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A Survey On Flower Image Retrieval Based On Saliency Map And Feature Extraction

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Abstract—*Content based Image Retrieval is a growing topic under image processing. The main purpose of CBIR System is to help users to retrieve revelent images based on their contents using several feature extraction technique such as color, texture and shape using saliency map. In this paper various extracting methods are discussed, analyzed and compared. To extract the color feature from the image the color moment will be used. To extract texture feature, the image will be in gray-scale and Gabor filter is performed on it. To extract Shape feature Zernike moment and Fourier Descriptor are used.*

Index Terms—CBIR, Flower Image Retrieval, Feature extraction, Saliency Map

I. INTRODUCTION

Information retrieval (IR) is finding material (usually documents or Images) of an unstructured nature (usually text) that satisfies an information need from within large collections (usually stored on computers).More specially, when the retrieved information is a collection of images, this field of knowledge is call Image Retrieval [1].
Image retrieval is a computer system for searching, browsing and retrieving digital images from database collection. This area of research is very active research since the 1970s [2]. Due to rapid advancement of information technology image retrieval for digital image has drastically [3]. That's why image retrieval has become important research topic nowadays by researchers.

The main aim of an image database is to store and retrieve an image or image sequences that are relevant to a query. Image retrieval systems categorized as image retrieval research and development and it has two approaches text-based information retrieval (TBIR) and content based image retrieval (CBIR).Text-based concept is by mean of image annotation information given for the images, or the keyword actions used for searching such images are the technique used for image retrieval process [3].

The saliency map combines information from each of the feature maps into a global measure where points corresponding to one location in a feature map project to single units in the saliency map. Saliency at a given location is determined by the degree of difference between that location and its surround [25].

In image retrieval research, researchers are moving from keyword based, to content based then towards semantic based image retrieval and the main problem encountered in the content based image retrieval research is the semantic gap between the low-level feature representing and high-level semantics in the images [3].

A. Keyword Based Image Retrieval

In the 1970s, the Keyword Based Image Retrieval system used keyword as descriptors to index an image [1]. In Fig.1General Framework of keyword based image retrieval is show.

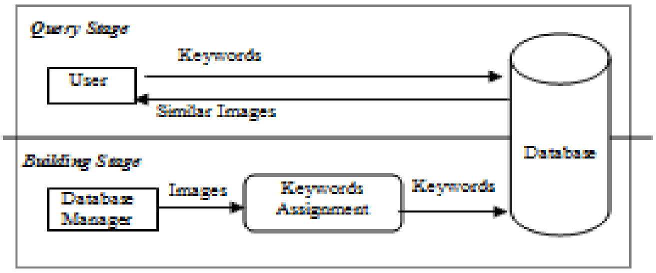


Fig.1 General Framework of Keyword Based Image Retrieval [2].

In this method images are stored in the database then they are examined manually and assigned keywords that are most appropriate to describe their contents. The Keyword which stored in the database, are stored as the part of the attributes associated to the image. During query stage, the image retrieval system will accept from the user one or many keywords which constitute the search criteria. A keyword matching process is then performed to retrieve images associated with the keywords that match the search criteria.

B. Content Based Image Retrieval

Content-based image retrieval plays a central role in the application areas such as multimedia database system in recent years. The work focused on using low-level features like color, texture and shape for image representation. In CBIR each image that is stored in the database has its features extracted and compared to the features of the query image [8].it divided in two steps.

1. Feature Extraction:

   In this step, process is to extract the image feature to a distinguishable extent[8].

2. Matching:

   The second step involves matching these features to yield a result that is visually similar [8].

The major aim of the CBIR system is to construct meaningful description of physical attributes from images to facilitate efficient and effective retrieval [3].

Fig.2 has shown the block diagram of the content based image retrieval.

