Face recognition with wave kernel signatures using a depth camera

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Introduction - Problem Definition

Face Recognition:

- identify a given face
- using a database of previously trained faces

Introduction - Motivation

Applications of Face Recognition:

- access control
- surveillance
- identification

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Figure: Example of identification: easy tagging in iPhoto

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- independent of illumination variations
- higher security
- additional information
- possibly higher recognition rates

Disadvantages:

- more sensitive to facial expression variations
- not available in many day-to-day situations

Introduction - Topics of this Talk

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Approach:

- data acquirement
- face detection
- face normalization
- face recognition

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  - determination of points of interest
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Challenges:

- expression variations
- pose variations
- occlusions

Overview of the Approach

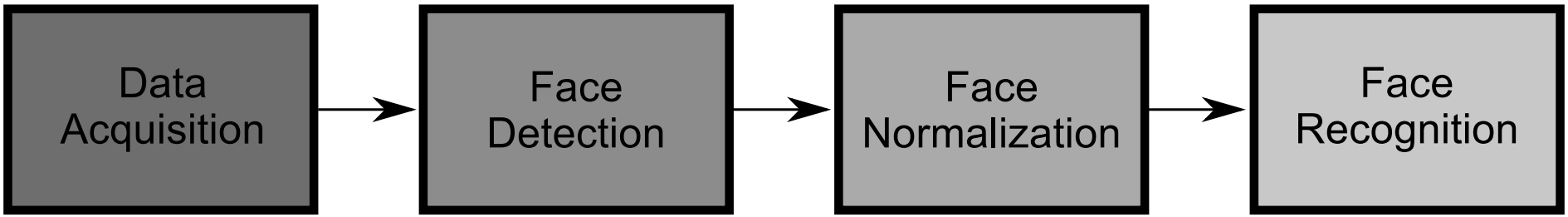
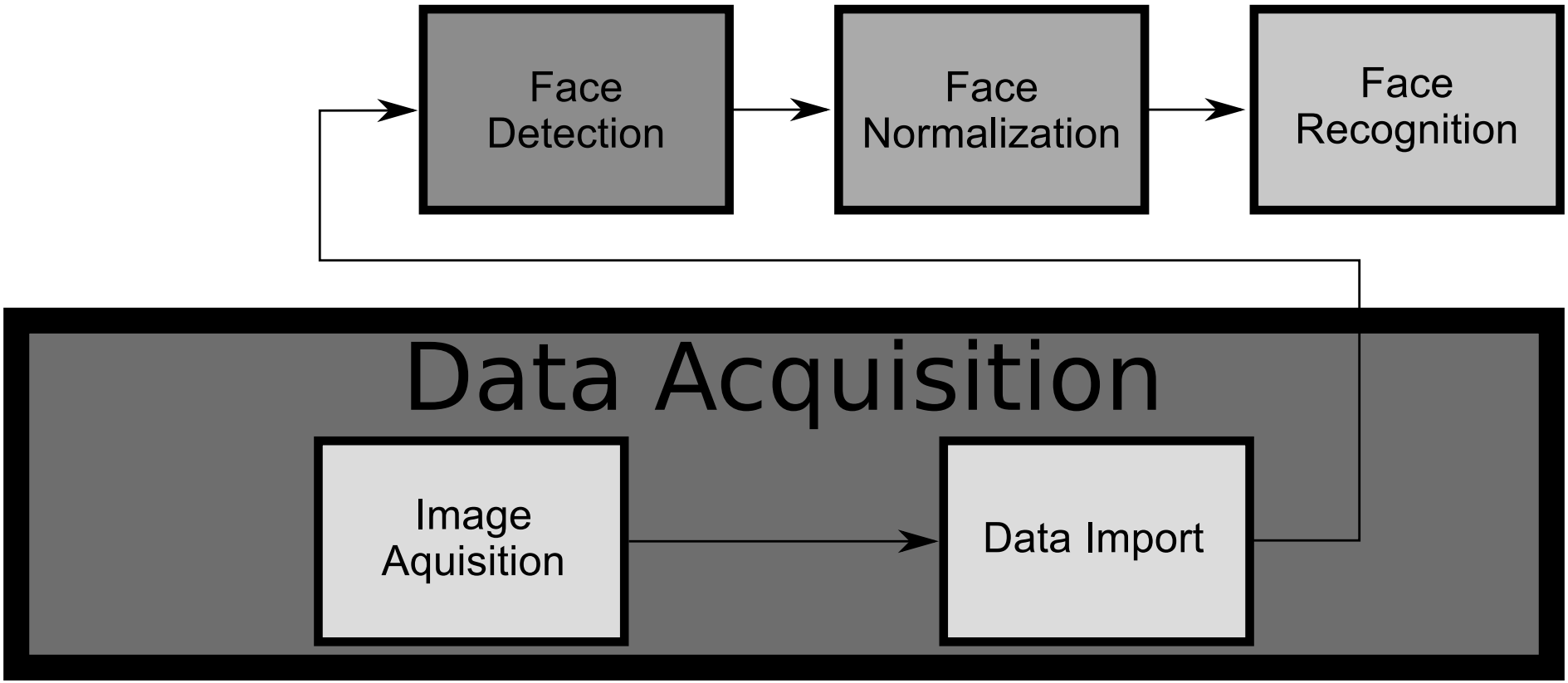


Figure: Data flow of our recognition approach

Data Acquisition - Overview



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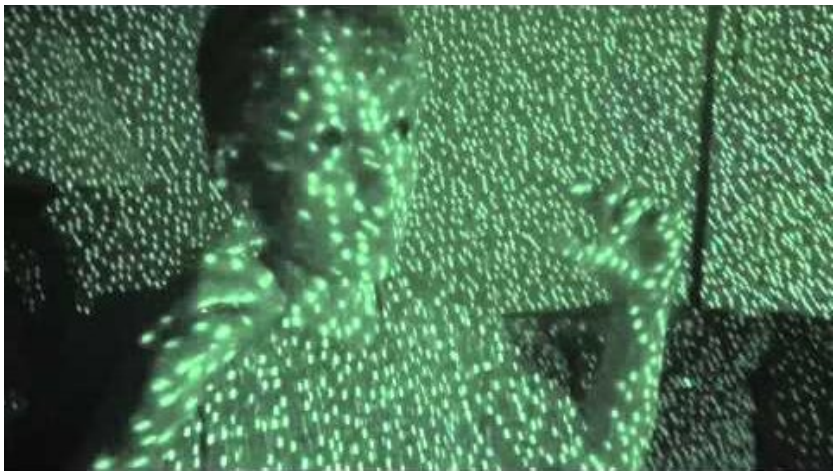

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- array of width w and height h
- each array element is a point in $\mathbb{R}^3$

