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Impact of LBP Topologies as Texture Descriptors on Ethnicity Identification

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Abstract

Many ethnicity identification techniques have been developed during the past years but the problem remains are the way of using these techniques, especially local binary pattern (LBP) method is one of these techniques which has shown its superiority in ethnicity identification. The original LBP operator mainly thresholds pixels in a specific predetermined window based on the gray value of the central pixel of that window. In this work, we comparativelystudy five different configuration neighborhood topology including circle, ellipse, parabola, hyperbola, and Archimedean topology. In the ellipse topology we used eight number of neighborhood pixels with different angle (0^o, 45^o, 90^o, and135^o), also in the circle topology we used vary the number of neighborhood pixels P: P = 8, P=10, and P = 12. K-nearest neighbor (KNN) has been used for identification task.A series of experimentations hasbeen performed on1200 face images were obtained from a collection of some standard databases. The topology computations that provide highly accurate identification consist of circle, and ellipse topology. In addition, the experimental results also indicate that a good accuracy and demonstrate by increasing the number of neighborhood pixel the result will be increase.

Introduction

In today's technological world, ethnicity identification is a critical task in real time system. The process of recognizing the ethnic group to which the individual of a given face image belongs is called ethnicity identification. The classification process includes extracting facial features from a given database, and determining the ethnic group of the query face image [1]. Ethnicity identification has been used in numerous applications including security system, demographic information collection and automatic annotation of face images. Ethnicity identification is different from gender classification and face recognition algorithms [2]. Dissimilar to gender classification where both of two classes are of relevance, ethnicity identification often manages different classes. In addition, face recognition where the identity of an individual face is of relevance, ethnicity identification involves the identity of a collection of faces of an ethnicity. LBP variants as texture descriptors for ethnicity identification are a focus of the study.

The paper is organized as follows. Section 2 presents related work on the standard LBP operator, LBP topology, database and ethnicity classification method used in this paper. The proposed framework is presented in Section 3. Experimental results are given in section 4, and the conclusion is presented in Section 5.

Related work

In this section, the principle of the image features is used, i.e. the standard LBP operator and discuss of some other methods for feature extraction in image processing. Furthermore, the LBP topologies are explained includes circle, ellipse, parabola, hyperbola, and Archimedean topology. Finally, description the collection of face images and ethnicity classification method used for this study.

1. Local Binary Patterns

Texture classification is an active research topic in computer vision and pattern recognition. The LBP is a type of feature used for texture classification in computer vision. LBP was first described in 1994. It has since been found to be a powerful feature for texture classification. Local binary patterns (LBP) have been proposed by Ojala et al [4], have been established as a standard feature based method for 2D image analysis. LBP is a local texture operator, which has a low computational complexity and a low sensitivity to changes in illumination. LBP have been successfully applied to a wide range of different applications, for instance, in texture classification [5], face recognition [6], smart gun [7], gender identification [8], and automated cell phenotype image classification [9]. LBP operator performs by thresholding the differences of the center value and the neighborhood in the 3x3 grid surrounding one pixel. The resulting values are then considered as an 8-bit binary number represented for that pixel [4,10]. The histogram of these binary numbers in the whole image can be used as a descriptor for the image. The original LBP operator labels the pixels of an image with decimal numbers, which are called LBPs or LBP codes that encode the local structure around each pixel. It proceeds thus, as illustrated in Figure 1. Each pixel is compared with its eight neighbors in a 3 × 3 neighborhood by subtracting the center pixel value; the resulting strictly negative values are encoded with 0, and the others with 1. For each given pixel, a binary number is obtained by concatenating all these binary values in a clockwise direction, which starts from the one of its top-left neighbor [10, 11]. The corresponding decimal value of the generated binary number is then used for labeling the given pixel. The derived binary numbers are referred to be the LBPs or LBP codes.

