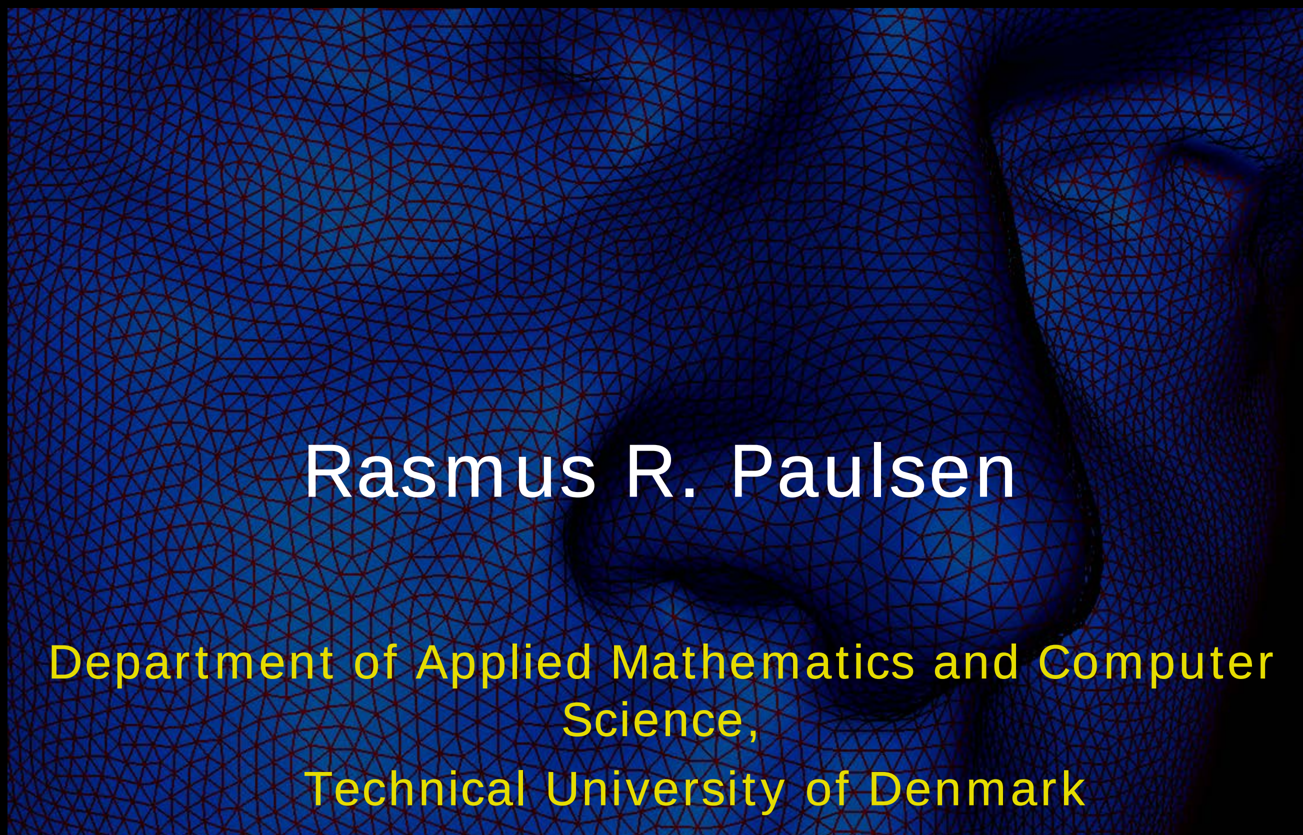
Face and Ear Analysis



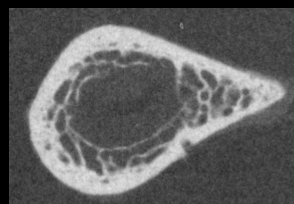
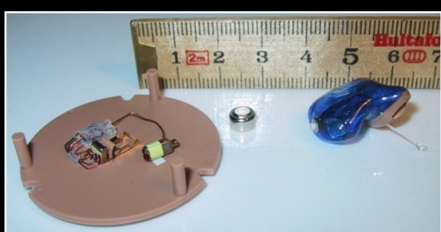
Rasmus R. Paulsen

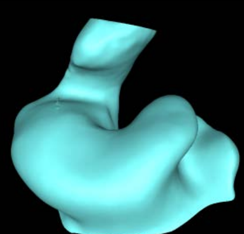
Department of Applied Mathematics and Computer Science,

Technical University of Denmark

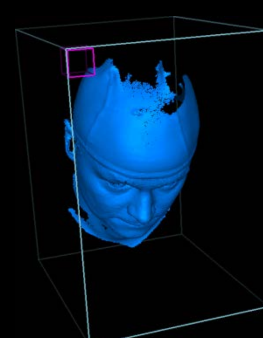
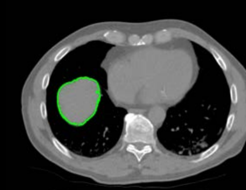
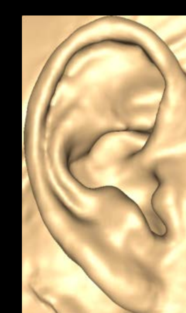
November 2013

Who am I



- Master of Science from DTU
- Oticon A/S: Industrial PhD student
  - Visit to INRIA in total 16 months
- Oticon A/S: R/D
- DTU Informatics: Associate Professor

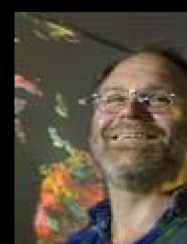
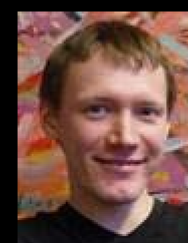




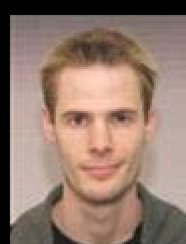
Who are we?

- Technical University of Denmark (DTU)
- Department of Applied Mathematics and Computer ScienceSection for Image analysis and computer graphics
  - 12 Faculty: Professors, Associate Professors, Assistant Professors
  - 30+ PhD students, Post-Docs, and research assistants