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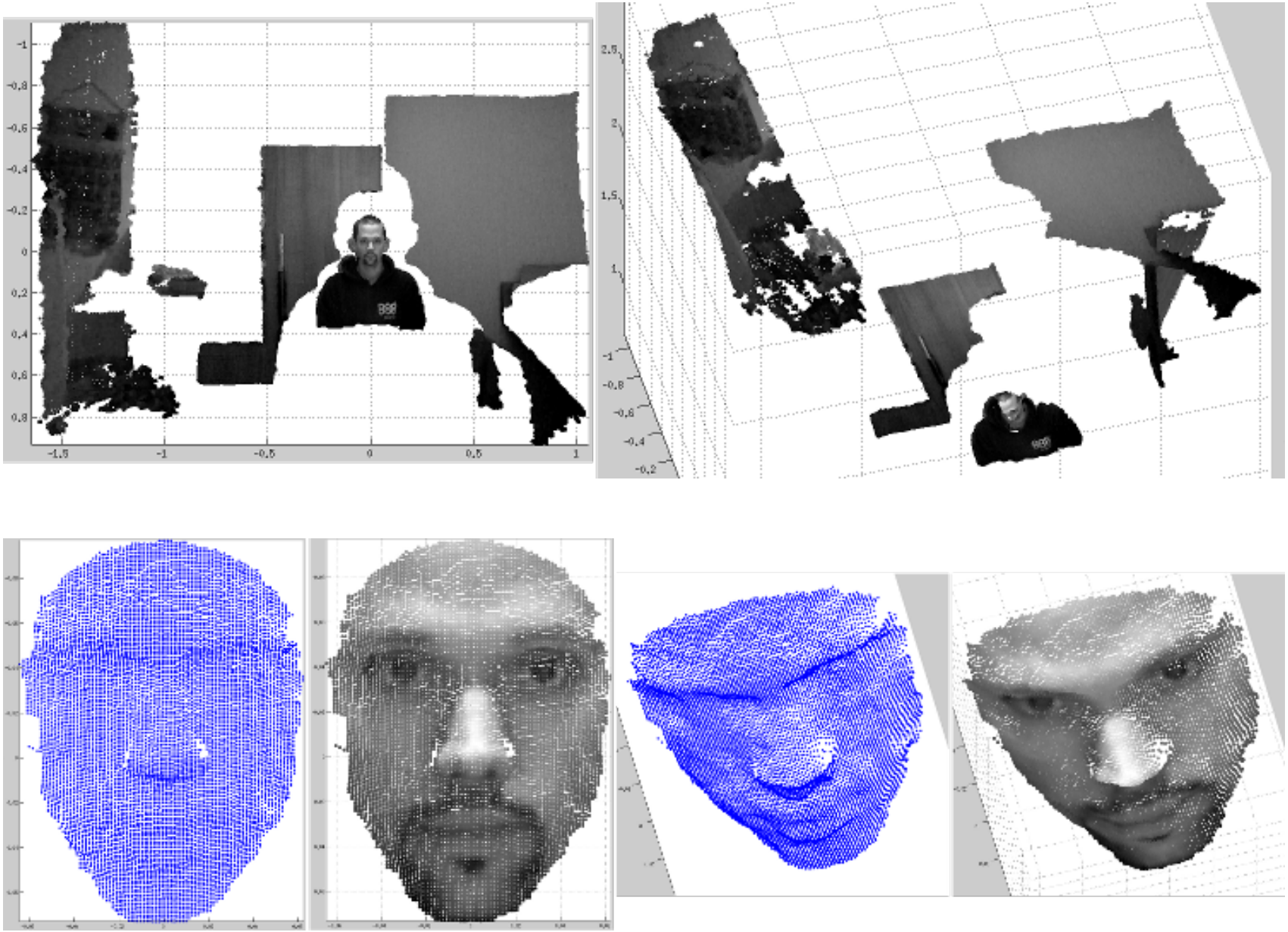
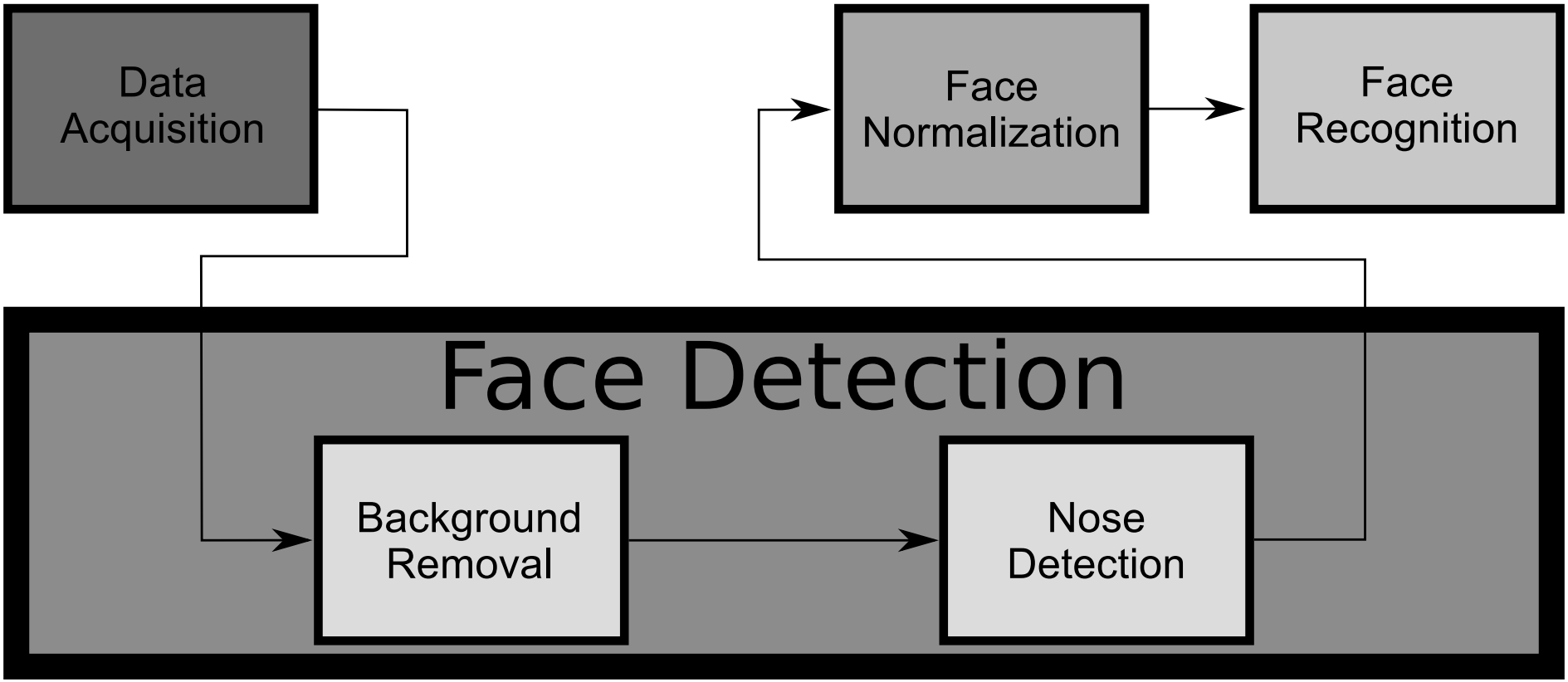
$$\Rightarrow \quad \mathcal{I}_P \in \left(\mathbb{R}^3 \cup (\perp \perp \perp)^T\right)^{w \times h}$$

