Quality & Features

Dr. Tushar Sandhan

What is the need

- Quantitative assessment
  - performance evaluation of image processing algorithms
    - e.g. denoising, compression
- Quantitative achievement
  - performance improvement via optimization based methods
    - e.g. enhance images to minimize MSE or improve PSNR

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PSNR

- Full reference measure
  - need a clear GT or reference image

- Generic error
  - p – norm
  - minkowski norm

$$d_p(\mathbf{x}, \mathbf{y}) = \left(\sum_{i=1}^{N} |e_i|^p \right)^{1/p} \quad \text{where} \quad e_i = x_i - y_i$$

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  - L is dynamic range

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$$\text{PSNR} = 10 \log_{10} \frac{L^2}{\text{MSE}}$$

MSE

- Good metric for optimization based methods
  - MSE: convex and differentiable
  - parameter-free, memoryless
  - energy minimization methods: relation to energy

- Uniformity with data communication signal measurements
- Distance metric

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  - nonnegativity: $d_p(\mathbf{x}, \mathbf{y}) \geq 0$
  - symmetry: $d_p(\mathbf{x}, \mathbf{y}) = d_p(\mathbf{y}, \mathbf{x})$
  - identity: $d_p(\mathbf{x}, \mathbf{y}) = 0$ if and only if $\mathbf{x} = \mathbf{y}$
  - triangular inequality: $d_p(\mathbf{x}, \mathbf{z}) \leq d_p(\mathbf{x}, \mathbf{y}) + d_p(\mathbf{y}, \mathbf{z})$

PSNR

reference image

Image features

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  - for a given image, outputs interesting locations (e.g. x, y)
  - tells nothing about the image properties at that region
  - capture important regions
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  - encode interesting info into a series of stable numbers
    - stability in the sense that those numbers do not change drastically over image transformations (invariant)
    - e.g. scale, rotation invariance
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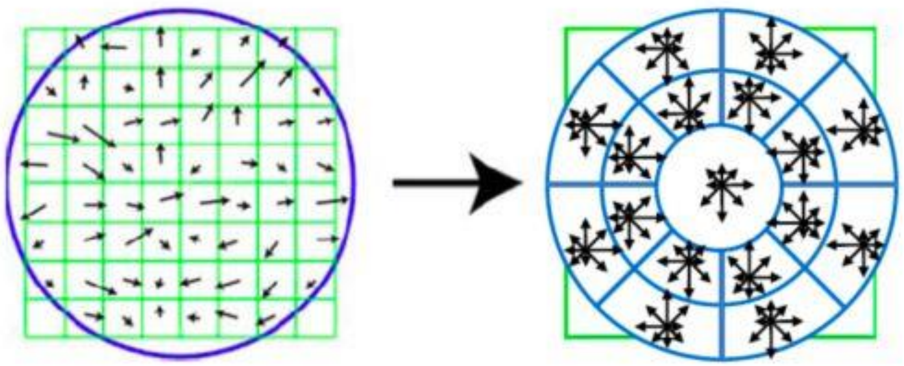

(a) image gradients

(b) keypoint descriptor

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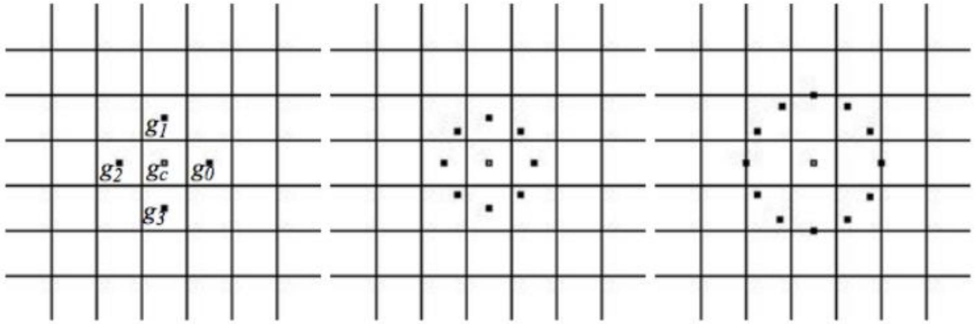
LBP