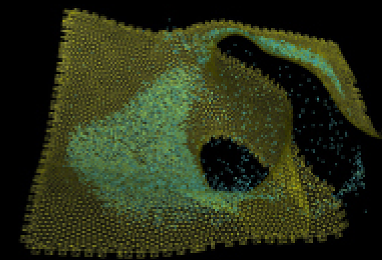


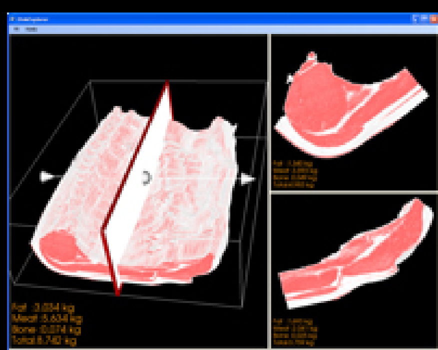



Research themes

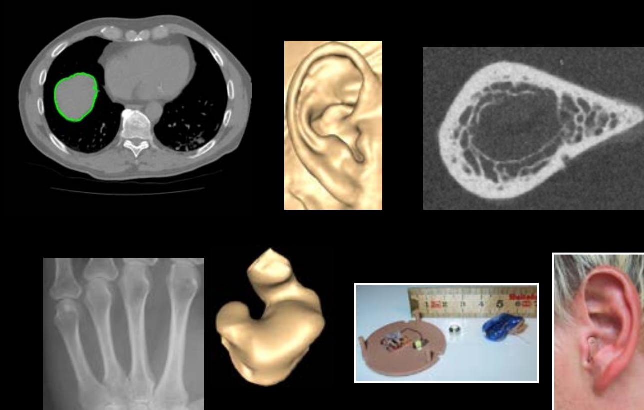
Computer Graphics
& Visualization



Computer Vision & 3D
Measurements



Industrial Inspection &
Food Quality



Medical Image Analysis

Today

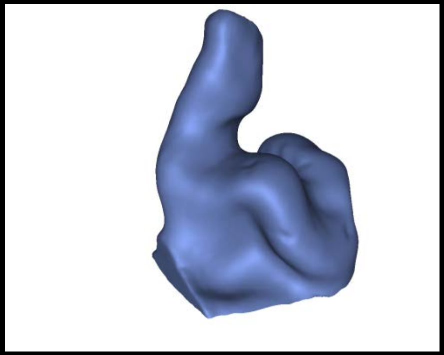
- Shape analysis of the ear
  - Rasmus R. Paulsen – PhD (2003)
  - Sune Darkner – PhD (2008)
  - Rasmus R. Jensen – PhD (2013)
- Full skull models for acoustical simulation
  - Stine Harder – PhD (2015)
- Face analysis for finding high genetic risk factors
  - Jens Fagertun – PhD (2013)
- 3D gender recognition
  - Jens Fagertun

Shape Analysis of the Ear - Background

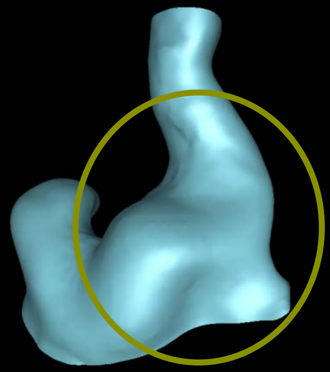
- An experienced hearing aid fitter has seen a lot of ears!
- Some hearing aid users are very difficult to fit. Why?
- Large variation in the shape of ears
- Ear canals change shape when people chews
- Is it possible to learn about the shape and use it?

Digitalisation

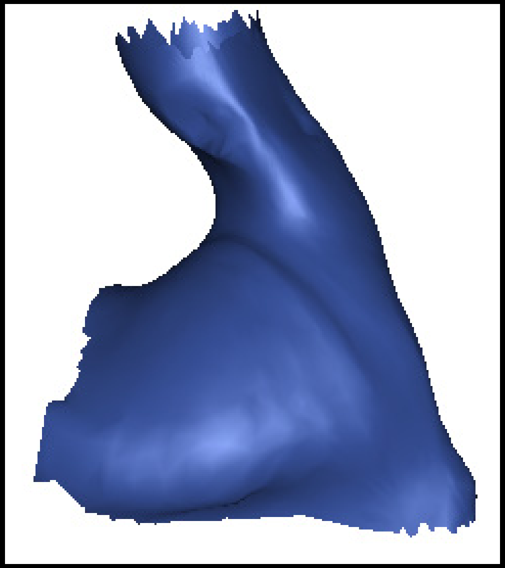
- Accurate surface description of ear impression
- Custom laser scanner



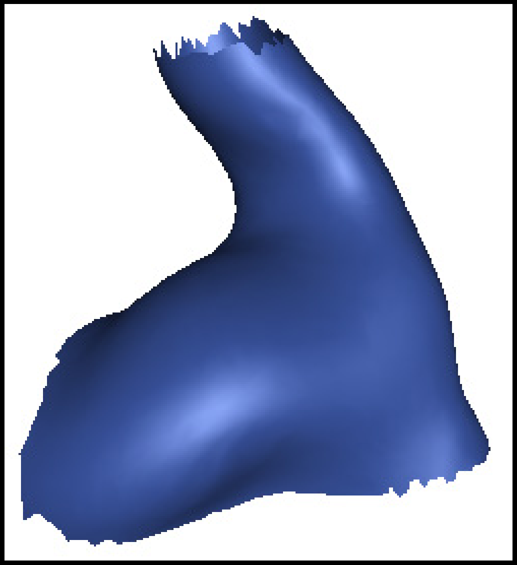
Some results



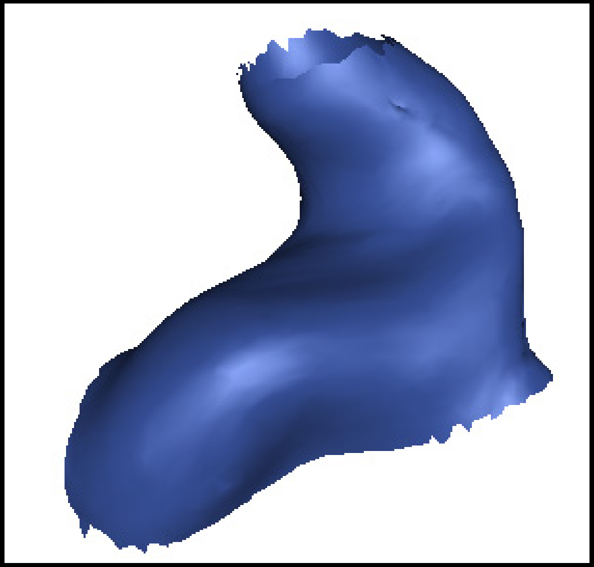
- Main variation of the shape of the ear canal
- Found using principal component analysis
- First mode of variation
- 7 modes explain 95% of the total variation



