Total Capture: 3D Deformation Model for Tracking Faces, Hands, and Bodies

Authors:

Hanbyul Joo

Tomas Simon

Yaser Sheikh

Best Student Paper Award

CVPR 2018

Presented by Anantapadmanaabha Prasannakumar

Problem

- Human interactions convey information.
- Information critical for machine understanding.

Image Source: The Panoptic Studio, CMU Robotics Institute

Problem

Marker-based system:

- Laborious process.
- Uncomfortable to the subject.

Image source: Lecture 3, Human Motion Modeling and Analysis, Prof. Yaser Sheikh Lecture Notes
The Robotics Institute, Carnegie Mellon University

Problem

Marker-based system:

- Doesn't capture occlusions.
- Concentrates on particular body part.

Image source: Lecture 3, Human Motion Modeling and Analysis, Prof. Yaser Sheikh Lecture Notes
The Robotics Institute, Carnegie Mellon University

Problem

Markerless systems:

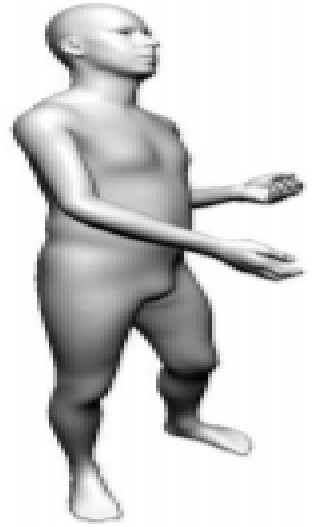
- Use Multi-video stereo camera and a template model.
- Detect keypoints to capture motion.
- Still part specific.

Image source: Markerless Motion Capture of Multiple Characters Using Multiview Image Segmentation, Yebin et al., TPAMI 2013

Proposed Solution

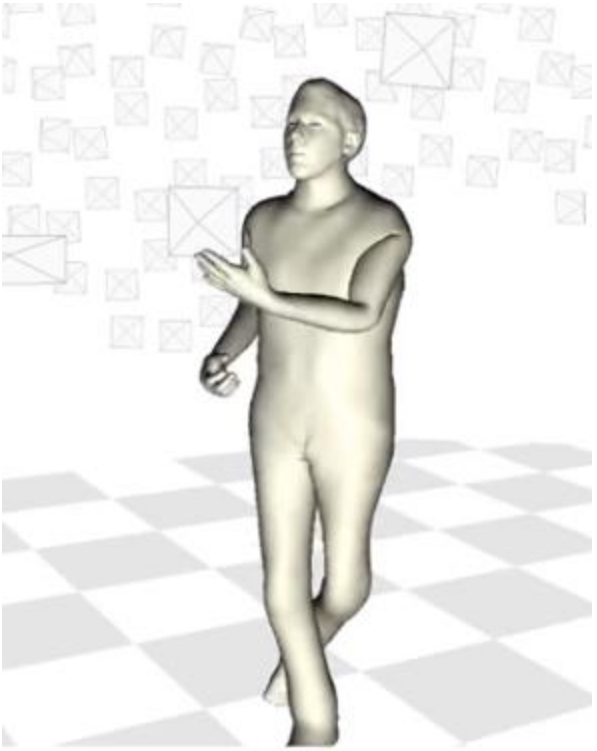
- Create a model for the entire body called Frank.

- Utilize Frank and body keypoints to capture entire human motion.



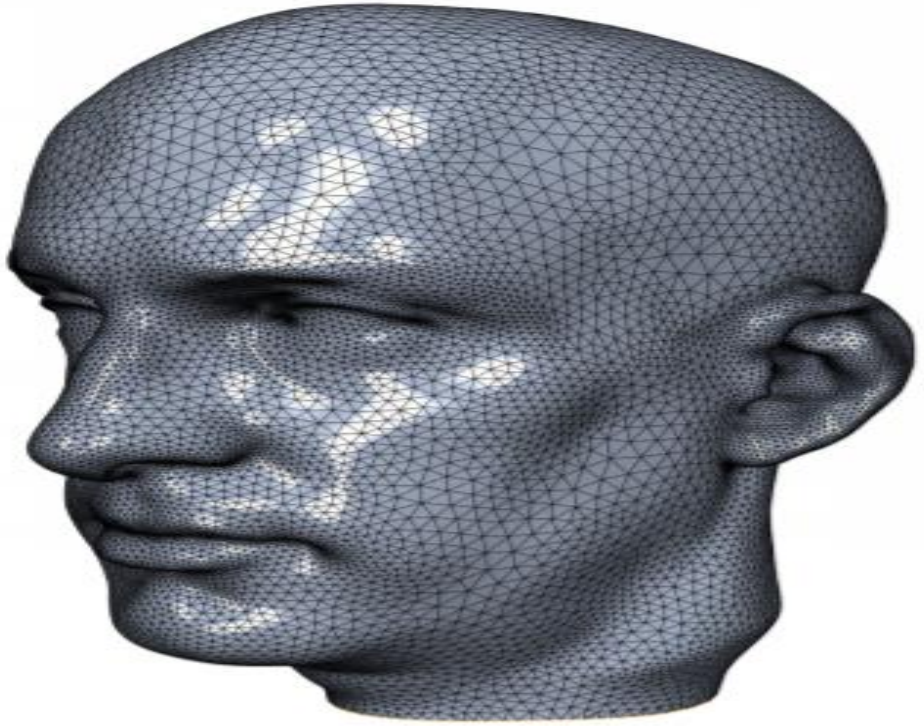
Proposed Solution

- Create a model for the entire body called Frank.
- Utilize Frank and body keypoints to capture entire human motion.
- Create Adam by leveraging Frank.



Building Block

- A mesh is made up of vertices and edges.
- Each vertex has its normal.
- They are orthogonal to each other.



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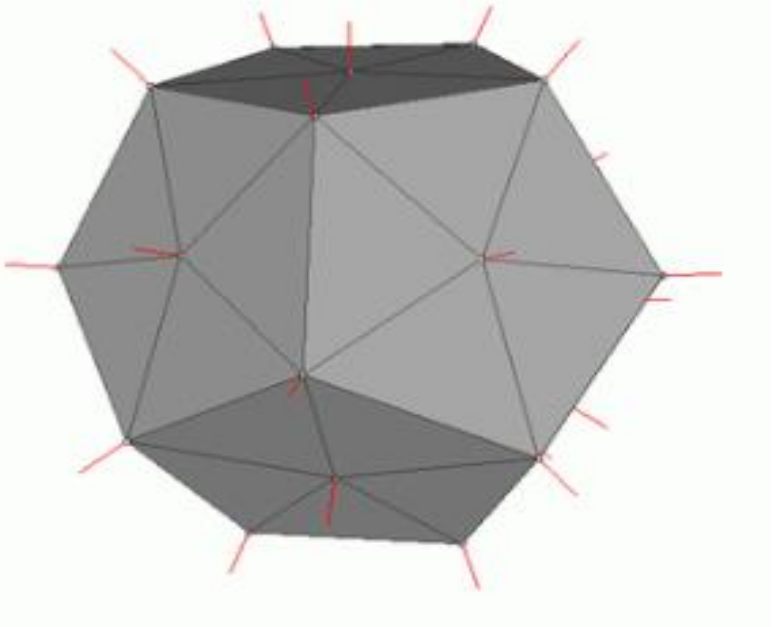
Computer Graphics and Geometry Processing Group, Bielefeld University

Building Block

- Orthogonality lost during transformation
- Inverse transformation is necessary.



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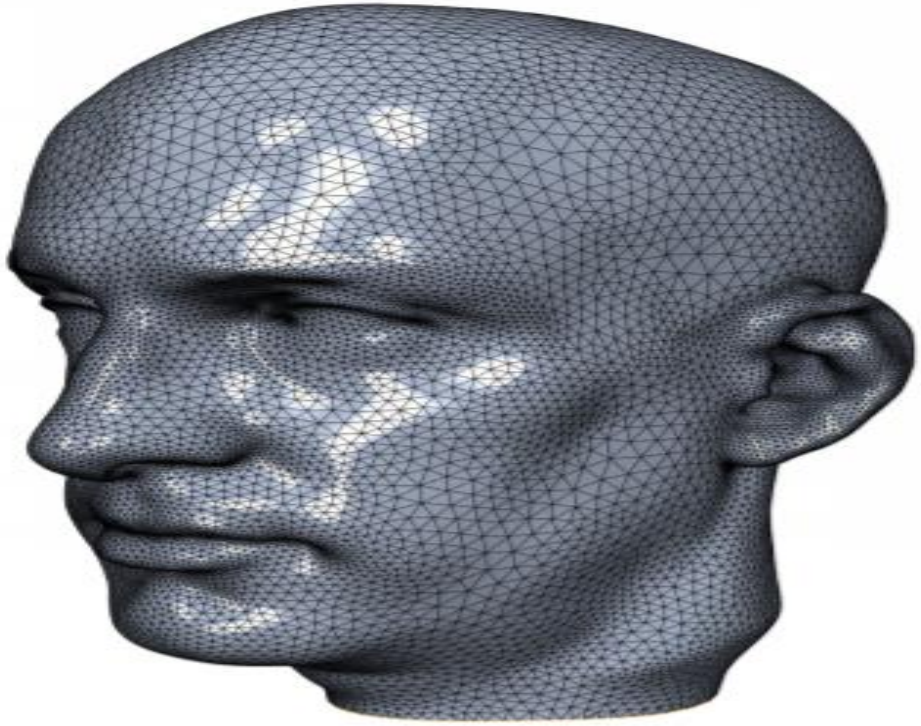
Building Block

- Triangles formed form the building block of a polygonal mesh.



