A Shape-based Image Retrieval System for Assisting Intervention Planning

Jill Lin

Biomedical and Health Informatics

Outline

- Background
- Related Work
- Preliminary Studies / Progress Report
- Research Design and Methods
- Conclusion

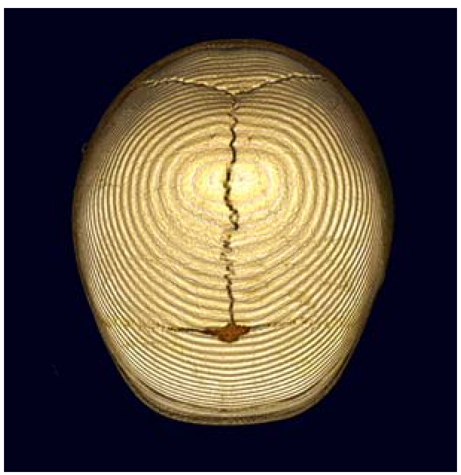
Background

- Craniosynostosis is a serious condition of childhood, affecting 1 in 2500 individuals
- It is caused by the early fusion of the sutures of skull which results in severe malformations in skull shapes
- Skull abnormalities are frequently associated with impaired central nervous system functions due to intra-cranial pressure, hydrocephalus, and brain anomalies

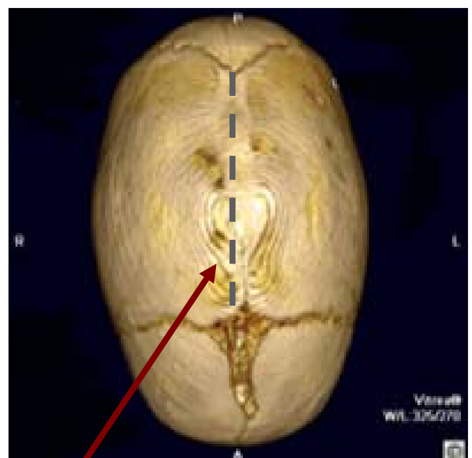
Background Cont.

- Skull grows perpendicular to the fused suture resulting in different head shapes

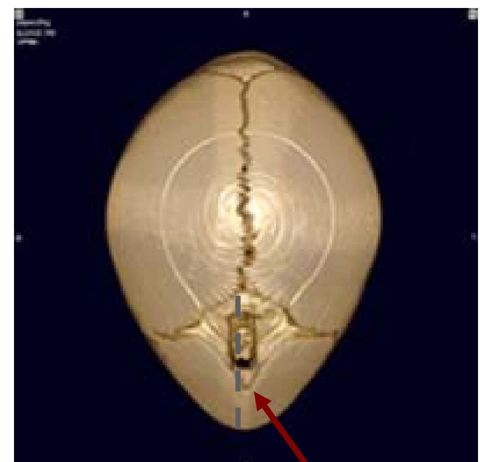
Normal



Sagittal Synostosis



Metopic Synostosis



Sagittal suture fused

Metopic suture fused

Background Cont.

- Physicians and surgeons have been using similar cases in the past experience as “guidelines” in preparation and evaluation of the reconstruction of the skull

- Similar cases are defined by similar shapes in case of craniosynostosis

- This “case-based” clinical decision support technique produces a need to retrieve images of similar shapes in patients with craniosynostosis objectively and reproducibly

Problem 1

- No image retrieval system currently exists for the surgeons and radiologists to retrieve cases of similar shapes
  - "Retrieval" of cases with similar shapes are based on physicians and surgeons memories and experiences – subjective and not reproducible

Problem 2

- Unavailability of quantitative methods to describe skull shapes handicaps attempts to define craniofacial phenotypes
  - Currently, the diagnosis of craniosynostosis and interpretation of these images are largely confined to radiologists' subjective judgment
  - Shape descriptions remain constrained to gross generalizations of the predominant form and are limited to traditional terms
  - Hinders quantitative and objective methods to define and measure the similarities and differences between skull shapes

Goal

- Design an automatic shape-based image retrieval system to aid the process of retrieving cases of similar shapes that are treated by different surgeons and at different craniofacial centers for “case-based” clinical decision making.

