Rejection Based Face Detection

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The Computer Vision Workshop

March 18th, 2002

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Part 1

Introduction of the Problem and Basic Considerations

1. The Task

Input image

Face (target) Detector

Comments:

1. Extension to color
2. Faces vs. general targets

2. Requirements

Detect frontal & vertical faces:

- All spatial position, all scales
- Any person, any expression
- Robust to illumination conditions
- Old/young, man/woman, hair, glasses.

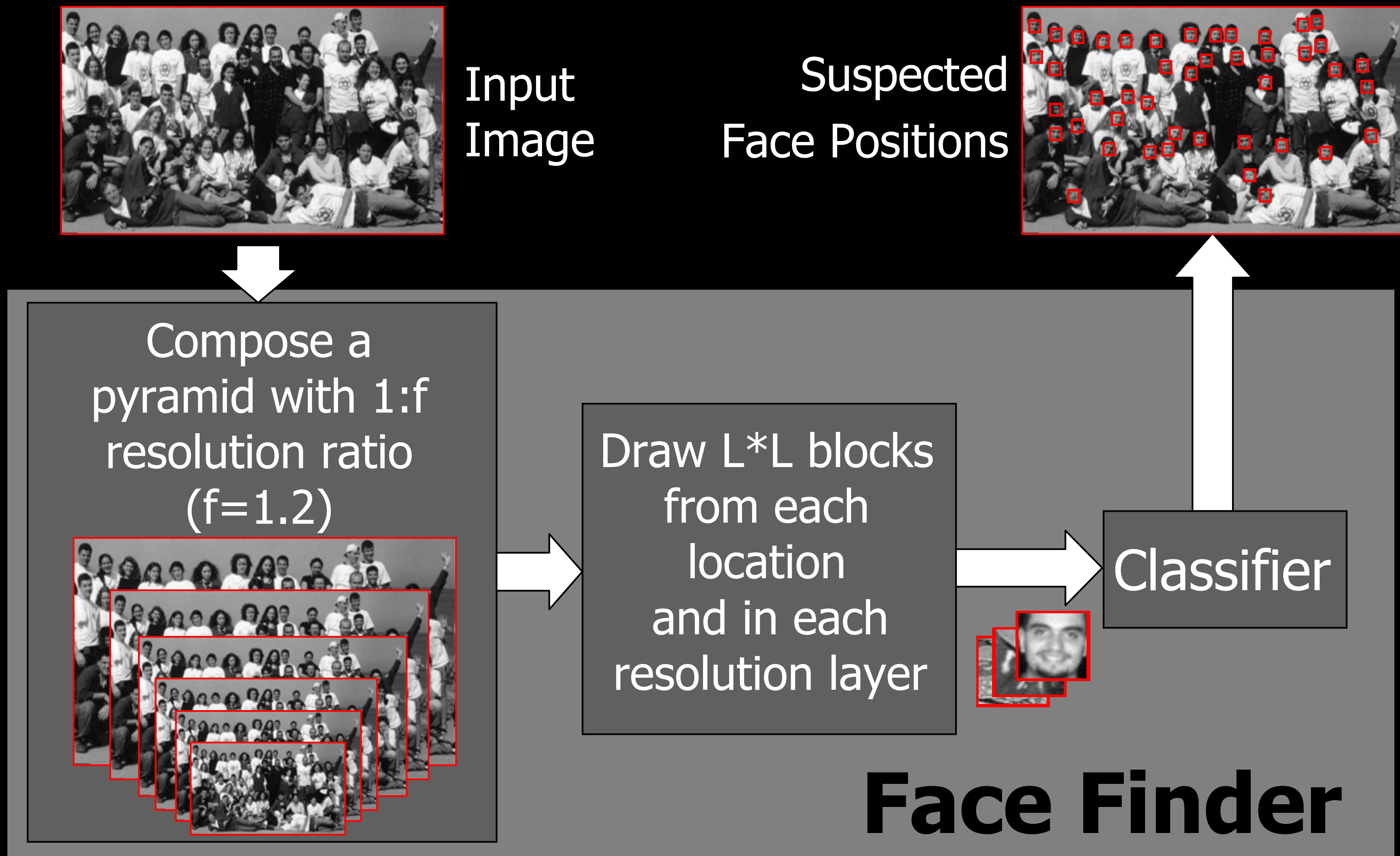
Design Goals:

- Fast algorithm
- Accurate (False Positive / False Negative)

3. Frontal-Vertical Faces

Taken from the ORL Database

4. Scale-Position



5. Classifier Design

A classifier is a parametric (J parameters) function $C(\underline{Z},\underline{\theta})$ of the form

$$C\{\underline{Z},\underline{\theta}\}:\ \Re^{L^2}\times\Re^{J}\to\{-1,+1\}$$

Need to answer two questions:

Q1: What parametric form to use? Linear or non-linear? What kind of non-linear? Etc.

Q2: Having chosen the parametric form, how do we find appropriate set of parameters $\underline{\theta}$?

6. Algorithm Complexity

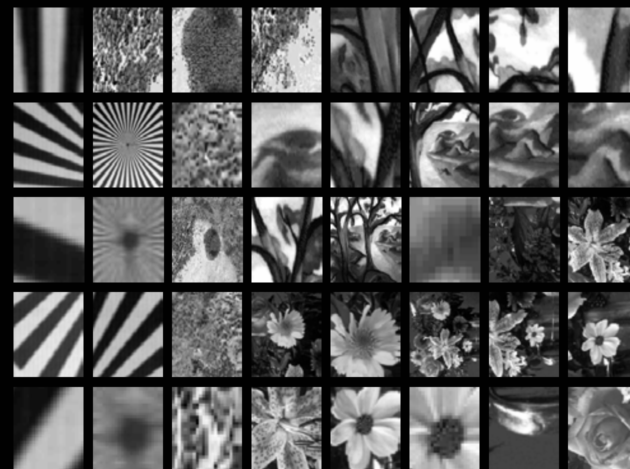
Searching faces in a given scale, for a 1000 by 2000 pixels image, the classifier is applied 2e6 times

(Q1) Choosing the parametric form: keep in mind that the algorithm's complexity is governed by the classifier complexity

7. Training by Examples

$\left\{\underline{X}_k\right\}_{k=1}^{N_X}$

$\left\{\underline{Y}_k\right\}_{k=1}^{N_Y \gg N_X}$



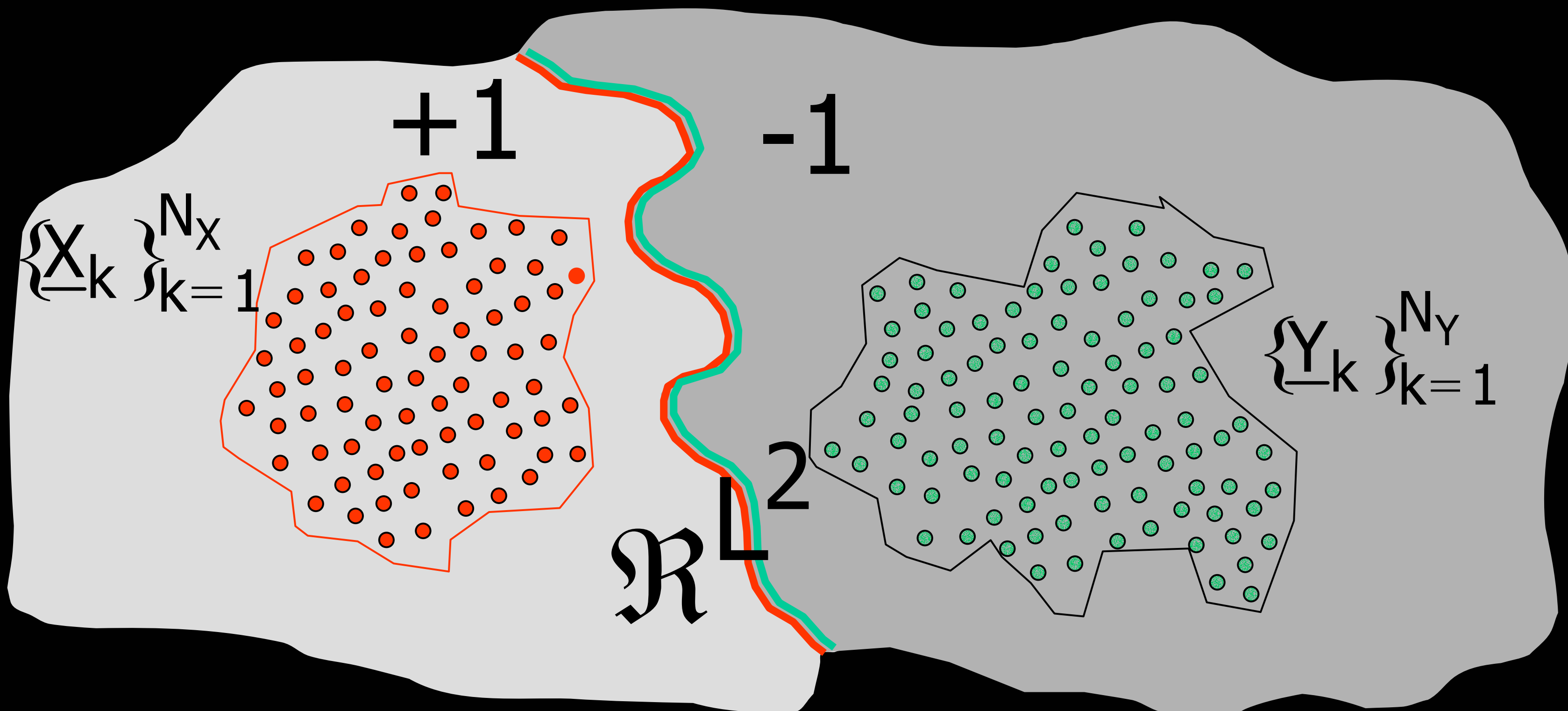
(Q2) Finding Suitable Parameters:

$$\forall 1 \le k \le N_X, \;\; C\left\{\underline{X}_k, \underline{\theta}\right\} = +1$$

$$\forall 1 \le k \le N_Y, \;\; C\left\{\underline{Y}_k, \underline{\theta}\right\} = -1$$

