Investigation on CBIR based on Color Description and Quantitative Image Fidelity Measurement

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***Abstract* – The aim of this paper is to investigate the feasibility of content based image retrieval (CBIR) by using 4 approaches. The first two approaches are histogram based: RGB (Red, Green, Blue) and HSV (Hue, Saturation, Value). The second two approaches are quantitative image fidelity measurement based: MSE (Mean Square Error) and SSIM (Structural Similarity Index). Quantitative image fidelity based measurement provides a certain amount similarity between two images. Lastly the precision rate for each image retrieval has been measured.**

Keywords- Image retrieval, color histogram, quantitative image fidelity measurement, precision performance.

I. INTRODUCTION

At present days, it is completely expected to have complication for searching digital picture in massive database. To mitigate this issue, CBIR has turned into an important research area. Content based image retrieval is also acknowledged as query by image content (QBIC). The algorithmic way of searching image from a large pool of data has been made easier with the accessible data available for the images. CBIR focuses on the content of the images for analyzing purpose. These contents are: textures, shapes and colors from image itself. Descriptions, tags or keywords associated with the image can be used to search image as well instead of using the color, shapes and textures to find it. However, using data like tag or description to search image is extremely time consuming. Using CBIR, image retrieval can be measured by precision and recall. Later the measurement can be arranged according to the comparison.

One main problem faced by CBIR system is semantic gap problem which is difficulty in obtaining unique correspondence between feature vector and image label. This is due to the fact that the computer cannot understand the semantic information in the image and the image are usually categorized using low-level features such as color, shape and texture. These results in different semantic labels can have closely similar value of feature vector which is undesirable. Some examples of CBIR are: FIRE [1], AMORE [2], STRSM[3] etc.

In this paper, the improved and effective image comparison is done based on the color histogram of RGB and HSV, SSIM and MSE.

II. IMAGE RETRIEVAL PROCESS

CBIR system is going to retrieve a collection of images which have similarity with the query image. In this paper, we are going to make an hypothesis in which we can say about the image that belong to the similar group will be having less Euclidean distance between the feature vectors and thus we can retrieve the images of the same category using CBIR system. Euclidean distance is a disparity distance metric which uses two feature vectors of the uniform extent and provides with a numerical value that tells us the degree of similarity between two images. The smaller Euclidean distance, the more those group of images will have similarity. The Euclidean distance between two color histogram h^1 and h^2

can be measured using:

$$L_2(h^1,h^2)=\sum_x\sum_y\sum_z(h^1(x,y,z)-h^2(x,y,z)) \qquad (1)$$

A. *Color Histograms*

Color histogram is the representation of frequency distribution of color bins in an image. We choose, in this paper, HSV color histogram as the feature vector for the images. To do this, we extract the RGB information from the images and convert it into HSV format using the formula given below [4][5]. After that, we construct the color histogram by applying quantization process in order to reduce the number of bins by putting similar color pixel into the same bins.

$$H=\begin{cases}60\left(\dfrac{G-B}{\max(R,G,B)-\min(R,G,B)}\right)+360 & if\ \max(R,G,B)=R\\ 60\left(\dfrac{B-R}{\max(R,G,B)-\min(R,G,B)}\right)+120 & if\ \max(R,G,B)=G\\ 60\left(\dfrac{R-G}{\max(R,G,B)-\min(R,G,B)}\right)+240 & if\ \max(R,G,B)=B\\ not\ \ defined & if\ \max(R,G,B)=0\end{cases}$$

$$S=\begin{cases}\dfrac{\max(R,G,B)-\min(R,G,B)}{\max(R,G,B)} & if\ \max(R,G,B)\neq 0\\ 0 & if\ \max(R,G,B)=0\end{cases}$$

$$V=\max(R,G,B) \qquad (2)$$

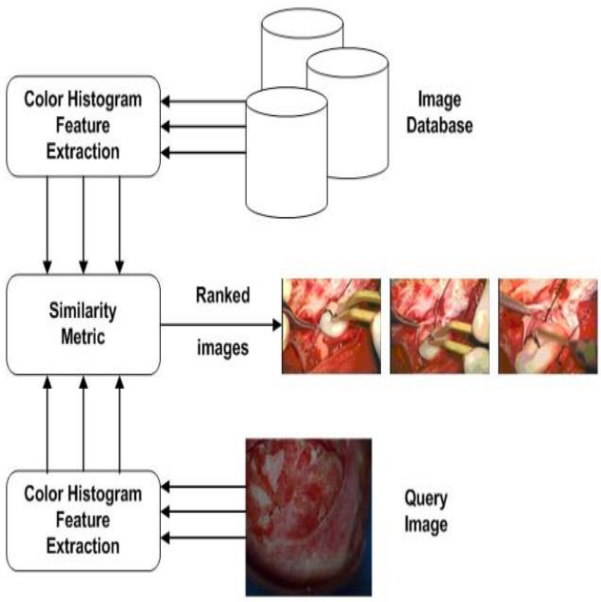

Figure1: Overview of Color Histogram retrieval process.

