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ORIGINAL PAPER

Face detection evaluation: a new approach based on the golden ratio Φ

M. Hassaballah · Kenji Murakami · Shun Ido

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Abstract Face detection is a fundamental research area in computer vision field. Most of the face-related applications such as face recognition and face tracking assume that the face region is perfectly detected. To adopt a certain face detection algorithm in these applications, evaluation of its performance is needed. Unfortunately, it is difficult to evaluate the performance of face detection algorithms due to the lack of universal criteria in the literature. In this paper, we propose a new evaluation measure for face detection algorithms by exploiting a biological property called *Golden Ratio* of the perfect human face. The new evaluation measure is more realistic and accurate compared to the existing one. Using the proposed measure, five haar-cascade classifiers provided by Intel© OpenCV have been quantitatively evaluated on three common databases to show their robustness and weakness as these classifiers have never been compared among each other on same databases under a specific evaluation measure. A thoughtful comparison between the best haar-classifier and two other face detection algorithms is presented. Moreover, we introduce a new challenging dataset, where the subjects wear the headscarf. The new dataset is used as a testbed for evaluating the current state of face detection algorithms under the headscarf occlusion.

M. Hassaballah · K. Murakami · S. Ido
Department of Computer Science, Ehime University,
Matsuyama 790-8577, Japan

K. Murakami
e-mail: murakami@cs.ehime-u.ac.jp

S. Ido
e-mail: ido@cs.ehime-u.ac.jp

M. Hassaballah (✉)
Department of Mathematics, Faculty of Science,
South Valley University, Qena 83523, Egypt
e-mail: m.hassaballah@svu.edu.eg

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1 Introduction

In the last decade, face detection has become one of the most active research topics in computer vision and pattern recognition for its interesting applications, such as face recognition, face tracking, facial expression analysis, human computer interface, and video surveillance. Recently, a number of promising face detection approaches have been developed. The neural networks or statistical learning-based approaches achieve the best results. The classical approach for face detection is to scan the input image with a sliding window and for each position, the window is classified as either face or non-face. The method can be applied at different scales and orientations for detecting faces of various sizes and orientations. The well-known methods proposed by Rowley et al. [11] and Kienzle et al. [6] belong to these approaches. More details about these methods and others are given in surveys [3,16].

Among the most recent face detection algorithms that has gained increasing attention due to its remarkable results is that of Viola and Jones [13], which has been integrated into Intel© Open Computer Vision library [4] with five haar-cascade classifiers. The basic idea of that method is based on using a boosted cascade of weak classifiers (i.e., each classifier has a high detection rate and a low true rejection rate). Each one uses a set of haar-like features acting as a filter chain. The image regions that pass through all the stages of the detector are considered to contain the face. For each stage in the cascade, a separated subclassifier is trained to detect almost all target faces in the image while reject a certain fraction of those non-face patterns that have been incorrectly accepted by previous stage classifiers.

On the other hand, a large number of the face-related applications mentioned earlier assumes that the face region is perfectly localized or detected. In order to adopt or use a certain face detection algorithm in these applications, evaluation of its performance is needed. Unfortunately, it is difficult to evaluate the performance of face detection algorithms due to the lack of universal criteria in the literature. In the same time, most published contributions do not mention the way they count the correct/fail hit that leads to computation of the success rates. For example, Rowley et al. [11] count a correct hit if the detected window contains the eyes and mouth, while Kienzle et al. [6] did not mention any thing about evaluation criterion focusing only on the speed achieved by the method. Lienhart et al. [7] consider the hit is correct if the Euclidean distance between the centers of the detected and ground truth face is less than 30% of the width of ground truth face, and the width of the detected face is within ±50% of ground truth face width.

Generally, the most ambiguous point in face detection methods is the way the performance is measured. Using different evaluation measures makes the objective comparison of published contributions difficult. Therefore, founding a standard terminology to describe the results of face detection is a must. Yann et al. [17] propose a methodology to evaluate face detection methods in the context of a face-related application. They consider face verification task for testing the proposed measure; due to its difficulty very few researchers considered it, such as [9]. The relative error measure of Jesorsky et al. [5] is also used extensively by researchers. The drawback of this measure is that it depends on the eyes position of the detected face, which requires that the face detection method should detect the position of eyes and this is not a trivial task.

