Using Line Features for 3D Face Registration

Bachelor Thesis Presentation

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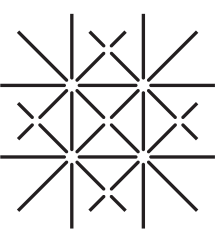
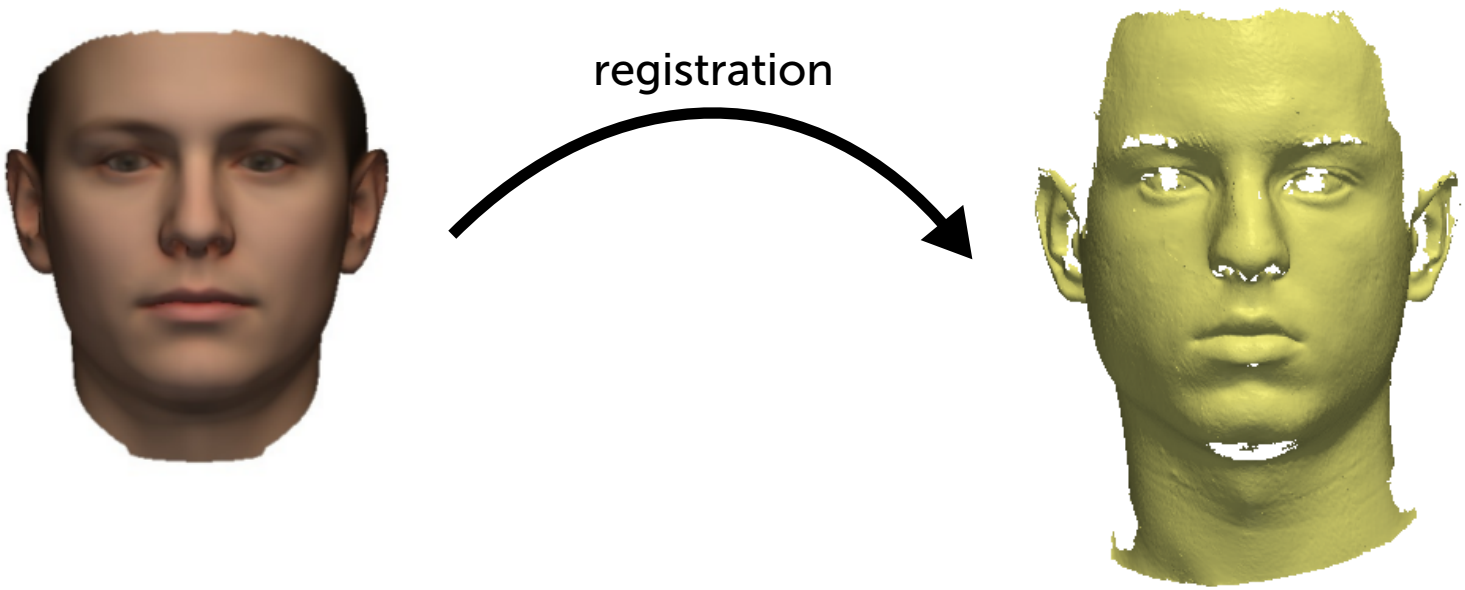


Registration Overview



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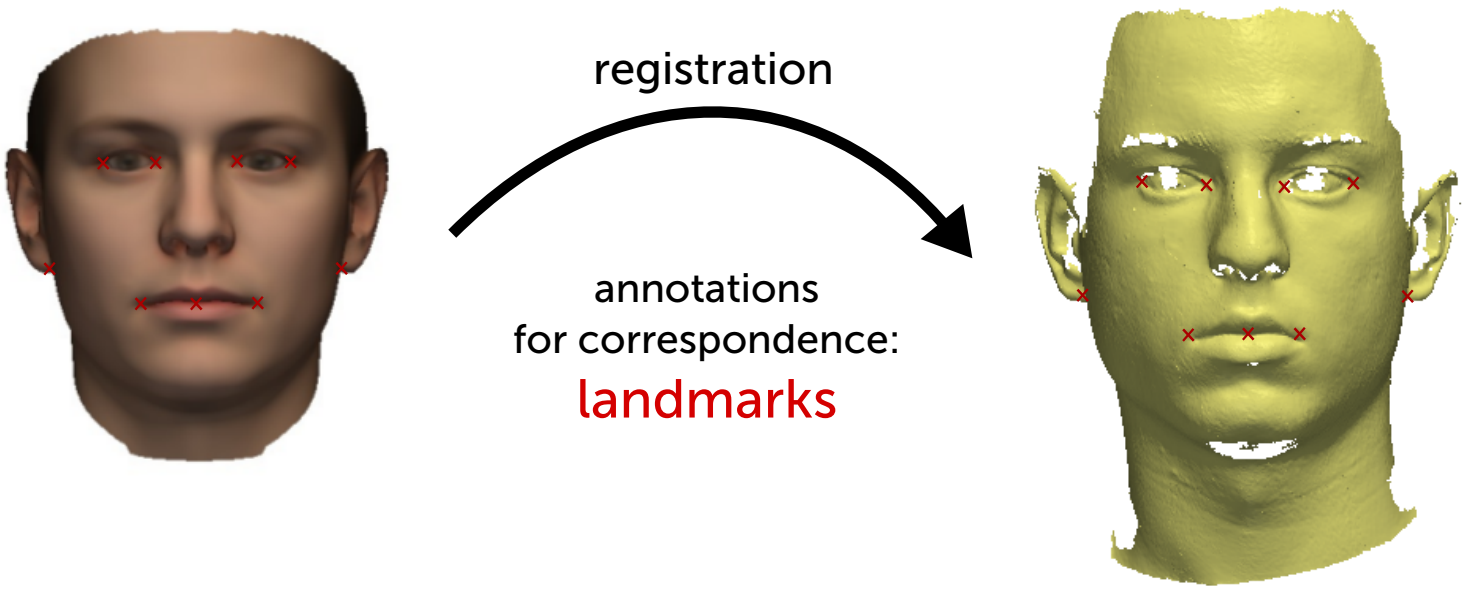
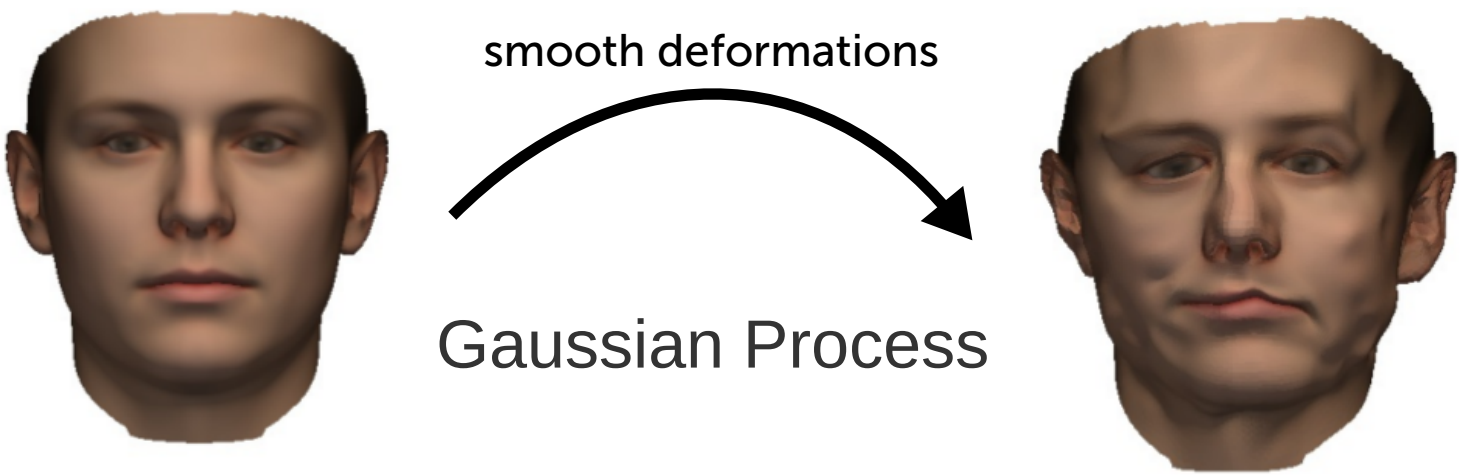


