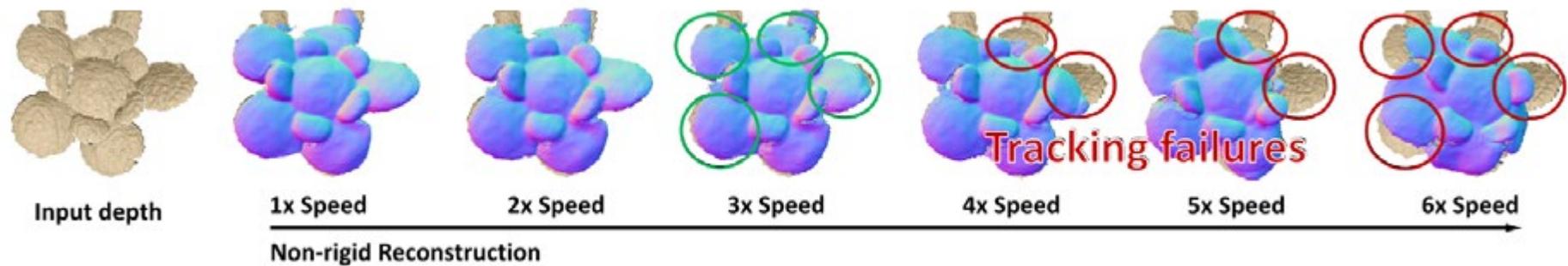


(f) Model Normals

Newcombe et al. "DynamicFusion: Reconstruction and tracking of non-rigid scenes in real-time"

Goals

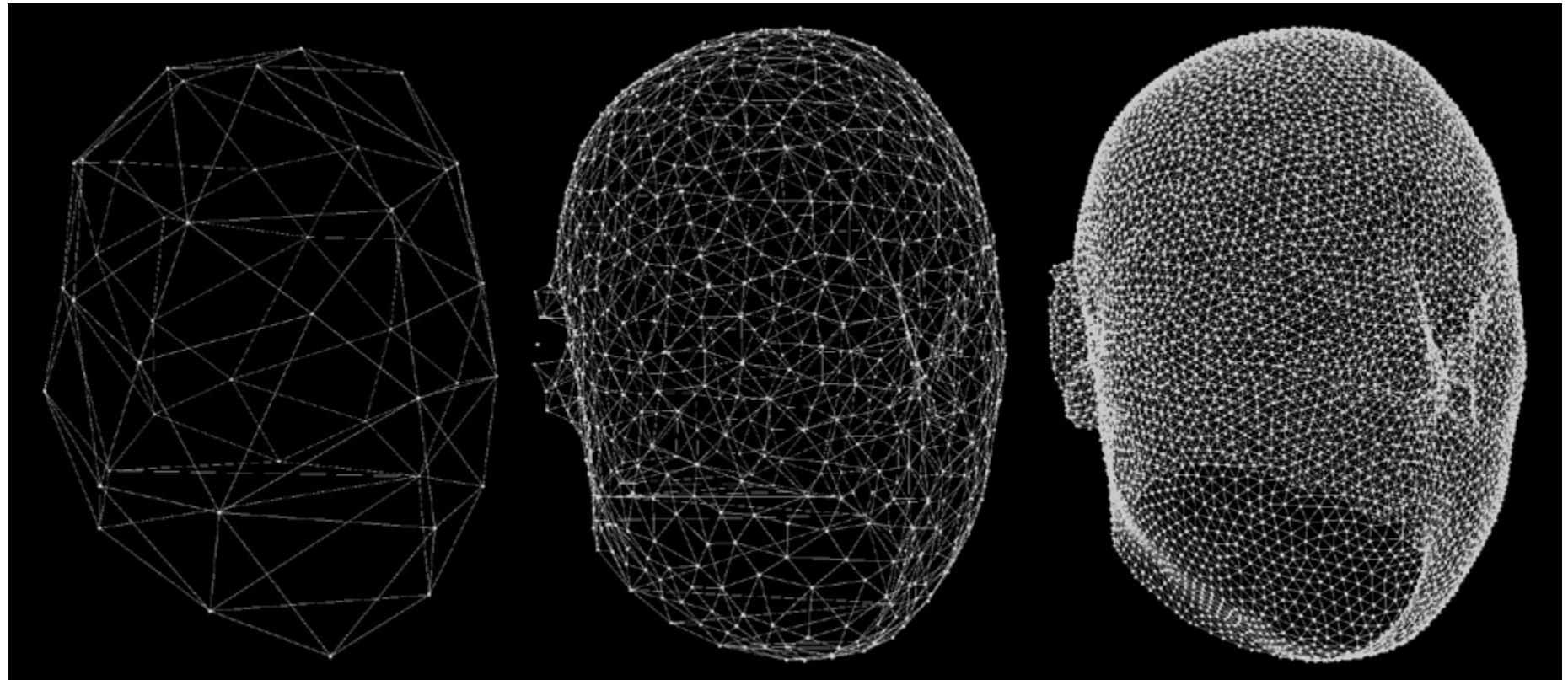
- Accurate 3D models from complex non-rigid objects
- Track deformations of an object over time
- Improving the robustness of non-rigid registration under high deformations