Point Images - Examples



Face Detection - Overview



Face Detection - Background Removal

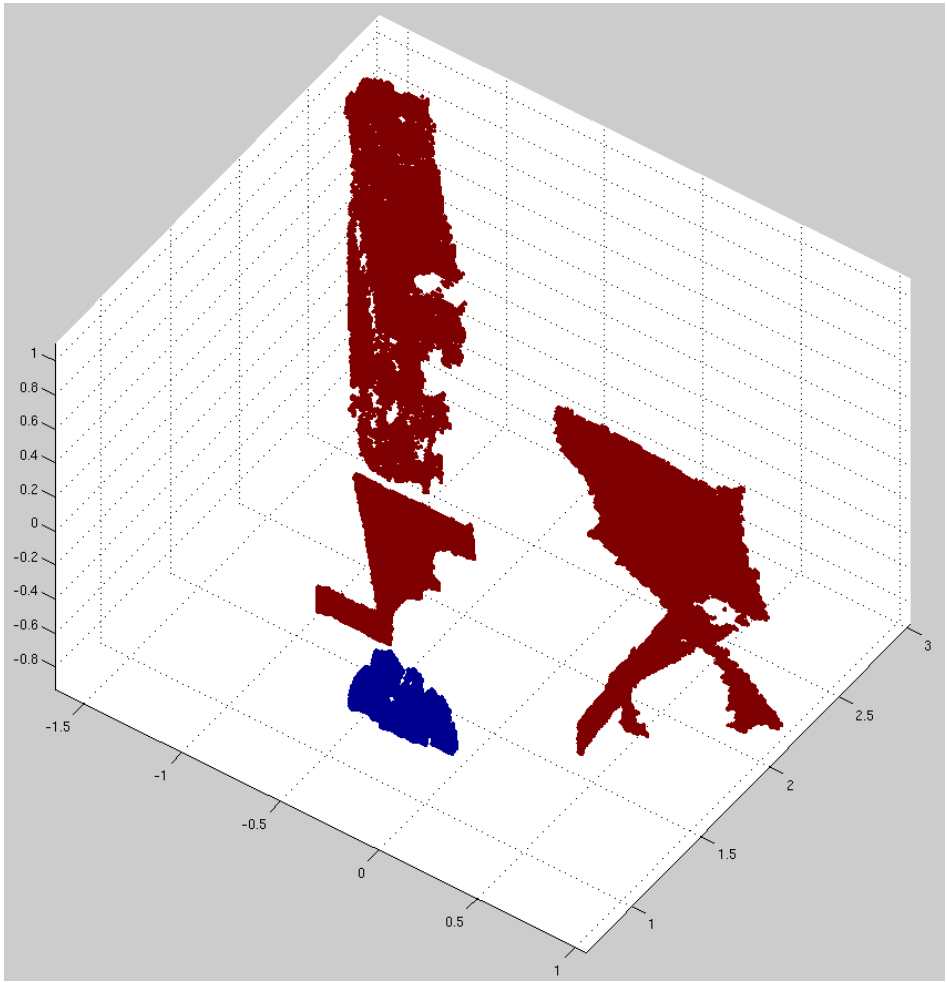


Figure: Segmented torso

Face Detection - Nose Detection

Nose Detection:

1. nose tip candiates: locally convex
2. inner eye corner candidates: locally concave

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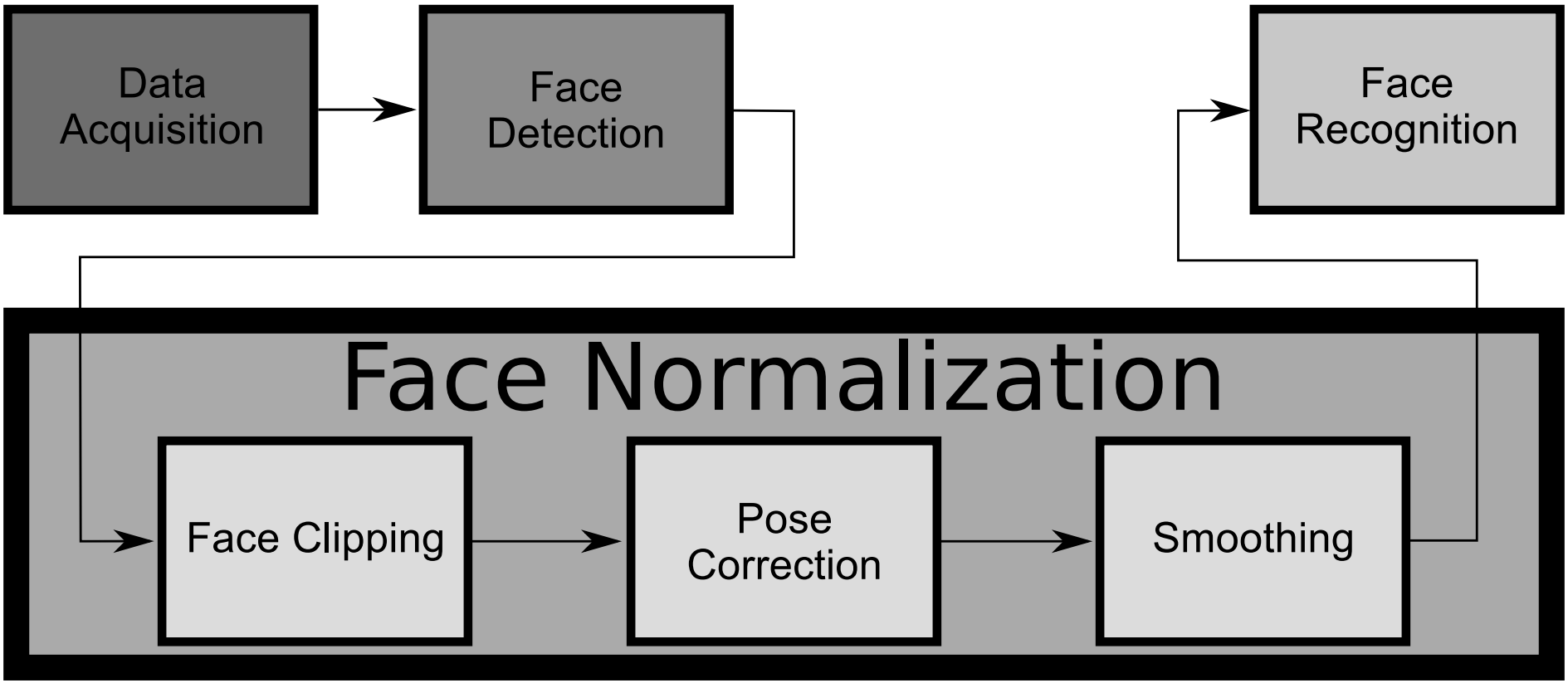
3. geometric candidate filtering scheme
4. verification of remaining candidates using a model face
5. choose nose tip candidate with least error
6. unless it exceeds a threshold

