A Study on Recent Image Features for Effective Classification and Retrieval

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Abstract— Image retrieval (IR) is a technique to retrieve images from an image database that are semantically relevant to the query image. IR uses the visual contents of the image to retrieve the desired image. Most of the proposed approaches emphasize on finding a meaningful descriptor based on different image features Today's challenge in IR is to develop a method that should be able to increase the retrieval accuracy and reduce the retrieval time. In order to improve the retrieval accuracy suitable feature should be extracted. In this paper, the recently developed image features extraction methods such as Local Binary Pattern(LBP), Local Ternary Pattern (LTP) and Local Derivative Pattern (LDP) are analyzed. Experimental results and observations made are presented.

Index Terms—Gray Level Co-Occurrence Matrix, Local Binary Pattern, Local Ternary Pattern, Local Derivative Pattern and Histogram Intersection

1. INTRODUCTION

In internet applications, at every fraction of seconds images are uploaded to the databases of the server, at the same time images are retrieved and downloaded from the database. Even though image retrieval has been a research area since 1970's, still there is a necessary for an efficient image retrieval system.

Image retrieval systems which were introduced in the early years were generally text based. In this image retrieval system [1], whenever the image is stored in the database of the server, it is stored with the annotated text descriptor. Actually the text descriptor is nothing but the textual description about the image. Generally, a lot of manpower is required for attaching the text descriptors to every image of the large database. Hence it is an intricate and expensive work [3]. There is also a problem of different annotation for a particular image by different people because of the difference in human perception.

The problems in text-based retrieval system was tried to remove by an image retrieval system which was evolved in early 1980's. In this system, the images are retrieved according to the visual information of the image. The prime goal of this system is to construct the meaningful descriptor based on the image features such as color, texture and shape of the images. Usually, these descriptors are automatically calculated by the computer to facilitate efficient and effective retrieval.

The color is one of the extensively used features to construct meaningful descriptor for the image [2]. Usually colors are defined in three dimensional color spaces. Among them some important color spaces are RGB (Red, Blue, Green), HSV (Hue, saturation, Value), and HSI (Hue, Saturation, Intensity).

Texture [11][8] is another important feature that describes about the structural arrangement of the surface i.e. something about the softness, roughness, and regularity. This texture information can be captured by several texture extraction methods. Gray Level Co-Occurrence Matrix (GLCM) [22] is one of the widely used methods for texture feature extraction. The GLCM express the spatial distribution of the gray level in the texture image. Finally different gray level co-occurrence matrices are estimated using many statistical features such as energy, entropy, contrast and homogeneity. Some other popular algorithms designed for texture analysis are the Tamura texture feature [23], the Markov random field model [13], Gabor filtering [14], Local Binary Patterns [15], Local Ternary Patterns [11] and Local Derivative Pattern.

Local Binary Pattern (LBP) [11] is one of the accepted texture classification features. The LBP encodes the pixel differences between the center pixel (P_c) and the neighboring pixels on a circle of radius into a binary number. LBP is very healthy to illumination and contrast variations as it focuses on the pixel difference. But, it is very sensitive to noise and small variations of pixel values. The problems in LBP could be minimized by the introduction of Local Ternary pattern (LTP) [11], one of the popular texture classifier. LTP creates three states (0,1,-1) while LBP uses creates two states (0,and 1). So, LTP is challenging to noise and small variations of pixel values [25]. Hence, in our proposed system Local Ternary Pattern (LTP) is used to evaluate the texture feature.

LDP is a general framework to encode directive pattern features from local derivative variation. The main process in this method is that an LDP captures local features in four directions: 0°, 45°, 90° and 135°, and concatenates the transition result as a 32 bit binary string [28].

In practice, texture features and color features can be combined to improve the retrieval performance. The most commonly gray- level texture features and color features can be combined for image retrieval. Some algorithms can in due course combine color and texture together is integrative co-occurrence matrices [16, the color edge co-occurrence histogram [19], the micro-structure descriptor [20], the multi-texton histogram [18], the texton co-occurrences matrix [17], and the texton co-occurrences matrix [17].

