

# Comparison between Local Binary Pattern and Chain Code Techniques for Image Retrieval using Sketches

P. Chandana<sup>1</sup>, P. Srinivas Rao<sup>2</sup>, Y. Srinivas<sup>3</sup>

Computer Science, Miracle Educational Society (MRCL), Vijayanagaram, India<sup>1</sup>

Computer Science, Andhra University, Visakhapatnam, India<sup>2</sup>

Information Technology, GITAM University, Visakhapatnam, India<sup>3</sup>

**Abstract:** The paper compares two Sketch Based Image Retrieval schemes used for the image retrievals. The various schemes for image retrieval are Local Binary Patterns (LBP), and Chain Code. In Local Binary Patterns (LBP), it describes the neighborhood of a pixel by its binary derivatives. To form a short code to describe the pixel neighborhood the binary derivatives are used. For pattern recognition the patterns are often used. In Chain Code Technique, it recognizes the shape of the object using contours as a feature to recognize the shape of an object. Contours play an important role in image processing and computer vision to detect various objects in image or sketch which is easy to implement.

**Keywords:** LBP, Chain Code, binary representation, countour.

## 1. INTRODUCTION

Today processors are becoming much more powerful, simultaneously the cost of memories becoming cheaper, so the use of large image databases for a variety of applications have now become practicable. Even the databases of various fields like defence, satellite and medical imagery have been attracting more and more users. Infact accessing desired images from large and varied image databases is necessary now.

The Content Based Image Retrieval (CBIR), extracts the visual content of the images in the database and describe the multidimensional factors."Content-based" means the search evaluate the actual contents of the image other than the metadata like keywords, descriptions or tags linked with the image. The Content Based Image Retrieval has become important because most web based image search engines rely purely on metadata and this produces a lot of false detection in the results. Also having humans enter keywords manually for images in a large database can be inefficient and may not capture every keyword that describes the image.

In this paper, we propose a model for Sketch based Image Retrieval scheme with an implementation of the two novel techniques i.e, Local Binary Pattern (LBP) and chain code mechanism where both are the pattern recognition mechanisms but presents the efficiency in image retrieval process.

LBP discusses about obtaining patterns using histograms summation and chain code mechanism represents pattern by contour tracing .

The above said algorithms are discussed in detail in the preceding sections as follows:

## 2. METHODOLOGY

The methodology for the SBIR is proposed as follows:

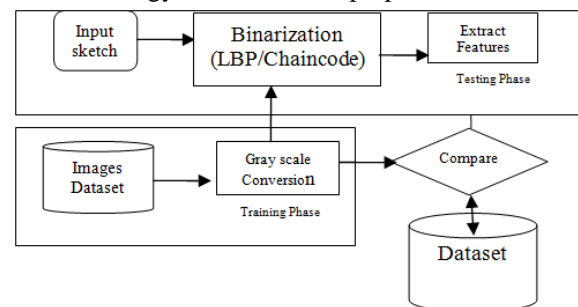


Fig 1.Block diagram of SBIR

The model is proposed in two phases, i.e testing phase and training phase, in which the set of images were preprocessed by converting images into gray scale and trained with set of histograms and chain codes basing on the methods choosen in a training phase and similarly, for the input sketch , the gray scale conversion and binarization is performed and features were extracted in the testing phase, and in the searching process, the test image is compared with a set of trained images in the dataset and relevant results were displayed.

The methods used for binarization are discussed below:

### 2.1. LOCAL BINARY PATTERN:

The Local Binary Pattern (LBP)[1][2] is an image operator. LBP transforms the image into an image of integer labels. These labels describe the features of the image and labels use histogram for the image analysis. Most commonly these are designed for still images and it has been extended for color images, videos and large datasets.

2.1.1 BASIC LBP: The LBP is a two-level version of the texture unit used to describe the textural patterns. The LBP operator considers 3\*3 pixel block of an image. Firstly, the threshold is calculated by its center pixel value in the block. Then it is multiplied by power of two. Finally it is summed to get the label for the center pixel. Here the neighboring pixels are 8 pixels, and the total of 28 = 256 different labels is obtained with different values.

2.1.2 Derivation of the Generic LBP Operator: The LBP operator was presented by Ojala et al. in a more standard improved form.

