Nonrigid Surface Modelling and Fast Recovery

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Outline

- Introduction
- Two-stage Scheme with Active Appearance Models for nonrigid surface recovery
- Progressive Finite Newton Approach to nonrigid surface detection
- Conclusion

Introduction

- Nonrigid surface modelling and detection are essentially the computer vision tasks in a variety of applications:
  – image alignment
  – medial imaging
  – augmented reality
  – human computer interaction
  – digital entertainment

Nonrigid Surface Modelling

- Data embedding: Principal Component Analysis
  - Active Appearance Models
  - Active Shape Models
  - 3D Morphable Models
- Physical model: Finite Element Model (FEM)
  - Active Contours (Snakes)
- Thin-Plate Spline
  - TPS-RPM
  - Shape Context
  - Gaussian Mixture Models based points set registration

Nonrigid Surface Recovery

- Appearance-based Method
  - Also known as direct method
  - Lucas-Kanade algorithm based methods [LK IJCAI'81]
  - Active Appearance Models [Cootes PAMI'01]
  - 3D Morphable Models [Vetter Siggraph'99, PAMI'01]
  - 2D+3D AAMs [Xiao CVPR'04]
- Feature-based Method
  - Shape context [Belongie PAMI'02]
  - TPS-RPM [Hui CVIU'03]
  - Kernel correlation [ECCV'04]
  - Gaussian mixture models [Jian ICCV'05]
  - Semi-implicit optimization scheme [Pilet CVPR'05, IJCV'07]

Part I

A Two-stage Scheme for Nonrigid Surface Recovery with Active Appearance Models

Part I: Structure

- Motivation
- Extended Active Appearance Models (AAMs) fitting
- Two stage scheme for nonrigid surface recovery
  - Offline construction of 3D shape model
  - Estimate 3D pose and non-rigid shape parameters
- Experiemental Results
- Summary of Part I

Motivation

- Nonrigid shape recovery for Augmented Reality
  - Rigid Object
    - L. Vacchetti et al. (PAMI‘04) proposed an efficient solution for 3D rigid object tracking
    - Two 2D AAMs approach for rigid object pose estimation
  - Non-rigid Object
    - V.Blandz: 3D Morphable Models
    - J.Ahlberg: 3D AAM with generic Model.
    - Jing X. (CVPR‘05) 2D+3D AAM

Active Appearance Models

- AAMs is defined by its shape and texture

$$\mathbf{s} = (x_1, \ldots, x_n, y_1, \ldots, y_n)^{\mathbf{T}}$$

- The 2D shape and texture are controlled by a statistical model. They can be represented as a base plus a linear combination of variations:

$$\mathbf{s} = \bar{\mathbf{s}} + \mathbf{P_s b_s} \qquad \mathbf{s} = \bar{\mathbf{s}} + \mathbf{P_s W_s^{-1} P_{cs} c}$$

$$\mathbf{t} = \bar{\mathbf{t}} + \mathbf{P_t b_t} \qquad \mathbf{t} = \bar{\mathbf{t}} + \mathbf{P_t P_{ct} c}$$

- Direct Appearance Models $\mathbf{b_s} = \mathbf{P_{cs} P_{ct}^{+} b_t}$

$$\mathbf{s} = \bar{\mathbf{s}} + \mathbf{Q_s b_t} \qquad \mathbf{Q_s} = \mathbf{P_s W_s^{-1} P_{cs} P_{ct}^{+}}$$

$$\mathbf{t} = \bar{\mathbf{t}} + \mathbf{P_t b_t}$$

Extended AAMs Fitting Algorithm

- Object:

$$|| I - Im||$$

- Idea: the proposed approach predicts shape directly from texture

$$\delta \mathbf{t} = \mathbf{R}_{\mathbf{t}} \mathbf{r} \ ,$$

$$\delta \mathbf{b}_{\mathbf{t}} = \mathbf{R}_{\mathbf{g}} \mathbf{r} \ .$$

where r = g*i* -g*m*, is the residual image

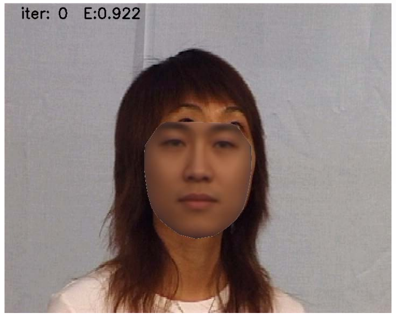
Extended AAM Fitting

The algorithm of AAM Matching

1. Generate texture vector $\mathbf{g}_m$ from model
2. Sample image below the model shape $\mathbf{g}_i$
3. Evaluate error vector $\mathbf{r} = \mathbf{g}_i - \mathbf{g}_m$ and error $\mathbf{E} = |\mathbf{r}|$
4. Compute displacements in pose $\delta\mathbf{t} = \mathbf{R_t r}$
5. Compute displacements in texture $\delta\mathbf{b_t} = \mathbf{R_g r}$
6. Update pose and texuture parameters with initial $k = 1$
7. Transform the shape by the estimated parameters
8. Repeat step 1-3 to form a new error $\mathbf{E}^{'}$
9. If $\mathbf{E}^{'} < \mathbf{E}$ accept the new estimate,
   otherwise goto step 6 to try other k=0.5, 0.25, ...

AAM Fitting Sample

The AAMs are built up with 140 still face image belonging to 20 individuals, 7 images for each. The fitting experiment is performed on an AAM with 14 shape parameters, 68 texture parameters, and 36335 color pixels.



Two-stage Scheme Nonrigid Surface Recovery

- Training and building offline basis

  Acquire the 2D shape of objects using the AAM fitting algorithm, then construct the 3D shape basis.

- Online tracking
  - Step 1. 2D AAM fitting and tracking
  - Step 2. estimate the 3D pose and shape parameters simultaneously via local bundle adjustment by building up the point correspondences between 2D and 3D.

