Recognizing Deformable Shapes

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(CSE/EE576 Computer Vision I)

Goal

- We are interested in developing algorithms for recognizing and classifying deformable object shapes from range data.

3-D Laser Scanner

Input 3-D Object

Range data

(Cloud of 3-D points)

Post-processing

3-D Output Surface Mesh

- 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.

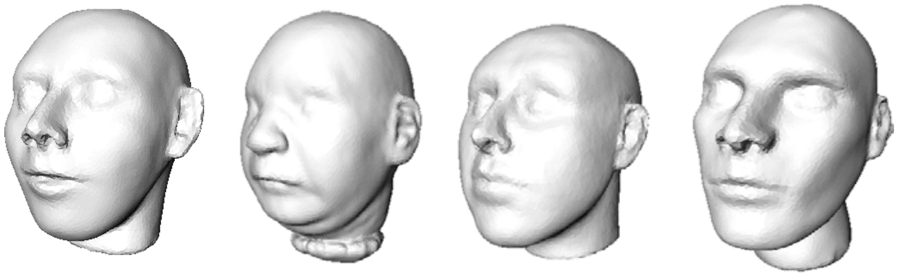
Basic Idea

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

Main Contribution

- An algorithmic framework based on symbolic shape descriptors that are robust to deformations as opposed to numeric descriptors that are often tied to specific shapes.

What Kind Of Deformations?



Mandibles

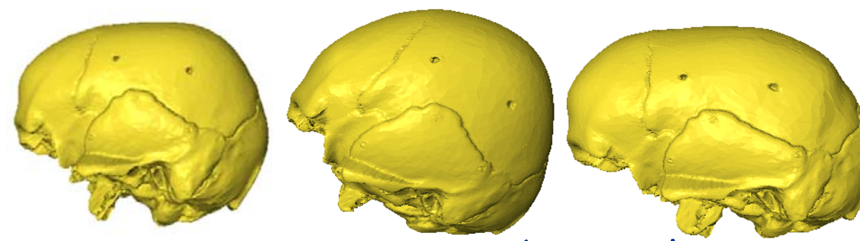
Normal

Abnormal

3-D Faces

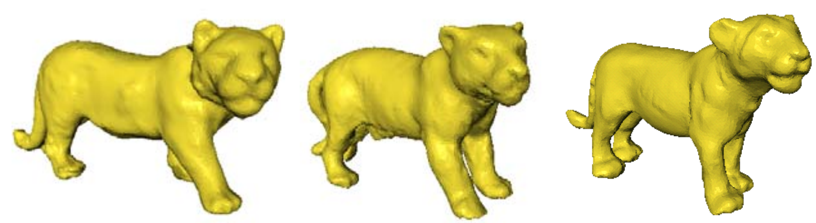
Neurocranium

Normal



Abnormal

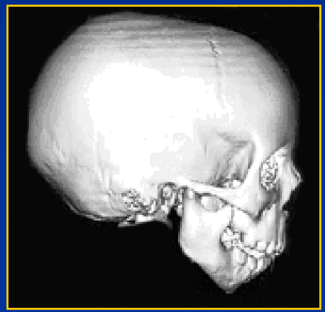
Toy animals



Shape classes: significant amount of intra-class variability

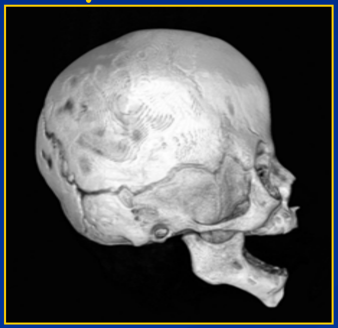
Deformed Infants' Skulls

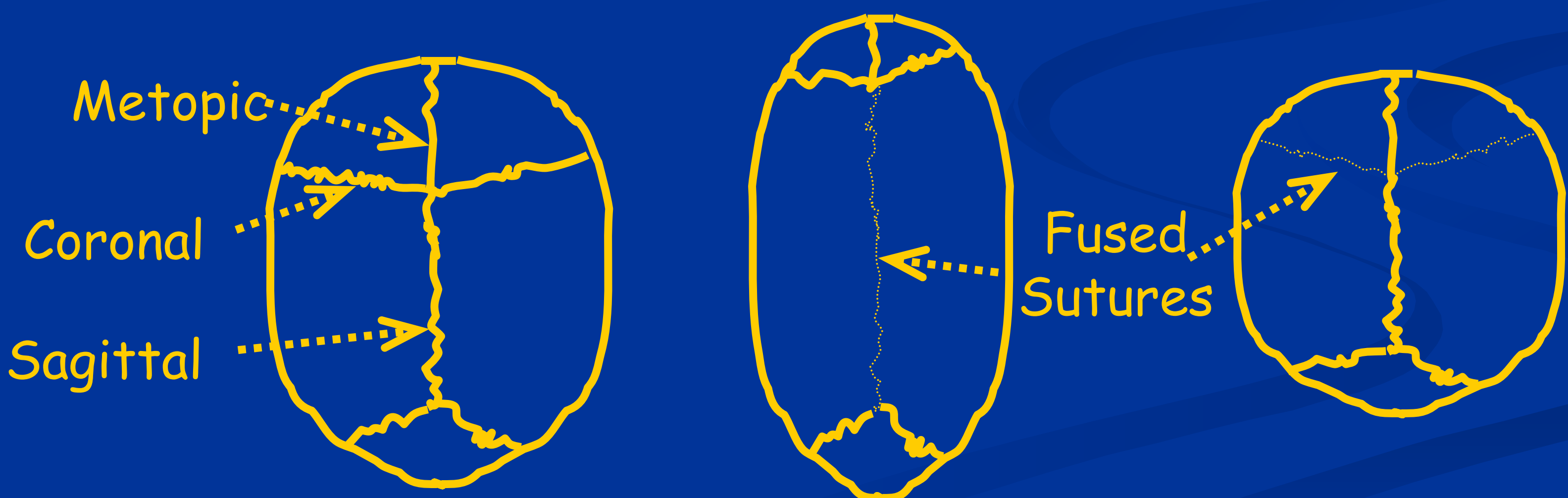
Normal



Sagittal Synostosis

Bicoronal Synostosis

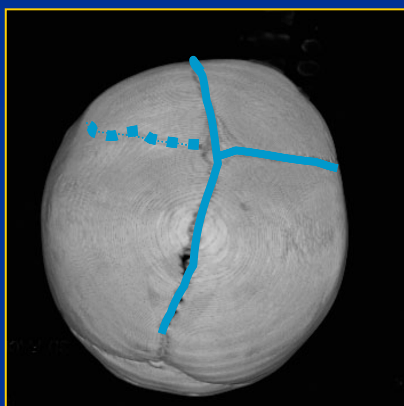




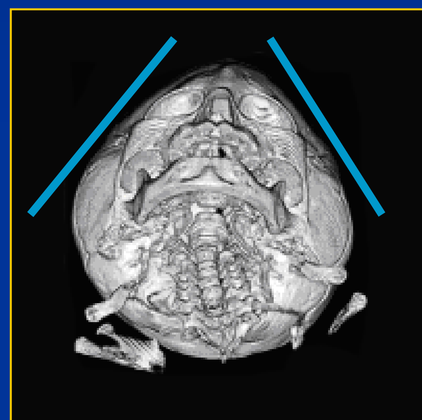
Occurs when sutures of the cranium fuse prematurely (synostosis).

More Craniofacial Deformations

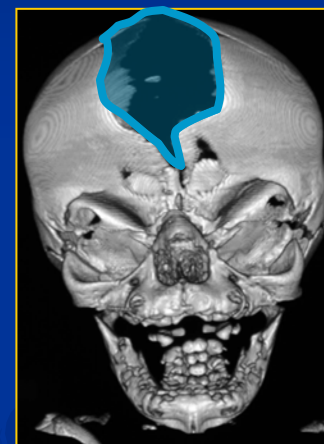
Unicoronal Synostosis

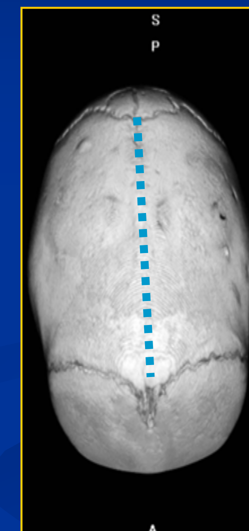


Metopic Synostosis

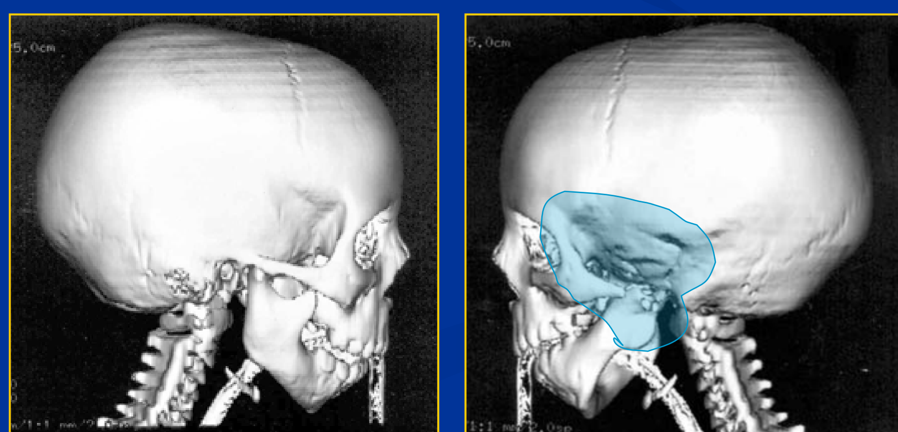


Bicoronal Synostosis





Sagittal Synostosis



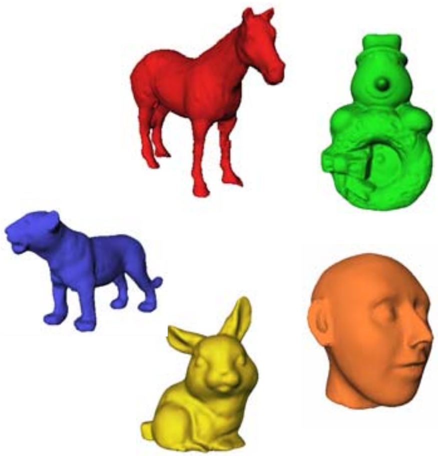
Facial Asymmetry

Alignment-verification

Objects Database

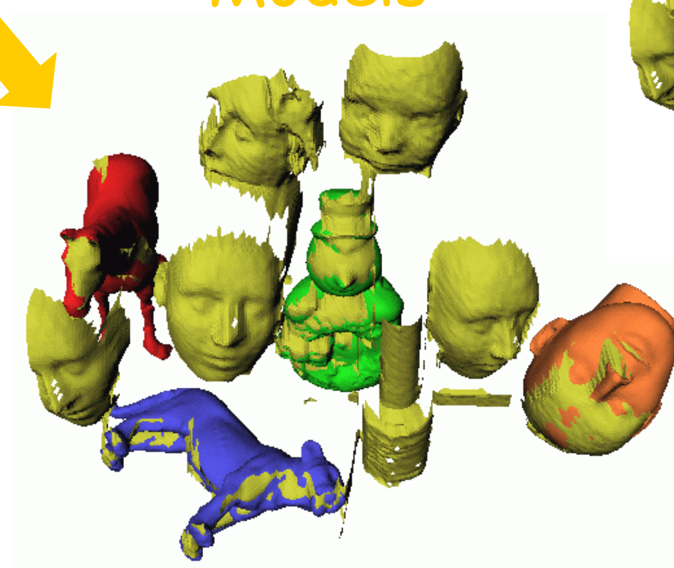
- Find correspondences using numeric signature information.
- Estimate candidate transformations.

