Recognizing Deformable Shapes

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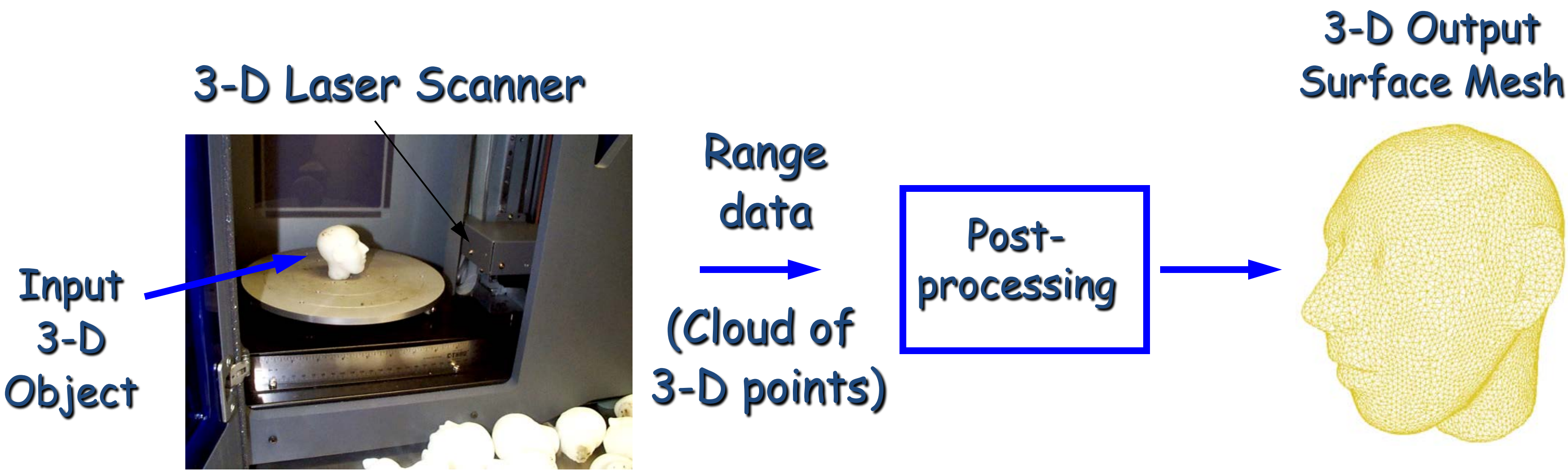
Goal

- 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

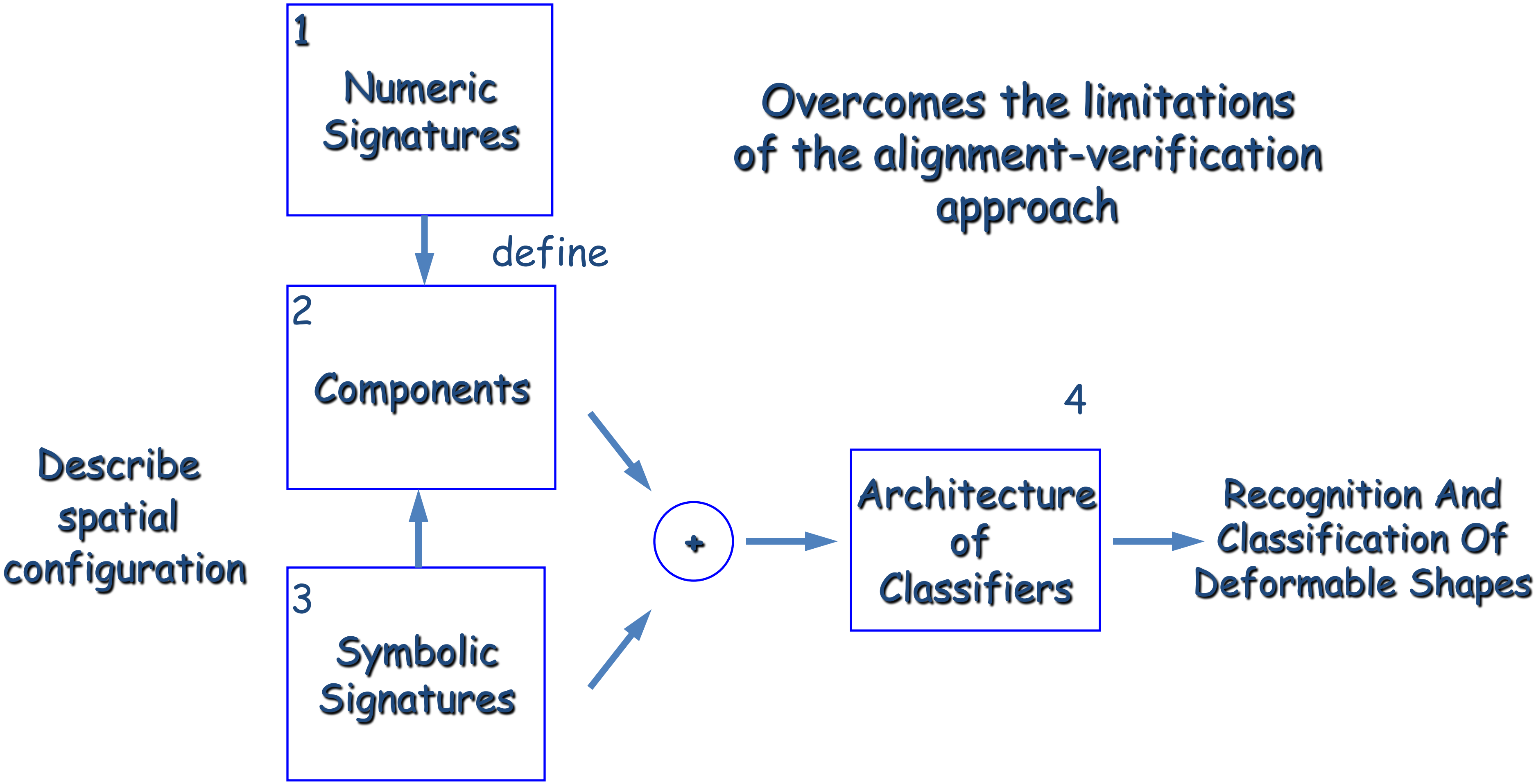
- Generalize existing numeric surface representations for matching 3-D objects to the problem of identifying shape classes.

Alignment-Verification Limitations

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

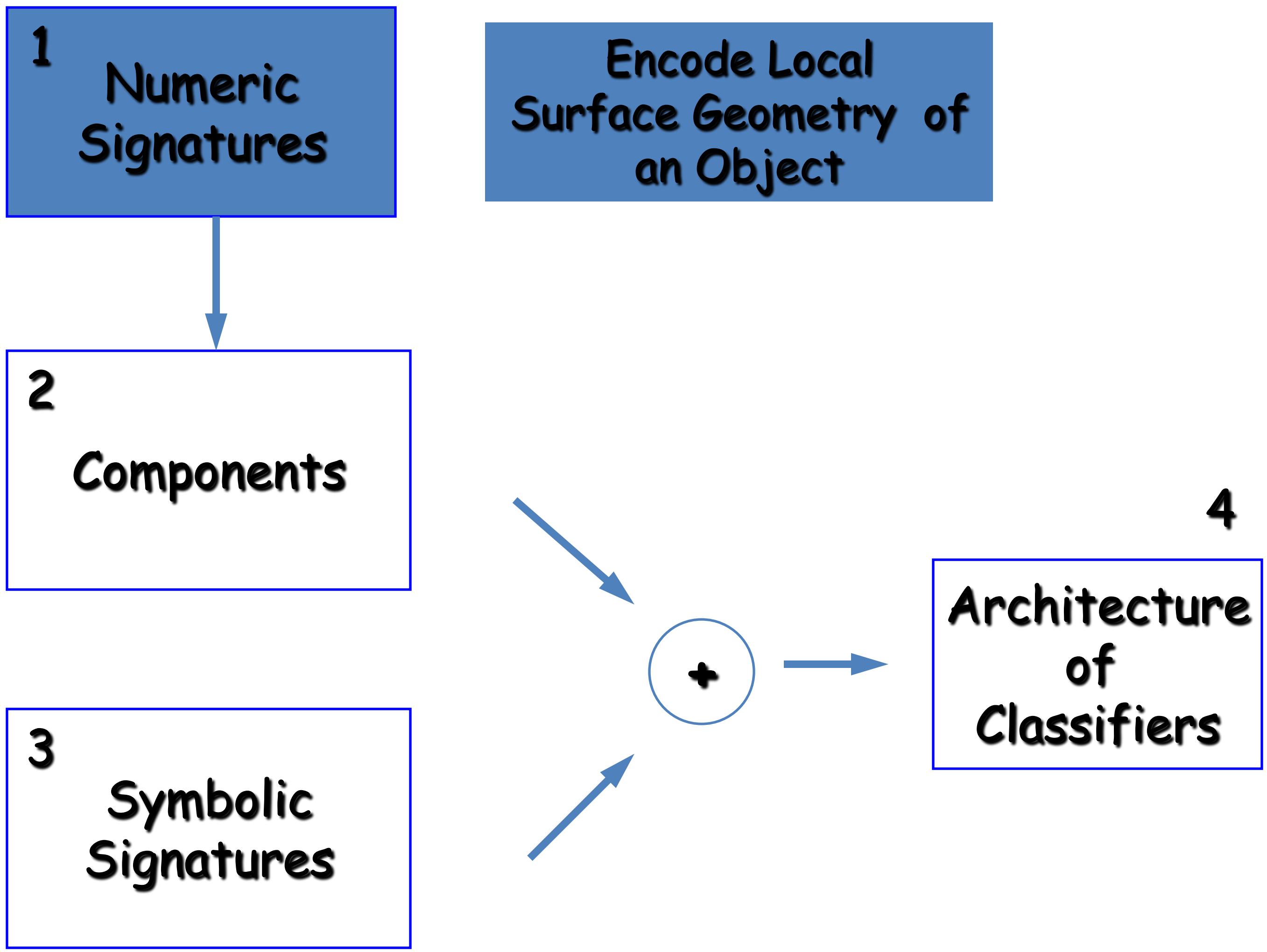
- Numeric shape representations are not robust to deformations.
- There are not exact correspondences between model and scene.
- Objects in a shape class do not align.