Building Offline 3D Model

- 3D shape

$$\mathbf{S} = \mathbf{S_0} + \sum_{i=1}^{m} p_i \mathbf{S_i} \qquad \mathbf{S}, \mathbf{S_i} \in R^{3\times n}, p_i \in R$$

- Weak-perspective projection

$$\begin{bmatrix} u_1 & u_2 & \cdots & u_n \\ v_1 & v_2 & \cdots & v_n \end{bmatrix} = \mathbf{R} \cdot (\sum_{i=0}^{m} p_i \mathbf{S_i}) + \mathbf{T}$$

Building Offline 3D Model

- Factorization method [Bregler CVPR'00, CVPR'01]

$$W = \begin{bmatrix} u_1^1 & u_2^1 & \cdots & u_n^1 \\ v_1^1 & v_2^1 & \cdots & v_n^1 \\ \vdots & \vdots & \vdots & \vdots \\ u_1^N & u_2^N & \cdots & u_n^N \\ v_1^N & v_2^N & \cdots & v_n^N \end{bmatrix} = \underbrace{\begin{bmatrix} \mathbf{R}_1 & p_1^1\mathbf{R}_1 & \cdots & p_m^1\mathbf{R}_1 \\ \mathbf{R}_2 & p_1^2\mathbf{R}_2 & \cdots & p_m^2\mathbf{R}_2 \\ \vdots & \vdots & \vdots & \vdots \\ \mathbf{R}_N & p_1^N\mathbf{R}_N & \cdots & p_m^N\mathbf{R}_N \end{bmatrix}}_{\mathbf{M}} \cdot \underbrace{\begin{bmatrix} \mathbf{S_0} \\ \mathbf{S_1} \\ \vdots \\ \mathbf{S_m} \end{bmatrix}}_{\mathbf{B}}$$

$$\mathbf{M} = \tilde{\mathbf{M}} \cdot \mathbf{G}$$

$$\mathbf{B} = \mathbf{G}^{-1} \cdot \tilde{\mathbf{B}}$$

Online Algorithm

- The optimization problem can be derived as:

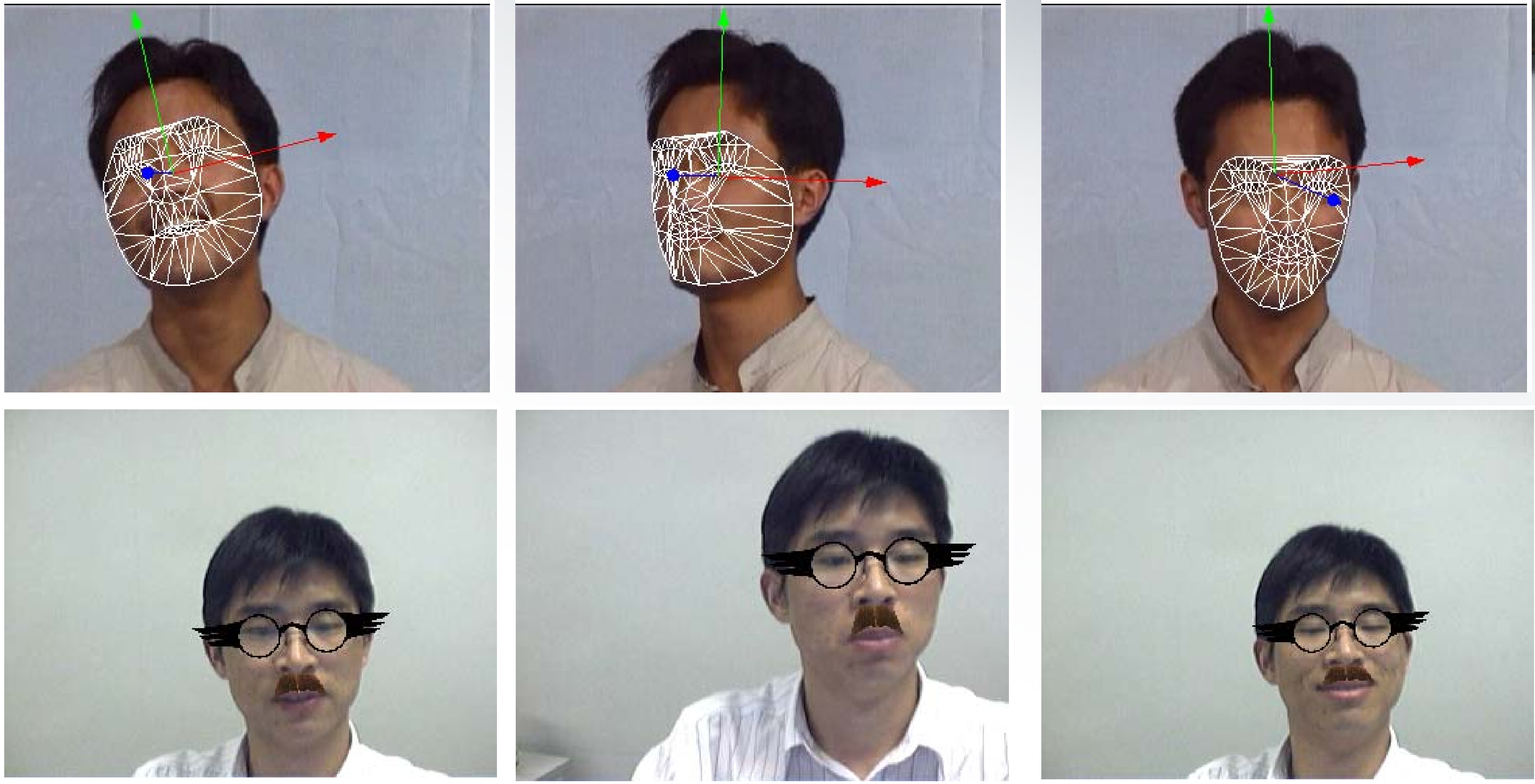
$$\min_{\mathbf{R},\mathbf{T},p} \rho\left(\mathbf{s}, \phi\left(\mathbf{A}[\mathbf{R}|\mathbf{T}], \mathbf{S_0} + \sum_{i=1}^{m} p_i \mathbf{S_i}\right)\right)$$

where

$$\rho(u) = \begin{cases} \frac{\alpha^2}{6}[1-(1-(\frac{u}{\alpha})^2)^3], & |u| \le \alpha \\ \frac{\alpha^2}{6}, & |u| > \alpha \end{cases}$$

$\phi\left(\mathbf{A}[\mathbf{R}|\mathbf{T}], \mathbf{S_0} + \sum_{i=1}^{m} p_i \mathbf{S_i}\right)$ denotes the projection of 3D shape given the parameters A, R and T.

