High Resolution Acquisition, Learning and Transfer of Dynamic 3D Facial Expressions

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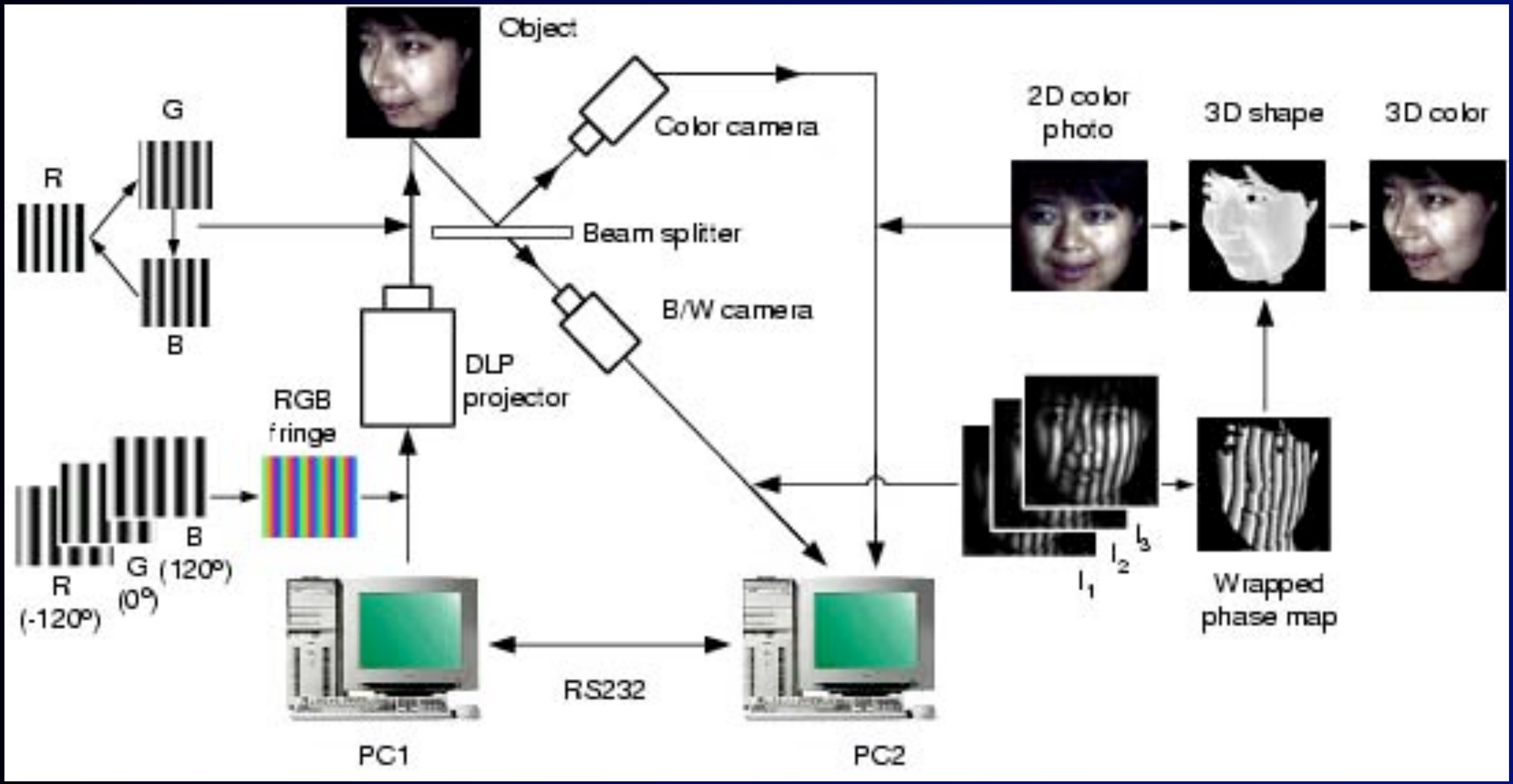
2 Sources of Facial Data

- High end: High frame-rate, accurate 3D points
  - Structured light scanning
  - Requires controlled set up
- Low End: Single Image
  - Statistical models
  - Ubiquitous

3D shape acquisition system

- Developed by Peisen Huang's group in Stony Brook



Face scan demo

3D data acquisition

Matching 3D Shapes

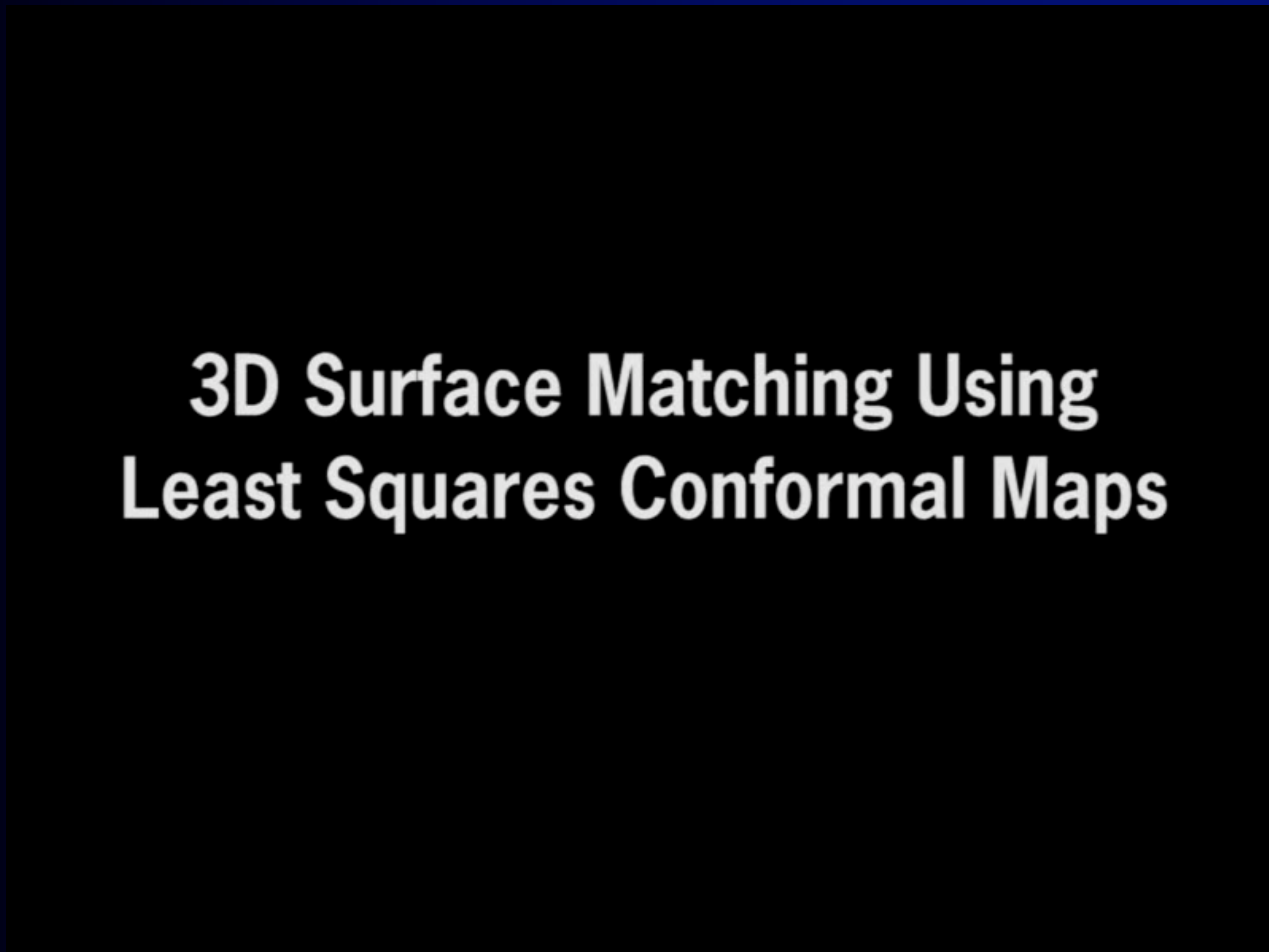
- We need to compare 3D shapes:
  - For Alignment
  - For Recognition
  - For Tracking
- Issues:
  - Noise
  - Occlusions / Partial Scans
  - Local Minima

Conformal Geometry to the rescue

- Analyze a family of conformal geometric maps when applied to 3D shape matching and registration.
- According to conformal geometry theory, each 3D surface with disk topology can be mapped to a 2D domain
- Highly accurate and efficient 3D surface matching algorithms can be achieved by using a family of conformal geometric maps
  - Harmonic Maps
  - Conformal Maps
  - Least Squares Conformal Maps
- Major challenge is the unreliability of CV features

- Joint work with Yang Wang, Sen Wang, Mohit Gupta, Miao Jin, Yun Zeng, Xianfeng Gu.

Demo



Recognition of 3D Faces

Table 2. Recognition results of conformal geometric maps and surface curvature technique.