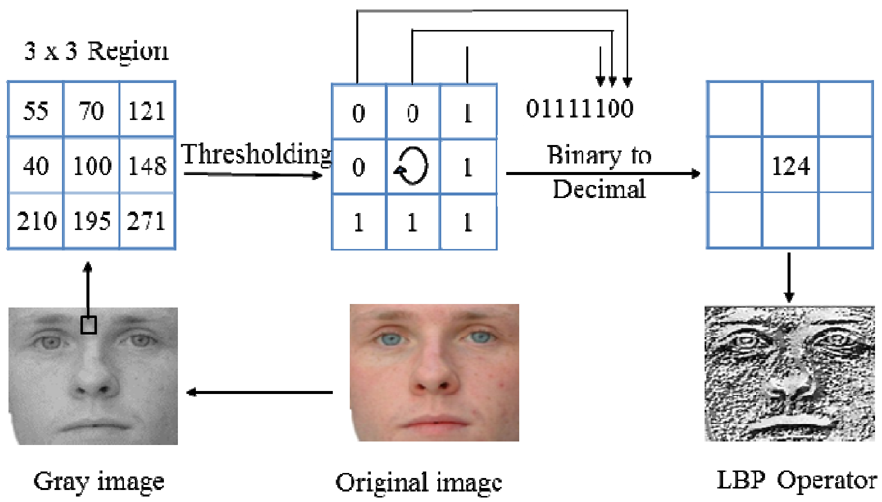


Figure-1: Basic local binary pattern operation

The general LBP features were computed from the pixel intensities in a neighborhood. The resulting LBP can be calculated in decimal form as shown in equation (1) [4]:

$$LBP_{P,R} = \sum_{n=1}^{P} S\,(P_n - P_c)\,2^n \qquad (1)$$

Where P is the total number of neighbors, R is the radius of the neighborhood, is the color intensity value of the central pixel, and the value of the neighboring pixels ordered clockwise from the top left.The thresholding operation is defined in equation (2):

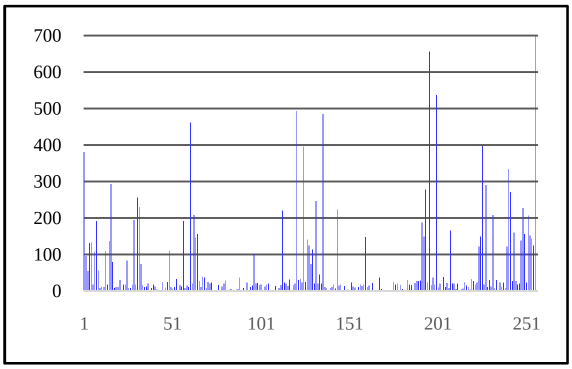
$$S\,(P_n - P_c) = \begin{cases} 1 & P_n - P_c \geq 0 \\ 0 & P_n - P_c < 0 \end{cases} \qquad (2)$$

By replacing all pixel values by their LBP values, the original image is transformed into an LBP image. After applying the operation on the original image the histogram of LBP labels computed over a region can be exploited as the texture feature vector for the image.

Suppose the original image is of size *R * C*. After the LBP pattern of each pixel is identified, a histogram *H(k)* is built to represent the texture image is defined in equation (3) [8] as follow:

$$H(k) = \sum_{i=1}^{R}\sum_{j=1}^{C} f(LBP_{P,R}\,(i,j),k) \quad ,k \in [0,k] \quad (3)$$

Where k is the number of different labels produced by LBP.The LBP histogram extracted from an image with circle and ellipse topology are shown in Figure 2 and Figure 3 respectively.