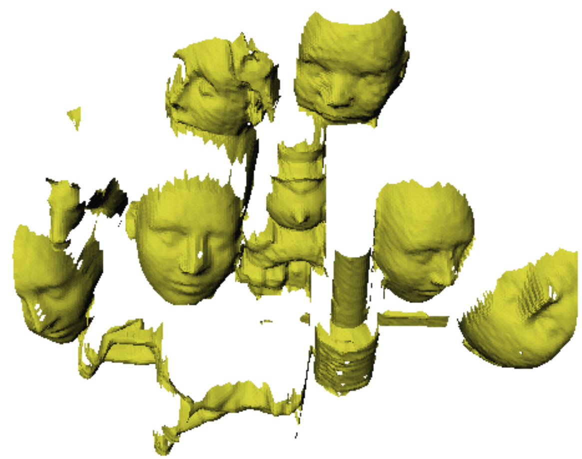
3-D Range Scene



Models

Recognized Models





- Verification process selects the transformation that produces the best alignment.

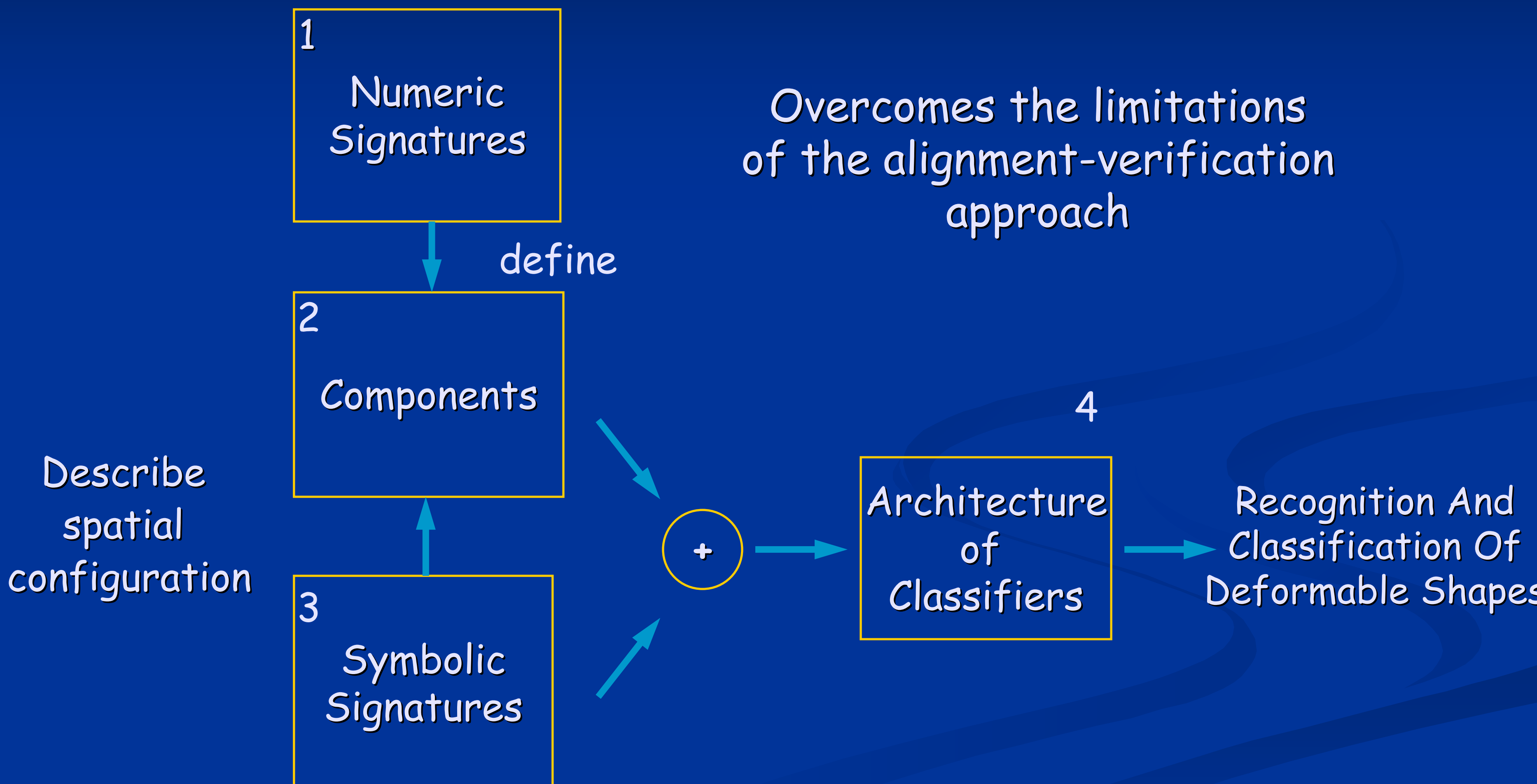
Alignment-Verification Limitations

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.

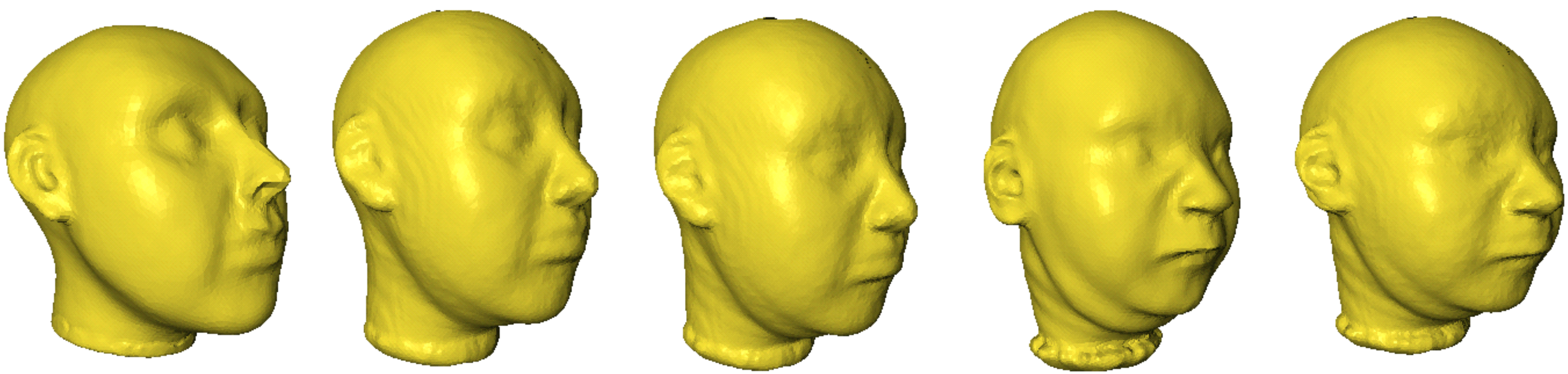
Component-Based Methodology

Overcomes the limitations of the alignment-verification approach



Recognition Problem (1)

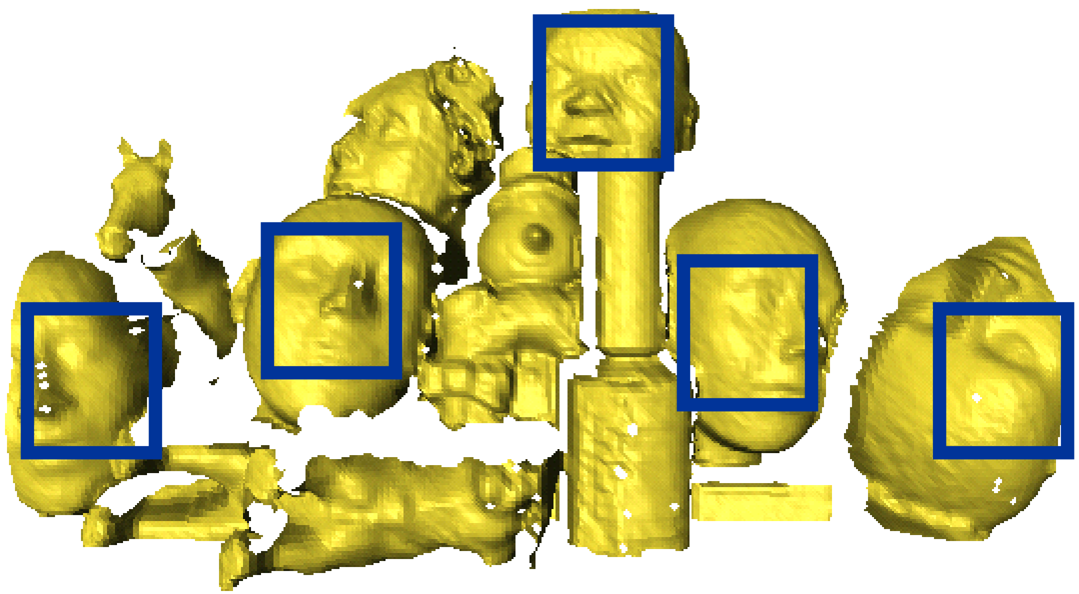
- We are given a set of surface meshes $\{C_1, C_2, \ldots, C_n\}$ which are random samples of two *shape classes* **C**



C_1 C_2 … C_k … C_n

Recognition Problem (2)

- The problem is to use the given meshes and labels to construct an algorithm that determines whether shape class members are present in a single view range scene.



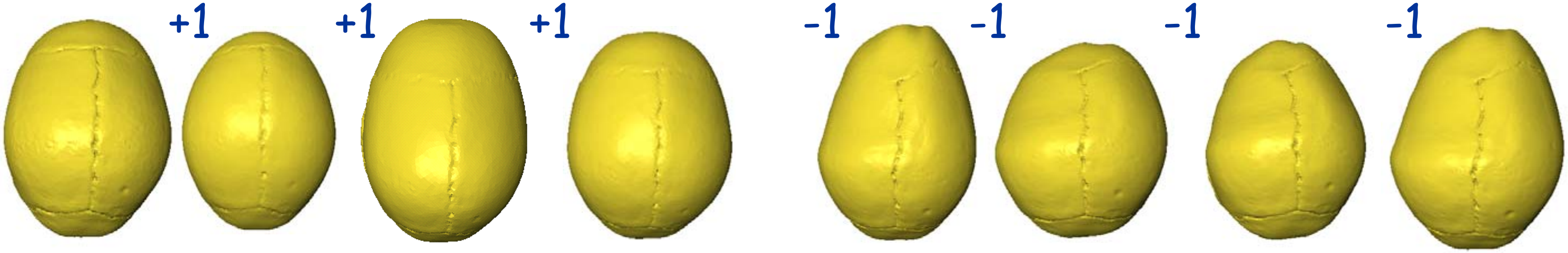
Classification Problem (1)

- We are given a set of surface meshes $\{C_1, C_2, \ldots, C_n\}$ which are random samples of two *shape classes* $\boldsymbol{C}^{+1}$ *and* $\boldsymbol{C}^{-1}$,
- where each surface mesh is labeled either by +1 or -1.