8. Geometric Interpretation

C($\underline{Z}$,$\underline{\theta}$) is to drawing a separating manifold between the two classes



Part 2

SOME

Previous Work

1. Neural Networks

- Choose C(Z,θ) to be a Neural Network (NN).
- Add prior knowledge in order to:
  - Control the structure of the net,
  - Choose the proper kind (RBF ?),
  - Pre-condition the data (clustering)
- Representative Previous Work:
  - Juel & March (1996), and
  - Rowley & Kanade (1998), and
  - Sung & Poggio (1998).

NN leads to a Complex Classifier

2. Support Vector Machine

- Choose C(Z,θ) to be a based on SVM.
- Add prior knowledge in order to:
  - Prune the support vectors,
  - Choose the proper kind (RBF, Polynomial ?),
  - Pre-condition the data (clustering)
- Representative Previous Work:
  - Osuna, Freund, & Girosi (1997),
  - Bassiou et.al.(1998),
  - Terrillon et. al. (2000).

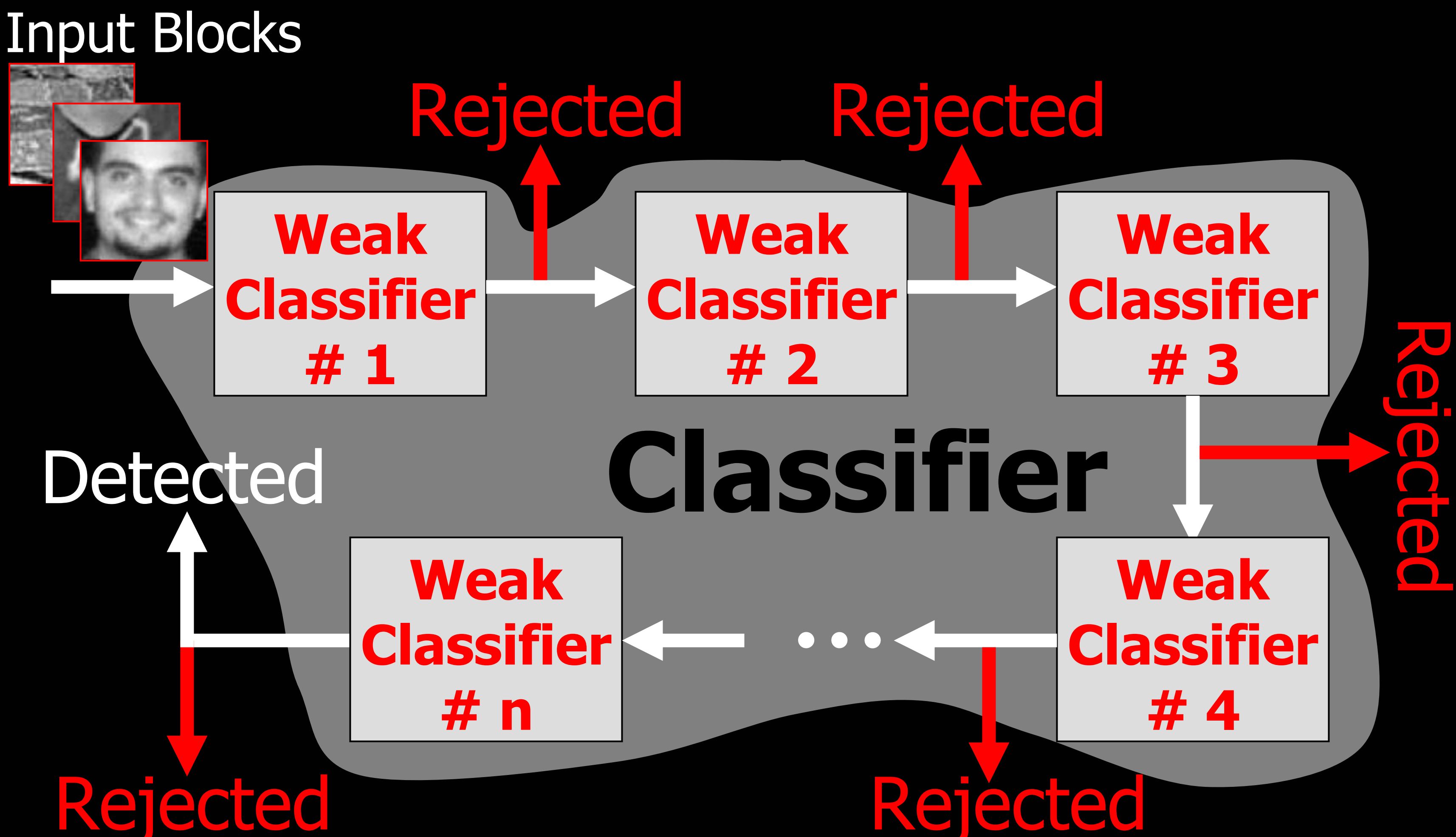
SVM leads to a Complex Classifier

3. Rejection Based

- Build C(Z,θ) as a combination of weak (simple to design and activate) classifiers.
- Apply the weak classifiers sequentially while rejecting non-faces.
- Representative Previous Work:
  - Rowley & Kanade (1998)
  - Elad, Hel-Or, & Keshet (1998),
  - Amit, Geman & Jedyank (1998),
  - Osdachi, Gotsman & Keren (2001), and
  - Viola & Jones (2001).

Fast (and accurate) classifier

4. The Rejection Idea



5. Supporting Theory

- (Ada) Boosting – Freund & Schapire (1990-2000) – Using a group of weak classifiers in order to design a successful complex classifier.
- Decision-Tree – Tree structured classification (the rejection approach here is a simple dyadic tree).
- Rejection – Nayar & Baker (1995) - Application of rejection while applying the sequence of weak classifiers.
- Maximal Rejection – Elad, Hel-Or & Keshet (1998) – Greedy approach towards rejection.