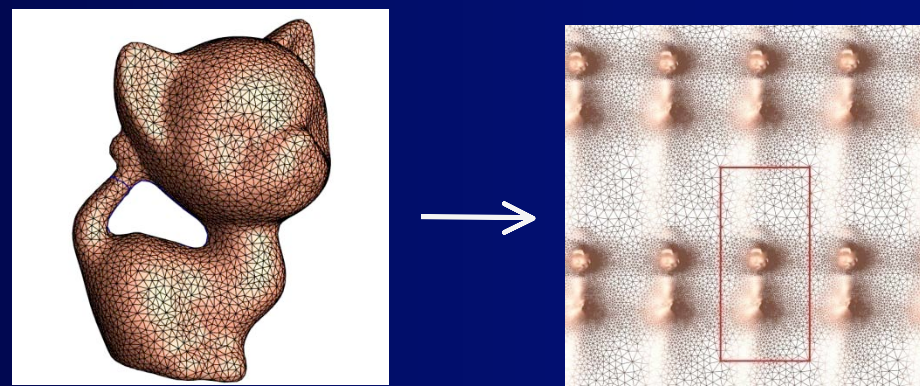
Recognition Result	Harmonic Maps	Conformal Maps	Least Squares Conformal Maps	Surface Curvature
Using shape information only	92.8%	95.7%	97.3%	84.0%
Using texture information only	93.5%	96.5%	98.0%	N/A
Using both shape and texture	93.9%	97.0%	98.4%	N/A

- Use a 3D face database which contains 100 3D face scans from 10 subjects captured by a phase-shifting structured light ranging system.
- Each face has approximately 80K 3D points with both shape and texture information available

Surface Ricci Flow

Ricci flow is a powerful tool to compute the metric [illegible] which satisfies the given target curvatures [illegible], from the original metric [illegible] in *S*.

[illegible]



This metric [illegible] deforms according to curvature, such that the curvature evolves like a heat diffusion process.

[illegible]

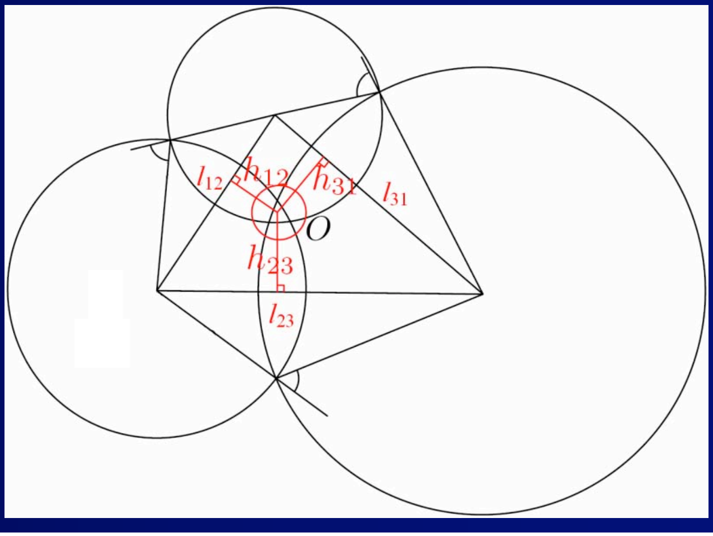
Discrete Ricci Flow Algorithm

Basic idea: Ricci flow is variational, the desired metric for a target curvature is the unique optimum of a specific energy function.

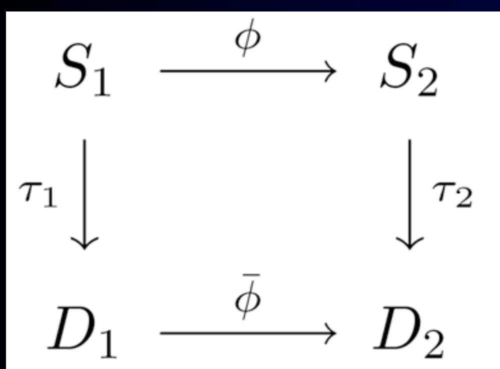
Ricci Energy:

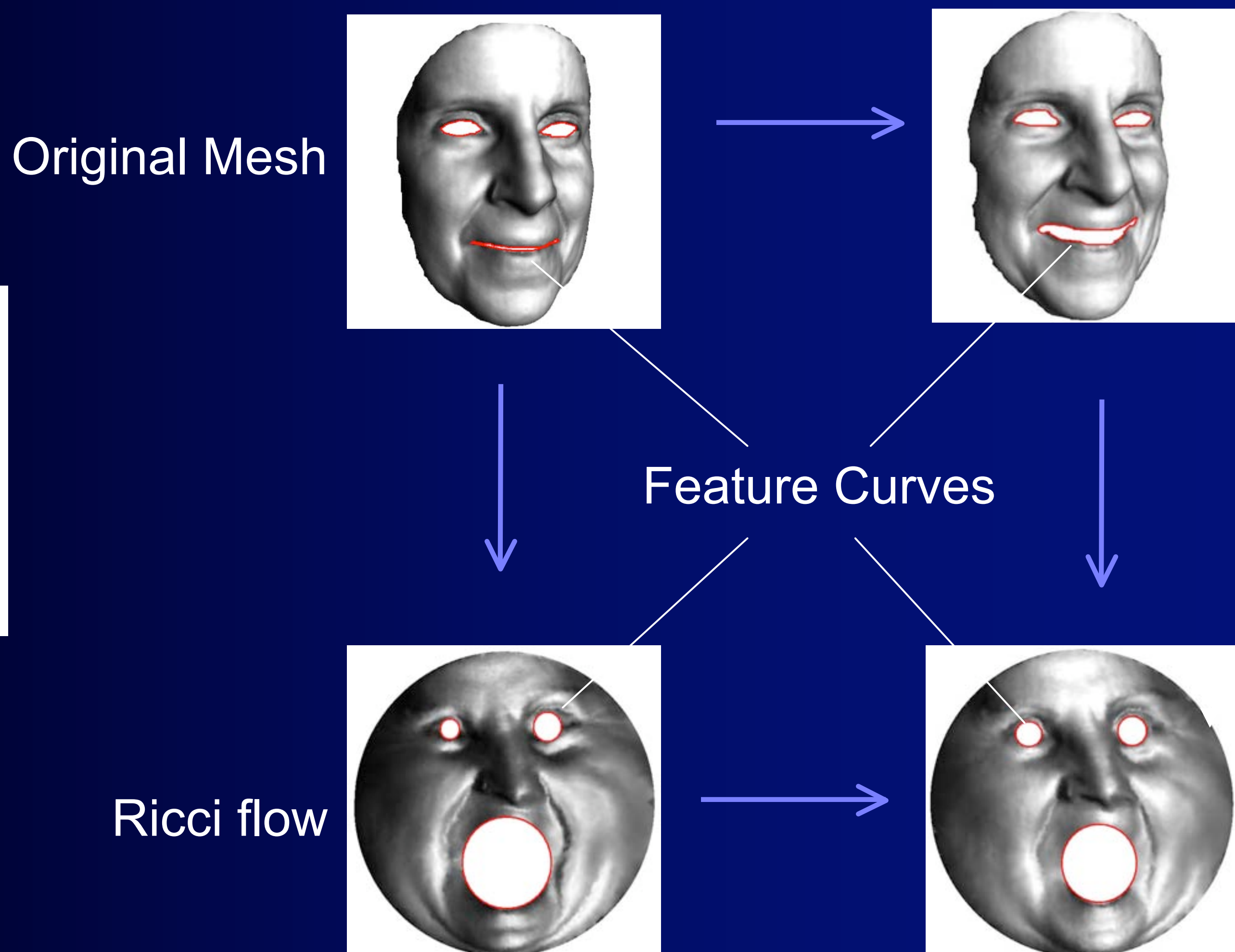
Newton's Method:
Hessian matrix of

Circle Packing Metric: each vertex of the mesh is the center of a circle, edge length is a function of circle radii ***r***, We can define

