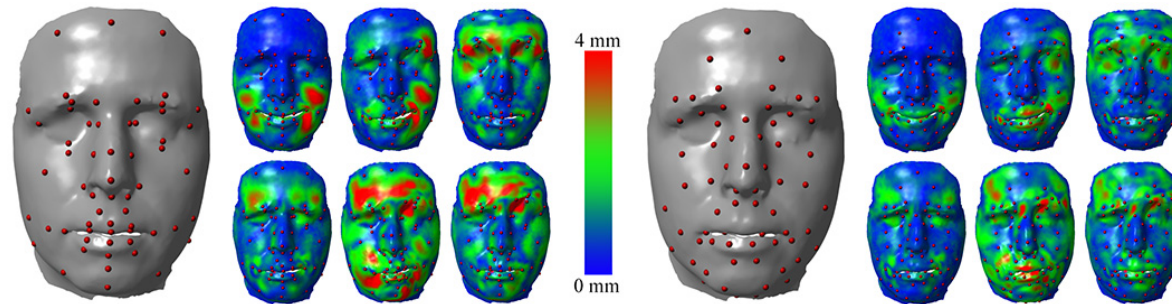


IEEE Transactions on Visualization and Computer Graphics (TVCG) 2013



Marker Optimization for Facial Motion Acquisition and Deformation

[†]*Binh Huy Le*, [‡]*Mingyang Zhu*, and [†]*Zhigang Deng*

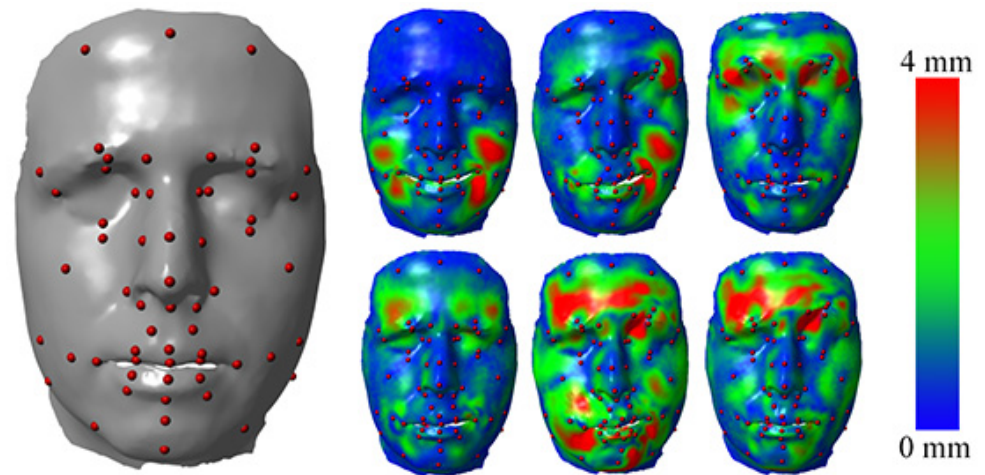
[†]UNIVERSITY of **HOUSTON**

[‡]  Nanjing University of Science and Technology



Roadmap

- Motivation
- Problem Formulation
- Algorithm
- Results & Validations
- Discussion
- Q & A



MOTIVATION



Optical Motion Capture

Marker-based

- × Low spatial resolution
→ Body capture

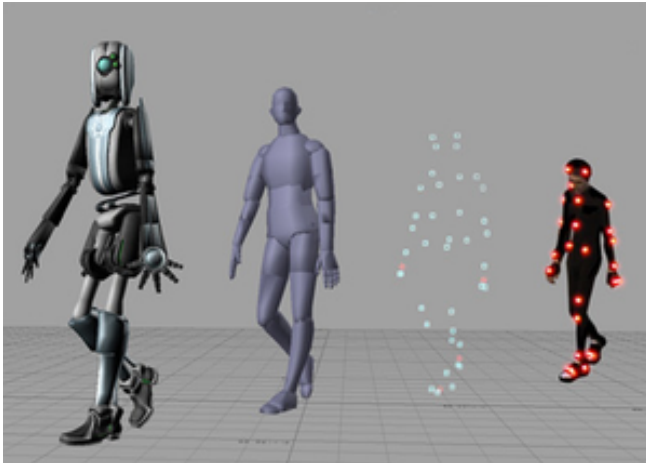


Image Courtesy of Wikipedia

Markerless

- ✓ High spatial resolution
→ Facial capture

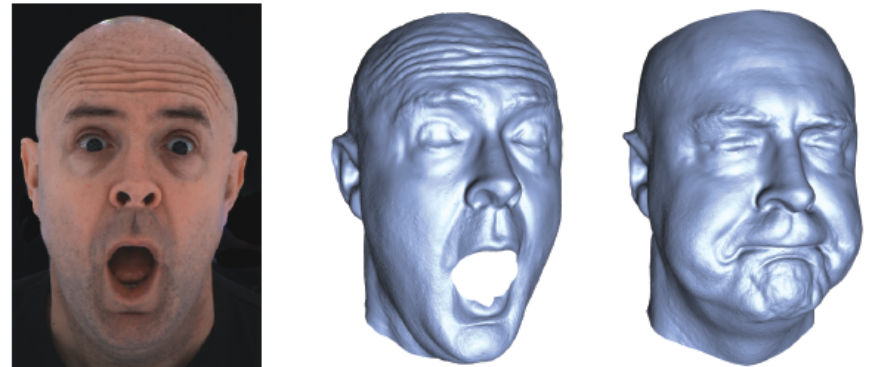


Image Courtesy of Beeler et al.





Optical Motion Capture

Marker-based

- × Low spatial resolution
- ✓ Robust tracking

Markerless

- ✓ High spatial resolution
- × Drifting

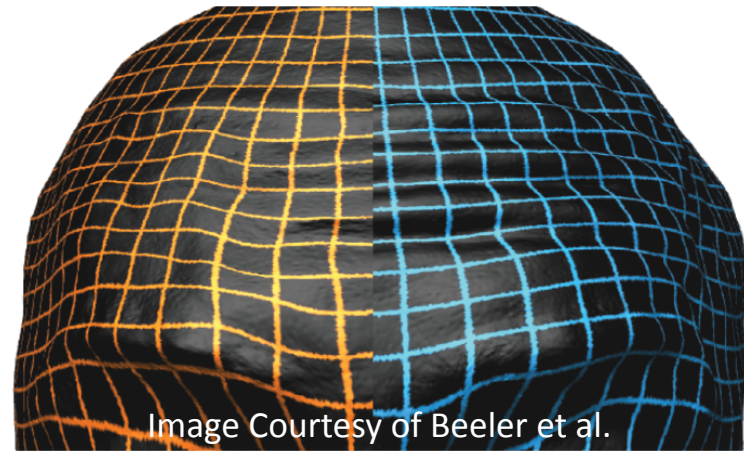


Image Courtesy of Beeler et al.





Optical Motion Capture

Marker-based

- × Low spatial resolution
- ✓ Robust tracking
- ✓ Large working volume
- ✓ Face + body capture



Making of The Polar Express movie

Markerless

- ✓ High spatial resolution
- × Drifting
- × More limited setup
- × Face or body capture only





Optical Motion Capture

Marker-based

- ✗ Low spatial resolution
- ✓ Robust tracking
- ✓ Large working volume
- ✓ Face + body capture
- ✓ You might have one already

Markerless

- ✓ High spatial resolution
- ✗ Drifting
- ✗ More limited setup
- ✗ Face or body capture only





Optical Motion Capture

Marker-based

- ✗ Low spatial resolution
- ✓ Robust tracking
- ✓ Large working volume
- ✓ Face + body capture
- ✓ You might have one already

→ Still good for facial capture

Markerless

- ✓ High spatial resolution
- ✗ Drifting
- ✗ More limited setup
- ✗ Face or body capture only





Marker-based Facial Motion Capture

How many markers should be put on the face?

- Putting more → time consuming
- Putting less → data loss

40 markers



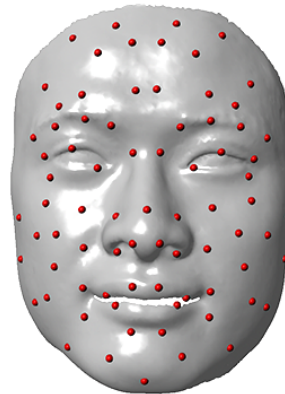
RMSE = 1.632

60 markers



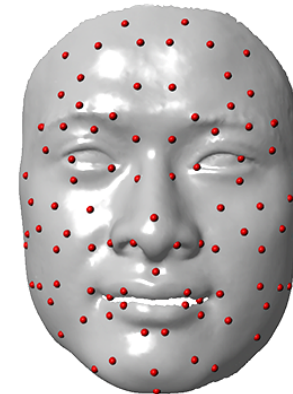
RMSE = 1.345

80 markers



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100 markers



RMSE = 0.934





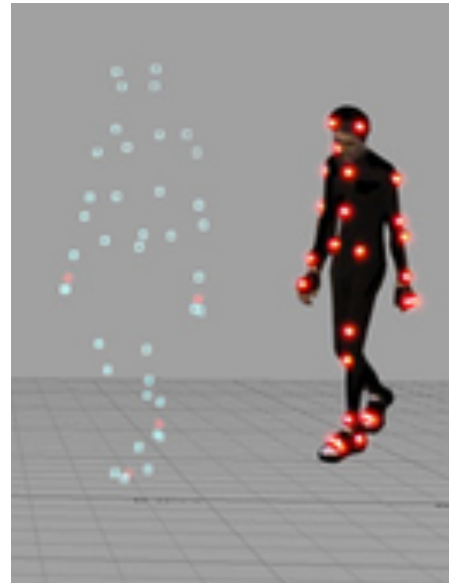
Marker-based Facial Motion Capture

How many markers should be put on the face?

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How to put markers?