In this paper, a general definition for the human face based on the golden ratio Φ [8] is introduced. Then, the well-known relative error measure of Jesorsky et al. [5] is discussed, avoiding its drawbacks a new modified measure is proposed. Using the proposed measure, the performance of five haar-cascade classifiers used in the OpenCV framework-based Viola and Jones algorithm is analyzed under various imaging conditions and new challenging dataset. Moreover, a comparison between the best classifier and two other face detection methods under the headscarf occlusion is reported in this paper.

The remainder of this paper is organized as follows: Sect. 2 introduces the proposed evaluation methodology, where we define the perfect face based on the golden ratios and the correct detection. The new dataset and OpenCV face detection framework are described in Sect. 3. The results and discussion of experiments are presented in Sect. 4. This is followed by conclusions in Sect. 5.

2 Evaluation methodology

The difficulty in comparison of face detection methods comes from two problems. First, there is no a clear definition for human face (i.e., what is the width/height of the face?). Second, there is no an accurate definition for what the correct detection is. While one algorithm may consider a successful detection if the bounding box contains eyes and mouth, another may require the entire face (including forehead and hair) to be enclosed in the bounding box for a positive result. An illustration for the problem is given in Fig. 1.

To inform this claim, we quoted two different evaluation protocols from [12] and [15] shown in Fig. 2a and b, respectively. Where the authors of these contributions define the correct detection for the same test image in different ways. In Fig. 2a, some facial features are lost such as left eye corner and lower part of lip, while in Fig. 2b, the detected faces contain a wide area of background. Thus, founding a standard terminology to evaluate accurately the performance of face detection methods is a goal of this paper. To this end, in the next subsections, we try to introduce solutions for the aforementioned problems by exploiting biological properties of the human face.

2.1 Face definition

The golden ratio [8], also known as the divine proportion, is a ratio or proportion defined by the number Phi, $\Phi = 1.618$. It

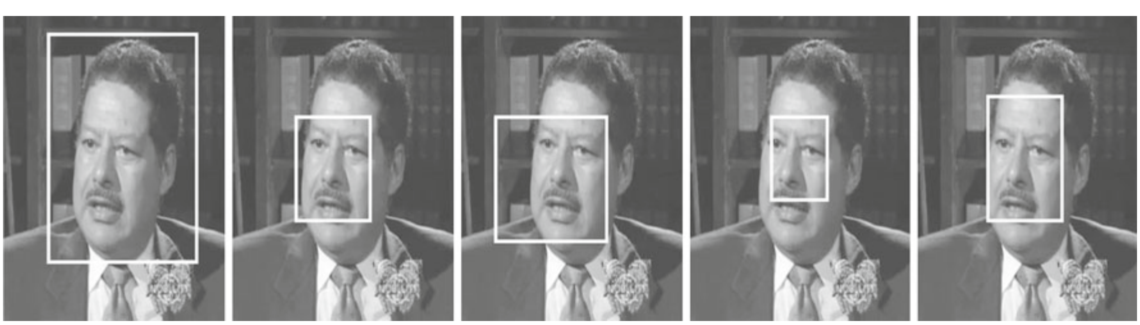

Fig. 1 Examples of various detections of the same face. Which one is a correct detection?

Fig. 2 Examples of different evaluation protocols for the correct face detection

(a) Successful hit of Shih and Liu [12] **(b)** Successful hit of Xiaohua et al. [15]

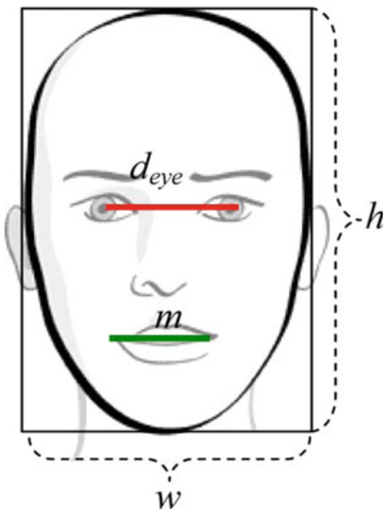

Fig. 3 Definition of the perfect face based on golden ratios between the elements of face

has been used for centuries in many fields, such as Egyptians pyramids and Leonardo da Vinci's Mona Lisa [14,1]. The golden ratio appears repeatedly in the physical proportions of the human body especially in the face [10]. There are many facial parts or face elements form among each other the golden ratio, such as height and width of the face. According to the golden ratio between the facial parts, we have these relations

$$\frac{h}{w} = 1.618, \quad \text{and} \quad \frac{d_{\text{eye}}}{m} = 1.618 \tag{1}$$

where h, w, d_{eye}, and m are the height of face, the width of face, distance between the centers of eyes, and the width of mouth, respectively as shown in Fig. 3.

