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Hybrid Method for Face Description Using LBP and HOG

Azhaar Abd. Hassan[1] Dr. Kadhim M. M. AlMousawi[1] Dr.Mustafa J. Hayawi[1]

[1]Department of Computer Science, College of Education for Pure Science University of Thi-Qar, ThiQar-Iraq

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Abstract:
Face recognition has become an important issue in our current life and it is a fundamental task for applications such as face tracking, red – eye removal, face recognition and face expression recognition.
In this paper we present a hybrid approach based on combination of local binary pattern (LBP)and Histogram of Oriented Gradient(HOG). LBP algorithms, which works with the shape and texture information are taken into consideration for representing the facial image. The hog algorithm of descriptor attributes is used to detect the object. It is computed using a dense grid of uniformly spaced cells and uses overlapping local contrast normalization for improved accuracy.
The ORL database was used to test each algorithm for a set of images. The efficiency of the LBP algorithm is evaluated by distinguishing a group of face images from 80%. The HOG algorithm achieved 90% classification accuracy obtained, while the hybrid method 94.25%.

Key word: *Face descriptor, hybrid, LBP, HOG*

1. Introduction:

The presence of various commercial systems for face recognition [1]. confirms the noteworthy advancement accomplished field [2]. In spite of the achievements made, the question of face recognition remains the focus of researches on computer vision. This can be ascribed to the fact that the performance of the existing systems is better under relatively controlled environments while it tends to suffer when variations in different factors (e.g. pose, illumination etc.) exist. Consequently, the present research is aimed at increasing the current systems` robustness in the face of different factors. Ultimately, our aim is to develop a system of face recognition able to mimic the outstanding capabilities of human visual perceptions. Attempts to reach this goal should be preceded by continuous endeavor to learn what weaknesses and strengths involved in the proposed techniques so as to identify new paths for any future improvement [3].

2. Face Description with Local Binary Patterns:

As introduced by Ojala et al [4], the original LBP operator is considered a powerful means for the description of texture. The pixels of an image are labeled by the operator through thresholding each pixel`s 3x3 neighbourhood with the center value and considering the result as a binary number.
Then the label`s histogram can be utilized as a texture descriptor. For an illustration of the basic LBP operator, see figure (1). The operator, Later, was extended to use different sizes neighbourhoods [5]. Through the use of circular neighbourhoods and bilinearly interpolating, any radius and number of pixels in the neighbourhood are allowed by the pixel value. For neighbourhoods, the notation (P, R), which means P sampling points on a circle of radius of R, will be used. See Figure (1) for an example of the circular (8.2) neighbourhood. The so called uniform patterns [5] are used as another extension to the original operator. When a local binary pattern contains at most two bitwise, it is termed uniform.

Figure (1) for an example of the circular (8.2) neighborhood
The LBP patterns locally encodes the textures of the facial regions while the construction of the face feature histogram recovers the whole shape of the face.

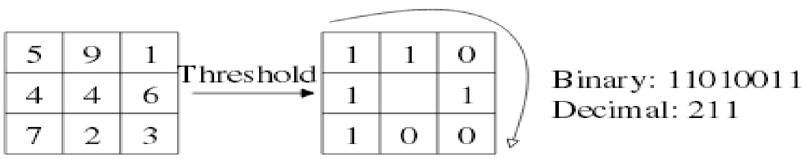
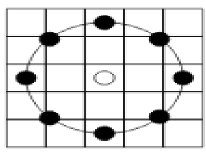


Fig. 1. The basic LBP operator.



The reason why the LBP features are used is that the face images may be viewed as composition of micro-patterns which are constant regarding monotonic grey scale transformations. Thus, It becomes possible to obtain a global description of the face image through combining these micro- patterns.
It has also been figured out that when LBP is combined with histograms of oriented gradients (HOG) descriptor, the detection performance improves considerably by this combination on some datasets.