- Guidance is not as clear as with body capture
- Hard to quantify how good a layout is





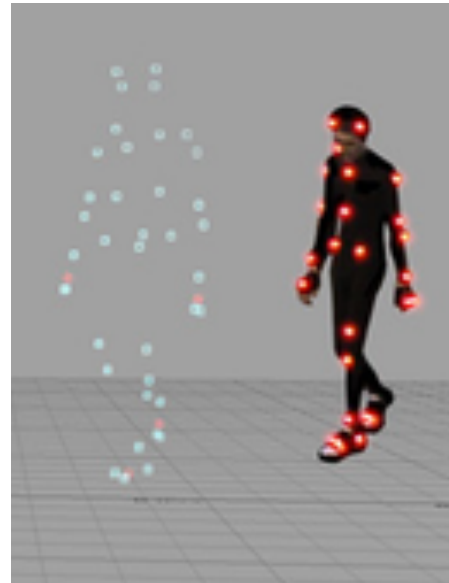
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Marker-based Facial Motion Capture

How many markers should be put on the face?

- Putting more → time consuming
- Putting less → data loss

How to put markers?

- Guidance is not as clear as with body capture
- Hard to quantify how good a layout is

Can we do something more than acquisition?

- Animation?
- Data compression?



PROBLEM FORMULATION



Main Idea

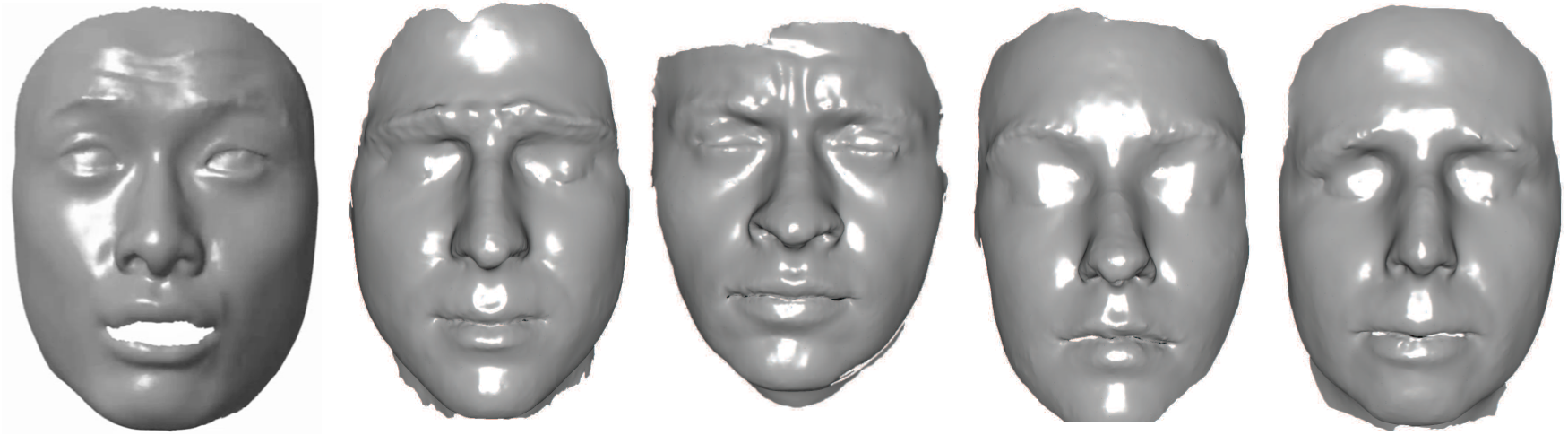
- Use performance capture data to explore optimal layout
 - Different facial poses





Main Idea

- Use performance capture data to explore optimal layout
 - Different facial poses
 - Different subjects





Main Idea

- Use performance capture data to explore optimal layout
 - Different facial poses
 - Different subjects
- Marker based capture as discrete sampling of facial surface
 - Given performance capture data (animated 3D mesh sequence)
 - Find **markers' locations** and **deformation model** to estimate input best
 - Some constraints, e.g. markers are on facial surface





Thin-shell Deformation Model

- Minimizing elastic energy: $\underbrace{-k_s \Delta d}_{\text{stretching}} + \underbrace{k_b \Delta^2 d}_{\text{bending}} = 0$





Thin-shell Deformation Model

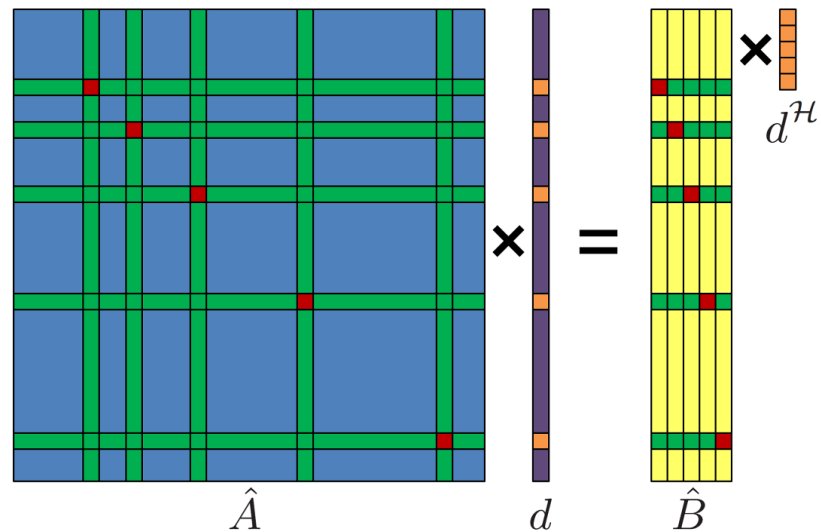
- Minimizing elastic energy: $-k_s \Delta d + k_b \Delta^2 d = 0$
 - Discretization: $(-k_s \mathcal{L} + k_b \mathcal{L}^2) d = 0$
- ↑ ↑
Laplacian matrix





Thin-shell Deformation Model

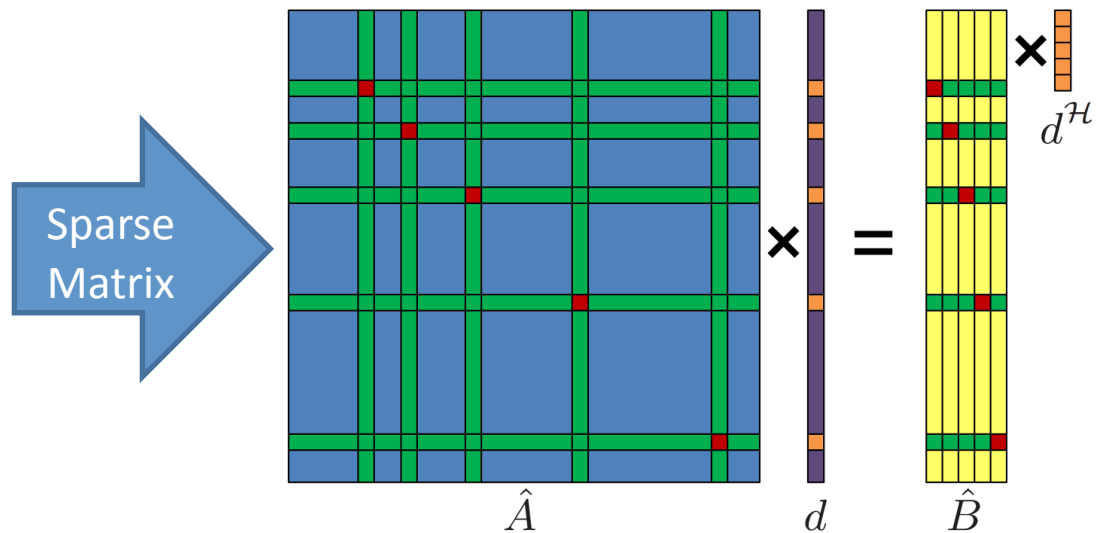
- Minimizing elastic energy: $-k_s \Delta d + k_b \Delta^2 d = 0$
- Discretization: $(-k_s \mathcal{L} + k_b \mathcal{L}^2) d = 0$
- Constraint some vertices (markers \mathcal{H}): $\hat{A}d = \hat{B}d^{\mathcal{H}}$





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- Constraint some vertices (markers \mathcal{H}): $\hat{A} d = \hat{B} d^{\mathcal{H}}$
- Solution: $d = \hat{A}^{-1} \hat{B} d^{\mathcal{H}} = W d^{\mathcal{H}}$
- Solve weights $W = \hat{A}^{-1} \hat{B}$ by Cholesky decomposition $\hat{A} = L^T L$





Thin-shell Deformation Model

- Minimizing elastic energy: $-k_s \Delta d + k_b \Delta^2 d = 0$
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\hat{A} computed from rest pose & **markers set** \mathcal{H}

$$\mathcal{H} \rightarrow W$$





Objective

- Minimizing reconstruction error

$$E = \min_{\mathcal{H}=\{h_1, \dots, h_M\}} \|X - HW^T\|_2^2$$

Markers Set

Vertices Displacement (from input data)

Markers Displacement

Weights



Objective

- Minimizing reconstruction error

$$\min_{\mathcal{H}=\{h_1, \dots, h_M\}} E = \min_{\mathcal{H}} \|X - HW^T\|_2^2$$

s. t.: $H_{i,j} = X_{i,h_j}, \forall i, j \rightarrow$ Markers are on the facial surface