Shape is another image feature which describes about the arrangement of an object such as outline or contour. It allows an object to be clearly distinguished from its surrounding background by its outline. Retrieval methods using shape feature [1] information distinguishes each contours of objects contained in an image. It is not affected by the object size and position. However, since contour of an object is sensitive to changes in shape or direction, contour extraction is difficult in itself. The most successful methods for shape categories are Fourier Descriptor and Moment Invariance

In addition to these image features, region based image retrieval methods were also adopted over segmented images to increase the retrieval accuracy of IR system. Of course the performance of these methods depends on segmentation.

Generally, IR technique involves two steps. The first step is mainly extracting image features to a noticeable extent. The second step is matching the image features of query image with each database images to retrieve the images that are visually similar.

The remainder of this paper is prearranged as follows: Section 2 discusses some of the earlier image retrieval research work. Section 3 discusses some image features which are used in the image retrieval in this paper. Section 4 describes about the proposed work. Section 5 describes the experimental results and provides comparative performance. Finally, Section 6 presents the conclusion.

2. RELATED WORK

Fan-Hui Kong proposed in his work HSV color space and texture characteristics are used as feature for the image [7]. In this paper, the author represents the one dimensional vector G by constructing a commutative histogram of the color characteristics of image after calculating non-interval HSV quantization for G. Texture features are extracted using Gray Level Co-occurrence Matrix (GCM) or Color Co-occurrence Matrix (CCM) respectively. Through the image retrieval experiment he indicates that the use of color features and texture based on CGM provides efficient retrieval.

P.S Hiremath [1] presented a novel method by combining color, texture and shape information for image retrieval and improved the higher image retrieval efficiency. In this paper, the image has been partitioned into equal sized non-overlapping tiles and the image features are computed on these tiles used as descriptors for color and texture feature. Gabor filter responses and color moments are used as texture and color features respectively. Also, GVF (gradient vector flow) is used to obtain the edge image, which captures the object's shape information; GVF fields give admirable results in determining the object boundaries irrespective of the concavities implicated. Invariant moments are used as shape features. A combination of these features provides a robust feature set for image retrieval.

Images are represented by three types of popular global features such as color, texture and shape in the work proposed by Wei Bian *et al* [2]. HSV histogram is used as color feature. For constructing histogram, Hue and saturation were both quantized into 8 bits but value into 4bits. A Pyramidal Wavelet Transfer (PWT) has used to extract texture feature. The edge directional histogram was calculated as shape feature. Finally, when a query is given, the visual features are extracted for the query and database images, and then all images in the database are sorted on the base of Euclidean measure. If the user is satisfied with the output, the retrieval process comes to an end. However, because of a poor retrieval performance, most of the time, Relevance Feedback (RF) is carried out. Biased Discriminate Embedding (BDEE) algorithm is proposed for RF. Also BDEE is compared with other popular RF algorithms.

Jing Zhang *et al* [3] explored a novel approach for color and texture based retrieval using three Region of Intersect (ROI). To extract color features, the hue histograms of HSV color space have been introduced. The GLCM matrix is used to take out certain properties related to the spatial distribution of the gray level in the texture image. In order to estimate gray level co-occurrence matrices, many statistical features like energy, entropy, contrast and homogeneity are extracted. The processing of selecting ROIs is simple and the computation is fast because it makes partial match. K-means algorithm is used to segment image to three regions and then one ROI is selected from every region. Finally color features and texture features are extracted from three ROIs. The similarity between the image is determined by calculating the similarities between pairs of ROIs. Retrieval performance is evaluated using nature images.

A user-oriented mechanism for CBIR method based on Interactive Genetic Algorithm (IGA) is proposed by Chih-Chih[4]. In this work, mean value and standard derivation and also the image bitmap of a color image are used as color features for retrieval. The entropy based on the gray level co-occurrence matrix and also edge histogram of an image is considered as the texture features. Again to reduce the gap between the retrieval results and the use's expectation, the IGA (Interactive Genetic Algorithm) is employed to help the users to identify the images which are most satisfied to the user's need.

Amit Satpathy et al [11], has introduced two sets of edge-texture features, Discriminative Robust Local Binary Pattern (DRLBP) and Ternary Pattern (DRLTP) for object recognition. Gwenole Quelle *et al* [6], concentrated on an adopted non-separable wavelet transform and performance is compared with an adapted separable wavelet transform**.**

Although, many methods as given in related works were proposed, each paper had their own limitations, particularly in retrieval accuracy and execution time. So, in order to reduce the limitation, various IR approaches are proposed in this paper.

