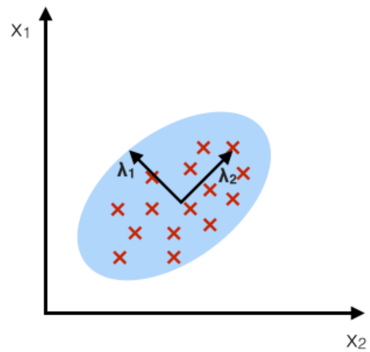
A CBR SYSTEM FOR EFFICIENT FACE RECOGNITION UNDER PARTIAL OCCLUSION

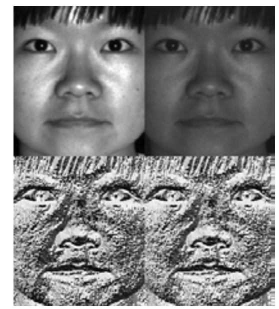
ICCBR 2017, TRONDHEIM, NORWAY

DANIEL LÓPEZ SÁNCHEZ, ANGÉLICA GONZÁLEZ ARRIETA, JUAN M. CORCHADO

UNIVERSITY OF SALAMANCA, BISITE RESEARCH GROUP

I. FACE RECOGNITION TRENDS OVER TIME





Eigenfaces (PCA)

Local Binary Patterns

1973

1997

2014

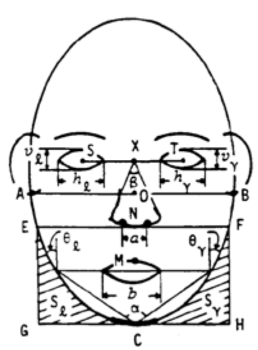
1991

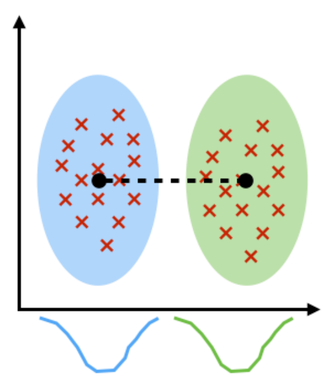
2004

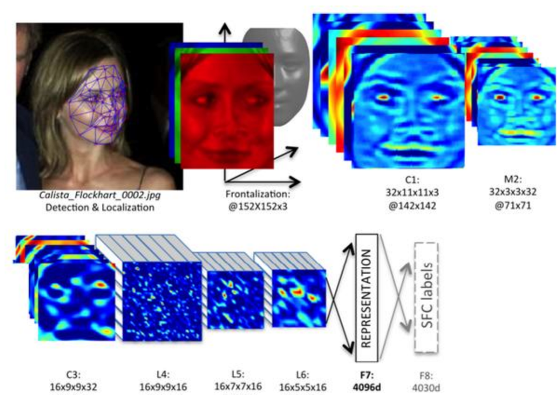
Geometric features

Fisherfaces (LDA)

Deep learning







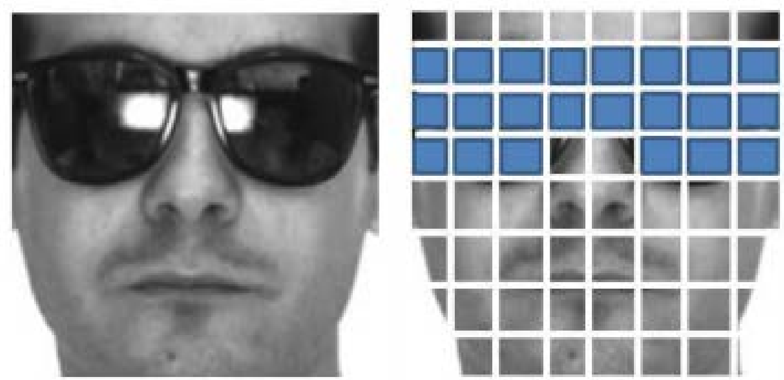
2. GOALS OF OUR WORK

Design an algorithm for effective face recognition **under partial occlusion** with the following features:

- Efficiency and scalability
- Effective even when only a few training images are available
- Agnostic to the nature of occlusion

3. PREVIOUS WORK IN FACE RECOGNITION WITH OCCLUSION

Color-based segmentation [1]

