

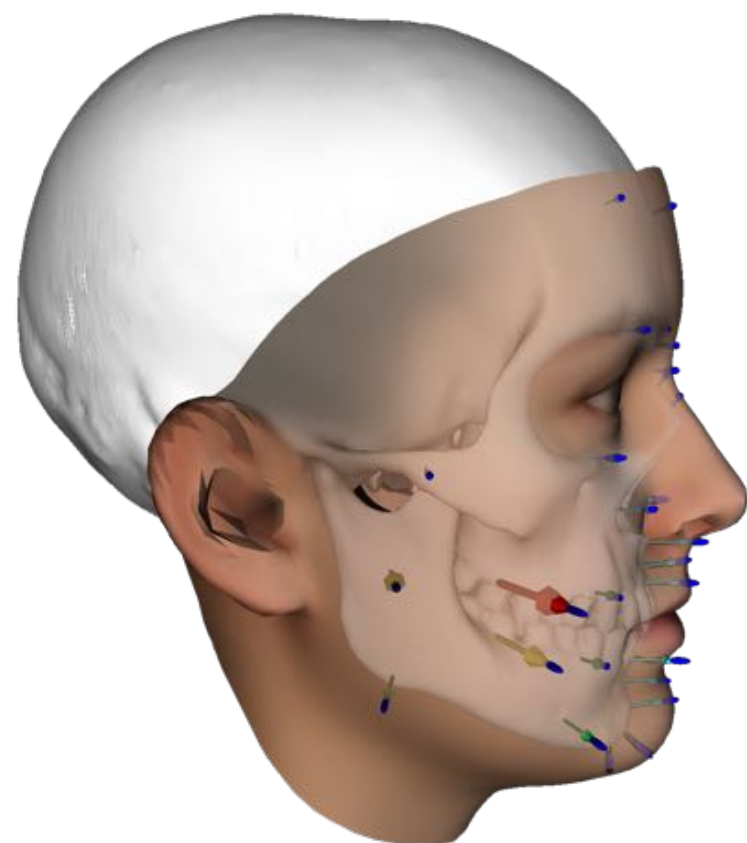
PROBABILISTIC JOINT FACE-SKULL MODELLING FOR FACIAL RECONSTRUCTION

Madsen D., Lüthi M., Schneider A., Vetter T.

Department of Mathematics and Computer Science, University of Basel



Abstract



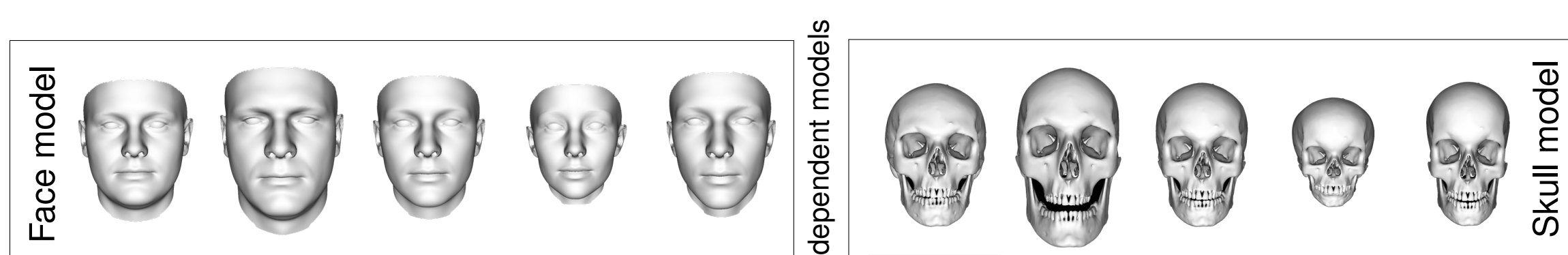
We solve the task of combining two independent Statistical Shape Models (SSM). We obtain the complete joint probability distribution of the human head by combining a face shape model [2] and a skull shape model [3]. The models are joint with independent tissue-depth information [4] using Markov Chain Monte Carlo (MCMC).

With the joint face-skull probability distribution we show how:

- facial reconstruction can be described as a conditional distribution of plausible face shapes given a skull shape.
- face photographs can be ranked according to their likelihood of corresponding to a given skull.
- to estimate the skull pixels in an MR-image.

