Recognizing Individuals from Unconstrained Facial Images

Radhey Shyam and Yogendra Narain Singh

Abstract This work makes an effort to address the problem of face recognition in unconstrained environments and presents a novel method of facial image representation based on local binary pattern (LBP). The method devises the appropriate descriptor that discriminates the facial features by filtering the LBP surface texture. The method, we name as augmented local binary pattern (A-LBP) works on the uniform and non-uniform patterns both. The non-uniform pattern is replaced with the majority voting of the uniform patterns which combines with the neighboring uniform patterns to extract pertinent information regarding the local descriptors. The recognition accuracy obtained by the proposed method is computed on Chi square and Bray Curtis dissimilarity metrics. The experimental results show that the proposed method performs better than the original LBP on publicly available face databases, AT & T-ORL, extended Yale B, Yale A and Labeled Faces in the Wild (LFW) containing unconstrained facial images.

Keywords Face recognition · LBP · Bray Curtis · Chi square

1 Introduction

Automatic facial image analysis is an active area of research in computer vision. Numerous face recognition methods such as PCA [1], LDA [2], Fisherface [3] have been designed that are performing satisfactorily in constrained environments. In many applications, e.g., image retrieval, biomedical image analysis, and outdoor scene analysis, the environments are not cooperative. Therefore, there is a need to devise an efficient method that accurately recognizes the individual's from their unconstrained facial images.

R. Shyam(✉) · Y.N. Singh
Department of Computer Science and Engineering,
Institute of Engineering and Technology (IET), Lucknow 226 021, India
e-mail: shyam0058@gmail.com, singhyn@gmail.com

S. Berretti et al. (eds.), *Intelligent Systems Technologies and Applications*,
Advances in Intelligent Systems and Computing 384,
DOI: 10.1007/978-3-319-23036-8_33

In literature, the methods that work in unconstrained environments are primarily based on texture representations that build several local representations of the face image and combining them into a global representation. The local features-based approaches to face recognition have drawn attention of the biometric researchers in the field of computer vision [4, 5, 6]. These methods are less sensitive to variations in pose and illumination than the traditional methods. Furthermore, an important reason for heeding the local features-based approaches are that the traditional methods which lose the local discriminatory features by averaging it, over the entire image. The major problems with the texture analysis is that, they are not uniform due to variations in orientation, scale, or, other visual appearances. A useful direction is, therefore, the development of powerful texture metrics that can be extracted and classified with a low-computational intricacy.

In unconstrained environments, the local binary pattern (LBP) is one of the most prevalent methods of face recognition which is computationally efficient [7]. This paper addresses the issues of face recognition in unconstrained environments and devises an efficient method that accurately recognizes human faces from variations in pose, illumination, and expression. A novel approach for facial image representation using LBP, called augmented local binary pattern (A-LBP) is presented. It combines the uniform and non-uniform patterns on the principle of locality which replaces the non-uniform patterns with the majority voting of uniform patterns and combined with the neighboring uniform patterns as a result. Finally, the local descriptors are generated that have shown discriminatory information to classify the facial images. The rest of the paper is organized as follows: The basics of LBP are given in Section 2. In Section 3, the theoretical and experimental demonstration of the proposed A-LBP method is presented. The performance of the A-LBP method is evaluated and the results are reported in Section 4. Finally, the conclusion is drawn in Section 5.

2 Local Binary Pattern

The Local Binary Pattern operator was first introduced in 1996 by Ojala *et al.*, for the study of texture of gray-scale images. It is a powerful means of texture representation. The intention behind using LBP operator for face representation is that, the face can be seen as a composition of various micro-patterns and it is insensitive to variations, such as pose and illumination. The LBP operator labels the pixels of an image with decimal numbers, which encodes the local structure around each pixel. Each pixel is compared with its neighborhood by subtracting the central pixel's value as a threshold. The resulting non-negative values are encoded with 1 and the others with 0. The derived binary numbers are referred to as a LBP [8, 9].