3. TEXTURE FEATURE

Texture is an image feature that describes about the structural arrangement of the surface. It defines the surface properties of an object and their relationship to the neighboring environment. Although several algorithms are available, LBP follows a simple algorithm where as LTP is more resistant to noise and small pixel variations. But LDP extracts higher order information by encoding various spatial relationships contained in a given local region.

3.1 Local Binary Pattern (LBP)

LBP encodes the pixel differences between the center pixel (P_c) and the neighboring pixels on a circle of radius into a binary number. For (3 x 3) neighboring pixel, the pixel differences between the neighbors and the center pixel is calculated by (P_i-P_c), where Pc is the center pixel and P_i is the seven neighbors around Pc on a circle. Fig.1 shows the pixel representation of 3×3 image blocks in LBP and LTP calculations. P_0, P1, P2, P3, P4, P5, P6 and P_7 are the neighbors around Pc.

P_0	P_1	P_2
P_7	**P_c**	P_3
p_6	P_5	P_4

Fig. 1. Pixel representation of 3×3 image block

The LBP code at (x,y) is calculated as follows:

$$LBP_{x,y} = \sum_{i=0}^{7} s(P_i - P_c)2^i \quad (1)$$

where s(z) is the threshold function

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

As LBP considers the pixel difference, it is robust to illumination and contrast variations [24]. But, it is very sensitive to little noise and small fluctuations of pixel values. As to handle this problem, Local Ternary pattern (LTP) has been proposed in this paper.

3.2 Local ternary Pattern (LTP)

LTP uses three conditions on the threshold value T which creates three states (1, 0 and -1) as compared to two in LBP (0 and 1). Thus, LTP is more tolerance to noise and small pixel variations.

The LTP code at (x,y) is calculated as follows:

$$LTP_{x,y} = \sum_{i=0}^{7} s'(P_i - P_c)3^i \quad (2)$$

$$\text{where } s'(z) = \begin{cases}1, & z \geq T\\ 0, & -T < z < T\\ -1, & z \leq -T\end{cases}$$

Generally T is a user-defined threshold value. In our proposed system T is selected empirically. The value of T is used as 7 in the proposed system as it gives better performance.

3.3 Local Derivative Pattern (LDP)

LDP creates the higher-order derivative information. LBP and LTP consider only the center pixels 8-neighbours but, it considers directional neighbours in 4 degrees, So it captures more discriminative features than LBP [26].

Given an image, the first-order derivatives along 0°, 45°, 90° and 135°. Directions are denoted as I'_α(N) where, α = 0°, 45°, 90° and 135°. Let N_0 be a point in I (N), and N_i , i = 1… 8 be the neighboring point around N_0 (Fig. 2). The four first-order derivatives at N =N_0 can be written as

$$\begin{aligned} I'_{0^\circ}(N_0) &= I(N_0) - I(N_4)\\ I'_{45^\circ}(N_0) &= I(N_0) - I(N_3)\\ I'_{90^\circ}(N_0) &= I(N_0) - I(N_2)\\ I'_{135^\circ}(N_0) &= I(N_0) - I(N_1) \end{aligned} \quad (3)$$

The second order derivative in α direction at N =N_0 can be defined as

$$LDP_\propto^2(N_\square) = \{ f(I'_\alpha(N_\square), I'_\alpha(N_1)), f(I'_\alpha(N_\square), I'_\alpha(N_2)), \ldots\ldots, f(I'_\alpha(N_\square), I'_\alpha(N_8))\} \quad (4)$$

Finally, the second-order Local Derivative Pattern, LDP^2(N), is defined as the concatenation of four 8-bit directional LDPs

$$LDP^2(N)=\{LDP_\propto^2(N) \mid \alpha=0°, 45°, 90°, 135°\} \quad (5)$$

The LDP operator labels the pixels of an image by comparing two derivative directions at neighbouring pixels and concatenates the transition result as a 32 bit binary string[27].