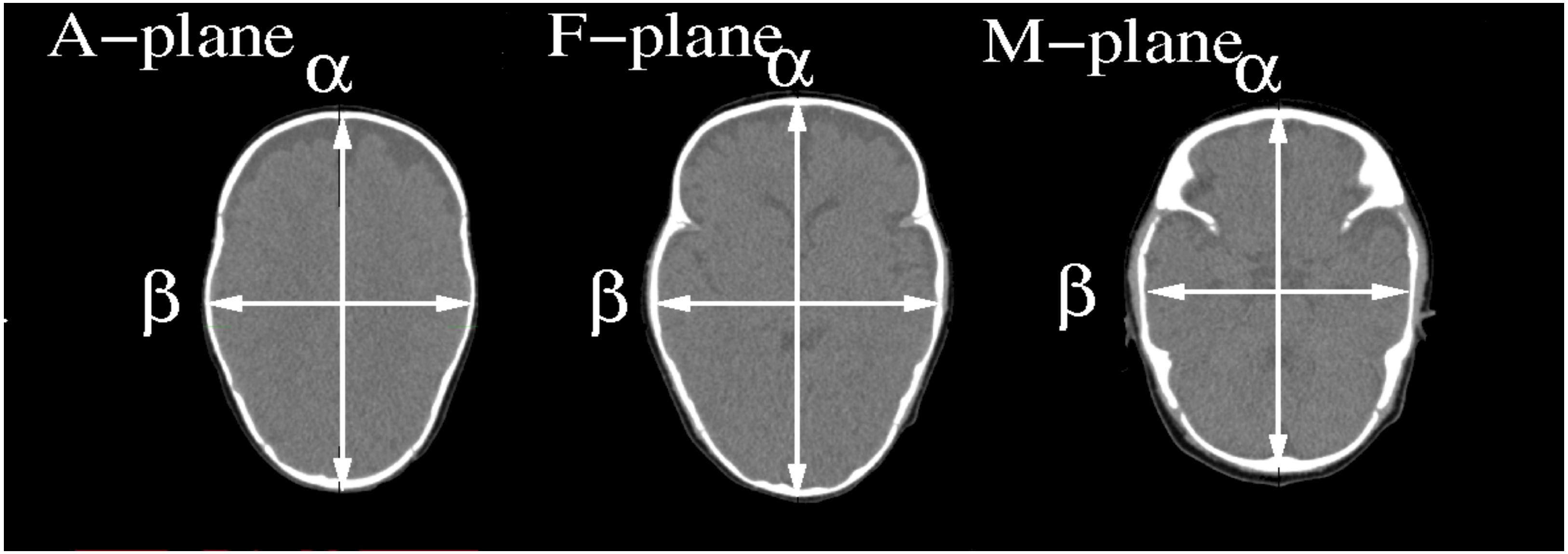
Aims

- Develop novel shape descriptors and efficient algorithms for quantification of skull shapes
- Discover subsets of shapes that share similar geometric properties
- Determine possible correlations between patients' head skulls and neurocognitive development
- Design a shape-based image retrieval system

Related Work

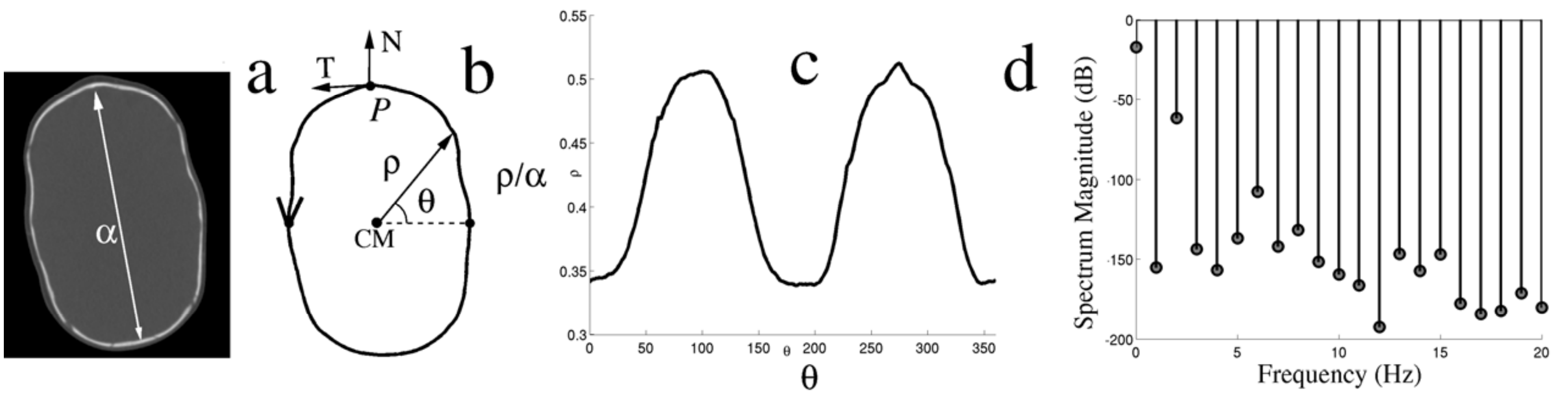
Scaphocephaly Severity Indices (SSI)

- The ratio of head width to length, β/α, at the three bone slices, SSI-A, SSI-F, and SSI-M
- Gold Standard Clinically



