Face Recognition with Local Line Binary Pattern

Amnart Petpon and Sanun Srisuk
Department of Computer Engineering, Mahanakorn University of Technology
51 Cheum-Sampan Rd., Nong Chok, Bangkok, THAILAND 10530
ta_tee473@hotmail.com, sanun@mut.ac.th

Abstract

In this paper, we introduce a novel face representation method for face recognition, called Local Line Binary Pattern (LLBP), which is motivated from Local Binary Pattern (LBP) due to it summarizes the local spacial structure of an image by thresholding the local window with binary weight and introduce the decimal number as a texture presentation. Moreover it consumes less computational cost. The basic idea of LLBP is to first obtain the Line binary code along with horizontal and vertical direction seperately and its magnitude, which characterizes the change in image intensity such as edges and corners, is then computed. Our experimental result is evaluated on the public Yale face database B as well as its Extended version and FERET database by using Linear Discriminant Analysis (LDA) as classification. The comparative results have shown that the LLBP is more discriminative and insensitive to illumination variation and facial expression than other methods.

1. Introduction

Face recognition is one of the major issues in biometric technology. It identifies and/or verifies a person by using a 2D/3D physical characteristics of the face images. The baseline method of face recognition system is the eigenface [14] by which the goal of the eigenface method is to project linearly the image space onto the feature space which has less dimensionality. One can reconstruct a face image by using only a few eigenvectors which correspond to the largest eigenvalues, known as eigenpicture, eigenface, Karhunen-Loeve transform and principal component analysis [14], [3]. Several techniques have been proposed for solving a major problem in face recognition such as fisherface [3], elastic bunch graph matching [18] and support vector machine [7]. However, there are still many challenge problems in face recognition system such as facial expressions, pose variations, occlusion and illumination change. Those variations dramatically degrade the performance of face recognition system. It is evident that illumination variation is the most impact of the changes in appearance of the face images because of its fluctuation by increasing or decreasing the intensities of face images due to shadow cast given by different light source direction. Therefore the one of key success is to increase the robustness of face representation against these variations.

In order to reduce the illumination variation, many literatures have been proposed. Belhumeur et. al. [3] suggested that discarding the three most significant principal components can reduce the illumination variation in the face images. Nevertheless, the three most significant principal components not only contain illumination variations but also some useful information, therefore, the system was also degraded as well. Wang et. al. [17], [16] proposed a Self Quotient Image (SQI) by using only single image. The SQI was obtained by using the weighted Gaussian function as a smoothing kernel function. The Total Variation Quotient Image (TVQI) and Logarithmic Quotient Image (LTV) [4], [5] have been proposed by which the face image was decomposed into a small scale (texture) and large scale (cartoon) images. The normalized image was obtained by dividing the original image with the large scale one. The TVQI and LTV has a very high computational complexity due to the second order cone programming [2] as their kernel function.

However these methods are suitable only for illumination variation but not for other variations. Whereas the face representation based method has more robustness. It is not insensitive to illumination variation but insensitive to facial expression as well, such as Local Binary Pattern (LBP) [10] and its extension [11], it was originally designed for texture description. The LBP operator assigns a label to every pixel of an image by thresholding the 3x3-neighborhood of each surrounding pixel with the center pixel value and a decimal representation is then obtained from the binary sequence (8 bits). The LBP image is subsequently divided into *R* non-overlapping regions of same size and the local histogram over each regions are then calculated. finally the concatinated histogram can be obtained as a face descriptor [1].

The rest of this paper is organized as follows. In section 2, we give a brief review of the face representation meth-

978-0-7695-3883-9/09 $26.00 © 2009 IEEE
DOI 10.1109/ICIG.2009.123

ods and then describes the details of our proposed method, LLBP operator. Experimental results and analysis will be given in section 3. Section 4 gives a conclusion.

2. Face Representation Methods

In this section, we give an overview of the original LBP method and its serveral extensions. We then describe a novel method for face represetation, called Local Line Binary Pattern (LLBP). The LLBP is used to extract face descriptor which is insensitive to facial expression and illumination variation.

