Illumination Invariant Face Recognition using SQI and Weighted LBP Histogram

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Received: Feb. 2013 Revised: May 2013 Accepted: August 2013

ABSTRACT:
Face recognition under uneven illumination is still an open problem. One of the main challenges in real-world face recognition systems is illumination variation. In this paper, a novel illumination invariant face recognition approach base on Self Quotient Image (SQI) and weighted Local Binary Pattern (WLBP) histogram has been proposed. In this system, the performance of the system is increased by using different sigma values of SQI for training and testing. Furthermore, using two multi-region uniform LBP operators for feature extraction simultaneously, made the system more robust to illumination variation. This approach gathers information of the image in different local and global levels. The weighted Chi square statistic is used for histogram comparison and NN (1-NN) is used as classifier. The weighted approach emphasizes on the more important regions in the faces. The proposed approach is compared with some new and traditional methods like QI, SQI, QIR, MQI, DMQI, DSFQI, PCA and LDA on Yale face database B and CMU-PIE database. The experimental results show that the proposed method outperforms other tested methods.

KEYWORDS: Face Recognition, Quotient Image, Illumination Normalization, Self-Quotient Image, Local Binary Pattern

1. INTRODUCTION

Face recognition has been studied for more than three decades. Many algorithms have been proposed which are effective for controlled environment like PCA [1], LDA [2] and ICA [3]. But in real-world applications with challenging conditions like illumination, pose and expression variations their performance degrades. Many approaches have been proposed to resolve these problems.

In [4-12] some algorithms are studied for illumination invariant face recognition. Such as Quotient Image (QI) [9], Self-Quotient Image (SQI) [8] and Morphological Quotient Image (MQI)[9]. Many methods are developed based on SQI and MQI. For example QIR [13], DMQI [14] and DSFQI[4] are among the successful ones.

References [15-17] have proposed some methods for face recognition robust to Pose variation. Pose variation attracted many attentions lately. Generally, local approaches such as EBGM[18] and LBP[19] are more robust to pose variations than holistic approaches such as PCA and LDA[17].

Moreover, variations in expression make recognition harder. Some recent studies have been done in this area[20-23]. Because of the complexity of this area, 3D methods are used commonly and more successfully than 2D methods [20], [23].

Facial occlusions create significant problems in automatic face recognition systems. Partial occlusion is very common in facial images which caused by objects like sunglasses and scarves. The proposed methods for solving this problem generally use one of the two following approaches[24], [25]. First, using the non-occluded face regions in recognition[26]. Second rebuilding the occluded area. The second approach is used in 3D methods more commonly.

But still face recognition under uneven illumination or with variation in pose and expression is an open and challenging problem.

In this paper, we proposed a novel face recognition approach which is robust to illumination variation. Our method is based on Self Quotient Image (SQI) and weighted Local Binary Pattern (WLBP) [27]. The SQI is used for eliminating illumination changes and the LBP is used for illumination invariant feature extraction. We experimentally proved that each part of our system is partially efficient. Like Why SQI is selected for eliminating the lighting effect in the image? What are the efficient settings for SQI? How many regions are suitable for better feature extraction? What are the efficient weights for each region to more emphasize on important regions in the faces? Finally the system tested on Yale face database B, CMU-PIE database and results are presented. We also tested some new and traditional methods like QI, SQI, QIR, MQI, DMQI, DSFQI, PCA and LDA on the database for comparison purpose.

The rest of the paper is organized as follows: LBP operator and its several important extensions are introduced in Section 2. Section 3 gives a detailed presentation of quotient image-based methods QI, SQI and MQI. In Section 4, the proposed system is introduced in detail. The experimental results are analyzed and compared in Section 5. Finally, the paper is concluded in Section 6.

2. LOCAL BINARY PATTERN

The Local Binary Pattern (LBP) operator was proposed by Ojala et al. for texture description. Local descriptors of human faces have gained much attention due to their robustness against the variation of pose and expression. The LBP is one the best local texture descriptors.Besides the robustness against pose and expression variation, the LBP is also robust to monotonic gray-scale transformations. The basic LBP operator is a non-parametric 3×3 kernel. It assigns a label to every pixel of the image by reaching the thresholdof eight surrounding pixels to the center pixel value and considering the result as a binary string. Finally, a histogram of the decimal equivalents of the labels is calculated and can be used as the texture feature. Fig. **1** shows more details.