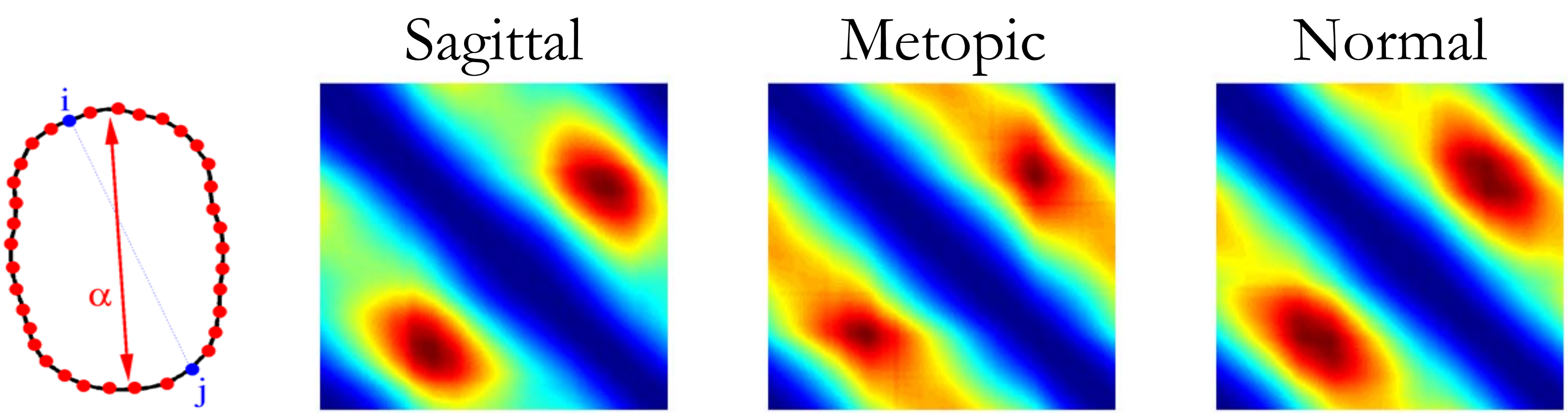
Cranial Spectrum (CS)

- Represent an outline as a periodic function
- Decompose the periodic function using Fourier analysis
- The outline is oriented: there is a direction associated with each outline (CCW direction)



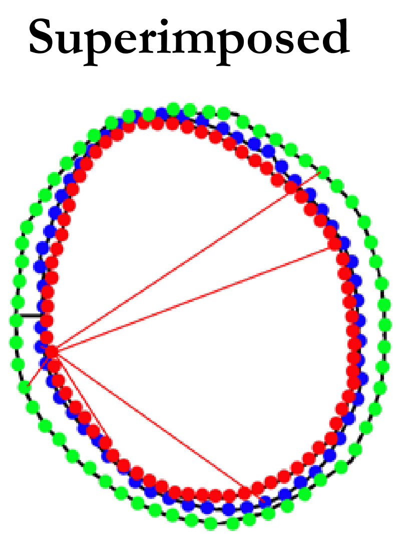
Cranial Image (CI) – Single Plane

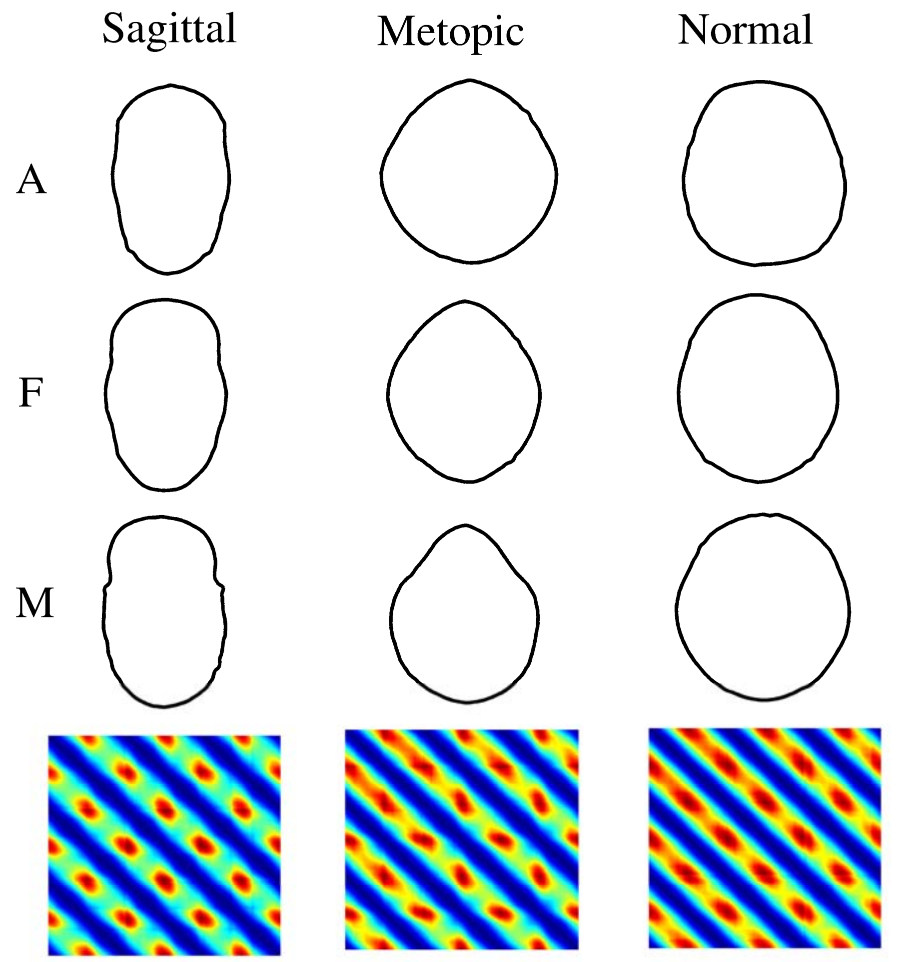
- Matrix representation of pairwise normalized square distances for all the vertices of an outline
- The matrix is defined up to a periodic shift along the main diagonal line because the outline is oriented



