



Ingeniería Eléctrica  
FACULTAD DE CIENCIAS  
FÍSICAS Y MATEMÁTICAS  
UNIVERSIDAD DE CHILE

# EL 5206 Identificación Periocular



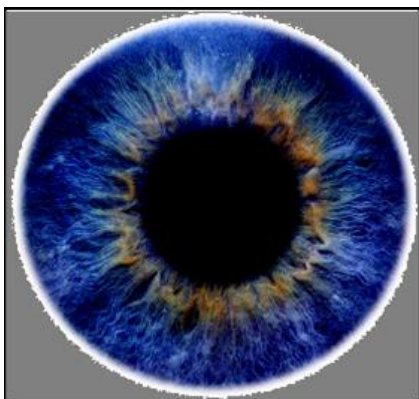
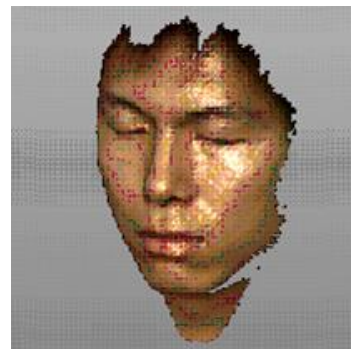
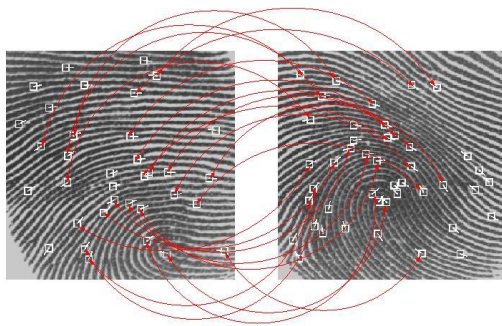
Claudio A. Perez  
Departamento de Ingeniería Eléctrica, Universidad de Chile

2022



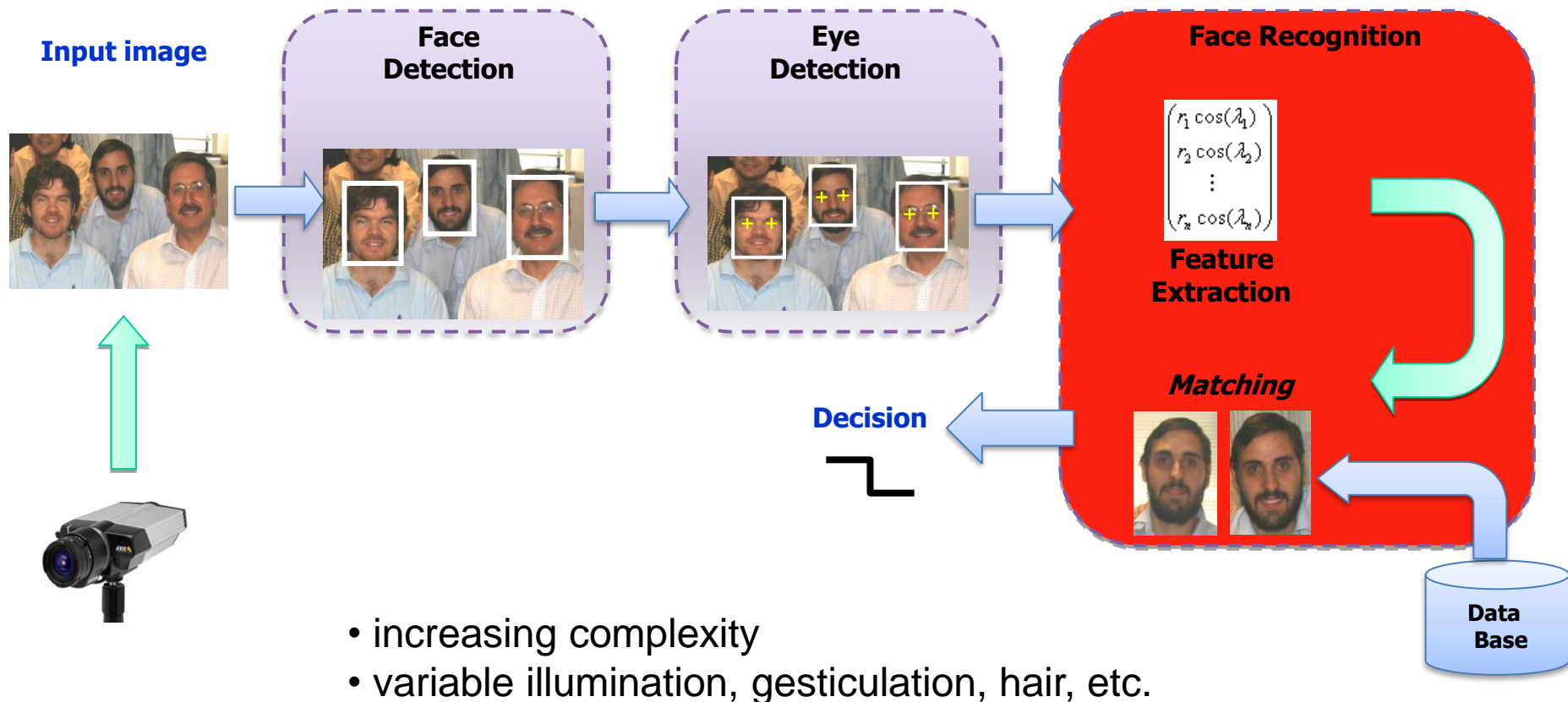
# Modalidades Biométricas más Frecuentes