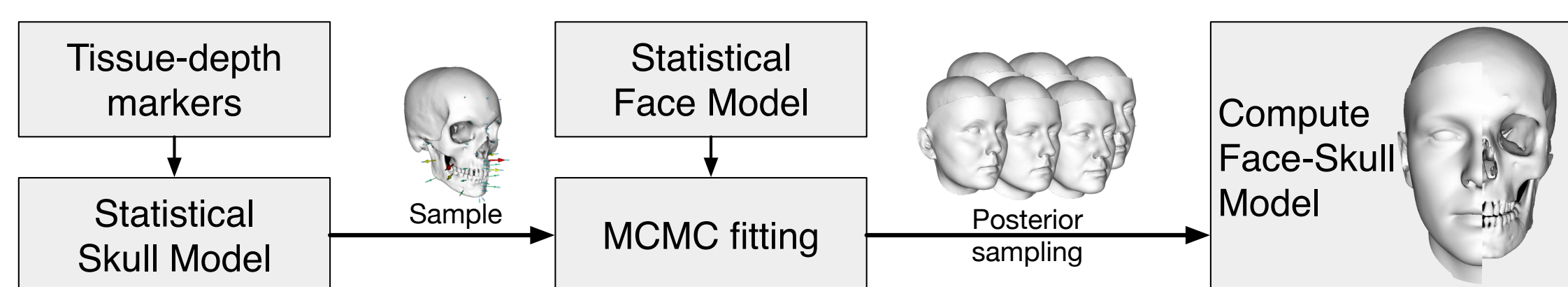
Statistical Shape Models

Our Statistical Shape Models (SSMs) are created as Gaussian Process Morphable Model (GPMM) [5]. The face and skull models are created independently from sets of example shapes.

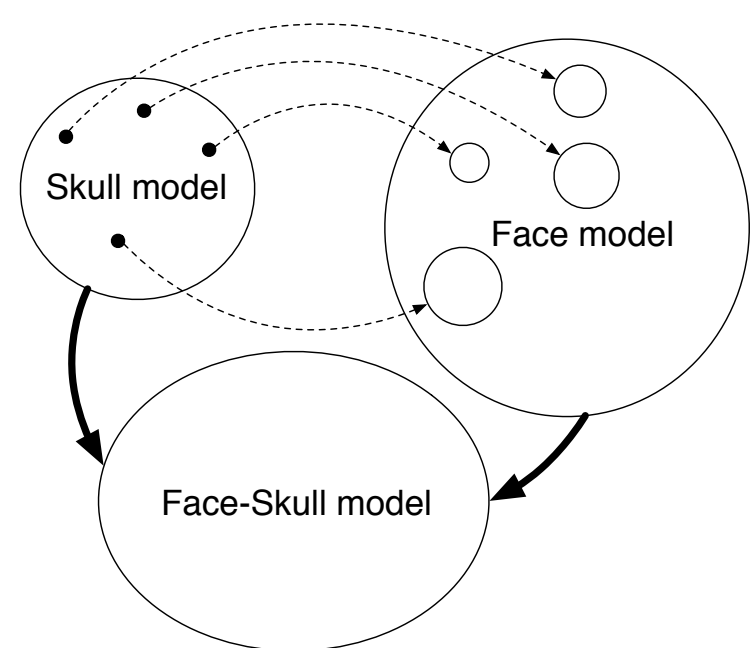
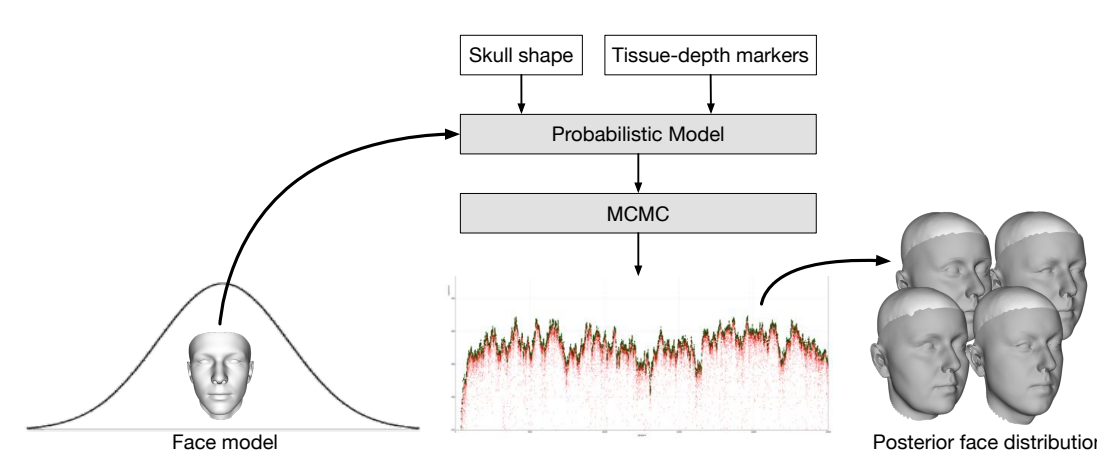


Mean shapes and the first 2 principal components (PC) of the face and skull shape models.

