International Journal of Science Engineering and Advance Technology, IJSEAT, Vol. 4, Issue 1 | ISSN 2321-6905 January -2016

IJSEAT International Journal of Science Engineering and Advance Technology

An Enhanced Image retrieval Technique based on Edge-Orientation Technique

Ch.Sushmitha[1] , Dr. D. Haritha[2]
[1]M.Tech Student, Dept of CSE , SRK Institute of Technology, Vijayawada, AP, India.
E-mail: susmithachirumamilla9@gmail.com
[2]HOD, Dept of CSE, SRK Institute of Technology, Vijayawada, AP, India.
Email: haritha@rediffmail.com

Abstract

With the tremendous development in Networking and Multimedia technologies, Image Retrieval plays significant roleand is used for browsing, searching and retrieving images from a large database of digital images. Image Retrieval techniques utilize annotation methods of adding metadata such as captioning, keywords or descriptions to the images. The manual image annotation is much time consuming laborious and expensive.As the data bases size increases, annotation becomes a tedious task. Thus automatic image annotationhas drawn the attention of the researchers in recent years.. The increase in social web application and the semantic web drawn attention of researchers in the development of several web-based image retrieval tools. This paper presents an easy, efficient image retrieval approach using a new image feature descriptor called Micro-Structure Descriptor (MSD). The microstructures are defined based on an edge orientation similarly while the MSD is built based on the underlying colors in micro-structures with similar edge orientation.In this method of Image retrieval the MSD extracts features by simulating human's early visual processing by effectively integrating color, texture, color lay out information and shape. The proposed MSD algorithm has high indexing performance and low dimensionalityas it has only 72 dimensions for full color images.The technique is examined on Corel datasets with natural images; the results demonstrate that this image retrieval method is much more efficient and effective than reprehensive feature descriptors, such as Gabor features and Multi Texton Histograms.

Index Terms— *Image retrieval,, Edge orientation Micro-Structure Descriptor*

1.INTRODUCTION

Image Identification is an application area where the techniques of Image Retrieval are used. Image identification or copy detection is given a query image, finding the original source from where it possibly derives, together with its relevant metadata. The metadata associated can becontext, keywords, titles, authors and copyright information, etc.The document is identified based on its context, and the lack of metadata reduces its usefulness to a great extent. This necessitates devising reliable ways of retrieving all the information related to a document, when only the visual evidence is available. Organizations like museums, archives and news agencies, are often asked to perform the identification of images fromnewspaper clippings, articles, books, published papers, thesis and, where the references are missing, tosummary, outdated or incorrect. One of the most prominent applications of image identification is the tracking of the documentscontaining images, either to fetch the historic significance of a given document, or to enforce the copyright. Another way of the handling this situation is separating the image and its metadata, within the boundaries of an organization, at one of the steps of a complex workflow. In this case, images with lacking quality or incorrect metadatawill be identified and rectified. Geometric transforms like translations, rotations and scale changes can be used. Sometimes, trapezoidal and spherical distortions resulting from the photographic reproduction may be present.

Photometric and colorimetric transforms are used to change brightness, contrast, saturation, color, and occlusion effects.The image may be cropped image or may contain labels, stamps, annotations, censor bars, etc.. The image maycontain compression artifacts, electronic noise from cameras and scanners. Theacquisition of the image, intrinsic quantization effects of digitization, half toning methods used for printing and more patterns; as well as reprinting and rescanning operations may be a source of important distortion. The large variety of transformation types and intensities makes the task very challenging.Images and graphics provide significant amount of information and are widely usedin human digital communication. With the rapid development of digital imaging techniques and internet facility, and availability oflarger set of images to public, the demand for effective and efficient image indexing and retrieval methods is increasing at rapid rate.In pattern recognition and artificial intelligence areas, image retrieval has become one of the most popular topics. An image retrieval system is used for searching and retrieving images from a bulk volume of digital images.

