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Eye detection based on the Viola-Jones method and corners points

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Abstract Eyes detection is a very interesting field of research that verifies the presence of eyes and locates their positions in an image. Similarly, it is often the first step in such applications such as face recognition, human machine interaction systems, facial expression recognition, and driver fatigue monitoring systems. In this paper, we proposed a robust eye detection method based on the Viola and Jones method and corner points. Firstly, faces are detected by a system composed of two detectors of Viola-Jones (one for the frontal faces and the other for the profile faces). Secondly, we used the Shi-Tomasi detector (to detect corner points) and K-means (for clustering the neighbor corner points) to determine eye candidate regions. Thirdly, the localization of eyes is achieved by matching of these regions with an eye template. The results obtained show that our method is robust and provides superior performance compared to other recently published methods.

Keywords Eye detection · Face detection · Viola-Jones detector · Corner points · Eye template

1 Introduction

The eyes detection is a very interesting field of research which is a crucial step in face recognition [7, 29], human machine interaction systems [37], facial expression recognition [34], and driver fatigue monitoring systems [8, 12, 16]. It is to verify the presence of the eyes in an image and locate their positions.

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Nevertheless, several challenges can limit the detection of the eyes, namely: the computation time, the orientation and shape of the eyes, lighting conditions, and the presence or absence of structural components such as glasses. To overcome these difficulties, various techniques have been developed in recent years and can be divided into four categories [2, 14, 36]: Template-matching methods, feature-based methods, appearance-based methods, and hybrid methods. In template-matching methods [1, 20, 28], an eye template is constructed and then compared with the different regions of the image to determine those that are the eyes. These methods are easy and quick, but they cannot be treated with eye variations in the scale, expression, rotation and lighting. The feature-based methods [3, 4, 9, 18, 35, 41] explore the characteristics of the eye such as shape, intensity or gradient information. Although these methods are generally effective, they lack precision in the images with low illumination. In appearance-based methods [11, 13, 21, 27, 31], eyes are detected on the basis of their appearance photometric. These methods treat the detection of eye as a classification problem (eye/non-eye). The classification is performed using a set of learning images and using learning algorithms such as Neural Networks, AdaBoost algorithm, and Support Vector Machine (SVM). These algorithms require a large number of training data to enumerate all the possible eyes appearances. Hybrid methods [5, 6, 10, 15, 19, 22–24, 26, 30, 32, 38] combine several methods to exploit their advantages and to avoid their disadvantages.

In this article, we present an efficient hybrid eye detection method. It is based on the Viola-Jones method [42] and the corner points detected by Shi-Tomasi detector [33]. Our technique involves three steps: in the first one, faces are detected using a similar system to that of Viola & Jones. This system consists of two Viola & Jones detectors, one for detecting the frontal faces and the other for detecting profile faces. In the second step, the feature points of the image (corner points detected by the Shi-Tomasi detector) are determined and the corner points neighboring are clustered. Each group of points neighboring determines an eye candidate region. In the third step, the eyes are detected by matching of eye template with different eye candidate regions.

The rest of this paper is organized as follows. In the second part, we provide a brief overview of the related word of the eyes detection. In the third and the fourth part, we dwell on our approach and its experimental results. The last part is devoted to the conclusion.

2 Related work

In recent decades, several eye detection methods are proposed and can be classified into four categories:

- *Template matching* methods, which consist of creating of an eye template and then compared it with the different regions of the image to determine those that are the eyes. Among the eye detection methods based on template matching there is the method developed by Kutiba Nanaa, et al. [28]. This method integrates the cross correlation function of various eye templates. It"s involves four steps: The first step is to find eye candidate pixels from face images. Second step describes eye template based detection and cross correlation of templates. The third step integrates single eye templates in one composite eye template. The fourth step generalizes the composite eye template to take into account shifts and irregular eye templates. The advantage of this method is that it can increase the detection rate compared to the use of simple correlation. However, poor detection is achieved in low light or when the eyes are closed. In addition this method is applied only on the frontal face images.

- *Feature-based* methods explore the characteristics of the eye such as shape, intensity or gradient information. For instance, in our article [9], we proposed a new method for detecting faces and eyes. It is based on the skin color, face shape and corners points of Harris. In this method, faces are detected by the segmentation of the skin areas and by using the shape operations (surface, ratio, eccentricity). Then, the eyes are located by matching of an eye template with a small areas determined by clustering of neighboring corners points. The proposed method provides a perfect detection of eyes regardless of the poses conditions, expressions or the presence of occlusions, but it is limited when there is low light. Abbas Cheddad, et al. [4] present a face segmentation and facial feature extraction algorithm for gray intensity images. To segment faces, the authors use the Voronoi diagram based on the fact that the face has an elliptical shape. And to detect the eyes, they use the Delaunay triangulation, the Voronoi diagram and an eye template. This method is robust to translation, rotation and scaling. However, the wearing of glasses and the presence of background intensities similar to face intensities in the image can cause problems for segmentation of faces and, consequently, influence eye detection. Lilipta Kumar et al. [3] develop an approach of facial feature extraction (eyes, nose, mouth) which takes place in three stages. First faces are detected by Sobel edge detector, and the intensity value of the edge. Then, in the detected faces the skin regions are extracted in the YCbCr space. After that, the left eye is located in the left part of the skin color image considering that point having a minimum intensity value as the position of the left eye. The right eye appears about the same distance from the center because of symmetry. This approach localizes the eyes with great accuracy for most images of frontal faces, but it is not applicable in the case of faces with rotations, profiles, with glasses, and the somber image.
- *Appearance-based* methods that treat eye detection as a classification problem (eye/non-eye). Many appearance-based approaches are proposed. For example, Cheolkon Jung, et al. [21] suggests a new method for detecting eye under different lighting conditions. First, the adaptive smoothing based on the retinex theory is used to remove the illumination effects. Second, the detection of eye candidates is performed using the edge histogram descriptor (EHD) on the illumination normalized facial images. Third, the classification by SVM is employed for eye verification. Finally, the eye positions are determined using eye probability map. This method achieves a high detection accuracy and fast calculation speed in detecting eye in different lighting conditions. However, it is limited in the case of rotated faces, or with glasses, and in real images. The eye detection method proposed by David Monzo, et al. [27] is composed of two steps. First, a couple of AdaBoost classifiers trained with Haar-like features are used to preselect possible eye locations. Then a support vector machine using histograms of oriented gradients descriptors is employed to obtain the best pair of eyes among all possible combinations of preselected eyes. The proposed algorithm achieves high accuracy of eyes localization at the images of frontal faces, with changes of scale, and lighting, but it failed in the images of profile face, and when the eyes are closed, semi-closed or occulted by glasses. The method for detection and localization of human eye centers presented by Zhaocui Han, et al. [13] is to use the Viola-Jones method to detect faces in an image, to extract the region combining eye and eyebrow neighbor with the Haar features, and to locate the eye with integrating gradient distributions and curvelet features and using of principal component analysis. The test of this approach on frontal face images taken in different lighting conditions and with complex background, gives very important results. However, its test on the face profile images can give bad results. Krzysztof Rusek, et al. [31] propose a solution to the problem of automatic eye localization using two feed-forward multilayer perceptron working in a cascade. The feature vector of the first neural

