Using Line Features for 3D Face Registration

BACHELOR THESIS PRESENTATION

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UNIVERSITÄT BASEL

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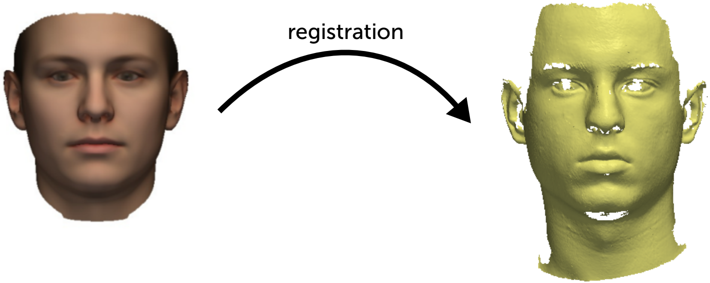
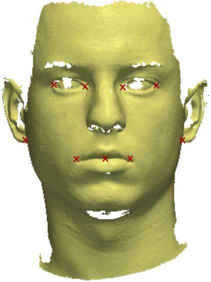
Registration Overview



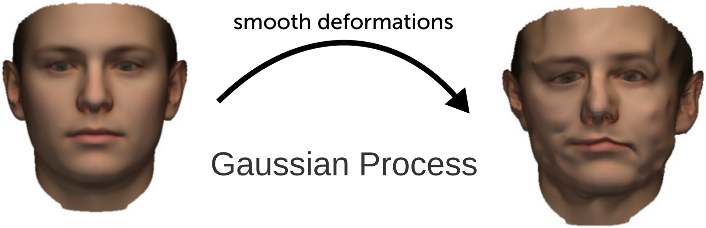
Registration Overview

registration

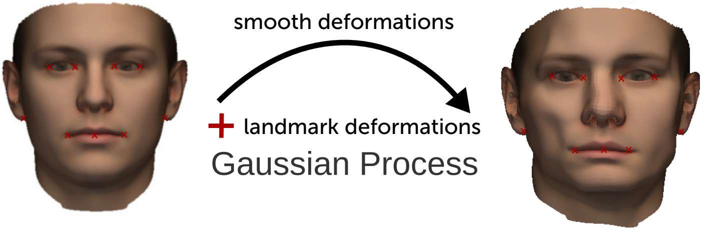
annotations
for correspondence:
landmarks



