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Content Based Image Retrieval using Line Edge Singular Value Pattern (LESVP): A Review Paper

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Abstract - In order to improve the retrieval correctness of content-based image recovery systems, research focus has been shifted from designing complicated low-level feature extraction algorithms to reducing the semantic gap between the image features and semantics. With increasing popularity of the network and development of multimedia technologies users are not satisfied with the traditional information retrieval techniques and for the same reason content based image retrieval are becoming a source of exact and fast retrieval. In this review paper the techniques of content based image retrieval are discussed, analyzed and new approach Line Edge Singular Value Pattern (LSVP) is proposed which integrate the concept of line Edge and Singular Value Decomposition (SVD).

Keywords -Content Based Image Retrieval(CBIR), Color Histogram, Texture, Local binary patterns (LBPs), Singular Value Decomposition (SVD)

I. INTRODUCTION

Recently, with the advances in various multimedia technologies, such as speedy network, compression and new digital image sensor technology, huge image databases are being created by technical, educational, medicinal, industrial and other applications. These large volumes of the images make complicated for a user to browse through the entire database. Therefore, an competent and automatic procedure is a need for indexing and retrieving images from databases [1,31]. Traditionally, two approaches are used to retrieve the images: text based and content based approaches. Images are first annotated either by hand manually or with the help of machine and then retrieved using traditional text retrieval techniques in text based approaches. Manual annotation is a cumbersome and expensive task for large image databases and often subjective in nature. Similarly the first hurdle in machine annotation is the proper segmentation of image itself. As a result, it is difficult for the traditional text-based methods to retrieve a variety of images from database. A new technique known as content based image retrieval (CBIR) evolved to resolve this problem. CBIR technique uses visual contents of an image such as color, shape and texture [3, 4, 5, 6, 7] to search images from large image databases.

Content Based Image Retrieval (CBIR) is an important research area for manipulating large multimedia databases and digital libraries. High retrieval efficiency and less computational complexity are the desired characteristics of CBIR system. Computational complexity and retrieval efficiency are the key objectives in the design of CBIR system [2]. However, designing of CBIR system with these objectives becomes difficult as the size of image database becomes huge. Features of an image should have a strong association with semantic meaning of the image. CBIR system retrieves the appropriate images from the image data base for the particular query image, by comparing the features of the query image and images in the database. Appropriate images are retrieved according to minimum distance or maximum similarity [8] measure calculated between feature of query image and every image in the image data base.

In this paper, we propose a new efficient approach Line Edge Singular Value Pattern (LSVP), which integrate the concept of line Edge and Singular Value Decomposition (SVD).

II. LITERATURE SURVEY

Texture is the most important feature for CBIR. Smith and Chang used the mean and variance of the wavelet coefficients as texture features for CBIR [5]. Moghaddam et al. proposed the Gabor wavelet correlogram (GWC) for CBIR [6,7]. Ahmadian and Mostafa used the wavelet transform for texture classification [8]. Moghaddam et al. introduced new algorithm called wavelet correlogram (WC) [9]. Saadatmand and Moghaddam[7,10] improved the performance of the WC algorithm by optimizing the quantization thresholds using genetic algorithm (GA).

Birgale et al. [11] and Subrahmanyam et al. [12] combined the color (color histogram) and texture (wavelet transform) featuresfor CBIR. Subrahmanyam et al. proposed correlogram algorithm for image retrieval using wavelets and rotated wavelets (WC + RWC)[13].

