Analyzing Cranial Shape Variability and its Application in Trauma Surgery

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Content

Introduction and Motivation

Quantifying phenotypic variability in humans is one of the central interests in biological anthropology. The aim hereby is usually to find causes and effects of this variability.
In the study presented here, however, we intended to exploit explicit knowledge about the shape variability of the ***cranial vault*** in a healthy sample in order to estimate and restore pathological defects.

$\Longrightarrow$This allows for simplifying and objectifying surgery planning.

Objective

Use the known variability of crania to estimate defect/missing parts (due to pathologies)

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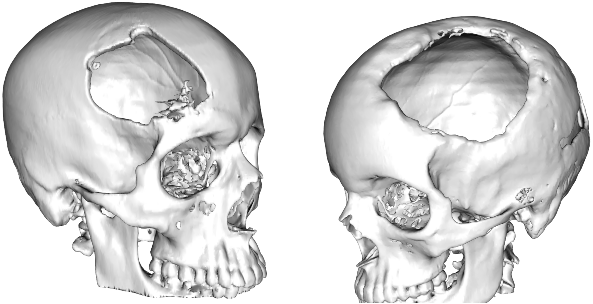

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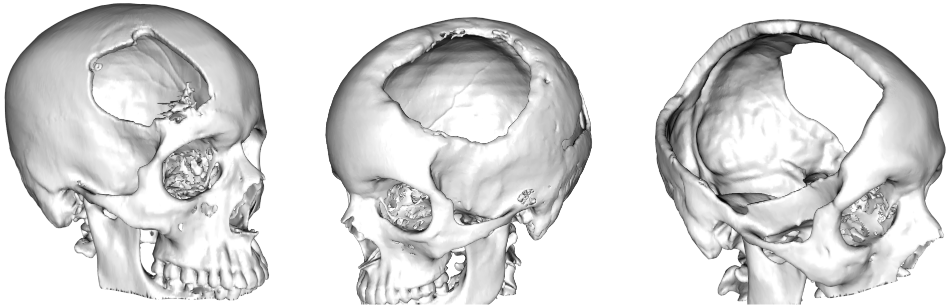


Content

Capturing morphological variability

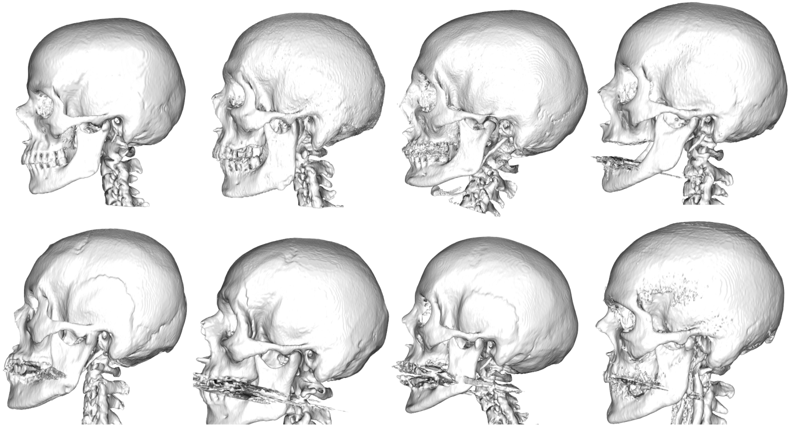
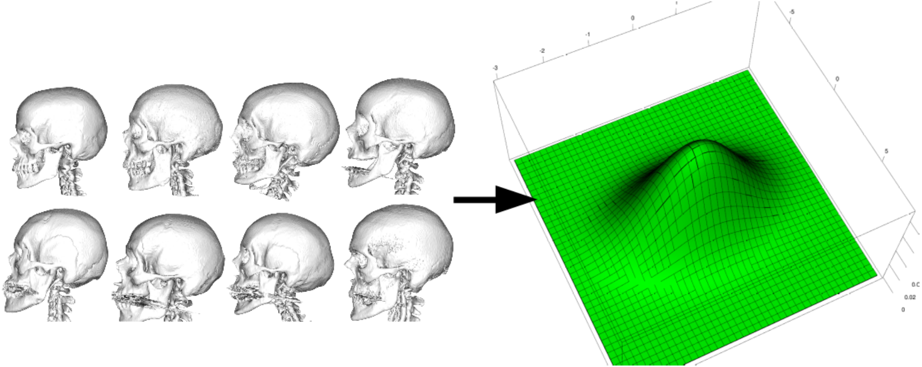


Figure: Variability of the cranial vault

From Variation to a Distribution of Shapes



Statistical Shape Model (SSM)

Prerequisites for generating an SSM:

