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CONTENT BASED IMAGE RETRIEVAL BASED ON SHEARLET TRANSFORM

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Abstract-Searching fascinated imageries founded on graphic belongings of pictures is a perplexing delinquent and it has conventional substantial consideration from scholars in the arenas like image processing, computer vision and multimedia systems. While the prominence and the consequence of the image topographies like color, texture and shape have been taken into an interpretation in many identifications, there have not been many revisions on the significance of the color spaces on the recital of Image Retrieval systems. In this paper we first experimentally study the effect of selecting color model on the enactment of content based image retrieval using Shearlet decomposition of each color channel. To this end, the retrieval outcomes of dissimilar color seats like RGB, YUV, HSV, YCbCr and Lab are evaluated. Then as anoutcome a new Content Based Retrieval model using Shearlet Transform in Lab color space and Color Moments is proposed. In order to intensification the competence of the planned model some separationsystems are taken into account which advances the concert of the proposed model. The proposed exemplarychallenges one of the essential restrictions in content based image retrieval, namely, the experimentamong the accuracy of retrieval and its time intricacy.

Keywords-CBIR, Shearlet Transform, Color models Lab Color Space.

1. INTRODUCTION

In the currentcenturies, due to the development of digital technology in creating digital cameras and obtainability of high-speed Internet networks, the quantity of digital imageries has been grownupquickly. Those characteristics have provided a reckless and modest way to produce and proliferate visual gratified worldwide. That capitals that anenormousamount of explicitinfogrowsaccessibleeach day to a cumulativequantity of users. Much of that visual material is offered on the Net, which has grown the main and furthermostdiverse image list so far. So there is acrucialrequest for image retrieval schemes [1] [2], which could be satisfied by content-based image retrieval (CBIR) schemes. In CBIR systems, mining image structures like color, shape and texture is a very significant step. This step is done by image descriptors. There are many papers studying and examining image descriptors [3]-[5]. Reviewing these identifications give readers understanding to select a set of appropriate descriptors grounded on the assignment at hand. Though, a very significant point is selecting the color interplanetary in which the image features are hypothetical to be removed. Color is one of the extensively used arrival features and applying more color

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spaces does not imply advantage of routine enhancement. That is for the deprivedrecital color spaces effect on the high ones. So it's important to assess the recital of different color models for CBIR. There are many color models in the turf image dispensation. Each color model has its own benefits and drawbacks. In this paper we try to address the above point by experimentally studying the results of image recoveryby wavelet transform. Wavelet transform has remained shown to be a very significantmethod in image processing and computer vision. Using multi resolve strategy an image can be disintegrated and represented on dissimilartenacities and measures with diverse amount of particulars [6], [7]. Wavelet transform have been positivelypractical to image denoising, image compression [9] and texture analysis [10]. In [11] authors propose a new CBIR system using colorand texture topographies. In this paper texture features are excavated using 2D-DWT and Euclidean distance portion was used as a comparisondegree between a query image and imageries in the catalogue. In [12] wavelet base was used to describe each query image and also to exploit the retrieval presentation in anexercise data set. Also, a reversionpurpose was used to approximation the finest wavelet filter for each interrogation image. Finally, a simple image descriptionfounded on the consistentinstants of the wavelet coefficient deliveries was presented. The authors claim that this feature extraction model is really fast. Investigationalconsequences show importantrecoverypresentation on medicinal image data set, a texture statistics set, a face recognition data set, and an object picture data set. In [13] separate wavelet transform and edge histogram were used to term the gratified of the image. First wavelet coefficients were mined in horizontal, perpendicular and slantingguidelines and then Edge Histogram Descriptor (EHF) was practical on particular wavelet factors to gather the evidence of overriding edge alignments. The mixture of DWT and EHD methodsupsurges the presentation of spitting imagerecoveryscheme for outline and consistencyfounded search. In [14] authors propose a new model in which wavelet transform and color consistency vector are collective to theory image feature descriptors. Christo Ananth et al. [8] discussed about a model, a new model is designed for boundary detection and applied it to object segmentation problem in medical images. Our edge following technique incorporates a vector image model and the edge map information. The proposed technique was applied to detect the object boundaries in several types of noisy images where the ill-defined edges were encountered. The proposed techniques performances on object segmentation and computation time were evaluated by comparing with the popular methods, i.e., the ACM, GVF snake models. Several synthetic noisy images were created and tested. The method is successfully tested in different types of medical images including aortas in cardiovascular MR images, and heart in CT images.