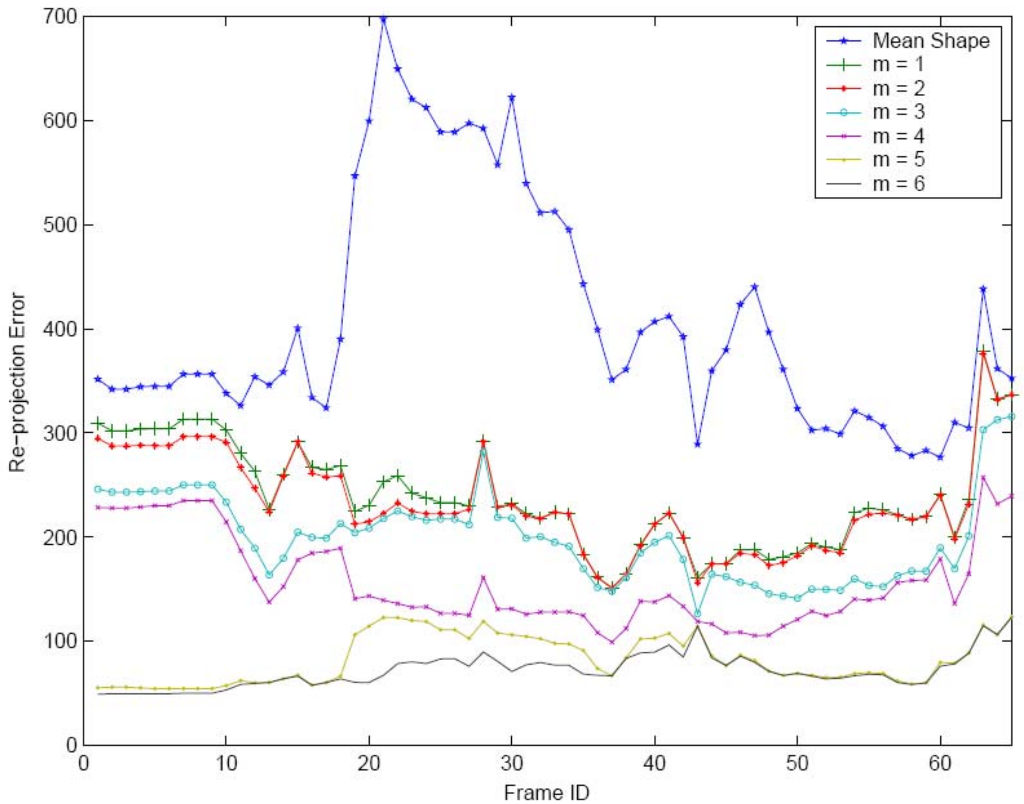
Experiemental Results I



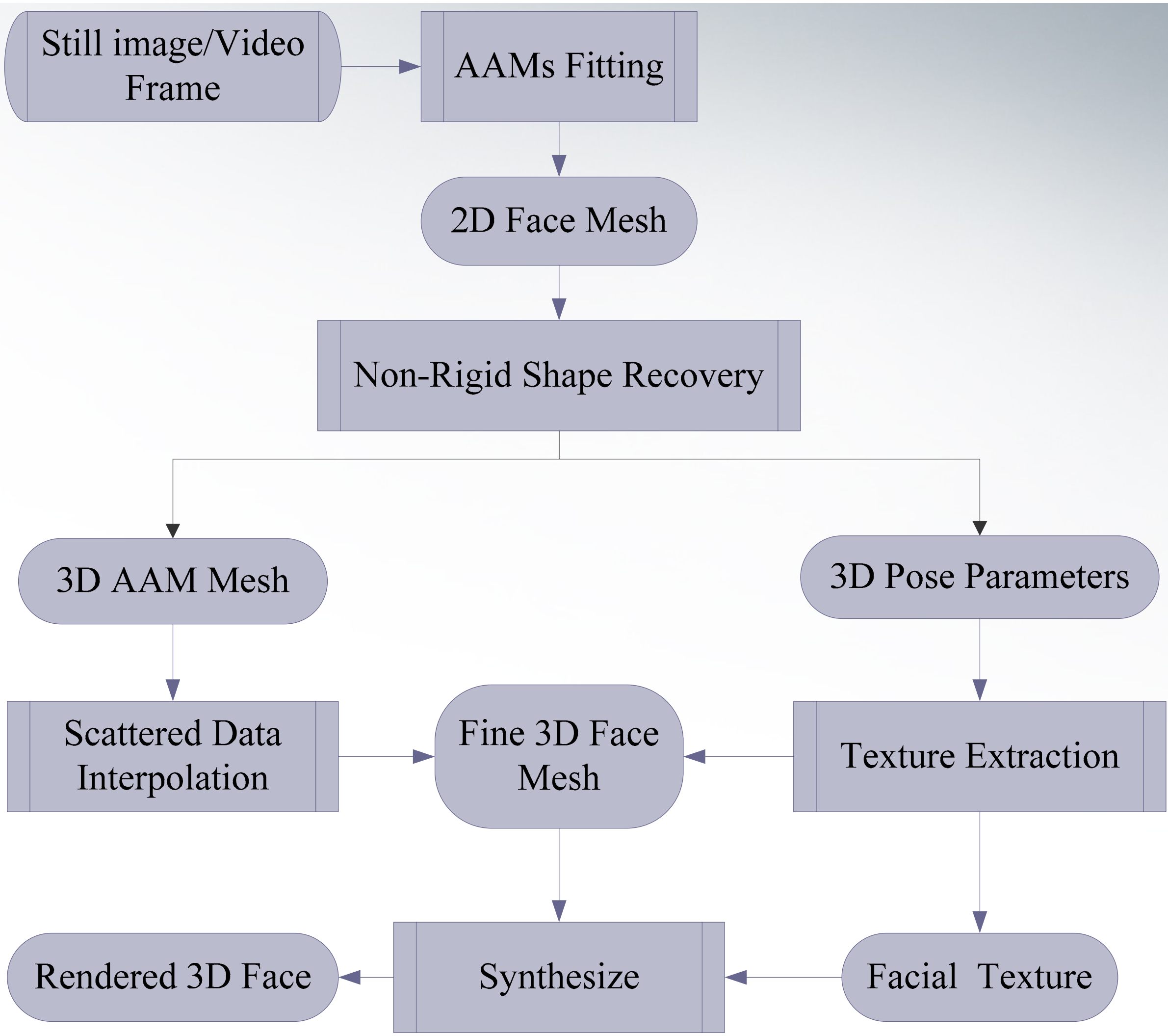
Pentium III 1GHz CPU, 200ms per image of size 352x288. AAM fitting takes 40ms and 3D recovery step takes 74ms. The AAM with 10 shape parameters, 52 texture parameters. 6 camera parameters and 6 3D shape parameters.