Normal Skulls $\boldsymbol{C}^{+1}$

Abnormal Skulls $\boldsymbol{C}^{-1}$

+1 +1 +1 +1 -1 -1 -1 -1



C_1 C_2 ... C_k C_{k+1} C_{k+2} ... C_n

Classification Problem (2)

- The problem is to use the given meshes and labels to construct an algorithm that predicts the label of a new surface mesh C_{new}.

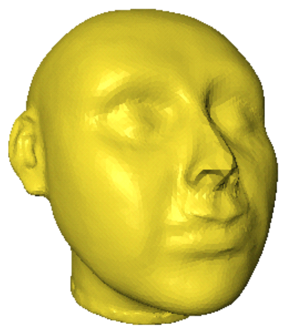
C_{new}

Is this skull normal (+1) or abnormal (-1)?

Classification Problem (3)

- We also consider the case of “missing” information:

Shape class of normal heads (+1)



Shape class of abnormal heads (-1)

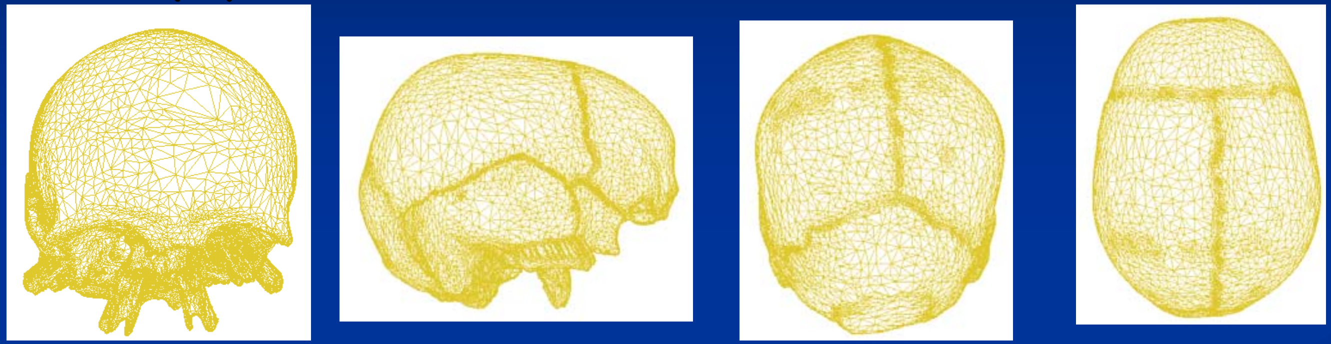
3-D Range Scene Single View

Clutter and Occlusion

Are these heads normal or abnormal?

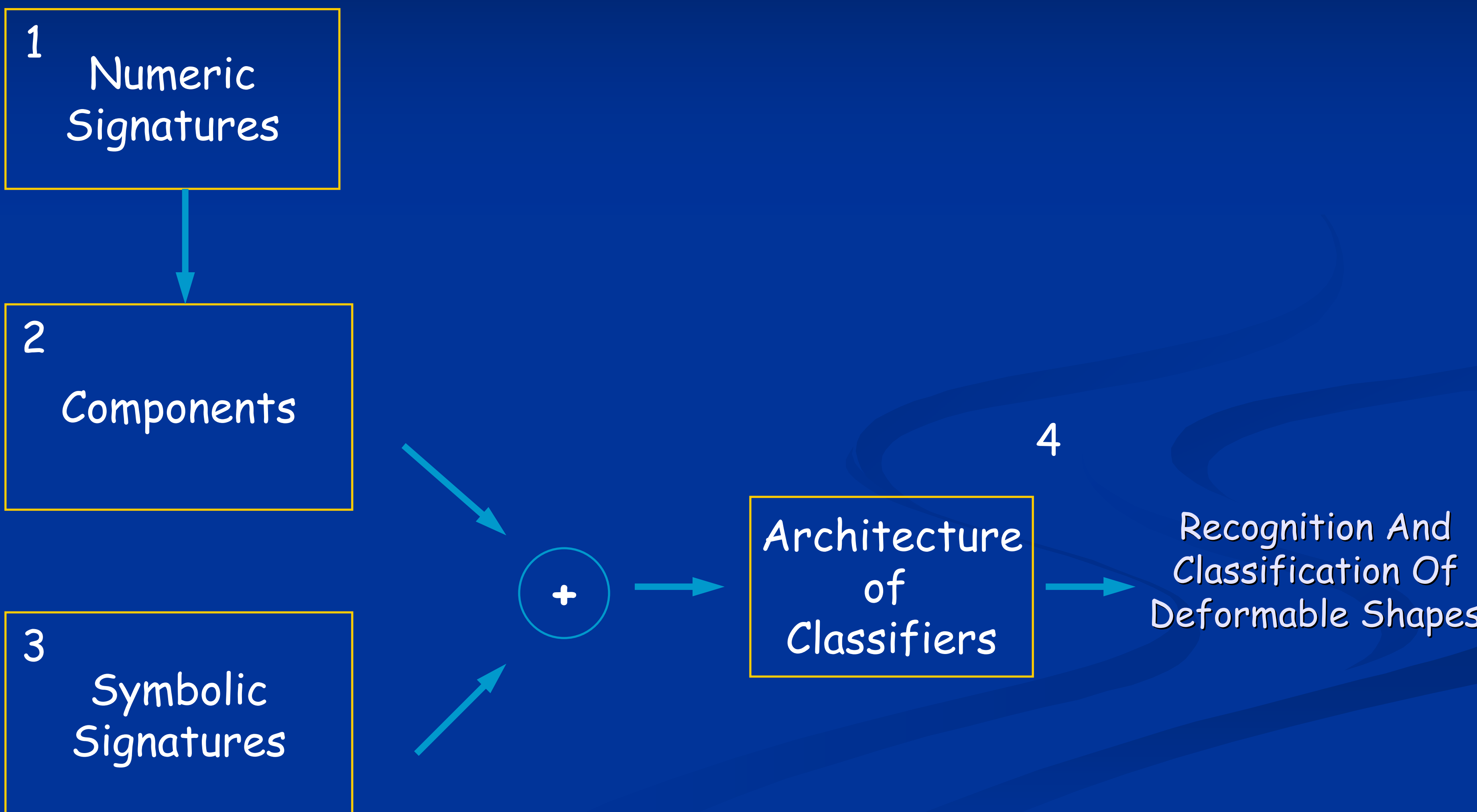
Assumptions

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

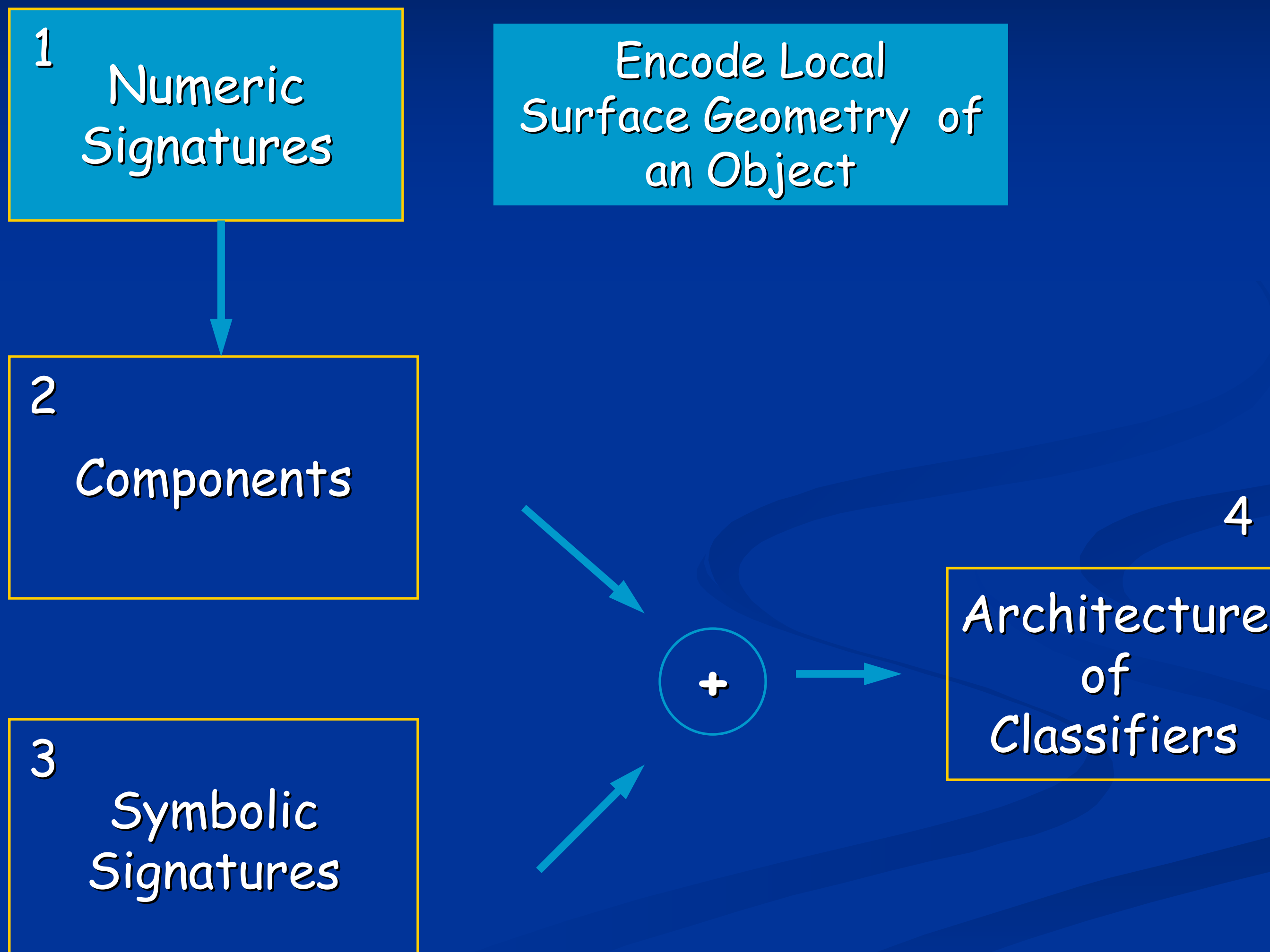


- The vertices of the meshes in the training set are in full correspondence.
- Finding full correspondences : hard problem yes … but it is approachable (use morphable models technique: Blantz and Vetter, SIGGRAPH 99; C. R. Shelton, IJCV, 2000; Allen et al., SIGGRAPH 2003).

