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FACE DETECTION AND CLASSIFICATION BASED ON LOCAL BINARY PATTERNS

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ABSTRACT:

Facial image analysis is an important and popular research topic in the computer vision and image processing area, which includes face detection, face recognition, facial expression analysis, and several other related applications. A critical step for successful facial image analysis is to derive an effective facial representation from the original face images. In recent years, Local Binary Patterns (LBP) has received increasing attention for facial description. This paper proposes a new approach to extract facial features for the purpose of face detection and classification. These features are obtained by generating an estimated local map representing the measured intensity similarity between any given image pixel and its surrounding neighbors within a certain window. The intensity similarity map is an average representation of the texture image dominant neighborhood similarity. The estimated dominant neighborhood similarity is robust to noise and referred to as image dominant neighborhood structure. The rotation invariant features are then extracted from the generated image dominant neighborhood structure. Features obtained from the local binary patterns (LBPs) are then extracted, in order to supply additional facial features to the generated features from the dominant neighborhood structure. Both features complement each other. The experimental results on representative face databases show that the proposed method is robust to noise and can achieve significant improvement in terms of the obtained classification accuracy in comparison to the LBP method.

Key words: Dominant neighborhood structure, Dominant local binary pattern, rotation invariance, faces detection.

1. INTRODUCTION

During the past several decades, facial image analysis has received much attention in the computer vision and image processing area, which contains face detection, face recognition, facial expression analysis, facial demographic classification, and so on [1,2]. This is driven by the theoretical interests of cognitive and psychological scientists, and also a wide range of critical applications such as human-computer interaction, biometric identification, surveillance and security, image/video retrieval, and computer animation. Current algorithms and systems can work well with face images captured in controlled environments with some certain assumptions [3, 4]. However, it is still difficult to develop an automated system capable of analyzing face images effectively in unconstrained scenarios. Computer recognition of face image involves two crucial aspects: facial feature representation and classifier design Facial representation is to derive a set of features from original face images for describing faces [6, 7]. If inadequate features used, even the best classifier will fail to achieve accurate recognition. Therefore, it is critical to extract discriminative facial features for facial representation. “Good” facial features are desired to have following properties first, can tolerate the within-class variations whilst discriminate different classes well; second, can be easily extracted from the raw images to allow fast processing; and finally, lie in a space with the low dimensionality in order to avoid computationally expensive classifiers [5]. Up to now, many algorithms have been applied to describe the faces: Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), and Independent Component Analysis (ICA) have been widely introduced for feature extraction, and recently, representations based on the outputs of Gabor filters at multiple scales, orientations, and locations have achieved superior performance for facial image analysis nevertheless, it is computationally expensive to convolve the face images with a set of Gabor filters to extract multi-scale and multi-orientation coefficients [8,9]. It is inefficient in both time and memory for high redundancy of Gabor-wavelet features. Local Binary Patterns (LBP), a non-parametric method summarizing the local structures of an image efficiently, has received increasing interest for facial representation recently. LBP was originally proposed for texture description, and has been widely exploited in many applications such as image/video retrieval, aerial image analysis, and visual the most important properties of LBP features are tolerance against the monotonic illumination changes and computational simplicity. In recent years, LBP features have been extensively exploited for facial image analysis, including face detection; face recognition, facial expression analysis, gender/age classification, and some other applications [12]. Meanwhile, different variations of the original LBP have been proposed for improved performance. LBP feature selection, i.e., how to select the most discriminative LBP features is another important problem, which has also been addressed in many papers [10]. As will be shown in this work, by combining both local and global texture features, the classification accuracy is highly improved. In addition noise robustness is increased [11]. The main contribution of this work is in the development of new local texture features for face detection that are not only rotation invariant but also highly robust to noise by design. In addition, the local texture features are fused with local feature set extracted using the local binary patterns method for face detection. As will be shown experimentally, the fused texture features produce higher face detection and classification rates than using either the global features or the local binary patterns features individually.

