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Implementation of a face recognition system as experimental practices in an artificial intelligence and pattern recognition course

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Abstract

In this paper, we present the methodology developed in a course of Artificial Intelligence and Pattern Recognition. The methodology is focused on building a face recognition system. For this purpose, we developed an own face recognition database named "Medfaces". This database contains controlled and wild images for the same subjects, and it also contains infrared images and facial expression labels. This methodology has been applied for teaching telecommunications engineering course at Miguel Hernández University of Elche (Spain). We also present the results of our teaching experience in terms of student satisfaction.

KEYWORDS

artificial intelligence, engineering education, face recognition

1 | INTRODUCTION

Today's society is immersed in technological revolution, and systems and algorithms based on artificial intelligence, pattern recognition, and machine learning are present in almost all industrial and service sectors and their effects are already noticeable. For this reason, the study of Artificial Intelligence in engineering degree courses on Computing or Telecommunications is considered to be almost mandatory. In this paper, we present the methodology developed in a course of Artificial Intelligence and Pattern Recognition (AIPR) in Telecommunications Engineering, where the students design and implement an artificial intelligence system for access control based on facial recognition.

The structure of the paper is as follows: first, we will present a short literature review on face recognition systems and face databases. Then, we will describe the structure and the main contents of the course and the details of the database developed for teaching and experimenting; and finally, we will show the teaching results obtained in terms of student satisfaction.

2 | LITERATURE REVIEW ON FACE RECOGNITION SYSTEMS: METHODS AND DATABASES

The main structure of a face recognition system is shown in Figure 1. There are three basic steps to build a face recognition system [15,19]: *face detection*, *feature extraction*, and *face recognition*. The purpose of the *face detection* step is to determine if the input image contains human faces or not. The main function of *feature extraction* step is to extract the features of the face images detected in the detection step to obtain a feature vector corresponding to the detected face (*signature*). And the last module, the *face recognition* step, takes the signature as input and compares it with known faces stored in a specific database. Among the most popular face detection algorithms, we can mention Viola–Jones detector [41,42],

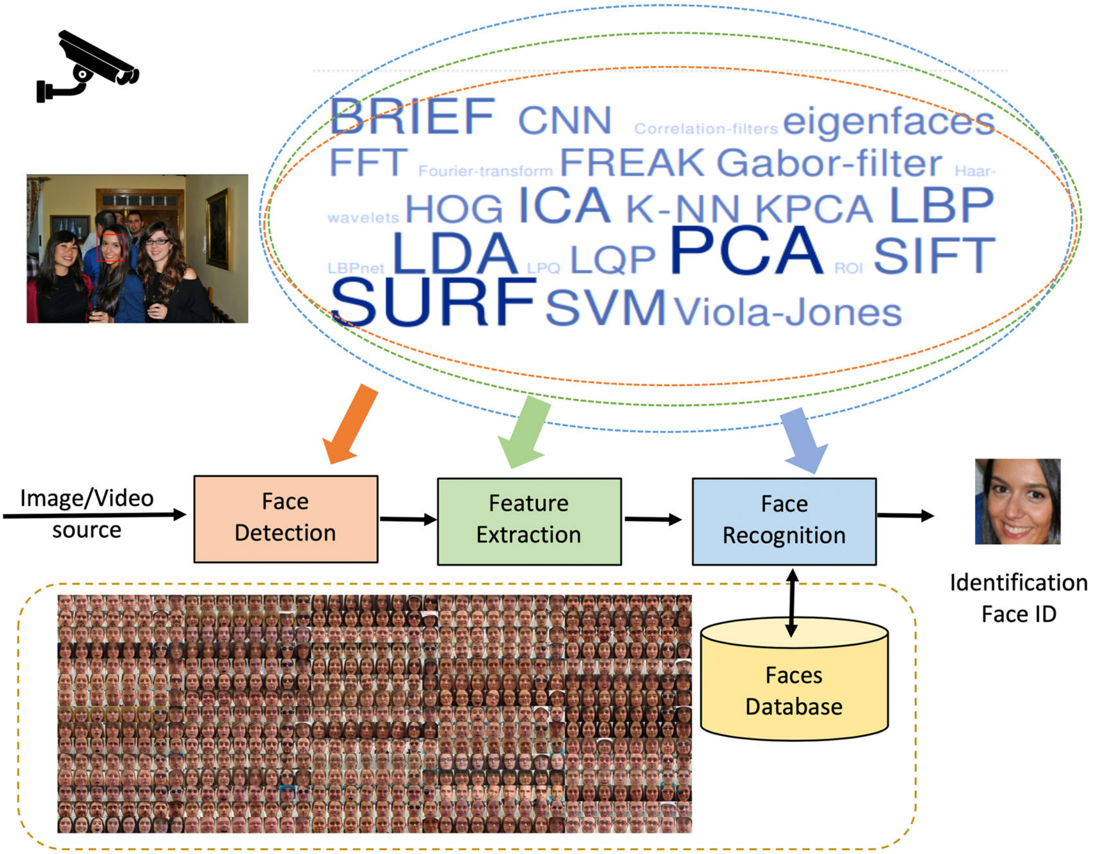

FIGURE 1 Main structure of a face recognition system

histogram of oriented gradient (HOG) [2,32], and Mathias detector [26]. The processes of feature extraction and face recognition can be quite interrelated depending on the type of features chosen to obtain the image signature; therefore, it is usual to use the term *face recognition methods* to name the algorithms used in the two last steps of the face recognition system [19].