2.1. Local Binary Pattern

Local binary pattern (LBP) is a popular technique used for image/face representation and classification. LBP has been widely applied in various applications due to its high discriminative power and tolerance against illumination changes such as texture analysis and object recognition. It was originally introduced by Ojala et al. [10] as gray-scale and rotation invariant texture classification. Basically, LBP is invariant to monotonic gray-scale transformations. The basic idea is that each 3x3-neighborhood in an image is threshold by the value of its center pixel and a decimal representation is then obtained by taking the binary sequence (Figure 1) as a binary number such that $LBP \in [0, 255]$.

i_0	i_1	i_2
i_7	i_c	i_3
i_6	i_5	i_4

1	2	4
128	0	8
64	32	16

Figure 1. LBP operator: (left) the binary sequence (8 bits) and (right) the weighted threshold

For each pixel, LBP accounts only for its relative relationship with its neighbors, while discarding the information of amplitude, and this makes the resulting LBP values very insensitive to illumination intensities. LBP is originally described as

$$LBP(x_c, y_c) = \sum_{n=0}^{7} s(i_n - i_c) \cdot 2^n, \quad (1)$$

where i_c corresponds to the grey value of the center pixel (x_c, y_c), i_n the gray values of the 8 surrounding pixels. $s(.)$ is defined as:

$$s(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{if } x < 0. \end{cases} \quad (2)$$

The original LBP is later extended to be multi-scale LBP [11] which uses a circular neighborhood of different radius sizes using bilinearly interpolating. $LBP_{P,R}$ indicates P sampling pixels on a circle of radius of R. The example of multi-scale LBP operator is illustrated in Figure 2. An another extension called uniform patterns [11] which contain at most two bit-wise 0 to 1 or 1 to 0 transitions (circular binary code). For example the patterns 11111111 (0 transition), 00000110 (2 transitions), and 10000111 (2 transitions) are uniform whereas the pattern 11001001 (4 transitions) is not. These uniform LBPs represent the micro-features such as lines, edges and corners.

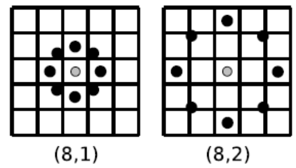


Figure 2. The multi-scale LBP operator with (8,1) and (8,2) neighbourhoods. Pixel values are bilinearly interpolated for points which are not in the center pixel

2.2. Enhanced Local Binary Pattern

Jin et al. suggests that the original LBP operator miss some local structures and they then proposed an improvement of LBP operator that considers both local shape and texture information instead of raw grayscale information and it is robust to illumination variation, called Improved Local Binary Patterns (ILBP) [8]. The main difference between ILBP and LBP is the comparison of all the pixels including the center pixel with the mean of all the pixels in the kernel. The decimal result of 9-bits can be mathematically expressed as,

$$ILBP(x_c, y_c) = \sum_{n=0}^{8} s(i_n - i_m) \cdot 2^n. \quad (3)$$

where i_m is the mean grey value in the kernel.

Qian Tao and Raymond Veldhuis [13] proposed simplified local binary pattern (SLBP) for illumination normalization by assigning equal weights to each of the 8 neighborhood. It was shown that the processed image becomes more robust to illumination change. There are two advantages for SLBP: the simplified one is not directional-sensitive and the coding number is largely reduced from 256 to 9 patterns. SLBP is defined as,

$$SLBP(x_c, y_c) = \sum_{n=0}^{7} s(i_n - i_c) \cdot 1. \quad (4)$$

However, LBP operator based method still has its small spatial support area (3x3 neighborhood), hence the bit-wise comparison made between two single pixel values is much affected by noise. The local 3x3 LBP threrfore does not capture large scale structure (macro-structure) that may be dominant facial feature. To overcome these limitations of LBP operator, Shengcai Liao et al [9] proposed a multi-scale block local binary pattern (MBLBP), by simply calculating the average sum of image intensity in each block (e.g. 3x3, 9x9, 15x15), 3x3 MBLBP operator is equivalent to the original LBP, and comparing to its surrounding block as shown in Figure 3. The average sum is then threshold by its center block.

$$MBLBP(B_c) = \sum_{n=0}^{7} s\left(B_n - B_c\right) \cdot 2^n \tag{5}$$

where B_c is the average sum obtained at central block and B_n is the average sum obtained at its neighbourhood. Note that the average sum over each block can be computed efficiently by using integral image [15].

