A Salient Multi-feature extraction using Enhanced Micro-Structure Descriptor (EMSD) for Image Retrieval

A.Srinagesh[1], P.Rama Krishna[2]

[1]asrinagesh@gmail.com

[2] mails4prk@gmail.com

Abstract— An enhanced salient multi-feature extraction using EMSD is proposed and implemented. Nowadays, Semantic Image Retrieval or User-Interactive based Image Search with more number of relevant retrieved images in the search process is desired by any user. To enhance the search in various applications a salient modified micro-texture is designed, developed, computed for each image and stored as data. When a test image is inputted as the query to the system, two-phase independent searches are performed and references are stored. The Euclidean distance measure is computed and the most relevant and required images are shown as output to the user. The results obtained through this indirect approach are very encouraging. The proposed method is extensively tested on Corel datasets with 1000 images, but, still, the retrieval process depends on nature and the input dataset.

Keywords— *Semantic Image retrieval (SIR), Texture, Color, Quantization, Color Space Structure elements descriptor (CSSD), Structure Element's Histogram (SEH), Texton detection, HSV color space, Similarity measure*.

I. INTRODUCTION

Image retrieval is one of the most prominent topics or area studied by researchers in the field of pattern recognition and artificial intelligence. Three categories of image retrieval methods are presently available in research. They are:

a) Text-based
b) Content-based
c) Semantic-based methods.

In this paper, the main aim is to develop a new feature detector and descriptor, namely microstructure descriptors (EMSD), to describe image features via micro-Structure. The microstructure is defined by computing edge orientation similarity and the underlying colors, which can effectively represent image local features. An Automatic image retrieval system for browsing, searching and retrieving images from a large volume of digital images is a necessity.

Content-based image retrieval is the task of searching images in databases by analyzing the image contents. In this connection, several image retrieval methods are currently proposed and developed which primarily implemented based on the color distribution of the images. For Example, in QBIC (Query-by-Image) or QBE (Query by Example), the user simply provides a Test-image and the search is based upon that input image. For some particular image retrieval types of applications generally, no relevance feedback implementations are mandatory or their implementation needs to be satisfied and the image retrieval process is very fast. The retrieved number of relevant images, as a result, is far less compared to the enhanced implementations and complex variations of these existing methods.

Various algorithms have been designed to extract the color and texture features for image retrieval. The color structure is invariant to orientation and scale, but the color structure is difficult to characterize image spatial Structure. Color descriptors have been proposed to exploit the spatial information, e.g. color correlograms. Texture features provide important information of the smoothness, coarseness, and regularity of many real-world objects such as humans, vehicles, cars, fruit, trees, clouds and other real-world objects.

The texton co-occurrence matrix (TCM) Proposed by G.H Liu, J.Y Yang[1] TCM represents spatial correlation of textons , and it can discriminate color, texture and shape features simultaneously, Edge orientation auto correlogram (EOAC) Proposed by Mahmoudi, The muti-texton structure (MTH) Proposed by Guang-Hai Liu, Lei Zhang, In the texton detection process, TCM is slower than MTH. In the texton detection of TCM, the 2x2 grid moves throughout the image with one pixel as the step –length, and detected textons in a neighborhood may overlap. There are numerous algorithms and implementations which are currently undertaken by researchers that combine color and texture features together, such as integrative co-occurrence matrix(ICM), Texton co-occurrence matrix(TCM), and multi-texton structure (MTH). The main aim of this work is to implement a micro-texture structure descriptor (MSD), which identifies edges in an image.

