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# An Image Retrieval Framework: A Review

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***Abstract:*** Content-Based Image Retrieval is a process to retrieve the similar images from the large set of image database corresponding to the query image. In CBIR low level or pixel level features such as color, texture and shape of the images are extracted and on the basis of similarity matching algorithm the required similar kind of images are retrieved from the image database. To understand the evaluation and evolution of CBIR system various research was studied and various research is going on this way also. In this paper, we have discussed some of the popular pixel level feature extraction techniques for Content-Based Image Retrieval and we also present here about the performance of each technique.

***Keywords:*** Content Based Image Retrieval; Color; Texture; Shape; Feature Extraction; Similarity Measurement.

## I. INTRODUCTION

The multimedia technology and network technology is growing day by day and the databases of digital images are also growing rapidly. Thus, we need an efficient, fast and accurate algorithm to retrieve the relevant images from a huge image repository. The goal of the image retrieval is to browse the large image databases and find out whether the image repository contains the query image pattern which is given by the user on the basis of similarity matrices.

There are two approaches Text-Based Image Retrieval (TBIR) [1] and Content-Based Image Retrieval (CBIR). From 1970's to the present, Image retrieval technology was enhancing from text-based techniques to content-based techniques. In the Text-Based Image Retrieval Technique, firstly images were annotated with the text or number or keyword, and then images are searched on the basis of textual text or keyword. Although, Text based technique is fast and reliable but also it is over dependent on manually annotation on images and the size of the database. There are various limitations of text-based image retrieval such as manual annotation of images with the text or number or keyword which is extremely insufficient, laborious, and time-consuming and obsolete method. For the large databases, it is not an appropriate method.

To overcome the limitations of TBIR, the concept Content Based Image Retrieval [2] came into the frame in 1990's which are efficiently used by peoples. CBIR is a kind of image retrieval technique of computer vision for retrieving the relevant images according to visual feature such as color, shape and texture of images from the large database based on some similarity measures. In a precise way, CBIR, a technique of image retrieval, that could frame out the images that are similar to querying images from the large image database. In CBIR, each image that is stored in the large database, its features are extracted and compared to the feature of the query image. At last, the relevant images can be displayed corresponding to query image. The CBIR figure is shown in figure 1.

The CBIR technology has been used in a several of applications such as fingerprint identification, digital libraries, crime prevention, medical diagnosis, historical research, architectural and engineering design, publishing and advertising, art, education, fashion and graphic design, geographical information and remote sensing systems etc.

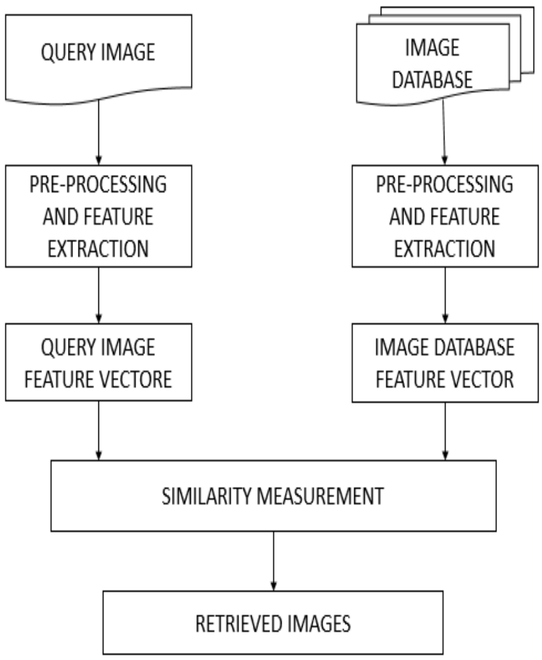


Figure 1. Content Based Image Retrieval

It contains main two parts.

### *A. Feature extraction*

The word 'feature' which specify the quantifiable property of an object or in another way we can say that it describes the object. The features are extracted from the image like spatial based on pixels level features such ascolor, texture and shape. The features play the important role in CBIR. Good features describe the image efficiently and make good effects on accuracy. The classification of feature extraction technique is shown in figure 2.

### *B. Similarity measurement*

Similarity measurement are used to calculate the similarity distance between the images in the large database and the query image and according to distance, they are ranked in order to retrieve most similar image first. It also plays an important role in CBIR. A good similarity measurement technique proceeds good retrieval rate of images.

