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Texture Classification and Pattern Retrieval Based on Sorted Consecutive Local Binary Pattern

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Abstract: this paper addresses the Sorted Consecutive Local Binary Pattern (SCLBP) and it is one of the classifications of Local Binary Pattern (LBP). The nature of LBP is to analyse the local feature of an image in a clock-wise direction. The Existing system is familiar with only two spatial-transitions and rotational-invariant concept is not applicable in LBP; K-d tree method is utilized to separate the data of an image with equal space. On an account, the earlier technique is not suited to proceed further due to its space and time complexity. To classify and retrieve the feature and similar pattern based on pattern recognition method and extracting a sequential pattern from an image to measure its performance, its individuality, against classification and retrieval, SCLBP is recommended. It encodes all the patterns with any number of spatial transitions at the same time it maintains the rotational-invariant to sort the feature of an image. The Complete Local Binary Pattern (CLBP) undergoes sign and magnitude components. Irrevocably, the future framework with SCLBP and Genetic Optimization with Fisher Criterion are combined and utilized. The paper concludes by evaluating the images from three data sets – OUTEX, CUReT and camera used image. The results will be compared with the conventional methods.

Key words: CLBP · SCLBP · Genetic optimization · Fisher Criterion

INTRODUCTION

Naturally the world is fenced in with many objects and each object possesses its own distinct feature and texture. Its wealth observes on both artificial and natural objects namely, wood, plants, materials and skin etc. Moreover natural textures are unique, yet often display contradicting properties. Extracting patterns from a texture and its classification is a research area in computer vision field. Several techniques are available for texture classification and pattern extraction. There are many textures specified in each objects. Those textures prefer common patterns of different dimensions and resolutions. In such a way Local Binary Pattern (LBP) is better for analyzing, classifying and extracting its necessary properties of an image. The operator defines gray-scale invariant texture measure. The analysis of LBP provides application in various fields such as bio-medical image analysis, visual inspection, outdoor scene analysis, thumb impression, iris recognition, pattern recognition etc. Local Binary Pattern is a very simple and efficient feature extractor, used for classification in many computer applications. The properties of LBP are stated in two ways, its features are resistance against illumination variations and its computational simplicity. To use the renowned technique of LBP, there are plenty of approaches, such as uniform pattern approach, Gabor and wavelets, matrix based approach, state of the art, spatial domain, filter based approach, rotation-invariant feature derived from the radon transform [1]. Genetic optimization with fisher criterion approach combined with SCLBP has further been used for texture classification as well as for pattern extraction. The above mentioned approaches are commonly found in Improved LBP, Hamming LBP, Extended LBP, Completed LBP etc. Despite the fact termed in LBP, it is discriminative method among local structures

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but exploiting spatial transition which has more than two, rotation-invariant; extracting patterns from texture has been exploited. The problem states by suggesting Sorted Consecutive Local Binary Pattern to extract all types of pattern from many textures, irrespective of the dimensions and resolution of an image.

The rest of this paper is catalogued for further procedure. Section II pursued with Related Work and to compare the performance and test the level of quality. The Benchmark Analysis is tagged in Section III. Proposed System is prioritized in Section IV. The Results and its analysis are prompted in Section V. Conclusively Section VI, revealed the Conclusion for texture classification.

Related Work: A literature review includes the current knowledge including absolute findings, theoretical and methodological improvement to a particular topic. A textured image has to be classified to adopt the best image from numerous textures. So, it would be the easiest way to sort the image in a prioritized way. A part of few strategies such as Classification, extraction, pattern evaluations are included while processing an image. These criteria's has been raised independently in image processing. In the Current paper, the aspect is to justify, texture classification; feature extraction and pattern evaluation to be combined with the usage of Sorted Consecutive Local Binary Pattern. The following five literature review attempts to demonstrate the fact and sight the survey parallel to the preceding survey.

The First survey paper of Local Binary Pattern and its Application to Facial Image Analysis: A Survey by Di Huang *et al*. on November 2011(vol.41, no 6) [1] put forward plentiful variations of LBP to improve the performance in different application. These variations focus on different aspects of LBP operator: improvement of its discriminative ability, improving the robustness, selection of its neighborhood. Di Huang *et al*. focused on Improved Local Binary Pattern (ILBP) [2, 1] and Extended Local Binary Pattern (ELBP) [4] enhances the discriminative capability, which considers the effect of centre pixels and cause high dimensionality. Local ternary Pattern (LTP) [3] and Soft LBP improves the robustness by bringing a new threshold value and cause high computational complexity. Elongated LBP is focused to choose the neighborhood and it is not uniform to rotation. The author describes that these methods are sensitive to monotonic illumination and limited with spatial transitions.