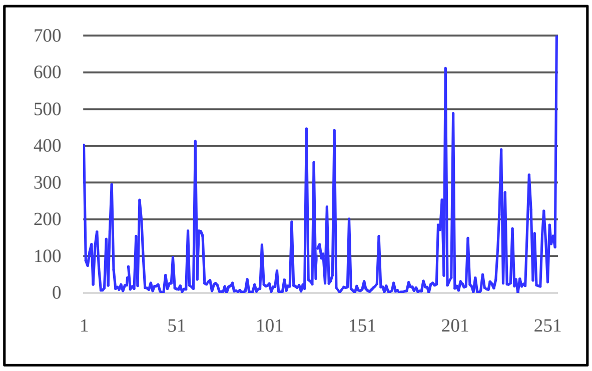
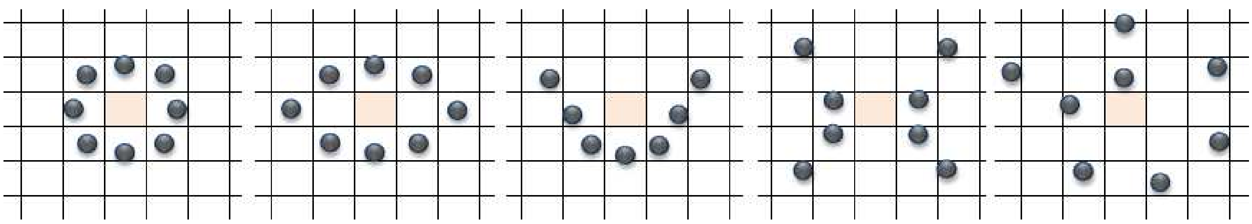


Figure-2: LBP histogram using circle topology Figure-3: LBP histogram using ellipse topology

2. LBP Topology

We describe the texture descriptors offered in this research, which are gained by allowing for different shapes for the neighborhood calculation with binary encodings for the estimation of the local gray-scale difference *[3]*. In our experiment five different configuration neighborhood topology circle, ellipse, parabola, hyperbola, and Archimedean topology have been computed.The LBP neighborhood topology used in this work, shown in Figure 4.



(a) (b) (c) (d) (e)

Figure-4: Neighborhood topology used in this study: (a) circle (b) ellipse (c) parabola (d) hyperbola (e) Archimedean.

2.1 Circle Topology

This topology means taking neighborhood pixels like circle shape in our experiments we use eight, ten and twelve neighbors. The mathematical equation of a circle topology with radius *r* is shown in equation (4)[3] and the circle topology with different number of neighborhood pixels is presented in Figure 5.

$$x^2 + y^2 = r^2 \qquad (4)$$

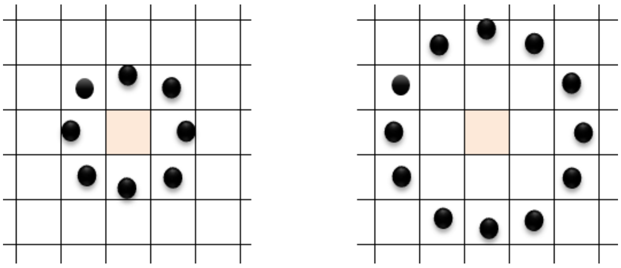


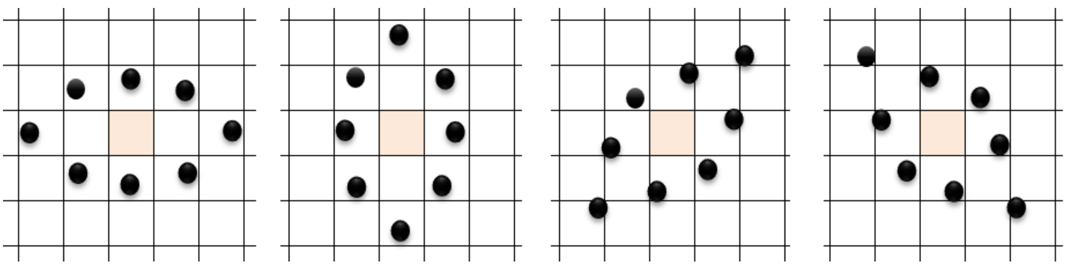
Figure-5: Circle topology

2.2 EllipseTopology

It means taking neighborhood pixels like ellipse shape, in this topology we use eight neighborhood pixel with different clockwise rotation of angels (0^o, 45^o, 90^o, and 135^o), as demonstrated in Figure 6. The mathematical equation for ellipse topology is shown in equation (5)*[3]*.

