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Face Recognition Using Robust Rule Based Local Binary Patter

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Abstract: *A novel efficient and robust methodology for quick face recognition by using Rule based Local Binary Pattern (RLBP) has been presented. The face image is said to be divided into a number of 3x3 regions, called as micro patterns, indicating the structure of the gray level pixels within a neighborhood to describe the spatial context of represented as rule number to evaluate the membership degree of the central pixel to the others within a neighborhood. A Local face distributor for each of the 3x3 neighborhood, called LBP descriptor, is obtained by applying Rules from which the RLBP feature distributions are extracted. Use of contributes to more than a single bin in the distribution of LBP values in the feature vector. The recognition is performed using a nearest neighbor classifier in the computed feature space. Experiments clearly show that the use of RLBP leads to improved reliable face recognition than to the original methods, LBP and Rule Based LBP.*

Keywords: *Local Binary Pattern, Face Recognition, RLBP.*

1. Introduction

Image segmentation partitions an image into non overlapping regions. A region is defined as a homogeneous group of connected pixels with respect to a chosen property. There are several ways to define homogeneity of a region that are based on a particular objective in the segmentation process. For example, it may be measured by color, gray levels, texture, motion, depth of layers, etc. Overlaps among regions are not permitted; therefore, each pixel belongs only to a Single region. Two neighboring regions should be merged if the new combined region is homogeneous. Accordingly, each region is imagined to be as large as possible under its certain classification Then, the total number of regions is condensed. Image segmentation has a variety of purposes. For example, segmentation plays an important role in the field of video object extraction [1–3]. Since identical regions correspond to meaningful objects (which are mostly non identical),many of the video object extraction algorithms first partition the image into identical regions, and then, in order to extract the moving object, the regions are combined according to temporal information of the series. In image compression [4–6], the input image is Divided into regions that should be separately compacted since better compacted is achieved as long as the Regions are more identical. Tracking systems that are regionally based [7–9] make use of the information of the entire Object's regions. They track the identical regions of the object by their color or texture. Then, a Unification technique that is based on motion estimation is used in order to obtain the complete object in the next frame. Image segmentation is also used in object recognition systems [10, 11]. Many of these system partition the object to be recognized into sub-regions and try to characterize each separately in order to simplify the matching process. Automatic segmentation in still image has been investigated [12,13] by many researchers from diverse fields of sciences. The active segmentation methods can be separated into the five primary approaches: 1) Histogram-based methods, 2) boundary based methods, 3) region-based methods, 4) hybrid-based methods and 5) graph-based techniques. In the digital images, the spatial distributions of gray values choose the textural features and hence, statistical methods analyze the spatial allocation of pixel values in the digital image. Based on the number of pixels defining the local feature, statistical methods can be categorized into first-order statistical methods, second-order statistical methods and higher-order statistical methods [14]. A large number of statistical face approaches have been proposed, range from first order statistics to higher order statistics. As first order statistical methods cannot model the face completely, higher order statistics are generally used for face recognition [15]. Gray level co-occurrence matrices [16], gray level differences [17] and Local Binary Patterns [18] are some of the popular second-order statistical face methods for face recognition. Geometrical methods are found on the idea that face could be seen as a spatial alliance of face primitives. 1n [19] proposed an idea in which the face image is viewed as face primitives, which are precise according to a placement rule and face recognition is a process of identifying those primitives or the placement rule. In [20] used a Fourier spectrum of a face image to detect face periodicity for the face recognition. In [21] examined the structures of face patterns in terms of their translation symmetries for the face recognition. In this paper robust rule based local binary pattern technique is implemented for face classification and analysis.

2. Local Binary Patterns

The original LBP operator labels the pixels of an image by means of decimal numbers, which are called LBP codes that encode the local structure around each pixel. It proceeds thus, as illustrated in Fig. 1: every pixel is compared with its eight neighbors in 3 ×3 neighborhood by subtracting the centre pixel value; the resulting strictly negative values are encoded with 0, and the others with 1. For each given pixel, a binary number is obtained by concatenating all these binary values in a clockwise direction, which starts from the one of its top left neighbor. The corresponding decimal value of the generated binary number is then used for labeling the given pixel. The resulted binary digits are referred as the LBPs or LBP codes.

