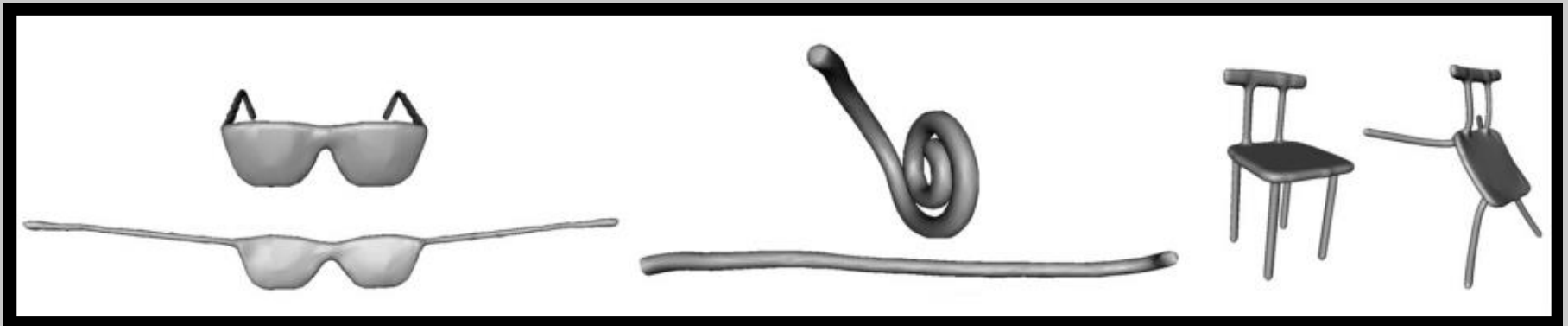


# Detail-Preserving Mesh Unfolding for Nonrigid Shape Retrieval



Yusuf Sahillioğlu and Ladislav Kavan

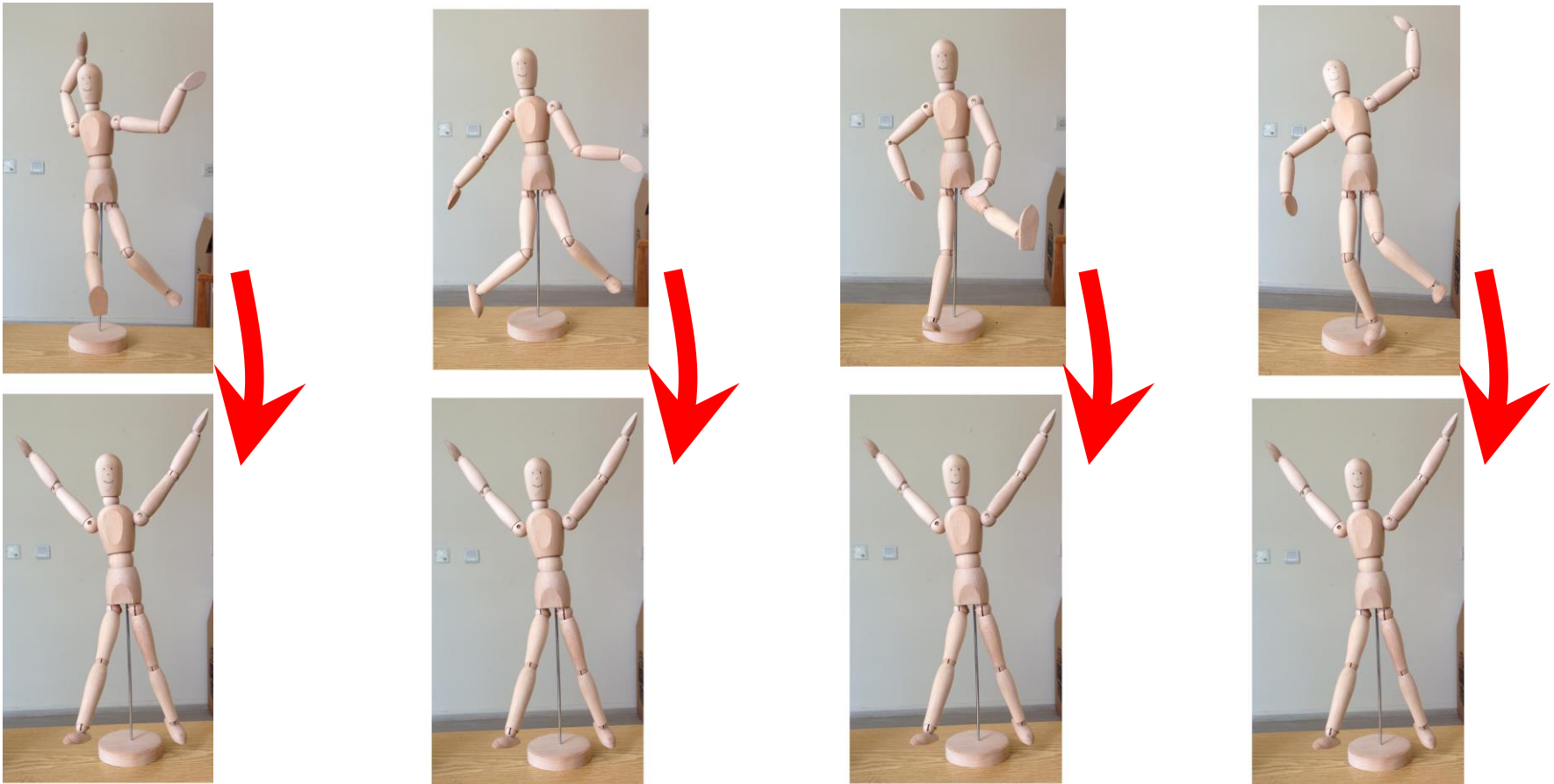
SIGGRAPH 2016



# Problem Definition

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**Goal:** Bring a 3D shape into a canonical pose that is invariant to nonrigid transformations.



# Applications

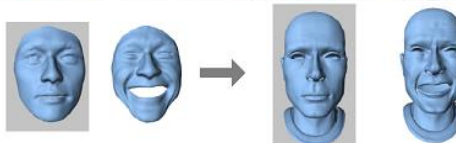
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Given a mesh in canonical form, we'd be able to do:

✓ Shape interpolation.



✓ Attribute transfer.