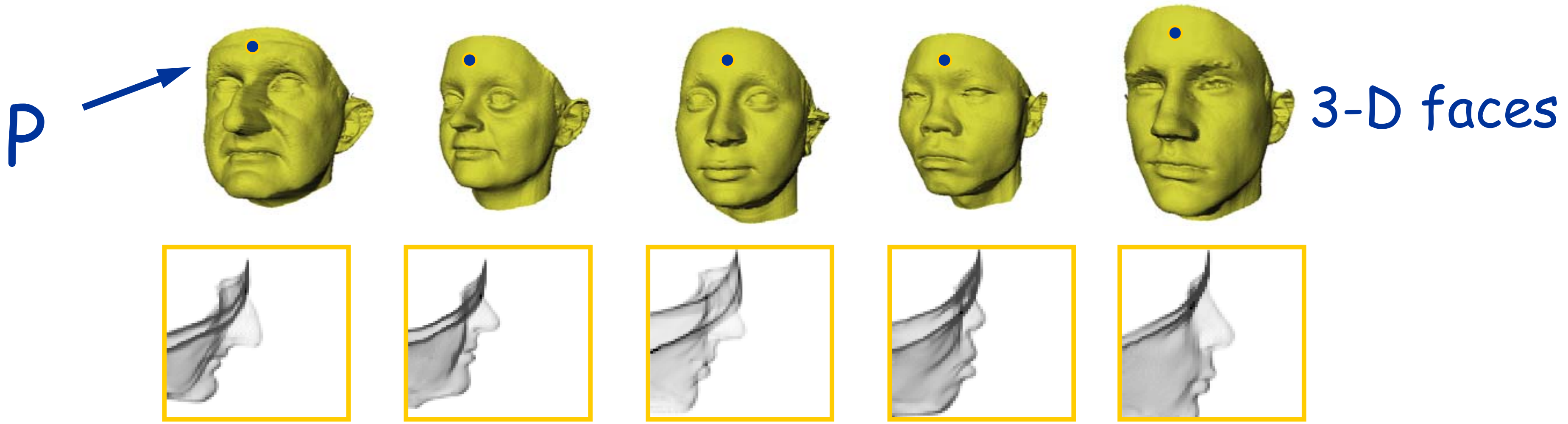
Four Key Elements To Our Approach



Numeric Signatures



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

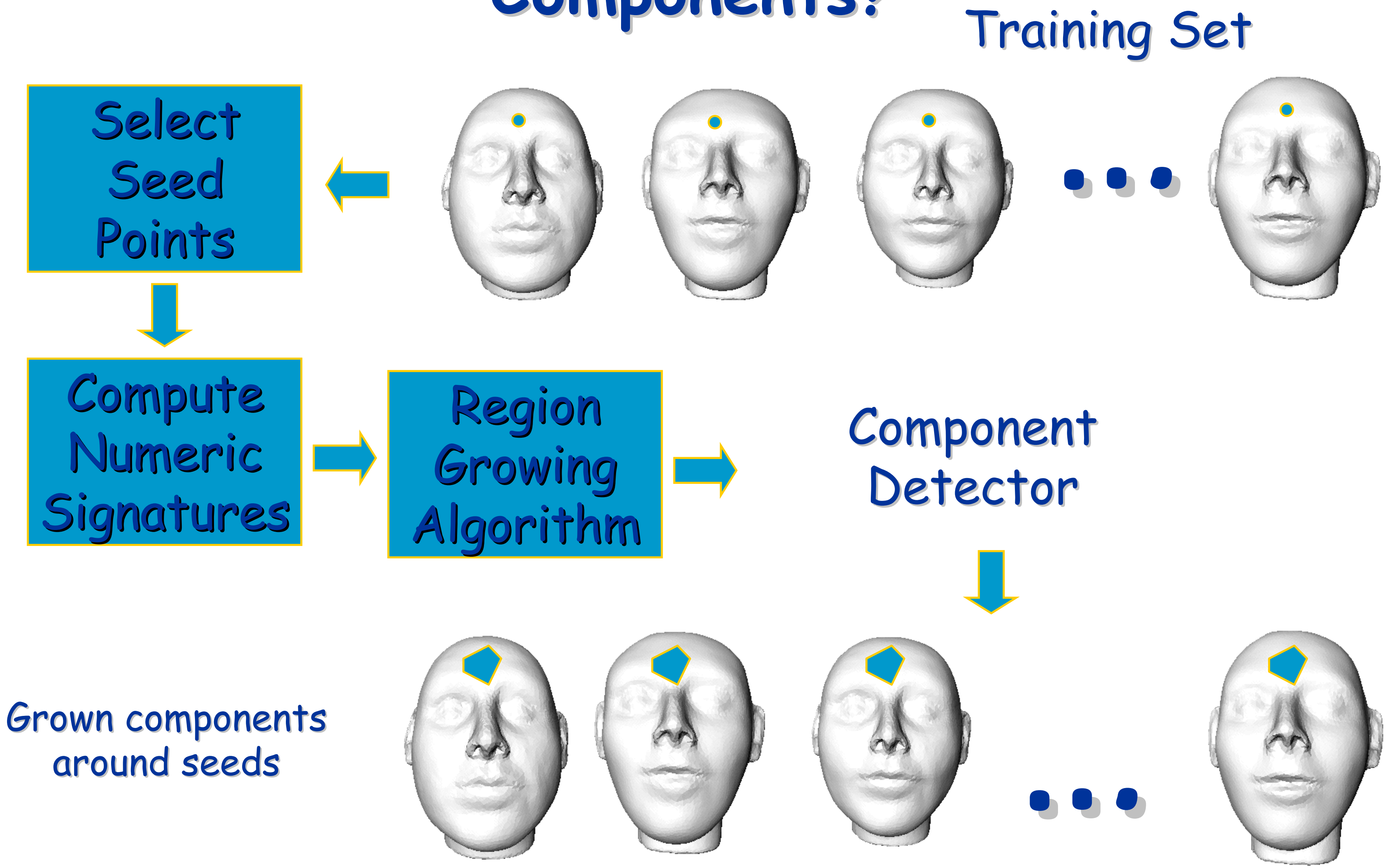
Equivalent Numeric Signatures:
Encode Local Geometry of a Shape Class

3
Symbolic Signatures

+

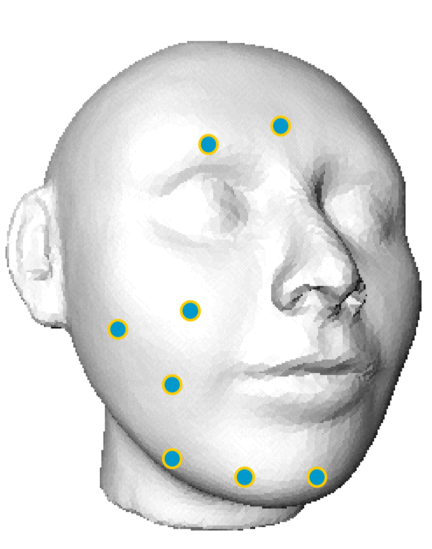
4
Architecture of Classifiers

How To Extract Shape Class Components?



