Robust Registration of Statistical Shape Models for Unsupervised Pathology Annotation

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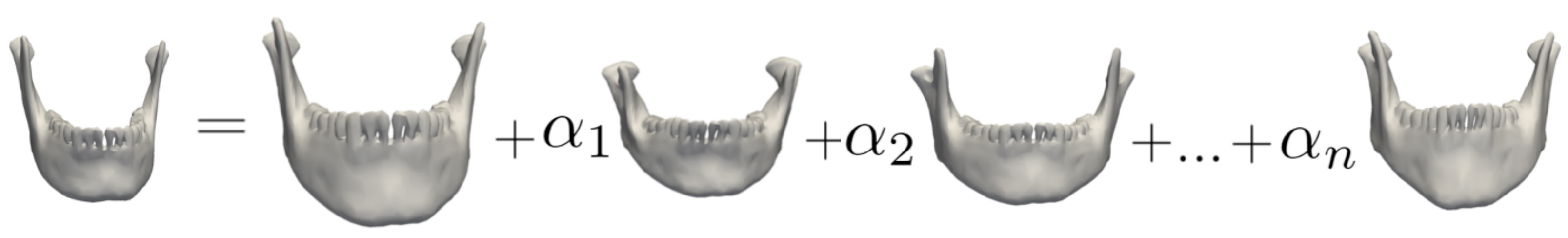
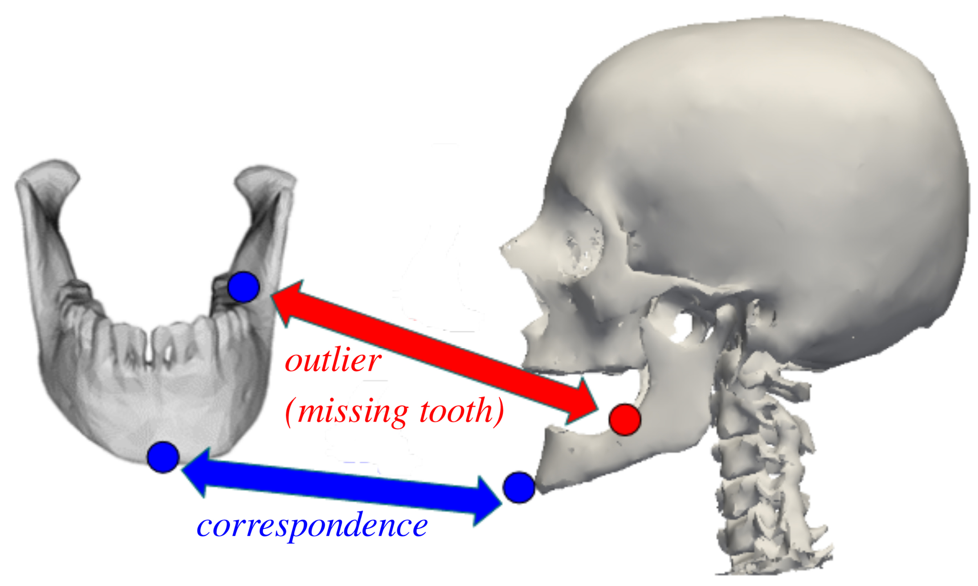
Problem Statement

Statistical shape model Generates shape Γ using coefficients $\vec{\alpha} \sim \mathcal{N}(0,1)$ and the set of principal components from PCA:



Model fitting Finding shape and pose parameters $\vec{\theta}$ given a target shape, by minimizing the distances between the model surface Γ and target:



Can we detect pathologies in a novel target given a healthy SSM?

