Reconstruction

EE/CSE 576
Linda Shapiro
3D model

- “Digital copy” of real object
- Allows us to
  - Inspect details of object
  - Measure properties
  - Reproduce in different material
- Many applications
  - Cultural heritage preservation
  - Computer games and movies
  - City modelling
  - E-commerce
Applications: cultural heritage

SCULPTEUR European project
Applications: art

Block Works Precipitate III 2004
*Mild steel blocks* 80 x 46 x 66 cm

Domain Series Domain VIII Crouching
1999 *Mild steel bar* 81 x 59 x 63 cm
Applications: structure engineering

BODY / SPACE / FRAME, Antony Gormley, Lelystad, Holland
Applications: 3D indexation
Applications: archaeology

• “forma urbis romae” project

*Fragments of the City: Stanford's Digital Forma Urbis Romae Project*

David Koller, Jennifer Trimble, Tina Najbjerg, Natasha Gelfand, Marc Levoy

Applications: large scale modelling

[Pollefeys08]

[Furukawa10]

[Goesele07]

[Cornelis08]
Applications: Medicine

(a) Radius difference
(b) Angle difference
(c) Curvature difference
(d) Edge difference

<table>
<thead>
<tr>
<th>expert’s order</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>images</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>learning</td>
<td>1</td>
<td>3</td>
<td>2</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>8</td>
<td>9</td>
<td>7</td>
<td>10</td>
</tr>
<tr>
<td>a-lmk</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>5</td>
<td>6</td>
<td>4</td>
<td>8</td>
<td>7</td>
<td>9</td>
<td>10</td>
</tr>
<tr>
<td>mirror</td>
<td>1</td>
<td>2</td>
<td>4</td>
<td>8</td>
<td>5</td>
<td>6</td>
<td>9</td>
<td>3</td>
<td>7</td>
<td>10</td>
</tr>
<tr>
<td>m-lmk</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>9</td>
<td>7</td>
<td>10</td>
<td>8</td>
</tr>
<tr>
<td>plane</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>5</td>
<td>4</td>
<td>6</td>
<td>7</td>
<td>9</td>
<td>10</td>
<td>8</td>
</tr>
</tbody>
</table>
Scanning technologies

• Laser scanner, coordinate measuring machine
  – Very accurate
  – Very Expensive
  – Complicated to use
Medical Scanning System
The “Us” Data Set (subset)
3d shape from photographs

“Estimate a 3d shape that would generate the input photographs given the same material, viewpoints and illumination”
Photometric Stereo

• Estimate the surface normals of a given scene given multiple 2D images taken from the same viewpoint, but under different lighting conditions.

• Basic photometric stereo required a Lambertian reflectance model:

\[ I = \rho \, n \cdot v \]

where \( I \) is pixel intensity, \( n \) is the normal, \( v \) is the lighting direction, and \( \rho \) is diffuse albedo constant, which is a reflection coefficient.
Basic Photometric Stereo
Basic Photometric Stereo
Basic Photometric Stereo

- $K$ light sources
- Lead to $K$ images $R_1(p,q), ..., R_K(p,q)$ each from just one of the light sources being on
- For any $(p,q)$, we get $K$ intensities $I_1, ... I_K$
- Leads to a set of linear equations of the form
  $$I_k = \rho n \cdot v_k$$
- Solving leads to a surface normal map.
Photometric Stereo

Inputs

3D normals
3d shape from photographs

Photograph based 3d reconstruction is:

- practical
- fast
- non-intrusive
- low cost
- Easily deployable outdoors
- "low" accuracy
- Results depend on material properties
Reconstruction

- Generic problem formulation: given several images of the same object or scene, compute a representation of its 3D shape
Reconstruction

- **Generic problem formulation:** given several images of the same object or scene, compute a representation of its 3D shape
- **“Images of the same object or scene”**
  - Arbitrary number of images (from two to thousands)
  - Arbitrary camera positions (camera network or video sequence)
  - Calibration may be initially unknown
- **“Representation of 3D shape”**
  - Depth maps
  - Meshes
  - Point clouds
  - Patch clouds
  - Volumetric models
  - Layered models
Reconstruction from silhouettes