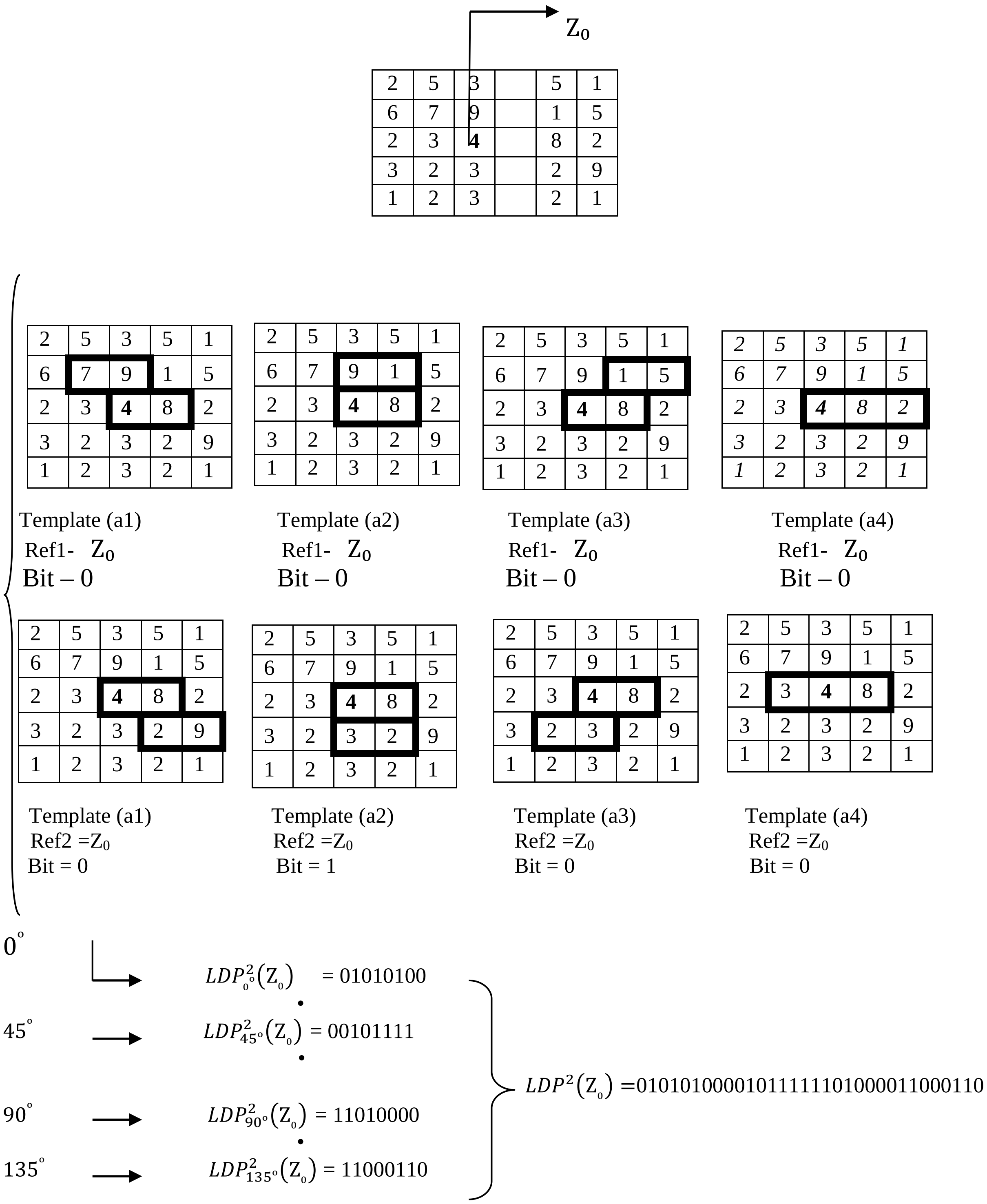


Fig.2. Steps to obtain second-order LDP micropattern

3.4 Gray Level Co-Occurrence Matrix (GLCM)

The GLCM extracts about the spatial distribution of the gray level in the texture image. The GLCM calculates how frequently a pixel with gray-level (grayscale intensity) value *i* occurs horizontally adjacent to a pixel with the value *j*. The gray level co-occurrence matrices can also be estimated using many statistical features such as energy, entropy, contrast and homogeneity and compared.

