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Improving Face Recognition Rate Based on Histogram of Oriented Gradients and Difference of Gaussian

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Abstract

Face recognition is a widely used identification method in the machine learning field because face biometrics have necessary distinction for detection and have more accessibility compared to other biometrics. Despite their merits, face biometrics have various challenges. Mainly, these challenges can be categorized into local and global challenges. Local challenges can be addressed using sustainable methods against change while global challenges such as illumination challenges require powerful pre-processing methods. Therefore, in this study, a sustainable method against light changes has been proposed. In this method, two stages of the Difference of Gaussian have been utilized for the illumination normalization. Then, the features of the normalized image are extracted using Histogram of Oriented Gradient (HOG) and the feature vectors are classified using 3 k-nearest neighbor classifiers, the support vector machine with linear kernel, and the support vector machine with Radial Basis Function (RBF) kernel. Testing the proposed method on Computer Vision and Biometric Laboratory (CVBL) data indicated that the recognition rate, at best for the illumination challenge in the whole face and a part of the face was 98.6 % and 97.9% respectively.

***Keywords**: Face recognition, Light challenge, Difference of Gaussian, Histogram of Oriented Gradients*

1.Introduction

Various types of face detection biometrics were identified in the first decade of the 21st century. Depending on each system requirement, these biometrics have their own advantages and disadvantages. Therefore, it cannot be definitely said which biometric is better. For example, the sensitivity and cost of Iris Recognition are relatively high but it is inevitably used in some cases that the system is expected to have a very high factor of safety, However, the use of Fingerprint biometrics, seems to be a good option regarding its implementation cost and procedures in cases where the required factor of safety is not very high,

Among various types of biometrics, face biometric is the most popular face recognition biometric due to its appropriate factor of safety, simplicity and low implementation cost, and the possibility of using in visible and infrared spectrums. During recent years, a wide range of studies has been carried out on the face recognition using face images, and these studies have addressed so many challenges in this area. The most important challenges which have had the highest impact on

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the results of the studies include face recognition with facial expressions, face hidden with glossary or scarf [1-3], plastic surgery [4], pose variation [5] and face under visible light conditions. Illumination challenge is considered to be very important since this global challenge changes the light intensity of pixels and causes fundamental changes in the values of feature vectors.

Previous studies have used various pre-processing techniques for illumination normalization. One of the most used tools for normalization of unbalanced illumination is histogram equalization [6-10]. Even its improved versions such as Contrast-limited adaptive histogram equalization (CLAHE) [11], oriented local histogram equalization (OLHE) [8], Adaptive histogram equalization (AHE) [12], and Region-based histogram equalization (RHE) [13] have been widely used for normalizing unbalanced illumination on the face. Li et al. introduced a method based on Gabor filter, principal components analysis, and SVM classifier. In their study, histogram equalization and Gaussian band-pass filter have been employed to solve the problem of illumination on the face. Then, Gabor wavelets have been used for feature extraction and principal components analysis has been utilized to reduce the dimension of the feature vector and finally, the feature vectors machine has been employed for the classification [9].

Among other methods aiming at illumination normalization, Gama [1-15] and logarithm transformations [12,16,17] can be mentioned. In some studies, normalization has been performed using coefficients and properties of descriptors, including wavelet-based methods [18-20] and cosine transforms [12,21,22]. What most of the mentioned studies have in common is focusing on small-scale facial components. Small-scale facial components consist of the border and edges of images while large-scale facial components include uniform facial textures. Tu et al. proved that large-scale components are more influenced by light compared to small-scale components and high frequency of face images (border and edges) are less vulnerable to light. Therefore, edge-based methods obtain better results in response to the illumination challenge. One of the most commonly used methods of extracting small-scale components (edges) of images is the Difference of Gaussian [24]. This method maintains high frequencies of face images and transforms low frequencies which are damaged due to light changes to a similar frequency area; however, one of the main challenges of the Difference of Gaussian is the total destruction of large-scale components. To address this challenge in the present paper, two stages of the Difference of Gaussian have been used. At the first stage, small-scale components of the face are extracted using small standard deviations values. In the second stage, some of the large-scale components of face damaged by the illumination are extracted using large standard deviations values. Then, the total image obtained from the first and second stages generates the normalized image. After image normalization and at the feature extraction stage, the employed descriptor should be selected based on the edge since the feature of the image normalized by the Difference of Gaussian is often located in the edge areas. One of the most powerful edge-based descriptors is the Histogram of Oriented Gradient (HOG). Using two Sobel edge detection filters, this descriptor extracts image features and finally, a distinctive feature vector is generated for face image of each class. After feature extraction, the dimensions of the feature vectors are reduced as much as possible using principal components analysis. Employing principal components analysis, in addition to dimension reduction, causes omitting the correlation among the feature vectors values and making a distinction among the feature vectors of each class. In the end, the feature vectors are classified using the k-nearest neighbor classifier. Yu et al. proposed a method based on Gabor texture, general model and Gaussian Gama. In this research, two strategies of Gabor based on texture display phase and Gabor based on texture display size are presented. Texture size based strategy utilized Gama density and texture phase-based strategy used Gaussian density to model Gabor distribution extension [25].

