A Shape-based Image Retrieval System for Assisting Intervention Planning

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Outline

- Background
- Related Work
- Preliminary Studies / Progress Report
- Research Design and Methods
- Conclusion
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.
Skull grows perpendicular to the fused suture resulting in different head shapes.
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, $\beta/\alpha$, 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.

Superimposed

<table>
<thead>
<tr>
<th></th>
<th>Sagittal</th>
<th>Metopic</th>
<th>Normal</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td><img src="image1.png" alt="Image" /></td>
<td><img src="image2.png" alt="Image" /></td>
<td><img src="image3.png" alt="Image" /></td>
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<tr>
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<td><img src="image5.png" alt="Image" /></td>
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<td>M</td>
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<td><img src="image8.png" alt="Image" /></td>
<td><img src="image9.png" alt="Image" /></td>
</tr>
</tbody>
</table>
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
Training Algorithm
- Step 1: Forming BOW (1)
Training Algorithm
- Step 1: Forming BOW (2)

\[
\begin{align*}
&d_{11} \ d_{12} \ldots \ d_{1n} \\
&d_{21} \ d_{22} \ldots \ d_{2n} \\
&\vdots \\
&d_{n1} \ d_{n2} \ldots \ d_{nn}
\end{align*}
\]

\[\text{K-means}\]

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

\[
P(d,w) = \sum_z P(z)P(d|z)P(w|z)
\]
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

\[
\begin{align*}
d_{11} & \quad d_{12} \quad \ldots \quad d_{1n} \\
d_{21} & \quad d_{22} \quad \ldots \quad d_{2n} \\
& \quad \ldots \\
d_{n1} & \quad d_{n2} \quad \ldots \quad d_{nn}
\end{align*}
\]
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 $S_{\text{new}}$
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 $\nu$-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

Outline skull shapes (BOWS)

Words
Classification Results – Single Plane

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

<table>
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## Classification Results – Multiple Planes

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Subclasses Identification

ASPECT 1  ASPECT 4  ASPECT 12  ASPECT 13  ASPECT 14