Component-Based Methodology



Overcomes the limitations of the alignment-verification approach

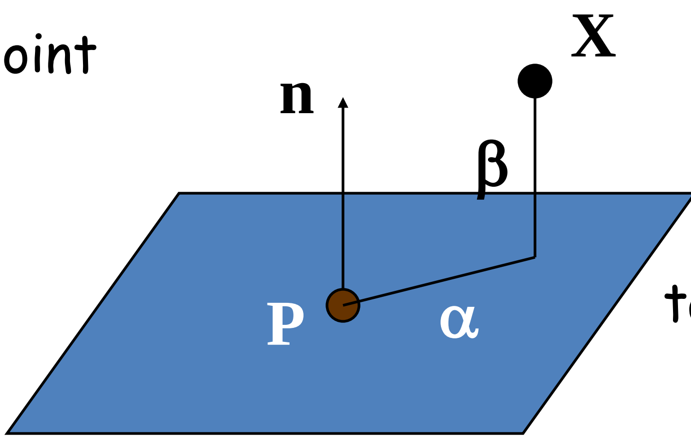
Numeric Signatures



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.

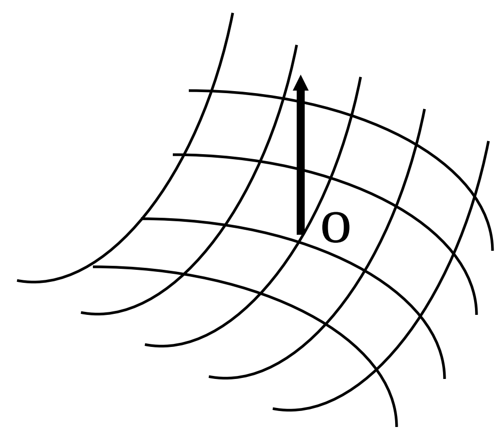
Spin Image Construction

- 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.

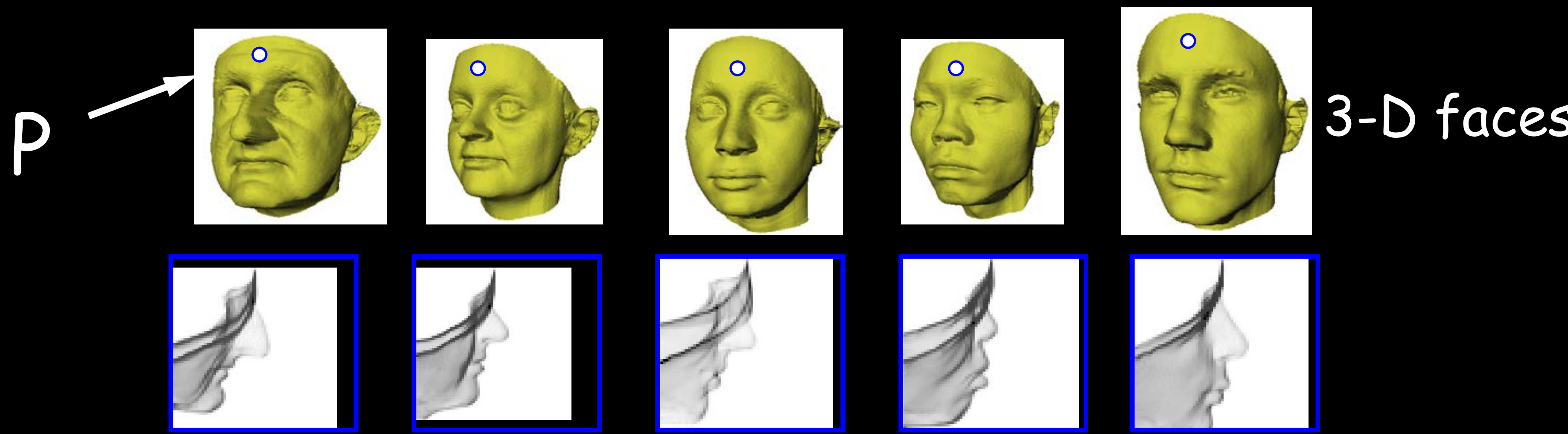
- It is stored as an array of accumulators $S(\alpha,\beta)$ computed via:

- For each point c in C(o)

