3D Face Modelling Under Unconstrained Pose & Illumination

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Agenda

- Problem Overview
- 3D Morphable Model
- Fitting Model to Image
- Model Fitting Example
- Algorithm Performance
- Future Work

Problem Overview

- Automated face recognition performance suffers when conditions for facial image capture are not constrained.
  - FRVT 2002 Evaluation [1]
    - Median rank-1 identification rate 0.19 at 45^{o} left/right rotation
    - Median rank-1 identification rate 0.34 at 30^{o} up/down rotation
  - FRGC Evaluation [2]
    - Median verification rate 0.91 with controlled illumination
    - Median verification rate 0.42 with uncontrolled illumination

Thesis Objective

QUESTION:

Is it possible to accurately predict the appearance of an individual and subsequently generate a frontal and uniformly illuminated view of their face from an image that is unconstrained in pose and illumination?

3D Morphable Model

- Introduced by Blanz & Vetter [3,4]
- What is it?
  - Generative three-dimensional face model that encodes face shape and texture in terms of model parameters.
- How is it useful?
  - Model parameters governing face shape and texture (and thus identity) are separated from image rendering parameters (such as pose and illumination).

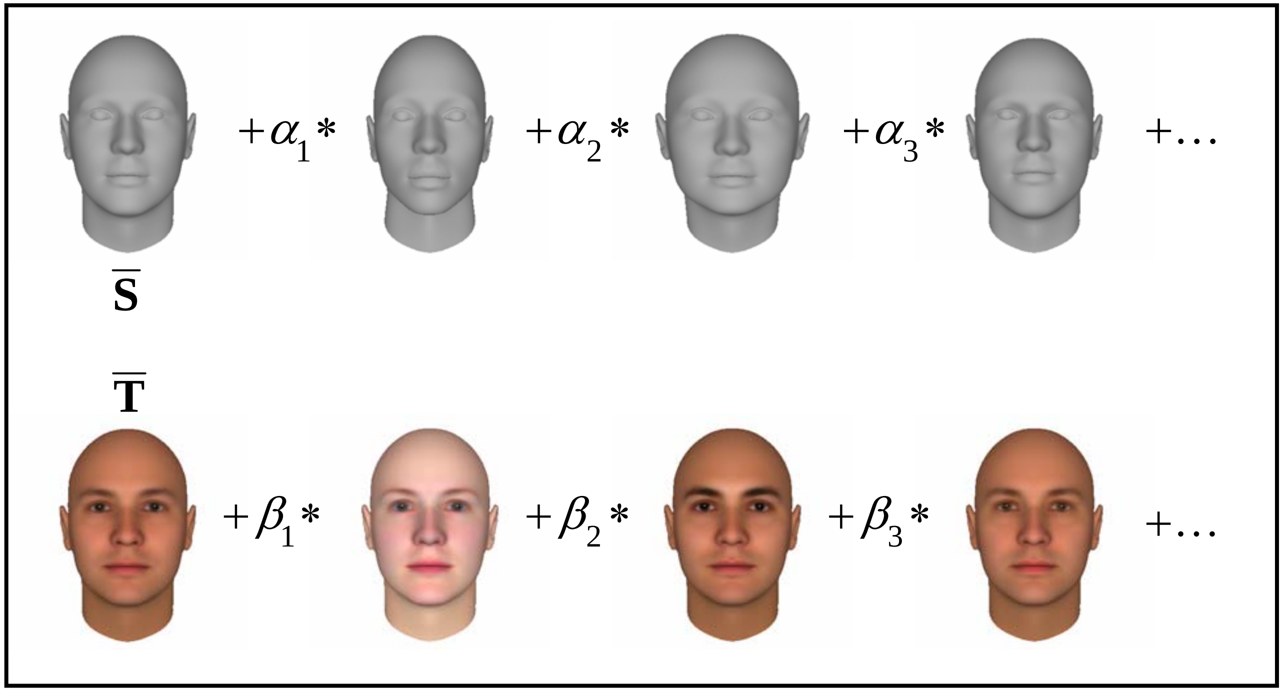
3DMM Details

Shape:

