Recognizing Deformable Shapes

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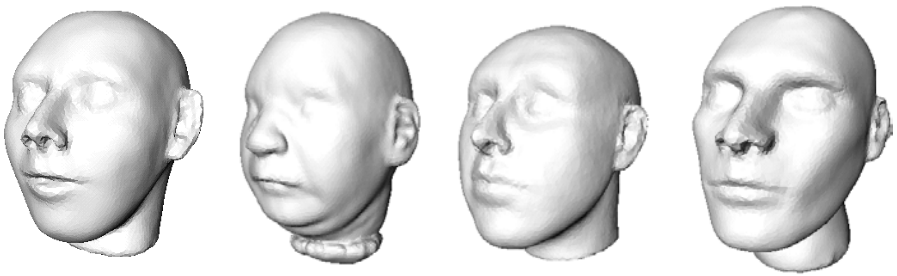
Ph.D. Thesis, Electrical Engineering

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

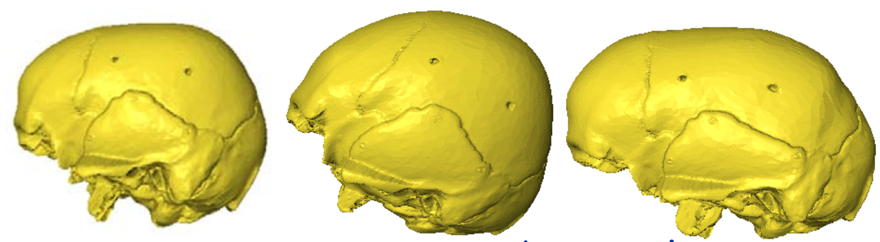
Normal

Abnormal

3-D Faces

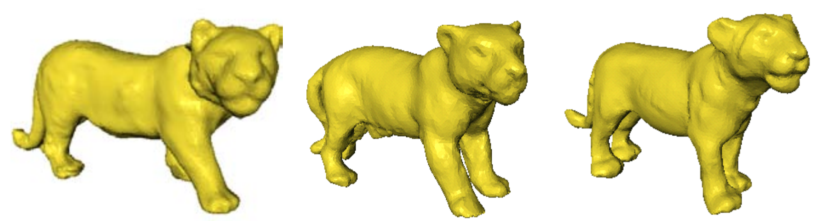
Neurocranium

Normal



Abnormal

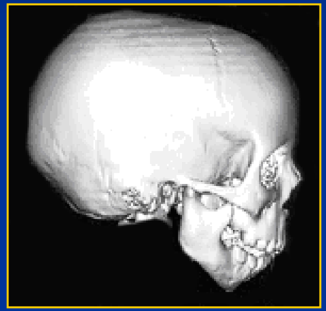
Toy animals



Shape classes: significant amount of intra-class variability