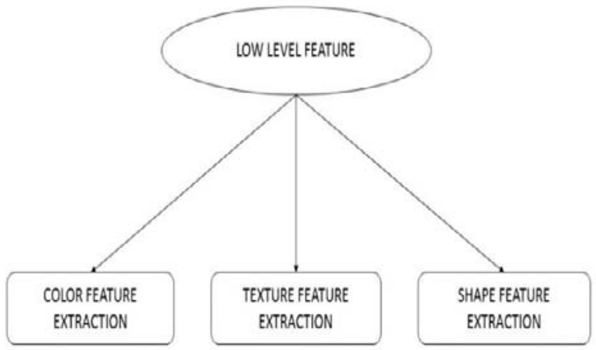


Figure 2. Classification of low-level features

There is some application of CBIR such as Trademark Registration, Medical Diagnosis, Crime Prevention, Web Searching, Surveillance, Remote Sensing, web-related application, Biomedical Applications etc.[3][4]..

## II. FEATURE EXTRACTION TECHNIQUES

There are various feature extraction techniques to extract low-level features from the images.

### *A. Color*

It is the sensitive, understandable, essential and widely used feature for image retrieval. The color is the property that is based on reflection of light and processing of that information in the brain. Before selecting the color descriptor, a color space must be chosen first because colors are defined in three-dimensional color space. The various types of color space, which are used widely, are RGB (Red, Green, Blue), HSV (Hue, Saturation, Value), opponent color space etc.

RGB is most widely used color space for displaying the images. It contains three color component which is red, green and blue which are called additive primaries. It is also be called additive color space. By mixing the components of RGB space, the desirable color can be produced. The RGB color space is device dependent and non-uniform color space [5].

HSV (Hue, Saturation, Value) is also widely used in computer graphics and it is the more intuitive way to represent the color, it is also be called HSL (Hue, Saturation, Lightness), or HSB (Hue, Saturation, Brightness) color space. It is most suitable for object retrieval because hue is invariant to changes in illumination and camera direction.

There is various type of type of color descriptors.

*1) Color moment*

Mean, Standard deviation and Skewness are effective color moments [6]. It is used to find out the distribution of colors in an image. The average color value in an image can be calculated by Mean (M). The square root of the variance of the distribution is calculated by Standard deviation (σ). Skewness (S) can be defined as a measure of the degree of asymmetry in the distribution. The moments are described as:

$$M_i = \frac{1}{N}\sum_{j=1}^{N} P_{ij} \tag{1.1}$$

$$\sigma_i = \sqrt{\frac{1}{N}\sum_{j=1}^{N}\left(P_{ij} - M_i\right)^2} \tag{1.2}$$

$$Si = \sqrt[3]{\frac{1}{N}\sum_{j=1}^{N}(f_{ij} - \mu_i)^3} \tag{1.3}$$

$P_{i,j}$= the value of the $i^{th}$ color component of the image pixel j.
N = number of pixel in the image.

Three moments for each of the three color component are used to describe the color content of an image. Color moment works well in L*a*b color space in compare to H*s*v color space.

*2) Color histogram*

Color histogram [7] is an efficient way to calculate the essential features from the image. It is the way of representation of the color content of an image. Any pixel of an image can be framed by the three components in certain color space such as red blue and green color components are described for RGB color space and hue, saturation and value are described for HSV color space. The distribution of color in the image in color space can be described by the color histogram. It contains the number of bins which can be defined for each component. The histogram contains a large number of the bin will only increase the computational cost as well as inefficient indexing also for image databases. So, it needs to quantize the bins. So, quantization process takes place in histogram techniques. It helps to reduce the number of the bins in histogram by taking the color that is similar to each other and putting those color in the same bin. It Histogram technique is two types.

*a) Global color histogram (GCH):* The GCH [8] calculate the single color histogram of one whole image. It is efficient and takes less computation. Sometimes GCH might not get the proper result because it does not include information concerning the color distribution of the regions.So, it doesn't give full information of the image.

*b) Local color histogram (LCH):* The LCH [9] gives more information about the image in compare of GCH. It is computationally high. It takes more time to execute. The main task of LCH is to divide the image into a number of blocks and calculate the Histogram for each block then combines that LCH of blocks and form a Histogram. It gives better results than GCH but due to its computational cost, we mostly prefer the GCH.

