Face Detection 2

Vorlesung “Computer Vision für Mensch-Maschine-Interaktion”
WS 2013/14

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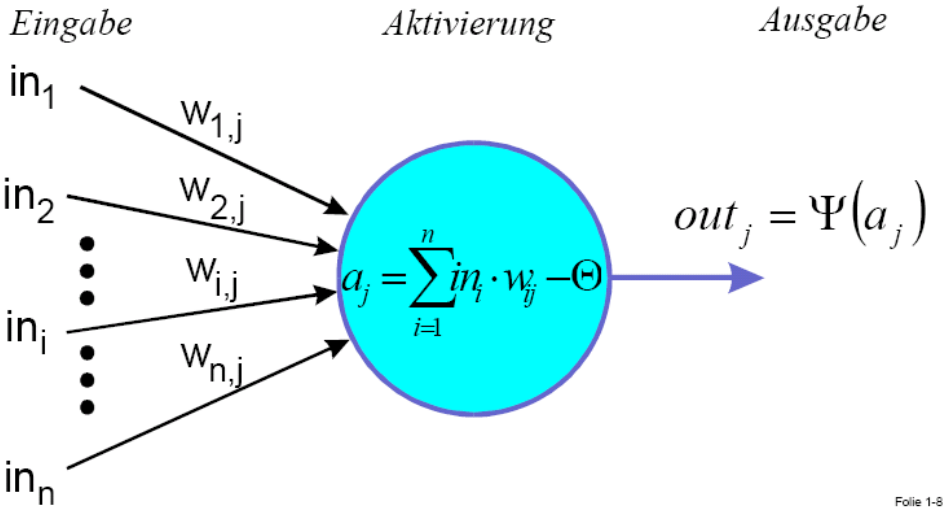
22.11.13

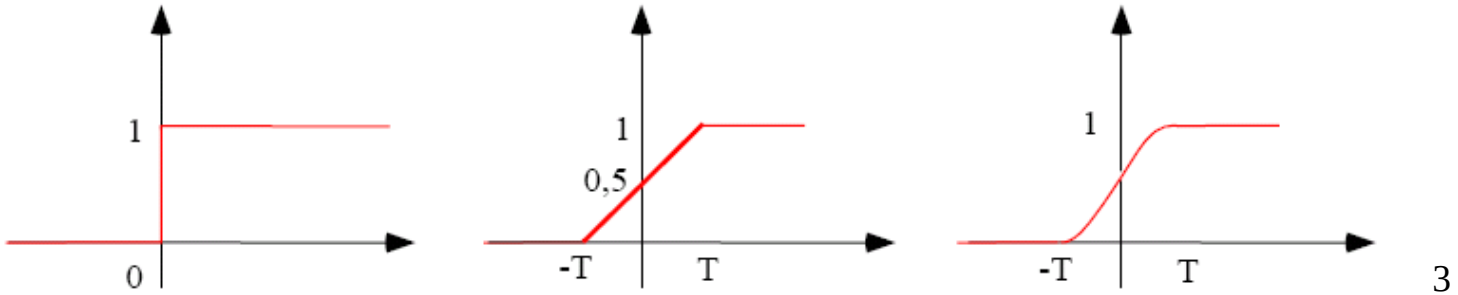
Roadmap

- Color based face detection
- An Ellipsoid head model
- **Artificial Neural Networks**
- Feature-based classifier cascades (Viola & Jones)

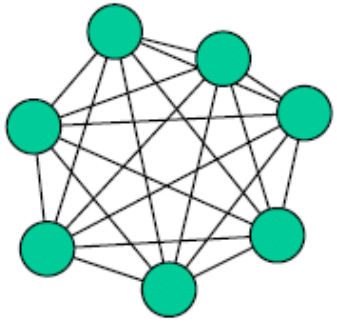
Neural Network Based Face Detection
A Simple Neuron Model



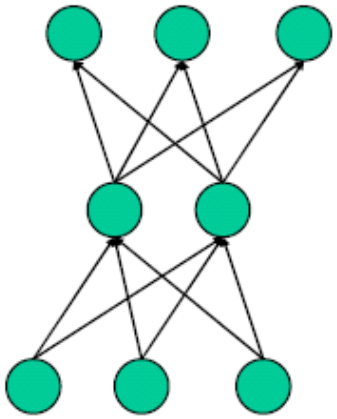
Different outputs possible, depending on activation function:



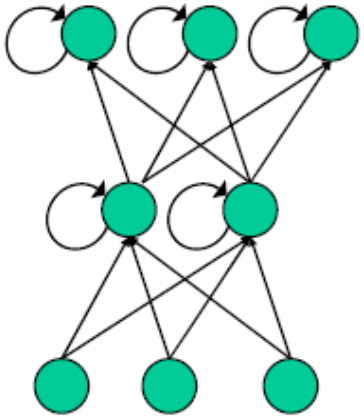
Neural Network Based Face Detection Topologies



Fully connected



Feed-forward

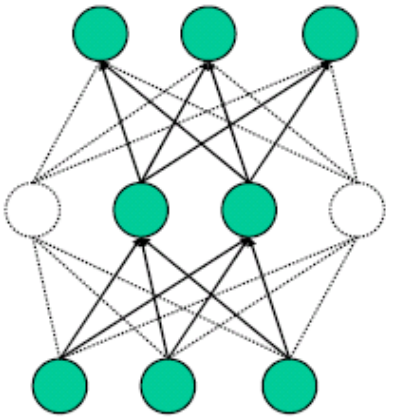


Recurrent

Neural Network Based Face Detection Parameters

Adjustable Parameters are

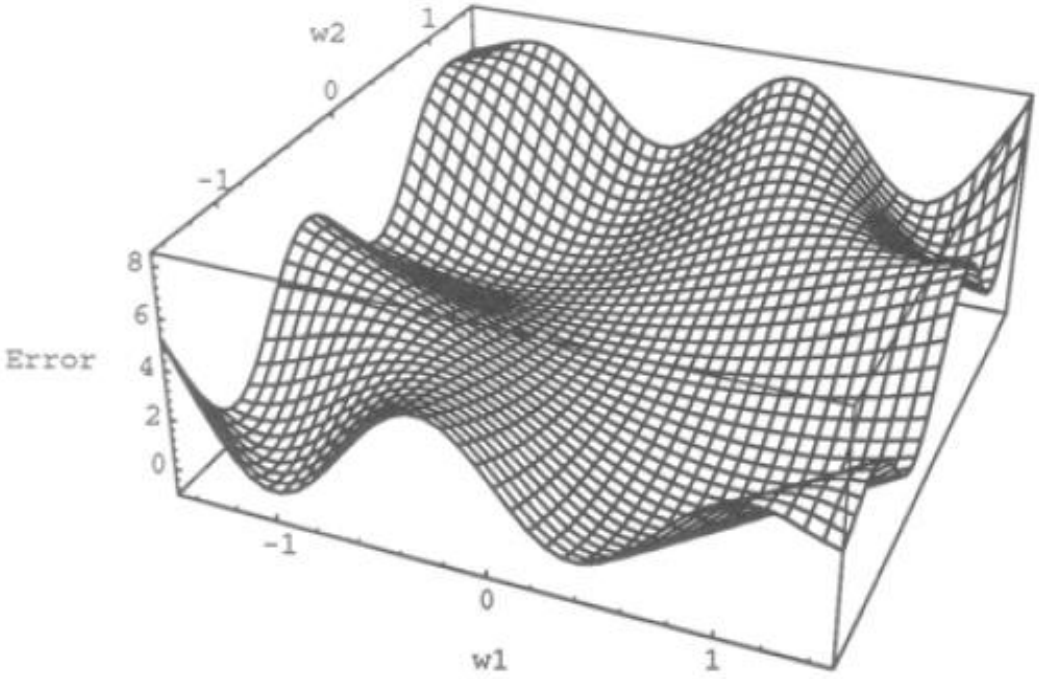
- Connection weights
  - are to be learned
- Activation function (fixed)
- Number of layers (fixed)
- Number of neurons per layer (fixed)



Neural Network Based Face Detection Training (1)

Learning the connectionist weights is achieved by descending the gradient of the resulting output error E: $\Delta W = -\eta \cdot \nabla E(W)$

(→ Backpropagation Algorithm)



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Neural Network Based Face Detection Training (2)

Standard Error Backpropagation (1):

Given sample patterns (p_1,t_1), …, (p_n,t_n) with specified target outputs (groundtruth) t_p for each pattern p

- Error function for a single pattern p accumulating over all output neurons j: $E_p = \frac{1}{2}\sum_j (t_{pj} - out_{pj})^2$
- Deriving from $\Delta W = -\eta \cdot \nabla E(W)$ weights are adjusted as

$$\Delta w_{ij} = \sum_p -\eta \cdot \frac{\partial E_p}{\partial w_{ij}}$$

Neural Network Based Face Detection Training (3)

