Face Recognition with Symmetrical Face Training Samples Based on Histograms of Oriented Gradients

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ABSTRACT

Face recognition technology is one of the advanced technologies that help to recognize and identify human faces using an image or video clip. Although many face recognition techniques have been proposed in the literature, a robust face recognition system is still a challenging task. It is known that, in general, increasing the number of training images also increases the performance of face recognition systems. In this paper, a new set of training samples is generated from the original samples, using the symmetry property of the face and the recognition performance is improved. The proposed method has three main stages: generating new images, feature extraction and classification. the symmetry property of the face is used to generate new images, the Histograms of Oriented Gradients is used for feature extraction and the Euclidean distance is used for classification. The proposed method is tested and evaluated using AR dataset which is widely used for testing and comparing the accuracy of face recognition systems. The experimental results show that the proposed method has a recognition accuracy rates higher than the traditional methods.

Keywords: face recognition; symmetry; histogram of oriented gradients

1 Introduction

With the development of the computers and computer-based systems, their application areas for computer vision-based systems have been increased based on demand for the daily life, One of the important demands for the computer-based systems is face detection and recognition for security systems.

Humans are identified by their physiological, behavioral, and biological properties by biometrics. Biometrics are divided into two categories: physiological biometrics, which include the identification of individuals by physiological and biological characteristics such as face, fingerprint, iris, eye, etc. The second category is the behavioral biometrics, which include the identification of individuals through human situations such as handwriting, signature ,walking, etc. [1].

Robust and accurate face recognition (FR) is one of the most important problems in computer vision applications. In literature, there are several methods used for FR, including holistic, local, and hybrid methods [2, 3]. However, recent research has revealed that a symmetry-based approach for FR is a useful method to increase the performance of the FR system; thus, it is possible to realize FR using the property of face symmetry [4, 5].
The benefit of using symmetry property in FR is studied by Allagwail et al as presented in [6, 7] however more study is presented in this paper.
There are many methods can be used to extract the features from the face images such as: the Local Binary Pattern (LBP) [8-10], the Gray Level Co-Occurrence Matrix (GLCM) [11], the Gabor Filter [12], and the Histograms of Oriented Gradients (HOG) [13], since these methods perform well for a texture feature extraction that could be used for the FR [14-16].
The performance of FR methods can be tested and examined using some benchmark facial datasets [4, 17, 18] such as: Olivetti Research Laboratory (ORL) [19],Yale [20] and AR datasets [5, 21, 22].

2 Materials and Methods

Although there are many image processing methods, only some of them are able to solve face recognition problem [23]. There are many methods proposed, for instance, Principle Component Analysis (PCA) [24], which is also called as Eigen faces [25], Linear Discriminant Analysis (LDA) [26]. The two most popular methods are eigenfaces [27], and Fisherfaces [28].
In this paper, we have implemented a face recognition system based on the original and symmetrical samples of the face images. In the first stage, more training images, for FR system, are generated using the symmetry property of the face, then in the second stage, the HOG technique is used to extract the features form the training and the testing images, these features are fit to the final stage, the classification stage, which classify the features or images according to their Euclidean distance to the tested images. The images which are used in the experiments are taken from AR dataset.

3 Theory and Calculation

3.1 Generating new images

In order to increase the size of the training data, new training images are generated using the symmetry property of the face, since those images reflect some appearance of the face that is not shown by the original images as illustrated in Figure 1.

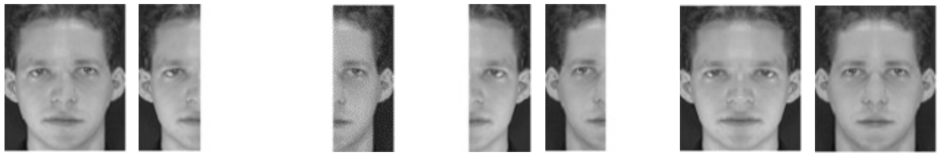

Figure 1: a) Original image, b) left side, c) right side, d) mirror of left side, e) mirror of right side, f) integrating left side with mirror, g) integrating right side with mirror

3.2 Feature extraction using Histograms of Oriented Gradients (HOG)

One of the very popular methods for feature extrication is the Histograms of Oriented Gradients (HOG). It is one type of descriptors that is used a lot in the human detection [13]. The HOG concept is to compute the gradient orientation and the gradient direct magnitude. To obtain the HOG of an image, first, the changes in X and Y are computed, then the magnitude and direction are obtained.