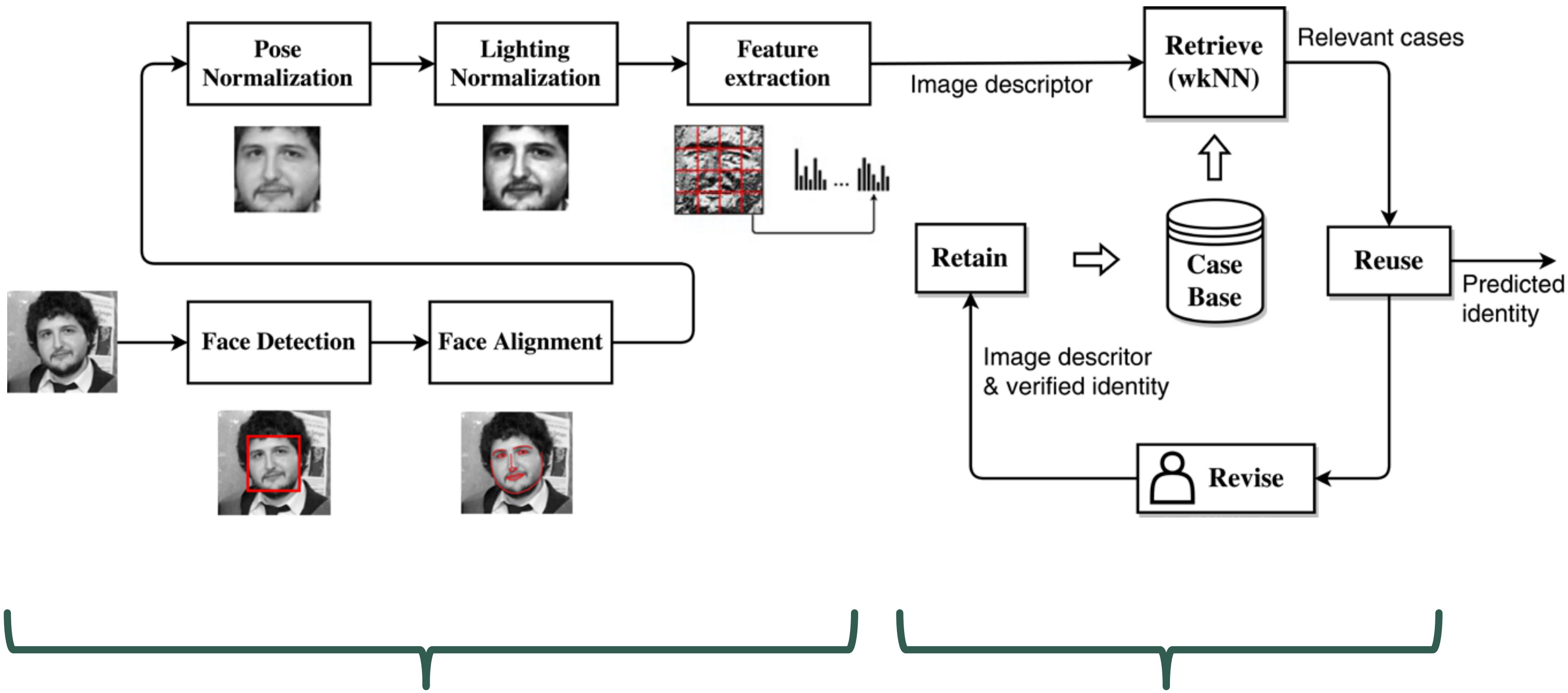


Explicit occlusion detection with block-level classifiers [2]

[1] Rui Min, Abdenour Hadid, and Jean-Luc Dugelay. Improving the recognition of faces occluded by facial accessories. In Automatic Face & Gesture Recognition and Workshops (FG 2011), 2011 IEEE International Conference on, pages 442-447. IEEE, 2011.

[2] Hongjun Jia and Aleix M Martinez. Face recognition with occlusions in the training and testing sets. In Automatic Face & Gesture Recognition, 2008. FG'08. 8th IEEE International Conference on, pages 1-6. IEEE, 2008.

4. PROPOSED APPROACH
GLOBAL ARCHITECTURE OF THE CBR SYSTEM

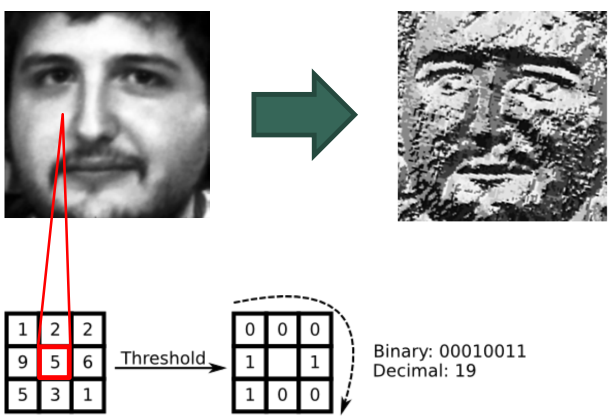


Preprocessing pipeline

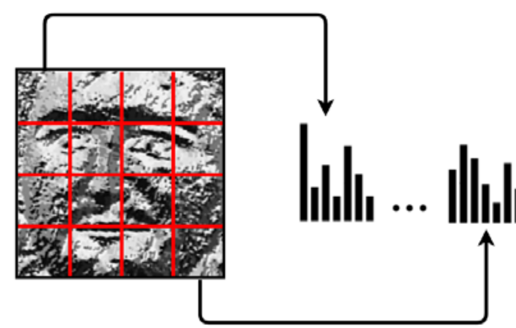
CBR

4. PROPOSED APPROACH
FEATURE EXTRACTION: LBPH

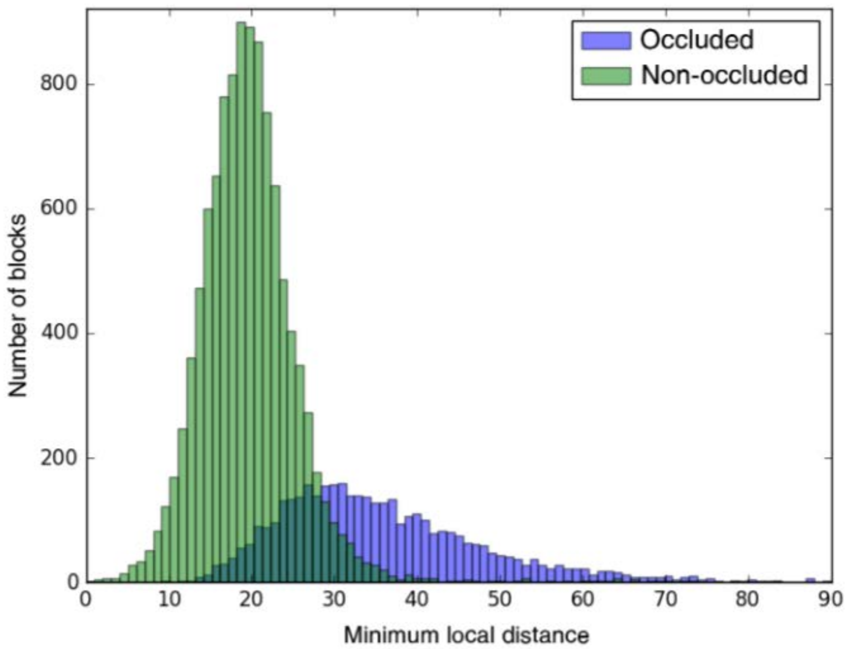
- Image *Local Binary Patterns* (LBP):



