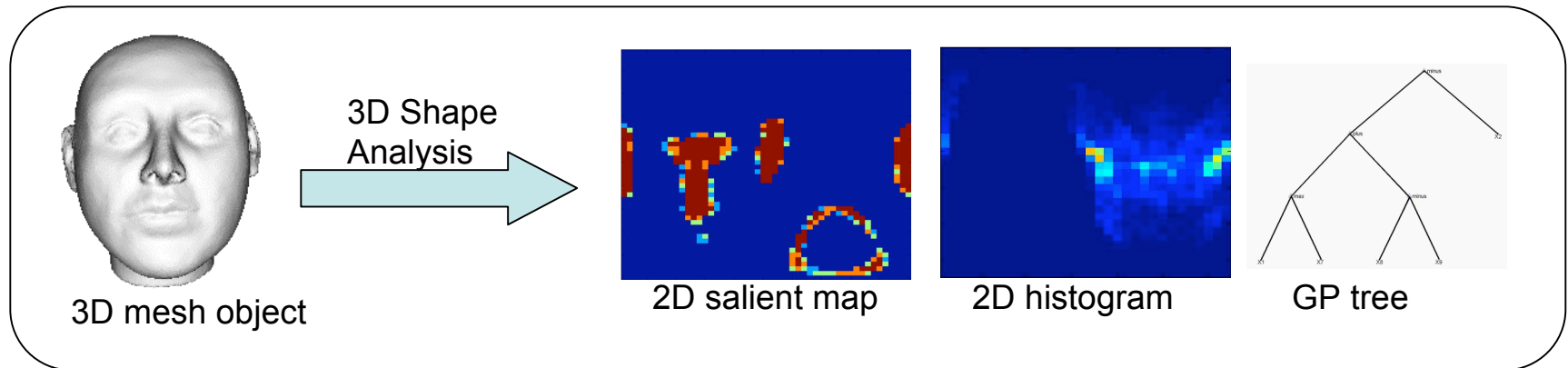


3D Shape Analysis for Quantification, Classification and Retrieval

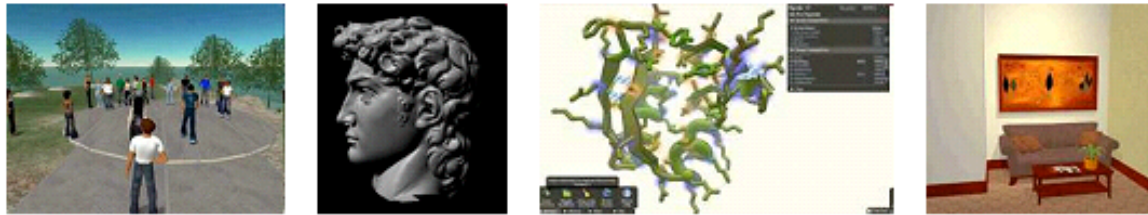


Indriyati Atmosukarto
PhD Defense

Advisor: Prof Linda Shapiro

General Motivation

- Increasing number of 3D objects available



- Want to store, index, classify and retrieve objects **automatically**
- Need 3D object descriptor that captures global and local shape characteristics

Medical Motivation

- Researchers at Seattle Children's use CT scans and 3D surface meshes
- Investigate head shape dysmorphologies due to craniofacial disorders
- Want to represent, analyze and **quantify** variants from 3D head shapes

22q11.2 Deletion Syndrome (22q11.2DS)

- Caused by genetic deletion
- Cardiac anomalies, learning disabilities
- Multiple **subtle** physical manifestations
- Assessment is subjective



Deformational Plagiocephaly

- Flattening of head caused by pressure
- Delayed neurocognitive development
- Assessment is subjective and inconsistent
- Need **objective** and **repeatable** severity quantification method



Plagiocephaly



Normal



Brachycephaly

Objective

- Investigate new methodologies for representing 3D shapes
- Representations are **flexible** enough to generalize from specific medical to general 3D object tasks
- Develop and test for 3D shape classification, retrieval and quantification

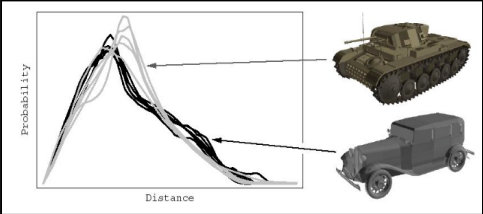

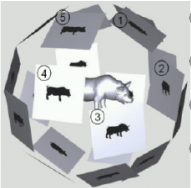
Outline

- Related Literature
- Datasets
- Base Framework
- 3D Shape Analysis
- Conclusion

Shape Retrieval Evaluation Contest (SHREC)

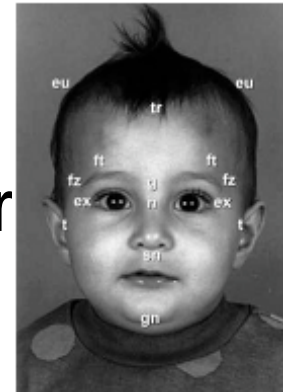
- Benchmark with common test set and queries
- **Objective**: evaluate effectiveness of 3D shape retrieval algorithms
- No descriptor performs best for all tasks

3D Object Descriptor

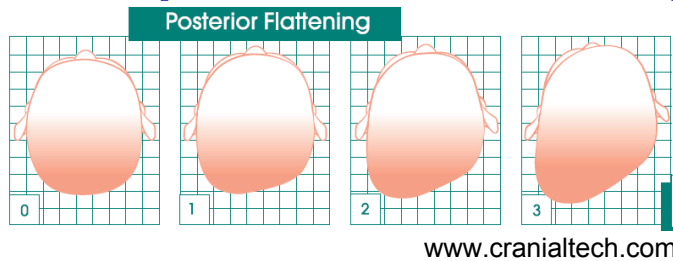
	Feature-based	Graph-based	View-based
Eg	Shape distributions 	Skeleton 	Light Field Descriptor 
+	Compact	Articulated object	Best in SHREC
-	Not discriminative	Computationally expensive	Computationally expensive

Deformational Plagiocephaly Measurements

- Anthropometric landmark
 - Physical measurements using caliper
- Template matching

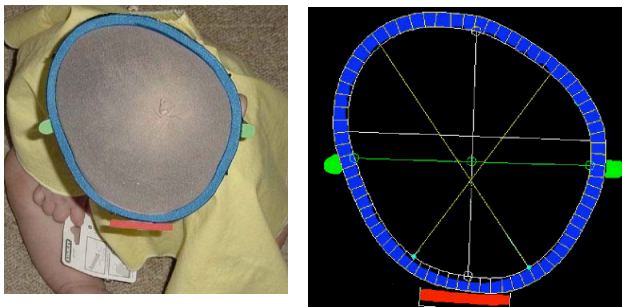


Kelly et al. 1999



- Subjective, time consuming, intrusive

- Landmark photographs

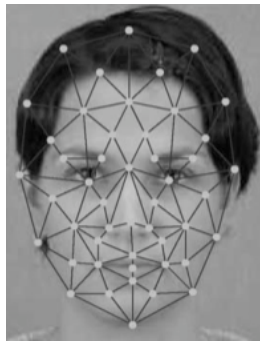


Hutchison et al. 2005

Cranial Index (CI)
Oblique Cranial Length Ratio (OCLR)

22q11.2DS Measurements

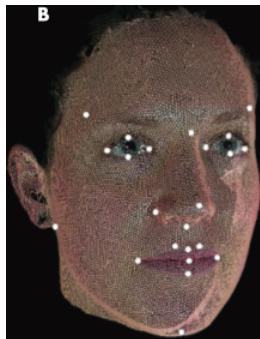
- Anthropometric landmark
- 2D template landmark + PCA



Boehringer et al.
Gabor wavelet + PCA to analyze 10
facial dysmorphologies

- Manual landmarks

- 3D mean landmark + PCA



Hutton et al.
Align to average face + PCA

Outline

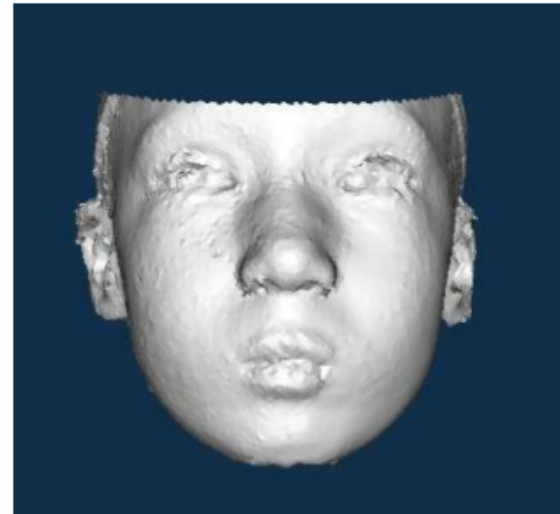
- Related Literature
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- Conclusion

Datasets

- 22q11.2DS
 - Deformational Plagiocephaly
 - Heads
- } similar overall shape
with subtle distinctions
- SHREC
- non similar shapes

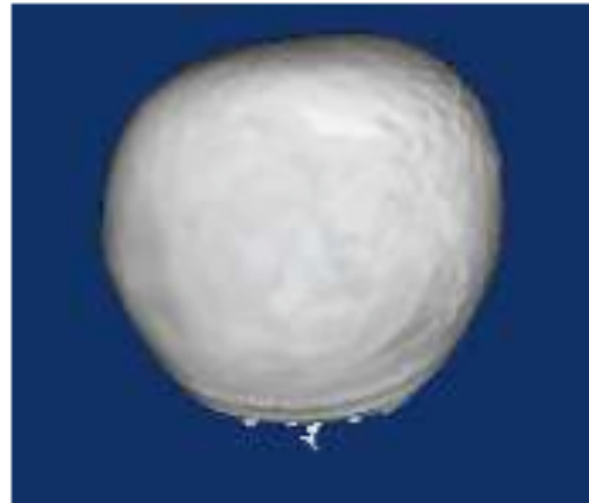
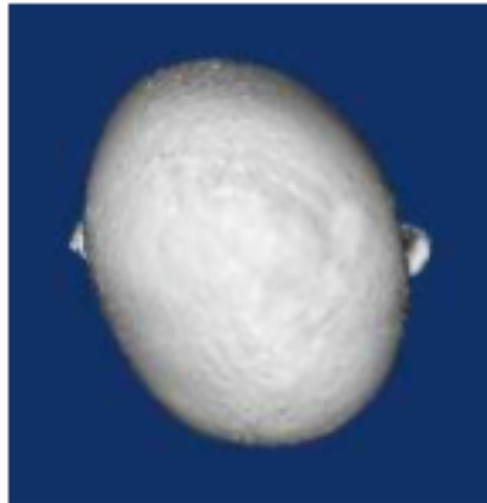
22q11.2DS Dataset

- Dataset: 189 (53 + / 136 -), 86 (43 + / 43 -)
- Assessed by craniofacial experts
 - Selected 9 facial features that characterize disease



Deformational Plagiocephaly Dataset

- Dataset: 254 (154+/100 -), 140 (50+/90 -)
- Assessed by craniofacial experts
 - 5 different affected areas of head