3.2.1 Computing Gradients

The main operation of HOG is the derivative, or the center difference, since, there are two derivatives, the x derivative and the y derivative, once these derivatives are obtained, the gradient magnitude and the gradient orientation can be computed.

$$f'(x) = \lim_{h\to 0} \frac{f(x+h) - f(x-h)}{2h} \tag{1}$$

The magnitude is given by:

$$s = \sqrt{s_x^2 + s_y^2} \tag{2}$$

And the orientation is given by:

$$\theta = arctan\left(\frac{s_y}{s_x}\right) \tag{3}$$

3.2.2 Blocks and Cells

Figure 2 shows a face image, it is assumed that this image is a 64x128 image, if this image is divided to 128 cells, then some blocks are taken, for example the first block is block 1 with 2x2 cells, then the second block is 50 % overlapped, which block 2, so, each block is consist of 2x2 cells with size 8x8 which means 16x16, with 7x15 = 105 blocks in total.

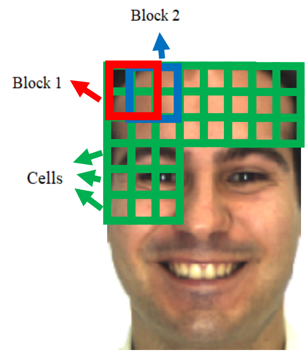

Figure 2: The blocks and the cells

3.2.3 HOG Feature Extraction Steps

To calculate the HOG for an image with 64 x 128, for example, the image is divided onto 16x16 blocks with 50% overlap, so therefore there are 7x15 with total of 105 of blocks, and each block consists of 2x2 cells, and the size is 8x8, then the HOG is quantized with 9 directions or bins, if the direction is not one of the bins then some kind of interpolation can be done, also, the Gaussian can be applied to smooth the histogram, then all the descriptors can be concatenated since there are 105 of these block and each one is 9 dimensional, this gives a very large described, about 3780 dimension descriptor and this for the whole image of the block in the image, as shown in Figure 3.

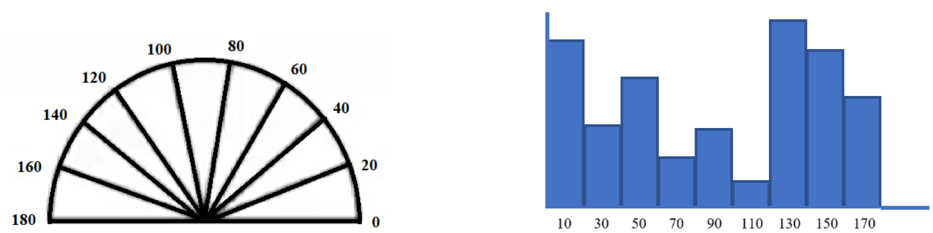

Figure 3: The histogram quantization to 9 bins

The procedure of HOG for feature extraction can be summarized in the following steps:

1. Compute the centered horizontal and vertical gradients with no smoothing.
2. Compute gradient orientation and magnitudes.
    - For color image, pick the color channel with the highest gradient magnitude for each pixel.
3. For 64x128 image,
4. Divide the image into 16x16 of 50% overlap.
    - 7x15=105 blocks in total
5. Each block should consist of 2x2 size 8x8.
6. Quantize the gradient orientation into 9 bins.

- The vote is the gradient magnitude.
- Interpolate votes bi-linearly between neighboring bin center.
- The vote can also be weighted with Gaussian to down-weight the pixel near the edges of the block.

Concatenate histograms (Feature dimension: 105x4x9 = 3780)

3.2.4 The Linear Interpolation

The better histograms can be found by doing the interpolation. If there are 9 bins, and the range of the gradient orientation is between [0^o 180^o], this range is quantized into these 9 bins, if the orientation has 85^o , and since, there is no bin with 85^o, in this case, this is split into couple of bins which are closest to that, these bins are 70^o and 90^o, since the difference between 70^o and 85^o is 15^o , and the difference between 90^o and 85^o is 5^o, the values is divided proportionally according to this ratio, that means (5/20 = 1/4) and (15/20 = 3/4), and the histogram is distributed according to this concept, as shown in Figure 4.

