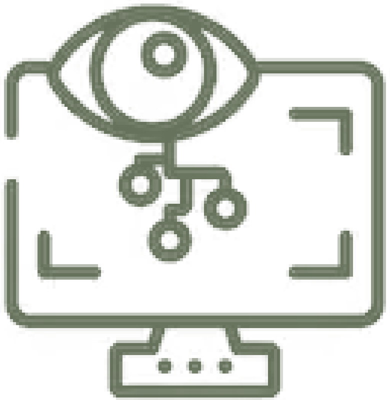


CS 554
Computer Vision

Face Processing

Hamdi Dibeklioğlu

Slide Credits: L. van der Maaten

Introduction

Face processing/analysis comprises a number of different tasks:

- Face detection (*“where is a face?”*)
- Face recognition (*“of whom is this face?”*)
- Face verification (*“are these faces the same?”*)
- Expression recognition (*“is this face happy or not?”*)

Face detection: Viola & Jones

Train a *classifier* to predict whether a bounding box contains a face or not:

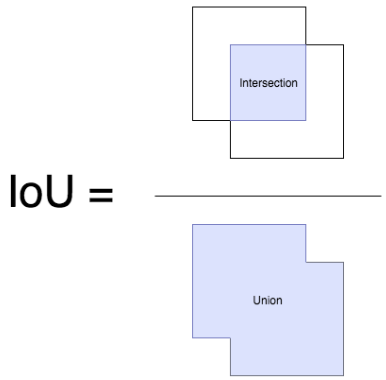
Face detection: Viola & Jones

At test time, use a sliding window detector for multiple scales:

Use *non-maxima suppression* in x-y-scale space to filter classifier predictions

Non-maxima Suppression

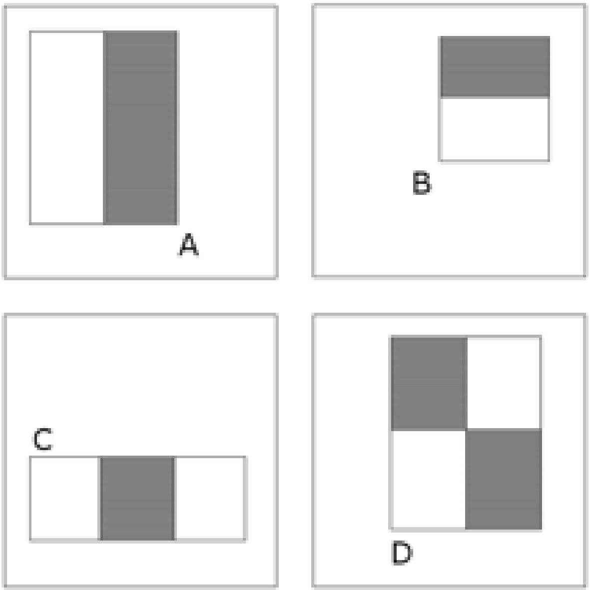
Algorithm:



1. Select the proposal with highest confidence, remove it from B and add it to the final proposal list D. (Initially D is empty).
2. Now compare this proposal with all the proposals (Intersection over Union). If the IOU is greater than the threshold N, remove that proposal from B.
3. Again take the proposal with the highest confidence from the remaining proposals in B and remove it from B and add it to D.
4. Again compute the IOU of this proposal with all the proposals in B and eliminate the boxes which have high IOU than threshold.
5. This process is repeated until there are no more proposals left in B.

Face detection: Viola & Jones

Extract *Haar features* from the image patch, using the *integral image*:



Feature Value =

∑ (pixels in white area) – ∑ (pixels in black area)

We find features that are common in faces, and use these as *weak learners*

Face detection: Viola & Jones

Features can be computed efficiently using the *integral image*:

12	8	2	4	7
2	11	3	6	8
3	2	0	1	10
1	5	2	7	2
0	0	2	3	2

12	20	22	26	33
14	33	38	48	63
17	38	43	54	79
18	44	51	69	96
18	44	53	74	103

Face detection: Viola & Jones

Features can be computed efficiently using the *integral image*:

12	8	2	4	7
2	11	3	6	8
3	2	0	1	10
1	5	2	7	2
0	0	2	3	2

→

12	20	22	26	33
14	33	38	48	63
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Face detection: Viola & Jones

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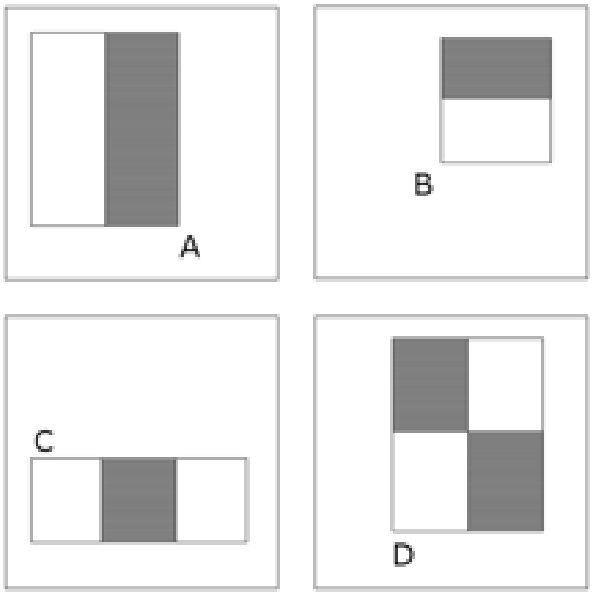
0	0	2	3	2

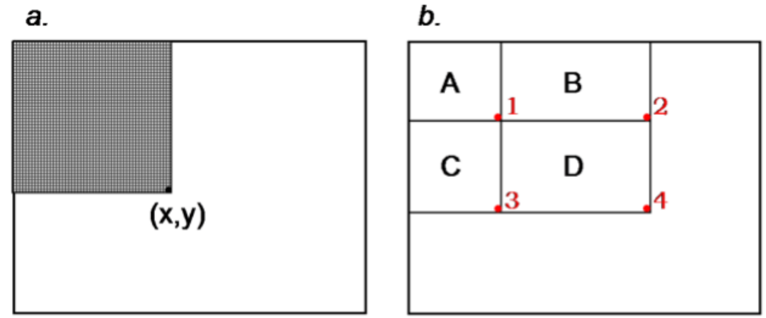
D			B	
12	20	22	26	33
14	33	38	48	63
17	38	43	54	79
18 C	44	51	69 A	96
18	44	53	74	103

A-B-C+D

Face detection: Viola & Jones

Extract *Haar features* from the image patch, using the *integral image*:





We find features that are common in faces, and use these as *weak learners*

Face detection: Viola & Jones

AdaBoost training on annotated data set; learns collection of *weak learners*:

$$h(\mathbf{x}) = \operatorname{sign}\left[\sum_{i=1}^{m} \alpha_i h_i(\mathbf{x})\right]$$

Face detection: Viola & Jones

AdaBoost training on annotated data set; learns collection of *weak learners*:

$$h(\mathbf{x}) = \text{sign}\left[\sum_{i=1}^{m} \alpha_i h_i(\mathbf{x})\right]$$

In Viola & Jones, the weak learners are *decision stumps*:

$$h_i(\mathbf{x}) = [f_i \geq \theta_i]$$

Face detection: Viola & Jones

AdaBoost training on annotated data set; learns collection of *weak learners*:

$$h(\mathbf{x}) = \text{sign}\left[\sum_{i=1}^{m} \alpha_i h_i(\mathbf{x})\right]$$

In Viola & Jones, the weak learners are *decision stumps*:

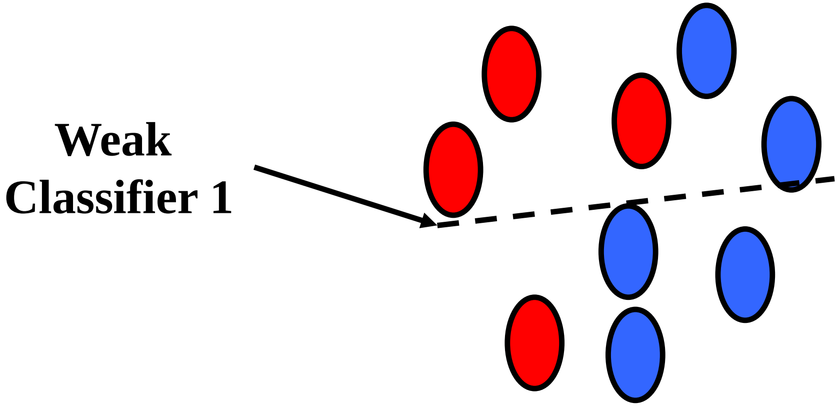
$$h_i(\mathbf{x}) = [f_i \geq \theta_i]$$

Iteratively select the learner that minimizes the *weighted* classification error:

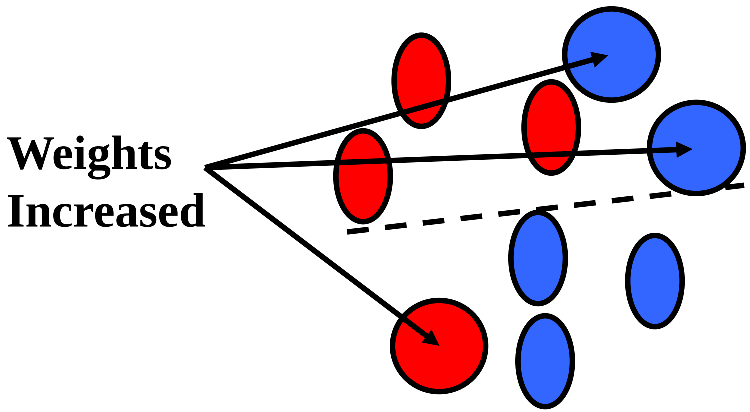
$$e_i = \sum_{n=1}^{N} w_{n,i}(1 - \delta(y_n, h_i(\mathbf{x}_n; \theta_i)))$$