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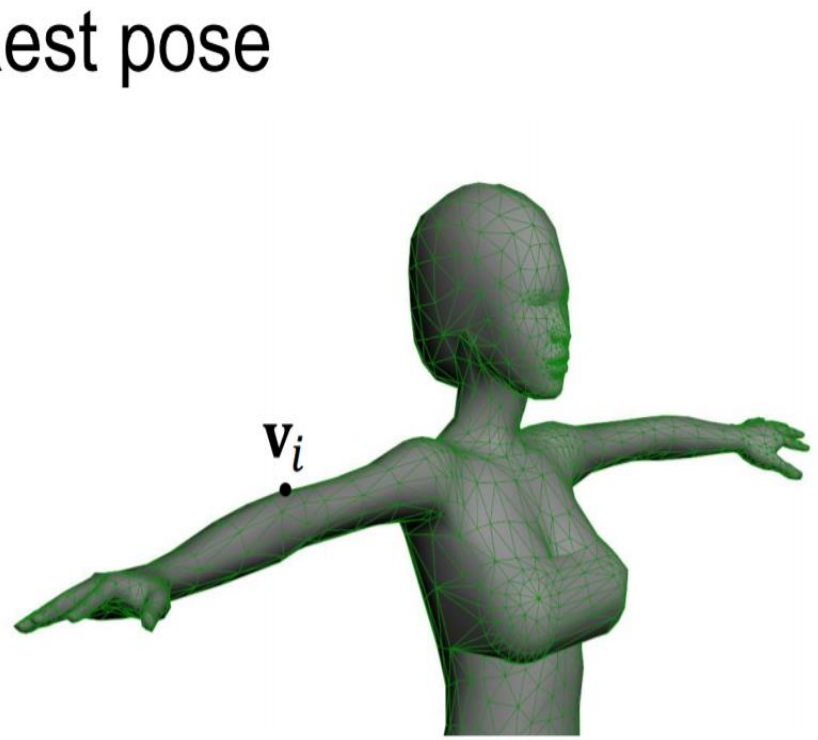
Skinning (Linear Blend Skinning)

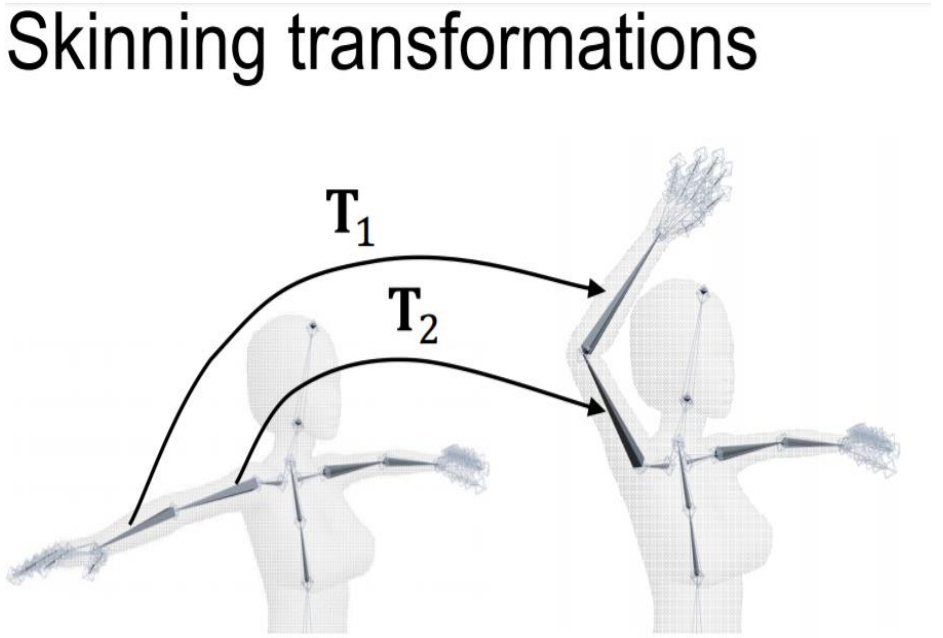
- Skinning is rendering a mesh around the joints.
- Vertices would be in rest pose.



Prof. Ladislav Kavan Course Notes, University of Utah
Skinning: Real-Time Shape Deformation, ACM SIGGRAPH 2014 Courses, skinning.org

Skinning (Linear Blend Skinning)

- Apply transformation to vertices to bind them to joints.
- If the joint position changes, the transformation matrix changes.



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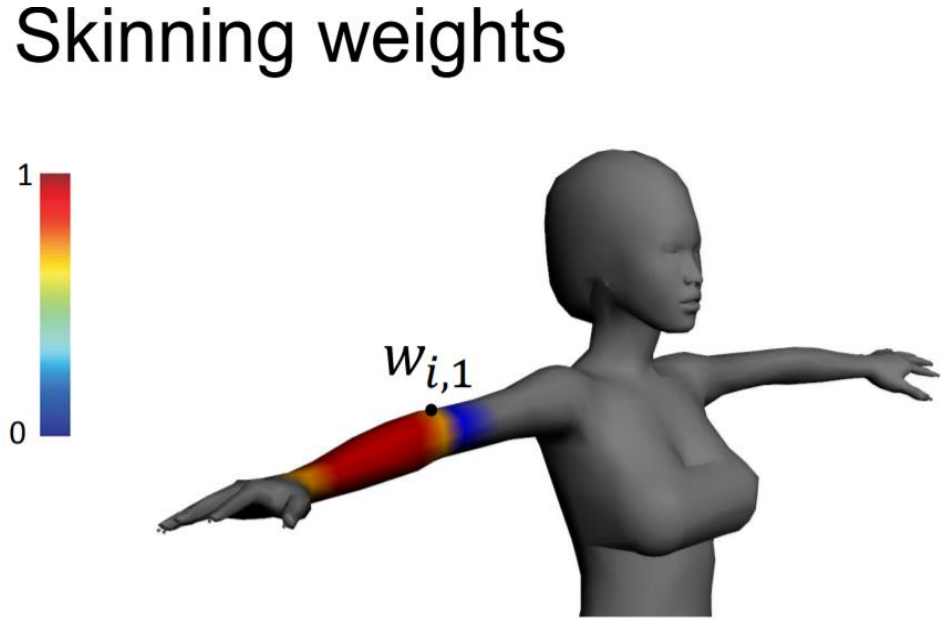
Skinning (Linear Blend Skinning)

- Associate each vertex to the joints.
- Transformation of the vertices depends on weights.



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Body Model

- Utilize modified SMPL model.
- Represented as: $\mathbf{V}^B = M^B(\boldsymbol{\theta}^B, \boldsymbol{\phi}^B, \boldsymbol{t}^B)$
- Where $\mathbf{V}^B = \{\mathbf{v}_i^B\}_{i=1}^N$ $\quad v_i^B \in \mathbb{R}^3$
- N = 6890 vertices.
- These vertices are in rest pose.

M^B *resembles body model*

θ^B *is the pose parameter*

ϕ^B *is the shape parameter*

t^B *is the global translation parameter*

Body Model Transformation

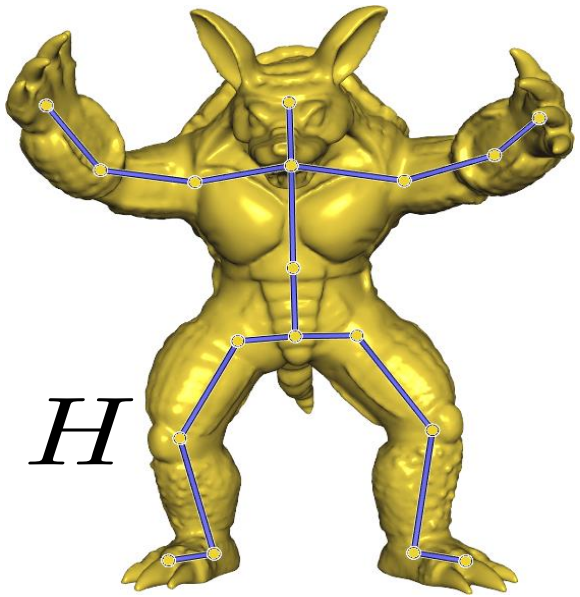
- Linear blend skinning applied to each joint.
- Posed mesh vertices given by:

$$\mathbf{v}_i^B = \mathbf{I}_{3\times 4} \cdot \sum_{j=1}^{J^B} w_{i,j}^B \mathbf{T}_j^B \begin{pmatrix} \mathbf{v}_i^{B0} + \sum_{k=1}^{K_b} \mathbf{b}_i^k \phi_k^B \\ 1 \end{pmatrix}$$

J^B = 21 joints

- $I_{3\times4}$ is the Identity Matrix
- W being the weights.
- T_j^B is the transformation matrix.
- $T_j^B \in$ SE(3)
- Sum of all weigths sum to 1.