- Specimens are represented as finite sets of 3D-pointclouds (optionally connected to form a triangular surface mesh)
- The position of each point (vertex of a mesh) needs to be pseudo-homologous throughout a given sample
- Differences due to spatial position have to be removed (by Procrustes alignment)

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Correspondences

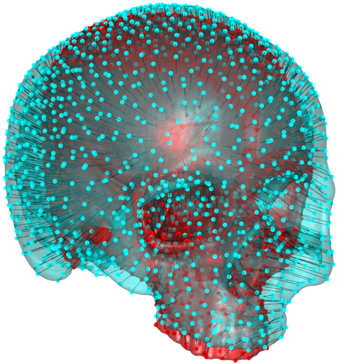

Figure: Point-to-point correspondences between two registered and aligned human crania.

PCA-models

In our work, we employ PCA-models [2, 4, 3], where each shape s can be parametrized as a linear combination of the eigenvectors of the sample's covariance matrix.

Details:

Be $\Sigma = \frac{1}{n-1}\sum_{i=1}(s_i - \mu)(s_i - \mu)^T$ the sample's covariance matrix, and $\Sigma = UD^2U^T$ its eigendecomposition, each shape within the model can be represented as
$s = s(\alpha) = \mu + UD\alpha =: \mu + Q\alpha$,
with the coefficient vectors being distributed according to $\mathcal{N}(0, I_n)$ and the shapes according to $\mathcal{N}(\mu, QQ^T) = \mathcal{N}(\mu, \Sigma)$.

$\Longrightarrow$This allows for applying Bayesian reasoning.

Approach

- Find SSM instance most similar to a given cranium with defects
- Detect the defect/missing area
- Find a deformation that maps the SSM instance seamlessly to the defect cranium, reconstructing the defect.

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Material: SSM Generation

SSM generation

An SSM was created based on registered[1] CT-scans:

- 131 pathologically unaffected individuals, taken in the course of medical treatment at the University Clinics Freiburg.
- 61 females and 70 males
- Average age = 53.2 years
- Slice thickness between 1 and 2 mm

[1] Registration was performed using the software ANTsR[1]

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SSM

Sampling from the distribution

Methods: SSM fitting

Registration of the SSM to the target cranium

- Place 6 anatomical landmarks to establish an initial correspondence between SSM and target shape
- Constrain the SSM to those landmarks (including an error margin due to placement errors)
- Fit SSM to target shape minimizing a symmetric mesh-mesh distance

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Landmark placement
Landmarks

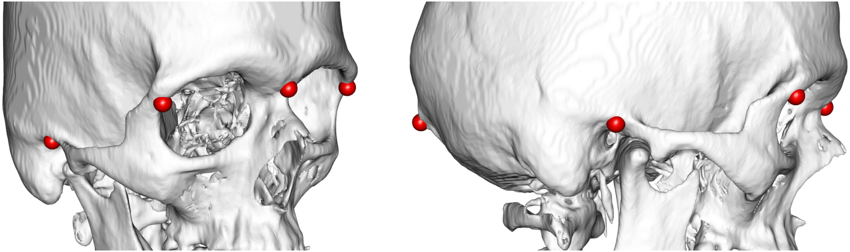

Figure: Landmark positions.

SSM Registration

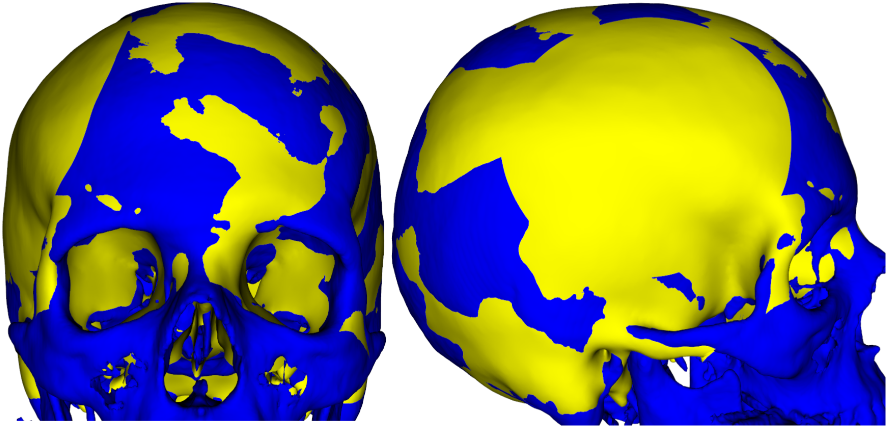

Figure: SSM instance (yellow) after fitting to the target (blue)

Methods: Detect Defects

Detection of defect areas

- 3000 semi-landmarks are sampled on the cranial vault of the best fitting SSM instance
- Semi-landmarks are projected onto the target surface.
- Distances to the target mesh and mesh topology are compared to properties on SSM instance.
- Discard unsuitable coordinates and deform the SSM instance to the target using a TPS-deformation.