The second paper by Antonio Hernandez *et al*. focus on ILBP in Evaluation of robustness against rotation of LBP, CCR and ILBP (2010), [2] which was formerly proposed by Di Huang *et al*. in a survey of LBP and its Application to facial analysis. In addition, Di Huang *et al*. [1] and Antonio Hernandez *et al*. [2] draw a conclusion that ILBP is the operator which compares all the pixels in an image block to provide accurate feature of an image. Antonio Hernandez *et al*. additionally compares ILBP with descriptors such as Coordinated clusters representation (CCR). It highlights rotational-invariant concepts where the number of circular patterns remains unchanged when the image rotates in both the directions.

The third review paper is about, The Relaxed Local Ternary Pattern proposed by Jianfeng Ren *et al*. (2013) [3] solves the problem by encoding the small pixel difference into a third state and it is very complex to find the sign and magnitude of an image. Unlike of the methodology used in Local Binary Pattern it encodes the pattern even if it is in the state of '0' or '1'. Encoding indefinite pixels will produce less sensitive to noise. Jianfeng *et al.* [3] exceeds the performance of LBP. LBP can be predicted with the help of Histogram, but LTP produces more than one Histogram and it is time consuming to prioritize the best histogram.

The fourth paper is in effect with ELBP [4] with the concept of Gender Classification by Abbas Roayaei *et al*. It generally follows the LBP method by comparing the centre pixels with their neighbour pixel and it forms different layers in which it encodes the Gray-Value Difference. Conversely, Di Huang *et al*. and Abbas Roayaei *et al*. have enforced ELBP in different sectors, namely texture, facial and gender classification. Also, two approaches have been utilized namely, Genetic Algorithm and Principal Component Analysis. The merits of PCA are focused on Lossy compression.

Irrevocably, Jongbin Ryu *et al*. [5] proposed Sorted Consecutive Local Binary for Texture Classification (2015). It highlights SCLBP encoding and K-d tree method to sort the texture and to store it in a database. It requires huge amount of space to store the database. The review is concluded by the Highlighting the classification and not anything about Feature Extraction and Pattern Evaluation.

Benchmarking: The concept of LBP has been used precisely used for texture classification. There are numerous classifications of Local Binary Pattern, out of which Sorted consecutive LBP is grasped with CLBP [6] for feature extraction of a textured image and further its classification and pattern extraction is obtained with Genetic Optimization with Fisher criterion. Abbas Roayaei Ardakany *et al*. proposed the concept of Genetic

Algorithm [4] with PCA to analysis the Gender of Humans with Facial Analysis. In Previous Mechanisms, LBP encodes only patterns whose spatial transitions are not more than two. Rotation-Invariant concept was not utilized. Moreover, SCLBP have been combined with K-d tree dictionary learning algorithm, but it is not feasible to produce the result as each and each and every iteration the child nodes has to be prioritized. It does not provide an efficient classification of texture [5]. At present the concept of LBP and CLBP is used with SCLBP to extract the feature of a texture image with Benchmarked dataset such as CURet, OUTEX, FERET, etc. and to make it more interesting and to justify that SCLBP also extracts the feature from captured image, irrespective of its resolution and its dimension. To proceed further, three techniques have been utilized for feature extraction, namely: LBP, Gaussian Filter, CLBP (sign, magnitude and centre). A detailed explanation of the techniques is followed.

Local Binary Pattern: LBP is a very simple and conducive operator used to extract features and used for classification, pattern recognition. It highlights the properties as its features are tolerated against illumination variations and its computational simplicity. These are widely used in real-time environment and have been widely used in facial, gender classification. At present it is been used for texture classification with the combination of feature extraction, classification and pattern retrieval. The trained as well as tested images are stored in the dataset with the reduced dimension of 180x180; if it is a tested image, the image is reduced by using Gaussian filter. The texture is divided into 3x3 patches. In each patch centre pixel is been applied to each block. The LBP of an image is computed by using the below Equation (1). Where, ‘p’, is the number of sampling pixels, ‘R’ is the Radius of a circle; Q (Z) is the quantization function.