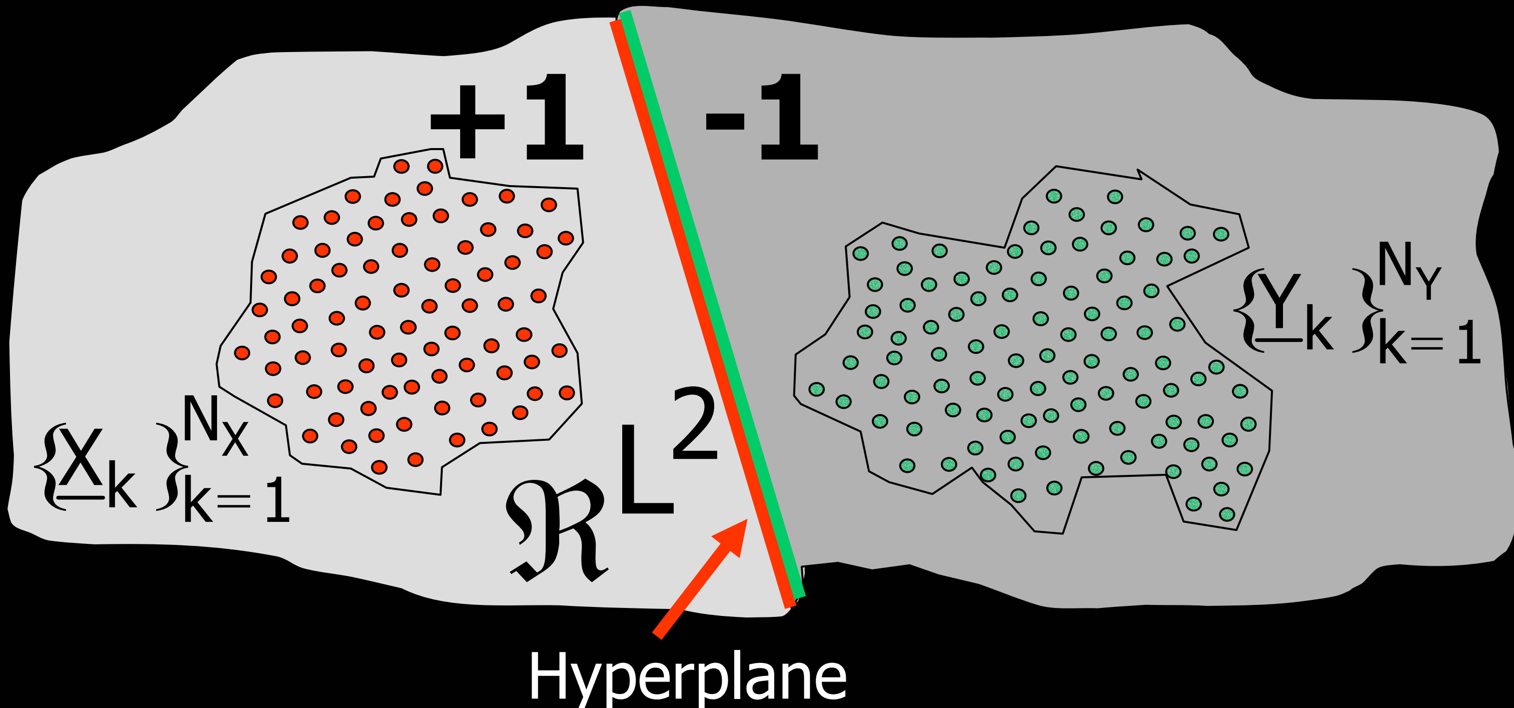
Part 3

Maximal Rejection Classification

1. Linear Classification (LC)

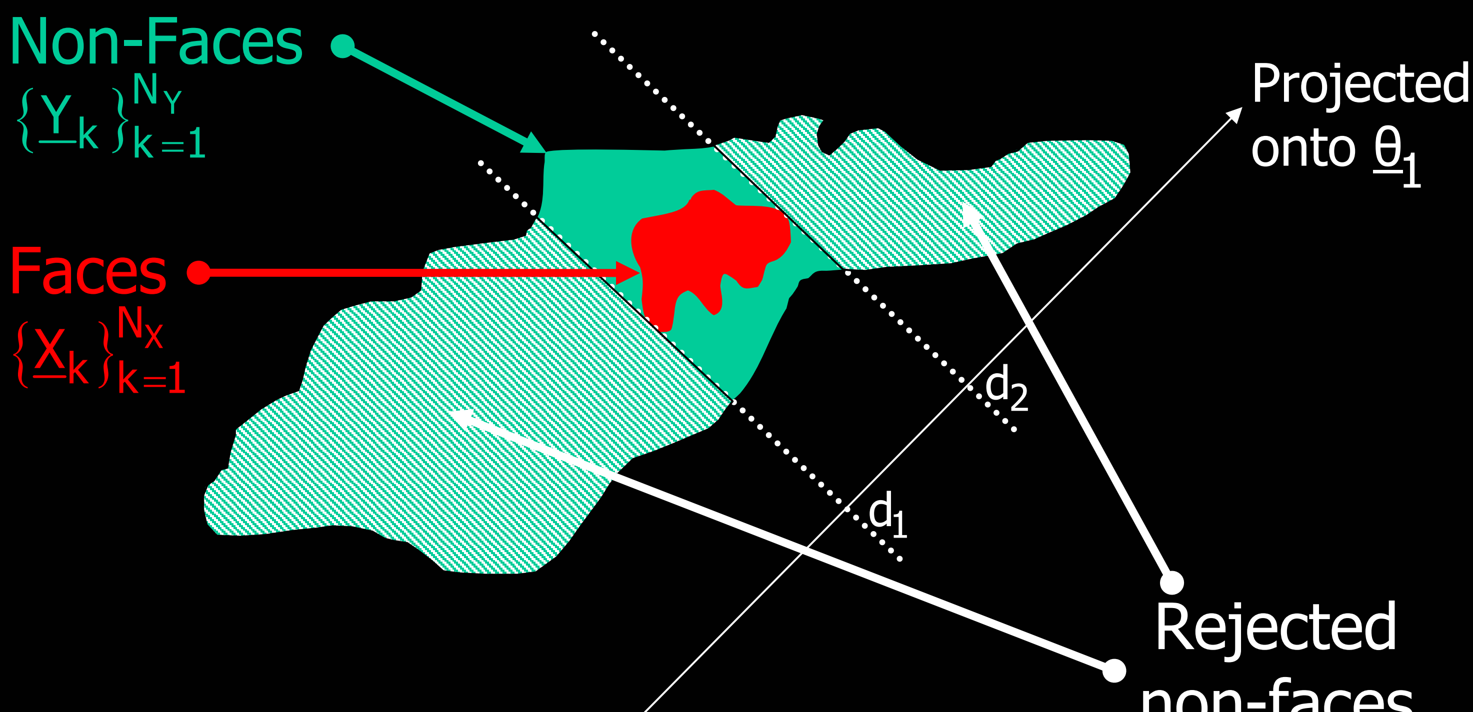
We propose LC as our weak classifier:

$$C\{\underline{Z},\underline{\theta}\} = \text{sign}\left\{\underline{Z}^T\underline{\theta} - \theta_0\right\}$$



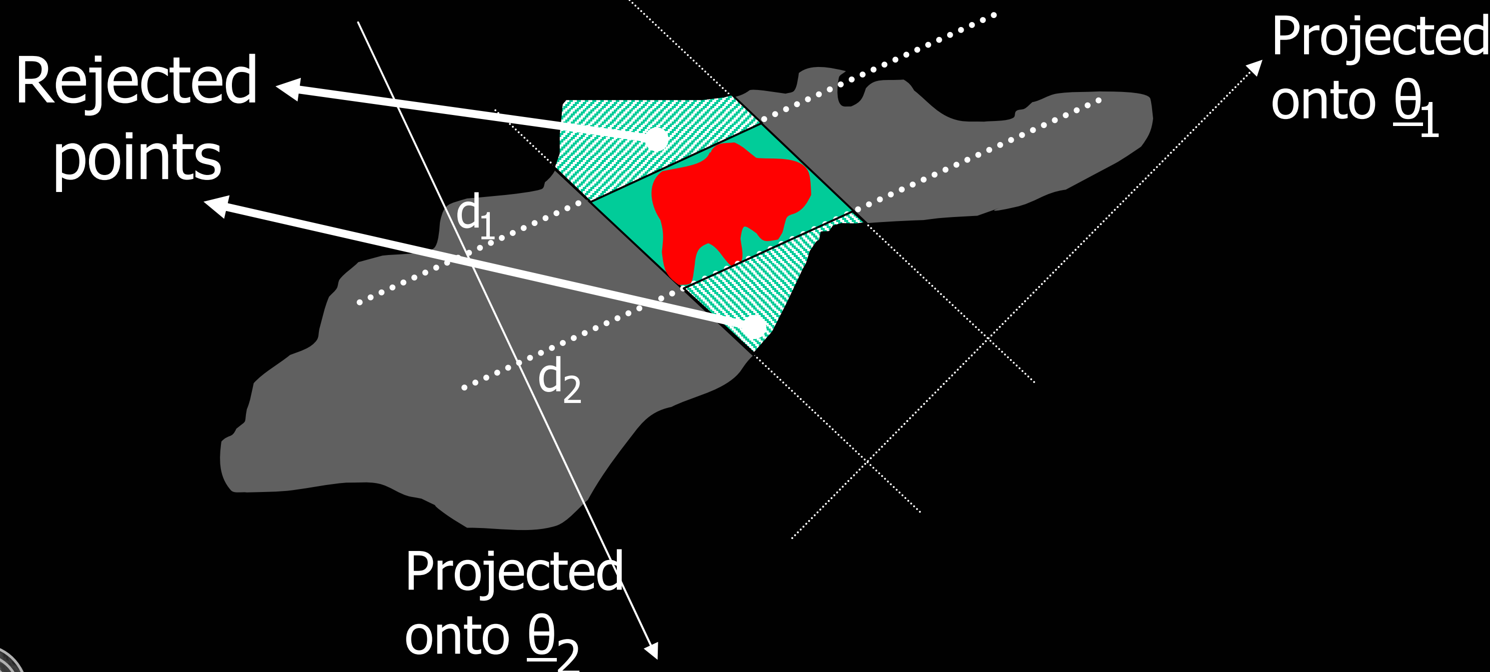
2. Maximal Rejection

Find $\underline{\theta}_1$ and two decision levels $[d_1, d_2]_1$ such that the number of rejected non-faces is maximized while finding all faces