II. PROPOSED ARCHITECTURE

Efficient Low-Level Feature extraction of is the essential requirement for an Effective Image retrieval system. To achieve this paradigm, various methods have been recently proposed. Most of these methods use the histogram or some variation for representing color and other descriptors which require a significant amount of space and extra similarity calculation. Here, an efficient content-based image retrieval (CBIR) system is proposed, which is based on the fusion of chromaticity-color moments, and color co-occurrence-based small dimension features using inverse variance weighted similarity measure. In this measure, a property of the varying weights reduces the effect of redundancy and effectively retrieves relevant images. In addition, this paper also proposes a supervised query image classification and retrieval model by filtering out irrelevant class images using Euclidean distance based measure computed for the feature library of the database. Basically, this model recovers the category of query images, and this successful categorization of images significantly enhances the performance and searching time of retrieval system. Descriptive comparative analyses confirm the effectiveness of this work. we obtained 83.83% for some images in Corel and 76.9% average precision for 12 and 20 images retrieval using weighted similarity measure together with 85.6% average precision and 84.4% recall for classification framework. THE PROPOSED METHOD IS IMPLEMENTED AS FOLLOWS:

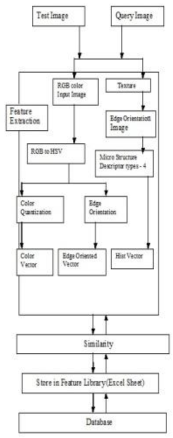

Fig 1: Proposed System Architecture

We propose and introduce a new image feature detector or descriptor namely enhanced feature descriptor (EFD) using neighborhood measure. This method improves the performance of retrieval traditional micro-structure descriptor by constructing and finding the similar neighborhood pixels by Euclidean distance measure also. The traditional way of defining micro-structure is based on an edge orientation similarity and the Color feature. EMSD is built based on the underlying colors in Structure as well as a 3x3 neighborhood with structure similar edge orientation considering both regular and irregular structures simultaneously. With regular micro-Structure serving as a bridge, the EMSD extracts features by simulating irregular structure by processing them a simulated regular structure which in turn have minimal effect on human visual processing and it effectively integrates color, texture, and color layout information as a whole for image retrieval both locally and globally.

A: Micro-texture feature representation:

The main aim of the work is to implement a micro-structure descriptor, which identifies edges in an image. Edge orientation image is taken as input for texture extraction process, because edge orientation is insensitive to color and illumination variation and it is independent of translation, scaling and small rotation

The values of a micro-structure image f(x,y) is denoted as f(x,y)=w, w€{0,1,…,L-1}.
P0=(x0,y0) the center position of f(x,y) and f(P0)=w0.
The eight nearest neighbors to P0 and f(Pi)=Wi.
where i=1,2,…,8.
Following equation to describe the microstructure features.
H(w0)=
where W0=Wi, i€{1,2,…,8}
The dimensionality of H(W0) is 72 for color images.
It can express how the spatial correlation of neighboring underlying colors distributes in the micro-structures image. The outlines of the steps are:

a) HSV color space and color quantization.
b) Edge orientation detection in HSV color space.
c) Micro-structure definition and map extraction.
d) Micro-structure image.
e) Micro-structure feature representation.

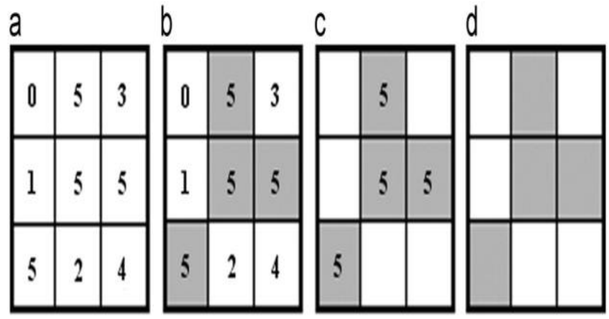

Fig 2: An example of microtexture detection(a) A 3 x 3 grid of edge orientation map (b) and (c) show the micro-texture detection process (d) shows the detected fundamental micro-texture

The Five step-strategy with 3- pixels as step-length: implemented is as follows:
Starting from (0,0) , compute M1(x,y).
Starting from (1,0) , compute M2(x,y) .
Starting from (0,1) , compute M3(x,y) .
Following equation to describe the micro-texture features.
$H(w_0)=W_i$, where $W_0=W_i$, i€{1,2,…,8}
Generate the hist vector.
Store the vector in feature library.
Repeat above steps for n-images for retrieval features
Starting from (1,1) , compute M4(x,y).
Compute M(x,y),
M(x,y)= Max { M1(x,y),M2(x,y),M3(x,y),M4(x,y)}.
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 .

i) Analyze the spatial correlation among neighboring micro-structures by the uniform color space.

ii) The values of micro-structure image is denoted as f(x,y)= w , w € { 0,1,….,L-1 }.