$W = \hat{A}^{-1} \hat{B} \rightarrow$ Thin-shell deformation

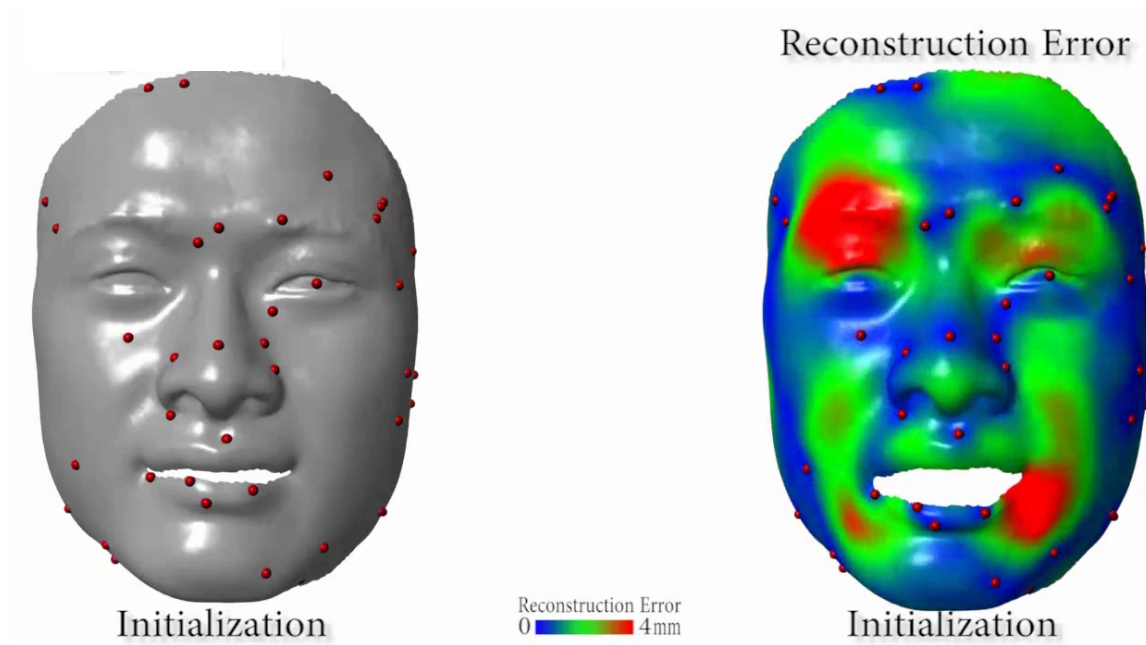


ALGORITHM



Overview

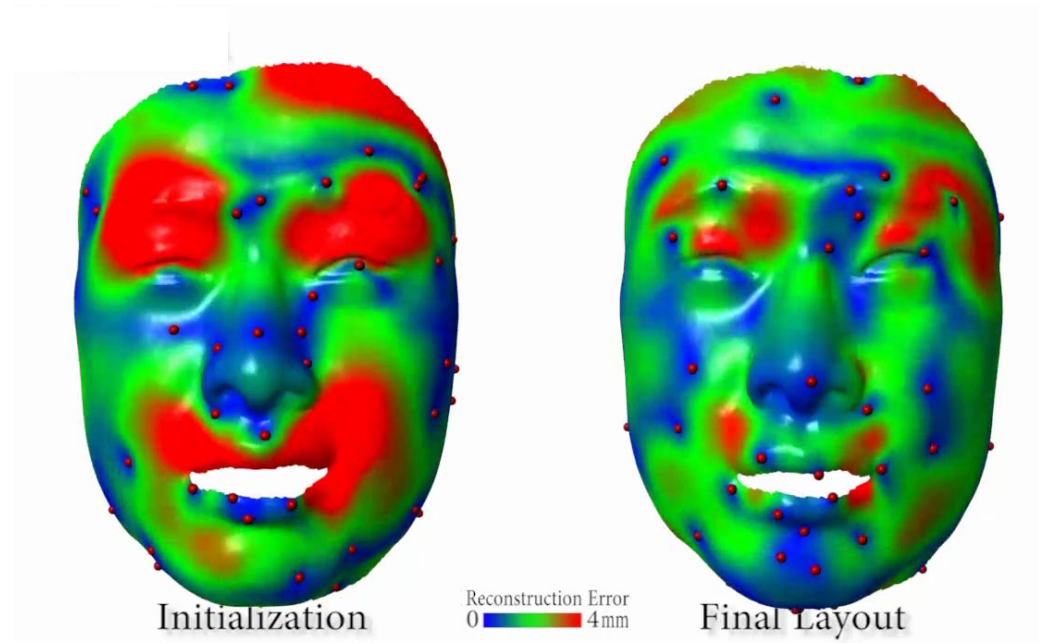
- Repeated update the markers' positions one by one to reduce the objective function (reconstruction error)





Overview

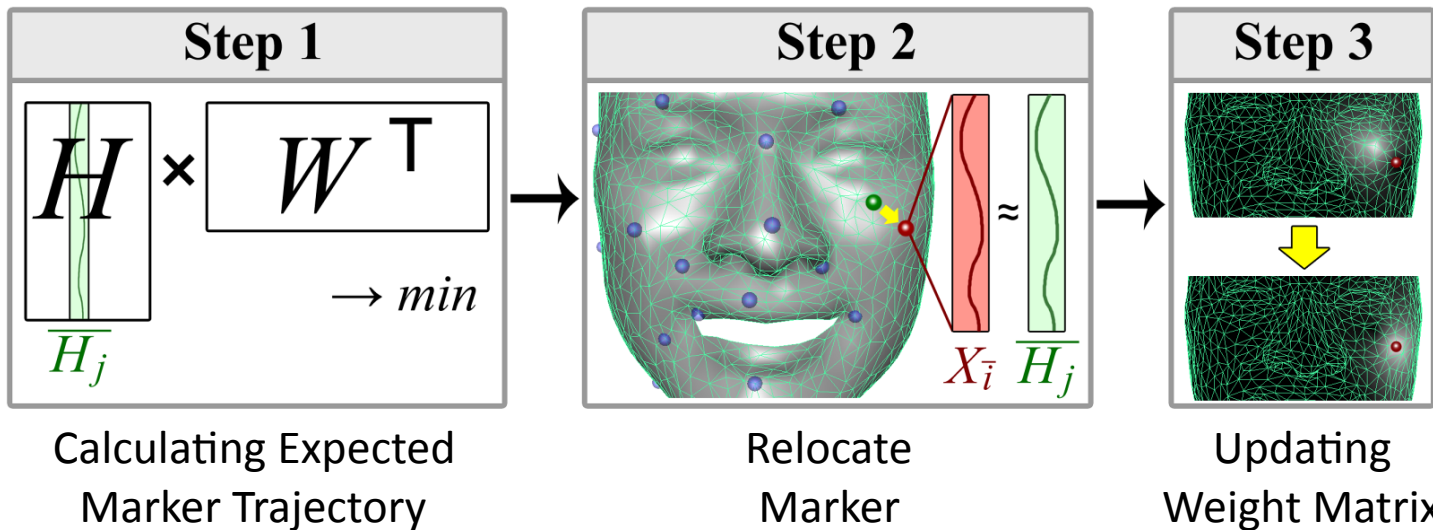
- Repeated update the markers' positions one by one to reduce the objective function (reconstruction error)





Overview

- Repeated update the markers' positions one by one to reduce the objective function (reconstruction error)
 - Update one marker





Step 1: Calculating Expected Marker Trajectory

- Minimizing objective function

$$\left\| \begin{array}{|c|} \hline H \\ \hline \end{array} \times \begin{array}{|c|} \hline W^T \\ \hline \end{array} - \begin{array}{|c|} \hline X \\ \hline \end{array} \right\|_F^2$$



Step 1: Calculating Expected Marker Trajectory

- Minimizing objective function

$$\left\| \begin{bmatrix} H \end{bmatrix} \times \begin{bmatrix} W^T \end{bmatrix} - \begin{bmatrix} X \end{bmatrix} \right\|_F^2$$

s.t. $H_j = X_{h_j}$



Step 1: Calculating Expected Marker Trajectory

- Minimizing objective function w.r.t. \overline{H}_j

$$\left\| \begin{array}{c} \boxed{H} \\ \overline{H}_j \\ \text{(expected trajectory)} \end{array} \times \boxed{W^T} - \boxed{X} \right\|_F^2$$

~~s.t. $\overline{H}_j \in X_{h_j}$~~



Step 1: Calculating Expected Marker Trajectory

- Minimizing objective function w.r.t. \overline{H}_j

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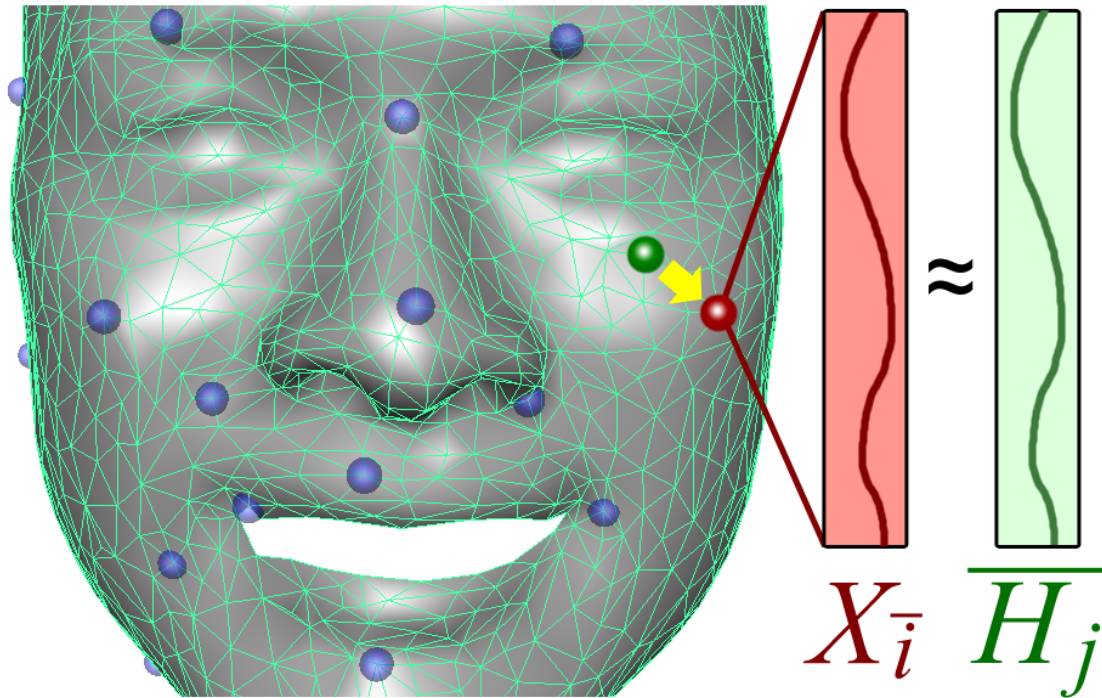
~~s.t. $\overline{H}_j \in X_{h_j}$~~

