International Journal of Research in Engineering and Science (IJRES)
ISSN (Online): 2320-9364, ISSN (Print): 2320-9356
www.ijres.org Volume 09 Issue 11 ǁ 2021 ǁ PP. 40-45

Improved Local Binary Pattern based on smoothness for Texture Classification

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ABSTRACT*: The texture is an essential property of an image that tells about the arrangements of pixels of different intensities in an image matrix. Researchers have used many descriptors for texture classification of the images in computer vision and image processing. Local Binary Pattern (LBP) is one of the descriptors, which is computationally efficient and straightforward for texture classification. In recent years, researchers have made many enhancements in the basic LBP method to improve an image's extracted features. This paper presents a Local Smoothness Binary Pattern (LSBP) descriptor for feature extraction of an image to increase LBP discriminative capability. This new descriptor extracts features from the local region of an image called partial feature vector, concatenates these local features to obtain a feature vector of an image. This feature vector is used as input to a classifier to classify the class of an image. We tested the proposed descriptor for the images available on CUReT and KTHTIPS2b databases with Support Vector Machine (SVM) and k-nearest Neighbors (KNN) classifiers. We have represented the experimental results obtained from the analysis process regarding classification accuracy and confusion matrix. Finally, we have presented a performance comparison between the proposed method, basic LBP descriptor, and its variants. Results show that the proposed descriptor gives much better results than other descriptors on the KTHTIPS2b Database when we use the KNN classifier.*
KEYWORDS:*.LBP, Local Binary Pattern; LSBP, Local Smoothness Binary Pattern; SVM, Support Vector Machine; KNN K-nearest Neighbors.*

Date of Submission: 12-11-2021 Date of acceptance: 28-11-2021

I. INTRODUCTION

The texture properties of an image are used for its classification. Several methods are proposed in the literature to extract the texture features of an image LBP [1]-[4] and Census Transform (CT) [5]. The LBP is a very efficient and powerful descriptor in extracting the local features of an image. In the last few decades, the LBP has inspired methods that are deeply studying or used in image processing and computer vision. To apply the LBP in any image generally image is divided into multiple regions. LBP is first applied on each reach of the image. To evaluate the LBP code for a region each pixel of the region is compared with its neighboring pixels. After evaluating the LBP code for every region wee evaluate the LBP histogram of the region. The histogram of all regions is concatenated to create the histogram of the image. This histogram represents a spatial feature vector of the image. LBP features conation two important properties; tolerance regarding monotonic illumination change and computational simplicity.

In recent years, LBP and its variants have been used in many applications and help to solve many problems like image analysis [6], face image analysis [7]-[10], image and video retrieval [11],[12], motion analysis [13],[14], environment modeling [15],[16], and remote sensing [17].

There is various information present in an image. Generally, the rough region of an image contains more information because corners and edges are present in this region. The corners and edges of an image provide more information. This information is extracted to identify the texture of an image. There are various descriptors present to extract information from a rough region, but the way to extract information is different. If we select more number of neighboring pixels around a pixel to calculate the LBP code, then we can tell in a better way the effect of neighboring pixels on a pixel. More precise and detailed information gives better texture classification of the images.

This paper proposes a new descriptor that increases the discriminative capability of an image and gives better texture classification results. Here LBP discriminative capability means how well a descriptor explains the binary number sequence formation process. If we choose more number of neighboring and next to neighboring pixels around a pixel, then we can tell more clearly the effect of neighboring pixels on a given pixel. This work also involves a comparison between the recent variants of LBP and the proposed descriptor.

The rest of the paper is organized into five sections. Section two reviews some recent research work related to texture classification. Section three describes the proposed method and explains it with the help of an example. Section four talks about the data set used in this research. Section five presents the results and its analysis. Finally, section six presents our conclusions and some future directions.

II. RELATED WORK

In recent years, the operator LBP has been come with plenty of variations to improve performance in different applications. Extended LBP [2],[18] has worked on the discriminative capability of LBP and shows improved results in comparison of LBP. It uses the GD between the central and its neighboring pixels. Guo et al. [19] proposed a new operator Complete LBP [19], which is very much similar to the extended LBP. It uses two things; sign and the GD between the central and its neighboring pixels. Local Smoothness Pattern [20] captures the local edge and curve patterns in an image. It uses non-linear modeling. Soft LBP [21],[22] was introduced with a fuzzy membership function to make LBP sensitive towards the noise in an image. Adaptive LBP descriptor [23] proposed to minimize the direction difference along with different orientations. It minimized the variation of means and standard deviation of differences. Liao et al. proposed a dominated LBP descriptor [24] to overcome the inability of the basic LBP to capture the shapes having high curvature edges, crossing boundaries, or corners by finding the dominated features in an image. Median Binary Pattern [25] uses the median value of the selected neighbor set for deciding the threshold value. LBP Histogram Fourier descriptor [26] uses the combination of uniform LBP descriptor and Discrete Fourier Transform. Ahonen et al. [27] proposed monogenic LBP to enhance the classification performance of basic LBP by combining uniform local binary patterns, local phase information, and local surface information. LBP Variance [28] was used as an adaptive weight to adjust the LBP contribution in Histogram calculation. It generates the histogram for different scales. Neighbor Intensity LBP [29] uses the basis of pixel intensity and pixel difference. They proposed four different descriptors and combined all four to form a joint histogram to represent texture.