- Efficient algorithms exist to find the threshold in linear time
- Update the *per-instance weights* based on the classification error of weak learner

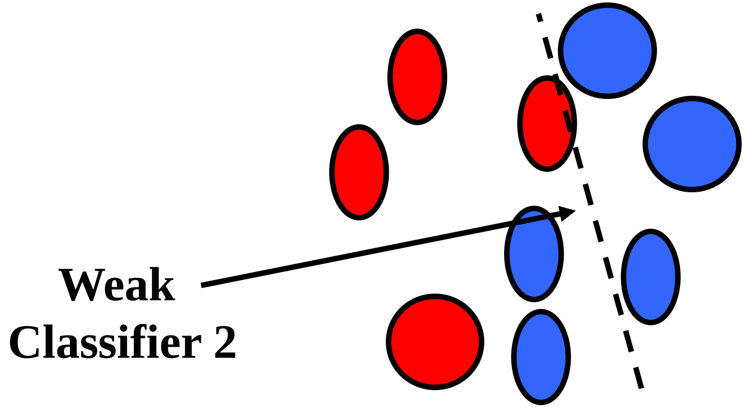
AdaBoost learning illustration



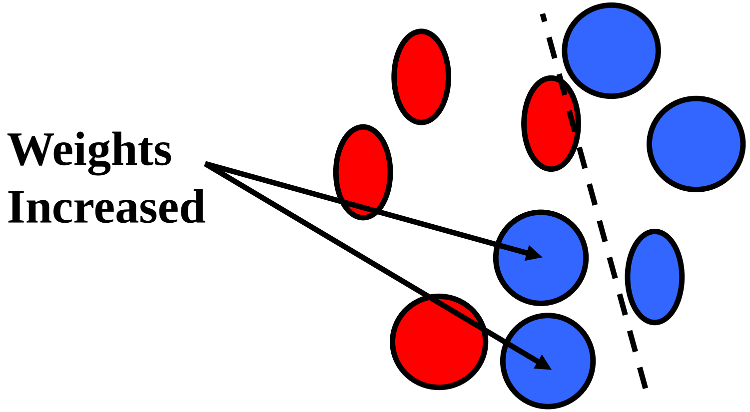
AdaBoost learning illustration



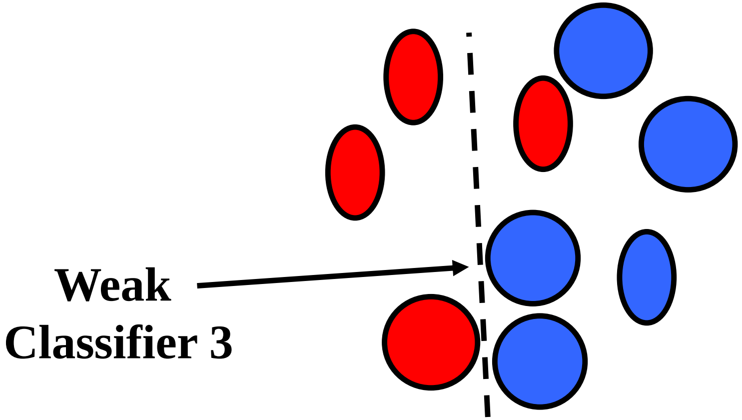
AdaBoost learning illustration



AdaBoost learning illustration

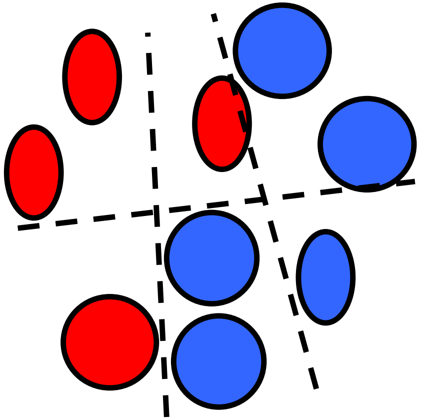


AdaBoost learning illustration



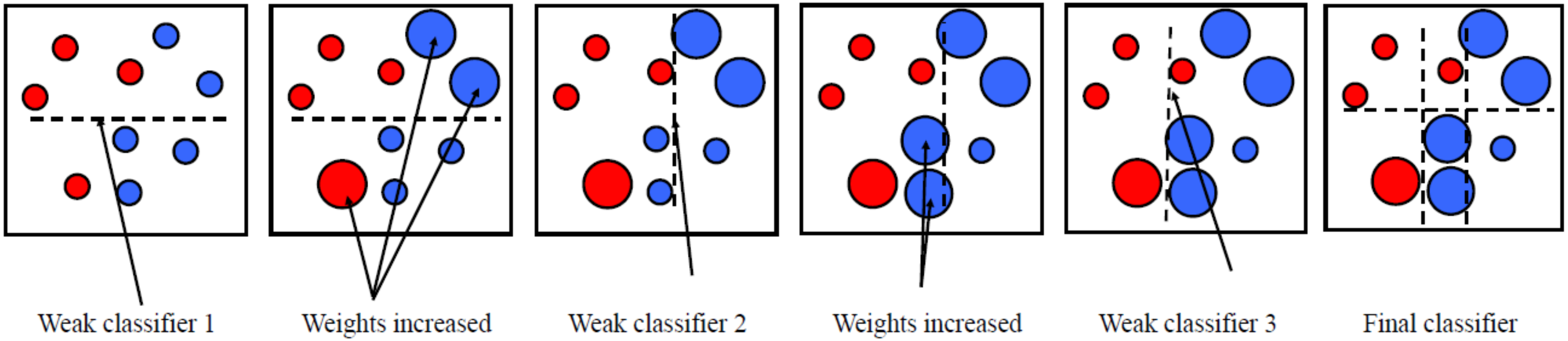
AdaBoost learning illustration

Final classifier is a combination of weak classifiers



Face detection

Schematic overview of AdaBoost learning with decision stumps:



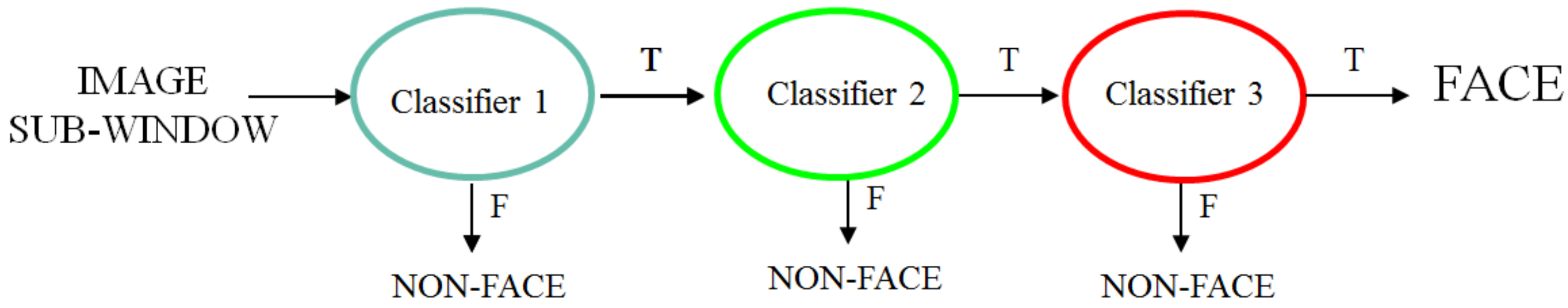
Update for per-instance weights: $w_{n,i+1} \leftarrow w_{n,i} \left(\frac{e_i}{1-e_i} \right)^{1-\delta(y_n, h_i(\mathbf{x}_n; \theta_i))}$

Weak-learner weights given by: $\alpha_i = -\log \left(\frac{e_i}{1-e_i} \right)$

Face detection: Viola & Jones

To perform the detection, we use a sliding window detector (at multiple scales)

The classification of a patch can be performed using a *cascaded classifier*:



Note that this is extremely fast at test time: for negative examples, we typically only need to compute a very small number of features!