*3) Color correlogram*

Color correlogram [10] is a very good technique in compare to Color Histogram because it not only describes the color distribution of pixels but also describes the spatial information of the pair of color. A color correlogram is indexed by the color pair. Where,

The $k^{th}$ entry for (i, j) specifies the probability of finding the pixel of color j at a distance k from a pixel of color I in the image.

Assume,

$$\gamma_{C_i}^{(k)}(I) \equiv \Pr[|\, p_1 - p_2 \,| = k,\, p_2 \in I_{C_i} \mid p_1 \in I_{C_i}] \qquad (2.1)$$

I = set of image pixels.

$I_{ci}$ = set of pixels whose colors are c(i).

Color correlogram can be described as:

Where i, j belongs to {1,2,…..,N}, k belongs to {1,2,…..,d} and $|P_1 - P_2|$ is the difference between pixels $P_1$, $P_2$. The size of the color correlogram is very vast if we are taking all the possible color pairs. Therefore, instead of this, a simplified version is used for extract the feature, called Color Auto Correlogram [11]. Color auto-correlogram captures only the spatial correlation between identical colors instead of taking color distribution as like color correlogram. That's the way the size is also reduced. In comparing to color histogram, the color auto-correlogram gives better result but it is computationally high.

Some another color feature extraction technique's that can be used in extracting the color's feature such as Edge histogram descriptor, Multi texton histogram, Dominant color descriptors etc.

### *B. Texture*

The texture is another feature extraction technique which describes various properties such as coarseness, smoothness, regularity of surface, randomness etc. it also specifies the how the surface is, its scene depth and orientation. It contains the general and significant information about the structure of surface. Texture can be analyzed by the qualitative and quantitative analysis [20].

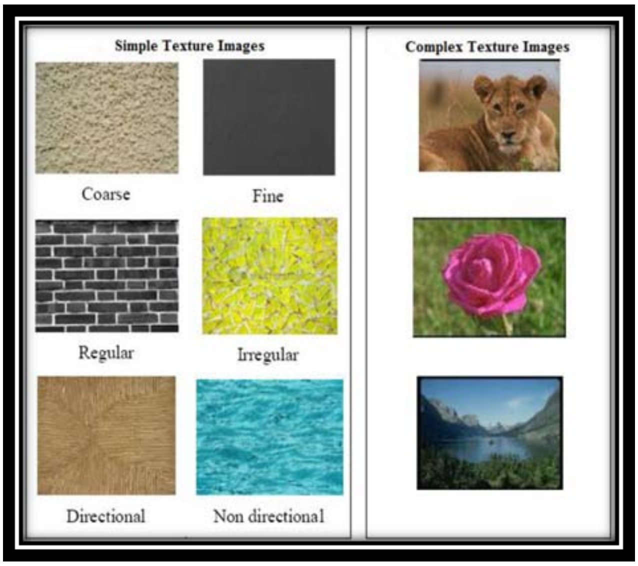


Figure 3. Examples of Texture Images

The surface can be repeated arrangement of pixels over the spatial space. Where, the random and unstructured surface can be displayed when it came into contact with noise. Texture is the visual descriptor of an image, which has homogeneity properties. There are different types of texture properties like regularity, directionality, smoothness, and coarseness, see left part of Figure 3. Texture perception might be more muddled. The different illumination intensities give the hike to a blend of the different human perception of texture as shown in right part of Figure 3.

There is various type of Texture Descriptors which are described below.

#### *1) Tamura feature*

The first texture descriptor based on quantitative analysis given by Tamura [14] [15]. Which gives the six different texture feature like Coarseness, Contrast, Directionality, Line-Likeness, Regularity, and Roughness. The well-known system such as QBIC uses first three component of Tamura feature.