Over the last few years, there has been a clear evolution in *face recognition methods* and *face databases*. Algorithms have evolved from initial global appearance

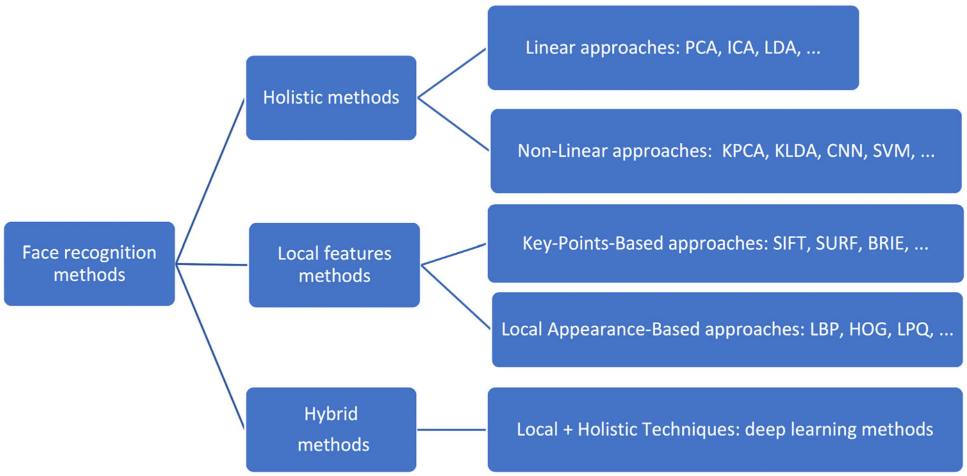

FIGURE 2 Summary of the classification of current face recognition methods [1,2,4–6,13,15,19,21,23,24,26,30,32,36–42]. BRIEF, binary robust independent elementary features; CNN, convolutional neural network; HOG, histogram of oriented gradients; KPCA, kernel PCA; LBP, local binary pattern; LDA, linear discriminant analysis; LPQ, local phase quantization; PCA, principal component analysis; SIFT, scale-invariant feature transform; SURF, speeded-up robust features; SVM, support vector machine

recognition methods (*holistic approaches*) to *local features approaches* and, currently, hybrid approaches, where deep learning methods stand out and require huge databases to be tested on. Global appearance methods mainly use principal component analysis and independent component analysis (principal component analysis [PCA]-ICA) [5,38–40], linear discriminant analysis (LDA) [6], improvements of basic PCA-LDA-ICA techniques [13,21], and nonlinear methods as kernel PCA [21], kernel LDA [4], evolutionary weighted PCA [36], nonlinear DCT, and KDVC [23]. Concerning methods based on local features, we can mention those based on scale-invariant feature transform (SIFT) descriptors [24] or local binary patterns and similar techniques [1]. Finally, some interesting examples of deep learning methods can be found in [30] and [37]. Figure 2 shows a summary of the classification of current face recognition methods.

With the constant improvement in algorithm performances, new, more challenging databases were needed for test purposes [31]. For this reason, databases have evolved from small controlled datasets (where all images were captured in a fixed scenario) to huge wild datasets (where images are usually obtained from the internet).

In a brief review of controlled databases, it is relevant to mention FERET [17], with 14K images of over 1K individuals taken during three years; CMU PIE [35], with 41K images of 68 subjects and multiple pose-lighting combinations; Multi-PIE [12], an extension of the former to 755K images of 337 individuals; Yale [10], with 16K images of 28 individuals also changing poses and lighting; AT&T (formerly known as ORL) [33], with 400 images of 40 subjects taken during three years; AR [25], with 4K images of 126 subjects and different face expressions; or even SCFace [11] (4K images, 130 subjects), with semi-controlled images captured from surveillance cameras; and PASC [7] (9K images, 293 subjects), with images are taken with point and shoot digital devices, following a systematic procedure for variations in pose and camera distance.

If we focus on databases with wild examples, we can see that most of them take their images from the internet. Among these datasets, we can mention Labeled Faces in the Wild (LFW) [16], with a total of 5,749 subjects and a number of images per subject ranging from 1 to 530; PubFig [20], with 200 subjects and a more uniform number of images per subject; Labeled Wikipedia Faces [14], where images have been obtained from Wikipedia; Unconstrained Facial Images [22], where images have been taken from the Czech News Agency; FaceScrub [28], with 197K images of 530 people; Social Face Classification [29] with 4.4 million faces of 4K people taken from Facebook (800–1,200 images per subject); and IARPA Janus Benchmark A [18], where nonfrontal images are also included.

Table 1 summarizes some important figures about these wild databases composed of 2D still images, in comparison with the dataset presented in this paper, MedFaces (MF), that will be fully detailed in the fourth section.

3 | DETAILS OF THE AIPR COURSE

The AIPR is a course in Telecommunications Engineering at Miguel Hernández University of Elche (MHUE), taught every semester, with a workload of 4.5 ECTS

TABLE 1 Wild 2D still images face datasets comparison

	LFW	PF	JB	LWF	UFI	FS	SFC	MF
Images	13K	59K	500	3.5K	9.2K	108K	4.4M	**1.8K**
Subjects	5.7K	200	5.7K	1.5K	1.1K	530	4.0K	**75**
>1	1.7K	200	5.7K	894	1.1K	530	4.0K	**75**
>20	57	200	36	0	0	530	4.0K	**75**
Controlled	N	N	N	N	N	N	N	**Y**
Wild	Y	Y	Y	Y	Y	Y	Y	**Y**
Visible	Y	Y	Y	Y	Y	Y	Y	**Y**
IR	N	N	N	N	N	N	N	**Y**
Expression	N	N	N	N	N	N	N	**Y**

Note: Columns: Labeled Faces in the Wild (LFW); PubFig (PF); IARPA Janus Benchmark A (JB); Labeled Wikipedia Faces (LWF); Unconstrained Facial Images (UFI); FaceScrub (FS); Social Face Classification (SFC); MedFaces (MF). Rows: number of total images; number of different subjects; subjects with more than one image; subjects with more than 20 images; controlled images; wild images; visible images; IR images; expression labels.
Bold values refer to the database, Medfaces. This table is comparing Medfaces database with similar datasets.