$$S = \bar{S} + \sum_{i=1}^{N_S} \alpha_i s_i$$

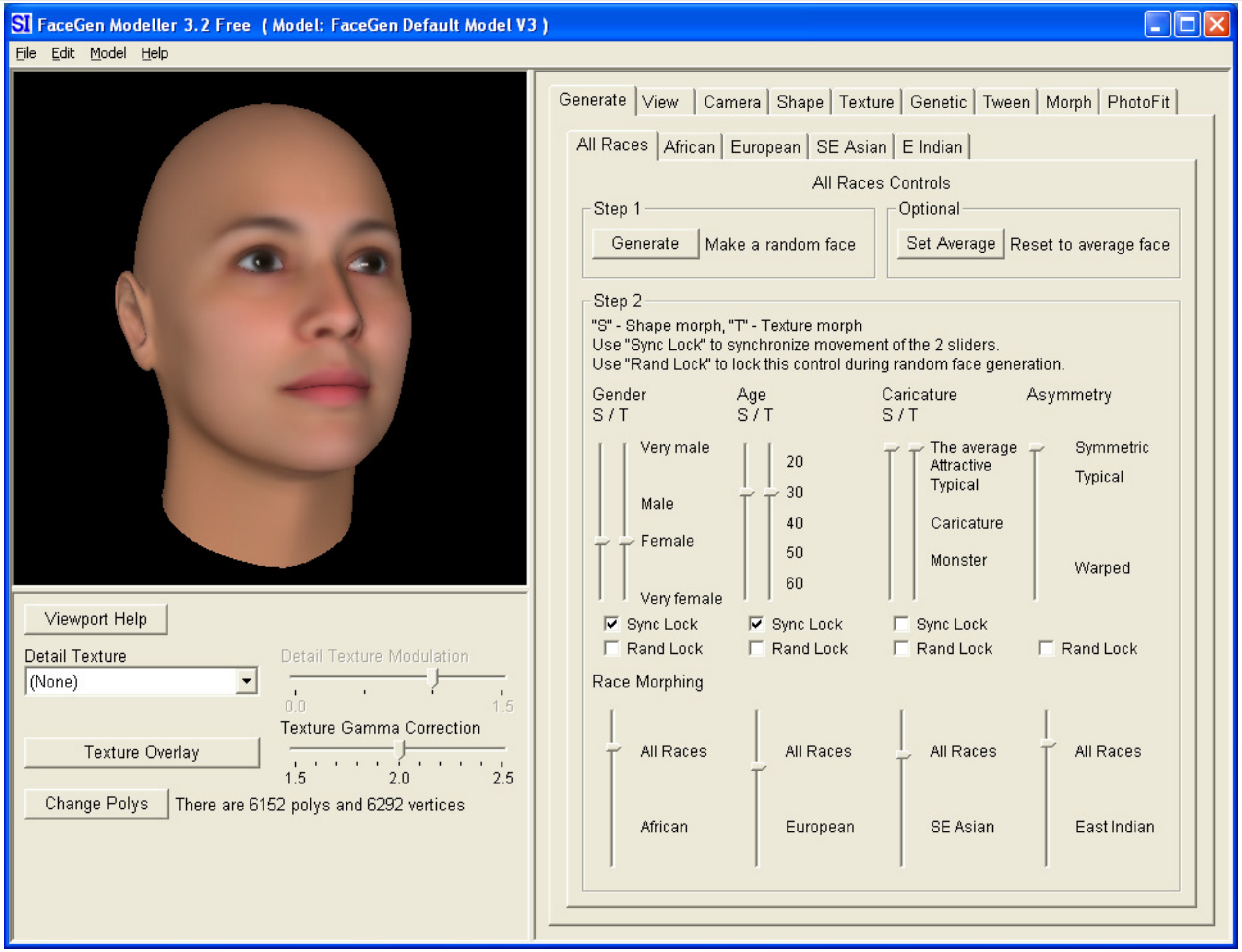
Texture:

$$T = \bar{T} + \sum_{i=1}^{N_T} \beta_i t_i$$

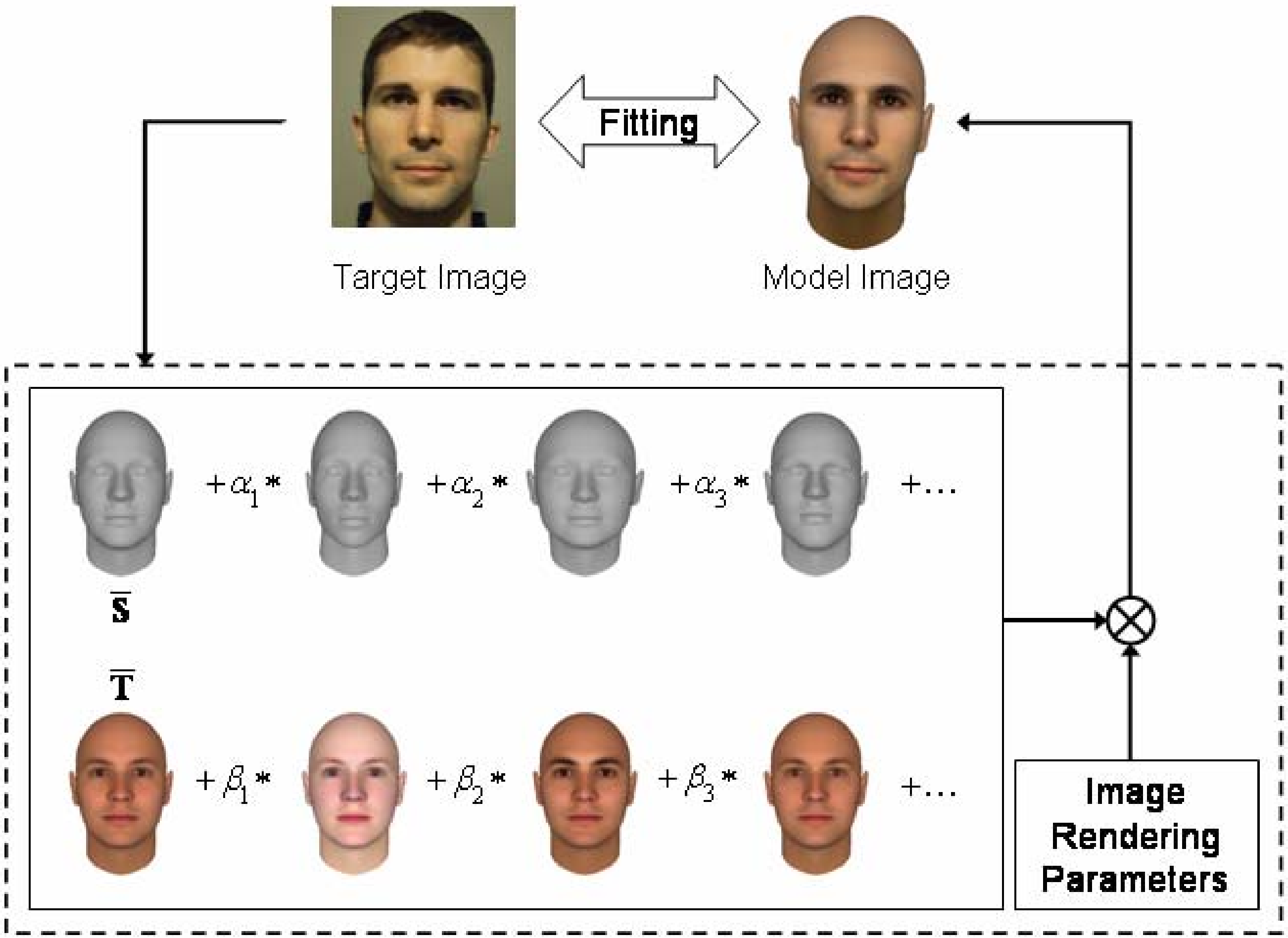


where $\bar{S}$ and $\bar{T}$ are average face shape and texture, α_i, β_i are shape and texture parameters, s_i, t_i are shape and texture principal components, and N_S, N_T are the number of these components.

FaceGen Modeller



Fitting Model to Image



Fitting Model to Image, cont.