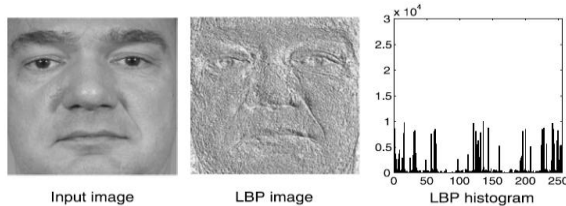


Fig. 2.1 Example of an input image, the corresponding LBP image and histogram

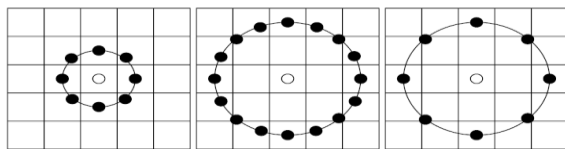


Fig. 2.2 The circular (8, 1), (16, 2) and (8, 2) neighborhoods.

Whenever the sampling point is not in the center of a pixel, the pixel values are bilinearly interpolated. The standard formulation of the operator does not have any limitations to the size of the neighborhood pixels.

The derivation of generic LBP is presented as follows: Consider a monochrome image  $I(x, y)$  where  $g_c$  denote the gray value of an arbitrary pixel  $(x, y)$ , i.e.

$$g_c = I(x, y).$$

let  $g_p$  denote the gray value of a sampling point in an evenly spaced circular neighborhood of  $P$  sampling points and radius  $R$  around point  $(x, y)$ :

$$g_p = I(x_p, y_p), p = 0, \dots, P - 1 \text{ and} \quad (2.1)$$

$$x_p = x + R \cos(2\pi p/P), \quad (2.2)$$

$$y_p = y + R \sin(2\pi p/P). \quad (2.3)$$

Fig. 1.2 represents examples of local circular neighborhoods.

Assuming that the local texture of the image  $I(x, y)$  is characterized by the joint distribution of gray values of  $P+1$  ( $P > 0$ ) pixels:

$$T = t(g_c, g_0, g_1, \dots, g_{P-1}). \quad (2.4)$$

The center pixel value can be subtracted from the neighborhood, without loss of information:

$$T = t(g_c, g_0 - g_c, g_1 - g_c, \dots, g_{P-1} - g_c). \quad (2.5)$$

In next step, the joint distribution is approximated by making the center pixel to be statistically independent of the differences, which allows factorization of the distribution:

$$T = t(g_c) t(g_0 - g_c, g_1 - g_c, \dots, g_{P-1} - g_c). \quad (2.6)$$

Now the first factor  $t(g_c)$  is the intensity distribution over  $I(x, y)$ . In view of local textural patterns analysis, it contains no useful information. Instead the joint distribution of differences

$$t(g_0 - g_c, g_1 - g_c, \dots, g_{P-1} - g_c) \quad (2.7)$$

can be used to model the local texture. The reliable estimation of this multidimensional distribution from image data can be difficult. One solution to this problem, is to apply vector quantization. Learning vector quantization with a codebook of 384 code words to reduce the dimensionality of the high dimensional feature space. The indices of the 384 code words correspond to the 384 bins in the histogram. The learning vector quantization based approach still has certain unfortunate properties which make its use difficult.

**First**, the differences  $g_p - g_c$  are invariant to changes of the mean gray value of the image but not to other changes in gray levels.

**Second**, for texture classification, the codebook must be trained similar to the other text on-based methods. In order to solve these challenges, only the signs of the differences are considered:

$$t(s(g_0 - g_c), s(g_1 - g_c), \dots, s(g_{P-1} - g_c)), \quad (2.8)$$

where  $s(z)$  is the thresholding (step) function

$$s(z) = \begin{cases} 1, & z \geq 0 \\ 0, & z < 0. \end{cases} \quad (2.9)$$

The generic local binary pattern[5] operator is derived from this joint distribution. As in case of basic LBP, it is obtained by adding thresholded differences weighted by powers of two. The  $LBP_{P,R}$  operator is defined as

$$LBP_{P,R}(x_c, y_c) = \sum_{p=0}^{P-1} s(g_p - g_c) 2^p \quad p=0..p-1. \quad (2.10)$$

Eq. 2.10 represents the signs of the differences in a neighborhood and interpreted as a  $P$ -bit binary number, resulting  $2^P$  distinct values for the LBP code. The local gray-scale distribution, i.e. texture, can be described with a  $2^P$ -bin discrete distribution of LBP codes:

$$T = t(LBP_{P,R}(x_c, y_c)). \quad (2.11)$$

In calculating the  $LBP_{P,R}(x_c, y_c)$  distribution (feature vector) for a given  $N \times M$  image sample ( $x_c = \{0, \dots, N - 1\}$ ,  $y_c = \{0, \dots, M - 1\}$ ), the central part is only considered because a large neighborhood cannot be traced on the borders. The LBP code is calculated for each pixel in the cropped portion of the image, and the distribution of the codes is used as a feature vector, denoted by  $S$ :

$$x \in \{[R], \dots, N - 1 - [R]\}, y \in \{[R], \dots, M - 1 - [R]\}.$$

$$S = t(LBPP,R(x, y)), \quad (2.12)$$

The original LBP is very much similar to LBP 8.1, with two differences. Firstly, the neighborhood is indexed circularly, making it easier to derive rotation invariant texture descriptors. Secondly, the diagonal pixels in the 3\*3 neighborhood are interpolated in LBP 8.1.