Lukas et al. proposed a new method of face recognition through implementing discrete wavelet transforms and DCT using radial basis functions (RBF). In this study, discrete wavelet transforms and DCT are applied to images and the recognition process is done using RBF [26].

Banerjee et al. employed a band-pass correlation filter in the frequency range required for face detection under various illumination conditions [27]. Paria et al. employed a set of logarithm transformation based techniques, histogram equalization, and cosine transform to solve illumination on the face. The combination of these three techniques is a type of pre-processing to solve unbalanced illumination on the face. The three above-mentioned algorithms are conducted on the image with the unbalanced illumination and finally, the normalized image is generated [28]. Wang et al. proposed a new method to solve illumination and pose variation. This method is implemented based on homogeneous local binary patterns and multiple HOG. In this method, after extracting the features from each block, each face block is weighted using entropy data. In the end, the feature vector of each image is generated and feature vectors are classified through one of the methods of radial Basis function, RE, SVM, and WSRC [29]. Satange et al. proposed a new method for face recognition by combining Gabor extractors and Zernike moments. In this research, forty sub-images are generated from the main images with the scale of 5 and the orientation of 8 using the Gabor filter. Afterward, four Zernike features are extracted from each sub-image and the results are classified using the k nearest neighbour classifier [30]. Fan et al. suggested a phase Gabor based illumination-invariant face recognition. In this study, face light intensity is first reduced by normalization. Then, a set of Violet Gabor filters are employed for deforming images in different directions. Then, multiple Gabor filters are combined to obtain the spectrum and the phase. Ultimately, illumination invariance is obtained after the feature stage [31]. Mclaghlin et al. employed a band-pass filter for pre-processing and occlusion reduction. Fourier-magnitude is used for feature extraction. Finally, the cosine similarity criterion is used to measure the similarity degree of the feature vectors [32].

2.Proposed Method

The face recognition system presented in this study includes an edge-based normalization method to address the illumination challenge. Also, for feature extraction, high-frequency features have been employed. Just like most of the face recognition techniques, this method includes pre-processing, normalization, feature extraction, dimension reduction, and classification. Figure 1 shows the block diagram of the proposed method.

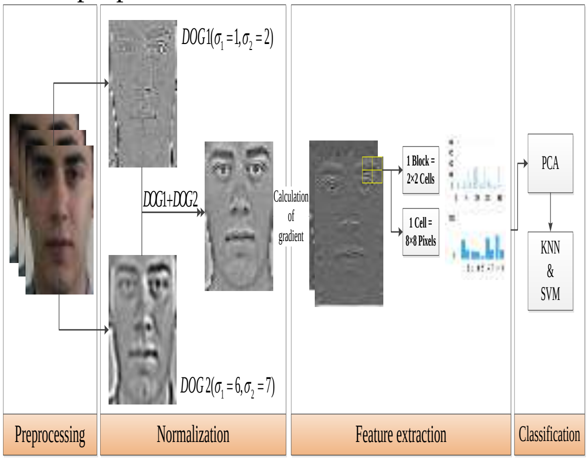

Fig. 1. The block diagram of the proposed method

2.1. Pre-processing

At the pre-processing stage, raw images have been transformed into ready-to-process images. In order to do so, the face area is firstly identified in the image and separated from the main image. However, since the face identification is not one of the objectives of this study, separation is manually performed using Image J Software. Figure 2 shows before and after separation.

(a) (b)

Fig. 2. (a): Before pre-processing. (b): After pre-processing

At the second stage of pre-processing, all the test images are resized to the equal size of 300*255 since the real size of the images is too large for processing and has a lot of computational complexities and high processing time.