Combining the models



The full distribution of face shapes over a given skull shape is estimated with MCMC by sampling random face shapes from the face shape model.



The joint face-skull distribution is modelled as a multivariate Gaussian distribution over face and skull shape.

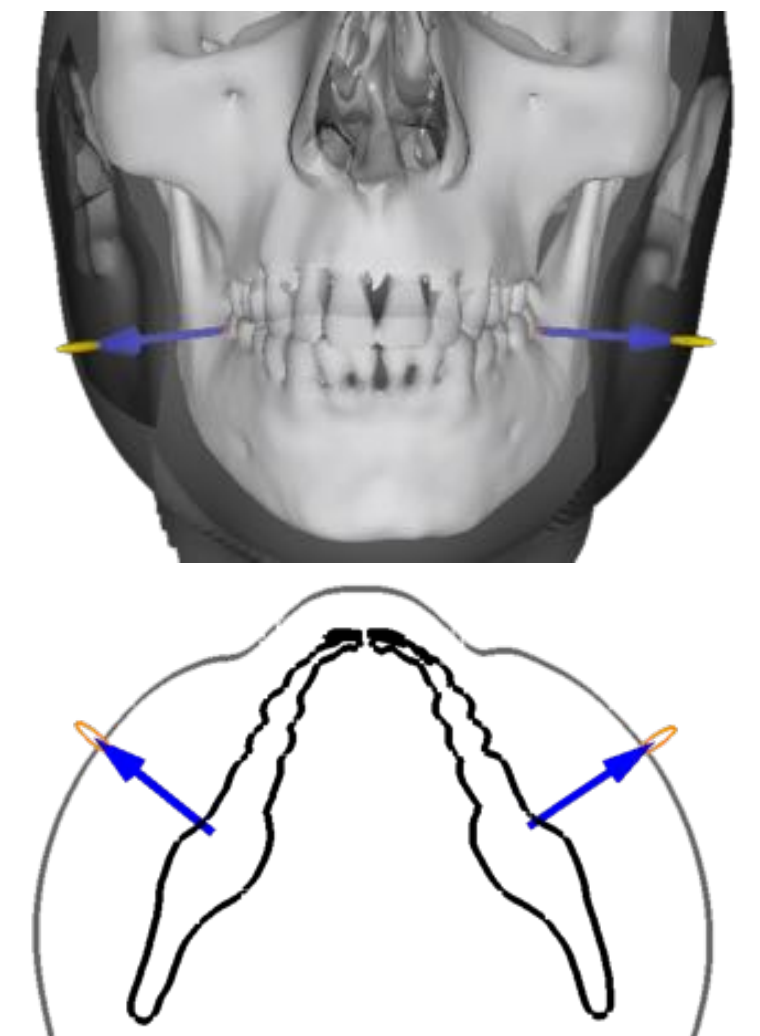
$$\Gamma_F, \Gamma_S \sim \mathcal{N}(\mu_F; \mu_S, \Sigma_F; \Sigma_S)$$

Simulating the Joint Face-Skull Distribution

The face distribution for each skull shape is defined by multiple likelihood terms:

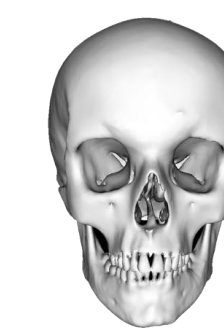
- Tissue-vector intersection depth
- Tissue-vector symmetry
- Face in skull detection
- Point correspondence (in a single point)

$$P(\vec{\theta} | D^{tvi}, D^{sym}, c, D^{cs}) \propto P(\vec{\theta}) P_{tvi}(D^{tvi} | \vec{\theta}) P_{tvs}(D^{sym} | \vec{\theta}) P_{fs}(c | \vec{\theta}) P_{cs}(D^{cs} | \vec{\theta}).$$