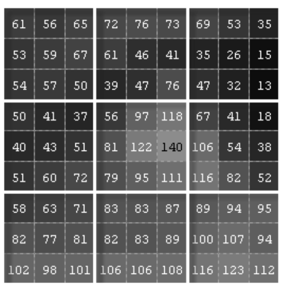


Figure 3. The 9x9 MBLBP operator

2.3. Local Line Binary Pattern

The motivation of Local Line Binary Pattern (LLBP) is from Local Binary Pattern (LBP) due to it summarizes the local spacial structure (micro-structure) of an image by thresholding the local window with binary weight and introduce the decimal number as a texture presentation. Moreover it consumes less computational cost. The basic idea of LLBP is similar to the original LBP but the difference are as follows: 1) its neighbourhood shape is a straight line with length N pixel, unlike in LBP which is a square shape. 2) the distribution of binary weight is started from the left and right adjacent pixel of center pixel (2^0) to the end of left and right side ($2^{\lceil N/2 \rceil - 2}$, e.g. $N = 9, 2^{\lceil 9/2 \rceil - 2} = 2^3$, where $\lceil \cdot \rceil$ is ceiling function) equally as illustrated in Figure 4. The algorithm of LLBP, it first obtains the line binary code along with horizontal and vertical direction seperately and its magnitude, which characterizes the change in image intensity such as edges and corners, is then computed. It can be mathematically expressed as in (6)-(8).

where $LLBP_h$, $LLBP_v$, $LLBP_m$ are LLBP on horizontal direction, vertical direction, and its magnitude respectively (The example of processed image for each direction and its magnitude are shown in Figure 5), N is the length of the line in pixel, $c = \left\lceil \frac{N}{2} \right\rceil$ is the position of the center pixel h_c on the horizontal line and v_c on the vertical line, h_n is the pixel along with the horizontal line and v_n is the pixel along with the vertical line, and s function is same as in LBP (1).

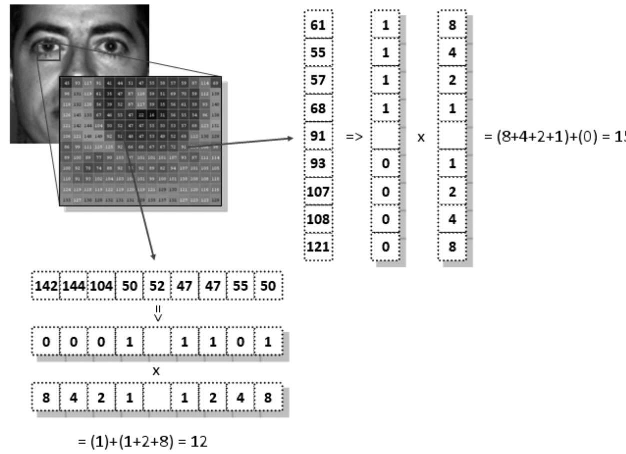


Figure 4. LLBP operator with line length 9 pixels, 8 bits considered


(a) (b) (c) (d)

Figure 5. Example of face image processed by LLBP operator with line length 9 pixels: (a) is original image, (b) and (c) are LLBP along with horizontal and vertical direction, and (d) is its magnitude

3. Analysis and Experiments

In this section, we give the analysis of LLBP and then present the evaluation of our algorithm with other methods on Yale face database B as well as its extended version [6] and FERET database [12].

3.1. Data Preparation

The Yale Face Database B contains 5,760 images of 10 subjects under 9 poses x 64 illumination conditions and the Extend Yale Face Database B contains 16,128 images of 28 subjects under 9 poses x 64 illumination conditions as well. Since we are not focusing in the pose variation, Thus only frontal face image for each subject with different 64 illumination shall be selected, 2,432 images in total from 38 subjects. In our experiment, These two databases will be incorporated as one single database. The database is regularly divided into 5 subsets according to the angle of the light source directions and the central camera axis as follows:

- Subset 1 (0° to 12°) - 7 face images under different illu-

$$LLBP_h(N,c) = \sum_{n=1}^{c-1} s(h_n - h_c) \cdot 2^{(c-n-1)} + \sum_{n=c+1}^{N} s(h_n - h_c) \cdot 2^{(n-c-1)}, \quad (6)$$
$$LLBP_v(N,c) = \sum_{n=1}^{c-1} s(v_n - v_c) \cdot 2^{(c-n-1)} + \sum_{n=c+1}^{N} s(v_n - v_c) \cdot 2^{(n-c-1)}, \quad (7)$$
$$LLBP_m = \sqrt{LLBP_h^2 + LLBP_v^2} \quad (8)$$

mination conditions, 3 corruped image was discarded, 263 images in total,

- Subset 2 (13° to 25°) - 12 face images under different illumination conditions, 456 images in total,
- Subset 3 (26° to 50°) - 12 face images under different illumination conditions, 1 corrupted image was discarded, 455 images in total,
- Subset 4 (51° to 77°) - 14 face images under different illumination conditions, 8 corrupted image was discarded, 532 images in total,
- Subset 5 (above 78°) - 19 face images under different illumination conditions, 16 corrupted image was discarded, 706 images in total.

In another database, the FERET database has been used, it contains the following sets,

- fa - 1,010 frontal face images with regular facial expresion from 1,010 subjects,
- fb - 1,519 frontal face images with alternative facial expresion from 1,009 subjects of fa set,
- ba - 200 frontal face images from another 200 subjects (not in fa set),
- bj - 200 frontal face images with alternative facial expresion from 200 subjects of ba set,
- bk - 200 frontal face images with different illumination from 200 subjects of ba set

All face images are from Yale face database B and FERET were manually rotated, resized and cropped to 100×100 pixels with 256 gray levels according to the coordinates of two eyes. They were cropped so that the only face regions are considered. The examples of these two face databases are shown in Figure 6.

3.2. LLBP Analysis

Due to the LLBP operator has its line length, N, as a parameter which uses for increasing or decreasing the length of local line in order to capture the change in image intensity, Thus we first determine the best length of local line

Figure 6. Some samples in Yale face database B and FERET database, the first row is the examples of Yale face database B and the second row is the examples of FERET database

that gives the best recognition rate. The experiment is conducted on Yale face database B by considering only sigle image per subject (38 subjects) as a training set and subset 3 as test set, subset 3 has been selected because it contains few illumination variation in the image which can degrad the efficiency of face recoginition. Finally Linear Discriminant Analysis (LDA) [3] is used for face classification because LDA aim to find projections with most discriminant information by maximizing the ratio of determinant of the projected between-class scatter matrix to the determinant of the within-class scatter matrix. Note that other similarity measures could be adpoted such as Template Matching, Chi-Square Histogram, and Histogram Intersection.

The example of processed images given by LLBP operator with different line length (starting from 3 to 25 pixels) are illustrated in Figure 8, it is shown that LLBP operator can reduce the illumination variation from the image, and Figure 7 shows the experimental result, it can be obviously seen that the best parameter of line length, N, can be 13 pixels (6 pixels for left and right side from the center pixel position), 15 pixels, 17 pixels, and 19 pixels. The reason is that neither less nor many number of patterns in an image can give such good performance but it should close to maximum number of gray-level color, 255 pixels, as detailed in Table 1 (e.g 126 possible patterns for 13 pixels and 254 possible patterns for 15 pixels).

As observed, the adventages of LLBP are as follows: 1) the edges can be emphasized. 2) the image patterns at left and right side of line are mirror (e.g. $N = 9$, $1110_2\_0000_2 = 14 + 0 = 14_{10}$ is equivalent to $0000_2\_0111_2 = 0 + 14 = 14_{10}$) due to LLBP computes binary weight of left and right line seperately and then sum it up. Hence the pattern of edges such as ramp or sharp edges while computing at entry and

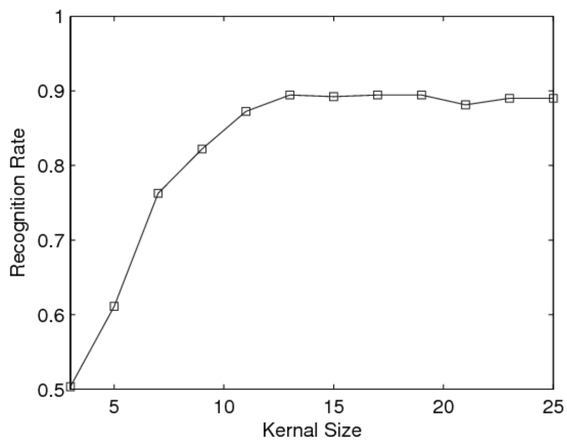


Figure 7. The recognition rate of varying the line length

Table 1. Relationship between the line length of LLBP operator and the number of patterns