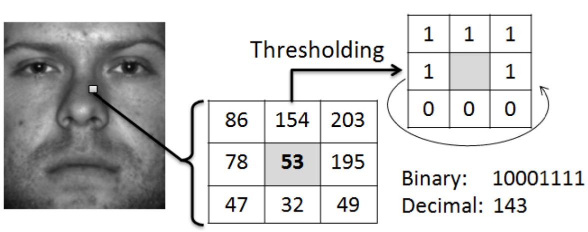

Fig. 1. The basic LBP operator

Because of human face structural features, the basic operator is extended to use circular neighborhoods. The extended LBP [19] uses different sampling points on a circle of different radius size and is more effective for human face. Bilinear interpolation is used when a sampling point does not fall in the center of a pixel. The notation $LBP_{P,R}$ refers to P sampling points on a circle of radius R. Fig. 2 shows several extended LBP patterns with different P and R. Equation (1) shows the calculation of $LBP_{P,R}$ for point (x, y).

$$LBP_{P,R}(x,y)=\sum_{i=0}^{P-1}s(g_i-g_c)2^i \tag{1}$$

Where $LBP_{P,R}(x,y)$ is the decimal label of point (x,y), g_c is the gray value of central point (x,y), g_i is the gray value of neighborhood sampling point

$$s(x)=\begin{cases}1 & x>0\\ 0 & x\le 0\end{cases} \tag{2}$$

and each LBP histogram bin can be calculated as:

$$H_i=\sum_{x,y}I\{LBP_{P,R}(x,y)==i\},\ \ i=0,\ldots,n-1 \tag{3}$$

Where i is the bin index, n is the number of different labels and

$$I\{A\}=\begin{cases}1 & A==true\\ 0 & A==false\end{cases} \tag{4}$$

Another extension to the original LBP operator is the definition of uniform patterns [19]. A local binary pattern is called uniform if the binary pattern contains at most 2 bitwise transitions from 0 to 1 or 1 to 0 when the binary string is considered circular. The authors noticed that the uniform patterns accounted for most of all patterns. So, usually all non-uniform patterns are classified into a single bin in the feature histogram and more attention is paid in uniform patterns. The notation $LBP_{P,R}^{u2}$ is used for uniform LBP operator.

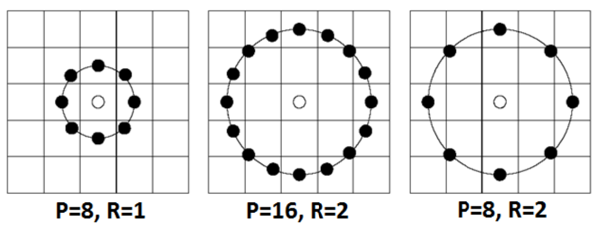

Fig. 2. Some extended LBP operator with different P and R

3. QUOTIENT IMAGE-BASED METHODS

3.1. Quotient Image

Recently, quotient image based methods are reported to be a simple and efficient solution to illumination variances problem. Quotient Image (QI) [9] is based on the Lambertian Model:

$$I=\rho n^T\bullet s \tag{5}$$

Where ρ is the surface texture(albedo)of face, n^T is the surface normal of face, $\bullet$ is the dot product and s is the point of light source. Let I_1, I_2, I_3 be three non-collinearly illuminated images of face a and s_1, s_2, s_3 be their corresponding lighting sources respectively.