*a) Coarseness:* The Granularity of the Texture can be measured by coarseness. An image contains reoccurred textures arrangement at dissimilar scales, the objects of coarseness is to find out the largest size at which a texture present.

$$A_k(x,y) = \sum_{i=x-2k-1}^{x+2k\_1} \sum_{j=y-2k-1}^{y+2_{k-1}-1} \frac{f(i,j)}{2^{2k}} \qquad (3.1)$$

Where, the average of neighborhood is $2^k * 2^k$size.

$$E_{k,h}(x,y) = |A_k(x + 2_{k-1}, y) - A_k(x - 2_{k-1}, y)| \qquad (3.2)$$

*b) Contrast:* The distribution of intensities adjusted in an image can be measured by contrast.

$$\text{Contrast} = \frac{\sigma}{(\alpha_4)} \qquad (3.3)$$

$$\text{where,} \quad \alpha_4 = \mu_4 / \sigma^4 \qquad (3.4)$$

*c) Directionality:* The directionality measures the frequency distributionof edges which are oriented locally against its directional angles.

$$\text{Dir} = 1 - rn_{peaks} \sum_{p=1}^{n_{peaks}} \sum_{a\epsilon w_p} (a - a_p)^2 H_{dir}(a) \qquad (3.5)$$

*d) Line-Likeness:* Line-Likeness in an image is the normal coincidence of direction of edges that co-happened in the sets of pixels separated by a distance along the edge direction in every pixel.

*e) Regularity:* Regularity is an essential property of tamura feature which evaluates the regular pattern present in image.

$$F_{reg} = 1 - r(S_{crs} + S_{con} + S_{dir} + S_{lin}) \qquad (3.6)$$

*f) Roughness:* Summation of contrast and coarseness measures are called Roughness.

$$Roughness = Contrast + Coarseness \qquad (3.7)$$

#### *2) Gray level co-occurrence matrix*

Gray level co-occurrence Matrix is an arithmetical method used for observing texture feature and distributing gray levels in the image. Gray level co-occurrence matrix create a matrix which shows how repeatedly pixels with intensity i occurs in a spatial relationship to pixel with intensity j. Haralick [16] [20] proposed 28 types of features of texture extracted from Gray level co-occurrence matrix (GLCM). Assume an image has H total number of pixels in Horizontal directions and V total number of pixels in Vertical directions and assume gray level at each pixel is quantized at N number of levels. Suppose $N_x$=1,2,3…..H consist Horizontal space and $N_y$=1,2,3,….V consist vertical space and G=0,1,2,3,…..N consist N quantized gray level. Gray level co-occurrence matrix is a regularity matrix and its levels are determined by image gray level. Expression shown the co-occurrence matrix in different directions.

$$P(i,j|d,\theta) = \frac{p(i,j|d,\theta)}{\sum_i \sum_j p(i,j|d,\theta)} \qquad (4.1)$$

This paper describes five feature of GLCM like Energy, contrast, Entropy, correlation, homogeneity.

*a) Contrast:* Contrast find out the intensity of a pixel and its neighbor over the whole image and for the constant image, it is considered zero. It is also be known as variance and moment of inertia.

$$C = \sum_{i,j} (i-j)^2 p(i,j) \qquad (4.2)$$

*b) Correlation:* How pixel is correlated to its neighbor over the whole image, it is defined by correlation.

$$C = \sum_{i,j} \frac{(i-\mu_i)(j-\mu_j)p(i,j)}{\delta_i \delta_j} \qquad (4.3)$$

*c) Entropy:* Entropy gives measures of complexity of the image and this complex texture tends to higher entropy.

$$E = \sum_i \sum_j P(i,j) \qquad (4.4)$$

*d) Energy:* Energy is the sum of squared elements in the GLCM and the default value of the constant image is one.

$$E = \sum_{i,j} (i,j)^2 \qquad (4.5)$$

*3) Local binary pattern*

T. Ojala et al. [17] proposed local binary pattern (LBP). LBP is an image indexing technique based on texture analysis of image which is gray scale rotation invariant local pattern measure operator. LBP computes the local feature representation of the image. The LBP representation is calculated by comparing each pixel with surrounding neighbor pixel. The computation of LBP is shown in figure 4.