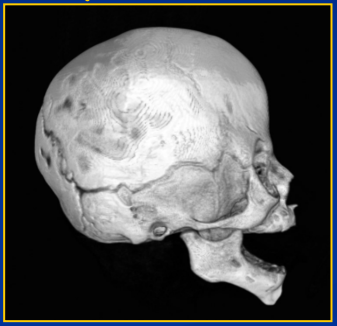
Deformed Infants' Skulls

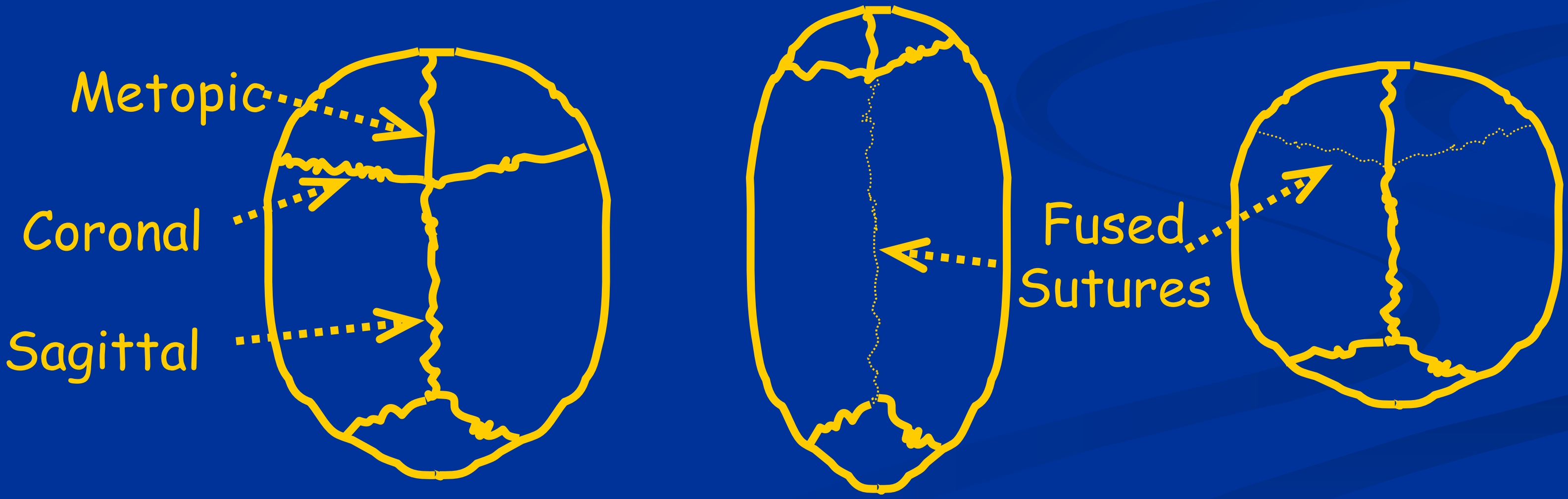
Normal



Sagittal Synostosis

Bicoronal Synostosis





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

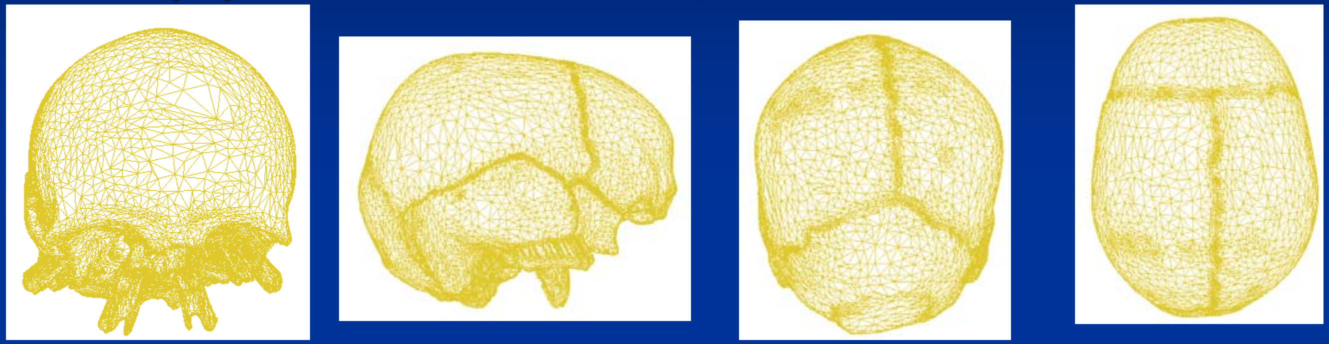
Alignment-Verification Limitations

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.

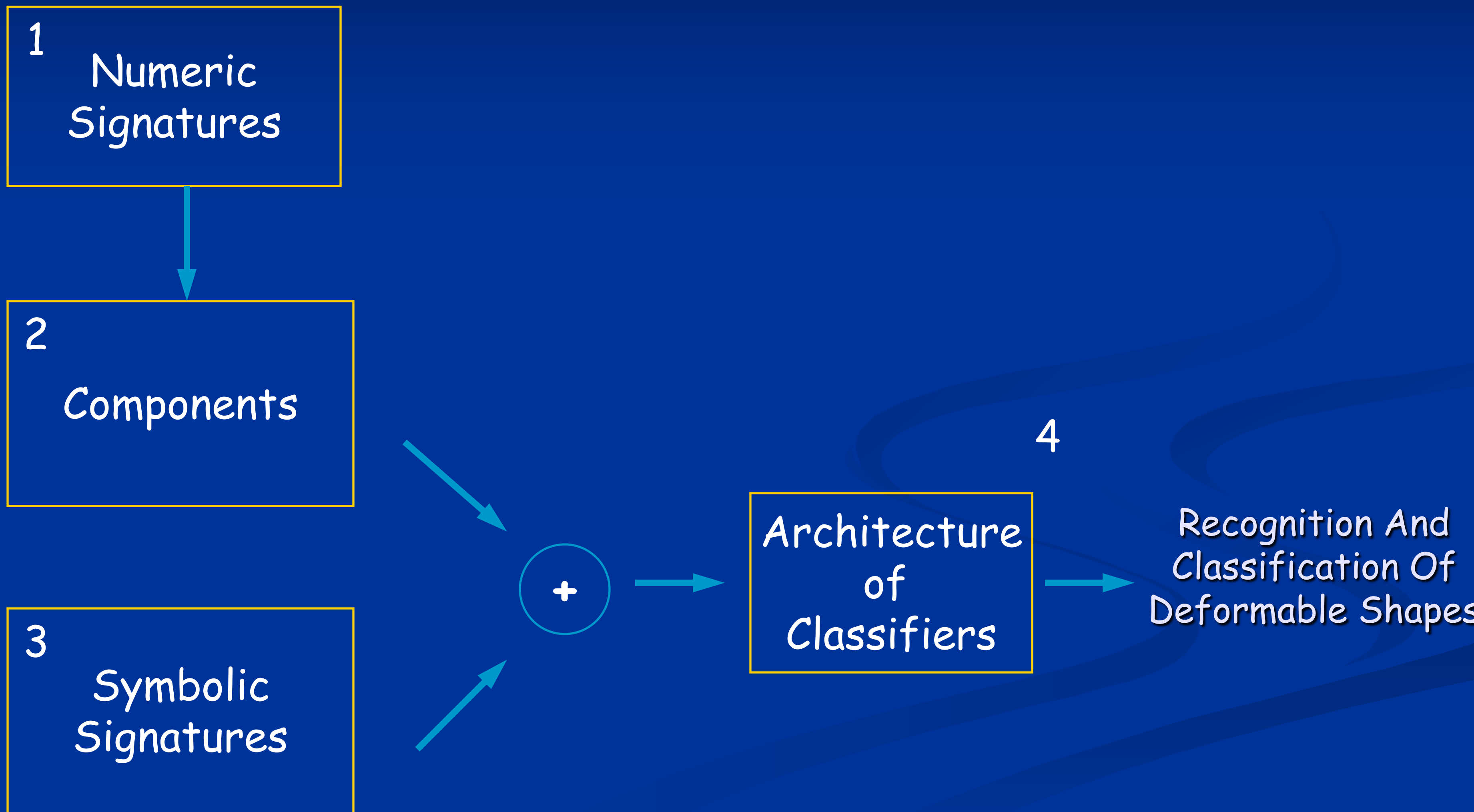
Assumptions

- 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).