Average-1. mode



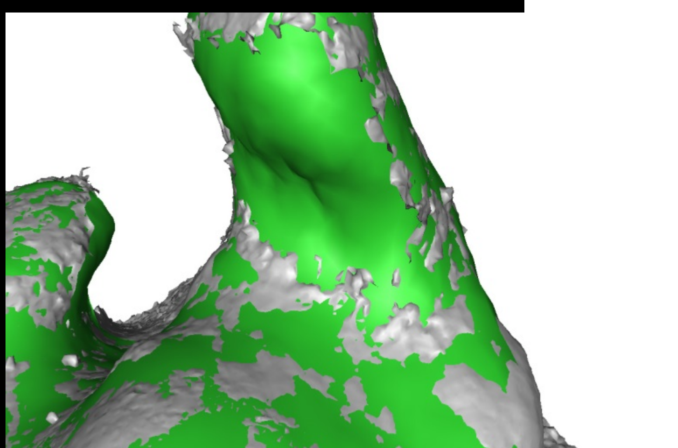
Average

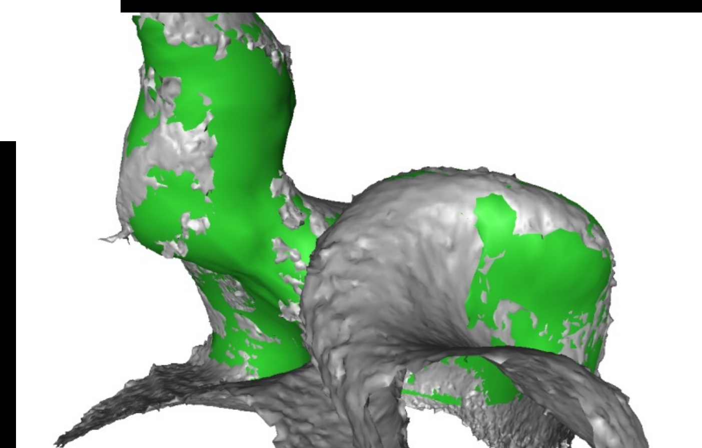


Average+1. mode

Previous and current use

- Hearing aid design
- Statistical surface recovery for direct ear scanning





3D head and torso database

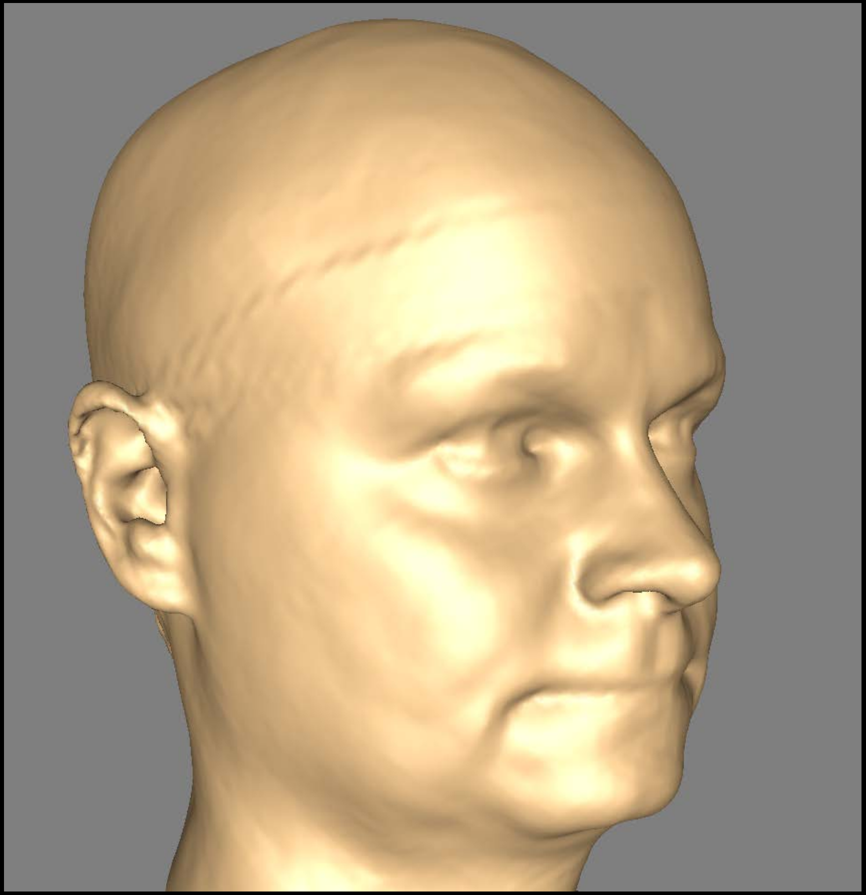
- Computer models are used increasingly in the design of
  - Hearing aids
  - Headsets
  - In the ear measurement devices – thermometers
  - Personal communication systems
- There is a need for high quality surface representations of the human ear, head, and upper torso
- Research project funded by the Oticon Foundation
  - Create an open database of scanned ears, heads, and torsos





