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Face Recognition under Local Occlusion Conditions and Varying Illumination

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Abstract

One of the most important challenges with which a face-recognition system is faced is the issue of face images with varying illuminations, or partly occluded images. In this case, face recognition systems will not be able to recognize the face. The aim of this paper is to address such challenges. The proposed method is mainly based on using the geometric features of a face. It is highly popular due to its simplicity and high speed. Given the fact that the system input is a partly occluded or unevenly illuminated image, one of the best applicable features is to discover the *key points* of the face. Therefore, the Viola-Jones object detection algorithm was used to discover the *key points*, and the Canny edge detector algorithm was employed to find the edges. Both algorithms are described in detail in the following. One of the most well-known datasets in face recognition is the Yale B dataset, which was also employed in this paper. It contains a total of 5760 images from 10 different individuals (576 images from each person). In the system proposed in this thesis, images were changed in different modes such as changing the luminous intensity, adding glasses, masks, facial hair, and so on. Finally, face recognition operations were performed on these images. Luminous was changed to different intensities including 10%, 20%, etc. The results were separately computed. These operations were performed on 100 different images of the Yale B dataset. In each step of comparison, the training data were selected at random [20]. Occlusion happens when a part of a face is covered with a beard, a hat, glasses, a mask, etc.

Keywords: *Biometrics, Face recognition, Local occlusion, Illumination, Geo metric features*

1. Introduction

One of the methods studied for human identification is face recognition using computers. It is usually referred to as face identification or face recognition. While recognizing the image of a face, the input image is identified with respect to the available information in a databank which contains specifications pertaining to the face images of identified individuals. Face recognition has many applications in identifying criminals, credit cards, security systems, and other various cases [4]. It has received a great deal of attention recently due to its many applications. Face recognition is among the most common reactions observed in human relations. Face recognition, as a major application of machine vision[15], has been introduced in order to facilitate the relationship between humans and machines. Nowadays it is one the most interesting research areas which is concerned with several scientific fields such as machine vision, computational intelligence, pattern recognition, and psychology. Some challenges of face recognition include occlusions such as a beard, a mustache, glasses or shadows in the image due to uneven illuminations. Both occlusions and varying illuminations result in the loss of information. In such conditions, face recognition systems will not be able to recognize a face. The aim of this paper is to address such challenges.

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2. Related works

Generally, face recognition methods[1],fall into two groups: holistic methods and local methods. Holistic methods, in turn, are divided into two classes named as "discriminative methods" and "reconstructive methods."

Discriminative methods, such as Linear Discriminative Analysis (LDA) [18], Marginal Fisher Analysis (MFA) [5], and Maximum Margin Criterion (MMC) [7,11], are known to yield better results in clean conditions. Reconstructive methods, such as Principle Component Analysis (PCA) [9], Independent Component Analysis (ICA) [10] and Nonnegative Matrix Factorization (NMF) [3,8], are reported to be robust for the problem of pixel corruption to a certain degree.

In holistic methods, the whole face is considered the input, and the images are presented in a subspace with smaller dimensions. However, these methods are unreliable because of occlusion[21]. To tackle this problem, local methods such as Local Nonnegative Matrix Factorization (LNMF) [17] were proposed.

By imposing localization constraint on the standard NMF, LNMF not only allows part-based representation of face images but also learns the spatially localized features which is less likely to be corrupted by occlusion than the holistic approaches [12], such as PCA and LDA. After dividing an image into several parts in the local methods, data are extracted from different levels. Then, the results of each part are recorded and consequently combined for making decisions.

Based on the local methods for face recognition, a method was proposed in this paper using the geometric features of a face under occlusion conditions and varying illumination.

3. Advantages and Innovations of the Proposed Method

I. Using the Geometric Features of a Face

The geometric features of a face have so far been used in various systems; however, it is a new idea to use such features in images with occlusions or varying illumination.

II. Using the Heuristic Algorithm to Discover the Key Points to a Face

In this system, a key point is extracted for each part of a face. For instance, the corner point of the eye is discovered. This key point is extracted in a way that the edges of an eye are computed after discovering an eye on a face. Then, the key point to the eye corner is found through the edges of the eye. A similar algorithm is employed for other parts of the face as well. In general, discovering the key points of a face through the heuristic method is an innovative technique.

III. Using Hierarchical Classification for Feature Comparison

In the proposed method, the image classification was first executed based on finding resemblances with respect to one part of a face. Then, the process was repeated using other parts of the face. Finally, the most similar image was selected.