Registration Overview



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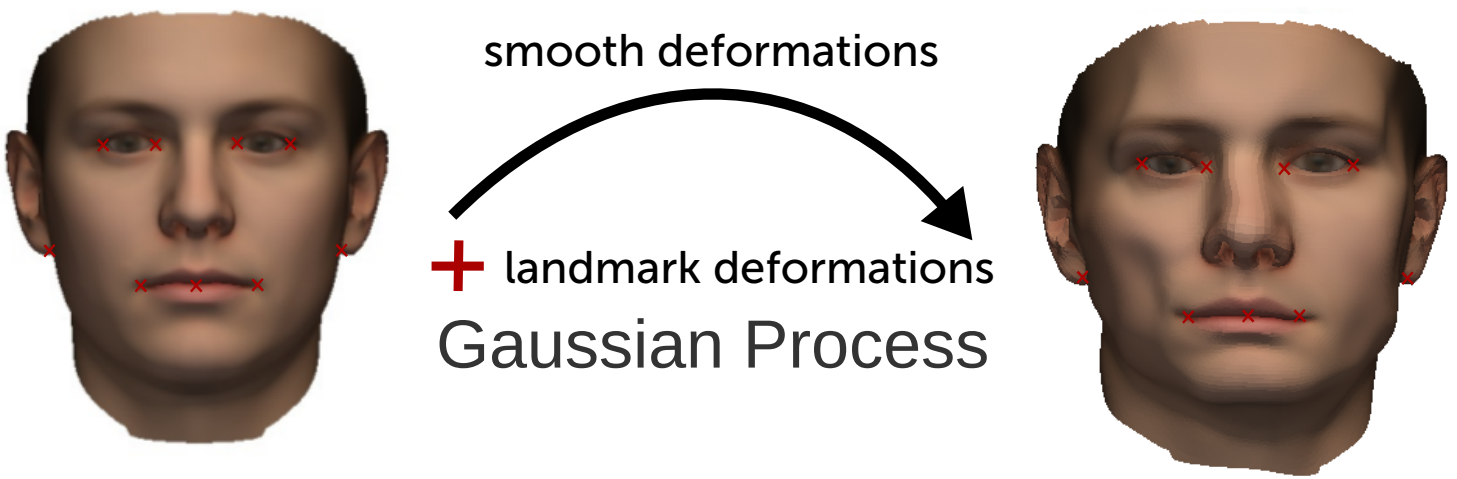
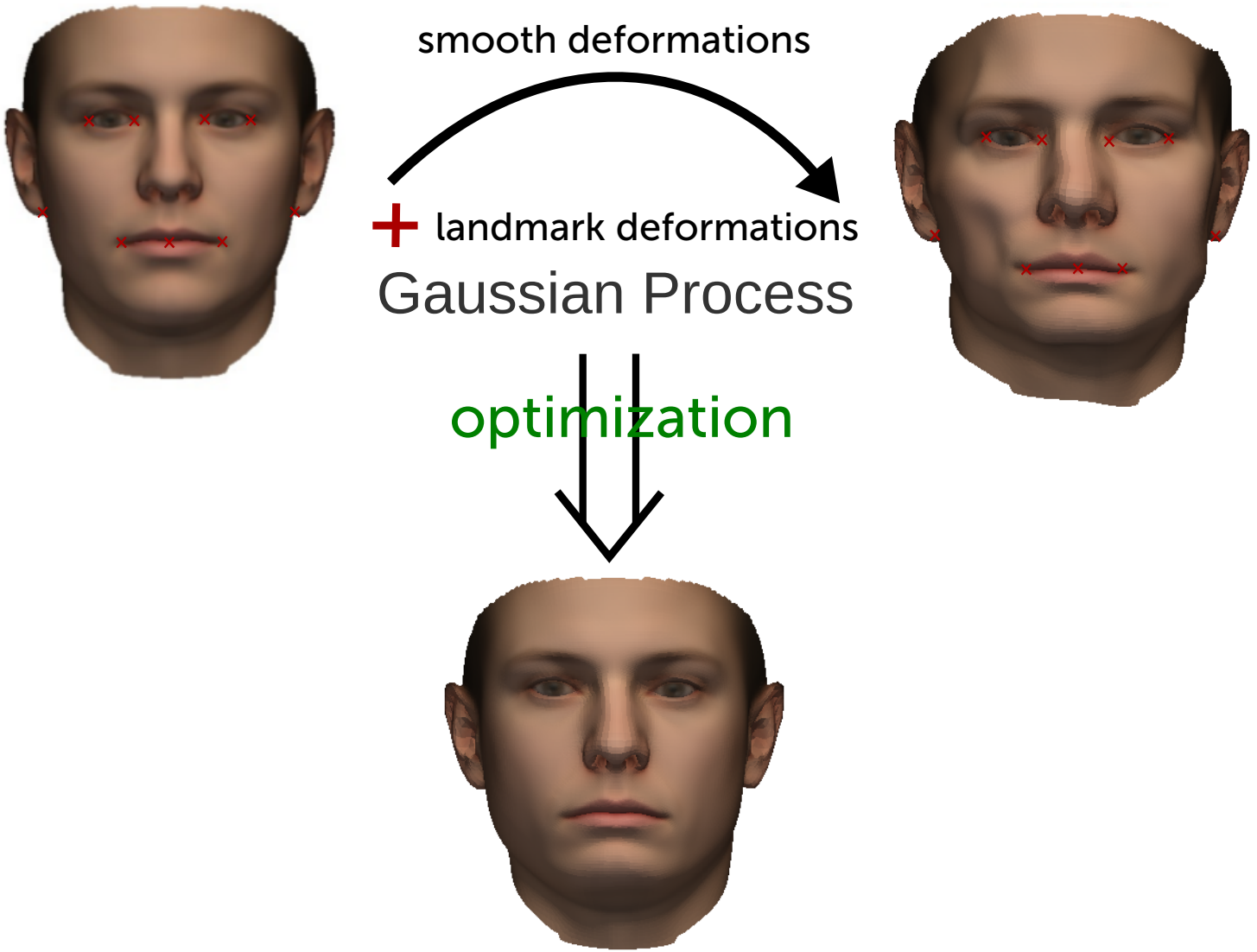
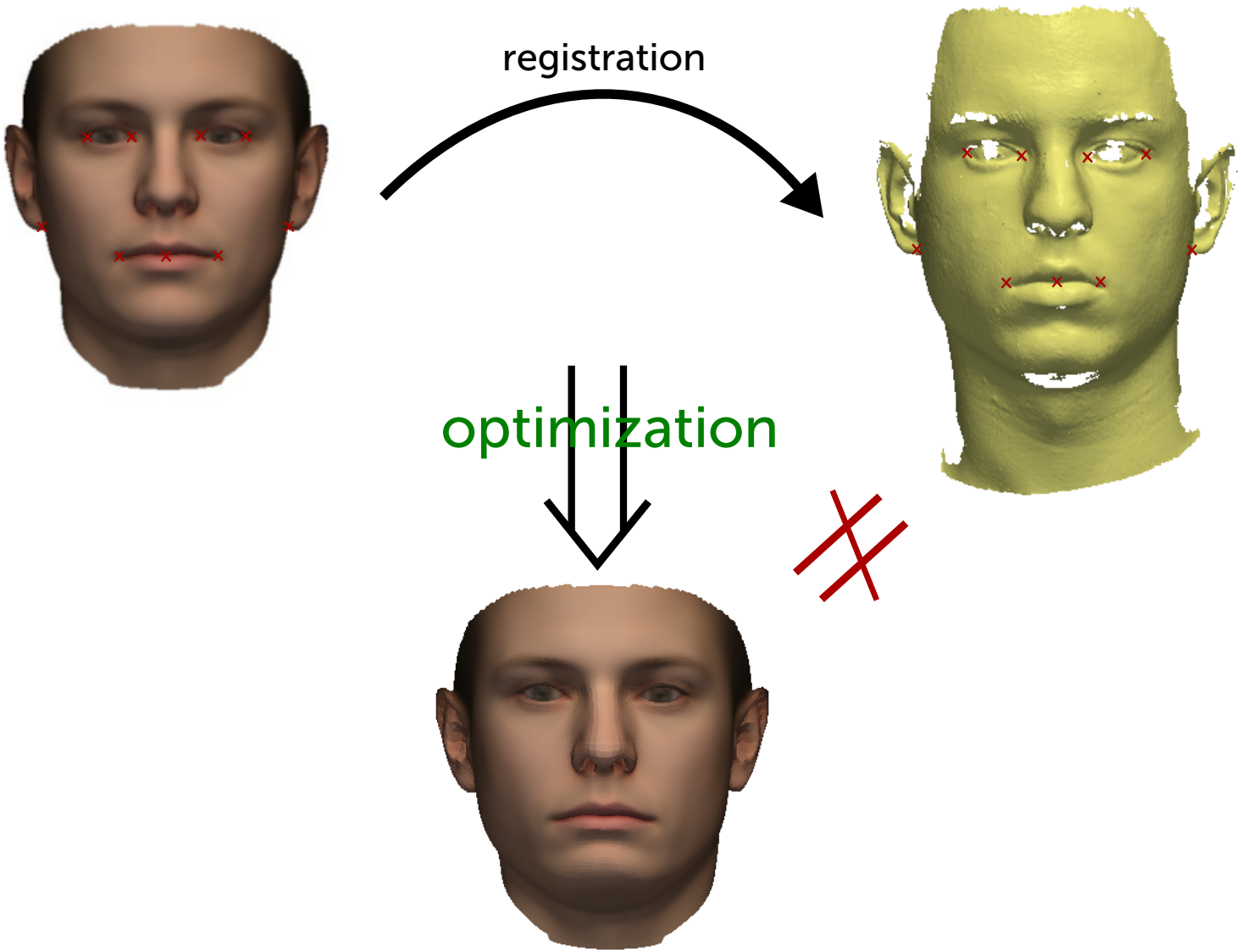