  1. compute α and β for c.
  2. increment $S(\alpha,\beta)$



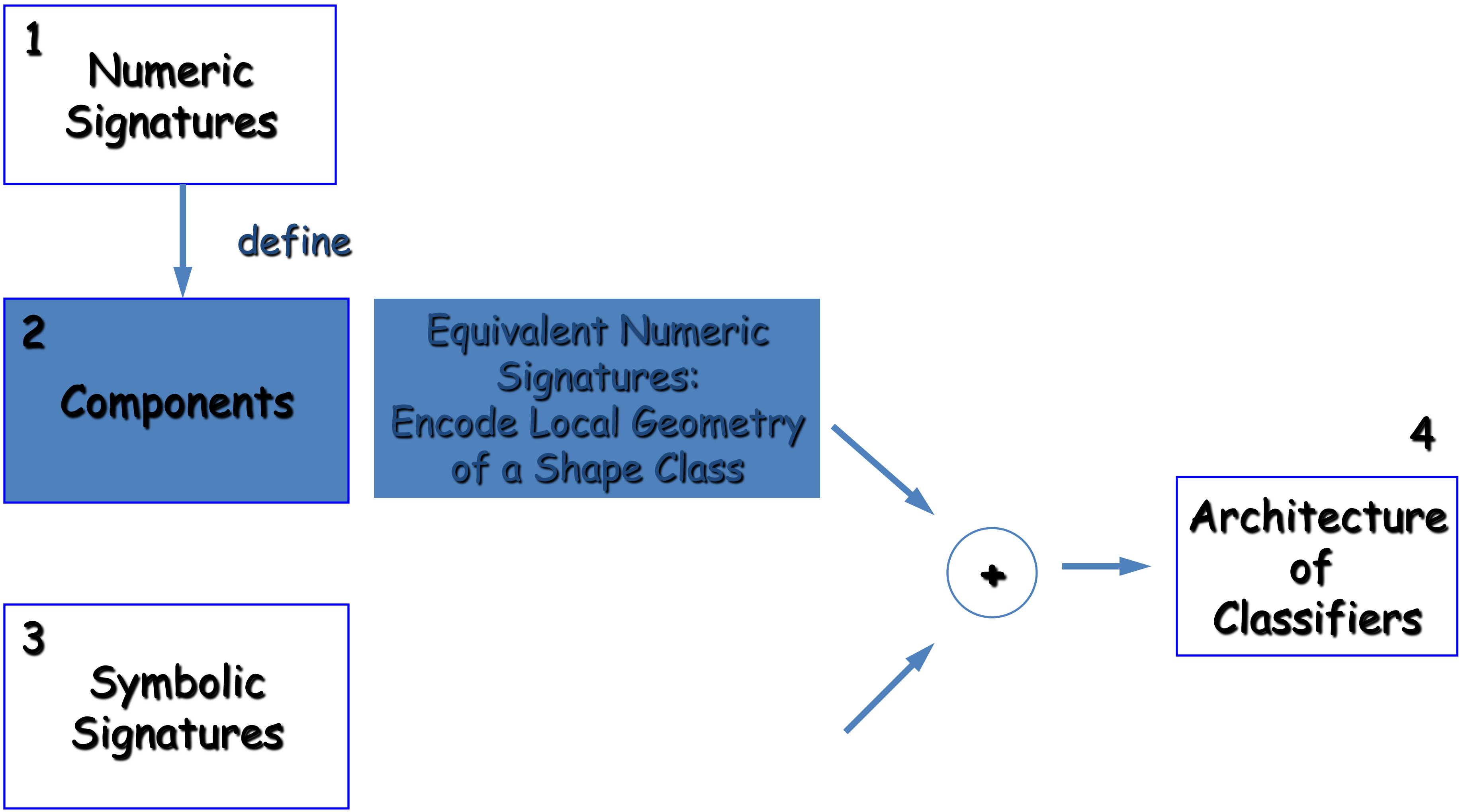
Numeric Signatures: Spin Images



Spin images for point *P*

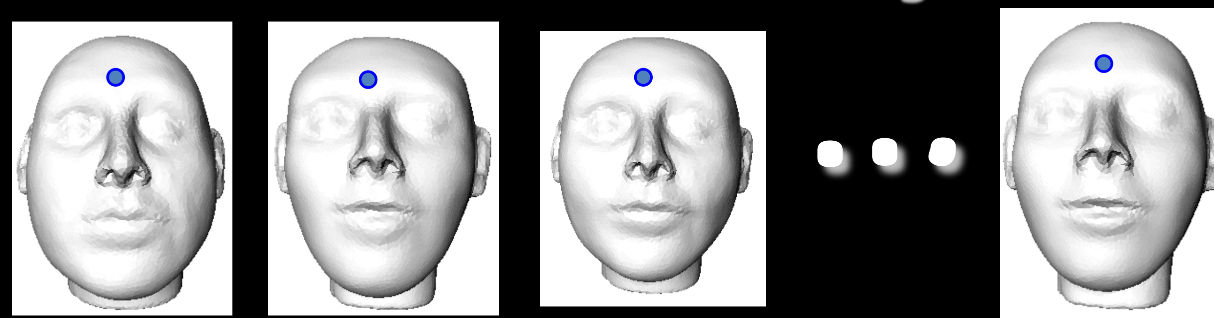
- Rich set of surface shape descriptors.
- Their spatial scale can be modified to include local and non-local surface features.
- Representation is robust to scene clutter and occlusions.

Components


1
Numeric Signatures
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?

Training Set



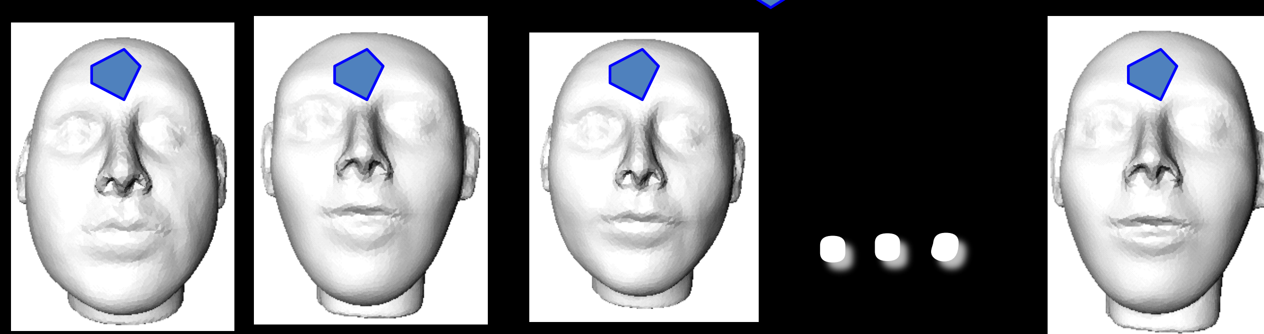
Select Seed Points

Compute Numeric Signatures

Region Growing Algorithm

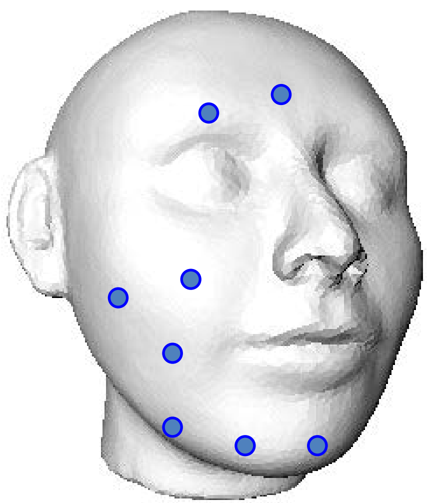
Component Detector

Grown components around seeds



Component Extraction Example

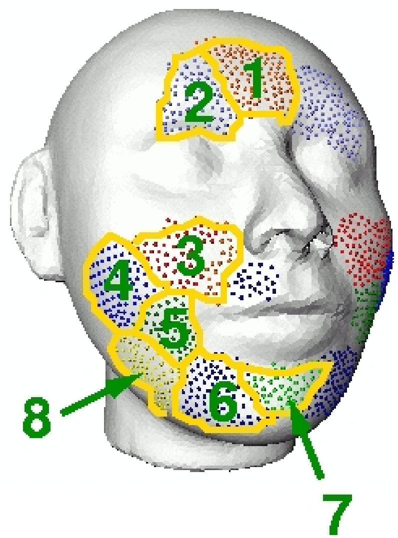
Selected 8 seed points by hand



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

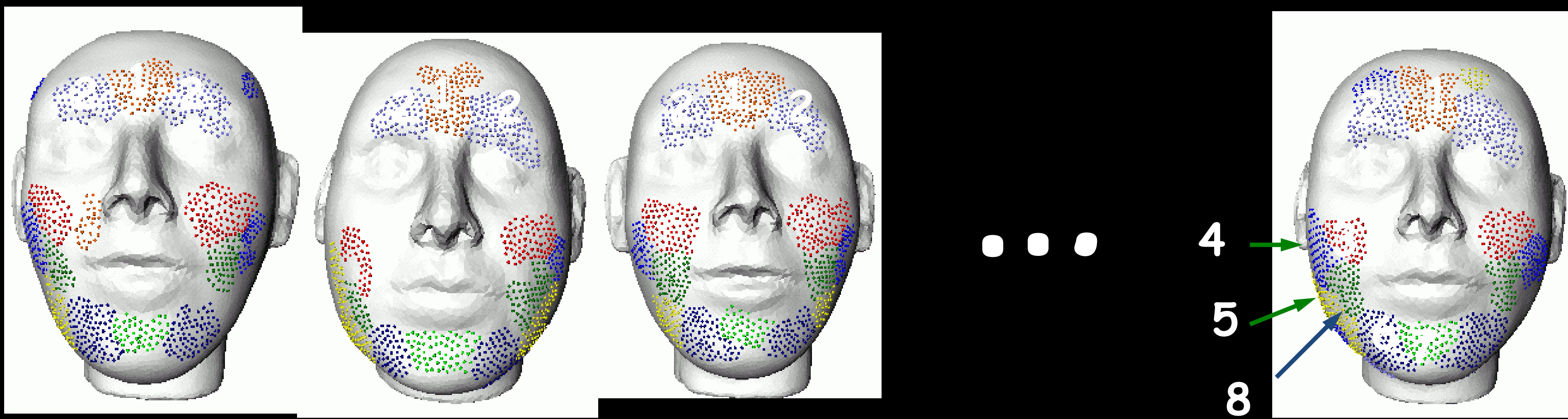
Region Growing

Labeled Surface Mesh



Detected components on a training sample

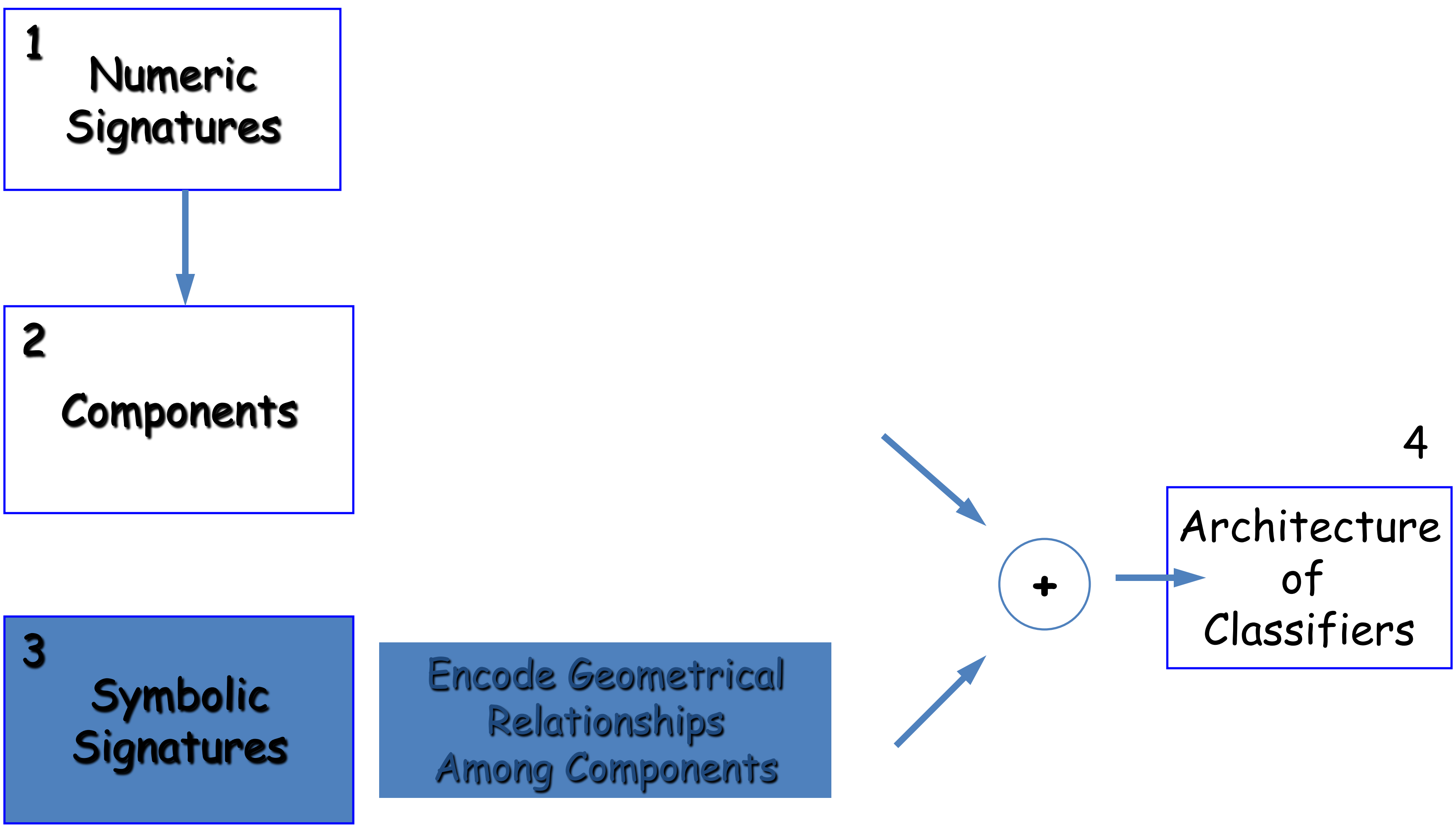
How To Combine Component Information?