- Inversion of the face modelling “function”
  - Non-linear optimization problem
- Define a weighted cost function:

$$C = w_I C_I + w_E C_E + w_P C_P$$

  - C_I measures residual pixel difference
  - C_E measures goodness-of-fit between detected edges
  - C_P measures likelihood of modelled face based on a statistical prior

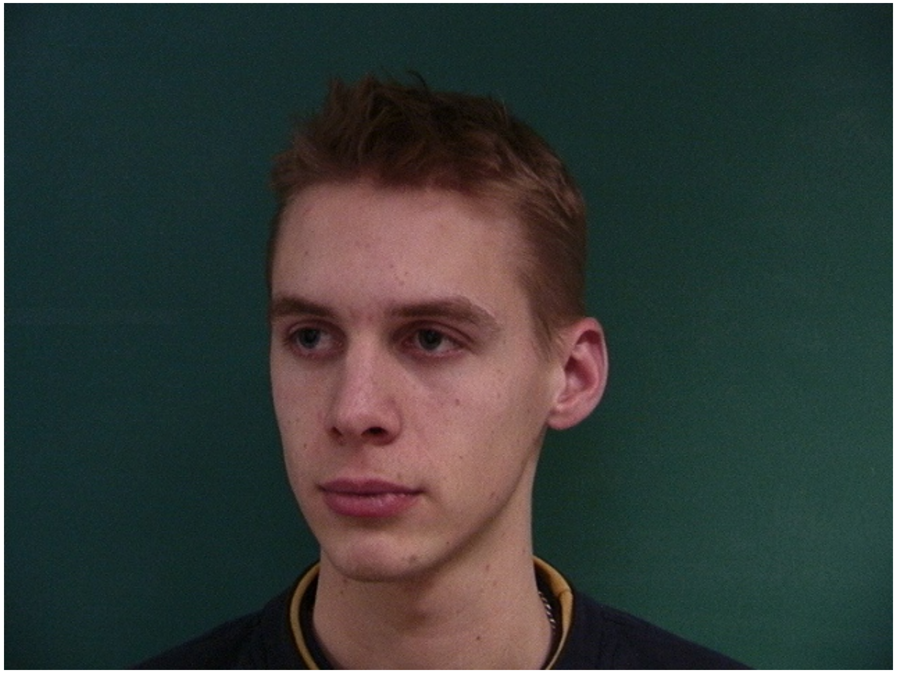
Optimization Strategy

- Levenberg-Marquardt method [5]
- Jacobian matrix populated with partial derivatives
  - Numerically calculated using perturbation method

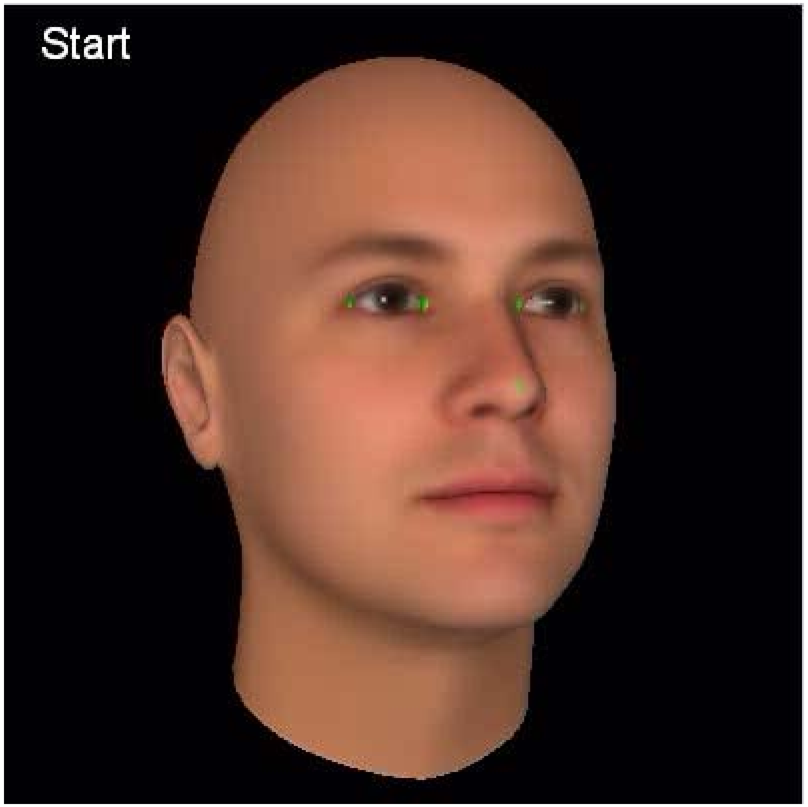
$$J_{ij} = \frac{\partial f_i(p)}{\partial p_j} \approx \frac{\Delta f_i(p)}{\Delta p_j}$$

Model Fitting Example

Target Image



Model



Model Fitting Example, cont.