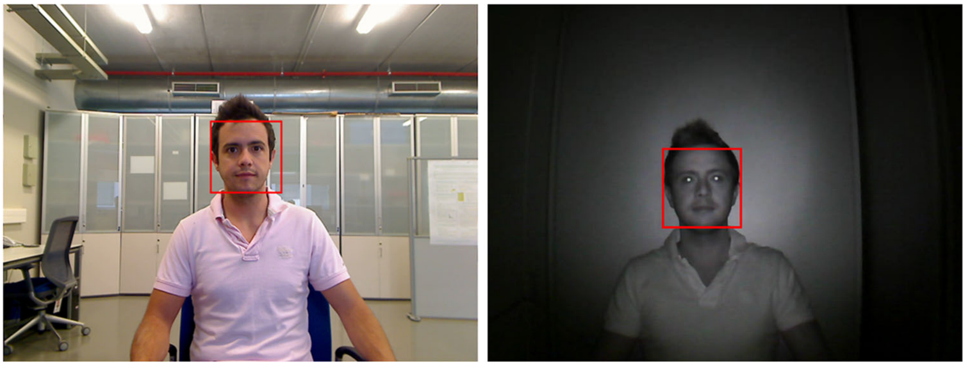

FIGURE 3 Example of visible and IR controlled images. IR, infrared

credits (60 lecture hours). The AIPR course is divided into two main units with the following topics:

- UNIT 1: Main topics are machine learning, nearest neighbor, decision trees, rule lists, neural networks, radial basis functions, data mining, reinforcement learning, and expert systems.
- UNIT 2: Main topics are pattern recognition systems, Bayesian decision theory, feature extraction, feature selection, face recognition systems, PCA approaches for feature extraction on face recognition, and SIFT descriptors for feature extraction on face recognition.

Theory sessions are based mainly on [8], whereas practice sessions are focused on testing different algorithms using MATLAB® code. Face recognition [19] is introduced in Unit 2 as an example of a complete pattern recognition problem.

Theory sessions related to face recognition cover a variety of feature extraction and classifiers; however, due to time limitations, practice sessions with MATLAB® are focused only on the most popular algorithms: PCA-ICA [5,38–40], SIFT descriptors [24], and convolutional neural networks (CNN) [30]. Although face recognition has always been present in AIPR course, there has been an important change since academic year 2014–2015. Before this year, face recognition practices were carried out using only external face databases, namely AT&T (formerly known as ORL) [33] and LFW [16]. During 2014–2015, we decided to build our own facial database MF. New tasks were given to the students: taking images of their classmates, organizing them, and maintaining the database, allowing them to learn important concepts like distinguishing between controlled and noncontrolled images, the importance of lighting, etc. Besides, new face recognition experiments were possible like real-time video access control with their own images.

4 | MF DATABASE FULL DESCRIPTION

Our database contains 75 different identities (43 male and 32 female) with ages ranging from 19 to 55 years (mean 25.5 years). Images were taken from January 2014 to January 2018, but the database also includes older photographs provided by the subjects. There are at least 24 images per subject, which can be classified into three groups: eight visible controlled images, eight infrared controlled images, and at least eight wild images.

FIGURE 4 Example of wild images

FIGURE 5 Wild image with subject of interest (blue bounding box) plus three extra subjects, two of them also belonging to the database and labeled (red bounding boxes)

Most individuals are students and staff of Miguel Hernandez University, so Mediterranean race is prevalent (hence the name MF). The absence of different races makes the database more challenging, as subjects are similar to each other.

4.1 | Main image groups

Visible controlled images were taken in a lab environment, with frontal pose, fixed distance to the camera (1 m.) and fixed lighting. A Logitech Sphere AF webcam was used. They are 1,600 × 1,200 color images, with the face occupying only a small portion of the scene. Coordinates of the face bounding box are supplied. An example is shown in Figure 3 (left).

Infrared controlled images were also taken in a lab environment and fixed conditions, in almost complete darkness. A RoboCam 21 IR camera was used. They are 640 × 480 color images, and the coordinates for the face bounding box are also supplied. An example is shown in Figure 3 (right).

Wild images were collected in two ways. Some of them (usually, images 1–4) were taken using a mobile phone in our university building or its surroundings. They are 1,936 × 2,592 color images. An example is shown in Figure 4 (left). The remaining images (usually, images 5–8) were supplied by the subjects. They took these images mainly from their Facebook photo galleries. Images are colored, with varying sizes, and more than one face may be present. An example is shown in Figure 4 (right).

Some of the wild images provided by the subjects show more than one member of the database. Bounding boxes and identity ground truth for all of them is available. An example is shown in Figure 5. The blue bounding box corresponds to the subject providing the image, and red bounding boxes correspond to other subjects included in the database, faces not belonging to the database may also appear. The extra-labeled subjects may be considered in the evaluation protocols for recognition algorithms.

The possibility of more than one database subject appearing in the same image avoids the recognition algorithms from learning that one and only one subject must be recognized in each image. Besides, the number of wild images per subject is increased.

Figure 6 shows the histogram of wild images per subject. All the 75 members of the database have at least 8 images, but a considerable number of them have extra images because they appear in other subject's photos. According to the values shown in the histogram, there are 25 students with at least 10 wild images, five students with at least 14 wild images, and one student (the most popular) with 17 wild images in our database.