$$\frac{x^2}{a^2} + \frac{y^2}{b^2} = 1 \qquad (5)$$

Where a andbare the semi major and semi minor axis lengths



(a) (b) (c) (d)

Figure-6: Ellipse topology: (a) 0^o angle; (b) 45^o angle; (c) 90^o angle; (d) 135^o angle

2.3 Parabola Topology

The graph of a parabola is a U-shaped curve that can either opens up or down (Figure 4). In this topologythe parabola shape has been used for calculatingthe central pixelintensity values of the 3×3 neighborhood with an image.The equation of parabola is can be written by equation (6)*[12]*.

$$\frac{-1}{\mathrm{c}}\mathrm{x}^2 + 2\mathrm{c} = 1 \qquad (6)$$

Where ‘c’ is the distance between vertex and focus.

2.4 Hyperbola Topology

A hyperbola is a pair of symmetrical open curves [13]. The central pixel intensity values of the 3×3 neighborhood have been computed by using hyperbola shape and the mathematical formula is defined as in equation (7) [14].

$$\frac{x^2}{a^2} - \frac{y^2}{b^2} = 1 \qquad (7)$$

Where a and b are the semi major and semi minor axis lengths of the hyperbola.

2.5 Archimedean Topology

An Archimedean spiral is a two-dimensional circular shape defined by a polar equation. In this topology the neighborhood pixels have been calculated like Archimedean spiral shape. The equation of a normal Archimedean spiral is given by equation (8) [15].

$$r = a + \theta b \qquad (8)$$

Where (r, θ) represent the polar coordinates and (b) controls the distance between successive turnings.

3 Database

There are a large number of face databases available to researchers in face recognition. These databases range in size, scope and purpose. Face recognition has benefitted greatly from the many databases that have been produced to study it. Most of these databases have been created under controlled conditions to facilitate such as position, pose, different lighting conditions, various facial expressions, background, camera quality, occlusion, age, and gender [16, 17]. Although the databases could be and have been used for ethnicity identification in the past, the very fact that they include many variations for different purposes makes it difficult to focus on demographic feature analysis and compare different methods.

A database of good quality frontal passport-type face images that are taken under the same lighting environments would be ideal. We have performed experiments on FERRET database, which is considered as a challenging database for face recognition. The database consists of frontal, left or right profile images and probably the one providing the largest number of subjects with a good diversification in terms of ethnicity, gender, illumination, pose, expression and lightning. Our database is a union of some different face data source such as: GUFD, PUT, YALE, FERET *[18]*, CUHK, CAS-PEAL, JAFFE, CASIA, PDA which are available in the public domain and some of them we collected in WWW.

In our experiments, we focus on three ethnicities: European, Oriental and African. We used 1200 face images; 500images for European, 500 images for Oriental, and 200 images for African. Table 1 summarizes the sampling details of our final mixed collection of face images. Each image is cropped to the size 128×128 pixels are shown below.

Table 1: Collected database for this Study

Ethnicity Class	Data Source	No. of Subjects	Total
European	GUFD	190	500
	PUT	85	
	YALE	45	
	FERET	180	
Oriental	CUHK	160	500
	CAS-PEAL	104	
	JAFFE	6	
	FERET	100	
	CASIA	130	
African	PDA	7	200
	FERET	85	
	Faces from	108	
		Total	1,200

In this work, we approach the problem of class imbalance: the number of European and Oriental are more than African images. To alleviate the class imbalance problem, we decided to draw a random sample of 50 Europeans and 50 Orientals, use them together with the 50 African images in our tests for three ethnicities. In our tests for 3 ethnicities, we repeat 10 times the training and testing to decrease the effects of randomness.