Heads Dataset

- 15 original objects - 7 classes
- Randomly morph each object



SHREC Dataset

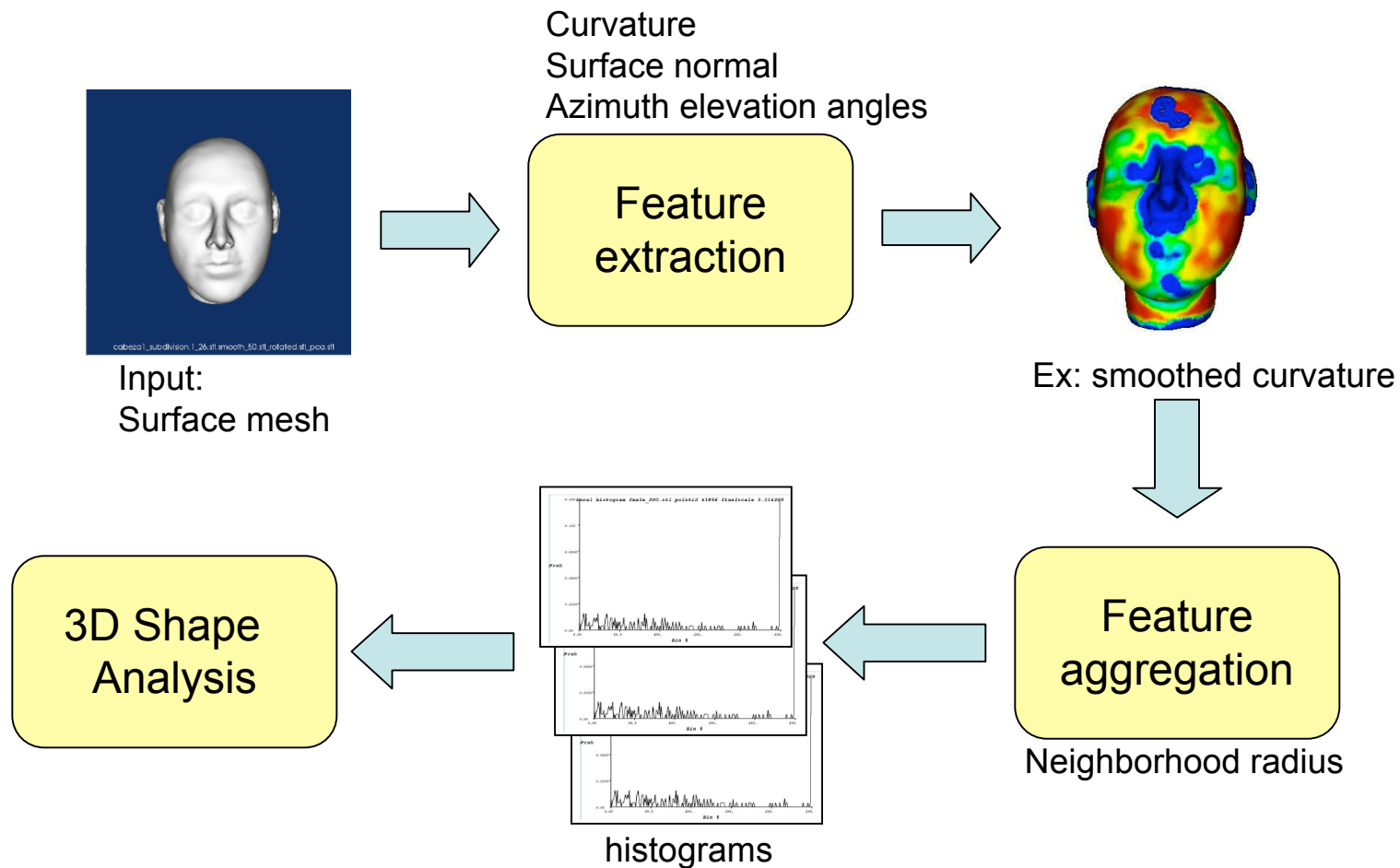
- 425 objects - 39 classes

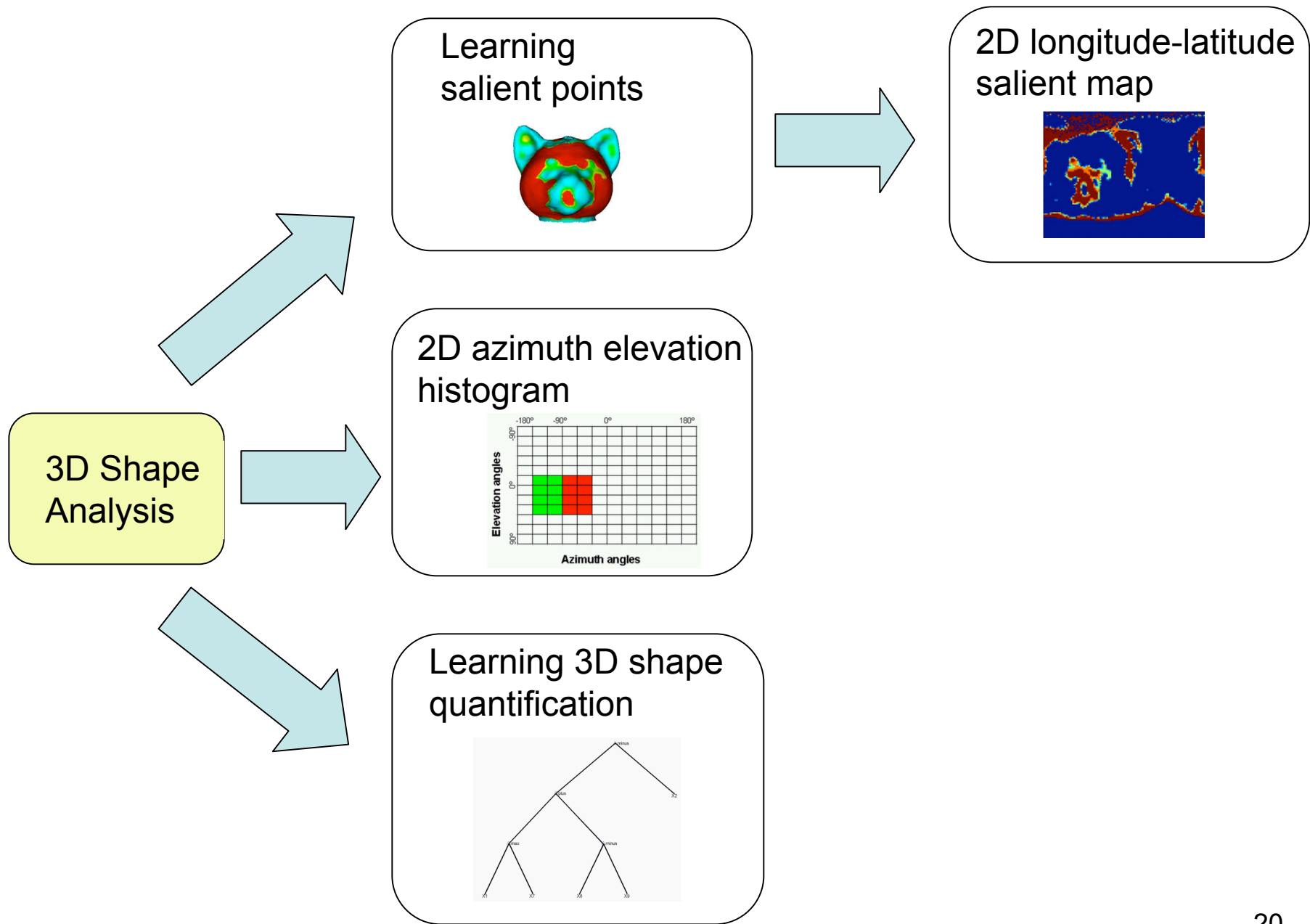


Outline

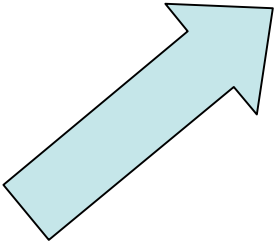
- Related Literature
- Datasets
- Base Framework
- 3D Shape Analysis
- Conclusion

Base Framework

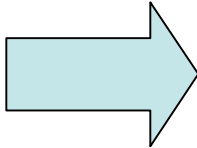
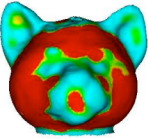




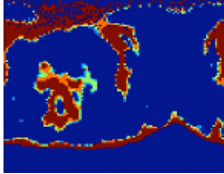
3D Shape Analysis



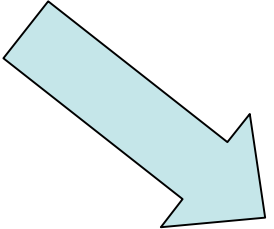
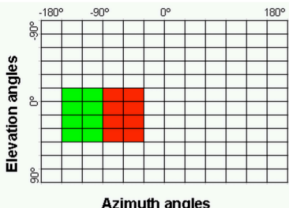
Learning salient points



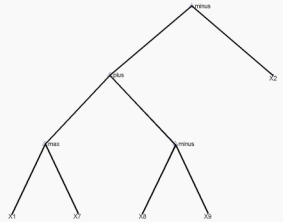
2D longitude-latitude salient map



2D azimuth elevation histogram

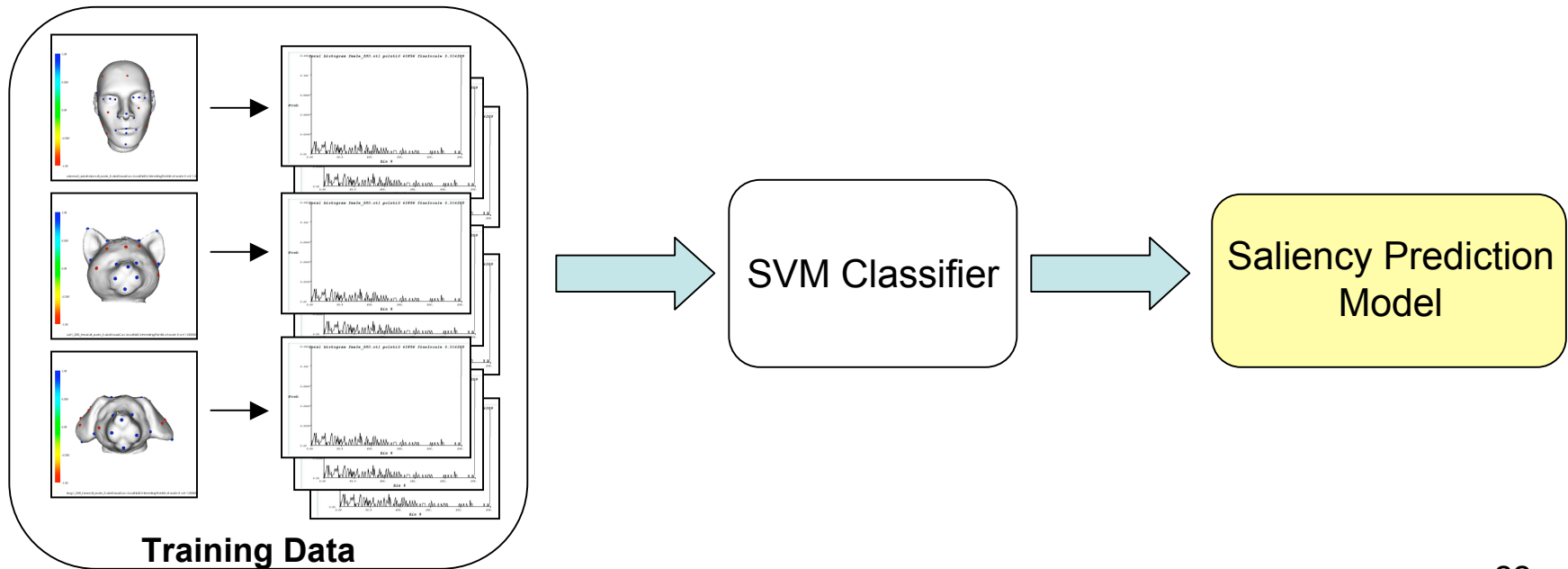


Learning 3D shape quantification



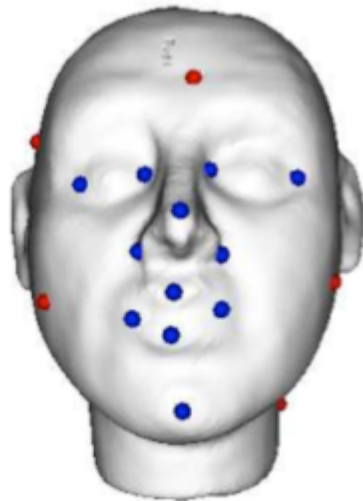
Learning Salient Points

- Salient points are **application dependent**
- Classifier learns characteristics of salient points