Plenty of LBP variants have been proposed in literature to improve the robustness of LBP operator in unconstrained face recognition. For instance, Liao *et al.* [10] proposed a dominant LBP which makes use of the most frequently occurred patterns of LBP. Center-symmetric LBP is used to replace the gradient operator used by the SIFT operator which is based on the strengths fusion of SIFT and LBP operators [11]. A multi-block LBP replaces the intensity values in computation of LBP with mean intensity value of image blocks [12]. Local ternary pattern was initiated by Tan and Triggs [13], to add resistance to the noise. Three-Patch LBP code is produced by comparing the values of three patches to produce a single bit value in the code assigned to each pixel. Four-Patch LBP codes compare two center symmetric patches in the inner ring with two center symmetric patches in the outer ring [14].

The pitfall of the LBP is that their insensitiveness to the monotonic transformation of the gray-scale. Moreover, LBP may not work properly for the noisy images. Furthermore, the original LBP uses only the uniform patterns, otherwise LBP would suffer from the curse of dimensionality. This reduction in size may result in the loss of important information.

3 Augmented Local Binary Pattern (A-LBP)

This section proposes a novel method that relies on the LBP, called augmented local binary pattern. Prior work on the LBP have not drawn much attention on the use of non-uniform patterns. They are either treated as noise and discarded during the texture representations, or used in combination with the uniform patterns. The proposed method considers the non-uniform patterns and extracts the discriminatory information available to them, so as to prove their usefulness. They are used in combination to the neighboring uniform patterns and extract useful information regarding the local descriptors.

The proposed method uses a grid-based region. However, instead of directly assigning all non-uniform patterns into 59^{th} bin, it replaces all non-uniform patterns with the majority of neighboring uniform patterns. For this, we have taken a filter of size 3×3 that is moved on the entire LBP generated surface texture. In this filtering process, the central pixel's value (c_p) is replaced with the majority of a set in case of the non-uniformity of the central pixel. This set contains 8-closet neighbors of central pixel, in which non-uniform neighbors are substituted with 255. Here 255 is the highest uniform value. The proposed A-LBP method is explained in Algorithm 1. The lookup table contains decimal values of 8-bit uniform patterns are used as given in [15]. The basic steps of filtering is shown in Fig. 1.

The classification performance of the proposed method is evaluated with Chi square (χ^2) and Bray Curtis dissimilarity (BCD) metrics. which are defined as follows:

$$\chi^2(p,q) = \sum_{i=1}^{N} \frac{(p_i - q_i)^2}{(p_i + q_i)} \tag{1}$$

$$BCD(p,q) = \frac{\sum_{i=1}^{N} |p_i - q_i|}{\sum_{i=1}^{N} (p_i + q_i)} \tag{2}$$

where N is the dimensionality of the spatially enhanced histograms, p is the histogram of the test image, q is the histogram of the training image, i represent the bin

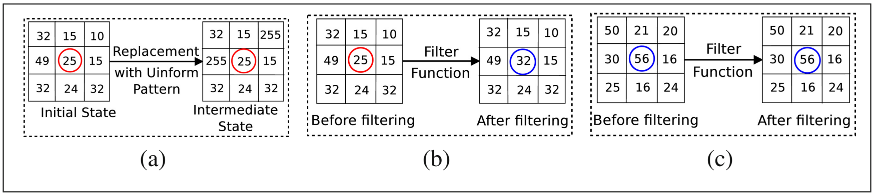

Fig. 1 Example of augmented local binary patterns (A-LBP) operator: (a) Neighboring non-uniform patterns of the central pattern are to be replaces with highest uniform pattern 255, (b) The value of central pattern 25 is a non-uniform pattern, which is replaced with majority value of 32, and (c) The value of central pattern 56 is already a uniform pattern, so it remains unchanged.

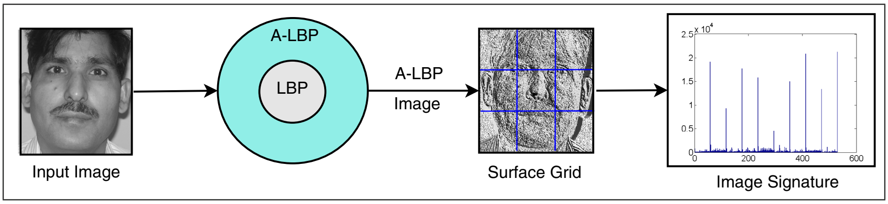

Fig. 2 Block diagram of augmented local binary patterns (A-LBP) for face recognition system.