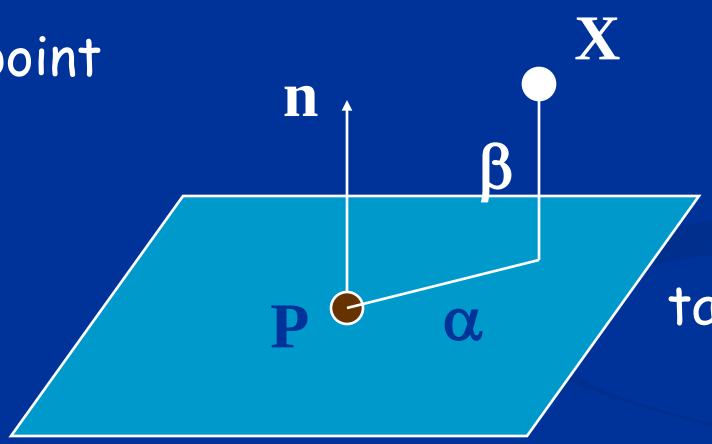
Four Key Elements To Our Approach



The Spin Image Signature

P is the selected vertex.

X is a contributing point
of the mesh.

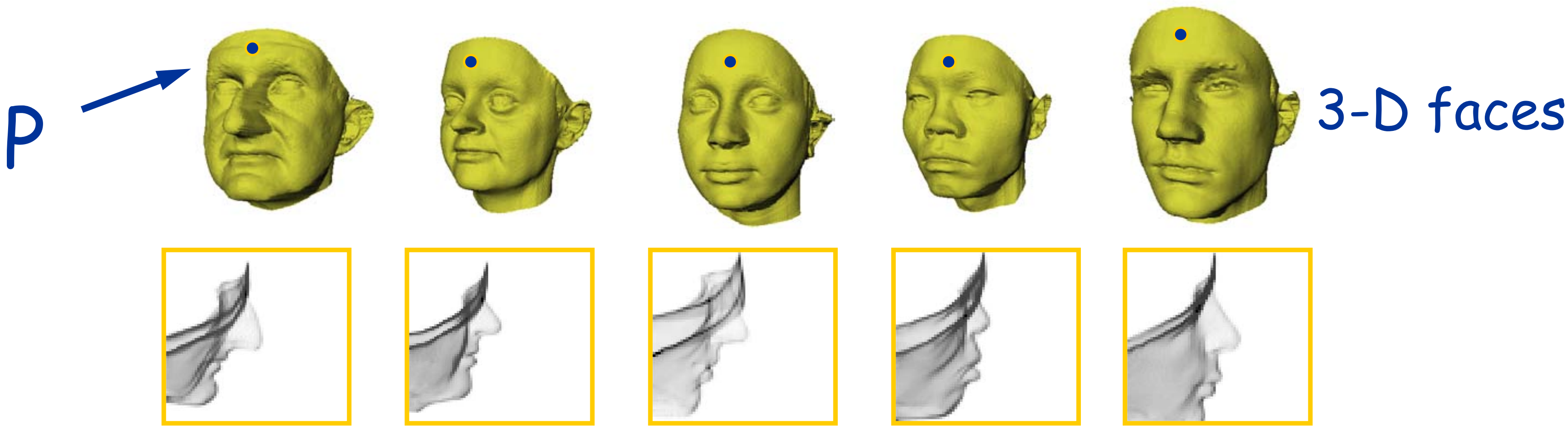


tangent plane at P

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.