→ Linear least squares



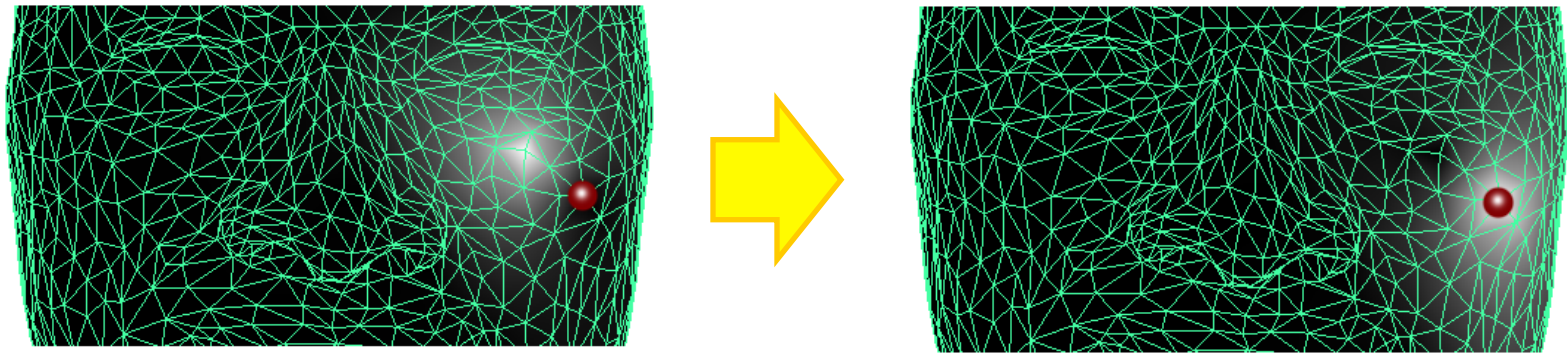
Step 2: Relocate Marker

to vertex with trajectory X_i closet to the expected $\overline{H_j}$ (L2-norm)





Step 3: Updating Weight Matrix



Marker on vertex j move to vertex j'

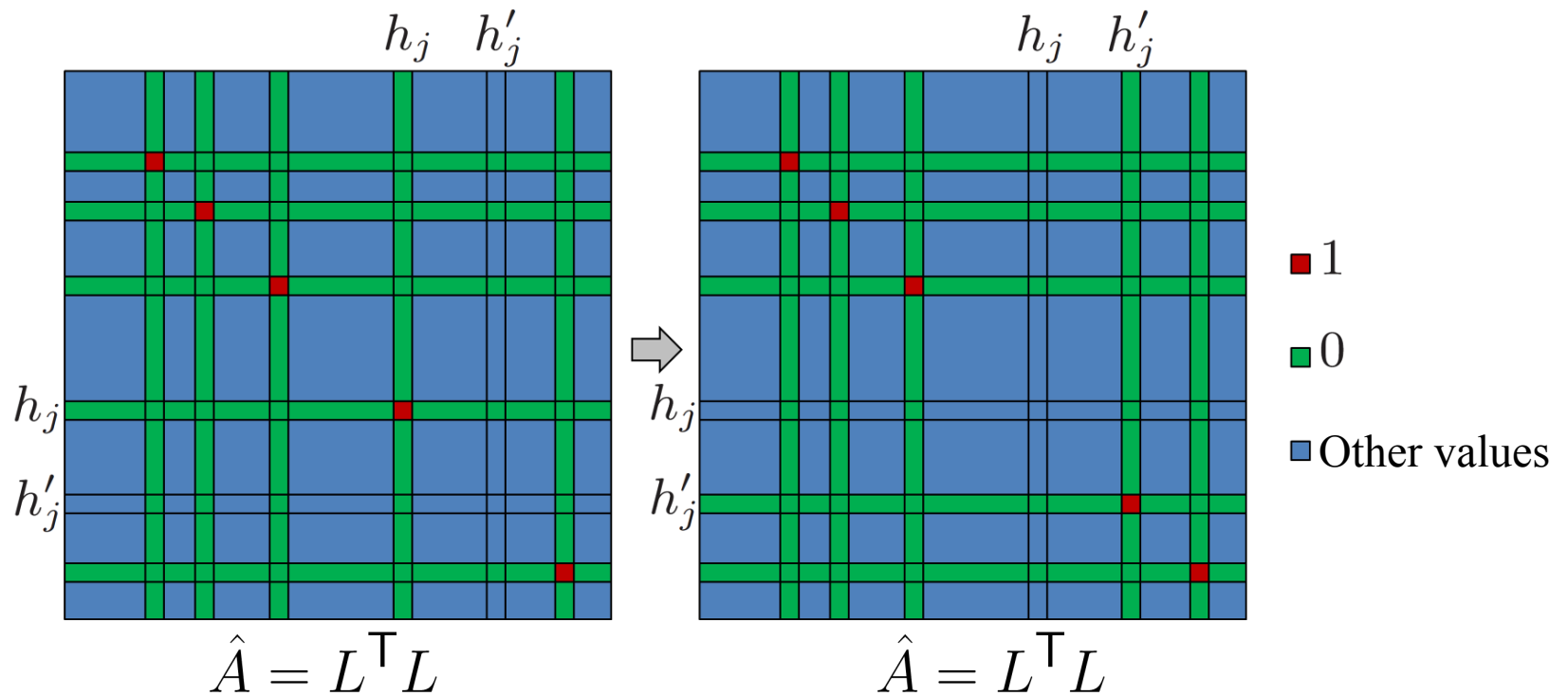
→ Update $W = \hat{A}^{-1} \hat{B}$

→ Update Cholesky decomposition $\hat{A} = L^T L$



Step 3: Updating Weight Matrix

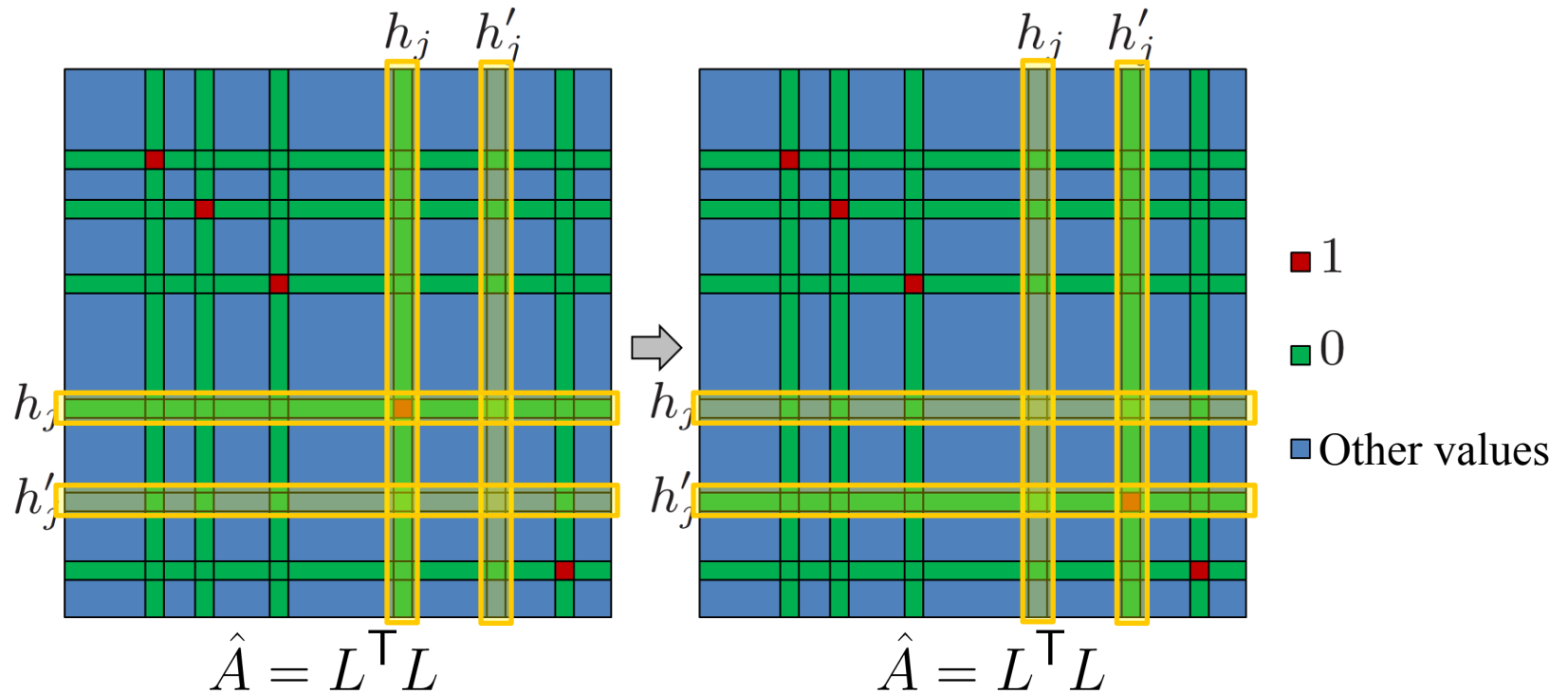
- Update 2 rows + 2 columns of \hat{A} (use CHOLMOD)