B: Algorithm for EMSD:

Input: Read an Image (I)
Output: Feature vector 3- D hist
Variables: C1,C2,C3:No. of Structure Bins, CSA,CSB.
Initialize nimages=1000 , CSA=72, CSB=6, C1=8,C2=3,C3=3.
for k=1 : nimages
Read the kth image
// Color Quantization
convert the input image (I) into 3 channels (R,G,B).
convert RGB color space to HSV color space.
Compute the image edges using Sobel operator.sobel edge detection: divide the 3 channels (H, S, V) into
Hx, Sx, Vx in x-direction.
Ry, Hy, Sy, Vy in y-direction
Given a color image of size W x N,
the image is quantized into 72 colors by using (c3 * c2) * VI + C3 * SI + HI , and its denoted by c(x , y).
c(x, y)= w, w € { 0,1,….,71 }
calculate the edge orientation Ø,
for this calculation :
H1 = S.cos(H).
S1 = S.sin(H).
V1= V.
gxx = Sqrt ((H1x)2 + (S1x)2 + (V1x)2)
gyy = Sqrt ((H1y)2 + (S1y)2 + (V1y)2)
gxy = H1x.H1y + S1x.S1y+ V1x.V1y.
[Ø(x,y) = acos(gxy / gxx.gyy)]
Ø = cos-1 (gxy / gxx . gyy)
Micro–texture definition and map extraction:
the edge orientation image Ø(x ,y) is used to define the micro-Structure.
Quantize that Ø(x ,y) into six levels
(0 to 5). size of Ø(x ,y) is W x N.

C: Image Retrieval:

The procedure for Image retrieval is as Follows:
In order to retrieve T (user-defined) query results, the following steps are executed:
The microstructure of the query image is computed. Then, the number of bins in each direction (i.e., HSV space) if they are same, Only one is stored.
For each image i in the database:
Load its structure Hist(i).
Use similarity for eliminating the number of bins in each direction.
For each hist bin, compute the distance (d) between the hist of thequery image and the i-th database image.
Keep only distances (d2) for which, the respective hist bins of the query image are larger than a predefined threshold T (let l2 the number of these distances).
Use the 2nd threshold: find the distance (D3) values which are smaller than t2, and let l3 be the number of such values.
The similarity measure is defined as: S(i) =l2 * average(d3) / (l3^2).
Sort the similarity vector and prompt the user with the images that have the M smaller S values.

III. MODIFIED QUERY SEARCH IMAGE ALGORITHM

1. The microstructure of the query image is computed. Then, the number of bins in each direction (i.e., HSV space) if they are same, Only one is stored.

2. For each image i in the database:

- Load its structure Hist(i).

- Use similarity for duplicating the number of bins in each direction.

- For each hist bin, compute the distance (D) between the hist of the query image and the i-th database image.

- Compute distances (d2) for which, the respective hist bins of the query image are larger than a predefined threshold T (let L2 the number of these distances).

- Use the 2nd threshold: find the distance (D3) values which are smaller than T2, and let L3 be the number of such values.

- The similarity measure is defined as: S(i) = L2 * average(D3) / (L3^2).

