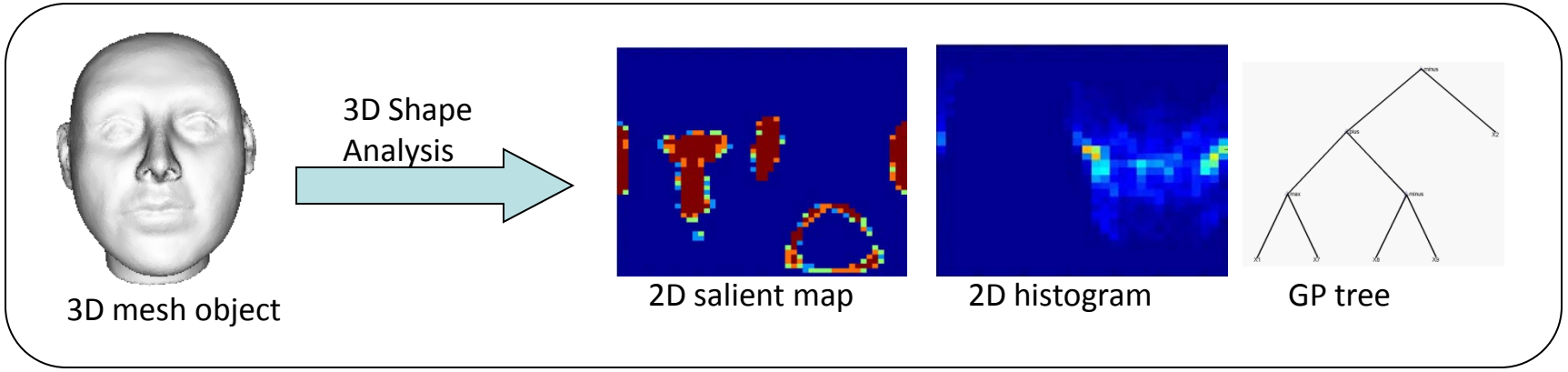
3D Shape Analysis for Quantification, Classification and Retrieval



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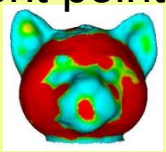
PhD Defense