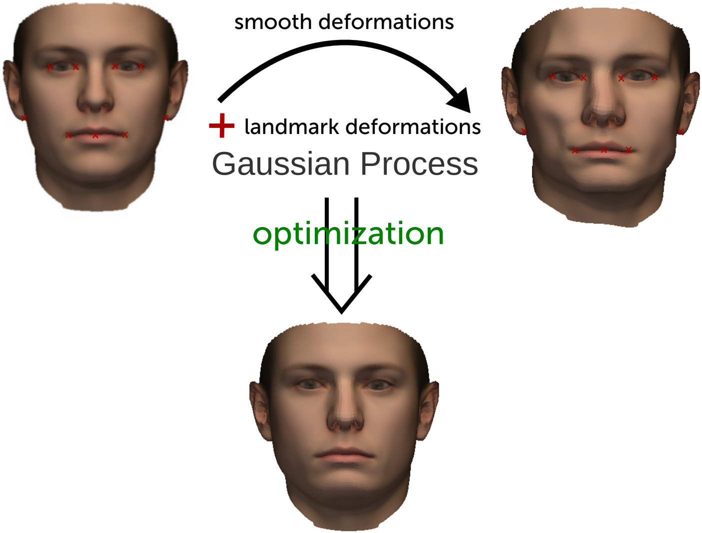
REGISTRATION OVERVIEW



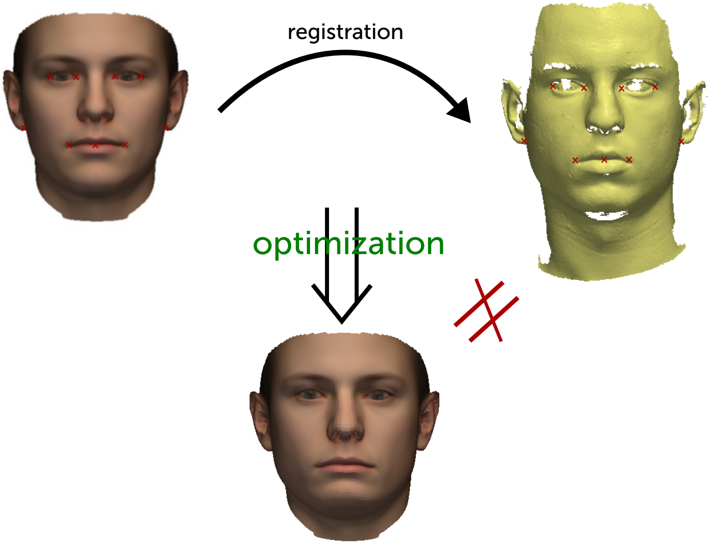
Registration Overview



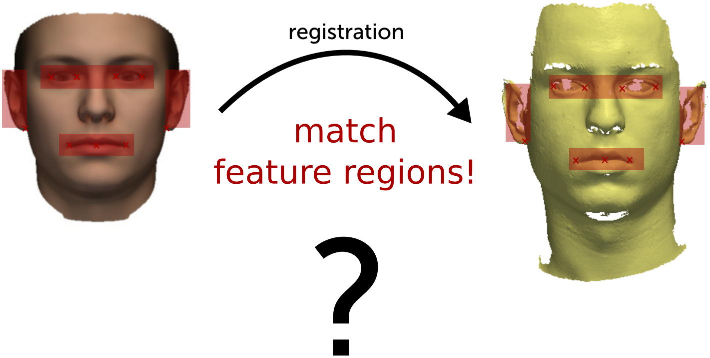
Registration Overview



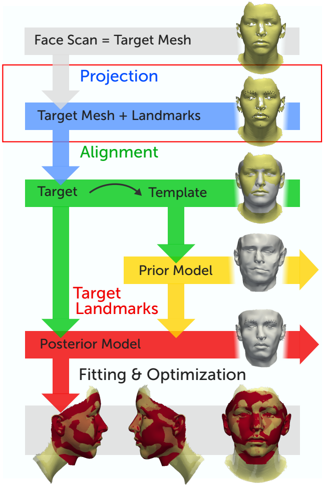
Registration Overview



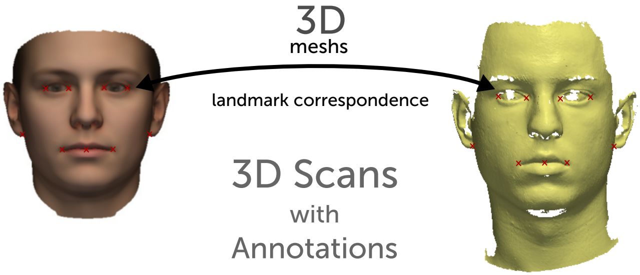
Registration Overview



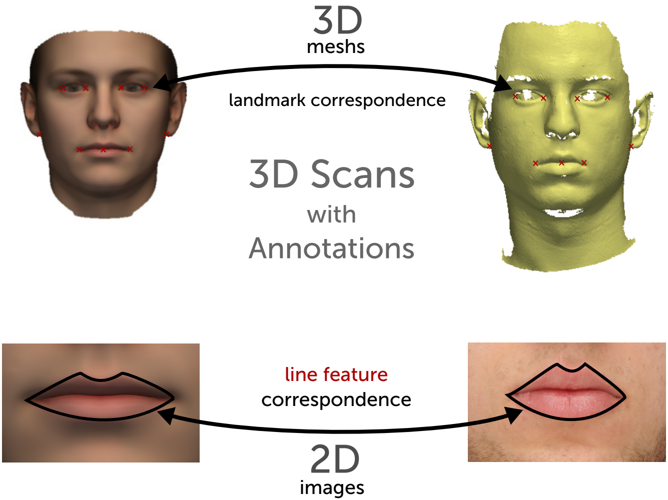
Pipeline


Face Scan = Target Mesh
Projection
Target Mesh + Landmarks
Alignment
Target
Template
Prior Model
Target
Landmarks
Posterior Model
Fitting & Optimization