Standard Error Backpropagation (2):

$$\Delta w_{ij} = \sum_p -\eta \frac{\partial E_p}{\partial w_{ij}}$$

For one p:

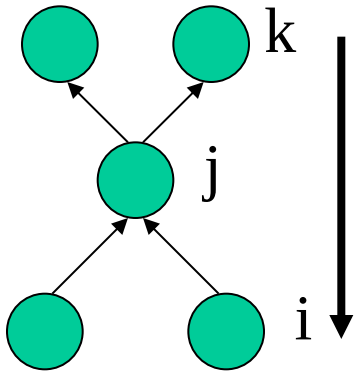
$$-\frac{\partial E}{\partial w_{ij}} = -\frac{\partial E}{\partial a_j}\frac{\partial a_j}{\partial w_{ij}} = -\frac{\partial E}{\partial \sum_{i=1}^{n} w_{ij} in_{ij}}\frac{\partial \sum_{i=1}^{n} w_{ij} in_{ij}}{\partial w_{ij}} = -\frac{\partial E}{\partial a_j} in_{ij} = -\underbrace{\frac{\partial E}{\partial out_j}}_{1}\underbrace{\frac{\partial out_j}{\partial a_j}}_{2} in_{ij}$$

Error signal that gets propagated through the network

Assume $\Psi(a)$ to be $\Psi(a) = \frac{1}{1+e^{-a}} \Rightarrow \frac{\partial \Psi(a)}{\partial a} = \Psi(a)(1-\Psi(a))$

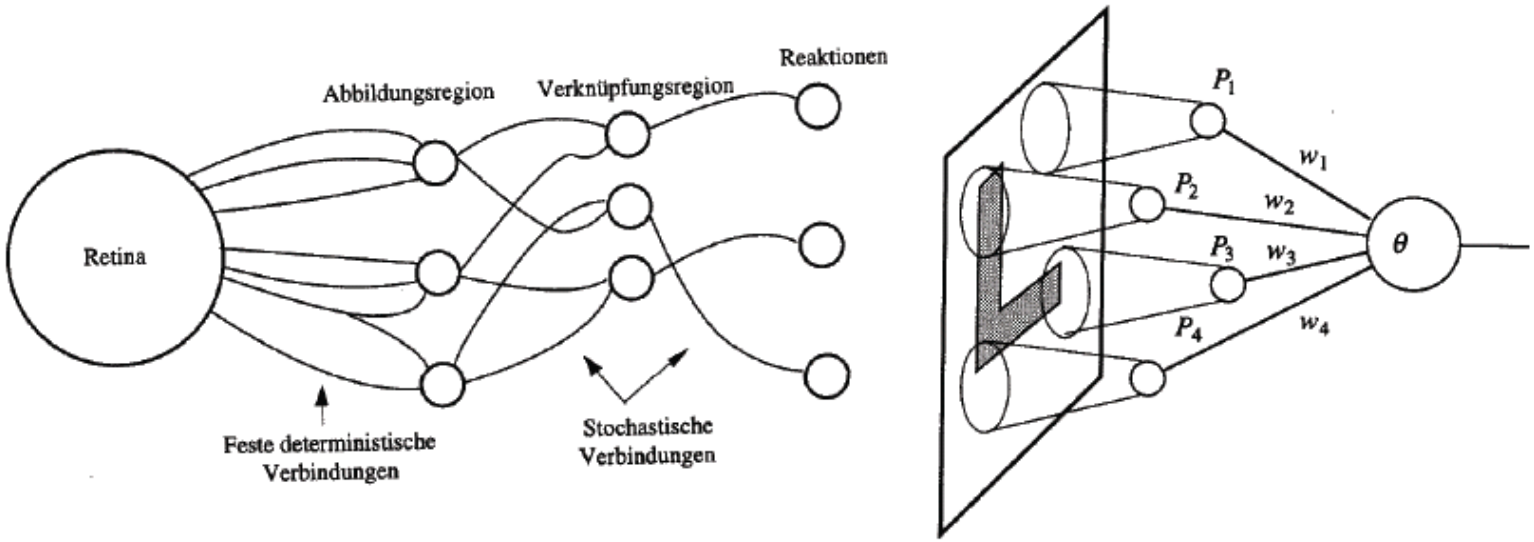
2) $$\frac{\partial out_j}{\partial a_j} = \frac{\partial \Psi(a_j)}{\partial a_j} = \Psi(a_j)(1-\Psi(a_j))$$

1)
$$\begin{cases} -\frac{\partial E}{\partial out_j} = (t_j - out_j), \text{ if j is output unit} \\ -\frac{\partial E}{\partial out_j} = \sum_k -\underbrace{\frac{\partial E}{\partial out_k}}_{1}\underbrace{\frac{\partial out_k}{\partial a_k}}_{2} w_{jk}, \text{ if j is hidden unit} \end{cases}$$



Neural Network Based Face Detection

Idea for image classification: remodel human visual perception



Neural Network Based Face Detection

General approach for detecting (upright, frontal) faces with NN:

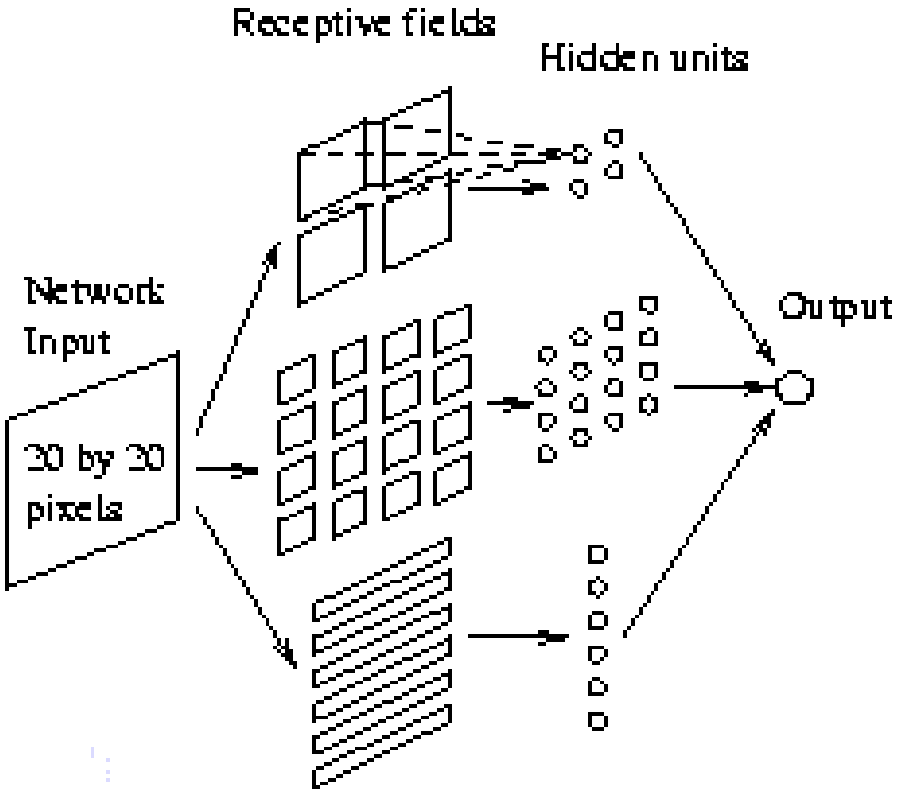
- Network receives as input a 20x20 pixel region of an image
- output ranges from -1 (no face present) to +1 (face present)
- the neural network „face-filter“ is applied at every location in the image
- to detect faces with different sizes, the input image is repeatedly scaled down

Neural Network Based Face Detection, by Henry A. Rowley, Shumeet Baluja, and Takeo Kanade. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, volume 20, number 1, pages 23-38, January 1998.