In order to get reference performance, in terms of accuracy of an algorithm for the face recognition, performance evaluation was carried out with the leave-one-out cross-validation (LOOCV) strategy to get unbiased estimation of the model performance [19]. We use the stratified 50-fold cross-validation method which is more reliable than the randomized re-sampling testing strategy. Therefore, we divide the sampled data set into 50 folds, and each fold contains 3 images (1 for each ethnicity). The reason is that the number of images for our study is limited and we want to apply as many training images as possible.

4. Ethnicity Classification

In the past, several attempts have been made in exploiting novel classification techniques such as support vector machines (SVM) [20], Gaussian mixture models (GMM), decision tree (DT) and neural networks (NN). In this work image feature extraction, we only use k-Nearest Neighbors classifier algorithm with classifier score i.e. 1-distance. It is a learning method bases on an instance that does not require a learning phase [20, 21]. The training sample, associated with a distance function and the choice function of the class based on the classes of nearest neighbors is the model developed. To avoid sensitivity, we set P > 1 (e.g. 5). The dissimilarity measure is simply the Euclidean distance function.

Euclidean distance is the most universal, between two vectors and, the Euclidean distance is defined in equation (9)[22].

$$d(xi, xj) = \sqrt{\sum_{r=1}^{n} \left(x_{ir} - x_{jr}\right)^2} \qquad (9)$$

The Framework and Main Steps

Many methods have been developed to capture facial features from the spatial domain and frequency domain for various recognition purposes. Some methods can be generally applicable to more than one recognition purpose, but specific methods for a specific type of recognition may be needed. The colored bands captured from the spatial domain are often used as a step of preprocessing for face verification but not for identification of ethnicity. The Framework is a methodology for our planning. We begin by understanding then thinking the broader of identification within which problems occur and the principles governing success within that system after that provide a practical set of design criteria that can be used to develop an effective way for identification. The framework of the system is demonstrated as a block diagram in Figure7.

