Recognizing Deformable Shapes

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Basic Idea

- Generalize existing numeric surface representations for matching 3-D objects to the problem of identifying shape classes allowing for shape deformations.
What Kind Of Deformations?

- **Mandibles**
  - Normal
  - Abnormal

- **3-D Faces**

- **Neurocranium**
  - Normal
  - Abnormal

- **Toy animals**

Shape classes: significant amount of intra-class variability
Deformed Infants' Skulls

Normal

Sagittal Synostosis

Bicoronal Synostosis

Metopic

Coronal

Sagittal

Fused Sutures

Occurs when sutures of the cranium fuse prematurely (synostosis).
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.
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

Recognition And Classification Of Deformable Shapes
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.

tangent plane at P
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.
Shape Class Components: Clusters of 3D Points with Similar Spin Images

1. **Select Seed Points**
2. **Compute Numeric Signatures**
3. **Region Growing Algorithm**
4. **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

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 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
Proposed Architecture (Classification Example)

Two classification stages

- Input: Surface Mesh
- Identify Components: Labeled Mesh
- Identify Symbolic Signatures: Verify spatial configuration of the components
- Class Label: -1 (Abnormal)
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

Setup

Rotary Table

Recognition

Classification

Laser
Enlarging Training Sets Using Virtual Samples

Global Morphing Operators

Originals

Morphs

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

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

Original

(14)

Physical Modeling

Morphs

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.
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)
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.