- *Local Binary Pattern Histogram* (LBPH) descriptor with a 4x4 grid size:



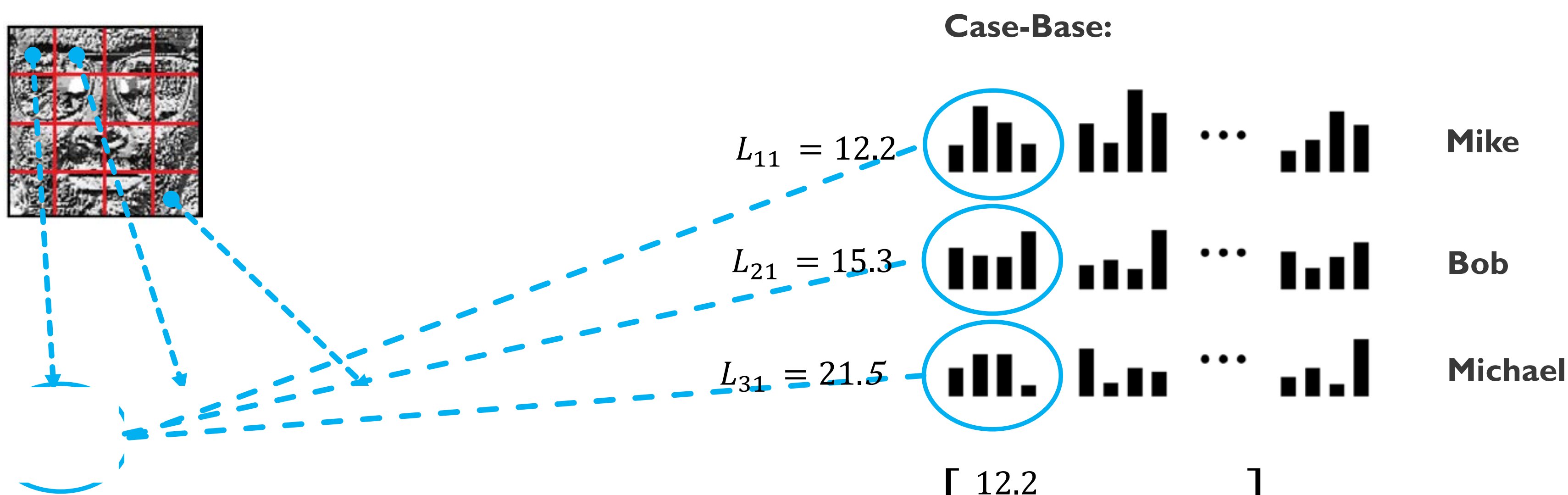
4. PROPOSED APPROACH
KEY CONCEPT: MINIMUM LOCAL DISTANCE



- *We define the **Mininum Local Distance** for the histogram of an LBP block as the minimum squared Euclidean distance obtained when comparing this histogram with the LBP histograms corresponding to the same facial region in the descriptors stored in the Case-Base*
- Our approach works under the assumption that **LBP histograms from occluded regions exhibit a higher Minimum Local Distance**

4. PROPOSED APPROACH
AN EXAMPLE

New case to solve:



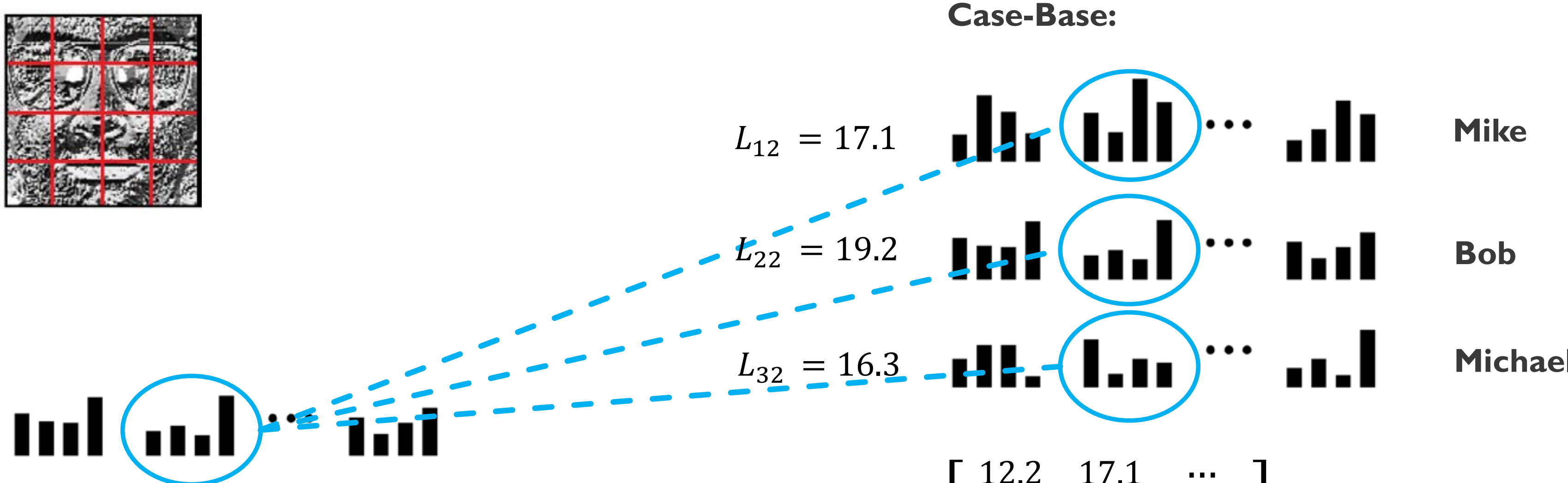
Minumum Local Distances:

12.2

$$L = \begin{bmatrix} 12.2 & \\ 15.3 & \\ 21.5 & \end{bmatrix}$$

4. PROPOSED APPROACH
AN EXAMPLE

New case to solve:



Minumum Local Distances:

12.2 16.3 … 13.1

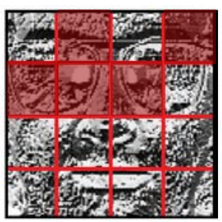
$$L = \begin{bmatrix} 12.2 & 17.1 & \cdots \\ 15.3 & 19.2 & \cdots \\ 21.5 & 16.3 & \cdots \end{bmatrix}$$

4. PROPOSED APPROACH
THRESHOLD OVER MINIMUM LOCAL DISTANCES

- We apply a **threshold** over the Minimum Local Distance to **inhibit the use of features from occluded regions**
- The **disimilarity function** used in the retrieval of cases **inhibits/ignores the occluded features**

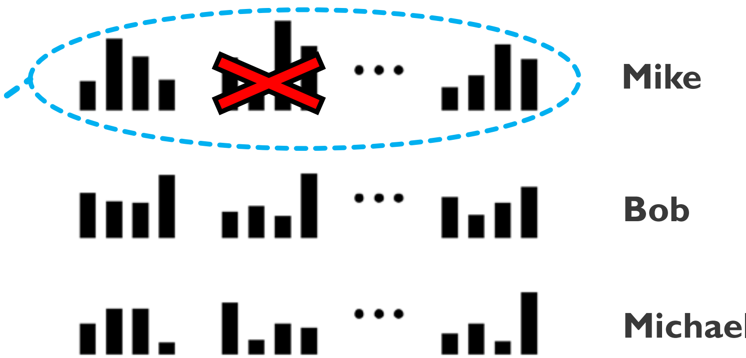
4. PROPOSED APPROACH
AN EXAMPLE (CONTINUED)

New case to solve:

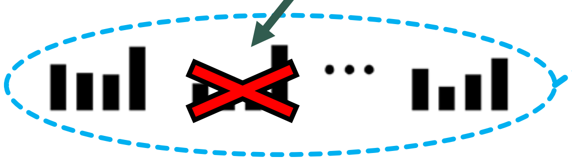


Case-Base:

Disimilarity = 32.3



Mark this historgam as occluded



<u>Minumum Local Distances:</u>

12.2 16.3 … 13.1

Threshold: 15

$$L = \begin{bmatrix} 12.2 & \cancel{} & \cdots \\ 15.3 & 19.2 & \cdots \\ 21.5 & 16.3 & \cdots \end{bmatrix}$$

Adds up to 32.3

4. PROPOSED APPROACH
FORMAL DESCRIPTION AND COMPLEXITY ANALYSIS

- Initialize the Case-Base:

  $$CB = \{(y^{(i)}, x^{(i)}), i = 1, 2, ..., n\}$$

- Compute the local distances between the histograms of the new case x and the cases $x^{(i)}$ stored in the CB:

  $$L_{i,j} = ||(x_{p(j-1)+1}, \cdots, x_{pj}) - (x^{(i)}_{p(j-1)+1}, \cdots, x^{(i)}_{pj})||^2$$
  $$\text{for} \quad i = 1, 2, \cdots, n \quad \text{and} \quad j = 1, 2, \cdots, d/p$$

- Compute a mask to inhibit the use of histograms form occluded regions when retrieving cases:

  $$M_j = T_h(\ min(\ col_j L\ )\ )$$

- Retrieve the k most similar cases from the CBR according to the following similarity measure:

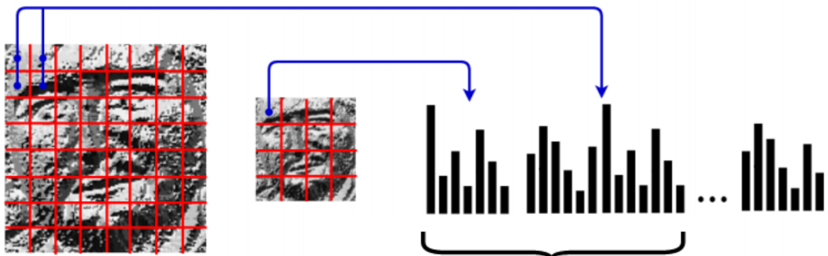
  $$d(x, x^{(i)}) = \sum_{j=1}^{j=d/p} M_j \cdot L_{i,j}$$

- Predict the most common identity among the retrieved cases as the identity of x

- Step 1. Case-Base initialization **O(1)**
- Step 2. Local distance calculation **O(nd)**
- Step 3. Occlusion mask estimation **O(d)**
- Step 4. Case Retrieval **O(nd)**
- Step 5. Case Reuse for identity prediction **O(k)**

Total complexity: O(nd)