Neural Network Based Face Detection
Network Topology

ANN Topology:

- 20x20 pixel input retina
- 4 types of receptive hidden fields
- One real-valued output



Neural Network Based Face Detection System Overview

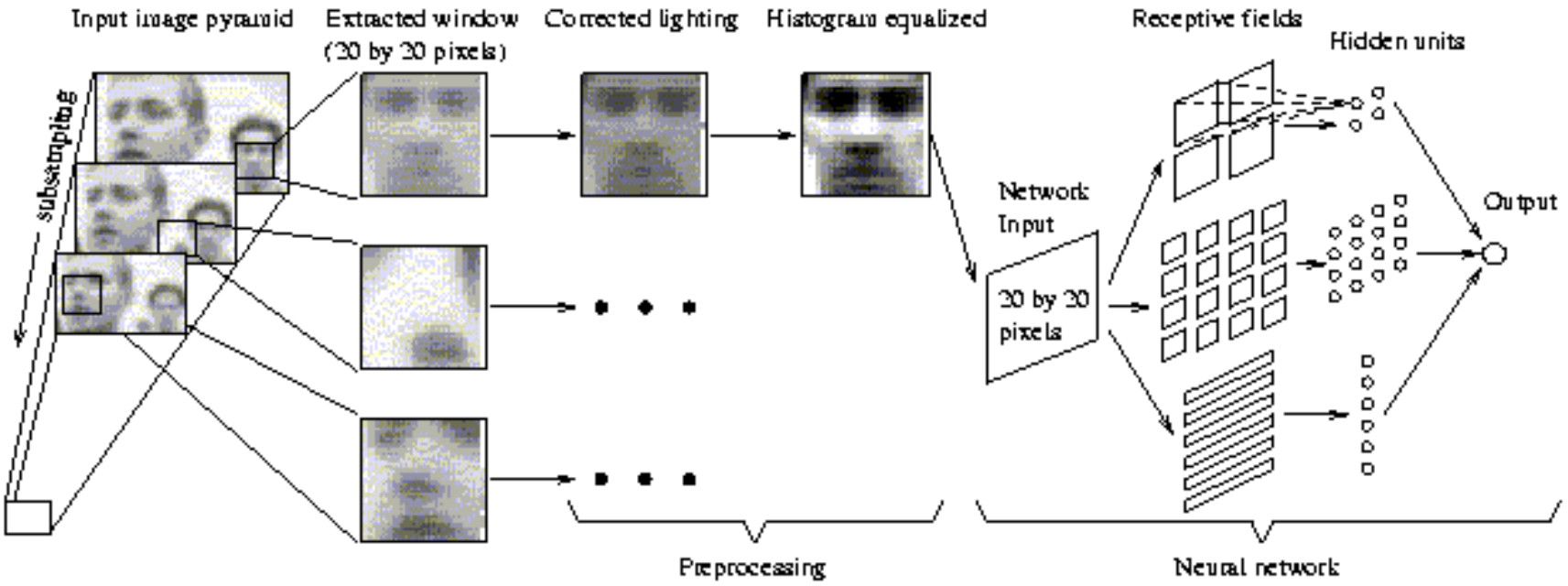
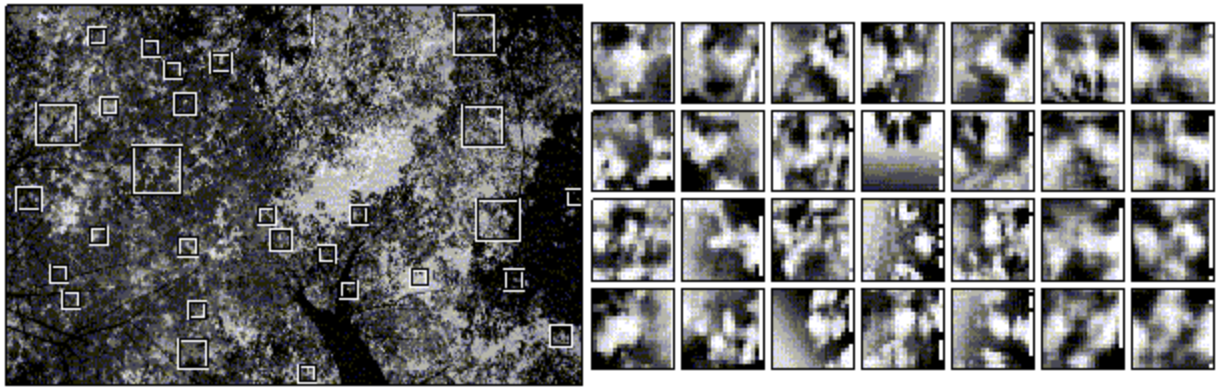


Figure 1: The basic algorithm used for face detection.

Neural Network Based Face Detection Trainingset

- **Training Set:**
  - 1050 normalized face images
  - 15 face images generated by rotating and scaling original face images
  - 1000 randomly chosen non-face images

Face Samples

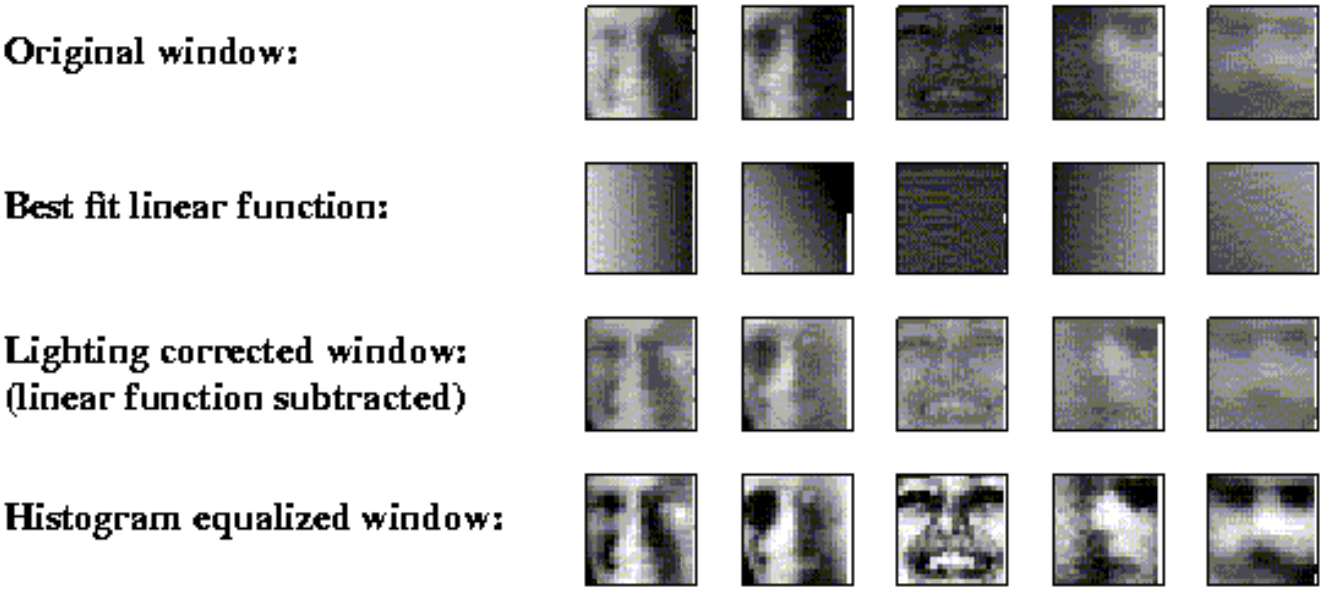


Non-Face Samples

Neural Network Based Face Detection Preprocessing

Preprocessing:

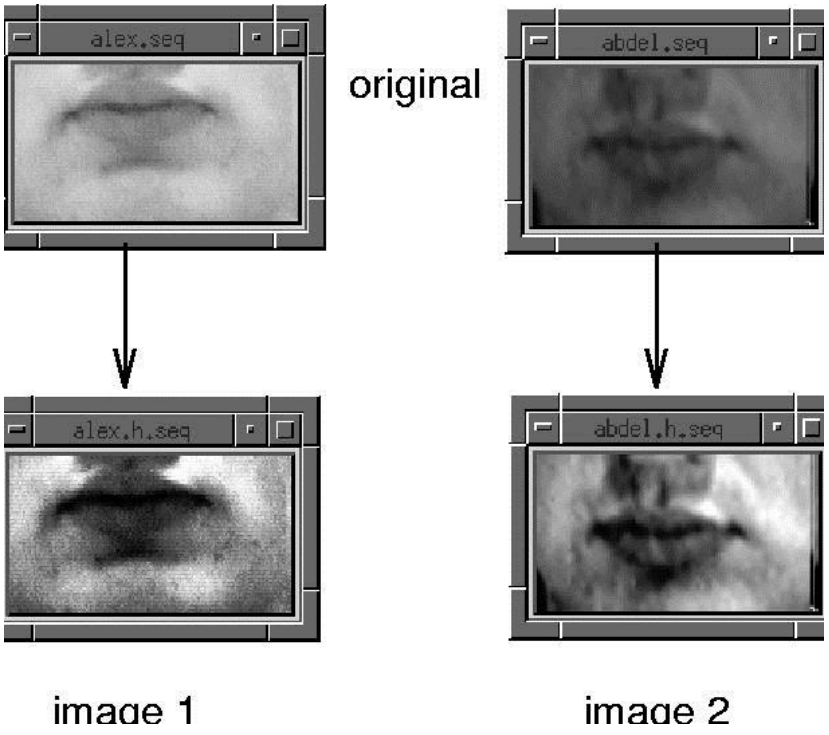
- correct for different lighting conditions (overall brightness, shadows)
- rescale images to fixed size
- Often: extract relevant features (edges, FFT, wavelets, PCA, DCT, …)