Cranial Image – Multiple Planes

- Accomplished by computing inter and intra-oriented outline distances of a skull.





Cranial Image – Multiple Planes Cont.

- The worst case computational complexity of the classification function is

$$O(ML^3N^3)$$

  - L=3 is the number of planes and
  - N=200 is the number of vertices per outline
  - M=112 is number of elements in the training set

Landmark-based Descriptor

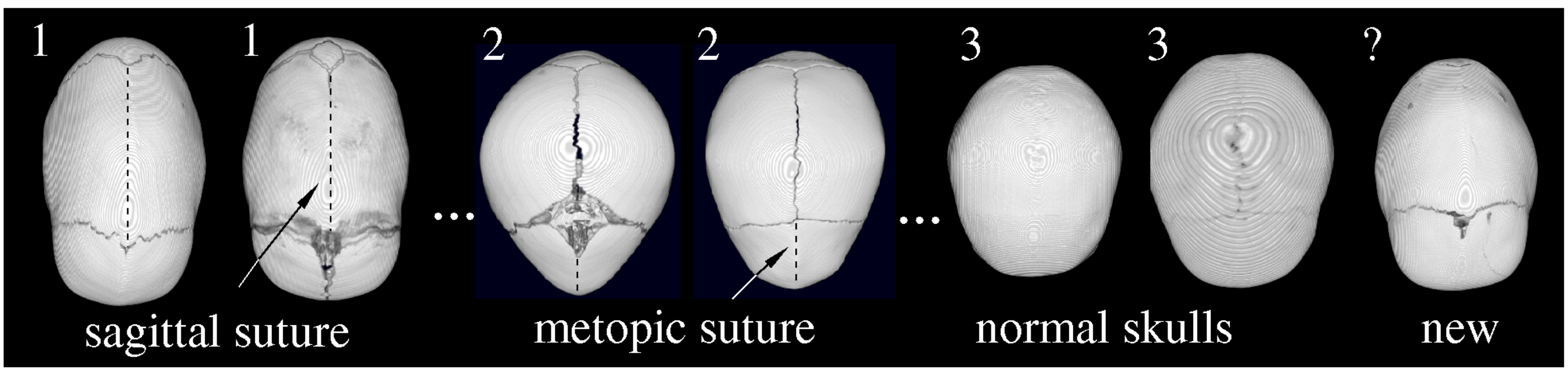
- Manual placement of landmarks – subjective and prone to variations
- High cross-validation error rates (32-40% average for sagittal synostosis, and 18-27% average for metopic synostosis) – Lale and Richtsmier

Symbolic Shape Descriptors - Motivation

- High computational complexity
- Limited generalizability
- Lack of ability to detect intra-class differences