- Local Binary Pattern
  - texture and local pattern detection
  - textures have no specific definition
    - complex patterns having more sub-patterns



courtesy: Ojala

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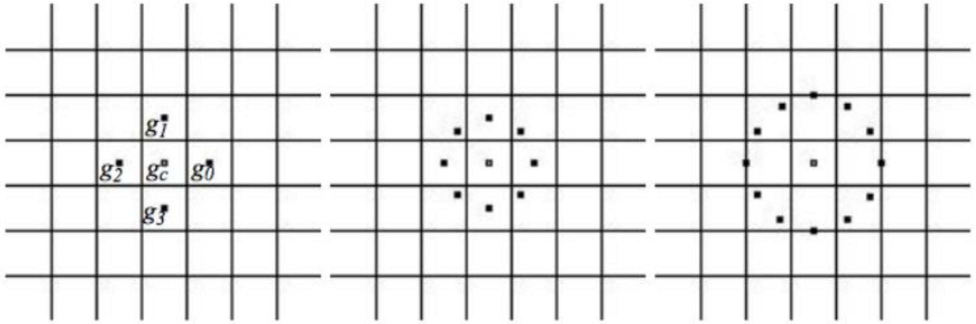
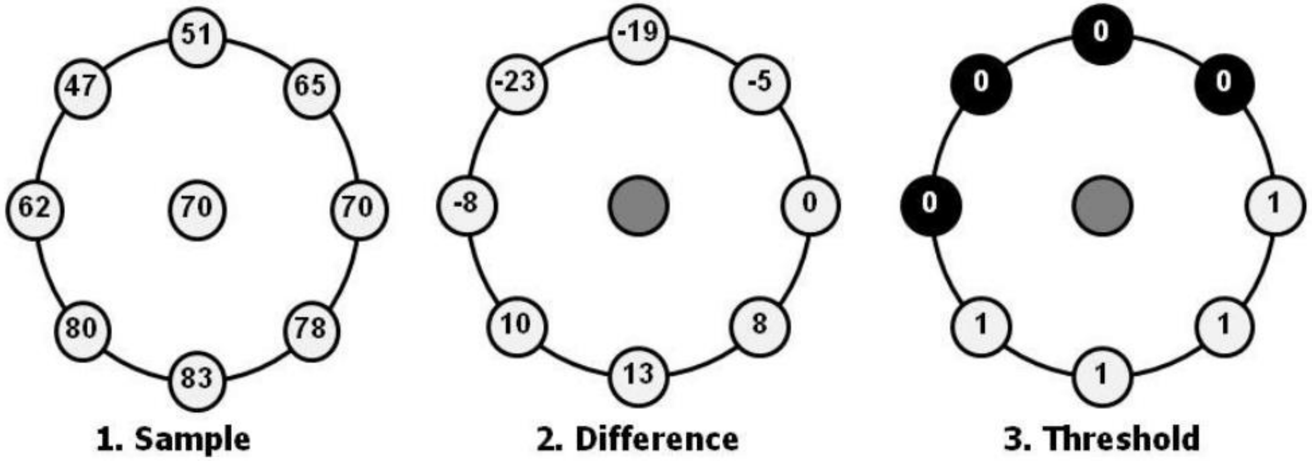
The value of the LBP code of a pixel (x_c, y_c) is given by:

$$LBP_{P,R} = \sum_{p=0}^{P-1} s(g_p - g_c)2^p \qquad s(x) = \begin{cases} 1, \; if \; x \geq 0; \\ 0, \; otherwise. \end{cases}$$