Image retrieval methods can be based on text, content and semantics. Human visual perception can be visualized as a process of interactions among neurons, which selects preattentive properties like low level visual features rapidly and suppresses irrelevant properties. Theclose association of human visual attention system with low level visual features can be used for image retrieval and is an important and still challenging to a certain extent. We usea feature detector and descriptor, namely Micro-Structures Descriptors (MSD), to extract features and effectively integrate color, texture, shape and image color layout information as a whole for image retrieval. MSDs are used to describe image local features in the form of micro-structures thatcan compute edge orientation similarity based on the underlying colors. The underlying colors mimic human color perception and are those colors that have similar edge orientation. The MSDs describe color, texture and shape features all together and makes use of combining both statistical and structural texture description approaches.

2.LITERATURE SURVEY

Liu presentedmulti-texton histogram (MTH) for image retrieval [1]. MTH can represent both the spatial correlation of texture orientation and texture color based on textons. It integrates co-occurrence matrix and histogram into one descriptor and represents the attribute of co-occurrence matrices using histograms. MTH has gooddiscrimination power of color, texture and shape features.Huet et al [2]used a graph-matching technique for recognizing line-pattern shapes in large image databases by developing a Bayesian matching algorithm that uses edge-consistency and node attribute similarity. The image retrieval using GLCM and CCG is outraged with Liu's work of determining higher order spatial co-relational occurrences using texton co-occurrence matrix helps in grading line –shape pattern to do perform better[3]. The Dai's work [4] introduced ahypergraph structure to formulate the relevance among 3- D objects. The Dai's work helps in presenting fusion/fission of graph construction of a overlapped image version or 3D image. In [5] an interactive system for sketch-based image retrievalon a large database of over one million images was presented and shown that the Tensor and HOG descriptors clearly out-perform other approaches.During image search, it is essential to make fast query result and also is from large image databases. The process of searching first for an image with similar structure, analyzing gradient orientations and then best matching images are clustered based on important color distributions, to offset the lack of color-based decision during the initial search lures effectiveness of query results much . The curve fitting across the continuous –domain total variation can be waived and made consistent through Fatemi's work and the generalized problem is discussed for selection of minimum perimeter and with a fixed length integral [6]. The phenomenon of feature extraction and training and selection of discriminator for resulting including poor quality image in a data set had been determined. It is essential to reach out this new benchmark with MSD descriptor in current work to merely obtain better results. MULLER, Henning, et al [7] presentedoverview of performance evaluation measures in CBIR. The extraction of the universal micro-structures in an image, also termed textures, describes them effectively as they can serve as common interfaces for the comparison and analysis of different map extraction after micro structure descriptor found, in transforming of an image into HSV color space and color oriented specific, declares feature integration theory proposed by Treisman, a two-stage approach helps here much in segregate color quantization problems and mere to fix in further to fatemi's work suggestable.

3. IMAGE RETRIEVAL SYSTEMS

3.1 Generaldiscussion

Image identification system is a specialization of CBIR techniques and share many characteristics. To find the similarity between the images, they use the concept of descriptor instead of comparing directly the raw visual contents. The two main issues concerned with every CBIR system are: To extract the information contained in the image in the form of a descriptor (or set of descriptors) that can be used to represent the visual, aesthetical or semantical characteristics and to create a dissimilarity criterion between descriptors (or set of descriptors), which simulates the human similarity perception.

Image retrieval can be done in three ways. They are Text-based, Content-based and Semantic based.

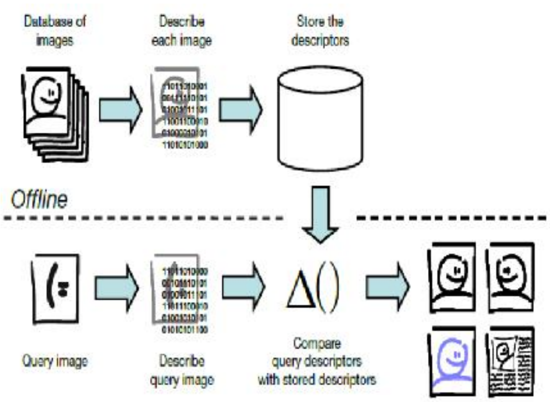


Figure 3.1: A CBIR system is based on a measure of dissimilarity between image descriptors.