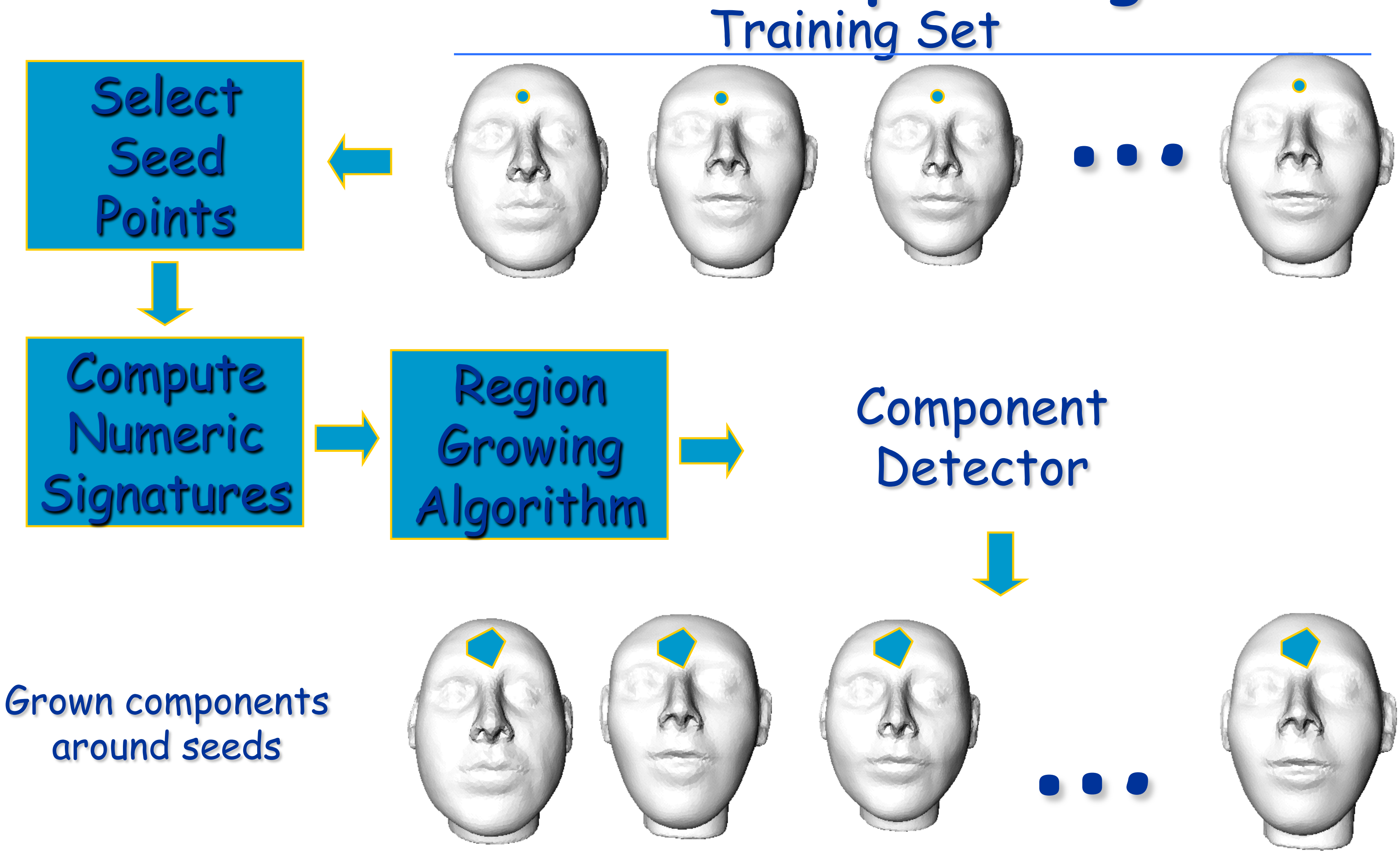
Numeric Signatures: Spin Images



Spin images for point *P*

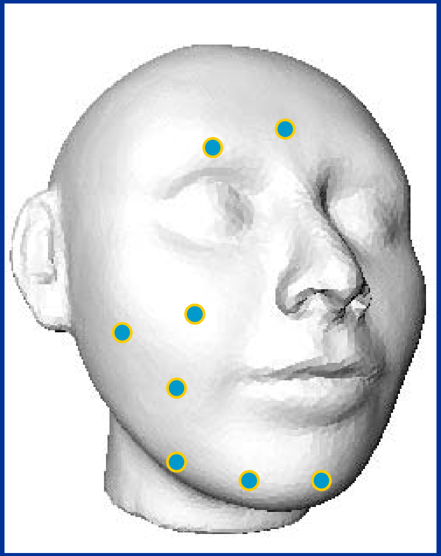
- Rich set of surface shape descriptors.
- Their spatial scale can be modified to include local and non-local surface features.
- Representation is robust to scene clutter and occlusions.