Step 3: Updating Weight Matrix

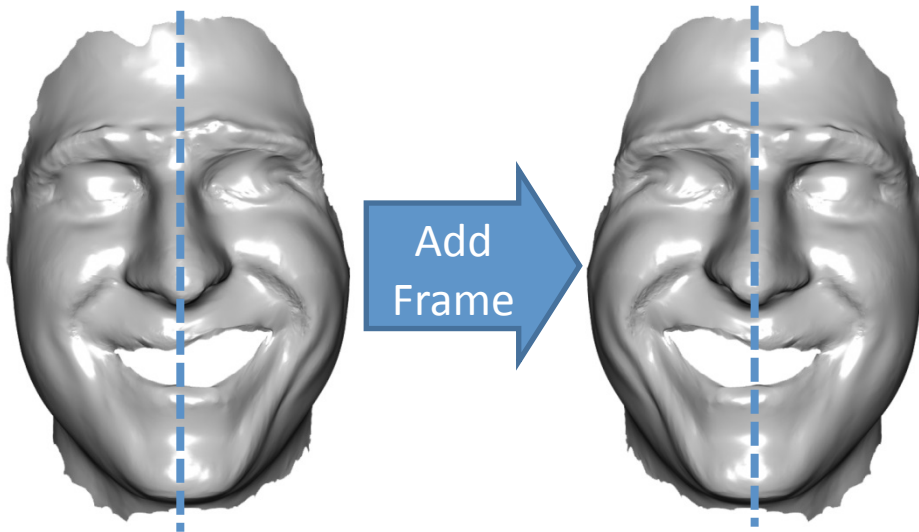
- Update 2 rows + 2 columns of \hat{A} (use CHOLMOD)





Handling Constraints

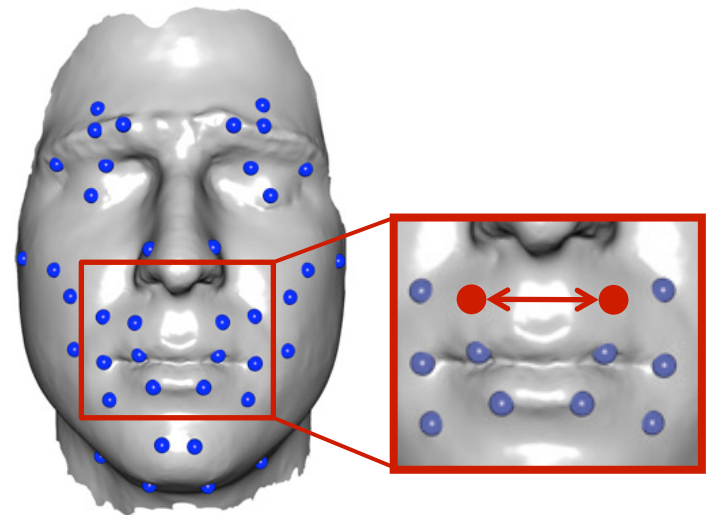
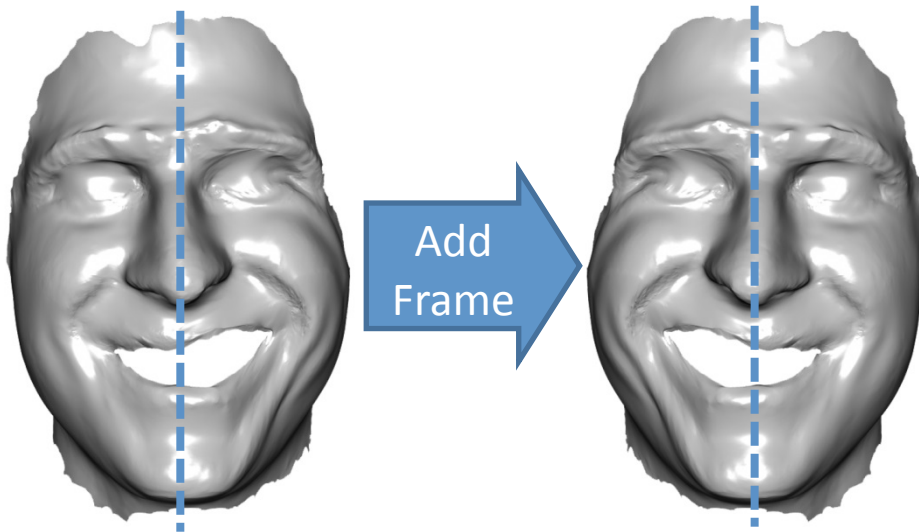
- Symmetry
 - Mirror input data





Handling Constraints

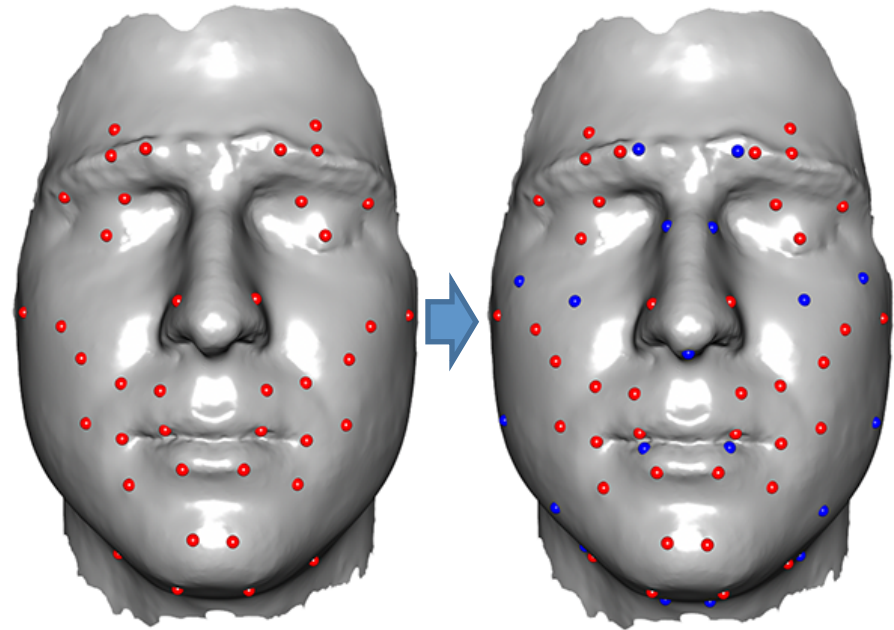
- Symmetry
 - Mirror input data
 - Enforce makers' positions





Handling Constraints

- Symmetry
 - Mirror input data
 - Enforce makers' positions
- Multi-resolution
 - Fix a subset of markers





Handling Constraints

- Symmetry
 - Mirror input data
 - Enforce makers' positions
- Multi-resolution
 - Fix a subset of markers
- Boundary
 - Add fixed virtual markers on boundary



With Boundary Constraint





Handling Constraints

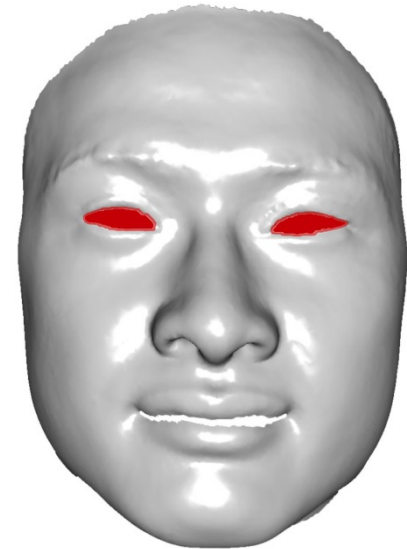
- Symmetry
 - Mirror input data
 - Enforce makers' positions
- Multi-resolution
 - Fix a subset of markers
- Boundary
 - Add fixed virtual markers on boundary
- Prohibited regions, e.g. eyes, lips
 - Remove vertices from input meshes





Handling Constraints

- Symmetry
 - Mirror input data
 - Enforce makers' positions
- Multi-resolution
 - Fix a subset of markers
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 - Add fixed virtual markers on boundary
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Combining Data from Multiple Subjects

- One dataset as reference
- Map other datasets to the reference
 - Non rigid registration on rest poses
Constructing dense correspondences for the analysis of 3d facial morphology [Mao et al. 2006]
 - Vertex to vertex correspondence across datasets found by nearest point search on registered rest pose





Combining Data from Multiple Subjects

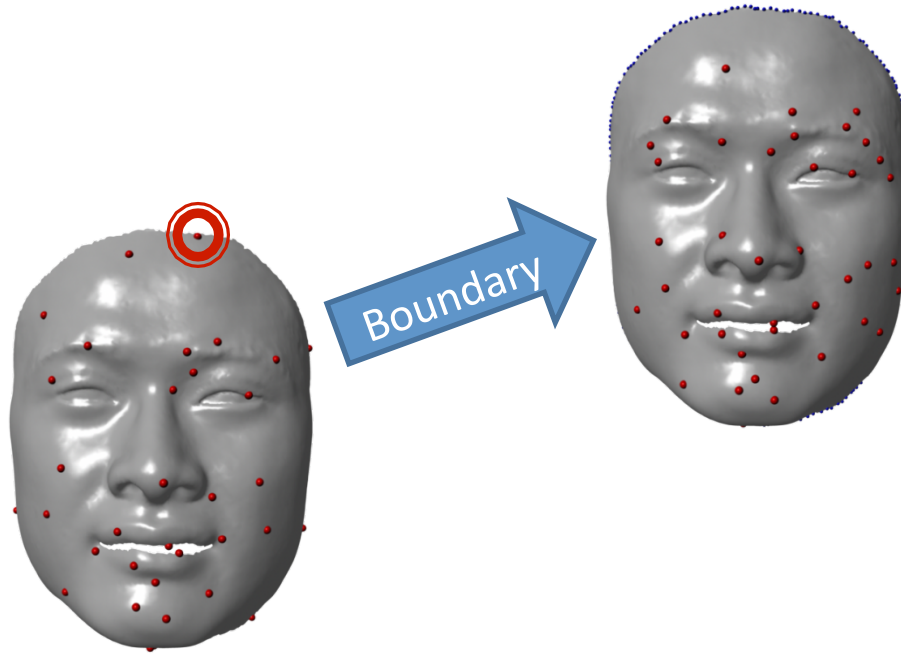
- One dataset as reference
- Map other datasets to the reference
 - Non rigid registration on rest poses
Constructing dense correspondences for the analysis of 3d facial morphology [Mao et al. 2006]
 - Vertex to vertex correspondence across datasets found by nearest point search on registered rest pose
- Optimization
 - Update only one marker layout on reference dataset then map to others
 - Different weights matrix for each dataset