Can be computed robustly
Can be computed efficiently
Reconstruction from Silhouettes

- The case of binary images: a voxel is \textit{photo-consistent} if it lies inside the object’s silhouette in \textit{all} views.
Reconstruction from Silhouettes

• The case of binary images: a voxel is photo-consistent if it lies inside the object’s silhouette in all views

Finding the silhouette-consistent shape (*visual hull*):
  • *Backproject* each silhouette
  • Intersect backprojected volumes
Calibrated Image Acquisition

Selected Dinosaur Images

Selected Flower Images
Space Carving in General

Space Carving Algorithm

- Initialize to a volume $V$ containing the true scene
- Choose a voxel on the outside of the volume
- Project to visible input images
- Carve if not photo-consistent (inside object’s silhouette)
- Repeat until convergence

Our 4-camera light-striping stereo system

(now deceased)
The idea is to snap images at different depths and get a lot of 2D-3D point correspondences.
Surface Modeling and Display from Range and Color Data

Kari Pulli  UW
Michael Cohen  MSR
Tom Duchamp  UW
Hugues Hoppe  MSR
John McDonald  UW
Linda Shapiro  UW
Werner Stuetzle  UW

UW = University of Washington
Seattle, WA USA
MSR = Microsoft Research
Redmond, WA USA
Introduction

Goal

- develop robust algorithms for constructing 3D models from range & color data

- use those models to produce realistic renderings of the scanned objects
Surface Reconstruction

Step 1: Data acquisition
Obtain range data that covers the object. Filter, remove background.

Step 2: Registration
Register the range maps into a common coordinate system.

Step 3: Integration
Integrate the registered range data into a single surface representation.

Step 4: Optimization
Fit the surface more accurately to the data, simplify the representation.
Carve space in cubes

Label cubes
- Project cube to image plane (hexagon)
- Test against data in the hexagon
3D space is made up of many cubes.
Several views

Processing order:
FOR EACH cube
    FOR EACH view

Rules:
    any view thinks cube's out
    => it's out
    every view thinks cube's in
    => it's in
    else
    => it's at boundary
Hierarchical space carving

- Big cubes => fast, poor results
- Small cubes => slow, more accurate results
- Combination = octrees

RULES:
- cube’s out => done
- cube’s in => done
- else => recurse
Hierarchical space carving

- Big cubes $\Rightarrow$ fast, poor results
- Small cubes $\Rightarrow$ slow, more accurate results
- Combination $=$ octrees

RULES:
- cube’s out $\Rightarrow$ done
- cube’s in $\Rightarrow$ done
- else $\Rightarrow$ recurse
The rest of the chair
Same for a husky pup
Optimizing the dog mesh

Registered points

Initial mesh

Optimized mesh
View dependent texturing
Our viewer
More: Space Carving Results: African Violet

Input Image (1 of 45)

Reconstruction

Reconstruction

Reconstruction

Source: S. Seitz
More: Space Carving Results: Hand

Input Image (1 of 100)

Views of Reconstruction
Stereo from community photo collections

- Up to now, we’ve always assumed that camera calibration is known
- For photos taken from the Internet, we need *structure from motion* techniques to reconstruct both camera positions and 3D points. (SEE POSTED VIDEO)
Head Reconstruction from Uncalibrated Internet Photos

Input: Internet photos in different poses and expressions

Output: 3D model of the head

work of Shu Liang
Recognizing Deformable Shapes

Salvador Ruiz Correa
(CSE/EE576 Computer Vision I)
We are interested in developing algorithms for recognizing and classifying deformable object shapes from range data.

This is a difficult problem that is relevant in several application fields.
What Kind Of Deformations?

- Toy animals
- 3D Faces
- Normal
- Abnormal

Shape classes: significant amount of intra-class variability
Component-Based Methodology

1. Numeric Signatures
2. Components
3. Symbolic Signatures

Overcomes the limitations of the alignment-verification approach

Describe spatial configuration

4. Architecture of Classifiers

Recognition And Classification Of Deformable Shapes
Assumptions

All shapes are represented as oriented surface meshes of fixed resolution.