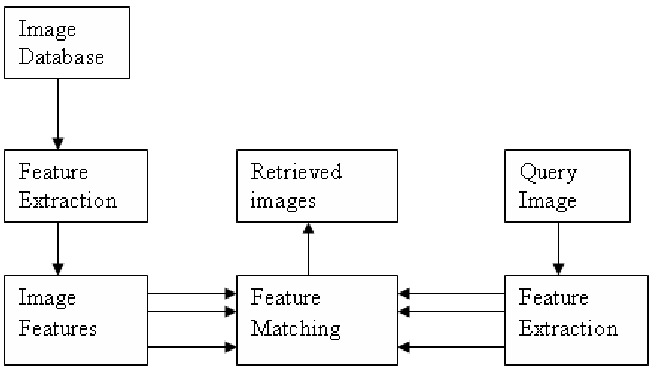


Fig.2 Block Diagram of Content Based Image Retrieval[8]

II. FEATURE EXTRACTION TECHNIQUES

Visual feature extraction is the basis of any content-based image retrieval technique. In this two features are include as text-based feature and visual feature. Visual feature can be further classified as low-level features and high-level features [1].Content based indexing low-level feature like color, shape and texture are used for indexing and retrieving images.All those features are describe below.

A. COLOR

The color is important feature that construct feasible the establishing of images. Color is a property that depends on the contemplation of light to the eye and processing of that information by brain [4].color are defined in three dimensional color spaces such as RGB, HSV, and HSB. A color has three values per pixel and they measure intensity and chrominance of light, The actual information stored in the digital image data is the brightness information in each spectral band, Quantization in term of color histograms refer to the process of reducing the number of bins by taking colors that are very similar to each other and putting them in same bins[4].

Many methods can be used for the description of color features. They are Color Histogram, Color Moment Conventional Color Histogram, Invariant Color Histogram, Fuzzy Color Histogram, Geometric Moment, Average RGB, Color Moment, Color Correlogram, and Color Coherence Vector.

I. COLOR HITOGRAM

The main method of representing color information of images in CBIR is through color histograms. A color histogram is a type of bar graph, where each bar represents a particular color of a color space being used. The most common form of the histogram is obtained by splitting the range of the data into equally sized bins. then for each bins, the number the color of the pixels in an image that fall into each bin are counted and normalized to total points, which gives as the probability of a pixel falling into that bin[1].

A color histogram for a given image is defined as a vector [5]:

$$H=\{H[1],H[2],H[3],H[4],\ldots\ldots.H[i],\ldots\ldots H[n]\}$$

Where i represents the color bin in the color histogram and $H[i]$ represents the number of pixels of color i in the image, and n is the total number of bins used in the color histogram [5]. Every pixel in an image must be assigning a bin of a color histogram of that image. In order to compare images of different sizes, color histograms should be normalized [5]. The normalized color histogram is defined as: H'

$$H' = \{H'[1],H'[2],H'[3],H'[4],\ldots\ldots H'[i],\ldots\ldots H'[n]\}$$

Where, $H'= H[i]/p$, p is the total number of pixels of image. However, color histogram has its own drawbacks. If two images have exactly the same color proportion but the colors are scattered differently, then we can’t retrieve correct images [5].

II. CONVENTIONAL COLOR HISTOGRAM

The approach used for the CBIR system is depend on the conventional color histogram(CCH),which contains occurrence of each color obtained counting all image pixels having that color. Each pixel is associated to a specific histogram bin only on the basis of its own color, and color similarity across different bins or color dissimilarity in the same bin are not taken into account [8].All the pixel in the image can be described by three component in a certain color space those are RGB and HSV[8].

Quantization in term of color histograms refers to the process of reducing the number of bins by taking colors that are very similar to each other putting them in same bin[8].256 is the maximum number of bins one can obtain using the histogram function.[8].

CCH is sensitive to noisy interferences such as illumination changes and quantization errors. it does not take into consideration color similarity across different bins and cannot handle translation and rotation[8].to solve this problem invariant color histogram is used.

III. INVARIANT COLOR HISTOGRAM

Color histograms have been widely used for object recognition. Though in practice these histograms often vary slowly under changes in viewpoint, it is clear that the color histogram generated from an image surface is intimately tied up with the geometry of that surface, and the viewing position [8].The Invariant Color Histogram is developed to create a color histogram with using color gradient and its invariant under any mapping of the surface which is *locally* affine and so that a very wide class of viewpoint changes [8].

IV. FUZZY COLOR HISTOGRAM

The classic histogram is a global statical feature, which describes the intensity distribution for a given image. The main advantage is that it is fast to manipulate, store and compare and insensitive to rotation and scale [8].

In the fuzzy color histogram color space is divided into a number of bins and then counting the number of pixels of image that related to each bin. The number of region that the color space is divided into quite large and thus the colors represented by near region have relatively small differences and due to this color problem arise. Image which are similar to each other but have small difference contain noise will produce histograms with dissimilar adjacent bins and vice versa due to the small distance that the regions are separated from each other [8].