Algorithm 1. Steps of augmented local binary pattern (A-LBP)

Input: LBP surface texture
Filtering procedure:

1. Check the uniformity of central pixel's value c_p.
2. If c_p is uniform, Then Go to step 1 with next c_p.
3. Otherwise, form a set N_8 containing 8 closet neighbors of c_p.
4. Replace all non uniform patterns in N_8 with 255.
5. Assign majority of N_8 to c_p.

Output: Augmented local binary pattern (A-LBP) surface texture

number and p_i, q_i are the values of the i^{th} bin in the histograms of p and q to be compared. The concatenation of all sub histograms constitutes the image's signature.

The Block diagram of the proposed A-LBP face recognition method is shown in Fig. 2.

4 Results

The proposed method is tested on the publicly available face databases, such as AT & T-ORL [16], extended Yale B [17], Yale A [18] and Labeled Faces in the Wild [19]. The images differ in variation in pose, illumination, expression, eye glasses and

Table 1 Face recognition accuracies (%) of methods on different databases using Chi square (χ^2) distance and Bray Curtis Dissimilarity (BCD) metrics.

Distance Metrics → Methods ↓	Database							
	AT & T-ORL		Extended Yale B		Yale A		LFW	
	χ^2	BCD	χ^2	BCD	χ^2	BCD	χ^2	BCD
LPB	92.50	94.52	74.11	81.83	61.19	60.00	65.00	65.29
A-LBP	**95.00**	**95.00**	**81.22**	**86.45**	**73.33**	**71.90**	65.00	**67.37**

occlusion. A total of 3455 images are used to recognize 113 distinct individuals from these databases. The system is trained for each database separately, whereas the test image is selected randomly from given images for each individual and the performance is computed.

The performance of the proposed A-LBP method is analyzed using equal error rate, which is an error, where the likelihood of acceptance is assumed to be same as to the likelihood of rejection of the people who should be correctly verified. The performance of the proposed method is also confirmed by the receiver operating characteristic (ROC) curves. The ROC curve is a measure of classification performance that plots the genuine acceptance rate (GAR) against the false acceptance rate (FAR).

4.1 Recognition Performance Using Chi Square Distance Metric

The face recognition accuracy of the proposed A-LBP method is compared to the LBP method on different databases. The experimental results show that the A-LBP performs better to LBP. For example, the AT & T-ORL database the A-LBP achieves 95% recognition accuracy, whereas LBP reports an accuracy of 92.5%. Similarly for extended Yale B and Yale A databases, the A-LBP performs better than LBP. For extended Yale B database the accuracy values are reported to 81.22% for A-LBP and 74.11% for LBP. For Yale A database, the proposed method reports a better accuracy of 73.33% in comparison to the LBP accuracy value of 61.19% (See Table 1).

The ROC curve for AT & T-ORL database is plotted and shown in Fig. 3(a). It shows that the GAR is found higher for the proposed A-LBP method and reported the value 78% when the FAR is strictly nil. As FAR increases, the GAR value is also increased. Such as, the GAR is found 93% for LBP and 96% for A-LBP at 5% of the FAR. The GAR is found maximum to 100% at 32% of FAR. The ROC curve for extended Yale B database is plotted and shown in Fig. 3(b). It shows that the GAR is found higher for A-LBP method and reported the value 32% when the FAR is strictly nil. As FAR increases, the GAR value is also increased for all methods, respectively. For example, the GAR is found 62% for LBP and 82% for A-LBP at 20% of FAR. The GAR is found maximum to 100% at 83% of FAR for LBP and 78% of FAR for A-LBP. The reported results show that A-LBP method achieves better recognition accuracy due to its insensitiveness to the change of illumination.