Component Extraction Example

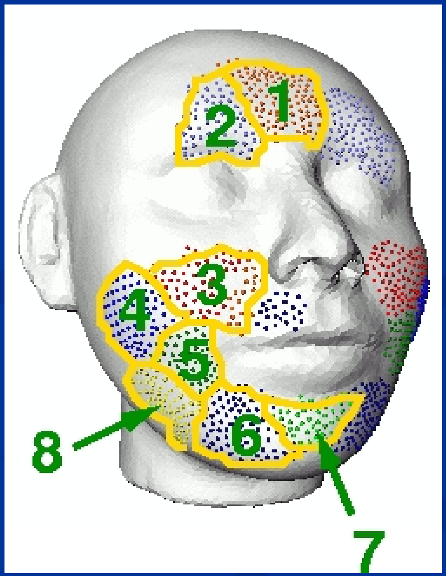
Selected 8 seed points by hand



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

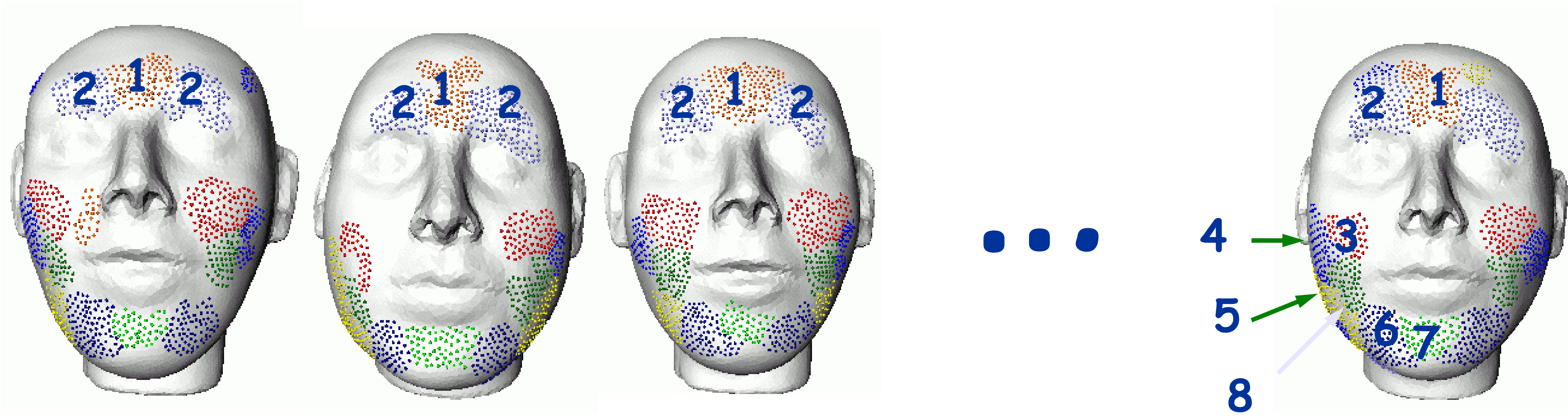
Region Growing

Labeled Surface Mesh



Detected components on a training sample

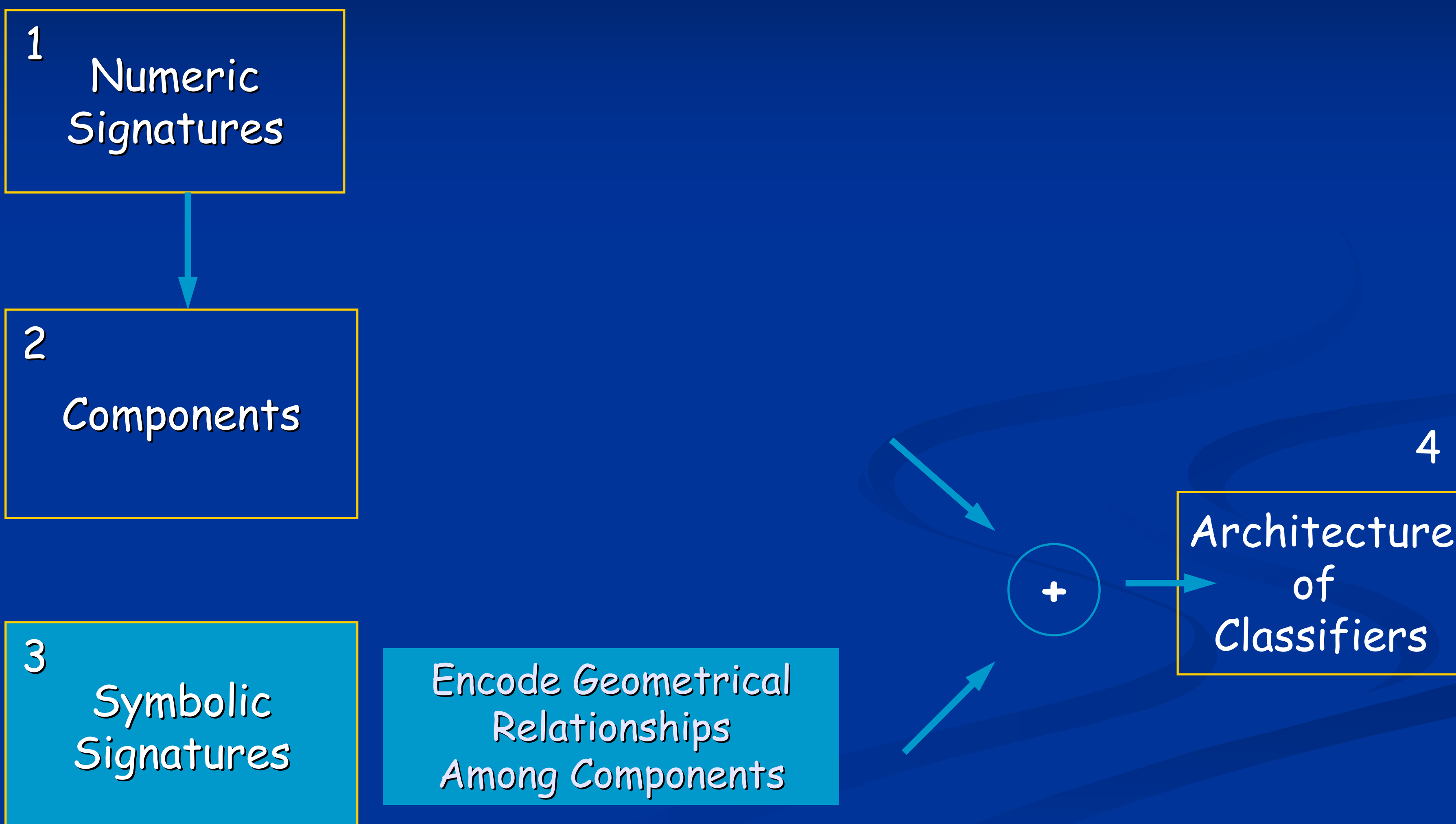
How To Combine Component Information?