- Identificación de individuos o caracterización de su comportamiento en base a datos medidos sobre su anatomía (huellas dactilares, rostros, iris, palma de la mano, etc.) o su comportamiento (voz, firma, caminata, desplazamientos, etc.).





# Feature extraction and matching

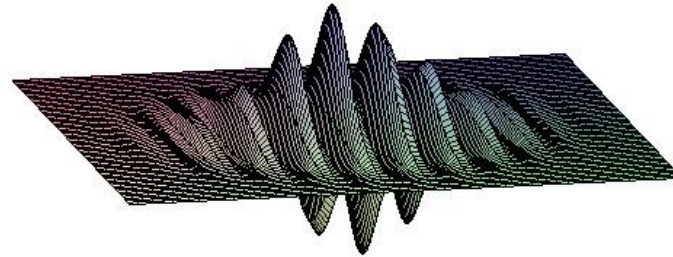


- increasing complexity
- variable illumination, gesticulation, hair, etc.



# Gabor Jets

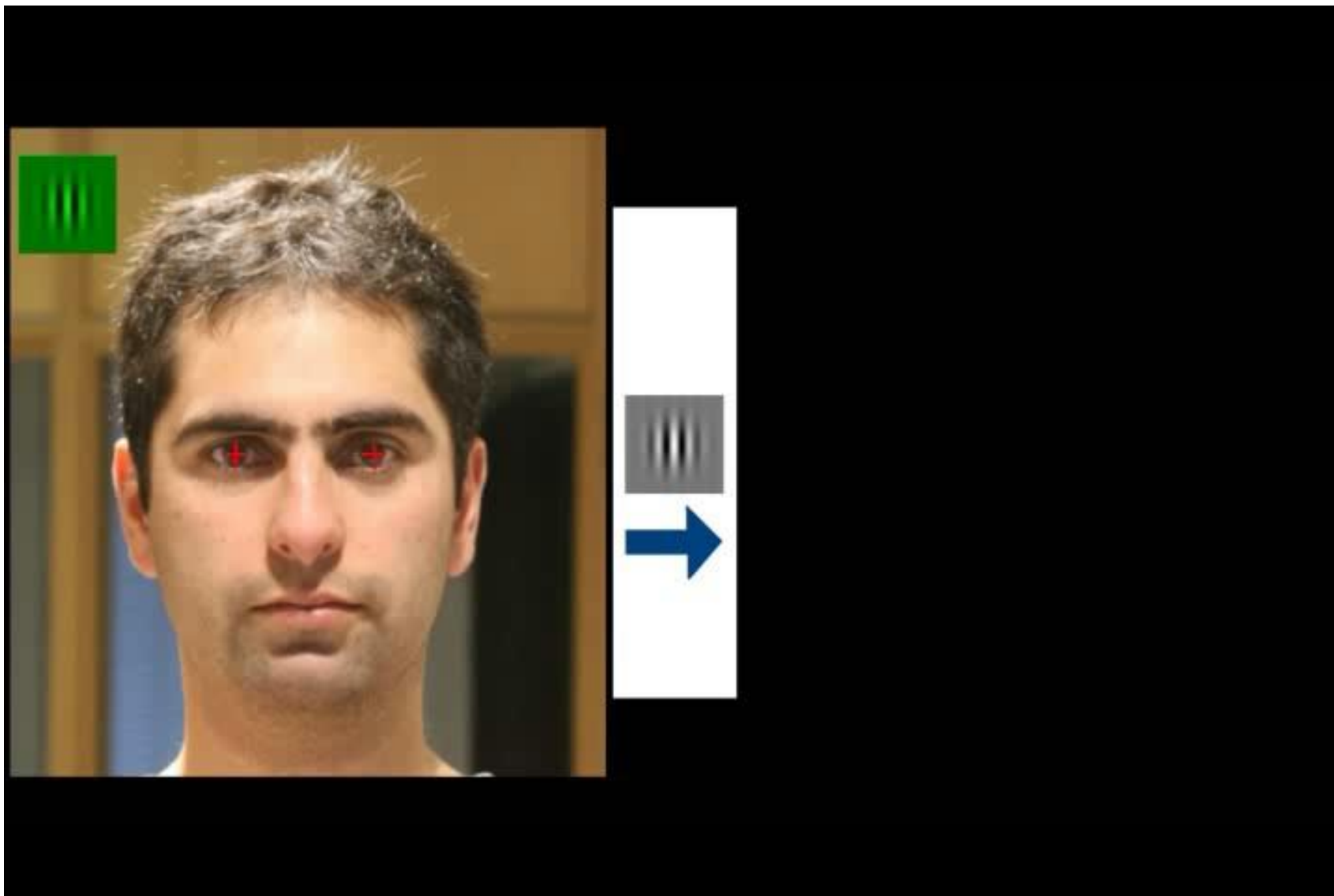
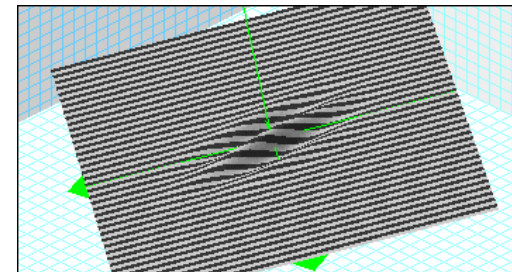