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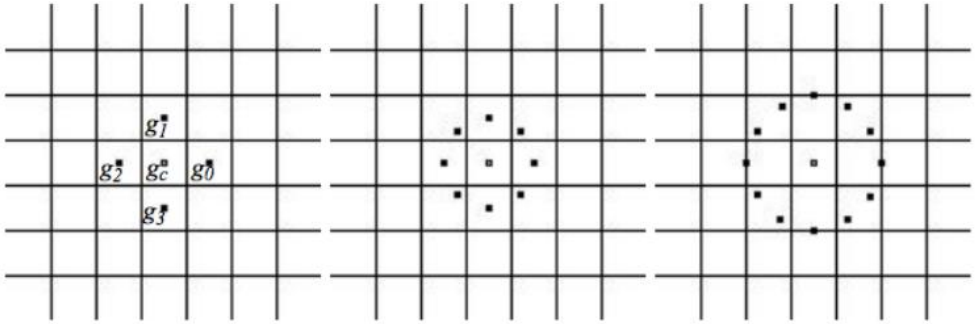

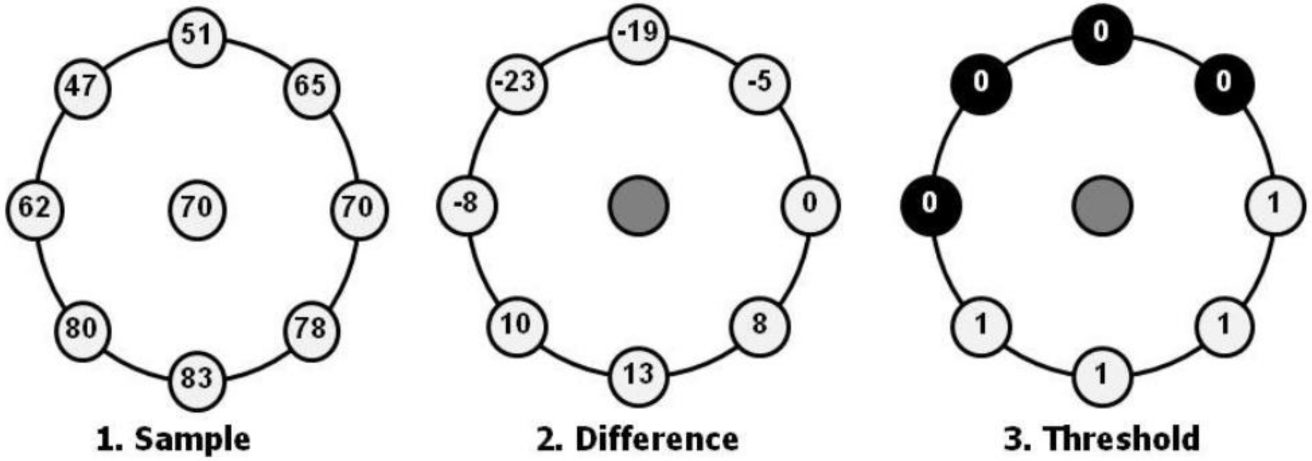

1*1 + 1*2 + 1*4 + 1*8 + 0*16 + 0*32 + 0*64 + 0*128 = 15

courtesy: Ojala

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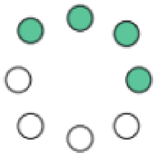
  - ilumination
    - shadow, reflection, brightness
    - relative difference between intensities remain same
  - rotation?



edge (15)

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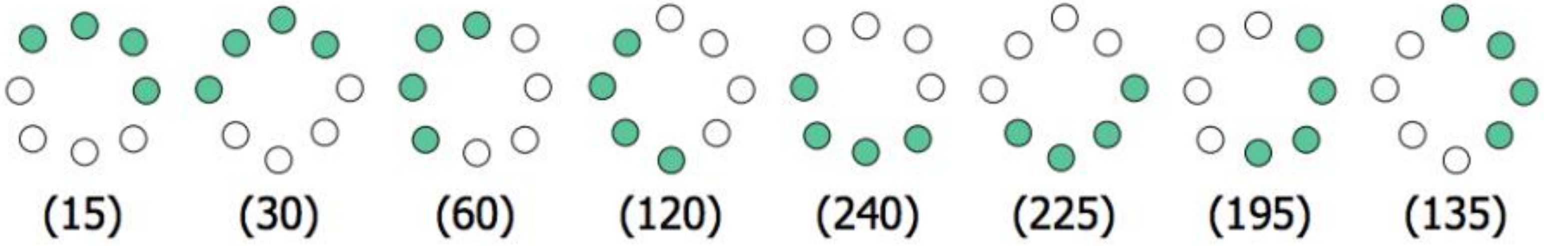

