International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878 (Online), Volume-7 Issue-5, January 2019

Ordered Local Binary Pattern (OLBP) For Classification of Textures

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Abstract*: *Conventional Local Binary Pattern (LBP) methods follow the patterns whose rotations are lesser than two or certain limited numbers are called rotation invariant binary patterns. In the conventional rotational-invariant encoding method has disadvantage due to neglecting information of the some patterns by its process of encoding. It ignores the patterns when their spatial transition is greater than two for maintaining the rotation-invariant nature. But these disregarded patterns will plays crucial role and have very much more discriminative power. Here, the present study proposing a novel model called OLBP by changing (sorting) the order of consecutive binary patterns without disturbing the property of rotational invariance. The result observed by experiments indicates the proposed work shows better classification rate which is worked on the standard databases when compared to previous existing methods.

Index Terms: Texture; Neighborhood pixel; Local Binary Pattern (LBP); Histogram; Rotational Invariance; Classification;

I. INTRODUCTION

This The classification of images based on their texture values is well known for the investigators and scientists in the area of digital image processing [1][2]. Surprisingly until now, there is no standard definition for the most important property of the image called "texture", which plays key role for deciding the classification criteria of the images.We can understand the texture as the arrangement or proper order of the pixels by their appearance such as surface of the material, natural scene and human skin and surface of stones or tiles. By understanding and analyzing these textures so many useful and real time applications including but the scope is not limited to stone, material, soil, wood and geographical area classifications. And the usage of texture analysis is for face re-cognition, age or gender classification and deceased leaf classification or quality grading of leaves and in mining soil/minerals recognition where human interaction is needed but difficult or impossible some times. Since the 1960's they are so many vide variety of techniques are developed for classify the textures based on certain criteria. There are four major categories of algorithms called statistical (or stochastic), mathematical, geometrical(structural), and signal processing methods proposed by Tuceryan and Jain [3]

A. Origin of LBP

Revised Manuscript Received on 30 January 2019.
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First, The concept of Local Binary pattern (LBP) invented and introduced by Ojala [1] and Pietkain in the year 1999 as a mathematical approach. It calculates a value that find the amount of relativity within a 3x3 grid of neighborhood pixels by using a certain value called as threshold value that is replicated (or multiplied) with their corresponding weights.

$$LBP_{P,R}\ P,R \sum_{p=0}^{i} \sum_{p=0}^{p-1} s(g_p - g_c)2^p, s(x) = 1, if x \ge 0;$$

s(x)=0 ,if x<0;

Here, g_c represents gray level value of the central pixel, g_p, value of its adjacent or neighboring pixels,
'P' is the total number of neighbor pixels participated.
'R' is the value of the neighborhood radius.
After obtaining the LBP pattern of each pixel, obtain the corresponding histogram is constructed to show the texture image.

$$Histogram(k) = \sum_{i=1}^{I} \sum_{j=1}^{J} f(LBP_{P.R}(i,j),k), k \in [0,K],$$

f (x , y) = 1, if x=y

= 0 in other case

Here, k represents max obtained LBP pattern value.

The U value is defined as total no of changes from 0 to 1 or 1 to 0 called spatially transition of bits in that pattern.

$$U(LBP_{P,R} = |s(gp-1-gc) - s(g0-gc)| + \sum_{p=1}^{p-1} |(\mathrm{gp}-\mathrm{gc}) - \mathrm{s}(\mathrm{gp}-1-\mathrm{gc})|$$

The pattern which has limited transactions (at maximum two) in the circular binary representation [1] defined as the uniform pattern.
Definition of locally rotational invariant pattern as given below:

$$LBP_{P,R}^{riu2} = \sum |(gp-gc) if\ U(LBP_{P,R}) \le 2$$

= P+1 in other cases

The mappings obtained from LBP_{PR} to $LBP_{P,R}^{riu2}$ has p+2 outputs which are different can be implemented.(the output values referred from lookup table.)

B. Pros and Cons of LBP

Pros:

- It is very easy to calculate but efficient in performance.
- It has good discrimination power.
- It is very strong to monotonic gray scale changes occur.

In LBP not only sign component, from magnitude component also we get additional information.

