Extrapolation of Missing Craniofacial Skeletal Structure via Statistical Shape Models

Collabortive Laboratory for BIGSS Biomechanical- and Image-guided Surgical Systems

Computer Integrated Surgery II
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Introduction

- Using publicly available CT Imagery (TCIA), we have created a Statistical Shape Model (SSM) of the human skull and skin of the head
- Using the SSM, we are able to extrapolate missing anatomical craniofacial skeletal structure
- A method for synthetic patient disfigurement was also designed for future use in SSM evaluation

Courtesy of Dr. Chad Gordon

The Problem

- We propose that the SSM-based extrapolation may be used for surgical planning in Face Transplant Surgery
- Without a pre-trauma medical scan of the patient, true cephalometrics are unknown
- Utilize extrapolated skull of patient to a more accurate estimate of cephalometrics, for a surgical plan that yields a higher probability of post-operative success

The Solution

- SSM Construction
  - Manual segmentation of the skull and skin of the template image
  - Deformable volumetric registration (Diffeomorphic via SyN, ANTs); Bootstrapped via mean displacement field
  - Template mesh creation and deformation to create all training meshes
  - PCA on training mesh vertices
- Extrapolation
  - SSM-to-Patient registration via a modified Active Shape Model search

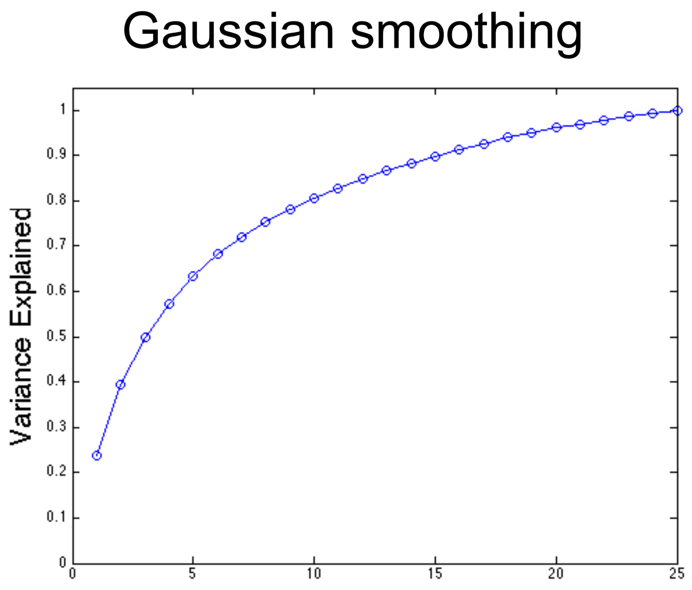
$$R(s, \boldsymbol{\theta}, \mathbf{t}, \boldsymbol{\alpha}) = D^{(\text{surface})}_{\text{mean}}(T(M_P; s, \boldsymbol{\theta}, \mathbf{t}), (\boldsymbol{\mu}_A + \mathbf{U}_A \boldsymbol{\alpha}, F_A))$$

$$\underset{s \in \mathbb{R}, \boldsymbol{\theta}, \mathbf{t} \in \mathbb{R}^3, \boldsymbol{\alpha} \in \mathbb{R}^{N_A}}{\operatorname{argmin}} R(s, \boldsymbol{\theta}, \mathbf{t}, \boldsymbol{\alpha}) \text{ subject to } |\alpha_i| \leq 3\sigma_{A,i} \text{ for } i \in \{1, 2, \ldots, N_A\}$$

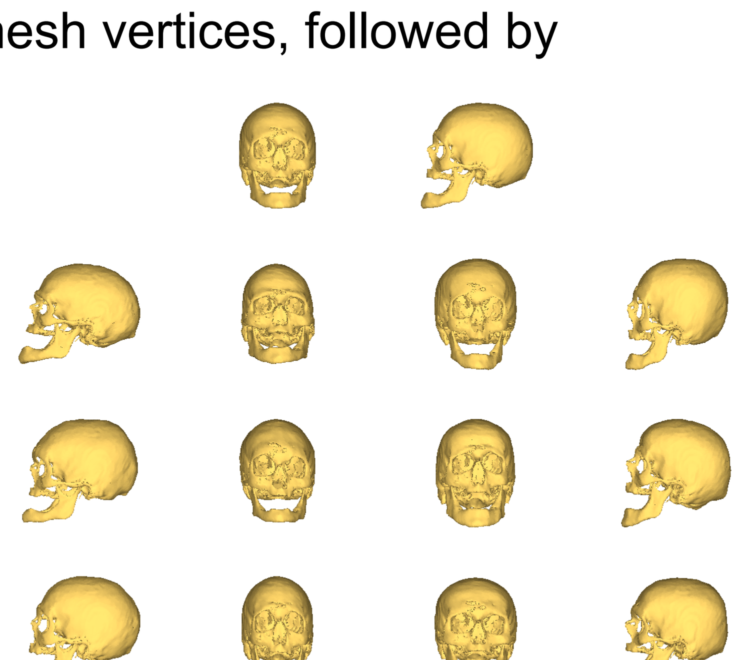
  - Approach 1: "Cut-and-paste" of the SSM estimate of the "missing region" into the patient mesh
  - Approach 2: Perform regression by modeling the "known" and "unknown" regions with a multivariate Gaussian model