As it can be seen wavelet transform has been positively employed in scheming CBIR structures. So, in this paper Shearlet transform is used to capture image features. The rest of the paper is organized as follows. In Section 2 shortly opinions to dissimilar color models used in this paper. Section 3 briefly describes the proposed model for CBIR. In Section 4 the investigationalfallouts are discussed. Lastly, the paper is concluded in Section 5.

2. COLOR SPACES

A color space is an intellectualaccurate model recitation the way colors can be signified as types of statistics, typically as three or four standards or color components (e.g. RGB and CMYK are color spaces). For getting more infoconcerningdiverse color spaces reader can refer to the references [15]-[17].

3. PROPOSED MODEL

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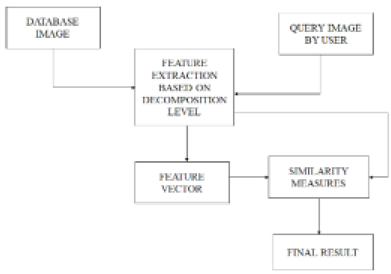

Figure 1. Block Diagram of Proposed Method

In this section a brief explanation of our proposed model is obtainable. At first, each image in catalogue is converted to the aforementioned color models. Then, for each color frequency features of the images in catalogue are mined using Shearlet transform. After a feature vector for each image is composed of Shearlet coefficients extracted from every image station. So, for image I in the data base feature path $f_1$is defined as follows in equation (1).

$$f1= (S_{c1}, S_{c2}, S_{c3}) \qquad (1)$$

Where, $S_{C1}$are first and second order moments of the Shearlet coefficients of the first channel of the image I in color space C. After that all the feature vectors will be reserved in mandate to be recycled in next steps of retrieval process. Another important structurechunk of image recoveryschemesremainsresemblance measure. In this paper 2 Lnorm is used as a similarity measure. When the enquiry image is existing, its feature vectors are extracted and used for computing the similarity amid this image and file images. Suppose that I is a database image with featureVector**f1= (S_{c1}, S_{c2}, S_{c3})** and Q is a query image with feature vector **f_Q= (S_{c1}', S_{c2}', S_{c3}')**. Now, the similarity between these dualistic images is calculated using the subsequent equation (2).

$$\mathrm{Sim(Q,I)}=\sqrt{(\mathbf{Sc1'} - \mathbf{Sc1})\mathbf{2}}+\sqrt{(\mathbf{Sc2'} - \mathbf{Sc2})\mathbf{2}}+\sqrt{(\mathbf{Sc3'} - \mathbf{Sc3})\mathbf{2}} \qquad (2)$$

Figure 1 shows the steps for image recovery using projected model. So, in order to do a relative study of the effect of selecting color interplanetary on the performance of the CBIR schemes in each color planetary the image features are extracted in the same way using the planned model. Also transformation from RGB color space and other color spaces has been done using the known models in the works [18].

4. EXPERIMENTAL RESULTS

The database used in our trials is Wang database [21]. It contains of 1000 images in 10 classes and 100 imageries in allgroup (Table1). In order to relate the effect of the color spaces on the recital of proposed CBIR model, arithmeticalevents namely Precision and Recall were used. These proceedings can be computed as follows: As it can be seen from Table 2, the most promising results were achieved using Lab color space.In demand to associate the effect of the color spaces on the recital of proposed CBIR model, statistical measures namely Precision and Recall were used. These measures can be computed as follows in equation (3).

In the next stage, in order to get better results, we decided to capture information from different parts of theimages. In this way extracted features can be supposed as local features since they have been extracted from different parts of image not from the entire image at once. These local features give us more discriminative power. So that we can get better results. In Figure 2(a). Image is 9 parts with the same size while in Figure 2(b). The image is alienated into 9 different portions and the size of the central part is 9/25 of the area of the image. In Figure 2(a). The image is divided into 5 parts. Each part is 1/4 area of the image. In Figure 2(d). The image is divided into 5 parts. Each part is 1/2 area of the image except the central part which is 4/9 area of the image. While extracting image features one can assign more weights to the central parts because in most of the images the core objects are likely to be appeared in the central part.

$$\text{Precision}=\frac{|TP|}{|TP+FP|}\text{ , Recall}=\frac{|TP|}{|TP+FN|} \qquad (3)$$

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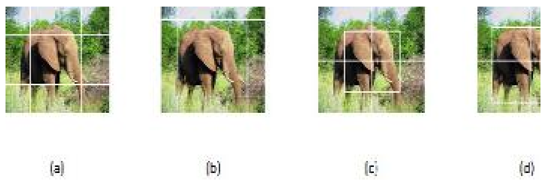

