Content Based Image Retrieval Using Color and Texture Features

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Abstract

In the last decade, content-based image retrieval (CBIR) was an important research subject. In this paper, a set of image features is proposed for image retrieval based on color and texture features. For color feature, color statistics values are calculated from HSV and LAB color spaces. For texture feature, Haralick feature is extracted from RGB and Gray scale image. A set of proposed features is applied Columbia Object Image Library (COIL-100) for image retrieval. The input of our system is the query image and the output is the relevant images for a query image. Precision and recall are measured to show the properties of proposed feature in content based image retrieval. In experiment, the combination of color and texture feature has the high precision(98.72%) and recall(97.25%) value in content-based image retrieval (CBIR) system.

Keywords: Content-based image retrieval (CBIR); color statistics Feature; Haralick Feature; Columbia Object Image Library (COIL-100); Precision and Recall;

1. Introduction

Nowadays images are commonly used. It has the benefit of visual representation, and other mediums are typically used to communicate. Storage and processing of a vast number of images became feasible with the exponential advancement of computers and networks. In recent decades, retrieval of images is increasingly important rather than retrieval of text. Content-based image retrieval (CBIR) is seen as one of the most effective ways to view visual content. Instead of annotated text, it deals with the image material itself, such as color, form and image composition.

In this paper, classification of melanoma has been proposed based on color and texture features of the images. Color feature is the feature that can represent the statistics of the color of an image in numerical representation. Color is an essential and the simplest aspect human beings perceive when viewing an image. Human visual system is more receptive to details about colors than gray tones, and color is the first choice used for extraction of the element. One common way of describing color compositions is the color histogram [1]. Texture is a feature used to separate images into parts of interest and identify certain areas. Texture provides details as colors or intensities are combined in an image in space. Texture is defined by the spatial distribution of Neighborhood intensity levels . The second order statistics of GLCM is also used as texture feature of an image [1,2].

Shape feature is closely connected to the contour or boundary notion. However, the boundary of a shape has a spectrum of points and is not, as such, generally amenable to finite recognition or data processing. Thus, in order to computationally define a form, its boundary must be distinct in a morphologically faithful fashion, i.e., maintaining its structural integrity, by finitely many lines . Shape, texture and color feature were combined for the best important feature in CBIR[3].

The low-level features most widely used include those reflecting images of color, texture, shape and distinguishing points [2]. Color is the most important feature due to the advantages of robustness, durability, ease of deployment and low storage requirements and almost all CBIR systems employ colors. Instead of the RGB vacuum, light is mirrored by HSV or CIELab and LUV spaces, because they are far better with respect to human vision [4].

The content-based image recovery (CBIR) approach is proposed using the image characteristics generated by a color layout descriptor (CLD) and the Gabor Texture descriptor. CLD defines the space distribution of color, with some non-linear, quantized, grid-based average color coefficients, while the Gabor filter functions as a local space frequency distribution band pass filter. These two descriptors are highly important for CBIR systems. The use of color and texture technology in CBIR systems also helps in a more precise image recovery. The performance of an image retrieval system is evaluated with average accuracy and recall for all queries [6].

CBIR proposes the method for reclaiming features using an efficient combination of color and texture [5]. Moments of distribution of pseudo-Zernike chromaticity in the opposite color spaces are used for color characteristics. The rotationally invariant and scale-invisible image descriptor is used to provide a solid and practical description of early processing of the human visual system as its texture characteristics. In pyramid controllable domain, integrating information on color and texture gives a potent imaging framework focused on image query [5].

Our proposed CBIR system used color and texture features to retrieve relevant images or collection of images for input image (query image). The color statistics values are calculate from HSI and LAB color spaces for color feature and Haralick features from GLCM are also calculated for texture feature. The combination of these features form a set of proposed feature for CBIR system. Euclidian distance measure is used to measure difference between query image and image collections. There are five parts in the structure of this article. Sections I and II provide an introduction and system overview. Section III describes a set of proposed extraction features and distance measurement. Section IV includes a summary of the benchmark dataset and the experimental performance. Ultimately, in section V, conclusions are provided.