Contribution

- Unsupervised probabilistic approach for pathology labeling on surfaces
- Robust registration algorithm for fitting SSMs to pathological data

Theory

Find $\vec{\theta}$ and label map $\vec{z}$ that maximize the posterior distribution given target $\hat{M}$, with the SSM shape prior $P(\vec{\theta})$ and a uniform distribution prior for $P(\vec{z})$:

$$P(\vec{\theta}, \vec{z} \mid \hat{M}) \propto L(\hat{M} \mid \vec{\theta}, \vec{z}) P(\vec{\theta}, \vec{z}) \tag{1}$$

Likelihood Evaluate similarity of model surface Γ and target, using point distances d_i and region distance likelihoods (l_h: healthy, l_o: outlier):

$$L(\hat{M} \mid \vec{\theta}, \vec{z}) = \prod_{i \epsilon \Gamma} l_h d_i(\vec{\theta}, \hat{M})^{z_i} l_o(d_i(\vec{\theta}, \hat{M})^{1-z_i} \tag{2}$$

Outlier detection (E-step) Fix $\vec{\theta}$. Maximize (2) with respect to $\vec{z}$ by classifying bi-directional correspondence [1] distances (k_h: healthy class, k_o: outlier class):

$$L(\hat{M}, \vec{\theta} \mid \vec{z}) = \sum_{i \epsilon \Gamma} \sum_{k \epsilon h,o} z_{i,k} l_k(d_i) \tag{3}$$

Outlier-aware fitting (M-step) Fix $\vec{z}$. Maximize (2) with respect to $\vec{\theta}$ by minimizing the distances of points within their classes [2]:

$$L(\hat{M}, \vec{z} \mid \vec{\theta}) = \sum_{i \epsilon k_o} l_o(d_i(\vec{\theta}, \hat{M}) + \sum_{i \epsilon k_h} l_h(d_i(\vec{\theta}, \hat{M}) \tag{4}$$

Future work

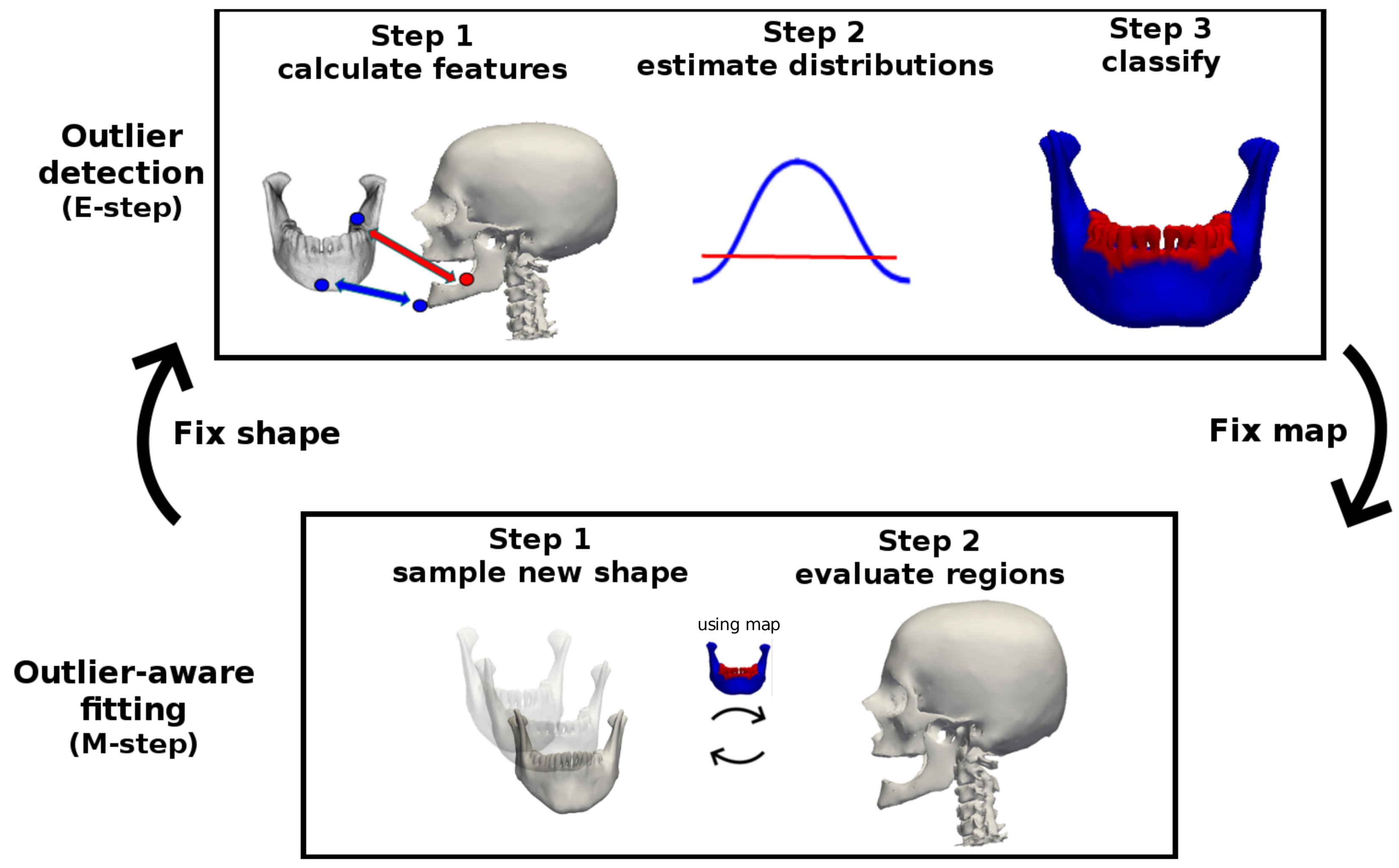
- Investigate replacements for distance metric in double-projection step
- Evaluate on public datasets for pathology detection on surfaces