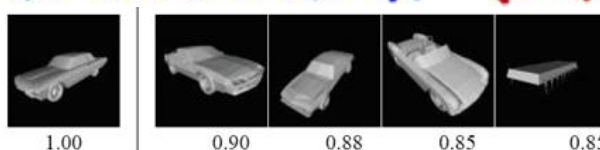
✓ Shape registration.



✓ Time-varying recon.



✓ Shape retrieval.



✓ Statistical shape analysis.



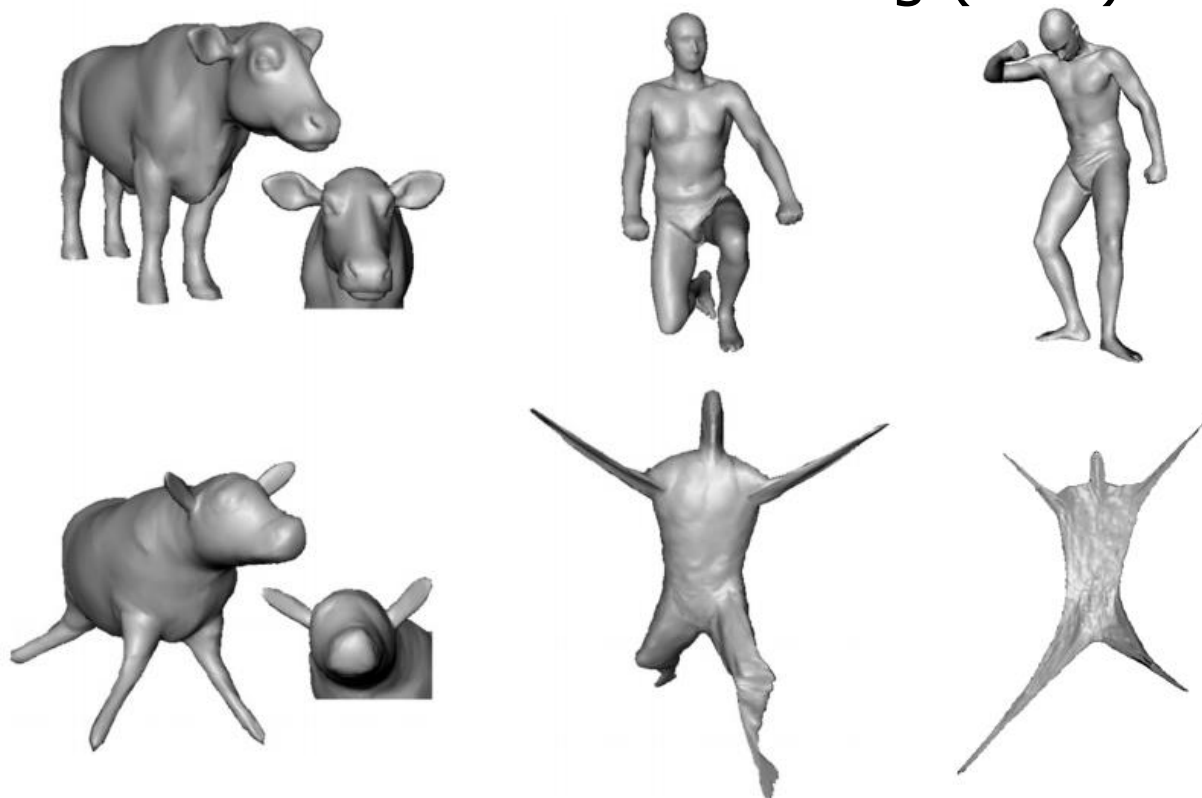
✓ Texture mapping, geodesic distance approximation, .....

# Contributions

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- ✓ Avoid geometric distortion that is introduced by classical approaches such as multidimensional scaling (MDS).

Euclidean  
embedding  
(e.g., MDS)

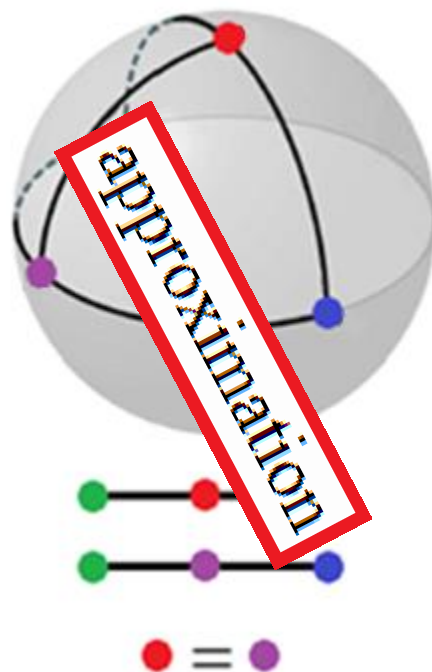


# Contributions

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- ✓ Avoid geometric distortion that is introduced by classical approaches such as multidimensional scaling (MDS).

Euclidean  
embedding  
(e.g., MDS)



# Contributions

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- ✓ While you are at it, put additional constraints in the minimization procedure to preserve details.
  - ✓ This leads to a better post-processing (in, e.g., shape retrieval).