Registration Overview



Registration Overview

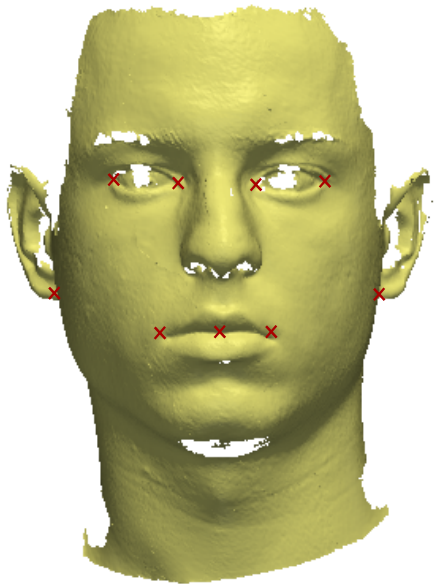


Registration Overview

registration

match
feature regions!

?



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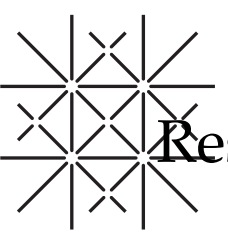
Outline

Data and Correspondence

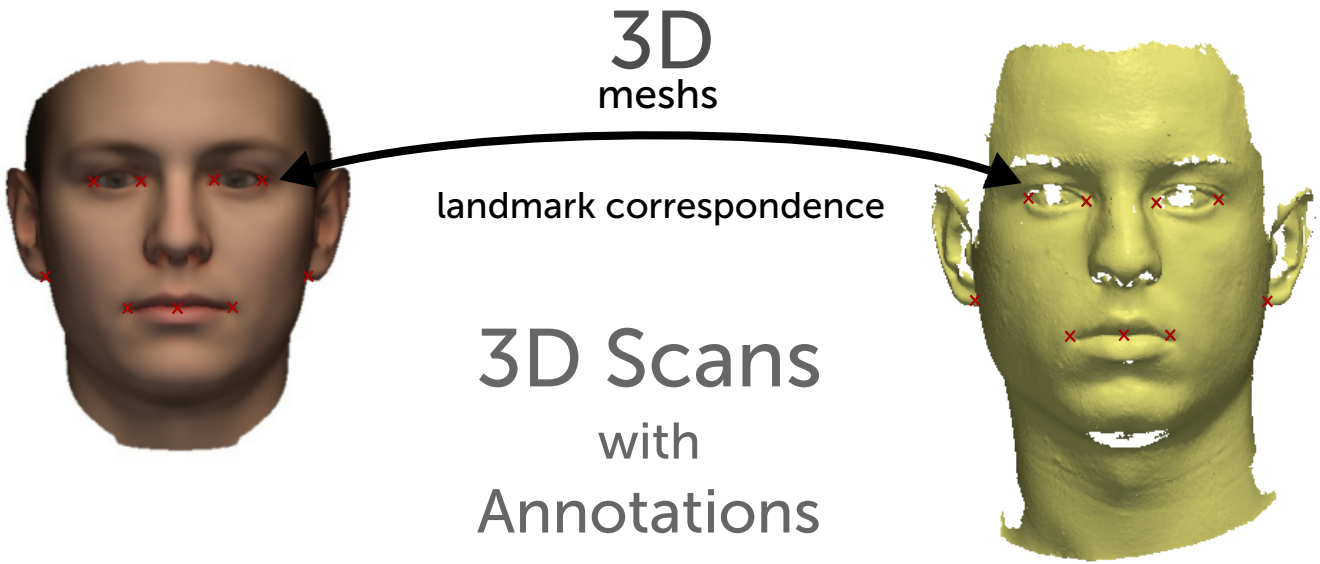
Using Line Features
- Sampling Line Features
- Projection: 2D to 3D
- Results of 3D representation

Gaussian Process Regression
- Gaussian Process
- GP Prior
- GP Posterior
- Application to 3D Face Registration
- Optimization

Results



Data and Correspondence



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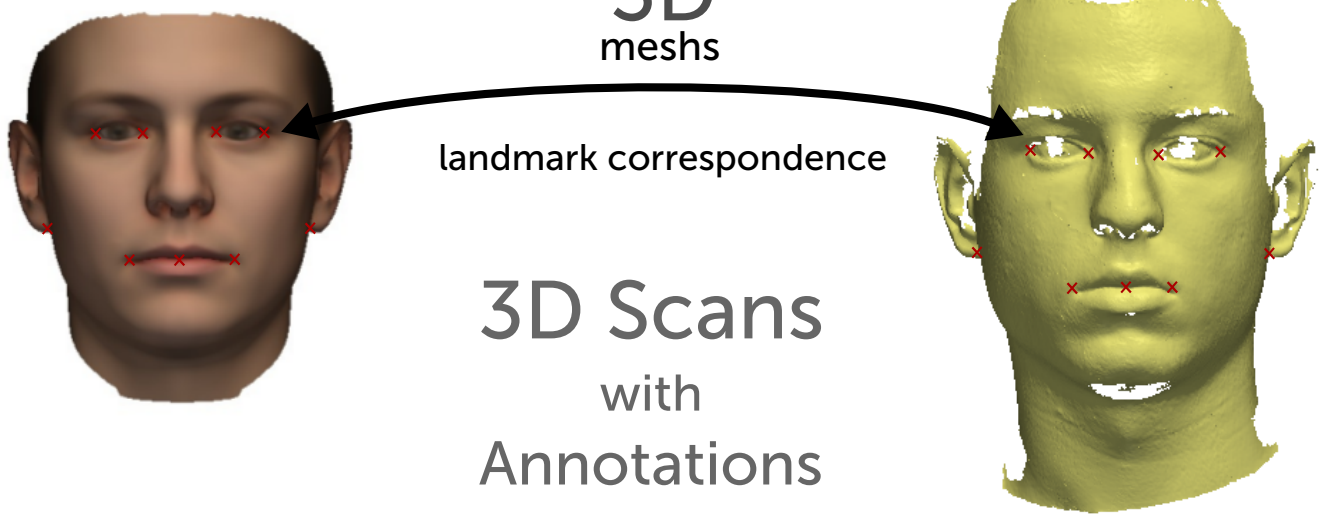