network is constructed from coefficients of a two dimensional discrete cosine transform of a face image. The second neural network generates corrections based on small image patches. This method increases the accuracy of eye localization compared to the use of a single network. It is effective for frontal face images, with complex background, but it may fail in the profile face images, and somber images.

- *Hybrid* methods that combine between several techniques to improve the quality of eye detection. More articles are cited: Muwei Jian, et al. [19] propose an efficient algorithm for the detection of facial features. In this algorithm, after face detection using a cascade of boosted classifiers, a wavelet saliency map is calculated on the detected face region, and verified by principal component analysis. Then the localization of the two eye positions is based on a pose-adapted eye template (this template has a black block in the center represents the black pupil of the eye, and two white blocks on the left and the right of the black block, which represent the white of the eye). This method can detect the eyes accurately even if the faces are under various lighting, and orientations. However, the use of a cascade boosted classifier for face detection can fail for the profile face detection. In the face images with glasses, the salience value is increased in the judgments and corners glasses, which results in an erroneous detection in these images. The pose-adapted eye template used is based on rectangles to the pupil and the white of the eye, against the form of closed eyes is very far from this model, which can cause a detection fails in the closed eyes. Shuo Chen, et al. [5] expose a method for eye detection using the discriminatory Haar features and the SVM. First, the Bayesian discriminating features method is applied to detect a face from an image and normalize the detected face to a predefined size. Second, the authors use some geometric constraints to extract an eye strip from the upper part of the detected face, and illumination variations are attenuated by means of an illumination normalization procedure. Third, the discriminatory features Haar are extracted using an extraction method of discrimination features applied on 2D Haar wavelets transform. Finally, the efficient SVM classifier is applied to the discriminatory Haar features for eye detection. This method is precise, efficient, and in real time. But it only works for the frontal faces. M. Hassaballah, et al. [15] suggest an eye detection method based on grey intensity variance and independent components analysis. Firstly, the face region is located by the boosted cascade face detector. Then, the upper half of the face is divided into a large number of overlapped windows, and the application of the variance filter can be selected from these windows which are eye candidates. Then all the selected windows are checked using the independent component analysis to select only two windows that are the right and left eyes. This method is robust and precise for eye localization in the frontal faces images without glasses, regardless of the lighting conditions. But it is limited in the profile face images, eyes with glasses and eyes closed or semi-closed. Mingxin YU et al. [26] present an eye detection method based on a gray intensity variance filter and the SVM. First, the variance filter is used to eliminate most of non-eye regions images to keep less eye candidate regions. Then, the precise location of the two eye regions is determined by the SVM classifier. The advantage of this method is that it is robust to occlusions (glasses), and lighting changes. Its disadvantage is that it is limited in the profile face images, and when the eyes are closed or semi-closed.

3 Eye detection based on the Viola-Jones method and corners points

Our method for eye detection contains three algorithms. In the first, we used a simple and efficient method for faces detection based on Viola-Jones method [42] (see section 3.1.).

The second algorithm presented in section 3.2, consists to determine eye candidate regions by clustering of the neighboring corner points (the corner points are detected by the Shi-Tomasi detector [33] and grouped by k-means method [25]). In the third algorithm, presented in section 3.3, the eyes are detected by matching of an eye template with the different candidate regions.

The different steps of our eyes detection method are presented in Fig. 1 below.

The performance of our eyes detection system is closely related in using of Shi-Tomasi detector to localize the eyes in the faces detected by a method inspired by the method of Viola-Jones. The face detector used allows discerning the frontal and profile faces simultaneously, this gives better detection than conventional Viola-Jones. The Shi-Tomasi detector can determine candidate regions with a high probability of being eyes. Therefore, any eye detection model can be applied to these regions and not all over the face, which reduces the computation time and the number of false detection.