Based on statistical analysis of hundreds of images from different races, we may approximately assume that

$$w \approx 0.70 \times m + d_{\text{eye}} + 0.70 \times m \tag{2}$$

Using the second relation in (1), we can rewrite (2) in the following form

$$w \approx 0.70 \times \frac{d_{\text{eye}}}{1.618} + d_{\text{eye}} + 0.70 \times \frac{d_{\text{eye}}}{1.618} = 1.865 \times d_{\text{eye}} \tag{3}$$

Also, from the first relation in (1) and using (3), we have

$$\begin{aligned} \frac{h}{w} &= 1.618, \text{ then } h = 1.618 \times w \\ &= 1.618 \times 1.865 \times d_{\text{eye}} = 3.018 \times d_{\text{eye}} \end{aligned} \tag{4}$$

Therefore, the width and height of the perfect human face can be estimated based on the distance between the eyes as

$$w = 1.865 \times d_{\text{eye}}, \quad \text{and} \quad h = 3.018 \times d_{\text{eye}} \tag{5}$$

Thus, the golden ratio helps in estimating the face size according to the distance between the centers of eyes. The perfect face size of three persons calculated using (5) is shown in Fig. 5 with the green rectangle. In this context, (5) represents an accurate estimation of the human face size based on his/her inter-ocular distance d_{eye} that is different from a person to another. There are several other facial parts having relations among each other closed to the golden ratio [10], which may be used in other fields, such as 3D facial models or facial features detection based geometric information. In this work, we focus only on two of these relations (1) (i.e., height/width of face and inter-ocular distance/mouth width), which are important for estimating the size of the human face.

2.2 Definition of correct detection

Jesorsky et al. [5] define the correct detection using the *relative error* measure based on the distances between the expected and the estimated eye positions. Because of its simplicity, the *relative error* measure is used widely in face detection evaluation. Let C_l and C_r be the manually (ground truth) extracted left and right eye positions of a face image, $\tilde{C}_l$ and $\tilde{C}_r$ be the estimated positions by the method, d_l be

Fig. 4 Examples for faces where Jesorsky et al. measure might fail in evaluating face detection methods accurately

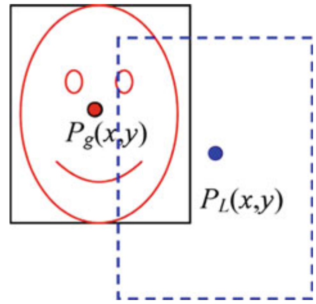

Fig. 5 Distance between the centers of ground truth and located face

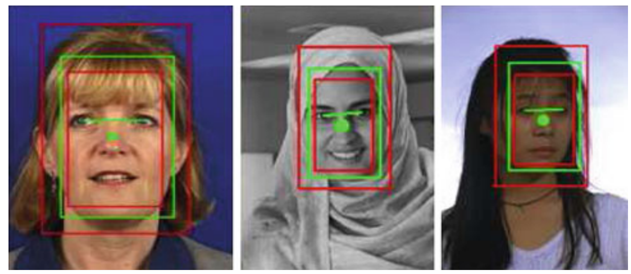

Fig. 6 Perfect face size (*green rectangle*) and the correct detected face boundaries (*red rectangles*)

the Euclidean distance between C_l and $\tilde{C}_l$, d_r be the Euclidean distance between C_r and $\tilde{C}_r$, and d_{lr} be the Euclidean distance between C_l and C_r. Then, the relative error of this detection is defined as

$$R_{\text{err}} = \frac{\max(d_l, d_r)}{d_{lr}} \leq T \tag{6}$$

If the *relative error* is less than or equal 0.25, the detection is considered to be correct. As explained in [5], a threshold value $T = 0.25$ means that the maximum allowable deviation from the actual eye center positions is half the width of an eye.