Innmann et al. "VolumeDeform: Real-time Volumetric Non-rigid Reconstruction"

Deformation Graph Refinement

- Adaptive deformation graph node distribution



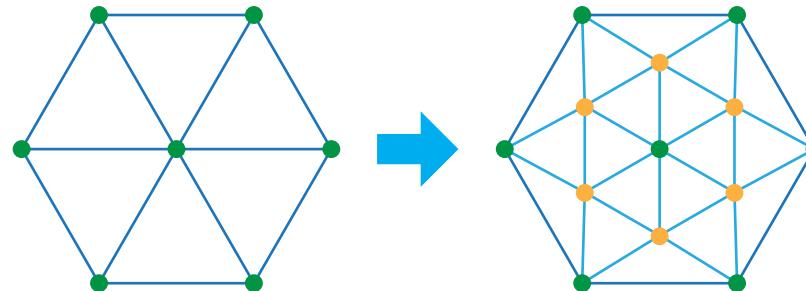
Li et al. "Robust Single-view Geometry and Motion Reconstruction"

Deformation Graph Refinement

- Uniform node distribution (sample distance $r_l = 4r_{l-1}$)
- Refine node if edge residual is high

$$\text{residual}(e_x) > \rho \max_{e \in \text{edges}(g)} (\text{residual}(e))$$

- Refine by inserting nodes of the next finer level



Li et al. "Robust Single-view Geometry and Motion Reconstruction"

Deformation Graph Refinement



Smoothness Reduction

- α_{smooth} balances between rigidity and deformation
- Reduce smoothness if the algorithm converges

$$\alpha_{smooth}^k = \begin{cases} \frac{1}{2} \alpha_{smooth}^{k-1} & , \frac{|E_k - E_{k-1}|}{E_k} < \gamma \\ \alpha_{smooth}^{k-1} & , \text{otherwise} \end{cases}$$

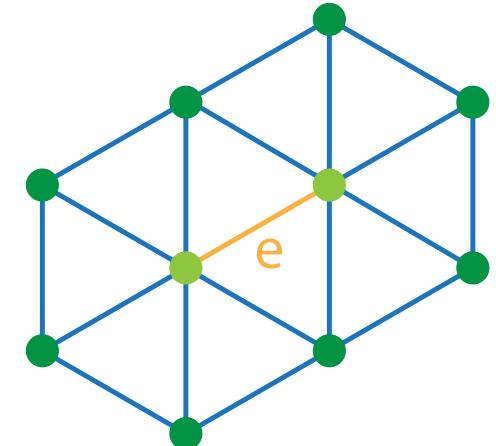
Li et al. "Global Correspondence Optimization for Non-rigid Registration of Depth Scans"

Smoothness Reduction



Rigidity Reduction

- ARAP with rigidity term per edge



$$E_{rr} = \sum_i \sum_{j \in N(i)} e_{\text{rigidity}_i}^k \| R_i(v_i - v_j) - (v'_i - v'_j) \|^2$$

- Reduce rigidity per edge if the edge residual is high

$$e_{\text{rigidity}_i}^k = \begin{cases} \frac{1}{2} e_{\text{rigidity}_i}^{k-1} & , \text{residual}(e_i)^k > \eta \\ e_{\text{rigidity}_i}^{k-1} & , \text{otherwise} \end{cases}$$