L*a*b* color space into a single histogram by means of a fuzzy expert system. The a* and b* components are considered to have more weight than L* as it is mostly the combination of the two which provides the color information of an image [8]. The L*a*b* color space was selected because it is a perceptually uniform color space which approximates the way that humans perceive color. In L*a*b*, L* stands for luminance, a* represents relative greenness-redness and b* represents relative blueness-yellowness [8]. All colors and grey levels can be expressed throughout a combination of the three components. However, L* does not contribute in providing any unique color but for shades of colors, white, black and grey. Thus, the L* component receives a lower weight with respect to the other two components of the triplet [8].

V. GEOMETRIC MOMENTS

The Geometric moment also known as Image moment. In geometric moment segmentation of an image is done, which is useful to describe the object itself. An image moment is ascertain particular weighted average (moment) of the image pixels' intensities [7]. With image moments Simple properties of the image are found, include area (or total intensity), its centroid, and information about its orientation. This feature use only one value for the feature vector, however, the performance of current implementation isn't well scaled, which means that when the image size becomes relatively large, computation of the feature vector takes a large amount of time [7].

VI. AVERAGE RGB

Average RGB is used to filter out images with larger distance at first stage when multiple feature queries are involved [7]. It uses a small number of data to represent the feature vector and it also uses less computation as compared to others that's why this feature is used. However, the accuracies of query result could be significantly impact if this feature is not combined with other features [7].

VII. COLOR MOMENTS

To avoid the quantization drawbacks, Stricker and orengo proposed using the color moment approach [1].color moments are the statistical moments of the probability distribution of colors and have been successfully used in many retrieval systems, especially when the image contains just the object [1].The first order(mean),the second(variance) and the third order (skewness) color moment have been proved to be efficient and effective in representing color distribution of images[1].

If the value of the *i*th color channel at the *j* th image pixel is *pi j* , then the color moments are as follows [6]:

Moment 1: Mean

$$E_i = \frac{1}{N}\sum_{j=1}^{N} p_{ij}$$

Moment 2: Standard Deviation

$$\sigma_i = \sqrt{\left(\frac{1}{N}\sum_{j=1}^{N}\left(p_{ij} - E_i\right)^2\right)}$$

Moment 3: Skew-ness

$$s_i = \sqrt[s]{\left(\frac{1}{N}\sum_{j=1}^{N}\left(p_{ij} - E_i\right)^3\right)}$$

VIII. COLOR CORRELOGRAM

Jing Huang et al propose the color correlogram as a means of encoding the color information of an image. This method, unlike color histograms and moments, incorporates spatial data in the encoded color information and therefore avoids a number of the problems of those representations [4]. The advantage of color correlogram is that it includes the spatial correlation of colors. Spatial correlation of colors can be used to describe the global distribution of local spatial correlation of colors and is simple to compute.

IX. COLOR COHERENCE VECTOR

CCV's are a more sophisticated form of histogram refinement, in which histogram buckets are partitioned based on spatial coherence. Our coherence measure classifies pixels as either

coherent or incoherent. A coherent pixel is a part of a sizable contiguous region, while incoherent is not. A color coherence vector represents this classification for each color in the image [13].
In CCV's first blur the image slightly by replacing pixel values with the average value in small local neighborhood (currently including the 8 adjacent pixels).we then discretize the color space, such that there are only n distinct colors in the image [13].

B. TEXTURE

The texture is a low-level features for image search and retrieval application same as color and shape. There is no unique definition for texture; however, an encapsulating scientific definition stated as, "Texture is an attribute representing the spatial arrangement of the grey level s of the pixels in a region of image" [17].Texture representation methods are classified into two main categories:1) structural and 2)statistical. Structural methods, including morphological operator and adjacency graph, describe texture by indentifying structural primaries and their rules[4].statistical methods, including Tamura feature, shift-invariant principal component analysis(SPCA),Fourier power spectra,Wold decomposition,co-occurrence matrices[4].The common Technique are used for texture feature extraction such as Discrete Wavelet Transform, Gabor -filter, co-occurrence matrices, Ranklet Transform, Haar Discrete Wavelet Transforms, Fourier Transform, discrete cosine transform, Hadamard Transform, Gaussian Pyramid, Laplacian Pyramid, Gabor Filter.