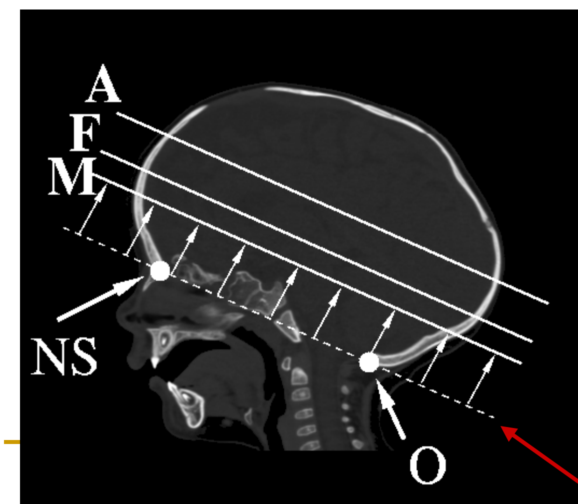
Performance Test

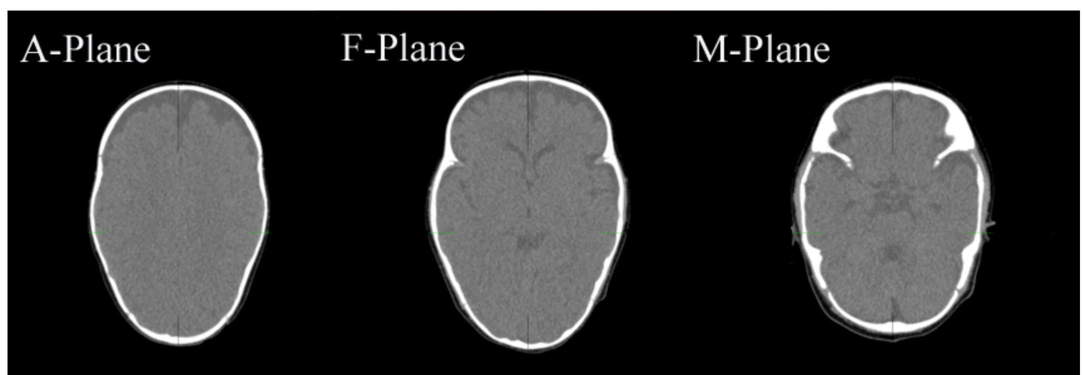
- Given a population of M skull shapes (training set) labeled as sagittal (1), metopic (2), and normal (3), predict with high accuracy the label of a new skull using our novel shape descriptors



Data Acquisition

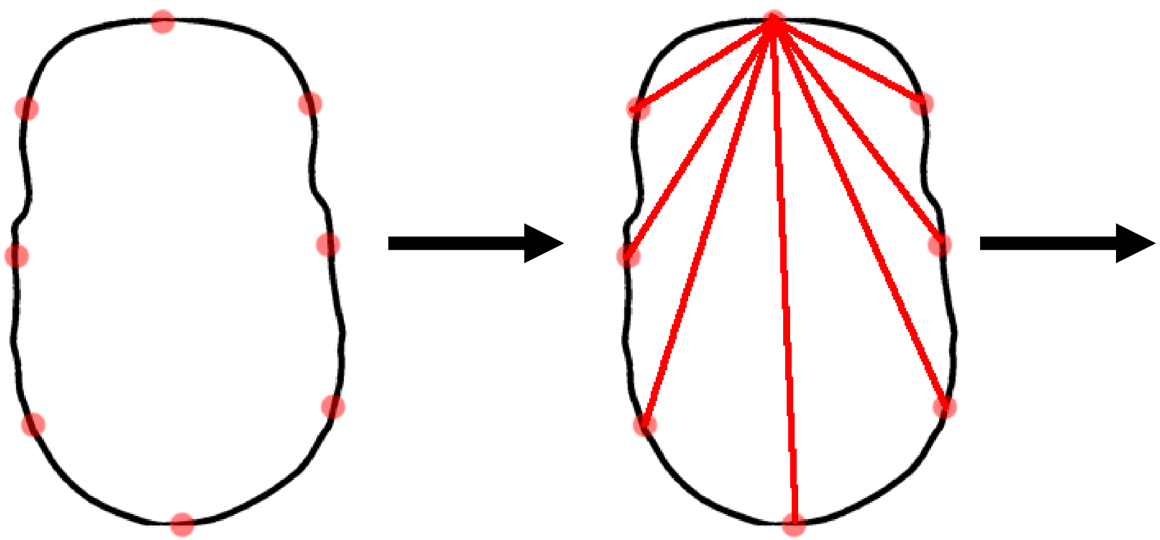
- CT scan images from 60 sagittal patients, 13 metopic patients, and 40 normal subjects
- 3 manually selected planes based on brain landmarks
  - A-plane: top of the lateral ventricle
  - F-plane: Foramina of Munro
  - M-plane: maximal dimension of the fourth ventricle





Skull Base Plane

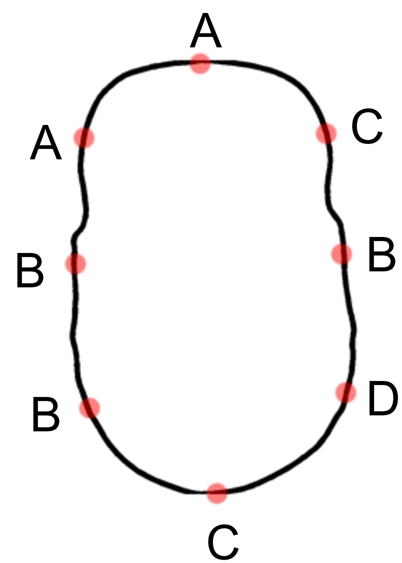
Training Algorithm
- Step 1: Forming BOW (1)



$$
\begin{pmatrix}
d_{11} & d_{12} & \dots & d_{1n} \\
d_{21} & d_{22} & \dots & d_{2n} \\
 & & \vdots & \\
d_{n1} & d_{n2} & \dots & d_{nn}
\end{pmatrix}
$$