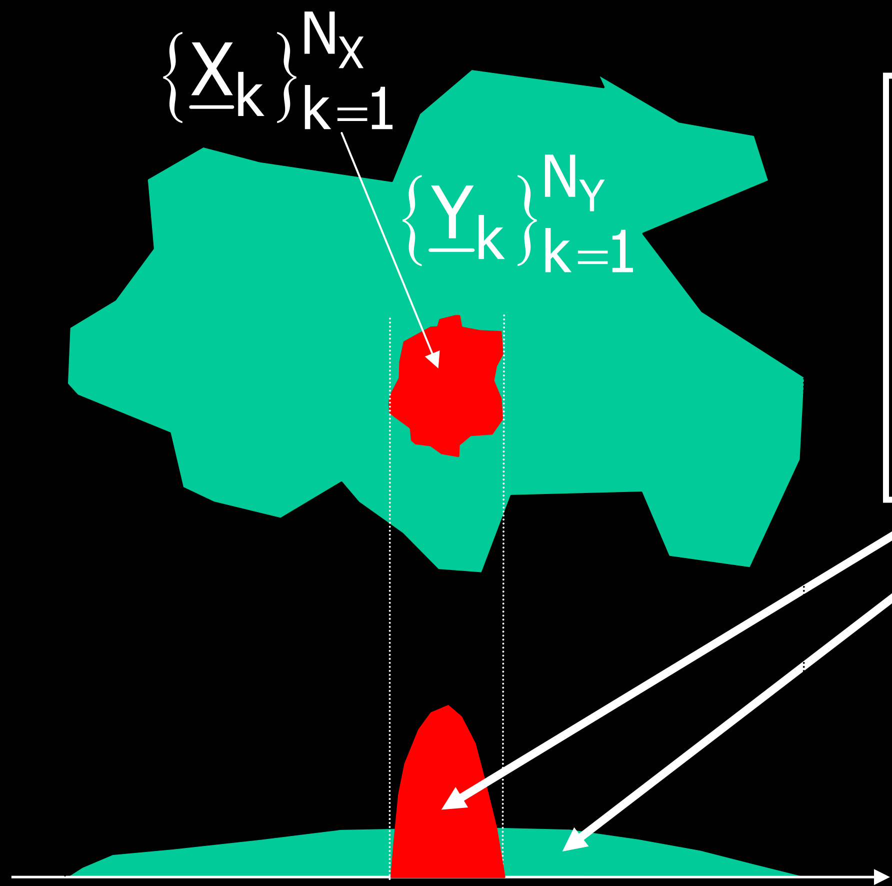


3. Iterations

Taking ONLY the remaining non-faces:
Find $\underline{\theta}_2$ and two decision levels $\left[d_1, d_2\right]_2$ such that the number of rejected non-faces is maximized while finding all faces



4. Maximizing Rejection



Maximal Rejection

Maximal distance between these two PDF's

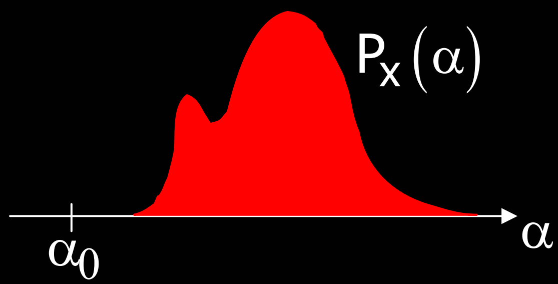
We need a measure for this distance which will be appropriate and easy to use

5. One Sided Distance

Define a distance between a point and a PDF by

$$D_1\left\{\alpha_0, P_x(\alpha)\right\} = \int_\alpha \frac{(\alpha_0-\alpha)^2}{r_x^2} P_x(\alpha)\, d\alpha$$

$$= \frac{(\alpha_0-m_x)^2 + r_x^2}{r_x^2}$$



$$D_2\left\{ P_x(\alpha), P_y(\alpha)\right\} = \int_\alpha D_1\left\{\alpha, Px(\alpha)\right\} P_y(\alpha)d\alpha = \frac{(m_x-m_y)^2 + r_x^2 + r_y^2}{r_x^2}$$

This distance is asymmetric !! It describes the average distance between points of Y to the X-PDF, $P_X(\alpha)$.

6. Final Measure

$$D_3\{P_x(\alpha),P_y(\alpha)\} = P(Y)\frac{(m_x-m_y)^2+r_x^2+r_y^2}{r_x^2}+P(X)\frac{(m_x-m_y)^2+r_x^2+r_y^2}{r_y^2}$$

In the case of face detection in images we have

P(X)<<P(Y)

We Should Maximize

(GEP)

$$f\{\underline{\theta}\} = \frac{\underline{\theta}^T\left\{\left[\underline{M}_X-\underline{M}_Y\right]\left[\underline{M}_X-\underline{M}_Y\right]^T+R_X+R_Y\right\}\underline{\theta}}{\underline{\theta}^T R_X \underline{\theta}}$$

7. Different Method 1

Maximize the following function:

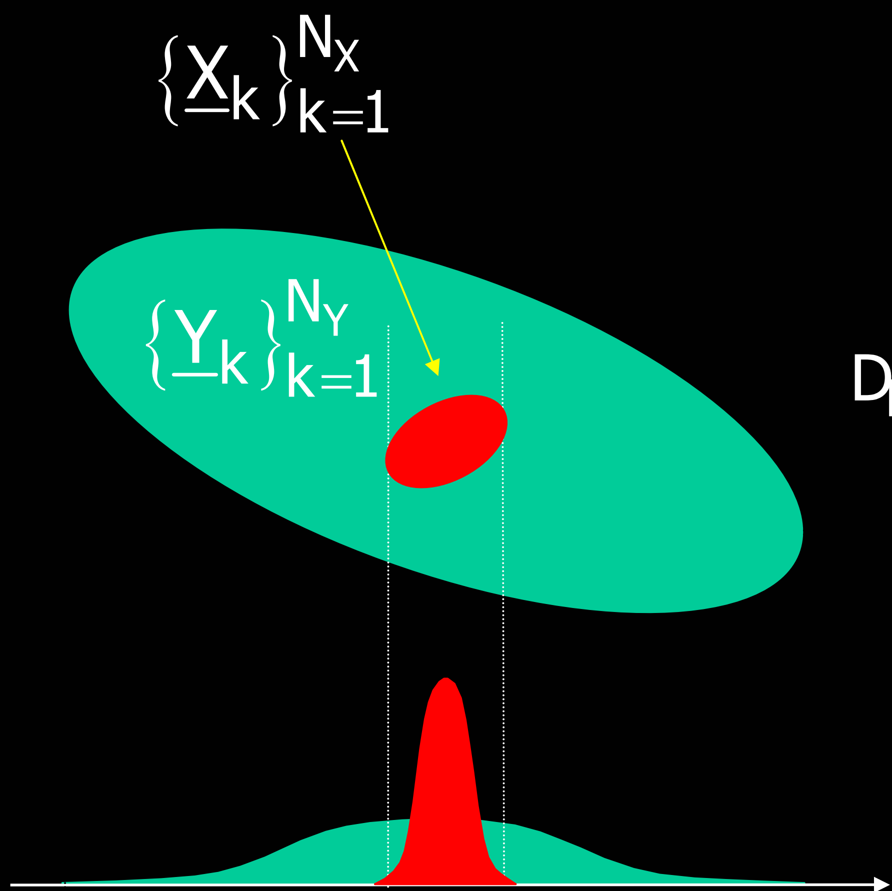
Maximize the distance between all the pairs of [face, non-face]

$$f\{\underline{\theta}\} = \frac{\sum_{j=1}^{N_Y} \sum_{k=1}^{N_X} \left[\underline{\theta}^T \underline{X}_k - \underline{\theta}^T \underline{Y}_j\right]^2}{\sum_{j=1}^{N_X} \sum_{k=1}^{N_X} \left[\underline{\theta}^T \underline{X}_k - \underline{\theta}^T \underline{X}_j\right]^2} = C \cdot \frac{\underline{\theta}^T \mathbf{R} \underline{\theta}}{\underline{\theta}^T \mathbf{Q} \underline{\theta}} =$$

The same Expression

Minimize the distance between all the pairs of [face, face]

8. Different Method 2



If the two PDF's are assumed Gaussians, their KL distance is given by

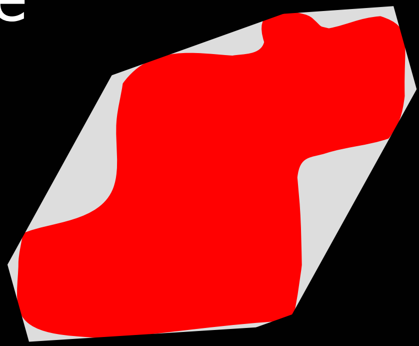
$$D_{KL}\{P_x, P_y\} = \frac{(m_x - m_y)^2 + r_x^2 + r_y^2}{2r_x^2} + \ln\left\{\frac{r_x}{r_y}\right\} - 1$$

And we get a similar expression

9. Limitations

- The discriminated zone is a parallelogram. Thus, if the faces set is non-convex*, zero false alarm discrimination is impossible – Solution: Second layer.

- Even if the faces-set is convex, convergence to zero false-alarms is not guaranteed. – Solution: Clustering the non-faces.