RESULTS & VALIDATIONS

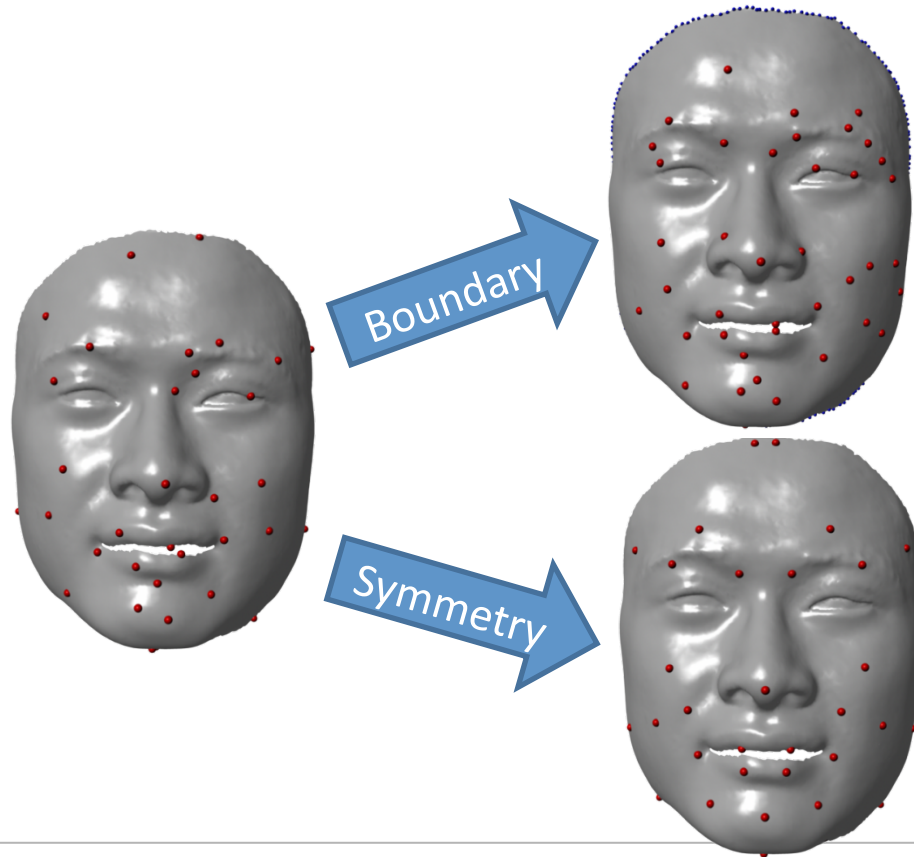


With Different Constraints



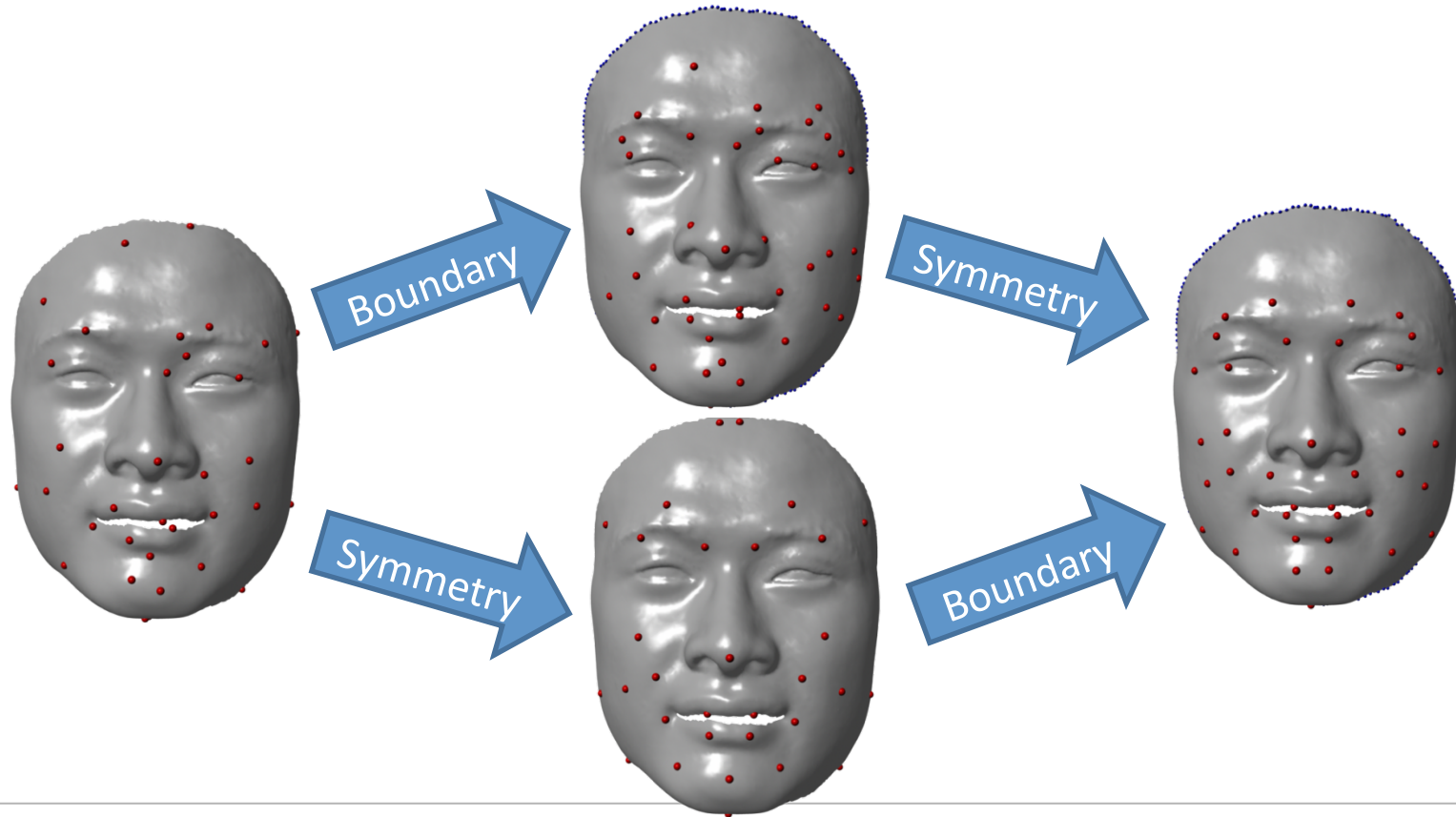


With Different Constraints





With Different Constraints





With Different Data Sources

- Combine 5 datasets and map to Model #1

40 markers



RMSE = 1.632

60 markers



RMSE = 1.345

80 markers



RMSE = 1.109

100 markers

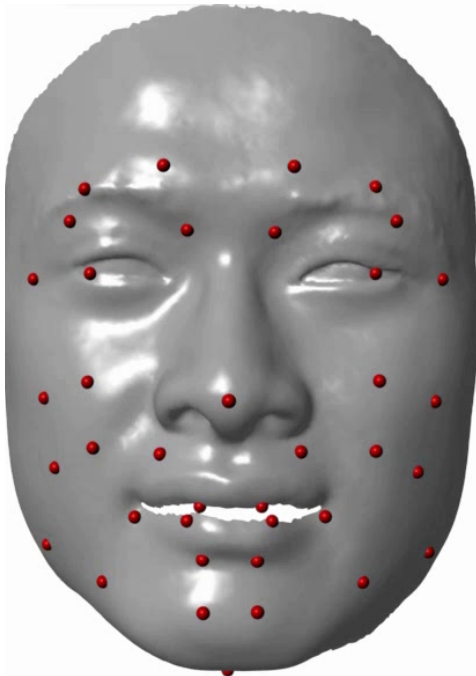


RMSE = 0.934

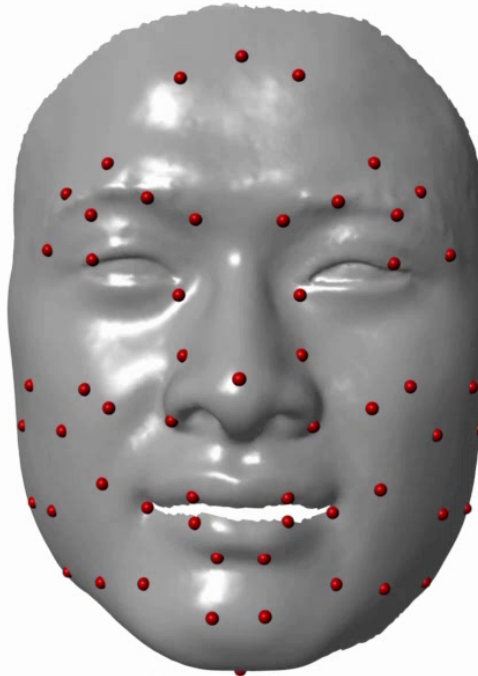




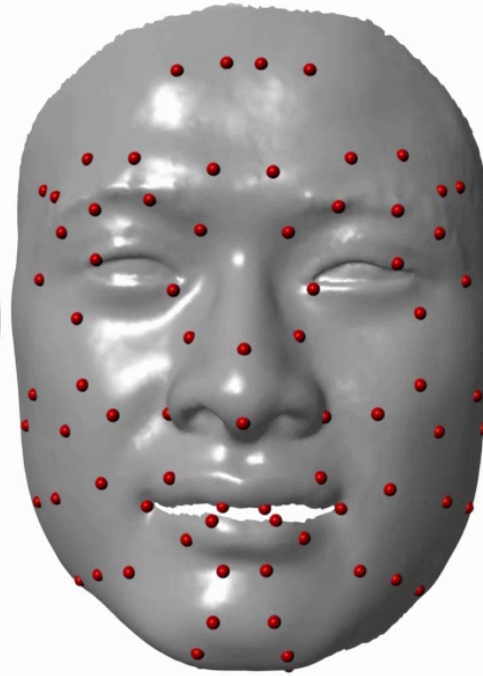
Deformation Error



40 markers



60 markers



80 markers

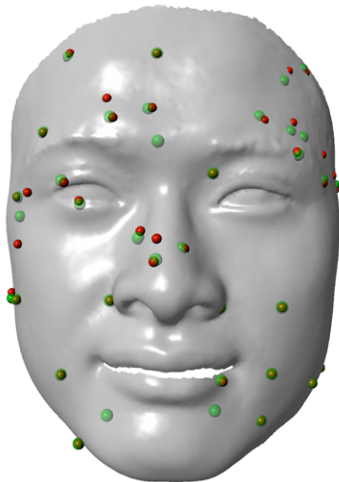




Validation

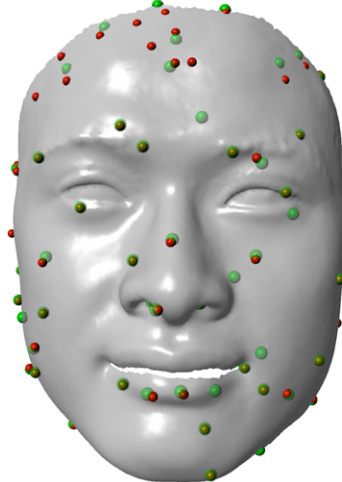
- Simulation data
 - Random markers on the rest pose