5. EXTENDING THE PROPOSED APPROACH
USE OF MULTI-SCALE FEATURES

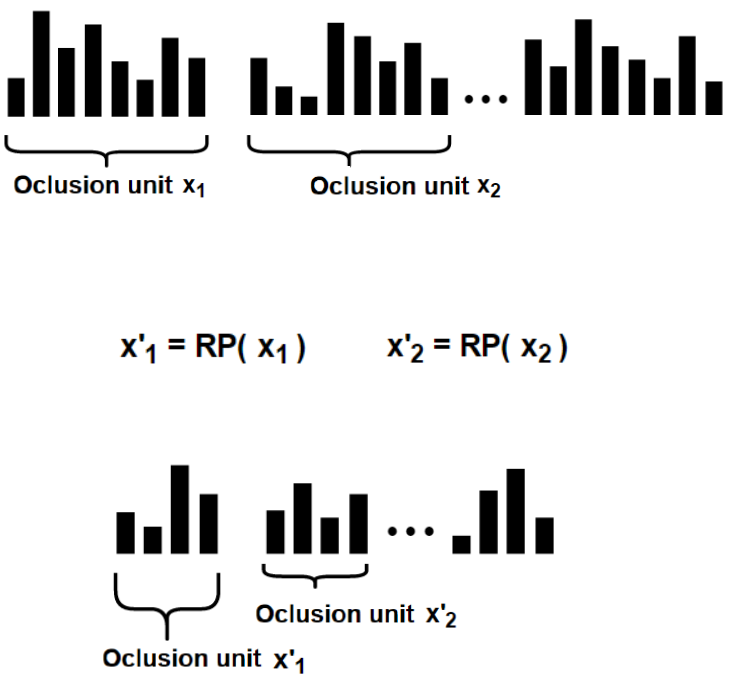


- The literature shows that extracting features at various scales is necessary to achieve high accuracy rates [2]
- This is in principle compatible with our approach
- The problem of high dimensionality arises

  (e.g. up to ~10.620 features for some grid sizes)
- The authors of [2] used an approximation of PCA to reduce the dimension of samples

[2] Chen, D., Cao, X., Wen, F., & Sun, J. (2013). Blessing of dimensionality: High-dimensional feature and its efficient compression for face verification. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 3025-3032).

5. EXTENDING THE PROPOSED APPROACH
LOCAL DIMENSIONALITY REDUCTION



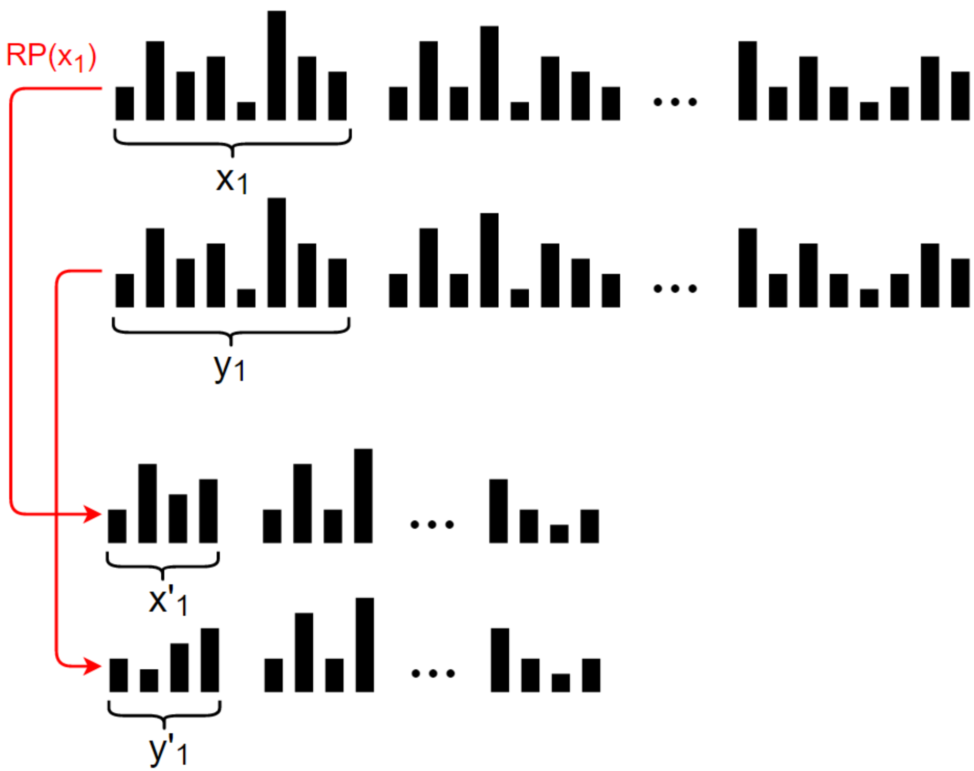
- To solve the problem of high dimensionality of cases, we used the Random Projection Algorithm in a local manner (RP):

$$RP(x) = \frac{1}{k}\, x\, R$$

Where R is a $d \times k$ matrix with its elements chosen at random from a standard normal distribution