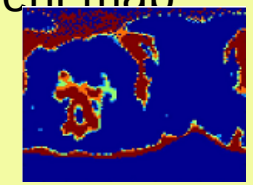
Advisor: Prof Linda Shapiro

3D Shape Analysis

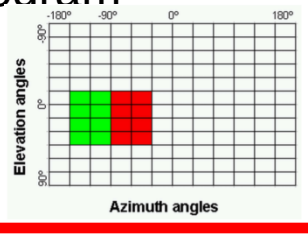
Learning salient points



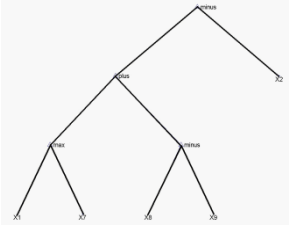
2D longitude-latitude salient map



2D azimuth elevation histogram



Learning 3D shape quantification

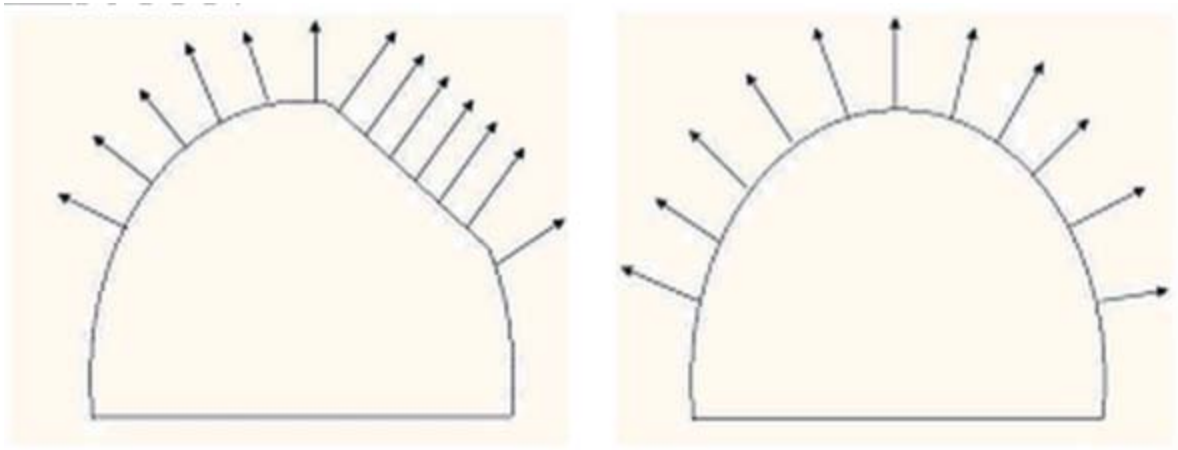


Global 2D Azimuth-Elevation Angles Histogram

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

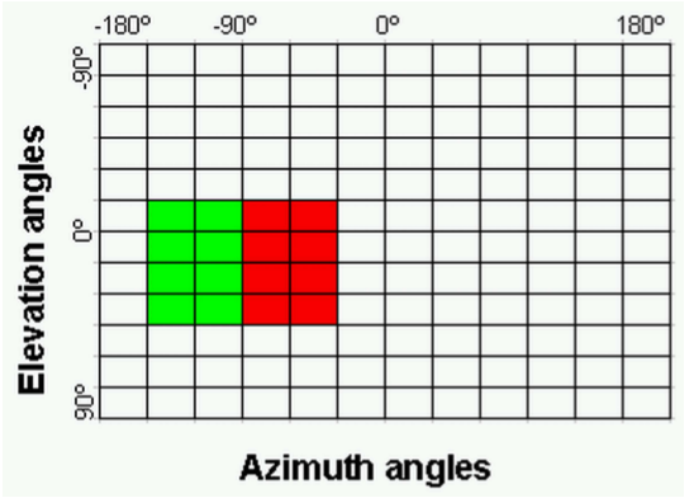
3D Shape Quantification for Deformational Plagiocephaly

- 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)

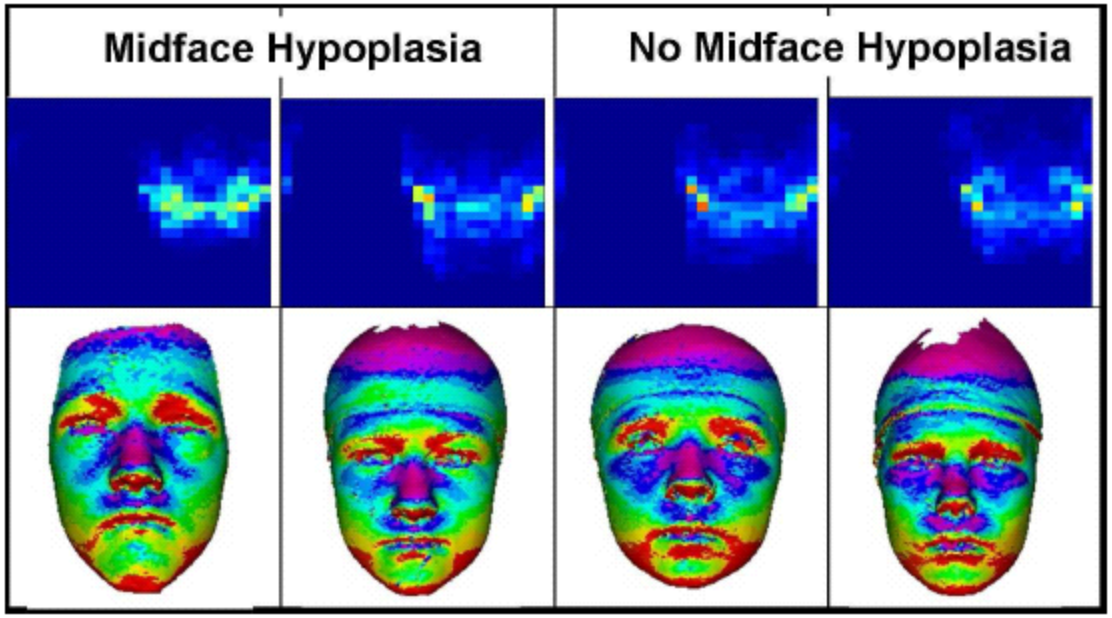


Classification of Deformational Plagiocephaly

- 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

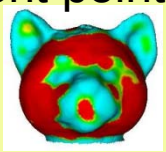
	8×8	16×16	24×24	32 × 32	Experts' median
Whole 2D hist	0.651	0.569	0.79	0.684	0.68

Classification of 22q11.2DS Facial Features

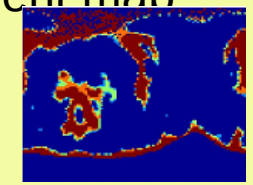
	8×8	16×16	24×24	32 × 32
Midface Hypoplasia	0.639	0.744	0.697	0.651
Tubular Nose	0.709	0.593	0.581	0.663
Bulbous Nasal Tip	0.593	0.581	0.581	0.639
Prominent Nasal Root	0.547	0.639	0.616	0.658
Small Nasal Alae	0.561	0.675	0.571	0.560
Retrusive Chin	0.526	0.674	0.560	0.546
Open Mouth	0.875	0.799	0.844	0.683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