- v_i^{B0} is the mean shape i-th vertex.
- K_b = 10, number of identity body shape coefficients.
- b_i^k is the vertex of the k-th blendshape.
- ϕ_k^B is the k-th shape coefficient.



$$\mathbf{v}' = \sum_{j \in H} w_j(\mathbf{v}) \mathbf{T}_j \begin{pmatrix} \mathbf{v} \\ 1 \end{pmatrix}$$

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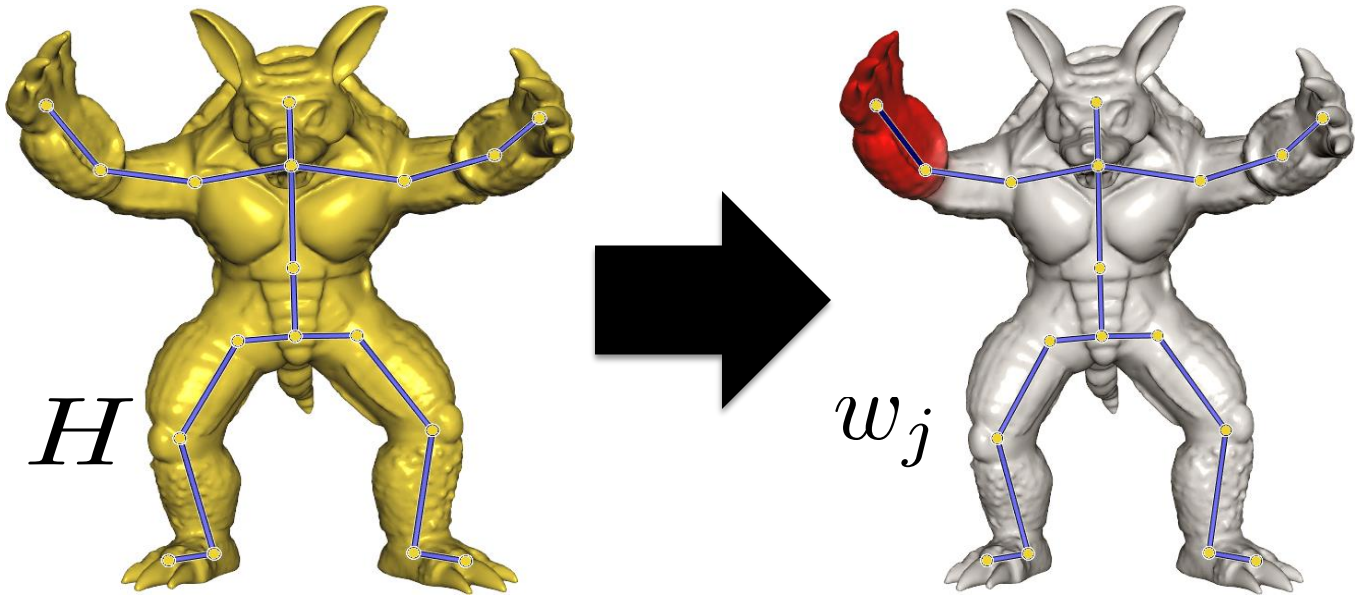

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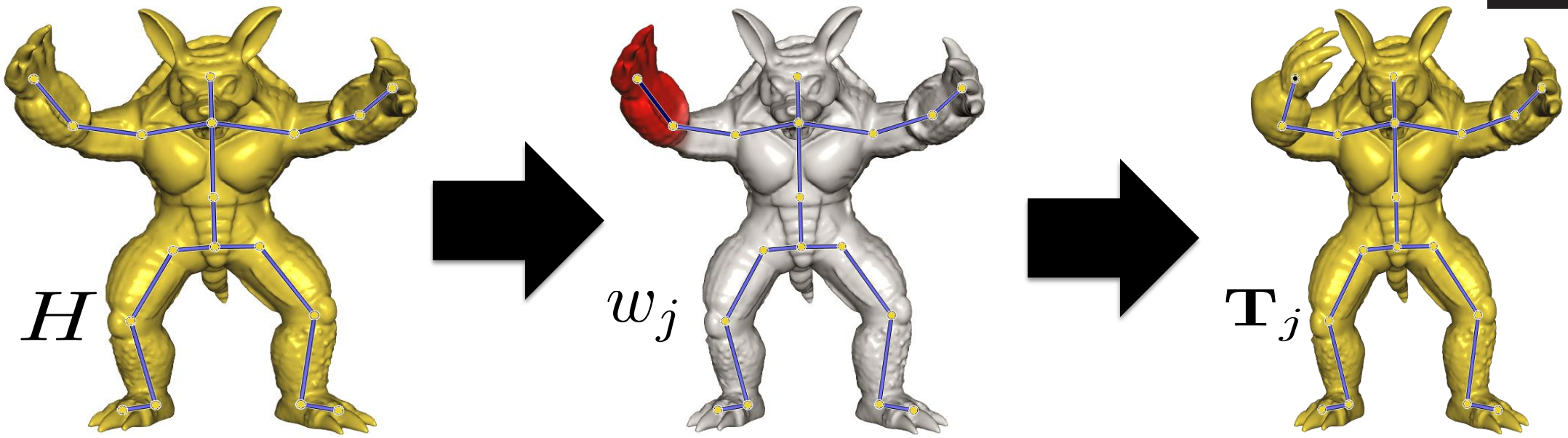

$$\mathbf{v}' = \sum_{j \in H} w_j(\mathbf{v}) \mathbf{T}_j \begin{pmatrix} \mathbf{v} \\ 1 \end{pmatrix}$$

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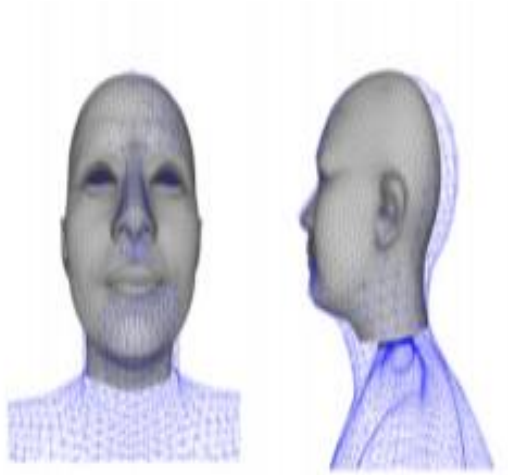
Face Model

- Align the facial mesh [1] with the body model.
- The face model is given by: $\mathbf{V}^F = M^F(\theta^F, \phi^F, \mathbf{T}^F)$
- Where $\mathbf{V}^F = \{\mathbf{v}_i^F\}_{i=1}^F$
- $N^F = 11510$

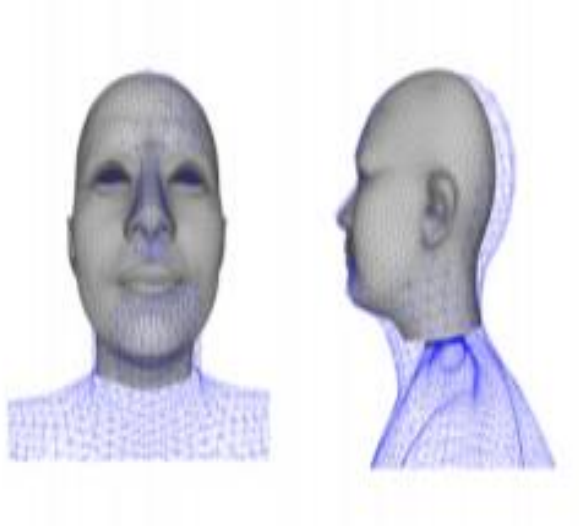


[1] FaceWarehouse: a 3D Facial Expression Database for Visual Computing, Cao et al., 2014

Face model

- Rest pose vertices:

$$\hat{\mathbf{v}}_i^F = \mathbf{v}_i^{F0} + \sum_{k=1}^{K_f} \mathbf{f}_i^k \phi_k^F + \sum_{s=1}^{K_e} \mathbf{e}_i^s \theta_s^F$$

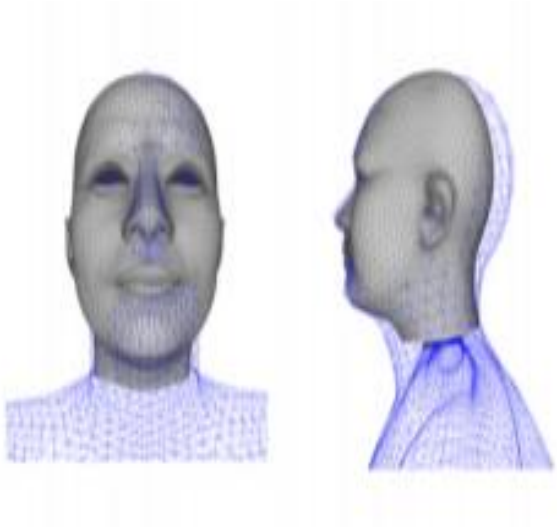


- V_i^{F0} is the mean shape.
- k_f = 150, is the identity blendshape.
- f_i^k is the vertex at k-th blendshape.
- ϕ_k^F is the shape coefficient.
- k_e = 200, is the expression blendshape.
- e_i^S is the vertex at s-th expression blendshape.
- θ_s^F is the pose blendshape parameter.

Face Model

- Each transformed vertex given by:

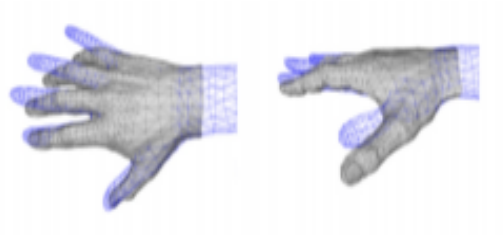
$$\mathbf{v}_i^F = \mathbf{I}_{3\times 4} \cdot \mathbf{T}_{j=F}^{B} \cdot \mathbf{\Gamma}^F \begin{pmatrix} \hat{\mathbf{v}}_i^F \\ 1 \end{pmatrix}$$



- $I_{3\times4}$: Truncated Identity Matrix.
- $T_i^B \in$ SE(3) denotes the transformation matrix.
- Γ^F is the alignment matrix.