Extracted components on test samples

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

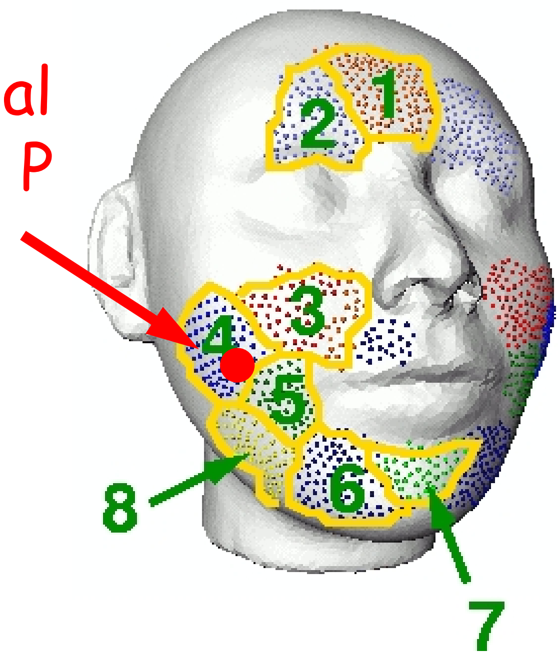
Symbolic Signatures



Symbolic Signature

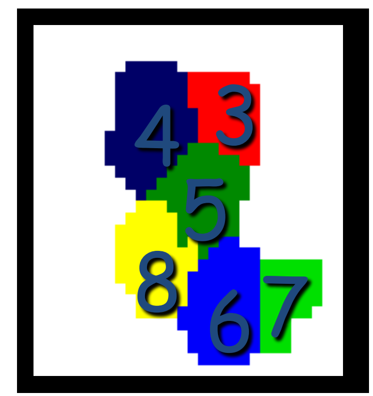
Labeled
Surface Mesh

Critical
Point P



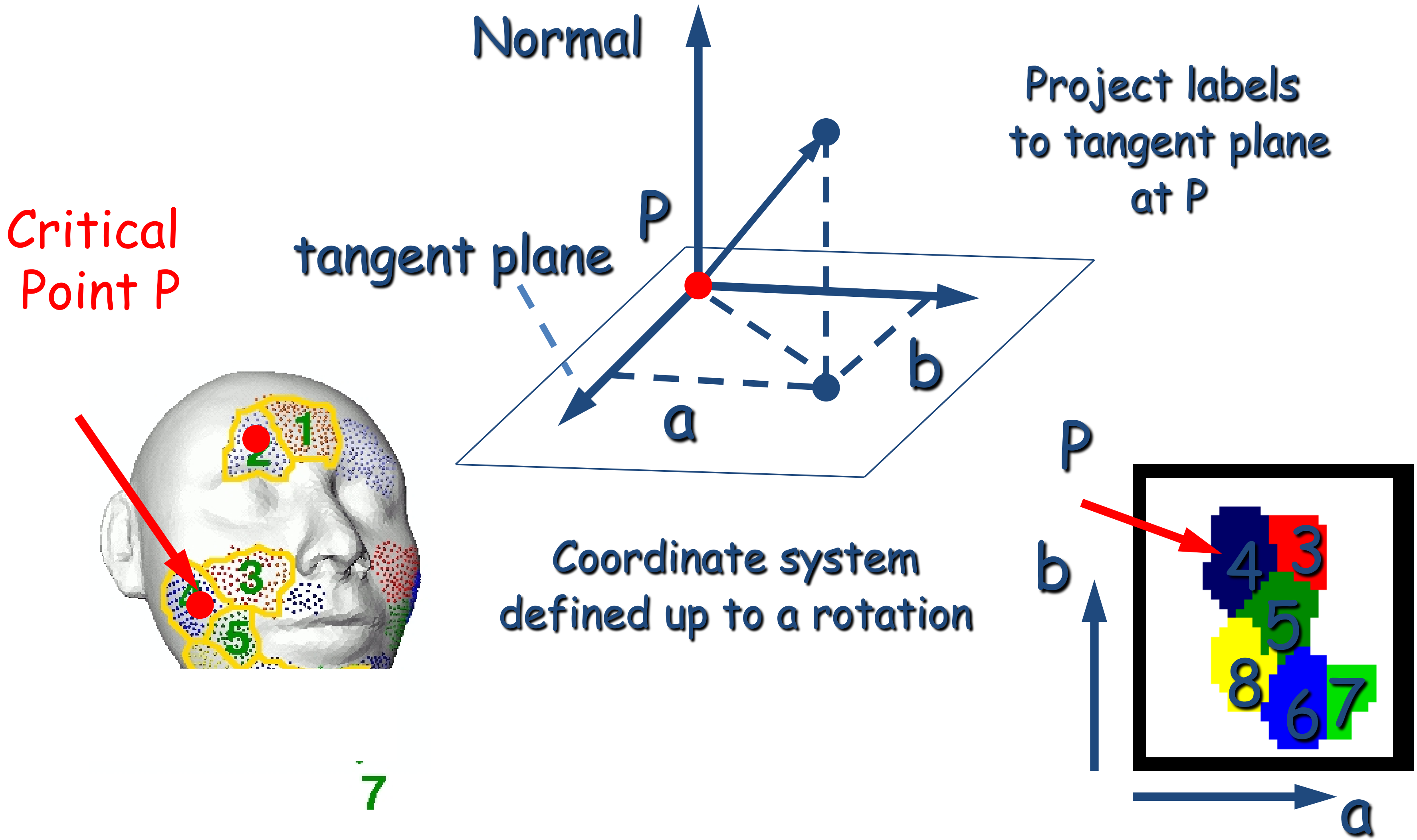
Encode
Geometric
Configuration

Symbolic
Signature at P

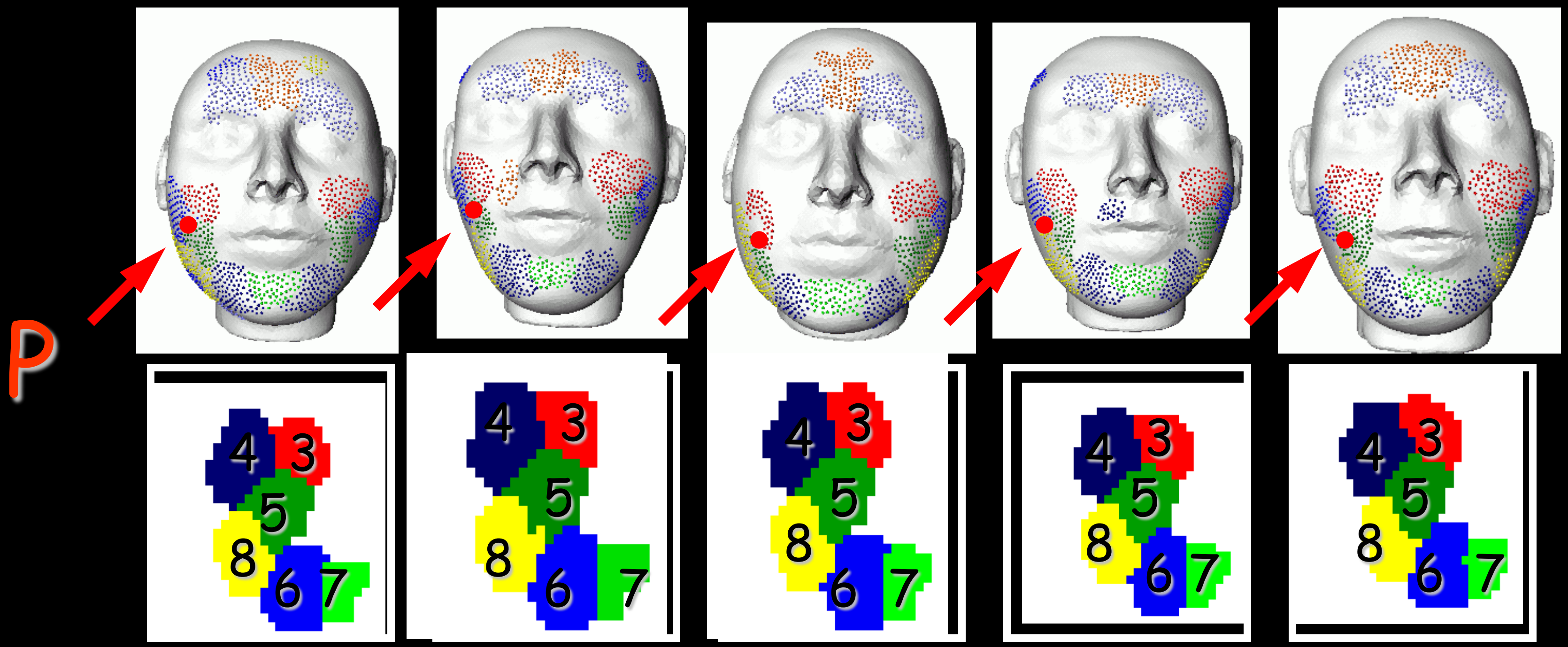


Matrix storing
component
labels

Symbolic Signature Construction

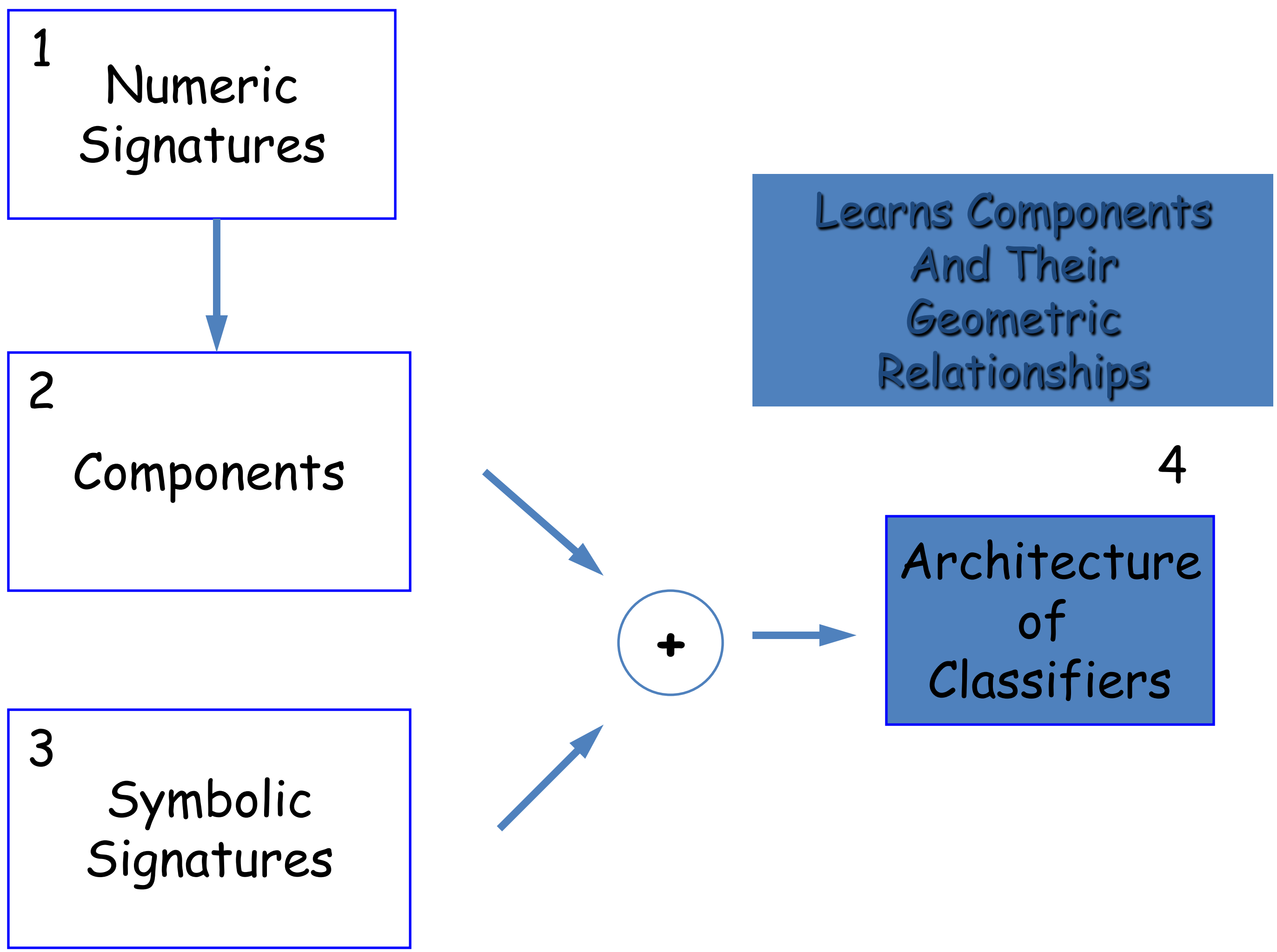


