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Face Recognition using Prominent LBP Model

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Abstract

The Local Binary Pattern (LBP) is a very popular descriptor for texture analysis. Various methods of face recognition are derived based on LBP, which describes the local property significantly. The histogram methods based on entire LBP is a complex task. To overcome this Uniform Local Binary Pattern's (ULBP) are proposed and ULBP's are treated as fundamental property of LBP. The ULBP approach treated all Non-Uniform Local Binary Pattern's (NULBP) into one miscellaneous label. Later the researchers proved that NULBP also contains a part of significant texture information. To address this, the present paper proposed the Prominent LBP (PLBP) which consists of the majority of the ULBP's and some of the NULBP's and treated the rest of them as Non-Prominent LBP (NPLBP). For this the PLBP used completely a new set of transitions other than ULBP. The present paper also derived Maximum PLBP (MPLBP), Smallest PLBP (SPLBP). The proposed PLBP approach is used for face recognition on Yale, Indian and American Telephone and Telegraph Company (AT&T) Olivetti Research Laboratory (ORL) databases with different combinations of neighboring pixels and radius. The results indicate that a good face recognition rate when compared to LBP and ULBP approaches.

Index Terms— LBP, ULBP, NULBP, local property, miscellaneous label.

I. INTRODUCTION

One of the challenging and interesting problems in the field of image analysis and computer vision is the face recognition. Many researchers showed a great deal of attention over the last few years in face recognition methods because it's applications are found in various domains. The face recognition problem can be formulated as follows: Given an input or query face image and a feature database of face images of known individuals, how can we verify or determine the identity of the person in the input image?. The face identification accuracies significantly decrease when the obtained images do not have adequate quality either due to a variety of facial expressions, subject's alignment problem to the camera, gaze deviations or facial hair [8, 12, 13, 22, 30].

Several Researchers worked for the recognition of unconstrained face images (images are taken without any particular background) [4, 12, 13, 14, 22, 30, 32]. These algorithms [4, 12, 13, 14, 22, 30, 32] yielded good results to some extent. The recent face recognition algorithms has resulted robust performance against different facial expressions, occlusions, and pose variations when compared to the holistic approaches [5, 26]. These algorithms are derived based on Gabor filters, Speeded Up Robust Features (SURF), Scale Invariant Feature Transform (SIFT), and histograms of LBP.

LBP has been broadly studied by many researchers [15, 24, 26, 27] and it is extensively used in face recognition [17, 19, 25, 26, 29], facial expression detection [7], remote-sensing [2], classification of biometrics [16], medicine [1,6], automated cell phenotype image classification [18], smart guns [31], finger print recognition [16] etc...

Some researchers [5, 26] used LBP operator to extract the discriminative facial features and this method may fail to detect the illumination variation and facial expressions accurately. Pre-processing methods of image processing are well proven methods to reduce noise. Noise is the crucial problem related to methods based on LBP also. To address this some researchers integrated by combining LBP descriptors with pre-processing methods to improve classification performance [16, 29]. For instance, in [29] LBP operator is combined with the Gabor wavelets to represent facial images. This method suffers with high dimensionality problem in representing faces due to the multiple Gabor transformations that are performed. This problem is addressed and to some extent, it is being solved by applying dimensionality reduction to the output of the LBP operators by Zhang et al. [29]. The present paper derived PLBP to reduce the dimensionality and complexity problems of ULBP's and NULBP's, and to present an efficient face recognition algorithm.

The present paper is organized as follows. The section II and III presents the methodology, results and discussion respectively. The section IV presents the conclusions.

II. PROMINENT LBP

Many researchers' expressed their views on the capability of ULBP and NULBP in terms of texture image analysis, recognition etc... Some of them are listed below.