 - Random markers' motion

40 markers



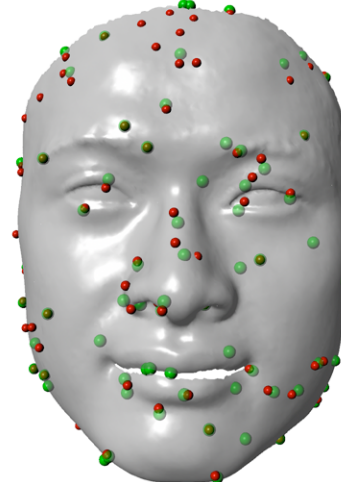
RMSE = 0.167

60 markers



RMSE = 0.172

80 markers



RMSE = 0.228

● Original
● Our solution

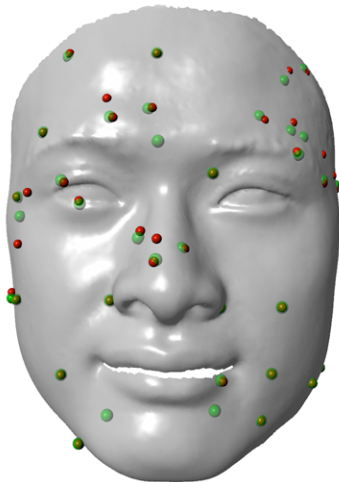




Validation

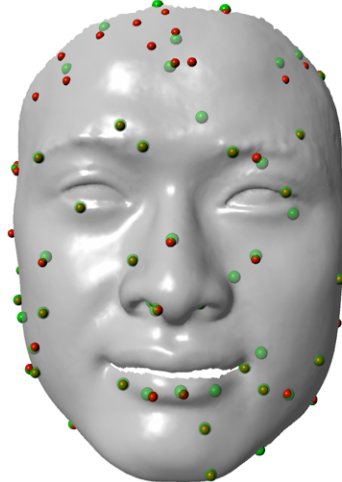
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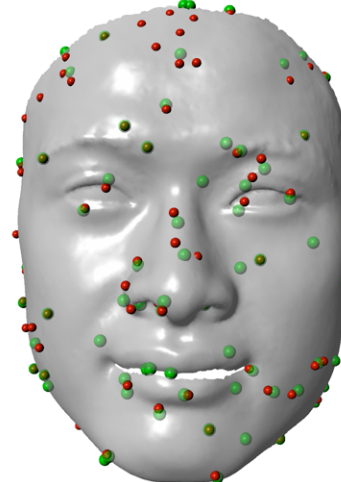
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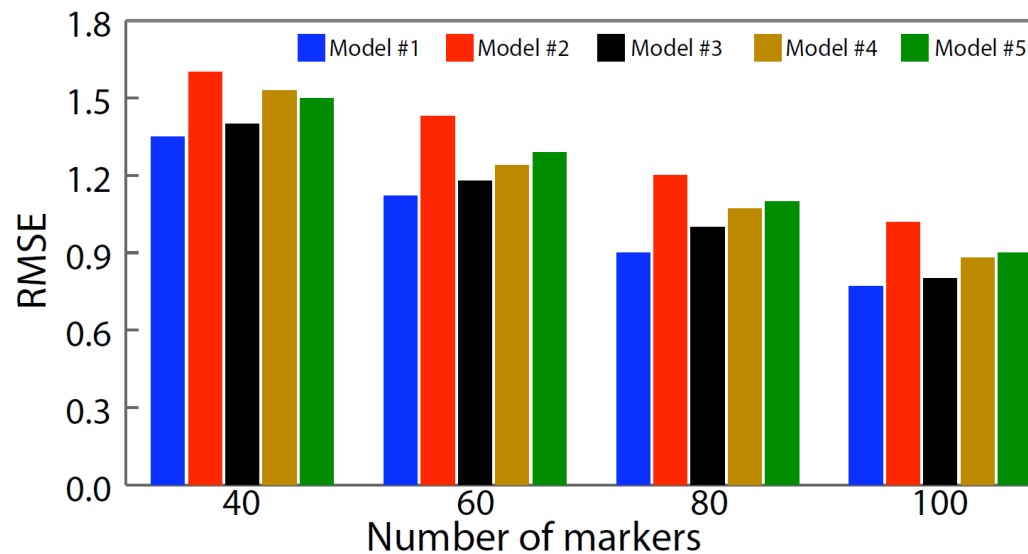
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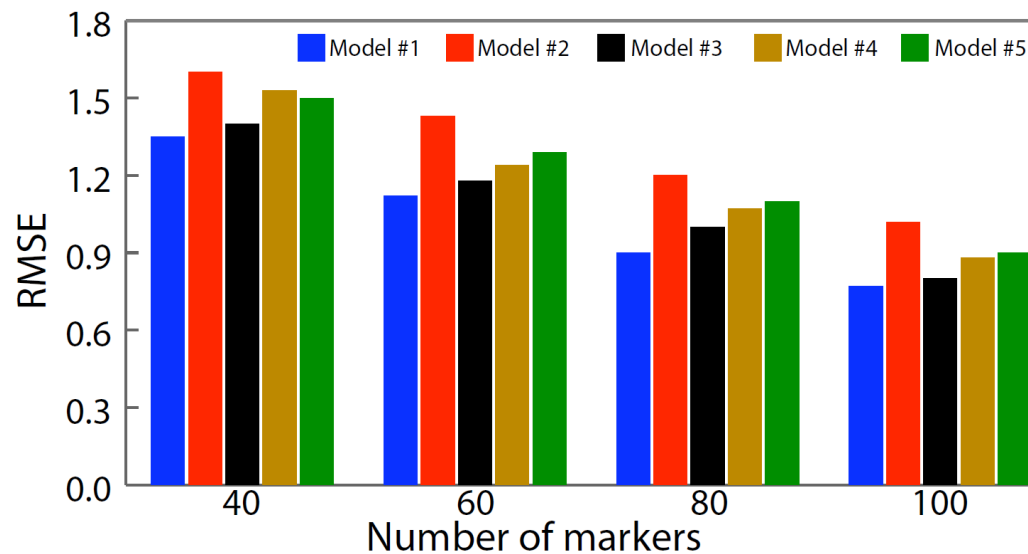
- Leave one out cross model validation
 - 4 models as training, 1 model as testing





Validation

- Leave one out cross model validation
 - 4 models as training, 1 model as testing