3D Shape Analysis

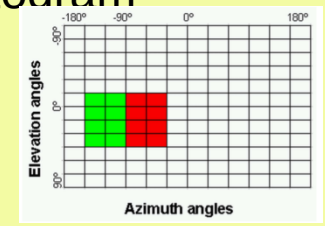
Learning salient points



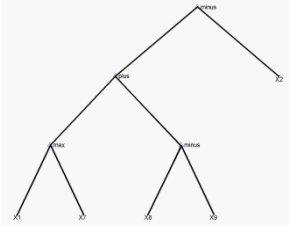
2D longitude-latitude salient map



2D azimuth elevation histogram

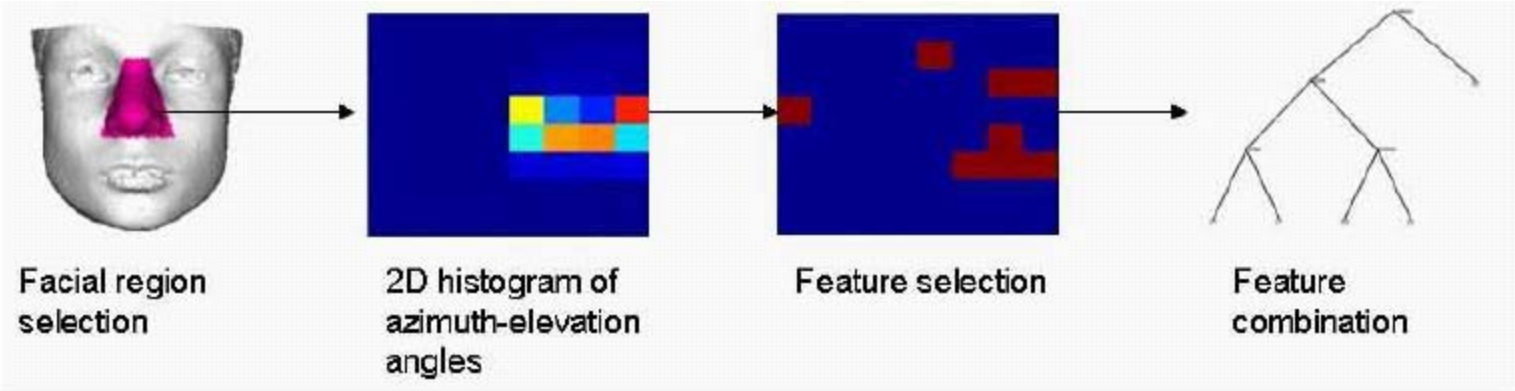


Learning 3D shape quantification



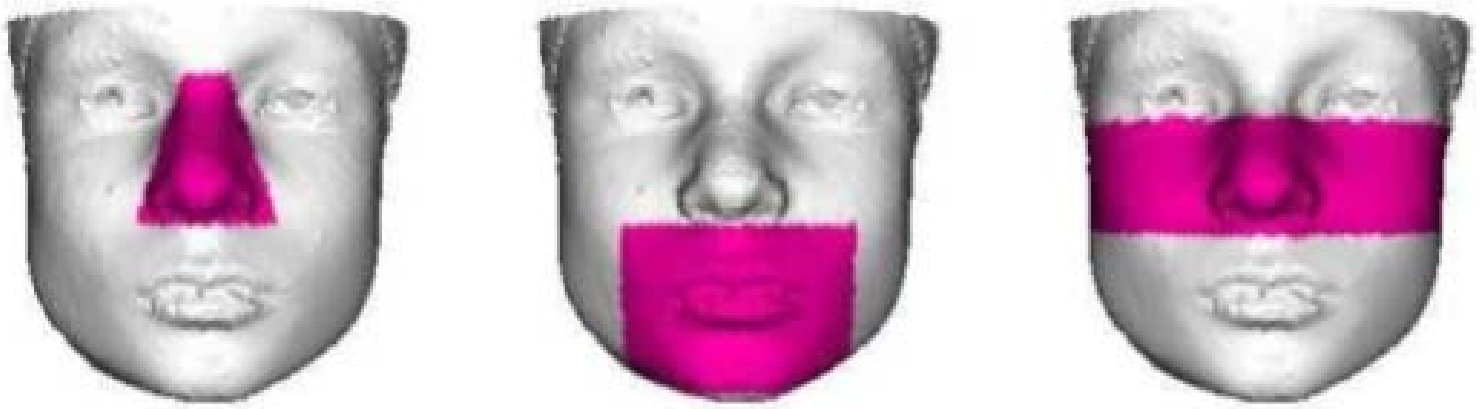
Learning 3D Shape Quantification

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



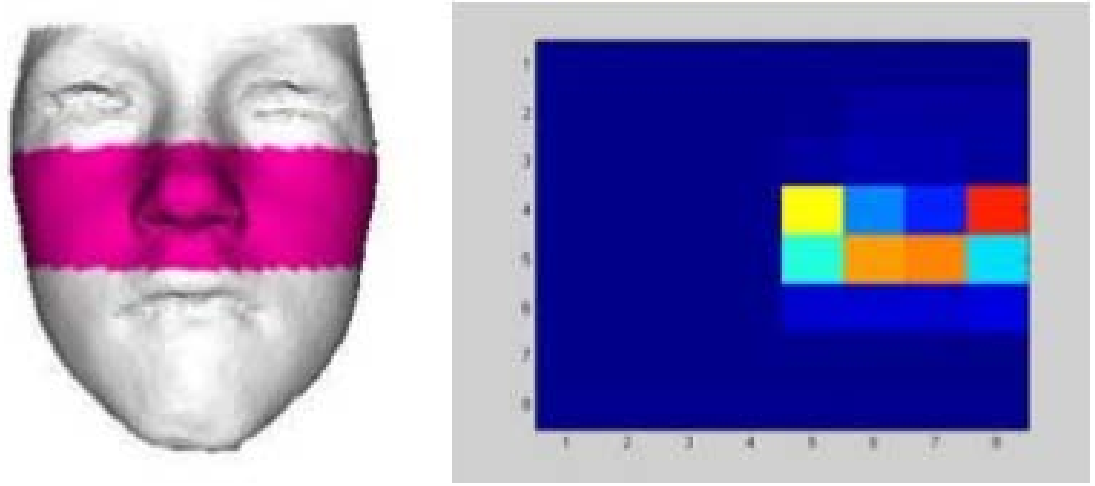
Learning 3D Shape Quantification - Facial Region Selection