Face detection: Viola & Jones

False positive rate of a cascade with K classifiers: $FPR = \prod_{i=1}^{K} FPR_i$

Detection rate of a cascade with K classifiers: $DR = \prod_{i=1}^{K} DR_i$

Face detection: Viola & Jones

False positive rate of a cascade with K classifiers: $FPR = \prod_{i=1}^{K} FPR_i$

Detection rate of a cascade with K classifiers: $DR = \prod_{i=1}^{K} DR_i$

Assume we have a cascade of K = 32 classifiers:

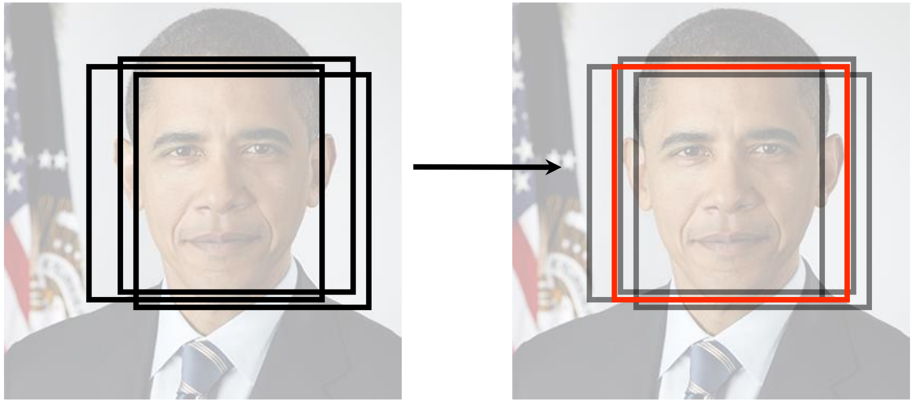
- To get a false positive rate of 10^{-6}, each classifier may have FPR of 65%
- To get a detection rate of 90%, each classifier should have DR of 99.7%

Face detection: Viola & Jones

Multiple locations near a face will typically yields multiple detections

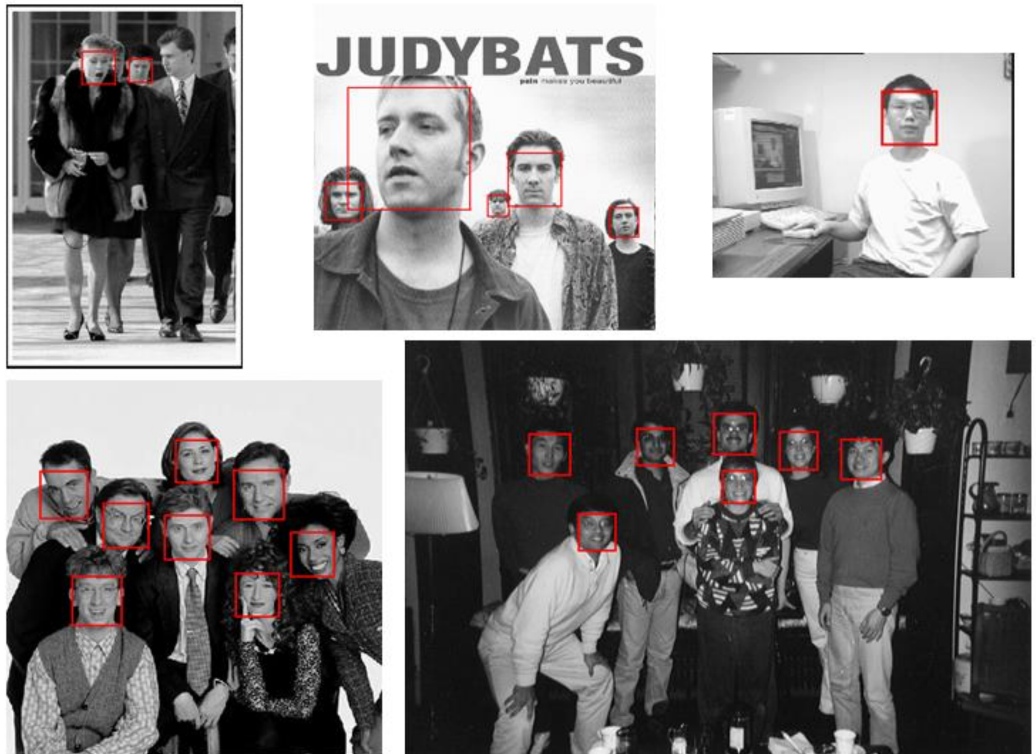
In the original V&J detector, the detections are post-processed as follows:

- Whenever two detections overlap, the bounding boxes are merged
- The final detection is the average of the corners of all merged detections:



Face detection: Viola & Jones

Examples of face detections (using V&J implementation in OpenCV):



Face detection: Viola & Jones

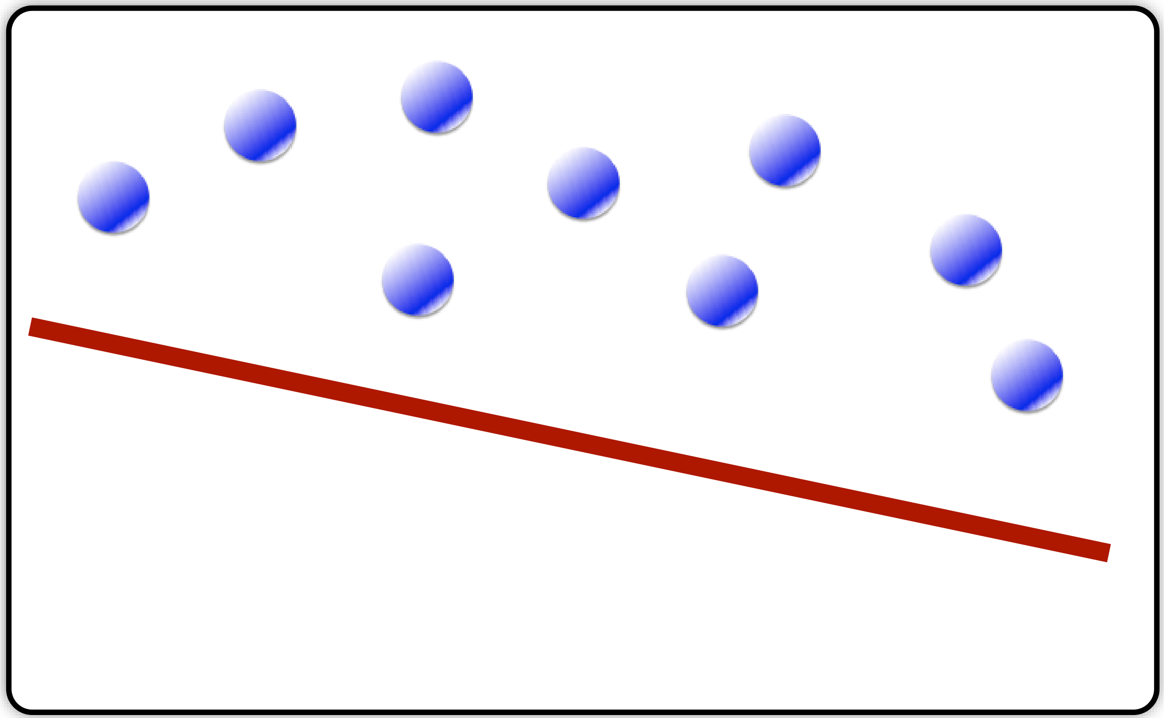
Detection of profile faces requires training on separate data set:

Face recognition: Eigenfaces

- Consider face images as high-dimensional data points
- Apply *dimension reduction* on the images to obtain low-dimensional features
- The reduction is performed using *principal components analysis*

Face recognition: Eigenfaces

Principal Components Analysis maps the data in a *linear subspace*, such that the *variance* of the projected data is maximized:



$\mathbf{w}^{\mathrm{T}}\mathbf{x}$

Face recognition: Eigenfaces

Our objective is to maximize variance: $\max\limits_{\|\mathbf{w}\|^2=1} var(\mathbf{w}^T\mathbf{X})$

Assuming zero-mean data: $var(\mathbf{w}^T\mathbf{X}) = [\mathbf{w}^T\mathbf{X}\mathbf{X}^T\mathbf{w}] = [\mathbf{w}^T\mathbf{C}\mathbf{w}]$

Enforce constraint using *Lagrange multipliers*:

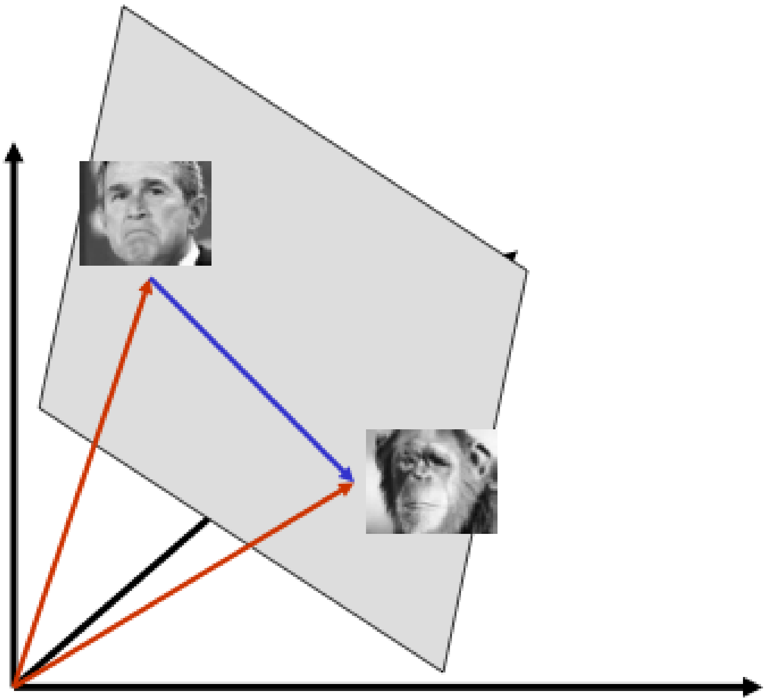
$$\max_{\|\mathbf{w}\|^2=1} var(\mathbf{w}^T\mathbf{X}) = \max_{\mathbf{w},\lambda} \mathbf{w}^T\mathbf{C}\mathbf{w} - \lambda(\mathbf{w}^T\mathbf{w} - 1)$$