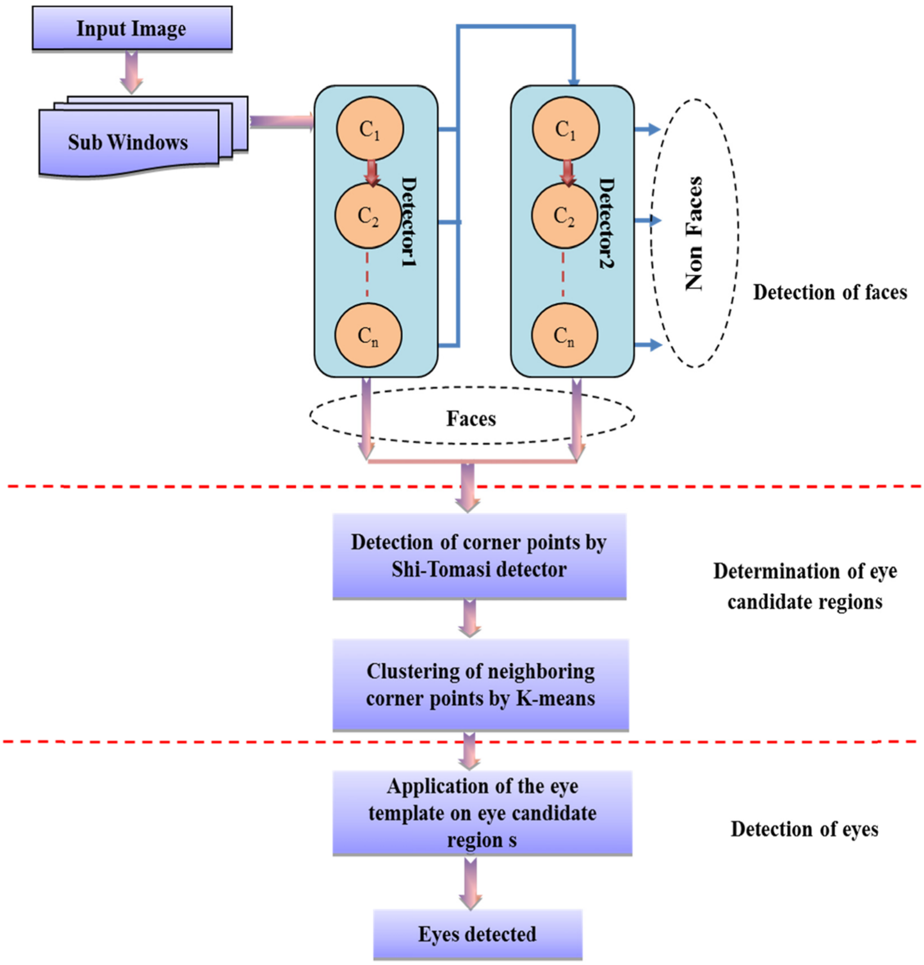


Fig. 1 Diagram of eyes detection by our method

3.1 Faces detection

Our face detection method is to scan an image with windows of different sizes. Then each window is presented to a system composed of two Viola-Jones detectors [42] (one for detecting the frontal faces and the other for detecting the profile faces) in order to classify them as face or non-face (see Fig. 1). Each detector contains a set of strong cascaded classifiers (see Fig. 2). The strong classifiers are trained by AdaBoost algorithm through a combination of the weak classifiers obtained from the features of Haar (see Fig. 3). The weak classifiers of the two detectors are trained, respectively, by a set of training images representing the frontal faces and profile faces.

A sub window can be classified as frontal face, profile face or non-face. So, if it is passed through all classifiers of the first detector, it is considered as a frontal face. If it is rejected by one of the classifiers of the first detector, and passed through all classifiers of the second detector, it is classified as a profile face. And if it is rejected by one of the classifiers from the first detector and a one classifier of the second detector, it is considered as non-face. Algorithm 1 shows the face detection steps by our method.

Algorithm 1: Face detection

Input
A window x
Output
Class of x : frontal face, profile face, non-face
Begin
1) **If** x passes all classifiers of the first detector **Then**
x is frontal face
End if
2) **If** x is rejected by a classifier C_i of the first detector **Then**
If x passes through all the classifiers of the second detector **Then**
x is profile face
Else
x is non-face
End if
End.

Figure 4 illustrates some results of face detection in different situations achieved by the own method.

3.2 Eye candidate regions detection

Generally, the eyes are located at the upper face and are also characterized by a strong variation of color, thus, the detection of the corner points (points characterized

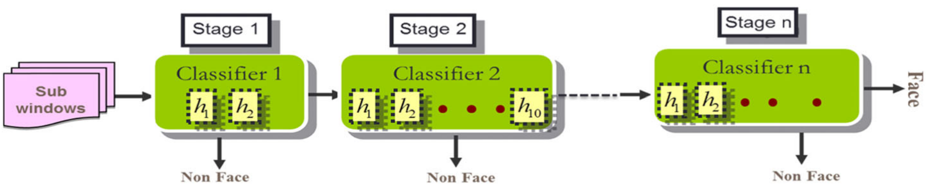


Fig. 2 Cascade of strong classifiers

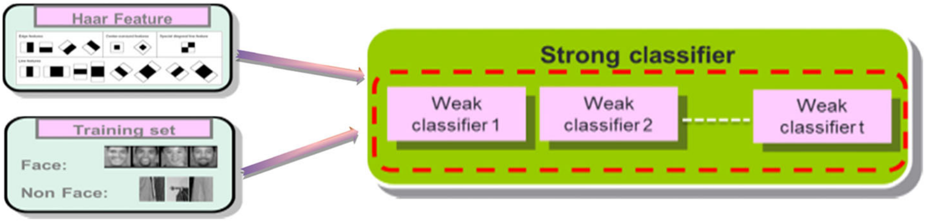


Fig. 3 Training of classifiers

by a strong change in the image signal) in the upper face allow to identify regions that can be eyes. In this step, the corners points are detected by the Shi-Tomasi detector (see section 3.2.1); then, the neighboring corner points are grouped by the K-means method (see section 3.2.2), which gives a set of candidate regions having a high probability of being eye.

3.2.1 Detection of corner points by Shi-Tomasi detector

Corner points are detected by the method of Shi-Tomasi [33], which uses the smallest eigenvalue of the following local structure matrix:

$$M = W(x,y) \otimes \begin{pmatrix} Ix^2 & Ix.Iy \\ Ix.Iy & Iy^2 \end{pmatrix} \tag{1}$$

With

W	is a Gaussian window.
$\otimes$	is the convolution product.
Ix, and Iy	are the first derivatives of the image according to x and y. They are calculated from the convolution of the image with the following derivative filters:

$$dx = [-1\ 0\ 1; -1\ 0\ 1; -1\ 0\ 1] \tag{2}$$

$$dy = [-1 -1 -1; 0\ 0\ 0; 1\ 1\ 1] \tag{3}$$

Algorithm 2 shows the steps of the detection of the corners points by Shi-Tomasi method.

Algorithm 2: Detection of corner points by Shi-Tomasi detector

1) Compute Ix and Iy over the entire image I(x,y)
2) For each image point *p* :
   a) Form the matrix M defined by the formula 1;
   b) Compute λ_1, and λ_2 , the eigenvalues of M ;
   c) Compute R=min(λ_1,λ_2) ;
   d) If R > threshold, save the *p* into a list C.
3) Sort C in decreasing order of R.
4) Scan the sorted list from top to bottom. For each current point, p, delete all points appearing further in the list which belong to the neighborhood of p.