Content Based IR retrieves stored images from a collection by comparing features automatically extracted from the images and is different fromthe text based retrieval,. The most common features used for CBIR are mathematical measures of color, texture or shape features. A typical system that allows users to formulate queries by submitting an example of the type of image being sought is shown in Figure 3.1. The system then identifies and displays the stored images whose feature values closely match with those of the query image. Theflow diagram forMicro Structure feature representation required for image retrieval is shown in Figure 4.1.

After the micro-structure image is extracted, the next step is to describe its features so that the different images can be compared for retrieval. The simulation ofhuman visual processing with this process of image retrieval has a greater significance. A visual scene may contain many objects not all of which are processed by human visual system. Only some draw maximum human attention while the others are being suppressed. We implement the proposed algorithm basedon representation of the perception image i.e. whatthe micro-structure is, where it is and spatial abstraction i.e. how it is correlated with others.

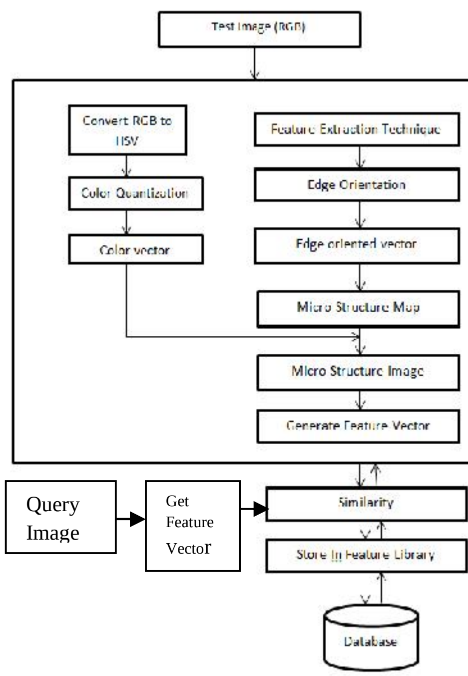


Figure 4.1.Flow diagram for Multi-Features Extraction in Image Retrieval.

4.2 Methodology

The goal of our work is to make the Image Retrieval more efficient by using the micro-structure descriptor. For that; we need various modules in-order to implement this.We have 5 main modules:

Step 1:-Color Quantization in HSV color space.

Step 2:-Edge orientation detection.

Step 3:-Micro-structure definition and map extraction.

Step 4:-Micro-structure Image

Step 5:-Micro-structure feature representation.

4.2.1 HSV color space and color quantization

The HSV color space defined by Hue (H), Saturation (S) and Value (V) matches with human perception and hence it is used in MSD. The H component describes the color ranging 0–360°, with red at 0°, green at 120° and blue at 240°. The S component refers to the relative purity and ranges 0-1. The V component represents the brightness of the color and ranges 0–1 [8].Weuniformly quantize the H, S and V color channels into 8,3 and 3 bins, respectively, so that in total 8×3×3=72 colors are obtained. The quantized color image is denotedby C(x,y) =w, $w \epsilon \{0,1,\dots,71\}$.

4.2.2 Edge orientation detection in HSV color space

As the HSV color space is based on the cylinder coordinate system, it is more appropriate to transform it into Cartesian coordinate system. Let (H,S,V) be a point in the cylinder coordinate system and (H',S',V') be the transformation of (H,S,V) inthe Cartesian coordinate system, $H' = S.cos(H), S' = S.sin(H), V' = V$. We apply Sobel operator to each of H^1, S^1, and V^1 channels of a color image g(x,y) in Cartesian coordinate system as it is less sensitive to noise than other gradient operators or edge detectors. The two vectors $a(H'_x, S'_x, V'_x)$ and $b(H'_y, S'_y, V'_y)$arethe gradients along x and y directions, where H'_xdenotes the gradient in H' channel along the horizontal direction, and so on. Their norm and dot product can be defined as

$$|a| = \sqrt{(H'_x)^2 + (S'_x)^2 + (V'_x)^2} \quad (4.1)$$

$$|b| = \sqrt{(H'_y)^2 + (S'_y)^2 + (V'_y)^2} \quad (4.2)$$

$$ab = H'_x H'_y + S'_x, S'_y + V'_x V'_y \quad (4.3)$$

The angle between a and b is then

$$\cos(\widehat{a,b}) = \frac{ab}{|a||b|} \quad (4.4)$$

$$\theta = arc\cos(\widehat{a,b}) = arc\cos\left[\frac{ab}{|a||b|}\right] \quad (4.5)$$

After the edge orientation θ of each pixel is computed, the orientation is uniformly quartized into m bins, where m∈{6,12,18,24,30,36}. Denoted by $\theta(x,y)$ the edge orientation map, as θ (x,y)= $\emptyset$, $\emptyset \in \{0,1,\dots,m\}$.Thus, the orientations are quantized into six bins with an interval of 30°.