Set gradient with respect to $\mathbf{w}$ to zero: $\mathbf{C}\mathbf{w} - \lambda\mathbf{w} = 0$

$$\mathbf{C}\mathbf{w} = \lambda\mathbf{w}$$

Face recognition: Eigenfaces

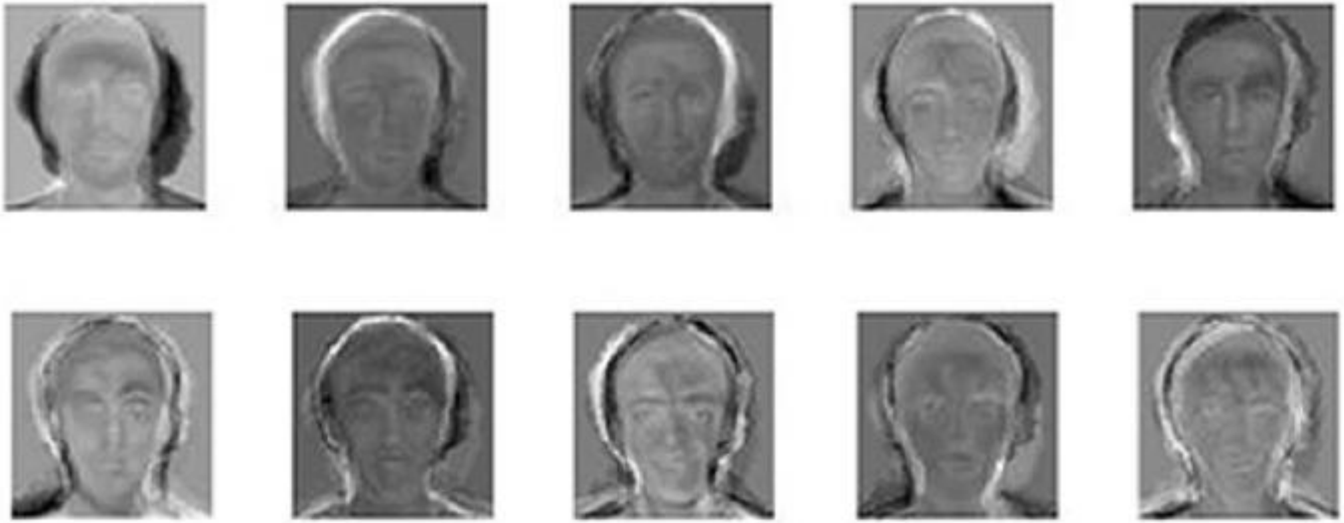
We can move through the PCA subspace to generate new faces:



$$\tilde{\mathbf{x}} = \bar{\mathbf{x}} + \sum_{i=1}^{p} z_i \mathbf{w}_i$$

Face recognition: Eigenfaces

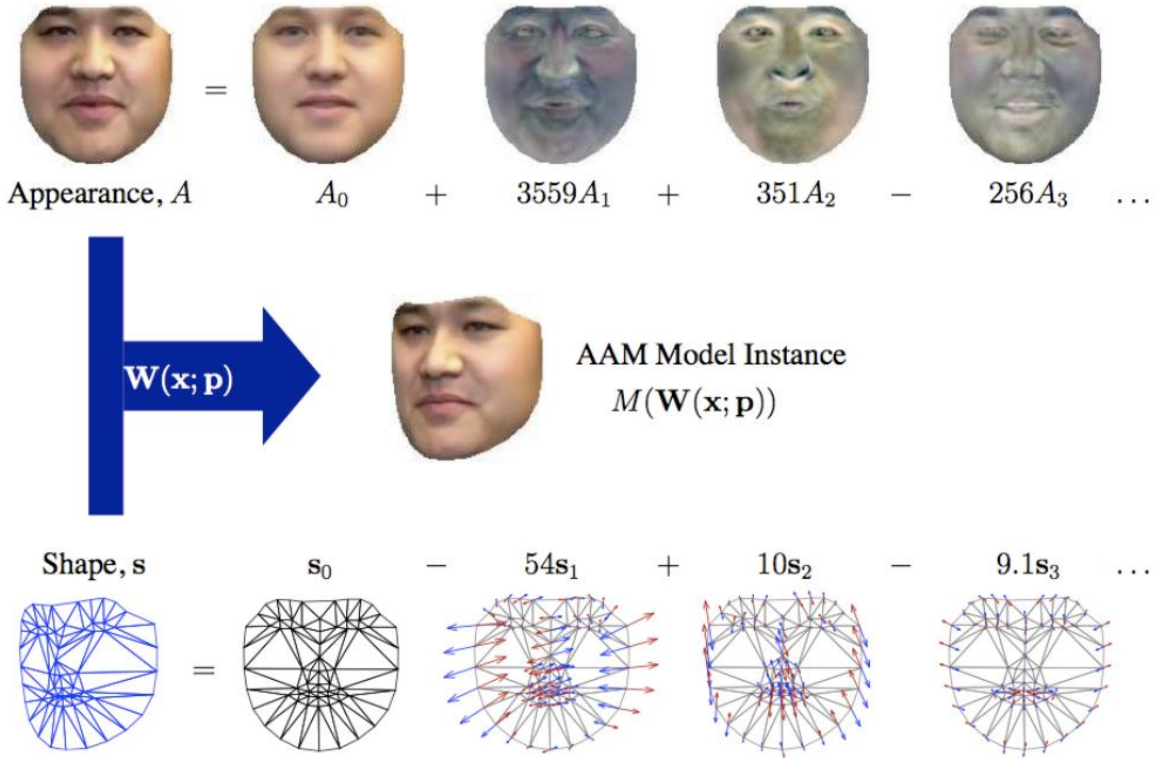
We can visualize the eigenfaces to show the main sources of variation:



We may use $\mathbf{z} = \left[\mathbf{w}_1^{\mathrm{T}}\mathbf{x}, \ldots, \mathbf{w}_p^{\mathrm{T}}\mathbf{x}\right]^{\mathrm{T}}$ as features for identity recognition

Face recognition: Active appearance models

Separates face variations into *shape* and *texture* variation:

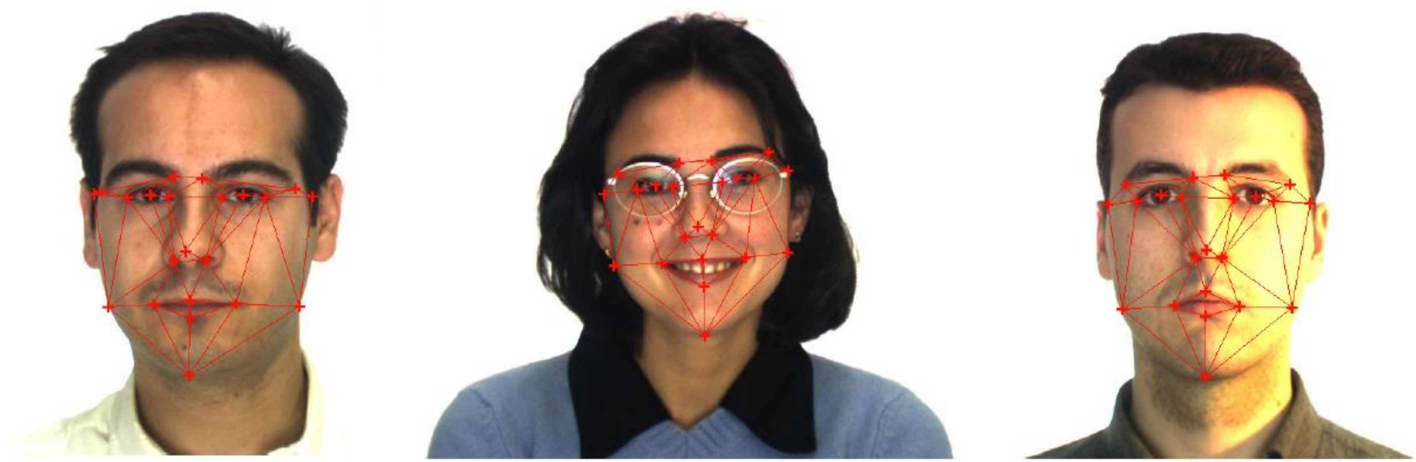


Face recognition: Active appearance models

Gather a data set of face images with annotated feature points

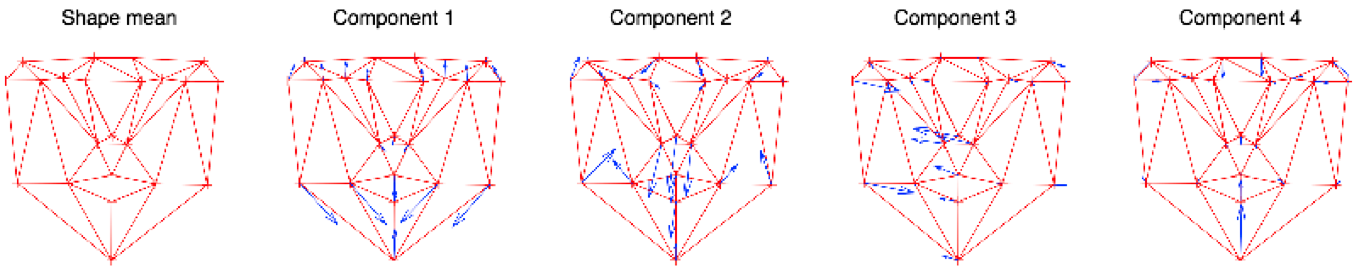
Remove translations and rotations from point annotations (Procrustes alignment)