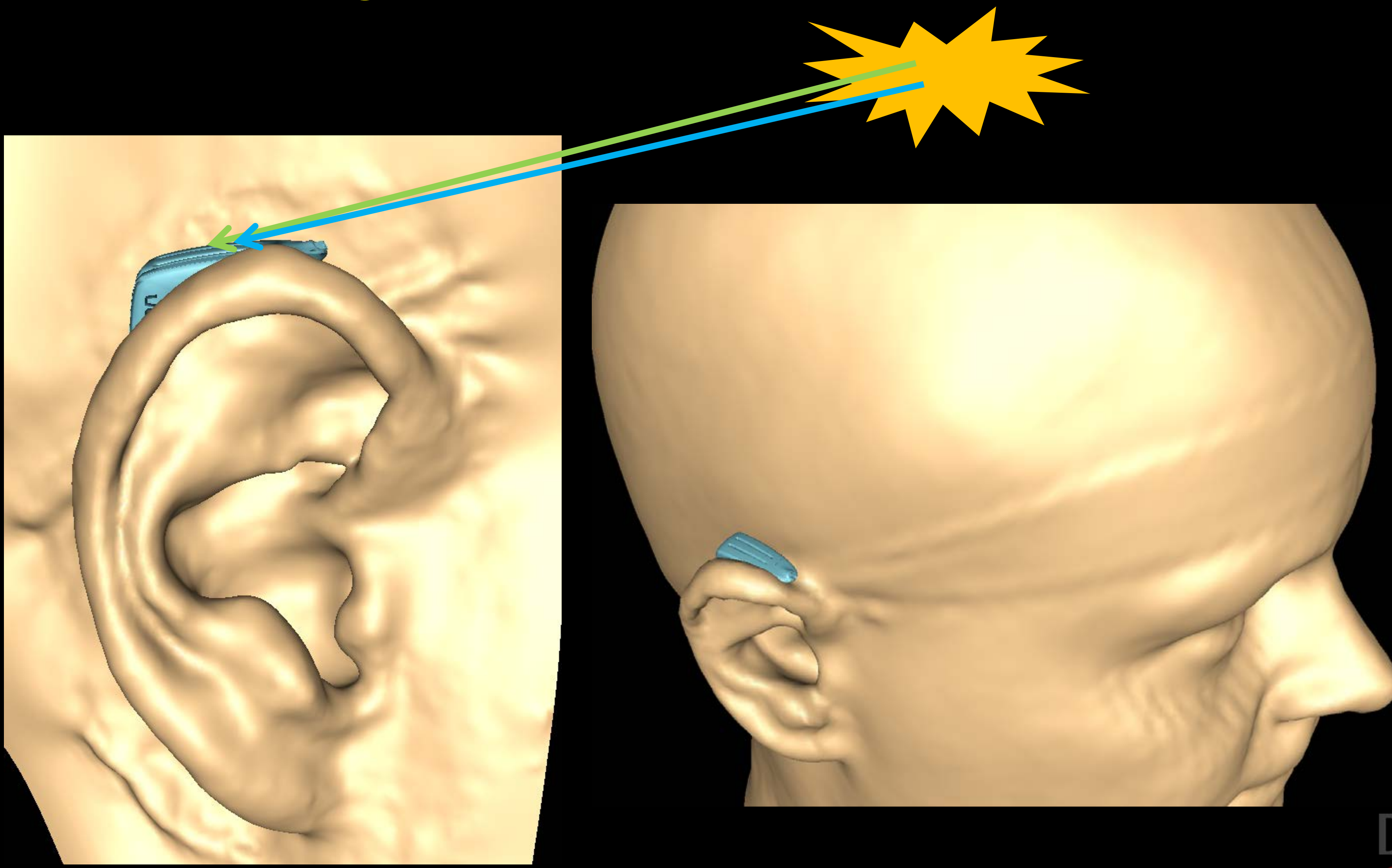

Hearing aid development

Overall project goal

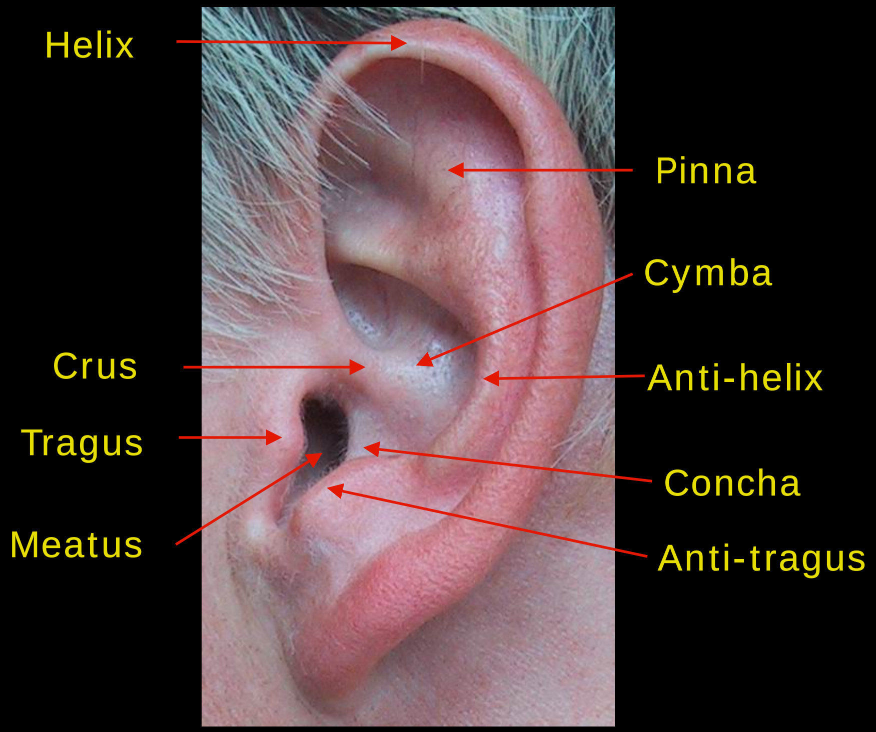


- Creation of a high quality database of ear, head and torso models
  - Surface models
- Combined with boundary element or finite element acoustical modelling
  - Virtual design

Virtual design and visualisation



The ear – so complicated!



- Most complicated anatomy seen from the outside
- Not possible to scan all parts of the ear at the same time
- Many occlusions
- Multiple scans from different directions is one solution
- Still not possible to capture the entire ear

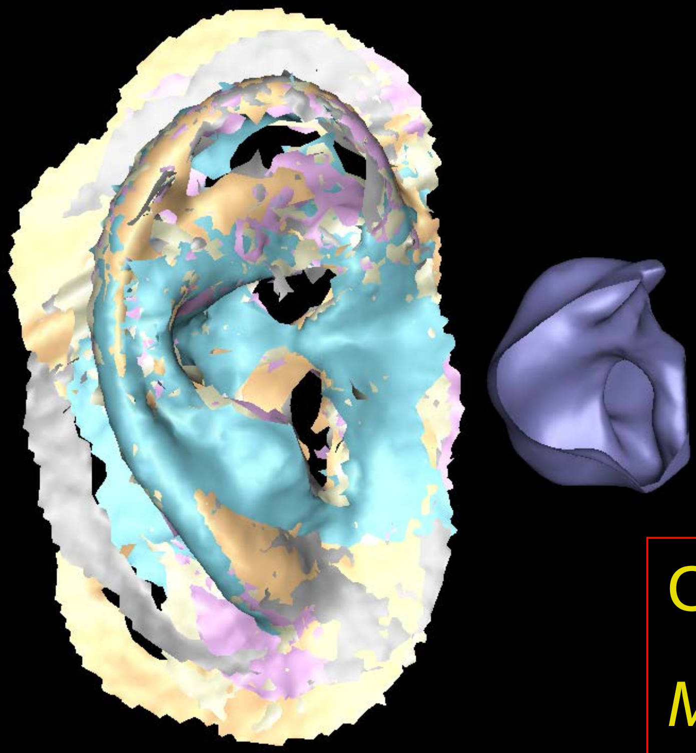
Scanner Setup

Canfield scientific Vectra M3

- Commercial facial scanner
- Three pods
  - two Canon 450D cameras per pod
  - Integrated flash system
- One-click 3D capture

Scanning the ear – an acrobatic exercise

Merging scans



- Scans pre-aligned
- How do we
  - Merge data from different scanners?
  - Fill out the missing parts?
  - Remove noise and outliers?
  - Create a nice triangulation?

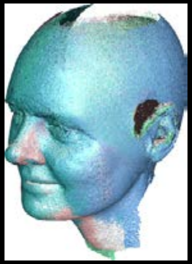
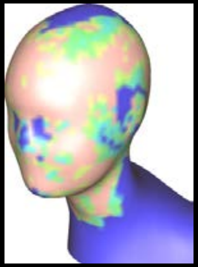
Our solution:

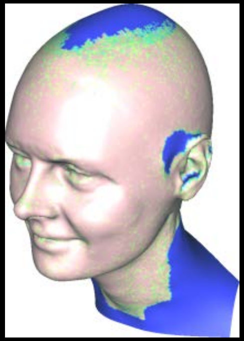
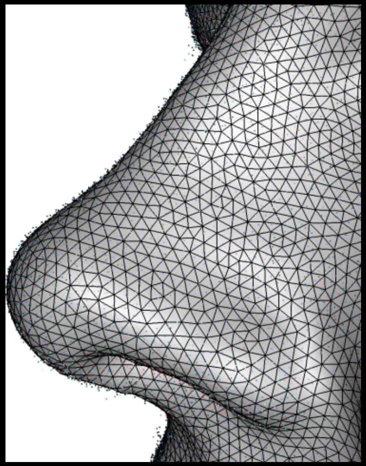
Markov Random Field surface reconstruction

Scan alignment and reconstruction

1. Merge sub-scans into one point cloud
2. Compute implicit surface (distance field)
3. Regularise implicit surface
4. Re-align scans to implicit surface

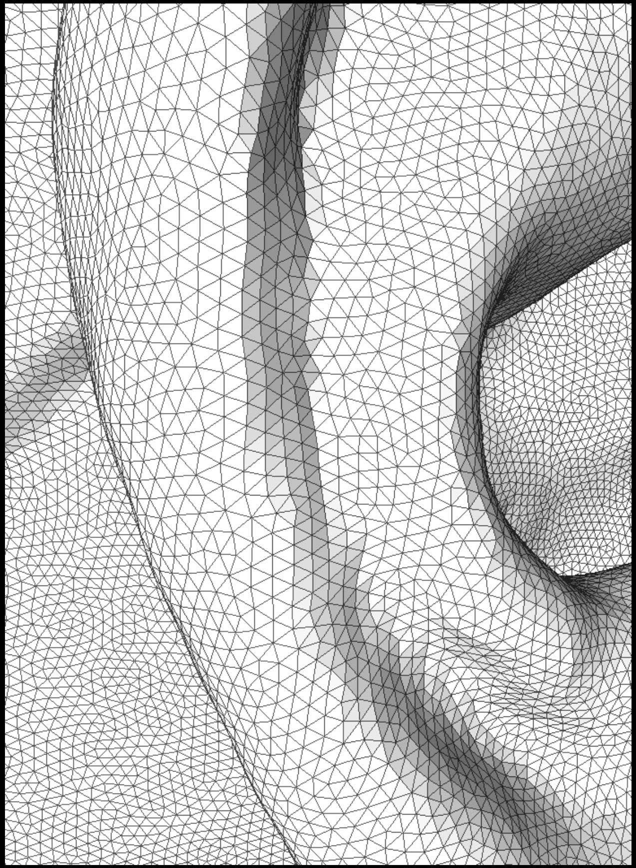
- Repeat step 1-4 in a multi-scale framework
  - Optimising implicit representation
- Extract triangulated surface