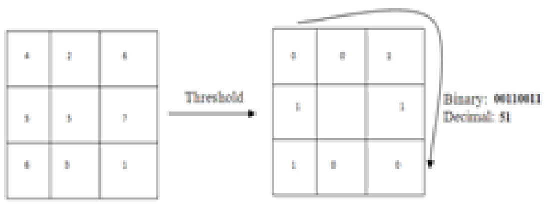
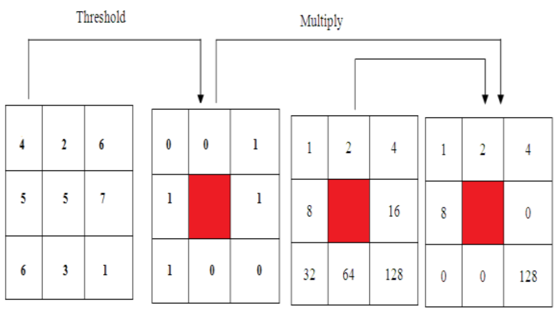


Figure 1. An example of the basic LBP operator.

While the LBP was, invariant to monotonic changes in gray scale, it was supplemented by an autonomous measure of local contrast. Fig. 2 shows how the contrast measure (C) was derived. The average gray level below the centre pixel is subtracted from that of the gray level above (or equal to) the centre pixel. Two-dimensional distributions of the Local Binary Pattern (LBP) and local contrast technique were used as features. This operator was called LBP/C, and extremely good discrimination rates were reported through textures.



LBP = 1+2+4+8+128 = 143

C = (5+4+3+4+3)/5 – (1+2+0)/3 = 2.8

Figure 2 Calculating the original LBP code and a contrast measure.

3. Rule Based Local Binary Patterns

Rule Based LBP can be generally described as discrete dynamic systems completely defined by a set of rules in a local neighborhood. The state of a system is represented as a regular grid, on which the rules apply to produce a new state. An interesting property of RLBP is that very simple rules can result in very complex behavior. Now consider sample window S3X3 and compare each pixel with significant centers of the sample window. All neighboring pixels with values greater than the centre to be replaced with the value 1 otherwise replace them with 0 such that gray images are converted to binary image. On the binary image the rules given below have been used to eliminate the uncertainty of image classification.

1) First calculate the column wise count

S_{3X3}

$$Z_i = \sum_{i=1}^{3} V\,(vi, p) \text{ where } p=1, 2, 3$$

If $Z_i >= 2$ then

$M_i=1$

Else

$M_i=0$

2) After that calculate the row wise count S_{3X3}

$$D_i = \sum_{i=1}^{3} V\,(v_i, a) \text{ where } a=1, 2, 3$$

If $D_i >= 2$ then

$O_i=1$

Else

$O_i=0$

3) To obtain diagonal B1 value count the left diagonal digits and right Diagonal B2 on sample matrix.

4) The Resultant matrix will be in form of

O1 B1 M1

O2 M2

O3 B2 M3

5) Calculate the LBP operator on new Sample

Matrix and restore the centre pixel value.

6) Repeat the same procedure from step 1 through step5 on entire images then it forms one new unambiguous image.

The result of this method can be conveniently represented a two-dimensional pattern that can be further be used in image processing. RLBP of 8-bit, segments the Image in better way even for the recognition rate has been improved for Noisy Images and the quality of the images are found to be improved than images obtained with the usual methods.

4. Experiments

The performance of the test has been conducted on ten different sample test images, of 130x150 of size, for the database. Each test set consists of 10 images and 50 images have been saved. The sample database is shown in Figure 2. In the query image the nearest distance matching tag in the database is displayed as the output. The performance of the Local Binary Pattern operator (LBP) RLBP and RLBP on the test images has been recorded in Table 1 of the query image as one of the images of the database. Hence, by having large no. of images of the same sample with expected different face expressions and physical deformations created using computer techniques may be used to identify the escaped/absconded non-social elements of the society

Figure3. *Sample Database Images*

Table 1. *Accuracy Rate*

Method	No.of Samples	Accuracy
LBP	30	66%
ELBP	30	53%
RLBP	30	96%

5. Conclusions

The presented RLBP method is useful for accurate face identification. The accuracy can be improved by having more images of the same sample in the database by changing focus in angle and partially covering the facial features. The limitation of the method is the non-absence of the query image in the database also finds matches with the nearest distance parameter value and hence unsuitable for security. The method is undoubtedly the best in marking attendance, of an employee/student/daily wage worker, on the day without the use of inconvenient biometrics techniques or smartcards adapted by just taking a snap, at the entrance of the venue, of only the enrolled/registered.

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