Rigidity Reduction



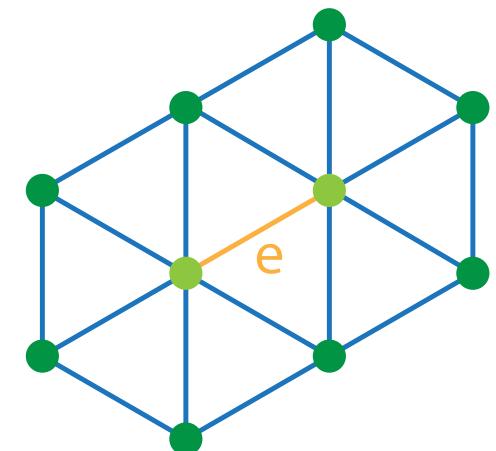
Adaptive Rigidity per Edge

- Simultaneously solves for deformations and optimal rigidity weight per edge

$$E_{ar} = \sum_i \sum_{j \in N(i)} \| e_{\text{rigidity}}^{ij} [R_i(v_i - v_j) - (v'_i - v'_j)] \|^2$$

$$E_{\text{rigidity}} = \sum_{e \in \text{edges}} \|1 - e_{\text{rigidity}}\|^2$$

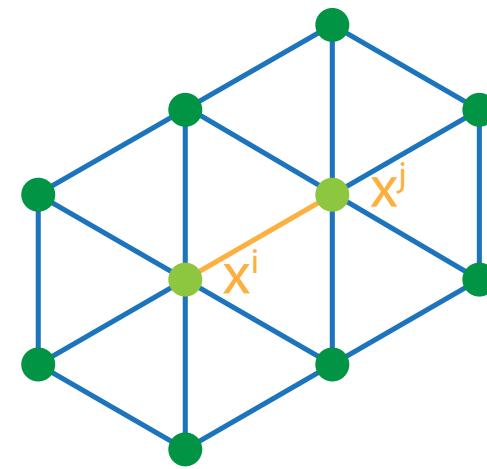
$$E_{\text{smooth}} = E_{ar} + \alpha_{\text{rigidity}} E_{\text{rigidity}}$$



Adaptive Rigidity per Vertex

- Simultaneously solves for deformations and optimal rigidity weight per vertex

$$e_{\text{rigidity}}^{ij} = \frac{(x_{\text{rigidity}}^i + x_{\text{rigidity}}^j)}{2}$$