Symbolic Signatures Are Robust To Deformations



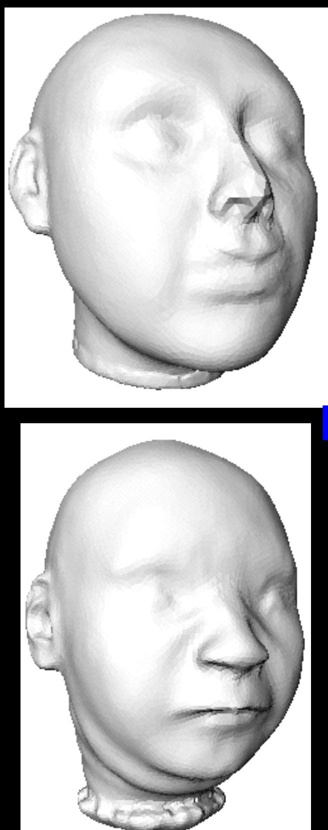
Relative position of components is stable across deformations: experimental evidence

Architecture of Classifiers



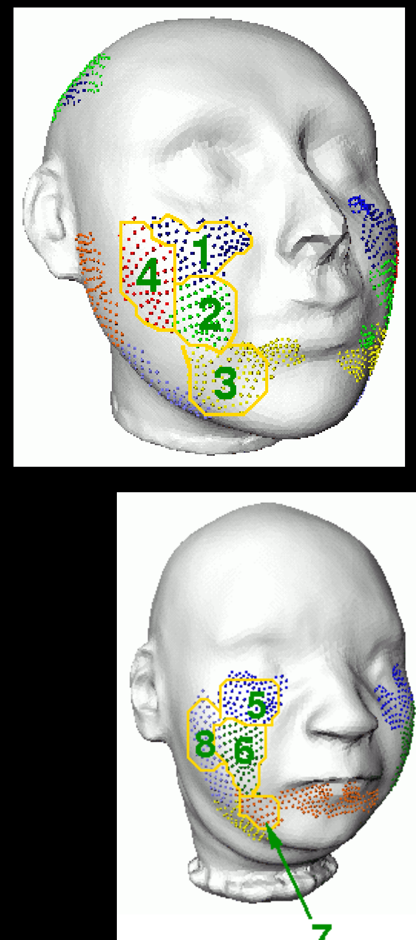
At Classification Time

Surface Mesh



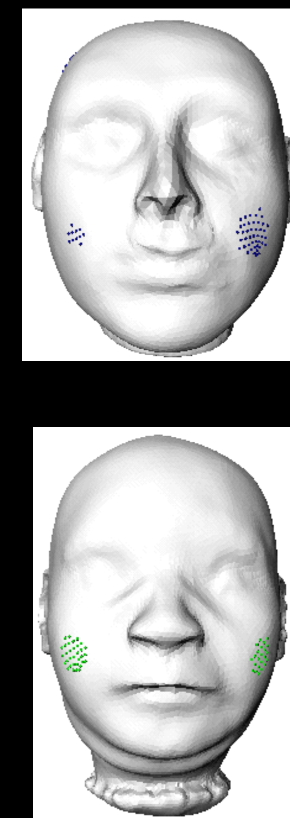
Labeled Surface Mesh

Component Classifiers



Multi-way classifier

+1



-1

Architecture Implementation

- ALL our classifiers are (off-the-shelf) 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