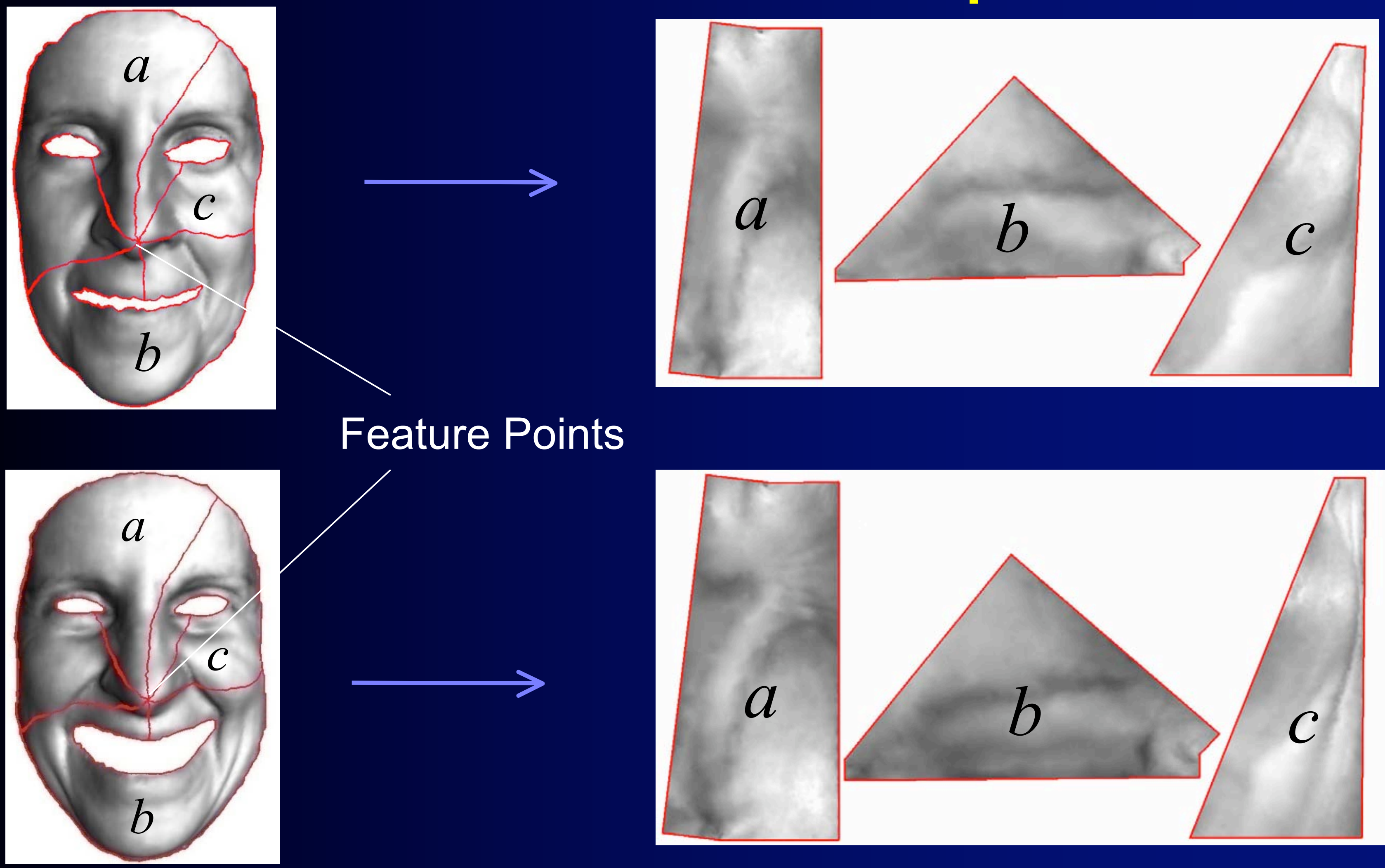


Surface Matching Using Ricci Flow with Feature Constraints





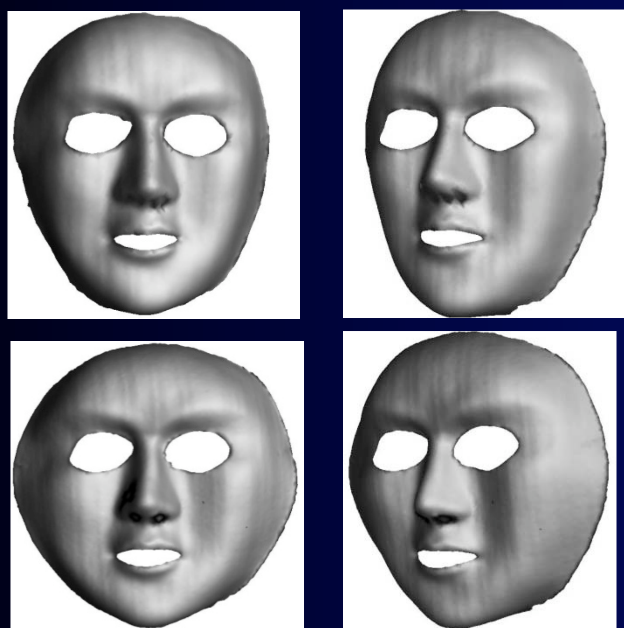
Shape Registration Using Feature Based Domain Decomposition



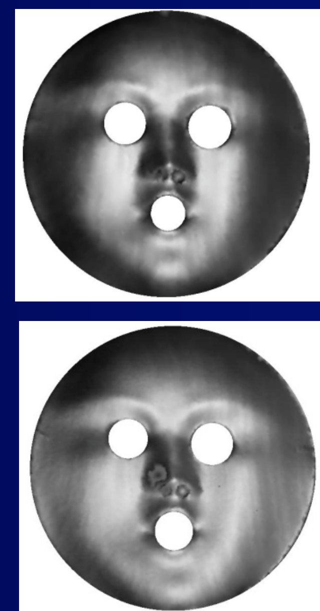
We randomly perturb the feature point around the nose tips. The average error of three different perturbations within a 3mm (resp. 6mm) radius is 0.045 (resp. 0.048).

Ricci Flow Invariance

Original Mesh



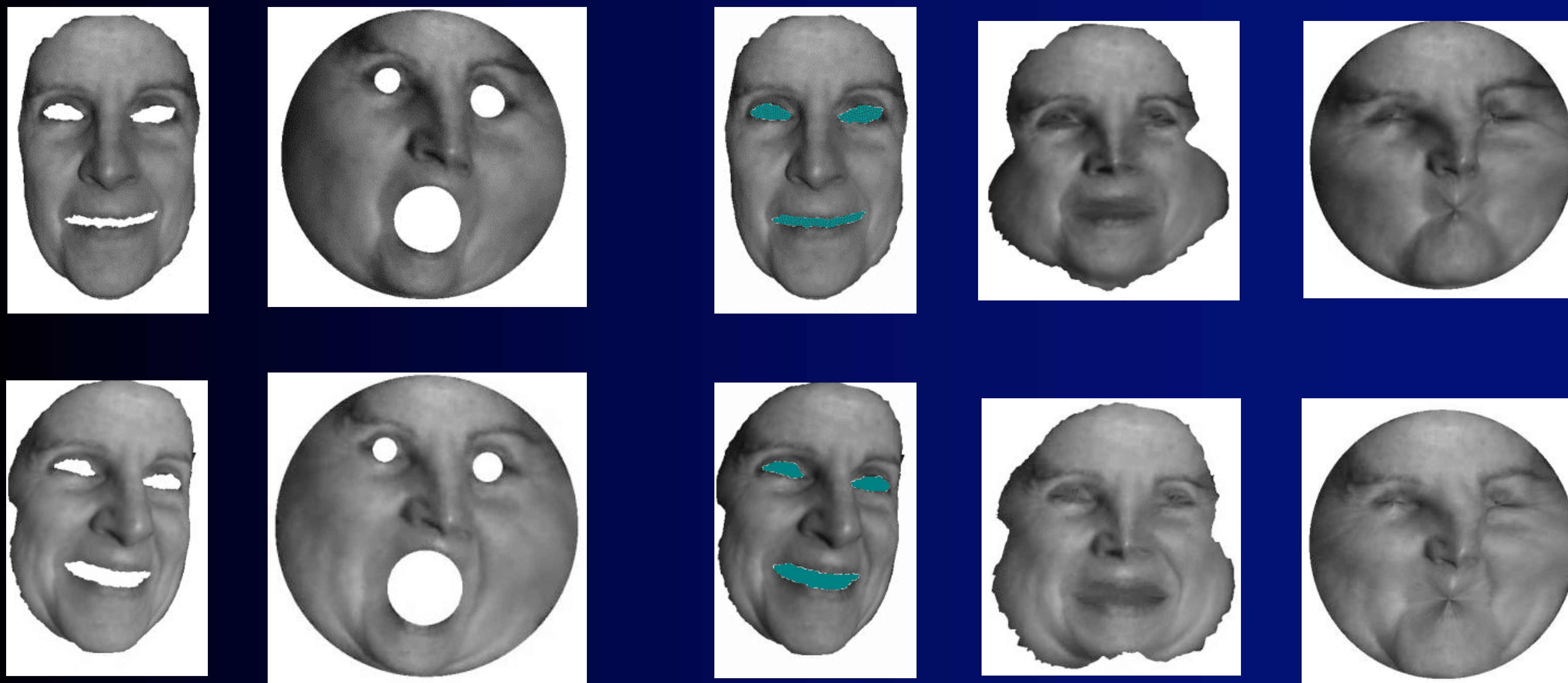
Ricci flow



Ricci flow is intrinsic: invariant under isometric, scaling, conformal deformations.

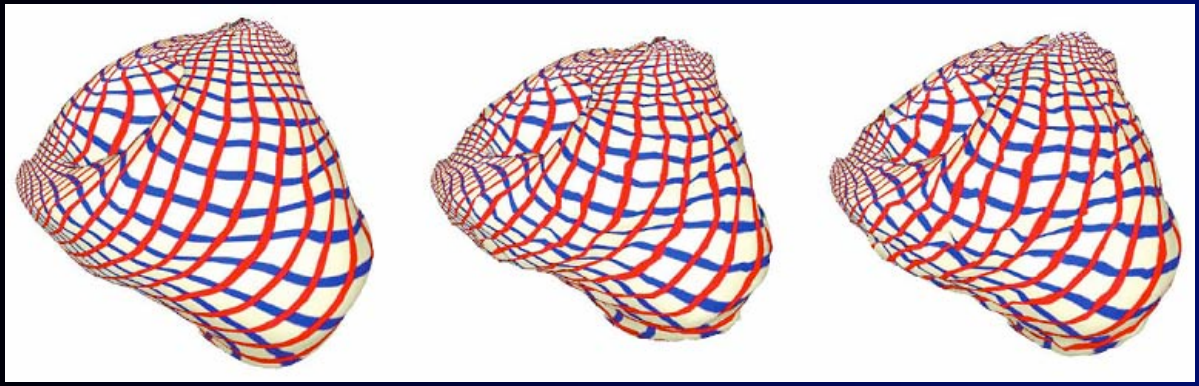
Comparing Ricci Flow

Original Mesh | Ricci Flow | Original Mesh with Hole Filling | LCSM | Harmonic Map

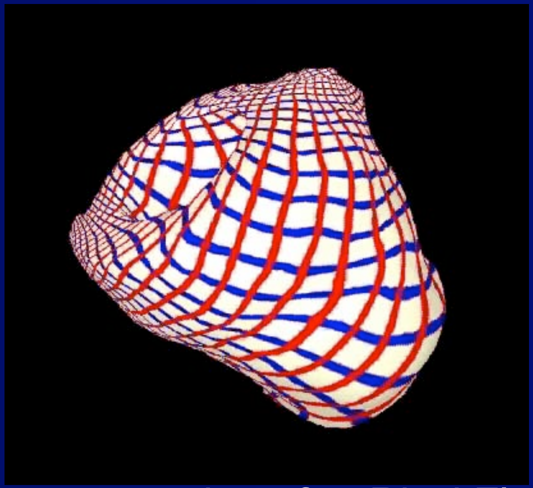


The registration error of Ricci flow is 0.0584, while, the registration errors (without including hole area) of LSCMs and Harmonics are 0.0723 and 0.0814, respectively.