Training Algorithm
- Step 1: Forming BOW (2)

$$\begin{pmatrix} d_{11}\ d_{12}\ \dots\ d_{1n} \\ d_{21}\ d_{22}\ \dots\ d_{2n} \\ \vdots \\ d_{n1}\ d_{n2}\ \dots\ d_{nn} \end{pmatrix} \xrightarrow{\text{K-means}}$$

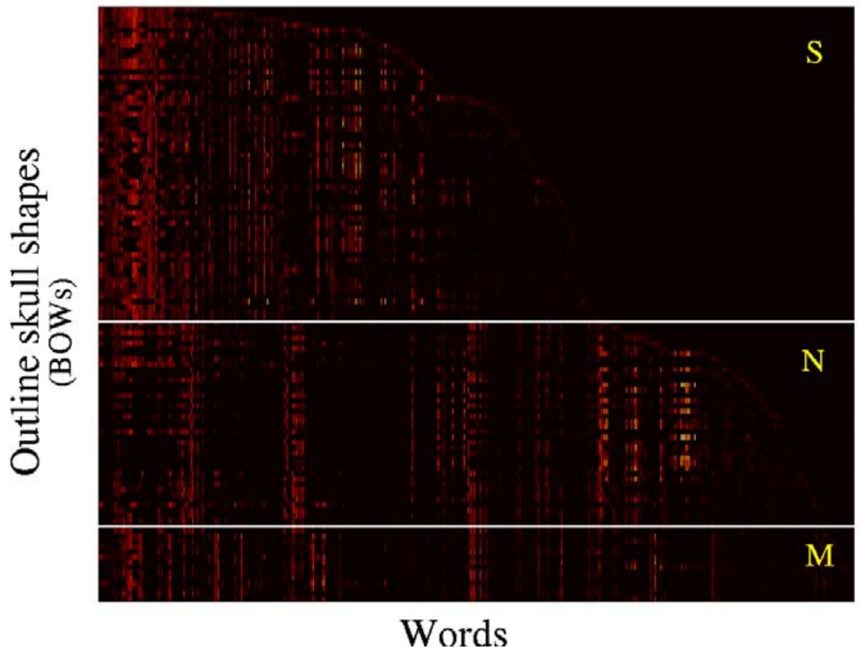


$\longrightarrow$

Document S1 =
{'CAA' 'AAB' 'ABB'
'BBC' 'BCD' 'CDB'
'DBC' 'BCA'}

Training Algorithm
- Step 2: Compute Co-occurrence Matrix

- Compute the frequency of each word in our vocabulary occurring in each document of the training set.



Training Algorithm

- Dimensionality reduction can be used to approximate the data and lower the complexity of the classification function
- We utilize a model called Probabilistic Latent Semantic Analysis (Hofmann 2001) that is commonly used in document and text retrieval to reduce complexity

Training Algorithm
- Step 3: Compute PLSA (1)

- Introduces a latent variable, which in our case is the topic, to the words and documents
- Each word in a document is a sample of a mixture model and is generated from a single topic
- Each document thus is represented as a list of mixing proportions for these mixture models

Training Algorithm
- Step 3: Compute PLSA (2)

- Introduces a latent variable z

Asymmetric parameterization

$$\xrightarrow{P(d)} d \xrightarrow{P(z|d)} z \xrightarrow{P(w|z)} w$$

d = document (skull)
w = word
z = topic (related to shape)

$$P(d,w) = \sum_{z} P(z)P(d|z)P(w|z)$$

Training Algorithm
- Step 3: Compute PLSA (3)

- Uses Expectation-Maximization (EM) algorithm for the estimation of the latent variable model