Therefore any point light source s_y can be taken as the linear combination of s_i with coefficient x_i ($i = 1,2,3$), $s_y = \sum_{j=1}^{3} x_j s_j$. The quotient image Q_y of face y illuminated by light source s_y against face a is defined by:

$$
\begin{aligned}
Q_y &= \rho_y(u,v) / \rho_a(u,v) \\
&= (\rho_y(u,v) n^T(u,v) \bullet s_y) / (\rho_a(u,v) n^T(u,v) \bullet s_y) \\
&= I_y(u,v) / (\rho_a(u,v) n^T(u,v) \bullet \textstyle\sum_{j=1}^{3} x_j s_j) \qquad (6) \\
&= I_y(u,v) / \textstyle\sum_{j=1}^{3} x_j I_j(u,v)
\end{aligned}
$$

From (6), we can conclude that the quotient image defined as the ratio between a test image I_y and linear combinations of three unknown independent illumination images I_j, which simulates the lighting direction of I_y. The quotient image depends only on the relative surface texture information and is illumination free.

3.2. Self - Quotient Image

The main drawback of QI is that its performance strongly depends on bootstrap database and known lighting conditions. Wang et al. [8] proposed Self Quotient Image (SQI) to overcome this limitations. The SQI is defined by a face image $I(x,y)$ and its smoothed version $S(x,y)$ as

$$
\begin{aligned}
Q(x,y) &= I(x,y) / S(x,y) \\
&= I(x,y) / (F(x,y) * I(x,y))
\end{aligned} \qquad (7)
$$

Where $*$ is the convolution operation and F is thesmoothing kernel which in this case is a weighted Gaussian filter.

SQI is almost illumination invariant and can be calculated from one image which is very important for real-world applications. Fig. 3 shows SQI's output for a sample image.

Fig. 3. Output of SQI for a sample image

3.3. Morphological Quotient Image

Morphological Quotient Image (MQI) was proposed by Zhang et al.[9]. The MQI uses morphological operation to smooth the image and estimate its luminance version. In[9], Morphological Closing operation is employed for the illumination estimation. The size of closing operator is a key parameter for the performance.The MQI is faster than the SQI but in its normal form, doesn't have a better performance than SQI. Fig. 4 shows the MQI's output for a sample image. The authors mentioned that the template size has important influence on the output image. So selecting the optimal template size should be considered in the algorithm. As a result, they presented a method named the DMQI which chooses suitable closing operator size. The DMQI has a better performance in comparison to the MQI, but is slower. Fig. 5 shows the effect of template size on the output quotient image [9].

Fig. 4. Output of MQI for a sample image

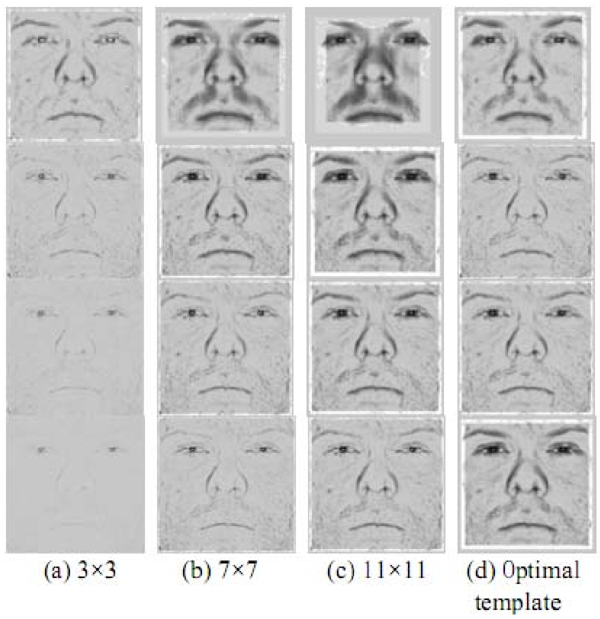

Fig. 5. Quotient image using different template size for different size of images (from the first row to the last row, the distance between eyes are 32, 80, 120 and 180 respectively) [9]

4. THE PROPOSED SYSTEM

Our proposed system has three layers. In the first layer, the SQI is used for eliminating illumination variation. Two weighted multi-region LBP with different regions count applied to face image separately in the second layer. At last, the extracted histograms in previous layer are concatenated together into a single feature vector. In order to maximize the accuracy of each part of the system, some experiments have done and the best setup is selected.