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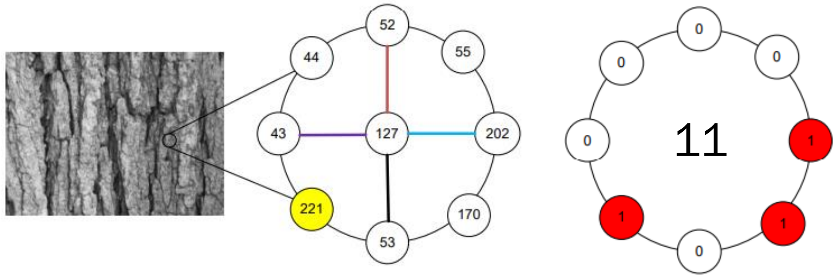

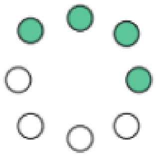

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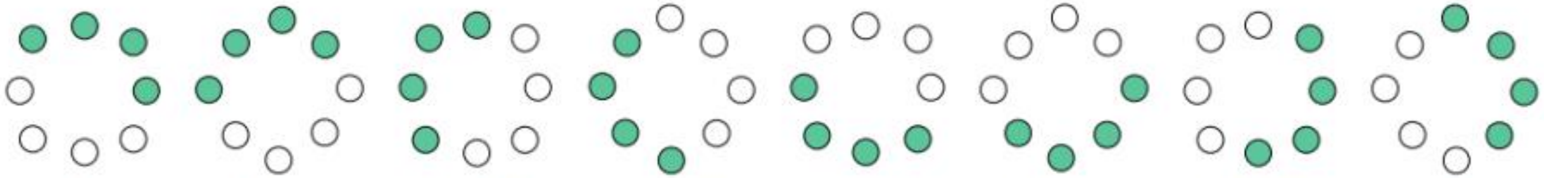

(15) (30) (60) (120) (240) (225) (195) (135)

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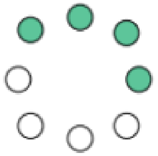

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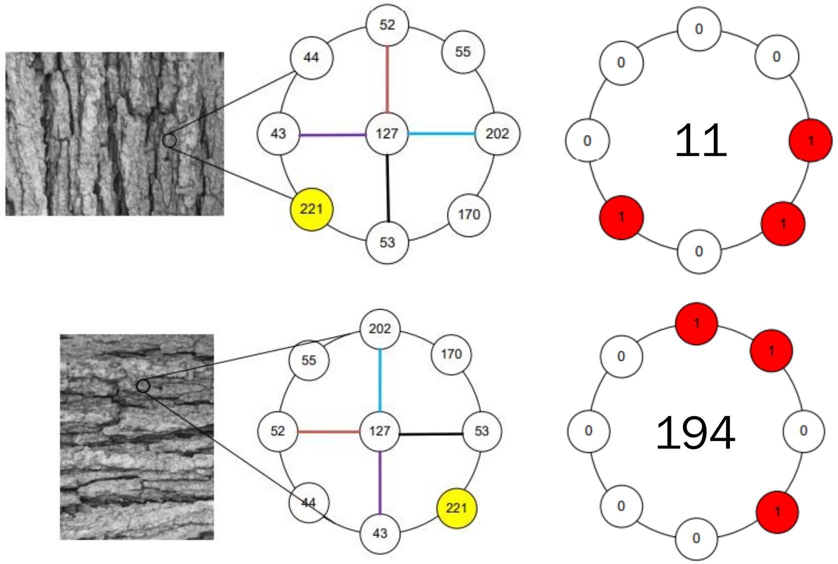