3. HISTOGRAM OF ORIENTED GRADIENTS

In the processing of computer vision and image, histogram of oriented gradients is feature descriptor utilized in object detection. Count of the appearance of gradient orientation in localized portions of image is made. This method is the same as that of scale invariant feature transform descriptors, shape contexts and edge orientation histograms, yet it involves the use of overlapping local contrast normalization and is computed on a dense grid of uniformly spaced cells in order to improve the accuracy [6].

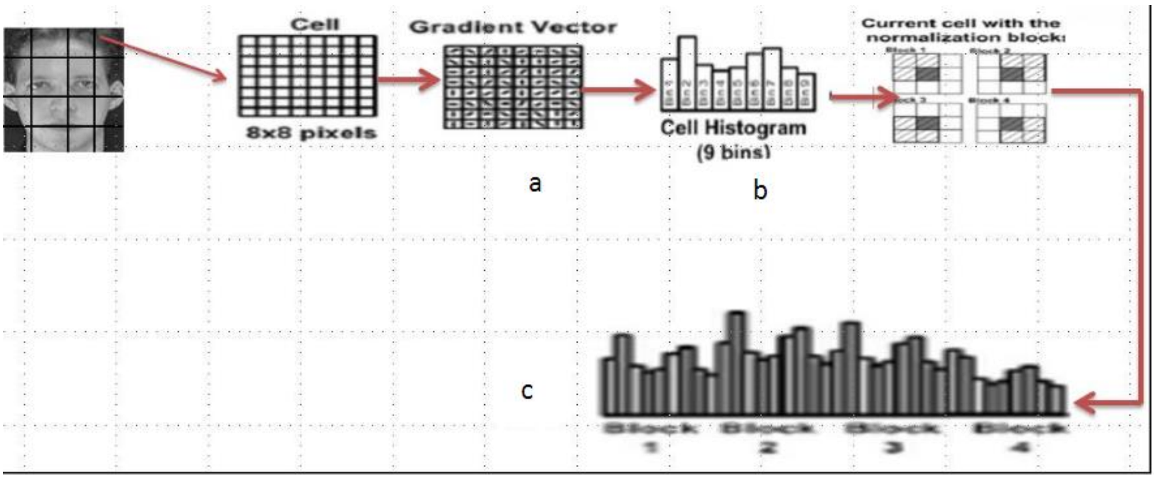
A. Basic Theory

As is the case in the SIFT and EBGM method, the HOG feature is generated for each key-point of an image. The neighboring area around each key-point in the image is divided into uniformly spaced cells.

For each cell a local 1-D histogram of edge orientations or gradient directions is accumulated over all the pixels of the cell. the histogram entries off all cells around that key-point forms the feature of a key point. The feature of a key-point is shaped by the histogram entries off all cells around that key-point. The image is represented by combining the histogram features of all key point. the histogram of oriented gradients (HOG) is considered a dense method of feature extraction for images. The meaning of dense here is extracting features for all locations in the image (or a region of interest in the image) as opposed to only the local neighborhood of key-points like SIFT (Scale Invarient Feature Transformation). Intuitively it tries to capture the shape of structures in the region through capturing information about gradients.

This is performed through dividing the image into small (usually 8x8 pixels) cells and blocks of 4x4 cells. Each cell consists of a fixed number of gradient orientation bins. Every pixel in a cell votes for the bin for orientation of gradient with a vote commensurate to the gradient magnitude at that pixel. For reducing aliasing, the pixel's votes are bilinearly interpolated. This interpolation takes place in both the orientation and position. This statement is important, it means that a pixel will vote both for its orientation bin, and to neighboring orientation bins (e.g. the gradient orientation at a pixel is 45 degrees, it will vote with a weight of 0.5 for the 35 to 45-degree bin and a weight of 0.5 for the 45 to 55-degree bin).