References

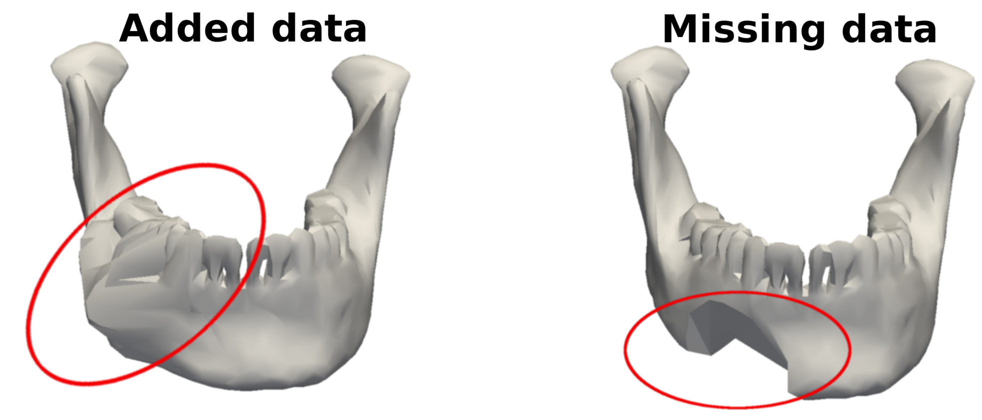
[1] D. Chetverikov, D. Stepanov, and P. Krsek, "Robust euclidean alignment of 3d point sets: The trimmed iterative closest point algorithm," *Image and Vision Computing*, 2005.

[2] B. Egger, S. Schönborn, A. Schneider, A. Kortylewski, A. Morel-Forster, C. Blumer, and T. Vetter, "Occlusion-aware 3d morphable models and an illumination prior for face image analysis," *IJCV*, 2018.

Pipeline



Evaluation on 25 surfaces



- **Detection** True positive rate (TPR) and F1 score, best at 1
- **Fitting** Hausdorff (HD) and Average distances (AD), best at 0 mm

	Standard SSM no detection	Robust SSM thresholded	**Outlier-aware SSM probabilistic**
TPR	-	0.39	0.56
F1	-	0.51	0.68
HD	4.48	6.07	1.98
AD	1.14	1.52	0.88

Application to clinical data

- **Radius** With added data (implants and overgrowth)
- **Skull** With missing data (teeth)