Input



Classical



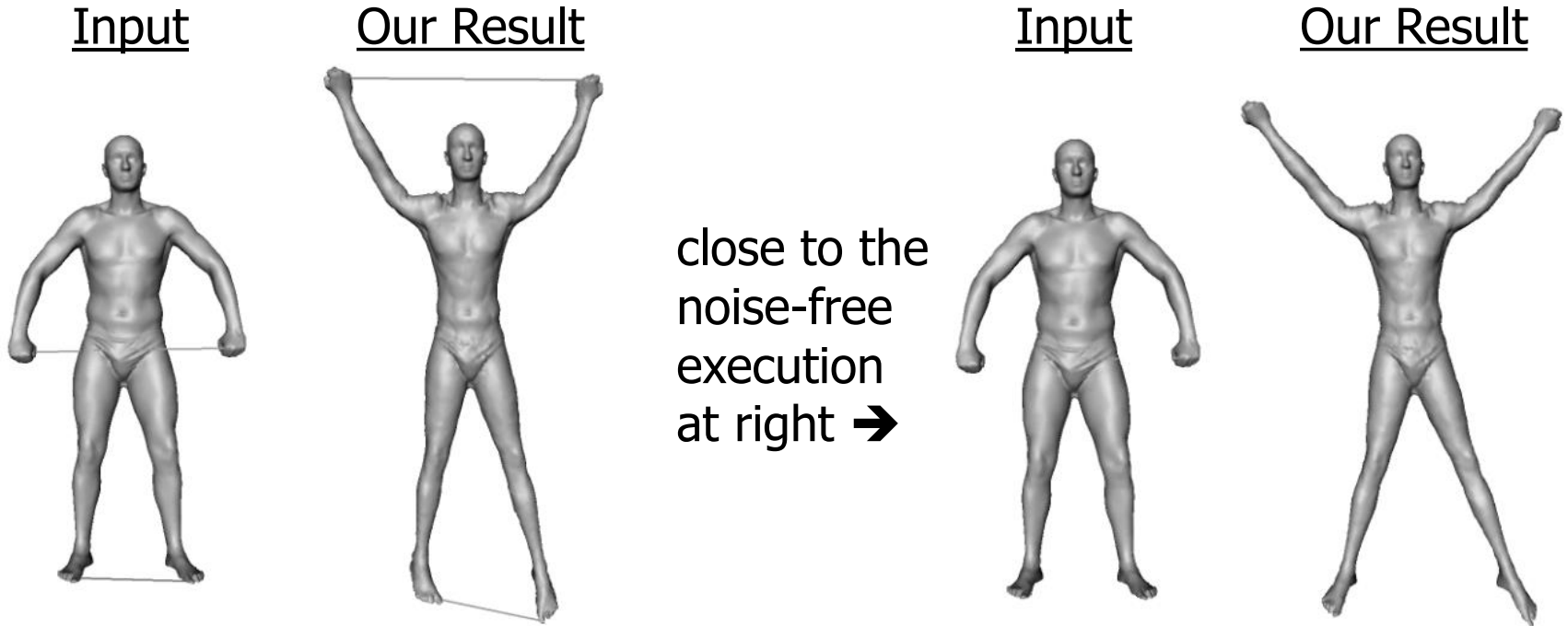
Our Result



# Contributions

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- ✓ Insensitivity to topological noise, as the 2<sup>nd</sup> contribution.
  - ✓ No topology-sensitive geodesic distance in our framework.



# Algorithm

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- ✓ Pre-processing.
  - ✓ For more realistic results, use volumetric elasticity, which requires tetrahedralizing the volume of the input mesh [Jacobson et al.].
- ✓ Our deformation algorithm seeks optimal vertex positions:

$$\mathbf{v}^* = \arg \min_{\mathbf{v}} E(\mathbf{v}).$$



# Algorithm

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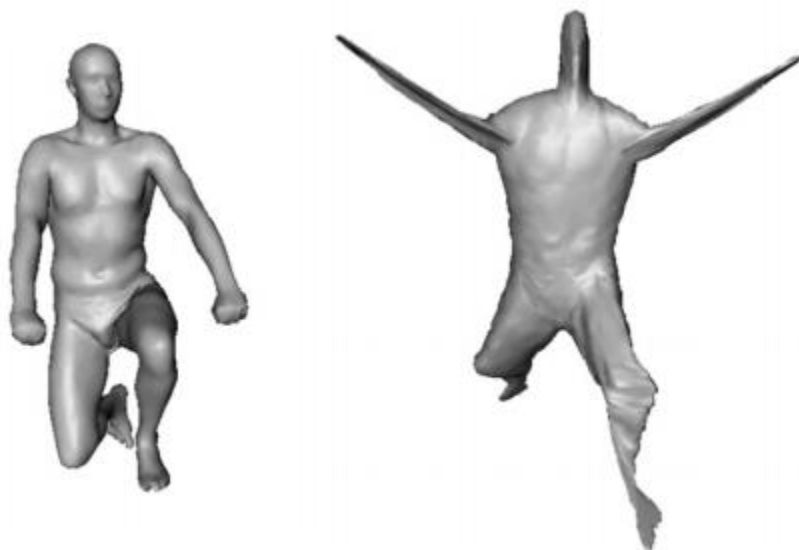
- ✓ Search space is reduced by exploiting the fact that  $\mathbf{v}^*$  for a bending-free pose
  - ✓ move every vertex as far away from each other,
  - ✓ while keeping the mesh in good shape with original details.

$$\mathbf{v}^* = \arg \min_{\mathbf{v}} E(\mathbf{v}).$$

# Algorithm

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- ✓ Consider  $E(\mathbf{v}) = \sum_{i < j} (\|\mathbf{v}_i - \mathbf{v}_j\| - g(i, j))^2$ 
  - ✓ move every vertex as far away from each other,
  - ✓ ~~while keeping the mesh in good shape with original details.~~

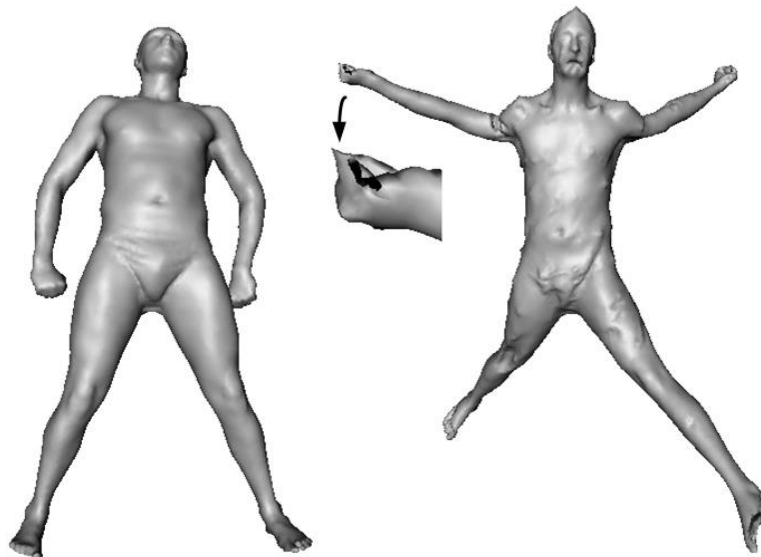


- ✓ This mass-spring system = least-squares MDS [Elad & Kimmel 03].