IV. Applicability of the Proposed Method to Colored Images

4. The Proposed Method Hypotheses

I. The first hypothesis is that the test image is not rotated in comparison with training images, and it has a fixed angle.

II. The training image and test image may have different sizes, and the proposed method is resistant in this regard.

III. Every image may be a little damaged due to varying illumination and face occlusion.

5. The Proposed Method

A face recognition system is a system which receives a face image to determine to which previously seen individual it belongs. The proposed model was mainly based on using the geometric features of a face. It is highly popular due to its simplicity and high speed. Given the fact that the system input was an image under occlusion conditions or varying illumination in this thesis, one of the best applicable techniques was to discover the locations of key points to a face.

The steps taken in the proposed method are as follows:

5.1. Feeding the Input Image

In this step, an image is fed to the system for identification (test image).

5.2. Preprocessing and Edge Detection

This step includes detecting the parts of face and then detecting edges [19].

5.2.1. Detecting Face Parts: The method used to detect face parts in this paper (face, eyes, nose, mouth, and so on) was the Viola-Jones algorithm [14].
The Viola-Jones object detection algorithm is the first of such algorithms which in terms of accuracy and speed can be compared with Paul Viola and Michael Jones's algorithms, introduced in 2001. Although this algorithm can be trained to detect different sorts of objects, it was intended for face detection in the first place.

Essentially, this algorithm includes 4 steps:

- Selecting Harr Features
- Creating the Whole Image
- Adaboost Training Algorithm
- Cascade Classification

First, the input image is divided into smaller images of N*N sizes. All of the possible sub-images are extracted from the input image. Using the following masks, four sample features are computed for each sub-image[14].

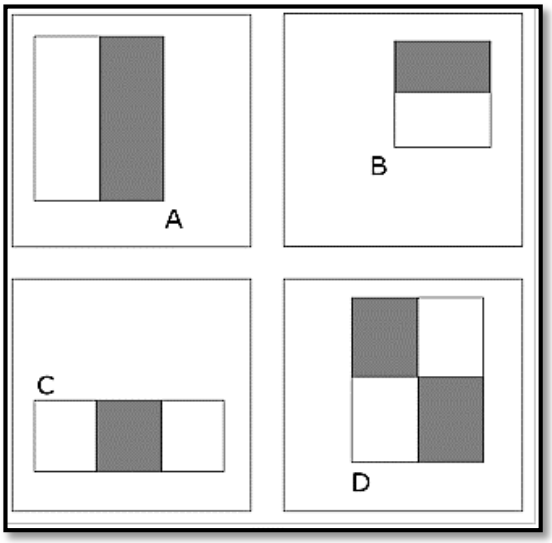


Figure 1: Dividing the input image into smaller image [14]

In each of these masks, the total number of pixels existing on the white level is subtracted from the total number of pixels existing on the gray level. The result is considered to be a feature.
An instance of Harr features can be seen in the following figure:

Figure 2: An instance of Harr features [14]

Assume that *M* features are extracted from the image. If they are named *h*, and a coefficient like α_j is attributed to each feature, this coefficient has an inverse relationship with the error rate of each feature.

$$h(x)=\text{sign}\left(\sum_{j=1}^{M} a_j h_j(x)\right) \tag{1}$$

A final threshold like Θ_j is considered to see whether the object was detected or not.

$$h_j(X) = \begin{cases} -s_j & if \quad f_j < \theta_j \\ s_j & otherwise \end{cases} \tag{2}$$

The training steps of algorithm are briefly explained in the following [14]:

Assume that there is a set of *N* training images with their tags such as (x^i, y^i). If the image *i* corresponds to a face, then y^i=1. Otherwise, y^i=-1.