2. LBP OPERATOR

LBP Operator codes a local window pattern from a texture patch, and its histogram is often treated as texture feature in face detection and classification problem. Recent studies have shown that excellent texture discrimination can be obtained with local binary patterns (LBP). In order to obtain a robust segmentation, we employ LBP Histogram of a local circular window to represent the feature of the center pixel. The LBP distribution of one region is also approximated by a LBP histogram. Thus we reassume that our goal of texture segmentation is to divide a face image into sub regions, where each local LBP histogram is similar to the global LBP histogram. The texture content of a region can be characterized by the distribution of Local binary pattern (LBP) [13]. This paper, gives brief introduction to the original LBP operator.

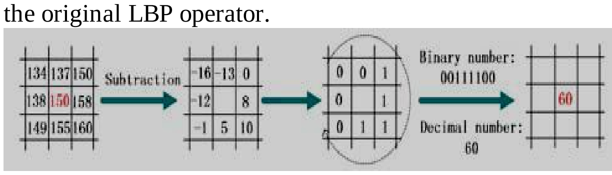


Figure 1. An example of the basic LBP operator

The LBP operator was first introduced as a complementary measure for local image contrast. The operator thresholds eight neighbors of a pixel with the value of that center pixel. Then the LBP code is computed by multiplying the threshold values by the binomial weights given to the corresponding pixels and summing up the results. Although LBP captures the spatial pattern of local texture, it fails to characterize the contrast of the texture. So LBP can be improved by taking into account the local contrast for a 3x3 neighbors. The local contrast C is calculated by subtracting the average of the gray levels below the center pixel from that above the center pixel. So the joint distribution of LBP and contrast C is used as texture features. Because it is difficult to find a general parametric model for this joint distribution, it is approximated by a two dimensional discrete histogram. Using LBP/C, very good discrimination rates were reported with textures.

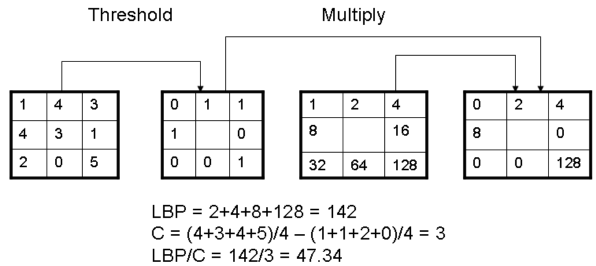


Figure 2. Computation of local binary pattern (LBP) & LBP/C

The most prominent limitation of the LBP operator is its small spatial support area and the contrast is a property of texture usually regarded as a very important cue for our version system, but the LBP operator is by itself totally ignores the magnitude of gray level difference. In many applications, especially is industrial usual inspection, illumination can be accurately controlled. In such a situation, a purely gray scale invariant texture operator may waste useful information and adding gray scale dependent information may enhance the accuracy of the method. To overcome, these drawbacks a new method is proposed.

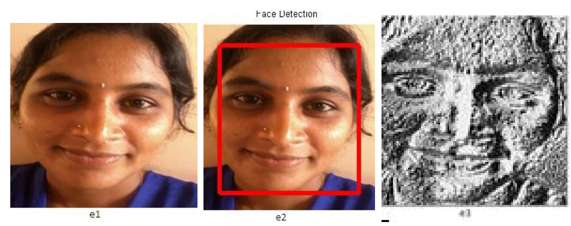


Figure 3: a) Original image b) Face detection c) LBP output

3. PROPOSED METHOD

In this approach, we first translate the given image into binary image .This is done, by applying thresholding on the original image. Threshold value is calculated by finding the average of all gray values of the image. We use 0, 1 to denote black and white resp. If image pixel value is greater than threshold value, then its central pixel is replaced by white (1), else by black (0) and then is plotted. The concept of rotation invariance is applied on the binary image to get the regions as shown in figure1.

