Face detection, validation and tracking

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Agenda

- Motivation and examples
- Face detection
- ▶ Face validation
- Face tracking
- Conclusion



Motivation

- Goal: Allow an automatic system to sense the presence of people somewhere in a room
- It can be used in a very different way
- Assists people in their work and make it easily
- A very long process because of the amount of data in a video



Applications

- Surveillance
- Facial recognition systems
- digital cameras use face detection for autofocus
- Assists elderly people







Face Detection

Viola Jones's algorithm

Face detection

- ▶ A learning approach for visual object detection
- Robust and rapid object detection
- Capable of processing images rapidly
- Don't use image differencing and skin color detection
- Use information present in a single grey scale image
- Using a Boosted cascade of simple features



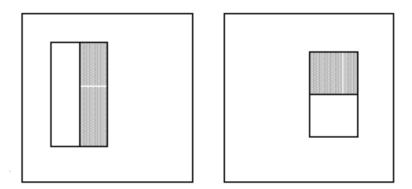
Face detection

- Features
- 2. A new image representation called the "integral image"
- 3. Learning algorithm based on AdaBoost
- Combining increasingly more complex classifiers in a "cascade"



Features

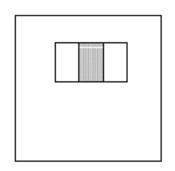
- Three different kinds of features:
- The value of 2 rectangle feature: difference between the sum of the pixels within two rectangular regions.



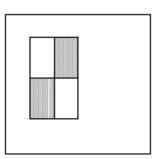


Features

The value of 3 rectangle feature: computes the sum within 2 outside rectangles subtracted from the sum in a center rectangle



The value of 4 rectangle feature: computes the difference between diagonal pairs of rectangles





Integral image

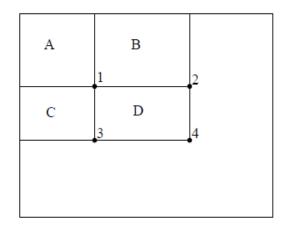
- A few operations per pixel
- To compute the rectangle features we use an integral image:

$$ii(x,y) = \sum_{x' \le x, y' \le y} i(x', y')$$

The integral image at location x,y contains the sum of the pixels above and to the left of x,y



Integral image



- The sum of pixel in rectangle D can be computed with four array references
- ▶ The sum within D can be computed as:

$$4+1-(2+3)$$

- A learning process
- Boost the classification performance of a simple learning algorithm
- Select a small number of critical visual features from a larger set and made an efficient classification
- Train the classifier
- ▶ A small number of these features can be combined to form an effective classifier
- Challenge: to find the features



Training set

A label: for N images xi. yi = 1, when an image is considered a face, yi = 0 otherwise.

combines T classifiers called "weak"

- Combine "weak" classifiers to have a new classifier called "strong".
- Each "weak" classifier consists of a single feature and an optimal threshold.
- "Strong classifier": A combination of T weak classifiers.
- It takes an image as input and produces a binary value (I or 0) on output.



- 3. A feature is computed for each image xi.
 - the image set {xi} can now be divided into two parts : negative and positive
 - The result can be compared with original labels {yi}
 - The threshold is chosen for each feature separately



4. A round:

- A round starts with a set of normalized weights associated with each image xi
- in each round it is estimated how well every classifier separates positive and negative example images, in comparison to their actual classification {yi}
- The classifier with a minimum classification error is chosen

5. After T rounds:

T selected "weak" classifiers (and their corresponding features)



Cascade classifiers

- Allows background regions of the image to be quickly discarded
- More computation on regions where they are objects
- More complex processing is reserved for these promising regions.