Experimental Results II

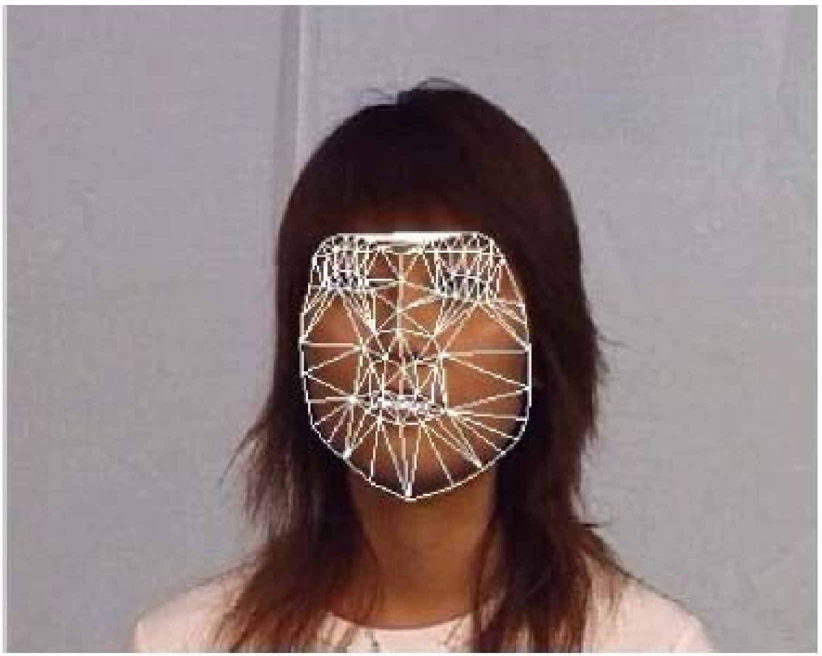
- Determine the number of 3D shape basis