Face Normalization - Overview



Face Normalization

Face Clipping:

- clip all points farther from the nose tip than a threshold

Pose Correction:

Smoothing:

Face Normalization

Face Clipping:

Pose Correction:

- translate nose tip to a defined position
- determine pose using the nose tip and the inner eye corners
- rotate the face into a defined configuration

Smoothing:

Face Normalization

Face Clipping:

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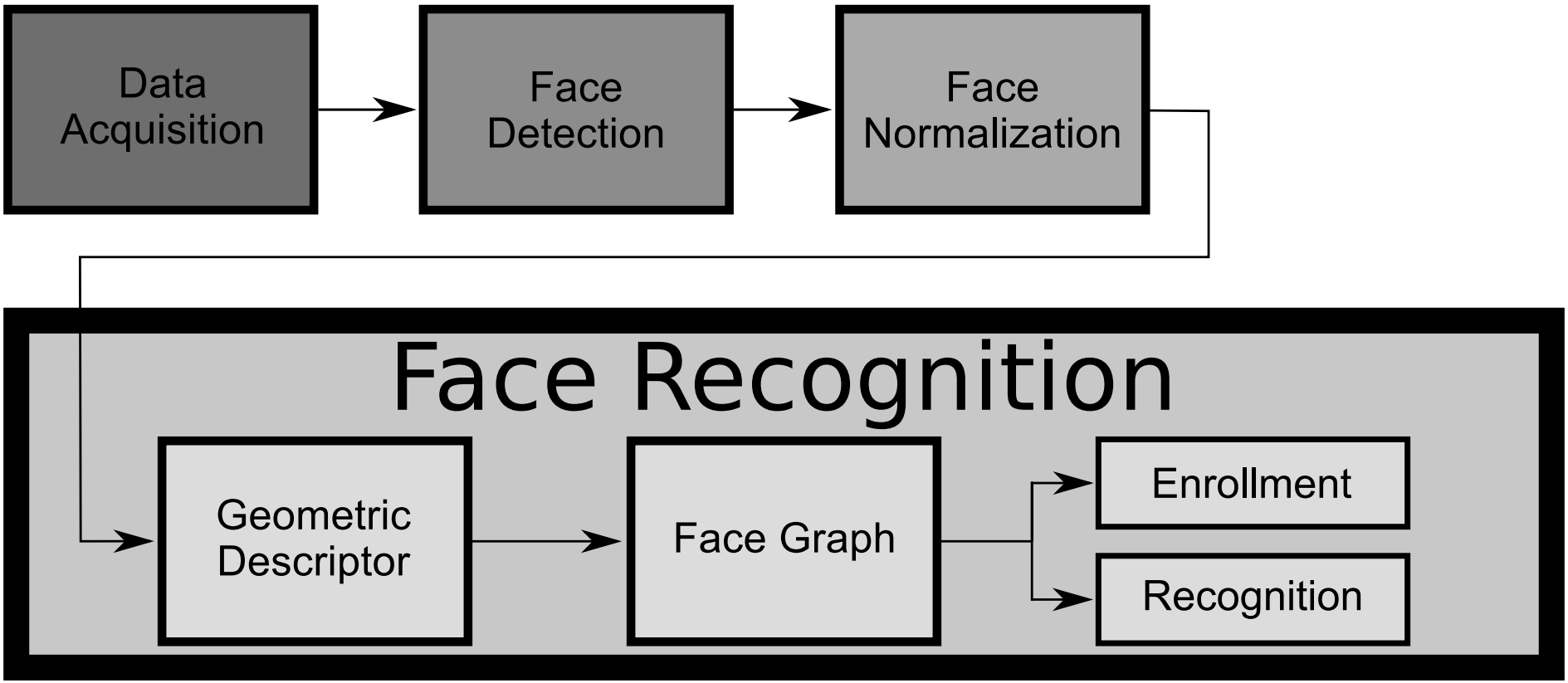
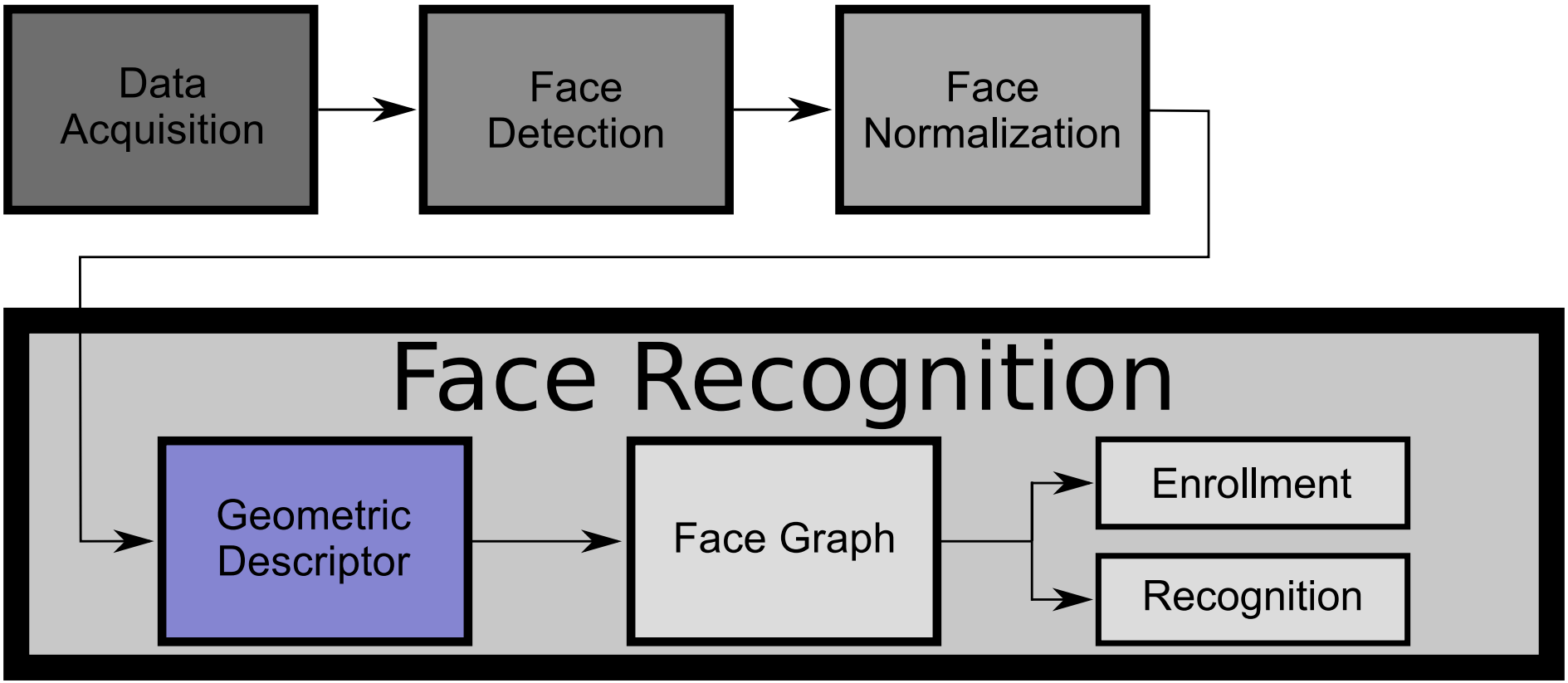
Smoothing:

- apply a Binomial filter to smoothen the depth values

Face Recognition - Overview



Face Recognition - Geometry Descriptor



Wave Kernel Signature - Derivation

Basic idea:

- quantum particle on a surface $\mathcal{X}$
- location is unknown
- approximate energy E is measured at time $t = 0$

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$$\Rightarrow \text{energy probability distribution } f_E^2(x, t)$$

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Wave function:

- solution to the Schrödinger equation $\frac{\partial \psi}{\partial t}(x, t) = i\Delta\psi(x, t)$, where Δ is the Laplace-Beltrami operator of surface $\mathcal{X}$

Wave Kernel Signature - Derivation

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Using them the wave function can be given as:

$$\psi_E(x,t) = \sum_{k=0}^{\infty} \exp(iE_k t)\,\phi_k(x)\,f_E(E_k)$$

Wave Kernel Signature - Definition

The WKS is introduced as:

$$\mathrm{WKS}(E, x) = \lim_{T \to \infty} \frac{1}{T} \int_0^T |\psi_E(x, t)|^2 \, dt$$

$\mathrm{WKS}(E, x)$ is

- over time average probability
- to measure the quantum particle
- with initial energy E
- at point $x \in \mathcal{X}$ on the surface

Wave Kernel Signature - Definition

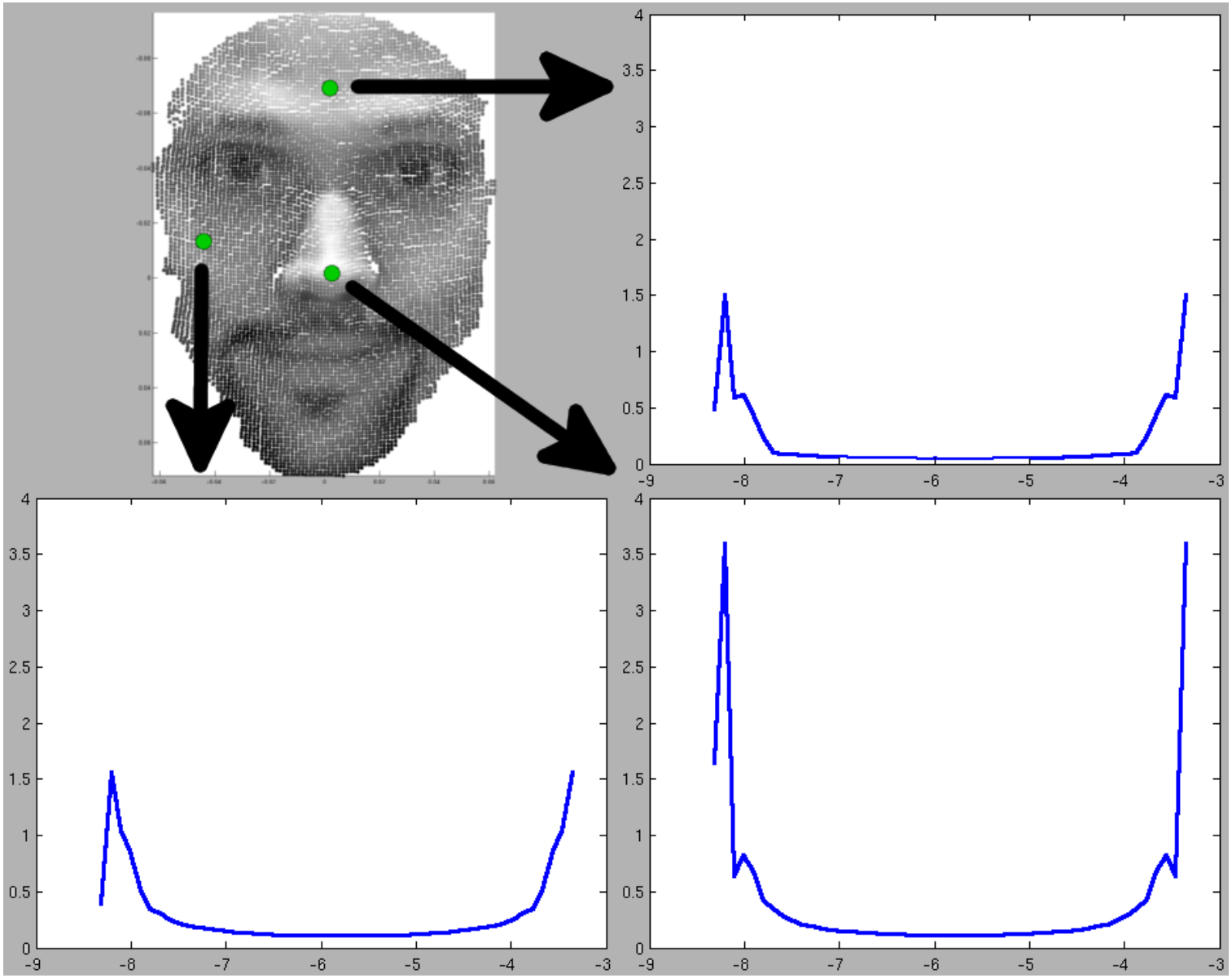
Definition (Wave Kernel Signature)

The WKS for a point $x \in \mathcal{X}$ and initial energy E is given as

$$\mathrm{WKS}(E, x) := \sum_{k=0}^{\infty} \phi_k(x)^2 \, f_E(E_k)^2$$

where f_E is the energy probability distribution for the initial energy E.

