Texture Classification Using Prominent Non Uniform Local Binary Patterns

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Abstract - ***Texture classification is an interesting and challenging problem and impacts important applications in many areas. Local Binary Pattern (LBP) has proven to be an effective descriptor for texture classification. The Local Binary Pattern (LBP) measures effectively local characteristics of the texture. The uniform LBP (ULBP) derived from LBP [1] contains the fundamental properties of texture. The Uniform LBP (ULBP) contains 0 or 2 transitions from 0 to 1 or 1 to 0. There are 59 ULBP's on a 3×3 neighborhood LBP. This paper presents an efficient method for texture classification by deriving a new set of transitions on LBP for selecting Prominent Non Uniform LBPs (PNULBPs). The proposed PNULBPs [2] are stable because it considered the transitions from two or more consecutive 0's or 1's. The proposed Prominent NULBP (PNULBP) along with Uniform LBP (ULBP) features improved texture classification rate. The performance of the proposed scheme is validated using various sand textures.***

Key Words: *Local Binary Pattern (LBP), Uniform LBP, Prominent NULBP (PNULBP), Steady transitions.*

1. INTRODUCTION

Texture analysis is important in many applications of computer image analysis for classification of images based on local spatial variations of intensity. A successful classification requires an efficient description of image texture. Important applications include industrial and biomedical surface inspection, for example for defects and disease, ground classification and segmentation of satellite or aerial imagery, segmentation [3] of textured regions in document analysis, and content-based access to image databases. However, despite many potential areas of application for texture analysis in industry there is only a limited number of successful examples. A major problem is that textures in the real world are often not uniform, due to changes in orientation, scale or other visual appearance. In addition, the degree of computational complexity of many of the proposed texture measures is very high.

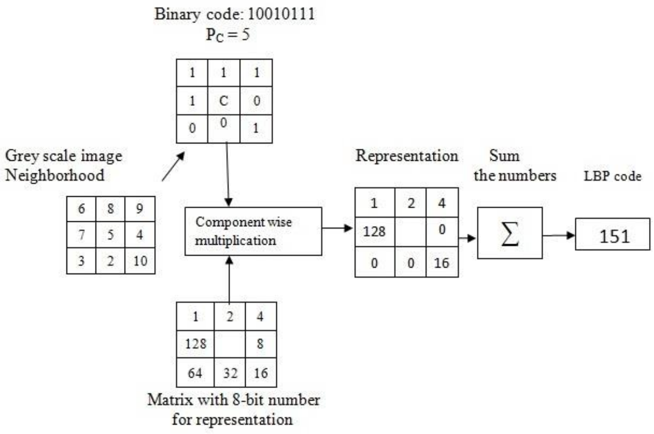
Today most of the texture classification algorithms are based on local features, because they are simple and robust. The most popular methods are based on Local Binary Patterns [LBP] extracted from intensity images uses a histogram of local pattern features [18] and in other methods local features are extracted from image orientation. There is a need to develop robust texture classification method that works well under a variety of situations. some researchers derived methods on unconstrained face images by using SIFT models, wavelet transforms, histograms of Local Binary Patterns, Speeded Up Robust Features, Histogram of Oriented Gradients, linear SVM, different similarity metrics are used to compare and evaluate textures. LBP [4, 5] 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 disadvantages of LBPs is considering the huge number of Non ULBP's under one label called miscellaneous by which some information may be lost. The present paper addresses this.

2. LOCAL BINARY PATTERN

The Local Binary Pattern (LBP) was introduced by Ojala et al [18] 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 texture classification [6, 7, 8]. 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 [13]. 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

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

Where n runs over the 8 neighbors i.e. 0 to 7 of the central pixel C. Pc 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.



A LBP generates 8 bit code ranging from 0 to 28 – 1 i.e. 0 to 255. These are called LBP codes or units in the literature. Considering such a huge number of LBP units (0 to 255) is a complex task for any type of image processing. LBP patterns are divided into Uniform LBP (ULBP) and Non-Uniform LBP (NULBP) based on the number of transitions from 0 to 1 or 1 to 0. Initially Ojala et al. observed that certain patterns of LBP forms fundamentals properties and these patterns are named as uniform LBP. The uniform LBP contains 0 or 2 transitions from 0 to 1 or 1 to 0. For example the LBP code 0 (00000000) and 255 (11111111) will have exactly 0 transitions. The LBP codes 16 (00010000) and 64 (01000000) will have exactly 2 transitions from 0 to 1 or 1 to 0. Ojala et.al treated the remaining LBP patterns as non-uniform LBP. The non-uniform will have more than 2 transitions. No LBP code forms an odd number of transitions. The total number of ULBP codes is 59. That means ULBP represent only 23.04% of total LBP codes. The total number of NULBP codes are 197 (i.e. 256-59) and falls into a large category of total LBP which represents 79.96% of total LBP codes. Ojala et al. proved that majority of texture features can be categorized by ULBP. Many researchers derived methods based on ULBP for various applications.