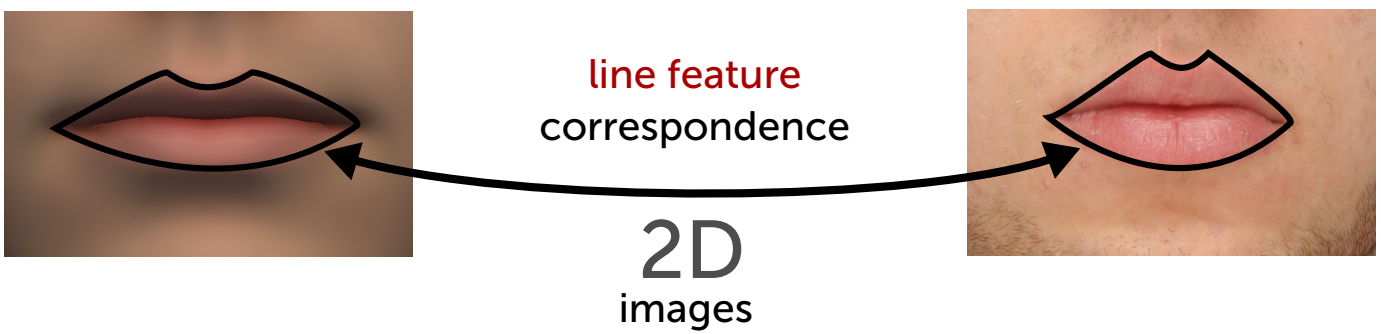

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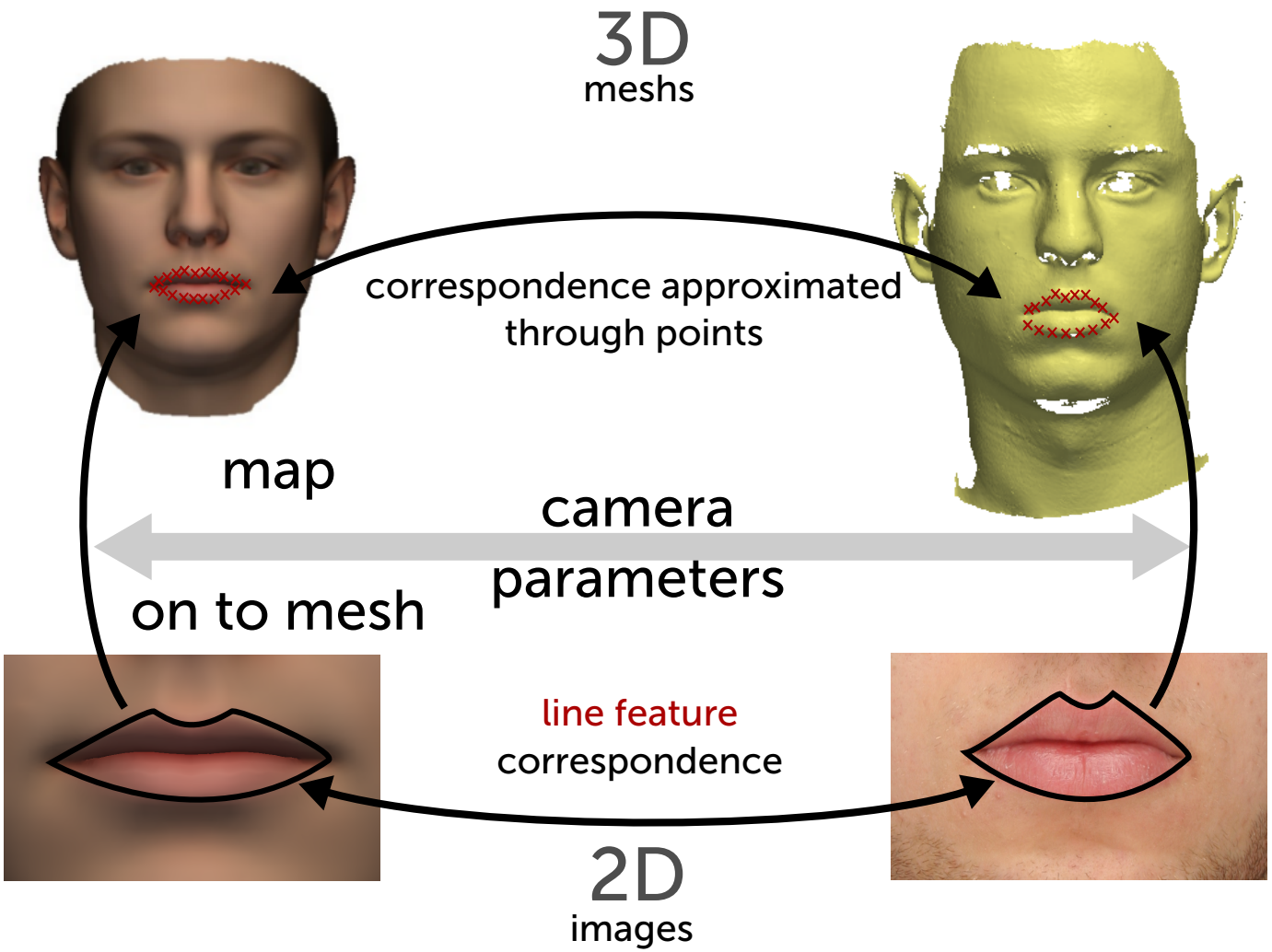
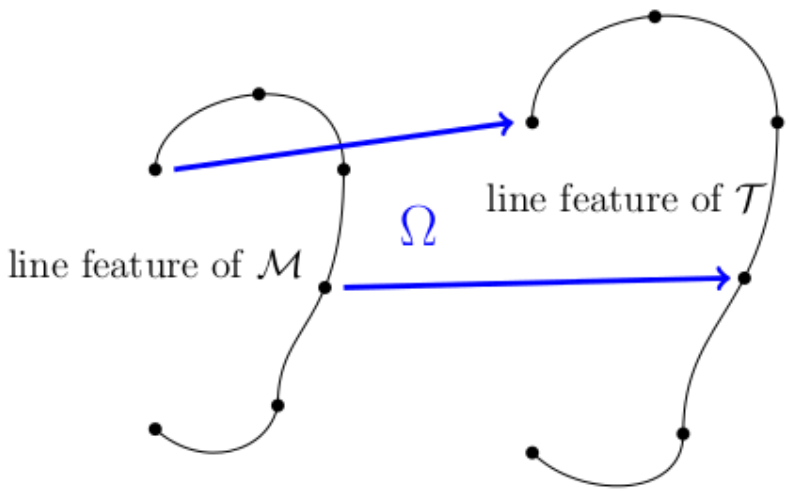
Data and Correspondence



Mapping Line Features

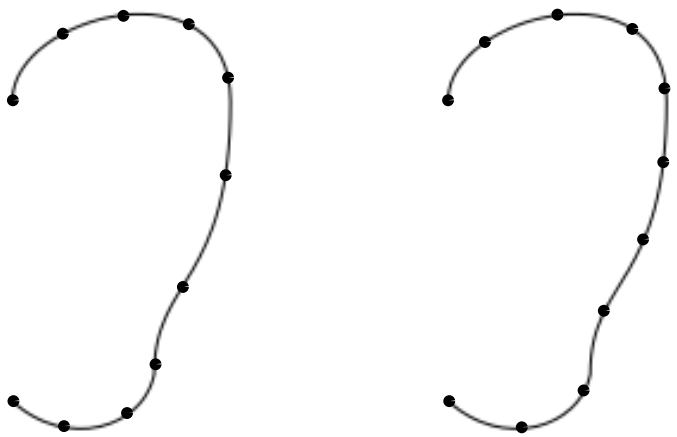
Idea: Sample points from the line features and use them as additional landmarks



What about correspondence?