Length of Line (pixel)	Bit Used (one side)	Possible Patterns (one side)	Possible Patterns (two sides)
3	1	1	2
5	2	3	6
7	3	7	14
9	4	15	30
11	5	31	62
13	6	63	126
15	7	127	254
17	8	255	510
19	9	511	1022
21	10	1023	2046
23	11	2047	4094
25	13	4095	8190

exit of the edges shall be same.

3.3. Experiment on Yale Face Database B and Extended version

To evaluate the LLBP operator robustness to the illumination variation, the first experiment is then conducted on Yale face database B and Extended version by selecting only single image per subject (38 subjects) as the training set and subset 1 to 5 were used as test set. The comparative results of each subset are shown in Table 2 and the average recognition rate are in Table 3. It is shown that our proposed method LLBP archived high average of recognition rate, 89.71%. Thus we conclude that LLBP is more robustness to illumination variation than other one.

Table 2. Recognition rates (%) on Yale face database B

Method \ Subset	Subset1	Subset2	Subset3	Subset4	Subset5
LBP [10]	90.11	100.00	83.52	85.88	78.75
SLBP [13]	64.26	93.86	54.73	57.63	40.93
MBLBP [9]	99.24	100.00	85.49	78.82	84.84
ILBP [8]	84.03	98.03	80.00	85.88	74.08
LLBP, N = 13	96.20	100.00	89.45	84.16	78.75

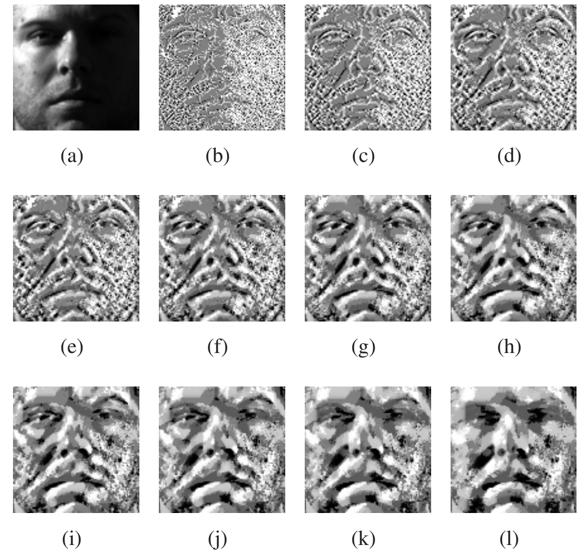


Figure 8. Example of face image processed by LLBP operator with different line length: (a) is original image, (b)-(l) are processed images with line length 3 (b), 5 (c), 7 (d), 9 (e), 11 (f), 13 (g), 15 (h), 17 (i), 19 (j), 21 (k), and 25 (l) respectively

Table 3. Average Recognition rates (%) on Yale face database B

	LBP	SLBP	MBLBP	ILBP	LLBP
Average	87.65	62.28	89.68	84.4	89.71

3.4. Experiment on FERET Database

In the second experiment, we evaluate our LLBP operator comparing to other methods but since the FERET database has a less number of different illumination for each subject, we did not classify the image into different subsets according to the angle of the light source direction. In this experiment, we group fa and ba set together (1,204 subjects) as the training set and then group face images under facial expression and illumination variation together, fb + bj + bk set (1,918 images), as the test set.

From Figure 9, it can be seen that the performance of our proposed LLBP (1^{st}-Rank = 48.49%) outperformed the orginal LBP, SLBP, and ILBP but a little bit worse than MBLBP (1^{st}-Rank = 49.69%). This becomes a disadvantage of our LLBP operator because LLBP did not capture macro-structure of the image as in MBLBP. Nevertheless, there are another two possible reason for the degradation in the face classification are: 1) the misalignment of the face image. 2) the facial structure (e.g. chin) is incomplete due to the face image was cropped.