- Gabor Jet: Conjunto de funciones Gabor 2-D complejas que coinciden en posición y longitud de onda ( $\lambda$ ), pero difieren en orientación



$$h(x, y; \sigma, \omega_0, \phi) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{1}{2} \frac{x^2 + y^2}{\sigma^2}\right) \cos(\omega_0(x \cos \phi + y \sin \phi))$$



# Face feature extraction



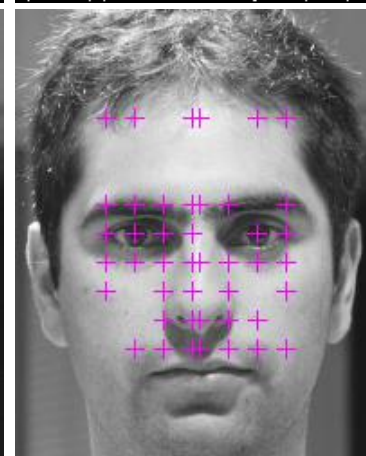
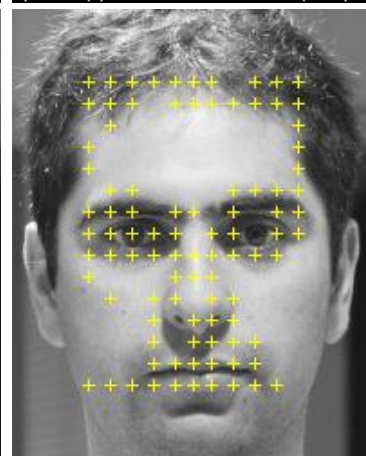
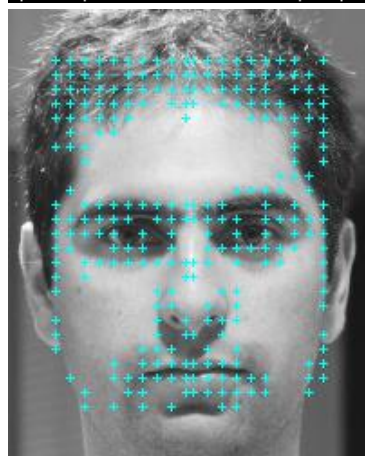
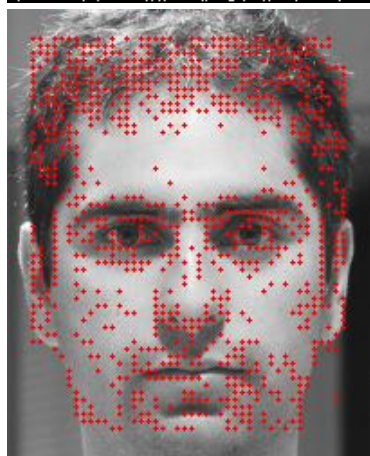