$$\begin{aligned}\hat{\mathbf{m}}_U &= \boldsymbol{\mu}_U + \mathbf{C}_{UK}\mathbf{C}_{KK}^{-1}(\mathbf{m}_K - \boldsymbol{\mu}_K) \\ &= \boldsymbol{\mu}_U + \mathbf{U}_U \boldsymbol{\Sigma}_U \mathbf{V}_U^T \mathbf{V}_K \boldsymbol{\Sigma}_K^{-1} \mathbf{U}_K^T (\mathbf{m}_K - \boldsymbol{\mu}_K)\end{aligned}$$

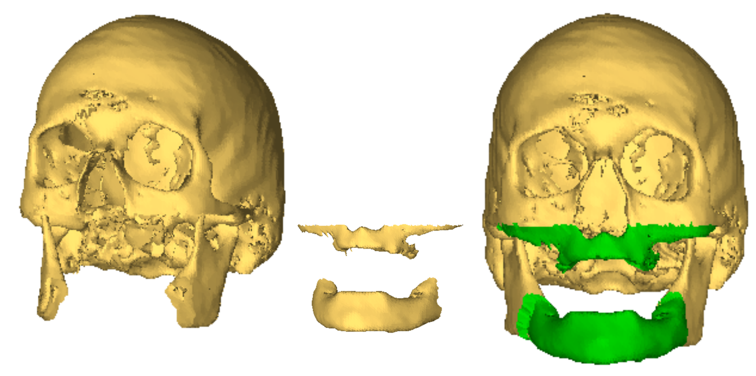
- Synthetic Disfigurement
  - Random displacement of mesh vertices, followed by Gaussian smoothing



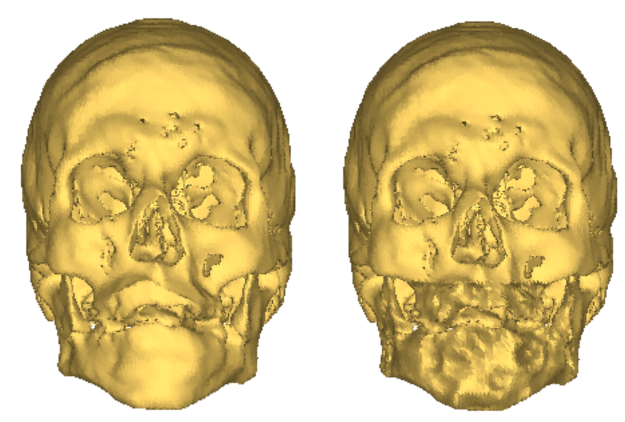
Cumulative Variance Explained by the Bone SSM