Ojala et al. proposed the local binary pattern (LBP) features for texture description [14] and these LBPs are converted to rotational invariant for texture classification [15]. Pietikainen et al. proposed the rotational invariant texture classification using feature distributions [16]. Ahonen et al. [17] and Zhao and Pietikainen [18]used the LBP operator facial expression analysis and recognition. Heikkila and Pietikainen proposed the background modeling and detection by using LBP [19]. Huang et al. proposed the extended LBP for shape localization [20]. Heikkila et al. used the LBP for interest region description [21]. Li and Staunton used the combination of Gabor filter and LBP for texture segmentation [22]. Zhanget

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al. proposed the local derivative pattern for face recognition [23].They have considered LBP as a non-directional first order local pat-tern, which are the binary results of the first-order derivative in images.
The block-based texture feature which use the LBP texture feature as the source of image description is proposed in [24] for CBIR. The center-symmetric local binary pattern (CS-LBP) which is a modified version of the well-known LBP feature is combined with scale invariant feature transform (SIFT) in [25] for description of interest regions. Yao and Chen [26] have proposed two types of local edge patterns (LEP) histograms. For image segmentation LEPSEG, and for image retrieval LEPINV. The LEPSEG is sensitive to dissimilarity in rotation & scale, whereas LEPINV is resistant to dissimilarity in rotation & scale. Subrahmanyam et al. [27] have proposed the DLEP which collects the directional edge information for image retrieval.

III. CONTENT BASED IMAGE RETRIEVAL

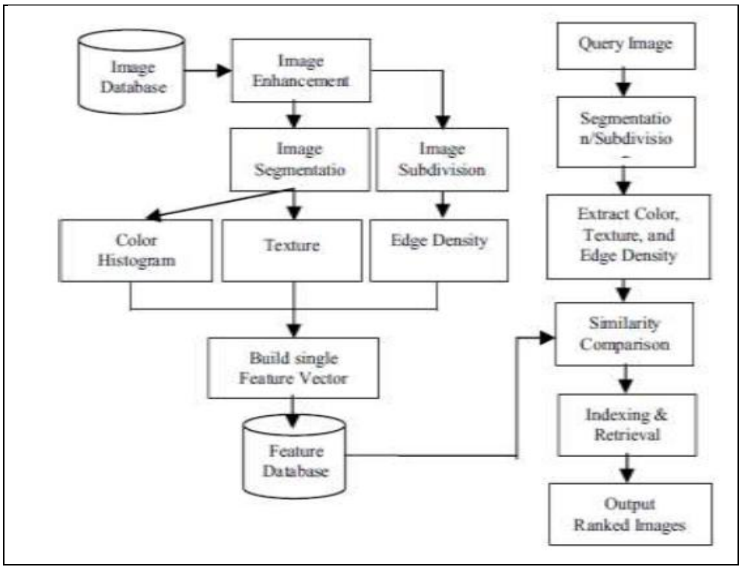


Fig 1 : Flow chart of Content Based Image Retrieval [30]

CBIR systems can be based on many features, viz., texture, color, shape and edge information. Texture contains significant information about the structural arrangement of surfaces and their relationship to the surrounds. Different techniques are developed for texture analysis [9,10]. Most of the textural features are founded from the application of a local operator, arithmetic analysis, or measurement in transform domain. In [11] color distribution and quantization is used for color image retrieval. Shape features are calculated assuming that images contain only one shape. Shape features include: modal matching [12], histograms of edge directions [13], and matching of shape components such as corners, line segments or circular arcs [14]. Recently Fu et al., [15] have proposed CBIR system based on features obtained by multi resolution Local binary patterns (LBPs) correlogram. Local binary patterns are used for texture feature extraction [16, 17].

Local binary patterns (LBPs)
The LBP operator was introduced by Ojala et al. [14] for texture classification. Success in terms of speed (no need to tune any parameters) and performance is reported in many research areas such as texture classification [14–16], face recognition [17,18],object tracking, bio-medical image retrieval and finger print recognition. Given a center pixel in the 3 × 3 pattern, LBP value is computed by comparing its gray scale value with its neighborhood based on Eq. (1) and (2):

$$\mathrm{LBP}_{P,R} = \sum_{p=1}^{P} 2^{(p-1)} \times f_1(I(g_p) - I(g_c)) \tag{1}$$

$$f_1(x) = \begin{cases} 1 & x \geq 0 \\ 0 & \text{else} \end{cases} \tag{2}$$

where I(gc) denotes the gray value of the center pixel, I(gp) represents the gray value of its neighbors, P stands for the number of neighbors and R, the radius of the neighborhood. After computing the LBP pattern for each pixel (j, k), the whole image is represented by building a histogram as shown in Eq. (3).