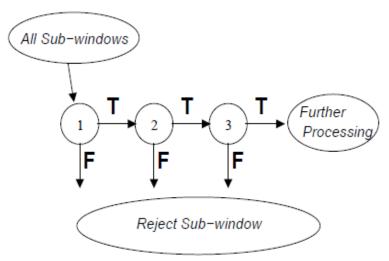
Cascade classifiers

- Combining increasingly more complex classifiers in a "cascade"
- Each stage in the cascade reduces the false positive and decreases the detection rate
- Complete face detection cascade have 38 stages over 6 000 features



Cascade classifiers

- Simpler classifiers are use to reject the majority of subwindows
- 2. More complex classifiers are called upon to achieve low false positive rate.
- Stages in the cascade are constructed by training classifiers AdaBoost and then adjusting the threshold to minimize false negative.





Face validation

Verifying, if a face detection returned by the face detector, is indeed a face

(otherwise, it is just a false positive)

Face validation: outline

- Motivation
- Types of face validation:
 - 2D image validation
 - 3D position validation
 - Color validation
 - Pattern validation



Face validation: outline

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Face detection: motivation

- Need for detecting resolution-limited faces of varying pose, expression and illumination
- Solutions:
 - Multiple situation-specific detectors and fuse their decisions: time consuming
 - Single generic less strict detector: a tradeoff between hits and false positives



Face detection: motivation

- The tradeoff of hits and false positives can be addressed by:
 - increasing the number of stages in Viola & Jones detector cascade;
 - using face validation as a post-processing step



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 Discarding one of two detections that are overlapping on the image plane.

Measure of overlap – common area ratio:

CAR = A[BBI \cap BB2] / min (A[BBI], A[BB2])



 2D spatial validation seldom removes actual faces, since partially occluded faces are not detected at all



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Idea:

- estimate 3D position of a face using a single calibrated camera
- discard faces which have an estimated 3D position outside the room

Underlying assumption:

human face is approximately 15 cm wide



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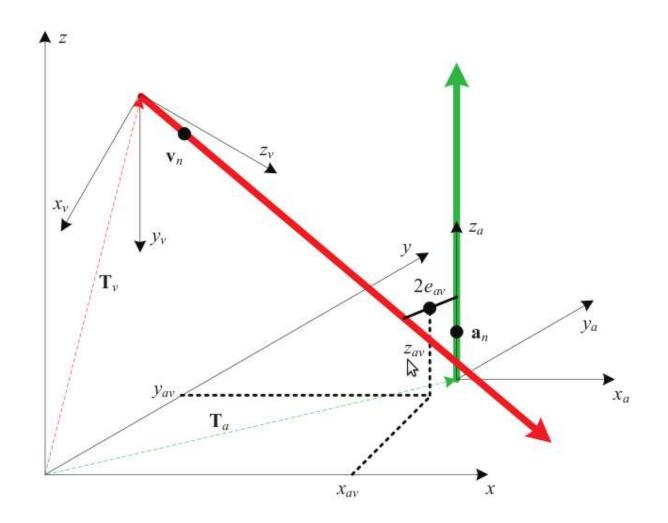


- Face 3D position estimation consists of:
 - Definining a mapping between an image pixel and a
 3D line in camera coordinate system
 - Using the obtained mapping, projecting mid-points of left and right borders of the face bounding box into a plane, where z = I
 - Obtaining face width Wn in this plane
 - Using the similarity of triangles and Wn, computing the actual z coordinate of the face in 3D
 - Using z coordinate to obtain x and y
 - Mapping {x,y,z} from camera to world coordinate system



- Definining a mapping between an image pixel and a 3D line in camera coordinate system:
 - Pixel {xp,yp} --> 3D line {xn ·zc,yn ·zc,zc}
 - {xn, yn} depth-normalized camera coordinates
 - Depth-normalized means z = I
 - Mapping is non-linear
 - Knowledge of intrinsic camera parameters needed