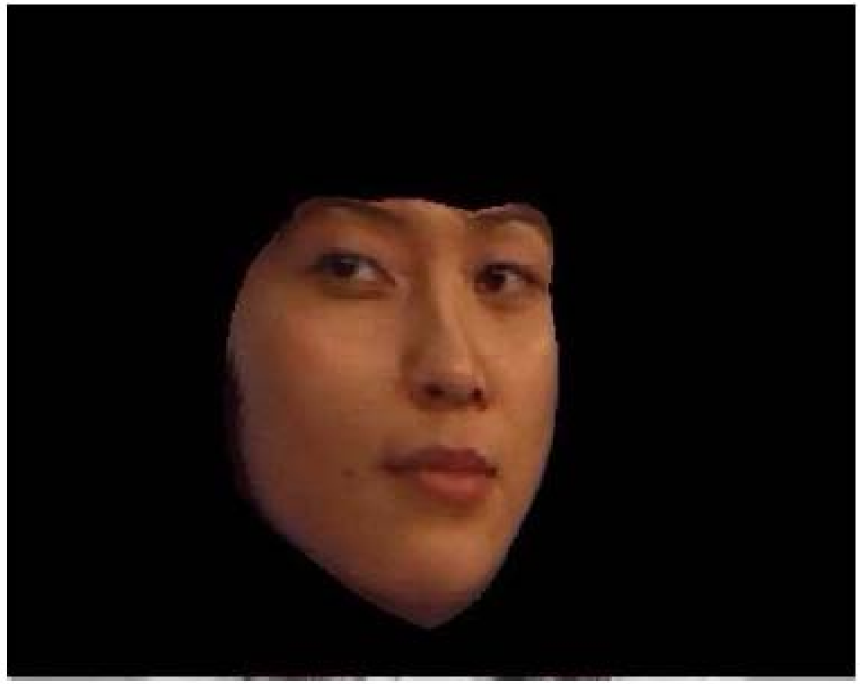


Automatic Face Modelling Scheme

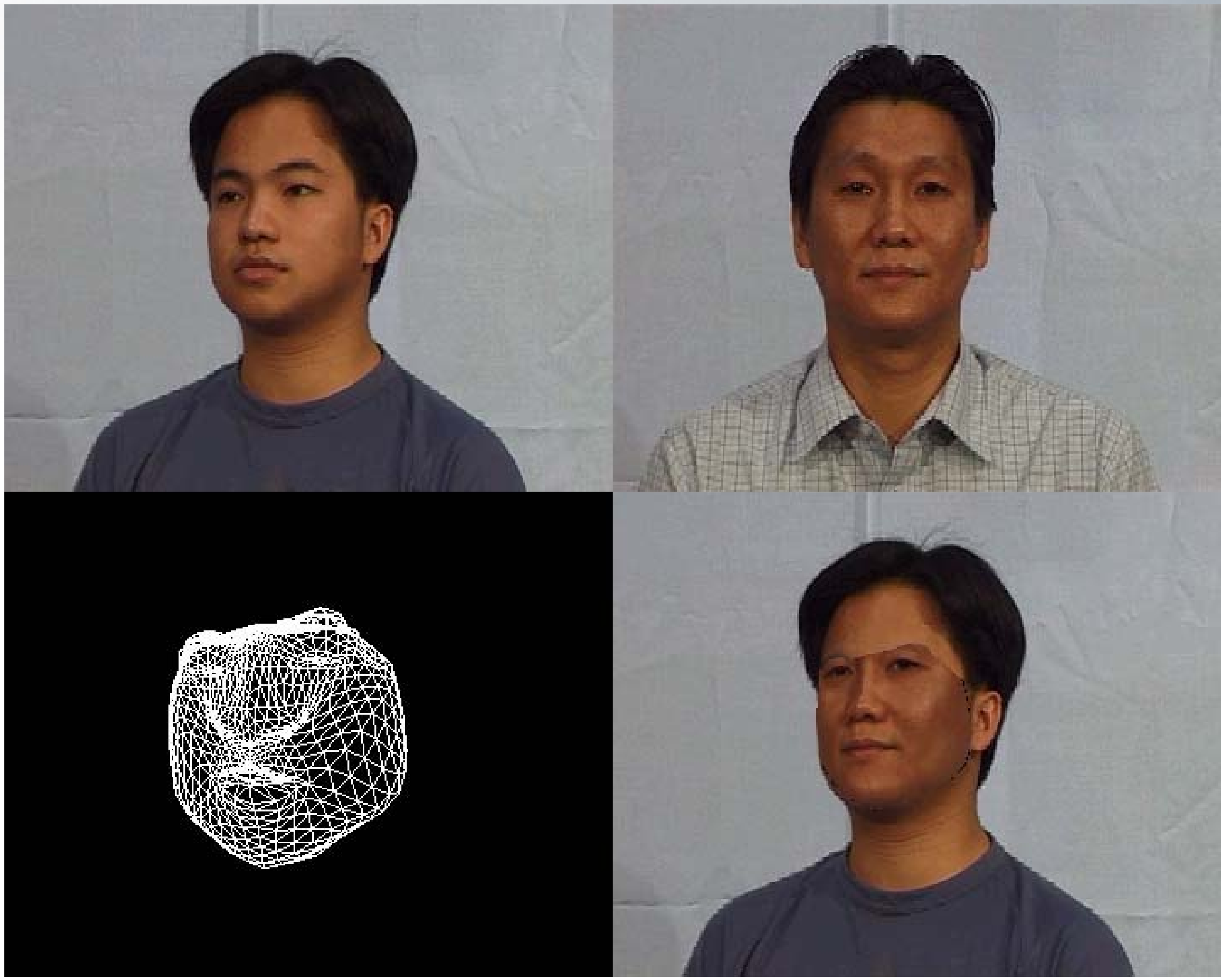


Rendering in Different View





Re-texturing face



Discussion

- Rigid vs. Non-Rigid
  - The prior model employed by L. Vacchetti et al. is only for rigid objects or deformable objects with small variations.
  - P. Mittrapiyanumic et al. do not take full advantage of AAM's deformation power
- Offline vs. Online
  - In contrast to the offline algorithms, our proposed method is able to work online by exploiting the 3D shape models that can be constructed offline effectively by AAM tracking
- Advantages for AR applications
  - Generic vs. person specific: handle large texture variations, fitting to different individuals
  - Combined 2D+3D AAM: weak-perspective model
- Disadvantages and Future Work
  - does not take full advantage of 3D information for speeding up AAM convergence.
  - Large rotation may be compensated by the 3D linear mode, therefore, the estimated pose is not so accurate.
  - Training the 3D AAM with the aligned 3D shapes instead of 2D shapes.

Summary of Part I

- A novel two-stage scheme for online non-rigid shape recovery toward Augmented Reality applications using AAMs.
- Obtain unbroken point correspondences across multiple frames to construct 3D shape models
- Provide 2D to 3D vertex correspondences in the online tracking.
- An efficient algorithm is proposed to estimate both 3D pose and non-rigid shape parameters via local bundle adjustment.

Part II

Progressive Finite Newton Approach to Nonrigid Surface Detection

Part II: Structure

- Motivation
- Progressive Finite Newton Approach to nonrigid surface detection
  - 2D nonrigid surface model
  - Feature-based nonrigid surface recovery
  - Finite Newton formulation
  - Optimization
- Experiemental Results
  - Computational efficiency and nonrigid surface detection
  - Augmented reality
  - Medical image registration
- Summary of Part II

Motivation

- **Nonrigid surface detection**: recovering the explicit surface with a few deformation parameters and finding out the correct correspondences from noisy data simultaneously.
- Unlike the rigid object, it is difficult to directly employ a robust estimator to remove the spurious matches for nonrigid surface detection.
- The iterative methods, such as TPS-RPM [CVIU’03] and Shape Contex [PAMI’02], are either sensitive to initial conditions and parameter choices, or involve too many iterations and a complex optimization procedure.
- Semi-implicit method: an automated approach, and can be applied for the real-time Augmented Reality. [Pilet et al CVPR’05, IJCV’07]