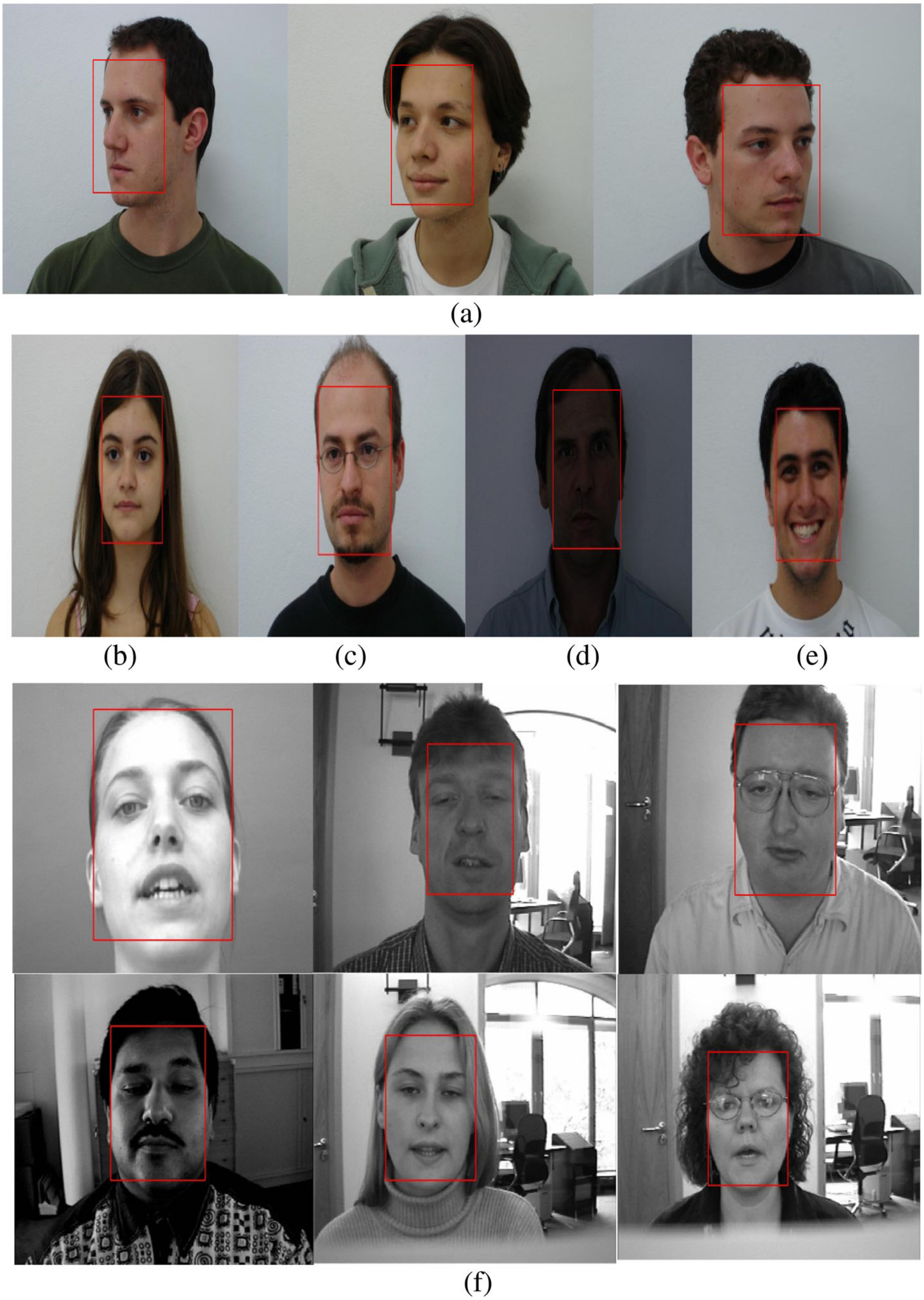


Fig. 4 Face detection performed by our method: profile face (**a**), frontal face (**b**), frontal face with glasses (**c**), image with low lighting (**d**), face with smile (**e**), grayscale images (**f**)

Figure 5 shows the result obtained after applying the Shi-Tomasi detector in the upper part of the face regions. It is clear that the majority of the corner points detected by the Shi-Tomasi detector are in the eye regions.

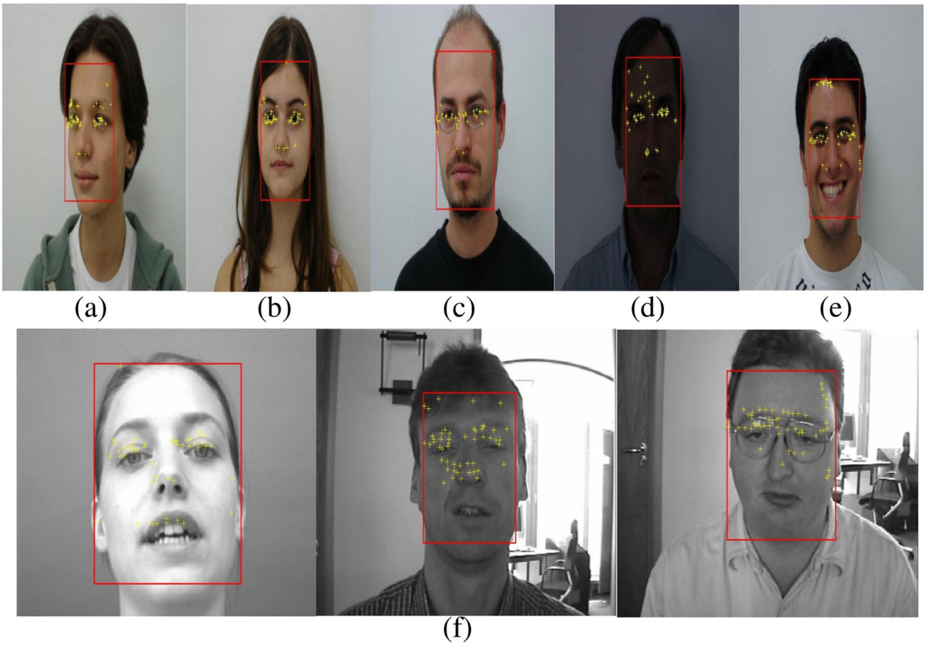


Fig. 5 Detection of corner points by Shi-Tomasi method for the faces displayed in Fig. 4

3.2.2 Clustering of neighboring corner points

The clustering of the neighboring corner points is to collect the set of neighboring points by the K-means method (see Algorithm 3) [25]. This gives a set of candidate regions (CR) having a high probability of being the eyes.