1) A weight like w_1^i=1/N is applied to each image.
2) The following steps are repeated for each feature.
3) The weights are normalized in a way that their summation is equal to 1.
4) Finding $\mathbf{s_j}$ and $\mathbf{\Theta_j}$ in a way that the following expression is minimized:

$$\theta_j, s_j = arg^{min}_{\theta\,,s} \sum_{i=1}^{N} w_j^i \varepsilon_j^i \; where \; \varepsilon_j^i = \begin{cases} 0 & if \; y^i = h_j(X^i, \theta_j\,, s_j) \\ 1 & otherwise \end{cases} \tag{3}$$

5) Attributing α_j to each feature in a way that it is inversely related with the error rate.
6) The weight is calculated for the next repetition. For example, w^i_{j+1} is reduced if classification is done correctly.
7) A classifier calculates the final results as follows:

$$h(x)=\text{sign}\left(\sum_{j=1}^{M} a_j h_j(x)\right) \tag{4}$$

5.2.2. Edge Detection: The Canny edge detection method was used to find the image edges in this method. Edge detection includes six steps this method[19]. The first step is to filter the initial image and eliminate the noise. For this purpose, the Gaussian filter can be applied with a simple mask which is exclusively used in the Canny algorithm. If the size of the Canny filter is considered to be (2k+1)*(2k+1), the Gaussian filter is defined as follows:

$$H_{ij} = \frac{1}{2\pi\sigma^2}\exp\left(-\frac{(i-k-1)^2+(j-k-1)^2}{2\sigma^2}\right) \tag{5}$$

For instance, if the filter is 5*5, the Gaussian filter is applied to the image in the following way:

$$B=\frac{1}{159}\begin{bmatrix}2 & 4 & 5 & 4 & 2\\ 4 & 9 & 12 & 9 & 4\\ 5 & 12 & 15 & 12 & 5\\ 4 & 9 & 12 & 9 & 4\\ 2 & 4 & 5 & 4 & 2\end{bmatrix} * A$$

Using gradient magnitude, the second step is to find strong edges on each point. For this purpose, the Sobel mask is usually used.

$$|G| = |Gx| + |Gy| \tag{6}$$

Using gradient magnitude which was calculated along the *x* and *y* axes in the previous step, the third step is to obtain the direction of image edges. The following formula is used to calculate the direction of edges:

$$theta = invtan\ (Gy\ /\ Gx) \tag{7}$$

The fourth step is to attribute the acceptable directions in the image to the ones which were obtained. For each pixel in the image, only four directions are possible: 0, 45, 90, and 135 degrees. Therefore, the obtained directions are mapped onto one of these 4 directions. The fifth step is non-maximum suppression. In this step, the directions of edges are checked, and then weaker edges are deleted. The sixth step is thresholding in edge detection. A method named Hysteresis is used in the Canny algorithm. Therefore, two high and low thresholds are defined. Every pixel having a higher gradient magnitude than the high threshold is accepted to be an edge. If it has a lower gradient magnitude than the low threshold, it is rejected. In the case where the value is between the lower and higher thresholds, it is accepted only if one of its neighbors was accepted.The Canny algorithm is highly accurate in comparison with other algorithms; however, it has more computational complexities [19].

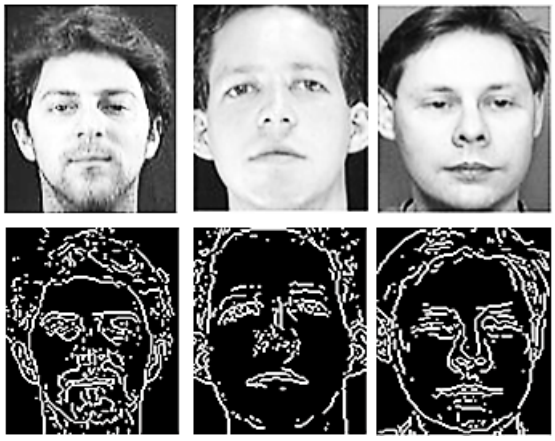


Figure 3: applying canny edge detector on input images

5.3. Extracting the Key Points of a Face

In this system, a key point is extracted for each part of a face. For instance, the eye corner is discovered as a key point of an eye. This key point is extracted in this way: first an eye is discovered on the face. Then its edges are computed. Through eye edges, the key point to the eye corner is found. A similar algorithm is also used for other parts of the face. Discovering the important points of face parts is a heuristic method. After that, the distance between face parts is used as a feature. These features are calculated for all of the training and test images. Then the features pertaining to each image are stored in an array.