Hand Model

- Each vertex is given by:

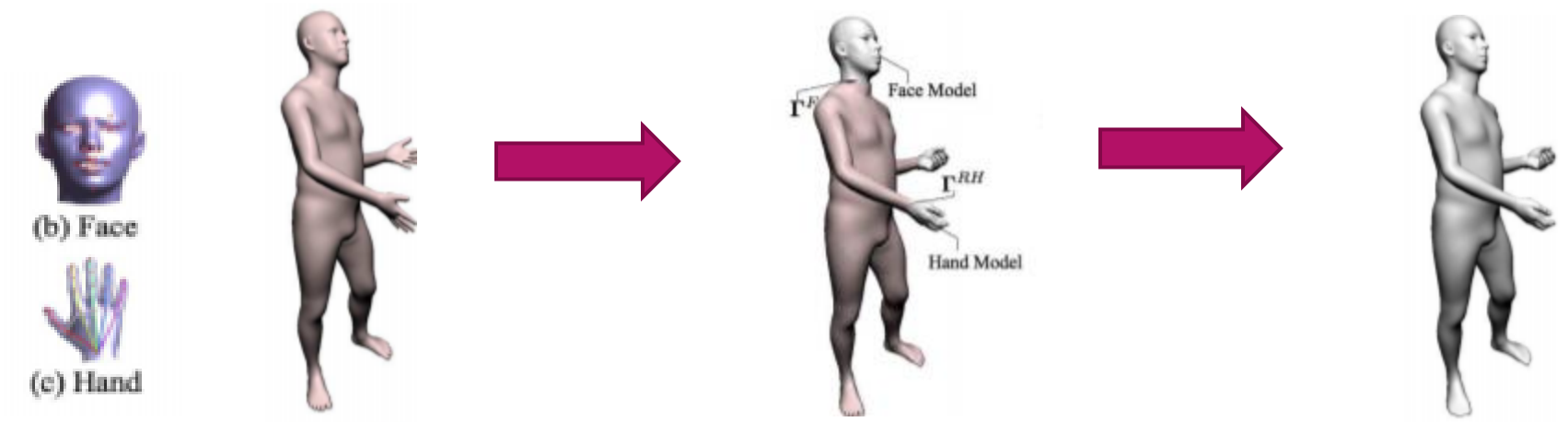


$$\mathbf{v}_i^H = \mathbf{I}_{3\times4} \cdot \mathbf{T}_{j=H}^B \cdot \Gamma^H \cdot \sum_{j=1}^{J} w_{i,j}^H \mathbf{T}_j^H \begin{pmatrix} \mathbf{v}_i^{H0} \\ 1 \end{pmatrix}$$

- $I_{3\times4}$ = Truncated Identity Matrix.
- T_j^B denotes the transformation matrix.

- v_i^{H0} is the mean shape.
- J indicates number of joints in hand, 16 joints.
- W indicates weights in the hand model.
- T_j^H is the matrix transformation.

Creating Frank



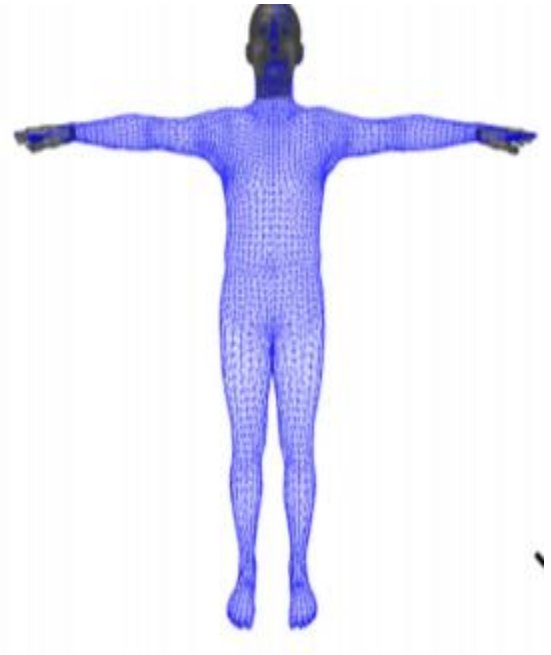
Different templates

Alignment

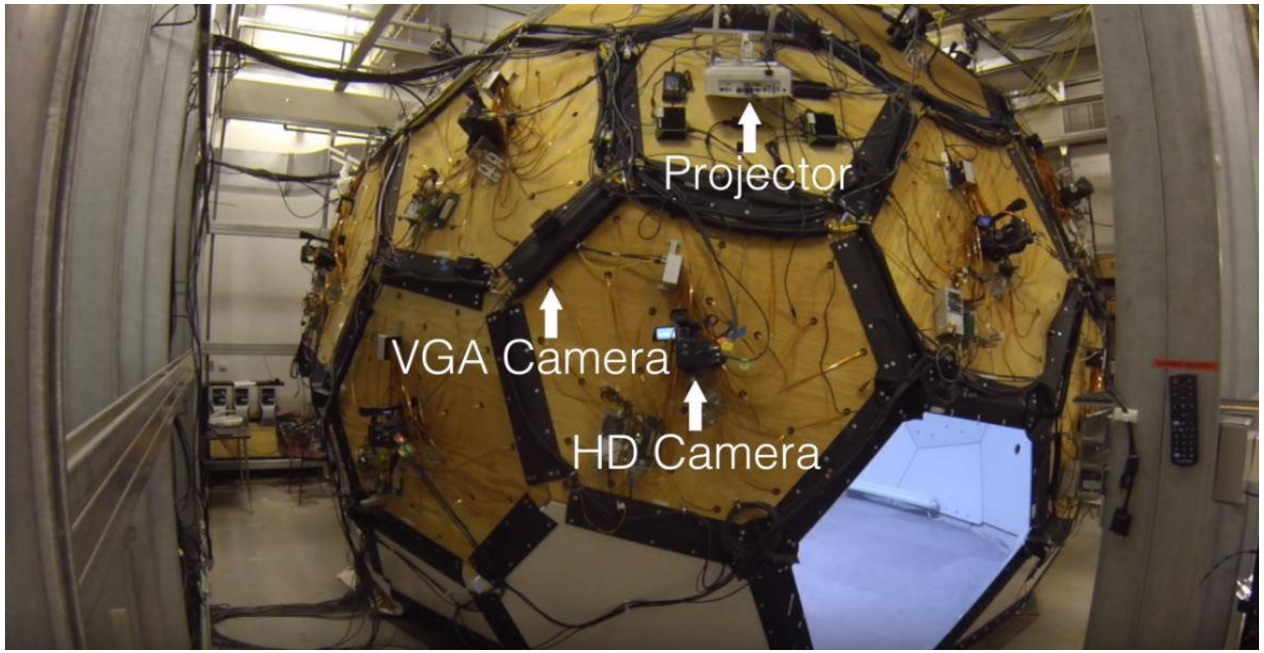
Frank model

Frank Model

- Frank model upon stitching body, face and hands is given by: $\mathbf{V}^U = M^U(\boldsymbol{\theta}^U, \boldsymbol{\phi}^U, \mathbf{t}^U)$
- Where $\mathbf{V}^U \in \mathbb{R}^{N^U \times 3}$
- $N^U = 18540$
- The linear blending matrix: $\mathbf{V}^U = \mathbf{C}\left[(\mathbf{V}^B)^T (\mathbf{V}^F)^T (\mathbf{V}^{LH})^T (\mathbf{V}^{RH})^T\right]$
- Where: $\mathbf{C} \in \mathbb{R}^{N^U \times (N^B + N^F + 2N^H)}$



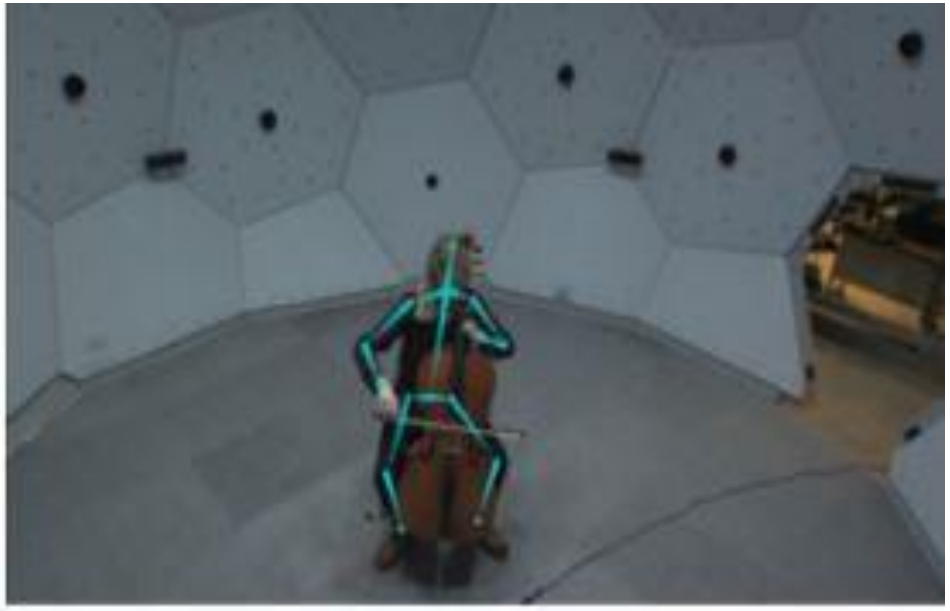
Dataset for Keypoints



- 540 Video Graphics Array Camera.
- 31 High Definition (HD) cameras.
- 10 Kinect cameras (RGB-D sensors).