2.1.3 ALGORITHM FOR LBP:

The main common steps of the algorithms consist of four main parts:

Step 1: Preprocessing: We begin by applying the Tan and Trigg's illumination normalization algorithm to compensate for illumination variation in the image. No further preprocessing, such as alignment is performed.

Step 2: LBP operator application: In the second stage LBPs are computed for each pixel, a fine scale textural description of the image is created.

Step 3: Local feature extraction: In this step, over local image regions, Local features are created by computing histograms of LBP.

Step 4: Classification: The comparison is performed using the local features obtained in the previous step.

The first two steps are performed by all the algorithms. The algorithms varies with the operation in the last two steps.

2.1.4. FLOWCHART FOR LBP:

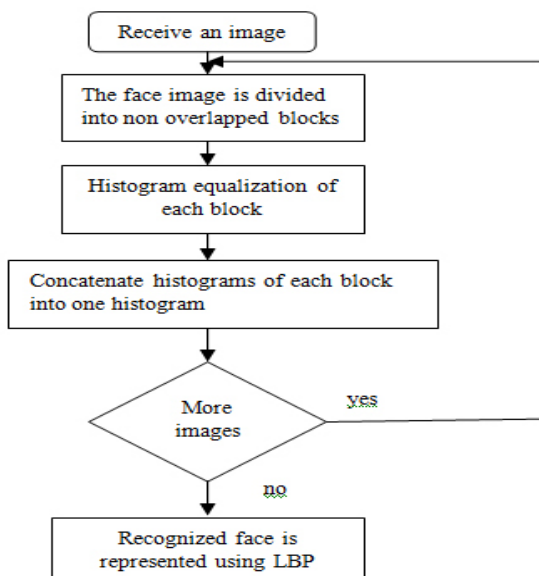


Table 1: List of LBP variations

Variations	Properties	Advantages
Mean LBP	Consider effects of center pixels	Enhances discriminative capability
Hamming LBP	Incorporate non-uniform patterns into the uniform patterns	Enhances discriminative capability
Local ternary patterns	Bring in new thresholds	Improves the robustness
Elongated LBP	Not invariant to rotation	Capable to choose different neighborhood
Volume LBP	Describe dynamic texture	Extending to 3D

2.2.CHAIN CODE:

A Chain Code<sup>[6][11][15]</sup> is a lossless compression algorithm for monochrome images<sup>[7]</sup>, which provide a good compression of boundary description. The first approach for representing digital boundary was introduced by Freeman in 1961 using chain codes ,which is basically a notation for recording list of edge points along a contour and which follow the contour in a clockwise manner and keep track of the directions<sup>[8] [11]</sup>when it move from one previous contour pixel to the current contour pixel.

Chain codes are used to represent a boundary<sup>[8]</sup> by a connected sequence of straight-line segments of specified length and direction. And the chain code depends on the start point of boundary following.

In this paper chain code is applied to contour based image retrieval from hand drawn sketches. In an image retrieval system accuracy and speed are important terms. Developing a practical image retrieval system is still a challenging task. To make the image retrieval system as user friendly and to reduce the search and extraction time, in this paper we propose chain code implementation in Sketch Based Approach.

Contour detection in sketches:

For the hand drawn sketches, find the contours depending on the work of freeman chain code. To find the contours based on 8connected 3X 3 window<sup>[3]</sup> traverse .the chain code traversed in either clockwise or anti-clockwise direction. While using chain code to recognize the shape of object ,segmentation is not required ,as the algorithm works on the contour tracing concept.

Pixels connectedness:

Contours founded by using Chain code depend on 4-connectedness<sup>[4]</sup> or 8-connectedness of the pixels. Here we use 8-connectedness to recognize the shapes of the objects more efficiently. The sketches which are taken as input are monochrome images only. So the background is white and the object is black or vise versa. The algorithm first searches the top most pixels, in opposite value to the background value . After finding the top most left pixel (of opposite value ) p(i,j),and then search from the previous pixel, from where it moves from to current position in clock wise direction and so on. From the obtained chain codes, a Normalized chain codes were identified, where normalized chain code is the optimized chain code, which is efficient for matching and retrieving.

