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Face Recognition Using Prominent Non Uniform Local Binary Patterns

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Abstract*— The face of a human being conveys a lot of information about identity and emotional state of the person. Face recognition is an interesting and challenging problem, and impacts important applications in many areas. Recently, Local Binary Pattern (LBP) has proven to be an effective descriptor for object and face recognition. This paper presents an efficient algorithm for face recognition by deriving a new set of steady transitions on LBP for selecting Prominent Non Uniform LBPs (PNULBPs). The proposed PNULBPs are stable because it considered the transitions from two or more consecutive 0's to two or more consecutive 1's. The proposed Prominent NULBP (PNULBP) along with Uniform LBP (ULBP) features improved facial texture recognition rate. The performance of the proposed scheme is validated using JAFFE facial dataset with various facial expressions.

***Keywords*— Prominent NULBP (PNULBP), Uniform LBP, Steady transitions, Face recognition.**

I. Introduction

Face recognition is an interesting and challenging problem, and impacts important applications in many areas such as identification for law enforcement, authentication for banking and security system access, and also personal identification among others. The face plays a major role in our social intercourse in conveying identity and emotion. The human ability to recognize faces is remarkable. Modern Civilization heavily depends on person authentication for several purposes. Face recognition has always a major focus of research because of its noninvasive nature and because it is peoples primary method of person identification. The researchers developed many successful face recognition systems [1, 2, 6, 8, 13, 15, 21]. The early work on face recognition extracted global features based on sub space methods like Eigen and Fisher faces methods [4,]. These methods projected the whole face into a linear subspace to acquire or identify face variations. Today most of the face recognition algorithms are based on local features, because they are simple and robust. The most popular methods are based on Local Binary Patterns [LBP] extracted from intensity images uses a histogram of local pattern features [16] and in other methods [9] local features are extracted from image orientation**.** There is a need to develop robust face recognition methods that works well under a variety of situation such as illumination and pose variations. In some applications especially when working with surveillance cameras, automatic tagging, and human robot interaction, it is not possible to meet these conditions. To address the above, some researchers derived methods on unconstrained face images by using SIFT models [5,], wavelet transforms [22], histograms of Local Binary Patterns [14], Speeded Up Robust Features [3], Histogram of Oriented Gradients [1], linear SVM [6,], different similarity metrics are used to compare and evaluate faces, the popular among them are distance based metrics such as Euclidian distance and angle based cosine similarity [15]. LBP [2, 9, 16, 19] are widely used in the many image processing applications because of their local computationally efficient nature and robustness in representing local features and illumination variation. One of the disadvantage of LBPs is considering the huge number of Non ULBPs under one label called miscellaneous by which some information may be lost. The present paper addresses this.

II. Local Binary Pattern

The Local Binary Pattern (LBP) was introduced by Ojala et al [14] in 1996. LBP is simple, computationally efficient, robust, and derives local attributes efficiently. With these features, many researchers started working with LBP in various domains and especially in face recognition [9, 10, 11, 12]. The LBP is a powerful tool to describe the local attributes of a texture. In the LBP the grey level image is converted into binary by taking the central pixel value as a threshold and this grey level value is compared with its neighborhood values. The resulting binary valued image is treated as a local descriptor. The basic LBP was initially derived on a 3×3 neighborhood. This LBP operator can also be represented with different variation of (P,R) where P represents the number of neighborhood pixels and R is the Radius. By this the basic LBP operator is represented as (8,1). The 8-bit binary representation or 8-neighboring pixels on a 3×3 neighborhood or (8,1) derives a LBP code that ranges from 0 to 255. The LBP operator takes the following form as given in equation 1.

$$\mathrm{LBP}(8,1) = \sum_{n=0}^{7} 2^n S(Pc - Pn) \qquad (1)$$

Where n runs over the 8 neighbors i.e. 0 to 7 of the central pixel C. P_c and P_n are the grey level intensities at c and n. S(u) = 1, if u ≥ 0 and 0 otherwise. The LBP encoding process on a 3×3 neighborhood is shown in Fig.1.