4.2.3 Micro-structure definition and map extraction

Human visual system is more sensitive to orientation and color. Orientation is more powerful feature to describe the subject depicted in an image. Strong orientation reveals a definite pattern; however, many natural scenes do not exhibit strong orientation and have no clear structure or specific pattern. Micro-structures are defined as the collection of certain underlying colors. The underlying colors are those colors which have similar or the same edge orientation in uniform color space.

In micro-structure description the 3x3 block is used for convenience. As an edge orientation is insensitive to color and illumination variation and is independent of translation, scaling and small rotation effects the edge orientation image θ(x,y) is used to define micro-structures. We quantize the orientation into six levels, and hence the values of the pixels in θ(x,y) can vary from 0 to 5.

To obtain micro-structure, in the 3×3 θ(x,y)block, if one of the eight nearest neighbors has the same value as the center pixel, then it remains the same otherwise it is set to empty. If all the eight nearest neighboring pixels are empty, then that 3×3 block is not considered as a micro-structure and all pixels in the 3×3 block are set to empty. Figure 4.3 shows an example of the micro-structure extraction. Suppose there is an edge orientation map θ(x,y) of size W×N.

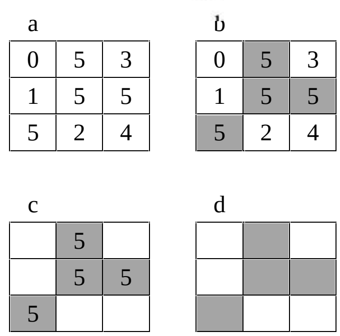
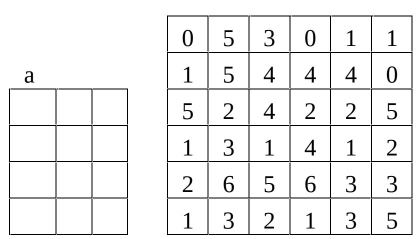


Figure 4.2:An example of micro-structure detection

The figure 4.2.ashows 3X3 pixel grid of edge orientation map; 4.2.b indicates the pixels similarity when compared with neighboring elements; 4.3.c shows the micro-structure detection process; and 4.3.d shows the detected fundamental micro-structure.