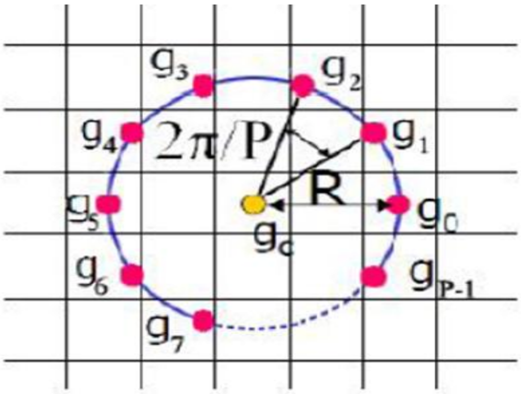

Figure 1:The Central Pixel g_c, And Its Neighboring Pixels With Radius Value R.

Cons:

- While rotating the images, the histograms generated by the Local Binary patterns are very long so it does not support high spatial values.
- In practical situations, there is no guaranty for the autonomic value of local differences between neighboring pixels and its central pixel.
- LBP is sensitive from the external noise so the patterns will disturb.
- In LBP only signed component plays important role as it will provides additional information about the image as classification descriptor.

C. LBP and its Extensions

Until now there are so many methodologies depended on Local Binary Patterns (LBP) invented and investigated. A No of variants to the LBP operator are developed due to its flexibility and make it suitable according to various problem types and to enhance its robustness and discriminative power, computational efficiency, illumination. Here, we are presenting different variants under various categories that describe their role in feature extraction. A few of the variant may come under more than one category [4].

Under the neighborhood topology category, Elliptical binary Patterns (EBP) was developed used for recognition of faces. The method called as Elongated Quinary patterns (EQP)[5] developed by using Quinary encoding in elliptical neighborhood for the analysis of Digital medical images. Local line binary Patterns (LLBP)[6] method uses lines in both horizontal and vertical directions for recognition of face. By using the patch based descriptor method Three-patch Local Binary Patterns (TPLBP)[7] and four-patch Local Binary patterns (FPLBP) used for face analysis. The major inspiration for this approach is CS-LBP [8].Under thresholding and encoding categories, The median value plays the key role to decide thresholding used in texture classification, this method is called as Median Binary Patterns (MBP)[9] method which uses the value of median within the neighborhood is utilized for thresholding used in texture classification. In improved version of LBP (ILBP)[10] calculates the local neighborhood mean value which is used for thresholding. In Local Ternary Patterns (LTP)[11] and Elongated Ternary Patterns (ELTP)[12] three values (1, 0, -1) are used for encoding. The extension for the LTP is Scale Invariant Local Ternary pattern (SILTP)[13] which handles illumination variations which is used in back ground subtraction. Elongated Quinary Patterns (ELTP) deal with five values from -2 to 2 (-2, -1, 0, 1, 2) which is used in digital medical image analysis. Soft and Fuzzy Local Binary Patterns(S/FLBP) and probabilistic LBP thresholding values are replaced by a fuzzy membership function and probabilistic functions respectively. Transaction coded LBP (tLBP)[14] used for car detection using encoding the association between neighboring pixels and Direction coded LBP(dLBP)[15] used for gender detection by related to CS-LBP ,but it also uses central pixel for encoding.In multi-scale analysis category, Gaussian filtering is used for texture classification by multi scale low-pass filtering method before feature extraction. The main theme of Cellular automata is for classification of texture by the technique of compactly encoding several LBP operators at different scales. Multi-scale block LBP (MB-LBP)[16] used for face recognition which compares values of average pixel within small blocks. Another variation of LBP method is Pyramid-based multi-structure LBP used for texture analyses which applies LBP on different layers of image pyramid. Multi resolution uniform patterns used for gait recognition by implementing multi scaling points ordered according to sampling angle.For handling of rotation, Adaptive LBP (ALBP) [17] used for texture classification by incorporated directional statistical information. LBP variance (LBPV) [18] it will obtain rotation variant LBP histogram values after that apply a global matching which used for texture classification. Coming to feature selection and Learning category, Dominant Local Binary Patterns (DLBP) [19] used for texture classification make usage of the information frequency of occurred patterns of LBP. The Extended LBP Analyzes the structure and occurrence probability of non uniform patterns.LBP with hamming distance which is used for face recognition uses Non uniform patterns. FSC_LBP [20] uses the method of Fisher separation criterion is used to find out the most prominent patterns types. By the method of fast correlation- based filtering use of the concept of filtering based on correlation to select LBP patterns for facial recognition and expression analysis.The Decision tree LBP uses decision tree algorithms which are to be learning discriminative LBP-like patterns for face recognition. Ada Boost algorithm is used for learning discriminative LBP histogram bins and selecting the local regions and LBP settings for boosting up LBP bins and histograms respectively. In Kernel Discriminative common vectors methods which are used for face recognition applied to Gabor wavelets and LBP features after PCA projection. Ada Boost-LDA method, from a large pool of multi-scale features we select most discriminative LBP features for face recognition.Other methods inspired by LBP developed for Texture analysis are Weber Law Descriptor (WLD) method codifies differential excitations and orientation components. Local Phase quantization (LPQ) method follows quantizing the Fourier transform phase technique in local neighborhoods. GMM-based density estimator improves the performance by avoids the quantization errors of LBP.