Histogram equalization

- Defines a mapping of gray levels p into gray levels q such that the distribution of q is close to being uniform
- Stretches contrast (expands the range of gray levels)
- Transforms different input images so that they have similar intensity distributions (thus reducing the effect of different illumination)

- Fast algorithm exists,
  - Transformation can be defined in terms of the cumulative histogram



Histogram Equalization (Algorithm)

- The probability of an occurrence of a pixel of level *i* in the image is $p(x_i)$:

$$p(x_i) = \frac{n_i}{n}, i \in 0, ..., L-1$$

- define *c* as the *cumulative distribution function*:

$$c(i) = \sum_{j=0}^{i} p(x_j)$$

- create a transformation of the form
  - $y = T(x)$
  - will produce a level *y* for each level *x* in the original image, such that the cumulative probability function of *y* will be *linearized* across the value range.

$$y_i = T(x_i) = c(i)$$

($y_i \in [0,1]$)

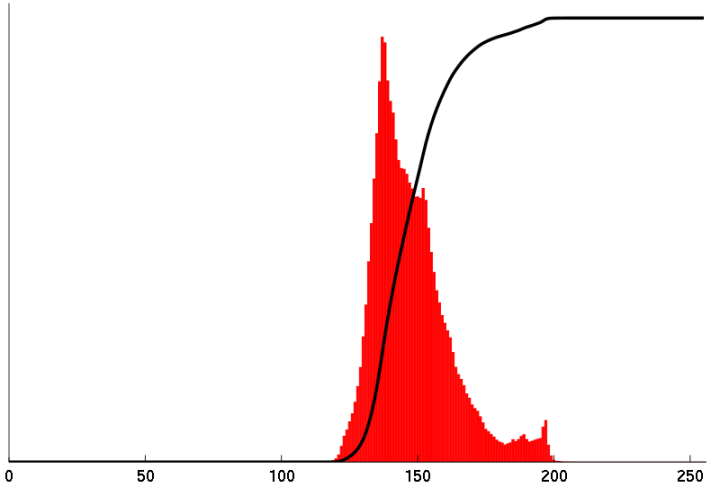
$$y_i' = y_i \cdot (\max - \min) + \min$$

($y'_i \in [\min, \max]$)

L: number of gray levels, n_i: number of occurences of gray level *i*

Histogram Equalization (Example)

Unequalized image



Equalized image

Corresponding Histograms

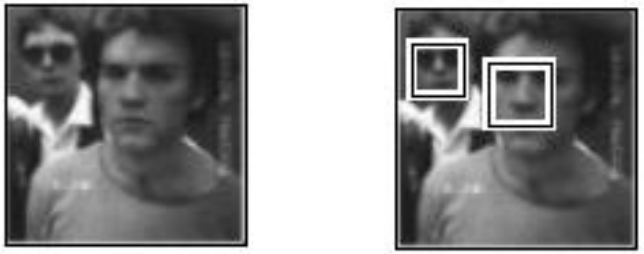
Neural Network Based Face Detection Training

Training Procedure:

1. randomly choose 1000 non-face images
2. train network to produce 1 for faces, -1 for non-faces
3. run network on images containing no faces. Collect subimages in which network incorrectly identifes a face (output > 0)
4. select up to 250 of these „false positives“ at random and add them to the training set as negative examples

Neural Network Based Face Filter

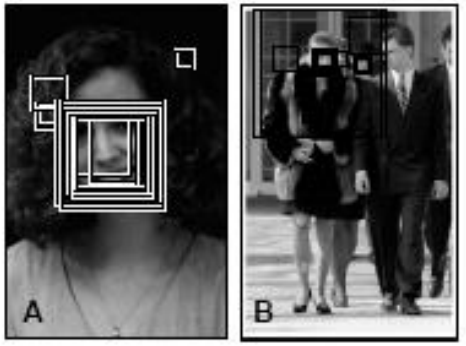
- Output of ANN defines a filter for faces
- Search
  - Scan input image with search window, apply ANN to search window
  - Input image needs to be rescaled in order to detect faces with different size



Different sizes

- Output needs to be post-processed
  - Noise removal
  - Merging overlapping detections

- Speed up can be achieved
  - Increase step size
  - Make ANN more flexible to translation
  - Hierarchical, pyramidal search



Overlapping detections

Classifying a hypothesis

- When comparing recognition hypotheses with ground-truth annotations have to consider four cases:

	Predicted positive	Predicted negative
Positive examples (Pos)	*True positive* (TP)	*False negative* (FN)
Negative example (Neg)	*False positive* (FP)	*True negatives* (TN)

- Example:




Prediction:	Yes	No	Yes	No
Case:	TP	FN	FP	TN

ROC

- Used for the task of classification
- Measures the trade-off between true positive rate and false positive rate:

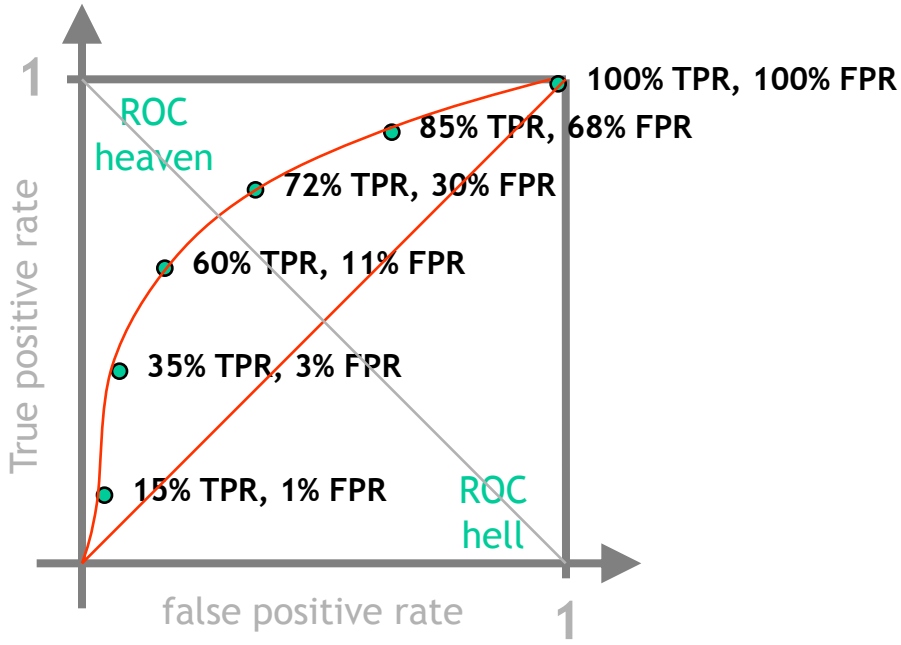
$$\text{true positive rate} = \frac{\text{TP}}{\text{Pos}} = \frac{\text{TP}}{\text{TP+FN}}$$

$$\text{false positive rate} = \frac{\text{FP}}{\text{Neg}} = \frac{\text{FP}}{\text{FP+TN}}$$

- Example:
  - Algorithm X detects 80% of all cups (true positive rate), while making 25% error on images not containing cups

ROC

- Each prediction hypothesis has generally an associated probability value or score
- The performance values can therefore plotted into a graph for each possible score as a threshold



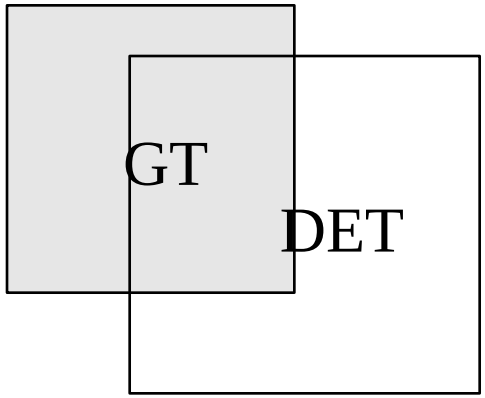
Localization and Ground-Truth

- For localization, the test data is mostly annotated with ground-truth bounding boxes
- It is often not obvious when to count a hypotheses as true or false detection
  - Misaligned hypotheses
  - Double detections

ground-truth
detection

Comparing hypotheses to Ground-Truth

- Overlap
  - O = area(GT ∩ DET) / area(GT ∪ DET)



- There is no standard for which values to choose
- Often used as threshold:
  - Overlap>50%
- Double detections are counted as false positive