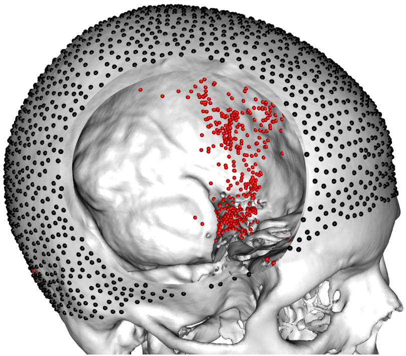

Figure: Identification of (potentially) unusable correspondences. Red spheres: projection of the semi-landmarks excluded from the warping. Black spheres: projections used in the final deformation.

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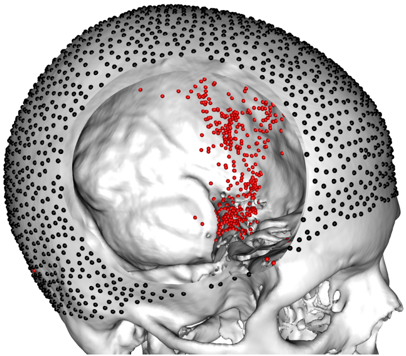

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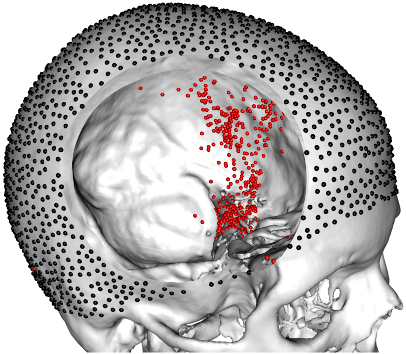

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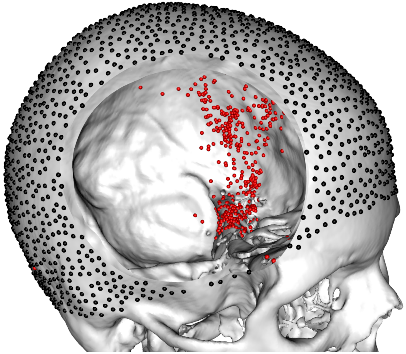

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Final deformation

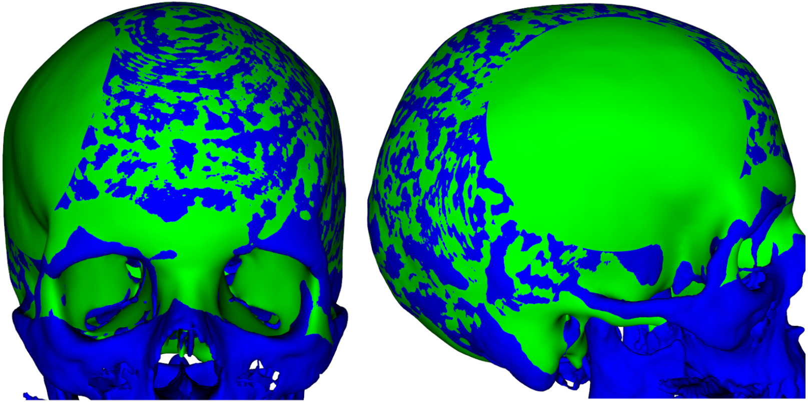

Figure: Green surface: The result from SSM fitting warped to the target surface (blue) using a TPS based on semi-landmarks.

Material: Evaluation

Result Validation

- 31 pathologically unaffected individuals – not included in the SSM to avoid statistical self-inference.

Methods: Evaluation

Evaluation

- Both unilateral and bilateral defects were created virtually on the cranial vault.
- Displacement at the entire defect as well as the borders was evaluated by measuring the distances between the reconstructed surface to the removed parts
- Additionally, the results for the unilateral case were compared to the current gold standard of mirroring, performed by a trained surgeon.