Yale Face Database B [28] is used in the tests. In all of the experiments, a single image with frontal illumination of each individual is selected for training. For the sake of run time, in this section, the methods didn't have run on the whole database. We randomly selected 60 images with all illumination conditions. These 60 selected images are used for this section's experiments.

4.1. Pre-processing

In [8], the SQI is proposed to be implemented with several scales. But the multi-scale version is slow and generally its accuracy is not far better than single-scale version. So we used single-scale version in our system.

1.1.1.Illumination variation elimination

In the experiments of [10], [29], the SQI and MQI have shown promising results. And because our system is robust to illumination changes, we selected these two algorithms for eliminating the illumination changes effect. For selecting the better algorithm, these two methods with their default settings are tested on the selected images and the results is shown in Table 1.

Table 1. Comparison between the SQI and MQI

Template and filter size: 7, SQI $\sigma = 1$	
Method	Accuracy
SQI	**70%**
MQI	65%

The authors mentioned that the template size 7 is a proper selection for MQI, therefore we used that. And for comparing two methods, SQI filter size is also set to 7. Table 1 shows that SQI has better accuracy in comparison with MQI. So we used SQI for this part of the system.

1.2.1.SQI configuration

Filter size and sigma value have a great influence on SQI accuracy. For selecting the efficient filter size, different filter sizes with the default sigma value 1 are tested on Yale B selected images. Filter sizes are odd. Table 2 shows the results.

Table 2. Comparison of different filter sizes of SQI

Filter size	Accuracy
7	70%
9	80%
11	85%
13	83.33%
15	**88.33%**
17	80%

According to the results, filter size 15 is selected. In the next step, different sigma values are tested with the selected filter sizes. Table 3 shows that sigma value 0.7 is the best. It has been seen in the experiments that using different sigma values for training and testing can be effective. As can be seen in Fig. 6, smaller sigma, gives us a smoother illumination free image. So by using larger sigma for train images and smaller sigma for test images, we can get a better recognition rate. Table 4 proves this idea. In this table, sigma value 0.7 with filter size 15 is used for training and different sigma values are tested on the selected images.

Table 3. Comparison between different sigma values of SQI

σ	Accuracy
2	75%
1.5	81.66
1	88.33%
0.9	88.33%
0.7	**90%**
0.5	88.33%
0.3	73.33%
0.1	40%

Fig. 6. Different sigma values of SQI (left to right: original image, $\sigma = 1$, $\sigma = 0.3$)

Table 4. Comparison between different sigma values for testing and training

Filter size: 15, training $\sigma = 0.7$	
Testing σ	Accuracy
1	88.33%
0.9	88.33%
0.7	90%
0.5	90%
0.3	**91.66%**

Based on experiments, the final settings of SQI are as follows:

- Filter size: 15
- Sigma value for training: 0.7
- Sigma value for testing: 0.3

4.2. Illumination invariant feature extraction

After SQI, $LBP_{8,2}^{u2}$ is used for illumination invariant feature extraction. We used weighted multi region uniform LBP. Fig. 9 shows the feature extraction process of the system.

Currently, multi-region LBP is used in face recognition field. In this method, the image is divided into local regions and feature histograms are extracted from each region independently and then concatenated together. The regions count depends on the size of images and faces. In multi-region LBP, some regions can be concentrated more, like eyes, nose, eyebrows and mouth. The regions count is very important. So we did some tests for selecting the appropriate regions count that can be seen in Table 5.

Table 5. Comparison of different LBP regions count

Filter size: 15, training $\sigma = 0.7$, testing $\sigma = 0.3$

Regions count	Accuracy
1×1	35%
4×4	46.66%
6×6	46.66%
7×7	90%
8×8	**91.66%**
9×9	71.66%
11×11	90%
13×13	91.66%
15×15	**96.66**
17×17	93.33
19×19	90%

15×15 multi-region LBP has the best result in table 5. In our system, we want to have a description of face in different levels of locality: 1.pixel level 2.regional level 3.global level. By using 15×15 regions, the regional level features will be very close to pixel level, because the regions are small. So we used both 15×15 and 8×8 regions which can be seen in Fig. 7. The feature histogram of 15×15 regions and 8×8 regions are calculated separately and concatenated together. Because 15 and 8 are odd and even and also, they are not dividable to each other, we can have different features from different area.