Extracted components on test samples

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

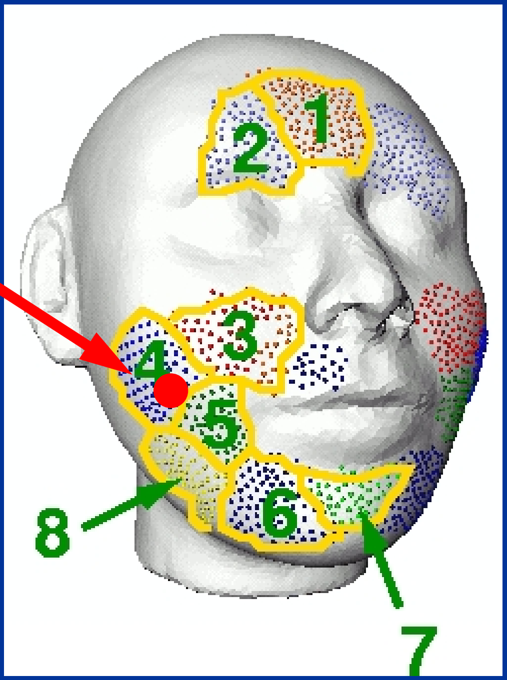
Symbolic Signatures



Symbolic Signature

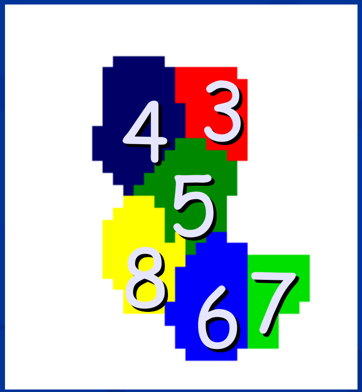
Labeled
Surface Mesh

Critical
Point P



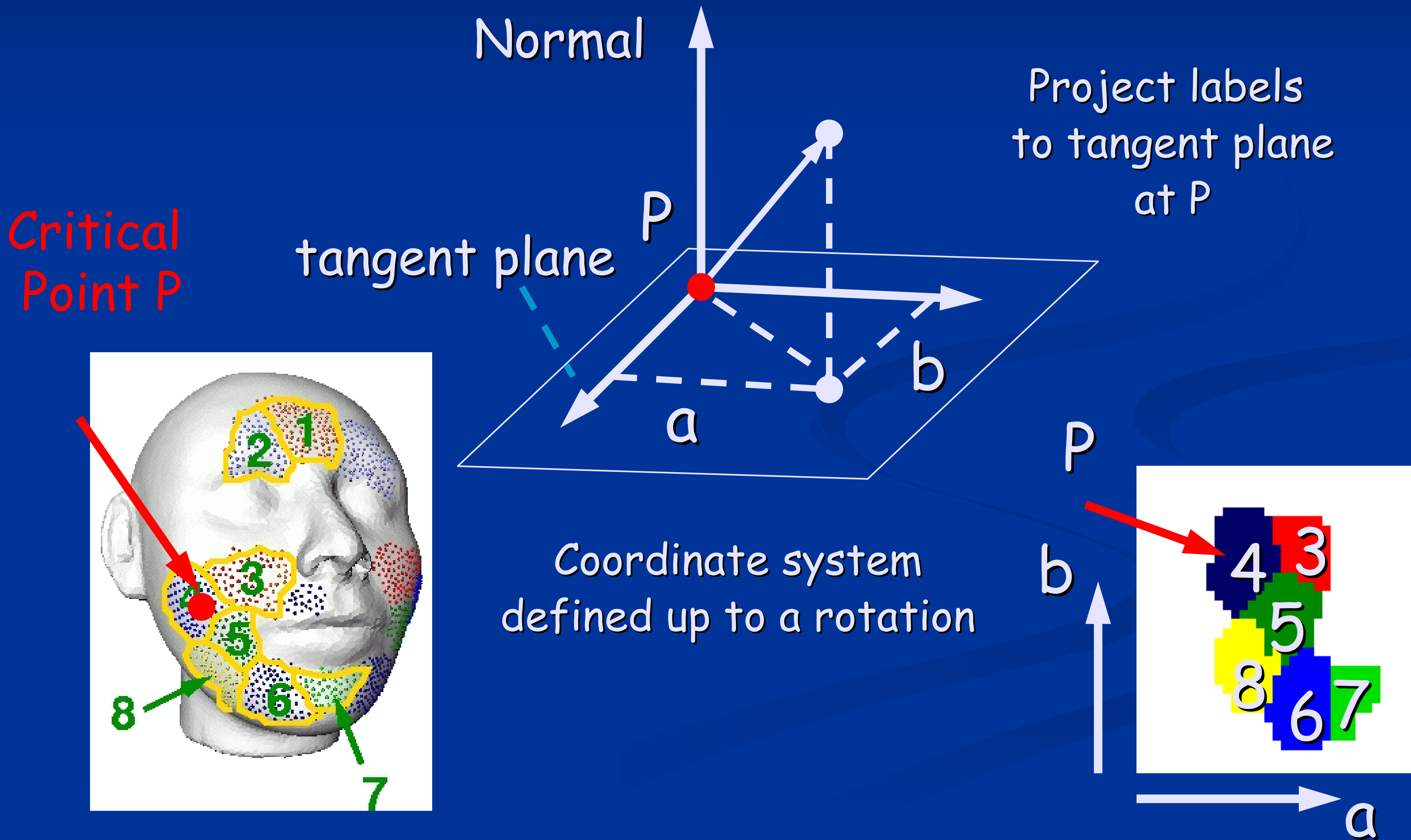
Encode
Geometric
Configuration

Symbolic
Signature at P

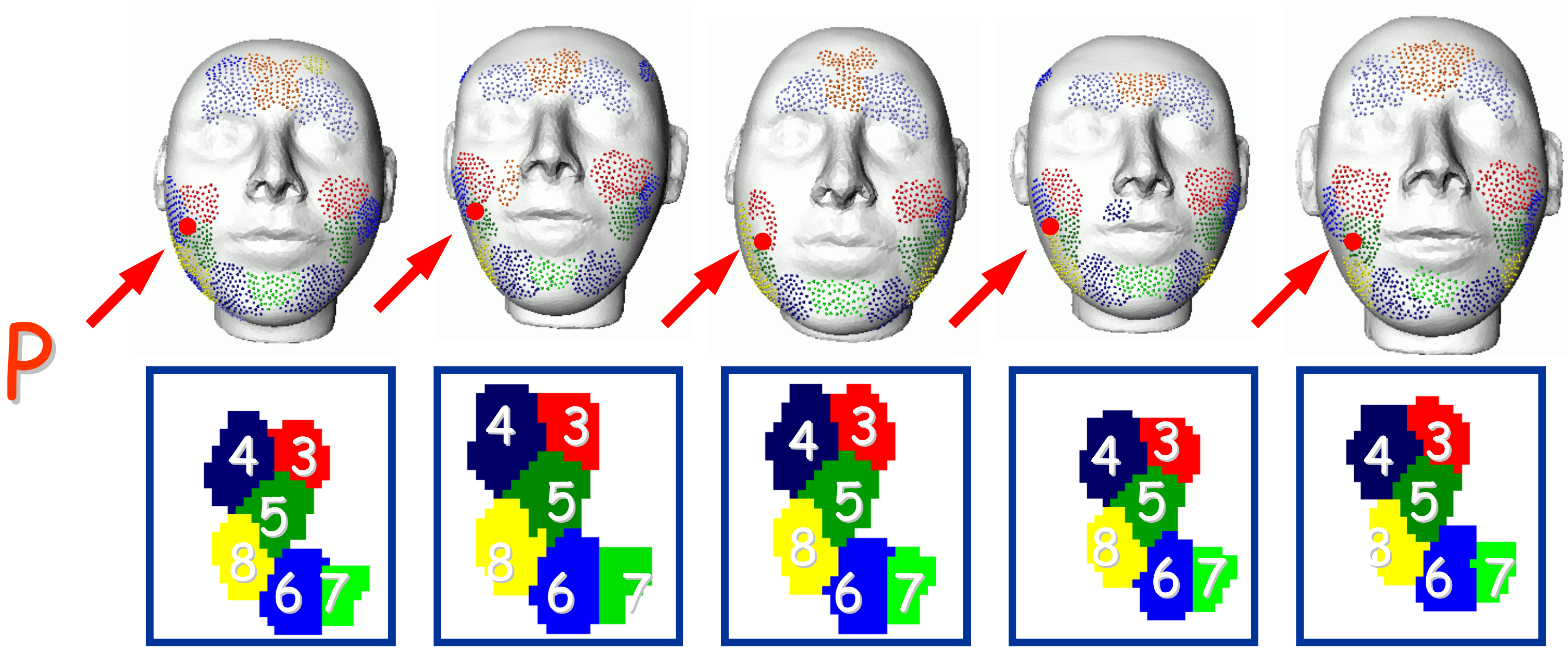


Matrix storing
component
labels

Symbolic Signature Construction

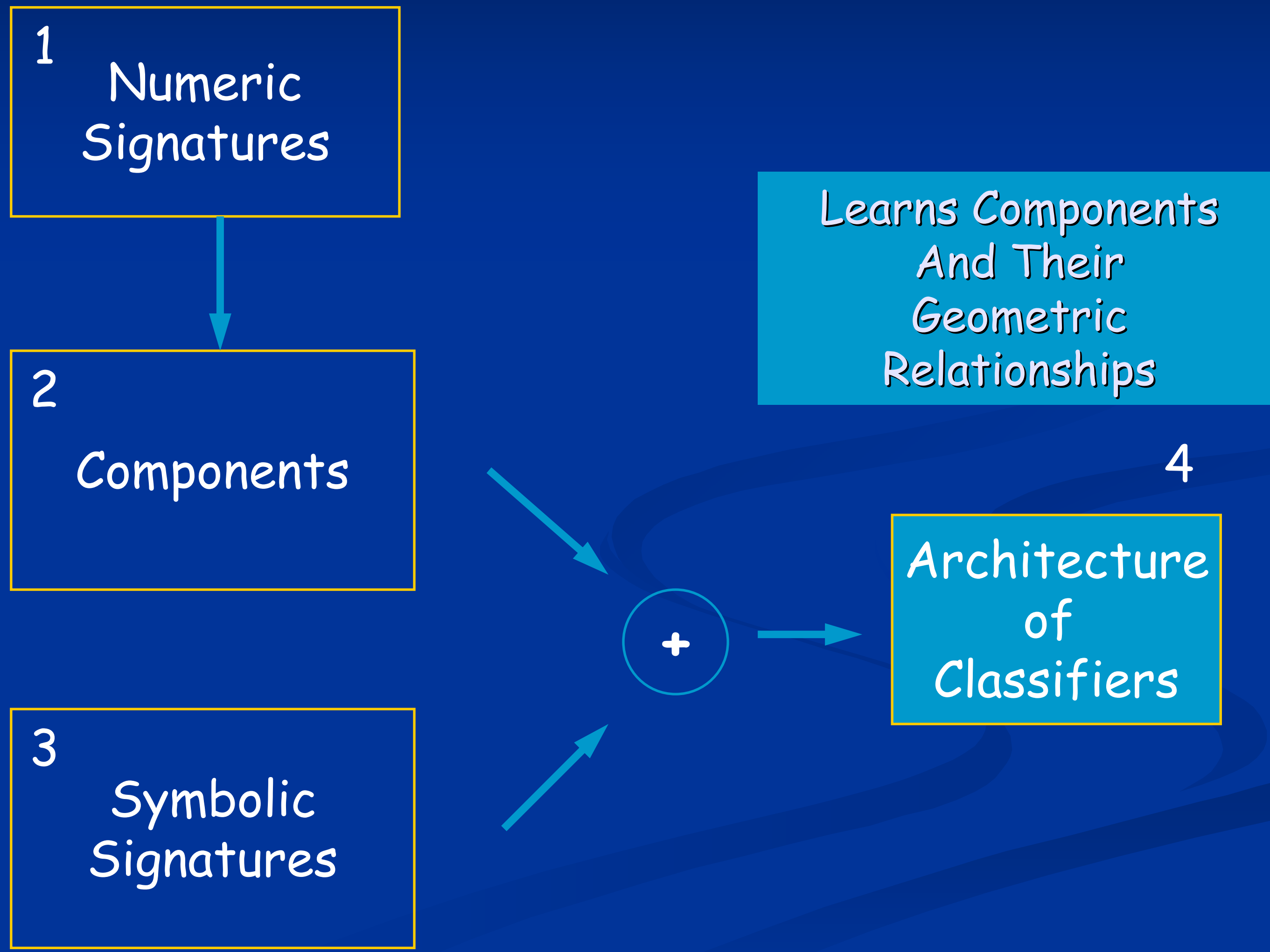


Symbolic Signatures Are Robust To Deformations



Relative position of components is stable across deformations: experimental evidence

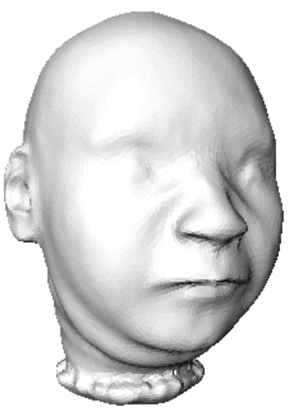
Architecture of Classifiers



Proposed Architecture (Classification Example)

Verify spatial configuration of the components

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



Surface Mesh

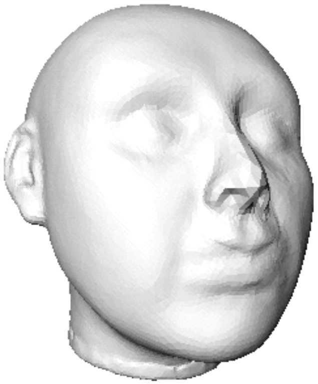
-1

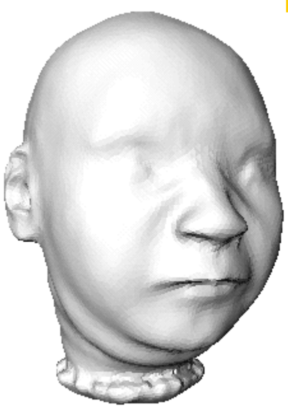
(Abnormal)

Two classification stages

At Classification Time (1)

Surface Mesh





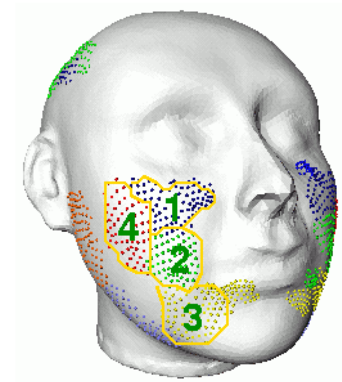
Bank of Component Detectors

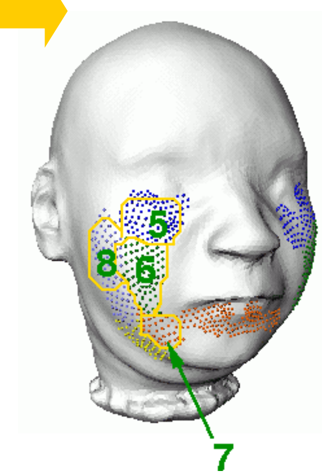
Multi-way classifier

Assigns Component Labels

Identify Components

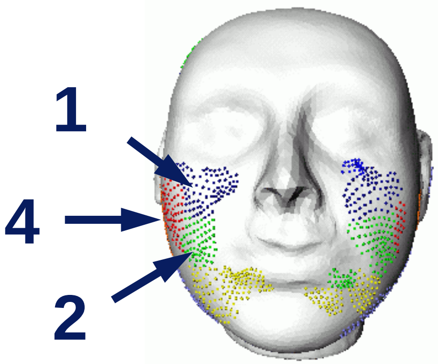
Labeled Surface Mesh

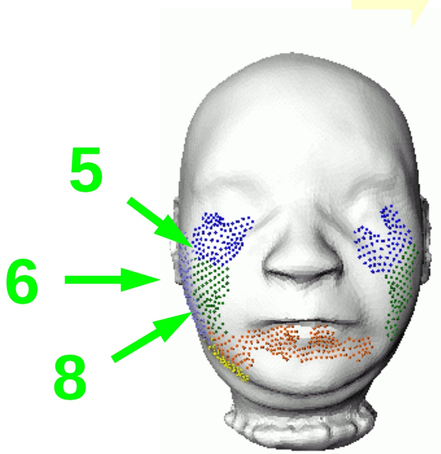




At Classification Time (2)