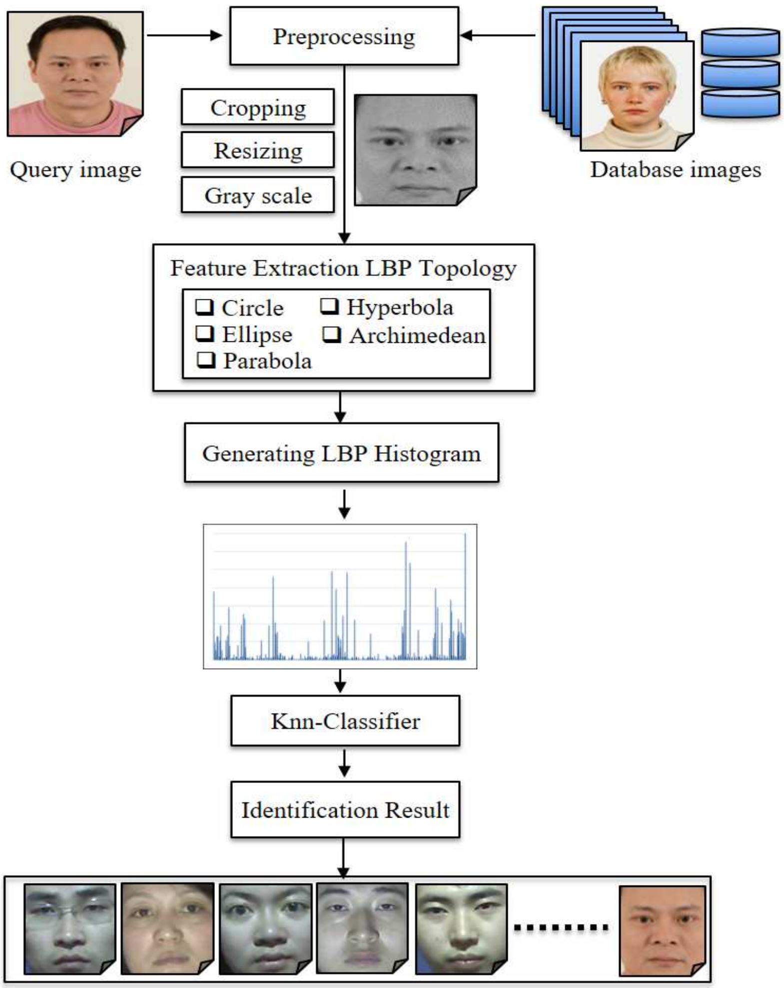


Figure-7: Framework of Proposed Method

The Framework has four main steps:

1. The pre-processing step: In the pre-processing step, a color image is first converted into a gray scale image, cropped, and probably resized depending on the image size. In this paper, the image size is fixed to 128 x128 pixels. Using gray scale image instead of the original color image is based on the finding that facial features rather than skin color is more relevant to the intended purpose, the gray level of each pixel which is an intensity feature. Pre-processing of expression image before feature extraction is essential. It includes gray scale processing and normalization.

2. The feature extraction step: the local features are extracted by conducting different topology of local binary pattern transformationto the whole face first. This paper will extract the expressional feature by block-based LBP method, which is an efficient texture descriptor. Original LBP operator is similar to template operation while extracting image features. Original LBP operator can be extended to neighbor of different size and shape.

3. Generating LBP histogram:In this step the local binary pattern histogram has been obtained to produce a single feature vector and store it for the feature selection. Using histogram as a set of features is robust to image translation and rotation to a certain extent andreduce the feature dimension from the image size.

4. The Classification step: classification is an important area to determine a limited number of search results. Because we want to calculate the accurate effectiveness of the result for the whole image database, every image in the database can be used as the query image. For each query image, the precision of the retrieval is obtained after that the k-nearest neighbor classifier is used to find 5 nearest subjects according to the Euclidean distance between the feature vectors of training images and query image.

Experiments and Results

We used the LBP transformation for the gray scale texture feature. The central pixel in an image, a binary pattern number is computed and compares the value of its neighbors. So, the original LBP operator used a 3x3 window size containing 9 values and the other LBP operators were generated by changing the window size. The initial LBP operator associates a label with each pixel of an image; the labeling process involves converting each pixel value in the 3 × 3 neighborhood of a pixel into a binary digit (0 or 1) using the center value as a threshold and concatenating the bits. Later the operator was extended to general neighborhood sizes. LBP was widely used in the face analysis, to distinguish texture features, the LBP showing the high discriminating power.

In this section, we analyze the performance of the proposed method using these databases as outlined in Section (2.3). These databases area standard test for face recognition technologies. In our experiments, we draw 50 out of 500 Europeans, 50 out of 500 Oriental, and combine them with the 50 out of 200 Africans images to form a random sample. Then to evaluate the performance of the proposed Approach using 50 folds' cross validation procedure i.e. 3 images for the test set (1 for each ethnicity) and the remaining for the training set. Then measure the recall rate as the level of accuracy. We repeat this test 10 times and then take the average on accuracy over the 10 rounds. Our experimental result is shown in Table 2. The average accuracy obtained from five different topologies are also shown graphically in Figures 8.

Table 2: Ethnicity Identification accuracy of the proposed method

Topology	**No. of pixel**	**Angle**	**Oriental**	**European**	**African**	**Total Average**
Circle	8	0	96.60	93.20	90.80	93.53
	10	0	96.00	92.40	94.20	94.20
	12	0	96.60	93.60	93.80	94.67
Ellipse	8	0	97.60	94.60	88.40	93.53
	8	45	95.60	92.60	89.60	92.60
	8	90	94.20	92.20	88.00	91.46
	8	135	95.20	94.20	89.80	93.07
Parabola	8	0	96.20	92.80	84.78	91.26
Hyperbola	8	0	93.60	92.40	84.06	90.02
Archimedean	8	0	93.80	91.00	78.99	87.93

In table 2, the columns represent the neighborhood topology used, the percentage of the ethnicity accuracy and the total average accuracy. The feature extraction parameters setting used for the LBP is reported in table 2. The setting depends on the dimension of the considered neighborhood.In our experiment five different configuration neighborhood topology circle, ellipse, parabola, hyperbola, and Archimedean topology have been used. The results reported using circle and ellipse topology give a good result for ethnicity identification task, while Archimedean topology give poor accuracy compared with other topologies.