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Defect creation

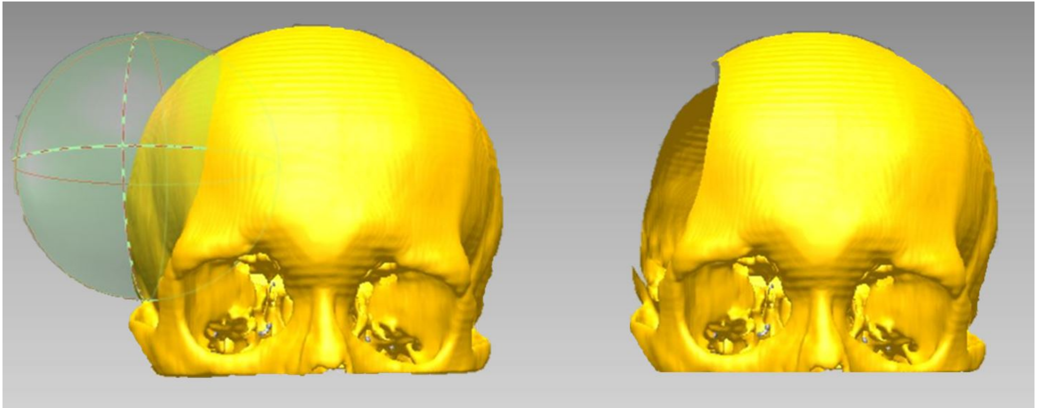

Figure: Creation of defects on the evaluation sample.

Content

Evaluation

The proposed method yielded very low estimation errors

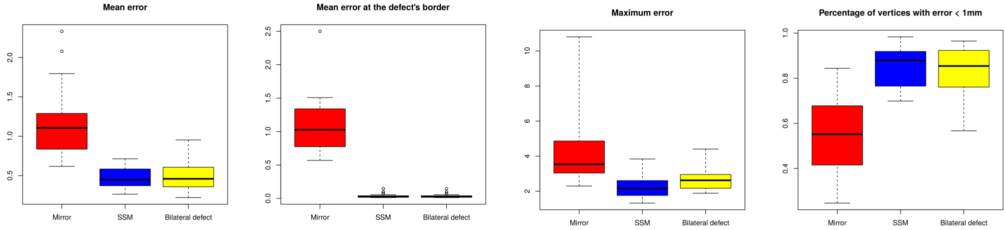

Figure: Boxplots with results for various error metrics.

Error distribution

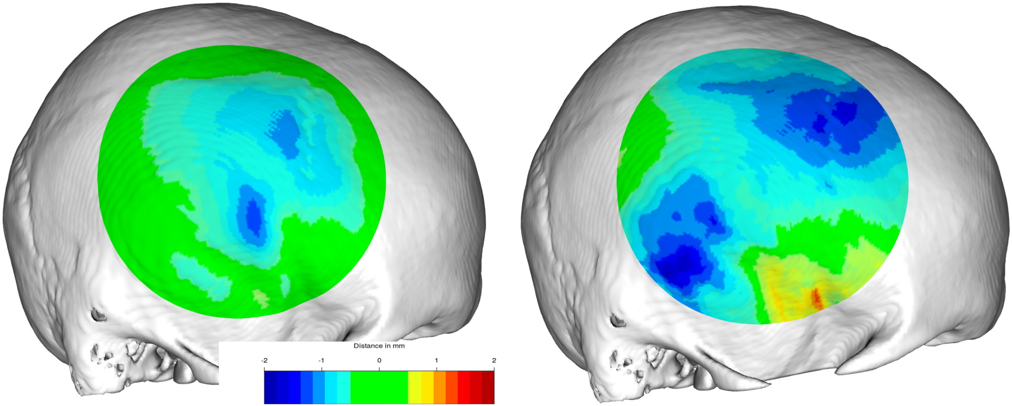

Figure: Average per-vertex estimation error for our method (left) and the gold standard using a mirroring technique (right).

Real world application

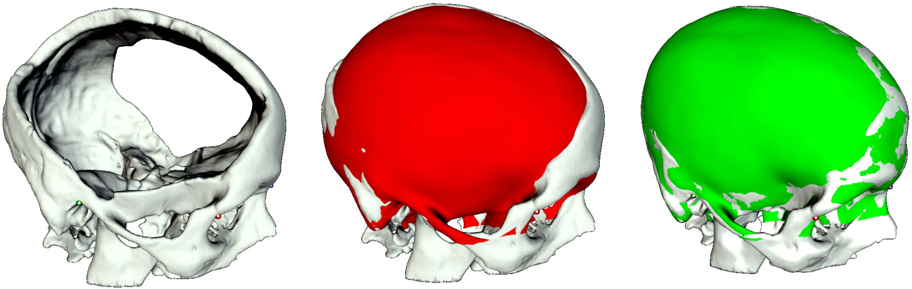

Figure: Application of the method to a cranium with severe defects. Left: target; center: SSM fitted to target; right: fitted SSM instance warped to target mesh.

Software

Thank you for your attention!

The software used in this study is available on https://github.com/zarquon42b (cf. [5])

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