Some of the researchers working on LBP for different applications and in different domains are on a view that feature vector extracted on non-uniform local binary patterns (NULBP) introduces noise and possesses high dimensionality. The present research argues that even simple noise on ULBP may convert it into NULBP and vice versa. Therefore, the present research strongly believes that one of the major problems of NULBP is its high dimensionality and its very low percentage of occurrences in the texture image. Some researchers [9, 23, 33] explored extensively and thoroughly NULBP's and they incorporated a few non-uniform patterns and uniform patterns in a feature vector and conducted experiments.

H. Zhou etal.., [9] suggested ULBP alone do not describe the stochastic attributes and characteristics of texture efficiently. As a result, texture primitive information represented by these patterns is lost, especially when large neighborhoods are considered. This single pattern makes the uniform patterns sensitive to noise. An extended version of LBP operator (LBP^{extend}) is also proposed in the literature [9], which tried to use more than one bin for describing non-uniform patterns and to reduce the effect of noise. They used Hamming's distance to assign each LBP code (noisy code) to certain LBP codes (with minimum distance). Several other attempts were also made in the literature to use non-uniform patterns to overcome limitation of the standard LBP [3, 21, 23, 25]. Some of the methods extracted rotation invariant non-uniform patterns [21, 23, 25]. The rotational invariant LBP's packs or groups several LBP's in to one. Thus they reduce overall LBP patterns and thus complexity will be reduced. The method [23] also tried to extract the dominant (uniform and non-uniform) patterns (LBP^{dom}) which cover 80% of all the existing patterns in the input image as texture descriptor. They discarded the information on type of pattern to reduce the effect of noise. These extensions could solve this problem partially. The hierarchical multi-scale LBP is also explored in the literature [33]. This approach [33] enhanced the performance by obtaining information from the non-uniform bins. A further improvement of this classical LBP operator [3, 20] is to make efficient use of non-uniform patterns in an appropriate way. To fulfill this purpose, all non-uniform patterns are classified into different subsets.

Based on the above, the present research argues that some useful information can be obtained by using NULBP's. This implies NULBP thus appear to contain useful information. However, the existing methods still suffer much from non-monotonic illumination variation, random noise. All the above researchers considered only a very few NULBP in their own way.

The aim of present paper is to develop a simple and convenient method for deriving a new set of LBP patterns that consists of some of ULBP's and NULBP's. For this the present research proposed a new set of transitions that are completely different from the formation of ULBP's and named it as Prominent LBP (PLBP). The proposed Prominent LBP (PLBP) considered the transitions that occurs after two or more consecutive zeros immediately followed by two or more consecutive ones and vice versa in a circular manner. The proposed PLBP contains a subset of ULBP and NULBP. For example the following LBP codes constitutes the PLBP 14(00001110), 27(00011011), 51(00110011), 177(10110001) and the following are Non PLBP (NPLBP) 26(00011010), 53(00110101), 148(10010100). The LBP code

26(00011010) does not fall in to PLBP because it consists of transitions from two or more consecutive zero's to two or more consecutive one's and vice versa is not there. That's why the LBP code 26 falls in to NPLBP.

The PLBP contains a total of 92 patterns of LBP with 8 neighboring pixels with a radius of 1 (on a 3 *3 neighborhood i.e. (P, R) = (8, 1), where P corresponds to the number of neighboring pixels considered on a circle of radius of R). The PLBP contains 40 number of ULBP out of 58 and 52 number of NULBP out of 198. This means the PLBP discards 18 ULBP's and 146 NULPB's into one label called "miscellaneous". For the efficient face recognition system, the present paper evaluated the histograms of PLBP, LBP, ULBP, MPLBP (PLBP U ULBP) and SPLBP (PLBP ∩ ULBP) on facial images.

The union of PLBP and ULBP contains a total of 110 patterns out of which 58 are ULBP's and 52 are NULBP's. This set is named as Maximum PLBP (MPLBP). The MPLBP (PLBP U ULBP) treats the remaining 146 NULBP's as miscellaneous set. The intersection of PLBP and ULBP (PLBP ∩ ULBP) is named as the Smallest PLBP (SPLBP). The SPLBP (Smallest PLBP) contains a total of 40 patterns out of which all 40 are ULBP's and it contains zero NULBP's. The SPLBP (PLBP ∩ ULBP) treats the remaining 216 LBP's (which contains 18 ULBP's and 198 NULBP's) as miscellaneous set.