The main drawback of this measure is that it depends basically on estimating the position of eyes in the detected face. This means that the face detection algorithm should also detect or at least estimate the position of eyes. Unfortunately, this task is not an easy at all for face detection methods. The face detection algorithm may be robust for face detection and weak for eye detection. Therefore, the estimated eyes positions will not be accurate, which will affect the evaluation results. For instance, Fig. 4 shows two frontal view faces where the evaluation measure of Jesorsky et al. [5] might fail due to the difficulty in estimating the eyes centers (i.e., $\tilde{C}_l$ and $\tilde{C}_r$) even with using sophisticated eye detection algorithms [2]. In other words, to use the relative error measure for evaluating the face detection results, the ground truth and estimated eyes positions should be known; thus one should find a mature method to label the estimated eyes position that does not exist yet. Therefore, to avoid this problem, the evaluation measure should not depend on the estimated eyes position in the detected face.

According to the definition of the perfect face size explained earlier, the size of the detected or located face by the algorithm must equal the perfect size, but this requirement is very difficult to achieve by any face detection algorithm. Therefore, the output of face detection algorithm is considered a correct hit, if the following two conditions are satisfied:

1. $w_1 \leq w_L \leq w_2\,, \quad h_1 \leq h_L \leq h_2$
2. $d(P_g, P_L) \leq \alpha \times d_{\text{eye}} \quad \alpha \in [0, 1]$

where $w_L, h_L, P_g(x, y), P_L(x, y)$, and α are the width and height of the located face, the center point of ground truth face, the center point of located face, and percentage from the distance between eyes centers "*Inter-Ocular Distance* (IOD)", respectively. The first condition is to control the width and height of the face as well as to guarantee that all facial features are within the detected face. While, the second condition is to guarantee that the detected face is not far from the right position as shown in Fig. 5.

The boundary parameters w_1, w_2, h_1, and h_2 can be determined experimentally without losing the generality that $h_1/w_1 = h_2/w_2 \approx \Phi = 1.618$, simply by resizing the perfect face size. These parameters are set to be $w_1 = 1.554 \times d_{\text{eye}}$, $w_2 = 2.425 \times d_{\text{eye}}$, $h_1 = 2.515 \times d_{\text{eye}}$, and $h_2 = 3.923 \times d_{\text{eye}}$. Consequently, the output region of face detection algorithm is a correct face if it satisfies that

1. $1.554\ d_{\text{eye}} \leq w_L \leq 2.425\ d_{\text{eye}}\,, \quad 2.515\ d_{\text{eye}} \leq h_L \leq 3.923\ d_{\text{eye}}$
2. $d(P_g, P_L) \leq \alpha\ d_{\text{eye}} \quad \alpha \in [0, 1]$

Otherwise, the detection is incorrect or a non-face. Figure 6 shows the perfect face size (green rectangle) calculated based on the distance between eyes of the person. The two other red rectangles represent the upper and lower boundaries of the correctly detected face as explained earlier. Note that the lower red rectangle is the minimum allowed face and smaller than this size leads to lose some facial features such as eye corners. In other words, the detected face size must be within these boundaries. Also, if the researchers interest in evaluation of whole head detection rather than face, the size of the upper boundary (i.e., w_2 and h_2) ought to be increased to include the whole head. The green circle represents the center of the ground truth face estimated from the distance between centers of eyes as $0.3 \times IOD$ below the midpoint of the line connected the center of two eyes. Using such evaluation measure does not require to estimate eyes position by face detection algorithms. Thus, the ground truth of the eyes centers is only required to calculate the distance between eyes d_{eye} and the center point of the right face. Moreover, this measure is more strict than that of Jesorsky [5]. Regarding the parameter α, the choice of [5] (i.e., $\alpha = 0.25$) still remains valid.

3 Face detection frameworks and image datasets

3.1 Face detection framework

It is well known that the OpenCV library provides the researchers with five haar-cascade classifiers. These classifiers have been used extensively and considered as testbed for comparing other classifiers. They have been trained with different training data and as far as we know such classifiers have not been compared among each other and their performance under different scenarios is questionable. Many researchers compare their face detection methods with OpenCV Viola–Jonse framework without mention which cascade classifier is used in the comparison. Also, there is no a comprehensive comparative evaluation for the performance of these classifiers on a standard dataset and a standard terminology for successful detection rate, thus one of the main goals of this work is to analysis and compare the performance of these classifiers. In this context, we will try to highlight their robustness and weakness and answer some questions such as what is the best one among them?, how much the speed of each one? The classifiers being tested and their labels are given in Table 1. Also, a comprehensive comparison is performed with two of the most successful neurally inspired face detection algorithms in literature; namely, Rowley et al. [11] due to its high performance and Kienzle et al. [6] due to its high speed.