Dynamic Heart Registration

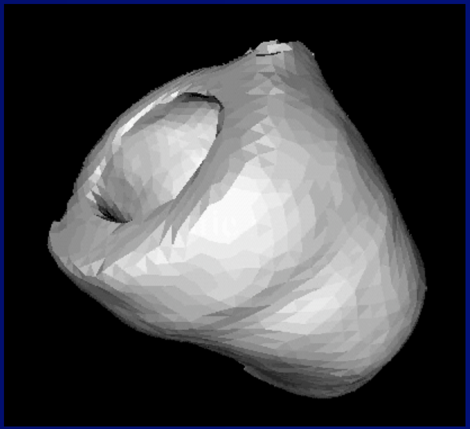


Result by Ricci Flow



Texture mapping after Ricci Flow

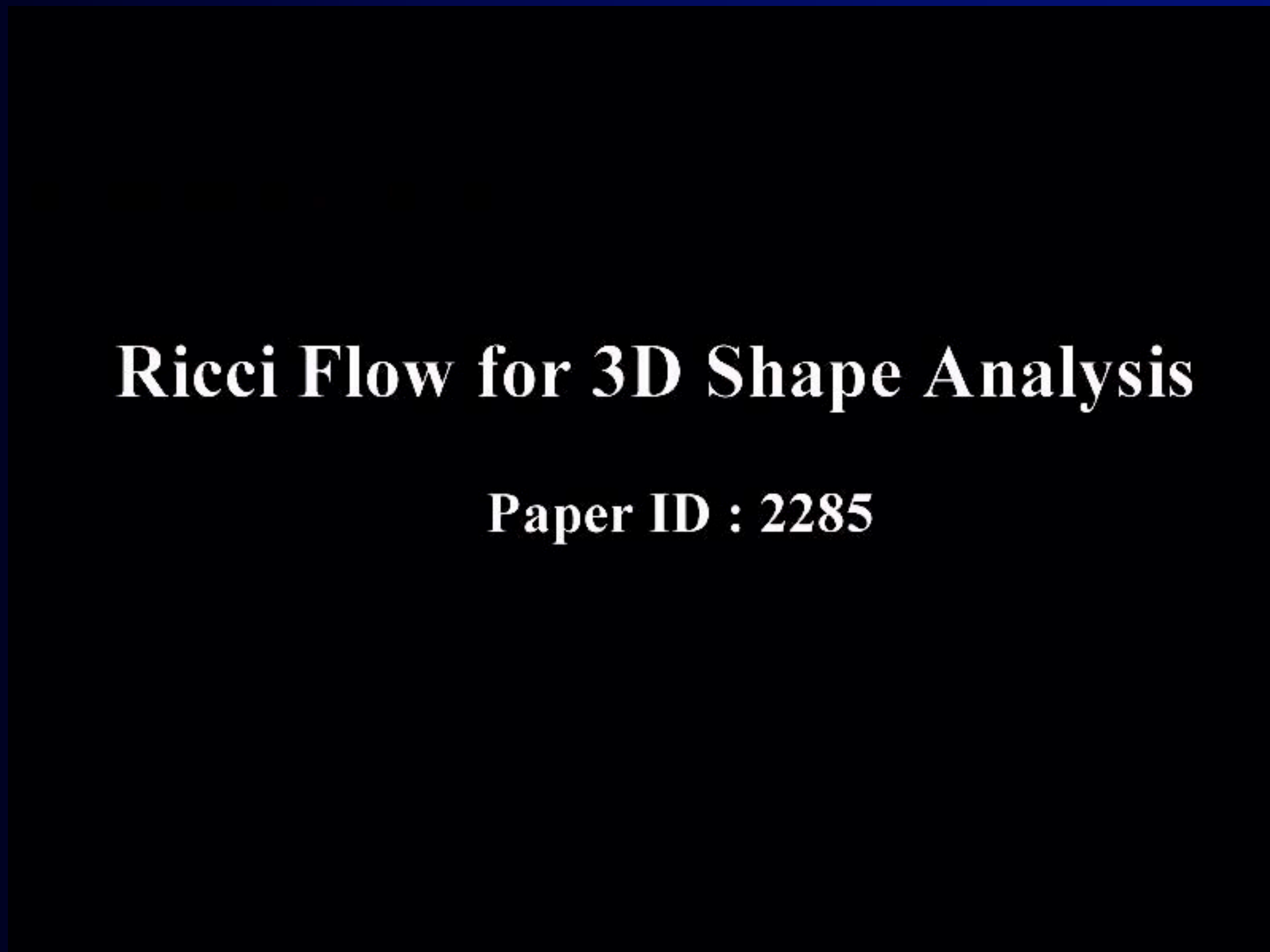
Result from Ground Truth



Dynamic heart data with shading

Data courtesy of D. Metaxas

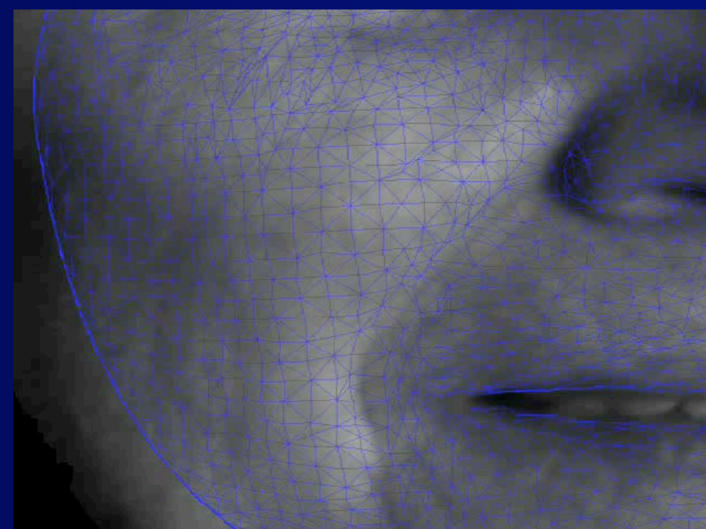
Ricci Flow for Shape Analysis



Harmonic Mapping for Deformable Registration

- Problem statement:

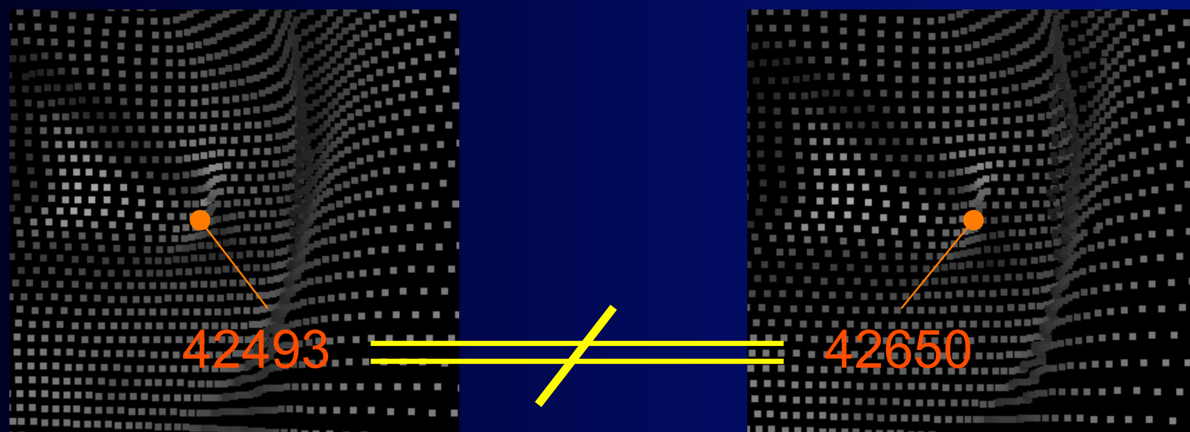
Dense point clouds of moving 3D geometry sampled at video rate → Track the subtle details of the non-rigid motion



- Harmonic maps : Tool for surface parameterization

Issues

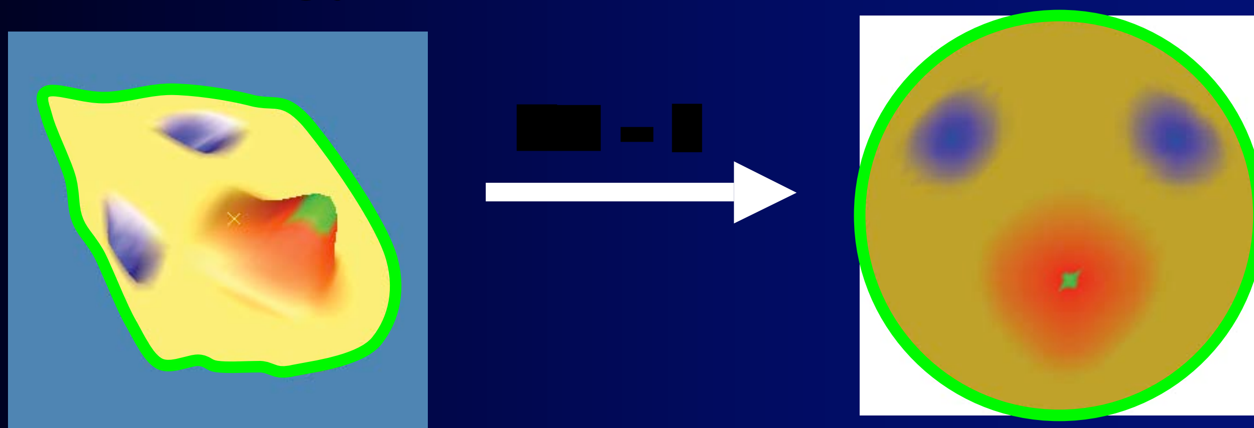
- Original data are not registered in object space



  - Number of data samples
  - Relative positions of the samples on the surfaces
- Non-rigid: All the points might have different motion vectors and velocities

Overview of Harmonic Maps

- H : M -> D, mapping from a manifold M with disk topology to a planar domain D.