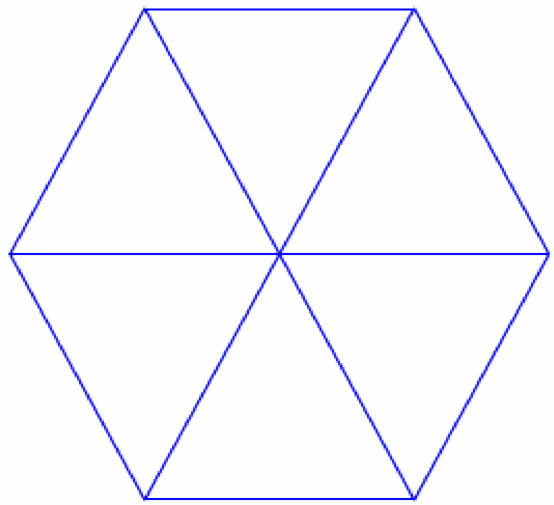
Robust Methods

- RANSAC
- PROSAC
- M-estimator
- Hough transform

2D Nonrigid Surface Model

$$\mathbf{s} = \begin{bmatrix} \mathbf{x} & \mathbf{y} \end{bmatrix}^\top = \begin{bmatrix} x_1 & x_2 & \dots & x_N & y_1 & y_2 & \dots & y_N \end{bmatrix}^\top$$

$$T_{\mathbf{s}}(\mathbf{m}) = \begin{bmatrix} x_i & x_j & x_k \\ y_i & y_j & y_k \end{bmatrix} \begin{bmatrix} \xi_1 & \xi_2 & \xi_3 \end{bmatrix}^\top$$



Where (ξ_1, ξ_2, ξ_3) are the barycentric coordinates for the point m.

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Nonrigid Surface Recovery

- Energy function

$$E(\mathbf{s}) = E_e(\mathbf{s}) + \lambda_r E_r(\mathbf{s})$$

  - Ee(s) is the sum of the weighted square error residuals for the matched points.

$$E_e(\mathbf{s}) = \sum_{\mathbf{m} \in M} \omega_{\mathbf{m}} \mathcal{V}(\delta, \sigma)$$

  - *Er*(s) is the regularization term that represents the surface deformation energy
  - λ_r is a regularization coefficient.

Regularization Term

- Er(s), also known as internal force in Snakes, is composed of the sum of the squared second-order derivatives of the mesh vertex coordinates.

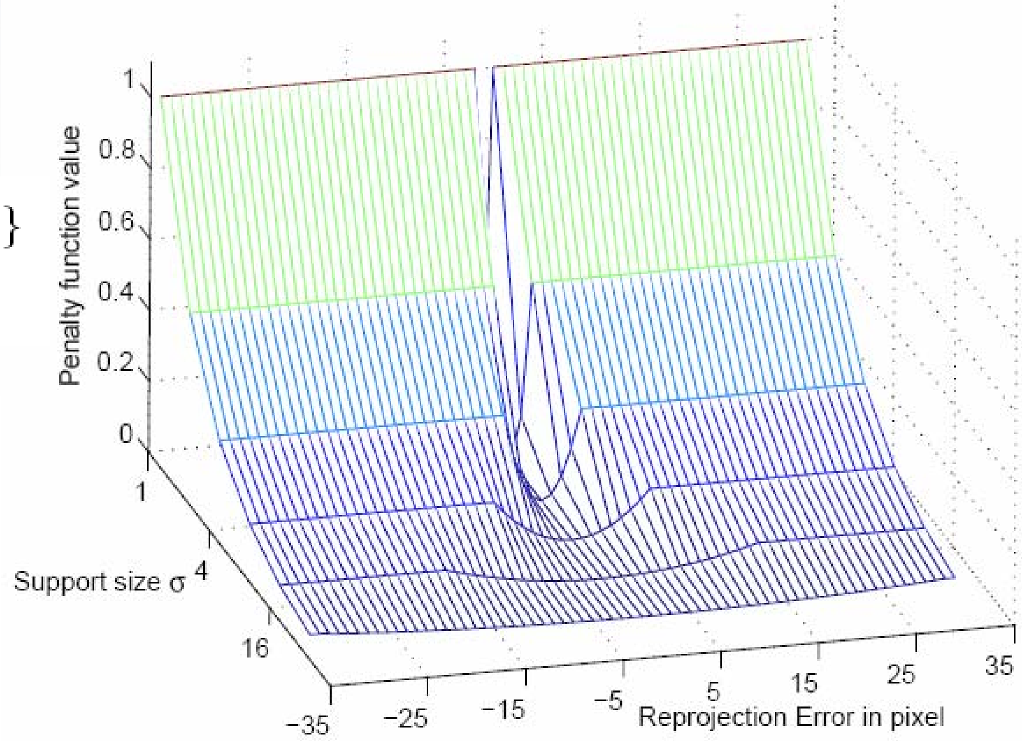
$$E_r(\mathbf{s}) = \mathbf{s}^\top \begin{bmatrix} K & 0 \\ 0 & K \end{bmatrix} \mathbf{s}$$

where K is a sparse and banded matrix which is determined by the structure of the mesh model.

Robust Estimator

- Define the residual error $\delta = \mathbf{m}_1 - T_\mathbf{s}(\mathbf{m}_0)$
- The robust estimator

$$\mathcal{V}(\delta,\sigma) = \begin{cases} \frac{\|\delta\|}{\sigma^n}, & M_1 = \{\mathbf{m} \mid \ \|\delta\| \le \sigma^2\} \\ \sigma^{2-n}, & M_2 = \overline{M_1} \end{cases}$$



*M*1 contains the inlier matches
*M*2 is the set of the outliers
The order n determines the scale of the residual.