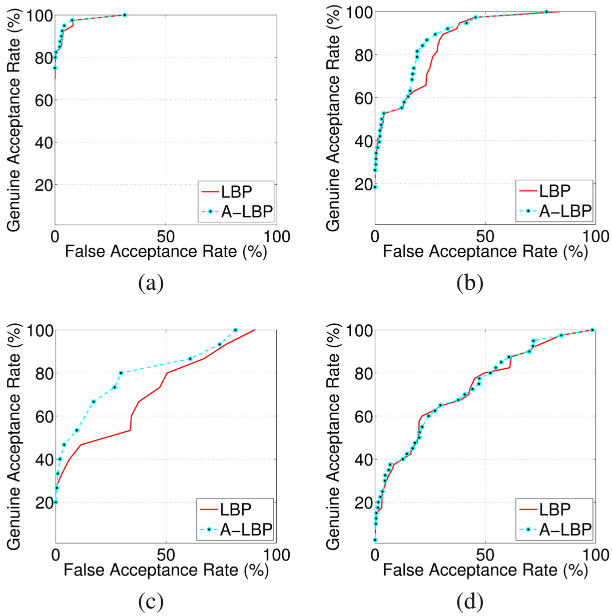

Fig. 3 ROC curves for LBP and A-LBP methods using Chi square (χ^2) distance metric on different databases: (a) AT & T-ORL, (b) Extended Yale B, (c) Yale A, and (d) LFW.

The ROC curve for Yale A database is plotted and shown in Fig. 3(c). It shows that the GAR is found higher for A-LBP method and reported value of 20% when the FAR is strictly nil. As FAR increases, the GAR value is also increased for all methods, respectively. Such as, the GAR is found 50% for LBP, 69% for A-LBP at 20% of the FAR. The GAR is found maximum 100% at 90% of FAR for LBP and 82% of FAR for A-LBP. The A-LBP method achieves better recognition accuracy due to its insensitiveness to the change of illumination. The ROC curve for LFW face database is plotted and shown in Fig. 3(d), which indicates that the GAR is found higher in A-LBP method and reported value of 15% at the zero FAR. As FAR increases, the GAR value is also increased for both methods, respectively. For example, the GAR finds 35% for LBP, 39% for A-LBP at 6% of the FAR. The GAR is found maximum 100% for both methods at 98% of FAR. A-LBP method shows the marginal recognition accuracy over the LBP on LFW database.

4.2 Recognition Performance Using Bray Curtis Dissimilarity Metric

The face recognition accuracy of the proposed A-LBP method is compared to the LBP method on different face databases. The experimental results show that the

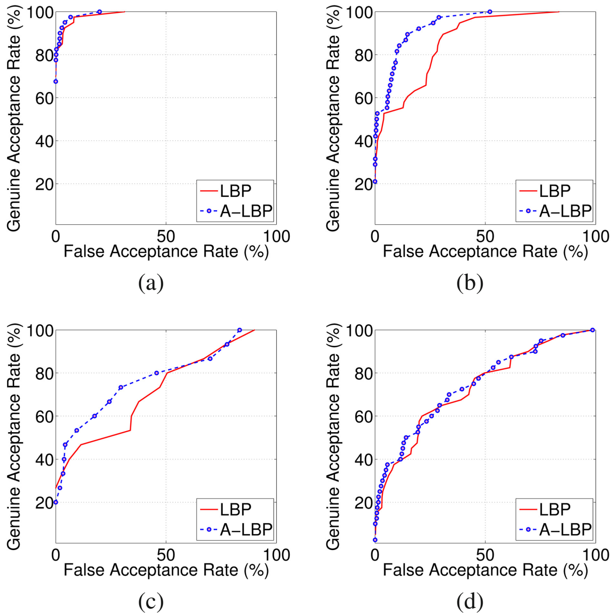

Fig. 4 ROC curves for LBP and A-LBP methods using Bray Curtis dissimilarity metric on different databases: (a) AT & T-ORL, (b) Extended Yale B, (c) Yale A, and (d) LFW.

A-LBP performs better to LBP. For example, the AT & T-ORL database the A-LBP achieved 95% recognition accuracy, whereas LBP reports an accuracy of 94.52%. Similarly for extended Yale B and Yale A databases, A-LBP performs better than the LBP. For extended Yale B the accuracy values are reported to 86.45% for A-LBP and 81.83% for LBP. For Yale A database, the proposed method reports a better accuracy of 71.9% in comparison to the LBP accuracy value of 60% (See Table 1).