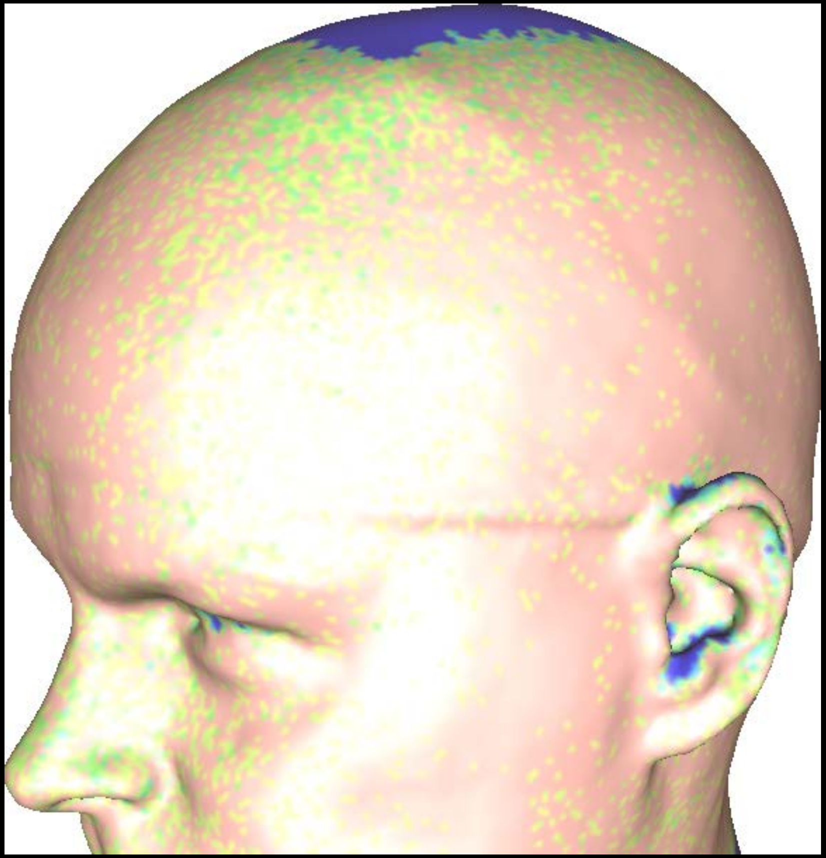



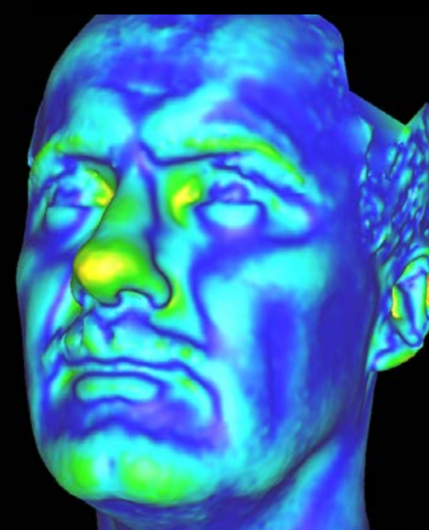
Software and data

www.imm.dtu.dk/MRFSurface





Connection between genetics and visible biometric features

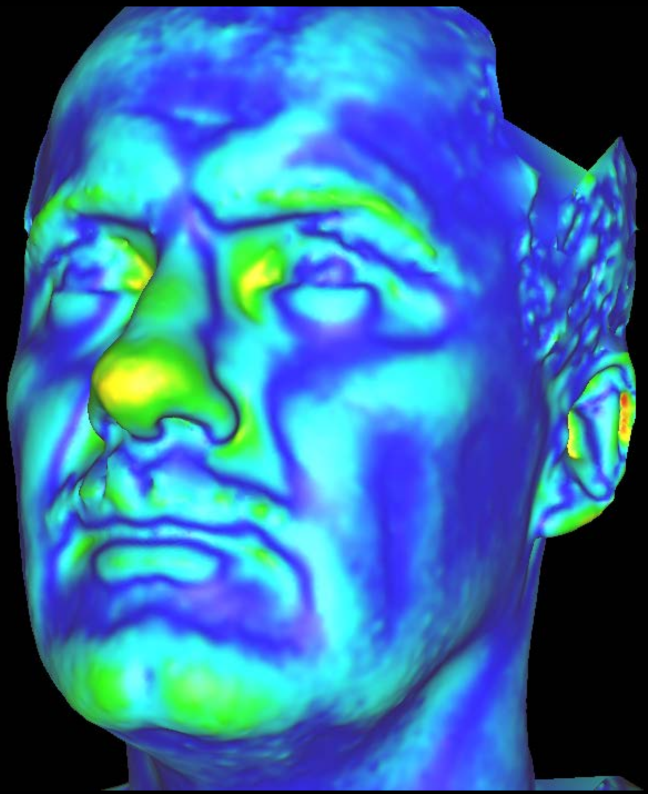


Canfield scientific Vectra M3

Setup

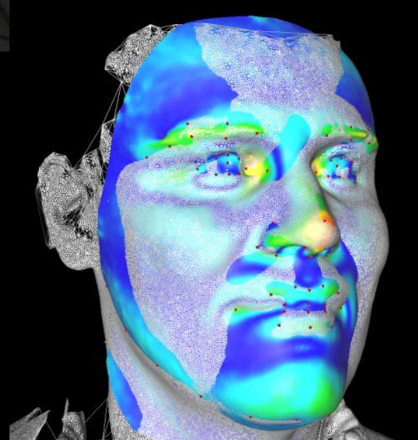
- Research Institute of Biological Psychiatry, Copenhagen University Hospital
- Several psychiatric centers
- 4 scanners
  - 1000+ controls from the Danish Blood Donor program
  - Patients with severe psychiatric disorders acquisition ongoing