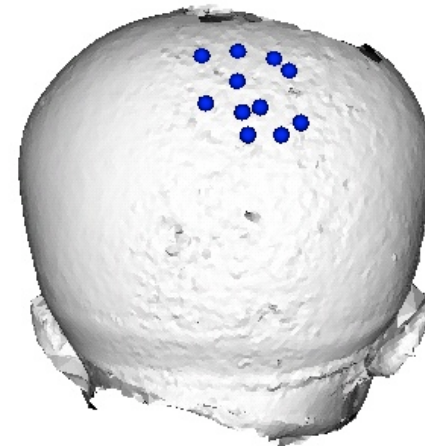


Learning Salient Points

- 22q11.2DS
 - Training on subset craniofacial landmarks

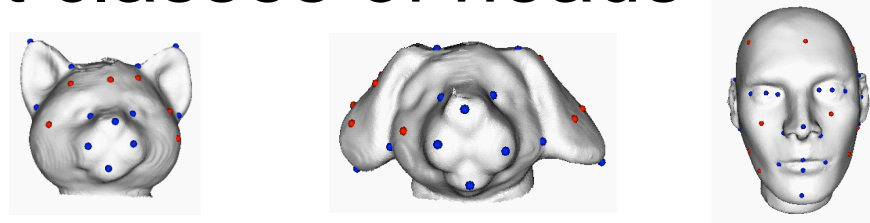


- Deformational Plagiocephaly
 - Training points marked on flat areas on head

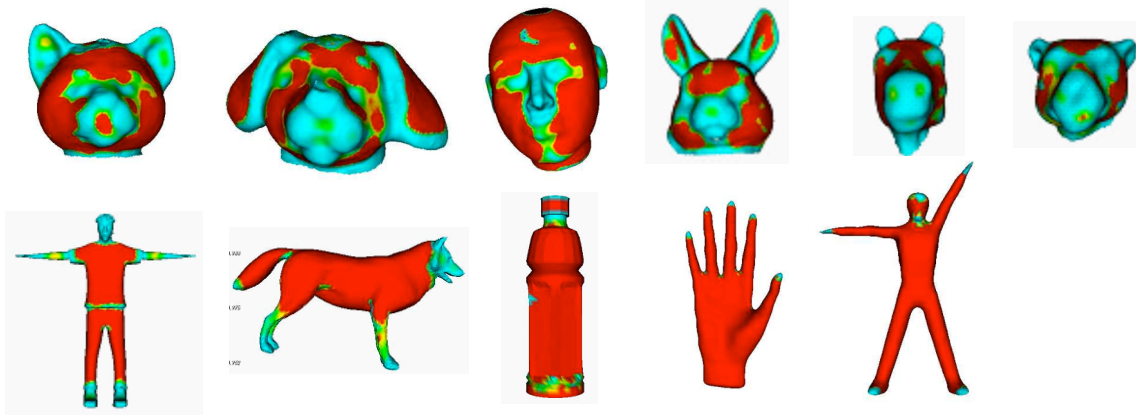


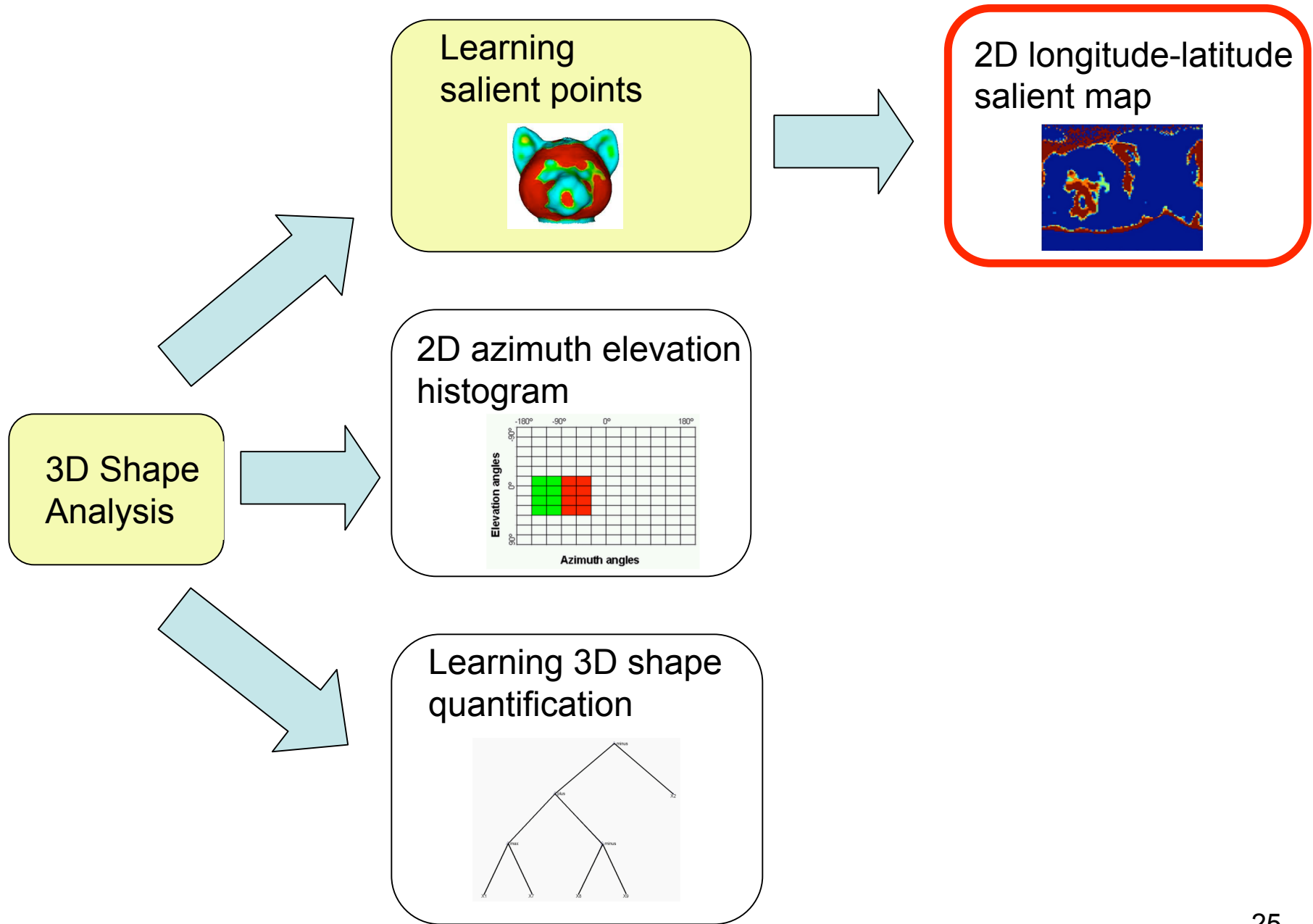
Learning Salient Points – General 3D Objects

- **Training** on craniofacial landmarks on different classes of heads

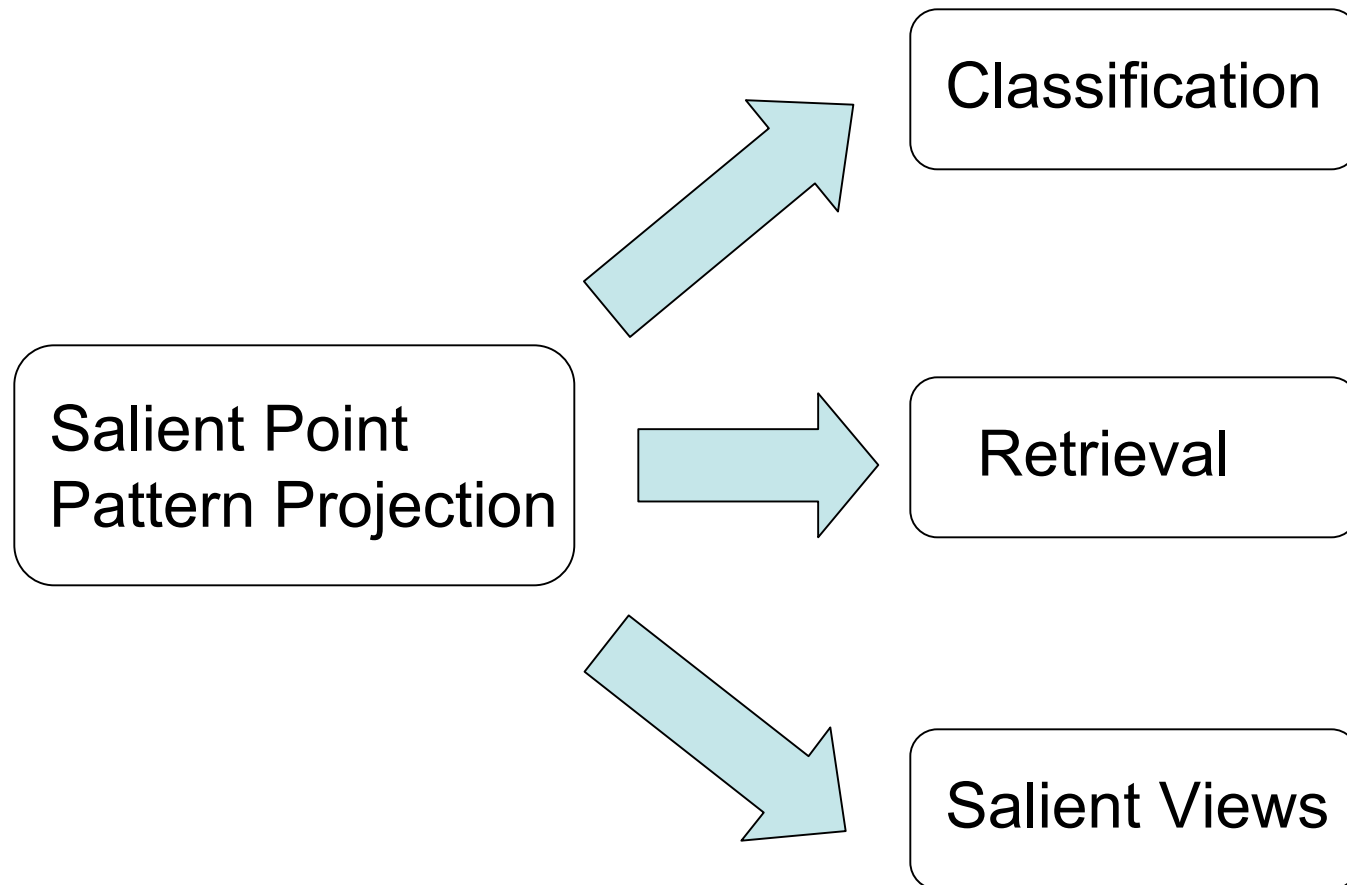


- **Predicted** salient points

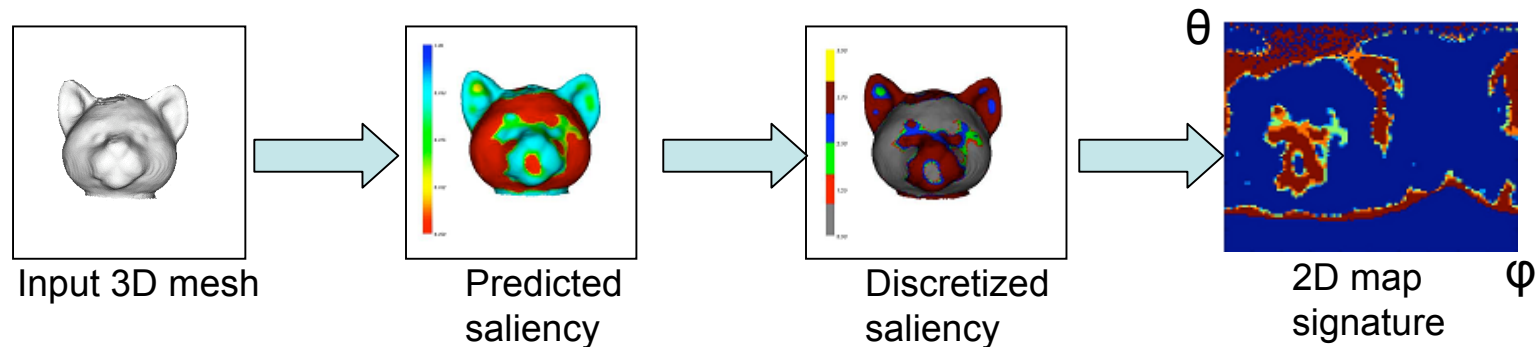




2D Longitude-Latitude Salient Map



Salient Point Pattern Projection



- Discretize saliency according to score
- Map onto 2D plane via **longitude-latitude transformation**