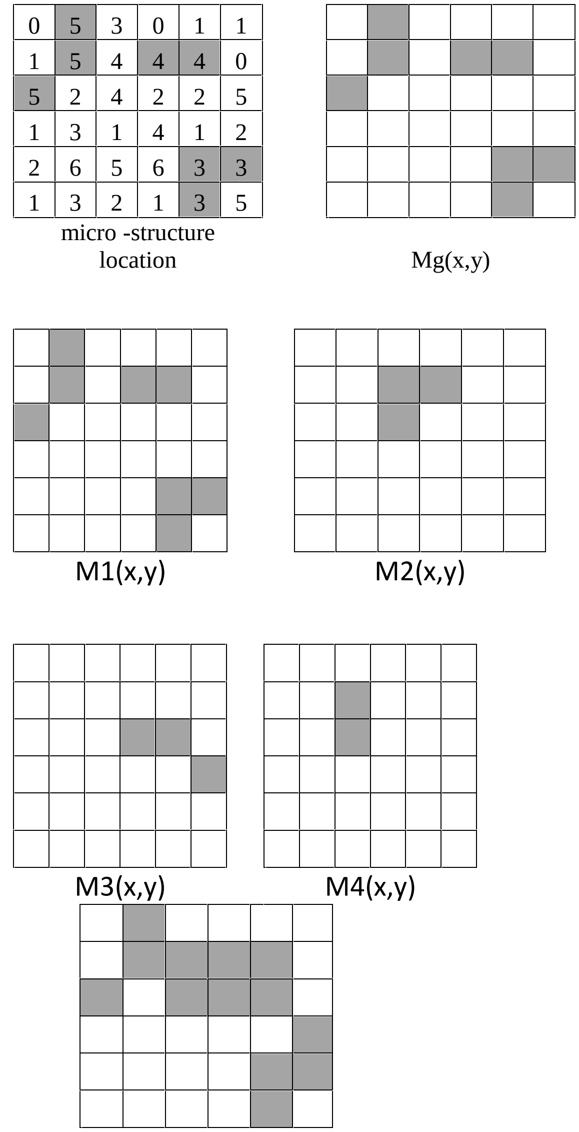


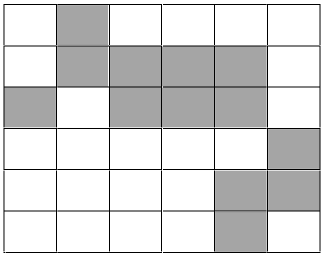
Figure 4.3: Illustration of micro-structure map extraction.

In the above figure4.3.a shows the extraction of micro-structuremapM1(x,y)**,**Maps M2(x,y), M3(x,y) and M4(x,y) can be extracted similarly with the starting pixels (0,0),(0,1),(1,0) and (1,1). Figure 4.3.b shows the fusion of the four maps to form the final micro- structure map M(x,y).

4.2.4Micro-structure image

The color and orientation information is processed separately, but simultaneously. After the micro-structure map M(x,y) is extracted from the edge orientation image θ(x,y), we use it as a mask to extract the underlying colors information from the quantized image C(x,y).

a b



M(x,y)

71	0	3	24	1	5
21	35	15	16	0	2
33	30	0	16	32	32
40	8	26	23	25	25
10	36	35	1	69	69
11	12	7	6	9	15

c

71	0	3	24	1	5
21	35	15	16	0	2
33	30	0	16	32	32
40	8	26	23	25	25
10	36	35	1	69	69
11	12	7	6	9	15

d

	0				
	35	15	16	0	
33		0	16	32	
					25
				69	69
				9	

Figure 4.4: Micro-structure image formation.

Figure 4.4.a indicates the detected micro-structure map M(x,y); Figure 4.4.b indicates the quantized color image C(x,y); Figure 4.4.c point out imposing the micro-structure map on the image; and Figure 4.4.d shows the micro-structure image f(x,y) by keeping only the colors within the micro-structure map.

4.2.5 Micro-structure feature representation

Values of a micro-structure image f(x,y) is denoted asf(x,y)=w, w$\in${0,1,...,L-1}. In each 3$\times$3 block of f(x,y), denotedby $P_{0=}(x_0,y_0)$ the center position of it and let $f(P_0)=w_0$. Denotedby $P_i=(x_i,y_i)$ the eight nearest neighbors to P_0 and let $f(P_i)=w_i$, i=1,2,…, 8. Denoted by N the co- occurring number of values w_0 and w_i, and by $\bar{N}$ the occurring number of w_0. Moving the 3$\times$3block from left-to-right and top-to-bottom throughout the microstructure image, we use the following equation to describe the micro-structure features.

$$H(w_0) = \left\{ \frac{N\{f(p_0) = w_0 \wedge f(p_i) = w_i || p_i - p_0| = 1\}}{8\ \bar{N}\{f(p_0) = w_0\}} \right.$$

Where $w_{0=}w_i, i \in \{1,2,\dots,8\}$

4.3 Algorithm: The algorithm steps for retrieval is described in detail here.

Step 1: Take 1st image in the database as the processing image.

Step 2: Take red values of each pixel into array 'r', green to 'g', blue values to 'b'.

Step 2.1: Convert r, g, b values into h, s, v values (hue, saturation, value)

Step 2.2: Transform cylinder co-ordinates into Cartesian co-ordinates by using the following:

H^1 = S.cos(H).

S^1 = S.sin(H).

V^1= V.

//Appling the sobel operator.

