Recognizing Deformable Shapes

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Goal

- 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.
Applications

- **Computer Vision:**
  - Scene analysis
  - Industrial Inspection
  - Robotics

- **Medical Diagnosis:**
  - Classification and
  - Detection of craniofacial deformations.
Basic Idea

• Generalize existing numeric surface representations for matching 3-D objects to the problem of identifying shape classes.
Alignment-Verification Limitations

The approach does not extend well to the problem of identifying classes of similar shapes. In general:

- Numeric shape representations are not robust to deformations.
- There are not exact correspondences between model and scene.
- Objects in a shape class do not align.
Component-Based Methodology

1. Numeric Signatures
   define

2. Components

3. Symbolic Signatures

Overcomes the limitations of the alignment-verification approach

4. Architecture of Classifiers

Recognition And Classification Of Deformable Shapes

Describe spatial configuration
Numeric Signatures

1. Numeric Signatures

2. Components

3. Symbolic Signatures

4. Encode Local Surface Geometry of an Object

Architecture of Classifiers
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

Spin images for point $P$

- **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
2. Components
3. Symbolic Signatures
4. Architecture of Classifiers

Equivalent Numeric Signatures:
Encode Local Geometry of a Shape Class
How To Extract Shape Class Components?

Select Seed Points

Compute Numeric Signatures

Region Growing Algorithm

Component Detector

Grown components around seeds

Training Set
Component Extraction Example

Selected 8 seed points by hand

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

Region Growing

Labeled Surface Mesh

Detected components on a training sample
How To Combine Component Information?

Extracted components on test samples

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

Critical Point P

Encode Geometric Configuration

Symbolic Signature at P

Matrix storing component labels
Symbolic Signature Construction

Critical Point P

Project labels to tangent plane at P

Tangent plane

Normal

Coordinate system defined up to a rotation

Critical Point P
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
4. Learns Components And Their Geometric Relationships

Architecture of Classifiers
At Classification Time

Surface Mesh

Labeled Surface Mesh

Component Classifiers

Multi-way classifier

+1

-1
Architecture Implementation

• 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

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

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

Global Morphing Operators

Physical Modeling

Originals

Morphs

Displacement Vectors (14)
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.
Task 1: Recognizing Single Objects (2)

- Snowman: 93%.
- Rabbit: 92%.
- Dog: 89%.
- Cat: 85.5%.
- Cow: 92%.
- Bear: 94%.
- Horse: 92.7%.
- Human head: 97.7%.
- Human face: 76%.

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 (1)

- No. Shape classes: 1.
- Training set size: 400 meshes.
- No. Experiments: 710.
- No. Component detectors: 8.
- No. Symbolic signature detectors: 2.
- Numeric signature size: 70x70.
- Symbolic signature size: 12x12.
Task 4: Recognizing Human Heads (2)

Recognition Rate

FP rate: ~1%

% Clutter < 40

(44, 0.9)

% Occlusion < 40

(40, 0.88)

% Clutter

% Occlusion
Task 4: Recognizing Human Heads (3)
Task 5: Classifying Normal vs. Abnormal Human Heads (1)

- 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: 50x50.
- Symbolic signature size: 12x12.
### Task 5: Classifying Normal vs. Abnormal Human Heads (1)

#### Five Cases

<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>

Full models

*convex combinations of Normal and Abnormal 1*
Task 6: Classifying Normal vs. Abnormal Human Heads In Complex Scenes(1)

• No. Shape classes: 2.
• 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: 100x100.
• Symbolic signature size: 12x12.
### Task 6: Classifying Normal vs. Abnormal Human Heads In Complex Scenes

<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>

- Clutter < 15%  
- and occlusion < 50%
Task 7: Classifying Normal vs. Abnormal Neurocranium (1)

- No. Shape classes: 2.
- Training set size: 400 meshes.
- Testing set size: 200 meshes.
- No. Experiments: 2200.
- No. Component detectors: 3.
- No. Symbolic signature detectors: 1.
- Numeric signature size: 50x50.
- Symbolic signature size: 15x15.
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>

No clutter and occlusion

100 Experiments

Normal

Superimposed models

Abnormal (sagittal synostosis)