$$LBP_{p_j} R \sum_{p=0}^{p-1} S(S_p - g_0) 2^p \tag{1}$$

$$Q(z) = \begin{cases} 1, & x < 0 \\ 0, & x \geq 0 \end{cases}$$

Gaussian Filter: The Gaussian Filter is a smoothing operator, specialized to remove noise and to filter blurred image. Images can have either positive or negative values. Convolution operator with a Gaussian kernel (filter) guarantees a non- negative result. The ‘I’ denotes the input of an image; σ and k denote the sigma and kernel size of G in the Equation (2).

$$I = I\, G_{a,K} \tag{2}$$

Complete Local Binary Pattern: CLBP is an extended version of a LBP method with a little difference. The effective feature of CLBP is to decide how the textures will be analyzed. Z. Guo *et al*. computes the local difference of sign and magnitude (LDSMT) of an image in each and every block. The processing of a texture classification is a step-by step process with the usage of completed local binary pattern. It does the preprocessing and calculates the “sign and magnitude of an image along with the centre pixel. CLBP_S, CLBP_M, CLBP_C. Discriminative information is been occurred when calculating the sign value of an image.

$$CLBP_S = sign(d_p) \tag{3}$$

$$d_p = s_p * m_p \tag{4}$$

$$m_p = |d_p| \tag{5}$$

$$CLBP_{M_{P,R}} = \sum\nolimits_{p=0}^{p-1} t(M_p, C)2^p,\ t(X,C) \tag{6}$$

$$t(x) = f(x) = \begin{cases} 1, & x < 0 \\ 0, & x \geq 0 \end{cases} \tag{7}$$

$$CLBP_{C_{P,R}} = t(g_g, C_I) \tag{8}$$

The above Equation (3), (4), (5) signify of calculating Sign component (CLBP_S) and Equation (6), (7) implies of calculating Magnitude Component (CLBP_M) and Equation (8) is used to calculate the centre Pixel (CLBP_C).

Comparison of Algorithms: The conclusion can be drawn from the comparison of the above stated algorithms. Every single method plays its vital role in different categories of Local Binary Pattern, which issues its drawback at last. In order to acknowledge for all the practical purpose of an image size, resolutions, trained and tested data, its rotation - invariant concept. In this paper SCLBP is combined with CLBP sign and magnitude components. The importance of choosing this method is, Zhenhua Guo *et al*. proposed CLBP in A completed Modelling of Local Binary Pattern Operator for texture Classification, to extract the image local grey level and focused only on the features of local difference of part of an image irrespective of whole image [6]. The texture alone is classified with local difference feature extraction.

Table I:

Algorithms	Advantages	Limitations
Binary Histogram Intersection Method [5]	Feature selection method from multiple scales.	It selects less redundant LBP features.
Uniform Pattern [1, 5, 7]	It contains even number of ones and zeroes.	Feasible with only high symmetry level.
LDA[1]	It deals with low dimension images and segmentation is handled separately.	Time and space complexities are considered.
Discrete Fourier Transform[2]	Deals with finite amount of data to control the noise.	Poor performance with software rotations
Genetic Algorithm [4]	Maximizes the accuracy and dimension of an image is reduced.	GA combined with LBP is not feasible for gender classification.
PCA[4]	Follows Lossy compression method.	Human image compared with LBP, LDP is not feasible to provide gender classification.
K-d tree dictionary learning [5]	Manages space transition and outperforms on rotation and scale variations by 24.9% and 4.3%.	Huge amount of space is required to store images. Child nodes have to be checked evenly.
Rotation -Invariant Pattern [2,1,8,6]	The rotated image produces same value irrespective of its dimensions.	Combined with uniform pattern is not expected to provide clear pattern of an image.
CLBP [9,6]	Provides better classification, feature extract when compared with state of art algorithm.	Sign and magnitude components cannot be predicted separately.