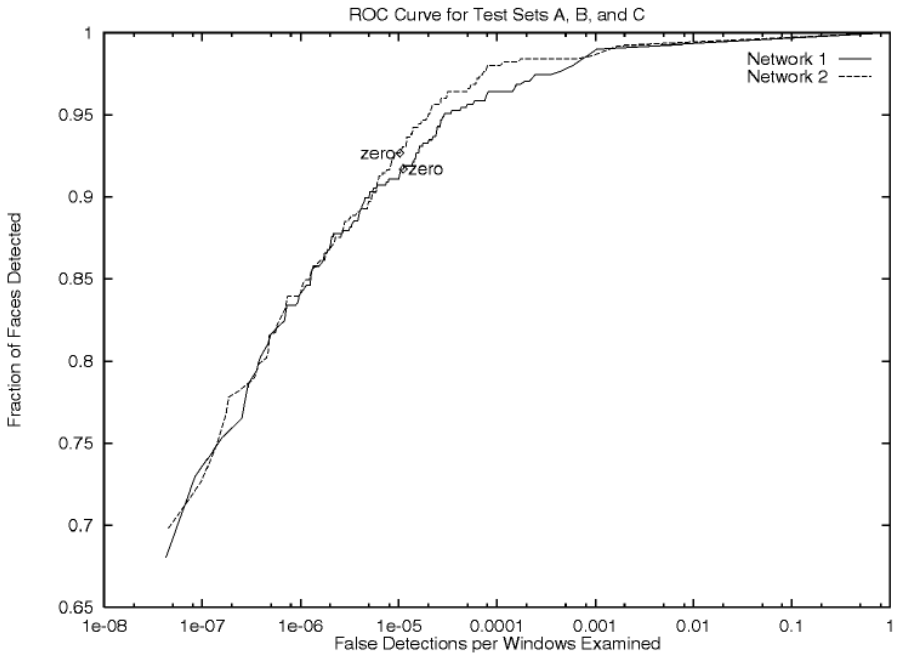
Neural Network Based Face Detection Results

Results on 130 images containing 507 faces (83Million subregions exmamined):

- 92.5 % detection rate at false detection rate of 1/96402 (862 false detections)
- 77.9 % detection rate at false detection rate of 1/41Mio. (2 false detections)

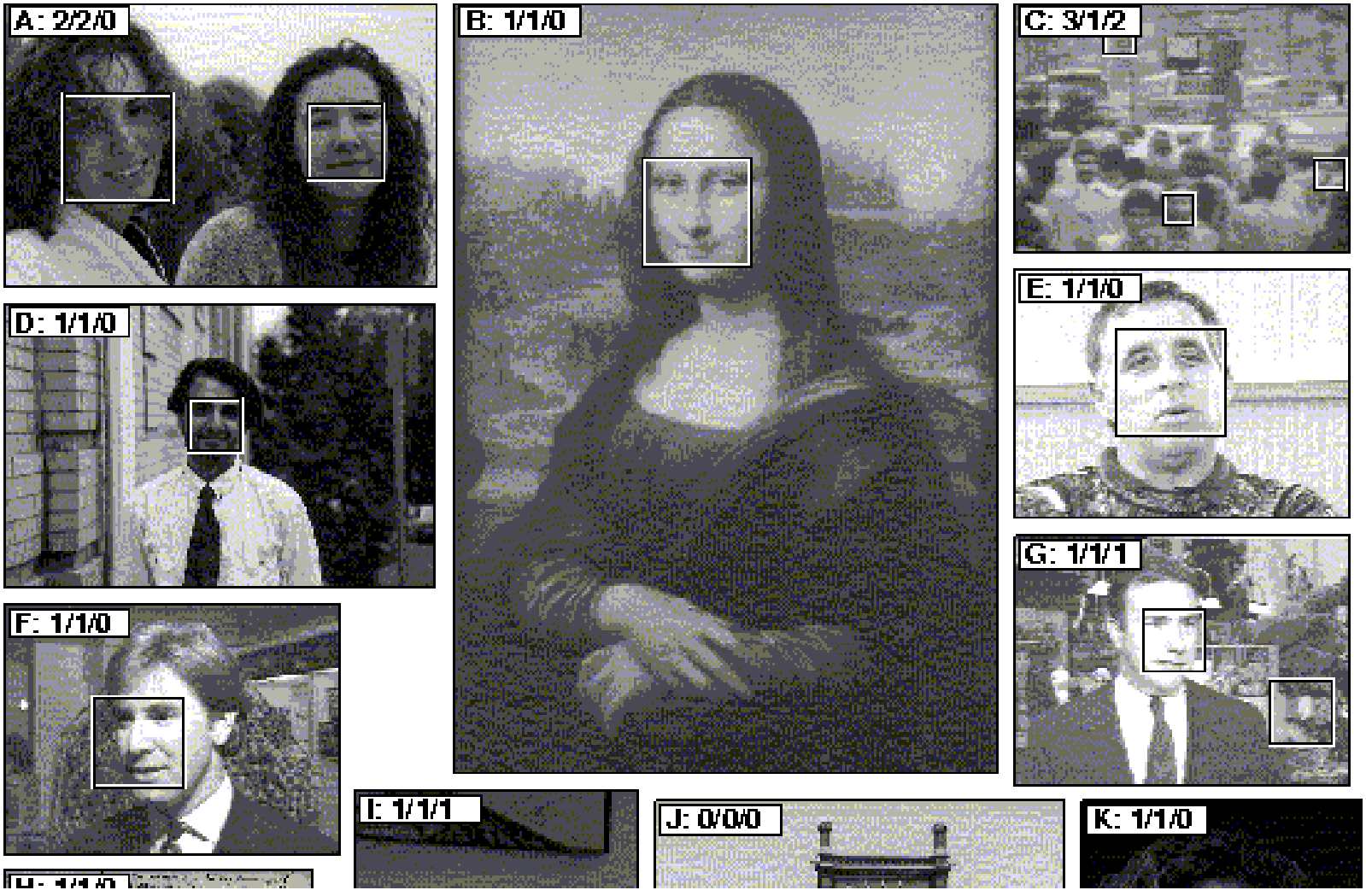
Speed:

- best system, using two networks: 383 seconds per image
- tuned for speed (77% detection rate) 7.2 seconds per image



Neural Network Based Face Detection Results

Neural Network Based Face Detection Results



Roadmap

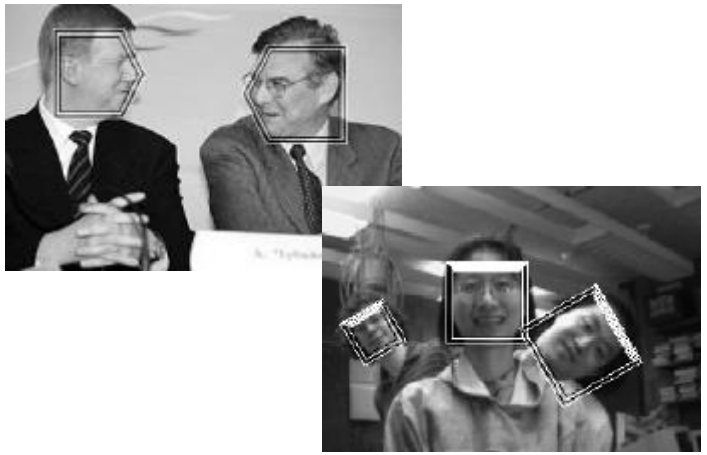
- Color based face detection
- Contour shaping
- Artificial Neural Networks
- **Feature-based classifier cascades (Viola & Jones)**

Feature-based Face Detection

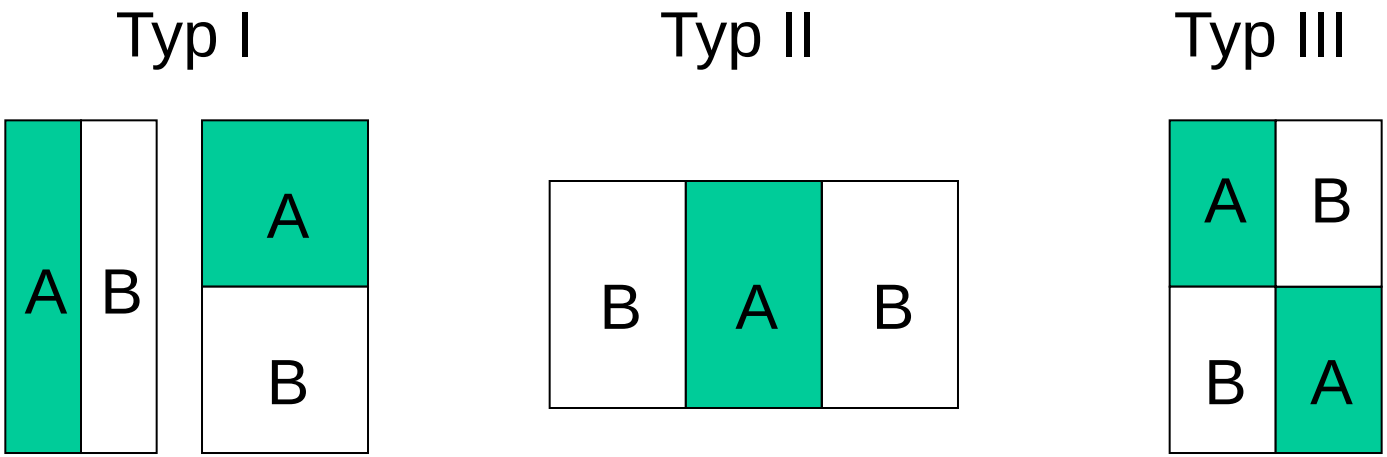
- Detection based on features, not pixels
  - Features can encode domain knowledge that is difficult to learn
  - Faster than a pixel-based system
  - Scale independent