Shape Class Components: Clusters of 3D Points with Similar Spin Images



Component Extraction Example

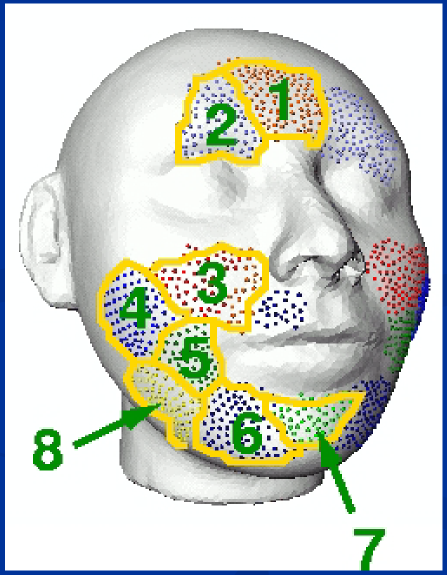
Selected 8 seed points by hand



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

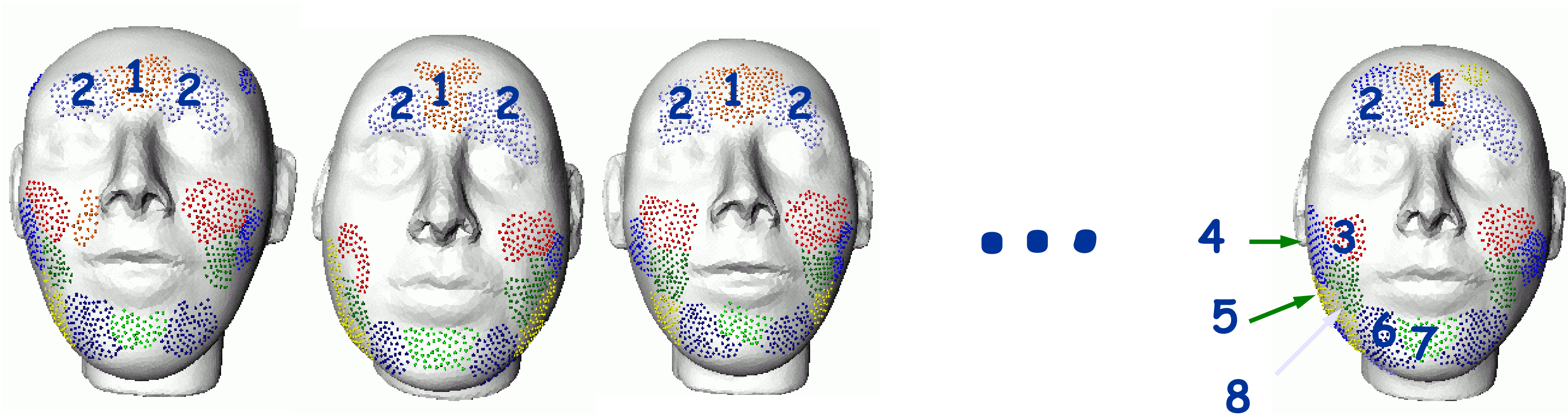
Region Growing

Labeled Surface Mesh



Detected components on a training sample

How To Combine Component Information?