Setup

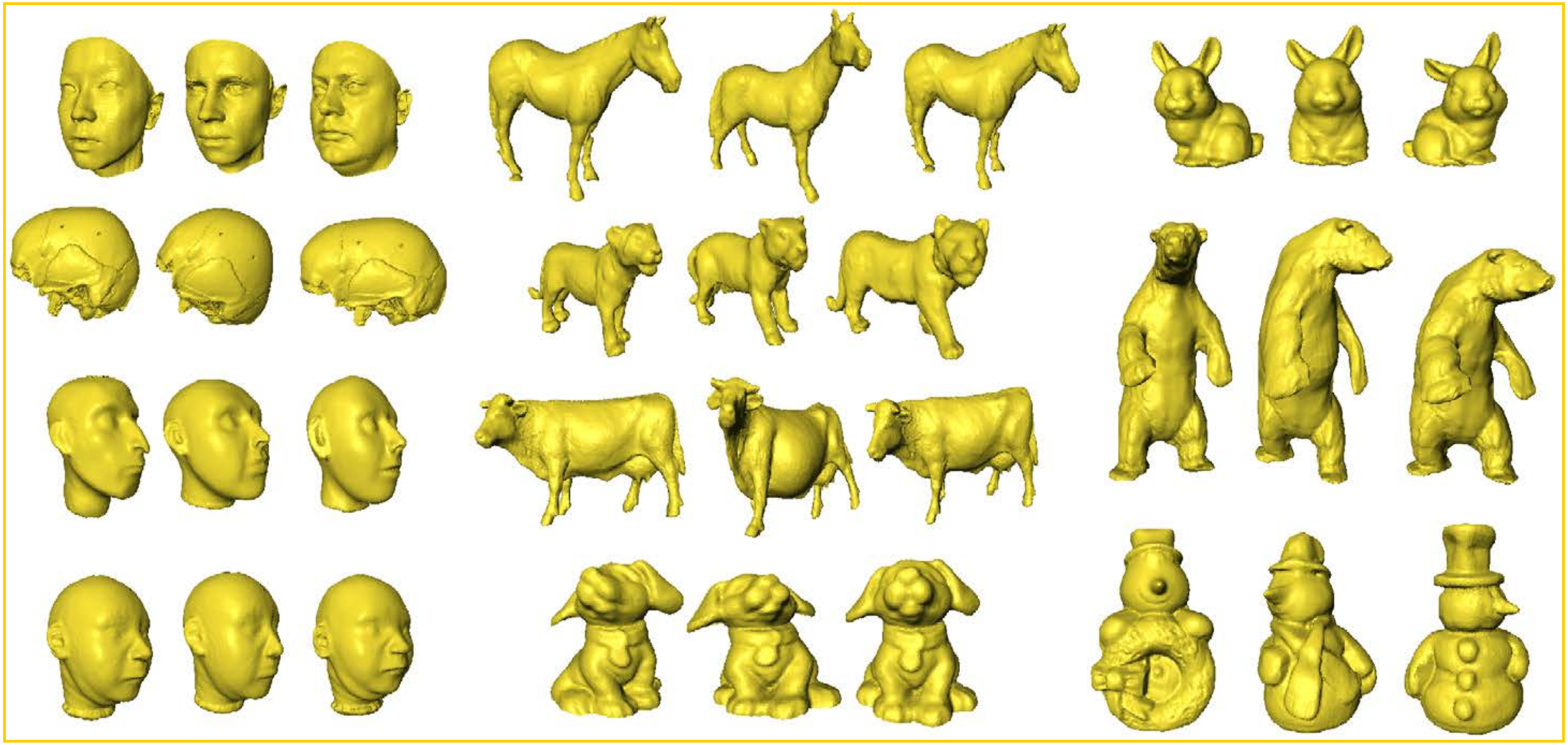
Rotary Table

Recognition

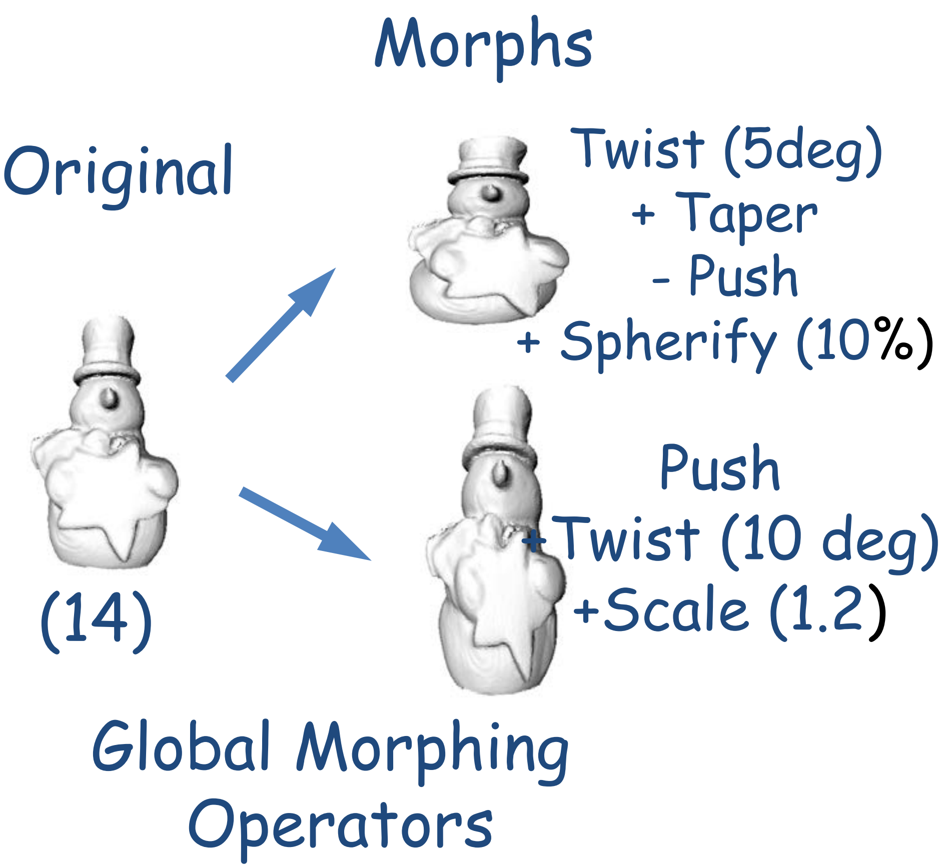
Laser

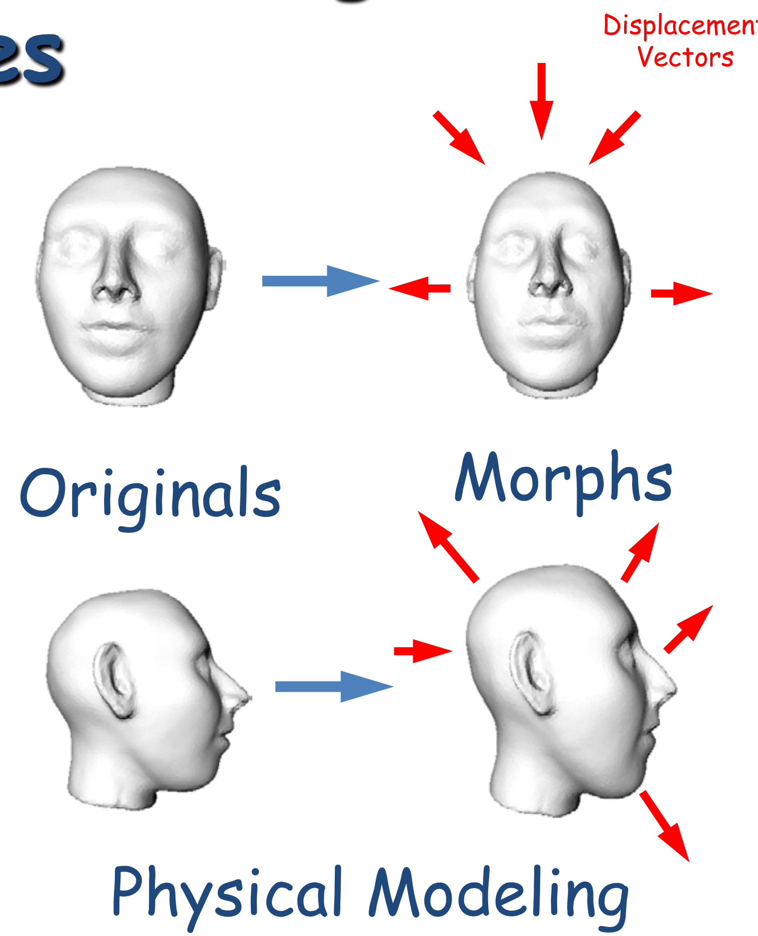
Classification

Shape Classes



Enlarging Training Sets Using Virtual Samples



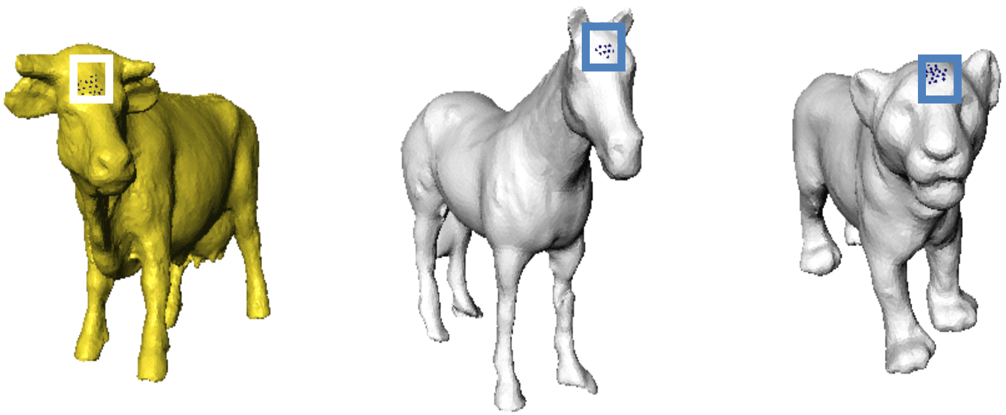


Task 1: Recognizing Single Objects (1)