Feature-based Face Detection

- Robust realtime detection of general objects consisting of
  - Features (for human faces)
  - Integral Image (to compute features)
  - Weak Classifier Cascade
  - Train the Cascade

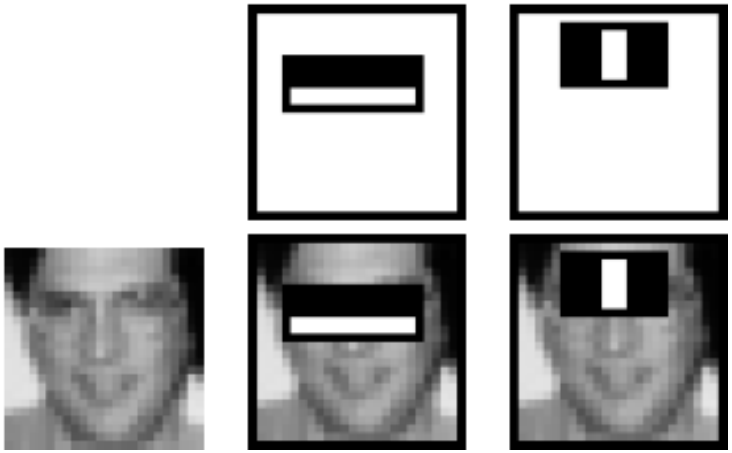


Feature-based Face Detection: Features (1)



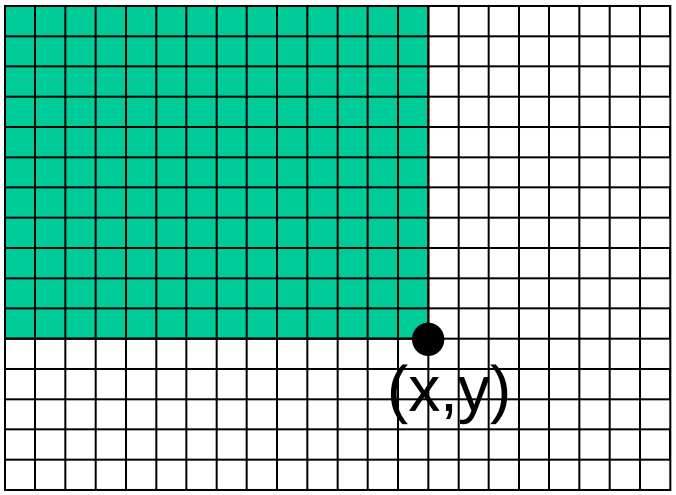
Feature-based Face Detection: Features (2)

Features applied on grayscaled subwindows of fixed size (e.g. 24x24 pixels)



- Over 180.000 rectangle features possible for each subwindow !
  (→ Different positions, sizes)
- Computing each feature‘s value independently takes way too long !!

Feature-based Face Detection: Integral Image



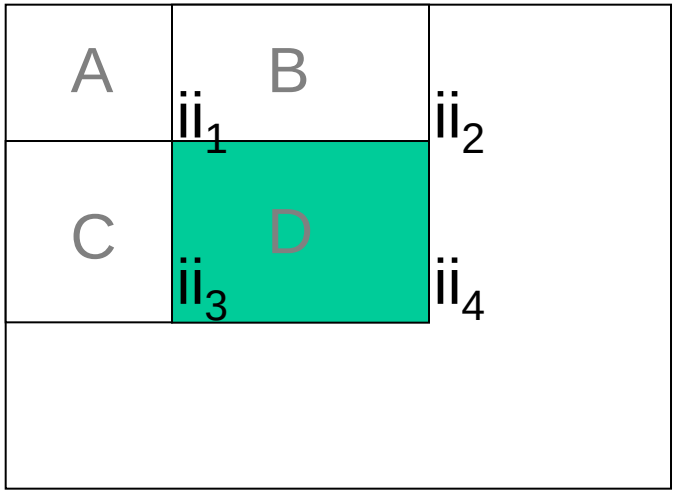
$$ii(x,y) = \sum_{x' \le x, y' \le y} I(x',y')$$

ii(x,y) is the integral image
i (x,y) is the original image

computing in two recurances: $s(x,y) = s(x,y-1) + i(x,y)$

$$ii(x,y) = ii(x-1,y) + s(x,y)$$

Feature-based Face Detection: Feature Evaluation (1)

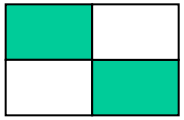


ii_1 = area(A)
ii_2 = area(A + B)
ii_3 = area(A + C)
ii_4 = area(A + B + C + D)

$\Rightarrow$ area(D) = $ii_4 + ii_1 - (ii_2 + ii_3)$

(4 array references)

Feature-based Face Detection: Feature Evaluation (2)

Feature	Array references
Rectangle 	4
Type I 	6
Type II 	8
Type III 	9

Feature-based Face Detection: Feature Evaluation (3)

- Computing one feature can now be computed very fast
  - Computing all features however still takes too much time!
- Still too many features to compute in real time

- Idea: Only learn significant features!

Feature-based Face Detection: AdaBoost (1)

- AdaBoost is used to boost classification performance of a simple learning algorithm (e.g. simple perceptron)
- Variant of AdaBoost is used to select features + train the classifier
- It combines a collection of weak classifier to form a stronger one

Feature-based Face Detection: AdaBoost (2)

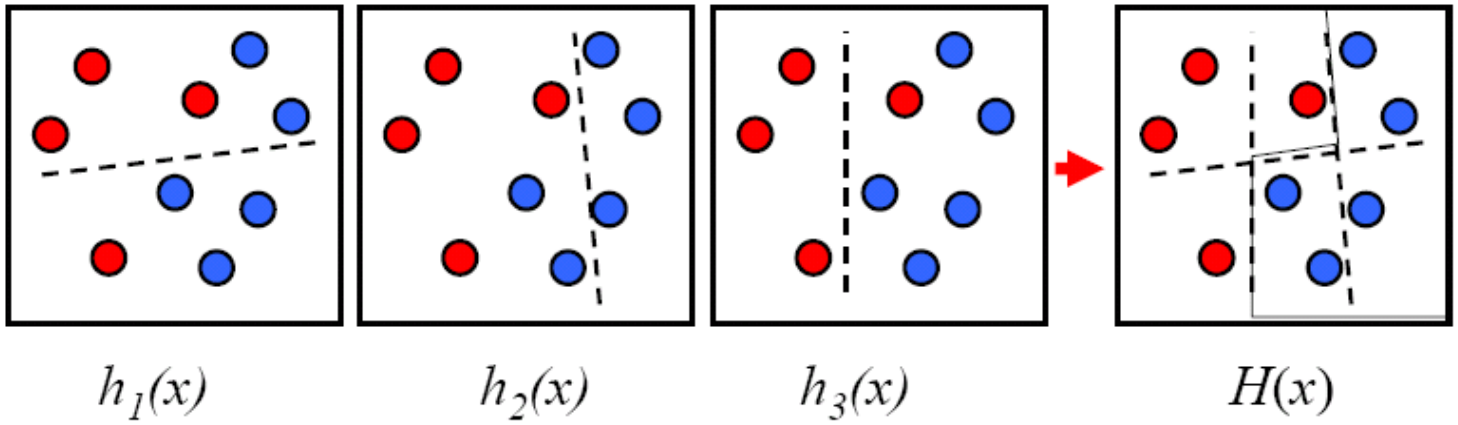
- A weak classifier *h* is a classifier with accuracy only slightly better than chance

- Boosting: combine a number of weak classifiers so that the ensemble is arbitrarily accurate
  - Allows the use of simple (weak) classifiers without the loss of accuracy

Feature-based Face Detection: AdaBoost (3)

- Combine weak classifiers $h_i \in \{-1, 1\}$ linearly to build a strong classifier H:

$$H = sign \sum_{i=1}^{N} w_i h_i$$



Feature-based Face Detection: AdaBoost (4)

Viola & Jones approach:

- Weak classifier $h_j(x)$ consists of a feature f_j, a threshold θ_j, and a polarity p_j

$$h_j(x) = \begin{cases} 1 & \text{if} \quad p_j f_j(x) < p_j \theta_j \\ 0 & \text{else} \end{cases}$$

Feature-based Face Detection: AdaBoost (5)

- AdaBoost…
  - searches over the set of possible weak classifiers and selects those with the lowest classification error
  - applies a greedy feature selection process
  - is efficient for selecting a small number of “good” features with significant variety

Feature-based Face Detection: AdaBoost (6)

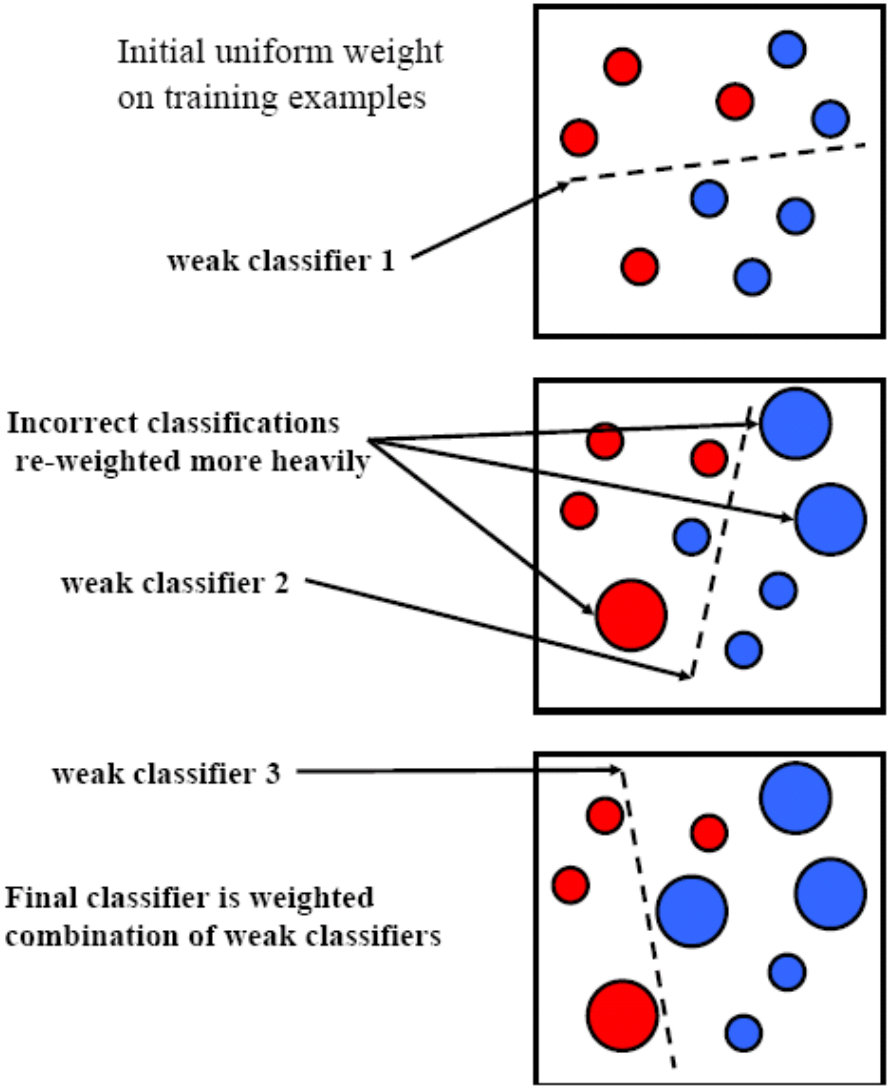
- Given examples x_i with annotations (x_i,y_i) where $y_i \in \{-1,1\}$
- Initialize weights: $w_{1,i} = \frac{1}{2m}, \frac{1}{2l}$
- For T=1..t:
  - Normalize weights: $w_{t,i} \leftarrow \frac{w_{t,i}}{\sum_{j=1}^{n} w_{t,j}}$
  - For each feature j, train a classifier h_j, restricted to using a single feature
    - That is, adjust threshold θ_j so h_j classifies best between the weighted positive and negative samples
  - Choose classifier h_t, with lowest error ε_t
  - Update weights: $w_{t+1,i} = w_{t,i}\beta_t^{1-e_i}$

    where e_i=0 if sample x_i is classified correctly, e_i=1 otherwise and $\beta_t = \frac{\varepsilon_t}{1-\varepsilon_t}$
- Finally, the strong classifier then is:

$$H(x) = \begin{cases} 1 \ \sum_{t=1}^{T} \alpha_t h_t(x) \geq \frac{1}{2} \sum_{t=1}^{T} \alpha_t \\ 0 \text{ otherwise} \end{cases}, \text{where } \alpha_t = \log \frac{1}{\beta_t}$$

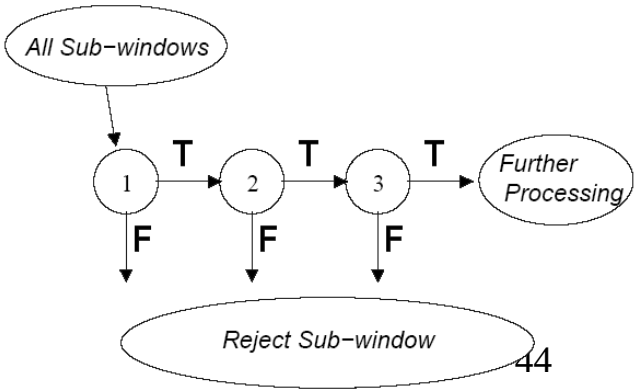
Feature-based Face Detection: AdaBoost (7)

Updating weights forces subsequent classifiers to focus on misclassified samples instead of the same general sampleset as classifiers before did.

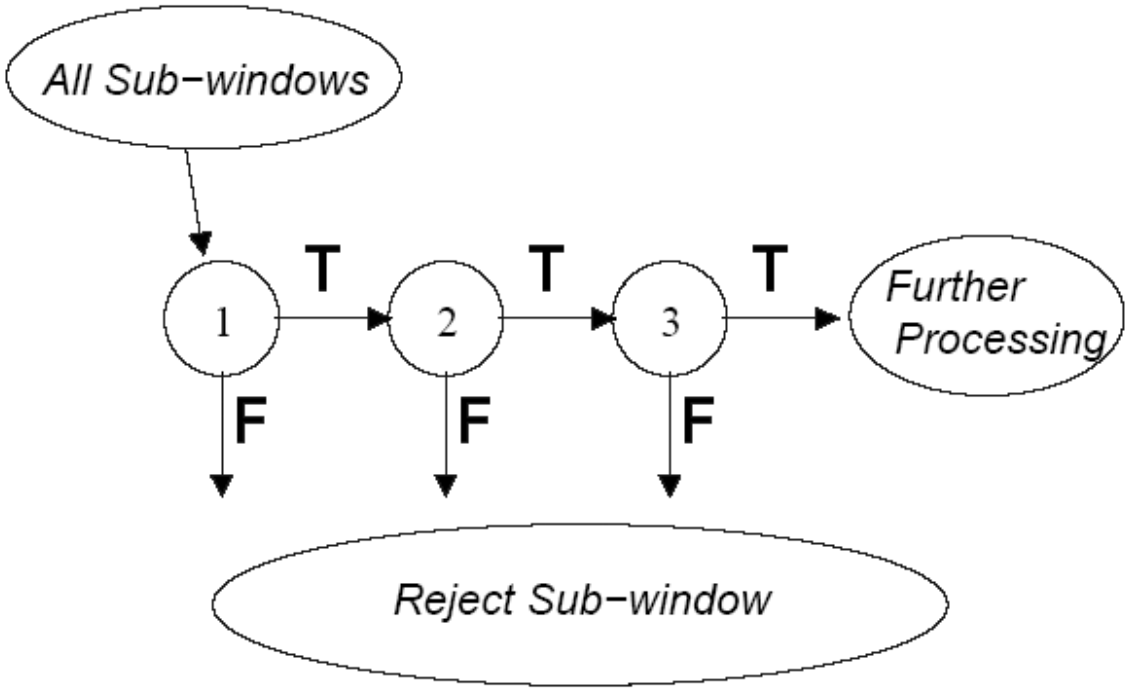


Feature-based Face Detection: Classifier Cascade

- Not all subwindows show faces but we need to apply our strong classifier on all subwindows still
- Idea: Build cascade of classifiers
  - Each subsequent classifier is more ‚precise‘
    - First layer detects all positive samples, but includes many false positives
    - Second layer focuses on false positives of first layer and is more complex
    - …
  - Fast rejection of non-face subwindows whereas face images will be passed through the cascade until the very end