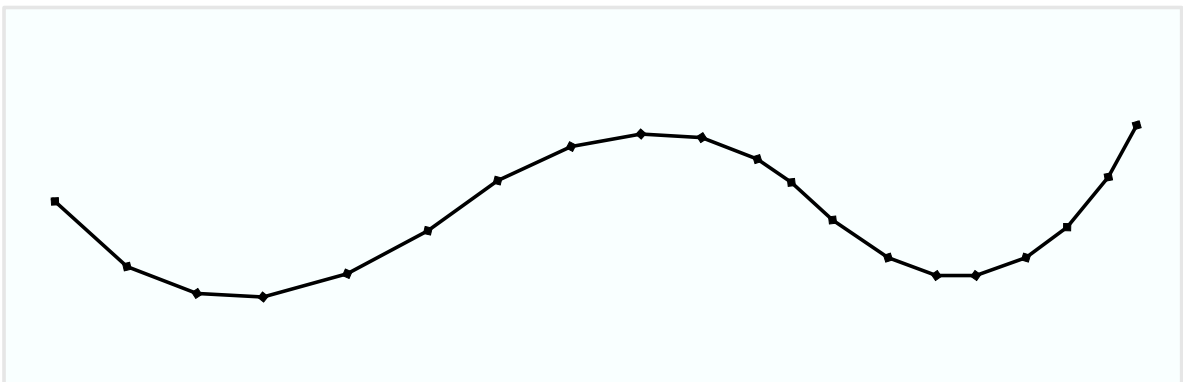
Equidistant Sampling

Approximate correspondance by sampling line features in equidistant intervals



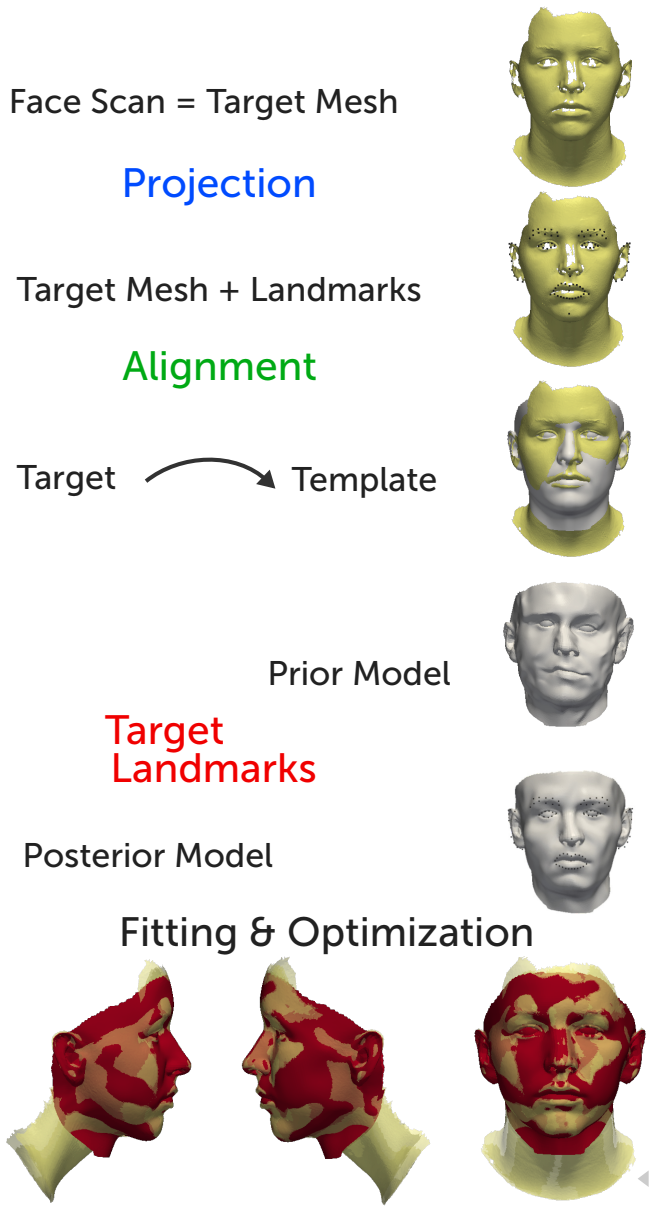
Bézier curves

Problem: Line features consist of Bézier curve segments
underlying parameter t is not linear
Approximate arc-length of curve through euclidean distance of sampled points

