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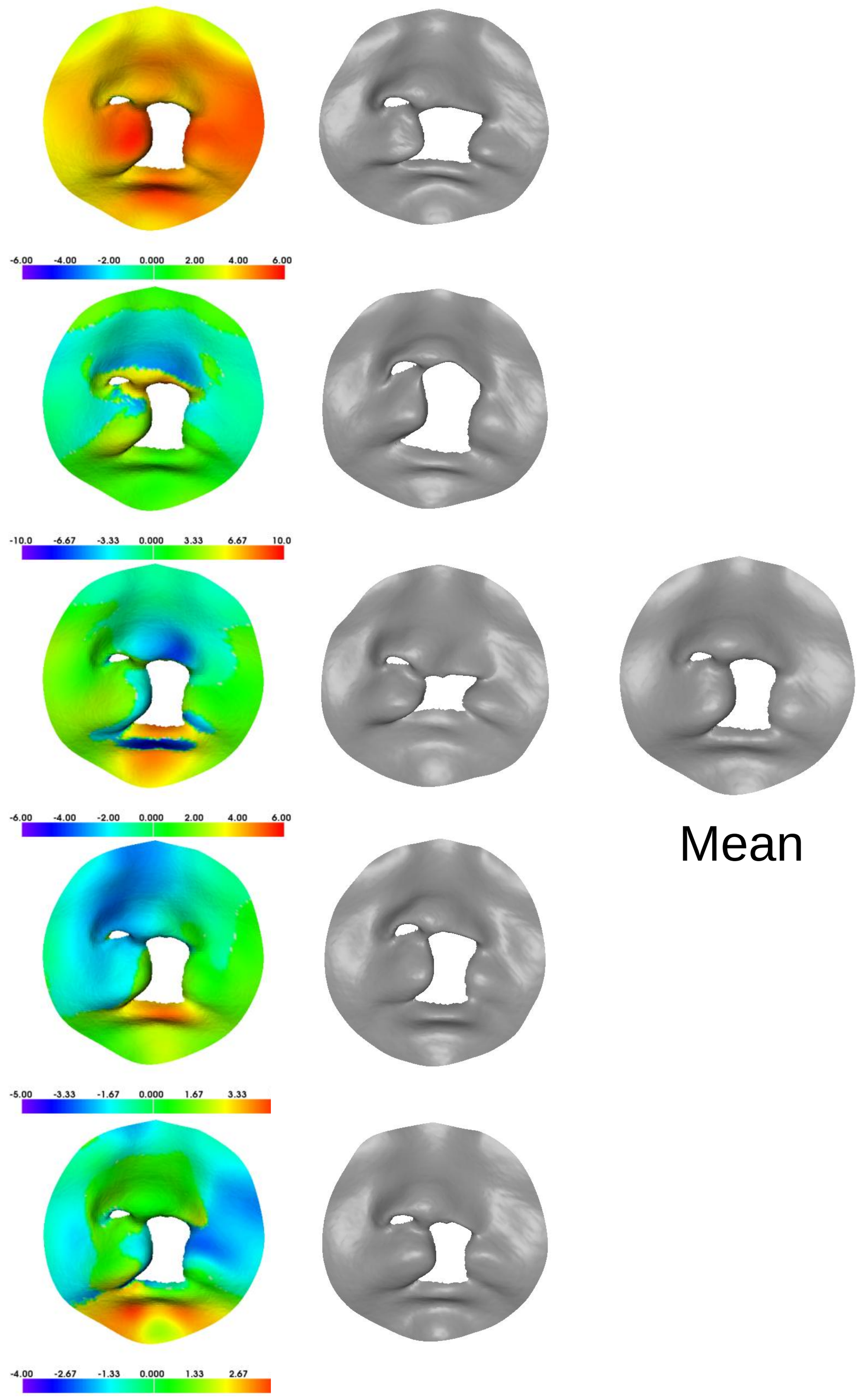