D. Major Applications of LBP

One of the major application areas is visual inspection of industrial products; the main goal is to classify products according to its quality. Detect the defective material according to their visual properties. By using human visualization it takes too much time and sometimes error prone. In visual inspection we can take help of texture features as supplement to color information. LBP is a good candidate for Computer vision used for the above application. Wood inspection is another common application of the LBP, which the operator has been used with color and texture measures. Similarly, Paper quality inspection is another succeeded application area with the LBP. The GLCM and LBP texture features which are based on SOM non-supervised segmentation method widely used for identifying defects in surface images. ontent based image retrieval (CBIR) method which is used to extract the images according to content in a meaningful manner from the huge amount of images and video material which are not properly organized. Many researchers have used LBP as the component of their CBIR systems. A new texture feature which is derived from LBP called "local edge Patterns" applied to an edge image instead of gray scale values directly give better retrieval rates as the results.For image segmentation LBP/C with split (or divide) - and - combine (or merge) approached unsupervised algorithm efficiently used for dividing large aerial images in the similarity regions. Similarly LBP/VAR operator is also another popular segmentation algorithm. Another most exotic useful application of LBP is detection of the person based on the hair. In this context LBP used as texture feature because of its real time nature of the problem.

E. Combined Local Binary Pattern (CLBP)

The rotationally invariant pattern of Local Binary Pattern (LBP) and Combined Local Binary Pattern (CLBP) is follows the condition U(x,y) ≤ β; where β value is 2 in majority of cases. Even if a pixel is encoded by 00011110 ($LBP_{P,R}^{riu2} = 4$) because its bit codes are simply shifted by 2 bits 01111000 and its situation is not changed [18][19].

This encoding procedure has suffering from one problem which is unavoidable and causes it to not considering by assigning the same code. P+1 is assign to $LBP^{riu2}_{P,R}$ when the spatial transition of LBP codes are more than two such as 01100110 or 00010111 consequently although the above are different pattern but they have same value of P+1. This leads $LBP^{riu2}_{P,R}$ to ignore the information about any local binary patterns of pixels whose spatial transactions are greater than two[20].The difference between 00010111 and 0110110 if β is set to 4 then some different pattern with same summation of bits those are not differentiable. i.e. 00010111 and 11110000 moreover 00010111 and 01100110 are distinct patterns but they are represented by the same code when β value is 4. Hence even though we ignore the information about some patterns are ignored most of the researchers use β=2 for rotationally invariant.

II. PROPOSED OLBP METHOD OVERVIEW

There is a remedy proposed by the current study for the above rotation-invariant LBP draw back. The proposed ordered LBP (OLBP) and dictionary learning technique based on knowledge decision -tree.

In ordered LBP method, sum of all continuous bit neighborhood patterns and sort out them. For ex 00010011 have continuous bits of 3,1,2,2.To show the difference for a bit 0 from 1, we segregate them into a zero-bit pattern (3,2) and a one-bit pattern.Because OLBP is a vector representation, it should be created to a code by construction of kd-tree for dictionary learning of OLBP.

A. OLBP Process

Now, in this section the current study presents detailed description of ordered LBP which is based on the LBP operator.

CLBP is an efficient method it is not considering the patterns whose spatial transitions are larger than β.