Goal



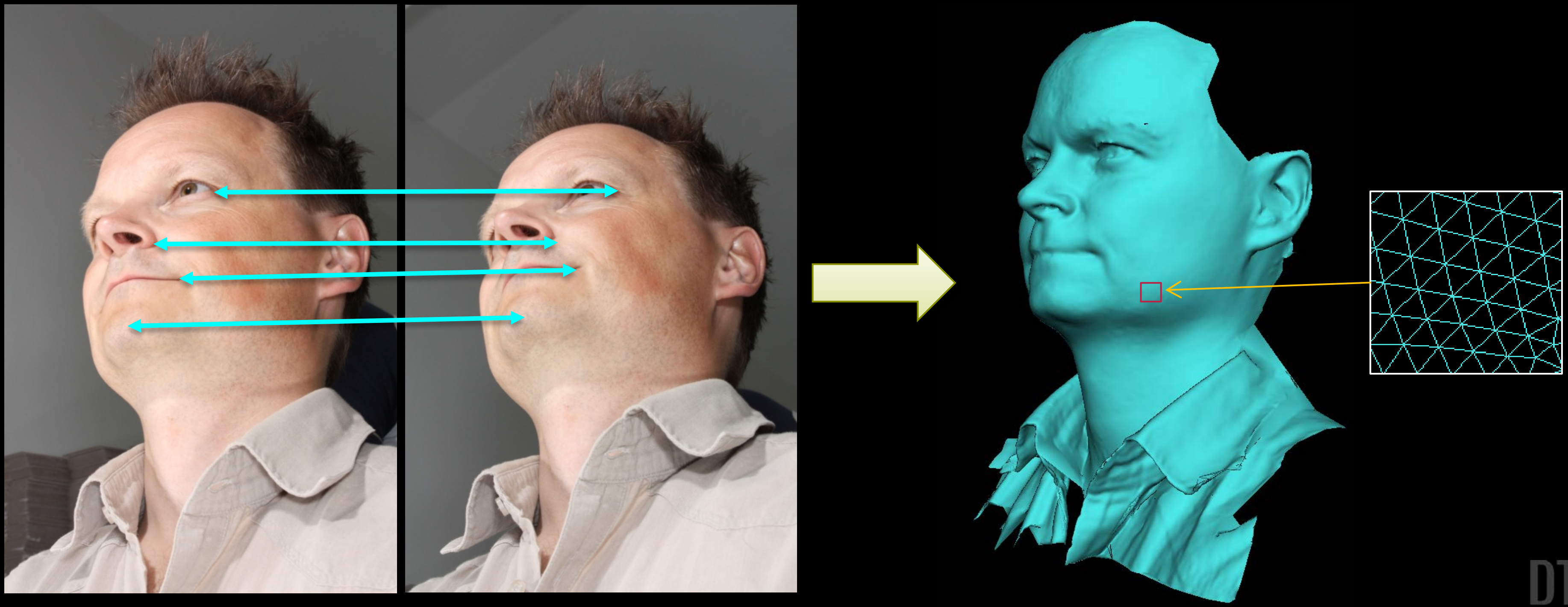
- Identify biomarkers
- High risk genetic variants

Methods

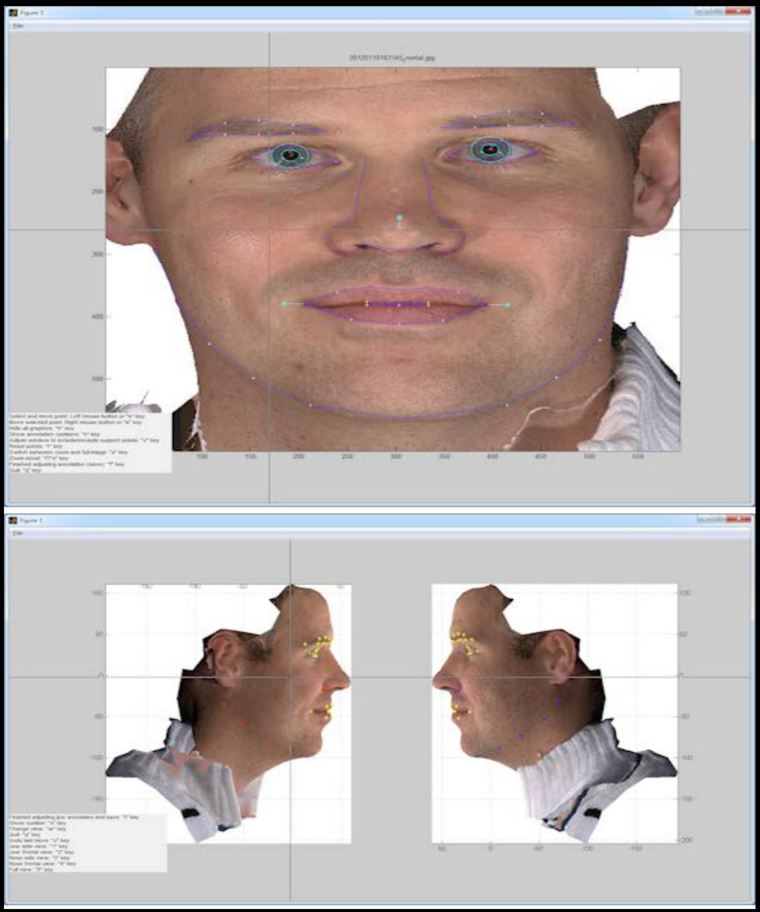


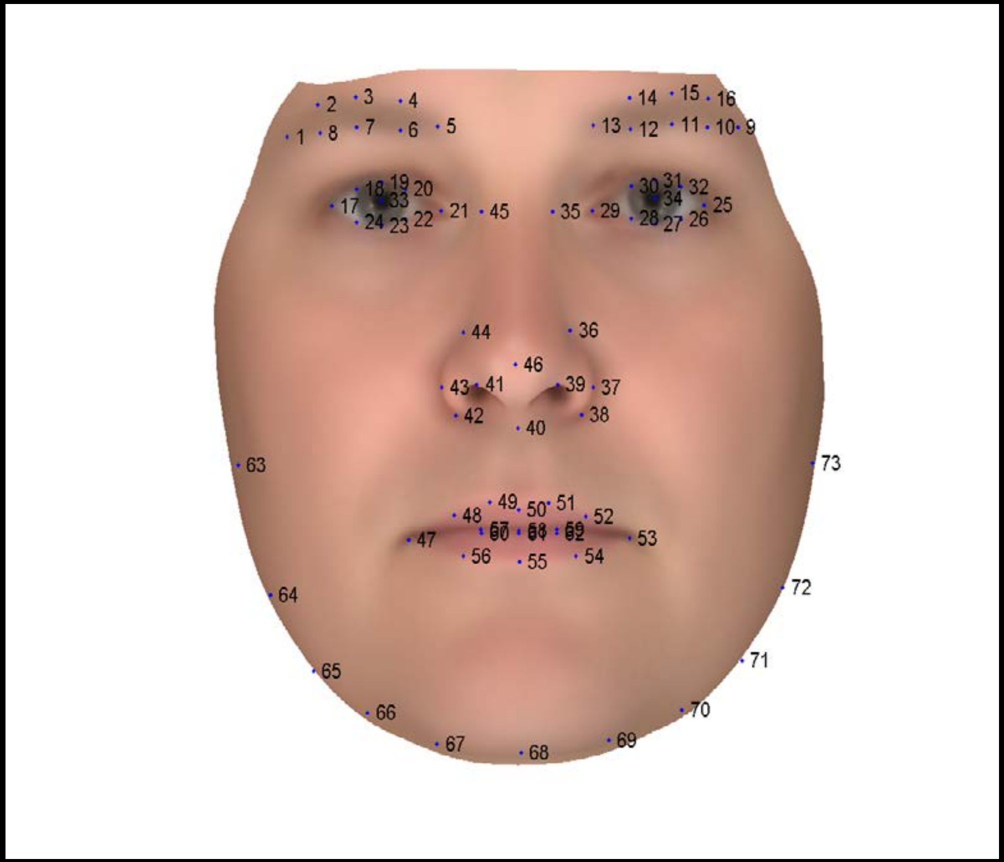
Stereo reconstruction

- Custom stereo reconstruction algorithm
  - Pairwise image correspondence
  - Pod-wise correspondence