Table 1 Haar-cascade classifiers provided by OpenCV face detection framework

Haar-cascade classifier	Label	Stage	Size
haarcascade_frontalface_default	HD	25	24 × 24
haarcascade_frontalface_alt	HT	21	20 × 20
haarcascade_frontalface_alt2	HT2	20	20 × 20
haarcascade_frontalface_alt_tree	HTR	46	20 × 20
haarcascade_profileface	HPF	26	20 × 20

Fig. 7 Transforming a square facial region into a *rectangle* region

It should be noted that the located region by the aforementioned face detection methods being tested is a square region. In order to evaluate the performance of these methods using the proposed measure, it is necessary to transform the detected region from a square to a rectangle. To do that, the golden ratio principle is applied as follows. The height h and width w of the detected square region satisfy that $h/w = 1$, while the height $\tilde{h}$ and width $\tilde{w}$ of the transformed region must satisfy that $\tilde{h}/\tilde{w} = 1.618$ or at least close to this ratio according to the perfect face definition, thus

$$\tilde{w} = w - \Delta, \quad \tilde{h} = w + \Delta \tag{7}$$

Therefore,

$$\frac{\tilde{h}}{\tilde{w}} = \frac{w + \Delta}{w - \Delta} = 1.618, \text{ then } \Delta = \frac{0.618w}{2.618} = 0.236w \tag{8}$$

$$\begin{aligned} \tilde{w} &= w - 0.236w = 0.764w, \\ \tilde{h} &= w + 0.236w = 1.236w \end{aligned} \tag{9}$$

In Fig. 7, the original detected facial region (green square) by a face detection method is transformed precisely using (9) into a rectangle region (red rectangle) confirming the robustness of the proposed transformation.

3.2 Image datasets

Three publicly available datasets as well as a new challenging dataset are used in the evaluation of the face detection methods. They are the XM2VTS, FERET, and BioID. For the FERET dataset, a set of 1823 images that has the ground truth of eyes positions are used. While, for the new dataset-Scarf, a total of 300 images are collected from the Internet. The subjects in this dataset wear headscarf with different views, while, the quality of images is good; it consists of 423 faces. The centers of eyes in each face are manually labeled. Neither of face detection methods have been evaluated under these situations before nor the current common datasets consider such imaging conditions (i.e., *headscarf occlusion*). There are many people who wear headscarf and they use cameras; they buy an expensive camera

Fig. 8 Examples of headscarf dataset

(due to face detection technology included in this camera). The question is, is this technology mature for them to buy it? The headscarf is a type of occlusion in the image, and it should be taken into account in evaluating the performance of face detection algorithms. Building the Scarf dataset helps in highlighting the above question and studying the effect of headscarf occlusion on face detection performance. Samples of the Scarf dataset are shown in Fig. 8. The dataset will be available soon for the researchers in our server.

4 Results and discussion

In the first experiment, more than 5000 images with different imaging conditions are used to justify the perfect face size derived in (5). Figure 9 shows that (5) is an accurate estimation for the human face calculated based on the distance between eyes- white line in Fig. 9. The small white circle represents the center point of the face. It is important to note that calculating the perfect face (drawing in Fig. 9) requires only the ground truth of eyes centers, which is done manually, and there is no need to estimate the eyes positions in the detected face by eye detection methods. This insures that the proposed evaluation measure is independent of the eyes position estimation. Therefore, the proposed evaluation measure does not affect by imaging conditions such as variation in illumination and occlusion. While, the existing measure of Jesorsky et al. [5] affects so much by these conditions, because it depends on both the estimated eyes position and the ground truth of eyes. Since, it is well known that these imaging conditions make detecting the eye position not only inaccurate but also a very difficult task.