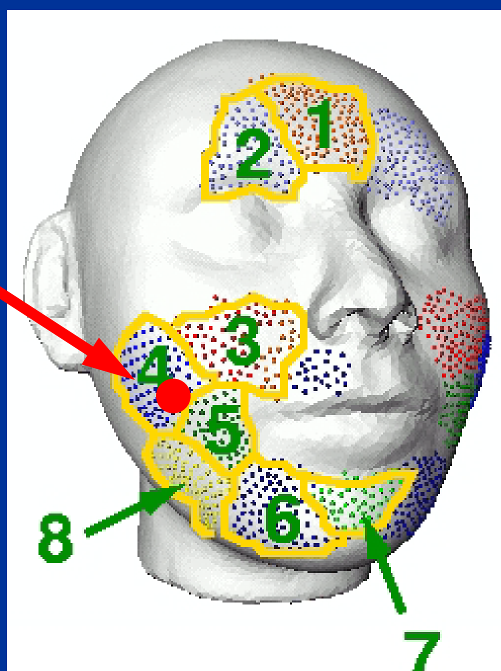
Extracted components on test samples

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

Symbolic Signature

Labeled
Surface Mesh

Critical
Point P

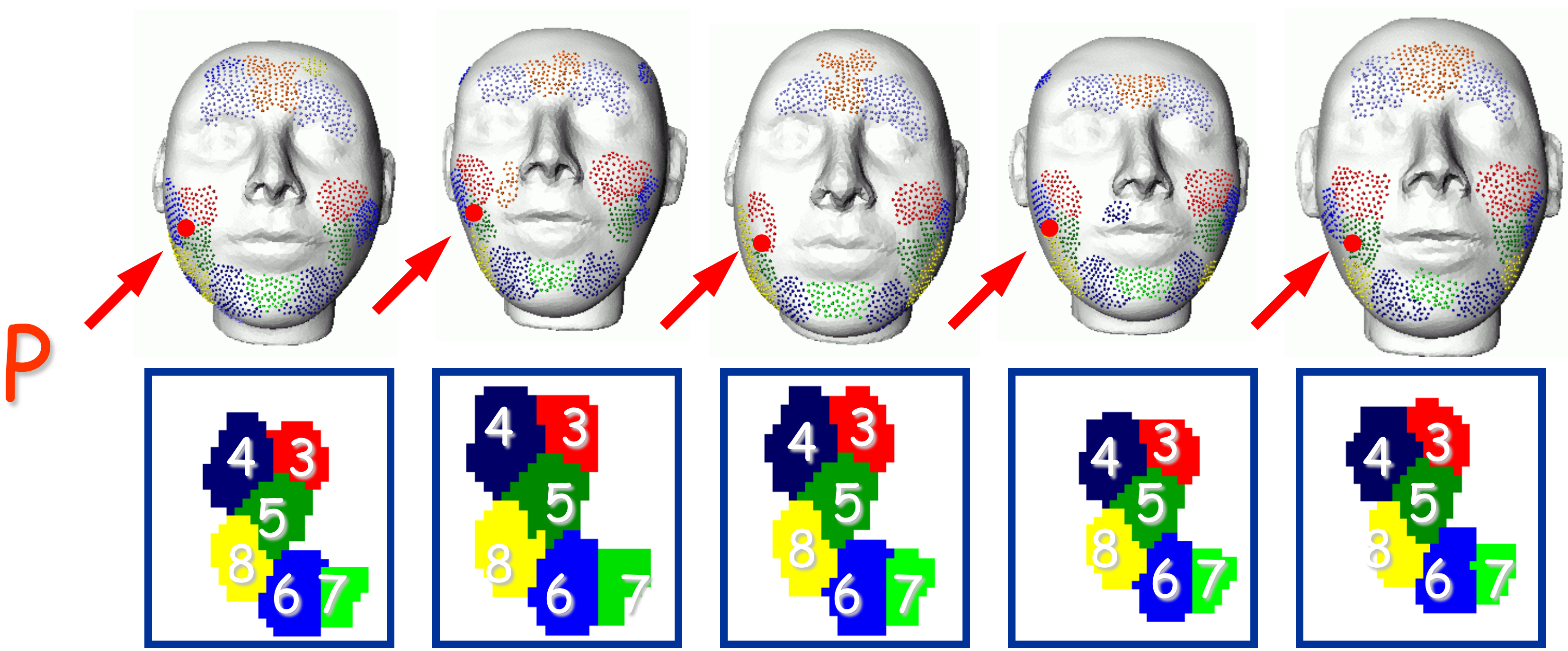


Encode
Geometric
Configuration

Symbolic
Signature at P

Matrix storing
component
labels

Symbolic Signatures Are Robust To Deformations

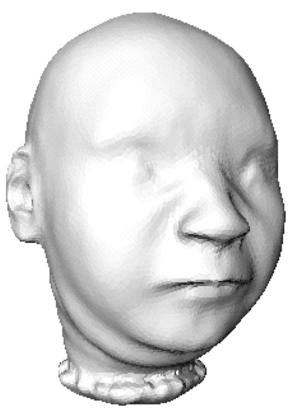


Relative position of components is stable across deformations: experimental evidence

Proposed Architecture (Classification Example)

Verify spatial configuration of the components

Input → **Identify Components** → Labeled Mesh → **Identify Symbolic Signatures** → Class Label



Surface Mesh

-1

(Abnormal)

Two classification stages

Architecture Implementation

- ALL our classifiers are (off-the-shelf) ν-Support Vector Machines (ν-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