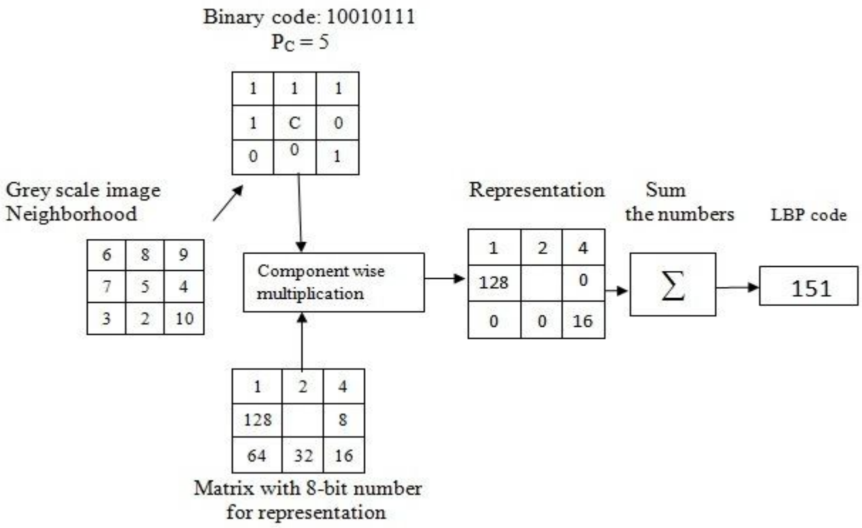

Fig.1. Encoding basic LBP operator

III. DERIVATION OF PNULBP

Researchers derived many conclusions by working on Uniform Local Binary Pattern (ULBP) and Non Uniform Local Binary Pattern (NULBP). Local Binary Pattern (LBP) is uniform if it contains zero or two transitions, for example 00000000/11111111 (0 transitions), 01000000 (2 transitions) and non uniform for more than 2 transitions, for example 00000101 (4 transitions), 00010101 (6 transitions), 10101010 (8 transitions). Some researchers [17, 18] considered only ULBPs for classification or recognition because they are treated as the fundamental properties of texture image moreover 80 to 85% of the texture images contain only ULBPs. Some other researchers [12] considered a part or few of NULBPs along with ULBPs and proved that this combination is better than by considering only ULBPs. From this one can understand that ULBPs can be treated as the fundamental properties of the texture image but considering them only may lose some basic information. Therefore it is better to consider a sub set of NULBPs. Different authors considered different sets of NULBPs. One of the method to solve the above problem is by using Prominent LBP (PLBP) [20]. The PLBP contains the combination of prominent ULBPs (not all ULBP's) and prominent NULBP's. The PLBP contains a new set of transitions that are completely different from the formation of ULBPs.

The PLBP considered the transitions that occur after two or more 2 consecutive 0's immediately followed by two or more consecutive 1's and vice versa in a circular manner. 92 different LBP forms the PLBP on a 3×3 neighborhood with a radius of one. Out of these 40 PLBPs belongs to ULBPs and 52 belong to NULBPs. Based on the above new transition rule the PLBP treats 18 ULBPs and 146 NULBPs under one label called miscellaneous. The present paper considered Smallest PLBP (SPLBP) by using PLBP ∩ ULBP. The SPLBP contains 40 ULBPs and treats the remaining 216 LBPs (which contains 18 ULBPs and 198 NULB's) as miscellaneous set. From the above discussion it is evident that the major problem is how to select a subset from NULPBPs to improve the overall performance and to reduce overall dimensionality. For this the present paper derived Prominent NULBP (PNULBP) which is a subset of NULBP. They contain transitions from two or more consecutive zeros to two or more consecutive ones and vice versa is not true. These transitions are measured in a circular manner and no ULBP's will have such transitions.

For example, ULBP codes 24 (00011000), 227 (11100011) doesn't belongs to PNULBP because they are not having transitions from 00 to 11 and also 11 to 00, therefore they are not PNULBPs. Similarly NULBP codes 18 (00010010), 85 (01010101), 183 (10110111) doesn't belongs to PNULBP because they are not having transitions from 00 to 11 at all. But the NULBP codes like 13 (00001101), 67 (01000011), 104 (01101000) belongs to PNULBP because they are having transition from 00 to 11 and not having transition from 11 to 00. The derived PNULBPs are stable because we are considering the transitions that occur from two or more consecutive 0's to two or more 2 consecutive 1's only, instead of 0 to 1 or vice versa. For efficient face recognition this paper combined the derived PNULBPs with ULBP, PLBP and SPLBP using union (∪) operation only. 90 different LBPs are formed out of 256 by PNULBP ∪ ULBP, in the same way there will be 124 and 72 different LBPs by using union operation in between PNULBP ∪ PLBP and PNULBP ∪ SPLBP respectively.

The PNULBP ∪ PLBP contains 40 ULBPs and 84 NULBPs. The PNULBP ∪ SPLBP contains 40 ULBPs and 32 NULBPs only. For efficient face recognition the present paper evaluated various features based on histograms of ULBP, PLBP, PNULBP, PNULBP ∪ ULBP, PNULBP ∪ PLBP and PNULBP ∪ SPLBP with different (P, R) (where P corresponds to the number of neighboring pixels considered on a circle of radius of 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 [7] method as given in equation 2.

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

Where

d, t: Two image features (histogram vectors)
R (d, t): Histogram distance for recognition.

IV. RESULTS AND DISCUSSIONS

The present paper considered 200 facial images with different facial expressions as shown in Fig.2 from JAFFE data base [23] and evaluated the above texture descriptors on different values of P and R. For efficient face recognition the present paper evaluated Chi-square distance by equation 2. The recognition rate for the database is shown in Table 1 and the observations are: (1) The face recognition rate is high for (P_2, R) when compared to (P_1, R), where $P_2 > P_1$, because for the same radius, considered neighborhood points are more. The reason for this is the number of NULBPs will be increased along with the number of neighboring points for the same radius. That's why one needs to consider PNULBPs to increase face recognition rate. (2) From PNULBP column, it is clearly evident that face recognition rate is increasing gradually by increasing R. This is because as we increase R the LBP contains more number of NULBPs. Therefore one should consider the proposed PNULBPs for accurate face recognition, as R increases. The comparison between all the methods is shown in Fig.3.