Labeled Surface Mesh





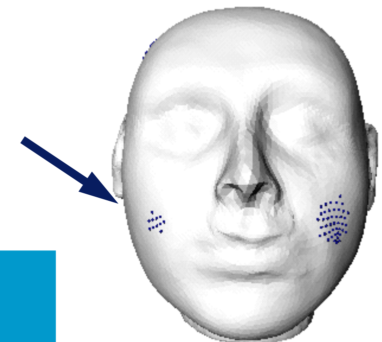
Bank of Symbolic Signatures Detectors

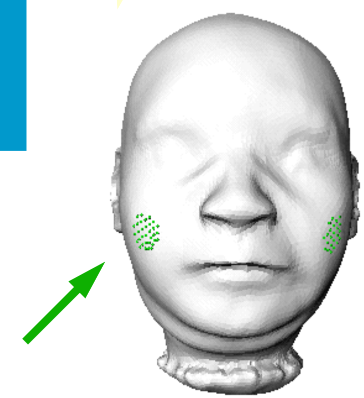
Two detectors

Assigns Symbolic Labels

Symbolic pattern for components 1,2,4

+1

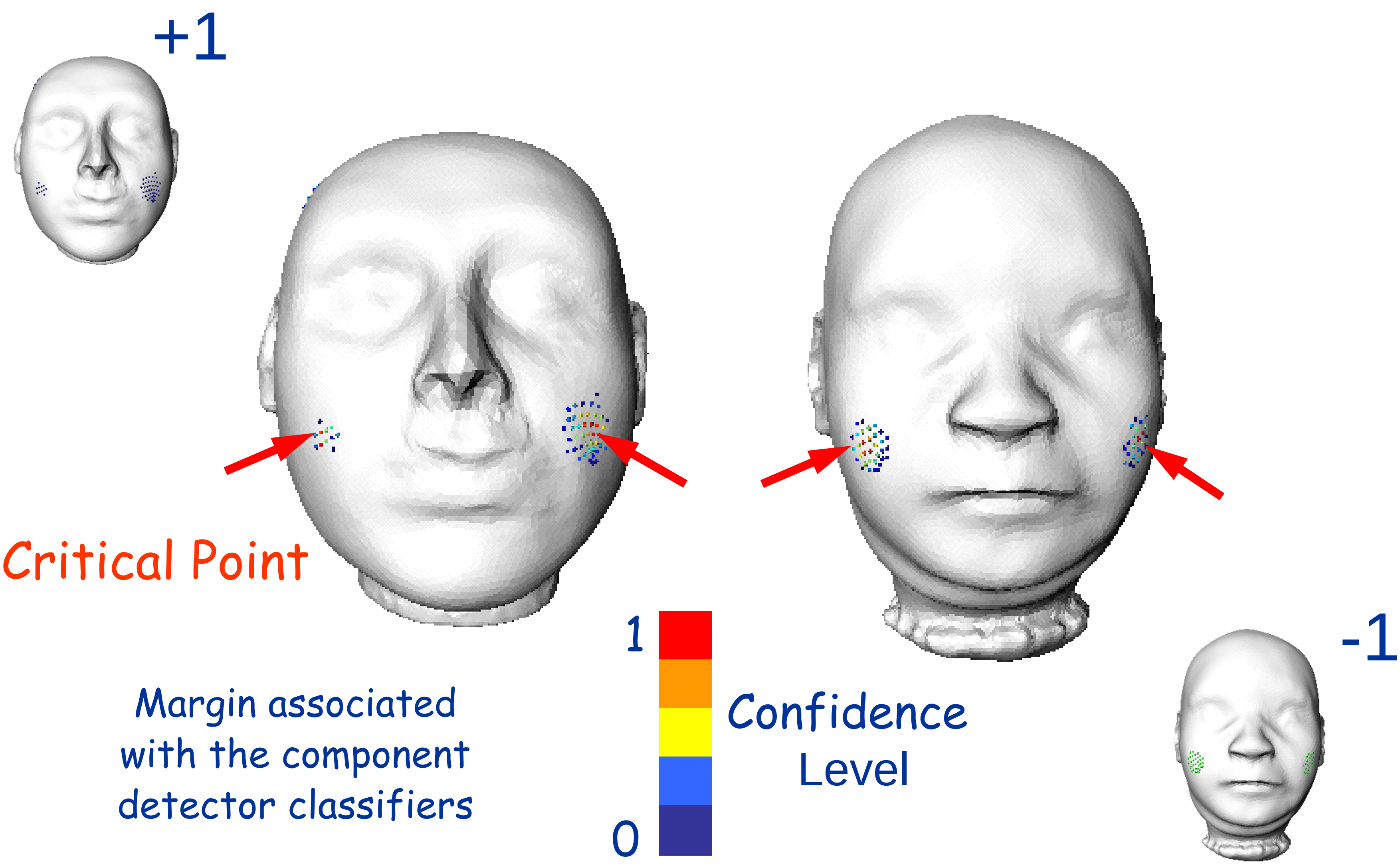




Symbolic pattern for components 5,6,8

-1

Finding Critical Points On Test Samples



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

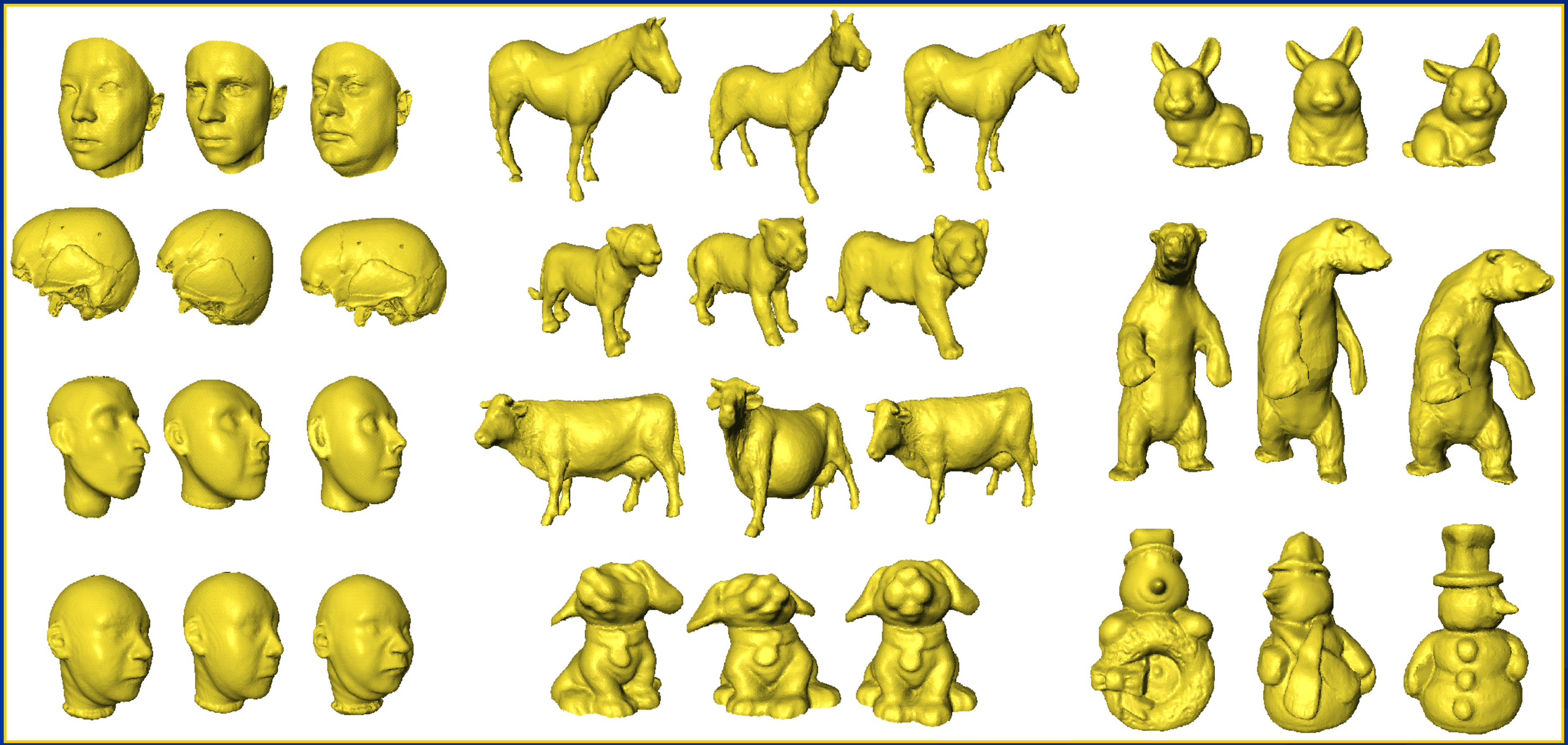
Setup

Laser

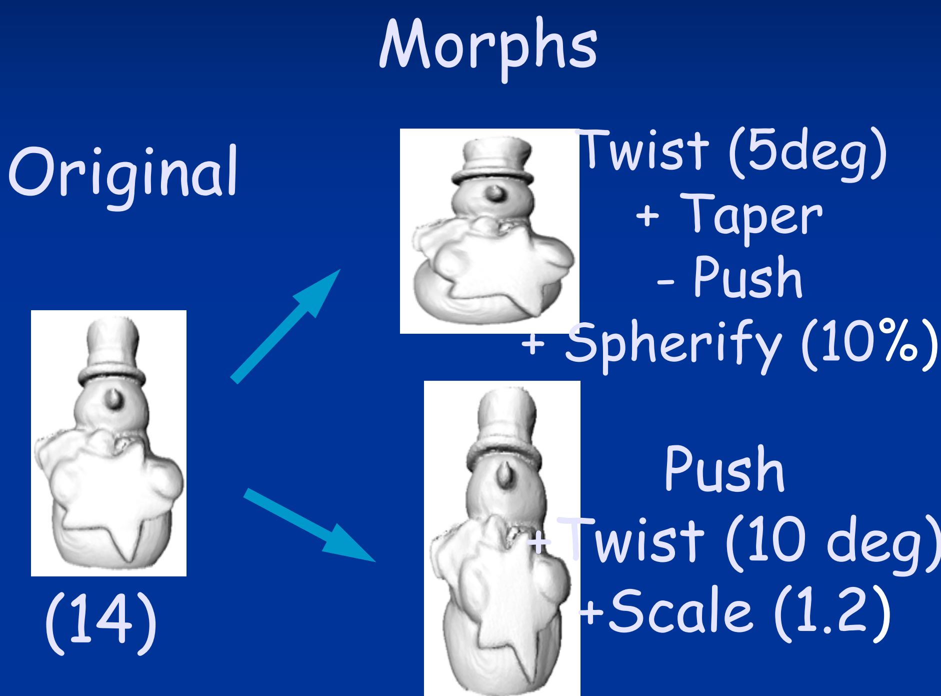
Recognition

Classification

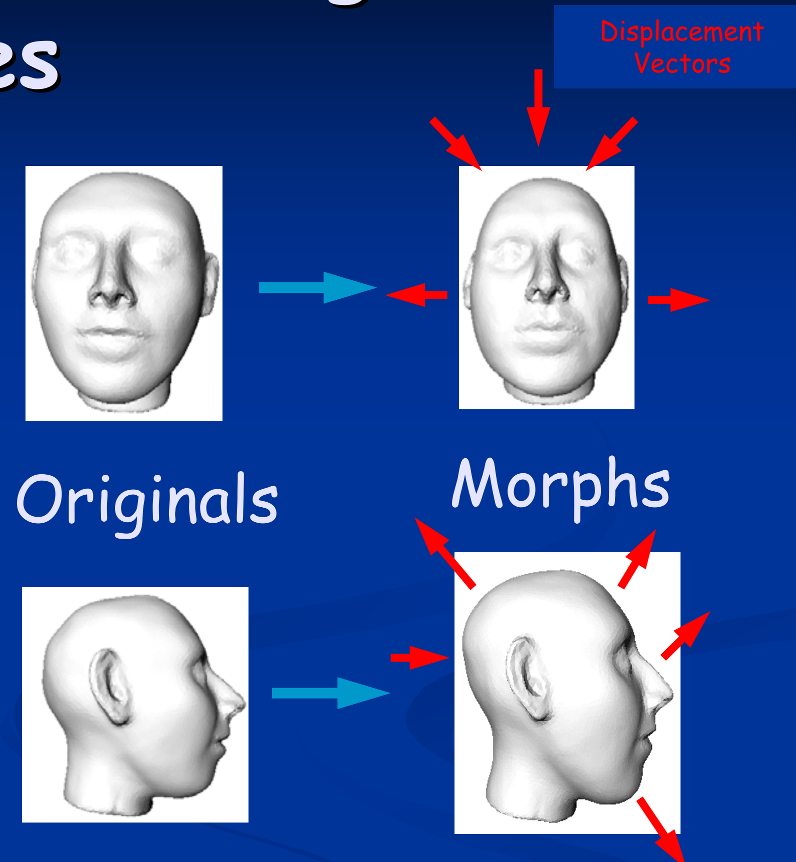
Shape Classes



Enlarging Training Sets Using Virtual Samples



Global Morphing Operators



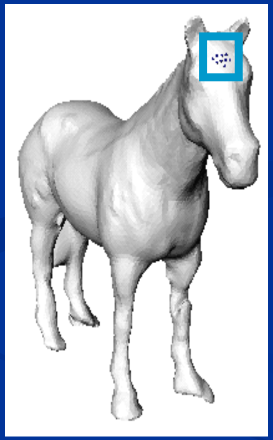
Physical Modeling

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

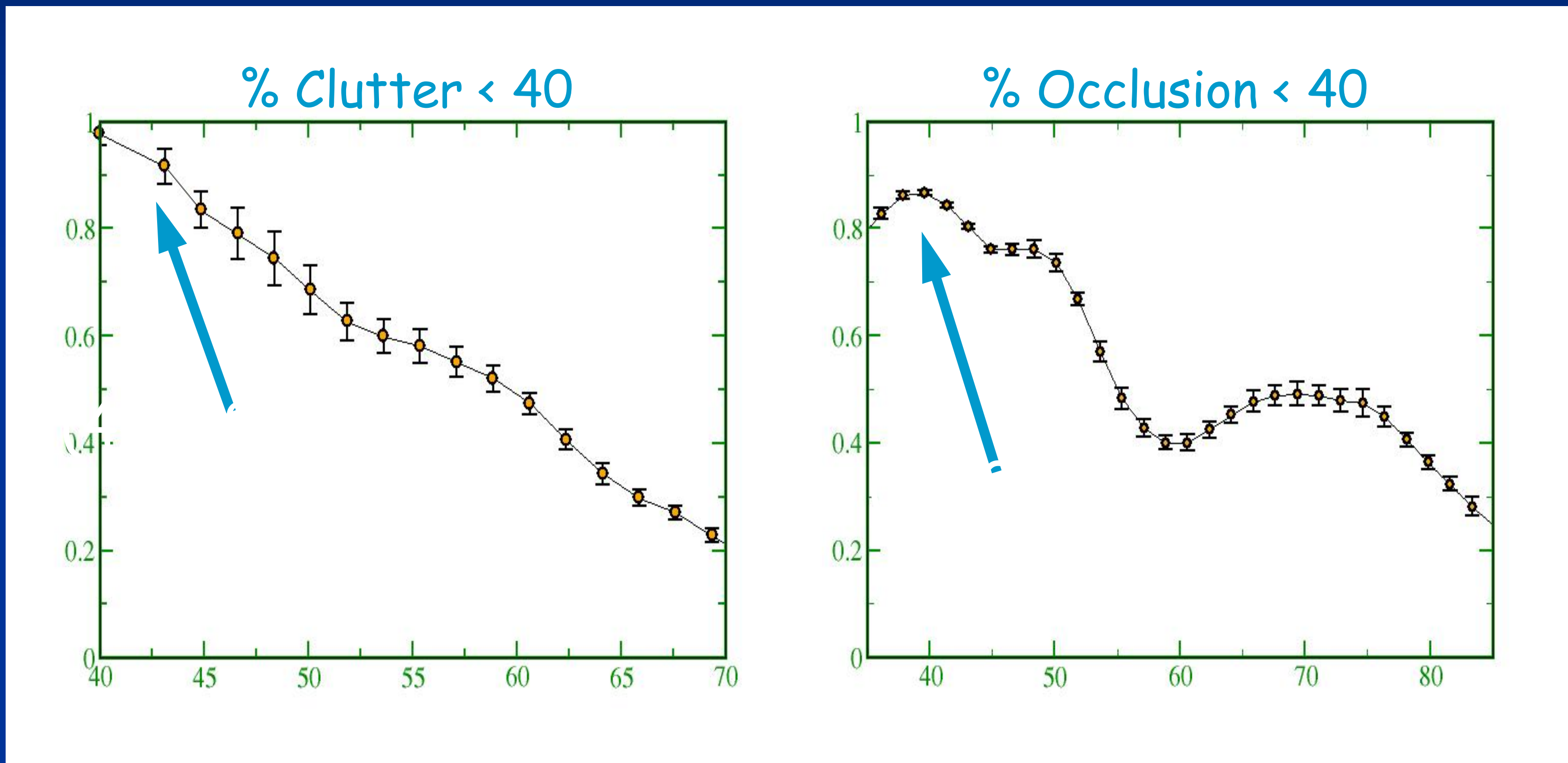
Task 2-3: Recognition in Complex Scenes (3)

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)

Recognition Rate

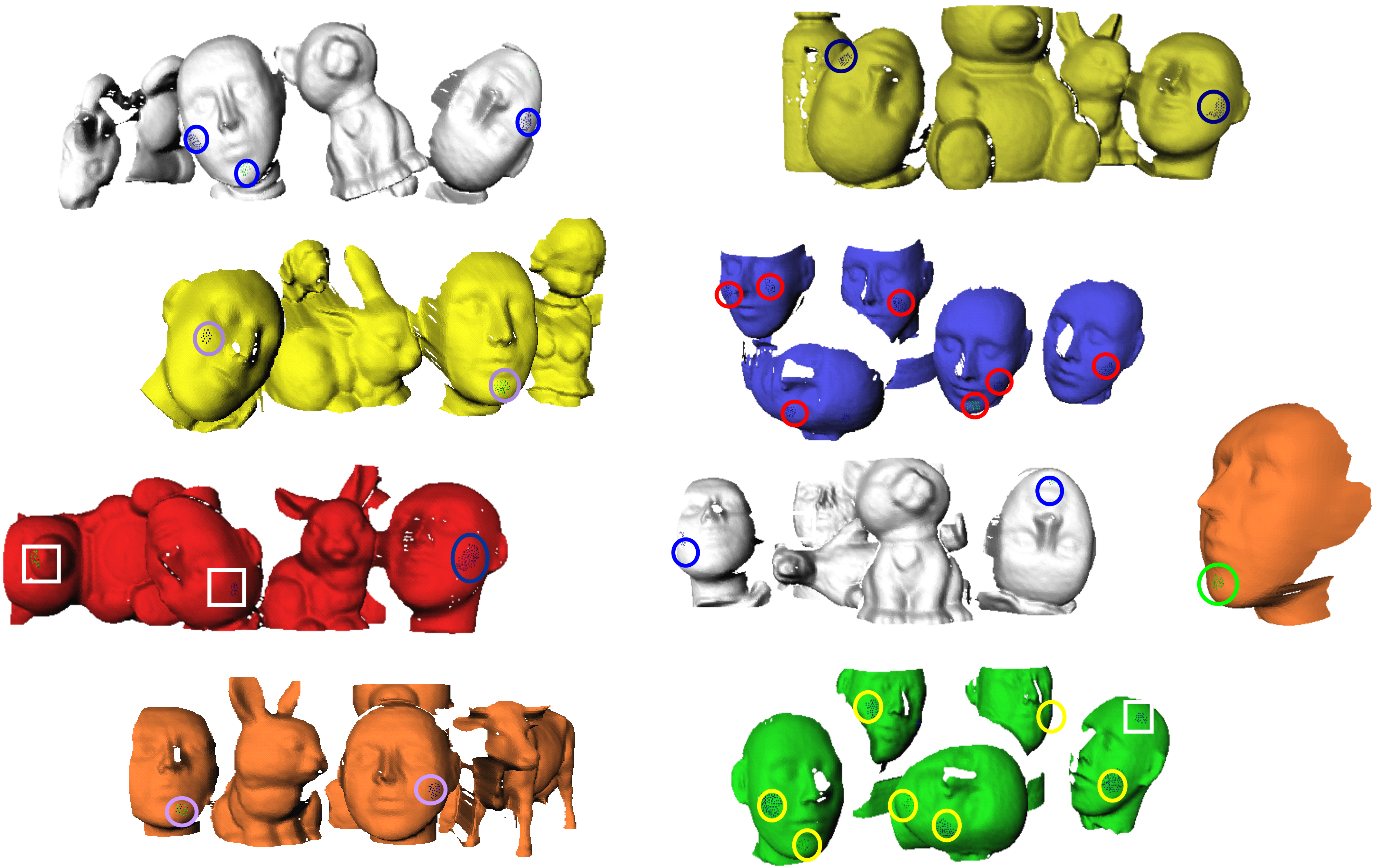


% Occlusion

% Clutter

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

65%-35%


4

50%-50%


5

25%-75%

(convex combinations of Normal and Abnormal 1)