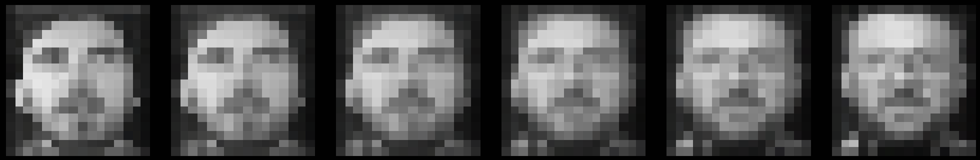
* More accurately, if in the convex hull of the face set there are non-faces

8. Convexity?

Can we assume that the Faces set is convex?

- We are dealing with frontal and vertical faces only

- We are dealing with a low-resolution representation of the faces



- Are they any non-faces that are convex combination of faces ?

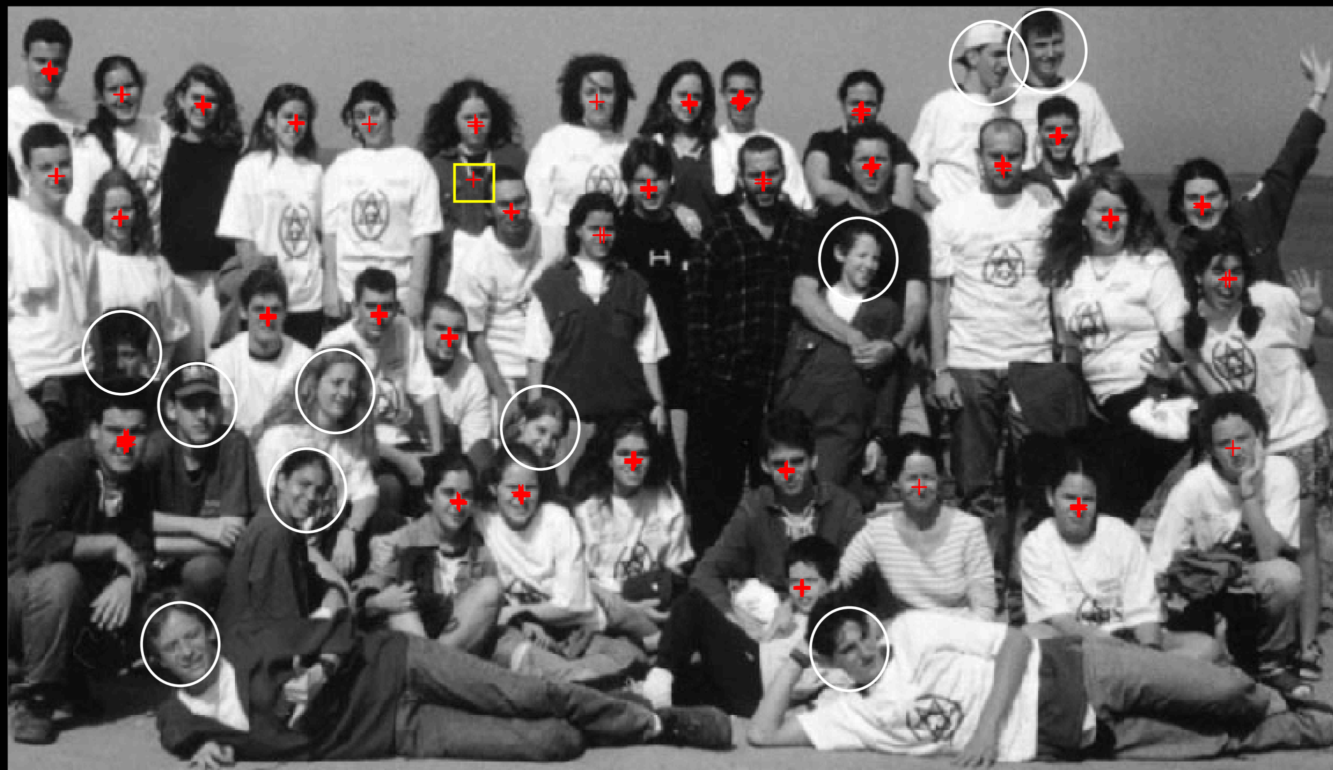
Chapter 4

Results & Conclusions

1. Details

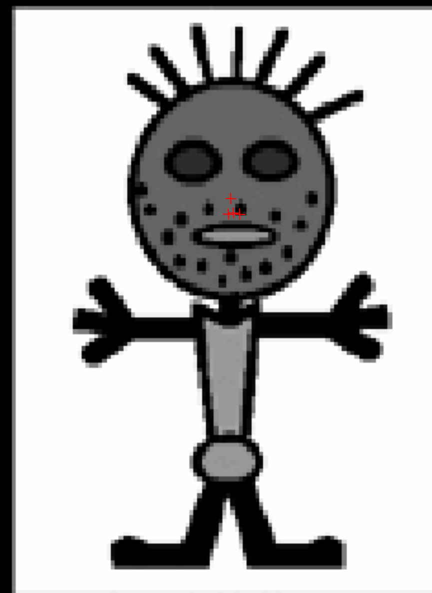
- Kernels for finding *faces* (15·15) and *eyes* (7·15).
- Searching for eyes and faces sequentially - very efficient!
- Face DB: 204 images of 40 people (ORL-DB after some screening). Each image is also rotated ±5° and vertically flipped - to produce 1224 Face images.
- Non-Face DB: 54 images - All the possible positions in all resolution layers and vertically flipped - about $40 \cdot 10^6$ non-face images.
- Core MRC applied (no second layer, no clustering).

2. Results - 1



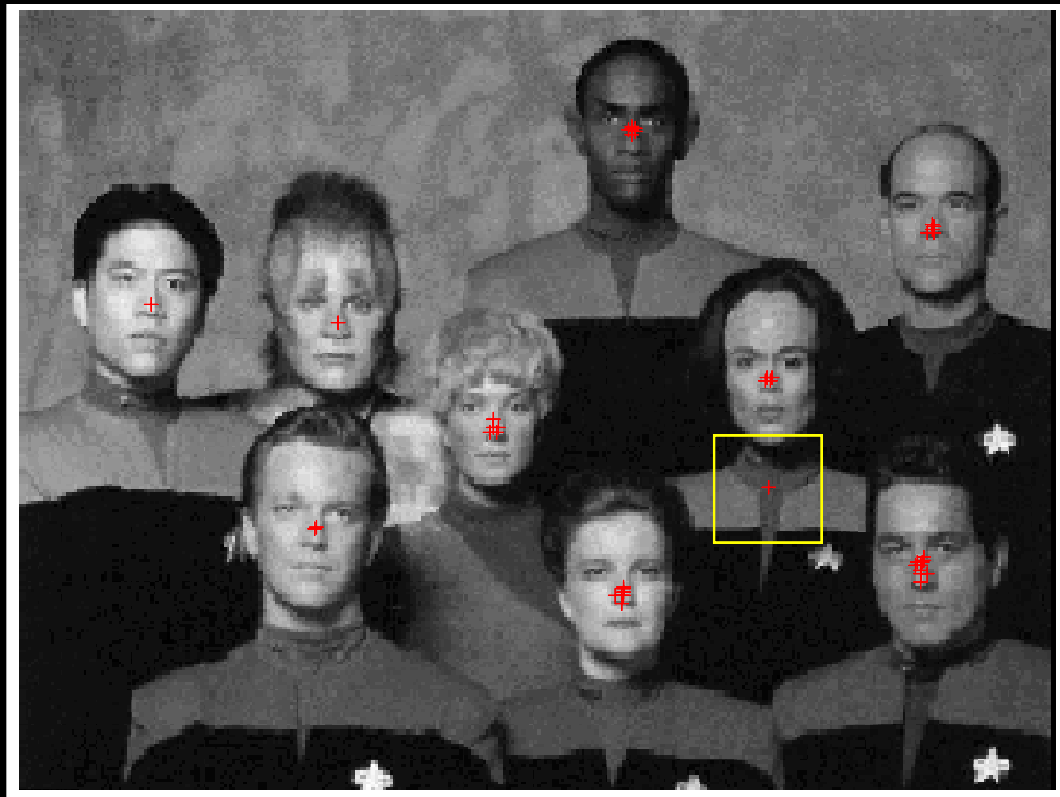
Out of 44 faces, 10 faces are undetected, and 1 false alarm
(the undetected faces are circled - they are either rotated or strongly shadowed)

3. Results - 2



All faces detected with no false alarms

4. Results - 3



All faces detected with 1 false alarm

(looking closer, this false alarm can be considered as face)

5. More Details

- A set of 15 kernels - the first typically removes about 90% of the pixels from further consideration. Other kernels give a rejection of 50%.
- The algorithm requires slightly more that one **convolution** of the image (per each resolution layer).
- Compared to state-of-the-art results:
  - Accuracy – Similar to (slightly inferior in FA) to Rowley and Viola.
  - Speed – Similar to Viola – much faster (factor of ~10) compared to Rowley.