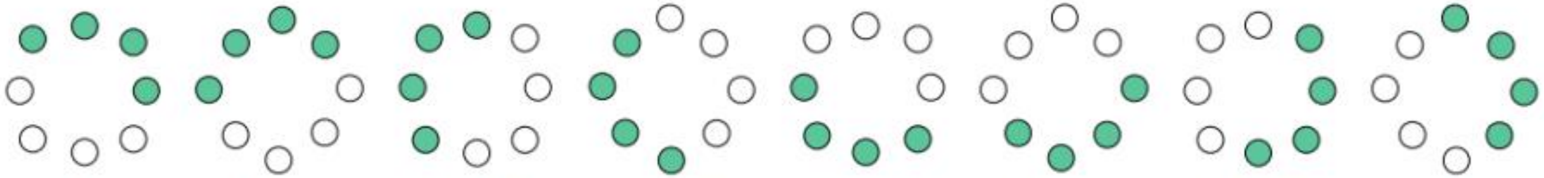

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  - 8 neighborhood gives 256 possible LBP codes
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  - LBP histogram 256D
    - probability of occurrence of each LBP code

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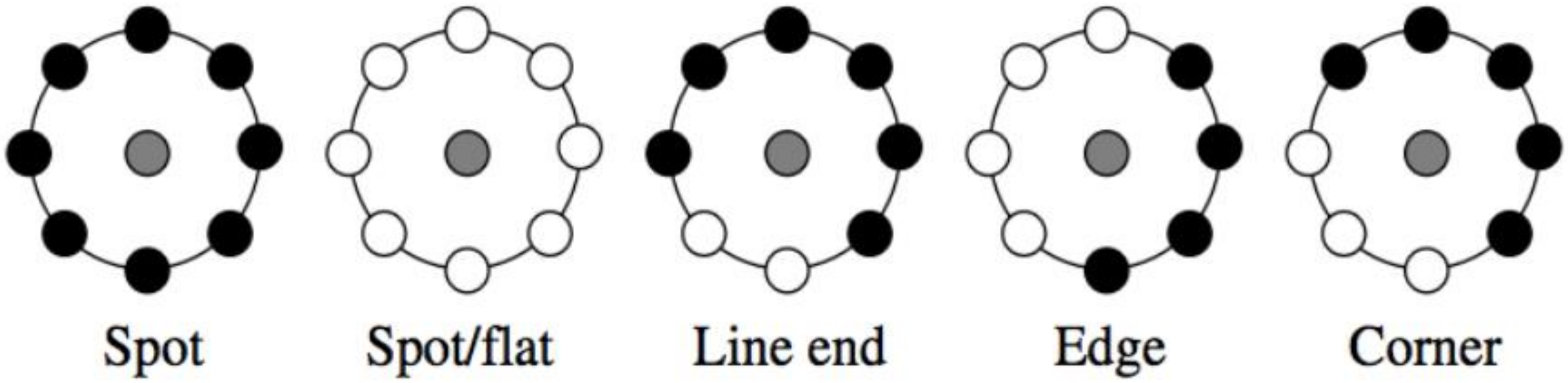
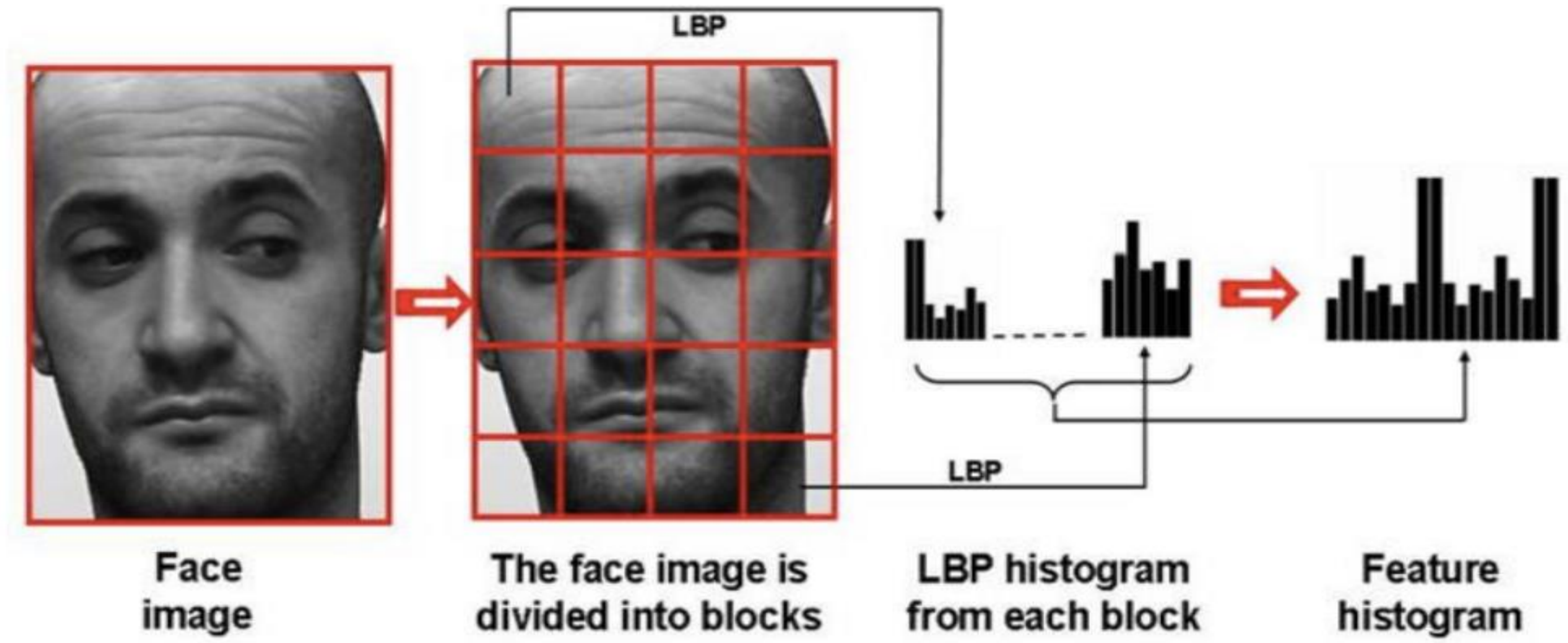