B. Mean Square Error (MSE)

Mean square error is used to measure the difference between the result images and the query image.

Let,

N = Number of pixels

x_i,y_i = i th pixel of the images x and y respectively

$$\mathrm{MSE}(x,y)=\frac{1}{N}\sum_{i=1}^{N}(x_i-y_i)^2 \qquad (3)$$

In the framework for optimization, due to the mathematical convenience, MSE is broadly utilized. Different from color histograms that determine the degree of dissimilarity between two images using Euclidean distance, mean square error (MSE) determines the degree of similarity using quantitative image fidelity measurement. MSE has high precision for retrieval of images that undergo orthogonal linear transformation, such as Fourier Transform.

C. *Structural Similarity Index(SSI)*

The image quality is usually measured with structural similarity index.

Lets,

N = Number of pixels

x_i,y_i = i th pixel of the images x and y respectively

SSIM incorporates the luminance – *l*(x,y), structure – *s*(x,y) and contrast – *c*(x,y) [6] to formulate:

$$\mathrm{SSIM}(x,y)=f(l(x,y),c(x,y),s(x,y)) \qquad (4)$$

$$l(x,y)=\frac{2\mu_x\mu_y+C_1}{\mu_x^2+\mu_y^2+C_1},\quad C_1=(K_1L)^2$$

$$c(x,y)=\frac{2\sigma_x\sigma_y+C_2}{\sigma_x^2+\sigma_y^2+C_2},\quad C_2=(K_2L)^2$$

$$s(x,y)=\frac{\sigma_{xy}+C_3}{\sigma_x\sigma_y+C_3},\quad C_3=\frac{C_2}{2} \qquad (5)$$

Using the equation (4) and (5) the following new equation can be computed:

$$\mathrm{SSIM}(x,y)=\frac{(2\mu_x\mu_y+C_1)(2\sigma_{xy}+C_2)}{(\mu_x^2+\mu_y^2+C_1)(\sigma_x^2+\sigma_y^2+C_2)} \qquad (6)$$

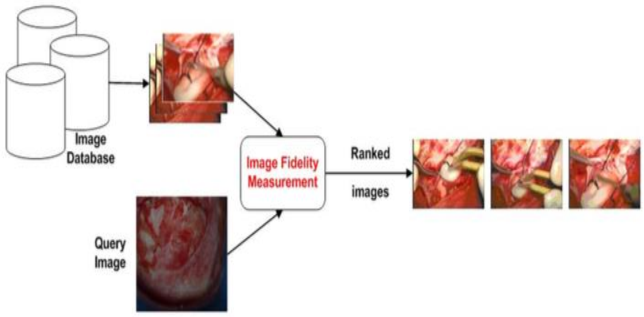

Figure 2: Overview of image fidelity measurement retrieval process.

III. EXPERIMENTAL RESULTS

In this experiment, Wang dataset which consists of 1000 images has been used. It has been divided into ten categories – African people (0.jpg – 99.jpg) beach (100.jpg – 199.jpg), building (200.jpg – 299.jpg), bus (300.jpg – 399.jpg), dinosaur (400.jpg – 499.jpg), elephant (500.jpg – 599.jpg), flower (600.jpg – 699.jpg), horse (700.jpg – 799.jpg), mountain (800.jpg – 899.jpg) and food (900.jpg – 999.jpg). Each category has 100 images and each image has been manually annotated to indicate it class type. To test the effectiveness of CBIR system, we choose one query image from each category and select 20 most similar images to calculate the precision. The formula for precision is given as below:

Precision rate PR = CI/NR   Recall rate RR = CI/NC
CI: number of relevant images retrieved for one query
NR: number of images retrieved for one query
NC: number of relevant images in the database

The precision result is tabulated as shown below:

Image Category	Category Label	Average Precision with RGB Colour Histogram/%
Africa	1	62.222
Beach	2	42.222
Building	3	42.222
Bus	4	42.222
Dinosaur	5	100.000
Elephant	6	37.778
Flower	7	68.889
Horse	8	77.778
Mountain	9	22.222
Food	10	31.111
Average from 10 categories		52.667

IV. CONCLUSION

CBIR system is an effective way to retrieve images of the same category as it does not involve human labor to do the labeling which is time-consuming and subjective. CBIR system is also more feasible than manual annotation when the involving database is very large. In this paper, the enhancement has been made for HSV color histogram, RGB color histogram, MSE and SSIM. The performances of precision of image retrieval have been measured by using a open access image database containing 100 images. The results of our simulation showed the best approach among all is HSV.

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