Target Image

Fitted Model

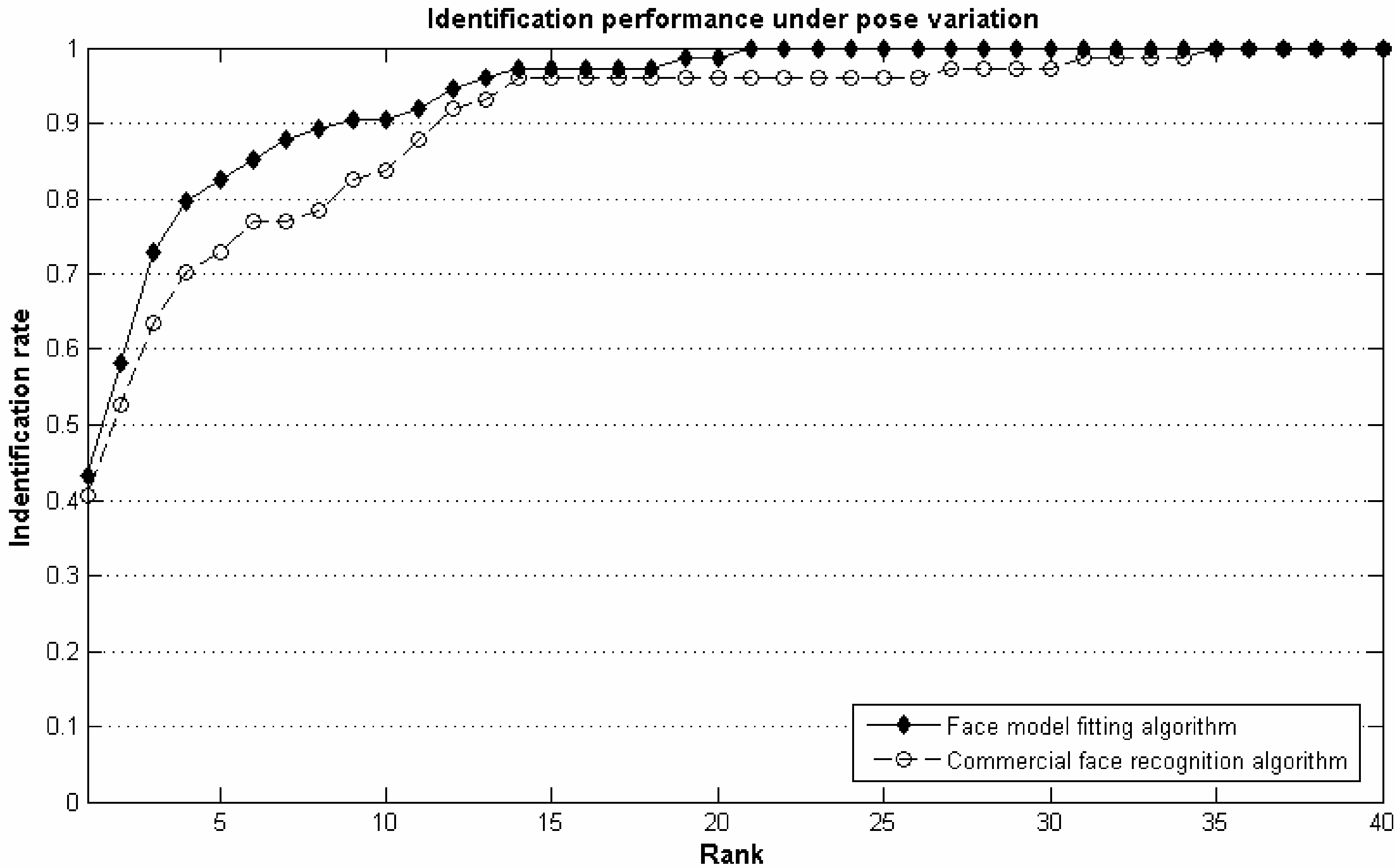
Create Novel View

Ground Truth for Comparison

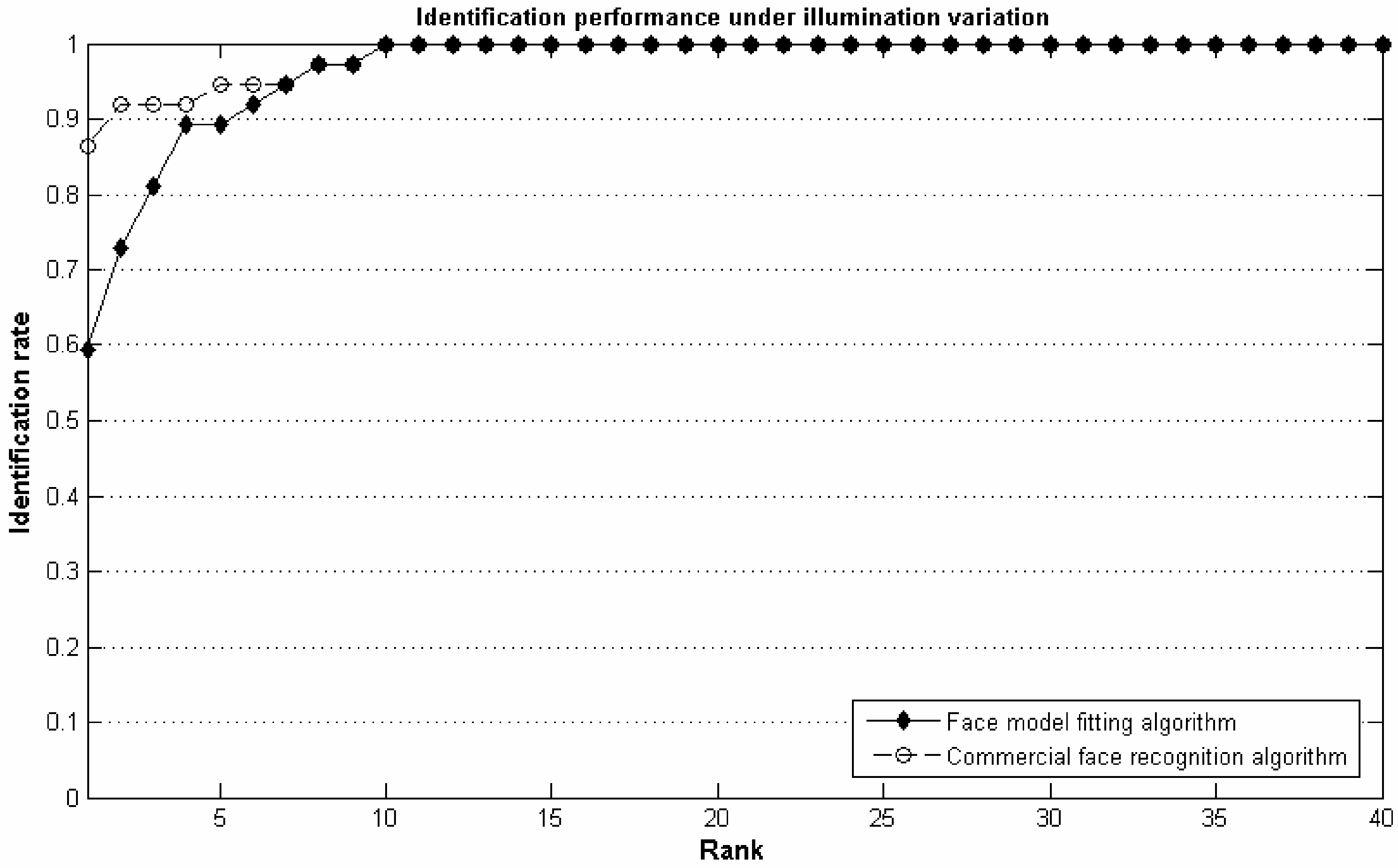
Algorithm Performance

- Results evaluated according to identification task by two distinct methods
  - Direct comparison of model parameters
  - Re-rendering of modelled face under constrained pose and illumination for testing with commercial face recognition system
- Tested on a database of 37 individuals
  - 2 images of each with variation in pose
  - 1 image of each with illumination variation