The ROC curve for AT & T-ORL database is plotted and shown in Fig. 4(a). It shows that the GAR is found higher in the proposed A-LBP method and reported value of 78% when the FAR is strictly nil. As FAR increases, the GAR value is also increased. For example, the GAR finds 95.5% for LBP, 97% for the A-LBP at 7% of the FAR. The GAR is found maximum 100% at 17% for A-LBP and 21% for LBP. The A-LBP method achieves better recognition accuracy due to its insensitiveness to the mild changes in illumination, facial expression and occlusion. The ROC curve for the extended Yale B database is plotted and shown in Fig. 4(b). It shows that the GAR is found higher in A-LBP method and reported value of 32% when the FAR is strictly nil. As FAR increases, the GAR value is also increased for all methods, respectively. Such as, the GAR finds 81% for LBP, 90% for A-LBP at 14% of the FAR. The GAR is found maximum 100% at 62% of FAR for LBP and at 51% of FAR for A-LBP. The A-LBP method achieves better recognition accuracy due to its insensitiveness to the change of illumination.

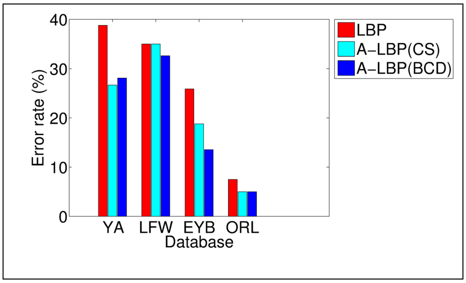

Fig. 5 Histogram of equal error rate for LBP, A-LBP(CS), and A-LBP(BCD) methods.

The ROC curve for Yale A database is plotted and shown in Fig. 4(c). It shows that the GAR is found higher in A-LBP method and reported value of 20% when the FAR is strictly nil. As FAR increases, the GAR value is also increased for all methods, respectively. Such as, the GAR finds 50% for LBP, 61% for A-LBP at 20% of the FAR. The GAR is found maximum 100% at 89% of FAR for LBP and 82% of FAR for A-LBP. The A-LBP method achieves better recognition accuracy due to its insensitiveness to the change of illumination. The ROC curve for LFW face database is plotted and shown in Fig. 4(d), which indicates that the GAR is found higher in A-LBP method and reported value of 15% at the zero FAR. As FAR increases, the GAR value is also increased for both methods, respectively. For example, the GAR finds 41% for LBP, 50% for A-LBP at 16% of the FAR. The GAR is found maximum 100% for both methods at 98% of FAR. In LFW database, the proportion of non uniform patterns is comparatively larger than the uniform patterns. As an effect, the feature descriptor of A-LBP becomes brighter that may loss the some discriminatory information. Therefore, a slight improvement in the result is only reported by our proposed method.

The histogram representation of recognition performance representing the error rate of the LBP, A-LBP (CS) using Chi square, A-LBP (BCD) using Bray Curtis dissimilarity metric on different databases, such as Yale A (YA), Labeled Faces in the Wild (LFW), extended Yale B (EYB) and AT & T-ORL is as shown in Fig. 5.

5 Conclusion

This paper has presented a novel method of face recognition under unconstrained environments. The proposed method has efficiently recognized the faces from variations, such as pose, illumination and expression. The experimental results has shown that the performance of the A-LBP method is improved to the original LBP for most of the databases. When there is a variation in illumination of images in the database, the BCD may be the better choice than the χ^2 metric. In such cases, the A-LBP shows better recognition accuracy than the original LBP. It is also found that the databases having variations in pose and facial expression, A-LBP performs superior than LBP.

Acknowledgments The authors acknowledge the Institute of Engineering and Technology (IET), Lucknow, Uttar Pradesh Technical University (UPTU), Lucknow for their partial financial support to carry out this research under the Technical Education Quality Improvement Programme (TEQIP-II) grant.