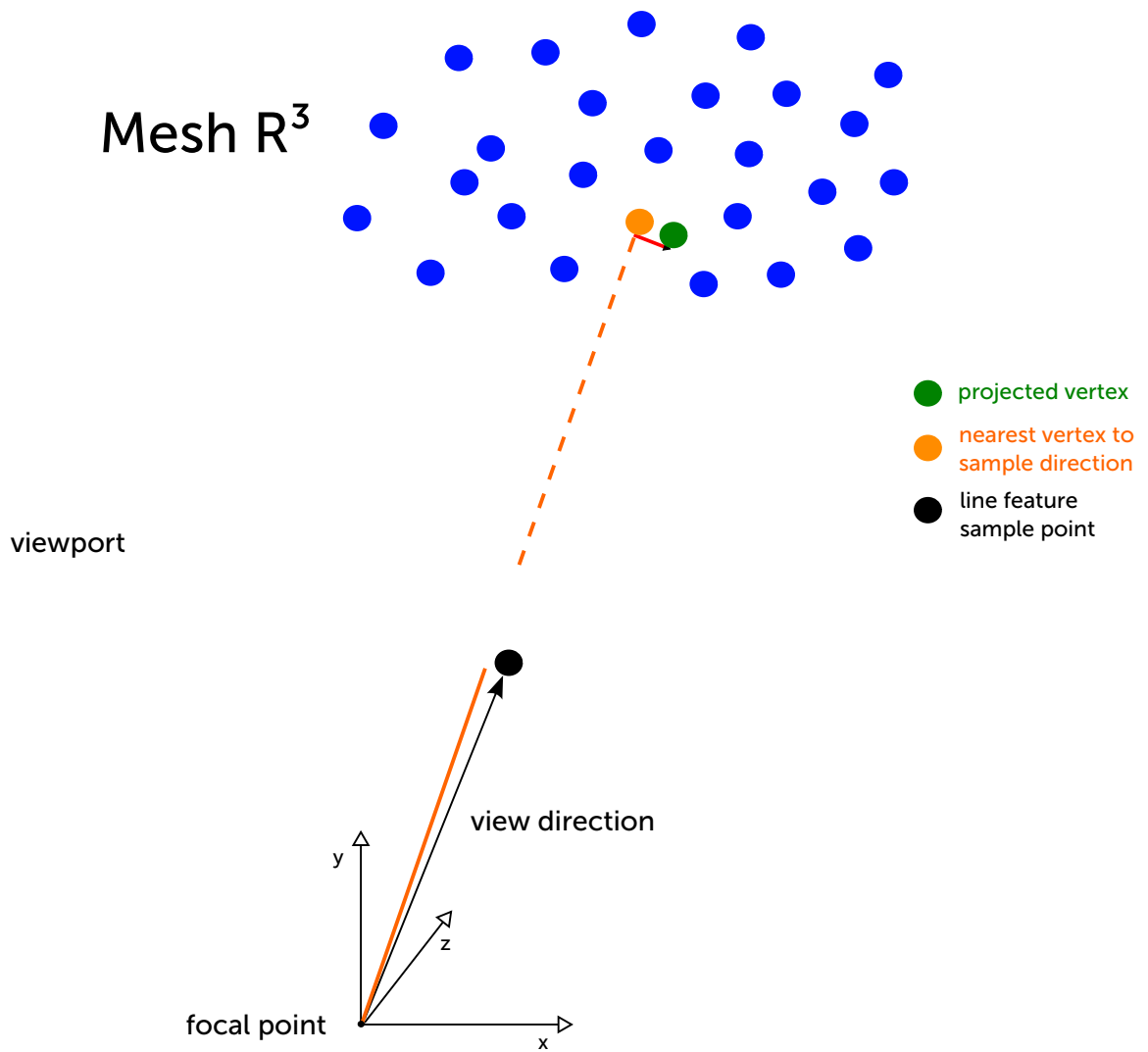


→ map point coordinates to approximated fractional length of curve

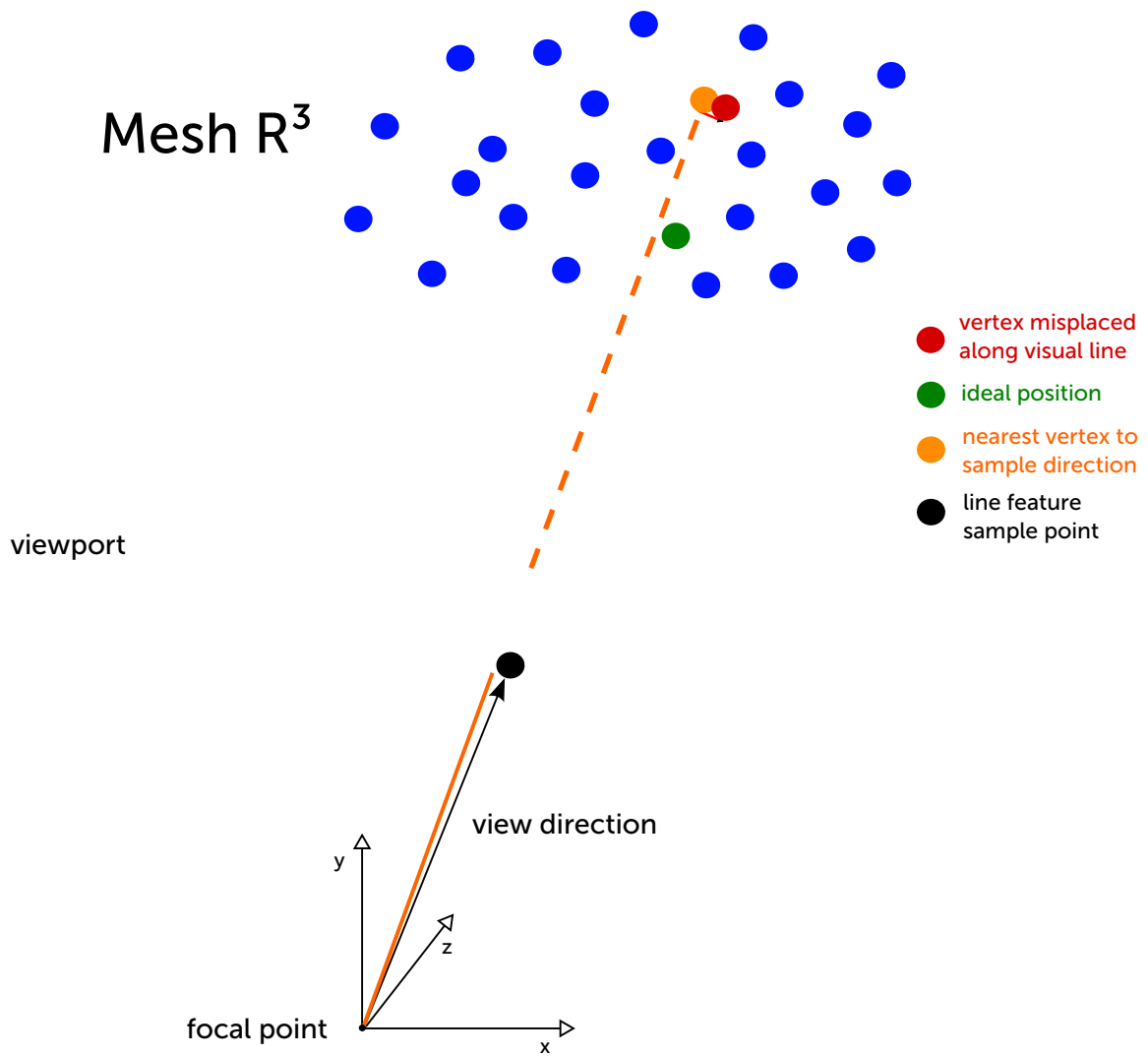
Pipeline: Projection



Projection: 2D to 3D

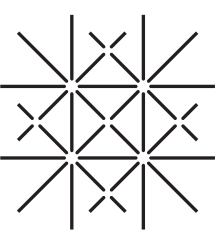


Projection: holes

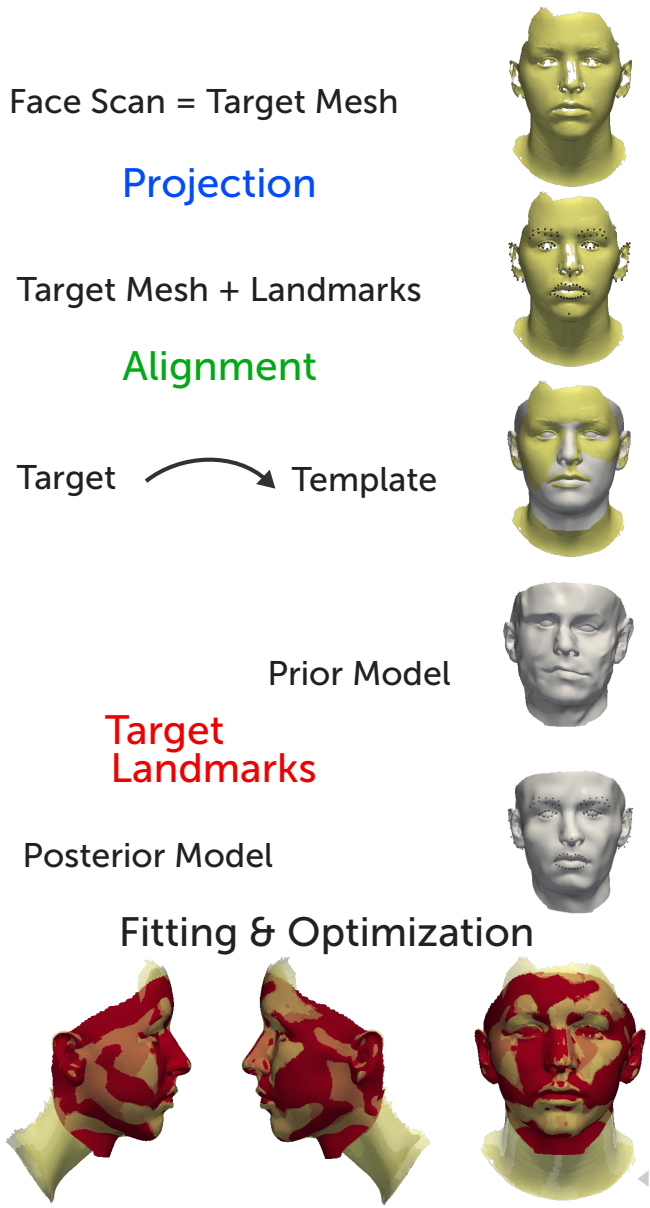


Results of 3D representation

show images of projected line features



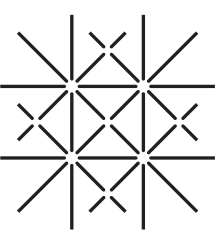
Template/Target Alignment



Gaussian Process

a stochastic process where a finite set of random variables has a normal distribution defined by mean and covariance function

$$GP \sim (\mu, \Sigma)$$



GP Prior

view Gaussian Process as a distribution over functions,
each random variable represents possible function values at specified input points $\mu : \mathbb{R} \rightarrow 0$ to simplify computations