Algorithm 3 : K-means

Input

Set of N points, denoted by x

Desired number of clusters, denoted by k

Output

A partition of K clusters $\{RC_1, RC_2, \ldots RC_k\}$

Begin

1) Initialize K centers μ_k ;

Repeat

2) Assignment : assign each point to the group whose center is the nearest ;

$$x_i \in RC_k \; si \; \forall j |x_i - \mu_k| = min_i |x_i - \mu_j|$$

With μ_k is the center of the region RC_k;

3) Representation : Calculate the centers associated with the new partition;

$$\mu_k = \frac{1}{N} \sum_{x_i \in C_k} x_i$$

Until the minimization of the total distortion defined by: $J = \sum_{i=1}^{K} \sum_{x_j \in C_i} \left\| x_j - \mu_i \right\|^2$;

End.

After a set of tests we have seen that the number of clusters suitable for the determination of candidate regions is k = 4. So with k = 4 the result the clustering of neighboring corners points is shown in Fig. 6 below. We can see that the K-means method gives better clustering of neighboring corner points.

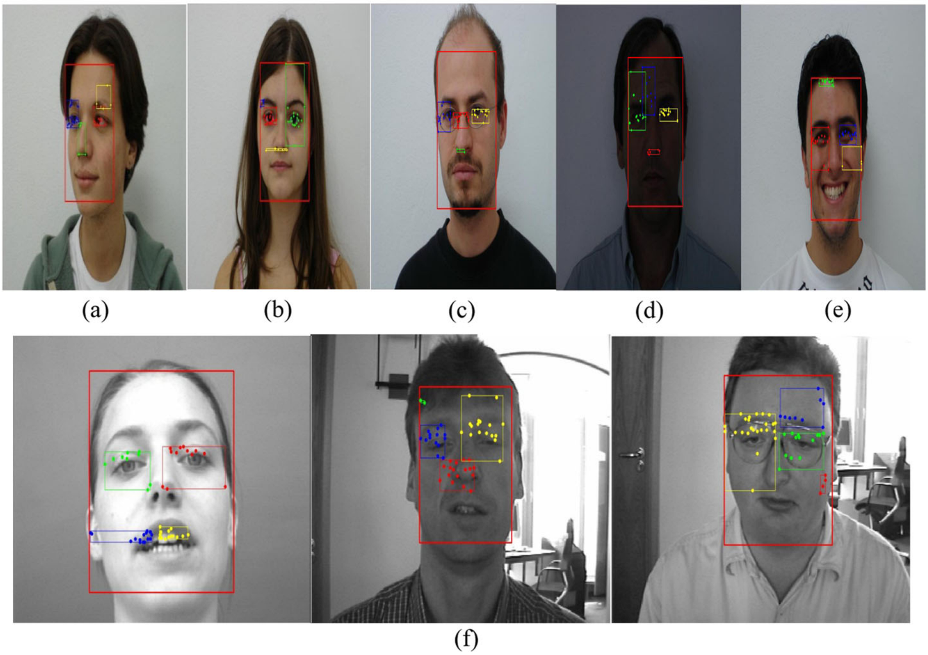


Fig. 6 Clustering of neighboring corner points by K-means method for the faces displayed in Fig. 4

3.3 Eye detection

For detecting eyes, an eye template is built, and then it is compared with the different candidate regions (**CR**) using the normalized cross-correlation function (**NCC**) defined by the formula 4 [1].

$$NCC(x,y) = \frac{\sum_{x,y} \delta_{I(x,y)} \delta_{T(x-u,y-v)}}{\left\{ \sum_{x,y} \delta_{I(x,y)}{}^{2} \sum_{x,y} \delta_{T(x-u,y-v)}{}^{2} \right\}^{0.5}} \tag{4}$$

Where:

$$u \in \{1, 2, 3, \ldots, p\},$$

$$\mathrm{v} \in \{1, 2, 3, \ldots, \mathrm{q}.\}$$

$$\chi \in \{1, 2, 3, ..., m-p+1\},$$

$$\mathrm{y} \in \{1, 2, 3, \ldots, \mathrm{q}-\mathrm{n}+1\}$$

$$\delta_{\mathrm{I(x,y)}} = \mathrm{I(x, y)} - \overline{\mathrm{I}_{\mathrm{u,v}}}$$

$$\delta_{T(x-u,y-v)} = T(x-u, y-v) - \overline{T}$$

$$\overline{I_{u,v}} = \frac{1}{pq}\sum_{uv} I(x, y)$$

$$\overline{T} = \frac{1}{pq}\sum_{uv} T(x-u, y-v)$$

I	is the input image
T	is a template
m and n	are the sizes of image.
p and q	are the sizes of template.

The matching of the eye template with the candidate regions (**CR**) is performed according to the following algorithm:

Algorithm 4 : Matching of the eye template with the candidate regions

```
Input
        Eye template T size (p,q)
        Candidate region CR size (n,m)
Output
        Center of the eye region: CE
Begin
    max := - 1
    xx := 1
    yy :=1
    For y :=1 to n-q+1
        For x :=1 to m-p+1
            Calculate NCC (x, y) using the formula 4
            If  max <  NCC (x, y) then
                max := NCC (x, y)
                xx :=x
                yy :y
            End if
        End For
    End For
    If max ≥ threshold then
        CE :=(xx,yy)
    End if
End.
```

This algorithm determines the positions where the correlation values with an eye template are maximum and greater than threshold value which is determined by calculating the correlation between a set of eye and non-eye images, and an eye template. In our method, we used a threshold equal to 0 , 4. We can find several regions having the correlation value greater than 0 , 4. In this case, if there are two overlapping regions, we keep the region of high correlation value, and if the number of remaining regions is greater than 2, we will keep only two regions having strong correlation values. Figure 7 illustrates the steps of matching the eye template with the candidate regions.