I. DISCRETE WAVELET TRANSFORM

Discrete Wavelet Transform (DWT) is applied on derived CBDIP and CBVLC. The simplest wavelet form among the wavelets, Haar wavelet is used here[15].Four sub bands of 3 level decomposition are shown in Fig.3.Figure shows the DWT process on CBDIP and CBVLC images for which steps are given below[15].

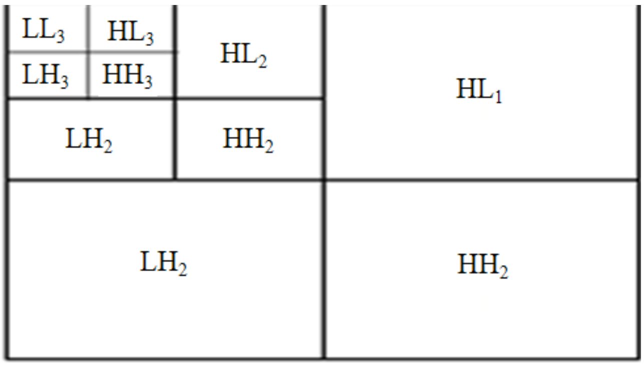


Fig.3 of Level decomposition [15].

For each CBDIP and CBVLC Image [15]:

Step 1: Decompose the image into 4 sub bands LL, LH, HL and HH using Haar Wavelet. As per the wavelet procedure, the original image fits intothe LL sub band and the remaining sub bands acts as detail matrices[15].

Step 2: Calculate Mean (μ) and Standard Deviation (σ) for the 4 sub bands as following Equation [15]:

$$\mu_m^n = \frac{1}{N_{mn}} \sum_{(i,j)\in W_m^n} W_m^n(i,j)$$

$$\sigma_m^n = \sqrt{\frac{1}{N_{mn}} \sum_{(i,j)\in W_m^n} (W_m^n(i,j)-\mu_m^n)^2}$$

Where, n and m denote decomposition level and sub band orientation respectively, N_{mn} is the number of coefficient in the mn_{th} sub band , W_m^n (i, j) the intensity of a pixel (i,j) in the sub band image and are the mean and standard deviation of absolute values of coefficients in the mn_{th} sub band respectively [15]:

Step 3: Repeat step 1 and step 2 till the decomposition Level reaches 3. (At each level, decomposition takes places only on LL sub band).For level 1 decomposition, three high band imagesW_1HL(i,j), W_1LH(i,j) and W_1HH(i,j) denotes horizontal, vertical and diagonal orientations Respectively and the original image fits into W_1LL(i,j).similarly sub bands are depicted at each level of decomposition [15].

II. GABOR WAVELET TRANSFORM

Gabor wavelet transform is the technique used for multichannel, multi-resolution analysis of the image which represents image variations at different scales. Gabor filters are a group of wavelets obtained from the appropriate dilation and rotation of Gabor function: a Gaussian modulated sinusoid [18]. Gabor filter having many of methods or techniques for image texture retrieval which is good in content based image retrieval application because of many reason. Being well suited for image signal expression and representation in both space and frequency domains.
- Presenting high similarity with human visual system as stated above.
- Offering the capacity for edge and straight line detection with variable orientations and scales.
- Not being sensitive to lighting conditions of the image [18].

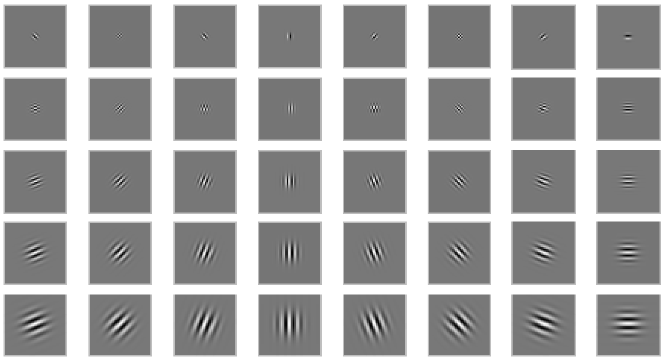


Fig. 4. A set of real impulse responses: multiscale, multi-orientation Gabor wavelet filters [18]

Gabor wavelet representation is suffer from some weaknesses such as their costly computational complexity. It has non invariance to rotation as well as the non orthogonal property of the Gabor filters that implies redundancy in the filtered images [18].