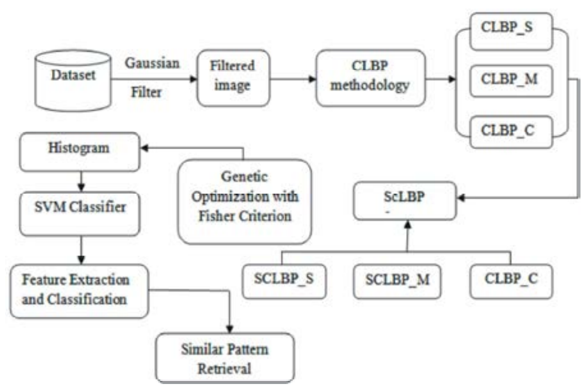

Fig. 1: system Architecture

On the whole, to gather the basic features of image processing i.e. Classification, Feature Extraction and Pattern Retrieval in this paper, CLBP is used as a medium to handle sign and magnitude components of an image. Further more for pattern retrieval and to select the best feature for classification genetic optimization with Fisher Criterion can be adopted.

Propsed System: The system architecture shown in Fig. 1, explains the proposition of Sorted Consecutive Local Binary Pattern. The Benchmarked dataset such as CURet, OUTEX, etc. and captured image is gathered with large number of images which consist of trained i.e. an accurate sized image which will be able to proceed the Local Binary Pattern and untrained image i.e. it can neither be a texture of different dimensioned image or it can be captured image. While capturing the image the dimension of an image cannot be buckled down. The specimen of an image has to be reduced to make it beneficial for the proposal. Resizing an image can be done in three ways as cropping, sampling and scaling. Image scaling is the process of resizing a digital image. The textured image can be of any format which should be related to image such as, jpeg, tiff, etc. to scale down an image to a particular size. Scaling is a non- trivial process that involves a trade-off between efficiency, smoothness and sharpness. The size of an image is reduced or enlarged; trained or tested texture is chosen from the dataset, to justify the method of Local Binary Pattern. The variation of an intensity in an image is adjusted by using filters, just like to filter the sediment part in the coffee preparation. Intensity is the measurable amount of a property, such as force, brightness, or a magnetic field. However image is concerned with noise, dust particles, over brightness, lack of resolutions. Hence the best choice to remove those noise particles, the properties Gaussian filter is utilized to make the image clear. The GF soothes the image based on producing blurs in the image and hence chances of extracting its feature with kernel size and the sigma value. The input images were filtered using Gaussian Kernel filtering. Image processing is specialized with Gaussian Filter, as its property supports in time domain which is equal to their support in the frequency domain. Hence the texture patterns can be more effectively extracted. The Gaussian blur is defined and is convoluted with the original image. The Gaussian blur is Usually it is defined as the Gaussian probability density function with kernel size and the sigma value. The kernel size defines the window size of an image and the sigma value denotes the amount of blur has to be avoided in the image. Next, step is to calculate the Sign, Magnitude component and Center Pixel of an image. It is classified into 2 processes LBP values for each block; calculation of CLBP. Local Binary Pattern is a very simple and efficient operator that is used to extract the features used for Classification if the centre pixel value is greater than the surrounding pixel value, then value 1 is assigned in that position otherwise value 0 is assigned. Equation (3), (4), (5) signify of calculating Sign component (CLBP_S) and Equation (6), (7) implies of calculating Magnitude Component (CLBP_M) and Equation (8) is used to calculate the centre Pixel (CLBP_C).

RESULT AND DISCUSSION

As a result of Texture classification and Pattern Retrieval based on Sorted Consecutive Local Binary Pattern, using CLBP the feature were extracted for a 180x180 sized image. The feature is denoted in the form of Sign, Magnitude and Centre Pixel values and the concatenation of CLBP is displayed. The texture selection from the data set and the noise removal part are considered to be the pre-processing method, after that extraction of CLBP for an image is calculated for feature extraction process. There are three processes, namely trained and untrained texture image from dataset; Resized image; Noise removal by Gaussian filter. This textured image consists of a size 256x256. The dimension of the texture is reduced to a size of 180x180, consists of 32400 pixels. Next Step is to resize the selected texture image. The Trained image is selected either from OUTEX or CUReT dataset as an input image, which consists of 200 texture patterns in each dataset. The noise is filtered by using Gaussian Filter. The Gaussian filtering process smoothes the texture based on content of blurs in the image and hence the texture patterns are extracted, with kernel size and the sigma value by the equation (2). The over brightness of the texture is reduced. Next step is to extract the Sign, Magnitude Component and its Centre Pixel of the image. Next, the for feature extraction CLBP is used, here the image is divided into 3600 blocks of 3x3 sizes. In each block 9 pixels cells are represented. For each and every block the Sign, Magnitude and Centre pixel value is calculated. Figure 4 shows table of CLBP_S, CLBP_M and CLBP_C pixels value in an 8- bit binary digit. The binary digit is obtained by using the equation (3), (4), (5), (6), (7), (8). The filtered image, CLBP image from OUTEX, CUReT and Photographic dataset is showed Figure (2), (3), (4) and CLBP Components and its Feature is tabulated in TABLE II, III and IV. This gives complete information of a texture. Fig. 5 shows the performance measure of sample CLBP Features from OUTEX, CUReT and Photographic datasets are represented in Bar chart. The photographic image is