Figure 8 shows the result of the eyes detection by our method. It can be observed that the proposed algorithm can detect eyes in color images with different lighting conditions, for frontal and profile faces, for faces with glasses, and faces with smiles. It can also detect in the gray images, with complex background, in uncontrolled light, for eyes closed open and with glasses.

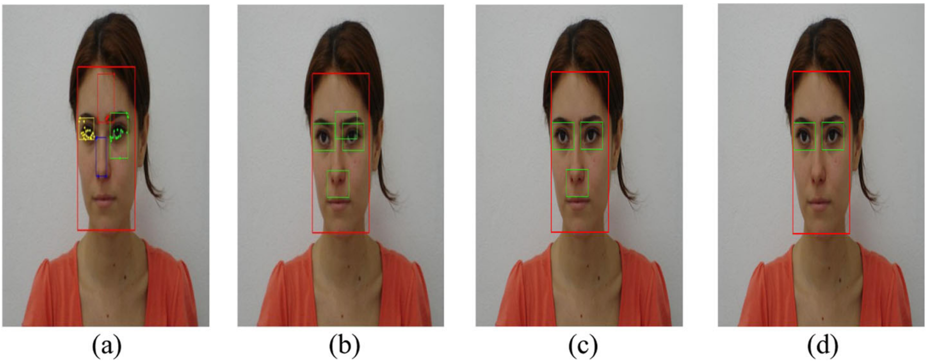


Fig. 7 matching of eye template with the candidate region: candidat régions (**a**), regions having strong correlation values (**b**), elimination of overlapping regions (**c**), Eye regions (**d**)

4 Experimental results

To evaluate the performance of our method and compare it with the other methods of eye detection, we used two face images databases (one contains a color image and another contains grayscale images), a set of additional personal pictures and other issues of Internet. The evaluation is based on two indicators: the correct detection rate (the number of correctly detected eyes over the total number of eyes), and the false detection rate (the number of false

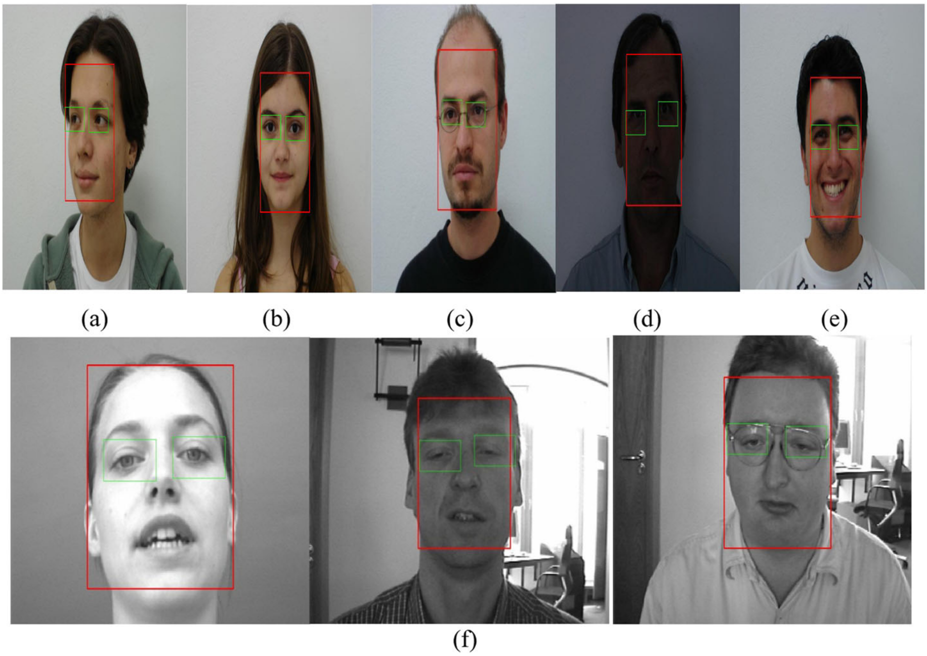


Fig. 8 Results of eyes detection for the faces displayed in Fig. 4

detected eyes over the number of detections). For the detection accuracy, we used the normalized maximum error [17] defined as follows:

$$e = \frac{\max(d_l, d_r)}{d_{lr}} \tag{5}$$

Where d_l and d_r are the Euclidean distances between the localized positions and the real positions of the left and right eyes respectively, and d_{lr} is the Euclidean distance between the two eyes of the reality. In our experiments, detection is considered correct if $e \leq 0.25$.

4.1 Simulation (dataset)

4.1.1 Color images

We tested our method on the FEI database [40] available online. It contains a set of images of 200 people taken in 14 different situations (lighting, pose ...). We tested our method in 2800 images; each image contains a single face. This test gives very important results (Table 1). Indeed, for all the images, we obtained a correct detection rate exceeds 98% and a false detection rate approximately 2%.

For frontal faces under standard conditions of lighting, and in the absence of occlusions (glasses), our method achieved a correct detection rate exceeding 98% and a false detection rate less than 1%. The rotation of faces makes detection of eyes difficult, which explains the high rate of false detection in the case of profile faces (8.28%). The low lighting, facial expressions and even the presence of occlusions do not affect the performance of our technique because the correct detection rate exceeds 97% for dark images, 98% for images of face with smile, and 96% for images of face with glasses.

The algorithms used for the detection of eyes are the Viola-Jones method, corner points of Shi-Tomasi, K-means method, and matching with an eye template. These different algorithms are robust to variations in pose (frontal faces and profile faces), lighting, facial expressions, and in the presence of glasses. This explains the good results achieved on the FEI database (Table 1).

Figure 9 shows an example of results which illustrates the detection of the eyes in the presence of the various factors which disturb the detection process. The red rectangles represent the detected face regions, and green rectangles represent the detected eye regions. We see that our method can detect eyes with precision, even for profile faces (a1 and a2) faces with smile (b1 and b2), face with glasses (c1 and c2), and dark images (d1 and d2).