The vertices of the meshes in the training set are in full correspondence.

Finding full correspondences: hard problem yes ... but it is approachable (use morphable models technique: Blantz and Vetter, SIGGRAPH 99; C. R. Shelton, IJCV, 2000; Allen et al., SIGGRAPH 2003).
Four Key Elements To Our Approach

1. Numeric Signatures
2. Components
3. Symbolic Signatures
4. Architecture of Classifiers
   + Recognize and Classification of Deformable Shapes
Numeric Signatures

1. Numeric Signatures
2. Components
3. Symbolic Signatures

Encode Local Surface Geometry of an Object

4. Architecture of Classifiers
The Spin Image Signature

P is the selected vertex.

X is a contributing point of the mesh.

α is the perpendicular distance from X to P’s surface normal.

β is the signed perpendicular distance from X to P’s tangent plane.
Spin Image Construction

- A spin image is constructed
  - about a specified oriented point $o$ of the object surface
  - with respect to a set of contributing points $C$, which is controlled by maximum distance and angle from $o$.

- It is stored as an array of accumulators $S(\alpha, \beta)$ computed via:

- For each point $c$ in $C(o)$
  1. compute $\alpha$ and $\beta$ for $c$.
  2. increment $S(\alpha, \beta)$
Numeric Signatures: Spin Images

Rich set of surface shape descriptors.

Their spatial scale can be modified to include local and non-local surface features.

Representation is robust to scene clutter and occlusions.
Components

1. Numeric Signatures
   - Define

2. Components
   - Equivalent Numeric Signatures: Encode Local Geometry of a Shape Class

3. Symbolic Signatures

4. Architecture of Classifiers
How To Extract Shape Class Components?

- Select Seed Points
- Compute Numeric Signatures
- Region Growing Algorithm
- Component Detector

Training Set

Grown components around seeds
Component Extraction Example

Selected 8 seed points by hand

Grow one region at the time (get one detector per component)

Region Growing

Detected components on a training sample

Labeled Surface Mesh
How To Combine Component Information?

Note: Numeric signatures are invariant to mirror symmetry; our approach preserves such an invariance.
Symbolic Signatures

1. Numeric Signatures
2. Components
3. Symbolic Signatures
4. Architecture of Classifiers

Encode Geometrical Relationships Among Components
Symbolic Signature

Labeled Surface Mesh

Encode Geometric Configuration

Critical Point P

Symbolic Signature at P

Matrix storing component labels
Symbolic Signatures Are Robust To Deformations

Relative position of components is stable across deformations: experimental evidence
Architecture of Classifiers

1. Numeric Signatures
2. Components
3. Symbolic Signatures

Learns Components And Their Geometric Relationships
Architectuer of Classifiers
Proposed Architecture

Input

Labeled Mesh

Verify spatial configuration of the components

Identify Components

Labeled Mesh

Identify Symbolic Signatures

Class Label

-1 (Abnormal)

Two classification stages

Surface Mesh
ALL our classifiers are (off-the-shelf) $\nu$-Support Vector Machines ($\nu$-SVMs) (Schölkopf et al., 2000 and 2001). Component (and symbolic signature) detectors are one-class classifiers.

Component label assignment: performed with a multi-way classifier that uses pairwise classification scheme.

Gaussian kernel.
Experimental Validation

Recognition Tasks: 4 (T1 - T4)
Classification Tasks: 3 (T5 - T7)
No. Experiments: 5470
Shape Classes
Enlarging Training Sets Using Virtual Samples

Originals

Morphs

Original

Twist (5deg)
+ Taper
- Push
+ Spherify (10%)

Push
+ Twist (10 deg)
+ Scale (1.2)

Global Morphing Operators

Physical Modeling

Displacement Vectors

University of Washington

Electrical Engineering
Task 1: Recognizing Single Objects (1)