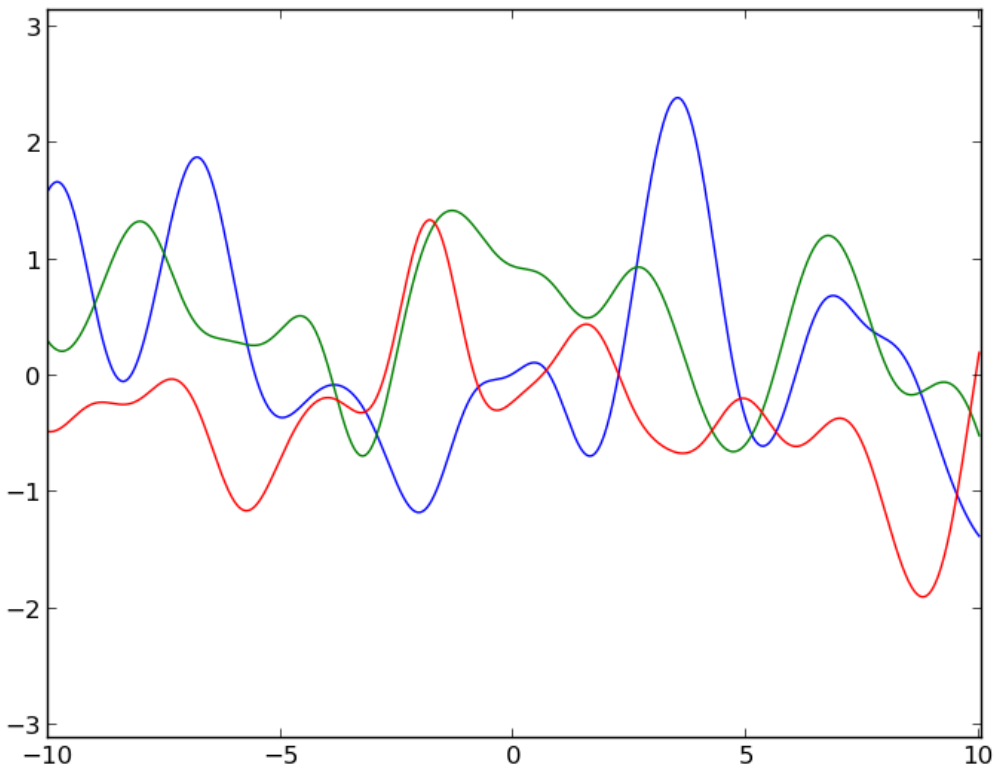


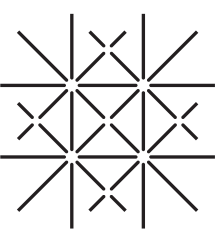
Figure: normal distribution over 1000 input points

GP Posterior

infer a set of possible functions by conditioning the distribution on the outputs y_i of a training set

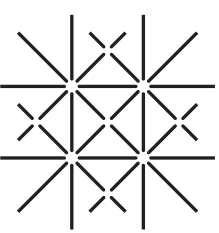
$$S = \{(x_1, y_1), \cdots, (x_n, y_n)\}$$

add noise $y = f(x) + \varepsilon$?



Joint Distribution

$$\begin{bmatrix} \mathbf{f} \\ \mathbf{f}_* \end{bmatrix} \sim \mathcal{N}\left(\mathbf{0}, \begin{bmatrix} \Sigma(X) & \Sigma(X, X_*) \\ \Sigma(X_*, X) & \Sigma(X_*) \end{bmatrix}\right)$$



Posterior Distribution

$$p(\mathbf{f}_*|\mathbf{f}=\mathbf{y}) \qquad \mu = K =$$

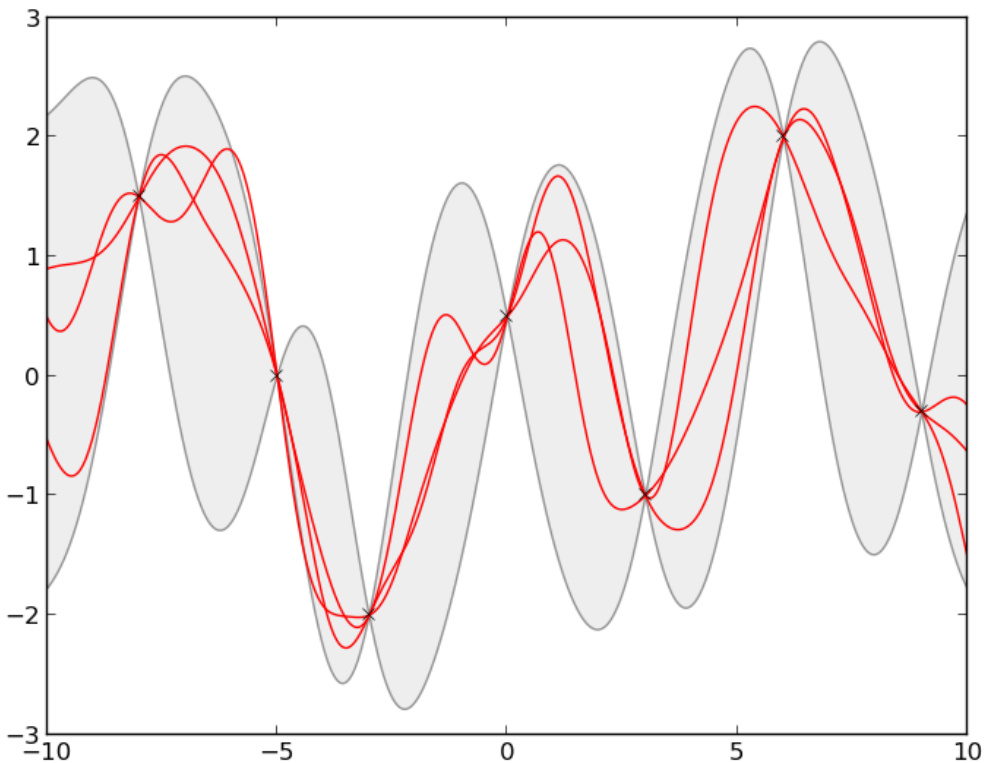
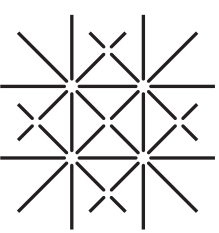


Figure: posterior distribution fixed at 7 input points

GPR in 3D Face Registration

definition of Vector-valued GP

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



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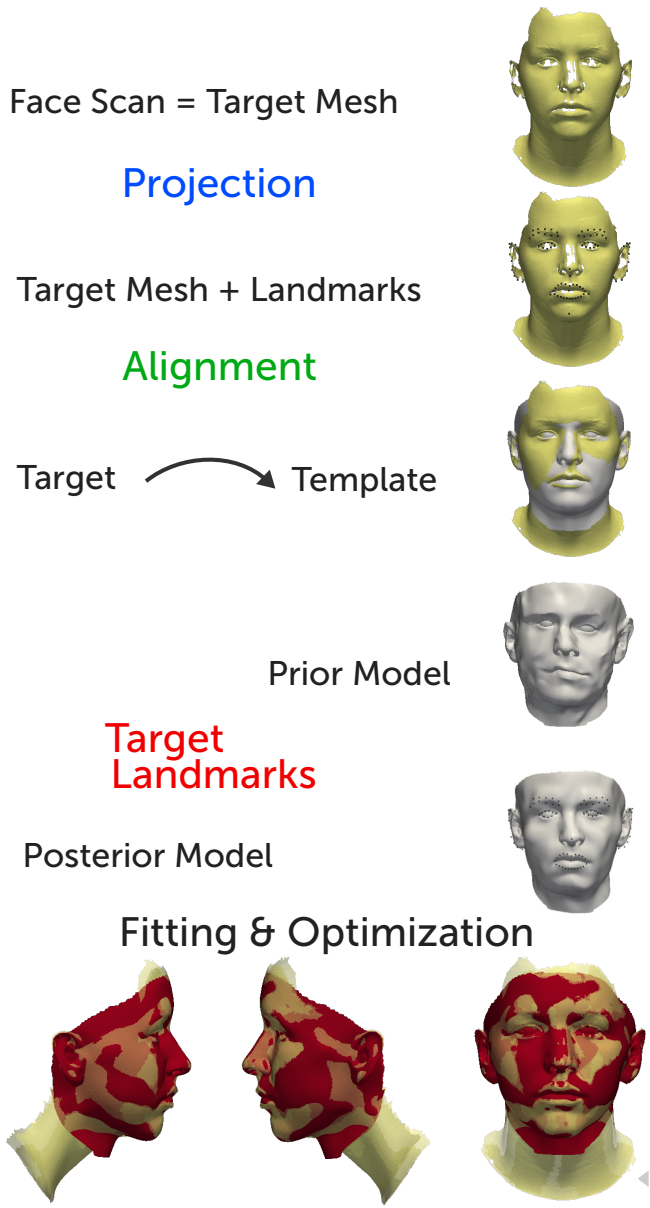
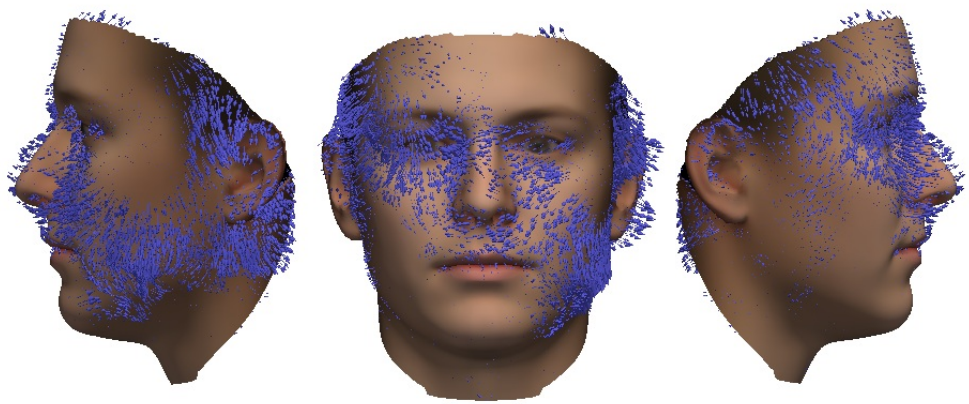
Pipeline: Deformation Prior