# Face feature extraction



Multi-resolution





# Base de Datos GrayFeret

- Imágenes de 256x384 en tonos de grises
- 5 subconjuntos:
  - Fa: 1196, 1 foto/individuo. Se utiliza como galería
  - Fb: 1195, 1 foto/individuo, mismo día, cámara e iluminación
  - Fc: 194, ~1 foto/individuo, mismo día, diferente cámara e iluminación
  - Dup1: 722, ~2 fotos/individuo, hasta 34 meses de diferencia
  - Dup2: 234, ~2 fotos/individuo, por lo menos 18 meses de diferencia
- Ejemplos



Fa



Fb



Dup1



Dup2



Fa



Fc

# Bases de datos

- Base de datos - Partición



bb  
+60°



bc  
+40°



bd  
+25°



be  
+15°



ba  
0°



bf  
-15°



bg  
-25°



bh  
-40°



bi  
-60°

FERET



c25



c09



c31



c22



c02



c37



c05



c27



c29



c11



c14



c34



c07

CMU PIE





**Table 4**  
Rank-1 face recognition rate on different subsets of FERET database for different face recognition algorithms published in the literature.

Methods	Accuracy (%)				Number of errors				
	Fb	Fc	Dup1	Dup2	Fb	Fc	Dup1	Dup2	Total
LMG [43] <sup>a</sup>	<b>99.5</b>	<b>99.5</b>	<b>85.0</b>	79.5	<b>6</b>	<b>1</b>	<b>108</b>	48	<b>163</b>
LGBPWP [41] <sup>a</sup>	98.1	98.9	83.8	<b>81.6</b>	23	2	117	<b>43</b>	185
Weighted LLGP_FR [40] <sup>a</sup>	99.0	99.0	80.0	78.0	12	2	144	51	209
Weighted HGPP [38] <sup>a</sup>	97.5	99.5	79.5	77.8	30	1	148	52	231
Weighted LGBPHS [37] <sup>a</sup>	98.0	97.0	74.0	71.0	24	6	188	68	286
LGT [39] <sup>a</sup>	97.0	90.0	71.0	67.0	36	19	209	77	341
Weighted LBP [37,26] <sup>a</sup>	97.0	79.0	66.0	64.0	36	41	245	84	406
GFC [37,35] <sup>b</sup>	97.2	79.9	68.3	46.6	33	39	229	125	426
EBGM [37,34] <sup>b</sup>	95.0	82.0	59.1	52.1	60	35	295	112	502

<sup>a</sup> Results extracted from original source

<sup>b</sup> Results extracted from the first referenced paper, and the original method is the second referenced paper.

**Table 5**

Face recognition rate on different subsets of the FERET database for our proposed methods and compared to the best results published up to date in the literature LMG [43]. Subindex 1 indicates FERET training set Train1, subindex 2 indicates FERET training set Train2.