6 .Conclusions

- Rejection-based classification - effective and accurate.
- Basic idea – group of weak classifiers applied sequentially followed each by rejection decision.
- Theory – Boosting, Decision tree, Rejection based classification, and MRC.
- The Maximal-Rejection Classification (MRC):
  - Fast – in close to one convolution we get face detection,
  - Simple – easy to train, apply, debug, maintain, and extend.
  - Modular – to match hardware/time constraints.
  - Limitations – Can be overcome.
- More details – http://www-sccm.stanford.edu/~elad

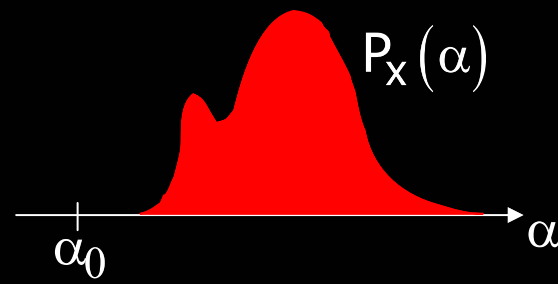
7 . More Topics

1. Why scale-invariant measure?
2. How we got the final distance expression?
3. Relation of the MRC to Fisher Linear Discriminant
4. Structure of the algorithm
5. Number of convolutions per pixel
6. Using color
7. Extending to 2D rotated faces
8. Extension to 3D rotated faces
9. Relevancy to target detection
10. Additional ingredients for better performance

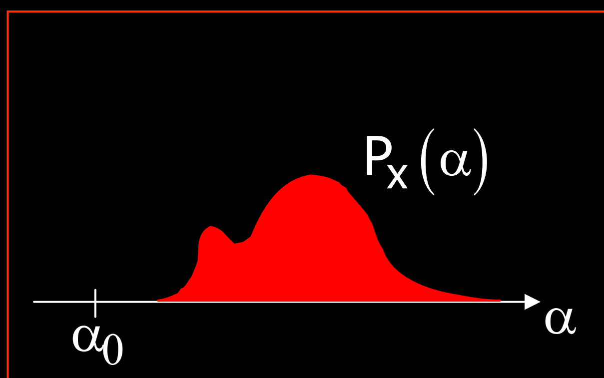
1. Scale-Invariant

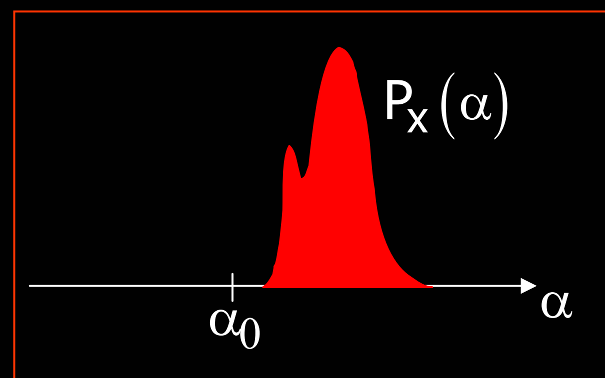
$$D_1\left\{\alpha_0, P_x(\alpha)\right\} = \int_\alpha \frac{(\alpha_0-\alpha)^2}{r_x^2} P_x(\alpha)\, d\alpha$$

$$= \frac{(\alpha_0 - m_x)^2 + r_x^2}{r_x^2}$$



Same distance for





$$f\{\underline{\theta}\} = \frac{\underline{\theta}^T \left\{ [\underline{M}_X - \underline{M}_Y][\underline{M}_X - \underline{M}_Y]^T + R_X + R_Y \right\} \underline{\theta}}{\underline{\theta}^T R_X \underline{\theta}}$$

In this expression:

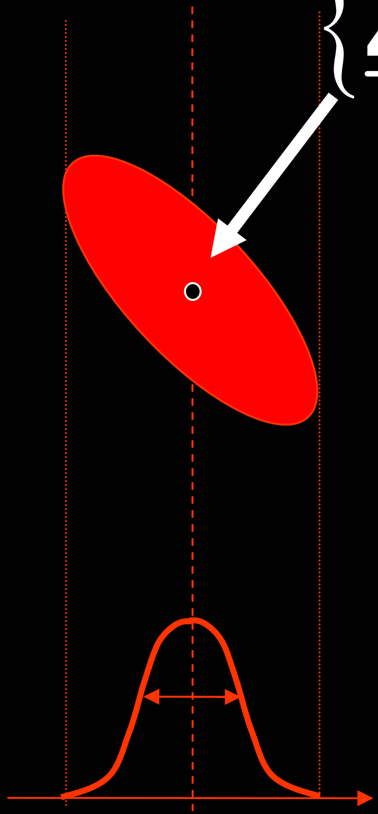
1. The two classes means are encouraged to get far from each other
2. The Y-class is encouraged to spread as much as possible, and
3. The X-class is encouraged to condense to a near-constant value

Thus, getting good rejection performance.

back

2. The Distance Expression

$$\left\{\underline{Z}_k\right\}_{k=1}^{N}$$



$$\underline{M} = \frac{1}{N}\sum_{k=1}^{N} \underline{Z}_k$$

$$\mathbf{R} = \frac{1}{N}\sum_{k=1}^{N} \left[\underline{Z}_k - \underline{M}\right]\left[\underline{Z}_k - \underline{M}\right]^T$$

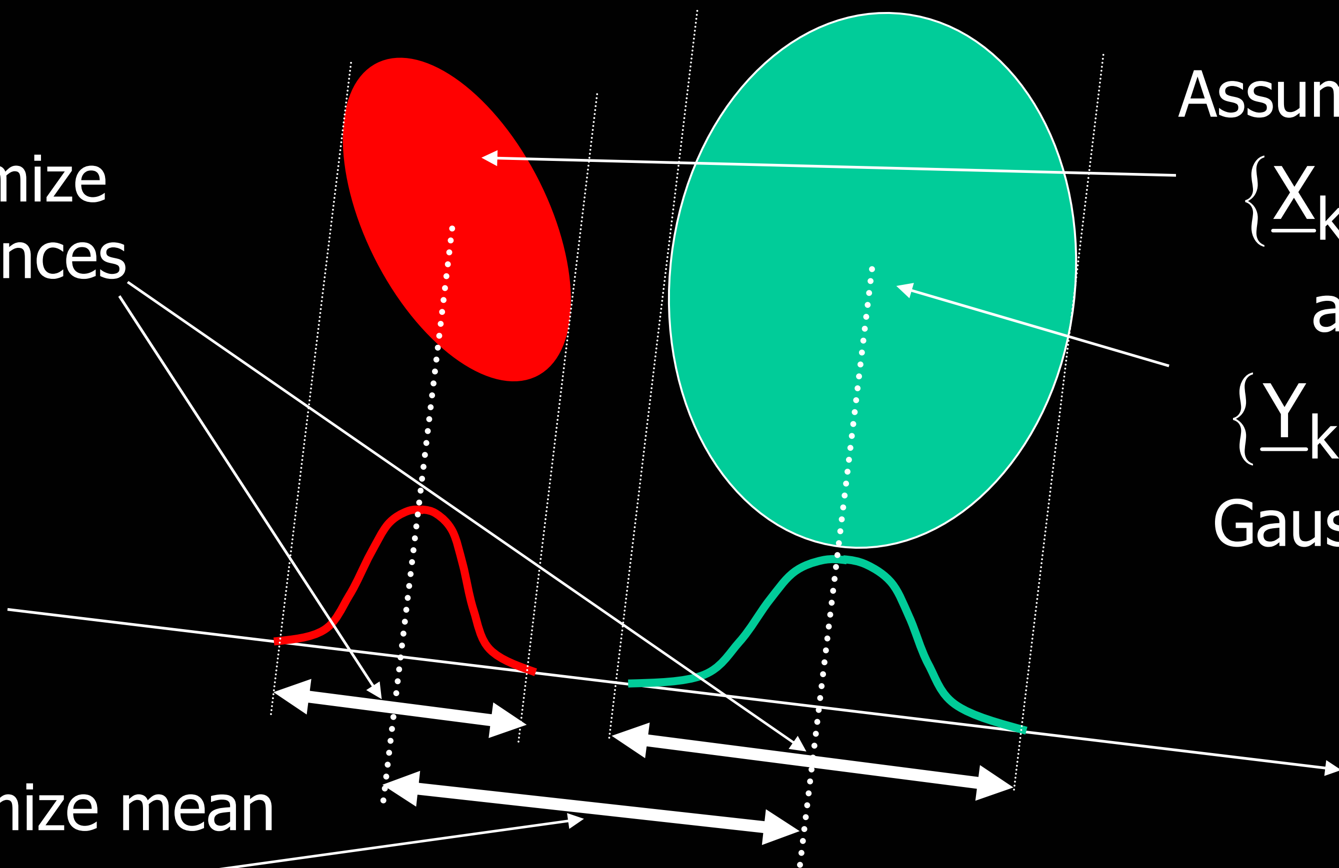
$$z_k = \underline{\theta}^T \underline{Z}_k \Rightarrow m = \underline{\theta}^T \underline{M}, \;\; r = \underline{\theta}^T \mathbf{R} \underline{\theta}$$