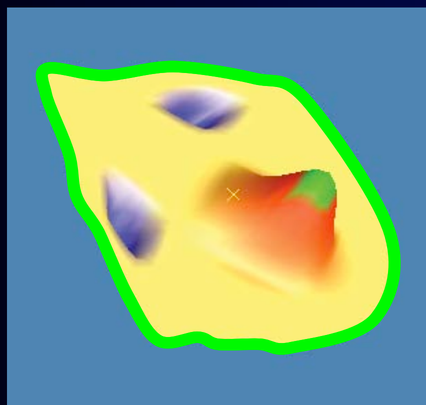
  - Obtained by minimizing the harmonic energy function: [redacted]
  - Uniquely determined if the boundary condition is given: [redacted]

Harmonic Maps for Tracking

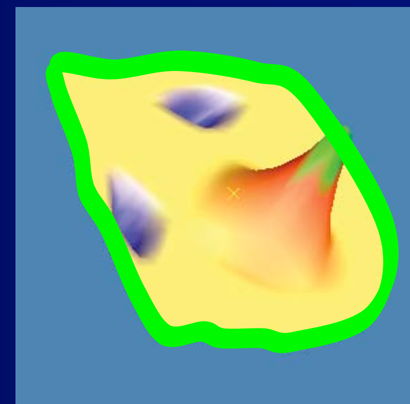
- Motivation: A common parametric domain for the source and the target frame
- Align the harmonic maps of the source and target frames for dense registration
  - Additional motion-representative, feature correspondence constraints
  - Soft boundary constraint (Neumann Condition)
    - Boundary points 'adjusted' to minimize the harmonic energy

Harmonic Map as a 'Rubber Sheet'

(M – Source Manifold, D – Target Disk)

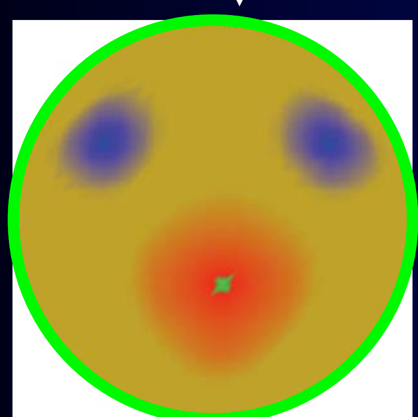


Initial Surface

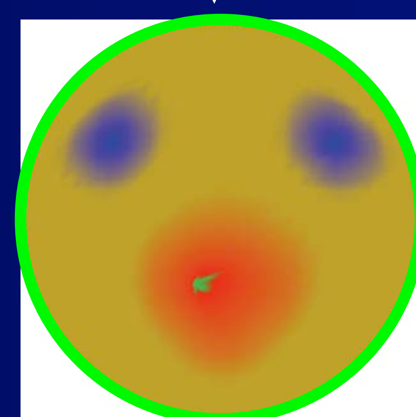


After Non-Rigid Deformation

Boundary Constraint Only

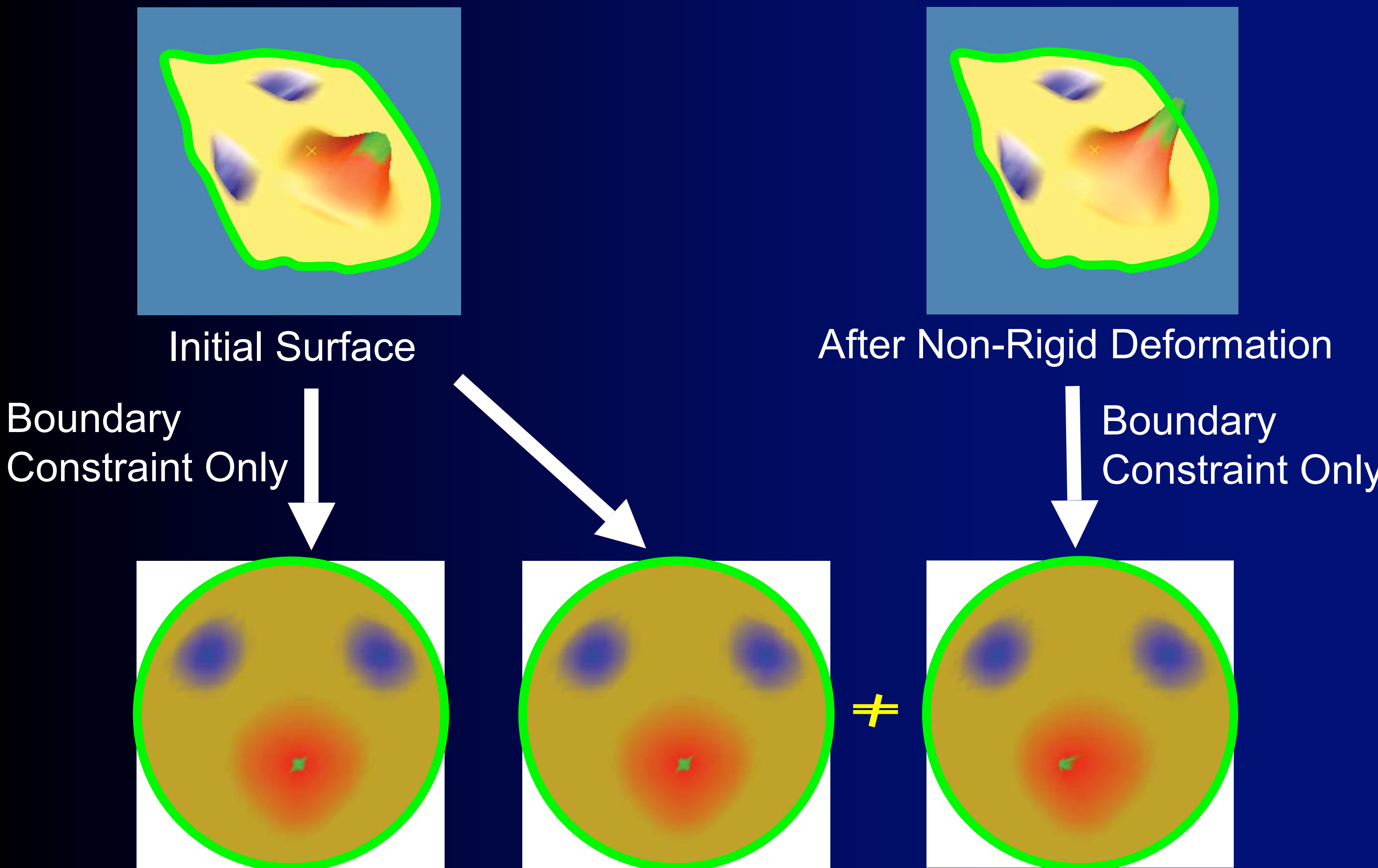


Boundary Constraint Only



Harmonic Map as a ‘Rubber Sheet’

(M – Source Manifold, D – Target Disk)