2.2. Normalization

In the face normalization section, two stages of the Difference of Gaussian with different standard deviations are sequentially used. Finally, the results of these two stages are integrated. Therefore, at the first stage, the Difference of Gaussian with the standard deviations of 1 and 2 are applied to the image. The image obtained from Eq.1 contains small-scale components. In Eq.1 σ is standard deviations and x,y are kernel sizes (x=3, y=3). Figure 3 shows the image achieved from the first stage.

$$DoG_1 = G_{\sigma_1} - G_{\sigma_2} = \frac{1}{\sqrt{2\pi}}\left(\frac{1}{\sigma_1} e^{-(x^2+y^2)/2\sigma_1^2} - \frac{1}{\sigma_2} e^{-(x^2+y^2)/2\sigma_2^2}\right) \quad (1)$$

$:\sigma_1 = 1, \sigma_2 = 2$

Fig. 3. The image obtained by the first stage (a. no balanced light; b. normalized by DoG1)

At the second stage of Difference of Gaussian, standard deviations of 5 and 6 are applied to the image. Unlike the image achieved from the first stage, the image which has been obtained from Eq. 2, contains large-scale components in such a way that the obtained image has parts of large–scale components which are less damaged due to the light exposure. In Eq.2 σ is standard deviations and x,y are kernel size (x=3, y=3). Figure 4 shows the image obtained from the first stage.

$$DoG_2 = G_{\sigma_3} - G_{\sigma_4} = \frac{1}{\sqrt{2\pi}}\left(\frac{1}{\sigma_3} e^{-(x^2+y^2)/2\sigma_3^2} - \frac{1}{\sigma_4} e^{-(x^2+y^2)/2\sigma_4^2}\right) \quad (2)$$

$:\sigma_3 = 5, \sigma_4 = 6$

(a) (b)

Fig. 4. The image obtained by DoG algorithm under $\sigma_3 = 5, \sigma_4 = 6$ (a. no balanced light; b. normalized by DoG1)

At the final stage of normalization, the two obtained images are integrated. The first normalization output contains small-scale components (high frequencies of the image: border and edges) and the second normalization output contains large-scale components (high frequencies of the image: uniform areas of the face). This integration is done using Eq.3.

$$DoG = DoG_1 + DoG_2 \quad (3)$$

Fig.5 displays three images from the first and second stages and their integration.

(a) + (b) = (c)

Fig. 5. How integration is done and the image obtained from the integration of the first and second normalization stages (a. DoG1 image; b. DoG2 image; c. DoG1 and DoG2 integration image)

As observed, the image obtained from the integration of the first and second stages has more features and is closer to the real face. This can be proved using statistical properties. Entropy degree in the first, second and the integrated image is calculated to be 0.0280, 0.1060 and 0.0021, respectively.

2.2. Feature Extraction

Feature Extraction section is one of the most challenging parts of face-related studies since face image can undergo various changes in facial expressions, aging and changes in the light intensity on the face.

In the system, the system descriptor mainly makes a distinction between feature vectors of each class. HOG is an edge-based descriptor since the Sobel filter has been used in this descriptor for feature extraction. It should be noted that HOG is not sustainable against changes and normalization is necessary before feature extraction. To compute HOG, firstly, images are filtered in x and y directions using Soble kernels to obtain the image gradients in x and y directions. This stage is done using Eq.4.

$$G_x = I * D_x \quad , \quad G_y = I * D_y \tag{4}$$

Where I is the main image, D_x and D_y are the Sobel kernels in x and y directions and * is convolution operator. Figure 6 shows the image achieved from the two Sobel kernels.

(a)

(b)

Fig. 6. The imaged obtained by Gradient of the two Sobel kernels (a. vertical gradient kernel, b. horizontal gradient kernel)

Then, the HOG of each cell is measured in 90 bins. Finally, the histogram of cells and then blocks are integrated and the gradient histogram of each image is calculated. However, one of the main problems with deep learning studies is generating feature vectors with large dimensions. This problem also exists in the present study and feature vectors extracted from face images have more than 13000 features. It should be noted that firstly, classifying these dimensions of the feature vectors for each classification is very hard and time-consuming; secondly, various tests have indicated that smaller dimensions determine the target class more easily. Therefore, principal components analysis has been used for reducing the dimensions of the feature vectors. In addition to selecting the largest variances containing the first components and most exact information about the feature vector, this algorithm reduces the correlation between data by computing the feature vectors variance which leads to more distinction of the feature vectors. Finally, after the reduction stage, a feature vector with 196 distinctive features is generated for each image. The generated feature vector contains new values with the dimensions smaller than the original dimensions and also results in generating more distinctive vectors compared to the primary vectors extracted by the descriptor in terms of quality.