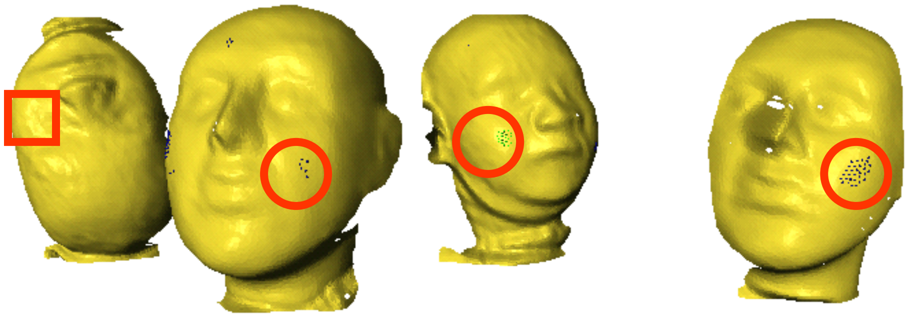
Task 6: Classifying Normal vs. Abnormal Human Heads In Complex Scenes(1)

- 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.

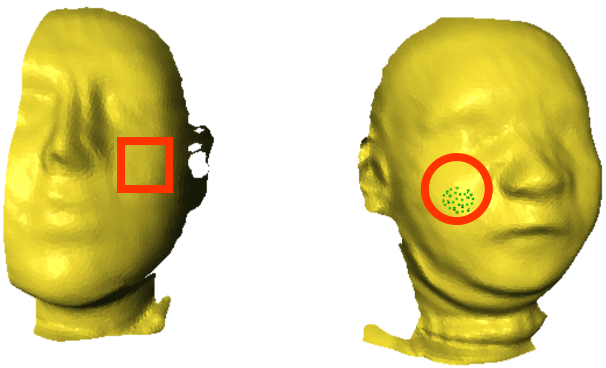
Task 6: Classifying Normal vs. Abnormal Human Heads In Complex Scenes(1)

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)

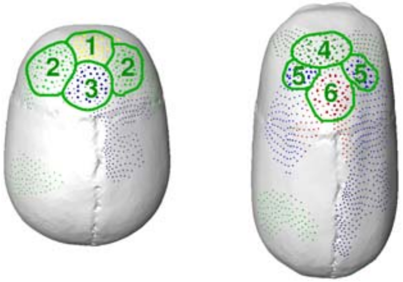
- No. Shape classes: 2.
- Training set size: 400 meshes.
- Testing set size: 200 meshes.
- No. Experiments: 2200.
- No. Component detectors:3.
- No. Symbolic signature detectors: 1.
- Numeric signature size: 50x50.
- Symbolic signature size: 15x15.

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

100 Experiments

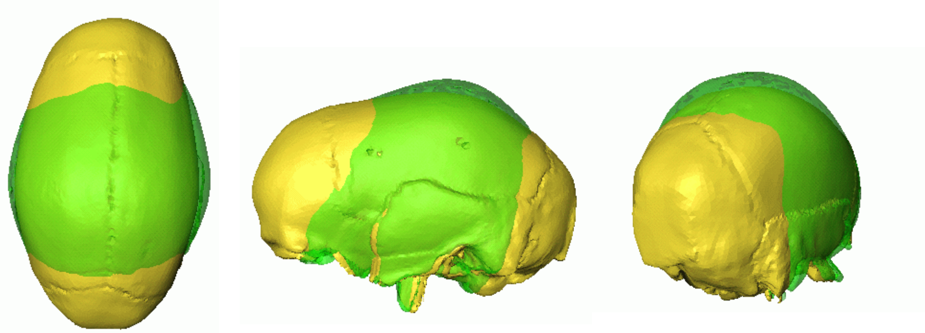
Shape Classes	Classification Accuracy %
Normal vs. Abnormal	89

No clutter and occlusion



Normal

Abnormal
(sagittal synostosis)



Superimposed models

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.

Main Contributions (3)

- Our approach:
- Is general can be applied to a variety of shape classes.
- Is robust to clutter and occlusion
- It Works in practice
- Is a step forward in 3-D object recognition research.