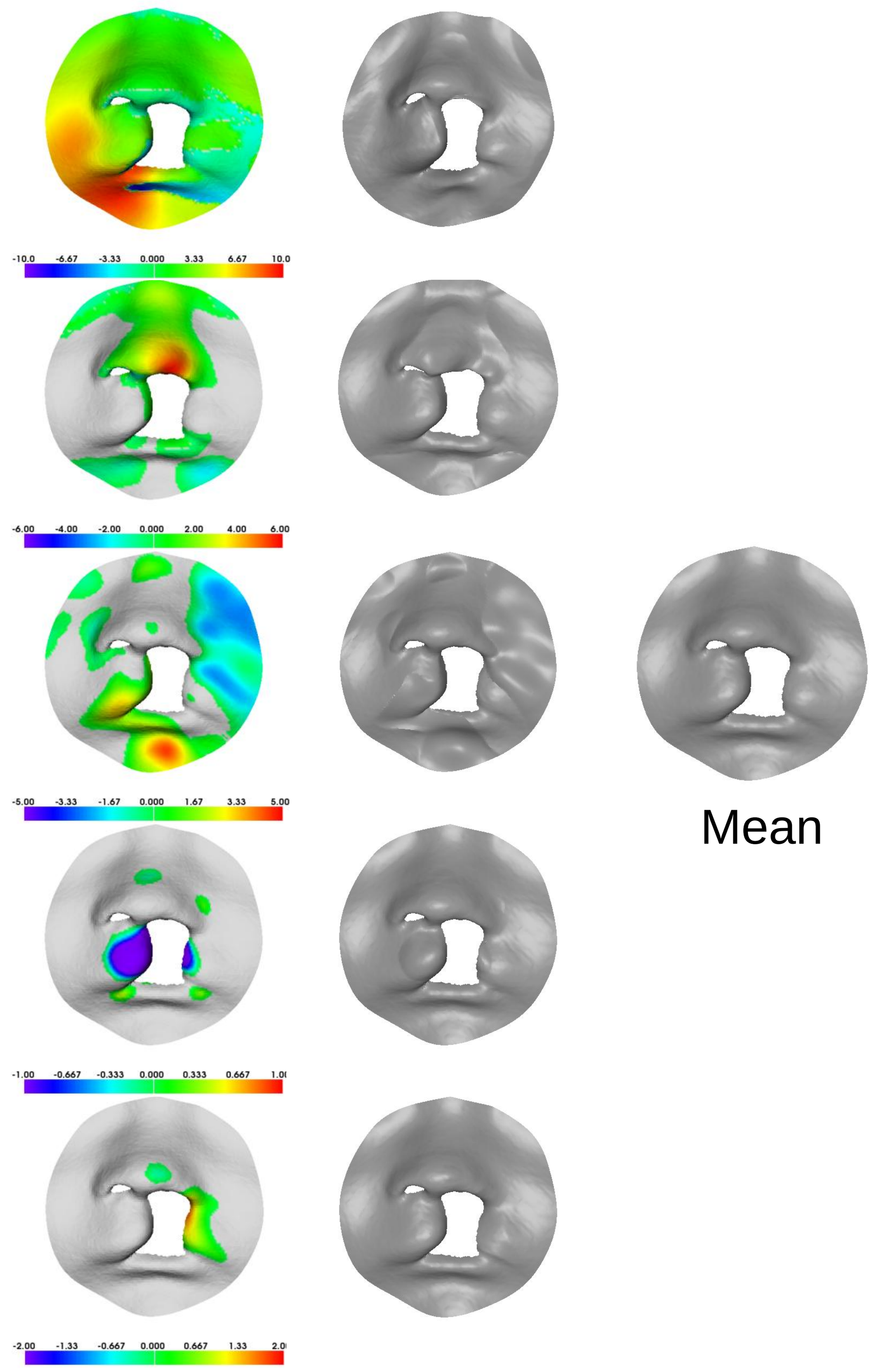
Cleft variation - PCA, SPCA