Finite Newton Formulation

- The robust estimator function is not convex
- The associated penalty function approximation problem becomes a hard combinational optimization problem
- Tackle this problem under the finite Newton optimization framework

Finite Newton Formulation

- An augmented vector: $\mathbf{t}_i = \xi_1 \quad \mathbf{t}_j = \xi_2 \quad \mathbf{t}_k = \xi_3$
- Then,

$$\begin{aligned} ||\delta|| &= (u - \mathbf{t}^\top \mathbf{x})^2 + (v - \mathbf{t}^\top \mathbf{y})^2 \\ &= u^2 + v^2 - 2(u\mathbf{t}^\top \mathbf{x} + v\mathbf{t}^\top \mathbf{y}) + \mathbf{x}^\top \mathbf{t}\mathbf{t}^\top \mathbf{x} + \mathbf{y}^\top \mathbf{t}\mathbf{t}^\top \mathbf{y} \end{aligned}$$

where (*u, v*) are the coordinates of m1.

Re-write the error term as

$$E_e = \sum_{\mathbf{m} \in M_1} \frac{\omega_{\mathbf{m}}}{\sigma^n} \left(u^2 + v^2 - 2 \begin{bmatrix} u\mathbf{t} \\ v\mathbf{t} \end{bmatrix}^\top \mathbf{s} + \mathbf{s}^\top \begin{bmatrix} \mathbf{t}\mathbf{t}^\top & 0 \\ 0 & \mathbf{t}\mathbf{t}^\top \end{bmatrix} \mathbf{s} \right) + q\sigma^{2-n}$$

where q is the number of outliers

Finite Newton Formulation

- Define vector b as:

$$\mathrm{b} = \begin{bmatrix} \mathrm{b}_x \\ \mathrm{b}_y \end{bmatrix} = \sum_{\mathrm{m} \in M_1} \frac{\omega_{\mathrm{m}}}{\sigma^n} \begin{bmatrix} u\mathrm{t} \\ v\mathrm{t} \end{bmatrix}$$

- Matrix A (N by N):

$$A = \sum_{\mathrm{m} \in M_1} \frac{\omega_{\mathrm{m}}}{\sigma^n} \mathrm{t}\mathrm{t}^\top$$

- Energy function

$$E = \mathrm{s}^\top \begin{bmatrix} \lambda_r K + A & 0 \\ 0 & \lambda_r K + A \end{bmatrix} \mathrm{s} - 2\mathrm{b}^\top \mathrm{s} + q\sigma^{2-n} + \sum_{\mathrm{m} \in M_1} \frac{\omega_{\mathrm{m}}}{\sigma^n}(u^2 + v^2)$$

Finite Newton Formulation

- The finite gradient of the energy function *E* with respect to s

$$\nabla = 2\left(\begin{bmatrix} \lambda_r K + A & 0 \\ 0 & \lambda_r K + A \end{bmatrix} \mathrm{s} - \begin{bmatrix} \mathrm{b}_x \\ \mathrm{b}_y \end{bmatrix}\right)$$

- Hessian

$$H = 2\begin{bmatrix} \lambda_r K + A & 0 \\ 0 & \lambda_r K + A \end{bmatrix}$$

- Rewrite gradient $\nabla = H\mathrm{s} - 2\mathrm{b}$

Finite Newton Formulation

- Update equation: $\mathbf{s} \leftarrow \mathbf{s} - \gamma H^{-1}\nabla$
- Set r = 1, and obtain the linear equation

$$H\mathbf{s} = \mathbf{b}$$

$$\begin{bmatrix} \lambda_r K + A & 0 \\ 0 & \lambda_r K + A \end{bmatrix} \mathbf{s} = \begin{bmatrix} \mathbf{b}_x \\ \mathbf{b}_y \end{bmatrix}$$

$$\mathbf{x} = (\lambda_r K + A)^{-1}\mathbf{b}_x$$

$$\mathbf{y} = (\lambda_r K + A)^{-1}\mathbf{b}_y$$

Optimization

- Coarse-to-fine scheme to deal with large outliers
  - Support σ of robust estimator is progressively decayed at a constant rate
  - λ_r is kept constant
  - Result is used as the initial state for next minimization
  - Stop when σ is close to the expected precision
  - Report a successful detection when the number of inlier matches is above a given threshold.

Optimization

- Start from a sufficiently large support σ
  - To avoid getting stuck at local minima
  - Needs a few iterations to compensate for the errors due to pose variations
- Modified RANSAC
  - Closed-form solution
  - Draw from progressively larger sets of top-ranked correspondences
  - Sample size

Experimental Setup

- In order to register the mesh model conveniently, a model image is acquired when the nonrigid surface contains no deformation.
- A random-trees based method [Lepetit PAMI’06] is used to build the correspondences between the model image and input image.
- A set of synthetic data is used to select the parameters
- The best regularization coefficient is found by grid searching.
- n = 4, decay rate is 0.5
- Pentium-4 3.0GHz PC with 1GB RAM
- A DV camera size of 720x576

Computational Efficiency

- The complexity of the proposed method is mainly determined by the number of vertices N
- Another factor is the number of inlier matches
- Proposed method: 8 iterations, around 18 frames per second
- Semi-implicit method [CVPR'05, IJCV'07]: 40 iterations, about 9 frames per second on Coffee mat video

Table 3.1. Computational time of proposed method at each step.