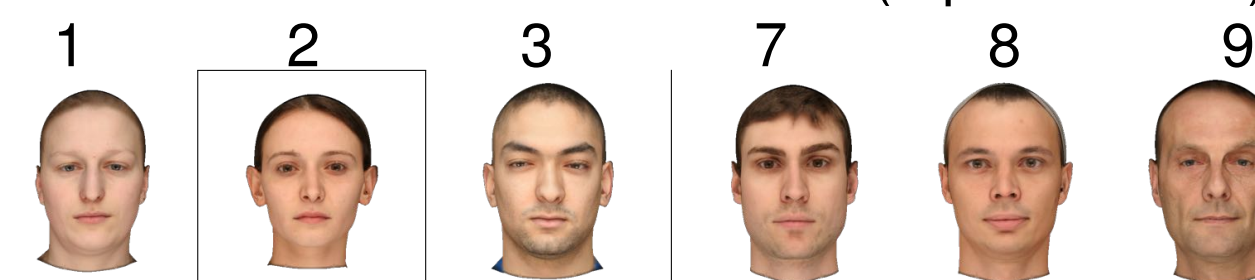


Experiment - Face identification given a skull

Unknown skull



Face identification for the skull (top+bottom 3)



The 3D face database is projected into the combined conditioned model. The faces are ranked according to their likelihood to fit the skull.

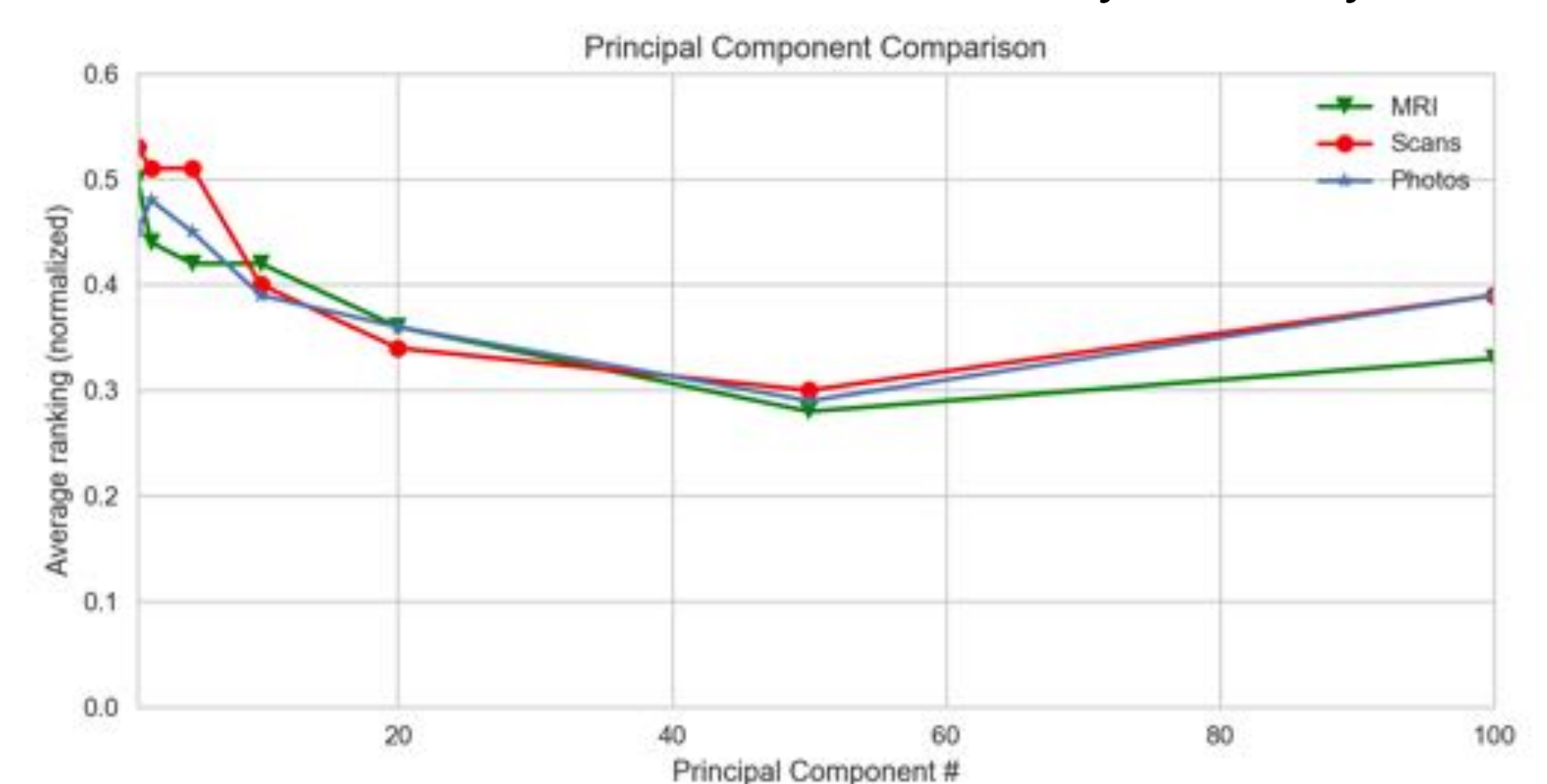
The number next to the experiment (listed below) mentions the number of faces in the face database.