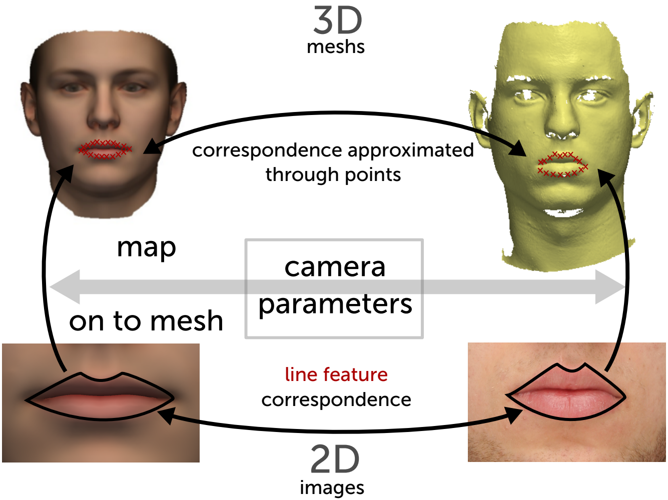
DATA AND CORRESPONDENCE



Data and Correspondence

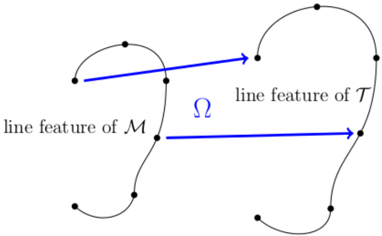


Data and Correspondence



Mapping Line Features

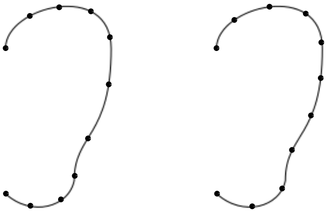
Idea: Sample points from the line features and use them as additional landmarks



What about correspondence?

EQUIDISTANT SAMPLING

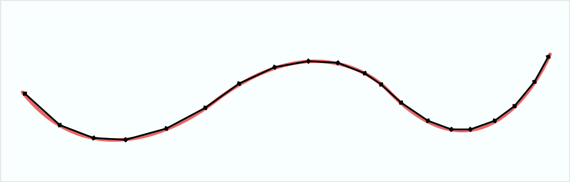
Approximate correspondance by sampling line features in equidistant intervals



Bézier curves

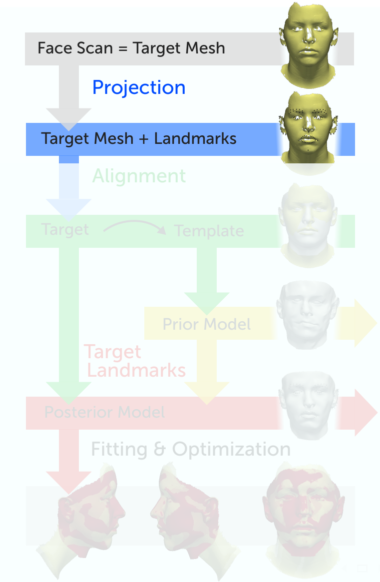
Line features consist of Bézier curve segments
$\rightarrow$ underlying parameter is not linear