References

1. Turk, M.A., Pentland, A.P.: Eigenfaces for recognition. J. Cogn. Neurosci. **3**(1), 71–86 (1991)
2. Lu, J., Kostantinos, N.P., Anastasios, N.V.: Face recognition using LDA-based algorithms. IEEE Trans. Neural Networks **14**(1), 195–200 (2003)
3. Belhumeur, P.N., Hespanha, J.P., Kiregman, D.J.: Eigenfaces vs. Fisherfaces: Recognition Using Class Specific Linear Projection. IEEE Trans. Pattern Anal. Mach. Intell. **19**(7), 711–720 (1997)
4. Shyam, R., Singh, Y.N.: A Taxonomy of 2D and 3D Face Recognition Methods. In: Proc. of 1^{st} Int'l Conf. on Signal Processing and Integrated Networks (SPIN 2014), pp. 749–754. IEEE, February 2014
5. Shyam, R., Singh, Y.N.: Identifying Individuals Using Multimodal Face Recognition Techniques. Procedia Computer Science, Elsevier **48**, 666–672 (2015)
6. Shyam, R., Singh, Y.N.: Face recognition using multi-algorithmic biometric systems. In: Fourth International Conference on Advances in Computing, Communications and Informatics (ICACCI-2015), Kochi, India. IEEE, TBA, August 2015
7. Ahonen, T., Hadid, A., Pietikainen, M.: Face Description with Local Binary Patterns: Application to Face Recognition. IEEE Trans. Pattern Anal. Mach. Intell. **28**(12), 2027–2041 (2006)
8. Ojala, T., Pietikainen, M., Harwood, D.: A Comparative Study of Texture Measures with Classification Based on Feature Distributions. Pattern Recogn. **29**(1), 51–59 (1996)
9. Shyam, R., Singh, Y.N.: Face recognition using augmented local binary patterns and Bray Curtis dissimilarity metric. In: Proc. of 2^{nd} Int'l Conf. on Signal Processing and Integrated Networks (SPIN 2015), Noida, India, pp. 779–784. IEEE, February 2015
10. Liao, S., Law, M.W.K., Chung, A.C.S.: Dominant Local Binary Patterns for Texture Classification. IEEE Trans. Image Processing **18**(5), 1107–1118 (2009)
11. Heikkila, M., Pietikainen, M., Schmid, C.: Description of Interest Regions with Local Binary Patterns. Pattern Recogn. **42**(3), 425–436 (2009)
12. Zhang, L., Chu, R., Xiang, S., Liao, S., Li, S.: Face detection based on multiblock LBP representation. In: Proc. of Int'l Conf. on Biometrics. (2007)
13. Tan, X., Triggs, B.: Enhanced local texture feature sets for face recognition under difficult lighting conditions. In: Zhou, S.K., Zhao, W., Tang, X., Gong, S. (eds.) AMFG 2007. LNCS, vol. 4778, pp. 168–182. Springer, Heidelberg (2007)
14. Wolf, L., Hassner, T., Taigman, Y.: Descriptor based methods in the wild. In: Proc. of Workshop Faces in Real-Life Images: Detection, Alignment, and Recogn., Marseille, France, October 2008. https://hal.inria.fr/inria-00326729
15. Shyam, R., Singh, Y.N.: Analysis of local descriptors for human face recognition. In: Proc. of 3^{rd} Int'l Conf. on Advanced Computing, Networking, and Informatics (ICACNI 2015), Orissa, India. Springer-Verlag, TBA, June 2015
16. Samaria, F., Harter, A.: Parameterisation of a Stochastic Model for Human Face Identification. In: Proc. of 2^{nd} IEEE Workshop on Applications of Computer Vision, Sarasota, FL, December 1994

17. Lee, K.C., Ho, J., Kriegman, D.: Acquiring Linear Subspaces for Face Recognition under Variable Lighting. IEEE Trans. Pattern Anal. Mach. Intell. **27**(5), 684–698 (2005)
18. UCSD: Yale (2007). http://vision.ucsd.edu/content/yale-face-database
19. Huang, G.B., Ramesh, M., Berg, T., Learned-Miller, E.: Labeled faces in the wild: a database for studying face recognition in unconstrained environments. In: Tec. Report, University of Massachusetts, Amherst, pp. 07–49 (2007)