Figure 2. Image Division with different schemes

Figure 3. The retrieval results of an image from the Wang database [21]

Table 1. Ten Classes of the Image Dataset

CATEGORY	SEMANTIC NAME
1	Aero plane
2	Elephant
3	Brain
4	Dolphin
5	Chair
6	Cell phones
7	Flowers
8	Lamp
9	Watch
10	Butterfly

Here we used color moments as another image features. These moments can be computed as in equation (4).

$$\mu_i = \frac{1}{N}\sum_{j=1}^{N} f_{ij}\ ,\ \sigma_i = \left(\frac{1}{N}\sum_{j=1}^{N}(f_{ij}-\mu_i)^2\right)^{\frac{1}{2}}\ ,\ s_i = \left(\frac{1}{N}\sum_{j=1}^{N}(f_{ij}-\mu_i)^3\right)^{\frac{1}{3}} \quad \textbf{(4)}$$

Where *fij*is the value of the i^{th} color module of the image pixel "*j*", and N is the entirequantity of pixels in the appearance. Therefore, using Shearlet transform in the Lab color space and computing color moments the feature vector of an image is constructed. Using this proposed model we could achieve a high performance as it can be seen from Table 3. Compared to other models reported in [20]-[23] our proposed model provides promising results. We also successfully implemented our proposed model on Li database [24] and we could achieve high rate of accuracy. Figure 3 shows the retrieval results of the proposedmodel.It should be noted that final results of the first 29 similar images are presented.

Table 3. The Average Precision and Recall of the Proposed Model Using Wavelet Transform In Lab Color Space and Color Moments

SEMANTIC NAME	PRECISION	RECALL
Aero plane	77.12	72.15
Elephant	79.15	77.25
Brain	78.16	74.47
Dolphin	77.15	74.16
Chair	86.19	82.71
Cell phones	82.16	79.15
Flowers	89.15	83.12
Lamp	84.16	80.12
Watch	92.15	88.16
Butterfly	95.16	89.46
AVERAGE	**86.14**	**80.805**

6. CONCLUSION AND FUTURE WORK

This paper gives an experimental study of the effect of choosing color space on the performance of a CBIR system while Shearlet transform is employed as image feature descriptor. The final results show that Lab color space provides the most promising results. Therefore, a new Content Based Retrieval model using Shearlet Transform and Lab color space and Color Moments is proposed. The proposed model challenges one of the significantprecincts in content based image retrieval, namely the experimentamong the accurateness of retrieval and its speed. The experimental results on a Wang database [19] and Li database [24] demonstrate the superiority of our proposed. In future, incorporating other image descriptors accompanied by an ensemble of classifiers targeting at

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attaining more talentedoutcomes on larger catalogues will be the bearing of our studies.

Table 2. The Average Precision and Recall of the Methods

SEMANTIC NAME	RGB-Shearlet		HSV-Shearlet		YUV-Shearlet		YCbCr-Shearlet		Lab-Shearlet	
	Precision	Recall	Precision	Recall	Precision	Recall	Precision	Recall	Precision	Recall
Aero plane	62.15	52.16	64.24	59.14	57.45	52.26	66.45	60.95	**76.12**	**72.15**
Elephant	68.14	60.15	69.45	64.74	60.48	53.45	70.16	64.19	**79.76**	**74.95**
Brain	64.15	57.16	66.12	60.11	62.14	54.42	61.13	51.21	**78.43**	**73.55**
Dolphin	69.15	60.79	70.15	64.15	64/14	57.16	64.18	57.15	**80.57**	**76.16**
Chair	72.16	62.42	70.15	64.41	61.15	59.15	67.16	57.16	**82.29**	**79.71**
Cell phones	74.15	62.41	74.26	68.15	62.15	57.49	69.15	62.16	**81.16**	**76.32**
Flowers	75.16	61.15	74.16	68.74	67.14	53.15	71.16	65.17	**86.92**	**82.21**
Lamp	75.49	64.12	77.19	72.15	68.16	59.78	72.18	67.14	**88.17**	**83.87**
Watch	79.45	62.15	81.15	71.11	68.73	62.15	64.82	59.13	**90.36**	**87.11**
Butterfly	82.15	68.15	84.15	75.15	70.49	63.78	72.16	68.15	**94.48**	**88.46**
AVERAGE	72.15	60.155	74.195	67.145	63.97	58.02	69.305	64.55	**85.3**	**80.305**

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