III. HAAR DISCRETE WAVELET TRANSFORMS

The wavelet transform represents a function as a superposition of a family of basis functions called wavelets [9]. Wavelet transforms extract information from signal at different scales by passing the signal through low pass and high pass filters [9].After the invention by HAAR, Haar Wavelet are being widely used. Haar wavelets are used to compute feature signatures, due to their fastest to computation and also have been found to perform well in practice. With Haar wavelets, it enables to speed up the wavelet computation phase for thousands of sliding windows of varying sizes in an image. The Haar wavelet's mother wavelet function can be described as [9]:

$$\Psi(t) = \begin{cases} \boxed{\begin{matrix} 1, 0 \le t \le \frac{1}{2} \\ -1, \frac{1}{2} \le t \le 1 \\ 0, otherwise \end{matrix}} \end{cases}$$

and its scaling function _(t) can be described as:

$$\Psi(t) = \begin{cases} \boxed{\begin{matrix} 1, 0 \le t \le 1 \\ 0, otherwise \end{matrix}} \end{cases}$$

IV. FOURIER TRANSFORM

The Fourier Transform is an important image processing tool which is used to decompose an image into its sine and cosine components. The output of the transformation represents the image in the Fourier or frequency domain, while the input image is the spatial domain equivalent. In the Fourier domain image, each point represents a particular frequency contained in the spatial domain image [21].

The practical implementation of the DFT on a computer nearly always uses the Fast Fourier transform (FFT). FFT is simply an algorithm (i.e., a particular method of performing a series of computations) that can compute the discrete Fourier transform much more rapidly than other available algorithms.FFT is surely the most widely used signal processing algorithm and is the basic building block for a large percentage of algorithms in current usage [21].

The 2D FFT pair is given by:

$$f[k,l] = \frac{1}{MN} \sum_{n=0}^{N-1} \sum_{m=0}^{M-1} F[m,n] e^{-j2\pi(\frac{mk}{M}+\frac{ni}{N})}$$

$$f[m,n] = \frac{1}{MN} \sum_{n=0}^{N-1} \sum_{m=0}^{M-1} F[k,l] e^{j2\pi(\frac{mk}{M}+\frac{ni}{N})}$$

Where, 0 m, k M-1,0 n,1 N-1.

V. DISCRETE COSINE TRANSFORM

Like any Fourier-related transform, discrete cosine transforms (DCTs) express a function or a signal in terms of a sum of sinusoids with different frequencies and amplitudes. Like the discrete Fourier transforms (DFT), a DCT operates on a function at a finite number of discrete data points. The obvious distinction between a DCT and a DFT is that the former uses only cosine functions, while the latter uses both cosines and sines (in the form of complex exponentials). It is a separable linear transformation; that is, the two-dimensional transform is equivalent to a one dimensional DCT performed along a single dimension followed by a one-dimensional DCT in the other dimension [21].

VI. HADAMARD TRANSFORM

The Hadamard Transform is simple than sinusoidal transforms, since no multiplications are required. The Hadamard transform is based on the Hadamard matrix which a square array is having entries of 1 and – 1.The Hadamard matrix of order 2 is given by [12]

$$H(2) = \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$$

Hadamard matrices of order 2n can be recursively generated using the kronecker product

H(2n) =H(2) × H (2n-1)
If n=1, H(2) =H (2)
n=2, H(4)=H(2) × H(2)

$$H(4) = \begin{bmatrix} H(2) & H(2) \\ H(2) & -H(2) \end{bmatrix}$$

If n=3

$$H(8) = \begin{bmatrix} H(4) & H(4) \\ H(4) & -H(4) \end{bmatrix}$$

Similarly, If n=7

$$H(128) = \begin{bmatrix} H(64) & H(64) \\ H(64) & -H(64) \end{bmatrix}$$

If f is a N ×N image and H (N) is a N ×N transformation matrix then Hadamard transform is given by

$$F = \left[\, H(N)\, f\, H(N) \,\right]$$

VII. GAUSSIAN PYRAMID

To extract features and remove noise form image, the Gaussian pyramid is used. It is also used to decompose images into information at multiple scales. The Gaussian pyramid consists of low-pass filtered, down-sampled version of the previous level of the pyramid, where the base level is defined as the original image. Fig. 6 shows the decomposition of an image into its Gaussian Pyramid representation [12].