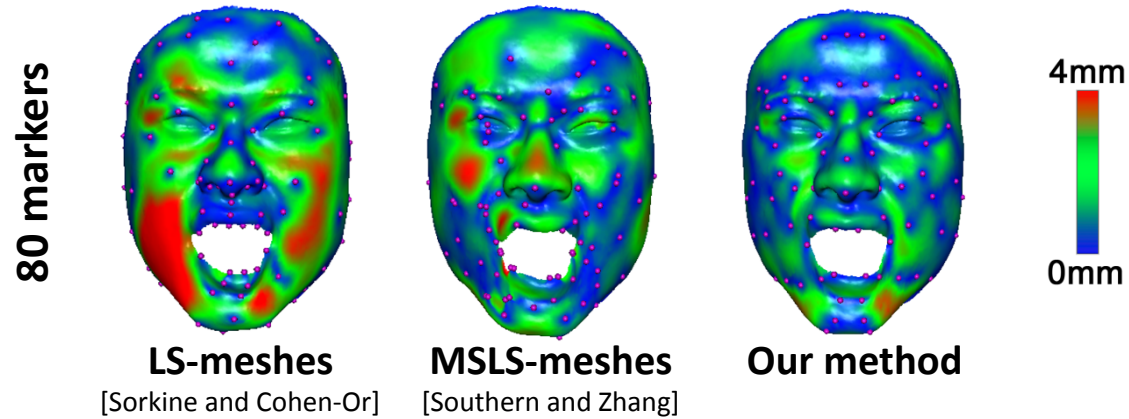
RMSE \approx 1mm





Comparisons

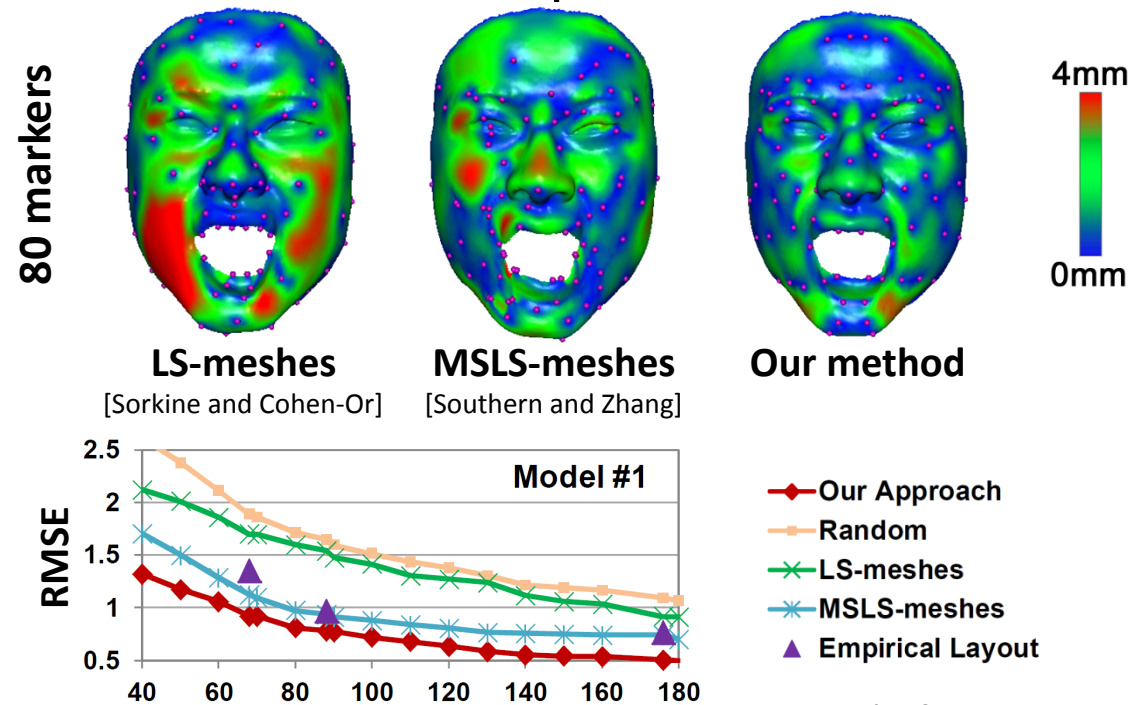
- Reconstruction error of the input data





Comparisons

- Reconstruction error of the input data



(refer to our paper for more results)



DISCUSSION



Applications

- Select key points $\{h_j\}$ for animated facial mesh sequence X
 - Compression
 - Editing
 - Linear Blend Skinning

$$X = HW^T$$





Applications

- Select key points $\{h_j\}$ for animated facial mesh sequence X
 - Compression
 - Editing
 - Linear Blend Skinning
 - Compare to matrix factorization: No need to store & transfer W

$$X = HW^T$$
$$\text{s.t. } H_j = X_{h_j}$$





Applications

- Select key points $\{h_j\}$ for animated facial mesh sequence X

- Compression

- Editing

- Linear Blend Skinning

- Compare to matrix factorization: No need to store & transfer W

$$X = HW^T$$
$$\text{s.t. } H_j = X_{h_j}$$

- More precise approximation

- EigenSkin Correction (EC) [Kry et al.]

- Key Point Subspace Acceleration (KPSA) [Meyer and Anderson]

Parameters		RMSE _(Compression Ratio)		
# Mkrs	Rank	Ours	Ours + EC	KPSA
40	20	1.598 _(106.8)	0.255 _(16.3)	0.771 _(17.1)
60	30	1.256 _(98.1)	0.157 _(11.3)	0.656 _(11.7)
80	40	1.080 _(90.6)	0.113 _(8.7)	0.626 _(8.9)
100	50	0.865 _(84.2)	0.085 _(7.1)	0.502 _(7.2)

(results on model #1 only, refer to our paper for more)





Conclusions

- ✓ Quantitative approach to optimize marker layouts
 - With optional constraints: symmetry, boundary, multi-resolution
- ✓ Applications with better performance than state of the art methods:
 - Animated mesh sequence compression: LS-meshes, MSLS meshes
 - Facial data compression: Key Point Subspace Acceleration





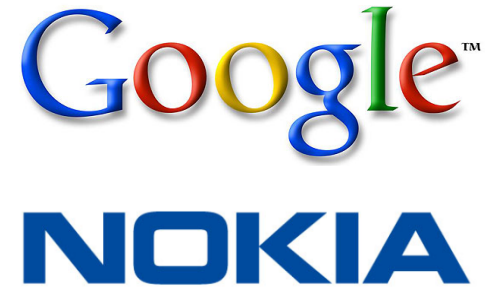
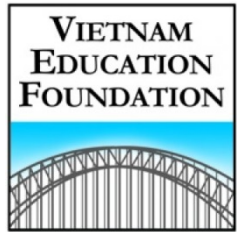
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 - With optional constraints: symmetry, boundary, multi-resolution
- ✓ Applications with better performance than state of the art methods:
 - Animated mesh sequence compression: LS-meshes, MSLS meshes
 - Facial data compression: Key Point Subspace Acceleration
- ✗ Data dependent (data driven approach)
- ✗ Linear deformation model
- ✗ Local optimum only





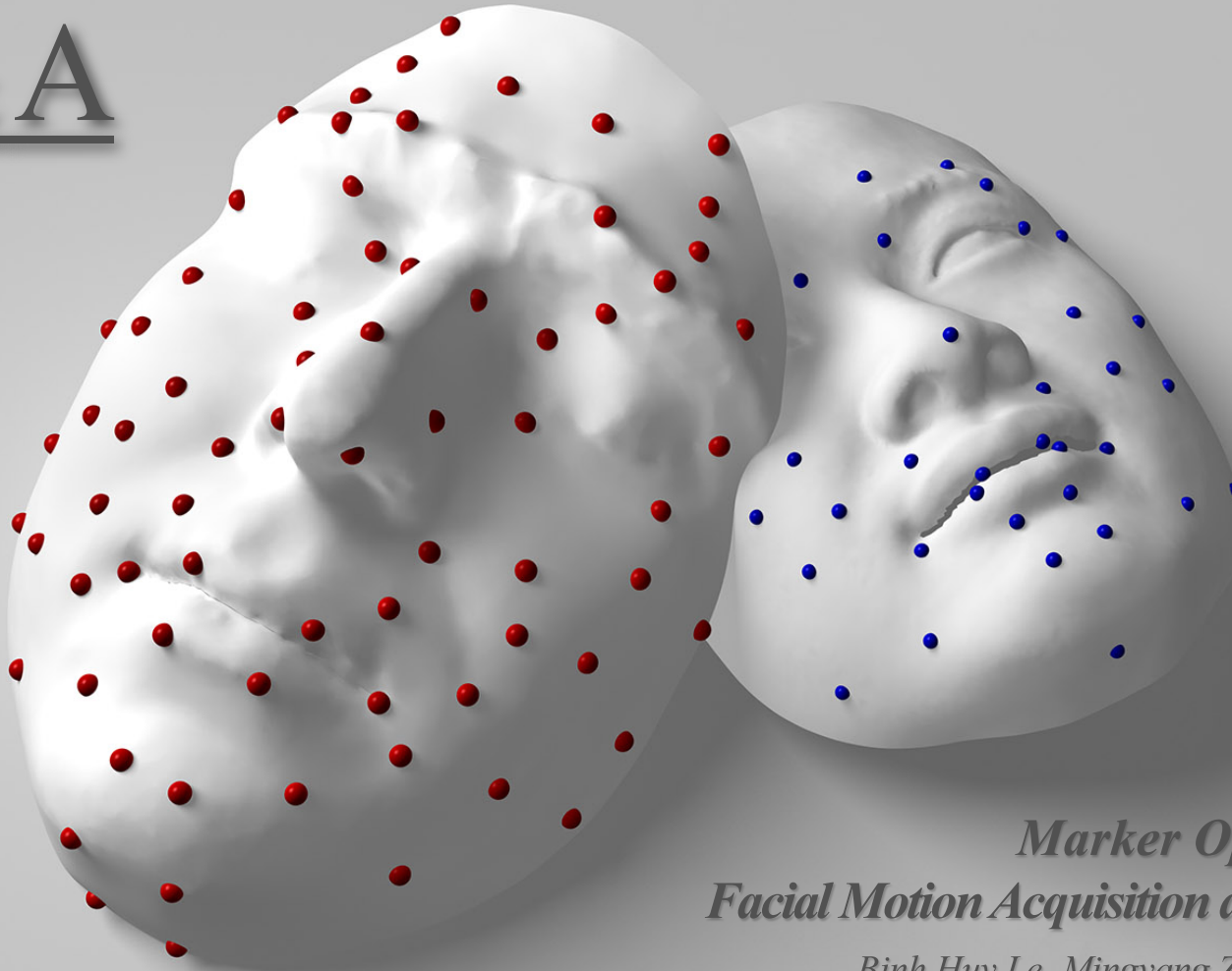
Acknowledgements



- Hao (Richard) Zhang for helps and discussion
- Li Zhang, Derek Bradley, and Thabo Beeler for providing datasets
- Anonymous reviewers for giving comments and suggestions



Q & A



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