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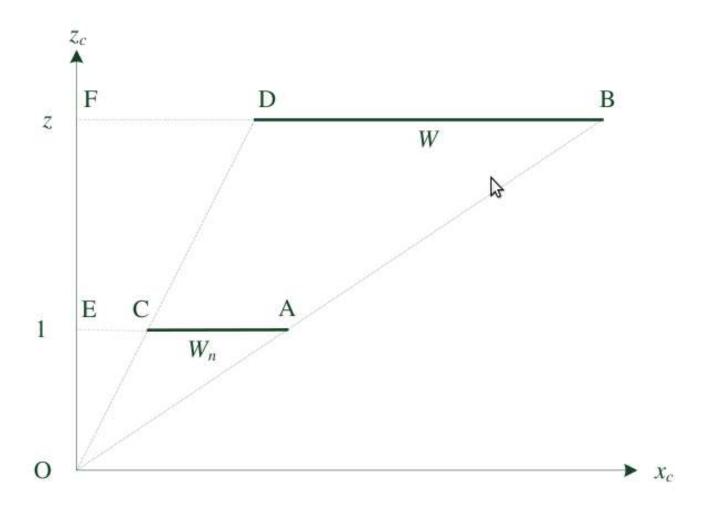


- Using the obtained mapping, projecting mid-points of left and right borders of the face bounding box into a plane, where z = I
 - Detected faces are represented as: {xf, yf, wf, hf}
 - {xf, yf} top left corner of a bounding box
 - wf width
 - hf height



- Using the obtained mapping, projecting mid-points of left and right borders of the face bounding box into a plane, where z = I
 - Left border mid-point: {xf, yf + hf /2}
 - Its projection: {xpl , yp}
 - **Right** border mid-point: $\{xf + wf, yf + hf/2\}$
 - Its projection: {xpr , yp}
- Note: as z = 1, it is enough to calculate x and y







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Obtaining face width Wn in this plane:

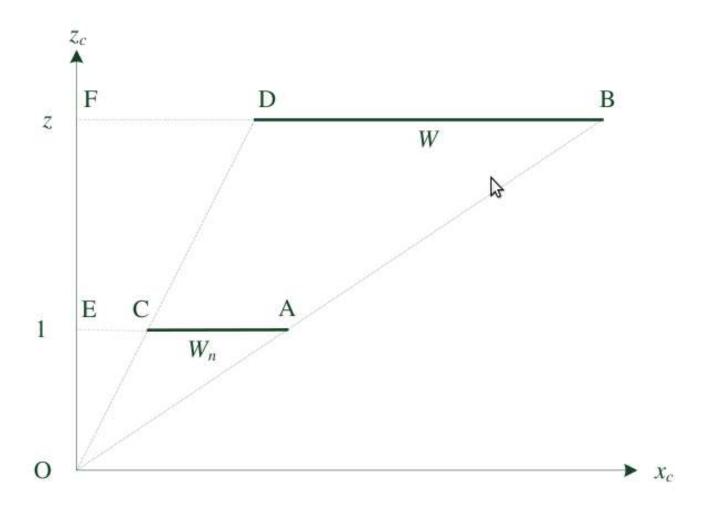
$$Wn = |xn| - xnr|$$



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- Using the similarity of triangles and Wn, computing the actual z coordinate of the face in 3D:
 - W / Wn = |OD| / |BD| = |OC| / |AC|
 - |OD| / |OC| = |OF| / |OE| = z / |
 - z = W / Wn



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- Using z coordinate to obtain x and y:
 - **Left** border mid-point in 3D:

```
\{xnl \cdot z, yn \cdot z, z\}
```

• **Right** border mid-point in 3D:

```
\{xnr \cdot z, yn \cdot z, z\}
```

• Face centre in 3D: their mid-point



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- Mapping from camera to world coordinate system
 - Produces {xw, yw, zw}
 - Mapping is linear
 - Camera extrinsic parameters needed



- Idea:
 - estimate 3D position of a face using a single calibrated camera
 - discard faces which have an estimated 3D position outside the room
- Underlying assumption:
 - human face is approximately 15 cm wide



- Height and floorplan constraints:
 - $zw \in [zmin, zmax]$
 - $xw \in [xmin, xmax]$
 - yw ∈ [ymin , ymax]



Face validation: outline

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- Types of face validation:
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Face validation: color validation