The GLCM [4][7] can be written mathematically as the probabilities of two pixels in an image, which are located with distance d and angle θ have gray levels i and j. GLCM is written as

$p(i,j;d,\theta) = n\{(x_1,y_1)(x_2,y_2)\}$

such that $g(x_1,y_1) = i$, $g(x_2,y_2) = j$,

$|(x_1,y_1) - (x_2,y_2)| = d$, and $\angle\ ((x_1,y_1),(x_2,y_2)) == \theta$ (6)

where 'n' denotes the number of occurrences of pixel in the gray image g, with i and j being the intensity levels of the pixels at position (x_1,y_1),and (x_2,y_2) respectively. In the proposed system GLCM is computed with θ=0 and d=1.

4. PROPOSED SYSTEM

The proposed system operates in five steps.

1) Querying: The user has to input an image as the query for the system.

2) Gray Scale Image: The system converts the query and all the database images into gray scale.

3) Pattern evaluation: The system calculates the pattern (using LBP, LTP or LDP) for the query image and for all the database images.

4) Disparity computation: The disparity between the query image pattern and all the database image pattern

are computed using equation 6 or equation 7.

5) Retrieval: The system retrieves four images that

have minimum disparity.

The disparity measure between the images is defined as

$$Disparity\ (q,C) = \sum |GLCM^q - GLCM^C| \qquad (7)$$

where $GLCM^q$ represent the GLCM value of the query pattern and $GLCM^C$ represents the GLCM value of the database pattern. q represents the query pattern and C represents the database pattern .

Another measurement used here is histogram intersection. It is used to measure the similarity between two histograms.

$$S_{HI}(H,S) = \sum_{i=1}^{B} \min(H_i, S_i) \qquad (8)$$

In this equation $S_{HI}(H,S)$ is the histogram intersection with $H=(H_1, H_2, H_3 \ldots\ldots\ldots.. H_A)^T$ and $S=((S_1, S_2, S_3 \ldots\ldots\ldots.. S_A)^T$. Equation (11) is used to calculate the similarity of the nearest neighbour classifier. This measure is a useful method for the calculation of common parts of two histograms[29].This is a very simple equation with simple operations.

5. EXPERIMENTAL RESULTS

The performance of the proposed system is computed by using the test images in the database. This section uses four databases for testing purpose. The first database is the standard database DB_CORELS which has about 1000 images of Corel type, the second one is the user contributed database named as DB_VEGETABLE database which has 210 of vegetable images. Third one is a standard JAFFE database with 13 faces for 10 categories. Fourth database is ORL with 40 categories, which contains 10 faces per category. The Fig. 7, 8, 9 and 10 expresses the sample test images used by this paper for the categories DB_COREL, DB_VEGETABLE, JAFFE and ORL.

5.1 Performance of the texture extraction methods

The performance of different method is given in Table 1 for DB_VEGETABLE database based on GLCM and Histogram Intersection. The performance is analyzed in four categories. For LBP 85% of success rate for 140 images In the same way, 87% of success rate when LTP is used on the same set of images. But, the LBP works well for large database.

Methods	Euclidean distance on GLCM			Histogram Intersection		
	40 images	140 images	210 imageS	40 images	140 images	210 images
LBP	90	85.71	90.95	82.5	79.28	84.7
LTP	85	87.85	83.33	67.5	87.12	60.9
LDP	92.5	81.42	80.95	75	75.7	80

Table 1

Percentage of Successful Classification for DB_VEGETABLE

Methods	Euclidean distance on GLCM			Histogram Intersection		
	40 images	140 images	210 imageS	40 images	140 images	210 images
LBP	90	79.28	85.71	82.5	80.71	82.38
LTP	95	78.57	78.09	67.5	67.85	76.66
LDP	65	82.14	81.90	75.5	78.57	79.52

Table 2

Percentage of Successful Classification for DB_CORELS

Table 2 shows the performance of DB_CORELS database based on GLCM and Histogram Intersection. The performance is analyzed in four categories. For LTP, 95%

of success rate for 40 images In the same way, 90% of success rate when LBP is used on the same set of images.

The performance on JAFFE database for different method based on GLCM and Histogram Intersection is given

in Table 3. For the JAFFE data set, LBP is better with 100% for histogram intersection.

The observation of ORL database for different method based on GLCM and Histogram Intersection is given in Table 4. For the ORL data set, LBP is works well with 99,5% for histogram intersection.