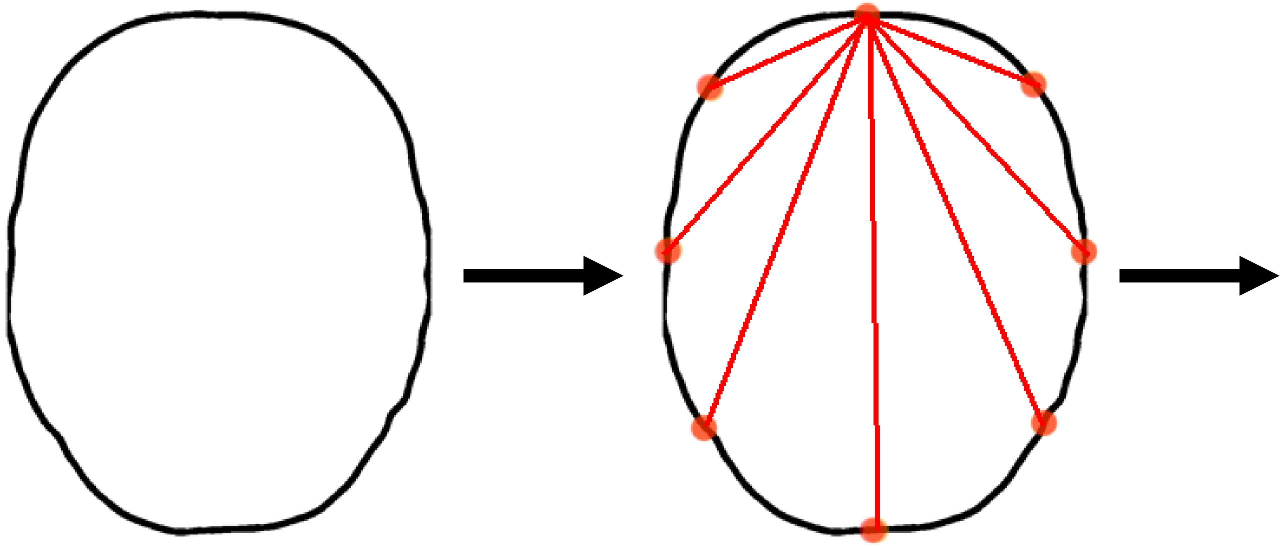
- Symbolic Shape Descriptors are

  $[P(S_i|Z_1), P(S_i|Z_2), \ldots , P(S_i|Z_p)]$

Training Algorithm
- Step 4: Model Selection

- Use off-the-shelf Support Vector Machines (SVMs) as our classification tool
- Use a radial basis function kernel
- Use bootstrap and leave-one-out techniques for model selection

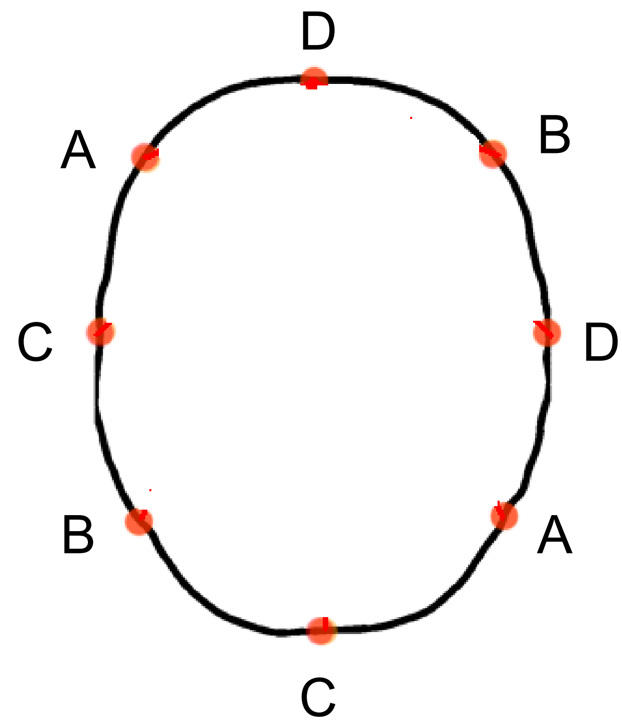
Classification Algorithm
- Step 1: Inputs



$$\begin{pmatrix} d_{11} & d_{12} & \ldots & d_{1n} \\ d_{21} & d_{22} & \ldots & d_{2n} \\ & & \vdots & \\ d_{n1} & d_{n2} & \ldots & d_{nn} \end{pmatrix}$$

Classification Algorithm - Step 2: Compute BOW

- Use the *k*-means cluster centers from training and a nearest neighbor rule to assign symbolic labels to the vertices
- *BOW* representation {'BDA', 'DAC', 'ACB', … 'DBD'}
- Compute the co-occurrence matrix of all skulls to include all new words from S_{new}



Classification Algorithm
- Step 3: Compute PLSA

- Apply PLSA to the new co-occurrence matrix and compute $P(s_{new}|z)$ for the test skull S_{new} to form the symbolic shape descriptor $[P(s_{new}|z_1),\ldots, P(s_{new}|z_p)]$

- Predict the label of S_{new} using the *v*-SVM classification function and the symbolic shape descriptors of S_{new}.