$$H_{\mathrm{LBP}}(l) = \sum_{j=1}^{N_1}\sum_{k=1}^{N_2} f_2(\mathrm{LBP}(j,k), l); \quad l \in [0, (2^P - 1)] \tag{3}$$

$$f_2(x, y) = \begin{cases} 1 & x = y \\ 0 & \text{else} \end{cases} \tag{4}$$

where the size of input image is N1× N2.Fig. 1 shows an example of obtaining an LBP from a given 3 × 3 pattern. The histograms of these patterns contain the information on the distribution of edges in an image.

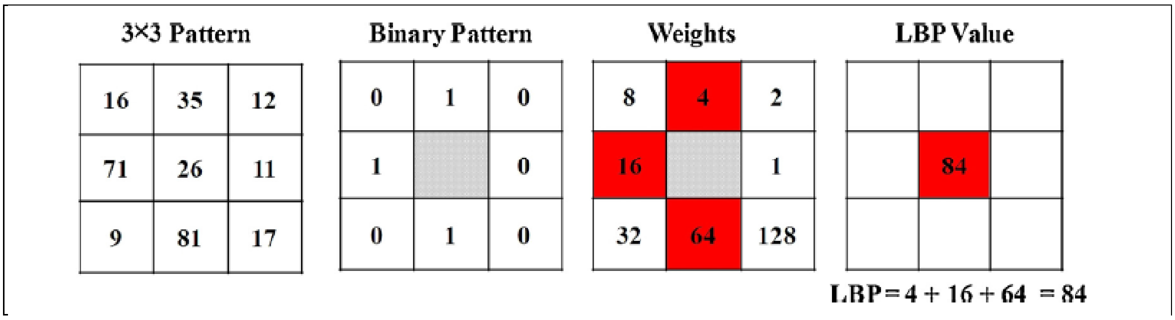


Fig. 2. Calculation of LBP[1]

Singular value decomposition (SVD)

In linear algebra, the **singular value decomposition** (**SVD**) is a factorization of a real or complex matrix. It has many useful applications in signal processing and statistics.

Formally, the singular value decomposition of an $m \times n$ real or complex matrix $\mathbf{M}$ is a factorization of the form $\mathbf{M} = \mathbf{U\Sigma V^*}$, where $\mathbf{U}$ is an $m \times m$ real or complex unitary matrix, $\mathbf{\Sigma}$ is an $m \times n$ rectangular diagonal matrix with non-negative real numbers on the diagonal, and $\mathbf{V^*}$ (the conjugate transpose of $\mathbf{V}$, or simply the transpose of $\mathbf{V}$ if $\mathbf{V}$ is real) is an $n \times n$ real or complex unitary matrix. The diagonal entries $\Sigma_{i,i}$ of $\mathbf{\Sigma}$ are known as the **singular values** of $\mathbf{M}$. The m columns of $\mathbf{U}$ and the n columns of $\mathbf{V}$ are called the **left-singular vectors** and **right-singular vectors** of $\mathbf{M}$, respectively[28].

Singular value decomposition takes a rectangular matrix of gene expression data (defined as A, where A is a n x p matrix) in which the n rows represents the genes, and the p columns represents the experimental conditions. The SVD theorem states:

$$\mathbf{A}_{nxp} = \mathbf{U}_{nxn}\, \mathbf{S}_{nxp}\, \mathbf{V}^{T}_{pxp}$$

Where

$$\mathbf{U}^{T}\mathbf{U} = \mathbf{I}_{nxn}$$

$\mathbf{V}^{T}\mathbf{V} = \mathbf{I}_{pxp}$ (i.e. U and V are orthogonal)

Where the columns of U are the left singular vectors (*gene coefficient vectors*); S (the same dimensions as *A*) has singular values and is diagonal (*mode amplitudes*); and V^T has rows that are the right singular vectors (*expression level vectors*). The SVD represents an expansion of the original data in a coordinate system where the covariance matrix is diagonal[29].