At the second stage, the size and direction in each pixel is calculated and the highest value is selected as the gradient size of that pixel. Gradient of each pixel is obtained according to Eq.5.

$$\begin{aligned} |G_x(i,j)| &= \sqrt{(G_x(i,j))^2 + (G_y(i,j))^2} \\ \theta_G(i,j) &= \tan^{-1}\frac{G_x(i,j)}{G_y(i,j)} \end{aligned} \tag{5}$$

Where absolute value of G is the size of gradient, θ_G is the direction of gradient, and i and j are the row and column of pixels, respectively. At the third stage, as shown in Figure 7, the image is divided into 16*16 pixel blocks without overlap. Each block has four 8*8 pixel cells without overlap.

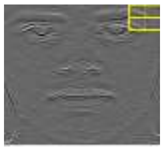

Fig. 7. Example of setting blocks and cellularization of gradient image

2.3. Classification

In this section, the SVM classifier and the k-nearest neighbour classifier are employed. Different types of SVM classifiers use different types of kernels, but in this paper, a linear kernel SVM and RBF kernel SVM have been used randomly. For more investigation, the k-nearest neighbour (KNN) classifier is also used. Euclidean distance and the value of 1 are used for the KNN.

3-Discussion and Results

In this section, the efficiency of the proposed method has been evaluated using the introduced database. Since the proposed method has different conditions and parameters at each stage of the feature extraction, normalization and classification, each stage has been evaluated through different conditions and parameters which are described in the following.

In the normalization section, the results of the study are evaluated in 4 conditions.

1. No normalization is done on the image and the feature is extracted directly from the face image with the unbalanced illumination.
2. Normalization is done only by DoG2.
3. Normalization is done only by integrating DoG1 and DoG2.

The above mentioned tests are conducted by the descriptor used in this study and under the conditions of 90 bin with the k nearest neighbour classifier. In the feature extraction stage, the results are evaluated in the following 4 conditions:

A. The number of HOG's bin is 60.
B. The number of HOG's bin is 90.
C. The number of HOG's bin is 120.
D. The number of HOG's bin is 180.

The HOG descriptor test is done under the condition of normalization of DoG1 and DoG2 integration using the k-nearest neighbour classifier. In the classification section, the research is evaluated by these three classifiers:

- K-nearest neighbor classifier
- SVM classifier with linear kernel
- SVM classifier with RBF kernel

The classifier test is done under the normalization of DoG1 and DoG2 integration condition and HOG descriptor with 90 bins. In the following, the employed image database is described and then, the results of the tests are determined and a comparison is made among the aforementioned methods.

3.1. Database

The database employed in this study has been collected by the researchers, containing 5000 images of 200 people in the visible spectrum in such a way that each person is photographed in 10 images without the illumination challenge, 10 images with unbalanced illumination on a part of the face and 5 images with unbalanced illumination on the whole face. Figure 8, presents the samples of the collected images.

(a) (b) (c) (d)

Fig. 8. Samples of the collected database images a) Without illumination; b) Light intensity at the left side of the image; c) Light intensity at the right side of the image; d) Light intensity on the whole image.

3.2. Results

Test image sampling in all the tests have been random and 5 images out of 10 images without the illumination challenge and 2 images out of images with light intensity challenge have been randomly selected. The dataset employed in these tests included 5000 images of 200 people (25 images of each people). All the tests have been repeated 10 times and identification accuracy have been calculated and recorded after each implementation. The recorded identification accuracy is the result of 10 observations. Also, considering the identification accuracy values achieved after 10 reiterations with the significance level of 95%, the confidence interval of all the tests have been calculated. The confidence interval in this study is calculated using equation 6.

$$\mathrm{CI} = \left[\bar{x} - z^{*} \times \frac{\delta}{\sqrt{n}} , \bar{x} + z^{*} \times \frac{\delta}{\sqrt{n}} \right] \qquad (6)$$

Where CI is confidence interval , x is the average identification rate of 10 observations; z^{*} is the level of confidence (its value equals to 1.96 when significance level is at 95%); n is the number of observations (10), and δ is the standard deviation.

3.3. Normalization evaluation

As mentioned earlier, the illumination challenge in the visible environments is a global and serious challenge and the identification rate will be substantially reduced if the necessary pre-processing is not conducted. In the previous section, the normalization methods are explained and the obtained results are presented in Figure 9.