# Algorithm

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- ✓ Consider  $E(\mathbf{v}) = \frac{1}{2} \sum_{(i,j) \in \mathcal{GU}\mathcal{E}} k_{ij} (\|\mathbf{v}_i - \mathbf{v}_j\| - r_{ij})^2$ 
  - ✓ move every vertex as far away from each other,
  - ✓ while keeping the mesh in good shape with original details.

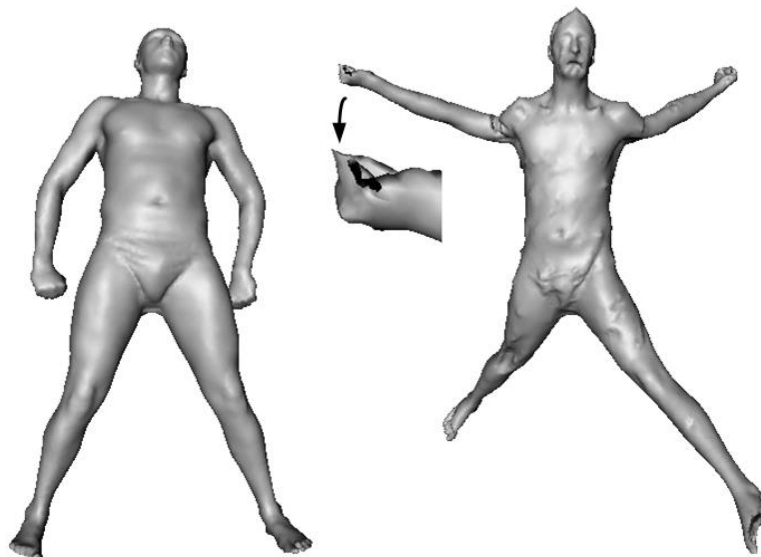


- ✓ Alleviates detail problem but has serious issues.

# Algorithm

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- ✓ Consider  $E(\mathbf{v}) = \frac{1}{2} \sum_{(i,j) \in \mathcal{G} \cup \mathcal{E}} k_{ij} (\|\mathbf{v}_i - \mathbf{v}_j\| - r_{ij})^2$ 
  - ✓ Rest length  $r_{ij}$  takes the value of geodesic distance (for  $\mathcal{G}$ ) or original edge length (for edge springs  $\mathcal{E}$ ).
  - ✓ Issues:
    - ✓ Geodesic distance dependence.
    - ✓ Pure spring-based approach to capture volumetric elasticity.



# Algorithm

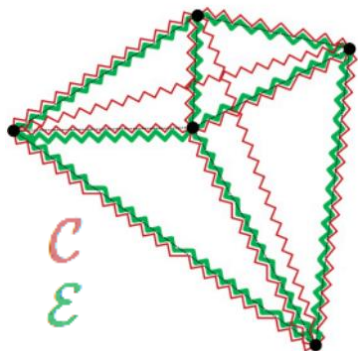
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✓ Proposed energy functional:

$$E(\mathbf{v}) = \frac{1}{2} \left( \underbrace{\sum_{(i,j) \in \mathcal{C}} -k_{ij} \|\mathbf{v}_i - \mathbf{v}_j\|^2}_{\text{Charge Springs}} + \alpha \underbrace{\sum_{(i,j) \in \mathcal{E}} k_{ij} (\|\mathbf{v}_i - \mathbf{v}_j\| - r_{ij})^2}_{\text{Edge Springs}} \right)$$

Move every vertex as far away from each other using charge springs ( $\mathcal{C}$ ). Here,  $r_{ij} = 0$ .

Keep mesh in good shape with original details using edge springs ( $\mathcal{E}$ ). Here,  $r_{ij} = \text{original edge len.}$



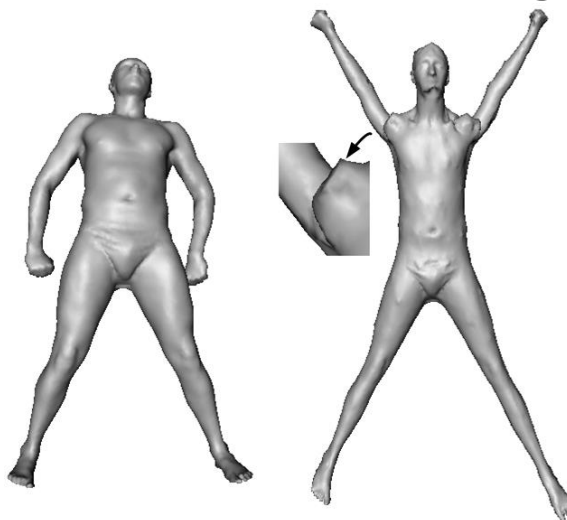
# Algorithm

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- ✓ Proposed energy functional:

$$E(\mathbf{v}) = \frac{1}{2} \left( \sum_{(i,j) \in \mathcal{C}} -k_{ij} \|\mathbf{v}_i - \mathbf{v}_j\|^2 + \alpha \sum_{(i,j) \in \mathcal{E}} k_{ij} (\|\mathbf{v}_i - \mathbf{v}_j\| - r_{ij})^2 \right)$$

- ✓ Without any FE constraints, this energy is still not perfect.



# Algorithm

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✓ Proposed FE regularization constraints:

✓ Preserve local volume in the neighborhood of each vertex:

$$c_i(\mathbf{v}) : \sum_{t \in \eta(i)} \text{vol}(t) = l_i \quad \forall i \in V$$

✓ Prevent inversions:

$$c_t(\mathbf{v}) : \text{vol}(t) > \epsilon \quad \forall t \in T.$$

# Algorithm

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- ✓ Final nonlinear constrained optimization problem:

$$\underset{\mathbf{v}}{\text{minimize}} \quad E(\mathbf{v})$$

$$\text{subject to} \quad c_i(\mathbf{v}), \forall i \in V \quad \text{and} \quad c_t(\mathbf{v}), \forall t \in T$$



# Algorithm

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- ✓ Final nonlinear constrained optimization problem:

minimize  $E(\mathbf{v})$   
 $\mathbf{v}$

subject to  $c_i(\mathbf{v}), \forall i \in V$  and  $c_t(\mathbf{v}), \forall t \in T$