$$\theta_i = \arctan\left(\frac{p_{iz}}{p_{ix}}\right) \quad \phi_i = \arctan\left(\frac{p_{iy}}{\sqrt{(p_{ix}^2 + p_{iz}^2)}}\right)$$

Classification using 2D Map

Dataset	2D Salient map	LFD	SPH	D2	AAD
22q11.2DS	0.867	0.741	0.746	0.619	0.73
Plagiocephaly	0.803	0.72	0.673	0.650	0.685
SHREC	0.569	0.759	0.715	0.502	0.549

LFD – Light Field Descriptor

SPH – Spherical Harmonics

D2 – Shape Distribution

AAD – Angle Histogram

Retrieval using 2D Map

- Retrieval on SHREC

2D Salient map	LFD	SPH	D2	AAD
0.144	0.097	0.120	0.361	0.349

2D salient map retrieval results

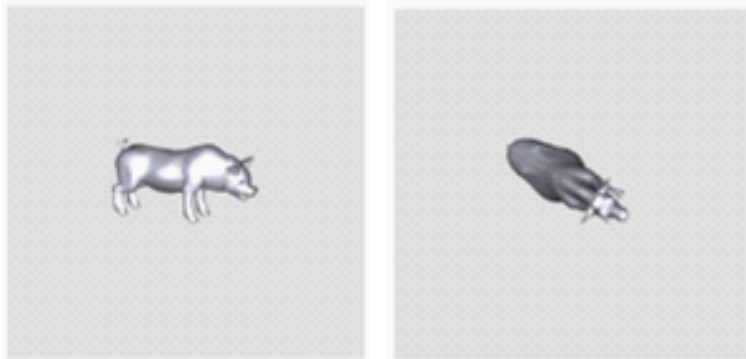


LFD retrieval results

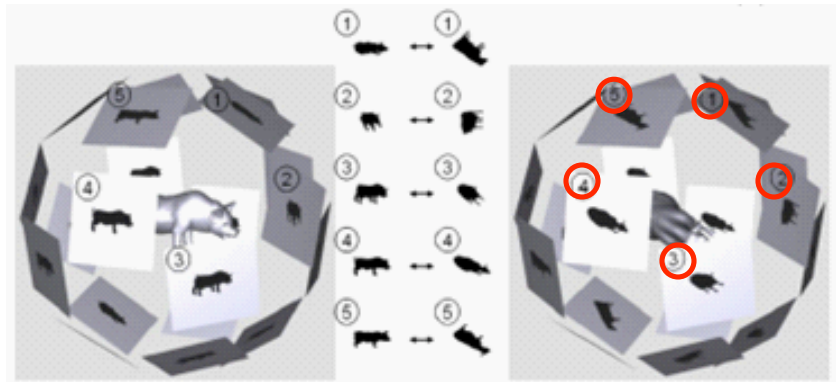


Related Work

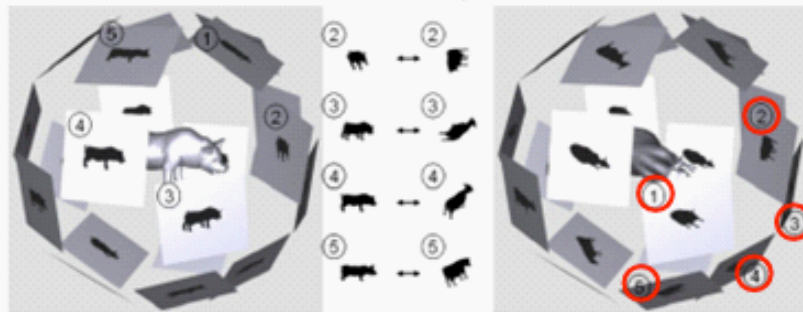
- Light Field Descriptor [Chen et al., 2003]



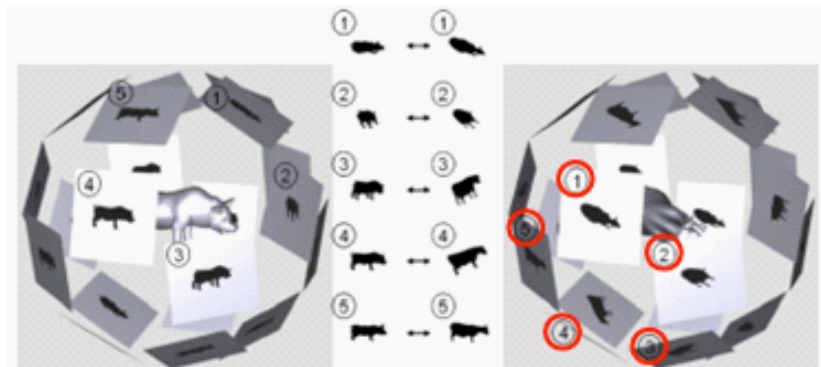
1. Given two 3D models rotated randomly



2. Compare 2D images from same viewing angles



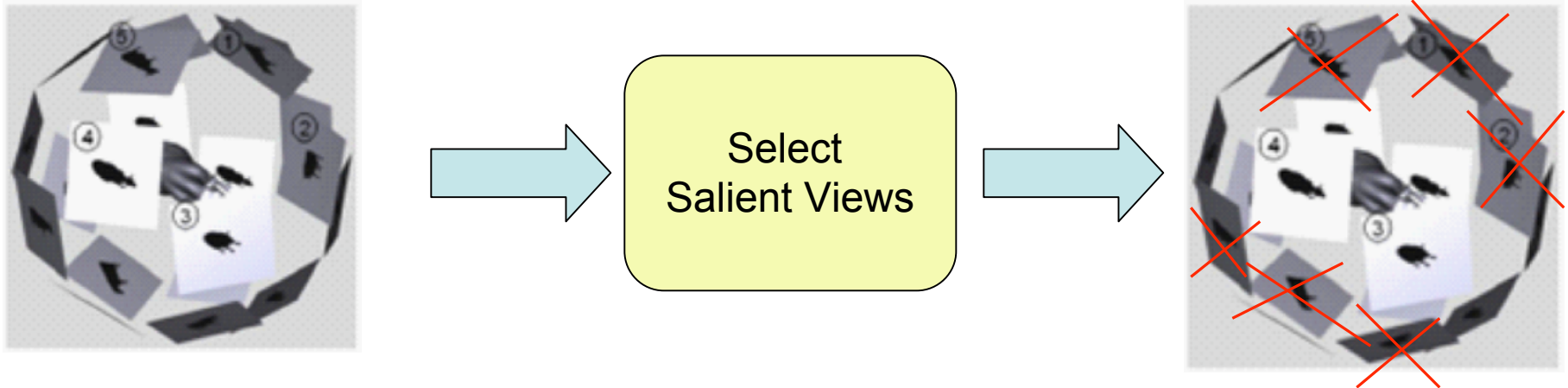
3. Compare 2D images from another angle



4. Best match = Rotation of camera position with best similarity

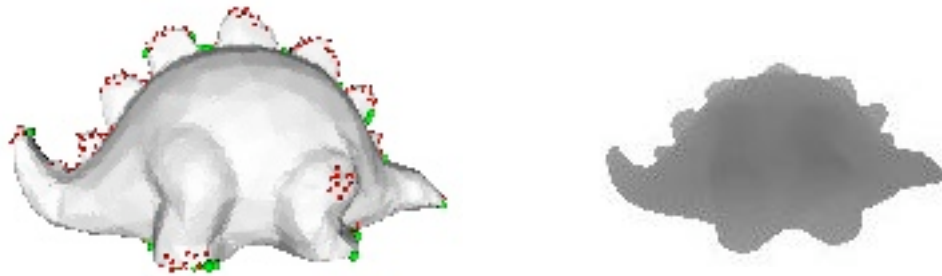
Salient Views

- **Goal:** improve LFD by selecting only 2D **salient views** to describe 3D object
- Discernible and useful in describing object

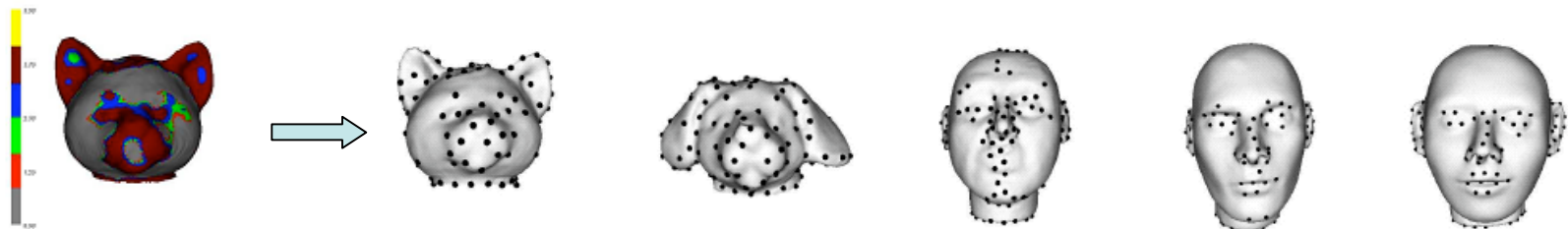


Salient Views

- Silhouette with **contour salient points**
 - Surface normal vector \perp camera view point



- Greedy clustering



Selecting Salient Views

- Accumulate # contour salient points
- Sort views based on # contour salient pts
- Select top K salient views



- Select top K **distinct** salient views (DSV)



Salient Views - Number of views

- Distinct Salient Views vs Light Field Descriptor

No	Class	# Objects	Avg # distinct salient views	Max distinct salient views score	LFD score
1	human-diff-pose	15	12.33	0.113	0.087
2	monster	11	12.14	0.196	0.169
3	dinosaur	6	12.33	0.185	0.169
4	4-legged-animal	25	12.24	0.274	0.186
5	hourglass	2	11.50	0.005	0.001
6	chess-pieces	7	12.14	0.085	0.085
7	statues-1	19	12.16	0.267	0.250
8	statues-2	1	13.00	0.000	0.000
9	bed-post	2	12.00	0.124	0.008
10	statues-3	1	12.00	0.000	0.000