The value of the LBP code of pixel ($x_c$,$y_c$) is given by

$$LBP_{P,R} = \sum_{p=0}^{P-1} s(g_p - g_c)\, 2^P \qquad (5.1)$$

$$s(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases} \qquad (5.2)$$

The computation of LBP is given below in figure 4.

| | | |
|---|---|---|
| 7 | 8 | 12 |
| 2 | 5 | 5 |
| 1 | 3 | 0 |

→

| | | |
|---|---|---|
| 1 | 1 | 1 |
| 0 | | 1 |
| 0 | 0 | 0 |

Figure 4. Computation of Linear Binary Partition

LBP = $2^0$*1+$2^1$*1+$2^2$*1+$2^3$*1+$2^4$*0+$2^5$*0+$2^6$*0+$2^7$*0=15

Where,

$g_c$= the gray-scale value of center pixel,

$g_p$ = the gray-scale value of its neighborhood pixel,

P = the no. of neighbors,

R = the radius of neighborhood.

For calculating LBP descriptor, first, convert the image into grayscale image. For every pixel of the grayscale image, a neighborhood of r size is defined with surrounding the center pixel. Then LBP value is calculated for each center pixels and is stored in 2D array vector which contains same height and width as the input image.

Due to highly discriminative, rotation invariant and gray-scale invariant, it is used in various application such as face recognition, image registration etc.

There are also various extensions of LBP which enhances the techniques of image retrieval such as CLBP, Dominant LBP, CS-LBP, Local tetra pattern (LTP), CS-LTP etc.[19].

There is some more texture extraction technique that is used to extract the feature from the images such as flourier transform, Walsh transform, Gabor descriptor, wavelet transform, co-occurrence matrix etc. [30] [33].

### *C. Shape*

The shape is known to play an important role in object recognition and perception. Visual shape features provide a powerful clue which shows object identity or we can also say that it describes the image content. The shape can be defined as it is part of space which is occupied by an object. The efficient shape feature must contain some properties such as identifiability, translation, the resistance of noise, affine invariance, statistically independent and some reliability. Humans can recognize objects solely from their shapes. The advantage of shape's feature taking into account for CBIR can be seen from the fact that every major CBIR system holds some shape features in one form or another [21]. Shape feature representations are two types. They are boundary-based and region-based. In region-based techniques, to obtain the shape representation, all the pixels within a shape are taken into account. Common region based methods use various moment descriptors to describe shape efficiently [22] [23] [38] [39]. In the boundary based techniques, to obtain the shape representation, only the boundary pixels within a shape are taken into account means that the boundary information will be extracted [23].

There is various shape feature extraction techniques are given below.

*1) Hu moments*

In shape-based image retrieval system, Hu moments [24] produces good results because it is the non-linear function which has various properties like translation, rotation and scaling invariability. Formulation of Hu moments is given below:

Two-dimensional $(p+q)^{th}$ order moments are given as follows.

$$m_{pq} = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} x^p y^q f(x,y)\,dx\,dy \tag{6.1}$$

If, the image function f(x,y) is a piecewise continuous bounded function, the moments of orders exist and the moment sequence $\{m_{pq}\}$ is uniquely determined by f(x,y) and correspondingly, f(x,y) is also uniquely determined by the moment sequence $\{m_{pq}\}$.

The moments may not be invariant when f(x,y) changes by translating, rotation or scaling. By the help of the central moments, the invariant feature can be obtained using central moments, which can be measured as:

$$\mu_{pq} = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} (x-\bar{x})(y-\bar{y}) f(x,)\,dx\,dy \tag{6.2}$$

Where, $\bar{x} = \frac{m_{10}}{m_{00}}$ and $\bar{y} = \frac{m_{01}}{m_{00}}$ (6.3)

The pixel point $(\bar{x},\bar{y})$are the centroid of the image f(x,y). The centroid moments $\mu_{pq}$ computed using the centroid of the image f(x,y) is equivalent to the $m_{pq}$ whose center has been moved to the centroid of the image. In this manner, the central moments are invariant to image interpretations. Scale invariance can be acquired by normalization. The normalized central moments are defined as follows:

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}^{\gamma}} \tag{6.4}$$

$$\gamma = (p+q+2)/2, p+q=2,3,\ldots. \tag{6.5}$$

Based on normalized central moments, Hu introduced seven-moment invariants:

$$\phi_1 = \eta_{20} + \eta_{02} \tag{6.6}$$

$$\phi_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2 \tag{6.7}$$

$$\phi_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \mu_{03})^2 \tag{6.8}$$

$$\phi_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \mu_{03})^2 \tag{6.9}$$

$$\phi_5 = (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})[(3\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \tag{6.10}$$

$$\phi_6 = (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03}) \tag{6.11}$$

$$\phi_7 = (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] - (\eta_{30} - 3\eta_{12})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \tag{6.12}$$

The first one, ϕ1, is similar to the moment of inertia around the image centroid, where the pixels' intensities are analogous to physical density. The last one, ϕ7, is skew invariant that able to distinguish mirror images or identical images [21].