Approximate arc-length of curve through euclidean distance of sampled points

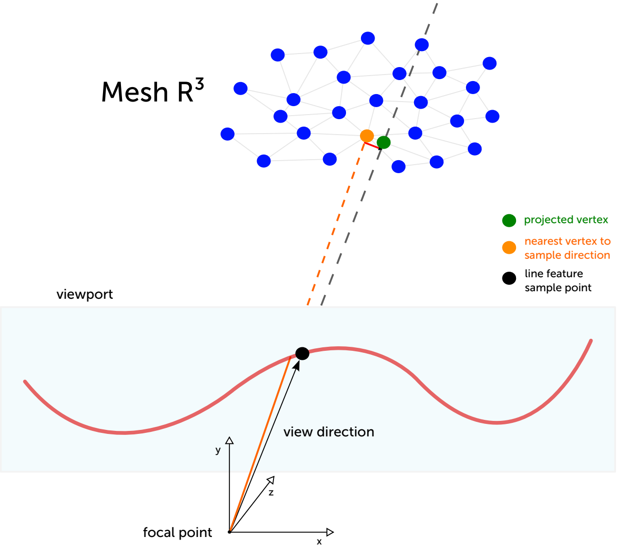


$\Rightarrow$ map point coordinates to approximated fractional length of curve

Pipeline: Projection



Projection: 2D to 3D



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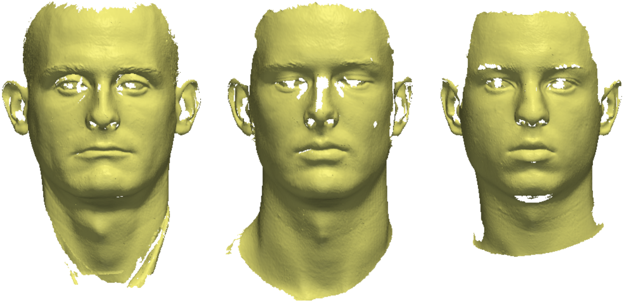
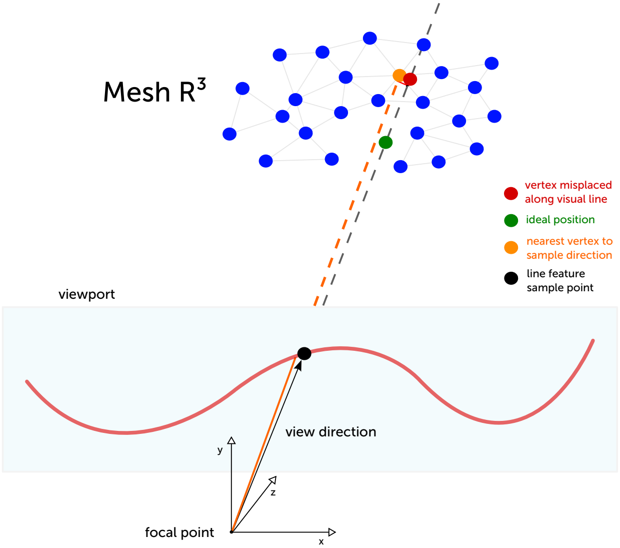
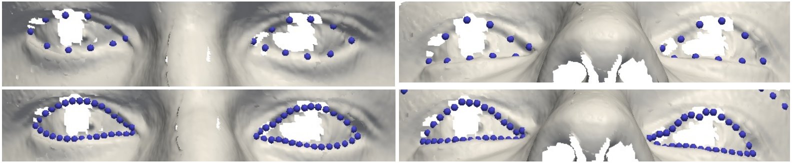
Target Mesh Holes