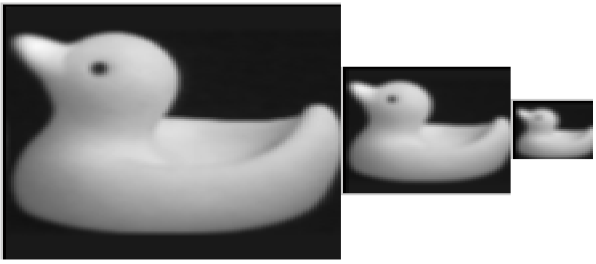


Fig.5. Gaussian pyramid decomposition

VIII. LAPLACIAN PYRAMID

The Laplacian Pyramid is describe as the decomposition of the original image into a hierarchy of images. Fig. 7 shows the decomposition of an image into its Laplacian Pyramid representation. The original image is at the upper left corner. The images immediately below and to the right of the original image are the coarse and detail signal respectively resulting from the first level of decomposition of the original image. The images adjacent to and below the coarse signal of the first level of decomposition are the detail and coarse signals respectively of the second level of decomposition [12].

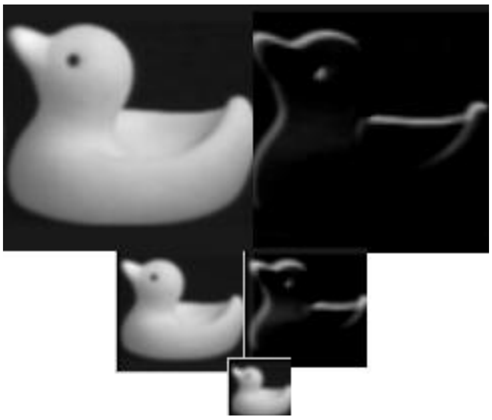


Fig.6. Laplacian Pyramid Decomposition

IX. GABOR FILTER

The Gabor filter has been widely used to extract image feature [21].various way are used to characterized texture of image based on Gabor filters. The basic idea of using Gabor filter to extract texture feature is given below [21].

A two dimensional Gabor function $g(x, y)$ is defined as[21]:

$$g(x,y) = \frac{1}{2\pi\sigma_x\sigma_y}\exp\left[-\left(\frac{1}{2}\right)\left(\left(\frac{x^2}{\sigma_x^2}\right)+\left(\frac{y^2}{\sigma_y^2}\right)+2\pi jw_x\right)\right]$$

Where σ_x are σ_y the standard deviations of the Gaussian envelopes along the x and y direction.

Given and image I(x,y) it's Gabor transform is defined as

$$w_{mn}(x,y) = \int I(x,y)g^{*}_{mn}\left(x-x_1, y-y_1\right)dx_1dy_1$$

Where * indicates the complex conjugate. Then the mean μ_{mn} and the standard deviation σ_{mn} of the magnitude of $w_{mn}(x,y)$

The texture similarity measurement of a query image Q and a target image T in the database is defined by

$$d(Q,T) = \sum_m \sum_n d_{mn}(Q,T)$$

Where

$$d_{mn} = \frac{\left|(\mu^Q_{mn} - \mu^T_{mn})\right|}{\left|\mu^Q_{mn}\right| + \left|\mu^T_{mn}\right|} + \frac{\left|(\sigma^Q_{mn} - \sigma^T_{mn})\right|}{\left|\sigma^Q_{mn}\right| + \left|\sigma^T_{mn}\right|}$$

If $f^Q_g = \left[\mu_{00,}\sigma_{00,}\mu_{01,}\sigma_{01,............}\mu_{35,}\sigma_{35,}\right]$ denote texture feature vector of query image And $f^T_g = \left[\mu_{00,}\sigma_{00,}\mu_{01,}\sigma_{01,............}\mu_{35,}\sigma_{35,}\right]$ denote texture feature vector of database image, then distance between them is given by:

$$d_2 = \sum_{i=1}^{d} \frac{\left| f_g^Q - f_g^T \right|}{\left| f_g^Q \right| - \left| f_g^T \right|}$$

C. SHAPE

Shape is one of the most important visual feature in image retrieval processes. For describe image content the basic feature Shape is used. When a 3-D real world object is projected onto a 2-D image plane, one dimension of object information is lost that's why Representation and description of Shape is a difficult task. As a result, the extracted image is only partially represents the projected object. For making the problem more difficult, shape is often corrupted with noise, defects, arbitrary distortion and occlusion. As a result, shape properties play an important role in content based image database systems devised by computer vision researchers [20].