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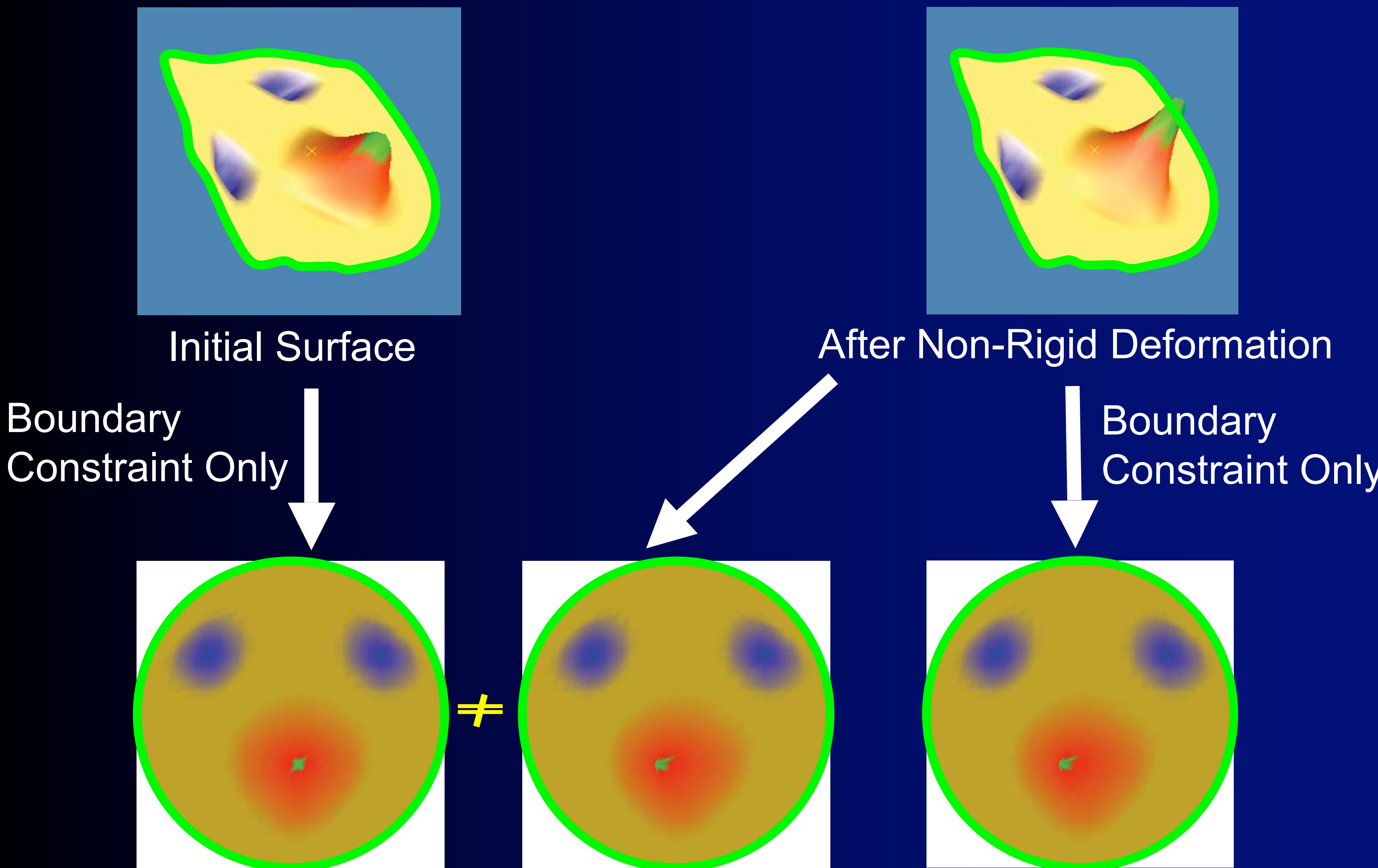

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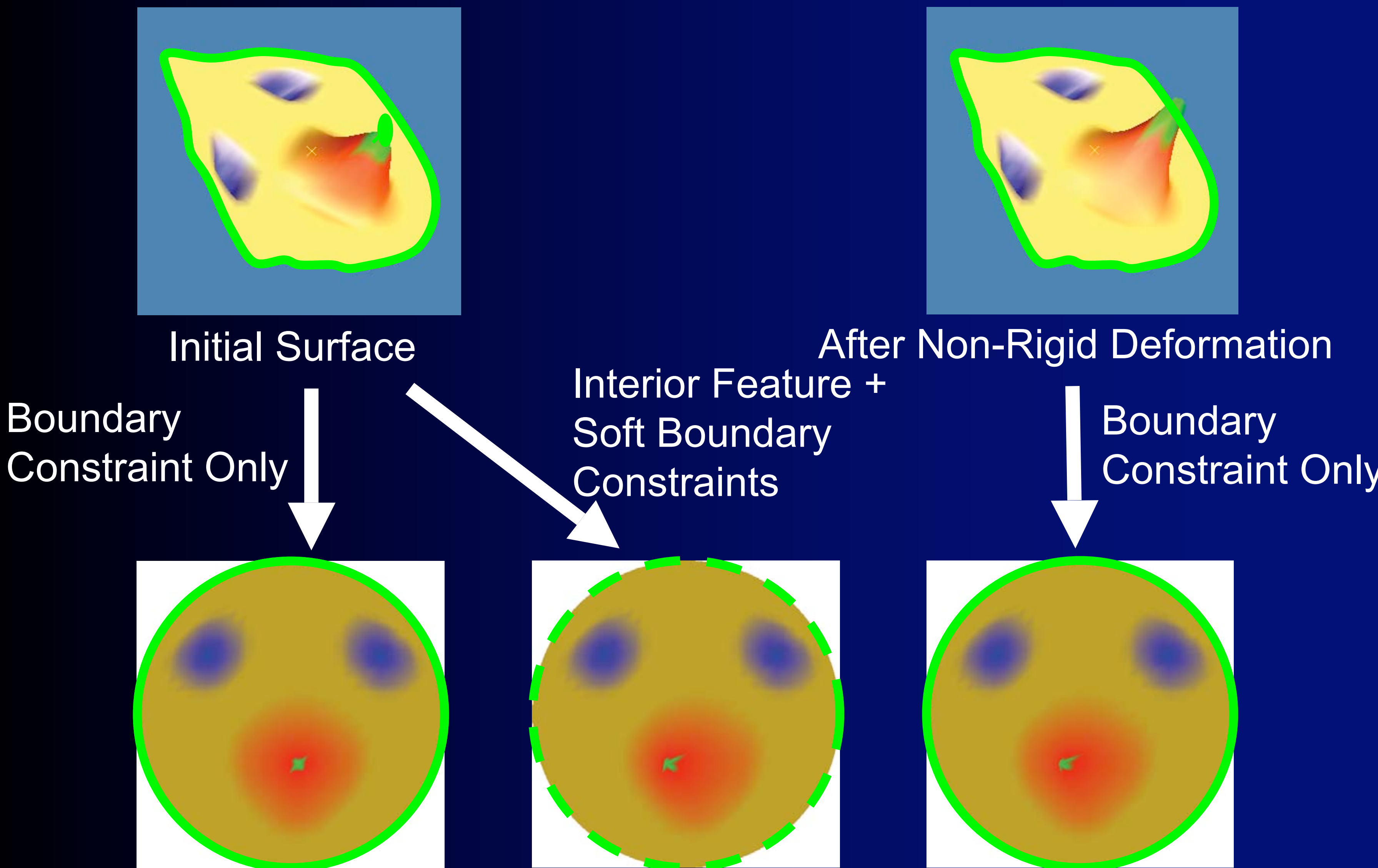


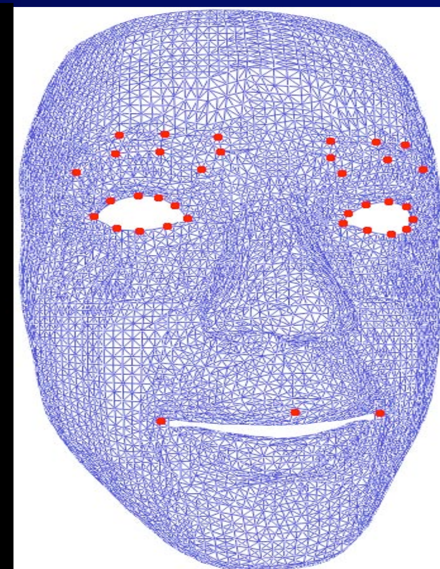
Merits of Our Method

- Minimal manual work involved
- Novel use of conformal geometry theory to non-rigid 3D tracking
  - Combining 2D appearance and 3D geometric features
- High precision tracking
- Ability to capture subtle expression details

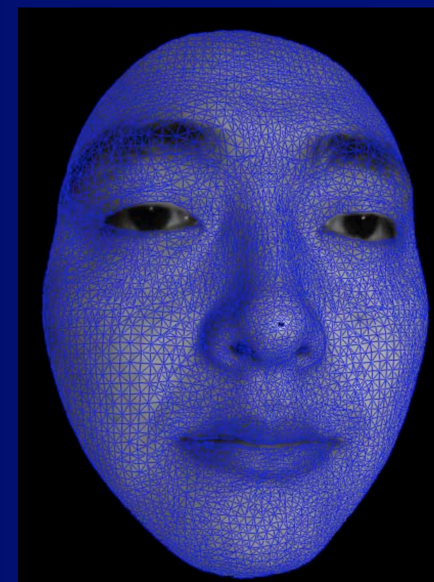
Example of Initial Fitting

Acquired 3D face scan data

3D face data with identified boundary (marked in green)



Generic face model with manually selected feature points (marked as red dots)