2. System Overview

There are two main parts in CBIR: feature database creation and relevant images retrieving according to query image. An efficient way for management and search relevant images is highly challenges in real world. Therefore, finding efficient image retrieval mechanisms has become a wide area of research interest. An overview of content-based image retrieval (CBIR) system is presented in Figure 1.

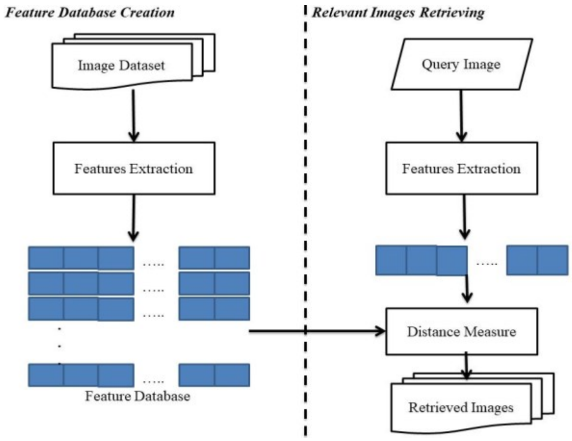

Figure 1. Overview of CBIR

In Figure 1, image dataset is the collection of images from dataset. In feature extraction step, color and texture features are extracted from these images and then feature vector for each image is obtained. Finally, the extracted feature vectors are collected and save as feature database for CBIR system. Query image is the input image that is the query to get similar or relevant images from image repository. The feature vector of query image is extracted at feature extraction step. After getting feature vector, distance measure between query image and images from dataset are performed, the relevant images are retrieved according to the distance measure results. The value of distance measure is between 0 and 1. The most similar images have the distance measure value close to 0. The input and output of the CBIR is query image and relevant images respectively.

3. Image Features Extraction and Distance Measure

A variety of features of the low-level image may be derived from an image. Low-level image characteristics are widely used: color, texting, form, location, etc. Our CBIR strategies use a combination of color and texture features to maximize the efficiency of retrieval. A set of features extraction is defined in this section, which is used in our CBIR research. The color and texture features of an image are extracted and then combine these three features to form a proposed feature as shown in Figure 2. Since COIL dataset already performed preprocessing image that is used in our system, there is no need to consider for preprocessing in our CBIR system.

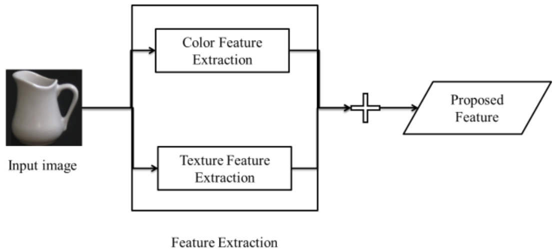

Figure 2: Flow of Feature Extraction

3.1. Color Feature

Color feature is the most widely used feature for an image in CBIR. It represents the image from statistical values based on pixel intensities. It represents the frequency distribution of color pixels in an image. It counts similar pixels and store it. The color statistics values of different color spaces is proposed as a global color descriptor which are calculated based on color frequency in an image.

The input image is convert HSI and LAB color spaces. The HIS color space of an image has three color channels called Hug, Illumination and Situation. The LAB also has three color channels: L* for the lightness from black (0) to white (100), a* from green (−) to red (+), and b* from blue (−) to yellow (+).

3.1.1. HSI and LAB Color Spaces

For image processing applications, **the HSI color space** is very significant and attractive as it equally reflected color as the human eye senses colors. The color with three components: hue (H), saturating (S) and intensity (I) is represented by the HSI-color model. The **LAB color space** is a color space defined by the International Commission on Illumination (CIE) in 1976. It expresses color as three values: $L*$ for the lightness from black (0) to white (100), $a*$ from green (−) to red (+), and $b*$ from blue (−) to yellow (+) [7].