- 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)

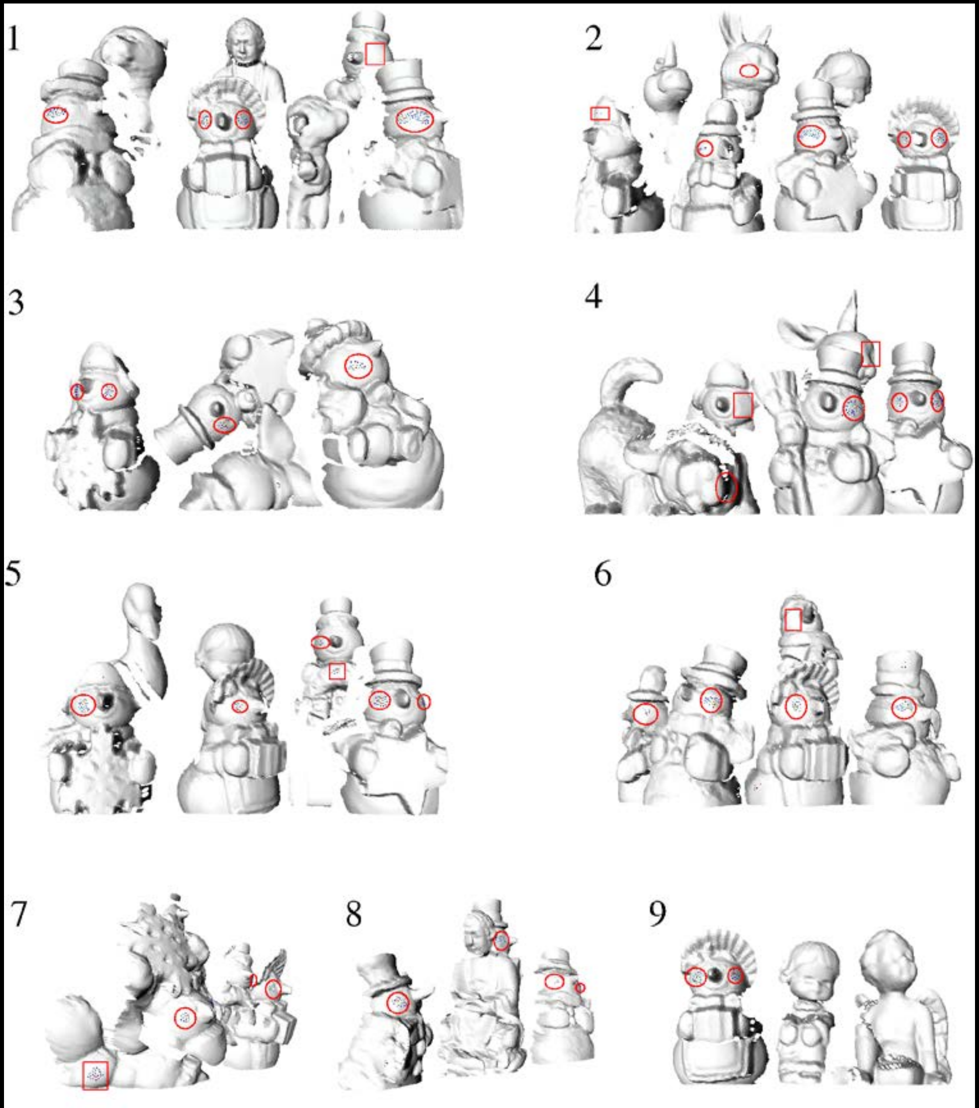
- No. Shape classes: 3.
- Training set size: 400 meshes.
- Testing set size: 200 meshes.
- No. Experiments: 1200.
- No. Component detectors:3.
- No. Symbolic signature detectors: 1.
- Numeric signature size: 40x40.
- Symbolic signature size: 20x20.
- T2 – low clutter and occlusion.

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

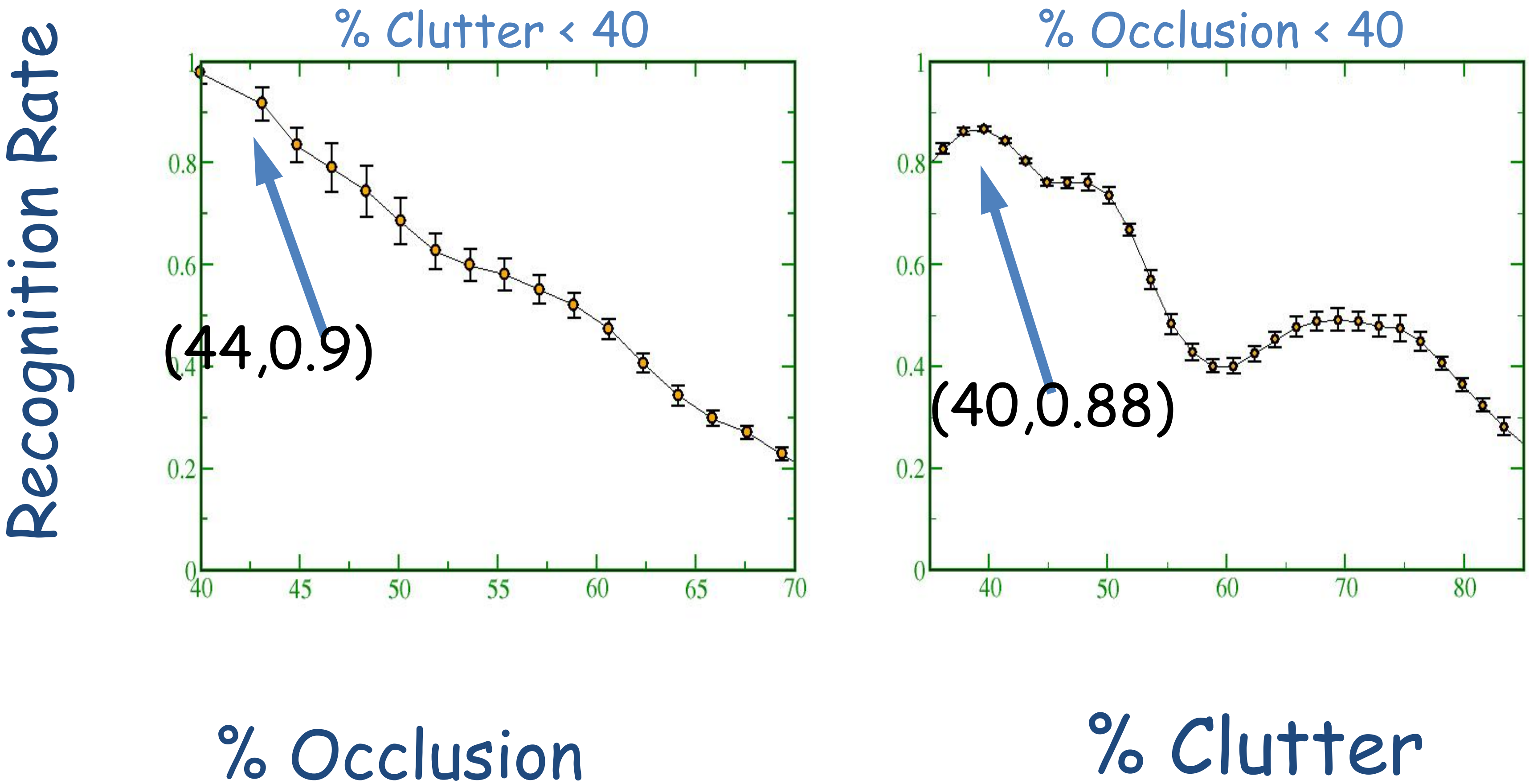
Task 2-3: Recognition in Complex Scenes (3)



Task 4: Recognizing Human Heads (1)