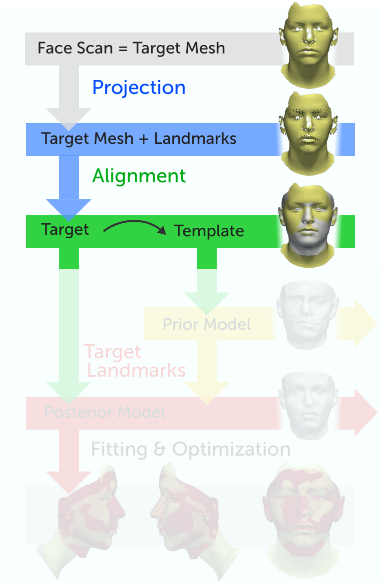
Projection: holes



3D representation



Template/Target Alignment



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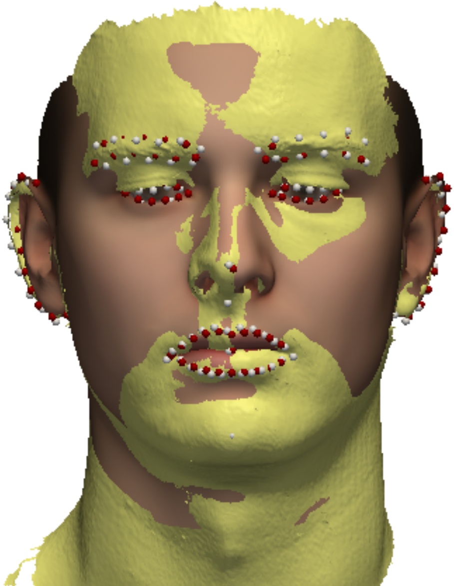
Template/Target Alignment



Gaussian Process

intuitive: a generalization of the normal distribution to functions

a stochastic process where each random variable represents possible function values at a specific input point

GP Prior

sample functions from the space of possible inputs
these functions are defined by the covariance of the input points

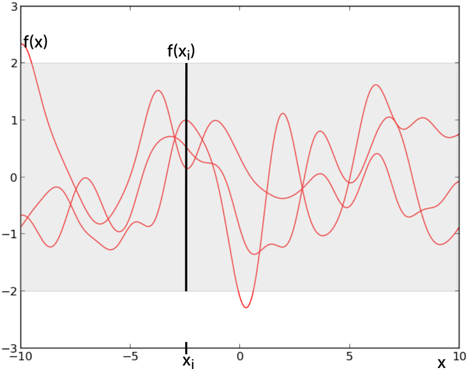


Figure: normal distribution over 1000 input points

GP POSTERIOR DISTRIBUTION

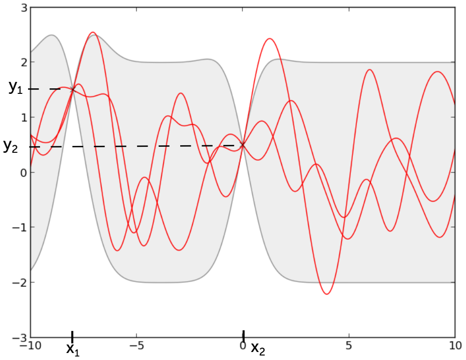


Figure: posterior distribution fixed at 2 input points

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GP Posterior Distribution

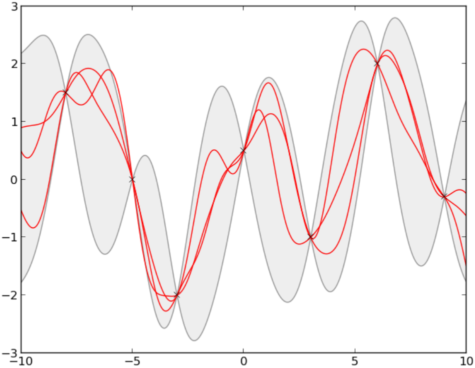


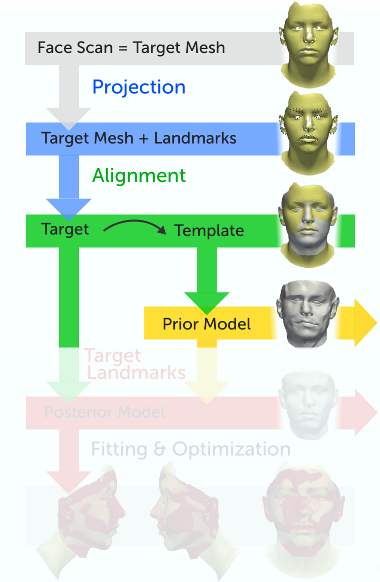
Figure: posterior distribution fixed at 7 input points

GPR in 3D Face Registration

definition of Vector-valued GP

$$\mu : \mathcal{M} \to 0$$
$$k : \mathcal{M} \times \mathcal{M} \to \mathbb{R}^3 \times \mathbb{R}^3$$