Idea:

discarding faces based on the similarity between their color histogram and the skin color histogram of Jones and Rehg



Face validation: color validation

Joint color histogram

$$c = \left\lfloor R \frac{N_h}{256} \right\rfloor + N_h \left\lfloor G \frac{N_h}{256} \right\rfloor + N_h^2 \left\lfloor B \frac{N_h}{256} \right\rfloor$$

- $c \in [0, ..., Nh^3 1]$
- Nh = 16 means 4096 bins in a histogram



Face validation: color validation

- Histogram similarity between detection and Jones and Rehg
 - Bhattacharyya coefficient:

$$BC(h_c, h_{JR}) = \sum_{n=1}^{N_h^3} \sqrt{h_c(n)h_{JR}(n)}$$

High similarity means that the face detection is valid



Face validation: outline

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- Idea:
 - Statistically measure the similarity between face detection and prototype frontal face
- Method used: **DFFS** (Distance From Face Space)



DFFS algorithm elements:

- Training data set: non-occluded frontal faces
- x_avg the average face vector of the data set
- W a face subspace projection matrix, obtained from the data set using Principal Components Analysis
- x face detection represented as a vector (rearranging columns of grey levels)



DFFS algorithm:

 Using matrix W, face vector x is projected to a a face subspace, where its difference d from x_avg is measured:

$$d_{proj} = \mathbf{x} - \left(W \left(W^T \left(\mathbf{x} - \overline{\mathbf{x}}_{AR} \right) \right) + \overline{\mathbf{x}}_{AR} \right)$$

d is used to find the measure of similarity:

$$DFFS = \sqrt{\frac{1}{N_{\mathbf{x}}} \sum_{n=1}^{N_{\mathbf{x}}} d_{proj}(n)^2}$$



High similarity (= low DFFS value) means a valid face detection



Face tracking

Outline

- The AIT tracking system
- Person tracking in enhanced cognitive care
- Joint Bayesian Tracking of Head Location



1. The AIT tracking system

- Tracking is widely used in surveillance
- Two approaches for face tracking: Stochastic and deterministic



Tracking system

- 2D face localization constrained in the body areas
- CAM-Shift tracker: Used when no association is made.
 Tracks similarly colored regions
- for all active tracks: check for duplicates



Body tracking module

- Provides the regions where to apply face detection.
- Dynamic foreground segmentation : adaptative background modeling, learning rates
- Kalman filter
- <u>Benefit</u>: solves the problem of targets fading into the background.
- Applications: tracking people in a meeting



Face tracking module

- Assigning detected faces to tracked targets (Munkres algorithm)
- Association conflict (occlusion, rotation..)
- CAM-Shift algorithm:
 - pending status
 - Trained color histogram
 - No update: uses only detections validated by GMM



Summary

- Overall performance improved. CAM-shift tracker complements the three face detectors
- Misses and false positives should be reduced:
 - Better detectors
 - Replacing CAM-Shift tracker by Kalman or particle filter tracker.



2. Person tracking in enhanced cognitive care

- Audiovisual system detecting movement in a cluttered and reverberant environment:
 - One camera
 - 3 microphones
- Audio will not be discussed further in the actual context



Visual tracker: prelude

- Face detection measurement
- Color model matching
- ▶ The visual tracker benefits from both the precise localization of the face detection and the presence of color model.



3. Joint Bayesian Tracking of head location

Tracking of people location supports proxemic studies



Appearance likelihood for pose tracking

- Target are described in terms of a low-dimensional representation: color and shape
 - Shapes identify image patch (head, torso)
 - Color describe the appearance of the body parts
- Histogram: offers robustness
- Part based definition: exploits appearance Independence
- State of the target: position + horizontal reference plane/torso orientation, and its head plan and tilt angles (3D space).



Summary

- New approaches
 - Particle filtering approach
 - Joint Bayesian tracking



References

References

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- Joint Bayesian Tracking of Head Location and Pose from Low-Resolution Video, Aristodemos Pnevmatikakis & Fotios Talantzis



Questions ©