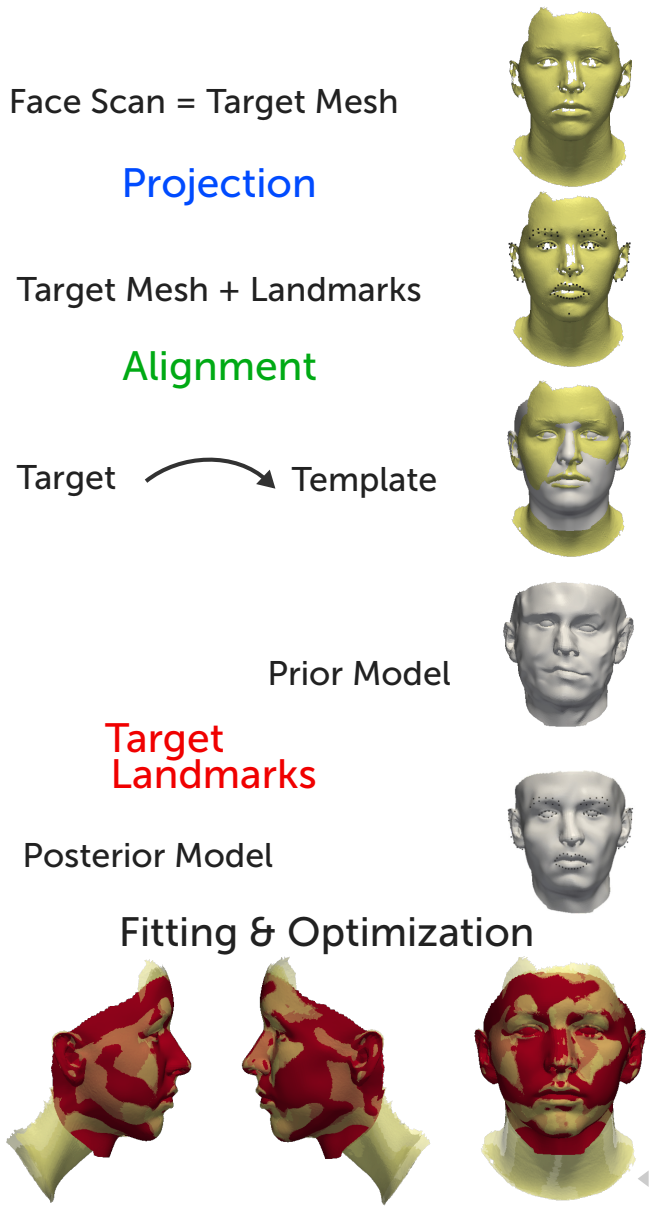


Deformation Prior

build GP Prior from template mesh vertices
$\rightarrow$ GP defines deformation on every vertex of the template



Pipeline: Deformation Posterior



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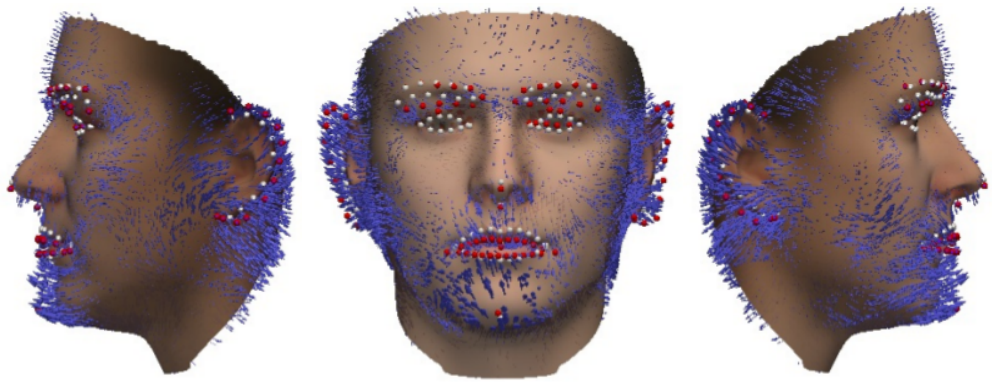
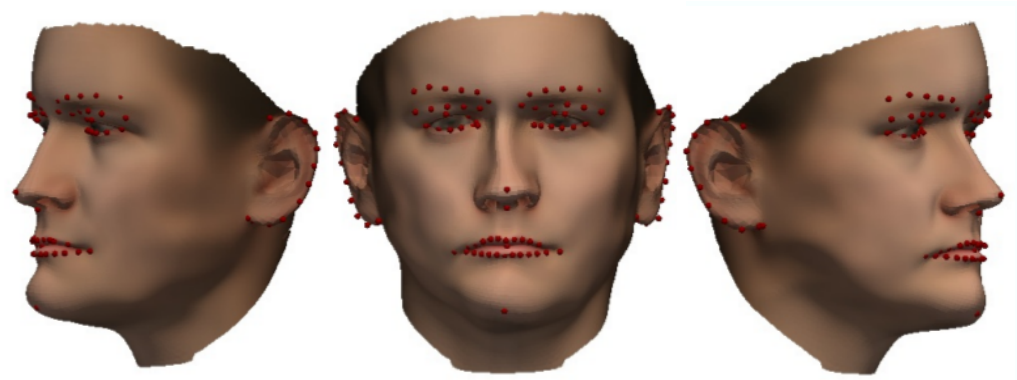
3D GP Posterior

Training data for inference in the space of possible template surface deformations:
comprised of the residuals of the line feature sample coordinates

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

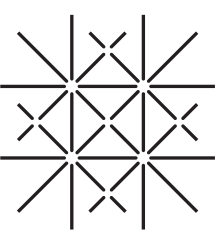


Posterior Meshs

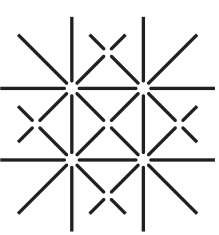


Parametric Model

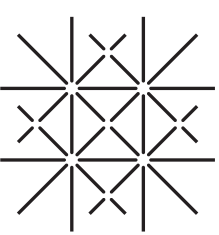
GP Posterior distribution of admissible deformations
How to optimize deformation samples?
Mercer's theorem: distribution $\rightarrow$ parametric model
$\rightarrow$ optimize model parameters



Loss function



Robust Estimators



Results