- By so doing, we lower the number of features per occlusion unit from d to k

5. EXTENDING THE PROPOSED APPROACH
LOCAL DIMENSIONALITY REDUCTION



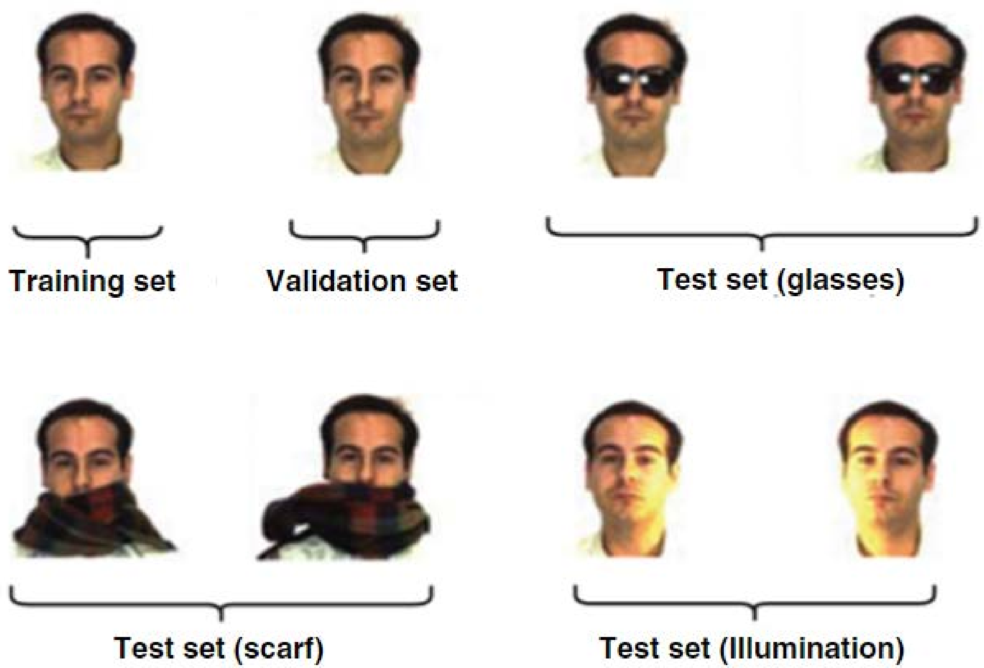
- *Random Projection* (RP) guarantees the approximate preservation of pairwise distances:

$$||x_1 - y_1||^2 \cong ||x_1' - y_1'||^2$$

- Given that our retrieval stage is based on Euclidean distances we can guarantee that, **for a sufficiently large k value, the system will provide the same results when executed over the reduced descriptors**

6. EXPERIMENTAL RESULTS
THE DATASET

- Experimental database: ARFace Database (126 subjects)



6. EXPERIMENTAL RESULTS

AUTOMATIC FACE DETECTION & ALIGNMENT

Table 1. Experimental results with automatic face alignment.

Features	**Classifier**	**Lighting**	**Scarf**	**Glasses**
$\mathrm{LBP}^u_{8,2}$	wkNN [6]	81.4%	39.4%	30.0%
$\mathrm{LBP}^u_{8,2}$	proposed CBR $p = 59$; *threshold* $= 27$	96.2%	83.6%	50.2%
$\mathrm{LBP}^u_{8,2}$	SVM (poly kernel)	78.1%	36.9%	25.1%
$\mathrm{LBP}^u_{8,2}$	Logistic Regression	84.8%	45.0%	23.4%
$\mathrm{LBP}^u_{8,2}$	Naive Bayes	82.5%	43.7%	20.1%
multi-scale $\mathrm{LBP}^u_{8,2}$	wkNN [6]	98.8%	73.3%	34.9%
multi-scale $\mathrm{LBP}^u_{8,2}$	proposed CBR $p = 295$; *threshold* $= 17$	99.2%	89.2%	50.6%
multi-scale $\mathrm{LBP}^u_{8,2}$	SVM (poly kernel)	88.1%	59.6%	27.9%
multi-scale $\mathrm{LBP}^u_{8,2}$	Logistic Regression	96.2%	75.1%	28.3%
multi-scale $\mathrm{LBP}^u_{8,2}$	Naive Bayes	86.29%	72.1%	37.03%
multi-scale $\mathrm{LBP}^u_{8,2}$ + RP	wkNN [6]	98.5%	66.5%	31.2%
multi-scale $\mathrm{LBP}^u_{8,2}$ + local RP (see sect. 3.4)	proposed CBR $p = 150$; *threshold* $= 100$	98.8%	90.5%	51.0%
multi-scale $\mathrm{LBP}^u_{8,2}$ + RP	SVM (poly kernel)	85.5%	55.3%	20.9%
multi-scale $\mathrm{LBP}^u_{8,2}$ + RP	Logistic Regression	93.3%	69.0%	25.5%
multi-scale $\mathrm{LBP}^u_{8,2}$ + RP	Naive Bayes	84.0%	54.5%	27.1%

6. EXPERIMENTAL RESULTS
MANUAL FACE DETECTION & ALIGNMENT

Table 2. Experimental results with manual face alignment.

Features	Classifier	Lighting	Scarf	Glasses
$LBP^{u}_{8,2}$	wkNN [6]	95.5%	76.5%	69.5%
$LBP^{u}_{8,2}$	Proposed CBR $p = 59$; *threshold* $= 30$	99.5%	91.5%	83.5%
$LBP^{u}_{8,2}$	SVM (poly kernel)	96.5%	75.0%	61.0%
$LBP^{u}_{8,2}$	Logistic Regression	98.5%	81.0%	68.0%
$LBP^{u}_{8,2}$	Naive Bayes	94.0%	76.5%	69.0%
multi-scale $LBP^{u}_{8,2}$	wkNN [6]	100%	92.0%	86.0%
multi-scale $LBP^{u}_{8,2}$	Proposed CBR $p = 295$; *threshold* $= 111$	99.5%	97.0%	92.0%
multi-scale $LBP^{u}_{8,2}$	SVM (poly kernel)	100.0%	92.0%	84.5%
multi-scale $LBP^{u}_{8,2}$	Logistic Regression	100.0%	93.0%	89.5%
multi-scale $LBP^{u}_{8,2}$	Naive Bayes	95.5%	93.5%	89.0%
multi-scale $LBP^{u}_{8,2}$ + RP	wkNN [6]	100%	92.0%	86.0%
multi-scale $LBP^{u}_{8,2}$ + local RP (see sect. 3.4)	Proposed CBR $p = 150$; *threshold* $= 111$	99.5%	97.0%	92.0%
multi-scale $LBP^{u}_{8,2}$ + RP	SVM (poly kernel)	100.0%	92.0%	84.5%
multi-scale $LBP^{u}_{8,2}$ + RP	Logistic Regression	100.0%	93.0%	89.5%
multi-scale $LBP^{u}_{8,2}$ + RP	Naive Bayes	95.5%	93.5%	89.0%