$$\frac{(m_y - m_x)(m_y - m_x)^T + r_y^2}{r_x^2} =$$

$$= \frac{\underline{\theta}^T \left[(\underline{M}_y - \underline{M}_x)(\underline{M}_y - \underline{M}_x)^T + \mathbf{R}_y\right]\underline{\theta}}{\underline{\theta}^T \mathbf{R}_x \underline{\theta}}$$

back

3. Relation to FLD*



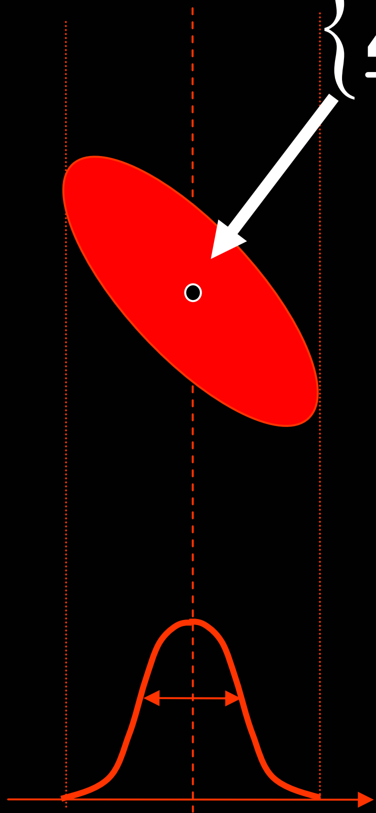
Minimize variances

Assume that $\{\underline{X}_k\}_{k=1}^{N_X}$ and $\{\underline{Y}_k\}_{k=1}^{N_Y}$ Gaussians

Maximize mean difference

*FLD - Fisher Linear Discriminant

$$\{\underline{Z}_k\}_{k=1}^{N}$$



$$\underline{M} = \frac{1}{N}\sum_{k=1}^{N} \underline{Z}_k$$

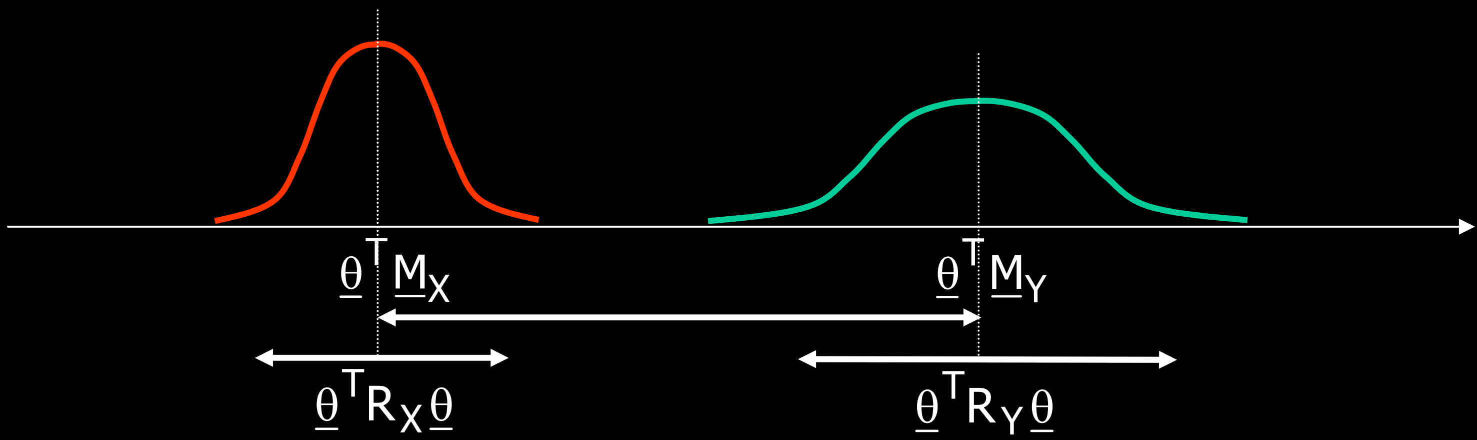
$$\mathbf{R} = \frac{1}{N}\sum_{k=1}^{N} \left[\underline{Z}_k - \underline{M}\right]\left[\underline{Z}_k - \underline{M}\right]^T$$

$$z_k = \underline{\theta}^T \underline{Z}_k \Rightarrow m = \underline{\theta}^T \underline{M}, \quad r = \underline{\theta}^T \mathbf{R} \underline{\theta}$$

Maximize

$$f\{\underline{\theta}\} = \frac{\left[\underline{\theta}^T \underline{M}_X - \underline{\theta}^T \underline{M}_Y\right]^2}{\underline{\theta}^T R_X \underline{\theta} + \underline{\theta}^T R_Y \underline{\theta}} = \frac{\underline{\theta}^T \left[\underline{M}_X - \underline{M}_Y\right]\left[\underline{M}_X - \underline{M}_Y\right]^T \underline{\theta}}{\underline{\theta}^T \left[R_X + R_Y\right]\underline{\theta}}$$

Minimize



In the MRC we got the expression for the distance

$$P(Y)\frac{(m_x - m_y)^2 + r_x^2 + r_y^2}{r_x^2} + P(X)\frac{(m_x - m_y)^2 + r_x^2 + r_y^2}{r_y^2}$$

If P(X)=P(Y)=0.5 we maximize

$$\boxed{\frac{(m_x - m_y)^2 + r_x^2 + r_y^2}{r_x^2}} + \boxed{\frac{(m_x - m_y)^2 + r_x^2 + r_y^2}{r_y^2}}$$

The distance of the Y points to the X-distribution

The distance of the X points to the Y-distribution

Instead of maximizing the sum

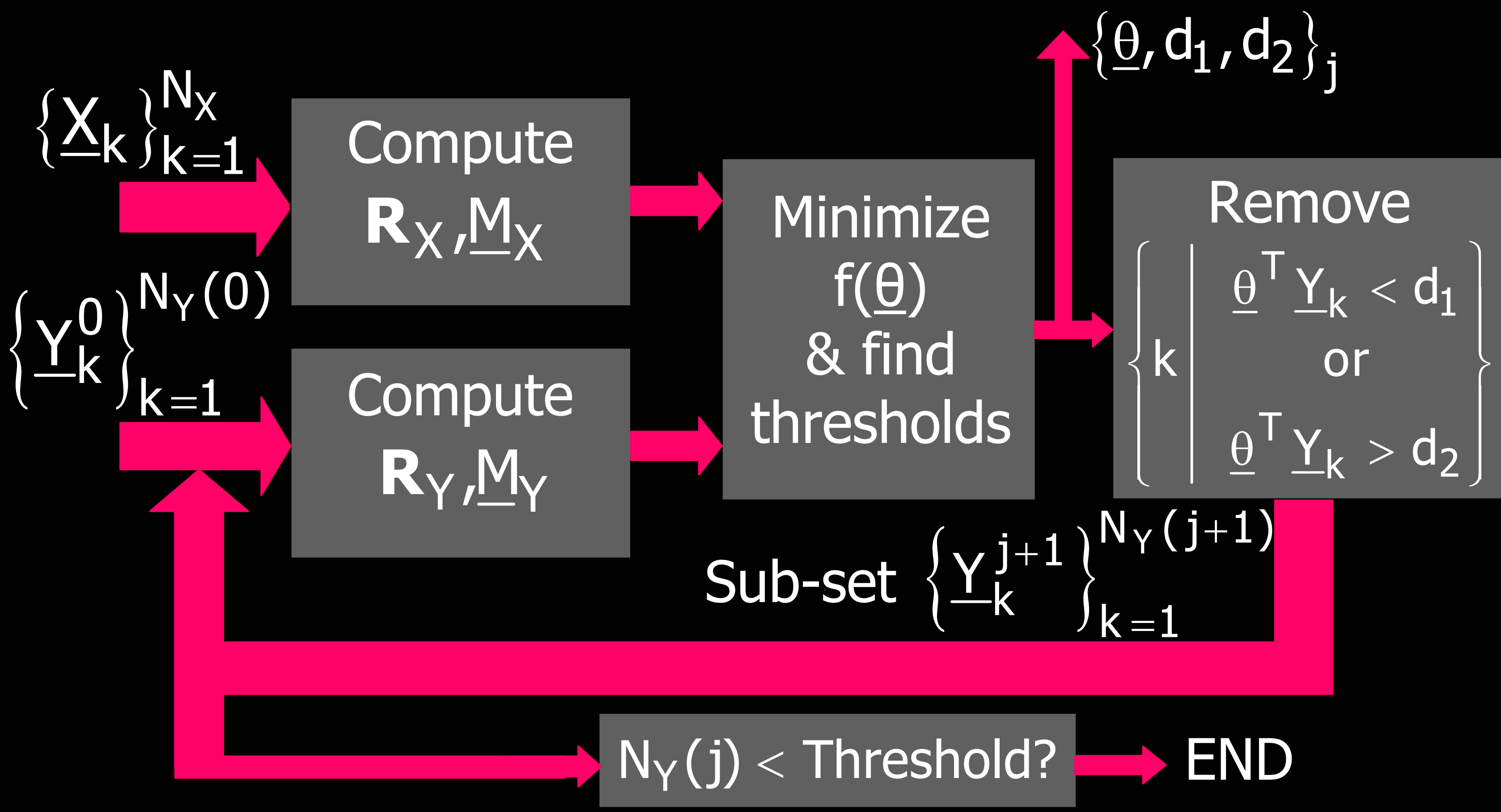
$$\frac{(m_x - m_y)^2 + r_x^2 + r_y^2}{r_x^2} + \frac{(m_x - m_y)^2 + r_x^2 + r_y^2}{r_y^2}$$