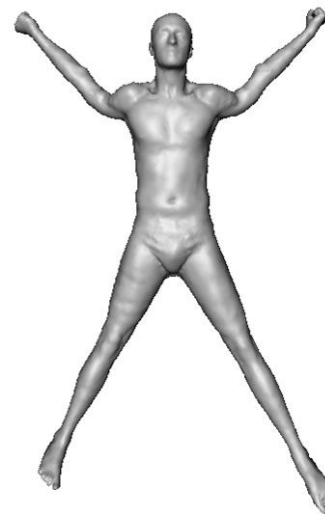
Input



Without Constraints



With Constraints



# Algorithm

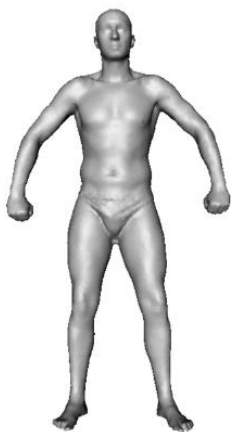
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- ✓ Final nonlinear constrained optimization problem:

minimize  $E(\mathbf{v})$   
 $\mathbf{v}$

subject to  $c_i(\mathbf{v}), \forall i \in V$  and  $c_t(\mathbf{v}), \forall t \in T$

Input



Without Constraints



With Constraints



# Algorithm

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- ✓ Final nonlinear constrained optimization problem:

minimize  $E(\mathbf{v})$   
 $\mathbf{v}$

subject to  $c_i(\mathbf{v}), \forall i \in V$  and  $c_t(\mathbf{v}), \forall t \in T$