Similarly, it will also vote for the other two orientation bins not only in its cell, but also in the neighboring four cells of its cell The distance of the pixel from the cell center is used to determine the weight. Histograms are also normalized on the basis of their energy (regularized L2 norm) across blocks. Since the block has a step size of one cell, a cell will be a part of four blocks. The four differently normalized versions of cell's histogram are defined accordingly. These four histograms are concatenated to get the descriptor for the cell.



Figure(2). Image divided into small regions called cells. Local 1-D histogram of edge orientation or gradient direction are accumulated and concatenated to form the final histogram feature.

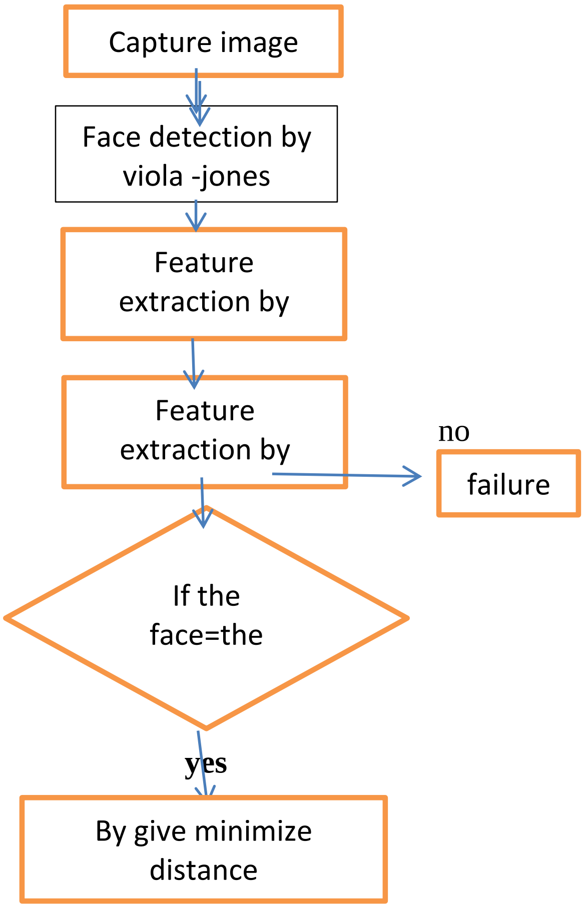


figure (3) block diagram

The proposed technique:

A. Viola –jones face detection method:

The first step of the viola-jones face detection algorithms is to change the input image into a new image representation termed an integral image that allows a very fast feature evaluation. The used features are reminiscent of haar basis functions. The viola-jones method analyzes a 24*24 sub-window using features consisting of more rectanfles. Each feature results in a single value which is calculated by subtracting the sum of the white rectangle(s) from the sum of block rectangle(s)

B. Local binary pattern:

Local binary pattern method was utilized to extract the relevant features of facial images. It is generally referred as the use of descriptor to Face recognition based on LBP. Descriptor is a allocation of faces, using both shape and texture information to represent face images. The face territory is first isolated into little districts from which Local Binary Pattern (LBP) histograms are extracted and concatenated into a single, spatially enhanced feature histogram efficiently representing the face image. The recognition is thorough using a nearest neighbour classifier in the computed feature space with Chi square as a dissimilarity measure