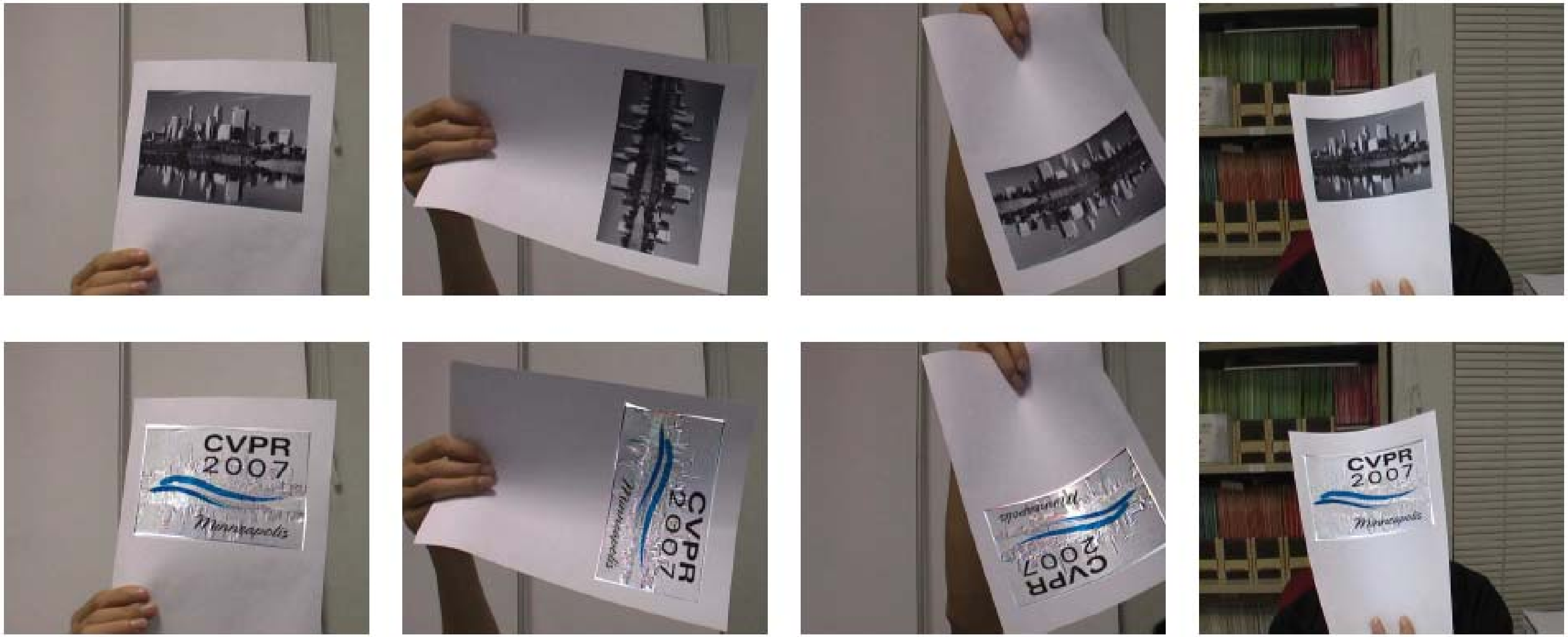
Total	Match	Optimization	Iteration	Other
57ms	27ms	14ms	$\sim$ 1.9ms	16ms

Coffee mat [Video demo]

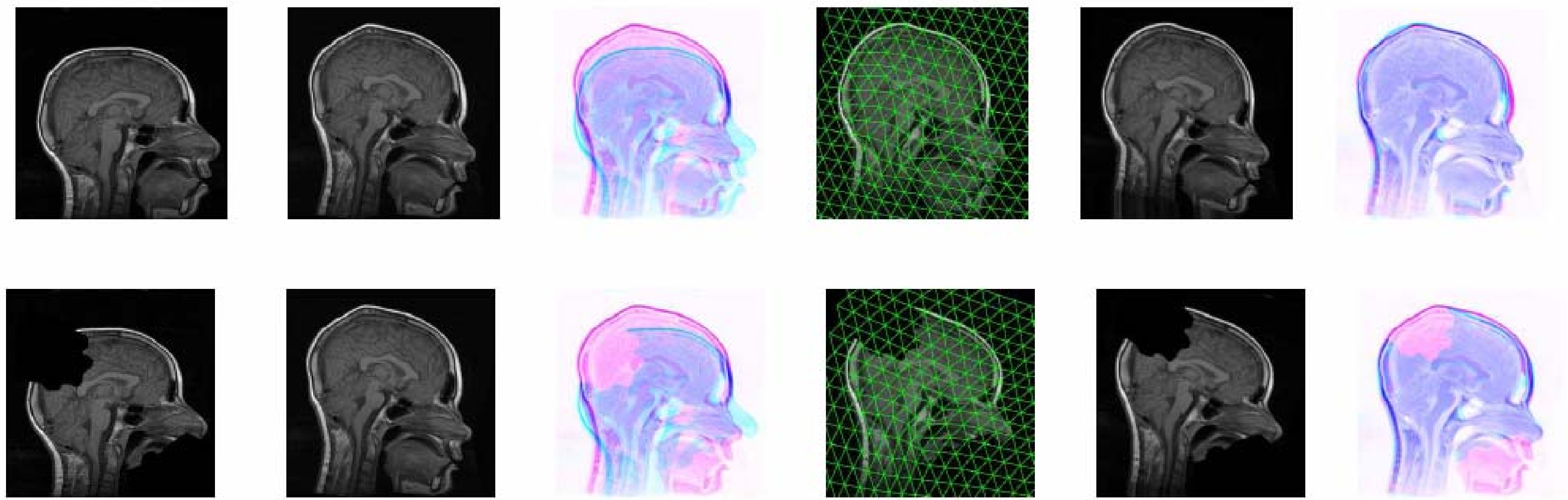
(a) Model image (b) Result (c) Result (e) Plastic cup

Re-texturing a T-shirt [Video demo]

Paper [Video demo]



Medical image



Summary

- A novel progressive scheme to solve the non-rigid surface detection problem
- In contrast to the previous semi-explicit method, we directly solve the unconstrained quadratic optimization problem by an efficient factorization
- Modified RANSAC scheme can handle high-dimensional spaces with noisy data.
- We have conducted extensive experimental evaluations on diverse objects with different materials.
- The proposed method is very fast and robust, and can handle large deformations and illumination changes.

Conclusion

- Two different approaches to nonrigid surface recovery have been investigated
- Appearance-based method:
  - Using more information, may be more accurate
  - Offering image coding capability
  - Tend to be computational expensive
  - Easy to stuck at the local optima
- Feature-based method
  - Automatic solution
  - Essentially fast
  - Taking advantage of the advances in feature matching and object recognition
  - Errors occur in the region lacking texture

Future work

- Fusion approach
- Explore new regularization method
- Find fast and accurate feature matching algorithm
- Including more features, such as edges and silhouette

The End

Thank you

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