Image source: Panoptic Studio, The CMU Robotics Institute

Dataset for Keypoints



- 140 VGA camera to get 3D triangulated keypoints.

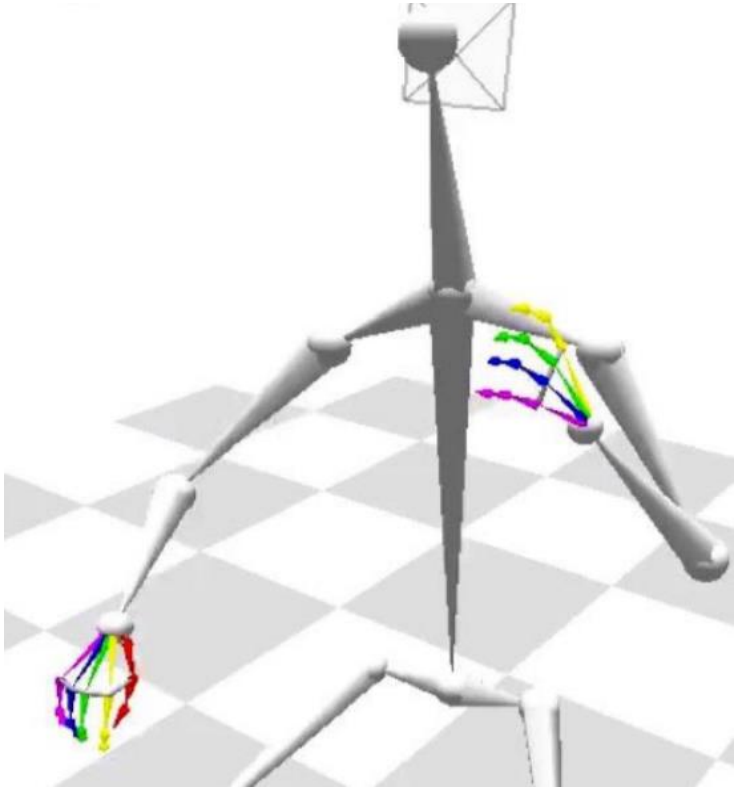
Image source: Panoptic Studio, The CMU Robotics Institute

Dataset for Keypoints

- 480 VGA cameras to detect 3D foot keypoints.

Image source: Panoptic Studio, The CMU Robotics Institute

Dataset for Keypoints



- 31 HD cameras to detect finger triangulated keypoints.

Image source: Panoptic Studio, The CMU Robotics Institute

Dataset for Keypoints

- 10 Kinect cameras to get Multi-View Stereo Pointclouds.

Image source: Panoptic Studio, The CMU Robotics Institute

3D Keypoints and Cloudpoints

- Use state-of-the-art methods [1] to get 2D keypoints.

[1] OpenPose: Realtime Multi-Person 2D Pose Estimation using Part Affinity Fields, Cao et al., CVPR 2018

3D Keypoints and Cloudpoints

- Use state-of-the-art methods [1] to get 2D keypoints.
- Use MVS cameras to get 3D triangulated keypoints

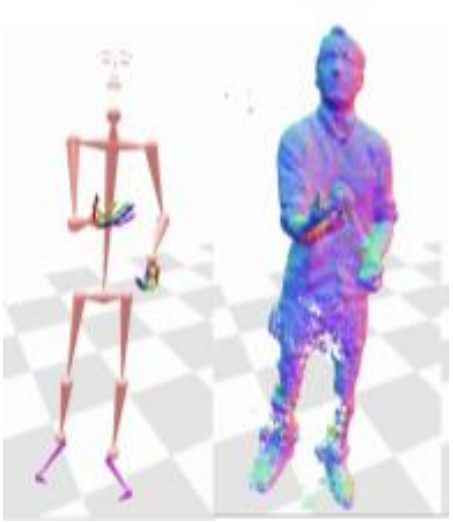
[2] Panoptic Studio: A Massively Multiview System for Social Interaction Capture, hanbyul et al. TPAMI 2017

3D Keypoints and Cloudpoints

- Use state-of-the-art methods [1] to get 2D keypoints.
- Use MVS cameras to get 3D triangulated keypoints
- Use RealityCapture [3] to 3D cloudpoints.

[3] realitycapture.com

Fitting Frank



3D Keypoints and Pointclouds

Fitting Frank to 3D data

Fitting result

Objective Functions

- Each frame is fit independently.
- Levenberg Macquardt for optimization purposes.
- A library called Ceres Solver is used.
- Overall cost function: $E(\boldsymbol{\theta}^U, \boldsymbol{\phi}^U, \boldsymbol{t}^U) = E_{\text{keypoints}} + E_{\text{icp}} + E_{\text{seam}} + E_{\text{prior}}$

Seam Cost

- Frank is composed of part models
- it would lead to discontinuities.
- Penalizing the distance between vertices of part models.

Seam Constraints

- The cost function is given by:

$$E_{\text{seam}} = \sum_{(i,j)\in\mathcal{C}^{LH}} ||\mathbf{B}_i\mathbf{V}^{\boldsymbol{B}} - (\mathbf{v}_j^{LH})^T||^2 + \sum_{(i,j)\in\mathcal{C}^{RH}} ||\mathbf{B}_i\mathbf{V}^{B} - (\mathbf{v}_j^{RH})^T||^2 + \sum_{(i,j)\in\mathcal{C}^{F}} ||\mathbf{B}_i\mathbf{V}^{B} - (\mathbf{v}_j^{F})^T||^2,$$

- $\mathbf{B}_i \in \mathbb{R}^{1\times N^B}$ where $\mathbf{B}_i\mathbf{1}_{N^B} = 1$

- C contains correspondences (i, j) where i denotes the cloud points, and denotes the ring

Anatomical Keypoint Cost

- Find correspondences between 3D keypoints and the mesh model.
- It includes joints in body and hands.
- Joints in face, finger tips and toes present on the surface.

Anatomical Keypoint Cost

❖The cost function: $$E_{\text{keypoints}} = \lambda_{\text{keypoints}} \sum_{i \in \mathcal{D}} \left\| \mathbf{J}_i \mathbf{V} - \mathbf{y}_i^T \right\|^2$$

❖ Where: *D* indicates available keypoints in a frame.

$\mathbf{J} \in \mathbb{R}^{C \times N^U}$ denotes regression matrix, resembling joints.

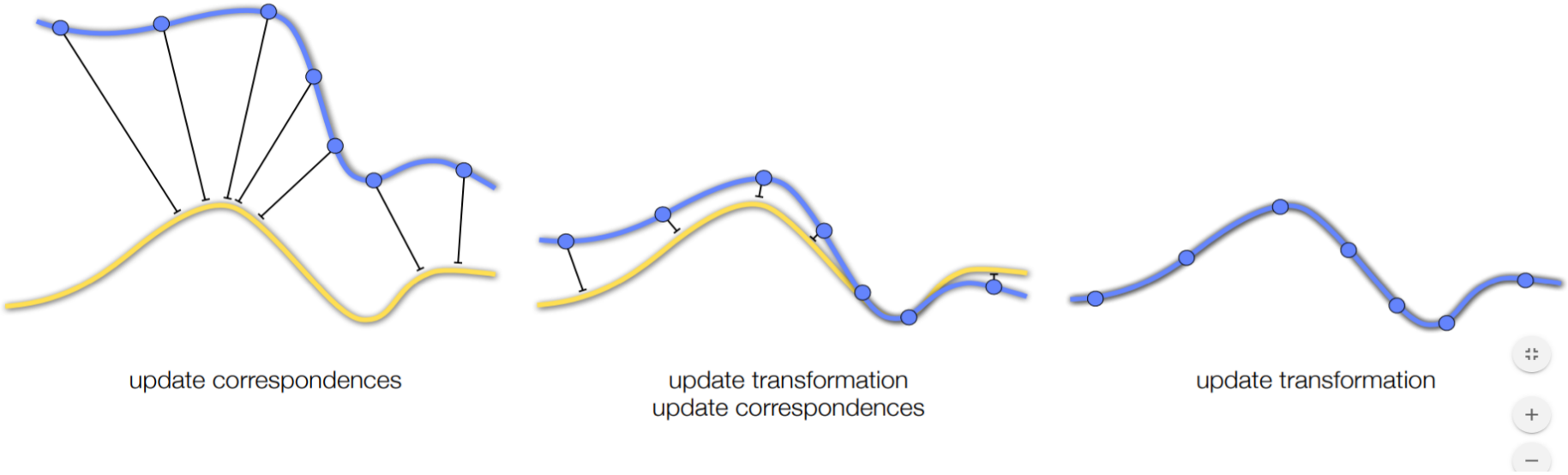
C is the number of correspondences.

N^U is the number of vertices in the mesh.

$y_i \in R^{3\times1}$, indicates 3D detections.