6. CONCLUSIONS AND FUTURE WORK

- **Conclusions:**
  - The proposed CBR system outperforms classical method in the context of face recognition under partial occlusion
  - Its computational complexity is equivalent to that of kNN
  - We have proposed, justified theoretically and evaluated a local dimensionality reduction approach to lower the size of cases in the proposed CBR

- **Future work:**
  - Development of occlusion-robust face alignment methods
  - Study the compatibility of the proposed CBR with alternative local image descriptors (e.g. *discrete cosine transform*)
  - Empirical comparison with Deep Learning methods for face recognition

A CBR SYSTEM FOR EFFICIENT FACE RECOGNITION UNDER PARTIAL OCCLUSION

ICCBR 2017, TRONDHEIM, NORWAY

DANIEL LÓPEZ SÁNCHEZ, ANGÉLICA GONZÁLEZ ARRIETA, JUAN M. CORCHADO
UNIVERSITY OF SALAMANCA, BISITE RESEARCH GROUP

THRESHOLD SETTING

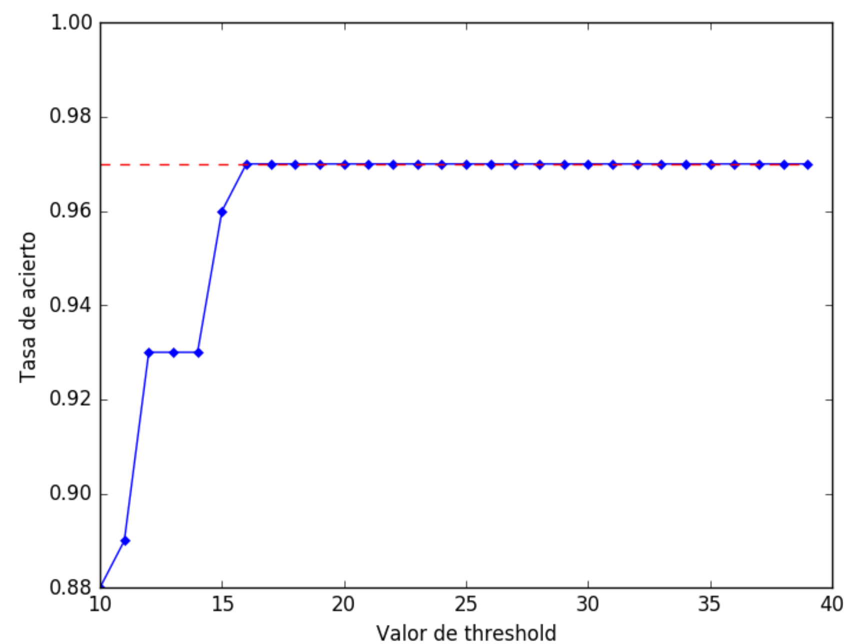


Figura 28: *Resultados de validación del método wkNN con inhibición para diferentes valores de threshold (azul) y resultado de validación para wkNN clásico (rojo).*

ESTIMACIÓN DEL *THRESHOLD*

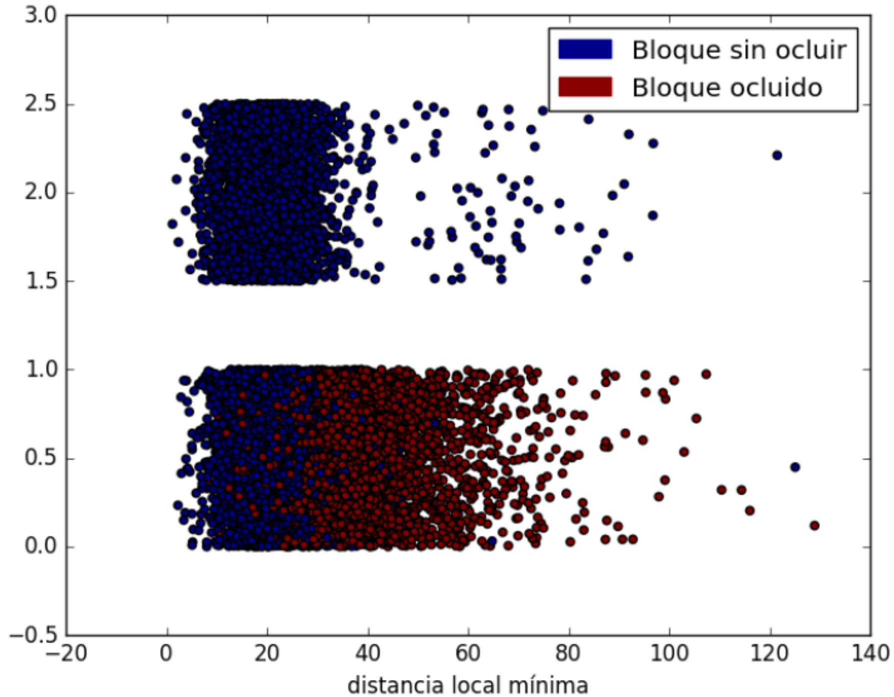
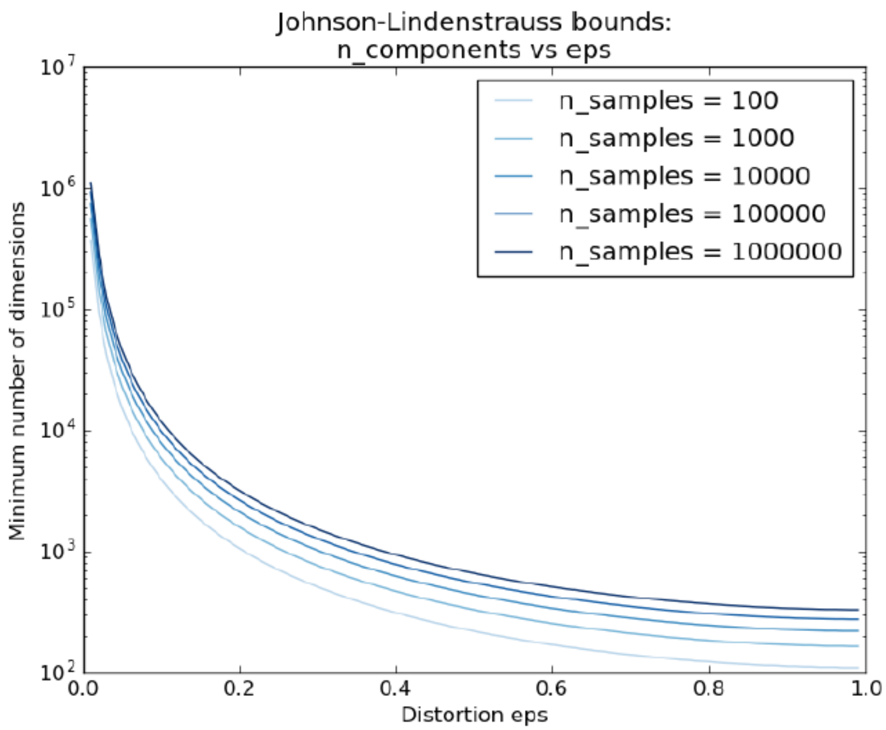