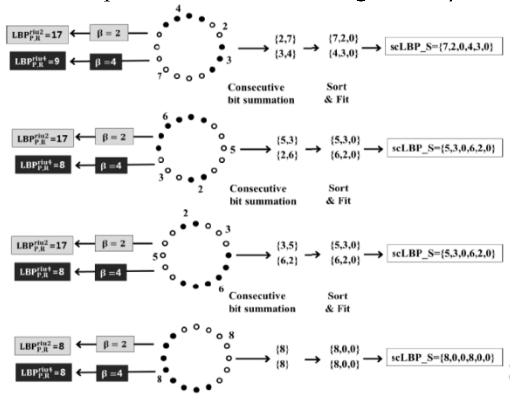

Figure 2: Process Of OLBP

Step 1: Preprocessing: We first submit the selected input images (I) to the convolution process. It will process the image (I) smooth and decreases overly compute patterns that have too many transitions because due to these patterns there is a possibility of feature which are less discriminative. The result of the Gaussian filtering is when we change the sigma value as larger the image becomes blurred therefore Gaussian filtering makes OLBP more powerful with an optimal proportion of complicated patterns by making patterns smooth and reduce the noise.

Step 2: after Gaussian filtering we will take ordered LBP (OLBP) on the sign and magnitude binary bits by the following algorithm

(a) Start
(b) Compute the bit patterns on S_p
(c) Count immediate adjacency bits of 0 and 1 (take rotation invariant pattern by sorting consecutive bits)
(d) Sort out the obtained bit patterns
(e) Concatenate the sorted ordered bits and fit them into level (Ex (k=6))
(f) End

Step 3: Construct K- Dimensional Tree for dictionary learning the **Pruning** Condition of kd-Tree pays an important role. The dimensionality of the histogram is decided by the no of leaf nodes on a kd-Tree. The factors used to determine the no of nodes are max depth, minimum threshold no of features.

Step 4: Generate histograms to the corresponding codes

Step 5: Normalized the Histogram.

Step 6: Choose the classification method.

Either nearest neighborhood classification or SVM algorithm is used as a classifier in the majority cases of texture analysis. NNC determines the category of query images by the measurement of distance.

SVM determine the class of query images by the distance from support vectors. Of these two classifiers, we choose SVM because of its significant advantage of computational advantage.

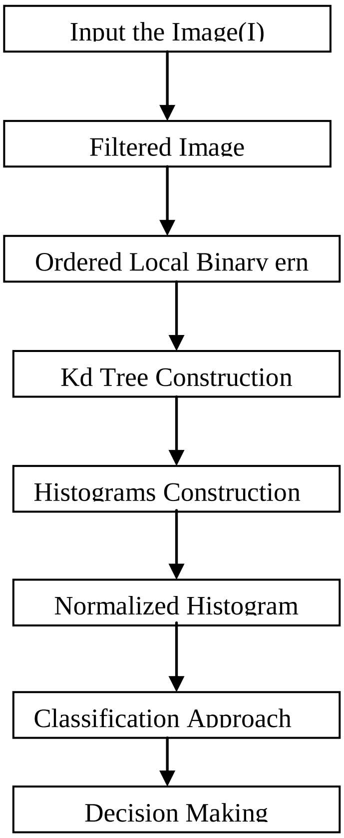

Figure 3: Overview of the Proposed Work

Step 7: Decision making for Obtain Classified image.

OLBP consists of 3 patterns Sign component (OLBP_S), magnitude component (OLBP_M^{+-}) and central pixel grey level (CLBP_C) in a rotational invariant manner.

So, we compare the proposed OLBP with LBP_S; LBP_M(OLBP_S, OLBP_M, OLBP_C) to show the performance of the separation of magnitude part as OLBP_M^{+}, OLBP_M^{-}

III. EXPERIMENTAL SETUP

For the analyzing the performance of the proposed OLBP algorithm we have taken the images of the leave in gray scale.(for the easy calculations we perform conversion from the color (RGB) images into grayscale images). For leaf classification we choose a challenging experimental setup and compared with the results which are obtained by traditional methods. We utilized the experiment results cited for the traditional methods in the relevant articles. The proposed OLBP shows best performance among the other datasets. We have conducted a series of executions with the following available datasets.

A. Austrian Federal Forest (AFF) datasets

Two varieties of leaves, with different shapes and colors. Here are some images along with their names The Experiments conducted on Austrian Federal Forest consists of nearly 134 pictures of leaves on pure white back ground. This database contains forty.

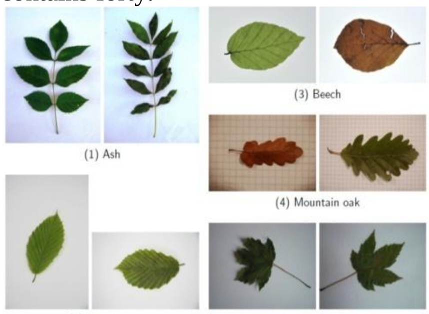

Figure 4: Sample Leaves Of Austrian Federal Forest (AFF) Datasets

B. Flavia Leaf dataset

This database contains 1097 varieties of leaves, with different shapes and colors from 32 plants. But in the experiments we have taken only 10 and 30 randomly chosen images per class for test and training classes respectively. Here are some images along with their scientific names.