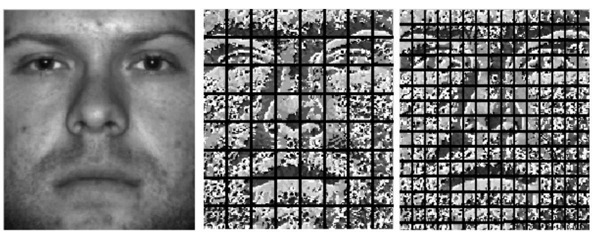

Fig. 7 Examples of multi-region LBP (left to right: original image, LBP8×8 , LBP15×15)

4.3. Weighted Comparison

The classifier used in the experiments is the nearest neighbor with Chi square statistic[30] for histogram comparison as in (8). For a more efficient histogram comparison, we used weighted Chi square as in (9).

$$\chi^2(H1,H2)=\sum_{i=0}^{n-1}(H1_i-H2_i)^2/(H1_i+H2_i) \quad (8)$$

$$\chi_w^2(H1,H2)=\sum_{i,j}w_j((H1_{i,j}-H2_{i,j})^2/(H1_{i,j}+H2_{i,j})) \quad (9)$$

Where $H1$ and $H2$ are input histogram and registered histogram. Indices i and j refers to i th bin in feature histogram corresponding to the j th channel and w_j is the weight of channel j .

The final feature histogram is built on all regions of the face image. But every region of the face does not have the same effect on face recognition process. Some parts like eyes, nose, mouth and eyebrows play a key role. Therefore we used weighted approach in measuring similarity of the face images. This weighted comparison is feasible by weighted Chi square. The weightsseen in Fig. **8** are selected through some experiments, so they can probably be not optimal, but definitely effective.

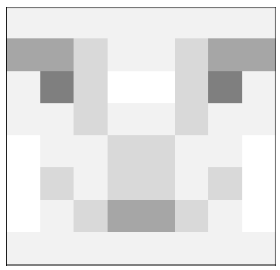

Fig. 8. The weighted approach used in comparison The darker a region is, the higher its weight is.

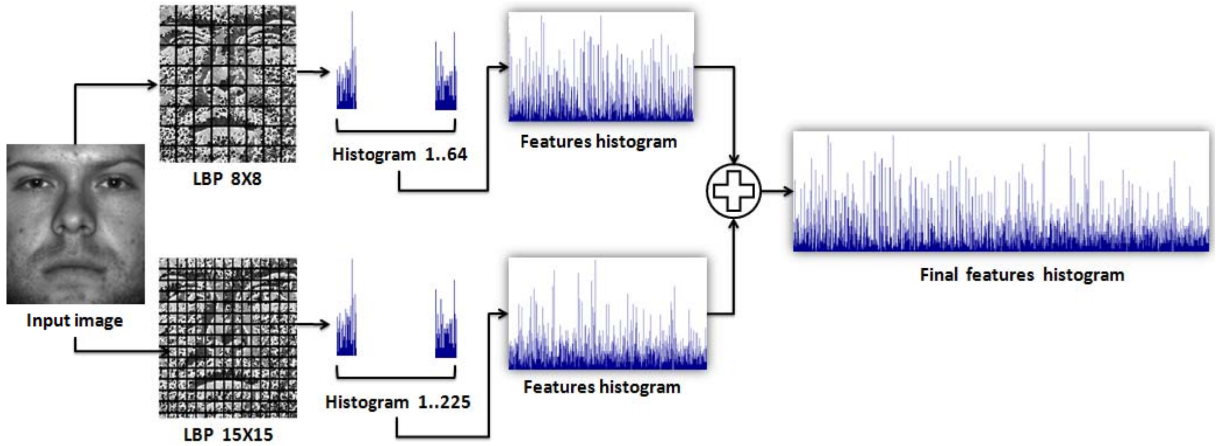

Fig. 9. Feature extraction process of the system

5. EXPERIMENTS AND RESULTS

We tested our system recognition performance on two most popular databases for illumination variation, Yale face databaseB and CMU-PIE [31]database. The methods QI, HE (Histogram equalization), SQI, QIR, MQI, DMQI, DSFQI, PCA and LDA are used for comparison with our method. Table 6 shows the evaluation results for all methods. The accuracy is in terms of correct recognition rate (RR).