In the second experiment, the proposed evaluation measure is used to compare face detection algorithms. To ensure that the comparison between different face detection algorithms is truly fair, the same evaluation criterion is used (i.e., the proposed measure). In addition, if two or more locations output by the algorithm satisfy the aforementioned criterion for same face, only one is considered as a correct face and the others are counted as false positives (FP). It is also important to note that the main goal of the comparison is to measure the accuracy of the face detection algorithm as a detector not as a classifier. We evaluate the performance of OpenCV haar-cascade classifiers. The successful detection rate of these classifier versus the parameter α (% of interocular distance) on the four datasets is shown in Fig. 10. It is clear that for XM2VTS and FERET datasets, where the images quality is good, four classifiers (i.e., HT, HT2, HD, and HTR) achieve similar performance and for the BioID and Scarf datasets, where there are some challenges in the images such as various illumination or headscarf, the performance of HTR classifier is decreased significantly, while the other three classifiers still achieve similar performance. All classifiers perform badly on the Scarf dataset compared to others datasets as shown in Fig. 10d. The highest detection rate on the scarf set is 75.6% achieved by HT2. Among the five classifiers, HPF is the worst one on all datasets even in the images of high quality, such as XM2VTS.

Looking closely, one can see that HT is slightly better than the others classifiers in most datasets followed by HT2 and HD. To be more accurate in this conclusion, the successful detection and false positive rates of the classifiers at $\alpha = 0.25$ are reported in Table 2. The highest detection rate and smallest number of false positive on each dataset are reported in **bold**. The HT classifier gives the highest detection rate, while HTR demonstrates the lowest false positive rate and the most speed one. The calculation time required for each classifier is also shown in Table 2. This time is the average calculation time of 500 runs on XM2VTS dataset, where the images are of 720 × 576 pixels, computed on Core(TM)2Duo CPU P8600 2.40 GHz, RAM 4 GB, and OS Vista 32-bit.

The performance of OpenCV using HT classifier is compared with the methods of Rowley et al. [11] and Kienzle et al. [6]. The results of this experiment are shown in Fig. 11, which shows that OpenCV outperforms the other two methods. The performance of OpenCV is similar on three datasets XM2VTS, FERET, and BioID with a high detection rate not less than 95%. While, there is a noticeable variation in the performance of the other methods according to the challenges in the images. The number of false positive and detection rate at $\alpha = 0.25$ as well as the computation time of each

Fig. 9 Justification of the perfect face size on different scenarios of faces

method is presented in Table 3. The performance of Rowley et al.'s method is less than that of OpenCV and higher than that of Kienzle et al.'s method, and its compuation time is about seven times of Kienzle et al.'s method [6] and 2.7 times of OpenCV as shown in Table 3. On the other hand, Kienzle et al.'s method demonstrates good speed, but it shows the worst performance on all datasets. It appears that this method affects much by the illumination in the image as it can be seen from Fig. 11c its performance on BioID decreases significantly compared to that on the Scarf dataset where the image quality is better than BioID. Also, the method achieves a little bit high detection rate on the XM2VTS where the quality of the images is good compared to other datasets.

In the summary, according to the results of the experiments carried out in this paper, the best haar-classifier provided by OpenCV framework is HT followed by HT2. Among the tested face detection methods, Kienzle et al.'s method is the fastest one with lowest detection rate. The performance of the methods that have been tested in this work on the scarf dataset is very poor which indicates that new algorithms considering the headscarf occlusion are required to overcome the drawbacks of the current face detection methods.

5 Conclusion

Direct comparison of face detection methods is a difficult task, mainly because there is not a clear definition for face and what the correct face detection is. In this paper, we introduced a definition for the face based on the golden ratio between the parts of the human face. Using this definition, a new evaluation measure is proposed. We proved that the proposed measure is more accurate and realistic for face detection evaluation. To study the effect of headscarf on the performance of face detection, a new challenging dataset, where the subjects wear headscarf, is also introduced