IV. PROPOSED ALGORITHM

Basic Steps for Line Edge Singular Value Pattern (LESVP):

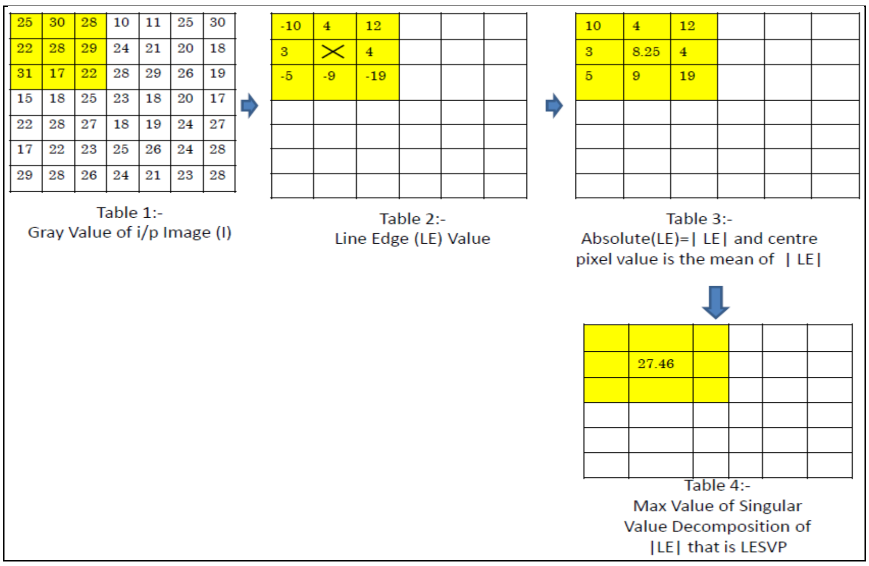
Step 1:- Load Original Image=I (Table -1),

PTN(gc)= the 3×3 pattern value of an image (I) with central pixel gc.

The line edges (LE) (shown in Table -2) are calculated by multiple of window functions (Wθ) with the gray values pattern.

$$LE(\theta) = sum\ (PTN(g_c) * W_\theta); \qquad \theta = 0°, 45°, \ldots\ldots, 315° \qquad (5)$$

Step 2:- Take the absolute of Line Edge matrix (LE) and Centre pixel value will be mean of absolute of LE(θ). That is shown in Table-3.



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Step 3:- Find out the Singular Value Decomposition (SVD) of Table-3 :

$$[U\ S\ V] = SVD(|\ LE\ |) \qquad (6)$$

Where, U=left singular Vectors, V= Right singular Vectors, S= Singular Value of the corresponding matrix (|LE|)

Step 4:- Centre pixel replaced by maximum value of Singular Value Matrix (S) (In Table-4) that is the LESVP of the 3×3 pattern- image .

Step 5:- After identifying the LESVP pattern of each pixel *(j, k)*, the whole image is represented by building a histogram:

$$H(l) = \sum_{j=1}^{N_1} \sum_{k=1}^{N_2} f_2(LESVP_{P,R}^{u2}(j,k), l); \ \ l \in [0,255] \qquad (7)$$

$$f_2(x,y) = \begin{cases} 1 & x = y \\ 0 & else \end{cases}$$

where the size of input image is *N1×N2*

V. Conclusion

In this paper we discussed the functionality of content based image retrieval systems which shows mostly color and texture features are used, whereas a small number of systems use shape feature. We proposed a new method Line Edge Singular Value Pattern (LSVP) which integrate the concept of line Edge and Singular Value Decomposition (SVD) to retrieve image.

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