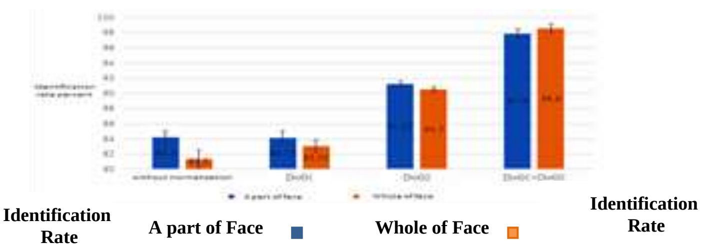

Fig. 9. The results of various normalization types

According to Figure 9, it can be concluded that the lack of conducting normalization of illumination on the face in the images of visible environment has a huge impact on the identification rate; therefore, an illumination normalization system seems necessary in all the methods based on visible environments. Moreover, normalization using the Difference of Gaussian in low standard deviations (DoG1) which leads to identifying edges and removing a high part of small-scale components is unable to improve the identification rate in the local and global light intensity and is no different than not conducting normalization at all. Hence, this type of normalization cannot be an appropriate method to address the illumination challenge. Besides, normalization using the Difference of Gaussian with large standard deviations leads to better results but the obtained identification rata is still far from the ideal rate. The last and the most important point is that using Difference of Gaussian with large standard deviation can highly improve the identification rate but after the normalization using the Difference of Gaussian with large standard deviations, high frequencies of the image are highly destroyed. To solve this issue as well as improve the identification rate, in this study, the image obtained from the normalization using Difference of Gaussian and low standard deviation (DoG1) and high standard deviation (DoG2) are integrated, resulting in the improvement of the identification rate up to 97.9% in the local intensity and 98.6% in the global intensity of the illumination on the face.

3.4. Feature extraction evaluation

As mentioned earlier, HOG is the descriptor used in this study. The most important parameters of this descriptor include the block size, the cell size and the number of histogram bins. Since the number of bins has a significant effect on the distinction of the feature vectors of each class due to change in dimensions and values of feature vectors, the effect of the number of bins has been evaluated in this study. Figure 10, shows the results obtained from the different numbers of bins. As it is shown in Figure 10, the best number of bins is 90. In other words, the frequency of each degree of gradients in a bar is computed. The low and high number of these bars causes an indistinctive and uniform histogram for different faces. Hence, 90 bars can be the best result for the most distinctive feature vectors. As observed in the figure, 90 bars of HOG have achieved the highest identification rate in the lower and higher bins with the identification rate of 98% in the global light intensity and 97.9% in the local light intensity.

3.5. Classification evaluation

In this study, three classifiers of SVM with linear kernel and RBF kernel and k-nearest neighbor have been employed for the classification. In this section, a comparison is made between these three classifiers to determine one of them as the most appropriate classification method. Figure 10 shows the results of this comparison.

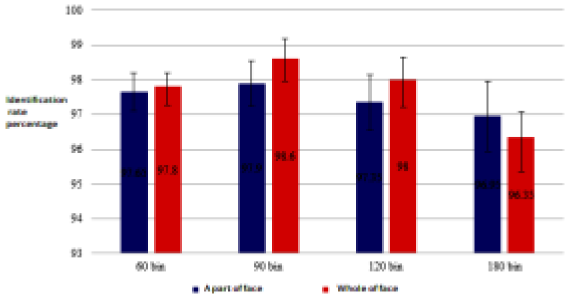

Fig. 10. The results obtained from changing the number of bins and HOG descriptors.

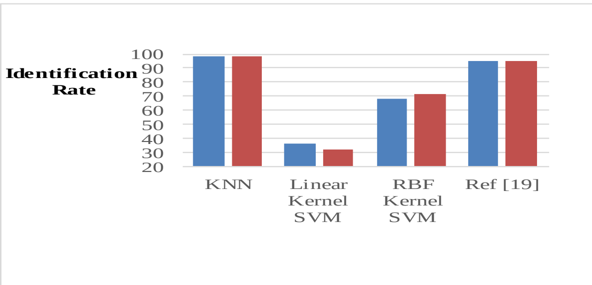

Fig. 11. The results obtained by comparing the three classifiers.