Adaptive Rigidity per Edge



Data Set



Paperbag



Puppet



Head

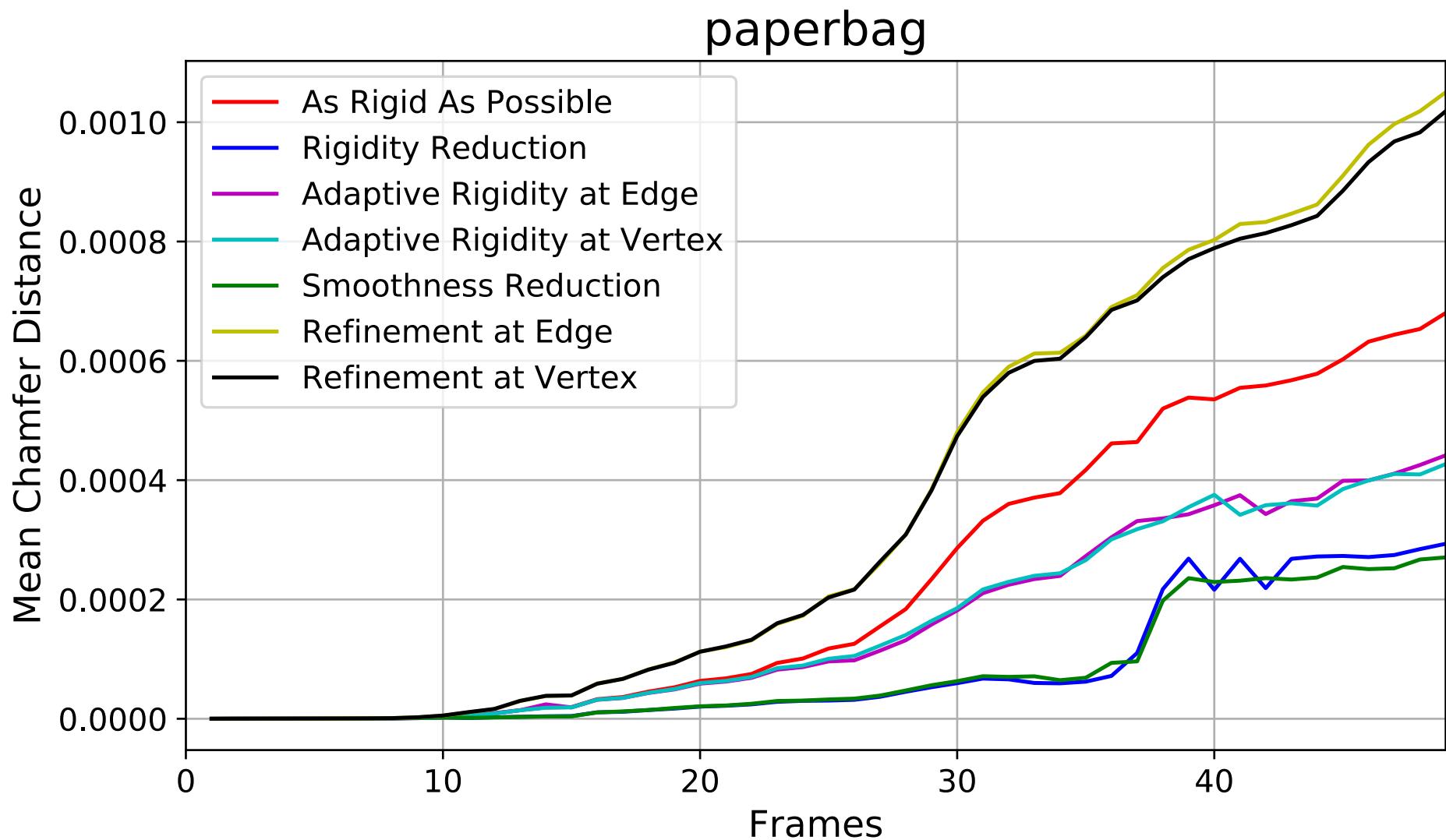


Hand

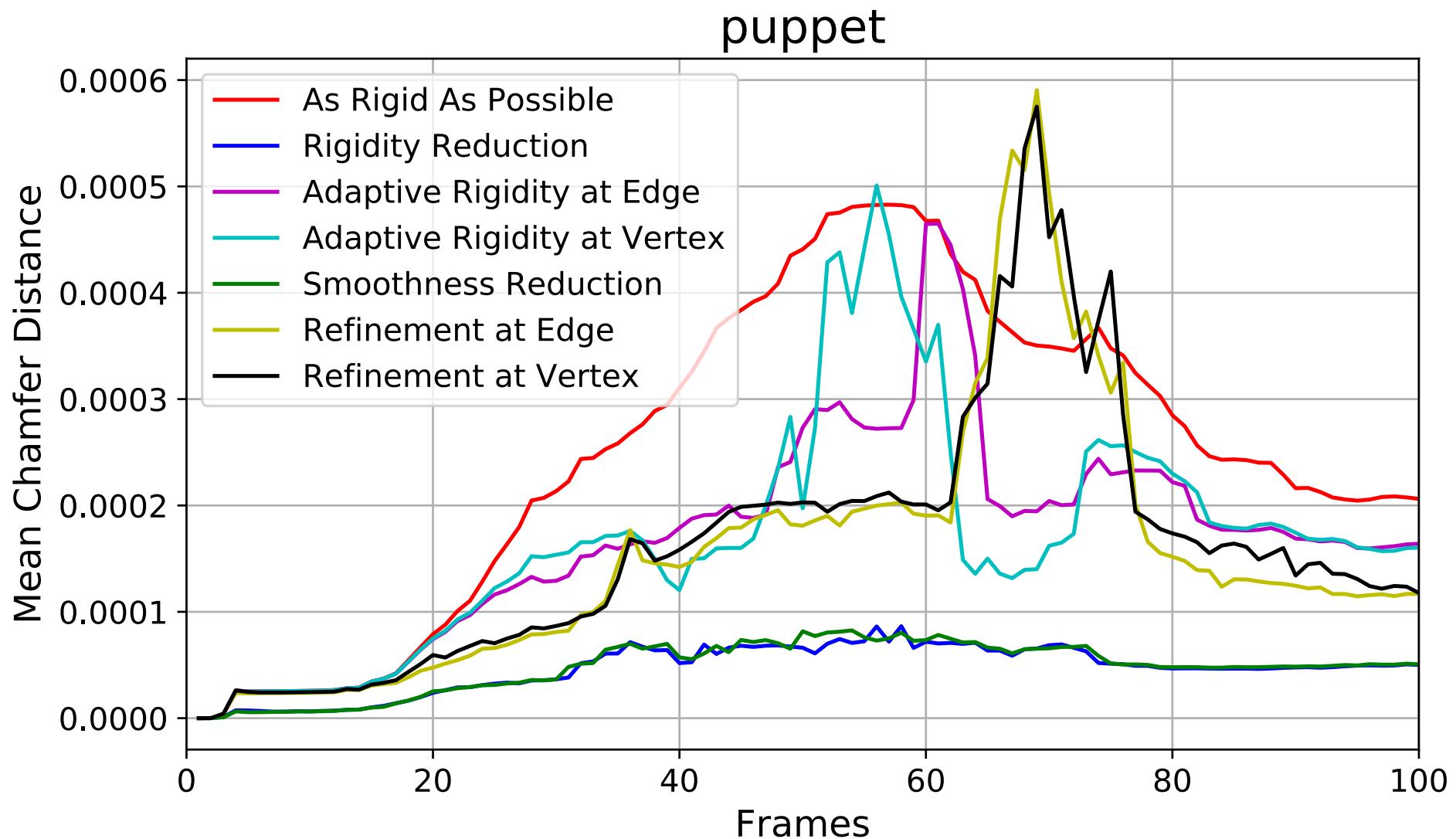


Li et al. "Robust Single-view Geometry and Motion Reconstruction"