Wave Kernel Signature - Example



Wave Kernel Signature - Implementation

Finite approximation L of Laplace-Beltrami operator Δ is needed

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- convert point image into a graph
- use weighted Graph Laplacian as approximation

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Contra:

- does not converge to Δ for increasingly finer discretizations

Implementation - Conversion into a Graph

1. create a graph vertex for every element of the point image

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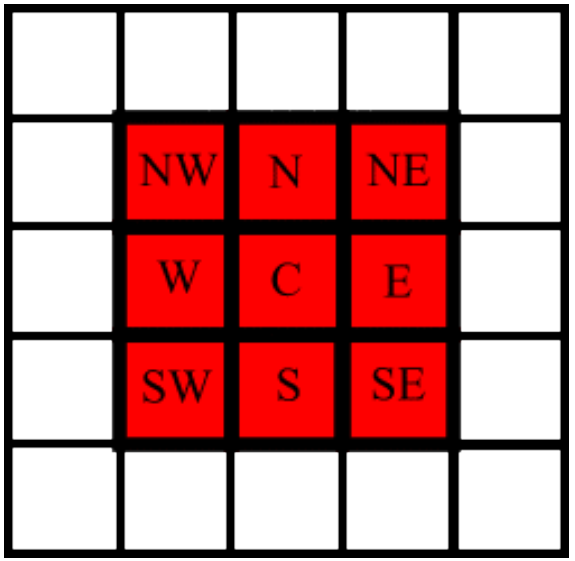
2. add edges between each vertex and the vertices of its 8-connected-neighborhood



Implementation - Conversion into a Graph

1. create a graph vertex for every element of the point image
2. add edges between each vertex and the vertices of its 8-connected-neighborhood
3. add edge weights depending on the vertex distances

$$w_{ij} = \exp\left(-\frac{\|v_i - v_j\|^2}{t}\right)$$

Implementation - Weighted Graph Laplacian

Definition (Adjacency Matrix)

$$A(i,j) = \begin{cases} w_{ij} = \exp\left(-\frac{\|v_i - v_j\|^2}{t}\right), & \text{if } \{v_i, v_j\} \in E \\ 0, & \text{else} \end{cases}$$

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Definition (Degree Matrix)

$$D(i,j) = \begin{cases} \sum_{k=1}^{n} A(i,k), & \text{if } i = j \\ 0, & \text{else} \end{cases}$$

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Definition (Graph Laplacian)