LBP

- LBP to global descriptor



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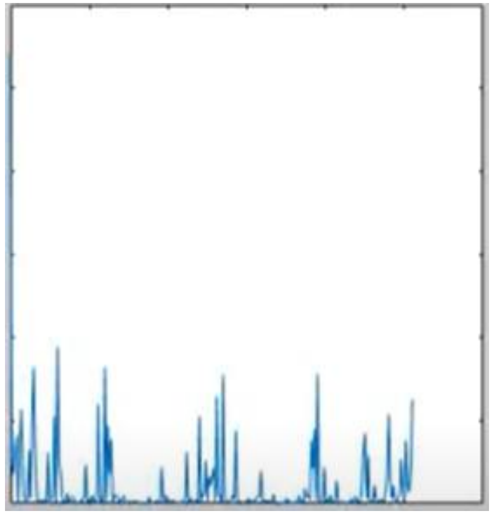

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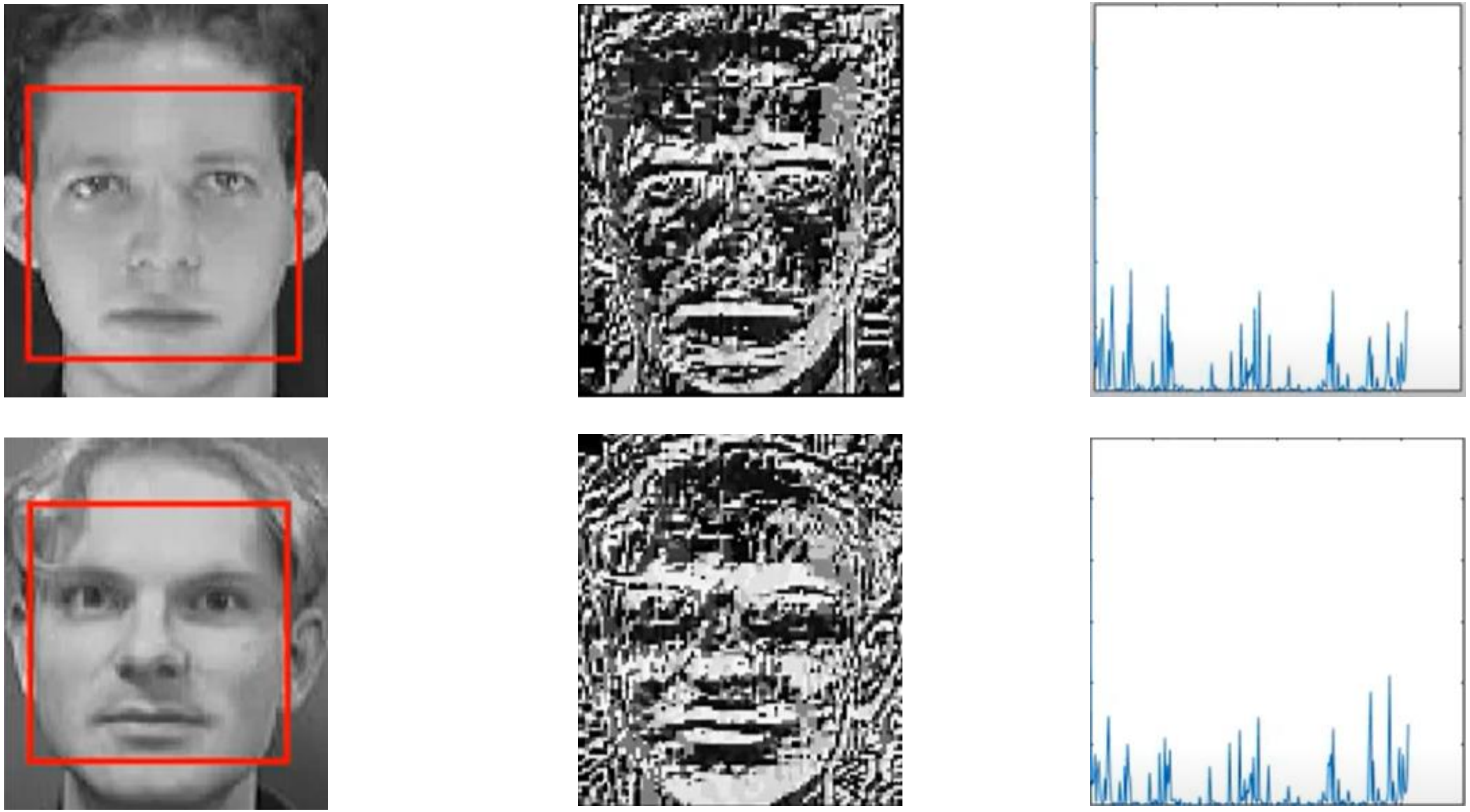
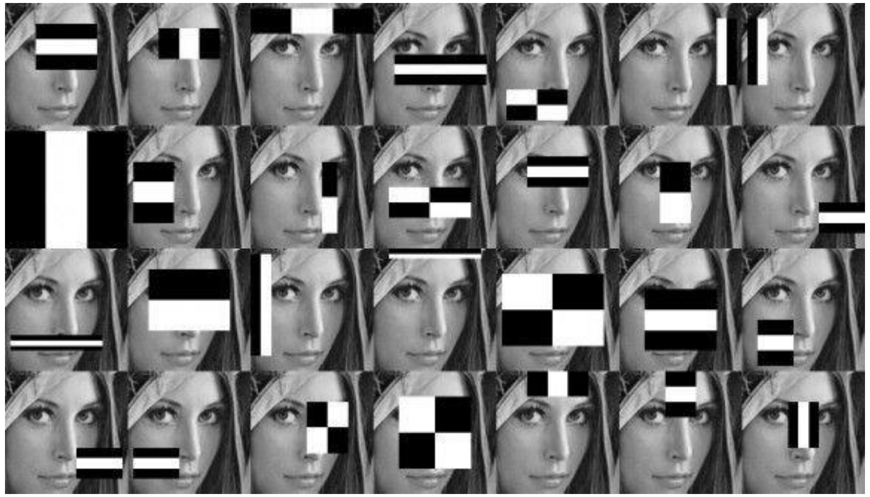
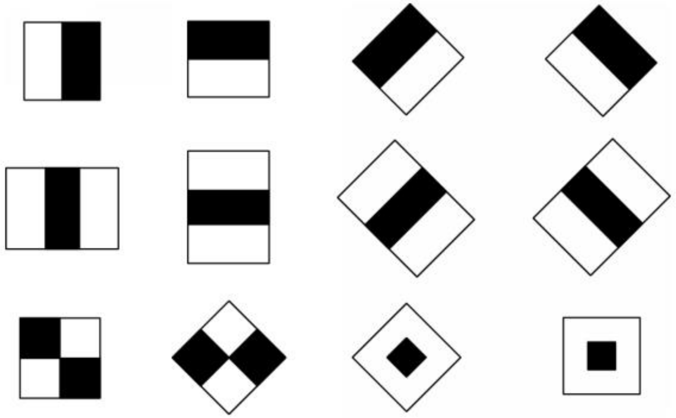