5.1. Yale Face Database B

Yale Face Database B includes 10 subjects, each with 64 frontal images under different light conditions. All the images are manually aligned and cropped to size 168×192 for removing the backgrounds effect. The images are divided into five subsets according to the angle between the light source direction and the camera axis. Some examples of face images in each subset are shown in Fig. 10. In the experiments, a single image with frontal illumination of each individual is selected for training.

Fig. 10. Examples of five subsets in Yale face database B (left to right: subset 1 to 5)

5.2. CMU-PIE Database

CMU Pose, Illumination and Expression (PIE) database includes 68 subjects with pose, illumination and expression variation. Because we are concerned with the illumination variation problem, only 21 frontal images (C27) per person under different illumination conditions are selected for the experiments. All the images are manually resized and cropped to 150×150 size. Some examples of CMU-PIE are shown in Fig. 11. In the experiments, a single image with nearly frontal illumination (f8) of each individual is selected for training and all the other images are used for testing.

Fig. 11. Examples of face images in CMU-PIE database with different illumination variation

The proposed method is tested on both Yale B and CMU-PIE databases. In the case of Yale B, a single image with frontal illumination is used for training and the 63 remaining images are tested. Also, the image with normal lightening condition in the CMU-PIE is used for training and 20 other images are used for testing.

Because of the single training image in both databases, the used KNN classifier is in fact a NN classifier with K=1.

Our method is compared with several state-of-the-art methods. Table 6 shows the results of this comparison. It can be seen from the results that our method outperformed other tested methods. Subset 5 is the hardest image set in Yale B database because its faces are mostly shadowed and higher recognition rate of our method on Yale B is mainly because of its better performance on this image set. The results also show that quotient image based methods like SQI, MQI, DMQI and DSFQI outperforms traditional methods like PCA and LDA. The performance of our method is superior to its non-weighted (NW) version and this proves effectiveness of the proposed weighted approach. Of course, speed is an important factor which should be considered. For example some methods like DMQI and DSFQI are slower than the others.

6. CONCLUSION

In this paper, we proposed a novel face recognition approach which is robust for illumination variation. Our method is based on the SQI and LBP methods. At pre-processing stage, the SQI algorithm is applied to the input image and made it almost illumination free. By using different sigma values for training and testing, the performance of the system is increased. Then multi-region uniform LBP operator is used to extract the features of the image. The feature extraction process did on two version of the input image simultaneously. The first is divided to 8×8 equal regions and the other is divided to 15×15 regions. The final feature vector is made of concatenation of two extracted histograms. This approach gathers information of the image in different local and global levels. Because of the importance of some regions in the face, we used weighted comparison which was very effective.

The results of experiments on Yale face database B and CMU-PIE showed that our proposed method is robust for illumination variation and outperforms other compared methods.

Table 6. The comparison results of different methods on Yale B and CMU-PIE

Method	Recognition Rate %						
	CMU	**Yale B**					
		Subset 1	Subset 2	Subset 3	Subset 4	Subset 5	Overall
PCA	54	-	-	-	-	-	50
QI	84	100	98.3	62.5	34.2	23.6	63.72
HE	-	100	95	88.3	50.7	46.8	76.16
LDA	-	-	-	-	-	-	79
QIR	-	100	100	100	90	82.1	94.42
SQI	98.38	100	97.5	100	96.4	97.8	98.34
MQI	98.75	100	98.3	98.3	98.5	97.3	98.48
Proposed Method (NW)	98.60	100	98.3	97.5	99.2	98.4	98.68
DMQI	-	100	100	98.3	98.5	97.8	98.92
DSFQI	-	100	99.1	99.1	98.5	98.4	99.02
Proposed Method	99.11	100	100	97.5	100	98.9	99.28

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