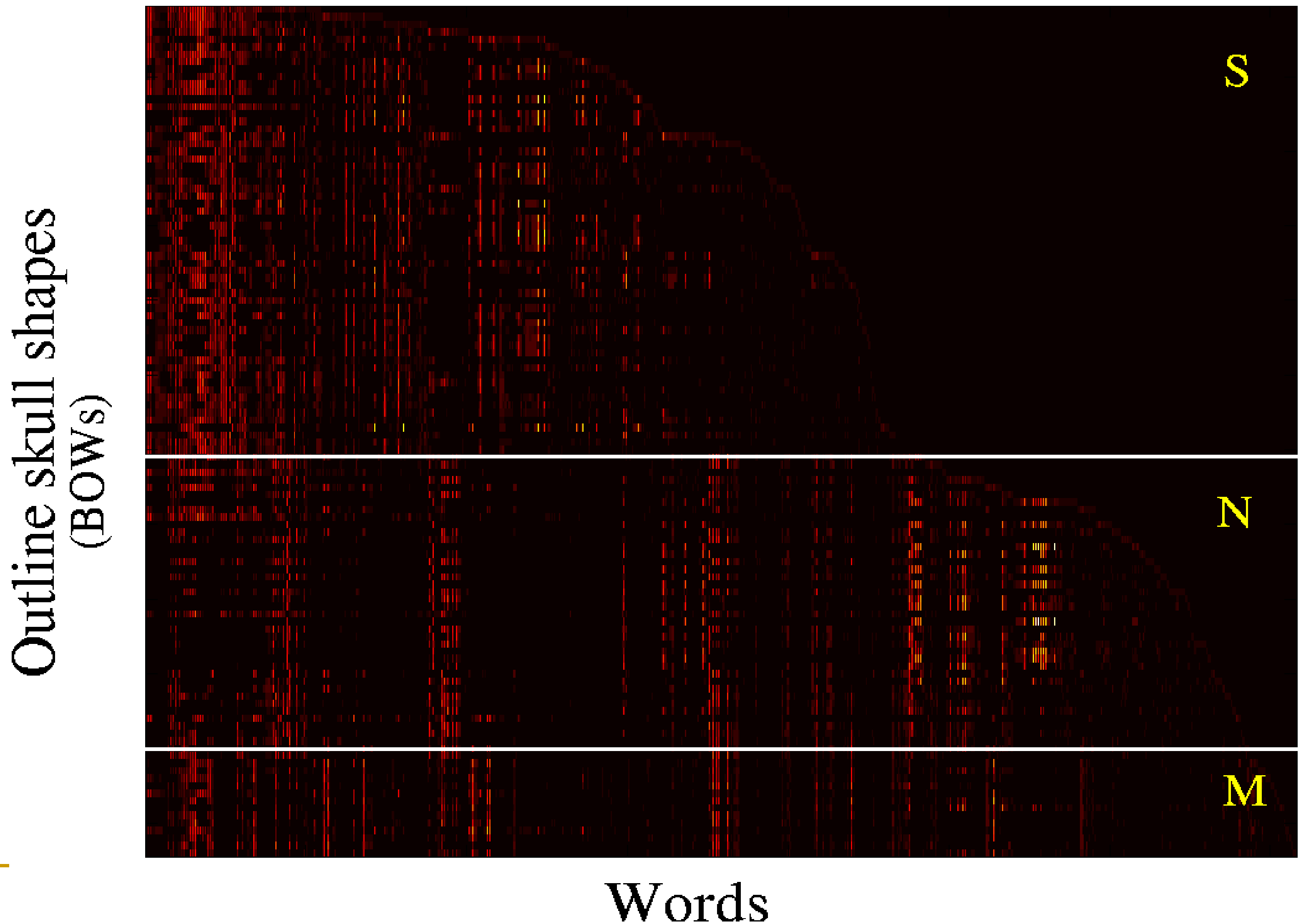
Computational Complexity

- Improved complexity at classification time:

$$O(P)$$

  - P=15 is the number of latent variables in the PLSA model

Co-Occurrence matrix



Classification Results – Single Plane

- Sagittal vs. metopic synostoses vs. normal skull shapes in the **F-plane**

SSI

	S	M	N
S	0.93	0.00	0.00
M	0.00	0.85	0.51
N	0.07	0.15	0.49

CI

	S	M	N
S	0.95	0.00	0.00
M	0.00	0.92	0.00
N	0.05	0.08	0.90

SSD

	S	M	N
S	**1.00**	0.00	0.07
M	0.00	**0.92**	0.05
N	0.00	0.08	**0.88**

Classification Results – Multiple Planes

	Sagittal	Metopic	Normal
Sagittal	**1.00** **[0.99 1.00]**	0.00 [0.00 0.01]	0.07 [0.05 0.09]
Metopic	0.00 [0.00 0.01]	**1.00** **[0.98 1.00]**	0.00 [0.00 0.02]
Normal	0.00 [0.00 0.01]	0.00 [0.00 0.06]	**0.93** **[0.90 0.96]**

Subclasses Identification