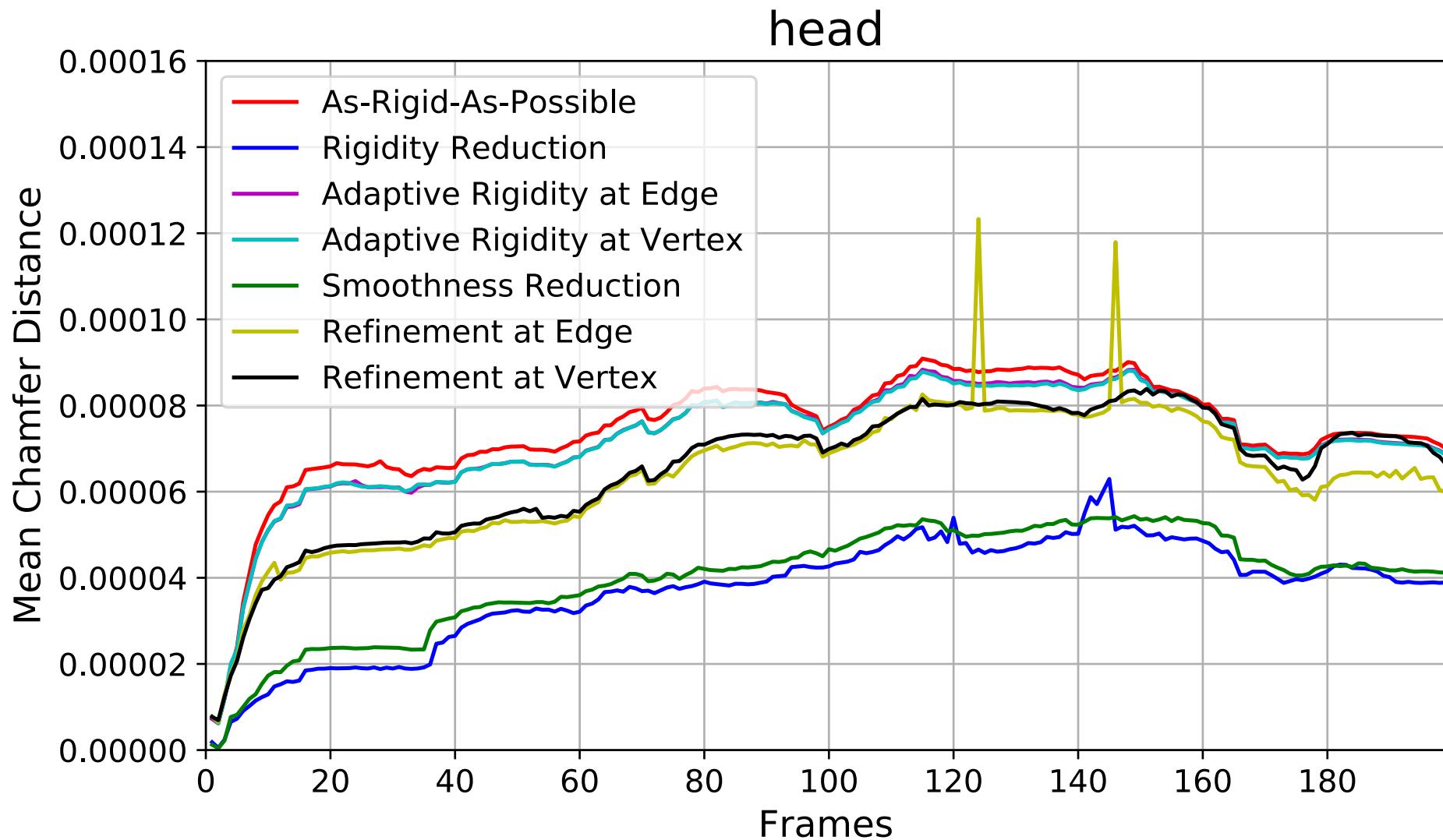
Results



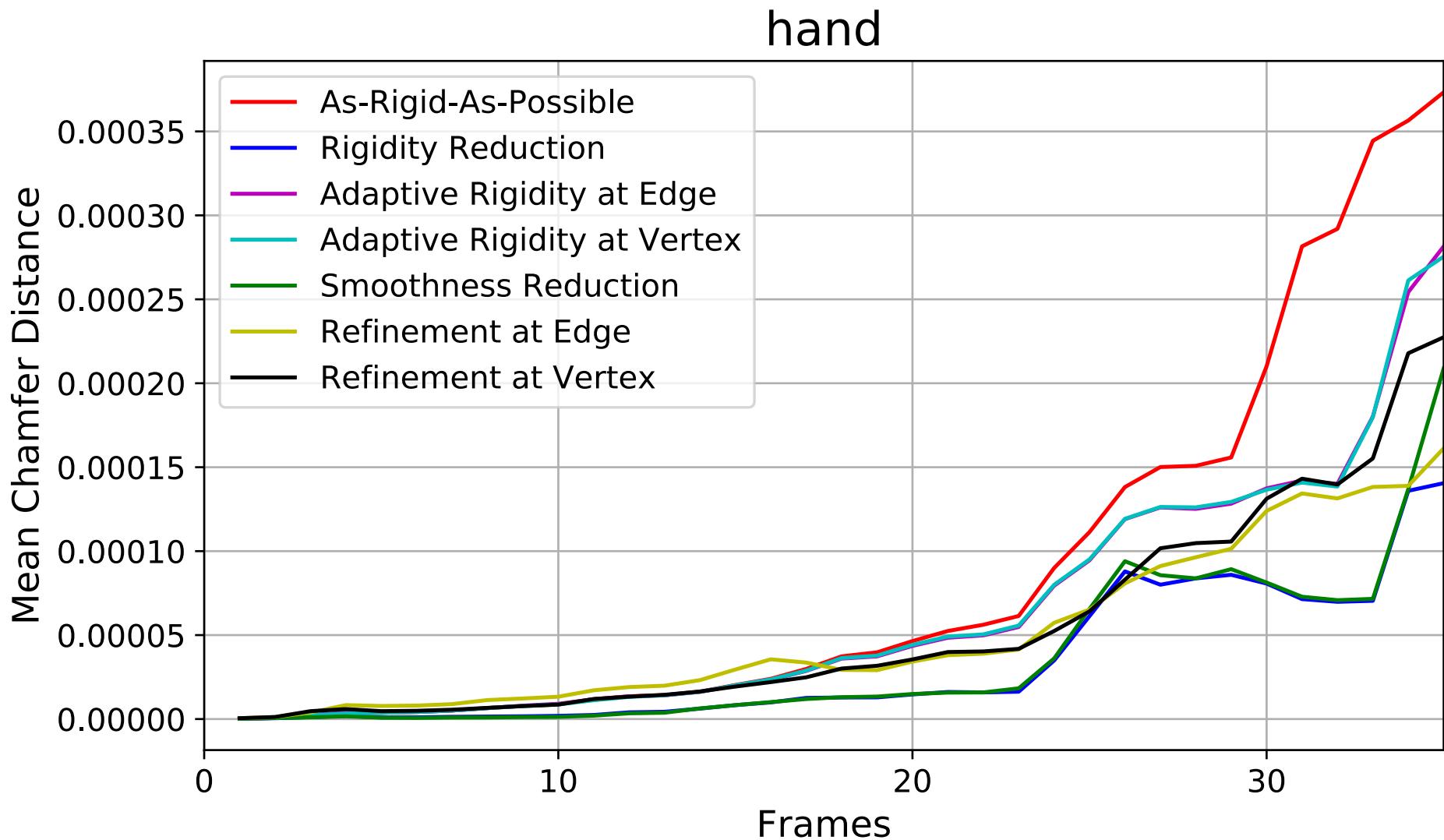
Results



Results



Results



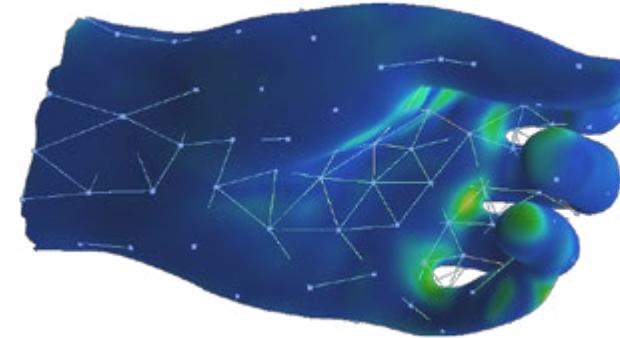
Results

Variant	relative error	relative error per node
As Rigid As Possible	1.0	1.0
Rigidity Reduction	0.3510	0.3510
Smoothness Reduction	0.3656	0.3656
Adaptive Rigidity at Edge	0.7578	0.7578
Adaptive Rigidity at Vertex	0.7562	0.7562
Refinement at Edge	0.8980	2.9831
Refinement at Vertex	0.9149	2.4175