For efficient face recognition the present paper evaluated histograms of LBP, ULBP, PLBP, MPLBP and SPLBP with different (P, R) on each individual facial image and placed in training database. In the similar way the above histograms are evaluated for test facial image and the face recognition is evaluated based on Chi-square distance method as given in equation 1.

$$R(d,t) = \min \left(\sum_{i=1}^{n} \left((d_i - t_i)^2 / (d_i + t_i) \right) / 2 \right) \qquad (1)$$

Where d, t are two image features (histogram vectors) and R(d,t) is the histogram distance for recognition.

III. RESULTS AND DISCUSSION

The present paper considered 120 facial images out of 15 persons with 11 different facial expressions per person as training set from Yale data base [10]. The present paper considered 472 facial images as training set from Indian database [11]. These 472 facial images correspond to 59 different individuals of both male and female, and on each individual 11 different expressions of Indian database. The present paper also considered 320 facial images as training set from AT&T ORL database [34] for face recognition.

The present paper evaluated histograms of LBP, ULBP, MPLBP, SPLBP on different (P, R). For an extensive and in-depth research and findings, the present paper evaluated Chi-square distance with various combinations of (P,R): (8 , 1), (8 , 2), (8 , 3), (8 , 4), (16 , 1), (16 , 2), (16 , 3) and (16 , 4). The present approach considered the remaining leftover images of Yale and Indian database, which are not considered for training set, as test images.

The Table 1, 3 and 5 shows the percentage of recognition rate for Yale, Indian and AT&T ORL database respectively with different (P,R) combinations of LBP, ULBP, PLBP, SPLBP, MPLBP by considering completely new test images which are not part of the training database. The Table 2, 4 and 6 shows the same for Yale, Indian and AT&T ORL database respectively by considering test images as a combination of new and training database images.

From the tables it is evident that PLBP, MPLBP and SPLBP have shown more or less same or little above recognition rate of ULBP.

Table 1: Recognition rate by considering new test images (not part of training database) for Yale database.

(P,R)	LBP	ULBP	PLBP	SPLBP	MPLBP
(8,1)	68.89	64.44	66.67	62.22	68.89
(8,2)	66.67	66.67	66.67	64.44	66.67
(8,3)	68.89	68.89	71.11	68.89	68.89
(8,4)	64.44	66.67	66.67	68.89	66.67
(16,1)	57.78	73.33	68.89	68.89	75.56
(16,2)	66.67	75.56	71.11	71.11	80.00
(16,3)	64.44	71.11	64.44	71.11	74.44
(16,4)	73.33	71.11	73.33	68.89	71.11
Average	66.39	69.72	68.61	68.06	71.53

Table 2: Face recognition rate for the combination of new and training set as test images for Yale database.

(P,R)	LBP	ULBP	PLBP	SPLBP	MPLBP
(8,1)	83.19	80.97	82.08	79.86	83.19
(8,2)	82.08	82.08	82.08	80.97	82.08
(8,3)	83.19	83.19	84.31	83.19	83.19
(8,4)	80.97	82.08	82.08	83.19	82.08
(16,1)	77.64	85.42	83.19	83.19	86.53
(16,2)	82.08	86.53	84.31	84.31	88.75
(16,3)	80.97	84.31	80.97	84.31	84.97
(16,4)	85.42	84.31	85.42	83.19	84.31
Average	81.94	83.61	83.06	82.78	84.39

Table 3: Recognition rate by considering new test images (not part of training database) for Indian database.