Identification using Model Parameters – Pose Variation



Identification using Model Parameters – Illumination Variation



Identification using Normalized Images

- Poor results
  - Mean identification rank of 18.5 on a gallery of 40 subjects
- Key limiting factor = Lack of extracted skin detail
  - Even adding skin detail not derived from the original target image can contribute to a significant improvement
  - Face recognition algorithm dependent?

Future Work

- Skin detail texture extraction
- Automatic facial feature detection
- Modelling from multiple images

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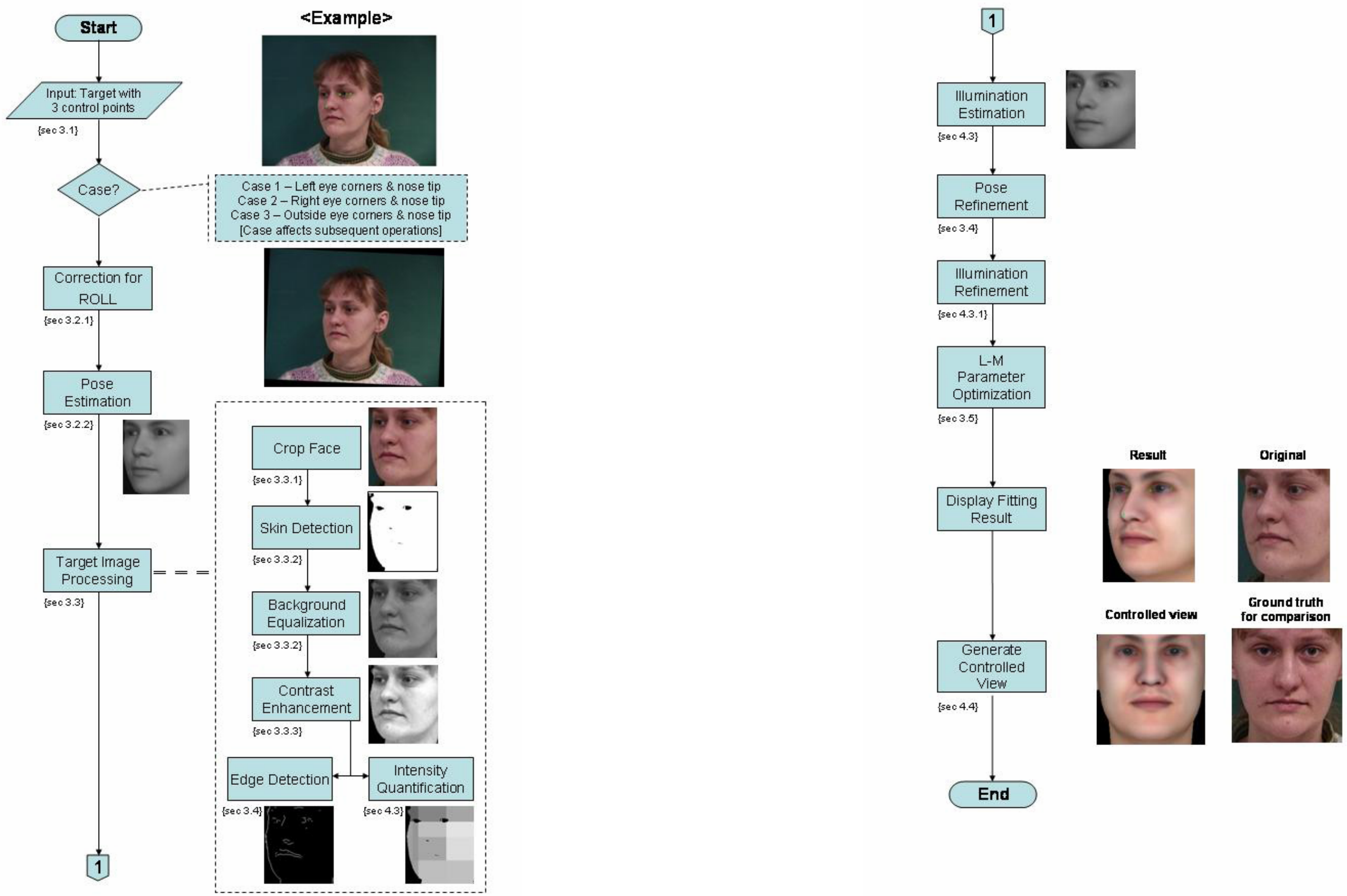
References