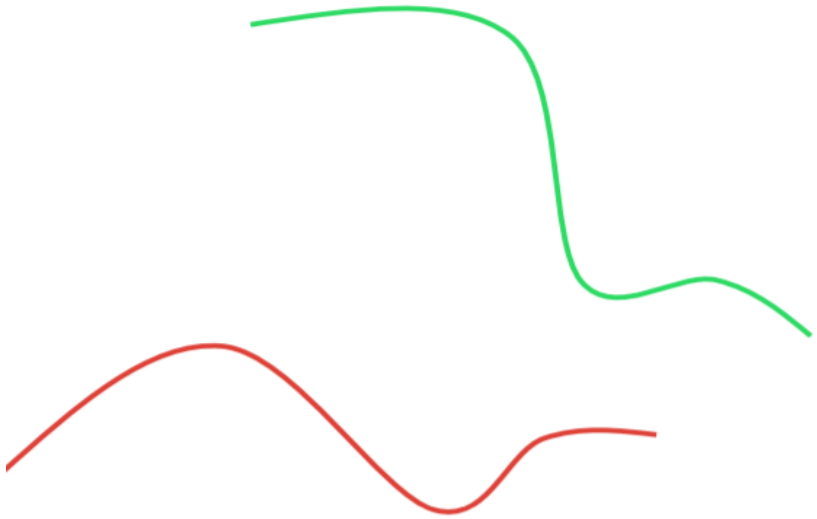
Iterative Closest Point Cost

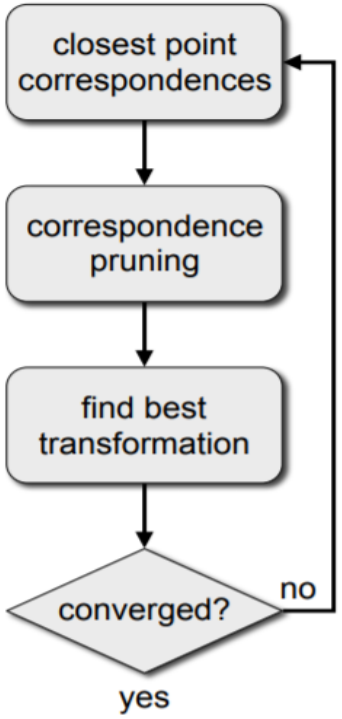
- **Step 1:** optimizing correspondences
- **Step 2:** optimizing transformations



https://lgg.epfl.ch/publications/2015/Htrack_ICP/slides.pdf

Iterative Closest Point Cost





Set of vertices and pointclouds.

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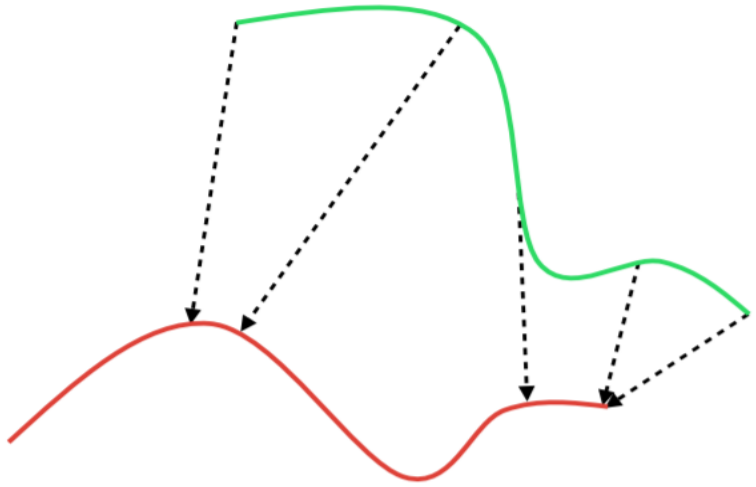
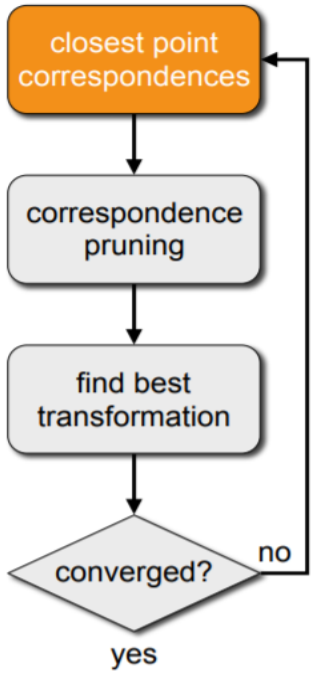
Iterative Closest Point Cost





Find correspondences

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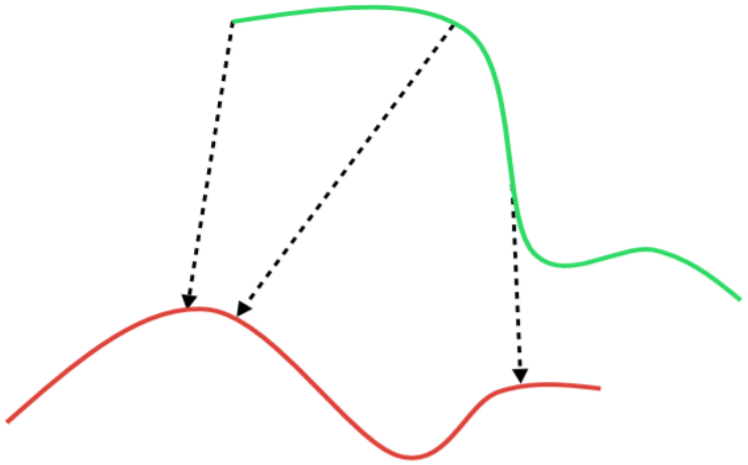
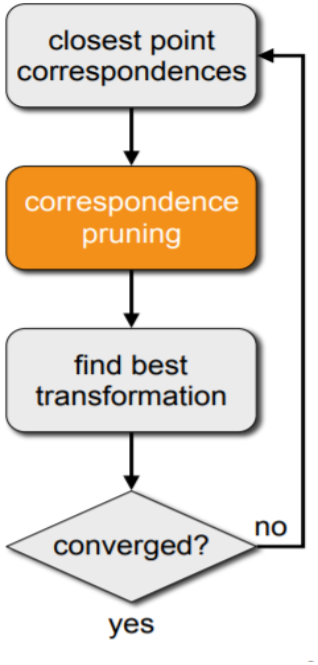
Iterative Closest Point Cost





Take out erroneous data.

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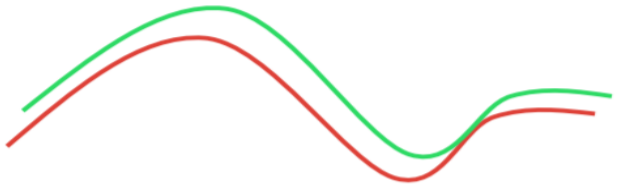
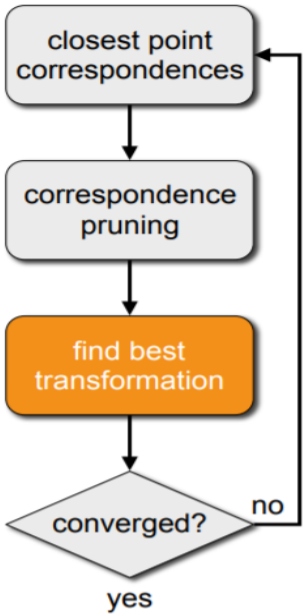
Iterative Closest Point Cost





Do necessary transformation.

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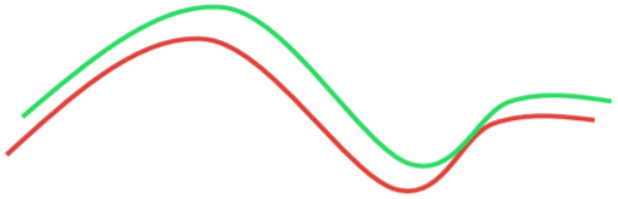
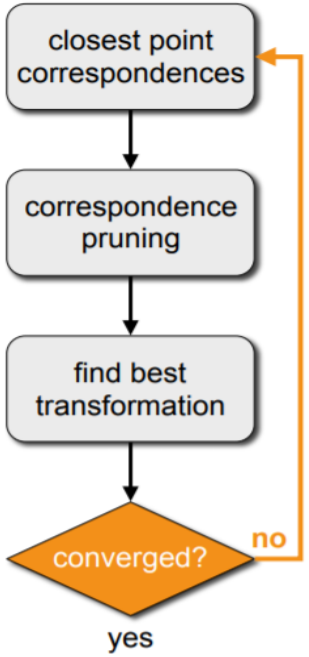
Iterative Closest Point Cost





Check for convergence.

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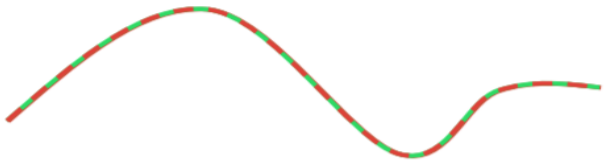
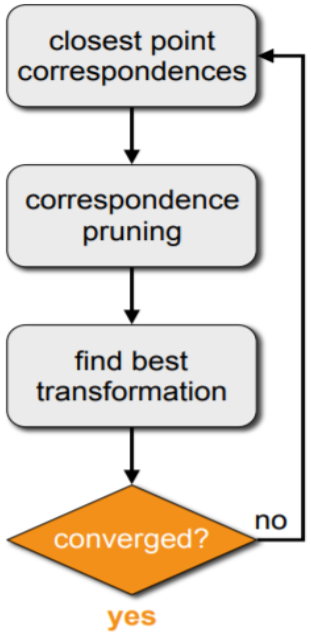
Iterative Closest Point Cost





Repeat till convergence.

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Iterative Closest Point Cost

- ICP is used to find the correspondences between the mesh vertices and the 3D Cloud Points.