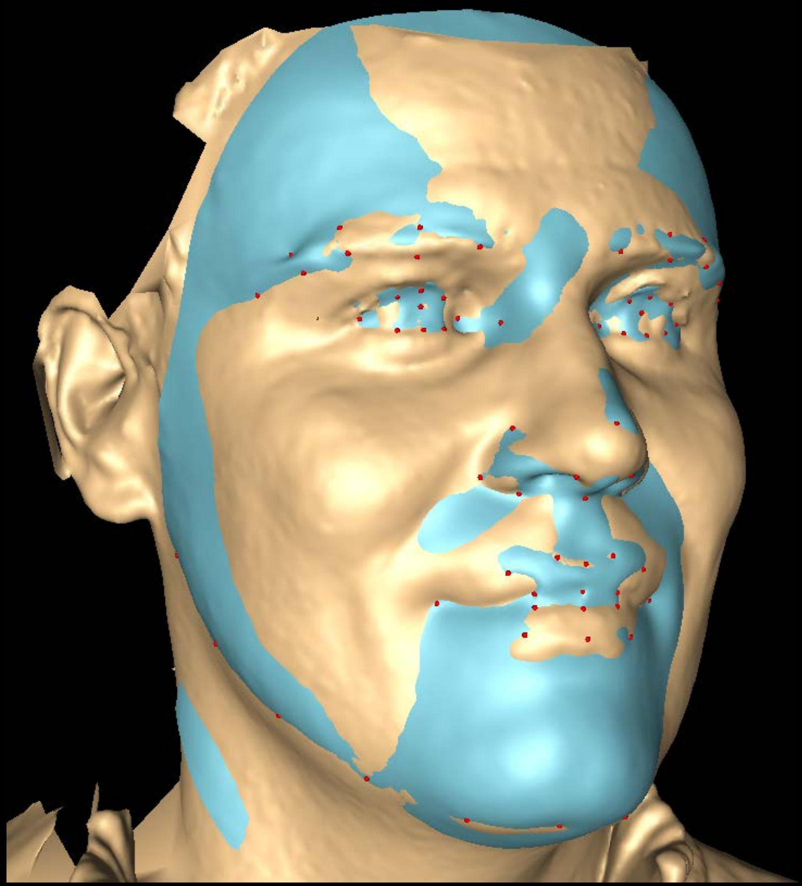


Standardised landmarking



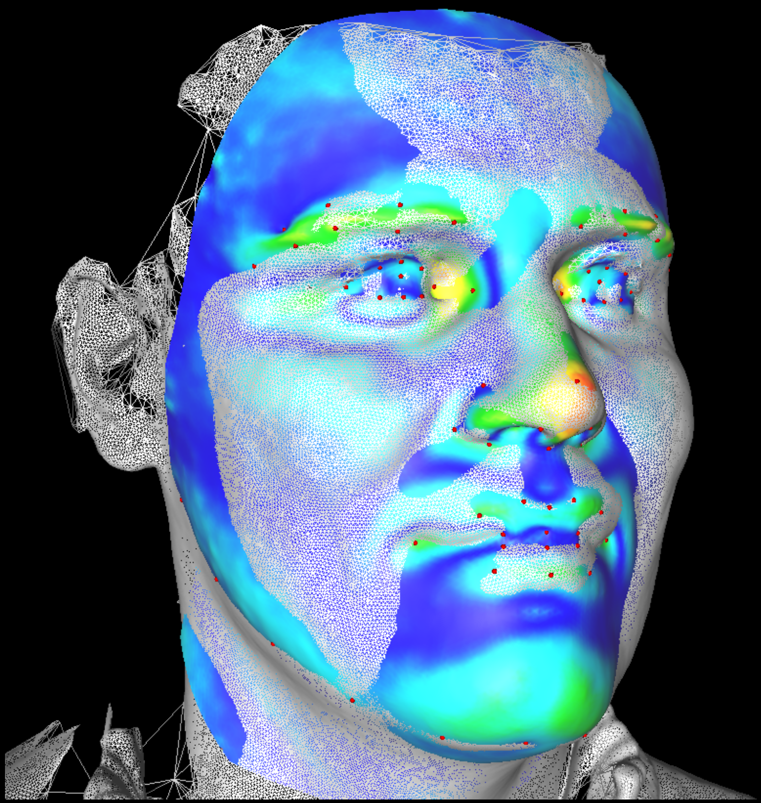


Dense Surface Correspondence



- Template warped to target

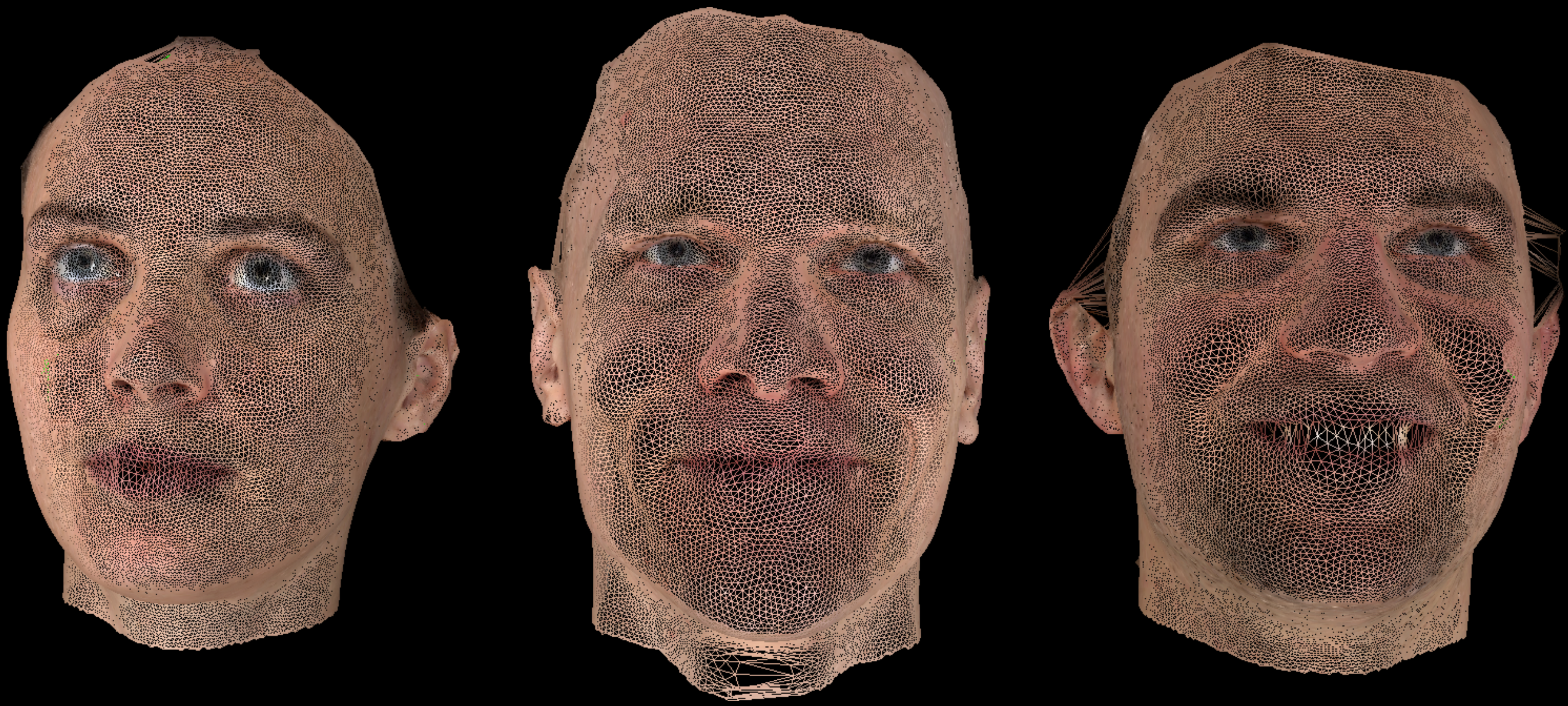
Dense Surface Correspondence



- Template warped to target
- Regularised dense correspondence
- Mean curvature used