Method	Euclidean distance on GLCM	Histogram Intersection
LBP	96.15	100
LTP	93.84	99.23
LDP	84.15	92.30

Table 3

Percentage of Successful Classification for JAFFE

Method	Euclidean distance	Histogram Intersection
LBP	95.5	99.5
LTP	95.5	99.5
LDP	87.75	93.25

Table 4

Percentage of Successful Classification for ORL

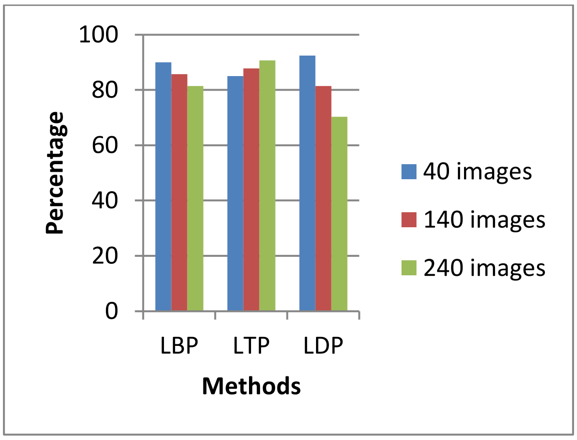


Fig.3 Percentage of Successful Classification for DB_VEGETABLE using GLCM

Fig. 3 shows the performance of feature extraction methods on DB_VEGETABLES using GLCM on different categories. The performance of feature extraction methods on JAFFE and ORL dataset is shown in Fig. 4 and Fig.5. Fig. 6 shows the performance of feature extraction methods on DB_CORELS using Histogram intersection on different categories.