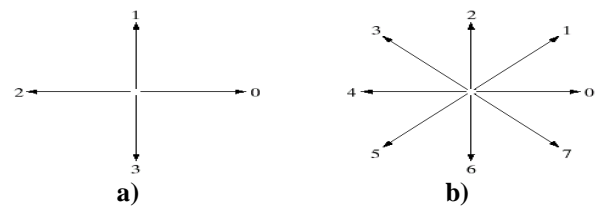


Fig.2:directions in freeman chain code  
a) 4-connectedness b)8-connectedness

The flow for Sketch retrieval process using chain code is represented as follows:

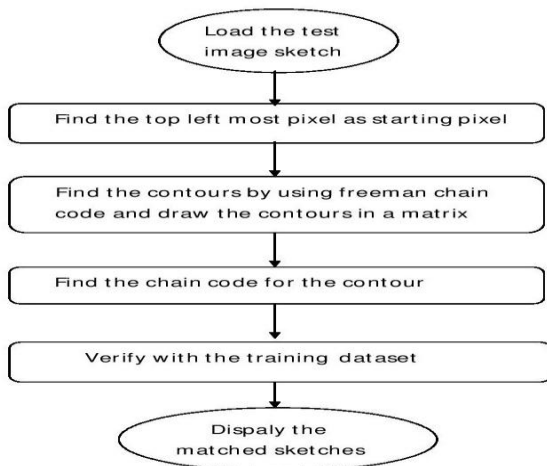


Fig 3:Proposed method for sketch retrieval

The following table shows that, the numbers from 0 to 7 are at various positions of pixels which might occur. The next pixel positions can be obtained by referring the table

Table 1: Direction of chain code

3	2	1
4	Current pixel (i,j)	0
5	6	7

This process is repeated till it reaches the end point. After completing contour tracing , the chain code values are stored in an array, this normalized chain code is compared with the stored normalized chain code values of the dataset and sketches that are similar are displayed.

Table 2: Position of next pixels might occur

Current pixel at coordinate (i,j)		
Code	Next row	Next column
0	i	j+1
1	i+1	j+1
2	i+1	j
3	i+1	j-1
4	i	j-1
5	i-1	j-1
6	i-1	j
7	i-1	j+1

### 2.2.1. ALGORITHM:

An Algorithm for generating chain code on the hand drawn sketches are given as follows:

**Step 1:** Free hand sketch drawn by user is taken as input

**Step 2:**  $P = \{p(i,j): i=1,2,...,M \& j=1,2,...,N\}$

**Step 3:** This input image traced in row wise manner, and mark the top most Pixel as first pixel,i.e,  $a=p(i,j)$ .

**Step 4:** Trace the next pixel by searching from the previous pixel position as

$$\{ \begin{matrix} p(i+1,j+1), & p(i,j+1), \\ p(i-1,j+1), & p(i-1,j), \\ p(i-1,j-1), & p(i,j-1), \end{matrix}$$

$$\{ \begin{matrix} p(i+1,j-1), & p(i+1,j), \\ p(i+1,j) \end{matrix}$$

**Step 5:** Find the chain code values tracing the contour, and then store these values in an array and store 1 in the corresponding pixel position in a matrix.

**Step 6:** If current pixel =starting pixel , contour tracing is completed. Else ,goto step 4.

**Step 7:** Identify the normalized chain code from the obtained Chain code.

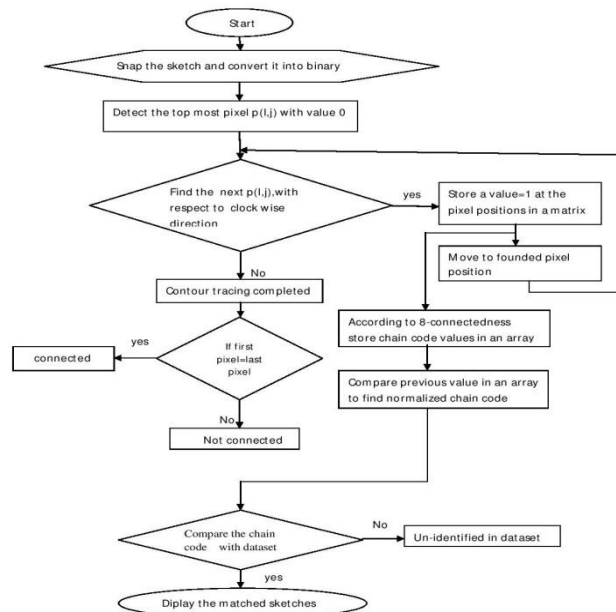
**Step 8:** Compare the test image normalized chain code with the dataset, if found display the relevant sketches

**Step 9:** Repeat the above steps till approximate sketches were found.

Using this algorithm, test chain code is verified with the training dataset, if any codes were matched, then those sketches are displayed. Here the sketches are displayed which are matched more then 70% with the test chain code.