Results of the identification experiment with 9 skulls. In all the experiments we get a consistent top 30% average identification result.

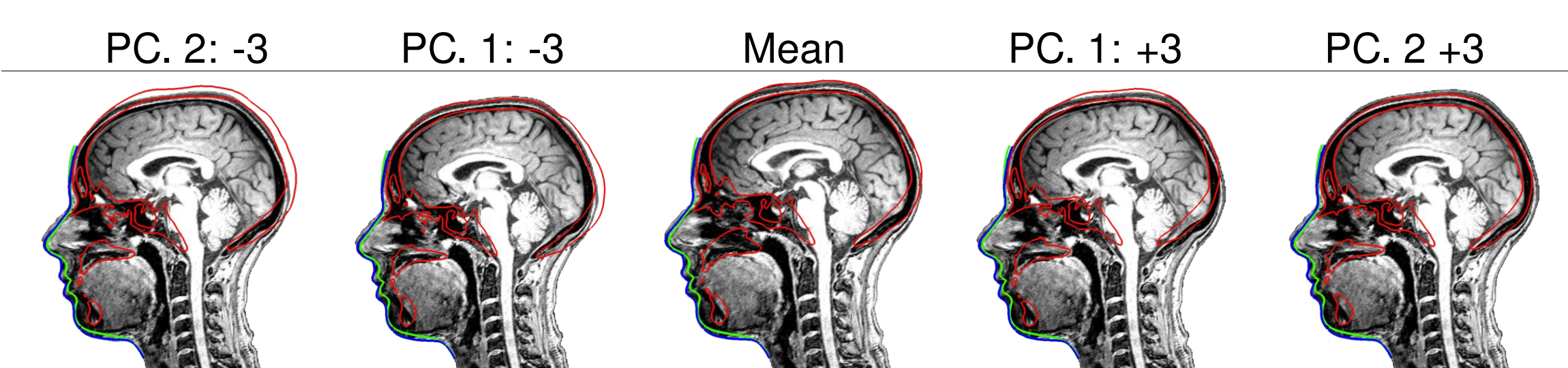
Experiment	μ	μ norm	σ	Min	Max
MRI (9)	2.44	0.27	1.67	1	5
Scan (9)	2.89	0.32	1.54	1	5
Photo (9)	3.00	0.33	1.80	1	6
Scan (306)	91.89	0.30	44.23	26	159
Photo (106)	31.56	0.29	27.03	4	82

Model evaluation

Evaluation of the number of PC's used in the face identification experiment. We find that around 50 PC's gives the best result. From this, we conclude that it is not only the size but a combination of different skull shape characteristics which are needed to identify the likely faces.



MRI Skull Segmentation: Conditioning the joint model on a face



References

- [1] D. Madsen, M. Lüthi, A. Schneider, and T. Vetter, "Probabilistic joint face-skull modelling for facial reconstruction," in *Computer Vision and Pattern Recognition, 2018. CVPR'18. IEEE Conference on*, IEEE, 2018.
- [2] P. Paysan, R. Knothe, B. Amberg, S. Romdhani, and T. Vetter, "A 3d face model for pose and illumination invariant face recognition," in *Advanced video and signal based surveillance, 2009. AVSS'09. Sixth IEEE International Conference on*, pp. 296–301, IEEE, 2009.
- [3] M. Lüthi, A. Forster, T. Gerig, and T. Vetter, "Shape modeling using gaussian process morphable models," *Statistical Shape and Deformation Analysis: Methods, Implementation and Applications*, p. 165, 2017.
- [4] C. N. Stephan, "The application of the central limit theorem and the law of large numbers to facial soft tissue depths: T-table robustness and trends since 2008," *Journal of forensic sciences*, vol. 59, no. 2, pp. 454–462, 2014.
- [5] M. Lüthi, T. Gerig, C. Jud, and T. Vetter, "Gaussian process morphable models," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2017.