$$L = D - A$$

Laplacian Eigenfunctions

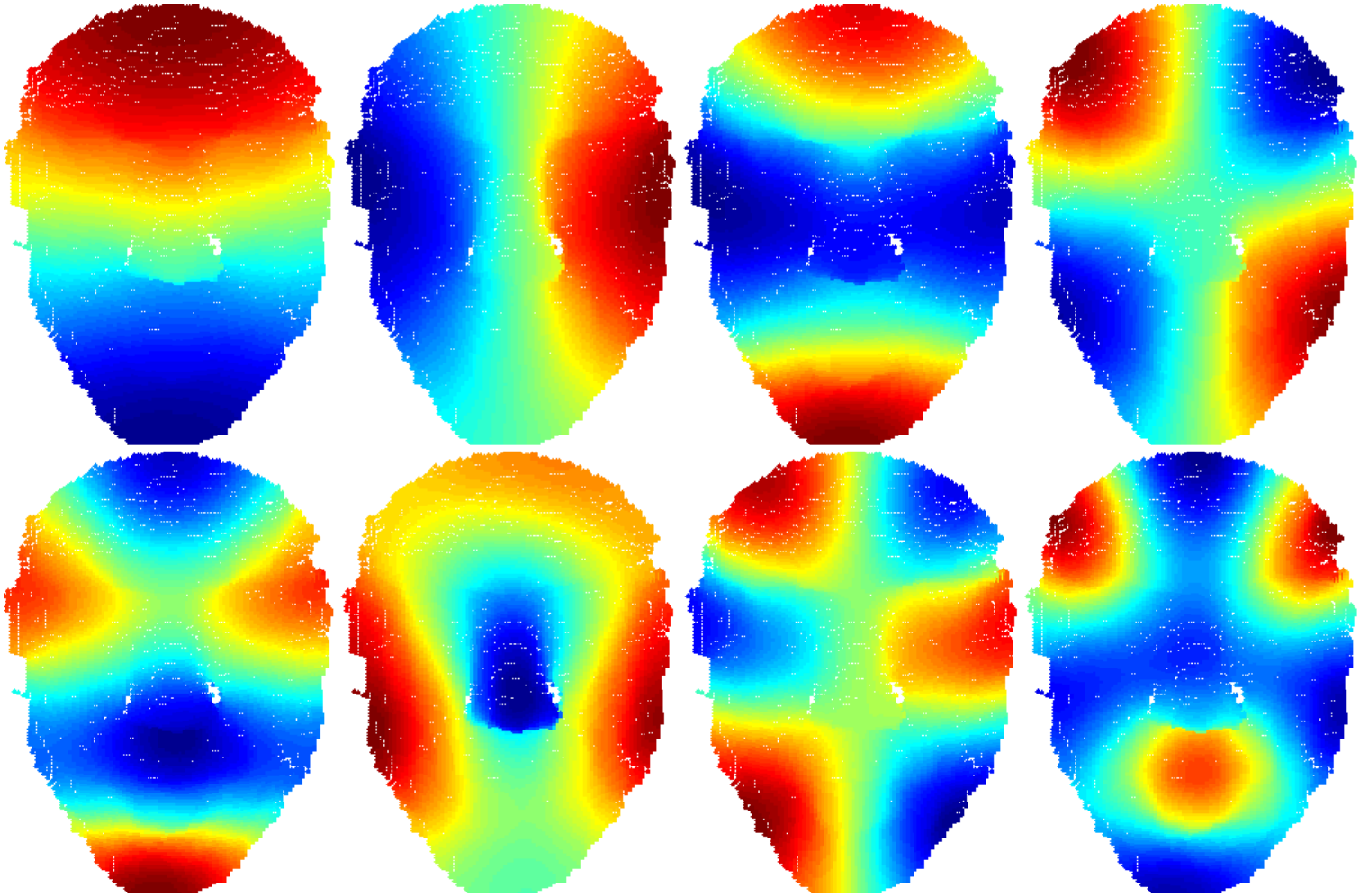


Figure: Corresponding eigenfunctions of the 8 least non-zero eigenenergies

Wave Kernel Signature - Examples

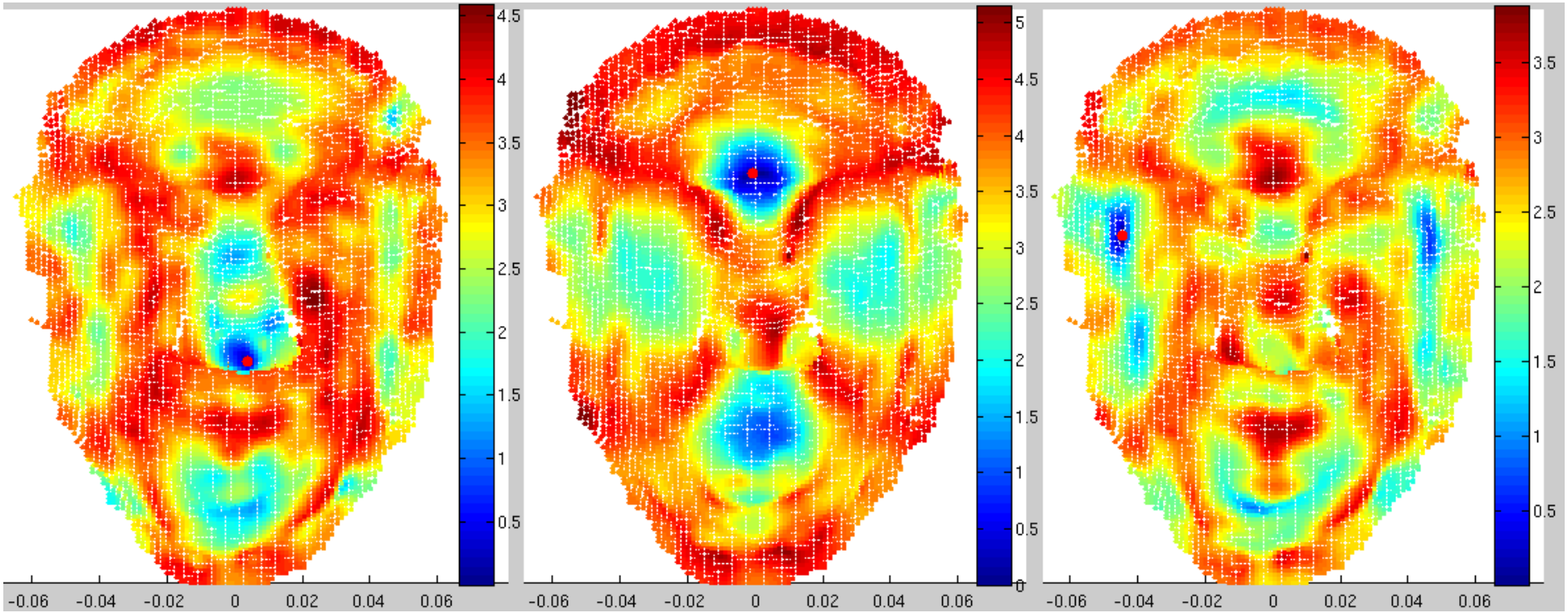
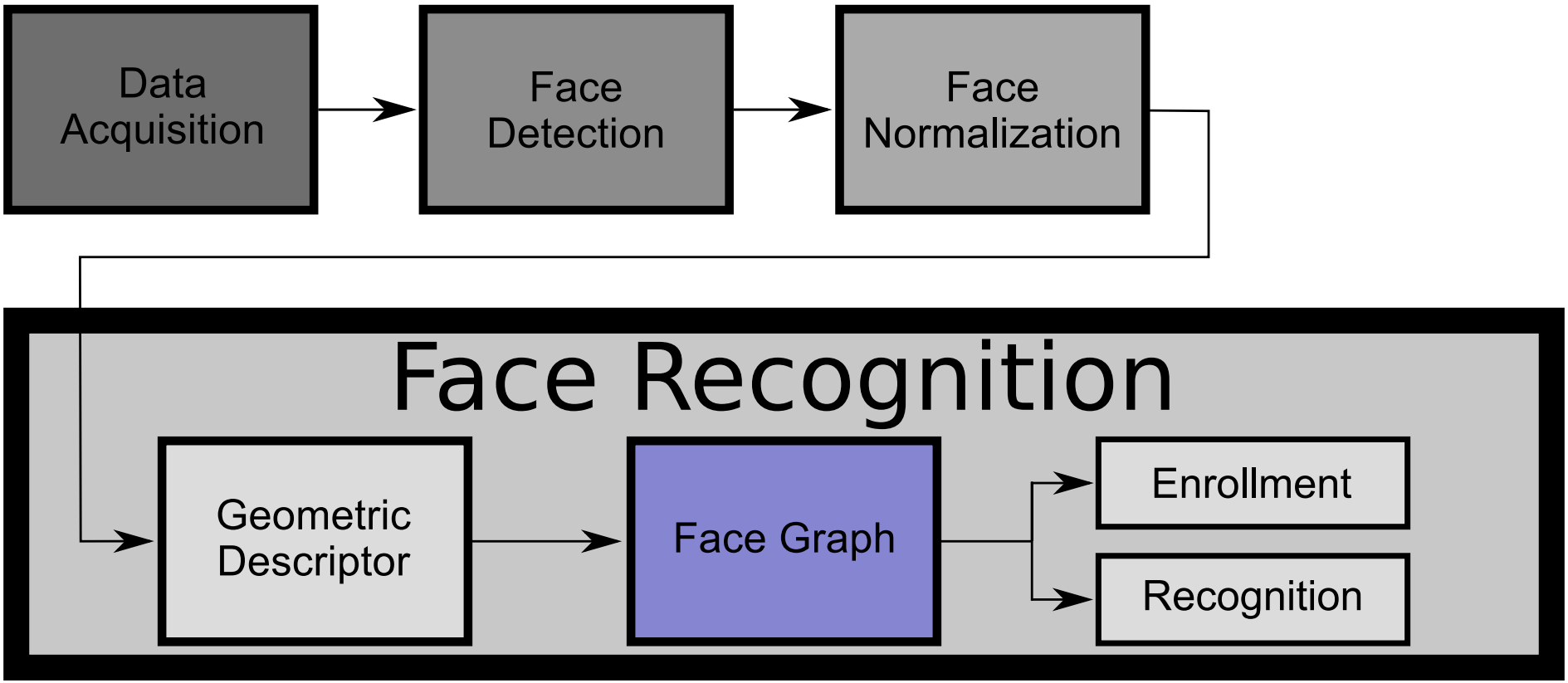
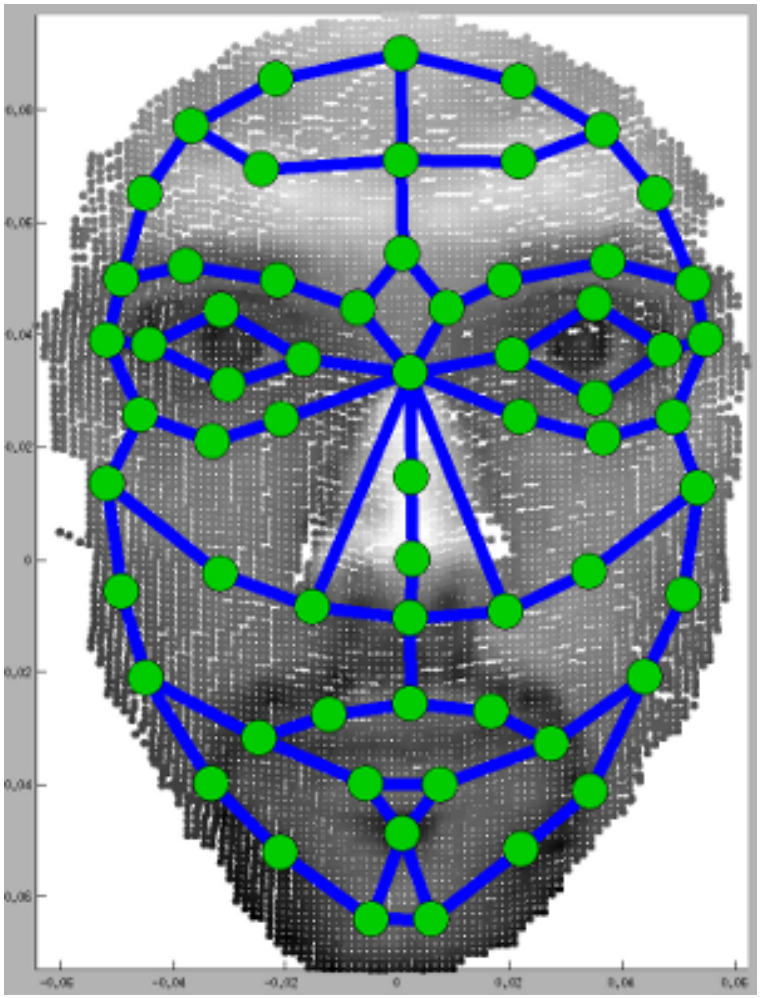