No. Shape classes: 9.
Training set size: 400 meshes.
Testing set size: 200 meshes.
No. Component detectors: 3.
No. Symbolic signature detectors: 1.
Numeric signature size: 40x40.
Symbolic signature size: 20x20.
No clutter and occlusion.
<table>
<thead>
<tr>
<th>Object</th>
<th>Recognition Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Snowman</td>
<td>93%</td>
</tr>
<tr>
<td>Rabbit</td>
<td>92%</td>
</tr>
<tr>
<td>Dog</td>
<td>89%</td>
</tr>
<tr>
<td>Cat</td>
<td>85.5%</td>
</tr>
<tr>
<td>Cow</td>
<td>92%</td>
</tr>
<tr>
<td>Bear</td>
<td>94%</td>
</tr>
<tr>
<td>Horse</td>
<td>92.7%</td>
</tr>
<tr>
<td>Human head</td>
<td>97.7%</td>
</tr>
<tr>
<td>Human face</td>
<td>76%</td>
</tr>
</tbody>
</table>

Recognition rates (true positives)
(No clutter, no occlusion, complete models)
Tasks 2-3: Recognition In Complex Scenes (1)

No. Shape classes: 3.
Training set size: 400 meshes.
Testing set size: 200 meshes.
No. Experiments: 1200.
No. Component detectors: 3.
No. Symbolic signature detectors: 1.
Numeric signature size: 40x40.
Symbolic signature size: 20x20.
T2 - low clutter and occlusion.
### Task 2-3: Recognition in Complex Scenes (2)

<table>
<thead>
<tr>
<th>Shape Class</th>
<th>True Positives</th>
<th>False Positives</th>
<th>True Positives</th>
<th>False Positives</th>
</tr>
</thead>
<tbody>
<tr>
<td>Snowmen</td>
<td>91%</td>
<td>31%</td>
<td>87.5%</td>
<td>28%</td>
</tr>
<tr>
<td>Rabbit</td>
<td>90.2%</td>
<td>27.6%</td>
<td>84.3%</td>
<td>24%</td>
</tr>
<tr>
<td>Dog</td>
<td>89.6%</td>
<td>34.6%</td>
<td>88.12%</td>
<td>22.1%</td>
</tr>
</tbody>
</table>
Task 2-3: Recognition in Complex Scenes (3)
Task 4: Recognizing Human Heads (3)
## Task 5: Classifying Normal vs. Abnormal Human Heads (1)

<table>
<thead>
<tr>
<th>Shape Classes</th>
<th>Classification Accuracy %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal vs. Abnormal 1</td>
<td>98</td>
</tr>
<tr>
<td>Normal vs. Abnormal 2</td>
<td>100</td>
</tr>
<tr>
<td>Abnormal 1 vs. 3</td>
<td>98</td>
</tr>
<tr>
<td>Abnormal 1 vs. 4</td>
<td>97</td>
</tr>
<tr>
<td>Abnormal 1 vs. 5</td>
<td>92</td>
</tr>
</tbody>
</table>

The full models are convex combinations of Normal and Abnormal 1 with the following accuracies:
- Normal: 65% - 35%
- Abnormal: 50% - 50% - 25% - 75%
### Task 6: Classifying Normal vs. Abnormal Human Heads In Complex Scenes(1)

<table>
<thead>
<tr>
<th>Shape Classes</th>
<th>Classification Accuracy %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal vs. Abnormal 1</td>
<td>88</td>
</tr>
</tbody>
</table>
Task 7: Classifying Normal vs. Abnormal Neurocranium (2)

<table>
<thead>
<tr>
<th>Shape Classes</th>
<th>Classification Accuracy %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal vs. Abnormal</td>
<td>89</td>
</tr>
</tbody>
</table>
Main Contributions (1)

A novel **symbolic signature representation** of deformable shapes that is robust to intra-class variability and missing information, as opposed to a **numeric representation** which is often tied to a specific shape.

A novel **kernel function** for quantifying symbolic signature similarities.
Main Contributions (2)

A region growing algorithm for learning shape class components.

A novel architecture of classifiers for abstracting the geometry of a shape class.

A validation of our methodology in a set of large scale recognition and classification experiments aimed at applications in scene analysis and medical diagnosis.