Hu moments take every pixel into account. The computational cost is much higher than boundary based invariants. To overcome this problem, Teague [25] suggested the use of orthogonal moment.

*2) Zernike moments*

Zernike moments [25] [26] are evaluated by using Zernike orthogonal polynomial. An orthogonal polynomial is present in the unit circle. It has less information redundancy as compared to the other method. It shows good rotation invariance. It is one of the most widely used shape descriptors.

Zernike moment is defined as:

$$Z_{mn} = \frac{m+1}{\pi}\iint_{x^2+y^2\le 1} f(x,y)[V_{mn}(x,y)]^*\,dx\,dy \tag{7.1}$$

Where, m = 0, 1, 2,…………,∞, $f(x,y) =$ image function, * represents hetero conjugation, n is an integer such that (m-|n|) is even and (|n|≤m).

Zernike moment can also be represented in the polar co-ordinates as follows:

$$Z_{mn} = \frac{m+1}{\pi}\int_0^{2\pi}\int_0^1 f(r,\theta)V_{mn}(r,\theta)\,r\,dr\,d\theta, r \le 1 \tag{7.2}$$

Where, $r = \sqrt{x^2+y^2}$ and $\theta = \tan^{-1}\left(\frac{y}{x}\right)$

Assume $V_{mn}(x,y)$ as a Zernike polynomial in polar co-ordinate and is defined as:

$$V_{mn}(r,\theta) = R_{mn}(r)\exp(jn\theta) \tag{7.3}$$

Where, $j = \sqrt{-1}$ and $(r,\theta)$values are defined in the unit circle.

Orthogonal radial polynomial $R_{mn}(r)$ is defined as:

$$R_{mn}(r) = \sum_{x=0}^{\frac{m-|n|}{2}} (-1)^s \frac{(m-s)!}{s!\left(\frac{m+|n|}{2}-s\right)!\left(\frac{m-|n|}{2}-s\right)!} r^{m-2s} \tag{7.4}$$

The integration can be converted into summation in case of digital image:

$$Z_{mn} = \frac{m+1}{\pi}\sum_x\sum_y f(x,y)\,[V_{mn}(x,y)]^* \tag{7.5}$$

Where, $x^2 + y^2 \le 1$

*3) Interest point detection using surf*

SURF [27] [29] is the most efficient shape-based feature extraction technique which is not only scale but also rotation invariant. Scale invariance and rotation invariance implies that an object can be distinguished despite the fact that if the representation of object gets scaled in size or it is rotated around an axis in its representation of an image. Invariance is a very important property of image features, as a measurement of similarity is possible only with respect to those features between two images which can't be duplicated.

The SURF feature technique is based on the Hessian matrix. To extract the scale and location of the descriptor, the determinant of Hessian matrix is used. The Hessian matrix is represented by $H(x,\sigma)$ for a given point $x = (x,y)$ in an image as follows:

$$H(x,\sigma) = \begin{bmatrix} L_{xx}(x,\sigma) L_{xy}(x,\sigma) \\ L_{xy}(x,\sigma) \quad L_{yy}(x,\sigma) \end{bmatrix} \tag{8.1}$$

Where, $L_{xx}(x,\sigma)$ is the convolution of the Gaussian second order derivative $\frac{\partial^2}{\partial x^2} g(\sigma)$ with the image I in the point x and similarly for $L_{xy}(x,\sigma)$ and $L_{yy}(x,\sigma)$.

The speed up robust feature approximates second order derivatives of the Gaussian with box filters. By using the integral images, the image convolutions can be calculated with these box filters. The determinant of the Hessian matrix is given as:

$$\mathrm{Det}(H_{approx}) = D_{xx}D_{yy} - (0.9D_{xy})^2 \tag{8.2}$$

*4) Convex hull*

Basically, the convex hull [13] [28] or convex envelope of a set X of focuses in the Euclidean plane or Euclidean space is the littlest convex set that contains X. Formally, the convex hull may be described as the intersection of all convex sets holding X or as the set of all convex combinations of points in X. Here, convex hull descriptor is used to create Region of Interest (ROI) in an image.