Table 1 Eye detection results obtained with our method

Characteristics of the database FEI [40]			Eye detection with our method			
Images	Number of images	Number of eyes	Number of correct detection		Number of false detection	
Frontal	1400	2800	2765	98,75%	17	0,61%
Profile	800	1171	1141	97,44%	103	8,28%
Dark lighting	400	762	746	97,90%	11	1,45%
facial expression (smile)	200	400	393	98,25%	3	0,76%
Occultation (glasses)	66	115	111	96,52%	7	5,93%
Total	2800	5133	5045	98,29%	134	2,58%

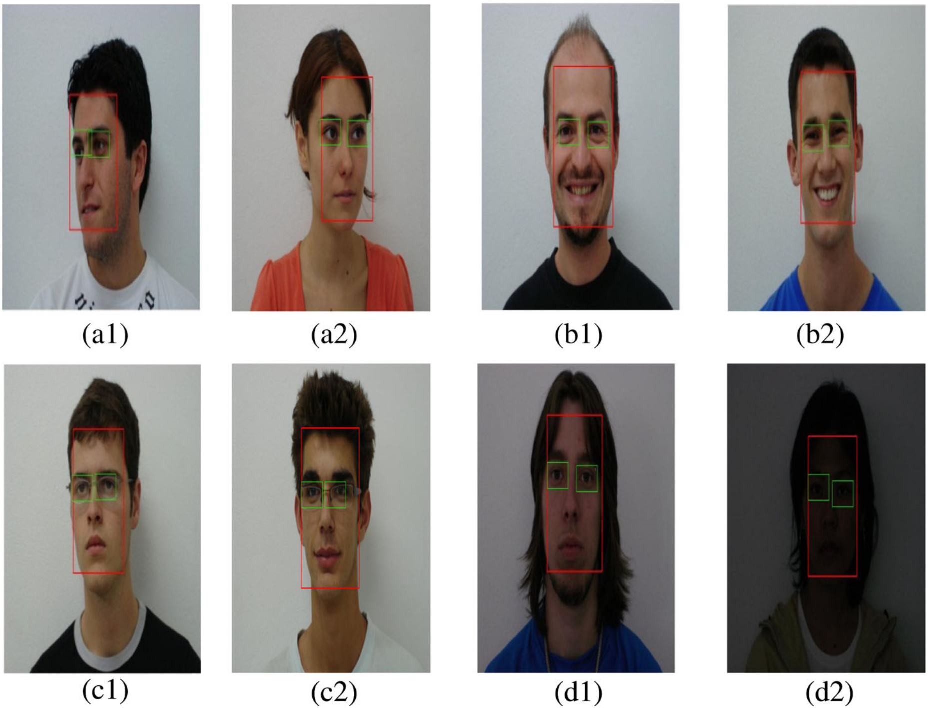


Fig. 9 Eye detection in the presence of various constraints: profile faces (a1, a2), faces with smile (b1, b2), faces with glass (c1, c2), dark images (d1, d2)

4.1.2 Grayscale images

For grayscale images, our method is tested on the BioID database [39], which consists of 1521 images of frontal faces of 23 people. These images are taken with the complex background under uncontrolled lighting for eyes closed, open and with glasses. The results obtained are very satisfactory (Table 2). Indeed, we detected 3004 eyes and 58 false detections. We achieved a correct detection rate nearly to 99%, compared to the false detection rate that remains low (1.89%). This demonstrates the robustness of our method to variations in lighting and complex background.

For open eyes without glasses, the detection is almost perfect. We got a correct detection rate of 99.41%, and a false detection rate very low (1.65%). Despite the change in the shape of the eye and low contrast in intensity when eyes are closed, we got a correct detection rate exceeding 93% and a

Table 2 Eye detection results obtained with our technical

Characteristics of the database BioID [39]			Eye detection with our method			
Images	Number of images	Number of eyes	Number of correct detection		Number of false detection	
Open eyes	1018	2036	2024	99,41%	34	1,65%
Closed eyes	30	60	56	93,33%	2	3,44%
Eyes with glasses	473	946	924	97,67%	22	2,33%
Total	1521	3042	3004	98,75%	58	1,89%

false detection rate approximately 3%. The presence of the glasses does not affect the quality of our approach since we got a correct detection rate of 97.67%, and a false detection rate of 2.33%.

Our eyes detection system is composed by algorithms (AdaBoost algorithm, Haar feature, Shi-Tomasi detector, K-means method, and the normalized cross-correlation function) which work correctly with gray images and that cannot be influenced by complex backgrounds and occlusions (glasses). This justifies the important results achieved on the database BioID (Table 2).

Figure 10 shows an example of results which illustrates the detection of the eyes in the BioID database. We noted that our method can accurately detect eyes opened (a), closed (b), and with glasses (c).

4.1.3 Comparison

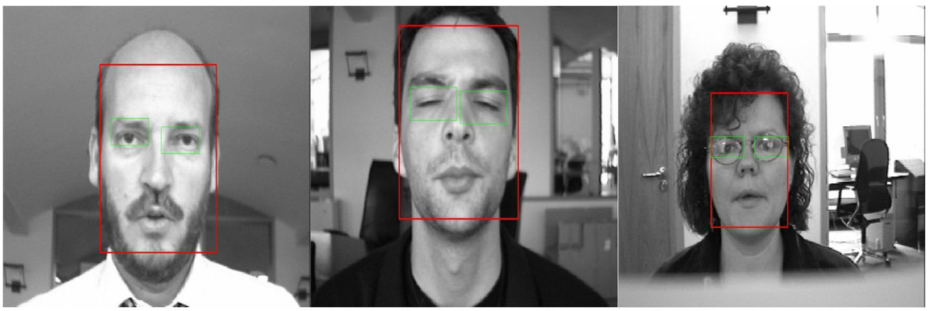
To confirm and demonstrate the quality of our approach, we compared our results with those of eight other eye detection methods recently published: for images of FEI database with the methods presented in [3, 9, 26] and for the BioID database with the methods presented in [4, 5, 15, 19, 26, 31]. The results obtained are shown in Table 3.

Table 3 shows the correct detection rate obtained with our method compared with that obtained with the other. We see that our method gives satisfactory results compared to other approaches. It gives a better rate than all other methods, except those presented in [5, 31]. It should be noted that these two methods assume that the face detection achieved a perfect result (i.e., the face detection rate is 100%), which is very difficult to obtain.