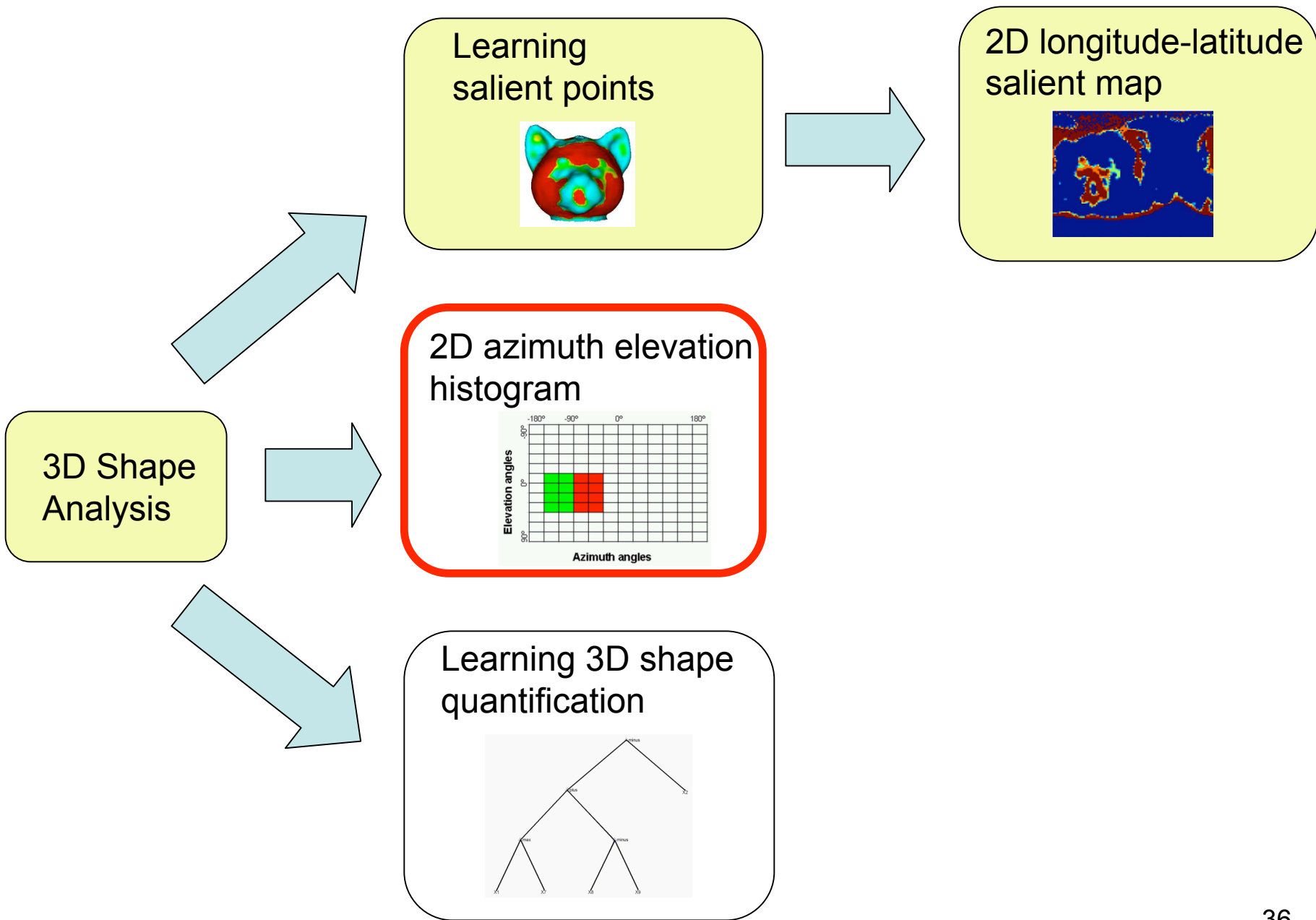
- Average score: 0.121 (DSV) vs 0.098 (LFD)
- Number of views: ~12 (DSV) vs 100 (LFD)

Salient Views - Runtime

- Bottleneck: feature extraction step
- Feature extraction runtime comparison

Method	Setup	View rendering	Descriptor construction	Total time
Max distinct views	0.467s	0.05s	0.077s	0.601s
LFD 100 views	0.396s	4.278s	4.567s	9.247s

- **15-fold** speed up compare to LFD
- Reduce number of views to **10%**

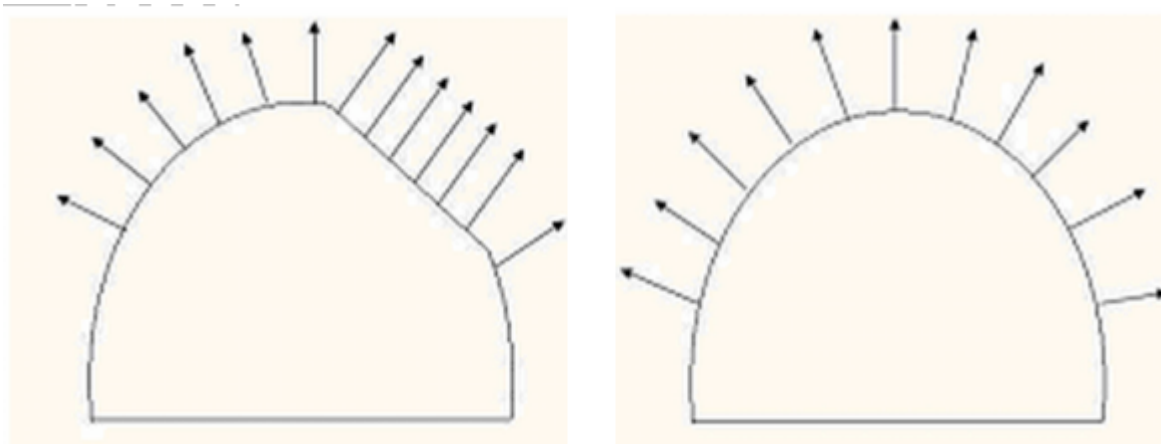


Global 2D Azimuth-Elevation Angles Histogram

- 3D Shape Quantification for Deformational Plagiocephaly
- Classification of 22q11.2DS

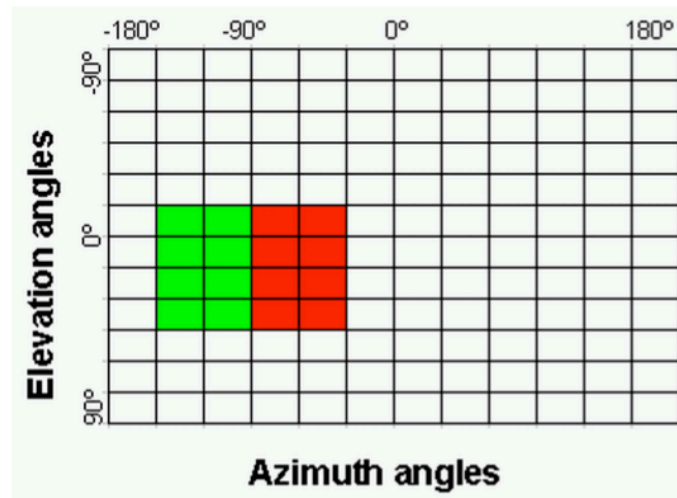
3D Shape Quantification for Deformational Plagiocephaly

- Discretize azimuth elevation angles into 2D histogram
- **Hypothesis:** flat parts on head will create high-valued bins



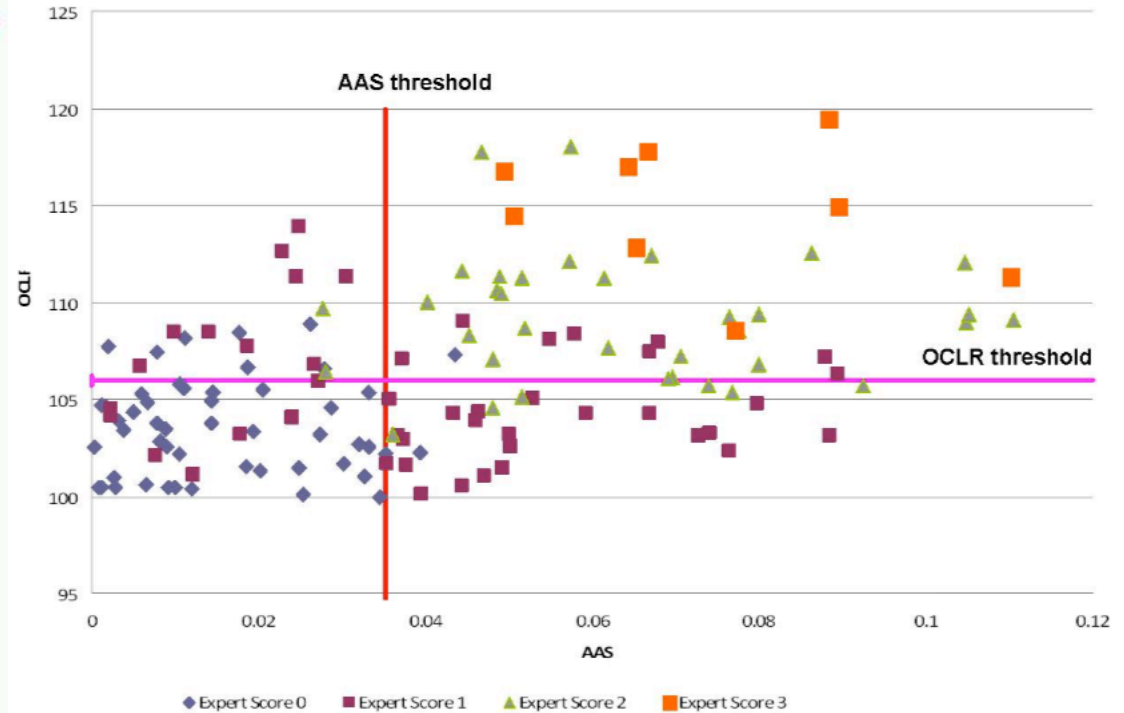
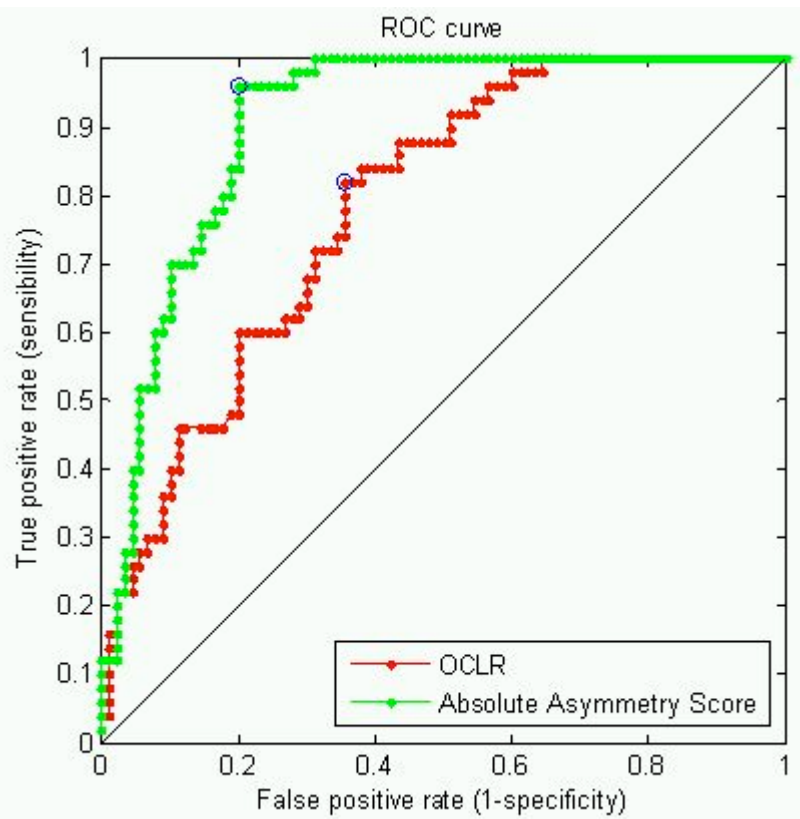
Shape Severity Scores for Posterior Plagiocephaly