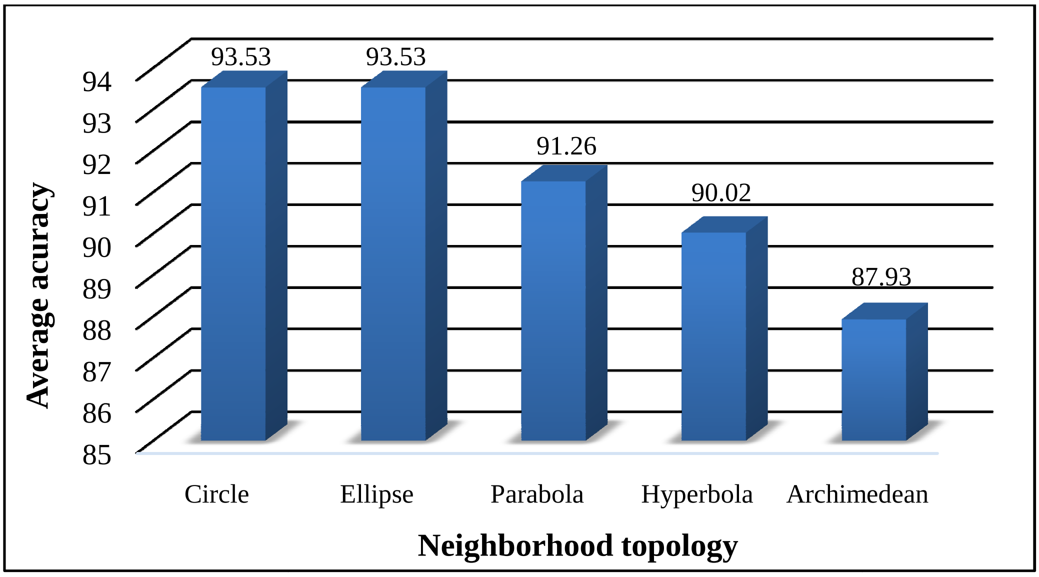


Figure-8: Accuracy obtained using different neighborhood topology

We also have compared the performance of LBP topology with two groups of test.In the first group of test experimentswe compare circle topology with varying the number of neighborhood pixels P: P = 8, P=10 and P = 12. The experiment results for circle topology show that a good accuracy and demonstrate by increasing the number of neighborhood pixel the best average accuracy will be 94.67% use P = 12 (Figure9). In the second group of test we compare the performance of ellipse topology of number of neighboring pixels (P=8) and the clockwise rotation of angels (0^o, 45^o, 90^o, and 135^o). As shown in table 2, comparing the ellipse topology with different angle and all case give good accuracy, the ellipse with angle 0 performers the best average accurate about 93.53% comparing with other, as illustrated in Figure 10.