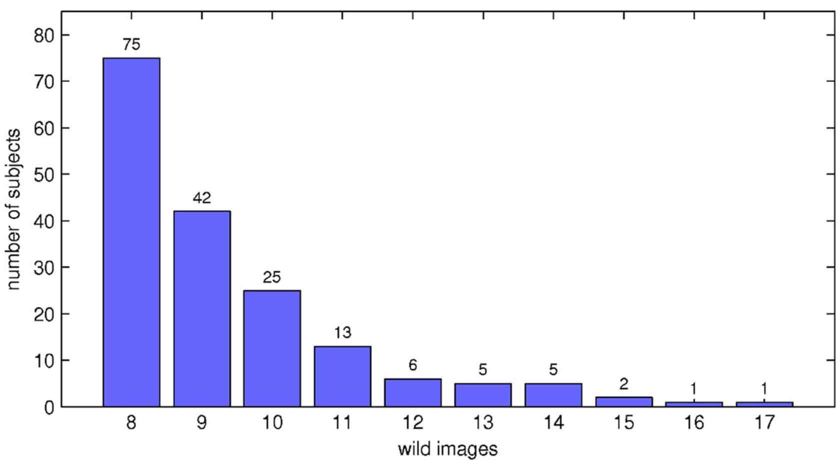

FIGURE 6 Histogram of wild images per subject

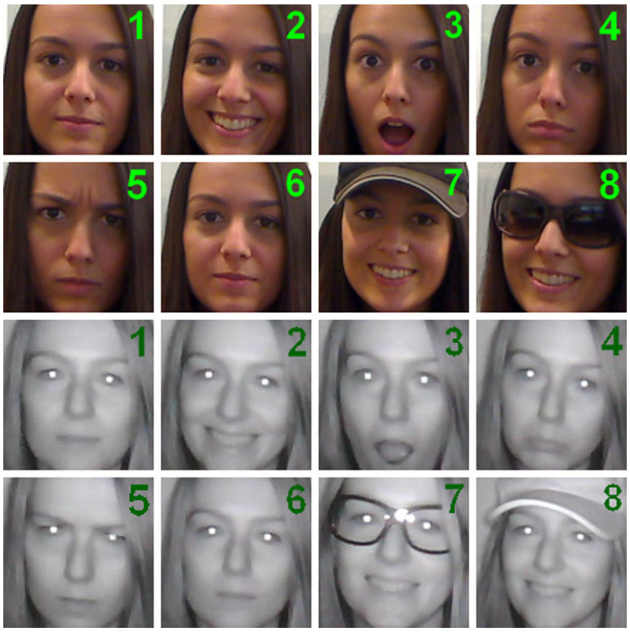

FIGURE 7 Controlled dataset for one subject

4.2 | Example of controlled dataset

The complete controlled dataset for one subject is shown in Figure 7. Only the bounding box area is represented.

Among the eight visible images, the subject was instructed to show a neutral expression in Images 1 and 6 and to show specific expression (in this order: happiness, surprise, sadness, and anger) in Images 2–5. Images 7 and 8 were taken with small occlusions like sun glasses, hats, scarfs, etc. The same instructions were given for the infrared dataset.

It must be stated that the subjects of the database are not actors (they are, for example, in IMFDB [34] or Bosphorus [3] databases). Therefore, expressions may not always be easily recognizable, and intensities of the different expressions may vary from subject to subject. Besides, Contempt, Disgust, and Fear (expressions common in Facial Action Coding System bibliography [9]) were considered too difficult for nonactors, and thus, they were not asked to make such expressions.

4.3 | Example of wild dataset

Figures 8 and 9 show the wild dataset for one subject. Figure 8 contains Images 1–4, which were captured in the University surroundings using a mobile phone camera (both full images and bounding box rectangle are displayed). Figure 9 contains Images 5–8, which were provided by a subject.

FIGURE 8 Wild dataset (Images 1–4) for one subject. These photographs have been captured in the university campus

FIGURE 9 Wild dataset (Images 5–8) for one subject. This subset of photographs has been provided by a subject

5 | FACE RECOGNITION EXPERIMENTS IN THE AIPR COURSE

Concerning face recognition experiments, the experiments performed by the students can be classified as follows:

- *Face detection experiments*: detecting and locating faces in images.
- *Face comparison experiments*: determining whether two images show the same person or not.
- *Search experiments*: finding a specific person in a set of images.
- *Expression recognition experiments*: detecting facial expressions in images.

Following subsections describe each experiment in more detail and the learning outcomes (or concepts reinforced for the students) when carrying out the experiments.

5.1 | Face detection experiments

Given an image, a face detection algorithm outputs a set of sub-images (rectangles) containing human faces. The process can be modeled as (1):

$$\begin{aligned} \text{detectFaces(image)} \rightarrow \{&\text{subimage} \\ &: \text{contains humanFace}\} \end{aligned} \tag{1}$$

Face detection is usually the first step of all face recognition processes, before feature extraction, face classification, or expression recognition.

There are different face detection algorithms, like Viola–Jones [41,42], histograms of oriented gradients [2,32], or other techniques [26]. Our students focus on Viola–Jones for didactic reasons, as it represents a usage example for different pattern recognition techniques studied in our course: integral images for fast processing, Haar feature extractors, classifier cascades, AdaBoost training, etc. Besides, it is implemented in the Computer Vision Toolbox of MATLAB® software.

The students apply Viola–Jones as a first step in other face recognition processes, but they also perform experiments related only to face detection. For example, the students measure processing time and detection performance of the algorithm for multiple resolution versions of the same set of images, to reach an optimum trade-off. An example result is shown in Figure 10, where the algorithm is applied to five different images (containing a variable number of faces), each of them at five different resolutions.

The main concepts reinforced by the students while performing face detection experiments are integral images, classifier cascades, and AdaBoost training.