3. Sort the similarity vector and prompt the user with the images that have the M smaller S values.

IV. EXPERIMENT AND RESULTS

The proposed method presented above in Figure 1 is implemented in Matlab2014b and the publically available Corel dataset is downloaded which is. is extensively tested on Corel datasets with 1000 images,

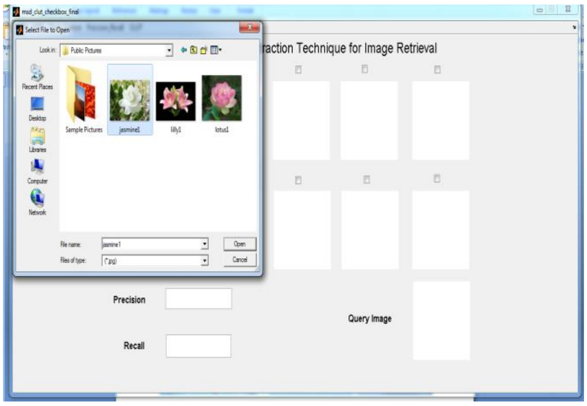

Fig 3: Adding Corel dataset images

TABLE 1: CALCULATION OF PRECISION, RECALL AND RELATIVE EFFECTIVENESS MEASURE (E)

S.No.	Category	Two Feature (C=72, T=6)			
		E=(1-(((1+b*b)*P*R)/((b*b)+R)))			
		Precision(P)	Recall (R)	b=0.5	b=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	Race car	0.916	0.11	0.628	0.866
Average Values		0.9164	0.11		

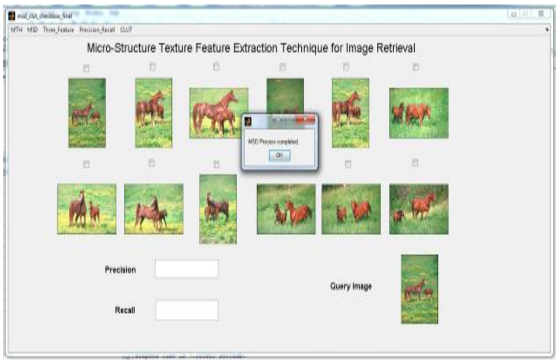

Fig 4: Implementation of EMSD

Table 2: Comparison Table for the Implemented three Techniques

S	Query	TCM		MTH		MSD	
		Precision	Recall	Precision	Recall	Precision	Recall
1	Q1	75	9	83.33	10	75	9
2	Q2	83.33	10	91.66	11	83.33	10
3	Q3	100	12	100	12	100	10
4	Q4	91.66	11	50	6	100	12
5	Q5	25	3	100	12	83.33	10
6	Q6	41.66	5	83.33	10	58.33	7
7	Q7	91.66	11	50	6	66.66	8
8	Q8	75	9	91.66	11	100	12
9	Q9	100	12	100	12	100	12
	Total	75.92	9.11	83.33	10	85.18	10.22

V. CONCLUSIONS

In EMSD, both Color and Texture features are used to retrieve the most relevant images when a query image is given. The EMSD algorithm has higher indexing performance and efficiency for image retrieval, but lower dimensionality which is only 72 for full-color images. The EMSD experiments on large-scale datasets show that the EMSD achieves higher retrieval precision than the existing representative image feature descriptor, such as MTH, for image retrieval.

In MMSD, both Color and Texture features are used to retrieve the relevant images. Specifically, it has only 72 vectors for full-color images, and hence it is very efficient for image retrieval. This method is extensively tested on Corel datasets with 1000 images. In conclusion, MMSD has good discrimination power of color, texture features, and layout information.

VI. REFERENCES

[1]. Liu, Guang-Hai, and Jing-Yu Yang. "Image retrieval based on the texton co-occurrence matrix." Pattern Recognition 41.12 (2008): 3521-3527.

[2]. Liu, Guang-Hai, et al. "Image retrieval based on multi-texton histogram." Pattern Recognition 7.43 (2010): 2380-2389.

[3]. Mahmoudi, Fariborz, et al. "Image retrieval based on shape similarity by edge orientation autocorrelogram." Pattern Recognition 36.8 (2003): 1725-1736.