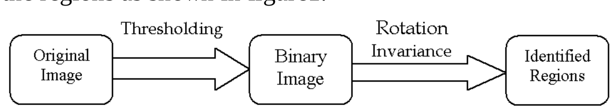


Figure 4: Direct implementation of Rotation Invariance to find Regions.

Due to the circular sampling of neighborhoods, it is fairly straightforward to make LBP codes invariant with respect to rotation of the image domain. "Rotation invariance" here does not however account for textural differences caused by changes in the relative positions of a light source and the target object. It also does not consider artifacts that are caused by digitizing effects. Each pixel is considered a rotation center, which seems to be the convention in deriving rotation invariant operators. With the assumptions stated above, the rotation invariant LBP can be derived as follows. When an image is rotated, the gray values gp in a circular neighbor set move along the perimeter of a circle centered at gc. Since the neighborhood is always indexed counter-clockwise, starting in the direction of the positive x axis, the rotation of the image naturally results in a different $LBP_{P,R}$ value. This does not, however, apply to patterns comprising of only zeros or ones which remain constant at all rotation angles. To remove the effect of rotation, each LBP code must be rotated back to a reference position, effectively making all rotated versions of a binary code the same. In short, the rotation invariant code is produced by circularly rotating the original code until its minimum value is attained. Patterns are called “uniform” if they have one thing in common: at most two one-to-zero or zero-to-one transitions in the circular binary code. To formally define the “uniformity” of a neighborhood G, a uniformity measure U is needed:

$$U(G_P) = |s(g_{P-1} - g_c) - s(g_0 - g_c)| + \sum_{p=1}^{P-1} |s(g_p - g_c) - s(g_{p-1} - g_c)|.$$

Patterns with a U value of less than or equal to two are designated as “uniform”. The rotation invariant uniform (riu2) pattern code for any “uniform” pattern is calculated as shown below:

$$LBP_{P,R}^{riu2} = \begin{cases} \sum_{p=1}^{P-1} |s(g_p - g_c) - s(g_{p-1} - g_c)| & , \; U<=2 \\ |s(g_{p-1} - g_c) - s(g_0 - g_c)| & , \; U>2 \end{cases}$$

With small patterns, not enough information can be collected to draw statistically sound decisions. Therefore, the number of scales is used. Due to border effects, a large neighborhood means that large features must be used. Since the correlation between the center and a neighbor decreases with distance, very large neighborhoods may not provide much useful information. With small textures, only unreliable measurements can be made, which may render the joint distribution of LBP codes and statistical stability rules both too sparse and too noisy. Due to the high correlation between neighboring pixels, it is likely that a sequence of three “ones” at scale 1 is likely to produce a “one” at scale 2. Based on this argument, one of the most likely rules for statistical stability is as shown in below Figure 2. In which a majority rule is used to judge the outcome. When the distance between scales grows, the resulting statistical stability rules probably no longer adapt to the correlation between pixels. In a sense, the statistical stability rules can be seen as a measure of correlation between the LBP codes at different scales.

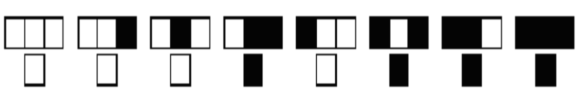


Figure 5: Statistical Stability rule

With a large amount of natural textures, reliable statistics on the occurrences of different rules can be derived. Then, the number of applicable rules can be reduced by discarding the least frequently occurring ones. Statistics calculated from the Outer textures show that 32 of the 256 Statistical Stability rules have a 94.6% share of all pixels. Another advantage is that the purging of the most infrequently occurring codes is likely to decrease the statistical instability in their distribution for noise elimination.

Figure 6: a) Original image b) Face detection c) Proposed Output

4. EXPERIMENTAL RESULTS

In the paper LBP and Proposed methods have been tested on face databases like ORL, PIE, Sterling and our own databases and produced results and only our own database images are kept in the results. Here two data bases of student’s with different illuminations, low contrasted and emotions are considered. The LBP operator produced better results but among ten images three images are overlapped so it has given 70% of recognition rate. However proposed method produced 100% recognition rate. The tables and graphs show the classification rate. This method works better for low contrasted, rotation variant and low emotions. However it fails for intentional emotional expressions.