- Distance along the normal direction is computed using:

$$E_{\text{icp}} = \lambda_{\text{icp}} \sum_{\mathbf{v}_j \in \mathbf{V}^U} \mathbf{n}(\mathbf{x}_{j^*})^T (\mathbf{x}_{j^*} - \mathbf{v}_j)$$

where: x_j is the closest 3D point to the j-th vertex v_j

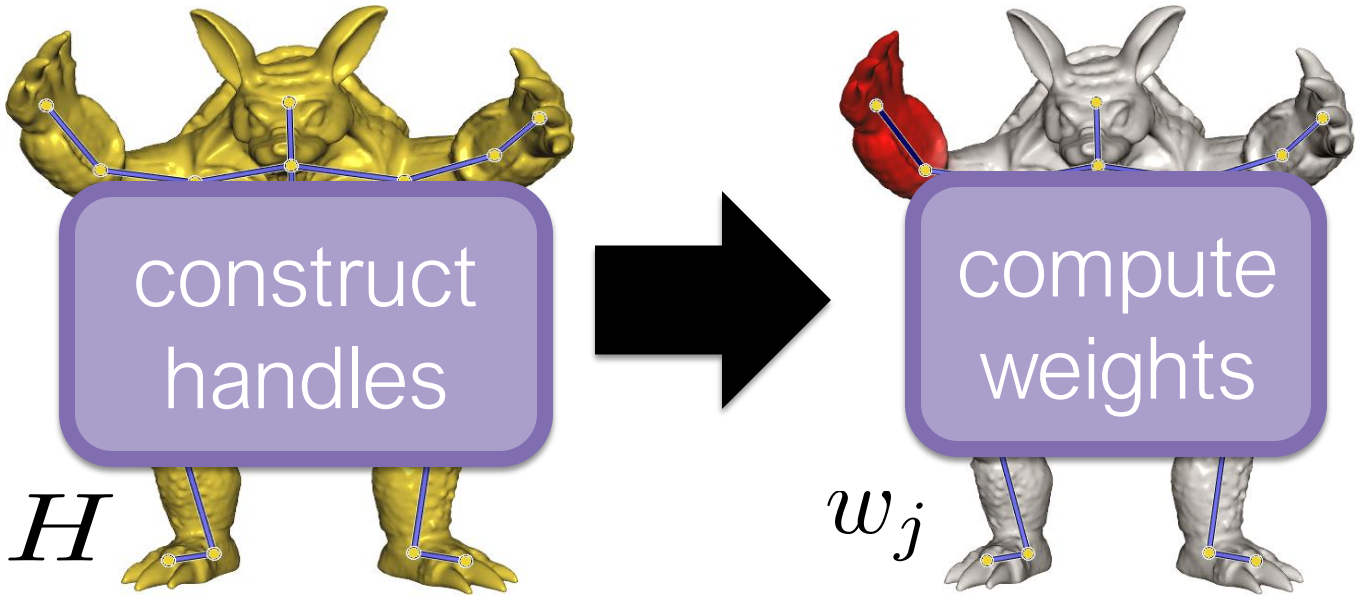
$n(\cdot) \in R^3$, is the point's normal.

λ_{icp} is the relative weight.

N^U is the number of vertices in the mesh.

$$\mathbf{v}' = \sum_{j \in H} w_j(\mathbf{v}) \mathbf{T}_j \begin{pmatrix} \mathbf{v} \\ 1 \end{pmatrix}$$

Prof. Alex Jacabson Course Notes, University of Toronto
Skinning: Real-Time Shape Deformation, ACM SIGGRAPH 2014 Courses, skinning.org



$$\mathbf{v}' = \sum_{j \in H} w_j(\mathbf{v}) \mathbf{T}_j \begin{pmatrix} \mathbf{v} \\ 1 \end{pmatrix}$$

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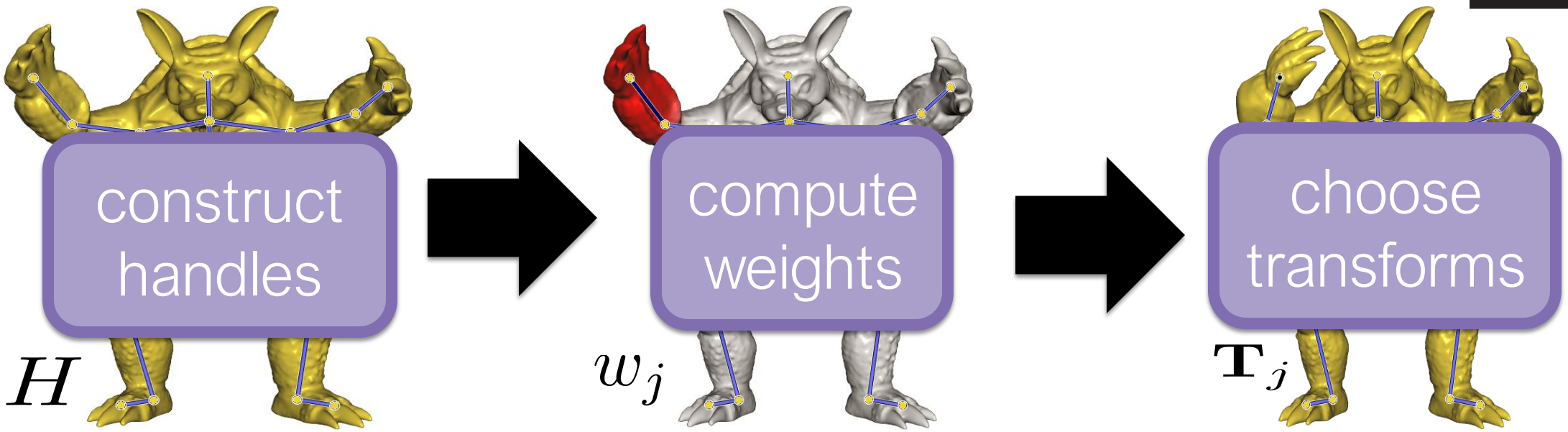

$$\mathbf{v}' = \sum_{j \in H} w_j(\mathbf{v}) \mathbf{T}_j \begin{pmatrix} \mathbf{v} \\ 1 \end{pmatrix}$$

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Prior Cost

- The 3D Point Cloud could be noisy.
- The SMPL and FaceWarehouse models doesn't consider hair and clothing.
- Joint locations of the model are not completely in sync with the 2D keypoints.
- For better fitting of the model to data: $E_{\text{prior}} = E^{F}_{\text{prior}} + E^{B}_{\text{prior}} + E^{H}_{\text{prior}}$

Drawbacks of Frank Model

- Frank model doesn't consider hair and clothing
- Don't have simple parameterization process.

Adam Model

- Leverage Frank model and train it on 70 subjects.
- Consider 5 frames for each subject, resulting in 350 meshes.
- Single joint hierarchy.
- Common parametrization for all parts.

Fitting Clothes and Hair

- Deform the each vertex along its normal,
- Deformed vertex represented as: $\tilde{v}_i = v_i + n(v_i)\delta_i$

where δ_i is the scalar displacement between mesh vertex and the 3D Cloud Point.

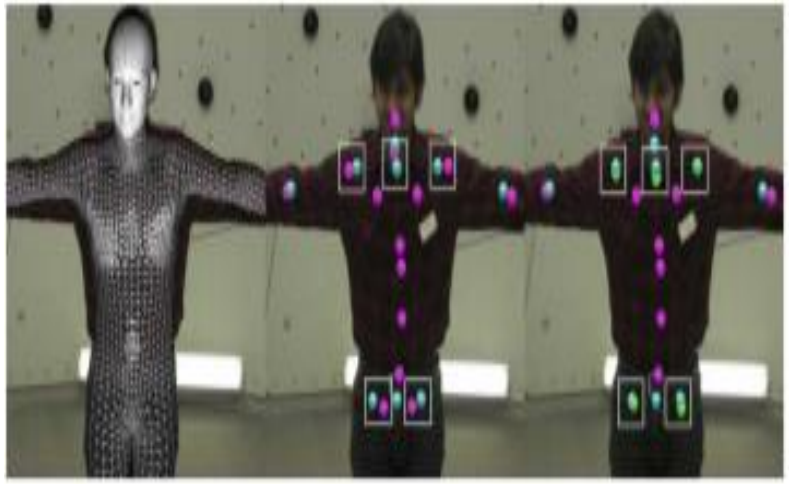
Fitting Clothes and Hair

- Pose the problem as a linear system.
- That is, $\begin{pmatrix} \mathbf{N}^T \\ (\mathbf{WLN})^T \end{pmatrix} \Delta = \begin{pmatrix} (\mathbf{P} - \mathbf{V}^U)^T \\ \mathbf{0} \end{pmatrix}$

Where Δ is the per-vertex displacement.

- P is the corresponding cloud point.
- V^U is the number of vertices in the mesh.
- N is the vertex normal.
- W is the diagonal weight matrix.
- L is the Laplace Beltrami operator to regularize the deformation.

Detection Target Regression



- In order to align the mesh with 3D keypoints properly, the vertices are aligned with 3D keypoints directly.

- The resulting mesh has 61 joints.

Adam model representation

- The model parameterized as: $M^A(\boldsymbol{\theta}^A, \boldsymbol{\phi}^A, \boldsymbol{t}^A) = \mathbf{V}^A$
- $\mathbf{V}^A = \left\{\mathbf{v}_i^A\right\}_{i=1}^{N^A}$ where $N^A = 18540$, is the number of vertices

  where $\hat{\mathbf{v}}_i^A = \mathbf{v}_i^{A0} + \sum_{k=1}^{K_A} \mathbf{s}_i^k \phi_k^A$

$\mathbf{v}_i^{A0}$ is the mean shape.

$K_A = 40$, number of blendshape coefficient.