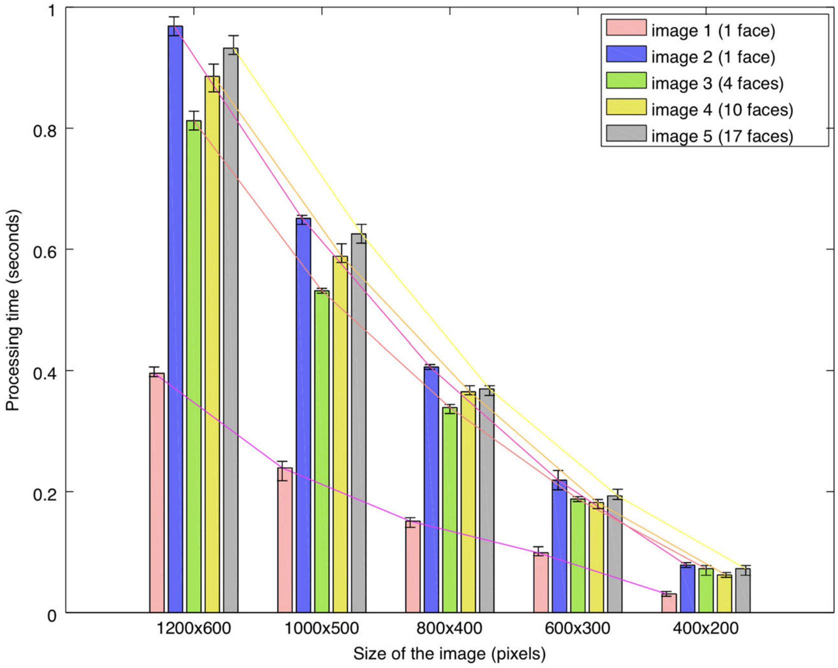

FIGURE 10 Processing time of the Viola–Jones algorithm for multiple resolution versions of the same set of images

5.2 | Face comparison experiments

The goal of face comparison is to determine whether two images correspond to the same person or not. In a real-life scenario, it can be used in access-control systems; the algorithm must decide whether you are the person you claim to be. A measure of distance between images is needed.

Face comparison is preceded by a feature extraction process, where each face image (or sub-image obtained after face detection) is represented by a set of features. Once each face is represented by a set of features, the distance between two faces is usually computed as the Euclidean distance, after feature normalization. The complete process can be modeled as follows:

$$\begin{aligned}
&\text{detectFaces(image)} \rightarrow \{\text{subimage} \\
&\qquad : \text{contains humanFace}\} \\
&\text{features}(\text{subimage}_i) \rightarrow \overline{r_i} \in \mathbb{R}^n \\
&\text{dist}(\text{subimage}_1, \text{subimage}_2) \rightarrow \|\widehat{r_1} - \widehat{r_2}\| : \widehat{r_i} = \frac{\overline{r_i}}{\|\overline{r_i}\|}
\end{aligned} \tag{2}$$

There are different algorithms for feature extraction that allow us to measure distance between images and, thus, to determine whether two images belong to the same person or not. Among these algorithms, in our course, we focus on global appearance approaches, like PCA or ICA [5,38–40]; local invariant approaches, like SIFT [24]; or CNN approaches, like [30].

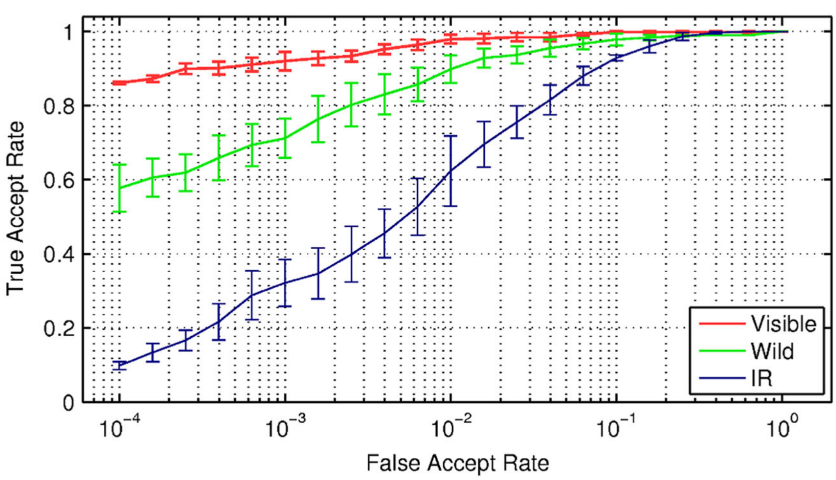

FIGURE 11 Example of an ROC curve for the Medfaces dataset. Features were extracted using [30]. ROC, receiver operating characteristic

As an example of the experiments carried out by the students, Figure 11 shows an example of an receiver operating characteristic (ROC) plot obtained from the MF database. ROC plots false accept rates (FAR) vs true accept rates (TAR) and is one of the best options to measure the
reliability of a face comparison algorithm. Higher area under the curve (AUC) values represent a better performance of the algorithm.

To compute the ROC plot, we need to compute distances between all possible pairs of database images (or sub-images). For a certain threshold, all image pairs whose distance falls below the threshold are considered by the algorithm as belonging to the same person. Among all these image pairs with distances below the threshold, those actually belonging to the same person account as true accepts, whereas those belonging to different persons account as false accepts. Repeating the process for different threshold values gives us the complete ROC plot. Figure 11 shows the ROC plot for each of the three MF datasets: visible, infrared, and wild. AUC values are 0.997 for the visible dataset, 0.986 for the wild dataset and 0.972 for the infrared dataset. Features are extracted using [30].

The main concepts the students learn when performing these comparison experiments are ROC plots and the trade-off between TAR and FAR, which may depend on the requirements of each particular application.

5.3 | Face search experiments

The goal of face search experiments is to find a specific subject in a set of images. A real-life scenario belonging to this set of experiments could be searching for a certain person of interest (e.g., a suspicious, a kidnaped person) in an image database or in real-time video images.

Search experiments also require to measure distance between images, so the same steps described in the previous section must be carried out: face detection, feature extraction, feature normalization, and distance computation.

Once these steps are carried out, we need tools to measure the performance of an algorithm in a face search scenario. In our course, we use cumulative match characteristic (CMC) and detection error trade-off (DET).