LBP variants that are used for texture classification vary according to the following points:

1. How to select the threshold value?
2. How to choose neighboring pixels, whether it is lying on the perimeter of a circle or ellipse or sphere (for 3D images) or square or rectangle?
3. The number of neighboring pixels.

LBP variant calculates LBP code by comparing the intensity of each neighboring pixel with a threshold value (also the possible intensity of a given pixel) or by comparing two neighboring pixels. So by reviewing many texture classification-related papers, which tells how we will choose neighborhoods around a given pixel and how we will compare each neighboring pixel with a given pixel. By reviewing all these papers, we knew how to select a neighborhood around a pixel, how we will compare each neighboring pixel with a given pixel, and how we will choose threshold values.

So taking inspiration from the above, we proposed a new descriptor to extract feature vector from the local region of an image by comparing pixels of a region with their neighboring pixels and neighboring pixel with their next neighboring pixel in a particular direction.

III. PROPOSED METHDOLOGY

In the proposed algorithm of texture classification with some labeled classes, we train a model that tells us the class of the images. To evaluate the performance of our model, we split the data into training and testing sets. The model learns using the training set. Their performance is measured using the testing set. Testing results allow us to measure how well the algorithm generalizes to unseen instances. The main measure of performance for a classifier is accuracy. It is the proportion of instances in the test set that are classified correctly. Steps of the algorithm with the proposed LRBP descriptor are described below:

Step 1: Select an image from the database.
Step 2: Add a padding bit in the image if the dimension of this image is not proper for the division.
Step 3: Divide the image into a number of regions.
Step 4: Apply Local Roughness Binary Pattern descriptor to calculate LBP code and new intensity for every pixel. Find mean and variance or histogram for each region as a partial feature vector.
Step 5: Prepare the feature vector by concatenating the partial feature vector obtained for each region.
Step 6: Apply feature vector obtained in step 5 to classification techniques.

Step 7: Repeat step 2 to 5 for all training images.
Step 8: For the images not included in the training set, repeat step 2 to 5 and test using the trained classification techniques.
Step 9: Analyze the results.

Fig.1. shows the flow chart of the procedure of the texture classification for one image by using the LSBP descriptor.

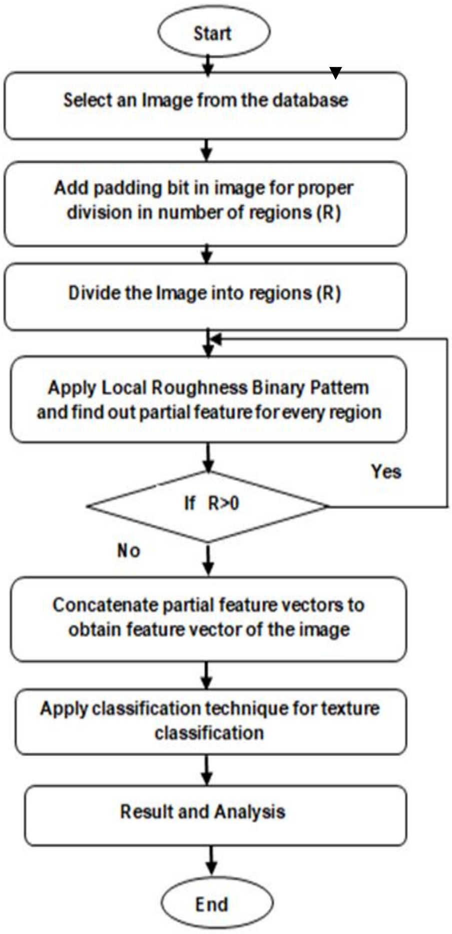

Figure.1. The flow chart shows a working procedure of texture classification for an image by using the proposed descriptor.

IV. RESULT ANALYSIS

We have divided the database into two parts; one is training, and another is testing. table 1 shows the results for the division of data into 80% and 20% ratio, and table 2 shows the results for the division of data into 50% and 50% ratio. These tables show the classification Accuracy (%) for both the CUReT and the KTHTIPS2b databases. Results are shown for models in which image features are extracted through mean and variance, and SVM and KNN classifiers are used.table 1. Classification Accuracy (%) on CUReT database for both SVM and KNN classifier and feature extraction through mean and variance

Table 1 Classification Accuracy (%) on CUReT database for both SVM and KNN classifier and feature extraction through mean and variance

Database	**SVM Classifier**	**KNN Classifier (for K=1 and K = 3)**
CUReT	71.11 %	63.943 % and 61.68%
KTHTIPS2b	62.35 %	53.78% and 54.21 %

Table 2. Classification Accuracy (%) on KTHTIPS2b database for both SVM and KNN classifier and feature extraction through mean and variance.