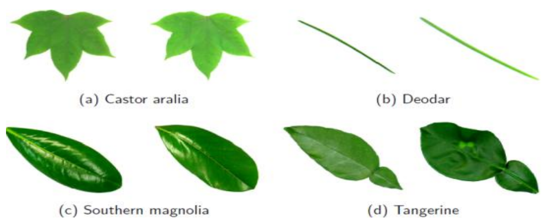

Figure 5: Sample Leaves Of Flavia Leaf Dataset

C. Foliage leaf dataset

This database contains forty two varieties of leaves, with different shapes and colors. The experiments consist of twenty five leaves per plant for the training set and another twenty for the testing purpose. Here are some with their names.

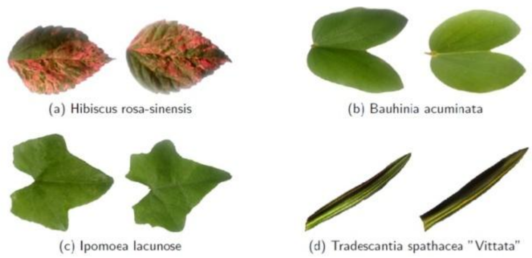

Figure 6: Sample Leaves Of Foliage Leaf Dataset

IV. EXPERIMENTAL RESULTS

We conducted experiments on the public available leaf databases applied the proposed method and compared the results with standard methods. For better results we selected random datasets and conduct the experiments several times on each data set.The proposed method showed the better performance comparatively with other existing methods.

The obtained results of the experiments are displayed in the tables' shows that OLBP achieved the best classification rate on each sample dataset comparatively with other existing conventional methods such as CLBP and discriminative CLBP as shown in the table 1.Here, the performance tested on different illumination conditions are inca, t184 and horizon and with different angles.

Table 1: Experimental Results For Each Scale on Austrian Federal Forest

Method	kd-tree	(P,R)=(8,1)			(P,R)=(16,2)			(P,R)=(24,3)		
		t184	Horizon	Avg	T184	Horizon	Avg	T184	Horizon	Avg
OLBP_S	U	74.80	73.50	74.15	80.67	81.40	81.03	83.61	80.57	82.09
OLBP_M^{+}	U	84.33	84.23	84.29	90.27	90.45	90.36	93.55	95.23	94.39
OLBP_S_M^{+-}	U	87.23	86.53	86.88	93.44	93.77	93.60	95.53	92.45	93.99
OLBP_S_M_C	U	90.12	91.22	90.67	95.02	95.12	95.07	96.72	97.23	96.97
OLBP	U	52.16	47.25	49.70	74.22	72.23	73.22	83.54	84.57	84.05
OLBP	S	91.53	91.53	91.53	95.23	96.54	95.88	97.20	97.22	97.21

Table 2: Experimental Results on Foliage Leaf Dataset

Method	kd-tree	(P,R)=(8,1)		
		t184	Horizon	Average
OLBP_S	U	88.45	53.48	70.96
OLBP_M^{+}	U	94.23	95.45	94.84
OLBP_S_M^{+-}	U	96.54	96.81	96.67
OLBP_S_M_C	U	97.54	98.26	97.9
OLBP	U	97.73	98.56	98.14

V. CONCLUSION

In this paper the proposed OLBP which encodes continuous LBP patterns in a ordered manner dictionary for OLBP based on kd-Tree data structure. OLBP encodes almost all types of patterns irrespective of spatial transactions. kd-Tree is used for dictionary learning process. Gaussian filtering reduces the complicated patterns and enhances the performance of our method. The majority contribution of our method is it encodes all LBP in a rotational invariant manner. But in conventional LBP based methods discard some patterns whose specifications are greater than two because they are not distinguishable on $LBP^{riu2}_{P,R}$

In contrast our OLBP with kd-tree data structure distinguish and assign unique patterns while maintaining the rotational unvaried characteristics with ordered approach

ACKNOWLEDGMENT

The Authors would like to say thanks to their Family members, management of the college, principal, teaching and non-teaching staff and students for their unconditional and continuous support both morally and physically, cooperation and encouragement in every aspect of the preparation of this work.

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