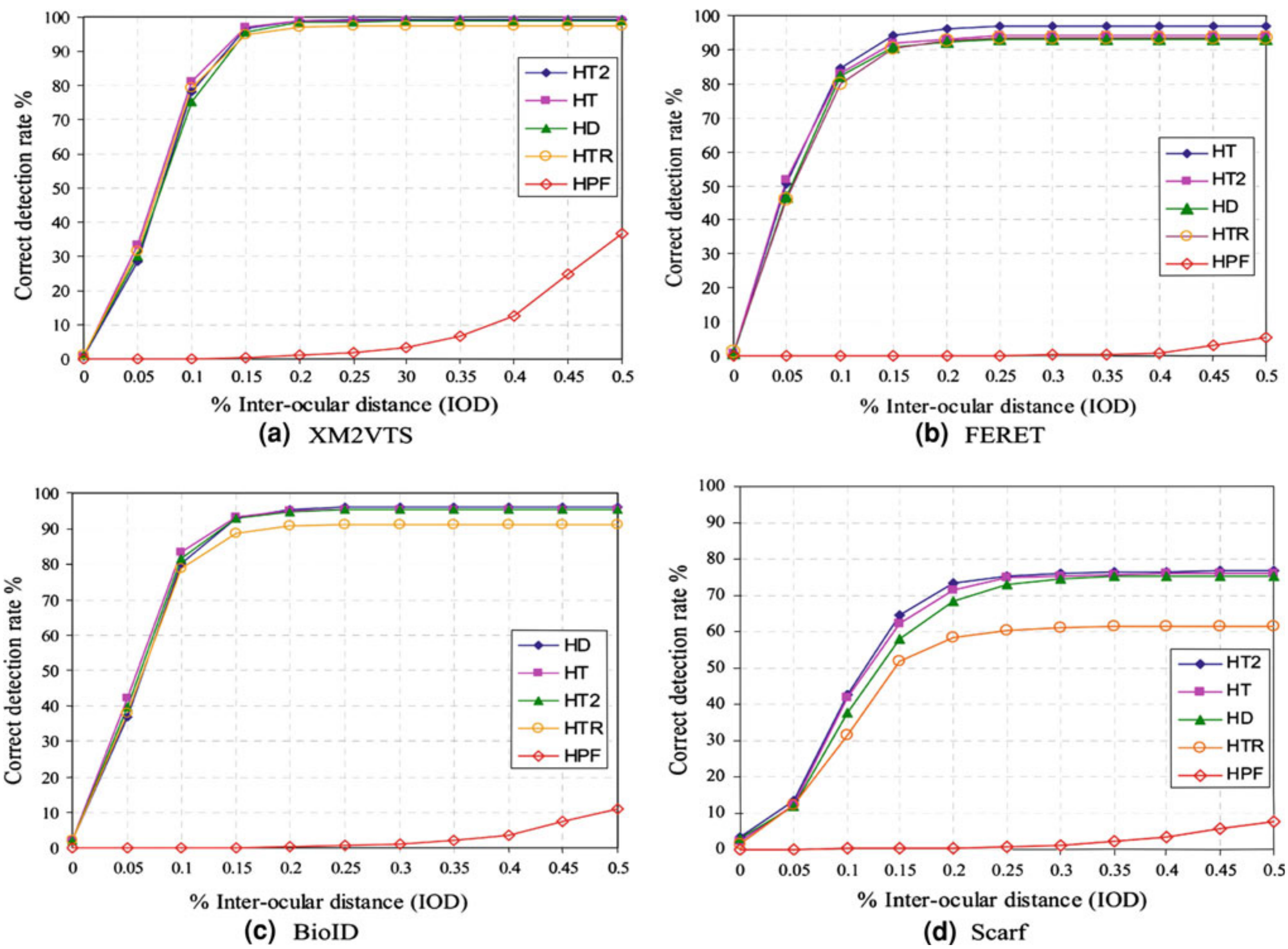

Fig. 10 Performance of OpenCV haar-classifiers on the four datasets

Table 2 Detection rate, number of false positive, and computation time of the OpenCV classifiers

Classifier	XM2VTS		FERET		BioID		Scarf		Time (ms)
	D. Rate (%)	FP	D. Rate (%)	FP	D. Rate (%)	FP	D. Rate (%)	FP	
HT	**96.9**	**42**	98.9	8	95.3	31	74.9	29	261.56
HT2	94.1	110	**99.3**	15	95.3	32	**75.4**	35	218.52
HD	92.9	206	98.7	66	**96.0**	117	73	87	249.18
HTR	93.3	52	97.3	**6**	91.2	**9**	60.5	**20**	**208.52**
HPF	0.1	260	2.0	988	0.7	352	0.7	98	280.88

as non of well-known face detection algorithms have been tested before under this type of headscarf occlusion. Five haar-cascade classifiers provided by OpenCV face detection framework have been compared on the Scarf dataset and three other common databases. Furthermore, a comparison between the best haar-classifier and other face detection methods has been done. Two conclusions have been reached: the performance of all tested methods is worse on the Scarf dataset and OpenCV framework achieves the best performance with high computation time compared to the other methods.