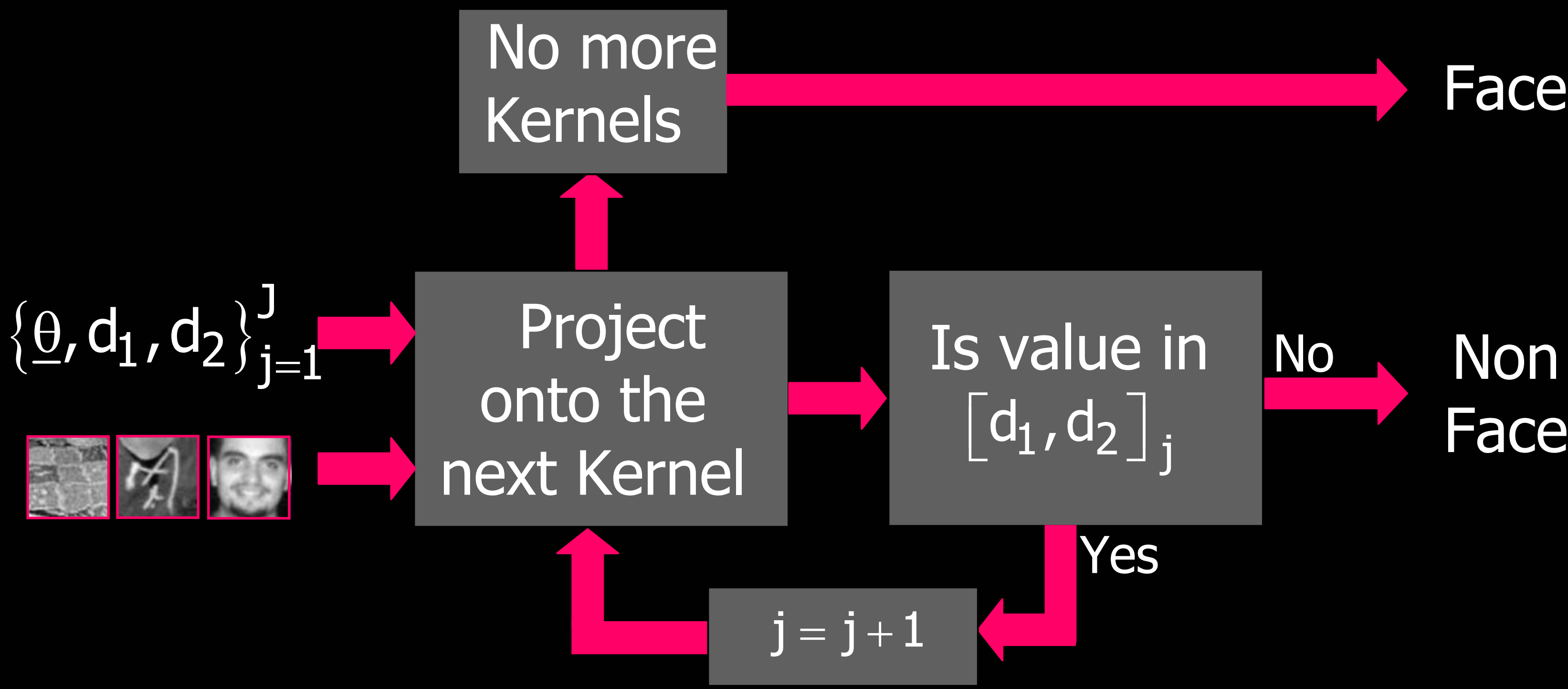
Minimize the inverse of the two expressions
(the inverse represent the proximity)

$$\text{Min} \ \frac{r_x^2}{(m_x - m_y)^2 + r_x^2 + r_y^2} + \frac{r_y^2}{(m_x - m_y)^2 + r_x^2 + r_y^2} = \text{Min} \ \frac{r_x^2 + r_y^2}{(m_x - m_y)^2}$$

back

4. Algorithm Structure




No more Kernels
Face
$\{\underline{\theta}, d_1, d_2\}_{j=1}^{J}$
Project onto the next Kernel
Is value in $[d_1, d_2]_j$
No
Non Face
Yes
$j = j + 1$

back

5. Counting Convolutions

- Assume that the first kernel rejection is $0<\alpha<1$ (I.e. α of the incoming blocks are rejected).
- Assume also that the other stages rejection rate is 0.5.
- Then, the number of overall convolutions per pixel is given by

$$\alpha \cdot 1 + (1-\alpha)\sum_{k=2}^{\infty} k \cdot 0.5^{k-1} = 3 - 2\alpha = \begin{cases} \sim 1 & \alpha = 0.99 \\ 1.2 & \alpha = 0.9 \\ 1.8 & \alpha = 0.6 \end{cases}$$

back

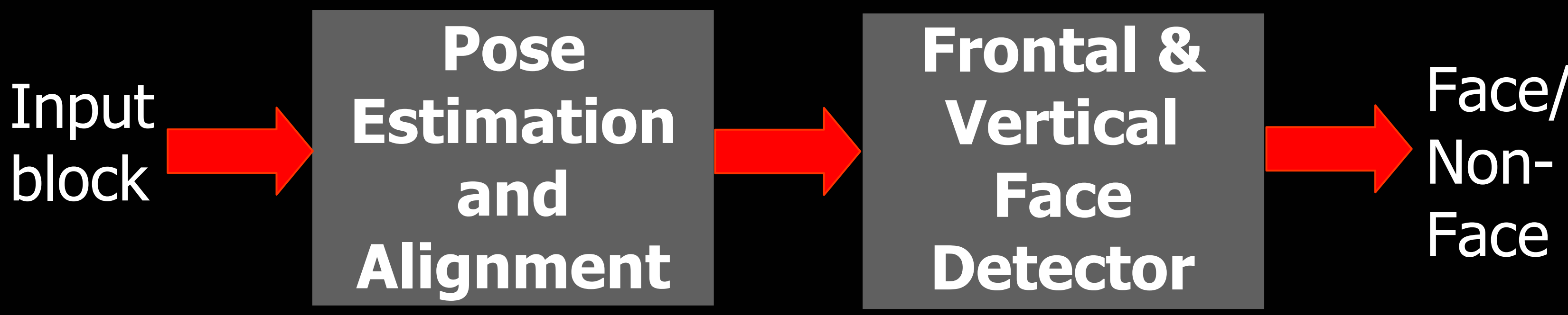
6. Using Color

Several options:

- Trivial approach – use the same algorithm with blocks of L-by-L by 3.
- Exploit color redundancy – work in HSV space with decimated versions of the Hue and the Saturation layers.
- Rejection approach – Design a (possibly non-spatial) color-based simple classifier and use it as the first stage rejection.

back

7. 2D-Rotated Faces



Remarks:

1. A set of rotated kernels can be used instead of actually rotating the input block
2. Estimating the pose can be done with a relatively simple system (few convolutions).

back

8. 3D-Rotated Faces

A possible solution:

1. Cluster the face-set to same-view angle faces and design a Final classifier for each group using the rejection approach
2. Apply a pre-classifier for fast rejection at the beginning of the process.
3. Apply a mid-classifier to map to the appropriate cluster with the suitable angle

Input block → **Crude Rejection** → **Mid-clas. For Angle** → **Final Stage** → Face/ Non-Face

back

9. Faces vs. Targets

- Treating other targets can be done using the same concepts of
  - Treatment of scale and location
  - Building and training sets
  - Designing a rejection based approach (e.g. MRC)
  - Boosting the resulting classifier
- The specific characteristics of the target in mind could be exploited to fine-tune and improve the above general tools.

back

10. Further Improvements

- Pre-processing – linear kind does not cost
- Regularization – compensating for shortage in examples
- Boosted training – enrich the non-face group by finding false-alarms and train on those again
- Boosted classifier – Use the sequence of weak-classifier outputs and apply yet another classifier on them –use ada-boosting or simple additional linear classifier
- Constrained linear classifiers for simpler classifier
- Can apply kernel methods to extend to non-linear version

back