TABLE 1
Face recognition rate.

(P,R)	ULBP	PLBP	PNULBP	PNULBP U ULBP	PNULBP U PLBP	PNULBP U SPLBP
(8,1)	65.45	66.87	12.22	76.76	76.44	65.11
(8,2)	63.34	65.65	16.52	60.54	63.51	64.21
(8,3)	62.67	65.43	33.91	76.78	75.61	65.76
(8,4)	65.22	67.12	41.24	74.21	79.49	74.44
(16,1)	71.13	73.32	14.25	69.32	70.81	66.09
(16,2)	76.47	76.54	23.76	65.53	69.32	72.71
(16,3)	73.54	67.36	25.18	66.56	70.75	60.23
(16,4)	71.19	75.87	38.43	71.61	69.06	79.21
Average	68.62	69.77	25.68	71.01	73.62	68.42

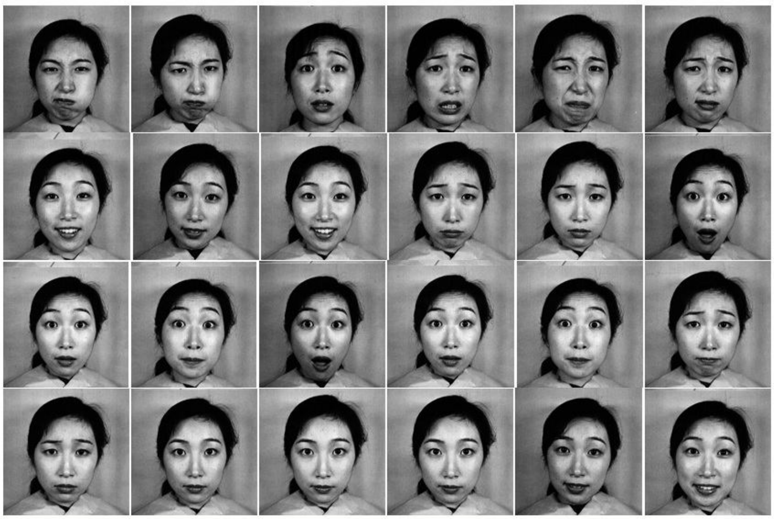

Fig.2. Different facial expressions - JAFFE database.

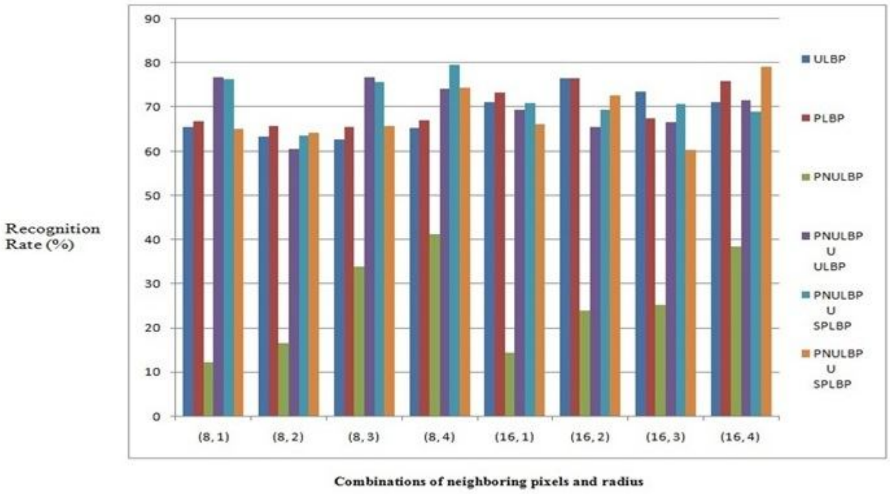

Fig.3. Discrimination rates for different methods.

V. Conclusions

Reason for considering NULBPs is if P or R or both increases, the number of NULBPs increases abnormally. If one treats such a huge number of patterns as miscellaneous then definitely some image content will be lost and this degrades the overall performance. To overcome this and to deal with dimensionality the present paper derived PNULBPs. The proposed PNULBPs are stable, because it considered the transitions two or more consecutive 0's or two or more consecutive 1's. The graph clearly indicates the proposed PNULBP ∪ ULBP, PNULBP ∪ PLBP has shown high performance when compared to ULBP alone. This clearly indicates the significance of the proposed PNULBP is improving overall face recognition rate. Further the PNULBP ∪ SPLBP shown almost similar face recognition rate when compared to PNULBP ∪ ULBP and ULBP alone.

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