1. P.J. Phillips, P. Grother, R.J. Michaels, D.M. Blackburn, E. Tabassi, and M. Bone. *Face Recognition Vendor Test 2002: Evaluation Report*, Mar 2003. http://www.frvt.org/FRVT2002/documents.htm.
2. P.J. Phillips, P.J. Flynn, T. Scruggs, K.W. Bowyer, and W. Worek. Preliminary Face Recognition Grand Challenge results. In *Proceedings, FGR 2006— International Conference on Automatic Face and Gesture Recognition*, pages 15–24. IEEE Computer Society, Apr 2006.
3. Volker Blanz and Thomas Vetter. A morphable model for the synthesis of 3D faces. In *Proceedings, 26th Annual Conference on Computer Graphics and Interactive Techniques (SIGGRAPH 99)*, pages 187–194, Aug 1999.
4. Volker Blanz and Thomas Vetter. Face identification across different poses and illuminations with a 3D morphable model. In *Proceedings, International Conference on Automatic Face and Gesture Recognition*, pages 192–197. IEEE, May 2002.
5. Donald W. Marquardt. An algorithm for least-squares estimation of nonlinear parameters. *SIAM Journal on Applied Mathematics*, 11(2):431–441, 1963.

Algorithm Block Diagram



Levenberg-Marquardt Algorithm

Set: $k := 0, \nu := 2, \mathbf{p} := \mathbf{p}_0$
Given: tol_1, tol_2 (tolerances); k_{max} (maximum iterations); τ
Algorithm:
$\mathbf{A} := \mathbf{J}^\mathsf{T}\mathbf{J}$; $\epsilon_\mathbf{p} := \mathbf{x} - f(\mathbf{p})$; $\mathbf{g} := \mathbf{J}^\mathsf{T}\epsilon_\mathbf{p}$;
$\mu := \tau * \max_{i=1,\ldots,m}(A_{ii})$;
while $(\|\mathbf{g}\|_\infty \geq tol_1 \quad \& \quad (k < k_{max})$
    $k := k + 1$;
    $\boxed{\text{Solve } (\mathbf{A} + \mu\mathbf{I})\delta_\mathbf{p} = \mathbf{g};}$
    if $(\|\delta_\mathbf{p}\| \leq tol_2\|\mathbf{p}\|)$
        break
    else
        $\mathbf{p}_{new} := \mathbf{p} + \delta_\mathbf{p}$;
        $\rho := \frac{\|\epsilon_\mathbf{p}\|^2 - \|\mathbf{x} - f(\mathbf{p}_{new})\|^2}{\delta_\mathbf{p}^\mathsf{T}(\mu\delta_\mathbf{p} + \mathbf{g})}$;
        if $\rho > 0$ [step improves solution]
            $\mathbf{p} = \mathbf{p}_{new}$;
            $\mathbf{A} := \mathbf{J}^\mathsf{T}\mathbf{J}$;
            $\epsilon_\mathbf{p} := \mathbf{x} - f(\mathbf{p})$;
            $\mathbf{g} := \mathbf{J}^\mathsf{T}\epsilon_\mathbf{p}$;
            $\mu := \mu * \max(\frac{1}{3}, 1 - (2\rho - 1)^3)$; $\nu = 2$;
        else
            $\mu := \mu * \nu$; $\nu := 2 * \nu$;
        endif
    endif
endwhile
$\mathbf{p}^* := \mathbf{p}$;

Sample Results