Rotary Table

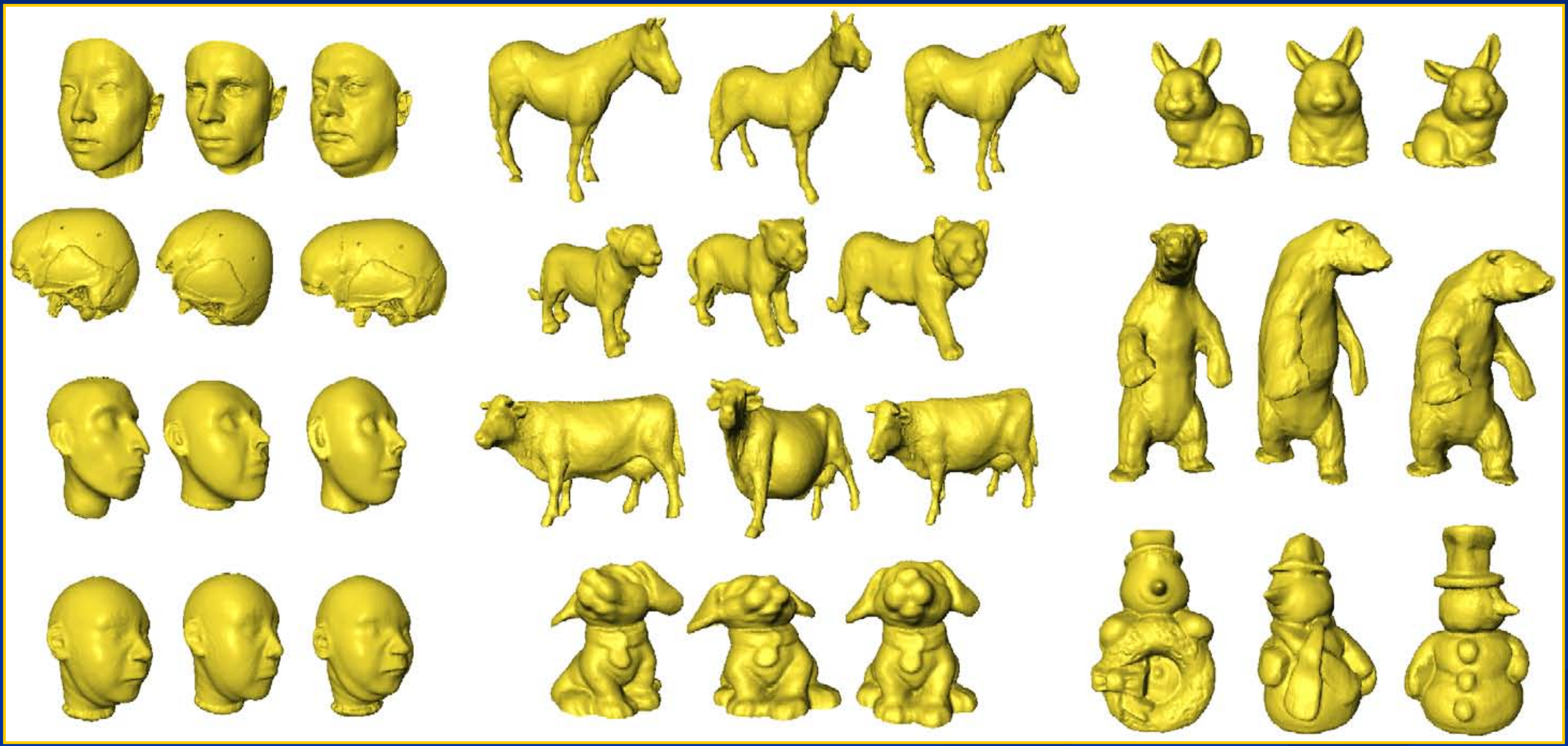
Setup

Laser

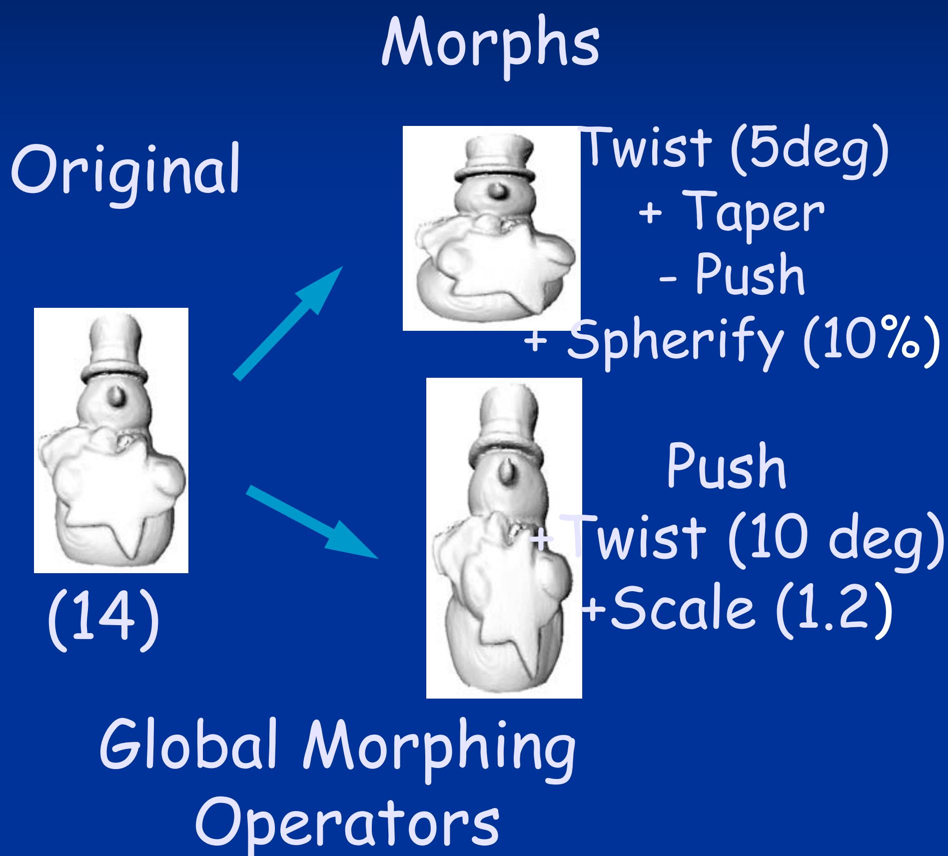
Recognition

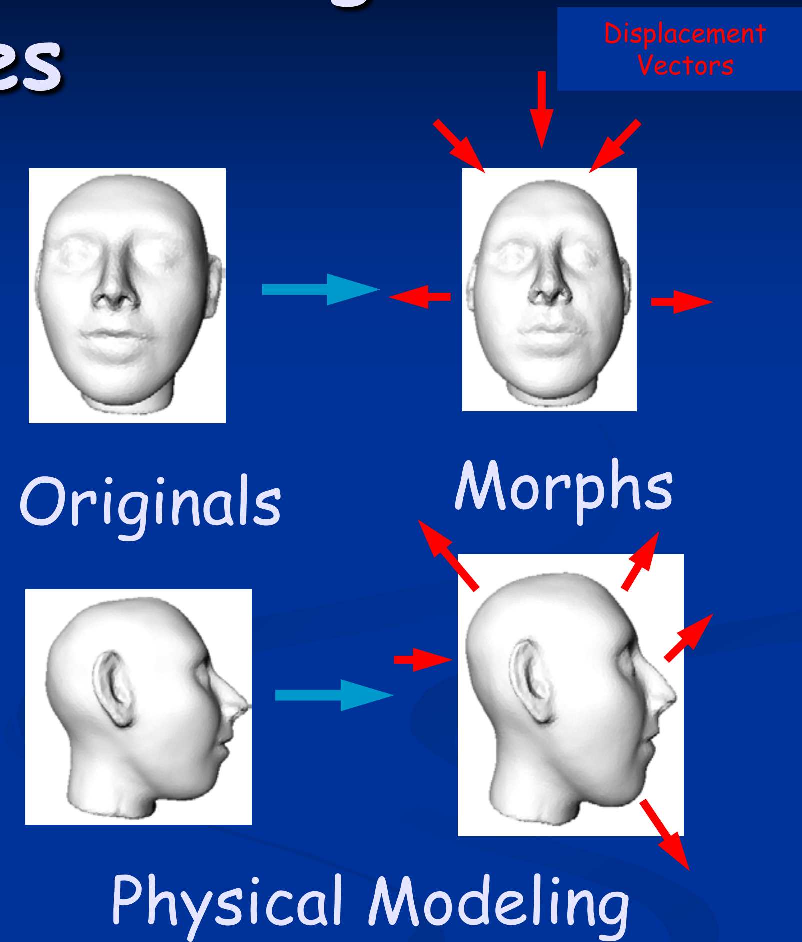
Classification

Shape Classes



Enlarging Training Sets Using Virtual Samples



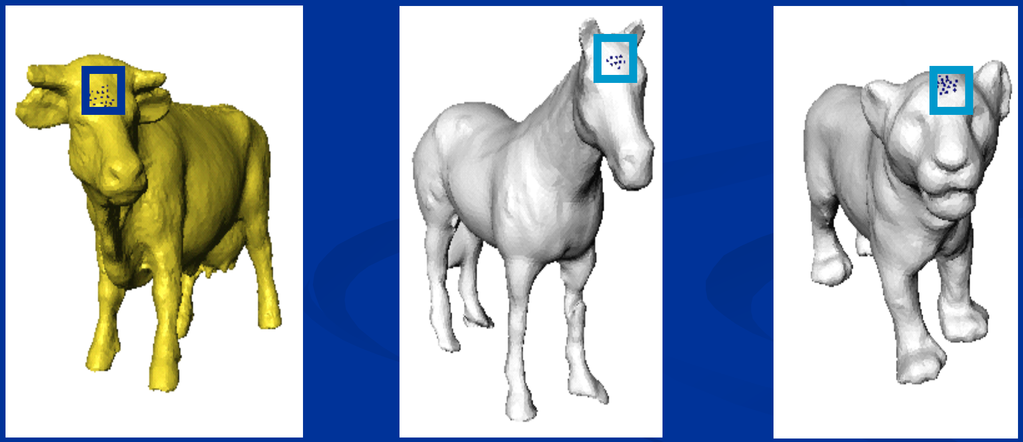


Task 1: Recognizing Single Objects (1)

- No. Shape classes: 9.
- Training set size: 400 meshes.
- Testing set size: 200 meshes.
- No. Experiments: 1960.
- 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)

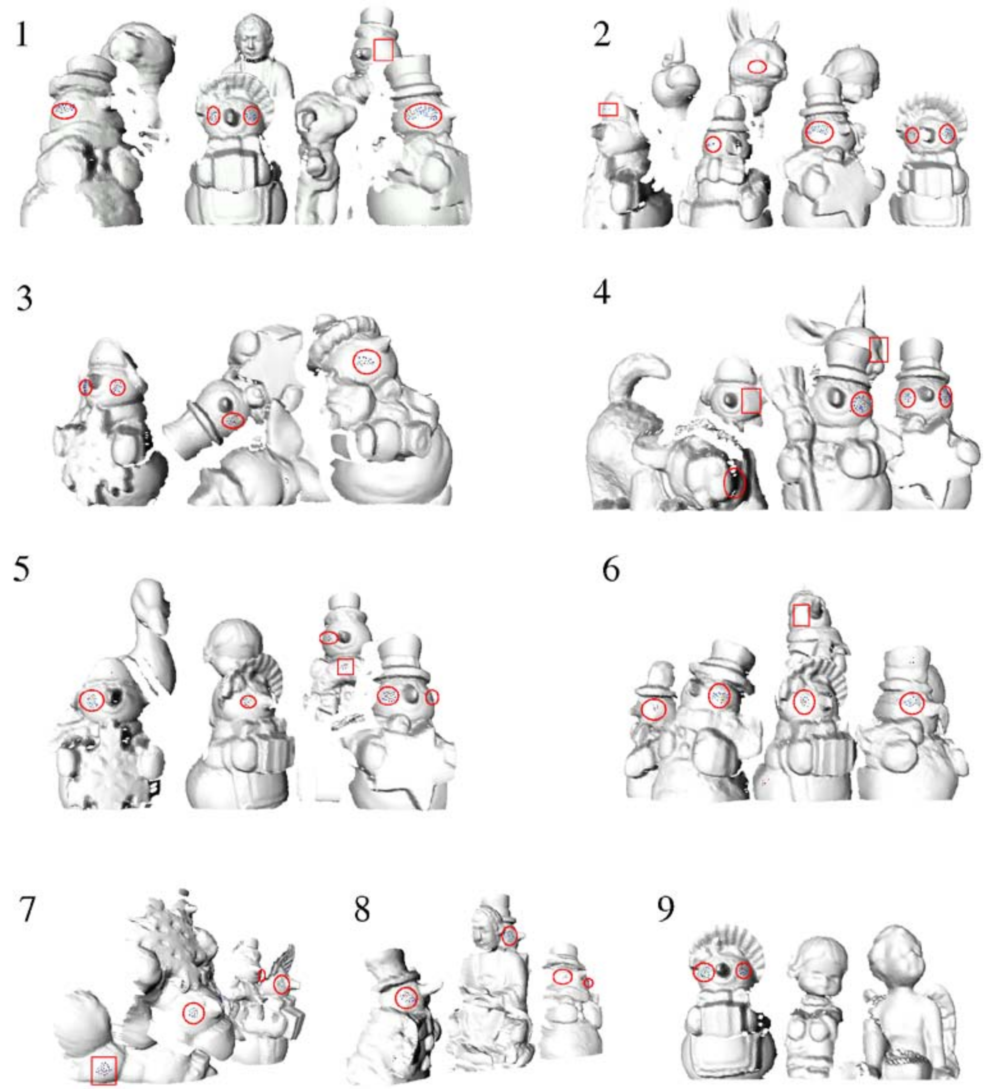
- No. Shape classes: 3.
- Training set size: 400 meshes.
- Testing set size: 200 meshes.
- No. Experiments: 1200.
- No. Component detectors:3.
- No. Symbolic signature detectors: 1.
- Numeric signature size: 40x40.
- Symbolic signature size: 20x20.
- T2 – low clutter and occlusion.

Task 2-3: Recognition in Complex Scenes (2)

Shape Class	True Positives	False Positives	True Positives	False Positives
Snowmen	91%	31%	87.5%	28%
Rabbit	90.2%	27.6%	84.3%	24%
Dog	89.6%	34.6%	88.12%	22.1%

Task 2 Task 3

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.