- Left Posterior Flatness Score (LPFS)
- Right Posterior Flatness Score (RPFS)
- Asymmetry Score (AS) = RPFS - LPFS
- Absolute Asymmetry Score (AAS)



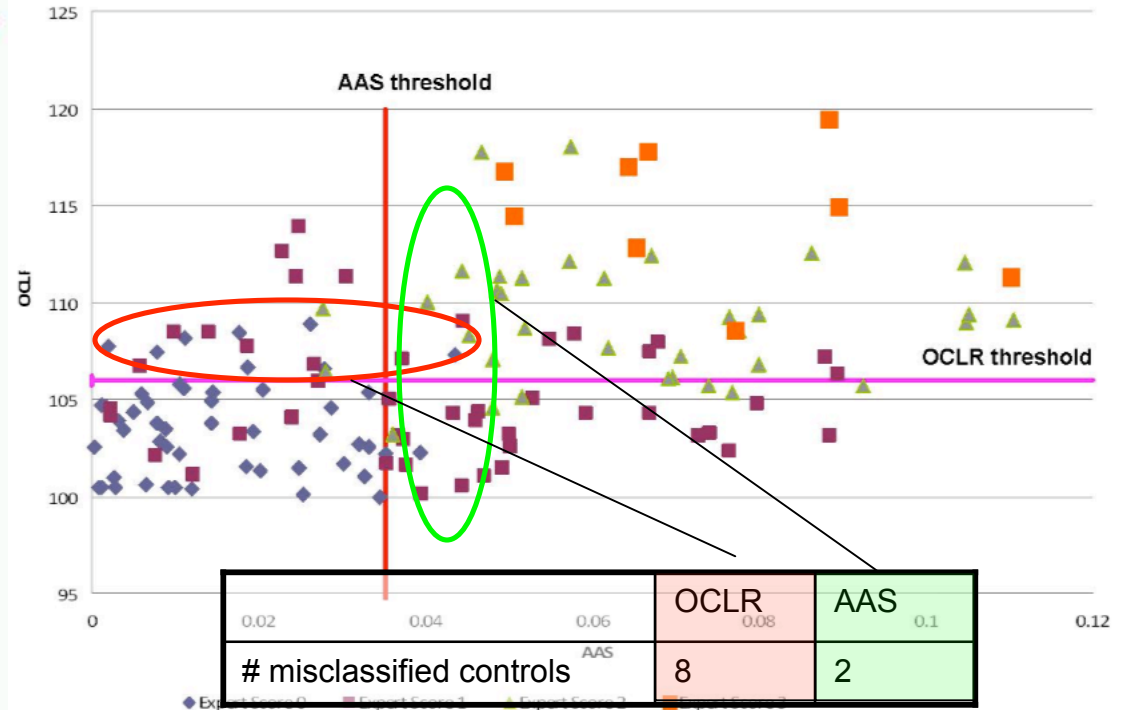
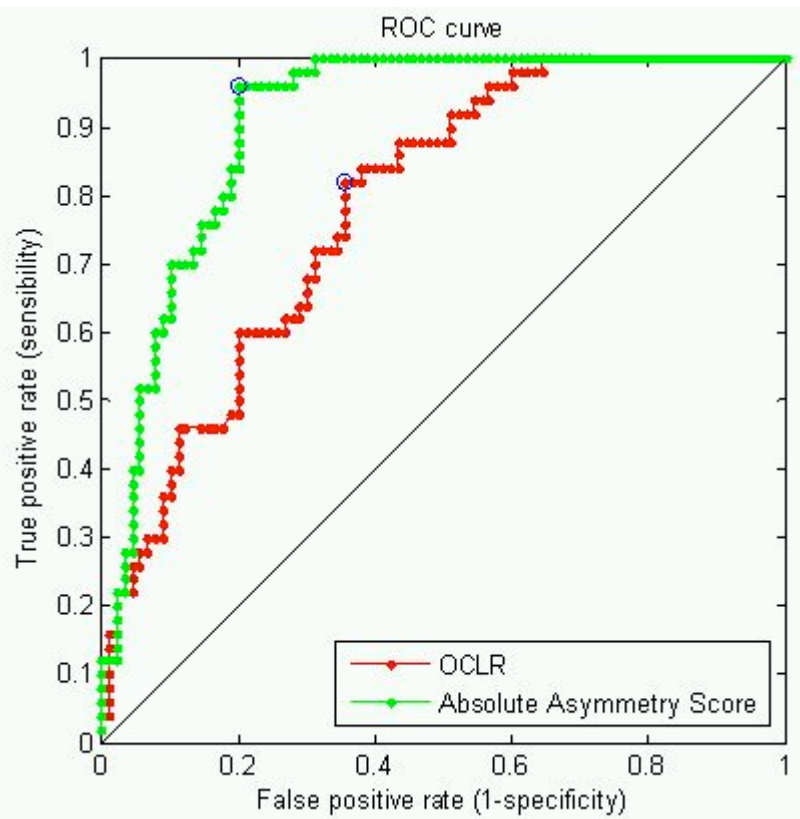
Classification of Posterior Plagio

Absolute Asymmetry Score (AAS) vs Oblique Cranial Length Ratio (OCLR)



Classification of Posterior Plagio

Absolute Asymmetry Score (AAS) vs Oblique Cranial Length Ratio (OCLR)

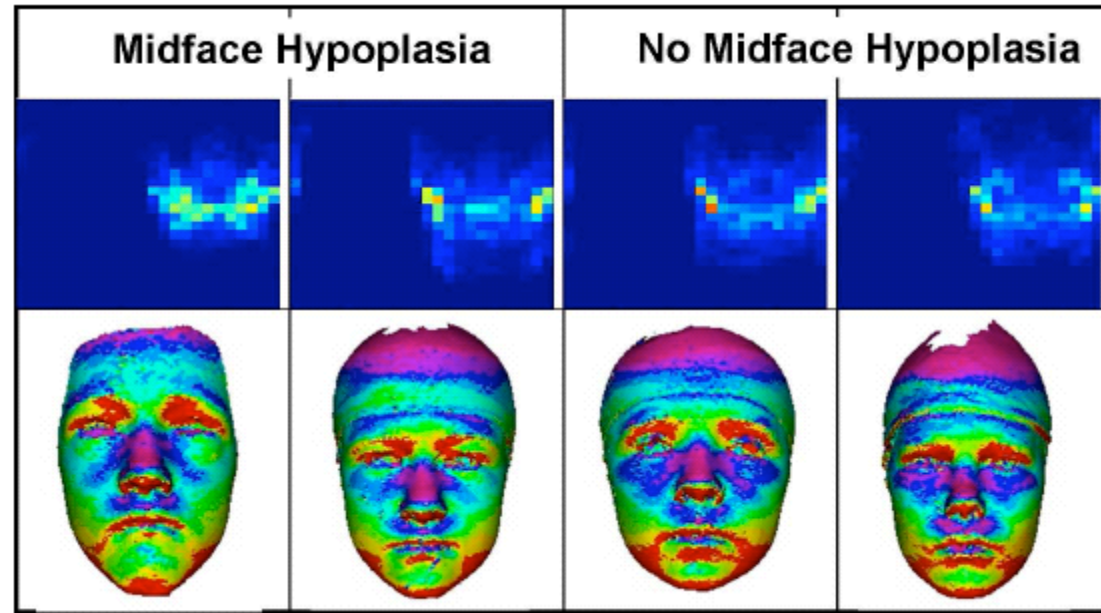


Classification of Deformational Plagiocephaly

- Treat 2D histogram as feature vector
- Classify five plagiocephaly conditions

Posterior plagiocephaly	Brachycephaly	Forehead asymmetry	Ear asymmetry	Overall severity
0.793	0.868	0.674	0.603	0.766

Classification of 22q11.2DS

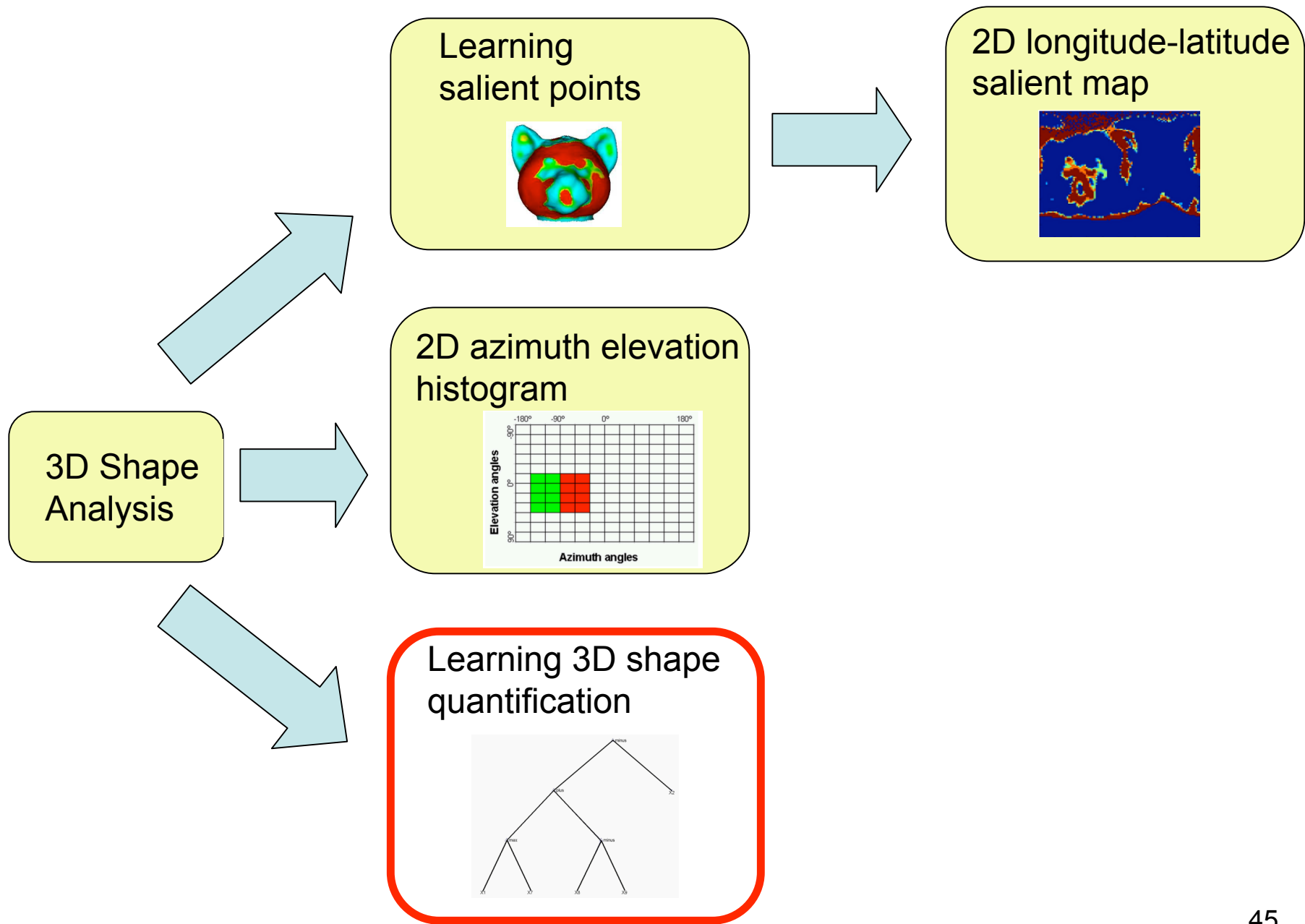


- Treat 2D histogram as feature vector

	8×8	16×16	24×24	32 × 32	Experts' median
Whole 2D hist	0.651	0.569	0.79	0.684	0.68