Fig. 2: Sample image of CUReT DATASET

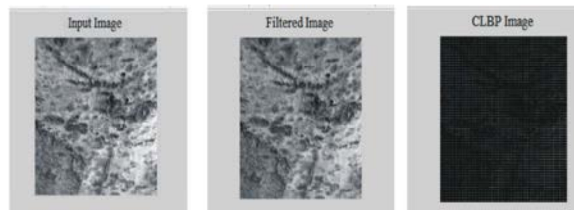

Fig. 3: Sample image of OUTEX DATASET

Fig. 4: Sample image of Photographic Image

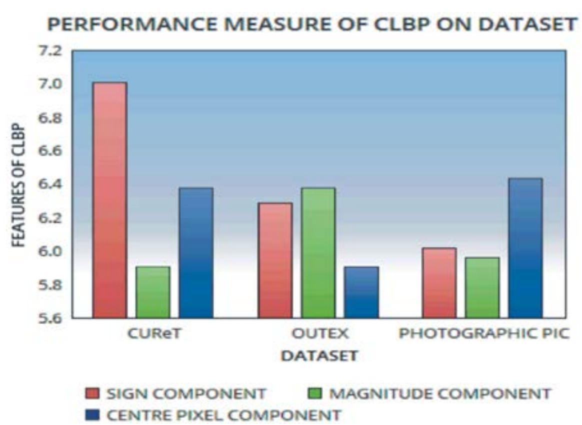

Fig. 5: Performance Measures of Sample CLBP Dataset

Table II: Experimental Results of Clbp on Curet

CLBP COMPONENTS	1ST BLOCK	2ND BLOCK	3RD BLOCK
CLBP_S	11111111	10110111	11010110
CLBP_M	101001111	000100110	110100110
CLBP_C	101001111	000100110	110100110
FEATURE EXTRACTION	7.0109	6.2879	6.0217

Table III: Experimental Resluts of Clbp on Outex

CLBP COMPONENTS	1ST BLOCK	2ND BLOCK	3RD BLOCK
CLBP_S	11101000	00000100	00010110
CLBP_M	111001000	001110110	100110110
CLBP_C	111001000	001110110	100110110
FEATURE EXTRACTION	5.9056	6.3770	5.9636

Table IV: Experimental Results of Clbp on Camera Image

CLBP COMPONENTS	1ST BLOCK	2ND BLOCK	3RD BLOCK
CLBP_S	01000000	100100110	00000001
CLBP_M	011010011	100100110	010010011
CLBP_C	011010011	100100110	010110011
FEATURE EXTRACTION	6.3770	5.9056	6.4350

stabilized with sign, Magnitude and centre pixel components and outperforms the other two datasets. Further, the Genetic Algorithm with Fisher Criterion is applied with the extracted features of CLBP for The purpose of texture classification and pattern retrieval. The Histogram is obtained, to test with the SVM classifier.

CONCLUSION

In this paper, the classification of texture based on Pattern Recognition method and the removal of noise by using Gaussian Filter before processing are performed successfully. The proposed CLBP is calculated by using Local-Difference Sign Magnitude Transform method to specify the Sign Component and Magnitude Component and the Center Pixel variations are displayed. Complete Local Binary Pattern act as a tool to proceed further. Moreover, the extracted CLBP values are used to calculate SCLBP_S, SCLBP_M and CLBP_C. A key contribution of our method is that it considers all local binary patterns in a rotation – invariant manner. Further pattern retrieval can be obtained by using Genetic Optimization with Fisher Criterion in future. These methods can be achieved by using well known-texture database. This work is the first study to use for the best of our knowledge CLBP for texture and photographic classification combined with SCLBP. The texture is selected from the dataset such as OUTEX, CUReT and captured image is stored in the dataset to perform LBP and CLBP. SVM classifier is used select the best texture image. We believe that Genetic Optimization with Fisher Criterion will be used for analyzing the texture patterns rather than for Gender classification.

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