The reason for choosing shape feature for describing an object is because of its inherent properties such as identifiability, affine invariance, and reliability and occlusion invariance, thus shape of the object has proved to be a promising feature based on which several image classification and retrieval operations can be performed [20].For describing the Shape of image the shape descriptor are required. The shape descriptor is classified into two major class namely Contour-based shape representation and description techniques and Region-based shape representation and description techniques. In the Counter-based shape techniques it uses only shape boundary information. In the Region based techniques it takes whole shape under consideration. There are some shape Descriptor methods like Geometric Moments Geometric Moments, Zernike Moments, Fourier Descriptor, Grid Method and Shape Matrix.

I. FOURIER DESCRIPTORS

By applying Fourier transform on shape boundary Fourier Descriptor can be carried out. The co-efficient of Fourier transform are called Fourier descriptor of the shape. Shape boundary is a set of coordinates (xi, yi), $i = 1, 2, \ldots, L$, which are extracted out in the preprocessing stage by contour tracing technique [20]. The *centroid distance* function is expressed by the distance of the boundary points from the centroid (xc, yc) of the shape

$$r_i = \left(\left[x_i - x_c \right]^2 + \left[y_i - y_c \right]^2 \right)^{\frac{1}{2}}, \quad i = 1, 2, \ldots, L$$

Where x_c, y_c are averages of x coordinates and y coordinates respectively. Due to the subtraction of centroid (which represents the position of the shape) from boundary coordinates, the centroid distance representation is invariant to shape translation [20].For applying Fourier transform normalized the boundary points of all the shape in database. The Fourier transform of r_i , i=1,2,……N-1 is given by [20]

$$u_n = \frac{1}{N} \sum_{i=0}^{N-1} r_i \exp\left(\frac{-j2\pi ni}{N} \right), n = 0,1,...., N-1$$

The coefficients un, $n = 0, 1, \ldots, N-1$, are usually called Fourier descriptors (FD) of the shape, denoted as FD_n, $n = 0, 1, \ldots, N-1$.

The following feature vector are used as the Fourier descriptors to index the shape [20],

$$f = \left[\frac{|FD_1|}{|FD_0|}, \frac{|FD_2|}{|FD_0|}, \ldots\ldots, \frac{|FD_{N/2}|}{|FD_0|} \right]$$

Robustness is nice properties Fourier descriptor. It is being able to capture some perceptual characteristics of the shape and easy to derive. With Fourier descriptors, coarse shape features or global shape features and the finer shape features are captured by lower order coefficients and higher order coefficients respectively. For Fourier Descriptor Noise is not a problem because at very high frequencies noise are truncated out.

II. CSS DESCRIPTORS

CSS descriptor is called Curvature scale Space. To obtain the CSS descriptor, first calculate the CSS counter map, the map is multi-scale organization of inflection points. To calculating CSS contour map, curvature is derived from shape boundary points (x_i, y_i), $i = 1, 2, \ldots, L$:

$$k_i = \left(\dot{x}_i \ddot{y}_i - \ddot{x}_i \dot{y}_i \right) \Big/ \left(\dot{x}_i^2 + \dot{y}_i^2 \right)^{\frac{3}{2}}$$

where $\dot{x}_i$, $\dot{y}_i$ and $\ddot{x}_i$, $\ddot{y}_i$ are the first and the second derivatives at location i respectively [20].In the next step the shape is smoothed by applying Gaussian smooth:

$$x_i' = x_i \otimes g(i,\sigma), y_i' = y_i \otimes g(i,\sigma)$$

Where $\otimes$ means convolution, and $g(i, \sigma)$ is Gaussian function. As σ increases, the evolving shape becomes smoother and smoother [20]. Until no curvature zero-crossing points are found, continuous this process. CSS descriptors are constant in the translation. To achieve the Scale invariance it should be normalizing all the shapes into fixed number of boundary points. To achieve the Rotation invariance it should be circular shifting the highest peak to the origin of the CSS map. The similarity between two shapes is measured by the sum of the peak differences between all the matched peaks and the peak values of all the unmatched peaks [20]. The difficulties are arrived in the matching between two set of CSS descriptors are the dimensions of the two set of CSS descriptors. They are usually different and the CSS peaks of two similar shapes are usually not matching.