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



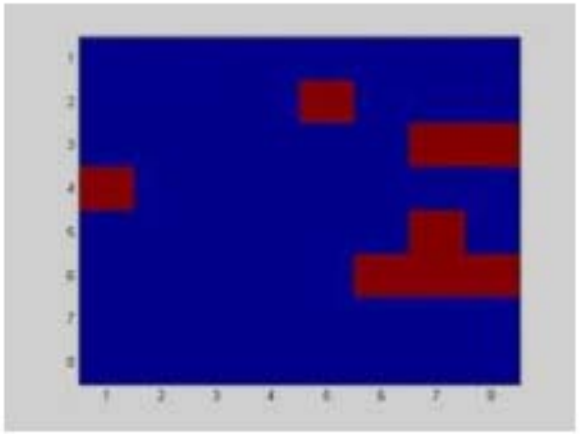
Learning 3D Shape Quantification - 2D Histogram Azimuth Elevation

- 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



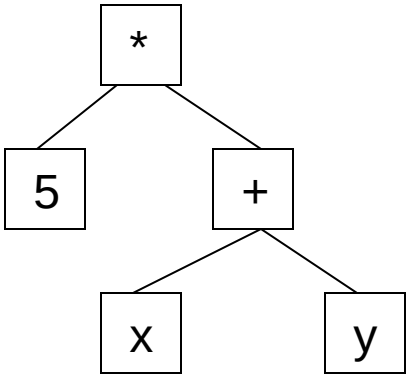
Learning 3D Shape Quantification - Feature Combination

- 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

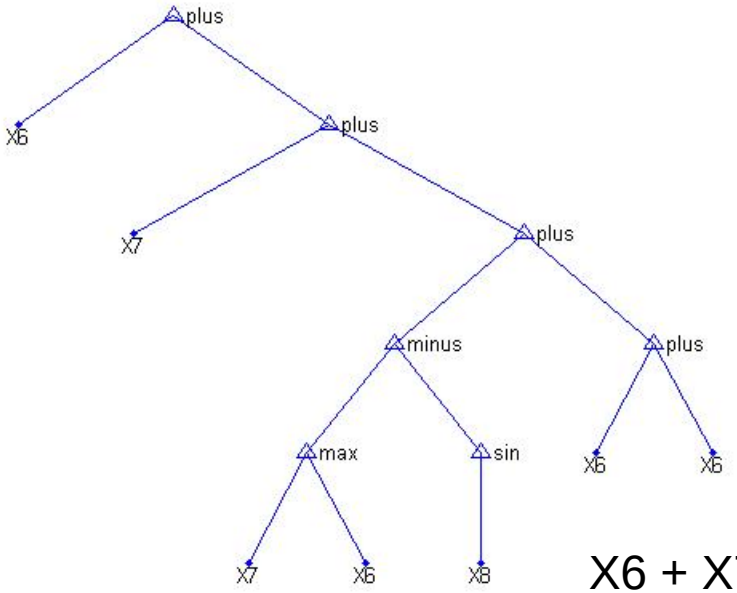
- 22q11.2DS dataset
  - Assessed by craniofacial experts
  - Groundtruth is union of expert scores