Another criterion in the face identification is precision. Figure 12 shows the result of precision in the proposed method. As figure 12 shows, the proposed method leads to better results in the KNN classifier It also has better results than reference [19]. Author in [19] have been used the combination of Discrete wavelet transform and Machine learning techniques for face recognition on ORL dataset. In the best reported recognition rate in experiments in [19] was 100% but in real condition and the average of experiments the reported recognition rate is 93.34%. In following proposed method are compared with reference [19]. Furthermore, the time required for the identification is shown in figure 13. The required identification time in the KNN classifier is less than the others.

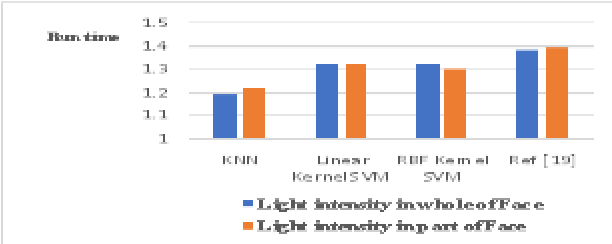

Fig. 12. The results obtained from comparing precision for three classifiers.

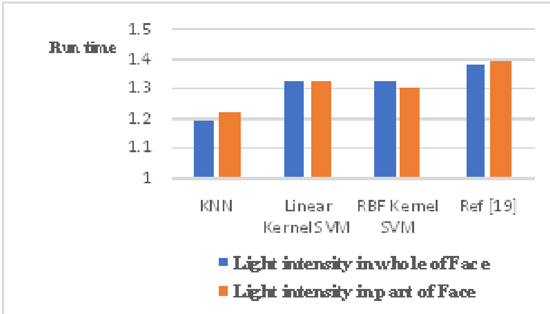

Fig. 13. The results obtained from comparing runtime for three

For more evaluation, the proposed method has been tested on ORL data set. There are 400 images of 40 subjects in different positions. The identification rate, precision and run time have been evaluated. Figure 14 shows the Identification rate, figure 15 indicates precision, and figure 16 shows run time. Evaluation is done using SVM classifier in RBF and linear kernels as well as KNN. As results indicate in figure 14-16, the KNN classifier achieved the best results.

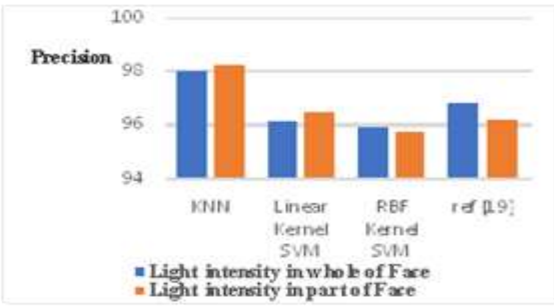

Fig. 14. The results obtained from comparing identification rate for three classifiers in ORL database

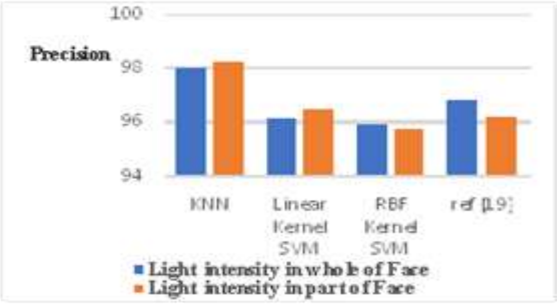

Fig. 15. The results obtained from comparing precision among three classifiers in the ORL database

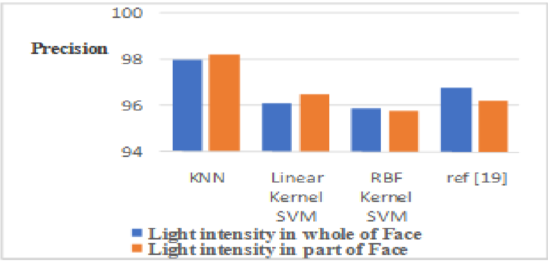

Fig. 16. The results obtained from comparing runtime among three classifiers in the ORL database

4.Conclusion

In this study, one of the main challenges in face recognition was addressed. In this regard, a new method based on Histogram of Oriented Gradient and two support vector machines and the k nearest neighbour classifier was proposed. The proposed method was investigated in two modes of illumination on the whole face and a part of the face. The proposed method was tested on CVBL data and ORL face database. The test results revealed that the identification rate, at best, was 98.6% for the whole face and 97.9% for a part of the face. Also, precision and run time were evaluated on the CVBL and ORL database. Among all the classifiers, The KNN classifier achieved the best results.

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