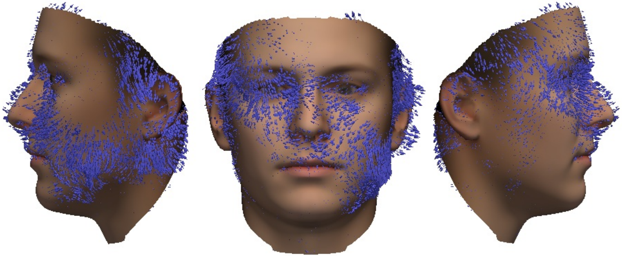
Pipeline: Deformation Prior



Deformation Prior

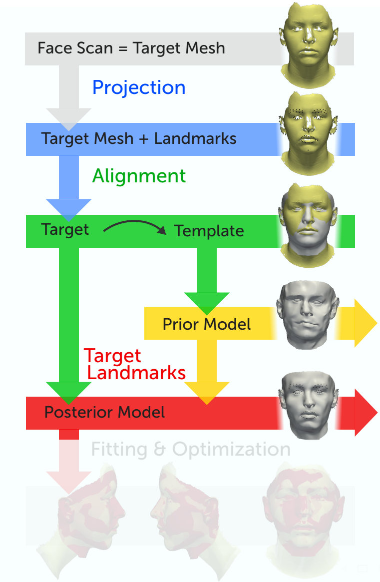
build GP Prior from template mesh vertices

$\Rightarrow$ GP defines a distribution of possible deformations of the template mesh



Prior faces

Pipeline: Deformation Posterior



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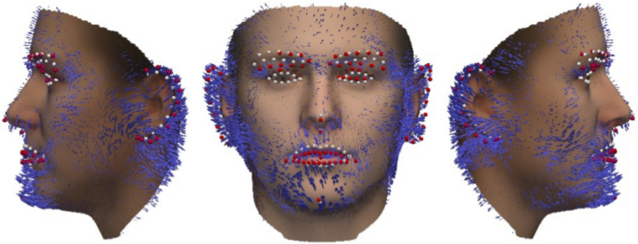
3D GP Posterior

inference in the space of possible template surface deformations

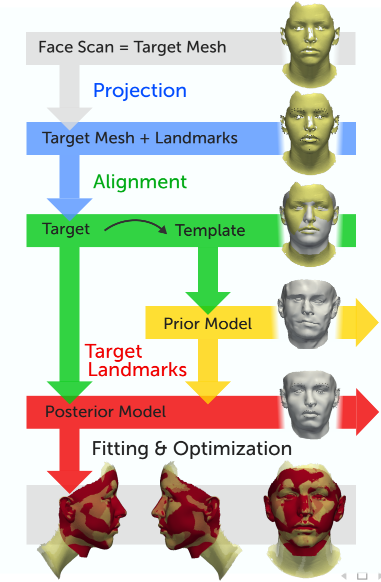
training data: residuals of the line feature sample coordinates:

$$R = \{t - m | t \in L_T, m \in L_M\}$$



Posterior Faces

Fitting & Optimization



PARAMETRIC MODEL

GP Posterior distribution of admissible deformations

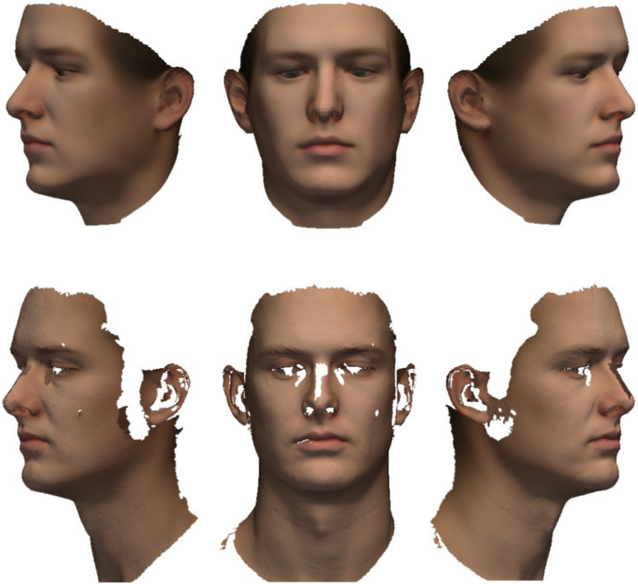
How to optimize deformation samples?