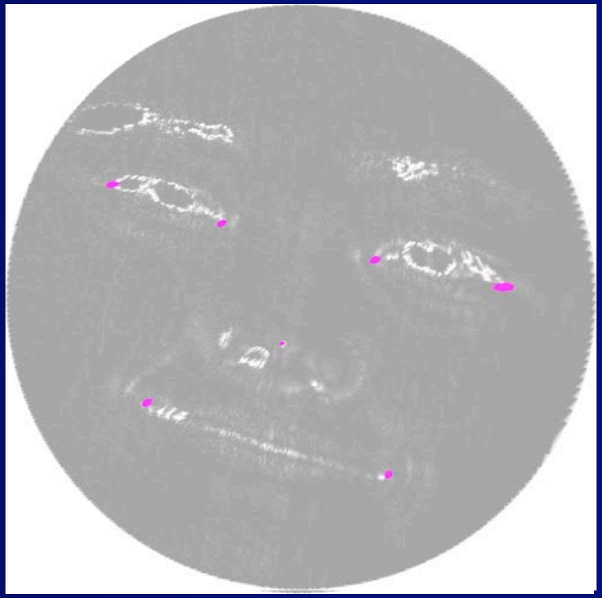


Result of the initial fitting to the 3D face scan data

Example of Motion Representative Features

Acquired 3D face scan data

Harmonic map with texture information

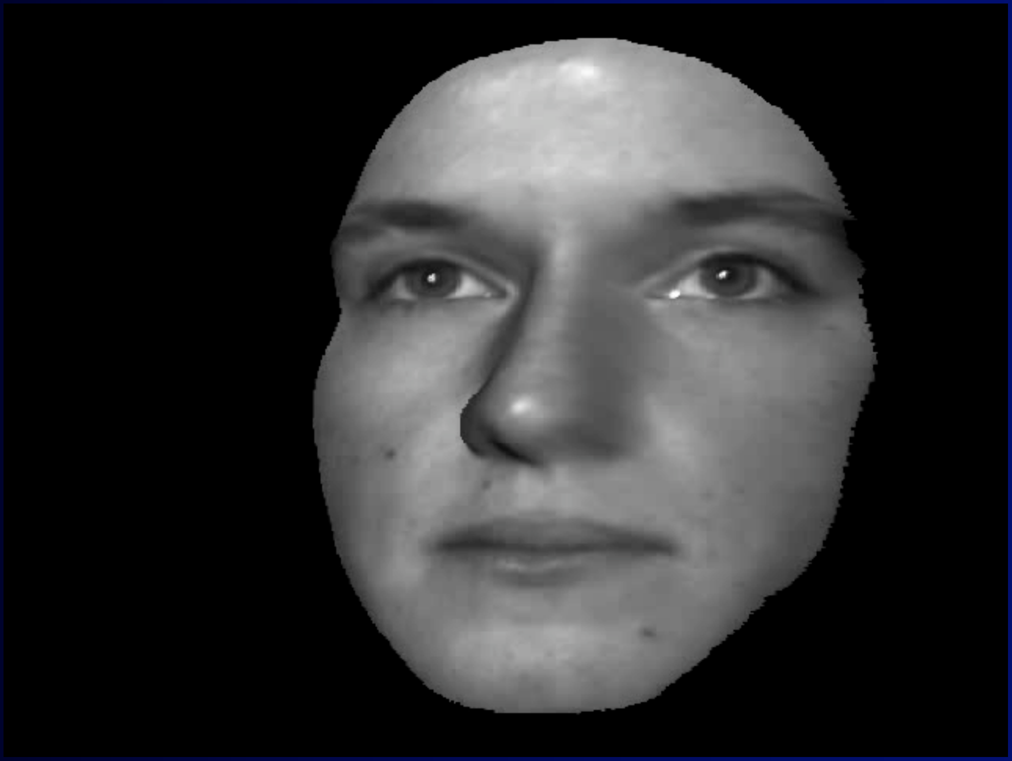


Harmonic map with curvature information

brighter intensity -> higher curvature

No Prior Expression Model Needed

- Asymmetric Smile / Smirk



Non-Disk Topology

- Big Smile with Mouth Opening

A Graphics Question:

- Joint work with Ahmed Elgammal, Dimitris Metaxas and their students in Rutgers

Geometry
of Subject 1

+

Expression
of Subject 2

= ?

How can Subject 1 smile "like" Subject 2?

Facial expression space

- A low dimensional manifold due to
  - Physical body constraints
  - Temporal constraints
- Different manifolds correspond to different people
  - Discover the underlying unified manifold
    - (LLE dimensionality reduction)
  - Decompose orthogonal factors
    - Content (expression configuration):
      - Characterizes the dynamics of the expression
      - Intrinsic facial configuration throughout the expression
      - Person invariant function of time
    - Style (people):
      - Characterizes the personal style of performing the expression
      - Time-invariant person parameters