Input



Without Constraints



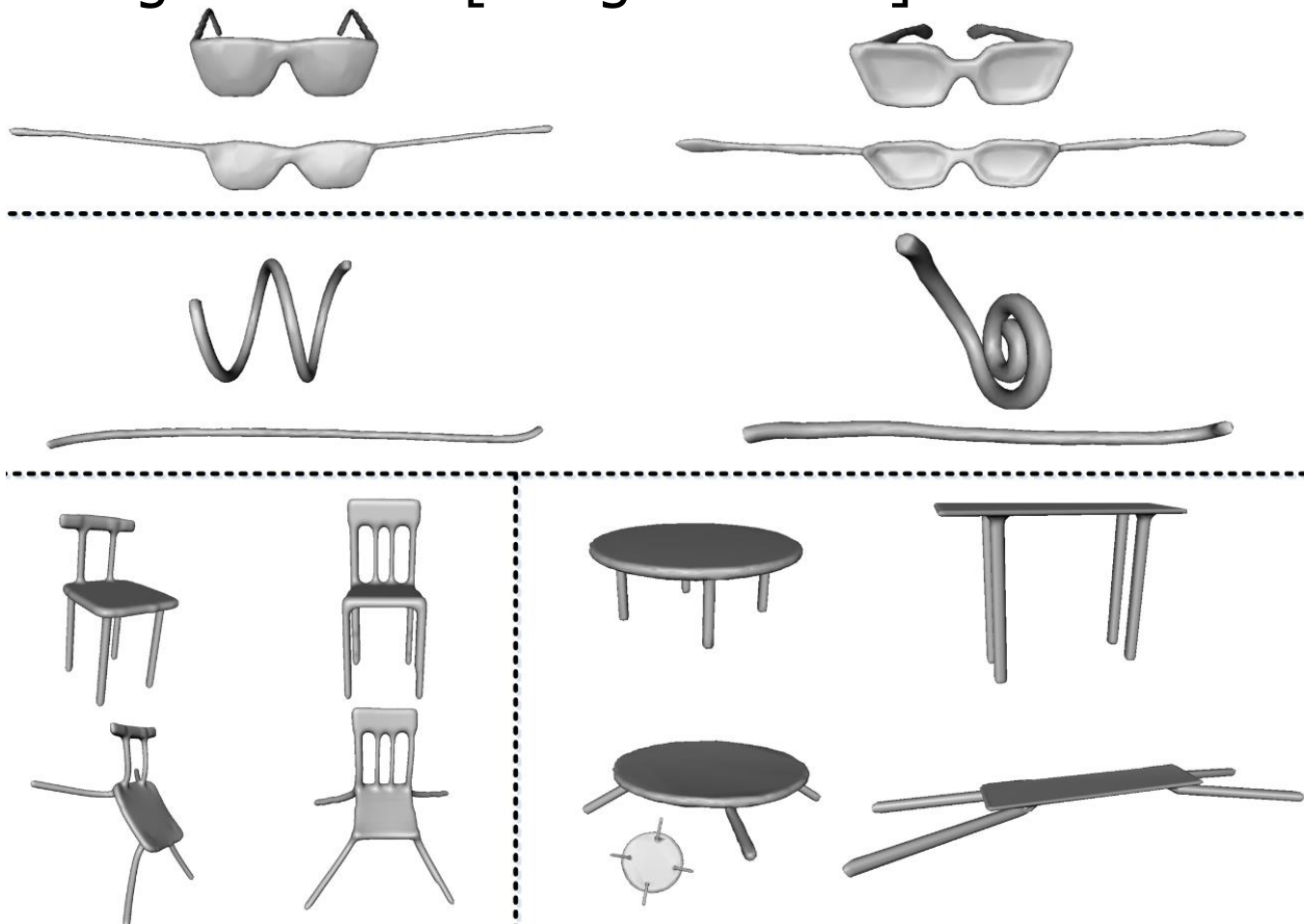
With Constraints



# Experimental Results

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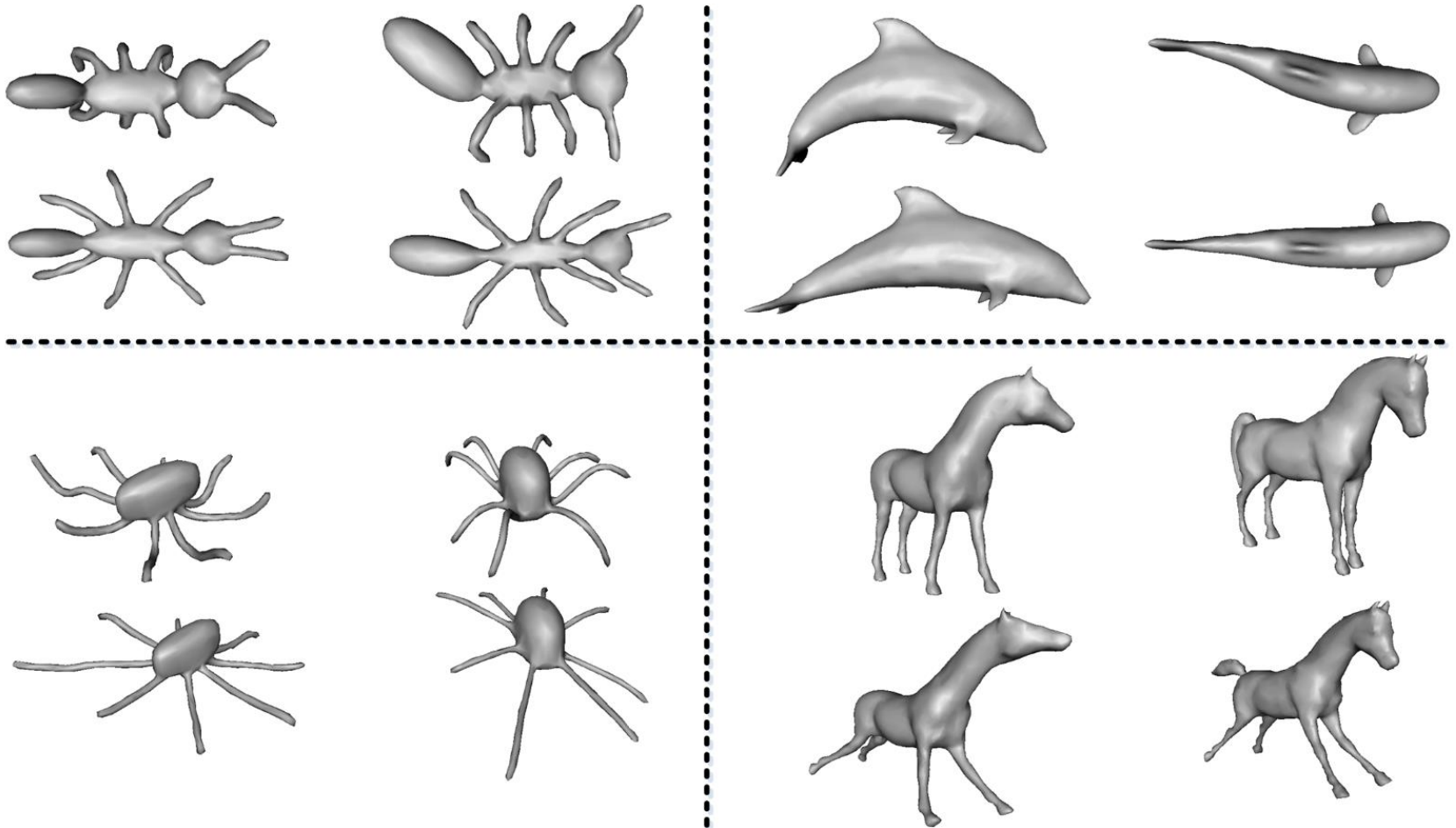
- ✓ Watertight dataset [Giorgi et al. 07].



# Experimental Results

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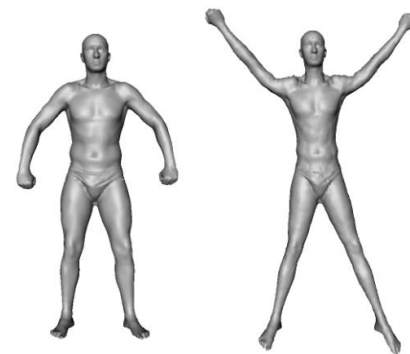
✓ Watertight dataset [Giorgi et al. 07].



# Experimental Results

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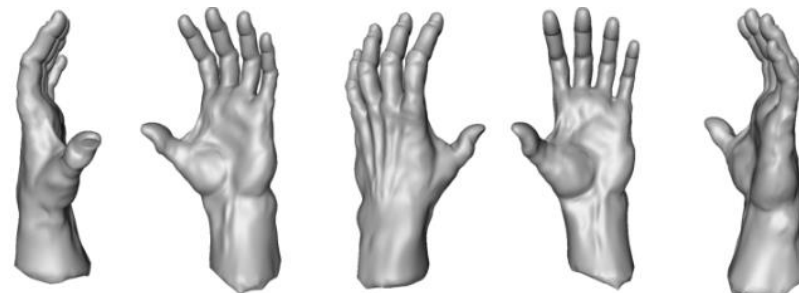
- ✓ Watertight dataset [Giorgi et al. 07].
- ✓ Timing on a 2.53GHz PC.
  - ✓ # of tets: 35K, 20K, 9K, 3K.
  - ✓ # of secs: 575, 280, 21, 4.
- ✓ Timing for SCAPE models (45K tets).
  - ✓ 985 seconds.
  - ✓ [Anguelov et al. 2005]
- ✓ Timing for Hand model (51K tets).
  - ✓ 1684 seconds.
  - ✓ [Panozzo et al. 2013]



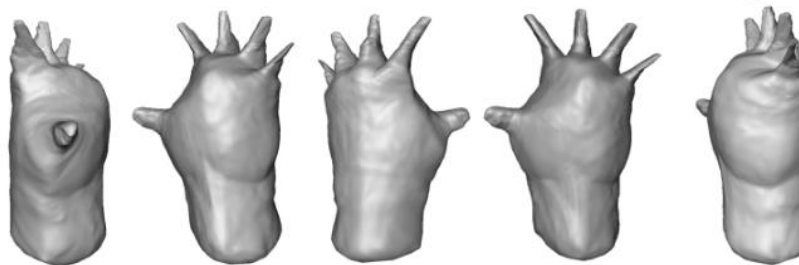
# Experimental Results

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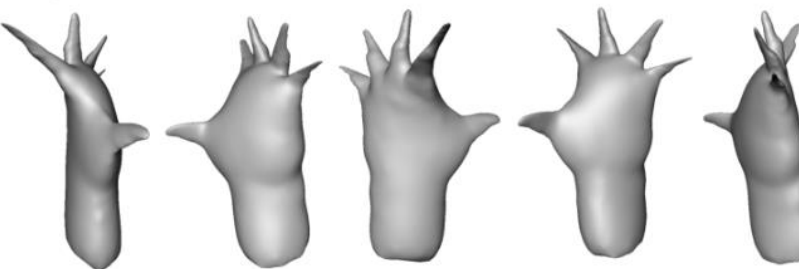
- ✓ Hand model  
[Panozzo et al. 13].