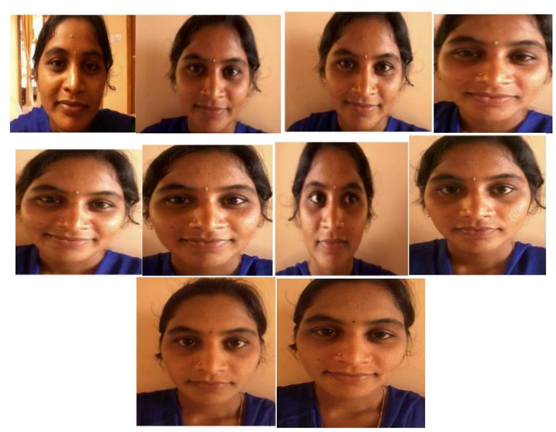
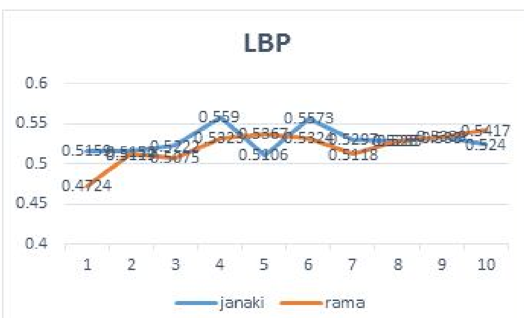


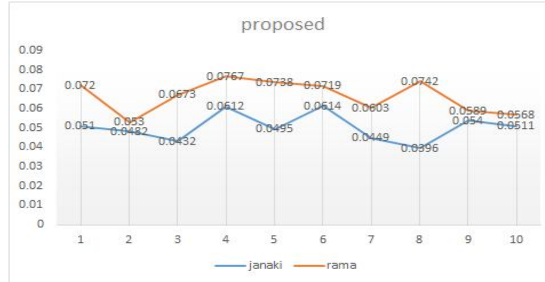
Figure 7: A Set of different variations in Face Images corresponding to Rama

Figure 8: A Set of different variations in Face Images corresponding to Janaki

janaki	rama
0.5159	0.4724
0.5152	0.5119
0.5222	0.5075
0.559	0.5323
0.5106	0.5367
0.5573	0.5324
0.5297	0.5118
0.528	0.5285
0.533	0.5399
0.524	0.5417



janaki	rama
0.051	0.072
0.0482	0.053
0.0432	0.0673
0.0612	0.0767
0.0495	0.0738
0.0614	0.0719
0.0449	0.0603
0.0396	0.0742
0.054	0.0589
0.0511	0.0568



5. CONCLUSIONS

Facial image analysis has many important applications, and a large number of approaches have been proposed during the last several decades. LBP has received increasing research attention in this area. The LBP operator is theoretically simple yet a very powerful method of analyzing textures. Through the extension developed in this paper, the LBP operator was made into a really powerful measure of face images, showing excellent results in terms of accuracy and computational complexity in many empirical studies. The next challenge could be using the LBP approach in analyzing not only pure face images but a wide range of different natural scenes. In its basic form, the LBP operator cannot properly detect intentional face image Structures, which can be considered its main shortcoming. The small local neighborhood also affects the rotation invariant version, as local artifacts tend to decrease its performance. It can be concluded that LBP features are effective for facial representation, which has been proved by plenty of experiments in face detection face recognition, facial expression analysis, and other related applications. Real-time face analysis systems based on LBP have been emerging.

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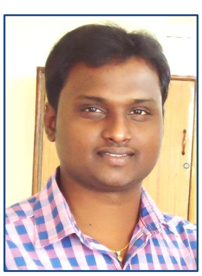

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