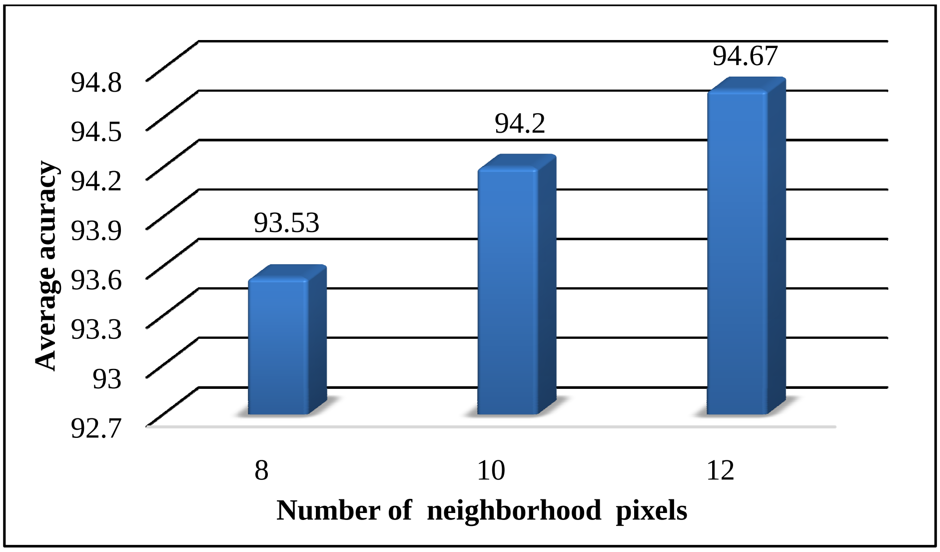


Figure-9: Accuracy obtained by circle topology using different neighborhood pixels

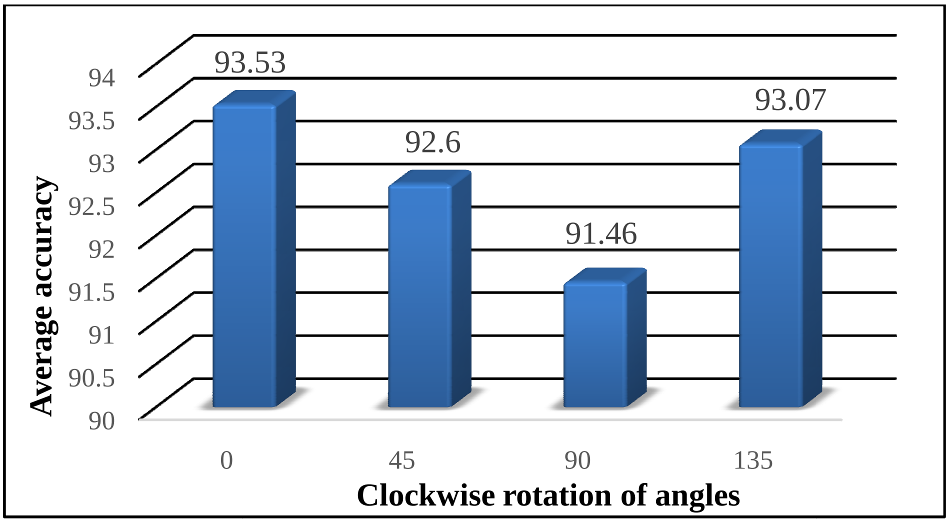


Figure-10: Accuracy obtained by ellipse topology with different angles

Conclusion

LBP is one of the most powerful descriptors to characterize local structures and it has been effectively used for many different image processing applications, such as facial image processing, motion analysis, aerial and biomedical image analysis. In this paperexperiments had been performed on five different configuration neighborhood topology forextracting local binary patterns from images and using them for identification task. In addition, we performed the two identification experiments. The first experiment was computed on the ellipse topology with eight number of neighborhood pixels and different angle (0^o, 45^o, 90^o, and 135^o).The second experiment was implemented on the circle topology withdifferent number of neighborhood pixels P: P = 8. P=10 and P = 12. The identification has been carried out using the k-Nearest Neighbor (KNN) classifier with the Euclidean distance function.The results of identification over datasetshowed that the circle and ellipsetopology are high accuracy, while the Archimedean topology haslow accuracy.Also, with our experimentation we concluded that the overall best performance was the ellipse with angle 0^oin comparing with other angles, yielding an average accuracy of 93.53%. Experimental results for circle topology indicate that a good accuracy is achieved by increasing the number of neighborhood pixel and result will be increase with average accuracy 94.67%.

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