Haar features

- Face detection



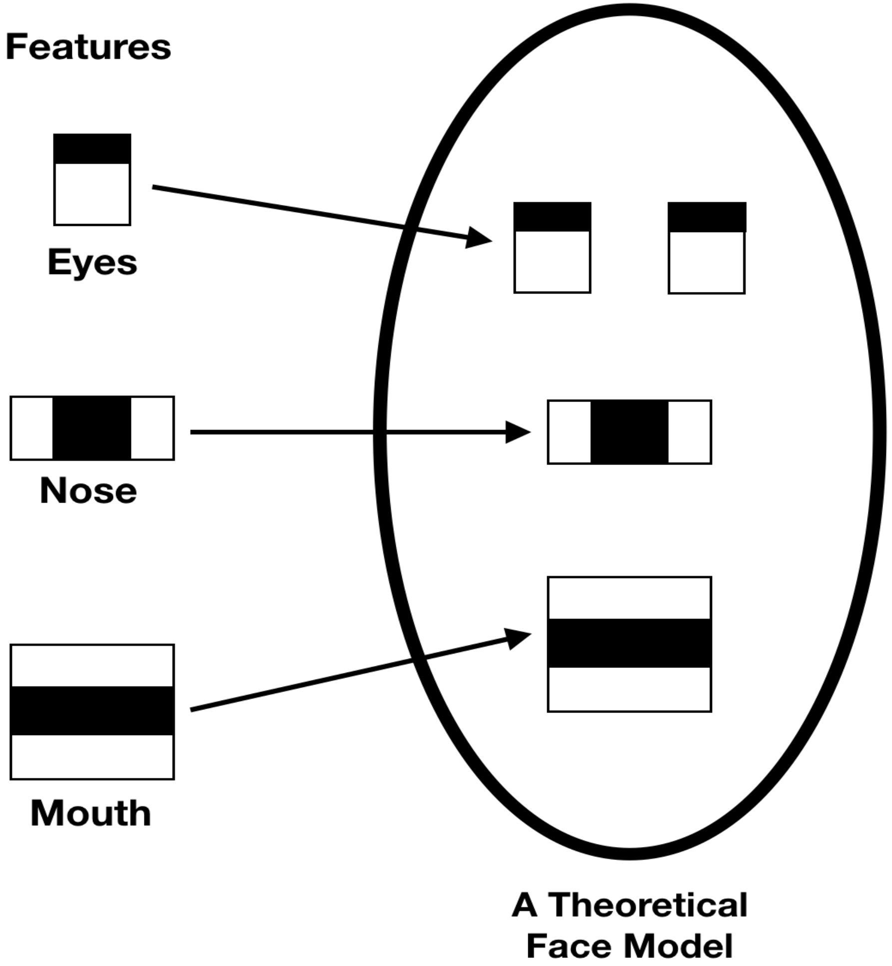
Haar feature: $f(x, y) = \sum I(R_{white}) - \sum I(R_{black})$



Haar filters
(based on Haar wavelets)

Conclusion

- Statistical descriptors
- LBP
- Haar



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