Step 3: Take 1st pixel as processing pixel and Compute H^1x, H^1y, S^1x, S^1y, V^1x, V^1y

Step 3.1: consider array 'h'

H^1x= (sum of right diagonal pixel + 2 * right pixel) - (sum of left diagonal pixel + 2 * right pixel)

H^1y= (sum of lower diagonal pixel + 2 * lower pixel) - (sum of upper diagonal pixel + 2 * upper pixel).

Step 4: Repeat step 3.1 by considering 's' and 'v' array for calculating S^1x, S^1y and V^1x, V^1y.

Step 5: Repeat step 3 and step 4 for each and every pixel of the image.

// Color Quantization.

Step 6: Divide the image pixel values into 8, 3, 3 bins for h, s, v.

Assign C1=8, C2=3, C3=3.

C(x,y) New pixel value= (C3 * C2) * VI + C3 * SI + HI, where VI, SI, HI is the bin number for which the hue, saturation, value pixel values of a pixel belongs to.

Step 7: Repeat step 6 for each and every pixel of an image.

Step 8:the orientation is uniformly quantized into 'm' bins.
Consider m=6.
//Edge Orientation Image

Step 8: Compute the angle (Ø) of each pixel as
theta(Ø(x ,y))=$\cos^{-1}$ (gxy/ (gxx*gyy))
gxx= Square root ($H^1x^2 + S^1x^2 + V^1x^2$)
gyy=Square root ($H^1y^2 + S^1y^2 + V^1y^2$)
gxy=Square root ($H^1x* H^1y + S^1x* S^1y + V^1x* V^1y$)
Step 9: Repeat step 8 for each and every pixel of an image.

// Micro–structure definition and map extraction :

Step 10: The edge orientation image Ø(x ,y) is used to define the micro-structures.

Quantize that Ø(x ,y) into six levels **(0 to 5).**

partition the image into 3 x 3 blocks.

Five step-strategy with 3- pixels as step-length:

i. Starting from (0,0) , compute M1(x,y).
ii. Starting from (1,0) , compute M2(x,y) .
iii. Starting from (0,1) , compute M3(x,y) .
iv. Starting from (1,1) , compute M4(x,y).
v. Compute M(x,y) by using following

M(x,y)=Max {M1(x,y),M2(x,y),M3(x,y),M4(x,y)}.

Step 11: Repeat step 10 for each and every block and obtain micro-structure map.

// Micro-structure image

map M(x,y) is used as a mask to extract the underlying colors information from the color quantized image C(x,y).

Micro-structure image is denoted as f(x,y).

// Micro-structure feature representation.

Step 12: Consider array, array having length of 72, which represents the no. of pixels having the pixel value 0-71. The feature vector of an image of length 72.

Step 13: Repeat step 1 to step 12 for each and every image in the database.
// Image retrieval
Step 14: Take the input image and calculate the feature vector.
Step 15: Calculate the distance between the input image and all the images in the database by applying the L1 distance.

Step 16: Display the images that are close to the input image, i.e., having less distance from the input image.
4.3.1 Pseudo code:
1. Read 1st image in the database into I.
2. Image X=Color Quantization (I);
3. Edge Orientation (Ø) =sobel(I);
4. Map M(x,y)= Micro-structure (Ø);
5. Micro-structure image f = micro-structure image(Image X, Ø);
6. Features=Features Representation (f);
7. Repeat the above steps until features of all the images in the dataset get extracted.
8. Save the features of all images into database.
9. I=read input image;
10. Dist=Distance (I, database);
11. SDist=sort (Dist);
12. Rimages (12) =SDist (1-12);
13. Output the top 12 images (Rimages) as retrieved images.