Figura 10: *En el eje horizontal se muestra la distancia local mínima de los bloques pertenecientes a rostros sin oclusión parcial (arriba) y con oclusión parcial (abajo). Los bloques ocluidos se muestran en rojo y los no ocluidos en azul. Se ha añadido ruido aleatorio al eje vertical para evitar el solapamiento.*

LEMA DE JOHNSON-LINDENSTRAUSS



$$k > 4 \cdot ln(n)/(\epsilon^2/2 - \epsilon^3/3)$$

$$(1-\epsilon)||u-v||^2 \leq ||f(u)-f(v)||^2 \leq (1+\epsilon)||u-v||^2$$

$$(1-\epsilon)\ L_{i,j} \leq L'_{i,j} \leq (1+\epsilon)\ L_{i,j}$$

$$\text{para} \quad i = 1, 2, \cdots, n \quad \text{y} \quad j = 1, 2, \cdots, d/p$$

PARTIAL SQUARED EUCLIDEAN DISTANCES

$$
\begin{aligned}
d(x, y) &= ||x - y||^2 = ||z||^2 = z_1^2 + z_2^2 + \cdots + z_n^2 + z_{n+1}^2 + \cdots + z_d^2 \\
&= ||(z_1, \cdots, z_n)||^2 + ||(z_{n+1}, \cdots, z_d)||^2 \\
&= ||(x_1 - y_1, \cdots, x_n - y_n)||^2 + ||(x_{n+1} - y_{n+1}, \cdots, x_d - y_d)||^2 \\
&= d((x_1, \cdots, x_n), (y_1, \cdots, y_n)) + d((x_{n+1}, \cdots, x_d), (y_{n+1}, \cdots, y_d))
\end{aligned}
$$

ESCALABILIDAD

- Initialize the Case-Base:

  $$CB = \{(y^{(i)}, x^{(i)}), i = 1, 2, ..., n\}$$

- Compute the local distances between the histograms of the new case x and the cases $x^{(i)}$ stored in the CB:

  $$L_{i,j} = ||(x_{p(j-1)+1}, \cdots, x_{pj}) - (x^{(i)}_{p(j-1)+1}, \cdots, x^{(i)}_{pj})||^2$$
  $$\text{for} \quad i = 1, 2, \cdots, n \quad \text{and} \quad j = 1, 2, \cdots, d/p$$

- Compute a mask to inhibit the use of histograms form occluded regions when retrieving cases:

  $$M_j = T_h(\ min(\ col_j L\ )\ )$$

- Retrieve the k most similar cases from the CBR according to the following similarity measure:

  $$d(x, x^{(i)}) = \sum_{j=1}^{j=d/p} M_j \cdot L_{i,j}$$

- Predict the most common identity among the retrieved cases as the identity of x

- Step 1. Training: ***O(1)***
- Step 2. Local minimum distances calculation:
- $O\left(n\left(\frac{d}{p} \cdot p + \frac{d}{p}\right)\right) = O\left(nd + n \cdot \frac{d}{p}\right) = O(nd)$
- Step 3. Occlusion Mask generation: O(d)
- Step 4. kNN distances calculation:
  - Depends on the implementation:
  - *Naive search*: $\mathrm{O}(\mathrm{n} \cdot \frac{\mathrm{d}}{\mathrm{p}} + \mathrm{kn})$
  - Quick-select: $\mathrm{O}\left(\mathrm{n} \cdot \frac{\mathrm{d}}{\mathrm{p}} + \mathrm{n}\right) = O(n \cdot \frac{d}{p})$
- Steps 5. kNN voting: ***O(k)***

Total: $O\left(nd + d + n\frac{d}{p} + k\right) = O(nd)$

Since $\mathrm{k} \leq n, \quad d \geq p \geq 1$