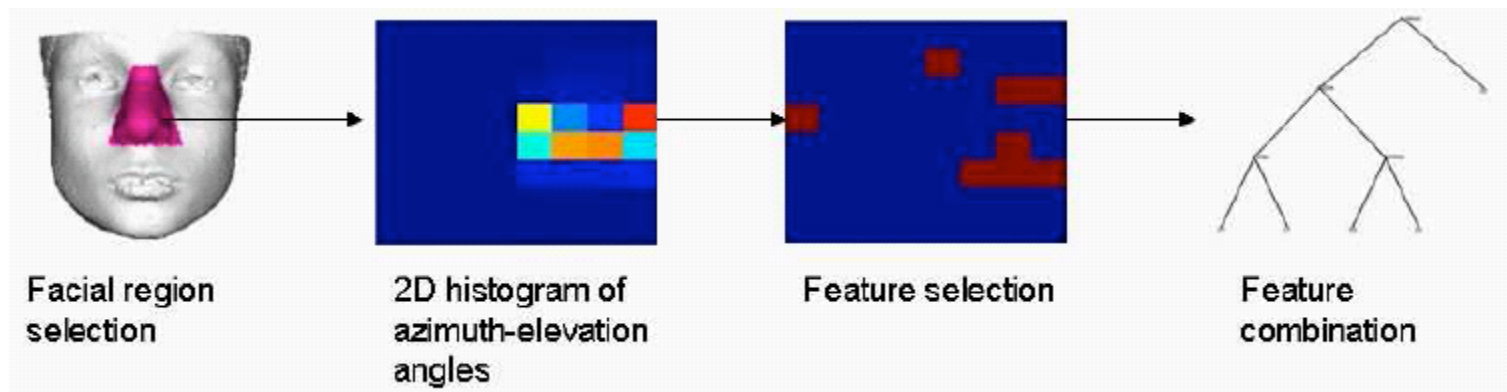
Classification of 22q11.2DS Facial Features

	8×8	16×16	24×24	32 × 32
Midface Hypoplasia	0.639	0.744	0.697	0.651
Tubular Nose	0.709	0.593	0.581	0.663
Bulbous Nasal Tip	0.593	0.581	0.581	0.639
Prominent Nasal Root	0.547	0.639	0.616	0.658
Small Nasal Alae	0.561	0.675	0.571	0.560
Retrusive Chin	0.526	0.674	0.560	0.546
Open Mouth	0.875	0.799	0.844	0.683
Small Mouth	0.671	0.526	0.752	0.585
Downturned Mouth	0.613	0.539	0.553	0.630



Learning 3D Shape Quantification

- Analyze 22q11.2DS and 9 associated facial features
- **Goal:** quantify different shape variations in different facial abnormalities



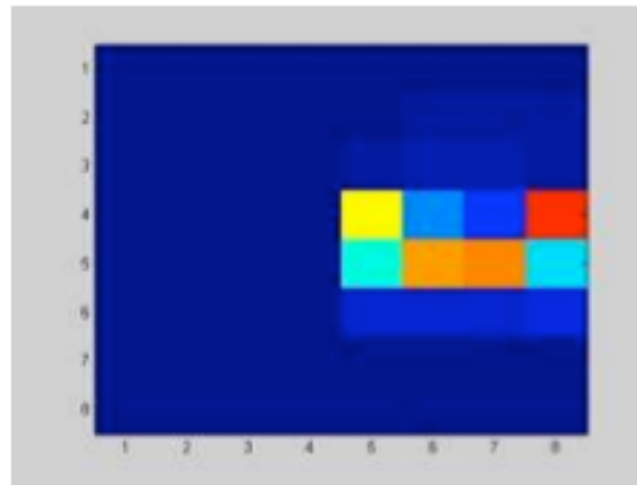
Learning 3D Shape Quantification - Facial Region Selection

- Focus on 3 facial areas
 - Midface, nose, mouth
- Regions selected manually



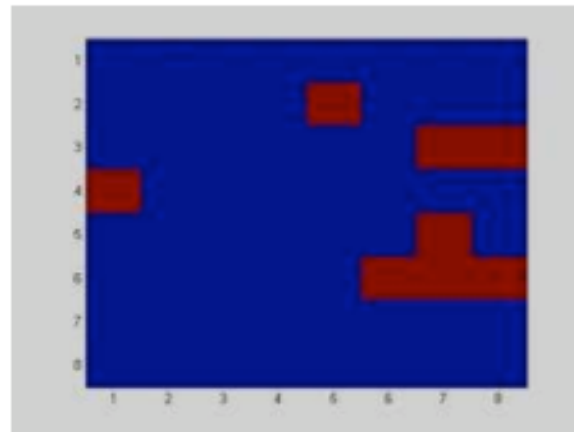
Learning 3D Shape Quantification - 2D Histogram Azimuth Elevation

- Using azimuth elevation angles of surface normal vectors of points in selected region



Learning 3D Shape Quantification - Feature Selection

- Determine most discriminative bins
- Use **Adaboost** learning
- Obtain positional information of important region on face

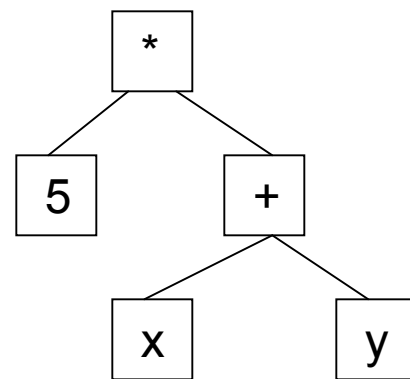


Learning 3D Shape Quantification - Feature Combination

- Use **Genetic Programming** (GP) to evolve mathematical expression
- Start with random population
 - Individuals are evaluated with fitness measure
 - Best individuals reproduce to form new population

Learning 3D Shape Quantification - Genetic Programming

- Individual:
 - Tree structure
 - Terminals e.g variables eg. 3, 5, x, y, ...
 - Function set e.g +, -, *, ...
 - Fitness measure e.g sum of square ...



$$5*(x+y)$$

Learning 3D Shape Quantification - Feature Combination

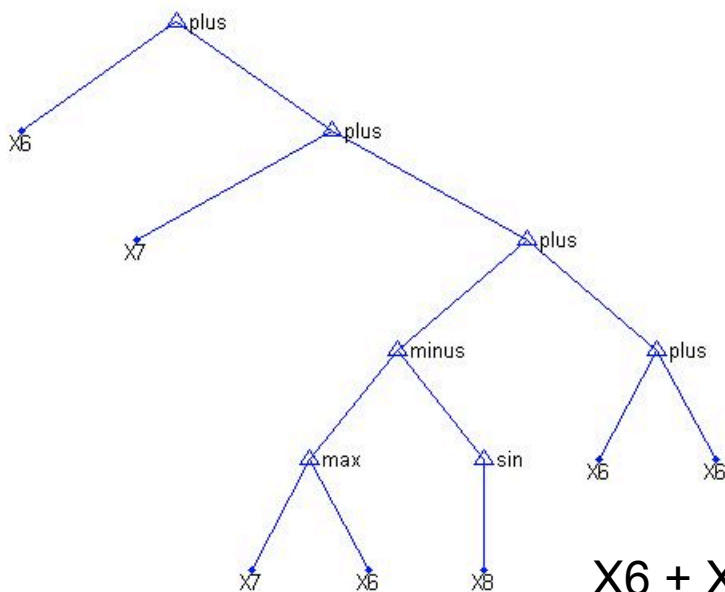
- 22q11.2DS dataset
 - Assessed by craniofacial experts
 - Groundtruth is union of expert scores
- **Goal:** classify individual according to given facial abnormality

Learning 3D Shape Quantification - Feature Combination

- Individual

- Terminal: selected histogram bins
- Function set: +, -, *, min, max, sqrt, log, 2x, 5x, 10x
- Fitness measure: F1-measure

$$F(\text{prec}, \text{rec}) = \frac{2 \times (\text{prec} \times \text{rec})}{\text{prec} + \text{rec}}$$



$$X6 + X7 + (\max(X7, X6) - \sin(X8) + (X6 + X6))$$

Learning 3D Shape Quantification - Experiment 1

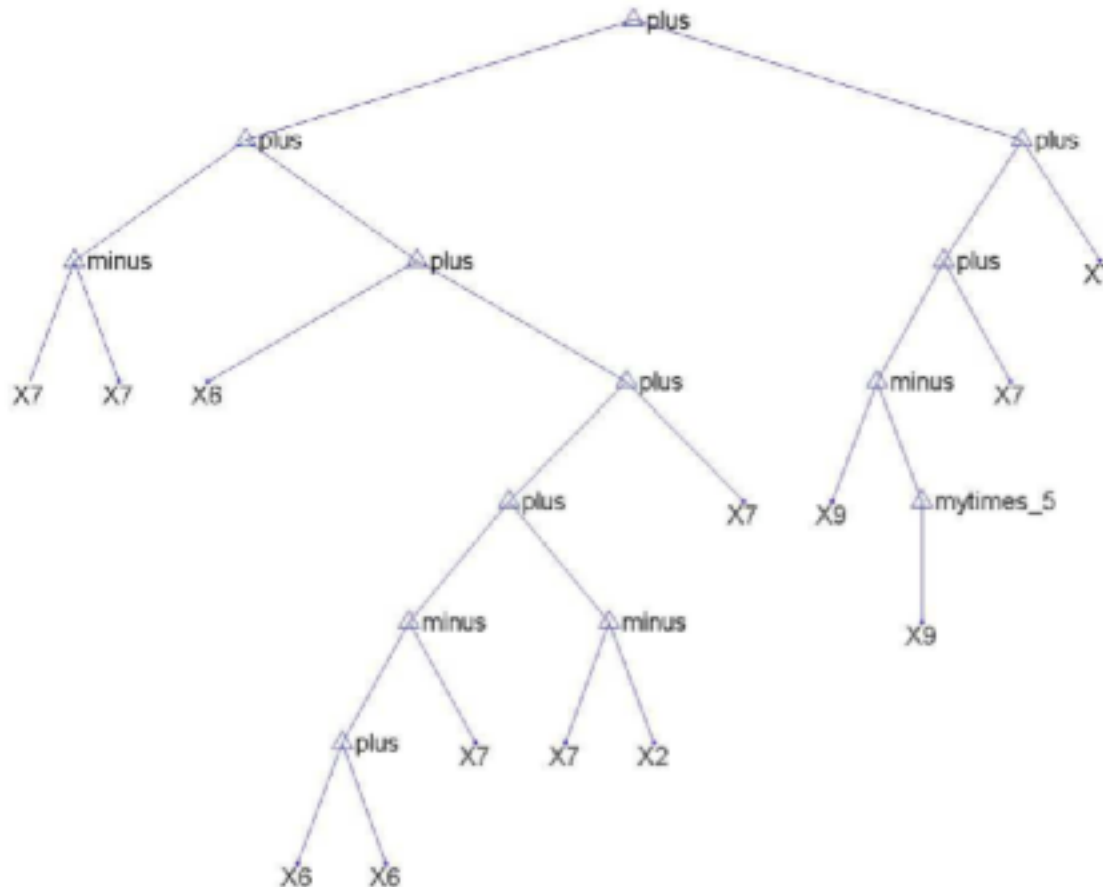
- **Objective:** investigate function sets
 - Combo1 = $\{+, -, *, \min, \max\}$
 - Combo2 = $\{+, -, *, \min, \max, \text{sqrt}, \log_2, \log_{10}\}$
 - Combo3 = $\{+, -, *, \min, \max, 2x, 5x, 10x, 20x, 50x, 100x\}$
 - Combo4 = $\{+, -, *, \min, \max, \text{sqrt}, \log_2, \log_{10}, 2x, 5x, 10x, 20x, 50x, 100x\}$