Imagine a scenario where a certain person of interest is searched for in an image database; we are interested in retrieving the correct image. CMC plots the percentage of subjects correctly retrieved in a certain rank, where the rank is the number of retrievals before retrieving the correct image (ideally one). Figure 12 shows an example of a CMC plot obtained from the MF database. To obtain a CMC plot, distances must be evaluated between each image and the remaining images. Then, these distances must be sorted in ascending order. Ideally, the image with the lowest distance should correspond to the same subject; in that case, we obtain rank one. In a general case, the rank represents the order of the first image, which corresponds to the same subject. Again, Figure 12 shows the results obtained for each of the three MF datasets: visible, infrared, and wild, using [30] for feature extraction. It becomes clear that the visible dataset is not a challenging one, 99% of gallery images are retrieved correctly (Rank 1). This is not a surprise, as images have been captured under controlled conditions (although with expression changes and small occlusions). The wild dataset is clearly more challenging, only 92.5% gallery images are retrieved correctly. Finally, the results with infrared images are poor, suggesting that a specific feature extraction algorithm should have been used with these images.

Now imagine a scenario where a certain person of interest is searched for in real-time images being

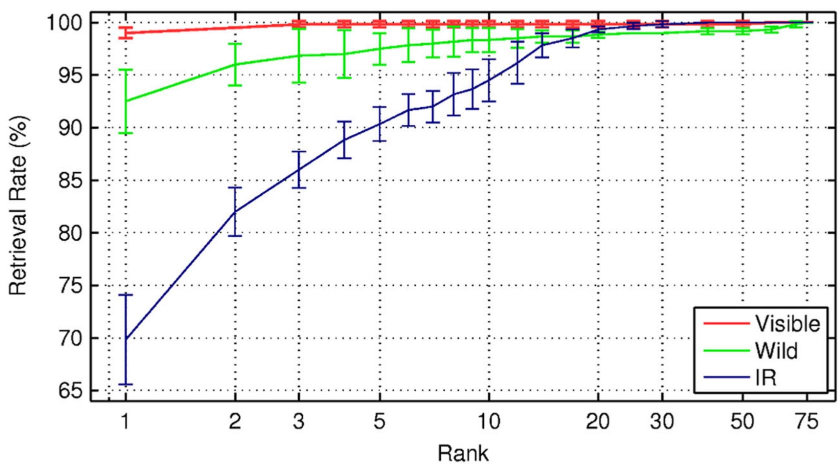

FIGURE 12 Example of a CMC plot obtained from the Medfaces database using the CNN approach [30]. CMC, cumulative match characteristic; CNN, convolutional neural networks

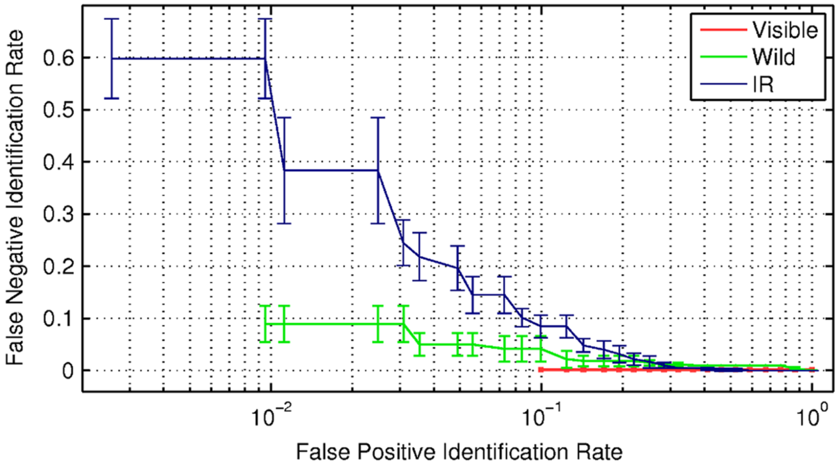

FIGURE 13 Detection error trade-off: plots false negative identification rate (FNIR) versus false positive identification rate (FPIR). Features were extracted using [30]

captured, for example, wanted criminal recognition at an airport. We are interested in the trade-off between false alarms (images wrongly considered as belonging to our person of interest) and misses (images of our person of interest that the algorithm failed to identify). DET plots false negative identification rate (FNIR, i.e., misses) versus false positive identification rate (FPIR, i.e., false alarms). Application requirements for face recognition systems are usually expressed as FNIR at a fixed FPIR (e.g., FNIR should be below 5% at a FPIR of 10%). Figure 13 shows an example of this plot. To compute a DET plot, every image must be cataloged as belonging or not belonging to each of the database subjects, according to the distance between features. Repeating the experiment for different threshold values gives us the complete DET plot. Figure 13 also shows the results obtained for each of the three MF datasets: visible, infrared, and wild. The visible dataset represents an easy task for the algorithm, and almost perfect results are obtained. The wild dataset is more interesting: an FNIR of 4.2% is obtained at FPIR of 10% and an FNIR of 9% is obtained at a FPIR of 1%. These results show that the database contains difficult examples. Again, poor results are obtained with the infrared dataset, where a different feature extraction algorithm should have been used. In all cases, feature extraction was carried out using [30].

The main concepts the students learn with these experiments are retrieval error rank, CMC, and DET.

5.4 | Expression recognition experiments

The goal of expression recognition experiments is to detect expressions in faces. Real-life applications of these experiments range from detecting smiles in camera apps to detecting the reaction of users in marketing tests.

To perform expression recognition experiments with the MF database, our students use the Microsoft Azure Face API [27]. However, this tool is not perfectly adapted to our database, as some of the expressions it looks for (contempt, disgust, and fear) are not present in our database (it only contains neutral, happiness, surprise, sadness, and anger).