5.EXPERIMENTAL RESULTS

Retrieval Phase: In the retrieval phase, the query image and top 12 images retrieved using MSD edge orientation are shown in Figure 5.1. The performance of the algorithm is measured using Precision and Recall as shown in Figure 5.2. The MSD performance is compared with MTH algorithm and is shown in Table 5.3

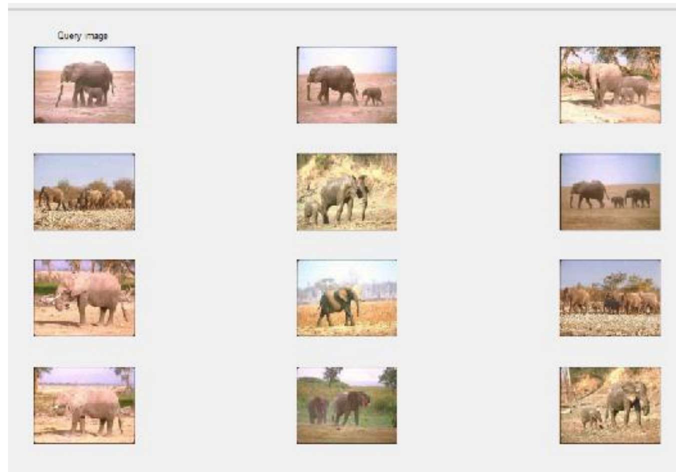


Figure 5.1: OutputImage retrieval

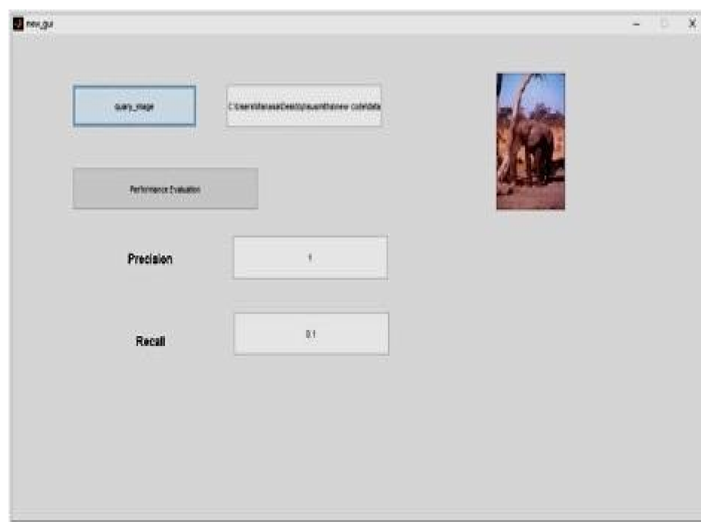


Figure 5.2: Performance evaluation

Performance Evaluation: The measures used for testing our algorithm are: Precision and Recall
Precision is defined as

$$P = I_N / N$$

Recall is defined as

$$R = I_N / K$$

Where I_N is the number of similar images retrieved, N is the total number of images retrieved and K is the total number of similar images.

S.No.	Category	Two Feature (C=72,T=6)			
		E=(1-(((1+β* β)*P*R)/((β* β)+R)))			
		Precision (P)	Recall (R)	E (β=0.5)	E (β=2)
1	Elephant	0.833	0.1	0.662	0.878
2	Flower	0.833	0.1	0.662	0.878
3	Glass	1	0.12	0.595	0.854
4	Horse	1	0.12	0.595	0.854
5	Racecar	0.916	0.11	0.628	0.866
Average Values		0.9164	0.11		

Table 5.1: Comparison of Precision and Recall valuesfor various image datasets

In the above table we retrieved the results based on the features that Effis van Rijsbergers measure as

E=(1-(((1+β* β)*P*R)/((β * β)+R)))

Here **β** denotes relative importance to user to determine Precision and Recall. If **β**value is taken as 2 the user is interested more in recall than in the Precision.If **β** is taken as zero the user is not interested in recall.

Category	MTH	MSD Two features (C=72,T=6)	MSD Three feature Color+Shape+ Texture
	Precision	Precision	Precision
Elephant	0.636	0.75	1
Flower	0.881	1	1
Glass	0.686	0.833	0.98
Horse	0.909	0.833	1
Race Car	0.08	1	1
Average values	0.808	0.833	0.996

Table 5.2: Comparison Of Precision Values

In the table5.2 we have compared the precision values by the previous technique MTH with MSD. It is evident that MSD with 3 features as shape, color and texture gave better result than comparing with 2 features color and texture.

category	MTH	Two features (C=72,T=6)MAD	Three feature(Color=Shape+ Texture)
	Recall	Recall	Recall
Elephant	0.01	0.1	0.15
Flower	0.1	0.1	0.12
Glass	0.1	0.12	0.14
Horse	0.1	0.12	0.15
Race Car	0.01	0.11	0.13
Average values	0.064	0.11	0.138

Table 5.3: Comparison Of Recall Features

In the table 5.3 we have compared the Recall values by the previous techniques MTH with MSD. It is evident that MSD with 3 features as shape, color and texture gave better result than comparing with 2 features color and texture.