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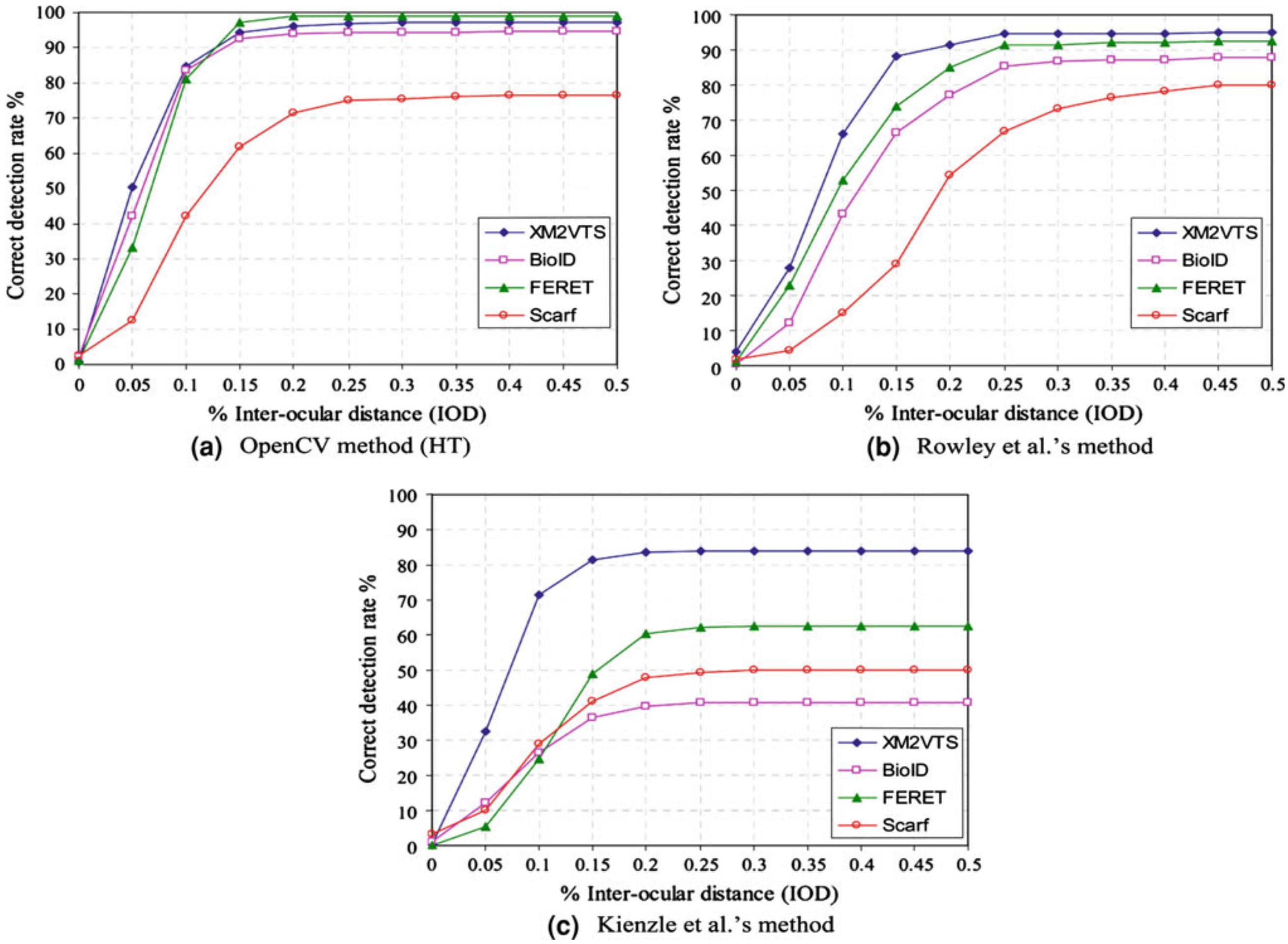

Fig. 11 Comparison of OpenCV (HT) with other face detection methods on the four datasets

Table 3 Performance comparison of different face detection methods

Face detection method	XM2VTS		FERET		BioID		Scarf		Time (ms)
	D. Rate (%)	FP	D. Rate (%)	FP	D. Rate (%)	FP	D. Rate (%)	FP	
OpenCV(with HT) [4]	96.9	42	98.9	8	95.3	31	74.9	29	261.56
Rowley et al. [11]	94.5	43	91.3	153	85.4	51	66.9	63	724.66
Kienzle et al. [6]	83.9	336	62.3	520	40.6	771	49.2	206	103.42

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