PCA modes 1-5 (top-bottom)



SPCA modes 1-5 (top-bottom)



Two methods for determination the cleft variation: PCA and sparse PCA.

Cleft lip and palate is the most common type of craniofacial malformation affecting approximately 1 in 500 live births. The aim was to study the variation in the cleft e.g. width, to be able to correlate with the goodness of the lip surgery outcome.

From CT images of a group of 19 Taiwanese children born with cleft lip and palate, a bias-corrected atlas was created [1]. Deformation-vectors between the atlas and the children were calculated using affine and non-rigid registrations [2-4], and PCA and SPCA were applied, see the results in the figure above.

For the PCA 16 of 18 modes were needed to explain 95% of the total variance, and the modes were not clear regarding the cleft even though only the nose region was used.

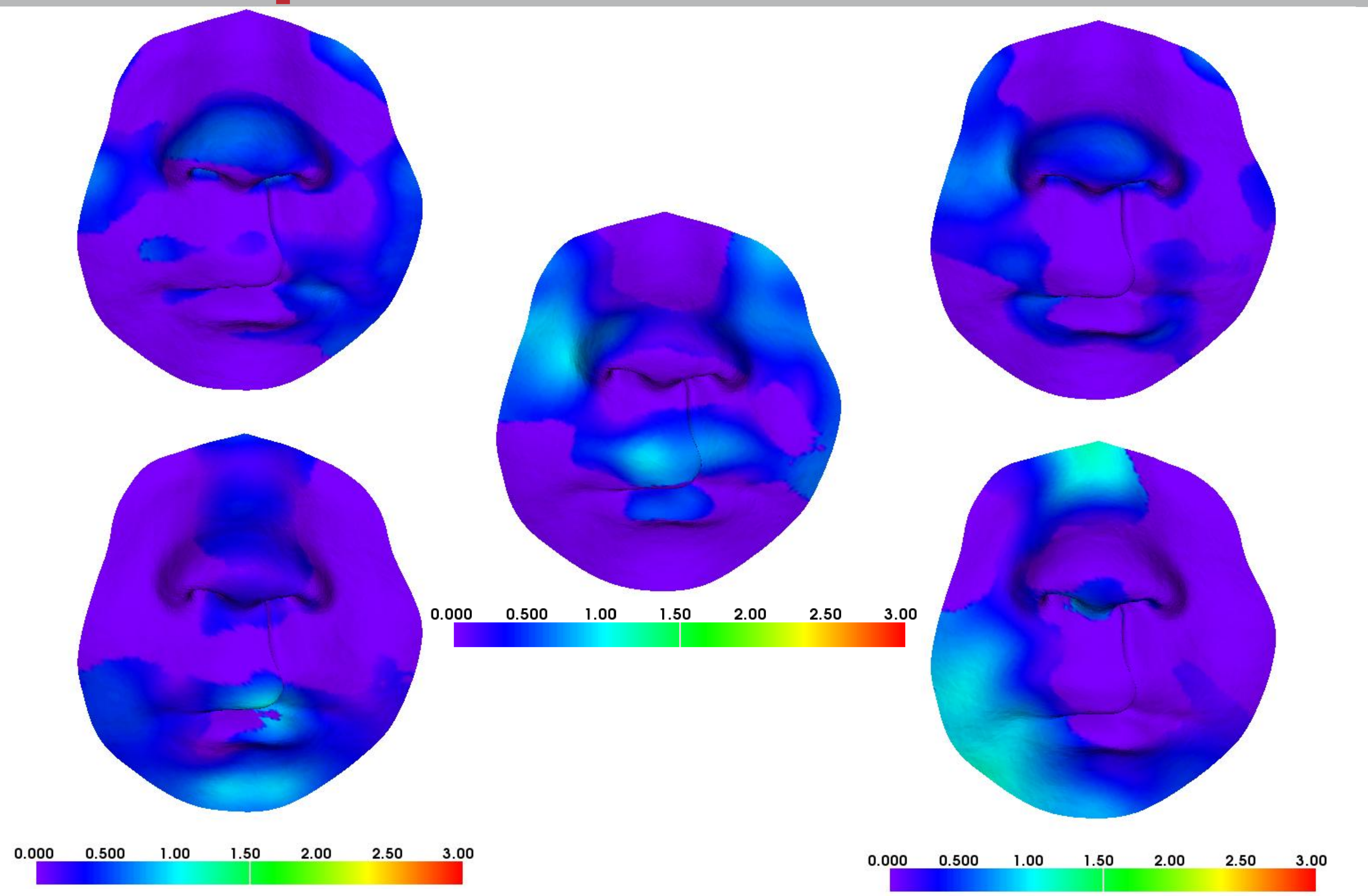
Applying parallel analysis [5], a method for determining significant principal components, to the data also revealed noise in the data. Only 5 modes could be retained.

Hence, SPCA was applied, with a mode 4 (and 5?) containing information about the cleft behavior, and nose (mode 2).

Improvement is still needed for determining the variation.

In the figures, the colorbar are used to enhance the interesting areas. The scale is in millimeters.

Cleft prediction - Linear regression



An attempt to predict the outcome of the lip adhesion procedure.

For this purpose the 19 Taiwanese children from before were used along with the CT images obtained after lip surgery.

Point correspondence between the before and after surgery images was obtained as in [5].

Using ridge-regression on the extracted surfaces (in point correspondence) to predict the after surgery extracted surfaces, a leave-one-out experiments was carried out.

The figure above shows the differences between the original after surgery extracted surfaces and the predicted surfaces. The differences are shown on the after-surgery atlas surface with a colorbar (in millimeters) to enhance the differences – purple is no difference and red is a large difference (actually, the largest occurring the in data). The surfaces to the left have the smallest mean errors, while the ones on the right have the highest mean errors.

In general it seems like the algorithm predicts the cleft quite well. But the errors might occur due to the choice of algorithm being insufficient i.e. the details we want to predict are too individual to predict.

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Thanks to Karl Sjöstrand for his SPCA matlab-package. http://www2.imm.dtu.dk/pubdb/views/publication_details.php?id=3897
For all image registrations The Image Registration Toolkit was used under Licence from Ixico Ltd.

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