3. 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 [9. 10] 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 [11] 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 methods to solve the above problem is by using Prominent LBP (PLBP) [14, 15]. 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.

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. Similarly NULBP codes 18 (00010010), 85 (01010101), 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), 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 texture classification derived PNULBPs are combined with ULBP, PLBP and SPLBP using union (U) operation. Different LBPs are formed out of 256 by PNULBP U ULBP, in the same way there will be 124 and 72 different LBPs by using union operation in between PNULBP U PLBP and PNULBP U SPLBP respectively.

The PNULBP U PLBP contains 40 ULBPs and 84 NULBPs. The PNULBP U SPLBP contains 40 ULBPs and 32 NULBPs only. For efficient texture classification the present paper evaluated various features based on histograms of ULBP, PLBP, PNULBP, PNULBP U ULBP, PNULBP U PLBP and PNULBP U 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 textural image and placed in training database. In the similar way the above histograms are evaluated for test textural image and the texture classification is evaluated based on Chi-square distance [16, 17] method as given in equation2.

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

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

4. RESULTS AND DISCUSSION

The present paper considered 200 sand textures as shown in Figure 1 from Google data base and evaluated the above methods on different values of P and R. For efficient texture classification the present paper evaluated Chi-square distance by equation 2. The classification rate for the database is shown in Table 1 and the observations are: The texture classification rate is high for (P2, R) when compared to (P1, R), where P2 > P1, because for the same radius, considered neighborhood points are more. That's why one needs to consider PNULBPs to increase classification rate. From PNULBP column, it is clearly evident that classification 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 texture classification, as R increases. The comparison between all the methods is shown in Figure 2.

Fig -1: Images of Sand textures

Table -1: Textures **c**lassification rate.

(P,R)	ULBP	PLBP	PNULBP	PNULBP U ULBP	PNULBP U PLBP	PNULBP U SPLBP
(8,1)	75.43	76.86	22.23	86.77	86.45	75.12
(8,2)	73.35	75.64	26.51	70.56	73.52	74.22
(8,3)	72.68	75.44	43.90	86.78	85.61	75.76
(8,4)	75.21	77.12	51.24	84.21	89.49	84.44
(16,1)	81.13	83.33	24.25	79.32	80.81	76.09
(16,2)	86.47	86.54	33.76	75.53	79.32	82.71
(16,3)	83.54	77.35	35.18	76.56	60.75	70.23
(16,4)	81.17	85.87	48.43	81.61	79.06	89.21
Average	78.62	79.77	35.68	81.01	83.62	78.42

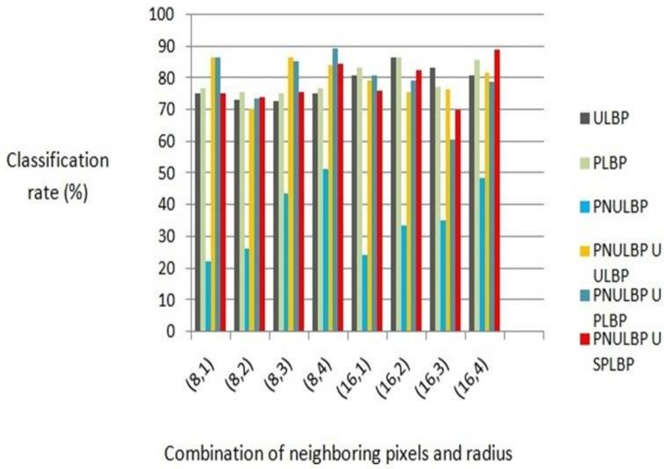


Figure -2: Discrimination between different methods.

6. CONCLUSIONS

Reason for considering NULBPs is if P or R or both increases, the number of NULBPs increases abnormally that which will cause of missing some image content and 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 1's. The graph clearly indicates the proposed PNULBP U ULBP, PNULBP U PLBP has shown high performance when compared to ULBP alone. This clearly indicates the significance of the proposed PNULBP is improving overall texture classification rate.

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BIOGRAPHIES

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