Figure: Signature distance of several points

Face Recognition - Face Graph



Face Graph - Model



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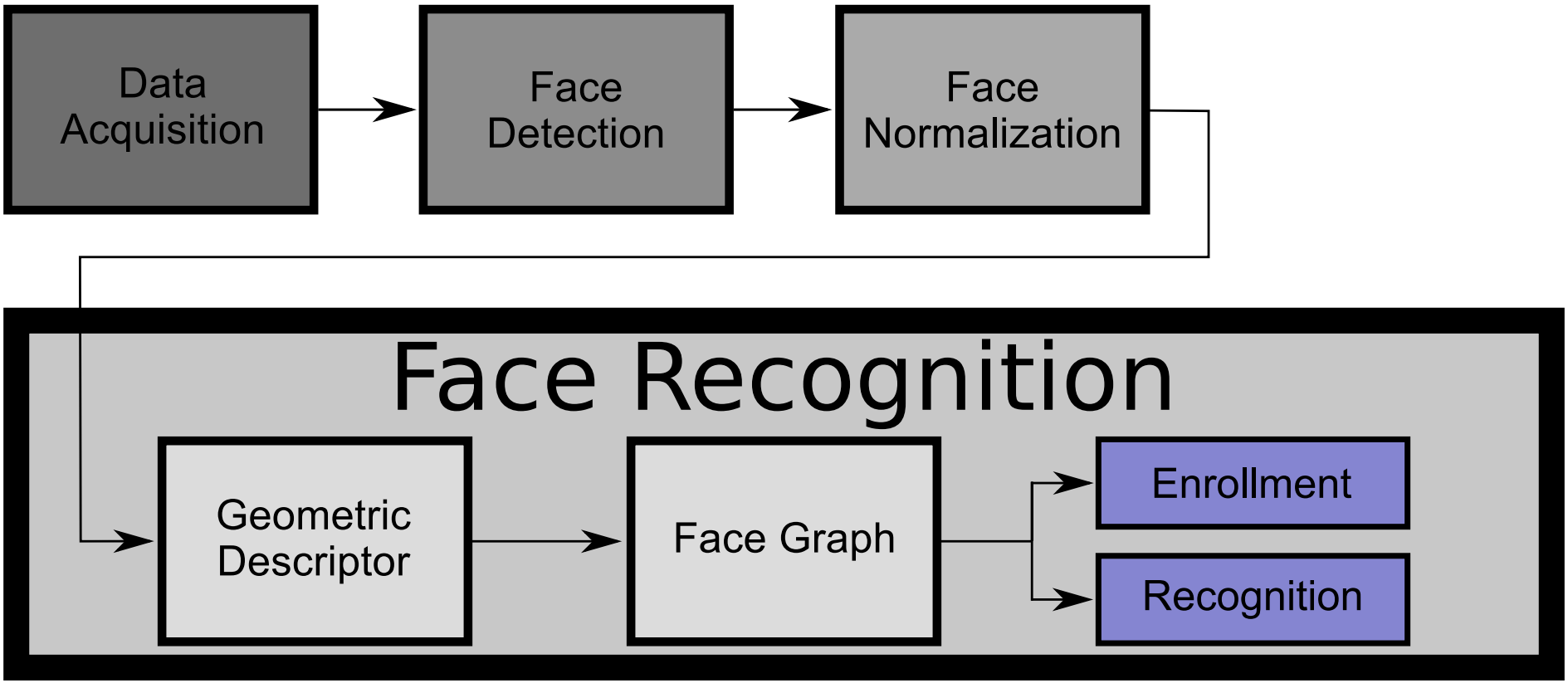
5. manual graph correction

Face Recognition - Enrollment and Recognition



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1. extract the WKS at every graph vertex
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3. recognition: compare the signatures with those in the database

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3. recognition: compare the signatures with those in the database
4. select the entry with the least signature distance

$$d_{\mathrm{WKS}}\left(x, x'\right)^2 = \int_{e_{min}}^{e_{max}} \left(\mathrm{WKS}\left(x, e\right) - \mathrm{WKS}\left(x', e\right)\right)^2 de$$

Face Recognition - Experimental Setup

- we recorded point images of 54 persons, a total of 2061 images
- one image per person used for training
- three images per person used for testing

  $\Rightarrow$ total of 157 recognition runs

Face Recognition - Experimental Results

Rank 1 recognition rate:	94	out of	157	59.9%
Rank 3 recognition rate:	114	out of	157	72.6%
Rank 6 recognition rate:	130	out of	157	82.8%

Table: Overall recognition rates

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Table: Overall recognition rates

Compilation of the graph Laplacian:	2.79	seconds	30.0%
Eigendecomposition of the graph Laplacian:	6.19	seconds	66.6%
Calculation of the WKS:	0.24	seconds	1.0%
Transformation into the SIWKS:	0.15	seconds	1.6%
Recognition:	0.07	seconds	0.8%
Total	*9.29*	*seconds*	

Table: Run-times

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- neutral and non-neutral expressions are recognized with equal rates
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- method is stable under mild occlusions and mild pose variations
- scales very good with database size
  theoretical runtime for 1000 DB entries is 1.4 seconds

Conclusions - Future Work

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Questions?

Thank you for your attention

Any questions?