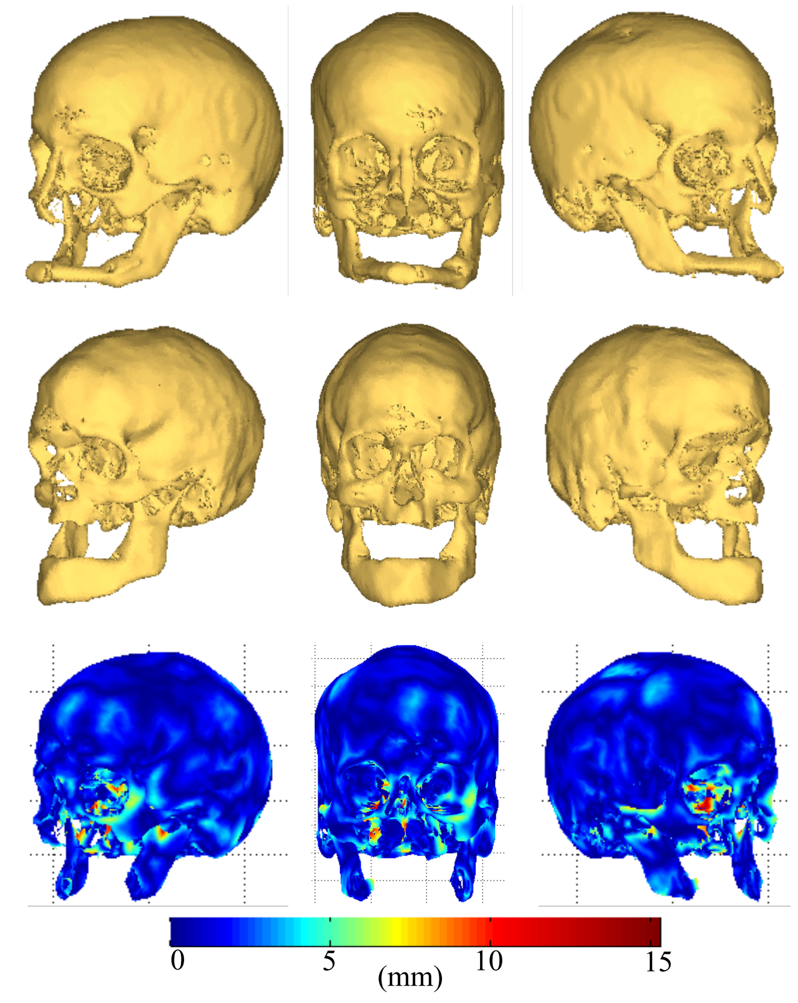
Mean Shape and Modes 1-3 of the SSM



Synthetic Removal of Structure and Extrapolation



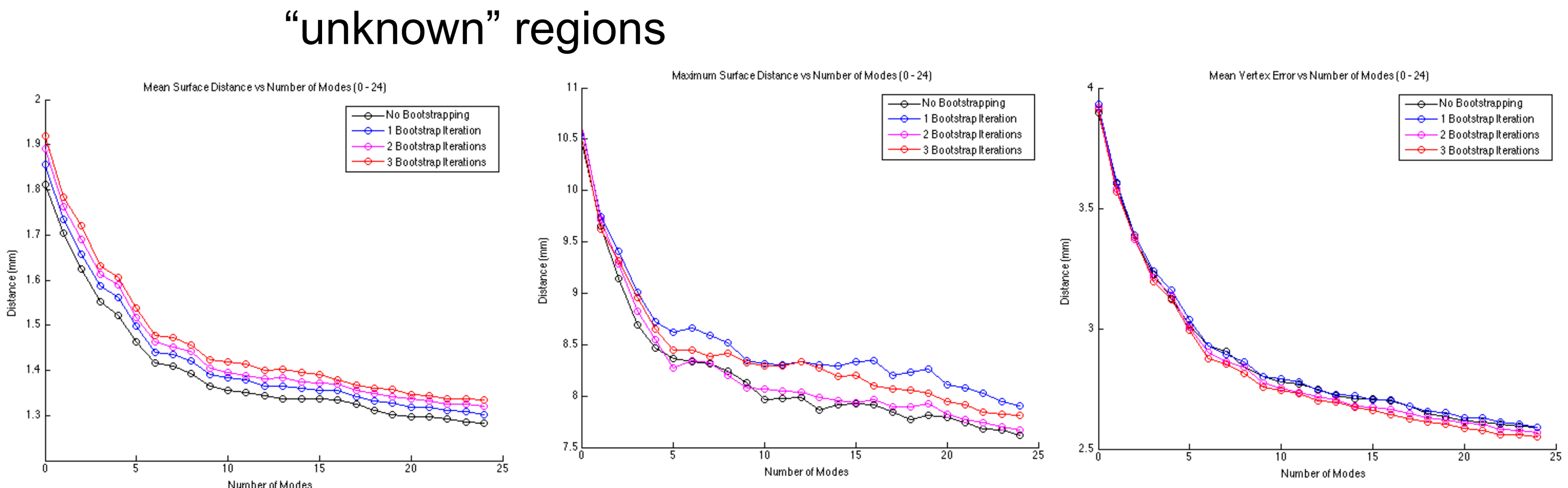
A Synthetic Disfigurement



(Top) Face Transplant Candidate (Middle) Patient Registered to SSM (Bottom) Heat Map of Surface Error Between SSM and Original Regions of Patient

Outcomes and Results

- Leave-one-out analysis used to evaluate SSMs
- Small surface distances about the neurocranium bias the mean surface distance metric
- Mean Surface Distance of 1.3 mm, Maximum Surface Distance of 7.6 mm (Bone)
- Extrapolation performed on known data, non-smooth transitions observed between the "known" and "unknown" regions



Future Work

- Finer CT resolution (1 mm)
- Other extrapolation approaches (e.g. Thin Plate Spline)
- Better segmentation; multiple segments
- Comparison of several Patient-to-Atlas registration techniques
- PCA applied to deformation fields
- Evaluation of incomplete disfigurement knowledge on SSM estimation

Lessons Learned

- Design everything to be processed automatically
- Good visualization tools are worth the time investment

Credits

- Robert Grupp: SSM pipeline, Extrapolation, Visualization
- Hsin-Hong Chiang: Synthetic Disfiguration, ANTs Bootstrapping

Publications

- Plan to submit to the *IEEE Medical Imaging Conference (MIC)* and *the Workshop* on *Modeling and Monitoring of Computer Assisted Interventions (M2CAI)*

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