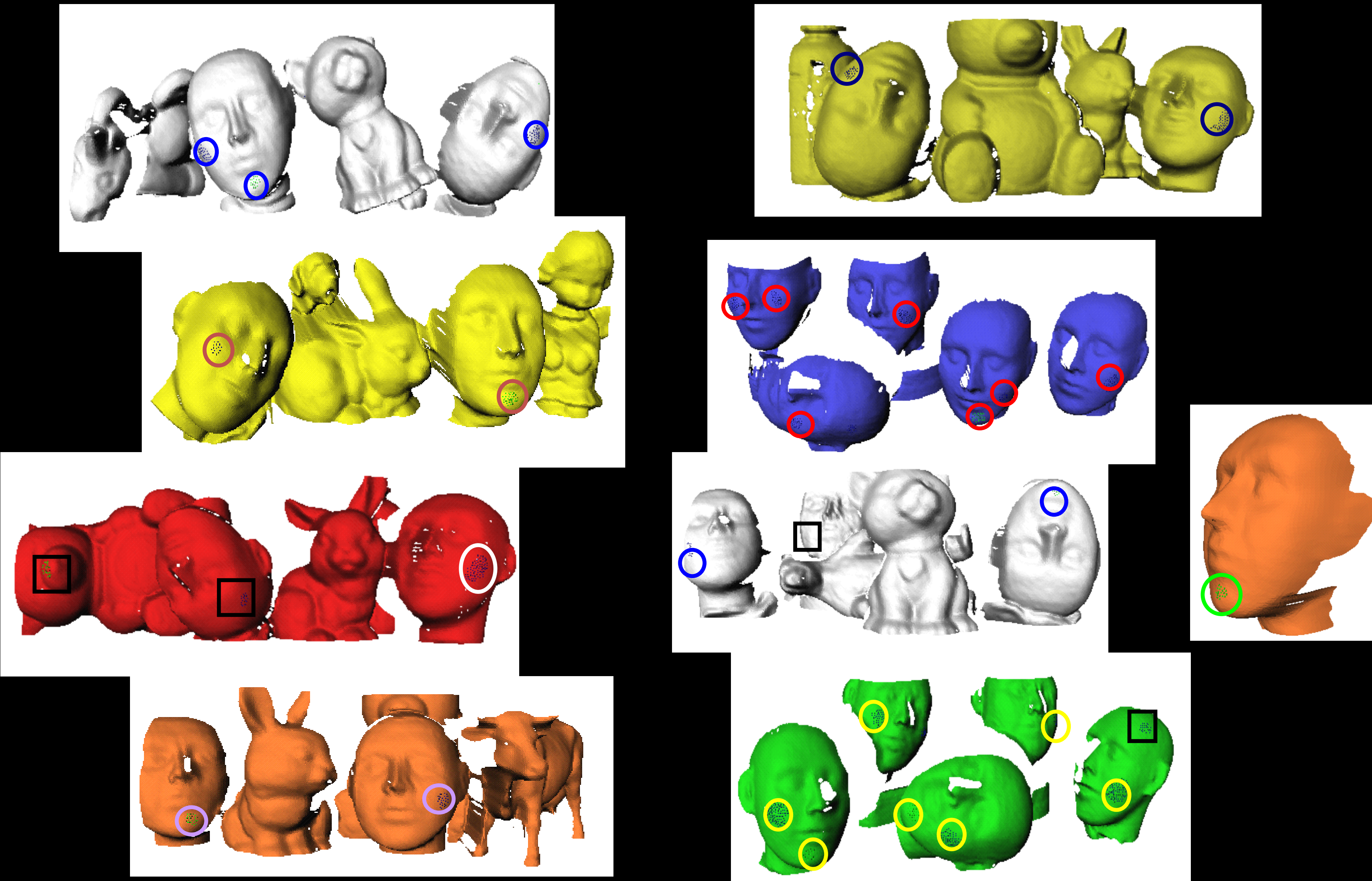
- No. Shape classes: 1.
- Training set size: 400 meshes.
- Testing set size: 250 meshes.
- No. Experiments: 710.
- No. Component detectors:8.
- No. Symbolic signature detectors: 2.
- Numeric signature size: 70x70.
- Symbolic signature size: 12x12.

Task 4: Recognizing Human Heads (2)



FP rate: ~1%,

Task 4: Recognizing Human Heads (3)



Task 5: Classifying Normal vs. Abnormal Human Heads (1)

- No. Shape classes: 6.
- 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

Shape Classes	Classification Accuracy %
Normal vs. Abnormal 1	98
Normal vs. Abnormal 2	100
Abnormal 1 vs. 3	98
Abnormal 1 vs. 4	97
Abnormal 1 vs. 5	92

Full models


Normal

Abnormal


1


2


3


4


5

65%-35% 50%-50% 25%-75%

(convex combinations of Normal and Abnormal 1)

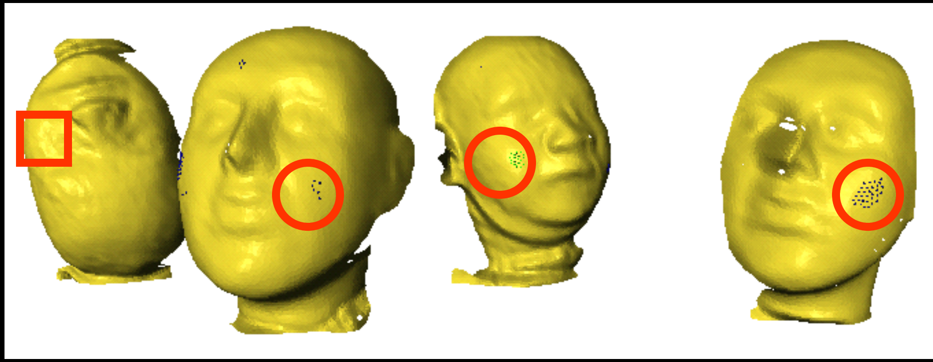
Task 6: Classifying Normal vs. Abnormal Human Heads In Complex Scenes(1)

- 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.

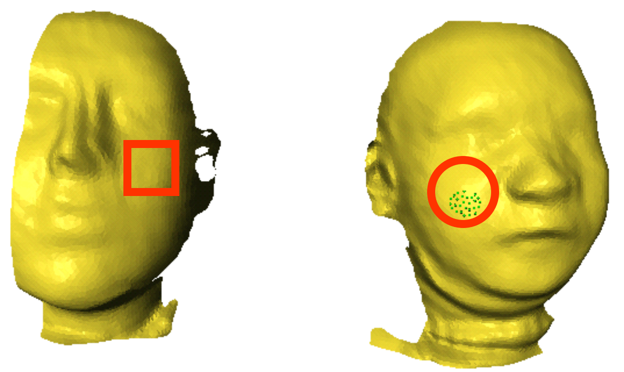
Task 6: Classifying Normal vs. Abnormal Human Heads In Complex Scenes(1)

Shape Classes	Classification Accuracy %
Normal vs. Abnormal 1	88

Clutter < 15%
and occlusion < 50%



Range scenes – single view



Task 7: Classifying Normal vs. Abnormal Neurocranium (1)

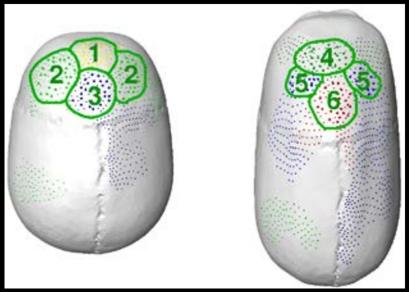
- No. Shape classes: 2.
- Training set size: 400 meshes.
- Testing set size: 200 meshes.
- No. Experiments: 2200.
- No. Component detectors:3.
- No. Symbolic signature detectors: 1.
- Numeric signature size: 50x50.
- Symbolic signature size: 15x15.

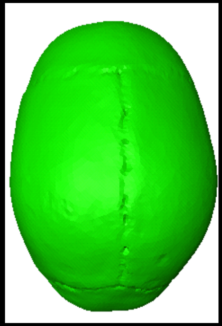
Task 7: Classifying Normal vs. Abnormal Neurocranium (2)

100 Experiments

Shape Classes	Classification Accuracy %
Normal vs. Abnormal	89

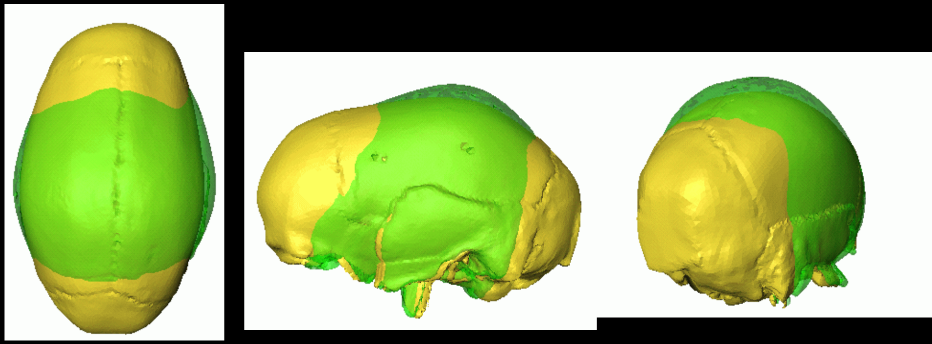
No clutter and occlusion





Normal

Abnormal
(sagittal synostosis)



Superimposed models