The flow for search and retrieval processs is carried out as shown in the flowchart :

### 2.2.2.FLOWCHART:



### 3. EXPERIMENTAL RESULTS

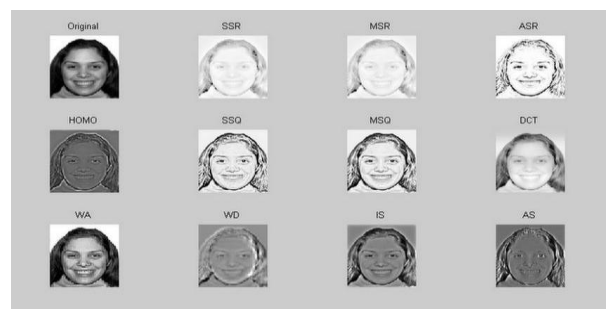


Fig4 :LBP Result<sup>[6]</sup>

LBP Method Reveals the shape and feature matching with respect to illumination conditions.

Table :

Method	Dataset	Accuracy(%)
Chain Code Scheme	100 images	90
Local Binary Patterns	>100 images	95%

Case1:

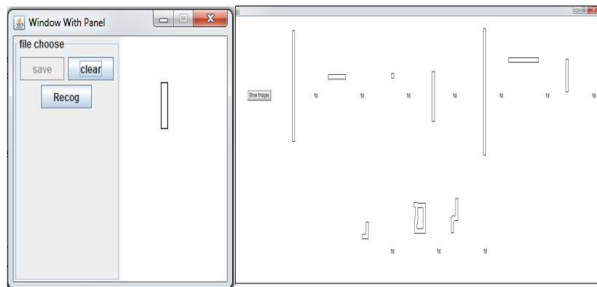


Fig 4:(a) Query Interface (b) Result

**Description:**

In fig 4, straight line is given as an input, for this normalized chain code is obtained basing on the contours, it is compared with the normalized chain codes available in the data set sketches, and relevant sketches were displayed.

Case2:

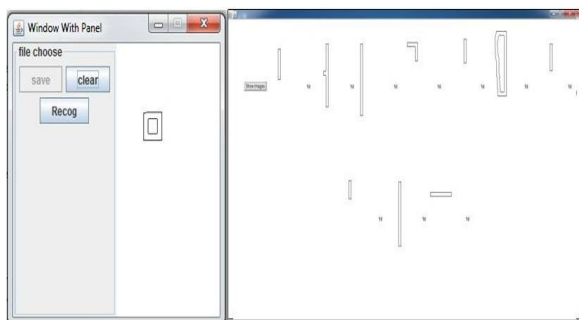


Fig 5:(a) Query Interface (b) Result

**Description:**

In fig 5 free hand drawn input sketch is a square, for this normalized chain code is found depending upon the contours, it is compared with the normalized chain codes of the data set sketches, and then the matched sketches were displayed.

Case3:

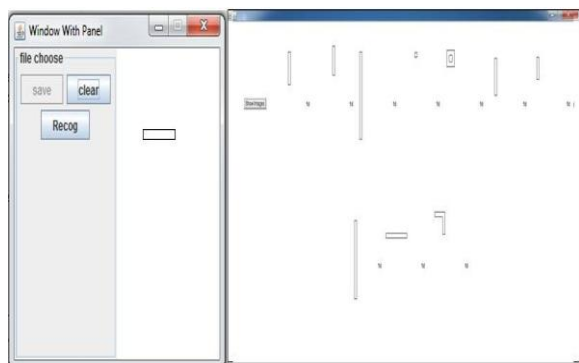


Fig 6:(a) Query Interface (b) Result

**Description:**

In fig 6, rectangle is given as an input, for this normalized chain code is obtained basing on the contours, and it is compared with the normalized chain codes available in the data set sketches, and thus relevant sketches with minimum of 70% match were displayed.

#### 4. CONCLUSION

This paper provides the comparison of two methods used in Sketch based image retrieval process, where both the methods are used for contour detection and matching process but still with respect to the increase in data set of images, chain code can be suited for contour detection well in case of still images, and thus exhibits poor performance in illumination conditions whereas, LBP method can be used for the same purpose even for the blurred image as it considers histogram approach.

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