Dense correspondence

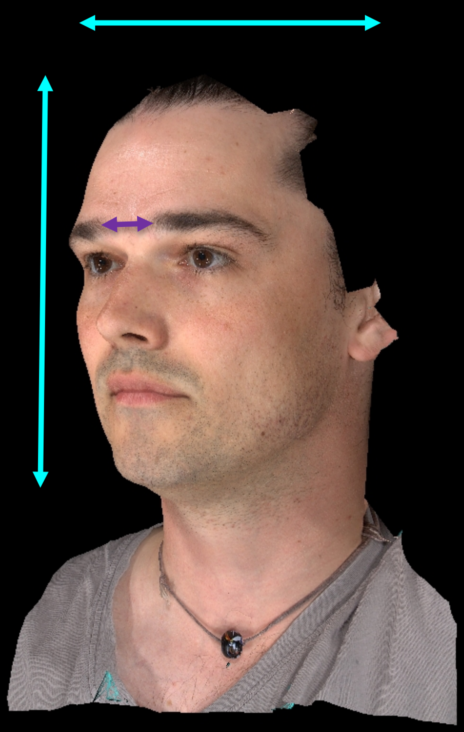
- 40000+ vertices
- Per vertex RGB coloring



Texture correspondence

- Vertex correspondence on the mesh
- Pixel correspondence on the texture map
- Shape and texture analysis

Minor anomalies vs. maximum variation



- PCA explains maximum variation
- We look for minor anomalies
  - Slight asymmetries
- PCA might not be the best choice
  - Future research topic

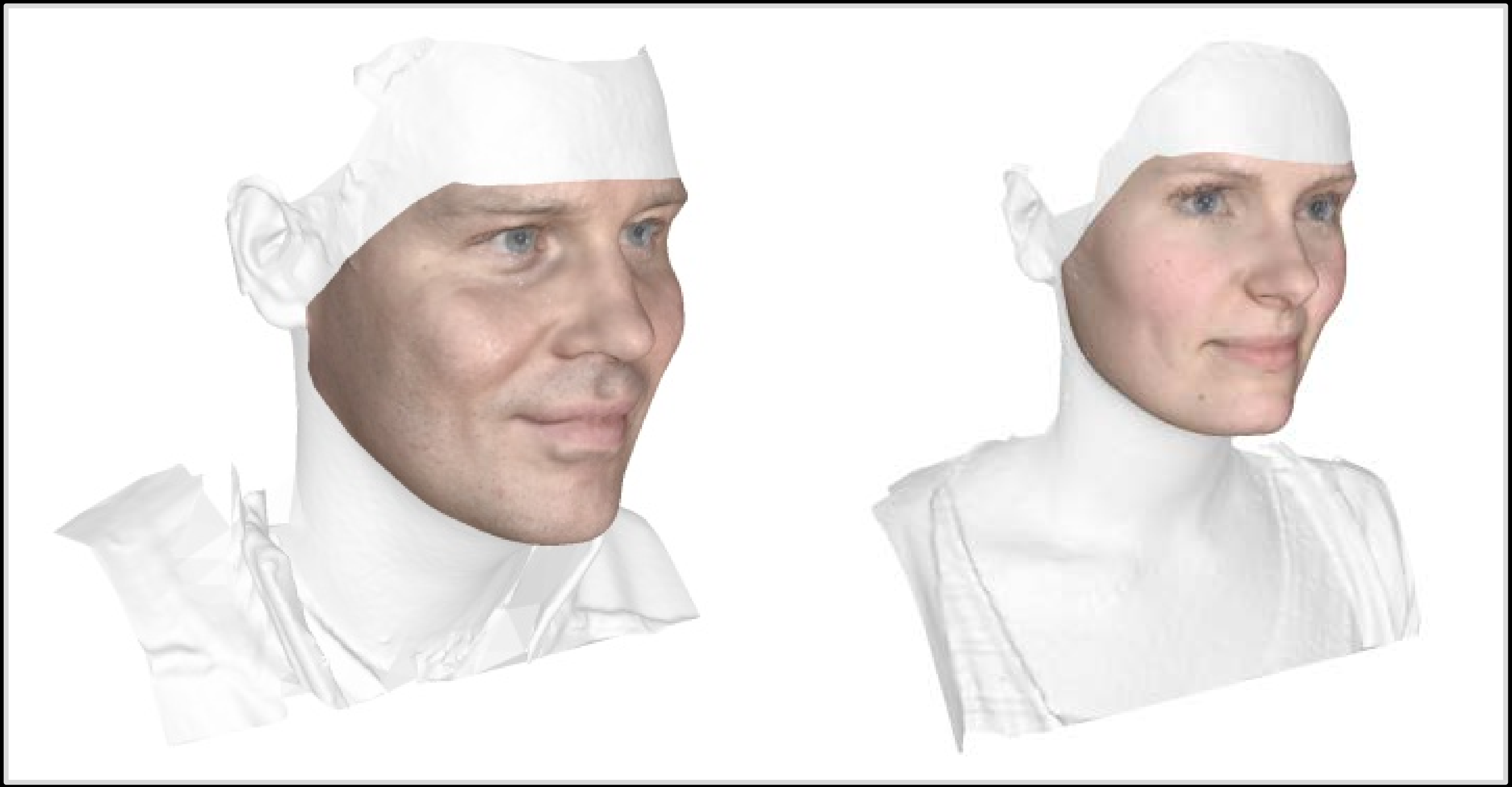
$$\mathbf{x} = [x_1, y_1, z_1, \ldots, x_N, y_N, z_N, R_1, G_1, B_1, \ldots R_M, G_M, B_M]^T$$

3D gender recognition using cognitive modelling

Jens Fagertun, Tobias Andersen, Thomas Hansen and Rasmus Paulsen

- Can we understand how humans perform the task of gender recognition?
- Can we use this information to enhance machine learning models?
- Gender recognition can be solved using cues from many different features like:
  - Hair style, Clothing, Postures and movement patterns, Speech, Body features
  - Facial features, Beard, Makeup

Data



720 3D facial scans cropped to only show the face, excluding neck, ears and hair.

Understanding Gender

- A gender strength variable is defined on the interval [0, 1]
- A cognitive test was devised to estimate the gender strength of each sample (facial scan).
- The gender strength variable is estimated as a latent variable encoded by the time it takes each of six participants to perform the gender classification task

Understanding Gender

- Estimated gender strength used when training our classifier
  - Ill defined facial samples removed

- Employing the gender strength variable to construct a refined (smaller) training set used in the training of LDA and SVM (both in a linear and non-linear version) gave an improvement



Conclusions

- Current research is focused on
  - Acquisition of very high quality surface models of the entire head
- A variety of applications
  - Hearing device virtual product development
  - Biometry and forensics
  - Genetics and facial features
  - Surgery planning and evaluation