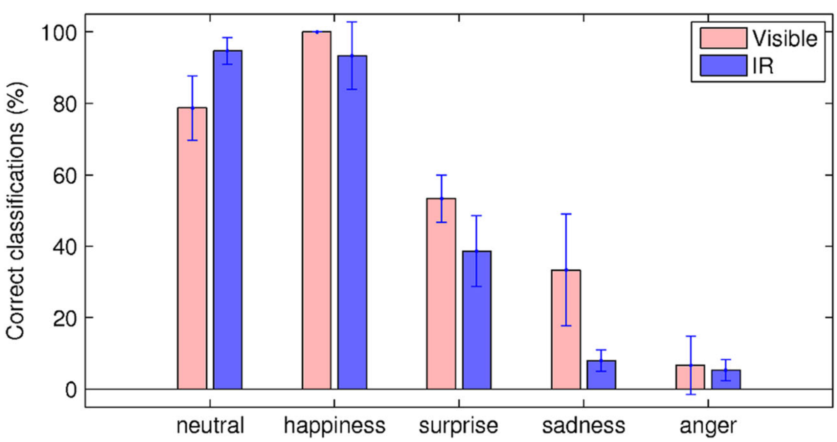

FIGURE 14 Facial expression recognition rates

TABLE 2 Visible expression recognition, confusion matrix

Classified as	Neutral	Happiness	Surprise	Sadness	Anger
Neutral	78.7	0.00	13.3	57.3	74.7
Happiness	20.0	100	33.3	5.33	6.67
Surprise	0.67	0.00	53.3	2.67	1.33
Sadness	0.67	0.00	0.00	33.3	9.33
Anger	0.00	0.00	0.00	0.00	6.67
Contempt	0.00	0.00	0.00	1.33	0.00
Disgust	0.00	0.00	0.00	0.00	1.33
Fear	0.00	0.00	0.00	0.00	0.00
No class	0.00	0.00	0.00	0.00	0.00

Note: Values are expressed as percentages.

The main experiments carried out by the students include classification accuracy tests (as shown in Figure 14) and confusion matrix computation (as shown in Tables 2 and 3). Please note that the algorithm detects three extra expressions not present in our database, so the confusion matrix has more rows than columns). The poor results obtained with certain expressions (particularly sadness and anger) suggest that (a) the algorithm does not perform well or (b) the expressions are not easily recognizable. Our future plans include the use of more facial expression recognition algorithms to study this behavior.

Meanwhile, a further experiment is carried out, to measure the clustering performance of the algorithm, that is, how accurate is the algorithm when splitting the database images into two, three, or more clusters (i.e., subsets).

To compute this measure, let us consider, first, a two clusters problem. Our dataset includes five different classes (neutral, happiness, sadness, anger, and surprise). There are $\binom{5}{2} = 10$ different ways of grouping these classes in two subsets. For each grouping, we measure the correct classifications, and we keep the maximum of these results, that is, the best clustering result considering two clusters. We perform a similar experiment for the 3-clusters problem, the 4-clusters problem, etc. (up to the number of classes minus one). An example of results obtained by our students can be found in Figure 15. In the figure, it can be seen that expressions can be clustered in two groups with recognition accuracies close to 90%. For the visible image dataset, the best grouping places neutral, sadness, and anger expressions in one of the clusters, whereas happiness and surprise expressions are placed in the other cluster. For the infrared dataset, the best grouping places neutral, sadness, anger, and surprise expressions in one of the clusters, whereas happiness is placed in the other cluster.

The main concepts the student learn with expression recognition experiments are confusion matrixes and clustering.

TABLE 3 IR expression recognition, confusion matrix

Classified as	Neutral	Happiness	Surprise	Sadness	Anger
Neutral	94.7	5.33	30.7	85.3	84.0
Happiness	3.33	93.3	29.3	4.00	5.33
Surprise	0.00	0.00	38.7	0.00	0.00
Sadness	0.00	0.00	0.00	8.00	1.33
Anger	0.00	0.00	0.00	0.00	5.33
Contempt	0.00	0.00	0.00	0.00	1.33
Disgust	0.00	0.00	0.00	0.00	1.33
Fear	0.00	0.00	0.00	1.33	0.00
No class	2.00	1.33	1.33	1.33	1.33

Note: Values are expressed as percentages.