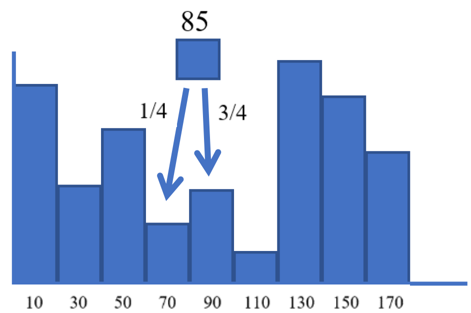

Figure 4: The HOG interpolation

3.2.5 Feature Vector

Each block has its histogram, all the histograms are concatenated to produce the final feature vector of the all image as shown in Figure 5.

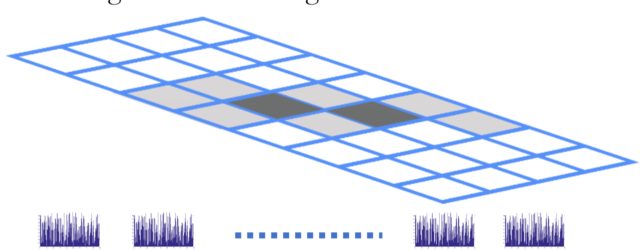

Figure 5: Concatenating the histograms

3.2.6 Visualization

The visualization of the HOG, as in Figure 6, with some blocks and each block has its histogram which corresponds to the face regions, and some blocks give the dominating direction for some certain region, which give the visualization of the representation that represents the face and calculates how much the distance from these different parts of the face.

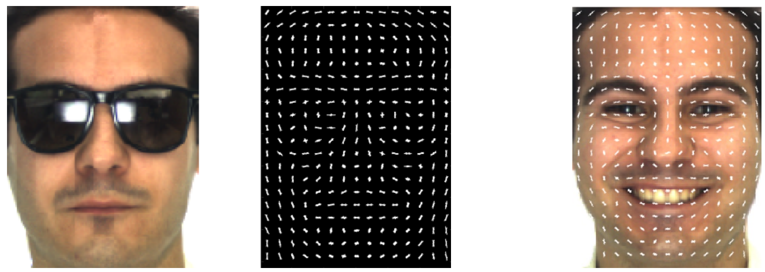

Figure 6: The HOG visualization

By looking to the presentation (middle figure), it is clear it is representing a face, and this is used to recognize the face. Once the descriptor exists, for lots of training examples (faces), then any train techniques such of machine learning can be used for face recognition by classifying the face according to their features.

The HOG is a very strong and popular descriptor, and it is a kind of global descriptor which looks at the whole image. Authors propose this descriptor and they use it for face detection [13] and face recognition [29].

3.3 Classification

The Euclidean Minimum Distance classifier is used for the classification stage since it is considered to be one of the most popular classifiers that can be easily designed and widely used [30]. In general, it is used to examine the similarities between objects.

The Euclidean distance d between two points i and j, where $i = (i_1, i_2,..., i_n)$ and $j = (j_1, j_2,..., j_n)$, in Cartesian coordinates, is the length of the straightest line between them. This distance is given by the formula:

$$d(i,j) = \sqrt{(i_1 - j_1)^2 + (i_2 - j_2)^2 + \cdots + (i_n - j_n)^2} \quad (4)$$

Therefore, if the two points are close to each other, then the value of d is small; otherwise, it is large. The Euclidean vector is the location of a point in a Euclidean n-space, where the length of this vector is measured by the formula of the Euclidean norm, given by:

$$\|I\| = \sqrt{i_1^2 + i_2^2 + \ldots + i_n^2} \quad (5)$$

This tool is used to test how similar one object (face) is to another by testing the similarities between their respective feature vectors.

3.4 Dataset

The AR dataset is used in many face recognition papers, it contains over 4000 color face images of 126 people, including 26 frontal views of faces with different facial expressions, illumination conditions and occlusions, like (smile, anger, scream, left light on, right light on, all side lights on, wearing sun glasses, wearing sun glasses and left light on, wearing sun glasses and right light on, wearing scarf, wearing scarf and left light on, wearing scarf and right light on). The images of 120 individuals are captured in two sessions and each session contains 26 color images [21]. Figure 7 shows some images form AR dataset.