3.5. Computational Time

Since the computational time is a significant factor in many practical applications, it is interesting to consider as well. To measure the computational time of each method, the experiment is therefore conducted by using 64 face

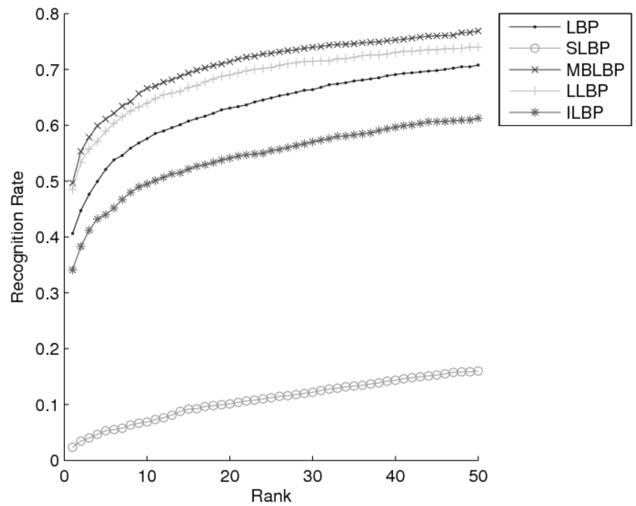


Figure 9. Cumulative match curves of fa+ba set againts fb+bj+bk set

images of one subject from Yale Face Database B and test them with each method (CPU:Intel(R)Core(TM)2 Duo 2.00GHz, RAM: 2.0 GB). Finally the average computational time in second is then obtained as decribed in Table 4,

Table 4. Average computational time in second

	LBP	SLBP	MBLBP	ILBP	LLBP
Elapsed Time	0.129	0.061	0.811	0.276	0.021

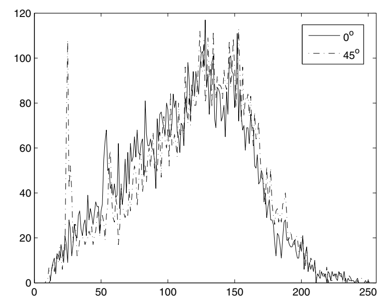
As a result, our implementation of LLBP is faster than the original LBP and other LBP based methods but note that the code might be optimisable.

3.6. Rotation Invariance

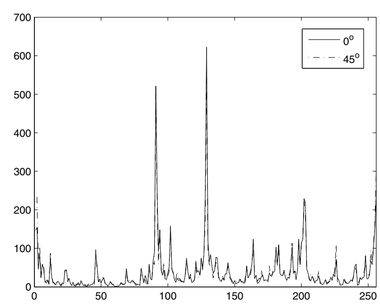
In the last experiment, the rotation invariance is archived by recognizing a test set, which consists of 71 rotated face images (its face orientation begins from 5° increased by 5° to 355°) of one subject, againts a training set, which consists of 38 frontal face image (0°) of 38 subjects from Yale Face Database B. Since this experiment is focusing on rotation invariant ability, the LDA could not be handle due to the perfect misalignment of the facial structure. Hence the global histogram of each processed face image shall be obtained and classified by Histogram Intersection instead.

The example of global histogram of face image for 0° and 45° obtained before and after processing with LLBP operator are illustrated in Figure 10.

From Table 5, It can be obviously seen that our LLBP is also a rotation invariant descriptor.



(a)



(b)

Figure 10. Global histogram of (a) original face image for 0° and 45°, and (b) processed face image

Table 5. Comparative Recongnition rates (%)

Method	Parameters	%
Raw	-	14.08
LBP [10]	-	87.32
SLBP [13]	-	71.83
MBLBP [9]	9×9	23.94
ILBP [8]	-	40.85
LLBP	$N = 13$	57.75
LLBP	$N = 15$	84.51
LLBP	$N = 17$	98.59
LLBP	$N = 19$	100.00

4. Conclusion

This paper proposes a novel face representation method, called Local Line Binary Pattern (LLBP), for robust face recognition under facial expression and illumination variation. The main difference between LLBP and original LBP are as follows: 1) the LLBP operator has a straight line shape, this will greatly assist LLBP operator in capturing the change in image intensity. 2) the image pattern at left and right side of the center pixel of the line are mirror because of the distribution of binary weight at left and right side are equal, Thus, the number of pattern can be reduced.