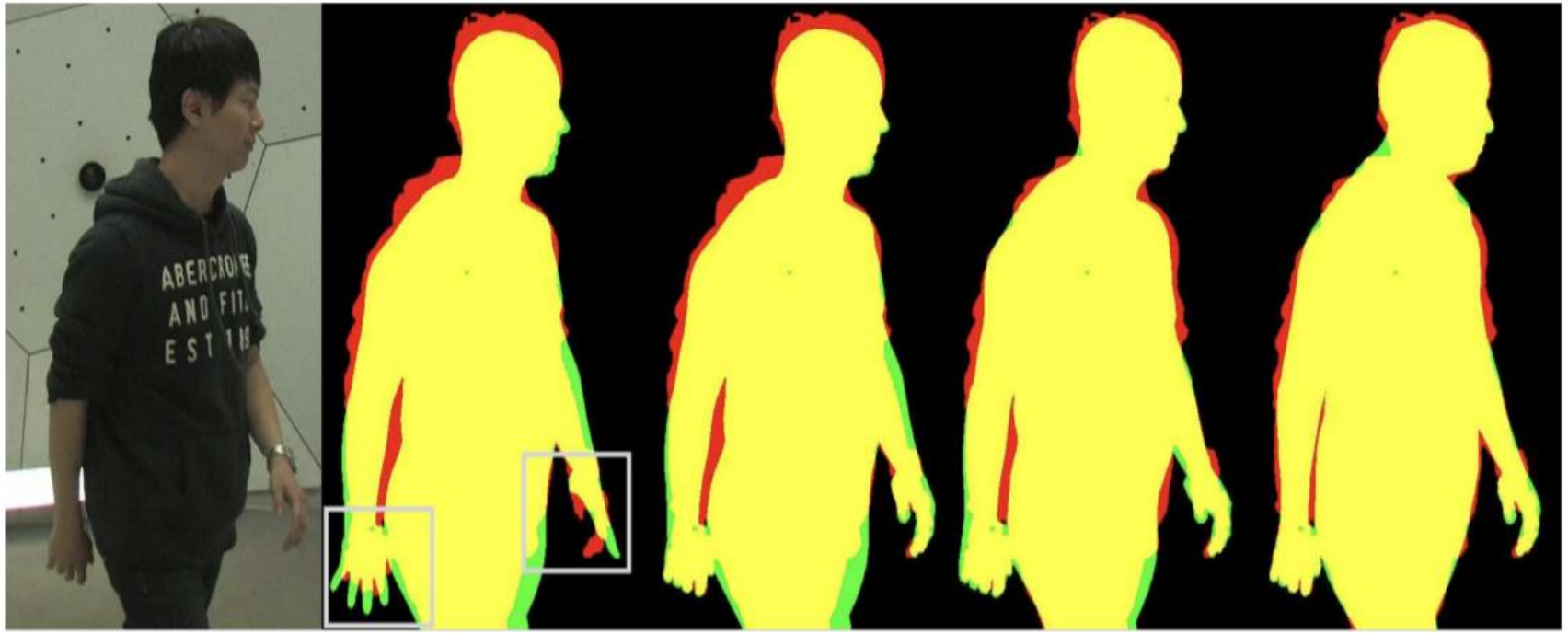
$\mathbf{s}_i^k$ is the vertex at k-th blendshape.

ϕ_k^A is the blendshape coefficient.

Adam Cost Function

- The Cost Function is given by: $E(\boldsymbol{\theta}^A, \boldsymbol{\phi}^A, \boldsymbol{t}^A) = E_{\text{keypoints}} + E_{\text{icp}} + E_{\text{prior}}$
- Does not require seam constraint
- Single set of unified shape and pose parameters for all parts
- Optical flow between frames to avoid jittery video.

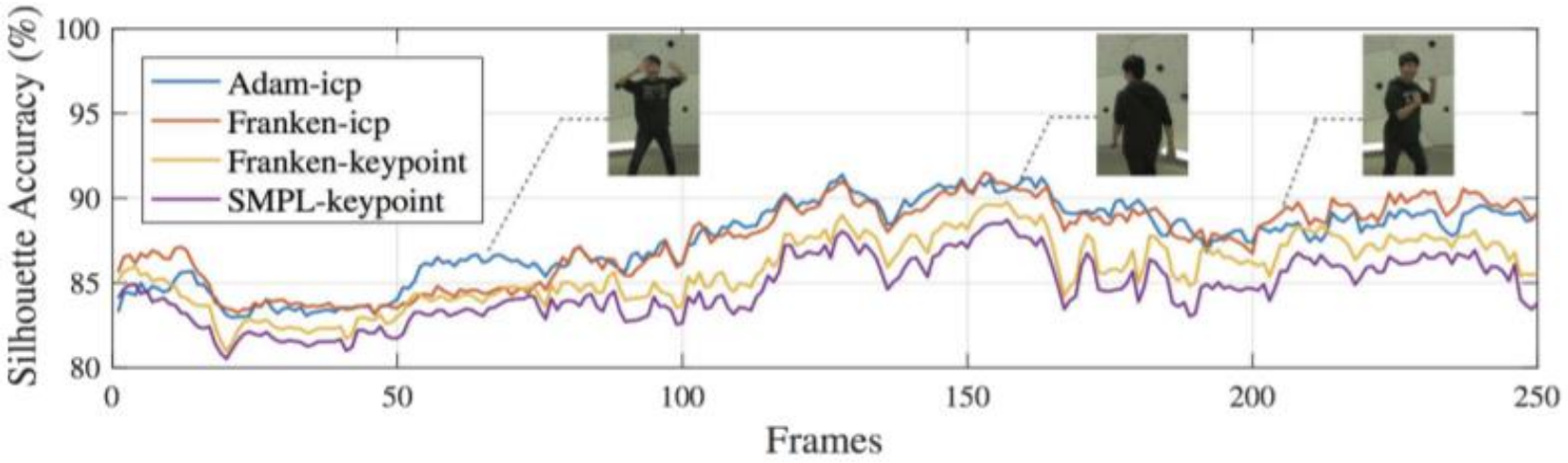
Results



(a) Input image | (b) SMPL keypoints | (c) Frank keypoints | (d) Frank keypoints + ICP | (f) Adam keypoints + ICP

- Red: Ground truth
- Green: Rendered silhouettes
- Yellow: Correctly overlapping areas

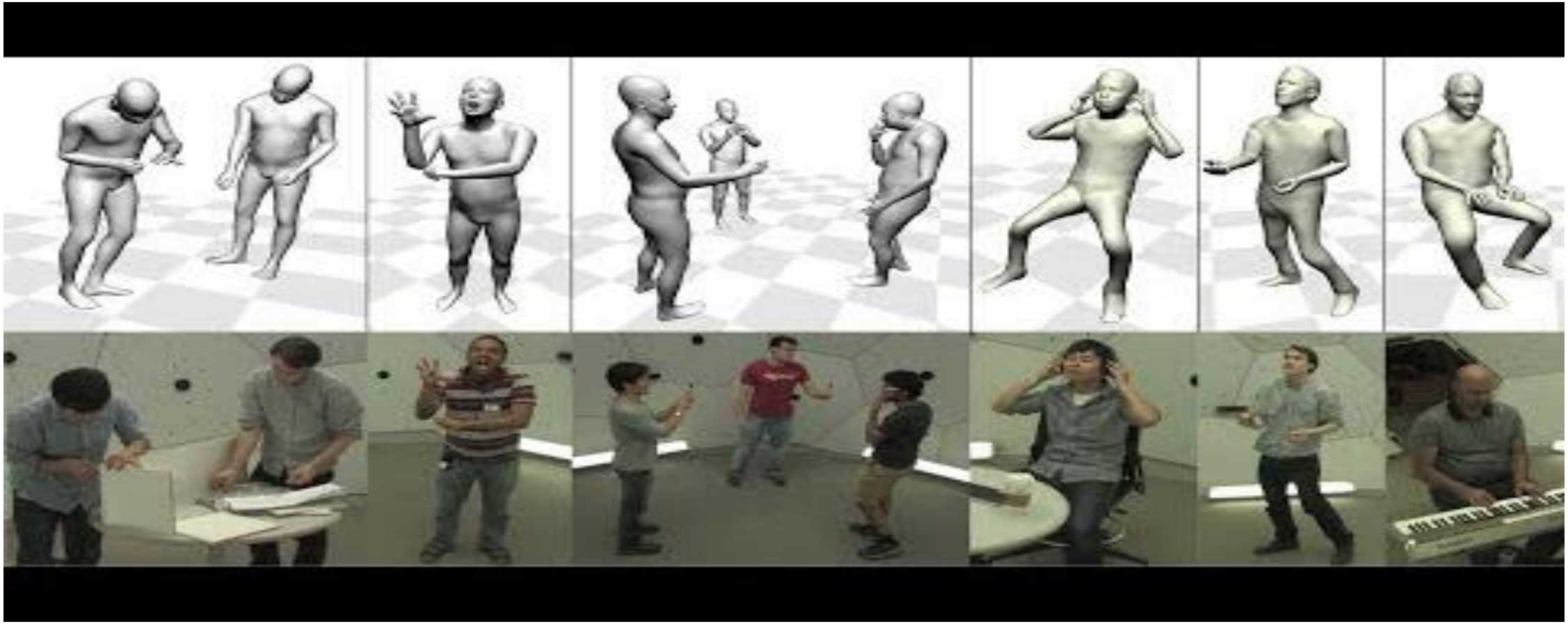
Results



- Silhouette Accuracy

	SMPL[34]	Frank	Frank ICP	Adam ICP
Mean	84.79%	85.91%	87.68%	87.74%
Std.	4.55	4.57	4.53	4.18

Results



Thank You