Methods	Accuracy (%)				Number of errors				
	Fb	Fc	Dup1	Dup2	Fb	Fc	Dup1	Dup2	Total
LMG [43]	99.5	99.5	85.0	79.5	6	1	108	48	163
LMG-GS <sub>J1</sub>	99.7	99.5	86.3	81.2	4	1	99	44	148
LMG-GS <sub>J2</sub>	99.7	99.5	86.3	82.1	3	1	99	42	145
LMG-EJS <sub>1a</sub>	<b>99.8</b>	<b>100</b>	<b>88.0</b>	84.2	<b>2</b>	<b>0</b>	<b>87</b>	37	126
LMG-EJS <sub>1b</sub>	99.4	99.5	<b>88.0</b>	<b>87.2</b>	7	1	<b>87</b>	<b>30</b>	<b>125</b>
LMG-EJS <sub>2</sub>	99.5	99.5	87.0	85.9	6	1	94	33	134
LMG-BIP <sub>1</sub>	99.6	99.5	86.0	82.9	5	1	101	40	147
LMG-BTH <sub>1</sub>	99.7	99.5	86.8	82.1	4	1	95	42	142



**Table 6**  
Face recognition rate on different subsets of the FERET database for our proposed methods combined and compared to the best results published up to date in the literature LMG [43]. Subindex 1 indicates FERET training set Train1, subindex 2 indicates FERET training set Train2.

Methods	Accuracy (%)				Number of errors				
	Fb	Fc	Dup1	Dup2	Fb	Fc	Dup1	Dup2	Total
LMG [43] <sup>a</sup>	99.5	99.5	85.0	79.5	6	1	108	48	163
LMG-GSJ-BTH-BIP <sub>1</sub>	99.7	99.5	86.6	83.8	4	1	97	38	140
LMG-GSJ-BTH-BIP <sub>2</sub>	99.6	99.5	86.8	83.8	5	1	95	38	139
LMG-EJS-BTH <sub>1</sub>	<b>99.8</b>	99.5	88.9	85.9	2	1	80	33	116
LMG-EJS-BTH <sub>2</sub>	99.5	<b>100</b>	88.1	86.3	6	<b>0</b>	86	32	124
LMG-EJS-BIP <sub>1</sub>	99.5	<b>100</b>	87.8	86.3	6	<b>0</b>	88	32	126
LMG-EJS-BIP <sub>2</sub>	99.2	99.5	87.4	86.3	10	1	91	32	134
LMG-EJS-BTH-BIP <sub>1a</sub>	99.5	<b>100</b>	88.8	<b>87.6</b>	6	<b>0</b>	81	<b>29</b>	116
LMG-EJS-BTH-BIP <sub>1b</sub>	<b>99.8</b>	99.5	<b>89.2</b>	86.8	2	1	78	31	112
LMG-EJS-BTH-BIP <sub>2</sub>	99.6	<b>100</b>	88.2	86.3	5	<b>0</b>	85	32	122

<sup>a</sup> Results extracted from original source.



# Mallas deformables

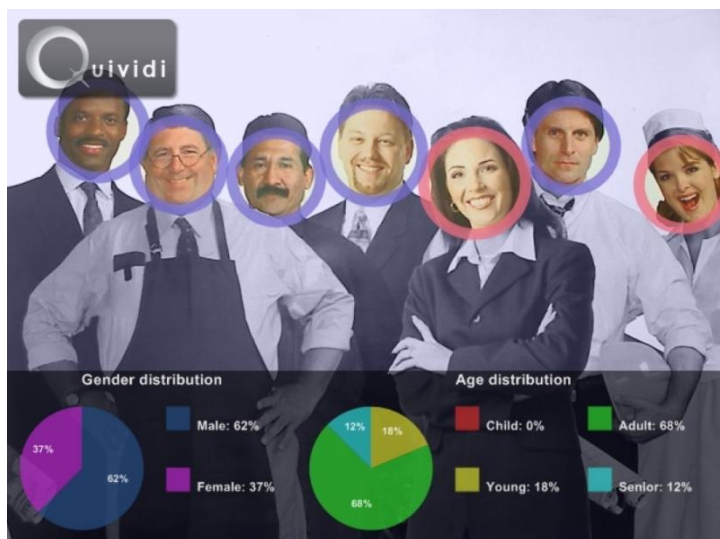






# Introduction

- Why gender classification?
  - The face provides crucial information about gender, age, ethnicity, age and identity
  - Retailers would like to know about the behavior of customers
  - Applications in real time electronic marketing, marketing research, demographic information collection, biometric authentication, social networks, and others







Hombre

Hombre



# LBP

- Si  $h(I(xc,yc),I(x,y))$  es un operador de comparación tal que  $h=1$  si  $I(xc,yc)<I(x,y)$  y  $h=0$  en otro caso, entonces

$$LBP(x, y) = \bigcup_{(x',y') \in N(x,y)} h(I(x, y), I(x', y'))$$

$N(x,y)$  una vecindad de  $(x,y)$  y  $\bigcup$  el operador de concatenación.