Database	**SVM Classifier**	**KNN Classifier (for K=1 and K = 3)**
CUReT	67.07 %	58.02 % and 54.95 %
KTHTIPS2b	59.09 %	51.87 % and 52.68 %

Figure 2 shows the Comparison of the proposed approach with some LBP variants on the CUReT Database. The proposed descriptor is not giving the result at par to the other descriptors. When we are using histogram to extract feature, then classification accuracy (%) for KNN classifier (for k=1) on CUReT database are 88.1996 %. Figure 4 represents the comparison between the proposed descriptor with some LBP variants on the CUReT Database, where the feature is extracted through Histogram.

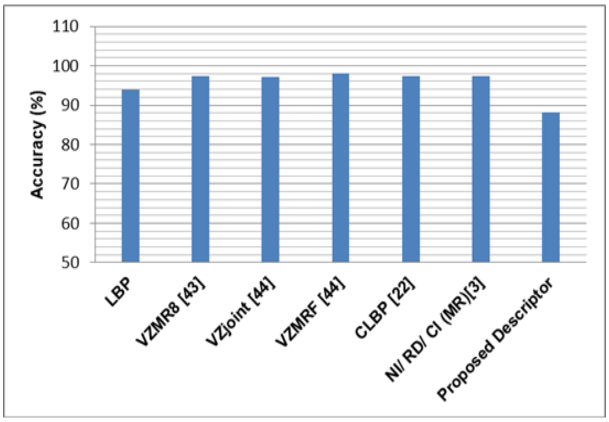

Figure 2: Comparing proposed approach with some LBP variants on CUReT Database where feature is extracted through Histogram

Figure 3 shows the classification Accuracy (%) of the proposed descriptor and LBP variants on the KTHTIPS2b database for the KNN classifier (for k=1) and feature extraction through Histogram. The proposed descriptor has got 80.90 % and 82.53 % classification accuracy when data is split into 50–50 ratio and 80–20 ratio respectively. Figure 5 shows the Comparison of the proposed approach with some LBP variants on the KTHTIPS2b Database. Results show that the proposed descriptor is giving much better results in comparison to other descriptors on the KTHTIPS2b Database

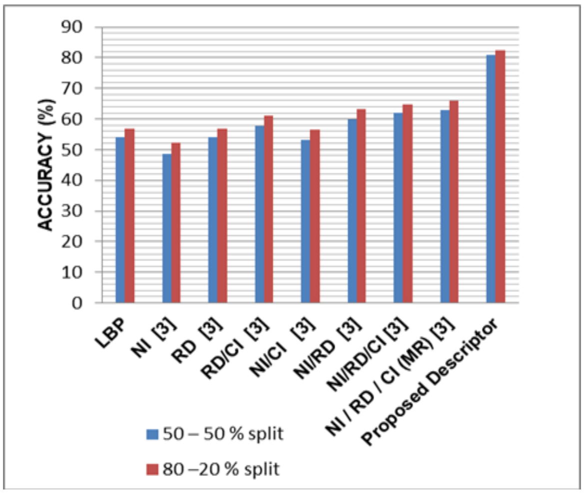

Figure 3: Comparing proposed approach with some LBP variants on KTHTIPS2b Database where feature is extracted through Histogram

V. CONCLUSION

An image contains various types of information. There are different descriptors used to extract information from an image for applications like texture classification and face recognition. LBP is one of the most commonly used descriptors. Many LBP variants were proposed by authors to avoid the limitations of the basic LBP approach by choosing different ways to select the threshold values and neighboring regions. Many researchers have combined the LBP approach with other approaches and use different types of image types (2D or 3D images). The proposed approach is also a variant of basic LBP, which gives more weightage to the roughness of the surface. The rough surface of the image conations more information, which helps to classify the image accurately. Experimental results show that the proposed approach with the KNN classifier has outperformed the other LBP variant.

In the proposed descriptor, we have used value one when there is not a regular increment or decrement in a particular direction, whether the difference is 1 or 100. In the future, we can introduce a threshold value (t) so that we can give value one for those whose difference is more than t when there is not a regular increment or decrements. Here we are introducing t because when the difference is almost one or two, then that region behaves like a smooth region. In our proposed descriptor, neighboring pixels of a pixel are lying on the square. There are many neighboring regions like a circle, ellipse, sphere (for 3D images), and rectangle are possible. If neighboring pixels lie on the perimeter of these regions, the performance of our proposed descriptor may improve. So in the future, we select different types of regions to check the performance of proposed descriptors. If we select different techniques to extract features, then the performance of the proposed method may vary. So in the future, we can try to check which feature extraction technique is better for our proposed descriptor in terms of accuracy's on KTHTIPS2b Database

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