F= {f1, f2, …., fn}

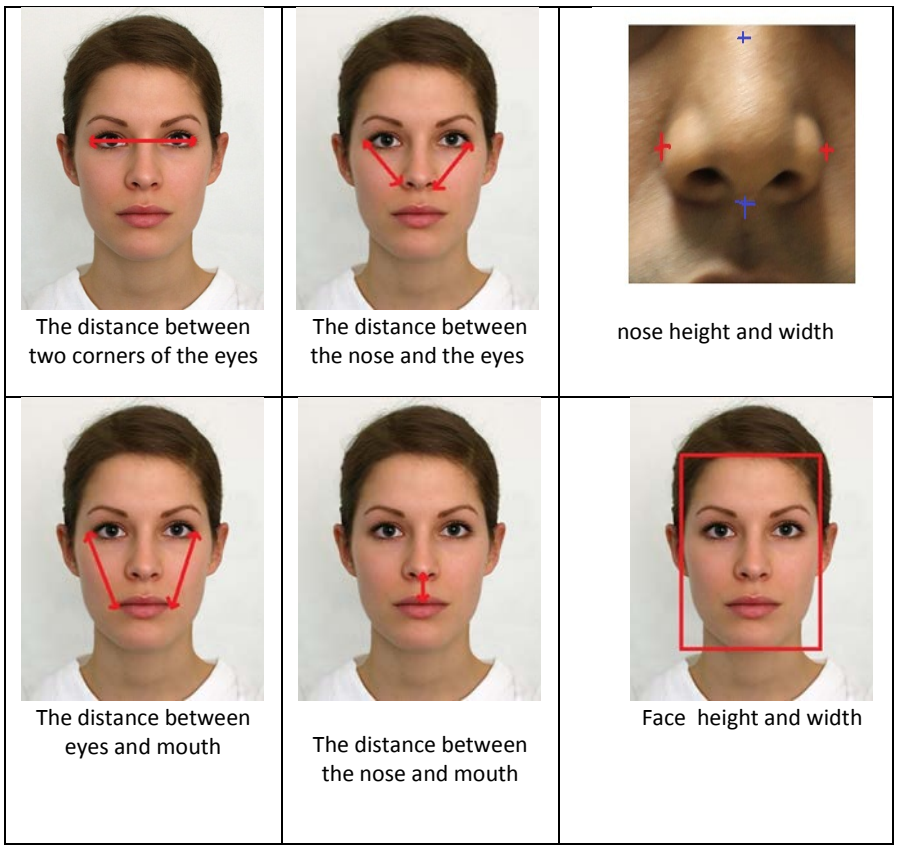
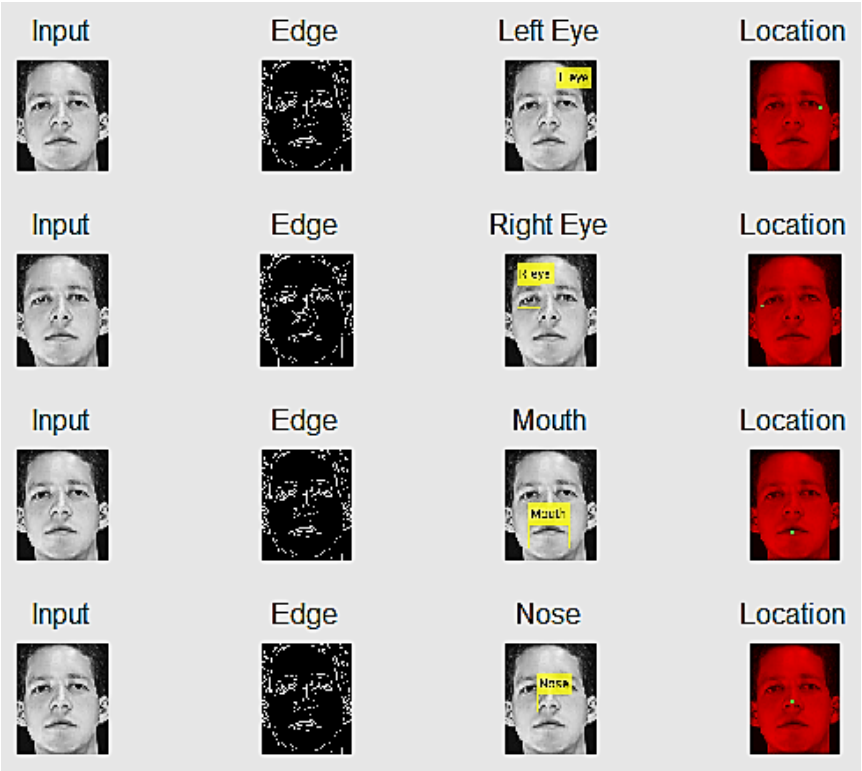