Mercer's theorem: distribution $\rightarrow$ parametric model

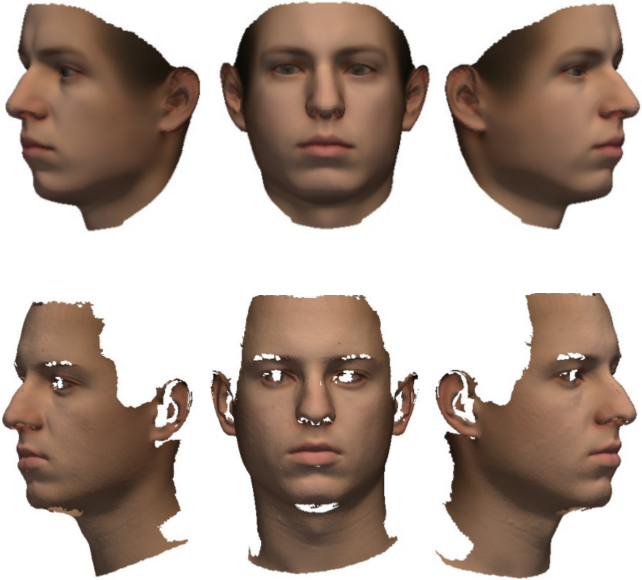
$\Rightarrow$ optimize model parameters
verify with loss function

Mean Squared Error

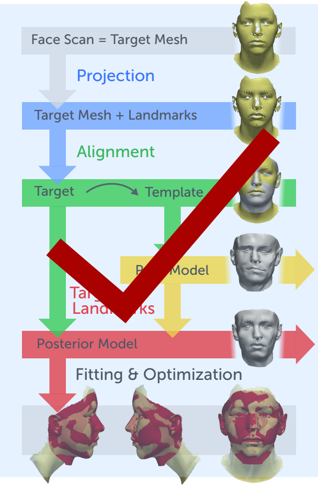
Robust Estimator



Robust Estimator



Pipeline: check



Results

- Comparison: with $\Leftrightarrow$ without line features
- Caricatures

Comparison - Mouth

Comparison - Eyes

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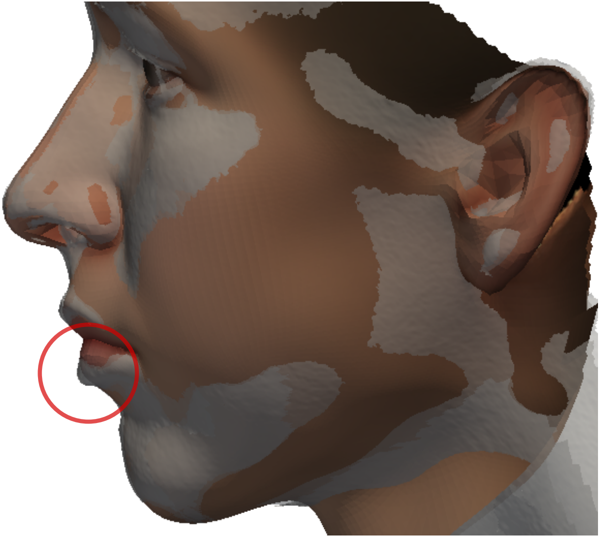
Comparison - Ears

CARICATURES

hi

EXPRESSIVENESS



Conclusion

- Incorporation of line features rendered good registration results

- Optimization process has to be further adapted for more expressiveness

Future Work

detect template regions corresponding to **holes** in target
detect template regions **missing** in target

by registering target on to template

$\Rightarrow$ use Mean Squared Error to perform optimization without artifacts

Thank you for listening!

Any questions?