40	50	45
25	30	27
40	15	20

Comparación  
Operador  $h$

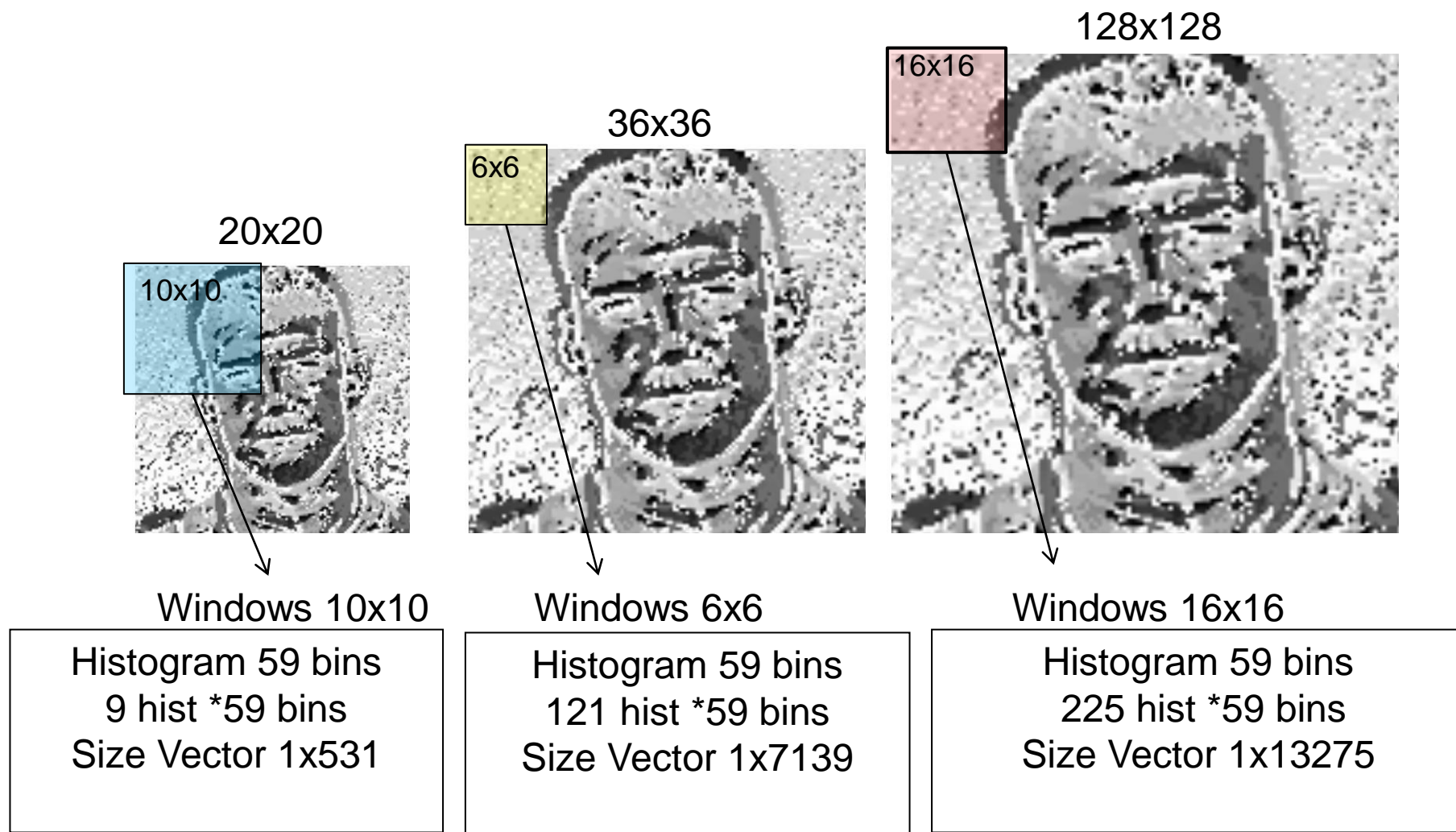
1	1	1
0		0
1	0	0

$\bigcup$

	11100010	



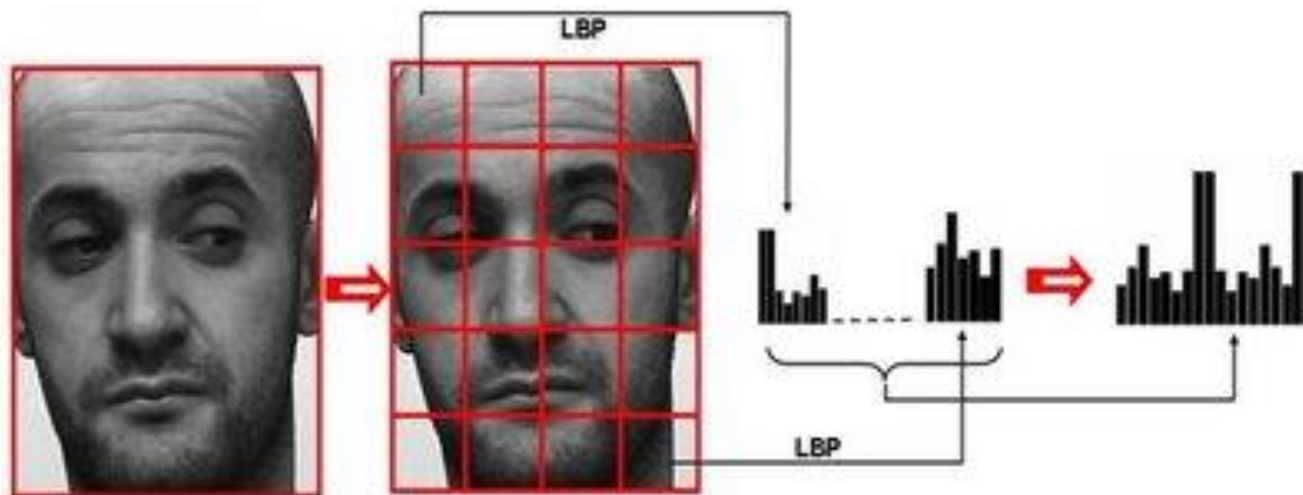