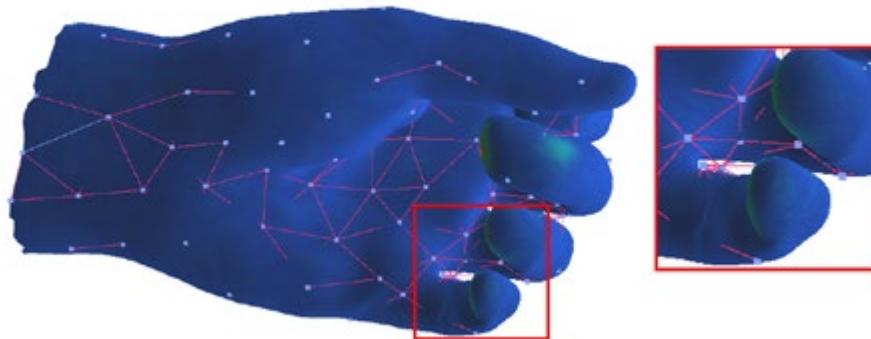
Results



Dataset



As-Rigid-As-Possible



Reduce Rigidity



Smoothness Reduction

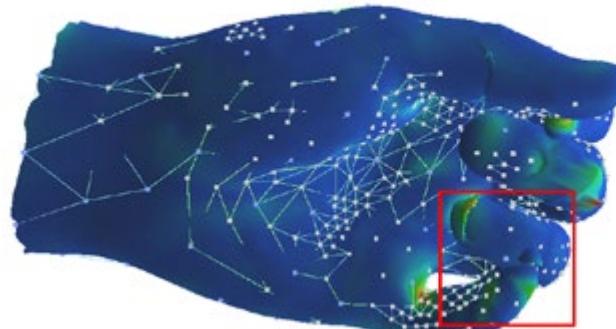
Results



Adaptive Rigidity at Edge



Adaptive Rigidity at Vertex



Refinement at Edge



Refinement at Vertex

Results – Combination of Variants

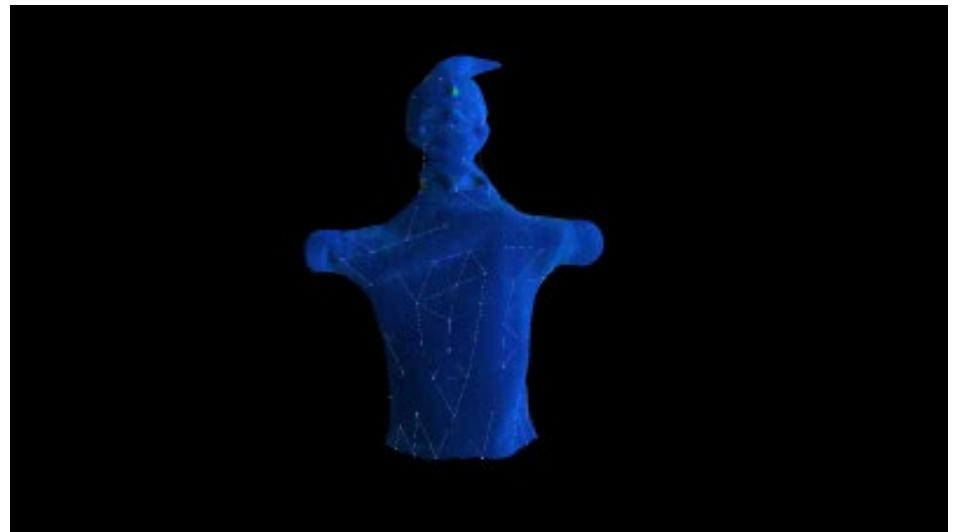


Rigidity Reduction & Smoothness Reduction

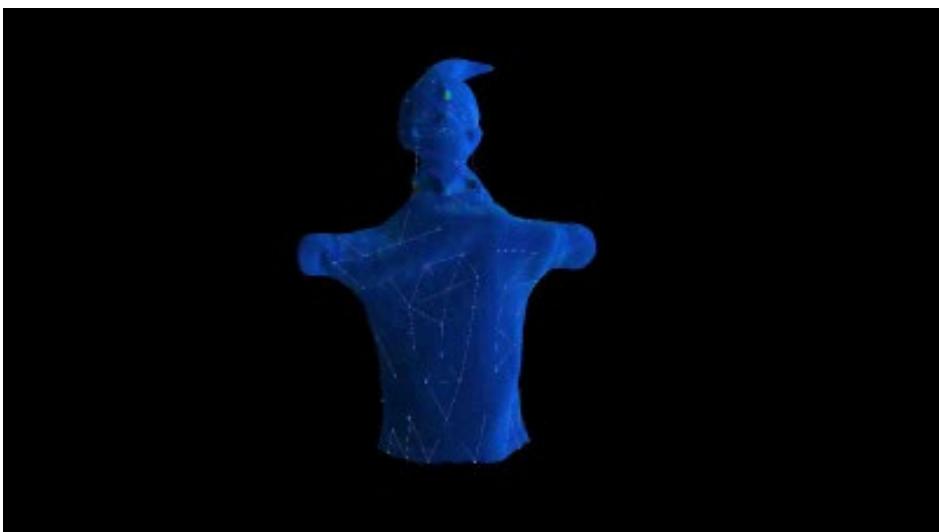
Results – Combination of Variants



Adaptive Rigidity at Edge & Smoothness Reduction



Adaptive Rigidity at Vertex & Smoothness Reduction



Adaptive Rigidity at Vertex & Rigidity Reduction



Adaptive Rigidity at Edge & Rigidity Reduction

Results – Combination of Variants



Refinement at Vertex & Smoothness Reduction



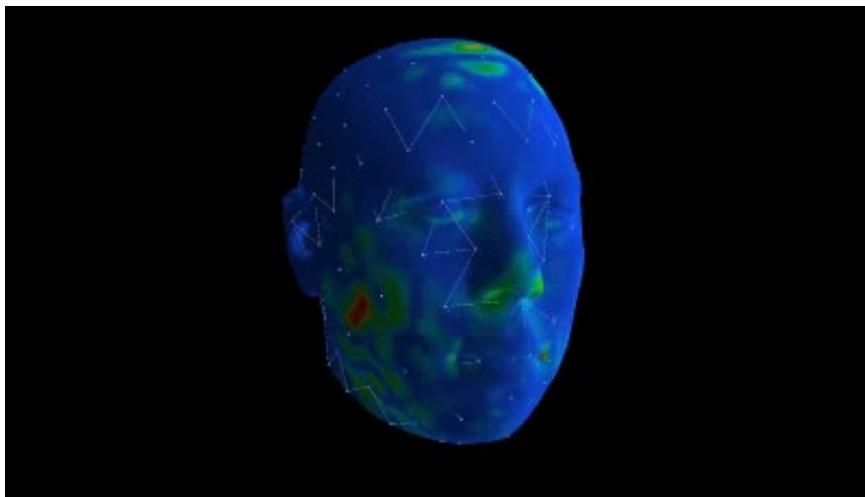
Refinement at Edge & Smoothness Reduction

Results

Variant	relative error	relative error per node
As Rigid As Possible	1.0	1.0
Rigidity Reduction	0.3510	0.3510
Smoothness Reduction	0.3656	0.3656
Adaptive Rigidity at Edge Smoothness Reduction	0.2993	0.2993
Adaptive Rigidity at Vertex Smoothness Reduction	0.3401	0.3401
Rigidity Reduction and Smoothness Reduction	0.3638	0.3638
Adaptive Rigidity at Vertex Rigidity Reduction	0.7264	0.7264
Adaptive Rigidity at Edge Rigidity Reduction	0.7566	0.7566
Refinement at Vertex Smoothness Reduction	0.7130	1.7327
Refinement at Edge Smoothness Reduction	0.7718	2.7361

Conclusion

- Adaptive Rigidity at Edge with Smoothness Reduction
- Improves stability and accuracy
- Incorporates the underlying kinematics of the object



Limitations

- Adaptive Rigidity
 - Only edge rigidity of previous frame
 - No learning of object kinematics
- Refinement
 - Only inserts new nodes
 - No optimal deformation graph
- Only tested on the reconstructed dataset



Future Work

- Learn rigidity bias per edge
 - Using rigidity confidence term updated over time
 - Or learn rigidity bias with machine learning
- Learn optimal weights for the current iteration
- Find optimal minimal graph structure

Questions ?