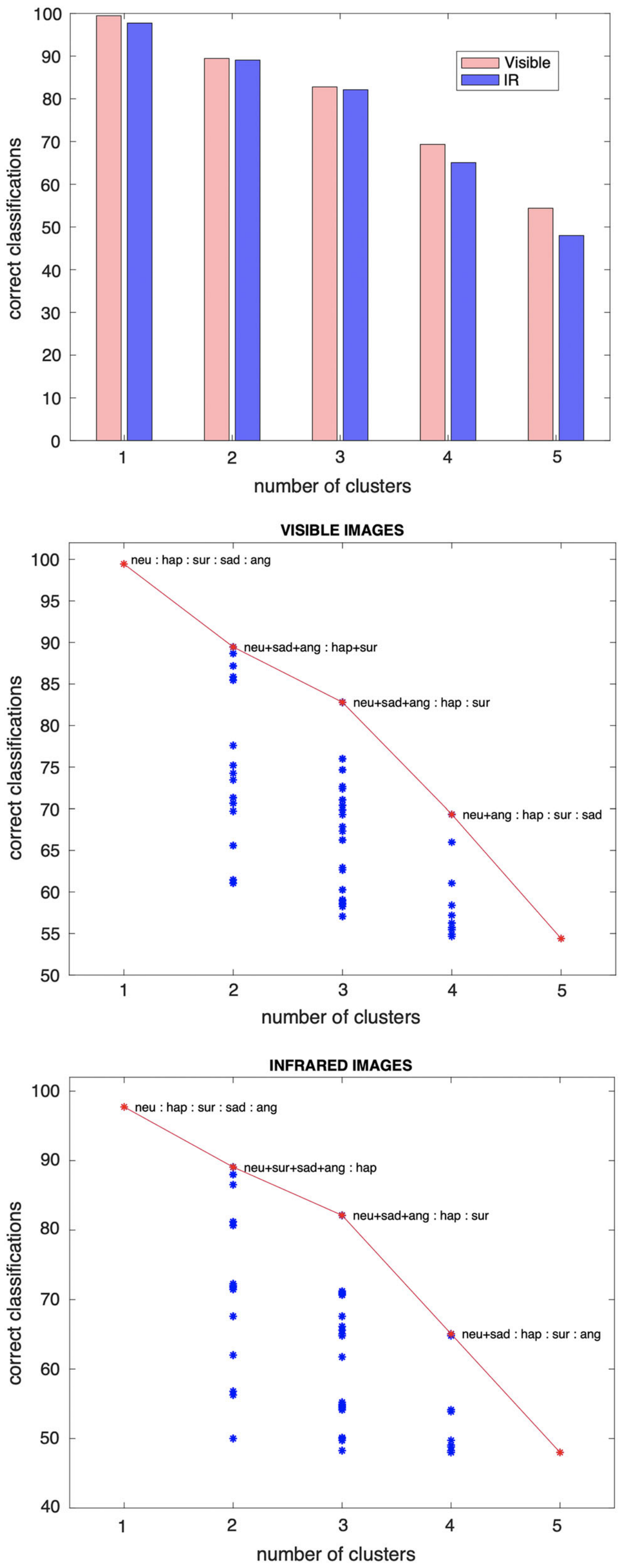

FIGURE 15 Clustering experiments for face expression recognition

TABLE 4 The following items is the survey questionnaire established by the MHUE for all subjects of engineering degrees

Q1. The evaluation criteria are clearly established from the beginning of the course.
Q2. The teacher explains the contents of the subject in a systematic and clear way.
Q3. The teacher has developed all the contents provided in the program.
Q4. The resources used by the teacher have favored my learning.
Q5. The teacher has adequately resolved the doubts that are they have raised in class.
Q6. Indicate your level of satisfaction with the work of the teacher.
Q7. Indicate your level of overall satisfaction with the subject.

Abbreviation: MHUE, Miguel Hernández University of Elche.

6 | STUDENT SATISFACTION ON THE METHODOLOGY

We measured student satisfaction through course surveys. The survey questionnaire consists of only seven questions with a 10-point Likert scale, and it is established by the MHUE equally for all subjects of engineering degrees. The survey questions are listed in Table 4.

The results obtained throughout the different academic courses since the beginning in 2004 have always been quite positive, always above the average of the subjects of the academic year; however, since we started using MF database (2014–2015), the results have improved substantially. In Table 5, we show the results over time; the value shown is the median value of the students answer. The survey is not carried out every year, as the

TABLE 5 Results of the surveys on the AIPR course

Academic year	Q1	Q2	Q3	Q4	Q5	Q6	Q7
04–05	8.37	7.61	7.53	8.30	7.11	8.13	9.10
05–06	9.11	7.10	6.65	6.12	6.85	7.85	8.51
09–10	8.73	6.78	6.89	6.39	7.02	8.33	9.32
11–12	8.12	7.12	6.17	6.89	6.52	7.12	8.03
14–15	8.16	8.56	8.85	8.45	8.24	9.05	9.21
17–18	9.29	9.29	9.14	9.33	8.86	9.00	9.14

Abbreviation: AIPR, Artificial Intelligence and Pattern Recognition.

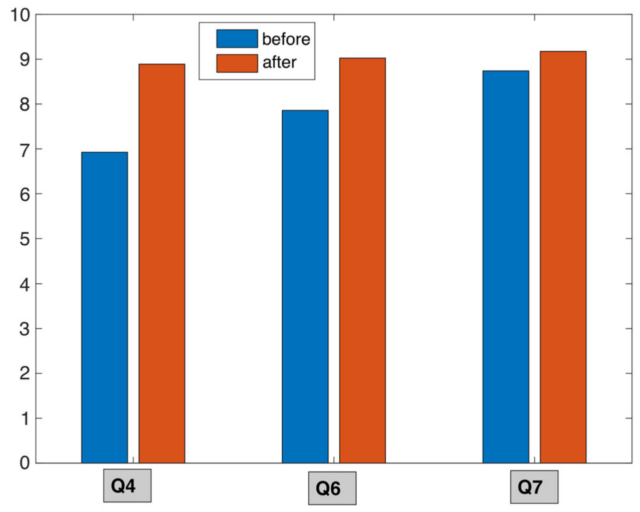

FIGURE 16 This plot shows the average value of the three responses of the survey most related to the contents of the subject (Q4, Q6, and Q7) for the surveys conducted in the courses before the use of this methodology (before) and in subsequent courses (after)

university randomly selects which subjects are evaluated every year. In a gray background, we see the values of student satisfaction before the creation of MF. In addition, Figure 16 shows the average value of the three responses of the survey most related to the contents of the subject (Q4, Q6, and Q7) for the surveys conducted in the courses before MF (before) and in subsequent courses (after). There is a clear improvement in student satisfaction since the adoption of the new methodology.

7 | CONCLUSIONS

This paper presented a methodology to teach the contents of the subject of AIPR by analyzing in detail the design and construction of an access control system based on facial recognition through images. The results of the surveys show a great acceptance on the part of the students for using their own images together with the MF database, making use of different methods of extracting features for facial recognition. The Medfaces database can be downloaded for teaching or scientific purposes, through http://lcsi.umh.es/medfaces. In future, we would like to investigate more in this field and introduce the use of video images within the experiments that students perform.

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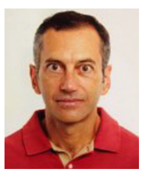

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