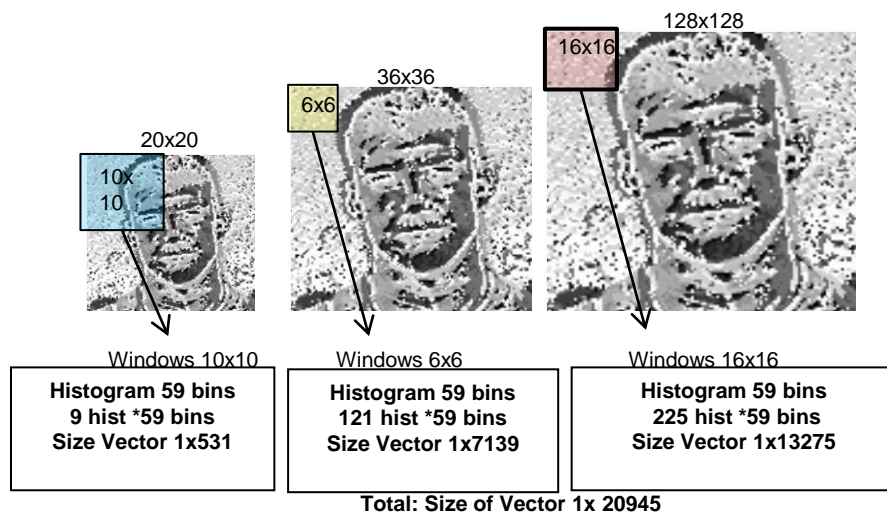
# LBP Features



Total: Size of Vector 1x 20945 (c/traslape ventanas)



# LBP Features





# Feature extraction and fusion