Figure 4: An Example of Key Points to a Face



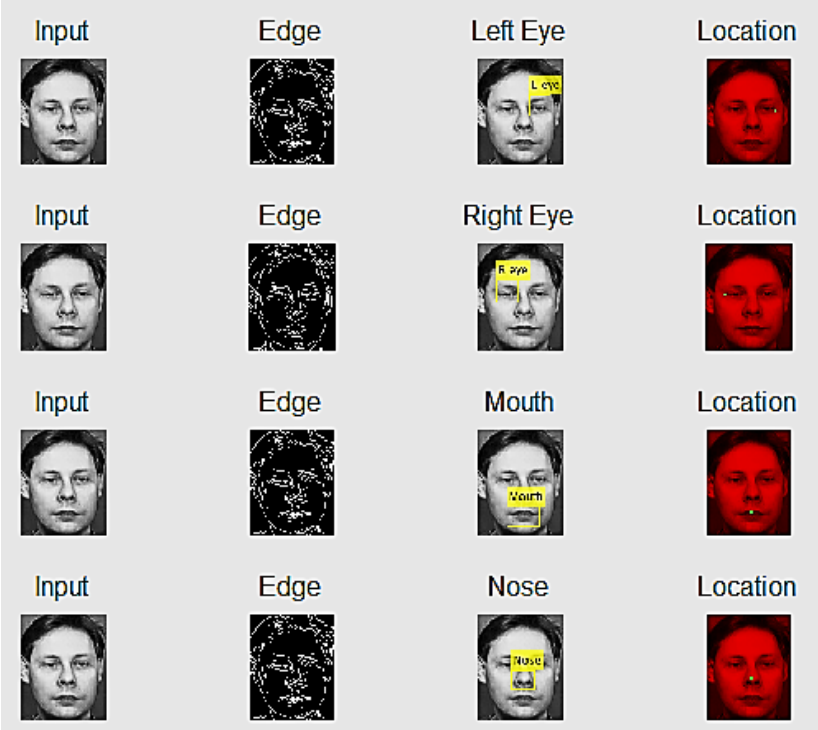


Figure 5: Extracting the Key Points of a Face

5.4. Feature vectors matching

After obtaining the key points to a face, the features of the input image should be compared with those of the training images. This comparison is done in a hierarchical manner. In each step, one of the face parts is considered, and the training images are sorted in terms of similarity in the ascending or descending order. Then, a similarity coefficient is attributed to each training image. Finally, the image with the highest similarity regarding different facial features is selected as the most similar image to the input image. In this regard, two proposed methods were introduced in order to find the most similar image to the input image. Each of them are described in detail in the following.

One of the common methods in face recognition is to use algebraic features. In such methods, the image can be considered a matrix. Then different algebraic operations and mathematical transforms are applied to it. Resulting from this process, algebraic features usually represent the intrinsic properties of an image. Principal Component Analysis (PAC) is among the important operations performed on the image matrix. Given the fact that the test image was studied under occlusion conditions or varying illumination in this thesis, the number of pixels were changed. Therefore, using this feature shall not result in high efficiency here.

Two models of the proposed method are presented in the testing phase here. In the training phase, the edges of the input image are detected in a similar way to the testing phase. After feature extraction, the edges are stored in the images databank. Due to the similarity of steps, the training phase is not described here. The main difference between Model 1 and Model 2 of the proposed method is in the step where the feature vectors are compared with each other to find the output image.

5.4.1. Model 1: In Model 1 of the proposed method, the geometric features of each face parts (the distance between the eye corners, noise center, and so on) are separately considered to be feature vectors. Based on each feature, the face recognition system retrieves 3 more similar images with respect to the closer neighbor model. Finally, there remain 3 images for each class and 12 images in total. Among these images, the one with the highest frequency is selected as the output image.

This method presented good results for the images with varying illuminations. However, the results were poor regarding the detection accuracy of images with more than 30% occlusions. Therefore, Model 2 of the proposed method was slightly modified.

5.4.2. Model 2: In Model 2 of the proposed method, the steps are similar to Model 1. The only difference is that after obtaining each of the features in the feature comparison phase, all of the vectors are uniformed under one feature vector, and the comparison is made with respect to the whole face as the feature vector, and not based on each feature. Model 2 of the proposed method is considerably accurate with regards to the two problems of varying illumination and occlusion. Therefore, Model 2 is more efficient than Model 1.