Color quantization levels	Precision (%)		Recall (%)	
	Texture orientation levels			
	6	36	6	36
192	0.855	0.916	0.11	0.12
72	0.833	0.844	0.1	0.11

Table 5.4:Average retrieval Precision and Recall values for various color and orientation quantization levels

The table 5.4 explains the average precision and recall values for various color and orientations that are used in the quantization techniques. We can observe that better Precision and Recall can be obtained as the level of quantization increases. In the above table color quantization levels are obtained as 192 with 48 bins in Hue , 4 bins in Saturation and 4 bins in Value. Performance is less for 72 color quantization levels when the no of bins of H,S and V are taken as 8, 3 , 3 bins respectively. Figure 5.5 depicts the recall values for CLUT, color with texture and color, shape with texture features taken.

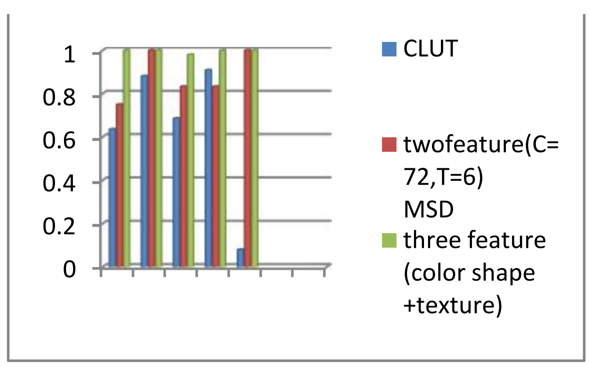


Figure 5.5: Comparison Graph for Recall for

Retrieved Images.

6. CONCLUSIONS

Image Retrieval using Micro-structure descriptor (MSD) is presented in this paper and is simple and efficient. The micro-structures are defined by an edge orientation similarity with the underlying colors used to represent image features more effectively. The underlying colors are colors with similar edge orientation, can mimic the human color perception well. The MSD the extended micro-structure can simultaneously extract color, texture and shape features of an image. In addition, this algorithm uses HSV color model that simulates human visual perception. The MSD algorithm has higher indexing performance and efficiency for image retrieval with lower dimensionality, which are only 72 for full color images and with a little increase even with 192. Our experiments on large-scale datasets show that the MSD achieves higher retrieval precision than the existing representative image feature descriptors, such as Gabor feature and MTH, for image retrieval.

REFERENCES

[1]Liu et al, "Image retrieval based on multi-textonhistogram",PATTERN Recognition 43 (7) (2010) 2380-2389.

[2] Huet et al, "Shape recognition from large image libraries by inexact graph matching" Elsevier Pattern Recognition Letters 20 (1999) 1259-1269

[3] Liu et al, "Image retrieval based on the texton co-occurrence matrix" Pattern Recognition 41 (2008) 3521 – 3527.

[4] Dai et al. "Efficient View-Based 3-D Object Retrieval via Hypergraph Learning" tsinghua science and technology ISSN 1007-0214 03/11 pp250-256 Volume 19, Number 3, June 2014

[5]MathiasEitz, Kristian Hildebrand, TamyBoubekeur and Marc Alexa et al, "An evaluation of descriptors for large-scale image retrieval from sketched feature lines" TU Berlin Telecom ParisTech - CNRS LTCI

[6]Fatemi ,Arash , Martin Vetterli et al, "Shapes From Pixels", ieee transactions on image processing, vol. 25, no. 3, march 2016

[7] MULLER, Henning, et al, "Performance Evaluation in Content-Based Image Retrieval: Overview and Proposals"

[8] R.C.Gonzalez, R.E.Woods, Digital Image Processing, 3rd Edition, Prentice Hall,2007.