III. ZERNIKE MOMENTS

Teague has proposed the use of orthogonal moments to recover the image from moments based on the theory of orthogonal polynomials, and has introduced Zernike moments [20]. Zernike moments are allows independent moment invariants to be develop an arbitrarily high order. The complex Zernike moments are derived from Zernike polynomials [14]:

$$V_{nm}(x, y) = V_{nm}(\rho\cos\theta, \rho\sin\theta) = R_{nm}(\rho)\exp(jm\theta)$$

And

$$R_{nm}(\rho) = \sum_{s=0}^{(n-|m|)/2} (-1)^s \frac{(n-s)!}{s!\left(\frac{(n+|m|)}{2} - s \right)!\left(\frac{(n-|m|)}{2} - s \right)!} \rho^{n-2s}$$

Where n and m are subject to n-$|m|$ = even, $|m|\leq n$. Zernike polynomials are become complete when set of complex valued function added over the unit disk, i.e., $x2 + y2 = 1$.Then the complex Zernike moments of order n with repetition m are defined as [20]:

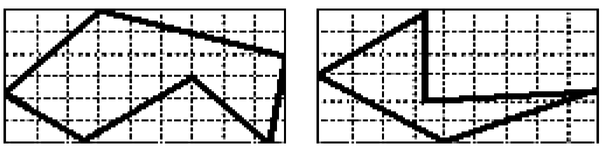
$$A_{nm} = \frac{n+1}{\pi}\sum_{x}\sum_{y} f(x,y)V^{*}_{nm}(x,y), x^2 + y^2 \leq 1$$

Zernike moments are as same as to the Fourier transform, to expand a signal into series of orthogonal basis. The number of Moments truncated from the expansion is called the precision of shape representation. Basis functions of Zernike moments take the unit disk as their domain. Before calculating moments unit disk must be specified. Zernike moments descriptors do not need to know boundary information, making it suitable for more complex shape representation [20]. To overcomes the drawback of geometric moments in which higher order moments are difficult to construct, Zernike moments descriptors are constructed to arbitrary order.

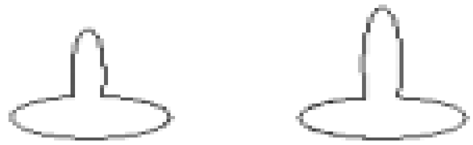
IV. GRID DESCRIPTORS

In grid shape representation, a shape is projected onto a grid of fixed size, 16×16 grid cells for example [20]. If grid cells are assigned the value 1 then they are covered by the shape and if value 0 is assigned to grid cells then they are outside the shape. A shape number consisting of a binary sequence is created by scanning the grid in left-right and top bottom order, and this binary sequence is used as shape descriptors to index the shape [20]. To achieve scale, rotation and translation invariance for comparison of two shape using Grid Descriptor, several normalized process have to be done. To achieve this first find out the major axis. To achieve Rotation normalization the shape will be turning on so that the major axis is parallel with x-axis. To avoid multi normalization results for mirrored shape and flipped shape, the centroid of the rotated shape may be restricted to the lower-left part, or a mirror and a flip operation on the shape number are applied in the matching stage [20]. To achieve Scale normalization Shape has to be resized so that the length of the major axis is equal to the grid width, after that shift the shape to the upper-left of the grid. In the set of Grid descriptor, the distance between two grid descriptors is simply the number of elements having different values. For example, the grid descriptors for the two shapes in Fig. 7 (a) and (b) are 001111000 011111111 111111111 111111111 111110011 001100011 and 001100000 011100000 111100000 111100000 011111100 000111000 respectively, and the distance between the two shapes will be 27 [20].

For example, the two shapes in Fig. 7 (c) and (d) are perceptually similar, but are very different under grid representation, for the major axis of shape (c) is horizontal while the major axis of shape (d) will be vertical [20].



(a) (b)



(c) (d)

Fig.7 Grid representation of shape

.

CONCLUSION

This paper proposes a new CBIR method that uses the combination of color, shape and texture. Many researches have been done to develop some algorithm that solve some problems and achieve the accuracy when retrieving images. All these technique given in this paper are good to individual. We get different result using the different techniques of color, texture and shape than previous one. With this paper it is conclude that by using combination of all different methods can get better result.

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