- 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

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



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

Learning 3D Shape Quantification - Experiment 1

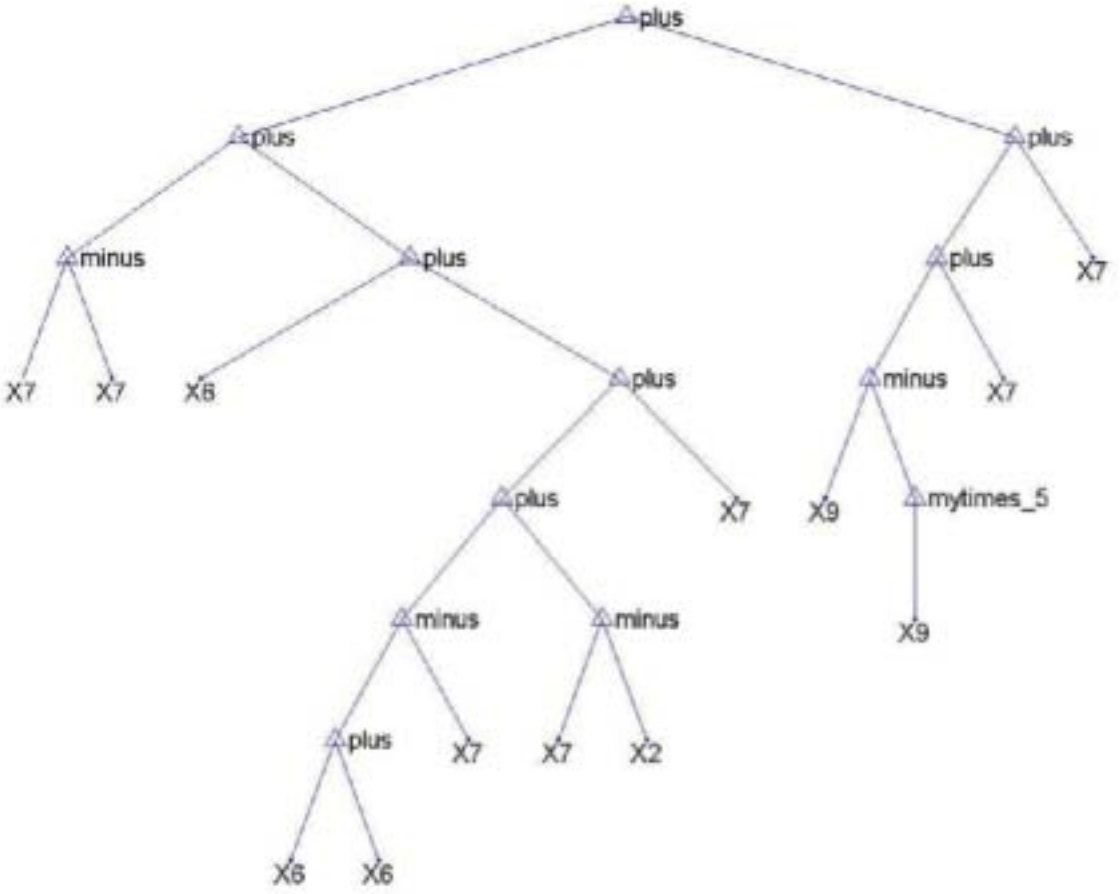
- Objective: investigate function sets
  - Combo1 = {+,-,*,*min*,*max*}
  - Combo2 = {+,-,*,*min*,*max*,*sqrt*,*log2*,*log10*}
  - Combo3 = {+,-,*,*min*,*max*, *2x*,*5x*,*10x*,*20x*,*50x*,*100x*}
  - Combo4 = {+,-,*,*min*,*max*,*sqrt*,*log2*,*log10*, *2x*,*5x*,*10x*,*20x*,*50x*,*100x*}

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)

Xi 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