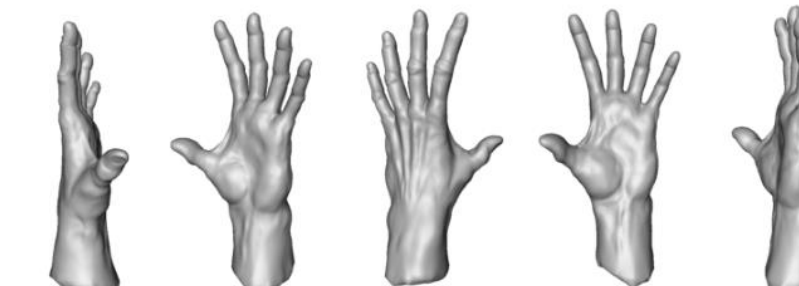
Input



Landmark  
MDS



[Panozzo  
et al. 13]



Our result

# Experimental Results

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- ✓ Nonrigid shape retrieval.
- ✓ Canonical poses computed by our algo are
  - ✓ rigidly aligned (PCA followed by ICP),
  - ✓ matched by the closest points in the aligned config, and



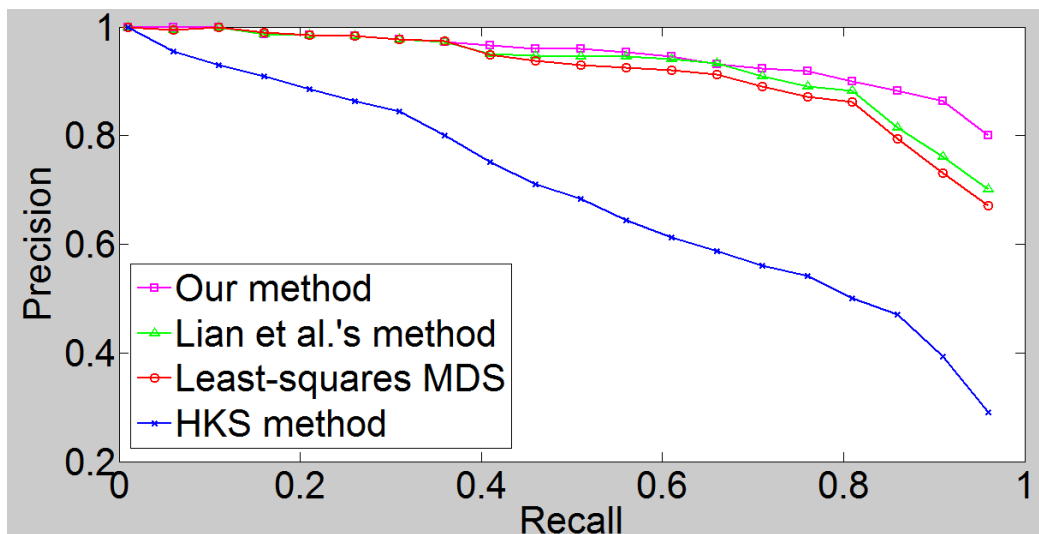
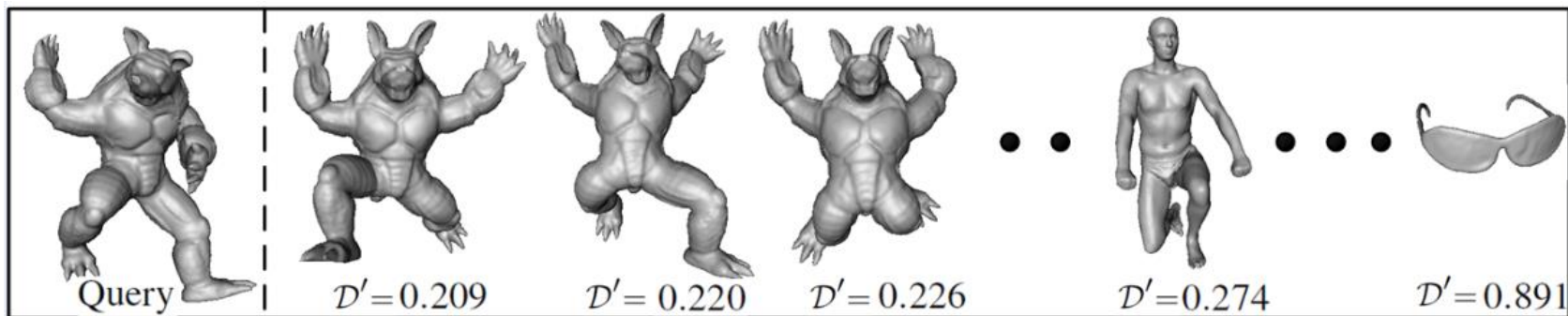
- ✓ exposed to the following similarity measure: 
$$\mathcal{D}'(\phi) = \frac{1}{|\phi|} \sum_{(i,j) \in \phi} \|\mathbf{v}_i - \mathbf{v}_j\|$$



# Experimental Results

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- ✓ Nonrigid shape retrieval.



# Experimental Results

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✓ Comparisons.

Input



Our result



Lian et al. 13



LS MDS



Classic MDS

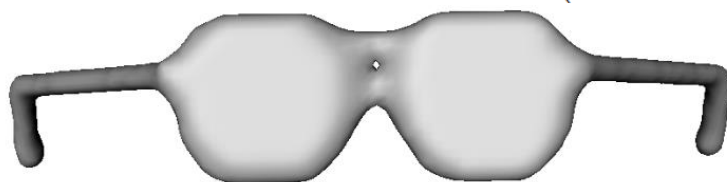


# Experimental Results

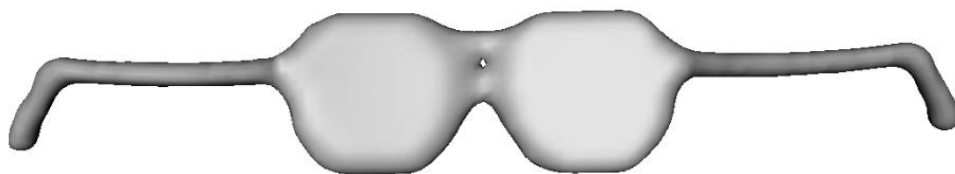
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✓ Regularization weight ( $\alpha$ ).  $E(\mathbf{v}) = \frac{1}{2} \left( \sum_{(i,j) \in \mathcal{C}} -k_{ij} \|\mathbf{v}_i - \mathbf{v}_j\|^2 + \alpha \sum_{(i,j) \in \mathcal{E}} k_{ij} (\|\mathbf{v}_i - \mathbf{v}_j\| - r_{ij})^2 \right)$