Learn *point distribution model* and *texture model* from the data

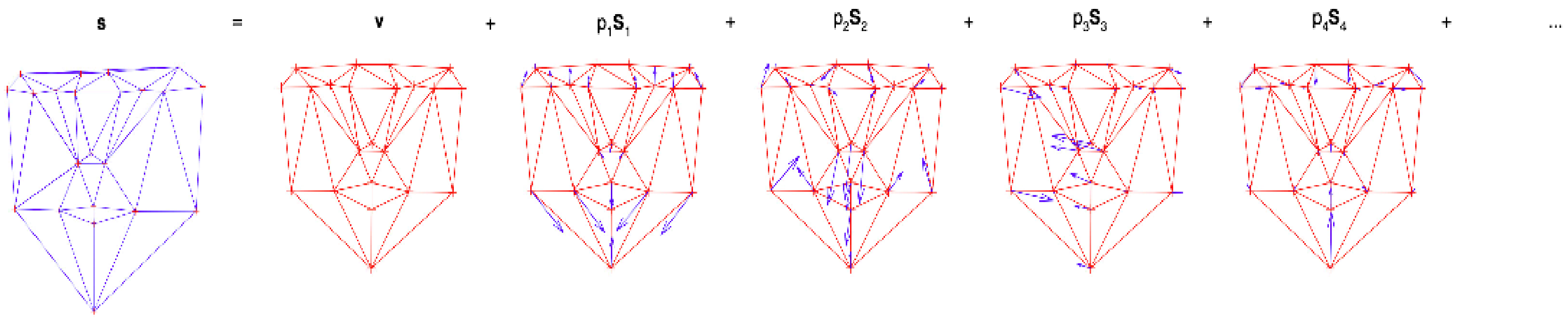


Face recognition: Active appearance models

Point distribution model is obtained using PCA:



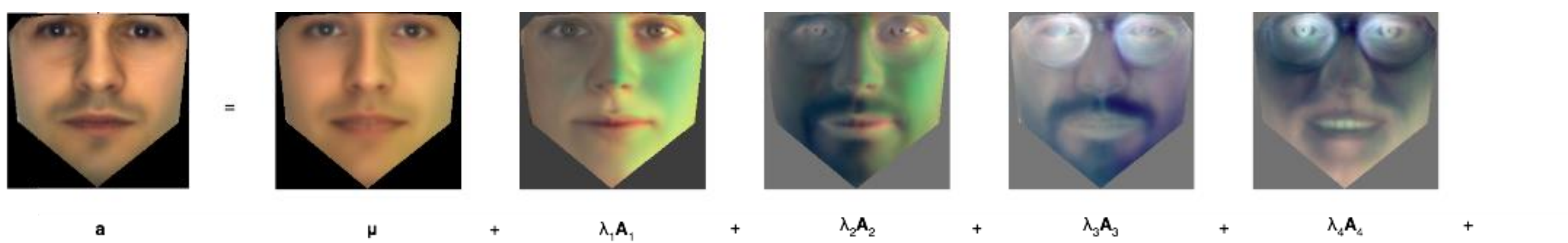
New facial shape is generated by linearly combining the components:



Face recognition: Active appearance models

Texture model is also obtained using PCA:

New facial textures are generated using a linear combination of components:



Face recognition: Active appearance models

We receive a new face image in which we want to measure facial features:

Now what do we do to fit the active appearance model to this new face?

- Find parameters of the model that best fit the face (minimizing sum of squared errors) using *Lucas-Kanade algorithm*

Image warping

We can *warp* between an arbitrary shape and the base shape (and vice versa):

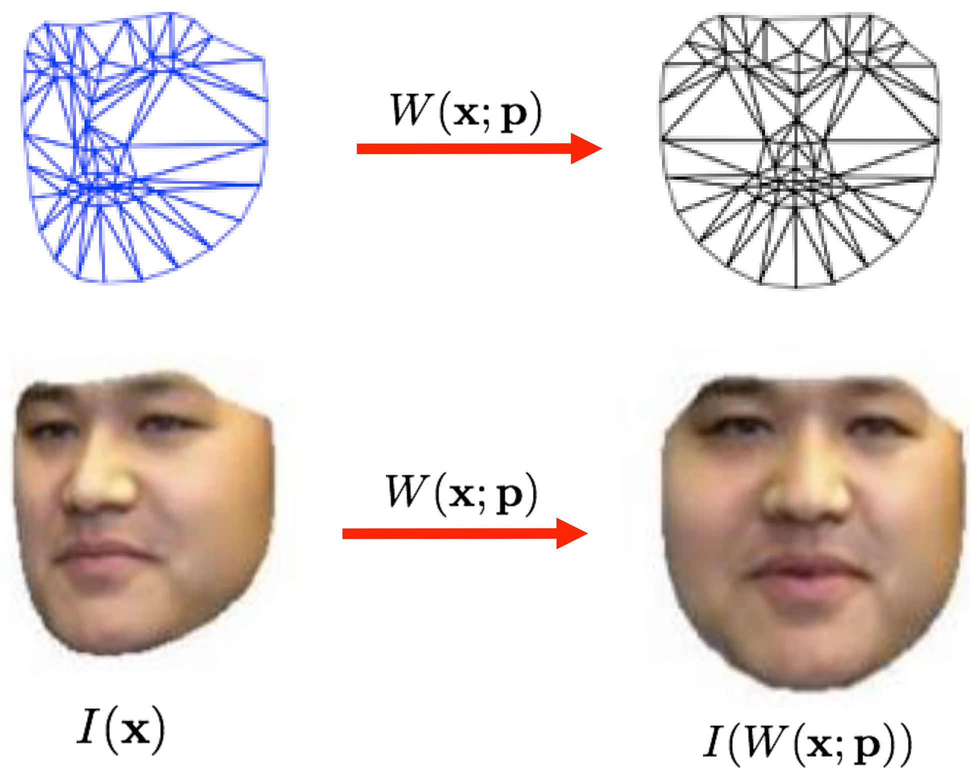
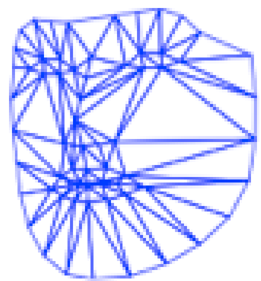


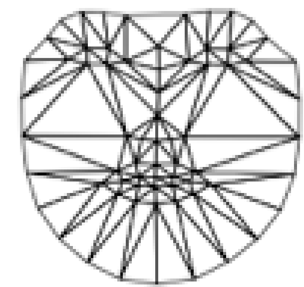
Image warping

We can *warp* between an arbitrary shape and the base shape (and vice versa):

This shape is governed by the shape parameters **p**



$W(\mathbf{x};\mathbf{p})$



This is a part of the image on which we are fitting the AAM
(*viz.* the convex hull of the current shape)

$I(\mathbf{x})$

$W(\mathbf{x};\mathbf{p})$

$I(W(\mathbf{x};\mathbf{p}))$

Lucas-Kanade algorithm

Minimizes sum of squared error w.r.t. $\mathbf{p}$ using *Gauss-Newton* algorithm:

$$\sum_{\mathbf{x}} [A_0(\mathbf{x}) - I(W(\mathbf{x};\mathbf{p}))]^2$$

Mean texture

-

Test image
after warp

Lucas-Kanade algorithm

Minimizes sum of squared error w.r.t. $\mathbf{p}$ using *Gauss-Newton* algorithm:

$$\sum_{\mathbf{x}} [A_0(\mathbf{x}) - I(W(\mathbf{x};\mathbf{p}))]^2$$

Mean texture

-

Test image
after warp

Goal: Set the shape parameters **p** such that the left image looks as much as possible like the right image

Lucas-Kanade algorithm

Minimizes sum of squared error w.r.t. $\mathbf{p}$ using *Gauss-Newton* algorithm:

$$\sum_{\mathbf{x}} [A_0(\mathbf{x}) - I(W(\mathbf{x};\mathbf{p}))]^2$$

Lucas-Kanade algorithm

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$$\sum_{\mathbf{x}} [A_0(\mathbf{x}) - I(W(\mathbf{x};\mathbf{p}))]^2$$

Iteratively solve for parameter increment $\Delta\mathbf{p}$:

$$\min_{\Delta\mathbf{p}} \sum_{\mathbf{x}} [A_0(\mathbf{x}) - I(W(\mathbf{x};\mathbf{p}+\Delta\mathbf{p}))]^2$$

Lucas-Kanade algorithm

*A Taylor expansion of $f(x)$ around a is given by: $\sum_{n=0}^{\infty} \frac{f^{(n)}(a)}{n!}(x-a)^n$

Iteratively solve for parameter increment $\Delta\mathbf{p}$:

$$\min_{\Delta\mathbf{p}} \sum_{\mathbf{x}} [A_0(\mathbf{x}) - I(W(\mathbf{x};\mathbf{p}+\Delta\mathbf{p}))]^2$$

This is strongly non-linear, so write down *first-order Taylor expansion*:

$$\min_{\Delta\mathbf{p}} \sum_{\mathbf{x}} \left[A_0(\mathbf{x}) - I(W(\mathbf{x};\mathbf{p})) - \nabla I \frac{\partial W}{\partial \mathbf{p}} \Delta\mathbf{p}\right]^2$$