Classifier Cascade



(auswendig lernen ☺)

Feature-based Face Detection: Cascade Training

- Reduce false positive rate & decrease detection rate with each subsequent layer
- For each stage, a target is set for minimum reduction und decrease. Target is achieved by adding more features to corresponding layer
- Adding layers until final target of false detections is met
- Each subsequent layers becomes more complex and include more features

Training the Cascade

Example: 10 stage cascade

Target detection rate: D = 0.9
Target false positive rate: F = 10^{-5}

$$F = \prod_{i=1}^{10} f_i \qquad D = \prod_{i=1}^{10} d_i$$

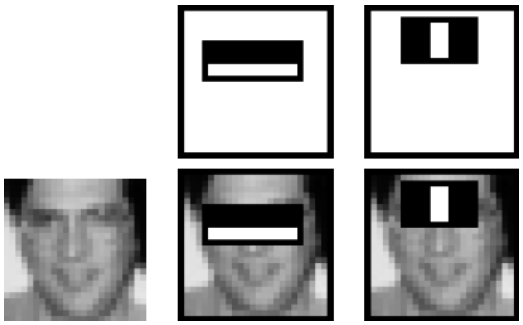
$\Rightarrow$ Each stage:
detection rate d = 0.99
false positive rate f = 0.3

Feature-based Face Detection: Cascade Training

Define Target Rates F and D of final detector;
Assign f_i and d_i to each cascade layer;
while (F not reached){
    add new layer i;
    j = 1;
    while (f_i not reached)   {
        train the classifier with j features;
        adjust threshold to meet d_i;
        j++;
    }
    delete detected negatives;
}

Feature-based Face Detection: Results (1)

- Training set:
  - 4916 hand labeled face images
  - 9544 non-face images
- Each layer was trained with all face images and 10.000 non-face subwindows (24x24 pixels)
  - For subsequent layers, this included previous false positives too
- 38 layers as target

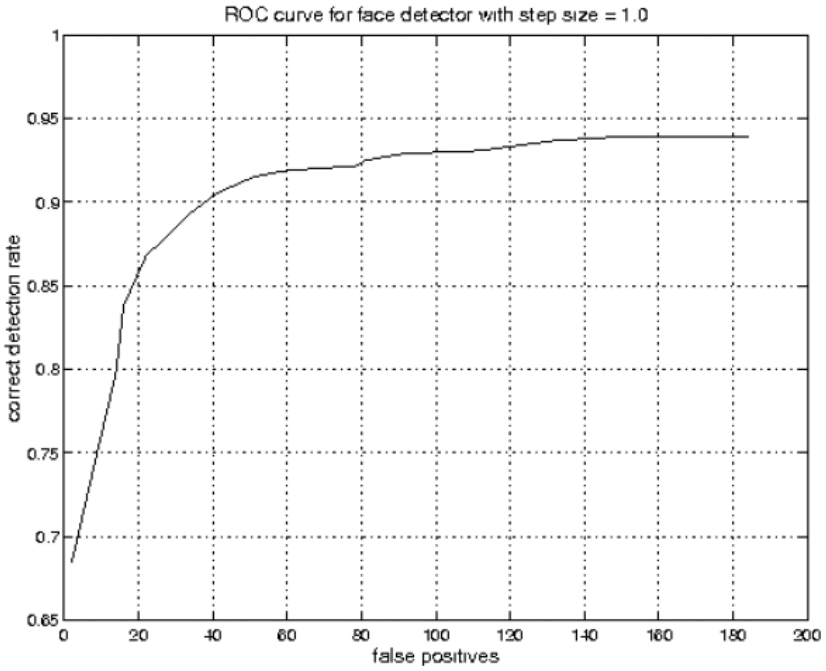


Feature-based Face Detection: Results (2)

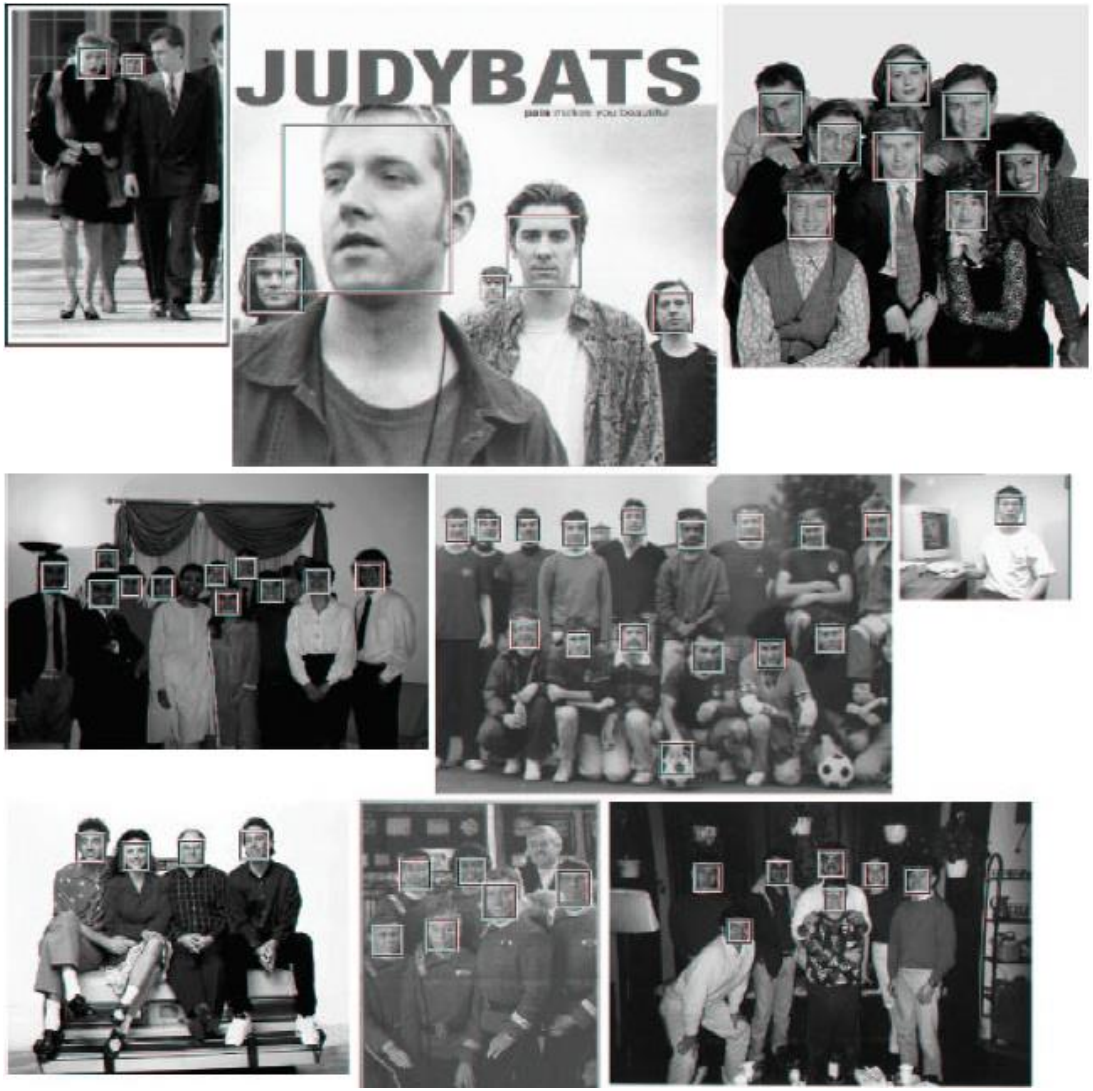
- Final number of features used in total: 6061
  - First layer: 1 feature
  - Second layer: 10 features
  - Fifth layer: 50 features
  - … (38 layers)
- Pentium 3, 700 MHz: total scan of 384x288 pixels in about 0.067 sec. (15 times faster than previous approaches!)
- Large majority of subwindows are rejected in first or second layer

Feature-based Face Detection: Results (3)

- Evaluated on MIT & CMU frontal face database
  - 103 images of 507 frontal faces (labeled)
  - Number of scanned subwindows: 75.081.800



Feature-based Face Detection: Results (4)



Feature-based Face Detection: Results (5)

Conclusion

- Approach that is 15 times faster than any previous approach
- Can also be applied to detect general objects
- Learning techique and cascades have impact on a variety of other tasks
- Comparable detection rates
- Easily detects multiple faces per images
- Robust against illumination variances (to some extent)

References

- H. Rowley, S. Baluja, and T. Kanade, *Neural Network-Based Face Detection*, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 20, No. 1, January, 1998, pp. 23-38.

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- Paul Viola & Michael Jones. *Robust real-time object detection*, Cambridge Research Laboratory, Technical Report,, February 2001, CRL 2001/01