3.1.2. Color Statistics values

The color statistics values are extracted from these converted six different color channels as shown in Figure 3. The color statistics computed from HSI and LAB color spaces to represent the color feature of an image.

$$\mu = \frac{\sum_{i=1}^{N} P_i}{N} \quad (1)$$

$$\sigma = \sum_{i=1}^{N} (P_i - \mu)^2 \quad (2)$$

$$\varepsilon = -\sum_{i=1}^{N} P_i \log(P_i) \quad (3)$$

where μ, σ and ε are the mean, variance and entropy respectively; and N is the total number of pixels in an images and Pi is the intensity value of pixel in corresponding color spaces.

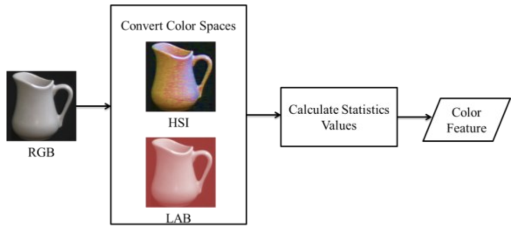

Figure 3: Flow of Color Feature Extraction

3.2. Texture Feature

Gray Level Co-occurrence Matrix (GLCM) is determined from the image of a gray scale. For finding the GLCM matrix, the relation pair occurrences of each situation pixel and its adjacent pixel are determined at a definite distance and angle. In order to get a normalized matrix, the matrix is divided by sum of all the occurrences. Figure 4 shows how GLCM is measured on the 4 x 5 image (I) gray scale for angle 0 degree and distance value 1.

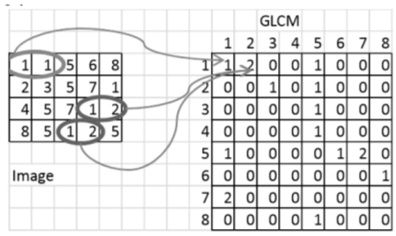

Figure 4: Calculation of GLCM from an Image

For different offsets different GLCM can also be measured. These offsets describe relationships between pixels of varying direction and distance. For different offsets, different GLCMs will be generated. These offsets describe relationships between pixels of varying direction and distance. In our CBIR system, four directions 0, 45, 90 and 134 degrees with distance 1 offsets are used to calculate four GLCMs. The four textural features extracted from each matrix i.e., Contrast, Correlation, Homogeneity and Energy as follow [9]:

$$c(d,\theta) = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} |i-j|^2 M(i,j) \quad (4)$$

$$o(d,\theta) = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \frac{i*J*M(i,j) - \mu_M}{\sigma_M} \quad (5)$$

$$E(d,\theta) = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} |M(i,j)|^2 \quad (6)$$

$$H(d,\theta) = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \frac{M(i,j)}{1+|i-j|^2} \quad (7)$$

where c, o, E and H are the contract, correlation, entropy and homogeneity respectively, and G is the number of co-occurrence levels in GLCM matrix (M) and M(i,j) is the frequency of gray level in matrix (M). The flow of texture feature extraction is shown in Figure 5.

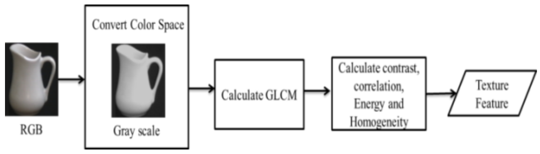

Figure 5: Flow of Texture Feature Extraction

3.3. Euclidean Distance Measure

In our CBIR system, Euclidean distance is extensively used to compare the similarity between the images. Distance between two images is used to identify similarities in the database between the query image and the images. The formula of Euclidean distance between two feature vectors of images is [11]:

$$D(p,q) = \sqrt{\sum_{i=1}^{n}(p_i - q_i)^2} \qquad (8)$$

where p and q are the feature vectors of two images and n is the number of attributes in each feature vectors. The minimum value of distance value for two images means most similar between two images and the value closes to zero.

4. Dataset and Experimental Results

In this section, the briefly description of Dataset and experimental results are presented. The Precision and Recall are measure to show the properties of proposed feature and our CBIR system.