Learning 3D Shape Quantification - Experiment 1

- Best F-measure out of 10 runs

Facial anomaly	Combo1	Combo2	Combo3	Combo4
Midface Hypoplasia	0.8393	0.8364	0.8527	0.80
Tubular Nose	0.8571	0.875	0.8667	0.8813
Bulbous Nasal Tip	0.8545	0.8099	0.8103	0.7544
Prominent Nasal Root	0.8667	0.8430	0.8571	0.8335
Small Nasal Alae	0.8846	0.8454	0.8454	0.8571
Retrusive Chin	0.7952	0.8000	0.7342	0.7586
Open Mouth	0.9444	0.9714	0.9189	0.9189
Small Mouth	0.6849	0.7568	0.6829	0.7750
Downturned mouth	0.8000	0.7797	0.8000	0.8000

Tree structure for quantifying midface hypoplasia



$$((X7-X7) + (X6+(((X6+X6)-X7)+(X7-X2))))+X7))+(X9-5X9+X7+X7)$$

X_i are the selected histogram bins

Learning 3D Shape

Quantification - Experiment 2

- **Objective:** compare local facial shape descriptors

Facial abnormality	Region Histogram	Selected Bins	GP
Midface hypoplasia	0.697	0.721	0.853
Tubular nose	0.701	0.776	0.881
Bulbous nasal tip	0.617	0.641	0.855
Prominent nasal root	0.704	0.748	0.867
Small nasal alae	0.733	0.801	0.885
Retrusive chin	0.658	0.713	0.800
Open mouth	0.875	0.889	0.971
Small mouth	0.694	0.725	0.775
Downturned mouth	0.506	0.613	0.800

Learning 3D Shape Quantification - Experiment 3

- **Objective:** compare GP to global approach

Facial abnormality	GP	Saliency Map	Global 2D Hist
Midface hypoplasia	0.853	0.674	0.744
Tubular nose	0.881	0.628	0.709
Bulbous nasal tip	0.855	0.616	0.639
Prominent nasal root	0.867	0.663	0.658
Small nasal alae	0.885	0.779	0.675
Retrusive chin	0.800	0.628	0.674
Open mouth	0.971	0.707	0.875
Small mouth	0.775	0.581	0.752
Downturned mouth	0.800	0.566	0.630

Learning 3D Shape Quantification - Experiment 4

- **Objective:** predict 22q11.2DS

Method	F-measure
Quantification vector with SVM	0.709
Quantification vector with Adaboost	0.721
Quantification vector with GP	0.821
Global saliency map	0.764
Selected bins of global saliency map	0.9
Global 2D histogram	0.79
Selected bins of global 2D histogram	0.9
Selected bins of global saliency map with GP	0.96
Selected bins of global 2D histogram with GP	0.92
Expert's median	0.68

Outline

- Related Literature
- Datasets
- Base Framework
- 3D Shape Analysis
- **Conclusion**

Contributions

- General methodology for 3D shape analysis
- Learning approach to detect salient points
- 3D object signatures
 - 2D longitude-latitude salient map
 - 2D histogram of azimuth-elevation angles
- Methodology for quantification of craniofacial disorders

Future Directions

- Analyze other craniofacial disorders
 - Cleft lip/palate, craniofacial microsomia
- Association of shape changes
 - Over time, pre/post op
- Genotype–phenotype disease association
- Translate 3D shape quantification into plain English language

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- Research Group
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Publications

- [1] **3D Head Shape Quantification for Infants with and without Deformational Plagiocephaly.**
I. Atmosukarto, L. G. Shapiro, J. R. Starr, C. L. Heike, B. Collett, M. L. Cunningham, M. L. Speltz.
Accepted for publication in *The Cleft-Palate Craniofacial Journal*, 2009.
- [2] **3D Object Classification using Salient Point Patterns With Application to Craniofacial Research**
I. Atmosukarto, K. Wilamowska, C. Heike, L. G. Shapiro.
Accepted for publication in *Pattern Recognition*, 2009.
- [3] **The Use of Genetic Programming for Learning 3D Craniofacial Shape Quantification.**
I. Atmosukarto, L. G. Shapiro, C. Heike.
Accepted in International Conference on Pattern Recognition, 2010.
- [4] **3D Object Retrieval Using Salient Views.**
I. Atmosukarto and L. G. Shapiro.
In *ACM Multimedia Information Retrieval*, 2010.
- [5] **Shape-Based Classification of 3D Head Data.**
L. Shapiro, K. Wilamowska, I. Atmosukarto, J. Wu, C. Heike, M. Speltz, and M. Cunningham.
In *International Conference on Image Analysis and Processing*, 2009.
- [6] **Automatic 3D Shape Severity Quantification and Localization for Deformational Plagiocephaly.**
I. Atmosukarto, L. Shapiro, M. Cunningham, and M. Speltz.
In *Proc. SPIE Medical Imaging: Image Processing*, 2009.
- [7] **A Learning Approach to 3D Object Classification.**
I. Atmosukarto, L. Shapiro.
In *Proc. S+SSPR*, 2008.
- [8] **A Salient-Point Signature for 3D Object Retrieval.**
I. Atmosukarto, L. G. Shapiro.
In *Proc. ACM Multimedia Information Retrieval*, 2008.

Back up slides

Kiran 3 months old



3D Descriptors

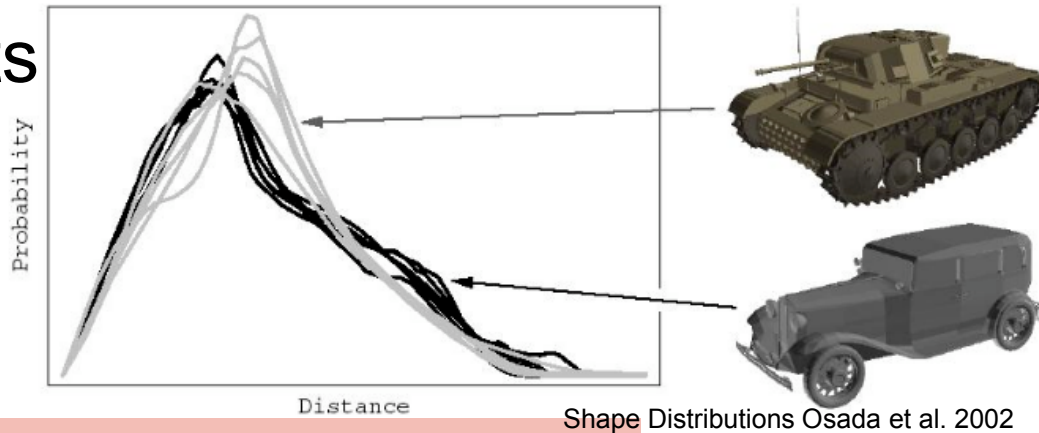
- Desirable properties:
 - Efficient
 - Discriminative
 - Rotation-invariant
- Descriptor representation:
 - Feature-based
 - Graph-based
 - View-based

Feature-based descriptors

- Represent as point in high-dimensional space
- Two shapes are similar if close in space
- Sub-categories:
 - Global features
 - Global feature distribution
 - Spatial map
 - Local features

Feature-based descriptors

- Global features
 - Volume, area, moments
- Global feature distributions
 - Distribution of distance between random points

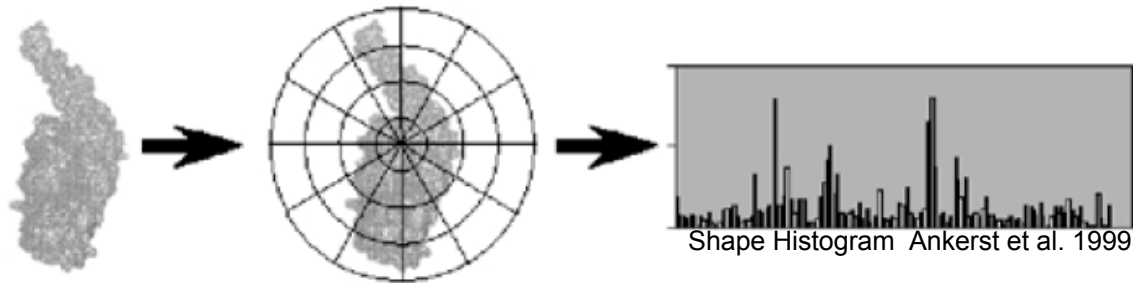


+ Compact, rotation invariant
- Not discriminative enough

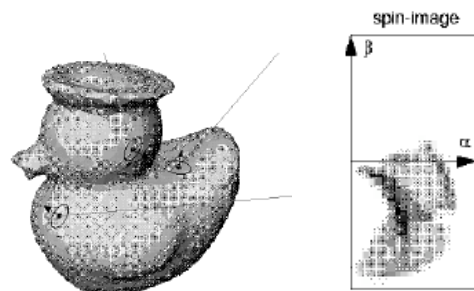
Feature-based descriptors

- Spatial maps
 - Shell and sectors

+ Compact
- Not rotation invariant



- Local features

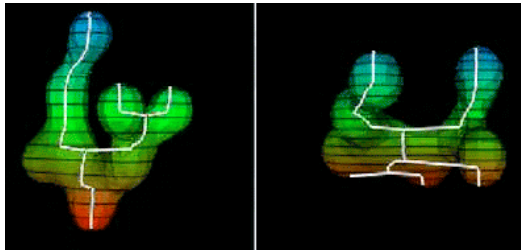


Spin Images Johnson et al. 1999

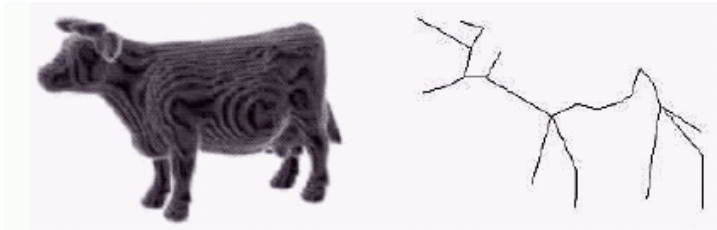
+ Allow partial matching
- More complex

Graph-based descriptors

- Extract geometric meaning by showing how components are linked
- Model graph, Reeb graph, Skeleton



Reeb Graph Hilaga et al. 2001

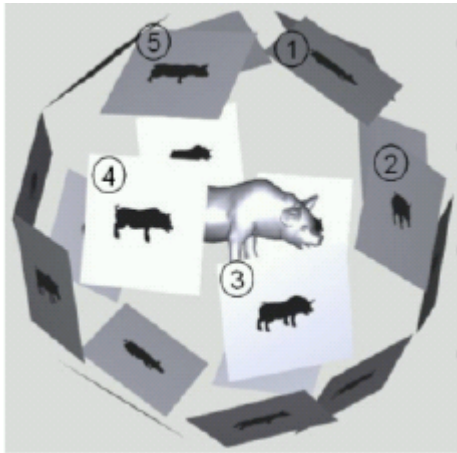


Skeleton Sundar et al. 2003

+ Good for articulated object
- Computationally expensive

View-based descriptors

- Two 3D objects are similar if they look similar from all viewing angles
- Light Field Descriptor



Chen et al. 2003

+ Best performer in SHREC
- Computationally expensive