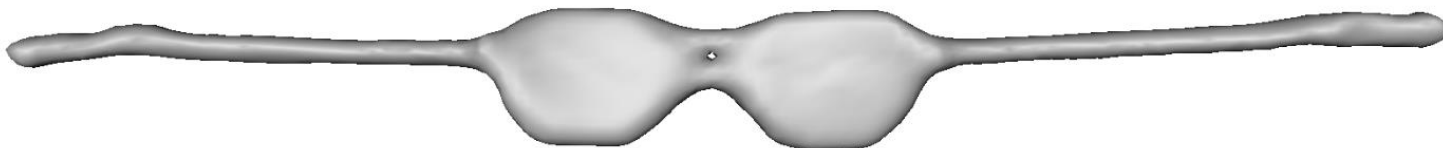
Input



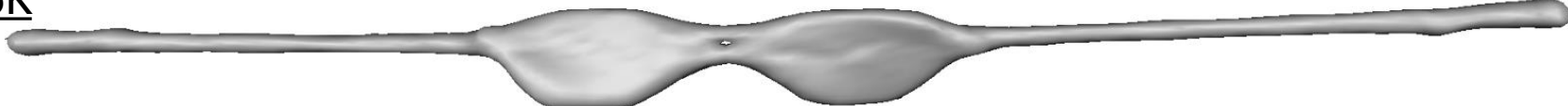
$\alpha = 100K$



$\alpha = 20K$



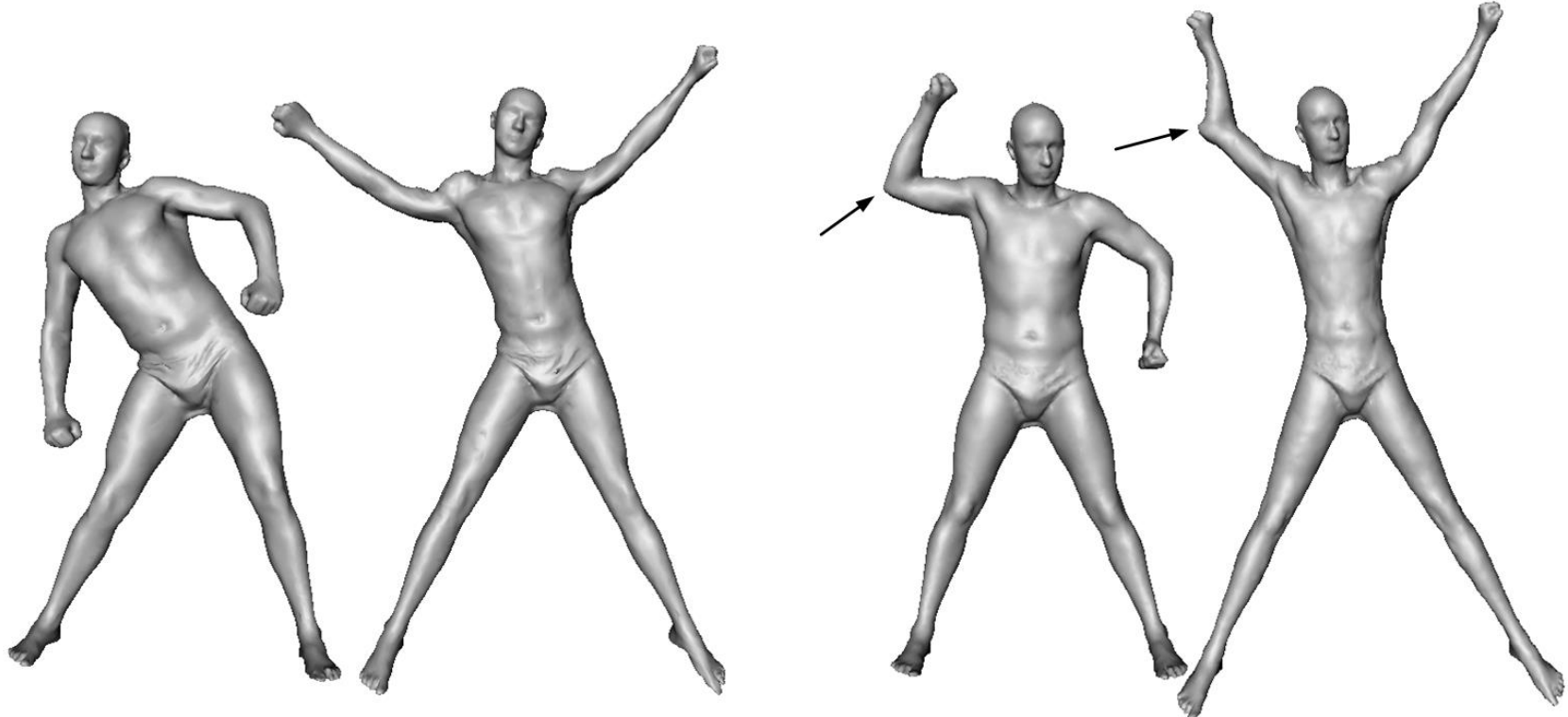
$\alpha = 5K$



# Limitations

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- ✓ Regularization slightly sensitive to the original pose.
- ✓ Decreases shape correspondence performance.
  - ✓ Such a loose mapping still useful for nonrigid shape retrieval app.



# Conclusion

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- ✓ A deformation algorithm that unfolds a 3D model without distorting its geometric details.
- ✓ This detail-preserving unfolding gives a canonical pose that is suitable especially for nonrigid shape retrieval.
- ✓ No geodesics, efficient, less topological noise sensitivity, arbitrary genus.
- ✓ Outperforms state-of-the-art retrieval applications.
- ✓ Future: Incorporate semantic parameters to create more specific poses, e.g., Vitruvian Man.

# People

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Yusuf Sahillioğlu,  
Asst. Prof.



Ladislav Kavan,  
Asst. Prof.