(P,R)	LBP	ULBP	PLBP	SPLBP	MPLBP
(8,1)	89.27	87.57	88.14	87.01	88.70
(8,2)	89.27	87.01	88.70	88.14	88.70
(8,3)	93.79	89.27	88.70	87.57	88.70
(8,4)	92.09	90.96	87.57	89.27	89.83
(16,1)	93.22	92.66	92.66	92.09	92.66
(16,2)	84.18	91.53	91.53	90.96	91.53
(16,3)	88.14	94.92	94.92	92.66	95.48
(16,4)	92.66	94.35	94.35	93.22	95.48
Average	90.32	91.03	90.82	90.11	91.38

Table 4: Face recognition rate for the combination of new and training set as test images for Indian database.

(P,R)	LBP	ULBP	PLBP	SPLBP	MPLBP
(8,1)	93.38	92.54	92.82	92.25	93.10
(8,2)	93.38	92.25	93.10	92.82	93.10
(8,3)	95.64	93.38	93.10	92.54	93.10
(8,4)	94.80	94.23	92.54	93.38	93.67
(16,1)	95.36	95.08	95.08	94.80	95.08
(16,2)	90.84	94.51	94.51	94.23	94.51
(16,3)	92.82	96.21	96.21	95.08	96.49
(16,4)	95.08	95.93	95.93	95.36	96.49
Average	93.91	94.27	94.16	93.81	94.44

Table 5: Recognition rate by considering new test images (not part of training database) for AT&T ORL database.

(P,R)	LBP	ULBP	PLBP	SPLBP	MPLBP
(8,1)	82.50	85.00	85.00	88.75	85.00
(8,2)	91.25	86.25	88.75	88.75	87.50
(8,3)	97.50	95.00	92.50	92.50	96.25
(8,4)	96.25	91.25	91.25	91.25	93.75
(16,1)	86.25	88.75	91.25	92.5	91.25
(16,2)	95.50	95	95.5	95	96.25
(16,3)	98.50	97.5	97.5	96.25	96.25
(16,4)	96.50	92.5	93.75	93.75	95
Average	94.19	93.43	94.5	94.38	94.69

Table 6: Recognition rate by considering new test images (not part of training database) for AT&T ORL database.

(P,R)	LBP	ULBP	PLBP	SPLBP	MPLBP
(8,1)	90.00	91.25	91.25	93.13	91.25
(8,2)	94.38	91.88	93.13	93.13	92.50
(8,3)	97.50	96.25	95.00	95.00	96.88
(8,4)	96.88	94.38	94.38	94.38	95.63
(16,1)	91.88	93.13	94.38	95.00	94.38
(16,2)	96.50	96.25	96.50	96.25	96.88
(16,3)	98.00	97.50	97.50	96.88	96.88
(16,4)	97.00	95.00	95.63	95.63	96.25
Average	95.27	94.45	94.72	94.92	95.08

IV. CONCLUSIONS

After an in-depth study on LBP especially the role of ULBP's and NULBP's in various classification, recognition analysis issues, the present study considers the opinion of treating all NULBP's into (which forms a large class of LBP's i.e. 198) one miscellaneous lable may discard some of the useful information. The present paper is in an opinion that by deleting few of ULBP's and by considering few of NULBP's may increases the overall classification rate.

By considering the above facts, the present paper proposed PLBP which consists 92 LBP patterns out of which 40 are ULBP's and 52 are NULBP's. The present paper after considering the importance of ULBP's derived MPLBP (PLBP U ULBP) and SPLBP (PLBP ∩ ULBP). The face recognition rates of LBP, ULBP, PLBP, SPLBP and MPLBP are evaluated for different combinations of (P, R) on Yale and Indian databases and listed in the tables. The tables clearly indicate the Smallest PLBP (SPLBP) which contains only 40 ULBP's out of 58 ULBP's derived the almost same recognition rate, when compared ULBP's alone. This derives a conclusion that all 58 ULBP's may not hold the texture image contents significantly.

The MPLBP derived slightly high recognition rate than ULBP and it derives a conclusion that treating all NULBP's under miscellaneous lable decrease the overall dimensionality and it reduces the classification rate. The present research concludes that to achieve high classification rate one should consider majority of ULBP's and some portion of NULBP's as set. This is achieved by the proposed PLBP.

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