4.1. Columbia Object Image Library (COIL)

Columbia Object Image Library (COIL) is a collection of certain objects with a color image. The artifacts were mounted on a motorized turntable, against a black background. The turntable was rotated at grade intervals by a different oscillation relative to the images of the camera. This corresponds to the images of objects per unit. That refers to a color camera attachment. The stabilized images have been converted to COIL, and can be accessed via ftp online [8]. According to different camera angles and positions, there are 72 images for each object. Therefore there are 7200 images (72x100) in Columbia Object Image Dataset. The main reason for choosing COIL dataset in our system is to show that the combination of color and texture feature can handle different camera angle variant.

Figure 6: Sample Objects Images from Columbia Objects Dataset

4.2. Precision and Recall

There are several metrics for measuring image retrieval, some of which are derived from the field of information recovery. Due to their relevant areas, various researchers use specific performance indicators. Precision and recall are the most common metrics used in Content-Based Image Retrieval (CBIR). Precision and recall will be used in this study to test the efficiency of our Content-Based Image Retrieval (CBIR) framework. Precision is defined as the ratio of the number of correct pictures obtained to the number of images in the recovered collection. A precision value is 1 if all the images that have been collected are important. Recall is the ratio of the number of right images recovered in the database to the number of appropriate images. If our system can retrieve all relevant images in the database, the value of a recall is 1 [10].

$$\text{Precision} = \frac{\text{No.of relevant images Retrieved}}{\text{Total No.of images Retrieved}} \qquad (10)$$

$$\text{Recall} = \frac{\text{No.of relevant images retrieved}}{\text{No.of relevant images in database}} \qquad (11)$$

5. Experimental Results

In experiment, there are 72 images for each object in which 70-30 images for each objects are used as feature database. Therefore, there are 7000-3000 (50x 100) images for 100 objects in feature database. The sample of image query and its relevant image retrieving is shown in figure 7 and precision and recall results according to different number of images for feature database are shown in table 1.

Table 1: Precision and Recall according to different Number of Images in Feature Database (Training)

Number of Images in Feature Database (Training)	Query Image (Testing)	Precision	Recall
7000	200	98.72 %	94.25 %
6000	1200	92.43%	91.32%
5000	2200	92.11%	91.87%
4000	3200	90.46%	90.02%
3000	4200	89.92%	88.94%

In table 1 shows average precision/ recall for a set of proposed feature with Euclidian distance measure. The precision and recall values of proposed CBIR technique are acceptable. The crossover point of precision and recall obtained for proposed technique is 98.72% and 94.25% for 7000 images in feature database, 92.43% and 91.32% for 6000, 92.11% and 91.87% for 5000 and 89.92% and 88.94% for 3000. The larger values of images in feature database may lead to higher precision and recall of system performance.

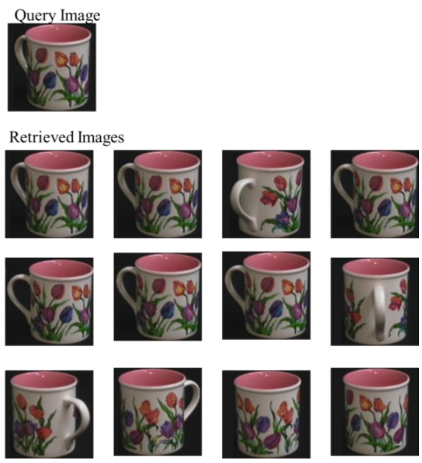

Figure 7: Example of Query Image and its Retrieved Images in CBIR system

5. Conclusion

In this paper, a set of features is proposed for image retrieval based on color and texture features extraction. The precision and recall values in proposed image retrieval techniques are acceptable results. So the combination of color and texture feature gives the better and effective CBIR system to support information and image management. Although our proposed feature has been successfully applied in CBIR system, we also need to try to applied this proposed feature in other image analysis applications such image classification and clustering. Since COIL dataset has 72 camera angle for each objects, our proposed feature has the rotation invariant property to represent image information. In future, we will develop our proposed feature by consideration of other semantic and statistics features in digital image processing methods.

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