[4]. Wang, Xingyuan, and Zongyu Wang. "A novel method for image retrieval based on structure elements' descriptor." Journal of Visual Communication and Image Representation24.1 (2013): 63-74.

[5]. Raikar, Poornima, and S. M. Joshi. "Efficiency of Methods in Retrieval Using Query by Sketch." Bonfring International Journal of Software Engineering and Soft Computing6.Special Issue Special Issue on Advances in Computer Science and Engineering and Workshop on Big Data Analytics Editors: Dr. SB Kulkarni, Dr. UP Kulkarni, Dr. SM Joshi and JV Vadavi (2016): 213-216.

[6]. Srinagesh, A., et al. "A modified shape feature extraction technique for image retrieval." International Journal of Emerging Science and Engineering (IJESE) ISSN (2013): 2319-6378.

[7]. Srinagesh A, Rao Nh, Vikas Dr. A Novel Texture And Shape Pattern-Based Feature Extraction Technique For Image Retrieval In Medical Images.

[8]. Julesz, B (March 1981). "Textons, the Elements of Texture Perception, and their Interactions". Nature. 290 (5802): 91–97. PMID 7207603. Doi:10.1038/290091a0.

[9]. G-H. Liu, L. Zhang, et al., Image retrieval based on multi-texton histogram, Pattern Recognition 43 (7) (2010) 2380–2389.

[10]. J. Huang, S.R. Kumar, M. Mitra, et al., Image indexing using color correlograms, in IEEE Conference on Computer Vision and Pattern Recognition, (1997) 762–768.

[11]. G-H. Liu, J-Y. Yang, Image retrieval based on the texton co-occurrence matrix, Pattern Recognition 41 (12) (2008) 3521–3527.

[12]. B. Julesz, Textons, the elements of texture perception and their interactions, Nature 290 (5802) (1981) 91–97.

[13]. B. Julesz, Texton gradients: the texton theory revisited, Biological Cybernetics 54 (1986) 245–251.

[14]. L. Chen, The topological approach to perceptual organization, Visual Cognition 12 (4) (2005) 553–637.

[15]. T. Lindeberg, Detecting salient blob-like image structures with a scale-space primal sketch: a method for focus-of-attention, International Journal of Computer Vision 11 (3) (1993) 283–318.

[16]. L. Itti, C. Koch, E. Niebur, A model of saliency-based visual attention for rapid scene analysis, IEEE Transactions on Pattern Analysis and Machine Intelligence 20 (11) (1998) 1254–1259.

[17]. T.Quack, U.Monich, L.Thiele, B.S.Manjunath, Cortina: a system for large-scale, content-based web image retrieval, in Proceedings of the12th annual ACM international conference on Multimedia, 2004.

[18]. J.R.Smith, S.-F.Chang, VisualSeek: A Fully Automated Content-Based Image Query System, In ACM Multimedia, Boston, MA, (1996)87–98.

[19]. R.Zhang, Z.Zhang, Effective image retrieval based on hidden concept discovery in image database, IEEE Transactions on Image processing 16(2) (2007) 562–572.

[20]. J.Amores, N.Sebe, P.Radeva, Context-based object-class recognition and retrieval by generalized correlograms, IEEE Transactions on Pattern Analysis and MachineIntelligence29 (10) (2007)1818–1833.

[21]. Y.chi, M.K.H.Leung, Part-based object retrieval in cluttered environment, IEEE Transactions on Pattern Analysis and Machine Intelligence 29(5) (2007) 890–895.

[22]. C.-H.Yao, S.-Y.Chen, Retrieval of translated, rotated and scaled color textures, Pattern Recognition36 (4) (2003)913–929.

[23]. J. Luo, D. Crandall, Color object detection using spatial-color joint probability functions, IEEE Transactions on Image Processing 15 (6) (2006) 1443–1453.

[24]. http://wwwqbic.almaden.ibm.com/

[25]. http://www.ci.gxnu.edu.cn/cbir/