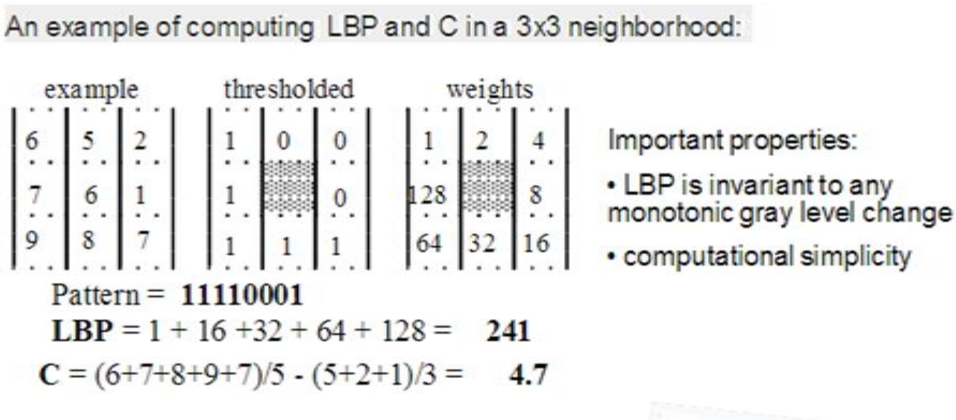


Figure (4) example of computing LBP

After the image is captured by a front camera, the image of the destination is determined by Viola Jones and the images are standardized to 201 * 201 and converted to gray and the LBP and HOG is send for, to get the advantages of the image and compare what was obtained with the database and the lowest value represents the corresponding image. The nearest two images are selected for the specified person from the set of pictures in the database. Which has the lowest value that is closer to the right person

c. Step of HOG calculation

1. **Gradients and orientations calculation**

Sobel filters are used to obtain the edge gradients and orientations. The gradient magnitude m (x, y) and orientation θ (x, y) are calculated using the x-direction and y-direction gradients dx(x,y) and dy(x,y) computed by

equation: -

$$m(x,y) = \sqrt{dx(x,y)2 + dy(x,y)2} \quad (1)$$

$$\theta(x,y) = \begin{cases} \tan^{-1}\left(\frac{dy(x,y)}{dx(x,y)}\right) - \pi \text{ if } dx(x,y) < 0 \text{ and } dy(x,y) < 0 \\ \tan^{-1}\left(\frac{dy(x,y)}{dx(x,y)}\right) + \pi \text{ if } dx(x,y) < 0 \text{ and } dy(x,y) > 0 \\ \tan^{-1}\left(\frac{dy(x,y)}{dx(x,y)}\right) \qquad \text{otherwisw} \end{cases} \quad (2)$$

HOG work through partitioned local region into small spatial area called “cell”. The size of the cell is 4×4 pixels, and then computed Histograms of edge gradients with 9 orientations for each of the local cells.

2. Histogram calculation:

Histograms of edge gradients are calculated from each of the local cells by taking with 8 orientations for each cell. Then the total number of HOG features becomes (8 × (4 × 4) =128) and they constitute a HOG feature vector. Gaussian weighting function is used to assign a weight to the magnitude of each pixel to avoid sudden changes in the descriptor with small changes in the position of the window, and to give less emphasis to gradients that are far from the center of the descriptor Gaussian weighting function with σ equal to one half the width of the descriptor window.

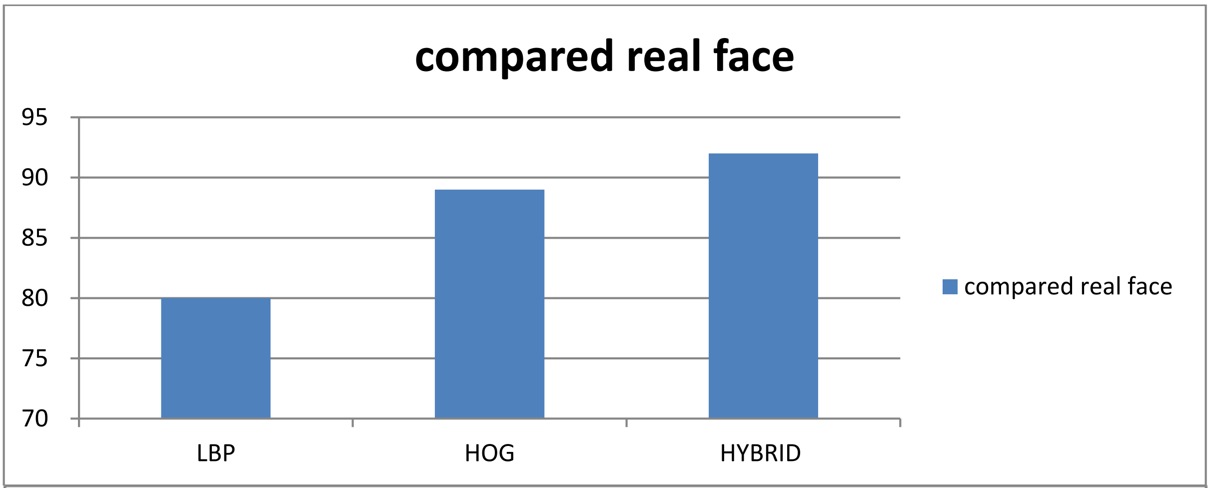
Experiment result:

In this paper, the methods of distinguishing faces are first compared to the LBP method and between the HOG and its hybrid (LBP + HOG) and using 2018 MATLAB and their applications with the ORL database containing 400 persons.

Where the application of LBP on the ORL database gives a matching ratio of 84%, while using the HOG on the same rule gives 93%. When combining the two methods (hybrid) give a ratio of 94.25% on the ORL database.

Table (1) sample of database

experiment	databace	LBP	HOG	Hybrid
1	ORL	84	90	94
2	Real face	80	89	92



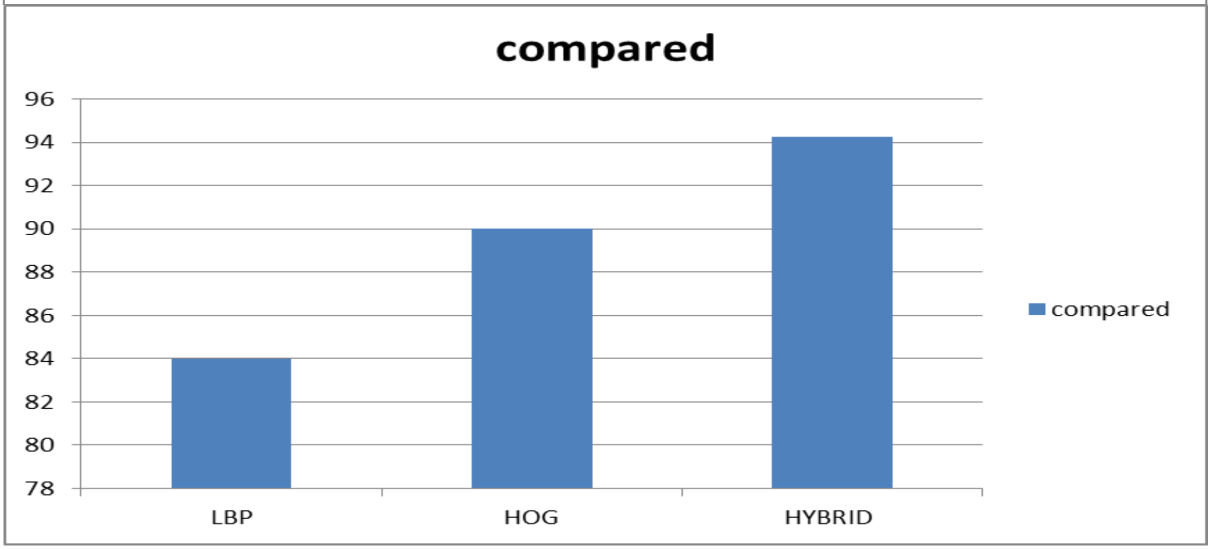


Figure (5) comparing of result for algorithms

Conclusion:

In this paper, the face descriptors were used to distinguish and determine the human destination. Matlab 2018b was compared and the LBP algorithm was independently compared to the real face database as well as the ORL database as well as the HOG algorithm was utilized on the same database. Batter results emerged when algorithms were combined.

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