Expression transfer

+

=

Geometry:
Subject 1

Style:
Subject 2

Subject 1 with synthetic smile transferred from Subject 2

Expression transfer

+

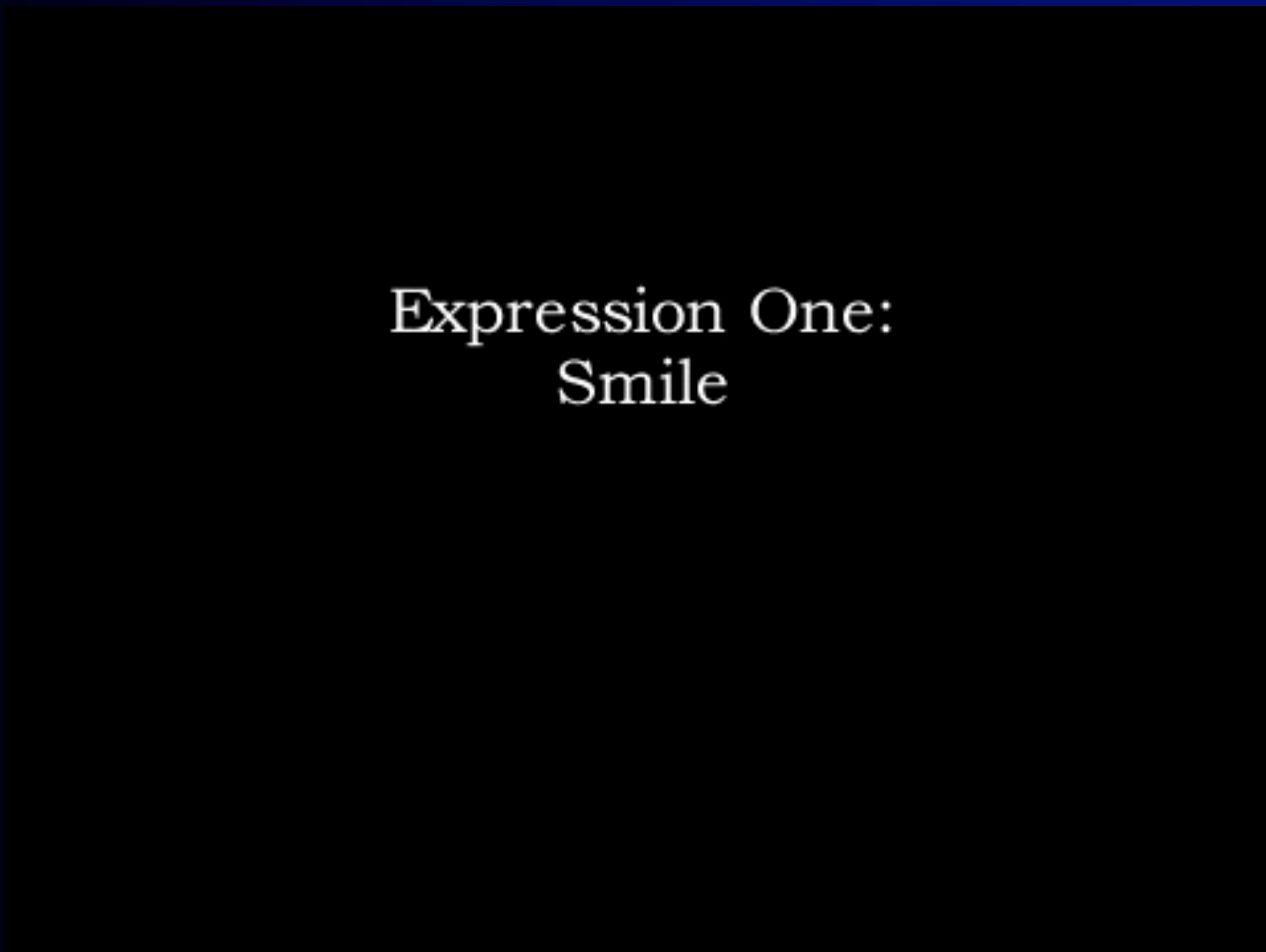
=

Geometry:
Subject 1

Style:
Subject 2

Subject 1 with synthetic smile transferred from Subject 2

Expression transfer demo



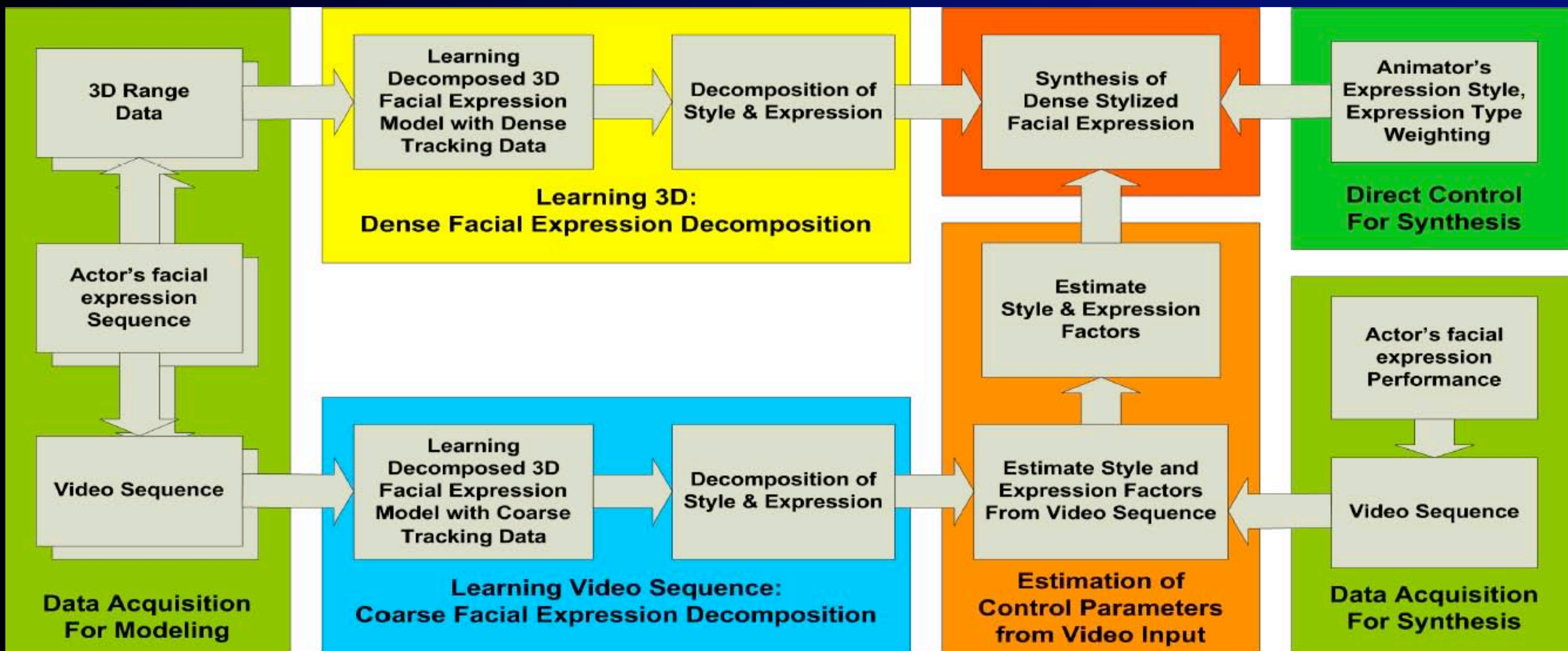
Expression and geometry morphing demo

Morphing of expression
and geometry from
Subject2 to Subject1

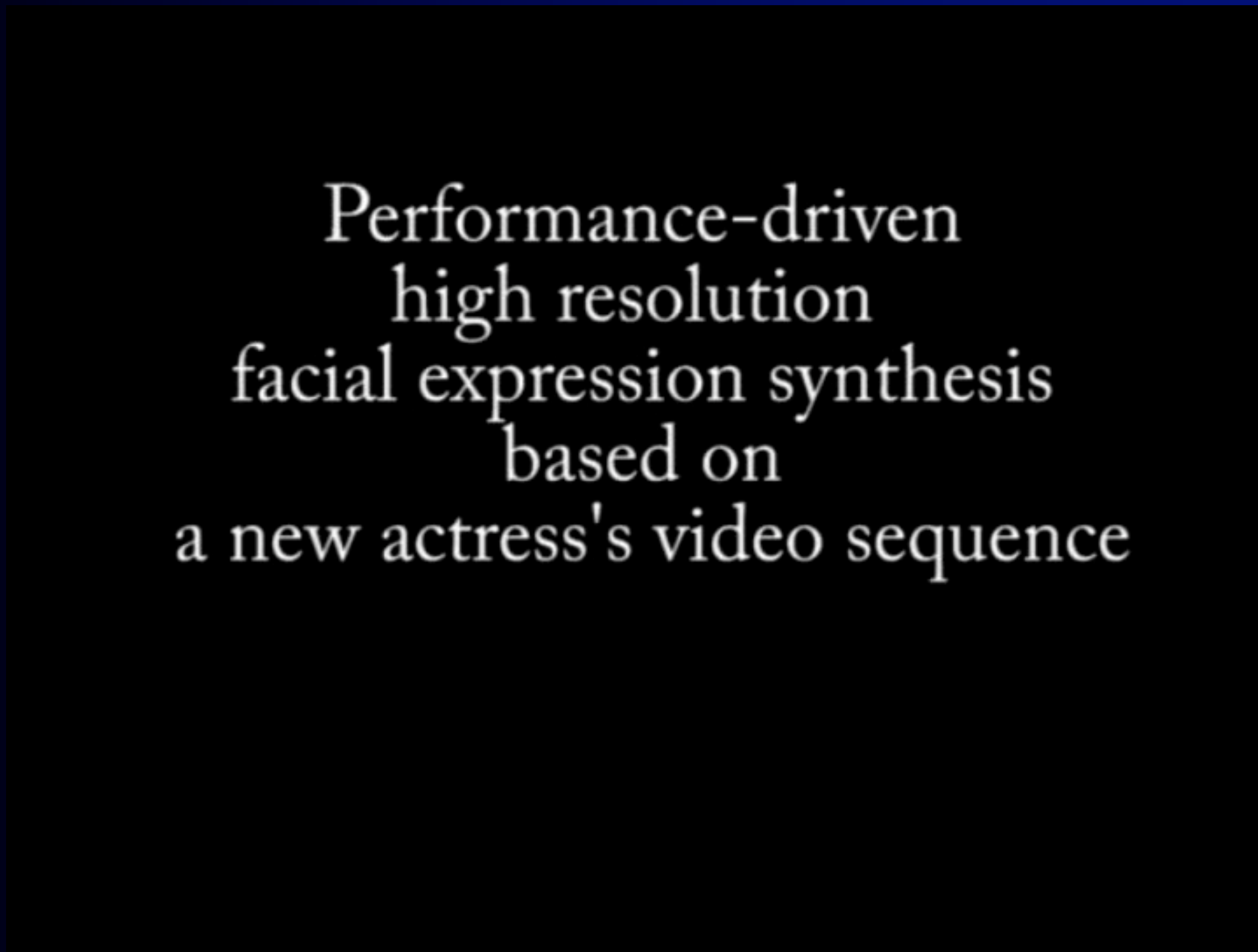
Video-based Synthesis

- We cannot get this level of detail from Video
- "Coarse" tracking loses expression subtlety
  - Cue integration on ASM models
- We can still drive a high-res model from low res input
- Possibly different manifolds from different inputs
  - Conceptually homeomorphic to a circle
- Decomposable Nonlinear Generative Models in Multiple People and Expressions
  - Multi-linear tensor analysis combined with a kernel map

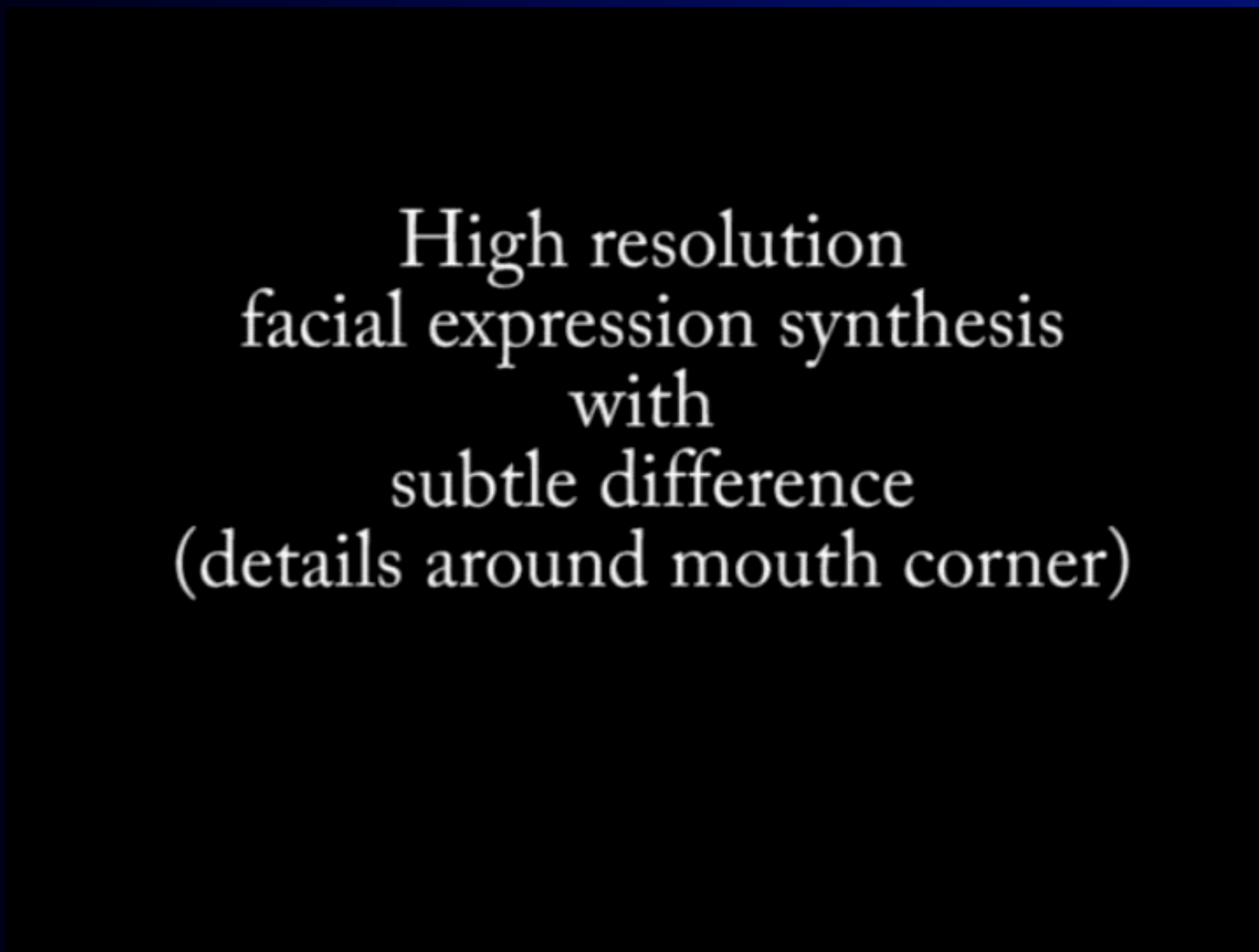
The Pipeline



Video-driven synthesis across subjects



Comparison between two different driving video performances



Conclusions

- New class of motion data poses new challenges and opportunities
- Very accurate and automatic tracking through conformal geometry
- Creation of expression databases is possible on which novel representations of style and content can be learned
- Transfer and Synthesis
- Open Question: how to incorporate intuitive animator control

Face Modeling and Analysis in Stony Brook University

STONY BROOK STATE UNIVERSITY OF NEW YORK

Computer Science

In Summary

STONY BROOK STATE UNIVERSITY OF NEW YORK