Figure 7: AR face database

4 Results and Discussion

These results are carried out using the images from AR dataset, In this part, all AR dataset is used to test the recognition system, the system is trained using 10% of dataset and the rest 90% is used for testing, then 20% for training and 80% for testing, up to 95% for training and 5% for testing. In this experiment, the Histograms of Oriented Gradients HOG is used for feature extraction, this technique extracts a lot of feature from the image and produce a long feature vector that describe the information in the image. The results are shown in Figure 8. The recognition system is examined one time using original training samples (OTS) and the second time using original with symmetrical training samples (OSTS).

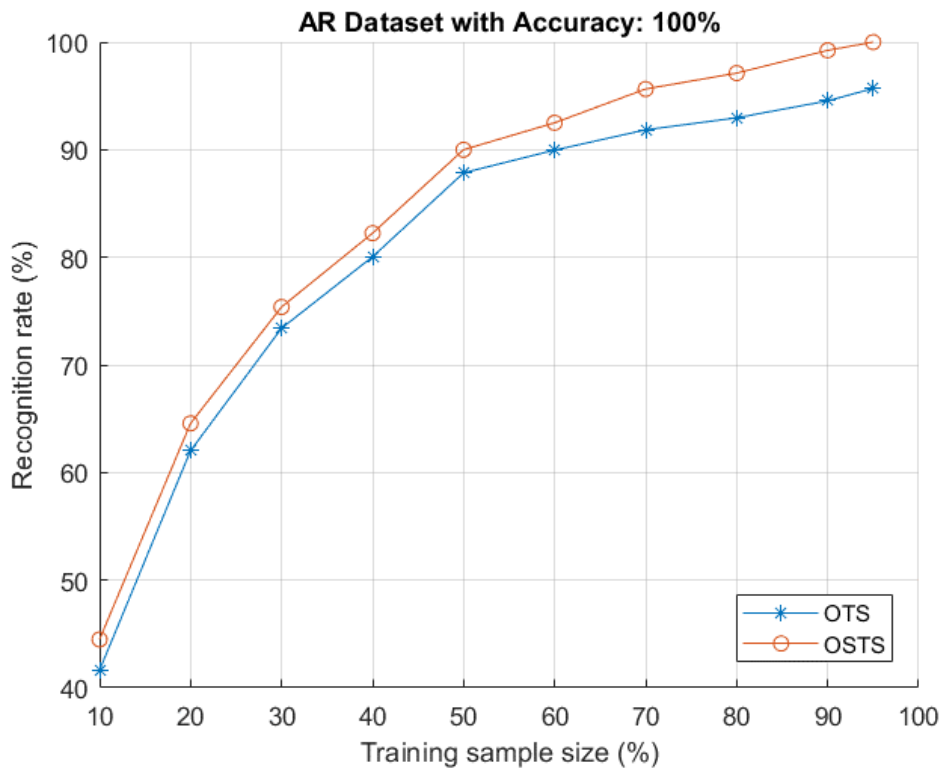

Figure 8: The recognition rate using HOG for OTS and OSTS

The obtained results are summarized in Table 1.

Table 1: *The recognition rates on the AR dataset, using the OTS and the OSTS*

Type of training samples	Training set %									
	10	20	30	40	50	60	70	80	90	95
	Recognition Rate %									
Original training samples (OTS)	42	63	73	82	89	91	94	96	97	98
Original with Symmetrical Training samples (OSTS)	44	65	75	82	90	93	96	97	99	100

As we can see from Figure 8 and Table 1, as the number of training samples increase, the accuracy increases too. Also, in general, the results using original with symmetrical samples are better than using only the original samples.

5 Conclusions

This paper presents an effective method to overcome the restricted number of the training sets using the symmetry property of the face. First, a new set of face images is generated using the left and right halves of each face. Second, the features of these samples are extracted using HOG method. Finally, the Euclidean classifier is used to obtain the results of the recognition. The experimental results show that the proposed method has a recognition accuracy rates higher than the traditional methods.

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