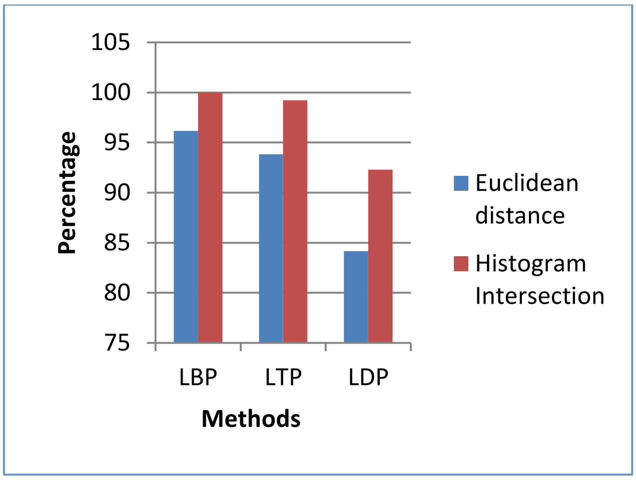


Fig. 4 Percentage of Successful Classification for JAFFE

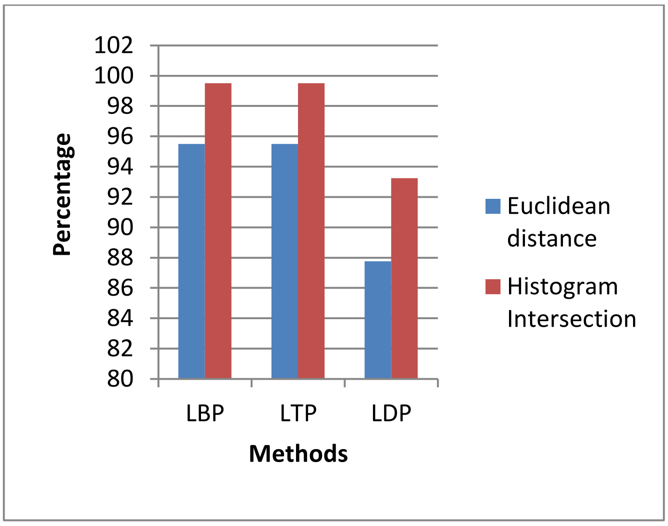


Fig. 5. Percentage of Successful Classification for ORL

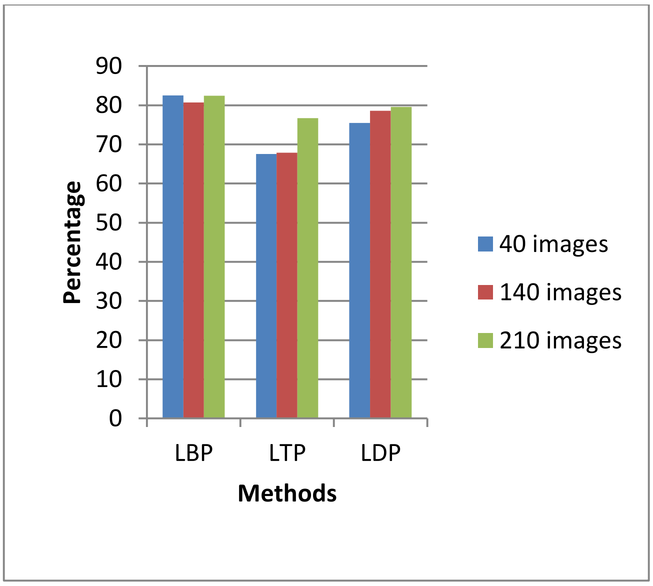
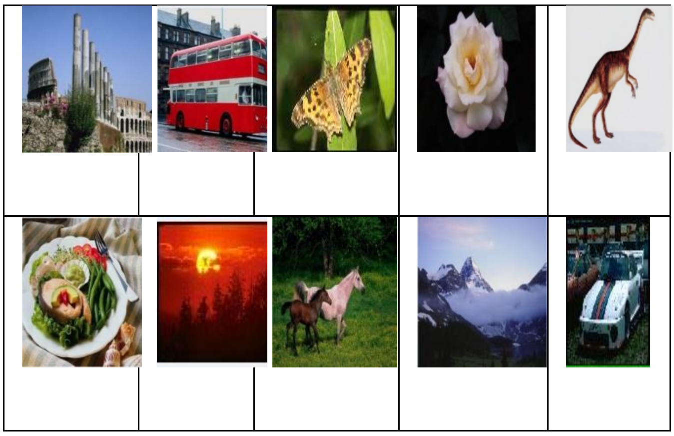


Fig. 6. Percentage of Successful Classification for DB_CORELS



Fig, 7.Sample Images of DB_COREL

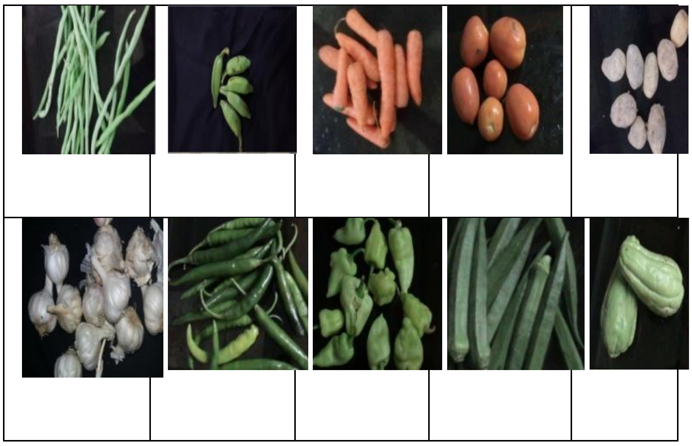


Fig. 8. Sample Images of DB_VEGETABLES

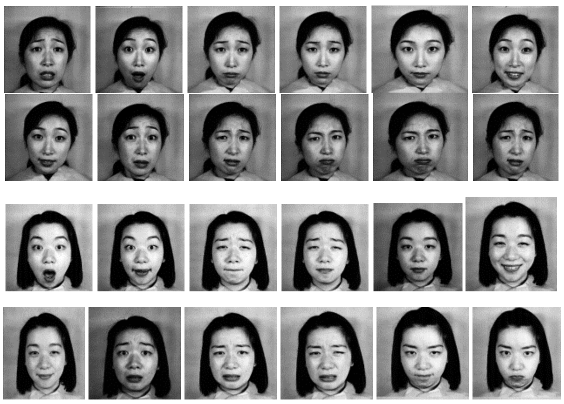


Fig. 9.Sample Images of JAFFE Data Set

Fig. 10. Sample Images of ORL Data Set

6. CONCLUSION

Under our observations, we observed that the performance of LBP is better for all databases (DB_VEGETABLES, DB_CORELS, JAFFE and ORL) we used than other feature extraction methods LTP and LDP. We experimented that LBP is good in terms of successful retrieval and classification. Also we perceived that feature selection needs to consider the type of database used.

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