There is some more shape-based feature technique such invariants, shape signature, contour segments, breakpoints etc. Some operator such as Sobel, Prewit, Cany edge detector etc. are also used to extract the edge features from the image.

## III. SIMILARITY MEASUREMENT

Normally, Similarity Measurement [31] [32] [36] [40] can be defined as a matrix distance. Some efficient similarity measurements are given below.

### *A. Minkowski distance metrics*

This distance can be measured as:

$$D^k(P,Q) = ( |x1-y1|^k + |x2-y2|^k ) \tag{9.1}$$

Where, P(x1, x2) & Q(y1, y2) are two points to calculate the distance.

### *B. Manhattan distance*

Manhattan distance is the most common metric which is used to evaluate the distance between two points in multi-dimensional space. The distance between two images P and Q with n-dimensional features vectors can be found as follows:

$$D(X,Y) = ( \textstyle\sum_{i=1 to\ n} [X_i - Y_i] ) \tag{9.2}$$

Where, D(X,Y) = Manhattan distance between query image X and each image Y in the image database.
$X_i$ = feature vector of the query image.
$Y_i$ = feature vector of database images.

### *C. Euclidian Distance*

The Euclidian Distance is frequently used in CBIR for similarity evaluation because it has greater accuracy as well as effectiveness. It measures the distance between two feature vectors of the image by following this equation.

$$D(X,Y) = ( \textstyle\sum_{i=1}^{n} (X_i - Y_i)^2 )^{1/2} \tag{9.3}$$

Where, D(X, Y) = Euclidian distance between query image X and each image Y in the image database.
$X_i$ = feature vector of query image.
$Y_i$ = feature vector of database images.

A number of other metrics which are used in CBIR like Mahalanobis, Earth Movers, Proportional Transportation, relative deviation, city block etc. matrix have been proposed for specific purposes.

## IV. PERFORMANCE METRICS

The performance of CBIR system can be expressed with these formula's [34] [35] [36] [37].

$$\text{Precision} = \frac{(\text{Number of relationally retrieved images})}{(\text{Total number of retrieved images})} \tag{10.1}$$

$$\text{Recall} = \frac{(\text{Number of relationally retrieved images})}{(\text{Total number of relevant images in the database})} \tag{10.2}$$

$$\text{Error Rate} = \frac{(\text{Number of nonrelevant image retrieved})}{(\text{Total number of image retrieved})} \tag{10.3}$$

The recall is the ability of the system to represent all relevant images. The measure of ability of the system to represent only relevant images is called precision. Error rate can be measured as the number of the non-relevant images present in total number of image retrieved. There are various types of image database available such as wang database, sift database, mnist database etc. [12]. On that we can perform various experiments.

## V. CONCLUSION AND FUTURE WORK

CBIR is a very active area where various active researches are going on. If, we are considering text based retrieval or searching then a text or keyword may not reflect or describe the whole image properly. In case, if an image having geographical representation then manual description (text or keyword or tags etc.) can't represent an image properly. So, here we can't say keyword matching is best retrieval technique of image. In this paper, a study of various pixel level feature retrieval technique for the image retrieval is performed as well as various similarity measurements techniques are studied. The performance of retrieval system may depend on the different type of database. It is impossible to get an appropriate as well as efficient result from single technique or algorithm because only a feature vector can't reflect the result more appropriately. So, it is required to combine two or more than two techniques and develop a hybrid approach. There is the considerable increase in efficiency when two or more than two feature extraction techniques or algorithm are combined. In image processing retrieval technique, Performance degradation is the major problem so for this we should have to use some mining technique so that we can reduce our database or can improve the efficiency of retrieval of the image. By the help of clustering and classification technique, the set of images is trained or grouped using supervised or unsupervised learning to enhance the retrieval efficiency and timing performance. For finding the best research, the modern approach is to focus on the high level as well as salience features with the descriptor of color, texture as well as shape at the processing stage. In CBIR, various optimization techniques as like fuzzy, support vector machine, ant colony optimization, the k-mean algorithm can be applied to get user corresponding results.

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