An Instance of Comparisons Made with Respect to Model 2 of the Proposed Method on YALE B Databases:

6. Comparison with Previous Methods

The Extended YaleB database consists of 2414 frontal face images of 38 individuals under various laboratory-controlled lighting conditions. The database is divided into five Subsets (see Fig. 7): Subset 1 consisting of 266 images(seven images per subject) under normal lighting conditions; Subsets2 and 3, each including 12 images per subject, characterizes light-to-moderate illumination variations, while Subset 4 (14imagesperperson) and Subset 5 (19imagesperperson) illustrate severe light variations. Subset 1is chosen for training, while other subsets are used for testing.

Figure 6: Five Subsets of Extended YaleB database. Starting from the top, each row illustrates samples from Subsets 1, 2, 3, 4 and 5.

The following table indicates the comparison between the proposed method with the previous methods under varying illuminations [20].

Table 1 : The comparison between the proposed method with the previous methods under varying illuminations.

Subset	2	3	4	5
Eigenfaces+NN	89.91	37.58	5.32	3.08
Fisherfaces+NN	100	97.14	38.59	5.74
LRC	100	100	88.59	43.13
SRC	100	100	67.87	17.51
CRC-RLS	100	100	90.68	45.10
Gradientfaces	100	100	89.73	83.33
RPCA (Weighted)	100	100	95.06	49.38
RPCA (Ratio)	100	100	54.18	38.12
Our method (Model1)	**100**	**100**	**96.25**	**51.50**
Our method (Model2)	**100**	**100**	**97.05**	**52.20**

The following table indicates the comparison between the proposed method with the previous methods under occlusion conditions. This comparison was made on 100 different images of the Yale B dataset. In each comparison step, the training data were selected at random [20].

Table 2: The comparison between the proposed method with the previous methods under occlusion conditions.

Percent occluded	10%	20%	30%	40%	50%
Eigenfaces+NN	85.53	81.58	75.22	57.89	44.3
Fisherfaces+NN	100	99.56	81.8	45.61	53.73
LNMF	77.63	73.46	62.72	39.69	28.07
LRC	99.34	98.03	94.74	72.15	49.12
SRC	100	98.9	94.96	67.54	41.45
RPCA	99.78	99.56	96.92	99.12	95.40
Our method (model1)	**100**	**100**	**95**	**78**	**55.90**
Our method (model2)	**100**	**100**	**97.52**	**89**	**67**

Overall Results and Future Challenges

In this day and age, security of life, property and information is an important challenge. Undoubtedly, biometric systems are among the most widely-used systems to achieve this goal. Biometric-based techniques were considered to be promising solutions for identity detection in recent years. It has been used to replace identification and entry authorization to physical and virtual areas based on passwords, PINs, smart cards, and so on [4].

Face recognition has many applications such as personal identification, criminal investigations, security measures, and login authentication. In recent years, researchers concluded that face recognition would be better in comparison with biometric methods due to the following reasons:

In biometric methods, the user is required to keep his or her hand still for fingerprinting. Similarly, the user should stand still in front of a camera for retina and iris recognition [6,22]. Moreover, the biometric-based techniques which work on a user's hand and fingers will result in incorrect processing

if the fingertip tissue is damaged. Voice recognition systems are also sensitive to background sounds in crowded places [16]. In face recognition, however, a part of user's image is worked on. This part is remotely captured with a camera. Identification using 3D images is resistant to the rotation of a face and luminous angle due to the fact that the geometric features are assessed instead of luminous intensity. On the other hand, these images are quite flexible to the changes in facial expressions. Causing noise and reducing the level of identification, facial hair is also problematic in this type of data. Therefore, it is used to identify some parts of a face which are resistant to such changes. On the other hand, 2D images of a face also have information of luminous intensity and face texture. Despite the aforesaid problems, this method presented an acceptable level of identification. Given the fact that hybrid systems work better than single-mode systems in most cases, a method which benefits from both types of geometric data (3D) and face texture data (2D) can lead to better results [13].

Despite recent developments, there are still various problems for detecting a face in non-imposed biometric recognition systems. Some of these problems are face angle and gesture, strong or weak illumination, different facial expressions, shutting the eyes, and computational costs on multi-megapixel images. The researchers at CASIS (Center for Advanced Studies in Identity Sciences) are developing bright and innovative solutions in order to enable biometric systems to use biometric data which were provided in sub-ideal conditions, to empower the production of biometric properties and models, and to increase the comparison efficiency of systems [2].

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