As expected, this is a standard *linear least squares* problem

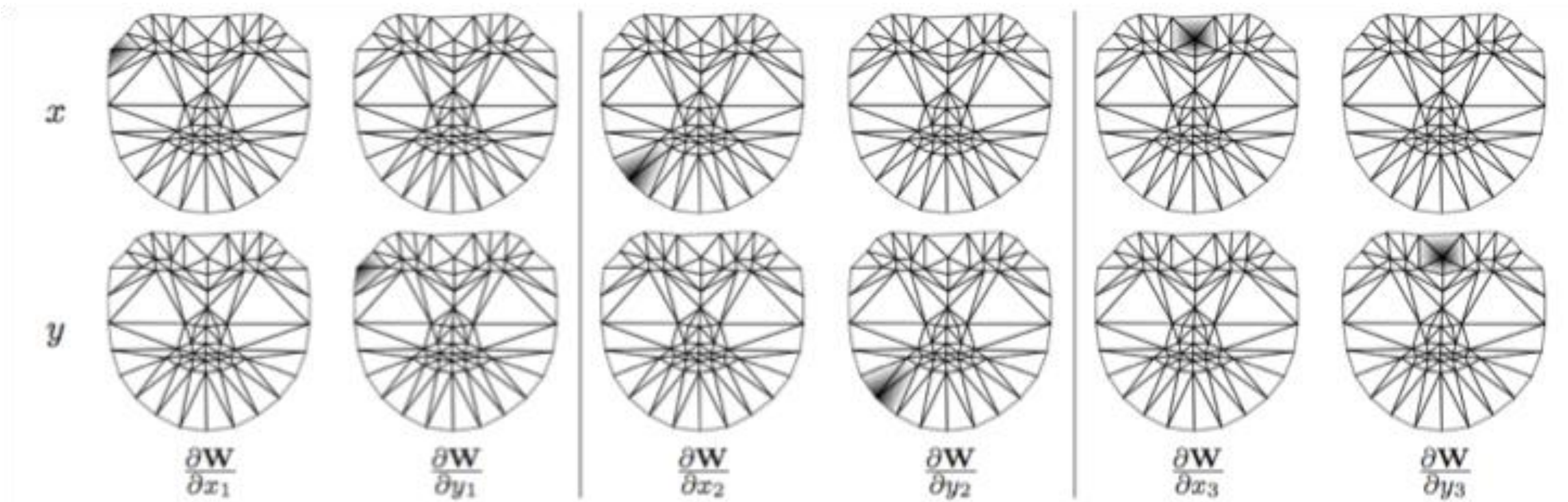
Gradient Images

Illustration of the image gradient ∇I

∇I_{x} ∇I_{y}

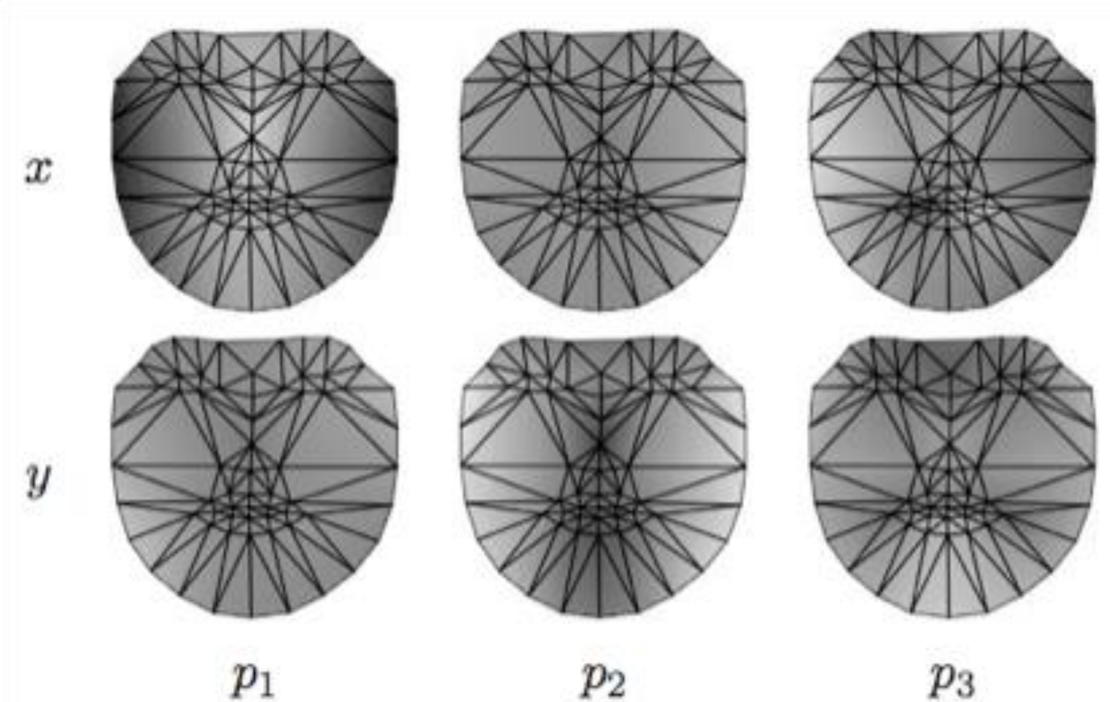
Lucas-Kanade algorithm

Illustration of the warp Jacobian: $\frac{\partial W}{\partial \mathbf{p}} = \frac{\partial W}{\partial \mathbf{x}} \frac{\partial \mathbf{x}}{\partial \mathbf{p}}$



Lucas-Kanade algorithm

Illustration of the warp Jacobian: $\dfrac{\partial W}{\partial \mathbf{p}} = \dfrac{\partial W}{\partial \mathbf{x}} \dfrac{\partial \mathbf{x}}{\partial \mathbf{p}}$



Lucas-Kanade algorithm

Closed-form solution for the parameter update:

$$\Delta \mathbf{p} = \mathbf{H}^{-1} \sum_{\mathbf{x}} \left[\nabla I \frac{\partial W}{\partial \mathbf{p}} \right]^{\mathrm{T}} \left[A_0(\mathbf{x}) - I(W(\mathbf{x}; \mathbf{p})) \right]$$

Herein, $\mathbf{H}$ is the Gauss-Newton approximation to the Hessian:

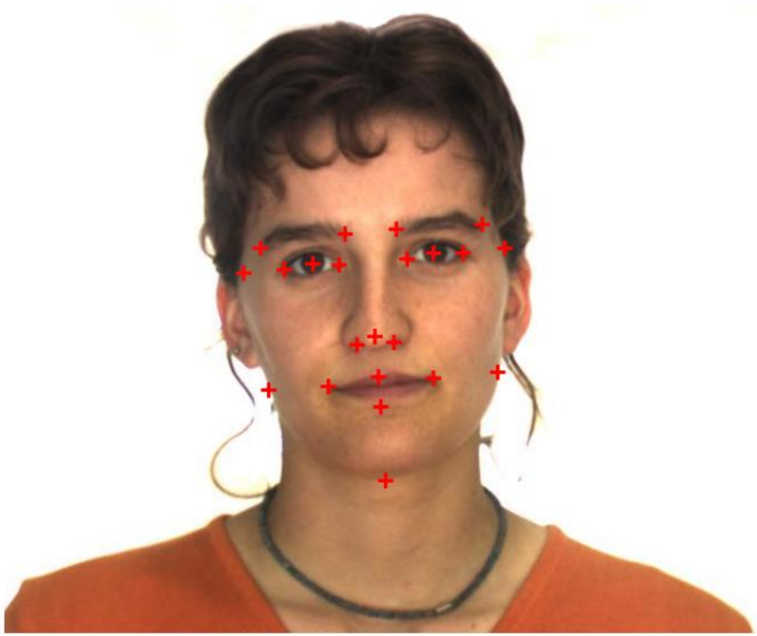
$$\mathbf{H} = \sum_{\mathbf{x}} \left[\nabla I \frac{\partial W}{\partial \mathbf{p}} \right]^{\mathrm{T}} \left[\nabla I \frac{\partial W}{\partial \mathbf{p}} \right]$$

Lucas-Kanade algorithm

1. Warp I with $\mathbf{W}(\mathbf{x};\mathbf{p}) \Rightarrow I(\mathbf{W}(\mathbf{x};\mathbf{p}))$
2. Compute error image $A_o(x) - I(\mathbf{W}(\mathbf{x};\mathbf{p}))$
3. Warp gradient of I to compute ∇I
4. Evaluate Jacobian $\dfrac{\partial \mathbf{W}}{\partial \mathbf{p}}$
5. Compute Hessian
6. Compute $\Delta\mathbf{p}$
7. Update parameters $\mathbf{p} \leftarrow \mathbf{p} + \Delta\mathbf{p}$ (repeat the process until the fitting)