The experimental results prove the effectiveness of the proposed method, the comparative results of original LBP and other LBP based methods conducted on Yale face database B are shown that the LLBP is more discriminative than other methods even in extreme illumination condition. The FERET database are also shown that the LLBP operator outperformes the original LBP, SLBP, and ILBP but a little bit worse than MBLBP which captures macro-structure of the image.

In our future work we will increase the discriminative power of the LLBP operator by capturing macro-structure of the image as in MBLBP.

References

[1] T. Ahonen, A. Hadid, and M. Pietikäinen. Face recognition with local binary patterns. In T. Pajdla and J. Matas, editors, *ECCV (1)*, volume 3021 of *Lecture Notes in Computer Science*, pages 469–481. Springer, 2004.

[2] F. Alizadeh and D. Goldfarb. Second-order cone programming. *Math. Programming*, 95:3–51, 2003.

[3] P. N. Belhumeur, J. P. Hespanha, and D. J. Kriegman. Eigenfaces vs. fisherfaces: Recognition using class specific linear projection. *IEEE Trans. Pattern Analysis and Machine Intelligence*, 20:71–86, 1997.

[4] T. Chen, W. Yin, X. Zhou, D. Comaniciu, and T. Huang. Illumination normalization for face recognition and uneven background correction using total variation based image models. In *Proc. IEEE Intl. Conf. Computer Vision and Pattern Recognition*, 2005.

[5] T. Chen, W. Yin, X. S. Zhou, D. Comaniciu, and T. S. Huang. Total variation models for variable lighting face recognition. *IEEE Trans. Pattern Analysis and Machine Intelligence*, 28:1519–1524, 2006.

[6] A. S. Georghiades, P. N. Belhumeur, and D. J. Kriegman. From few to many: Illumination cone models for face recognition under variable lighting and pose. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 23:643–660, 2001.

[7] G. Guo, S. Z. Li, and K. Chan. Face recognition by support vector machines. In *Proc. Intl Conf. Automatic Face and Gesture Recognition*, pages 196–201, 2000.

[8] H. Jin, Q. Liu, H. Lu, and X. Tong. Face detection using improved lbp under bayesian framework. *Image and Graphics, International Conference on*, 0:306–309, 2004.

[9] S. Liao, X. Zhu, Z. Lei, L. Zhang, and S. Z. Li. Learning multi-scale block local binary patterns for face recognition. In S.-W. Lee and S. Z. Li, editors, *ICB*, volume 4642 of *Lecture Notes in Computer Science*, pages 828–837. Springer, 2007.

[10] T. Ojala, M. Pietikäinen, and D. Harwood. A comparative study of texture measures with classification based on featured distributions. *Pattern Recognition*, 29(1):51–59, 1996.

[11] T. Ojala, M. Pietikäinen, and T. Mäenpää. Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 24:971–987, 2002.

[12] P. J. Phillips, H. Moon, S. A. Rizvi, and P. J. Rauss. The feret evaluation methodology for face-recognition algorithms. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 22(10):1090–1104, 2000.

[13] Q. Tao and R. N. J. Veldhuis. Illumination normalization based on simplified local binary patterns for a face verification system. In *Biometrics Symposium 2007 at The Biometrics Consortium Conference, Baltimore, Maryland*, pages 1–7, USA, September 2007. IEEE Computational Intelligence Society.

[14] M. Turk and A. Pentland. Eigenfaces for recognition. *J. Cognitive Neuroscience*, 3:71–86, 1991.

[15] P. Viola and M. Jones. Robust real-time object detection. In *International Journal of Computer Vision*, 2001.

[16] H. Wang, S. Li, and Y. Wang. Face recognition under varying lighting conditions using self quotient image. In *IEEE Intl. Conf. Automatic Face and Gesture Recognition*, 2004.

[17] H. Wang, S. Li, and Y. Wang. Generalized quotient image. In *Proc. Intl. Conf. Computer Vision and Pattern Recognition*, 2004.

[18] L. Wiskott, J. M. Fellous, N. Kruger, and C. V. D. Mals-burg. Face recognition by elastic bunch graph matching. *IEEE Trans. Pattern Analysis and Machine Intelligence*, 19:775–779, 1997.