The high rate of our method on the FEI database is justified by the fact that it is applicable on dark images, images of faces profiles and with glasses; however, the methods presented in [3, 9, 26] are limited in some cases. For example, algorithm [9] is not applicable in dark images, [3] is not applicable on the images of face profiles, with glasses and dark images, and [26] is not applicable on profiles of face images, and with glasses.

The high rate of our method on the BioID database is justified by the fact that our method is able to detect the eyes on images with complex backgrounds, under different lighting conditions, in the presence of the glasses, and even if the eyes are closed. However the method presented in [4] is limited by the presence of the glasses and the backgrounds complex, method presented in [19] is failed when the eyes are closed, and methods presented in [15, 26] are disturbed by the presence of the glasses and when the eyes are closed.

For more visibility, Fig. 11 illustrates that the correct detection rate of our method is higher than all other methods, except those presented in [5, 31]. These two methods are developed to



(a) (b) (c)

Fig. 10 Eye detection: **a** open eyes . **b** closed eyes. **c** eyes with glasses

Table 3 Results of eyes detection obtained with our method and compared to those in the literature

		Correct detection rate
FEI	Our method	98,29%
	S.E.Kaddouhi et al. [9]	97,55%
	L.K.Bhatta et al. [3]	96,5%
	Mingxin YU et al. [26]	95,2%
BioID	Our method	98,75%
	Abbas Cheddad et al. [4]	95,14%
	Krzysztof Rusek et al. [31]	99,9%
	Muwei Jian et al. [19]	98,62%
	S.Chen et al. [5]	98,98%
	M. Hassaballah et al. [15]	97,1%
	Mingxin YU et al. [26]	96,3%

be applied for images of frontal faces, so it is normal that they will be best for the BioID database that consists only by frontal face images.

The increase in the correct detection rate and the decrease in false detection rate do not affect the speed of our method. Therefore, we have achieved both high detection accuracy and speed of fast calculation. This is due to the following reasons: (1) Applying a detector better than Viola-Jones to detect the frontal and profiles faces in different lighting conditions, and in the presence of occlusions. (2) Using of the Shi-Tomasi detector for determining the corners points and K-means for clustering these points. (3) Applying an eye template only on the candidate regions determined by the neighboring corner points, and not on the entire image.

4.2 Real data

To show the quality of our algorithm in the case of complex images, we tested our method on 50 images containing 424 eyes. These images are characterized by complex background, are taken in different lighting conditions and are distributed in images containing a single face, images containing two faces, images containing three faces, images containing four faces, and images containing more than five faces. The results obtained (Table 4) show, once again, the

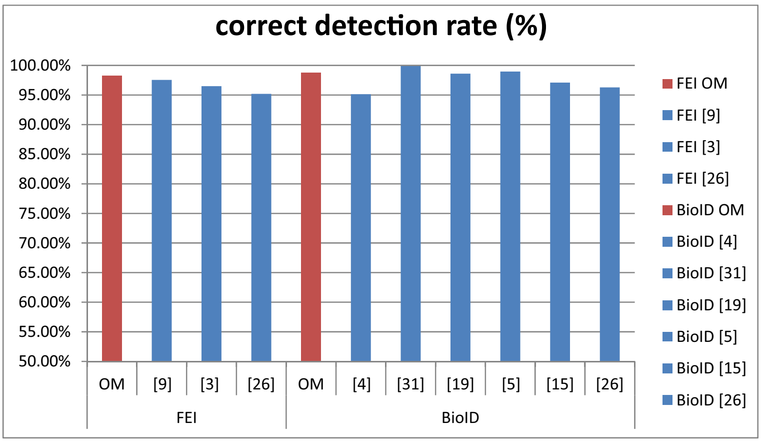


Fig. 11 Comparison of eye detection results

Table 4 Eye detection results obtained

Number total of eyes	Number of eyes detected		Number of false eyes	
424	402	94.81%	23	5.41%

performance and robustness of our technical towards previous constraints, because we got a correct detection rate over than 94% and a false detection rate less than 6%.

Our method is essentially based on the Viola-Jones algorithm, the Shi-Tomasi detector of the corner points, and eye template matching. These algorithms are robust to complex backgrounds, lighting variations and scales (sizes faces). So, the application of our method on real images gives encouraging results (Table 4).

Table 5 Some eyes detection results obtained by our method in real images

RGB Image	Face detection	Detection and clustering of corner points	Eye detection results
			
A1	**A2**	**A3**	**A4**
			
B1	**B2**	**B3**	**B4**
			
C1	**C2**	**C3**	**C4**
			
D1	**D2**	**D3**	**D4**
			
E1	**E2**	**E3**	**E4**

Table 5 presents the results of five images chosen among the 50 images used and which are characterized by complex backgrounds.

4.3 Discussion

In comparison with existing eye detection methods, our method has the following advantages:

- The algorithms used for eyes detection are the Viola-Jones method, the Shi-Tomasi detector of corner points, the K-means method, and matching with an eye template. These algorithms are not affected by the illumination variation, facial expressions, and in the presence of glasses. Therefore our method is robust to various factors cited.
- Our method can accurately detect eye for images of frontal faces and profile faces. This is due to the use of a system consisting of two Viola-Jones detectors (one for the frontal face and the other for profiles faces) for detecting the faces and applying algorithms that work with the frontal and profile faces for detecting eyes.
- Our method is essentially based on the Viola-Jones method and the Shi-Tomasi detector of corner points. These two methods are robust to complex background, lighting variations and scales (sizes faces). Thus our method can be applied successfully on real images.
- The second part (detection and grouping of corners points) of our method limits the search space of the eye positions. So the computational complexity of our proposed method is low.

5 Conclusion

In this article, we presented an efficient method for the accurate detection of the eyes. We used the Viola-Jones method to detect faces in images, next, the Shi-Tomasi detector and the k-means method are used to determine regions likely to be eyes, and then we applied an eye template on these regions for detecting eyes. The proposed method allows accurate detection of the eyes regardless of the variation of pose and expression, presence of occlusions, or images with complex background. The results obtained show that this technique has many advantages in terms of quality and speed of the detection.

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