Face recognition: Active appearance models

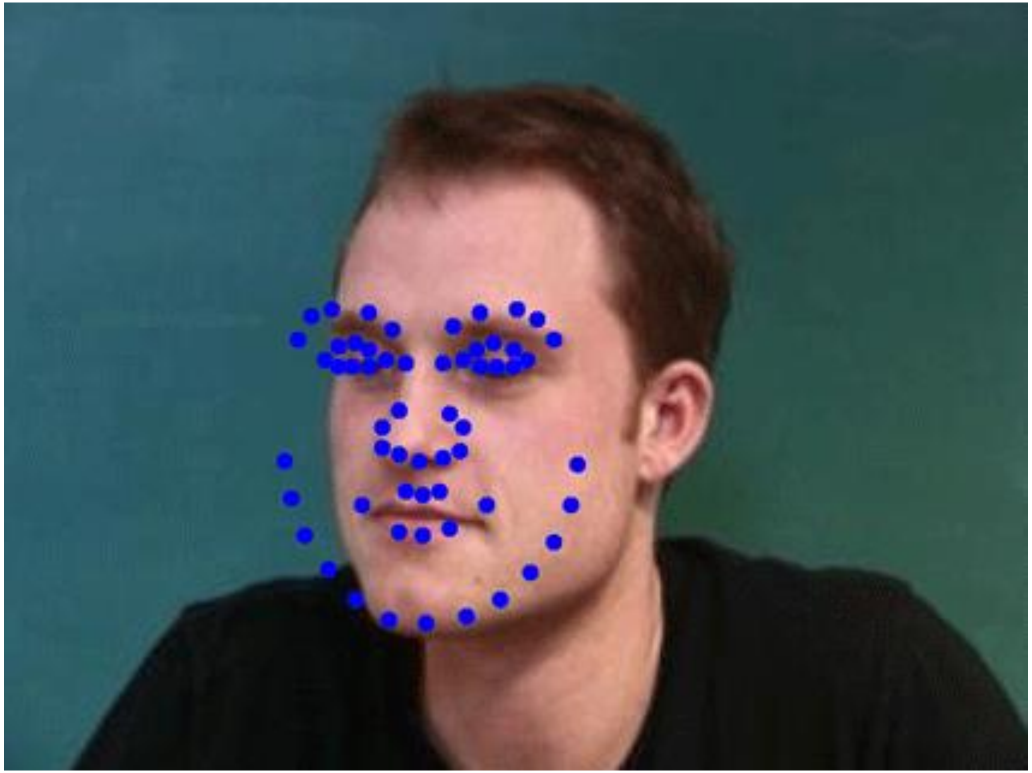
Face recognition: Active appearance models



Face recognition: Active appearance models

Face recognition: Active appearance models

Illustration of fitting a shape model:



Face recognition: Active appearance models

Face recognition: Active appearance models

Face recognition and expression analysis

Facial feature points (landmarks) can be used for a number of tasks:

- ***Facial expression analysis***:
  - Measure variations of landmark locations over time (shape variation); use texture features to measure presence of wrinkles (texture variation), *etc.*

Face recognition and expression analysis

Facial feature points (landmarks) can be used for a number of tasks:

- ***Facial expression analysis***:
  - Measure variations of landmark locations over time (shape variation); use texture features to measure presence of wrinkles (texture variation), *etc.*
- ***Facial identity recognition* or *face verification* (passport control):**
  - Measure characteristics that are invariant under expressions but person-specific: inter-ocular distance, relative position of nose, *etc.*
  - Build skin models:

Example: Recognition of Action Units (FACS)


AU 1
Inner brow raise


AU 2
Outer brow raise


AU 4
Brow lower


AU 6
Cheek raise


AU 9
Nose wrinkler


AU 12
Lip corner pull


AU 15
Lip corner depress


AU 20
Lip strecher

Example: Recognition of Action Units (FACS)

Inner brow raiser:

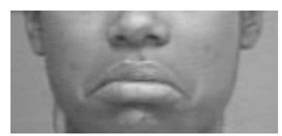
Outer brow raiser:

Brow lowerer:

Upper lid raiser:

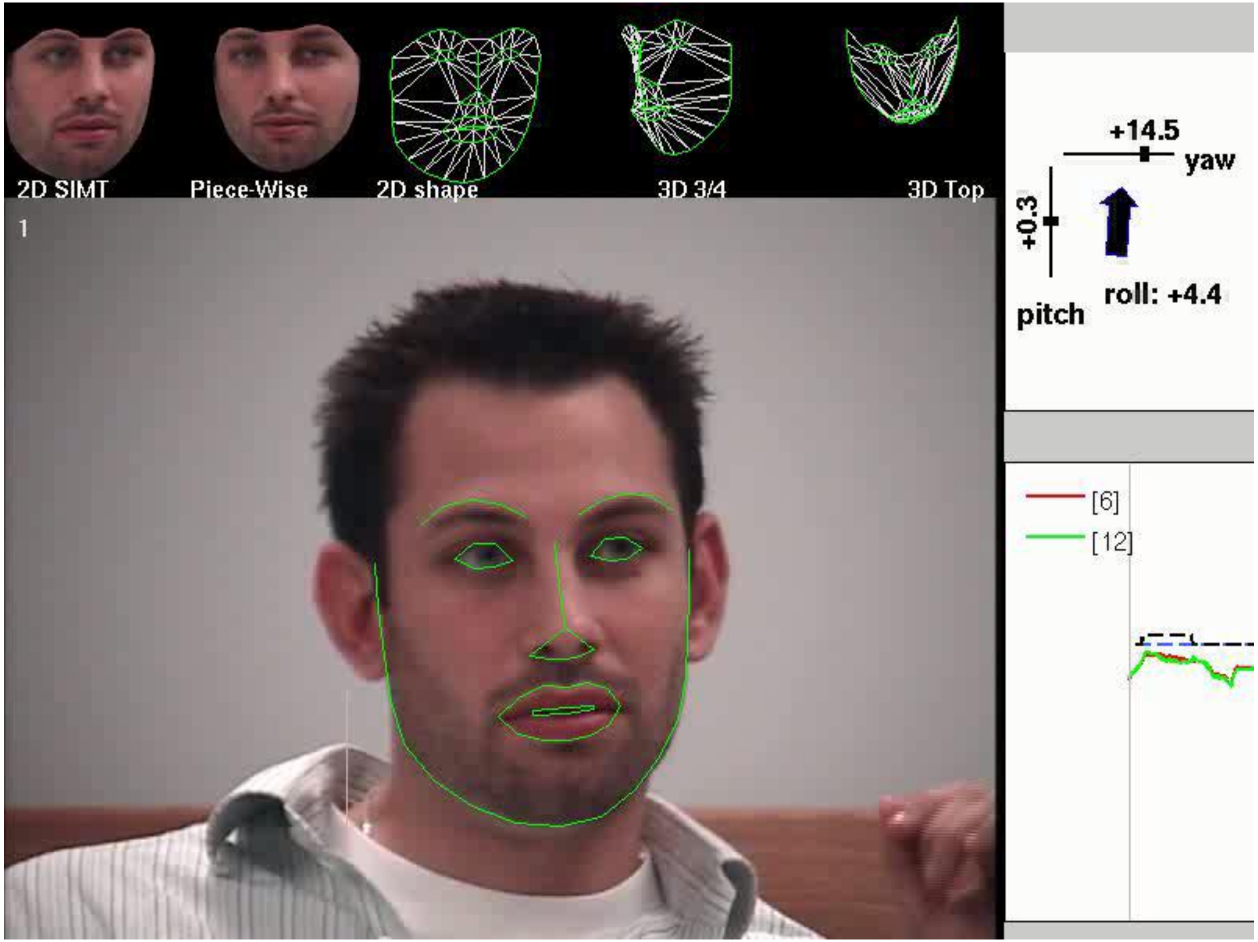
Nose wrinkler:

Lip corner depressor:

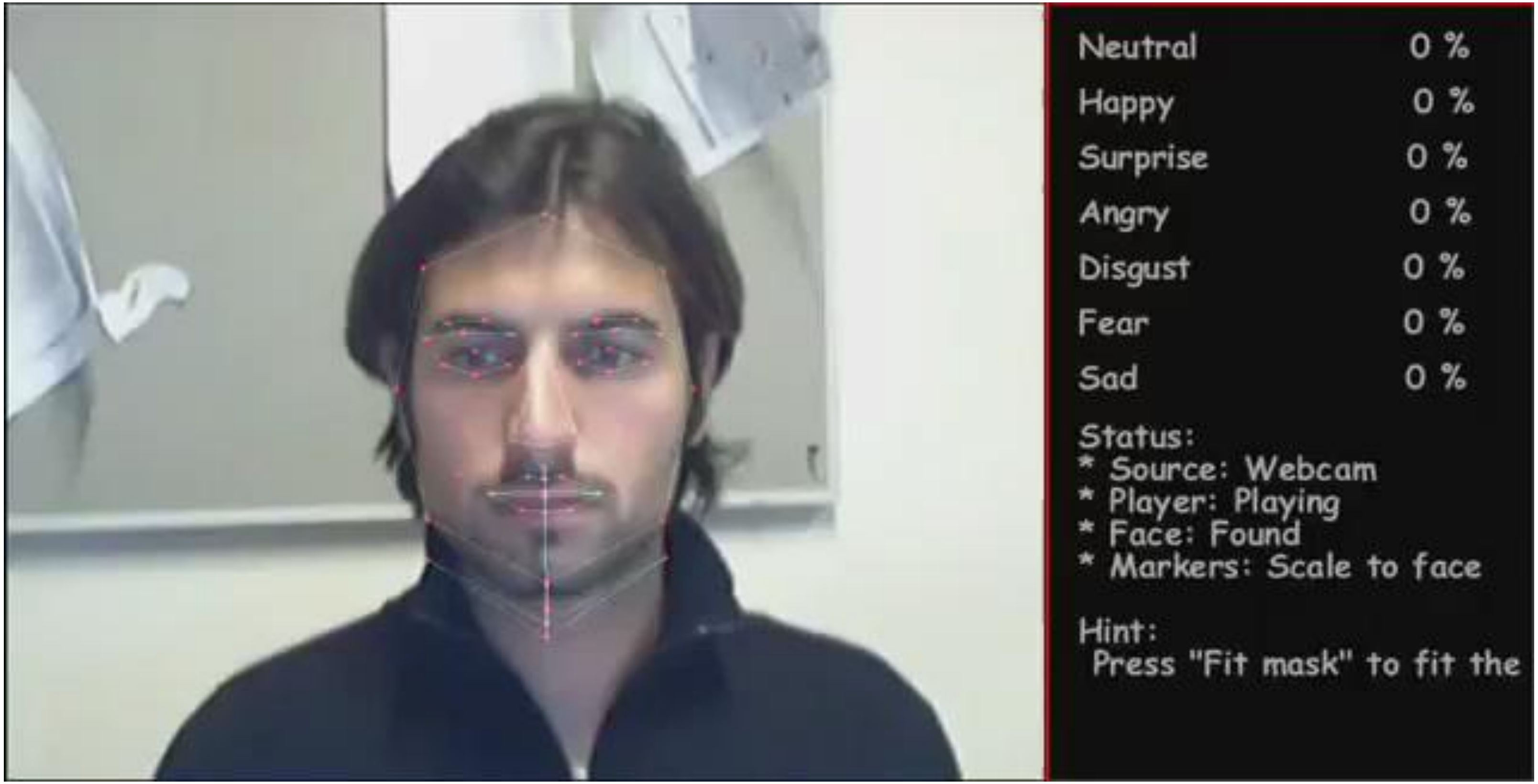


Etc...

Example: Recognition of Action Units (FACS)

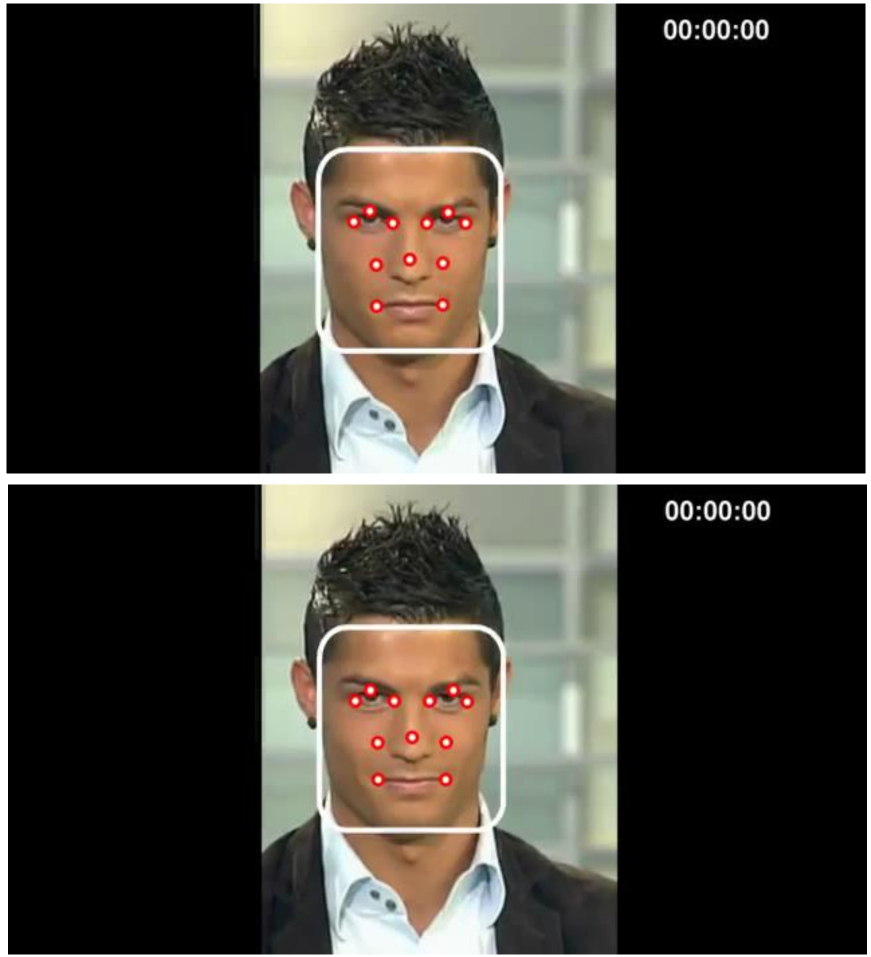


Example: Emotional Expression Recognition



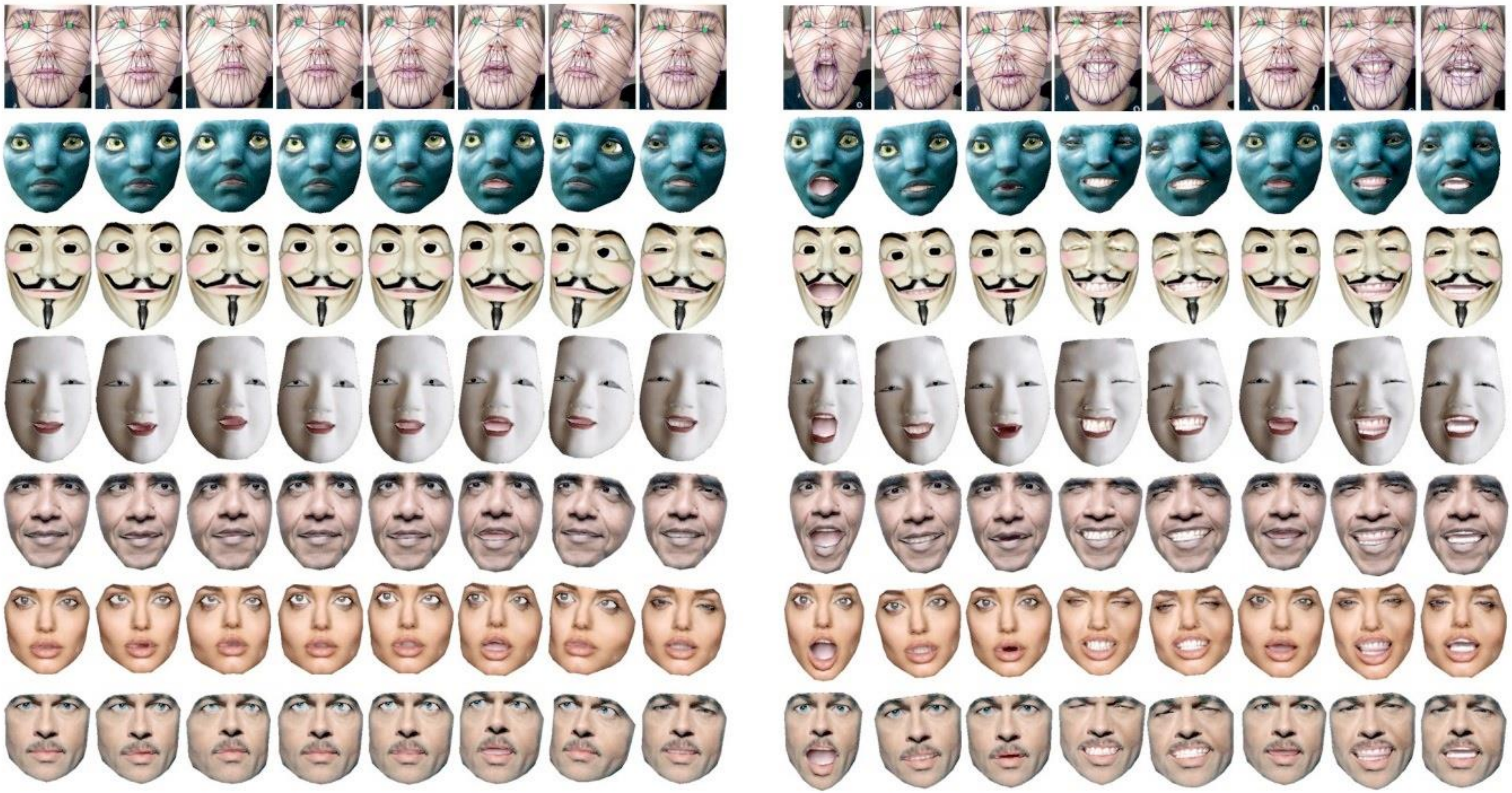
Example: Detection of Expression Spontaneity

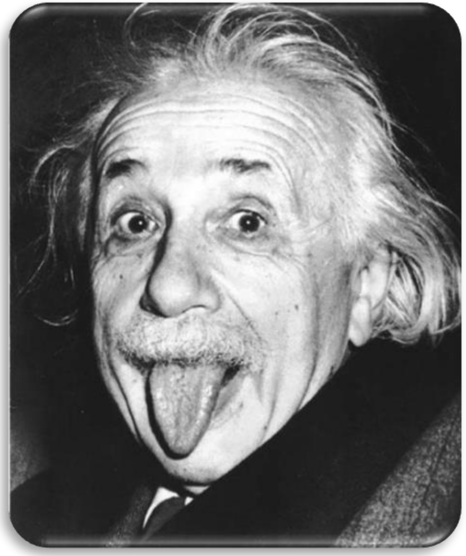
Example: Detection of Expression Spontaneity



Example: Expression cloning

Example: Expression cloning





Reading material:

Section 14.1 and 14.2 of Szeliski

Section 1 and 2 of "Lucas-Kanade 20 Years On: A Unifying Framework," *International Journal of Computer Vision* 56(3), 221–255, 2004.