Computer Engineering and Intelligent Systems
ISSN 2222-1719 (Paper) ISSN 2222-2863 (Online)
Vol.4, No.7, 2013

Content Based Image Retrieval based on Shape with Texture Features

Capt. Dr. S. Santhosh Baboo
Reader, Postgraduate & Research, Department of Computer Applications
DG Vaishnava College, Chennai - 600 106, Tamil Nadu, India.
E-mail: santhos2001@sify.com

Sudhir Ramadass
Research Scholar of Manonmaniam Sundaranar University
E-mail: sudhir.ramadas@gmail.com

Abstract
In areas of state, domain and hospitals, massive collections of digital pictures are being created. These image collections are the merchandise of digitizing existing collections of analogue images, diagrams, drawings, paintings, and prints. Retrieving the specified similar image from a large dataset is very difficult. A new image retrieval system is obtainable in this paper, for feature extraction HSV color space and wavelet transform approach are used. Initially constructed one dimension feature vector and represented the color feature it is made by that the color space is quantified in non-equal intervals. Then with the help of wavelet texture feature extraction is obtained. At last by using of wavelet transform combined the color feature and texture feature method. The illustration features are susceptible for different type images in image retrieval experiments. The color features opted to the rich color image with simple variety. Texture feature opted to the complex images. At the same time, experiments reveal that HSV texture feature based on wavelet transform has better effective performance and stability than the RGB. The same work is performed for the RGB color space and their results are compared with the proposed system. The result shows that CBIR with the HSV color space is retrieves image with more accuracy and reduced retrieval time.
Keywords--Content Based Image Retrieval, HSV, RGB

Introduction

CONTENT-based image retrieval is used to investigate and examine the actual contents of the image. In this perspective expression 'content' related to colors, shapes, textures, or any other information that can be derived from the image itself. Without the skill to examine image content, searches must rely on metadata such as captions or keywords, which may be laborious or expensive to produce. Different methods of content – based retrieval methods are available and it is color, texture and shape. In this paper, HSV Color Space and Texture Features based Image retrieval is proposed. Selection for this method is based on two reasons. In first stage to make very good retrieval presentation by using of color based system. The reason is to select this is because of very simple implementation. Unlike the shape based methods and texture based, it doesn't require image segmentation which itself is a hard image processing problem.

Comparison of CBIR with already established method using text index, this method find out and get the image visual characteristics it directly establishes index in accordance with the characteristics of image information. Method of image retrieval is obtained through their similarity of image features. CBIR is a highly challenging problem for general-purpose image databases for the reason of large size database [1, 2, 12]. The most significant visual features are Color and texture. In the field of computer graphics, multimedia, computational science HSV color space is used. [3]. Discriminate colors in this space are used by Hue, perceived light intensity are called as value then by adding percentage of white light to a pure color is called saturation. The capability to separate chromatic and achromatic components by using of HSV color space it is one of the advantages for this. Therefore, this paper prefers the HSV color space to extract the color features based on hue, saturation and value. Texture feature does not depend on color or intensity and reflects the essential occurrence of images it is one of the class of visual characteristics.

To develop the accuracy of HSV depends on the combination of both color and texture features. The rest of the paper is organized as follows. Section II gives the literature survey. Section III discusses the RGB and HSV feature extraction techniques. Section IV displays the experimental results and the paper is concluded in section V.

Literature Survey

In the literature survey, several methods have been proposed for the content based image retrieval with the HSV color space and texture features. Among the most recently published works are those presented as follows

S. Sclaroff et.al, [4] proposed a CBIR technique. Image Rover may be a search by image content navigation tool for the globe wide internet that is WWW. To assemble images inadvisably, the image assortment scheme utilizes a distributed fleet of World Wide Web robots running on completely different computers. The image robots gather data concerning the images they notice, computing the acceptable image decompositions and indices, and store this extracted data in vector type for searches supported image content. At search time, users will iteratively guide the search through the choice of relevant examples. Search performance is created economical through the utilization of approximate, optimized k-d tree algorithmic rule. The system employs a completely unique relevancy feedback algorithmic rule that selects the distance metrics acceptable for a selected query

J. Vogel et.al, [5] investigated the face recognition problem through energy histogram of the DCT coefficients. There are various recognition performances are discussed, distinctly the histogram bin sizes and feature sets are consider. In addition to this the author proposed a method of choosing a classification threshold incrementally. Yale face database are taken for experimental and results indicated that the threshold obtained via the proposed technique provides a balanced recognition in term of precision and recall. In addition to this it demonstrated that the energy histogram algorithm outperformed the well-known Eigen face algorithm.

A. Pentland et.al, [6] described an idea to create features from an image database for use in indexing and retrieving. Most important regions that suddenly attract the eye are large color regions that usually control an image. Allowing searching the image by using features obtained from here that are similar perceptually. By human psychophysical measurements of color appearance, algorithm of multiband smoothing are generated. From this multiscale representation of the image are considering using this author calculate the color features and Gabor color texture features on regions. The combined feature vector is then worn for indexing all salient regions of an image. Using a multipass retrieval and ranking mechanism retrieval images are selected that had more similar regions to the query image. Matches are found using the L2 metric. The results displays that the proposed method performs very well.

J. Wang et.al, [7] projected a fuzzy logic approach, UFM (unified feature matching), for region-based image retrieval. For this recovery system, an image are represented as a set of segmented regions, in which color, texture, and shape properties of each image are reflected by a fuzzy feature. Finally an image is related with a family of fuzzy features corresponding to regions. Transition between regions (blurry boundaries) within an image by using of fuzzy features and incorporate the segmentation-related uncertainties into the retrieval algorithm. The overall similarity between two families of fuzzy features are known as similarities of two images and then it is measured by a similarity measure, UFM measure, which integrates properties of all the regions in the images. Compared with similarity measures which are based on individual regions and on all regions with crisp-valued feature representations and provides a very intuitive quantification and greatly reduces the influence of inaccurate segmentation by using of UFM measure. The UFM has been implemented as a element of the experimental simplicity image retrieval system. The presentation of the system is pictorial by means of examples from an image database of about 60,000 general-purpose images

Methodology

First the feature extraction in RGB image is explained. An image I_{WxH} of a 2-dimensional array of pixels is considered. There are W columns and H rows in each image. Each pixel is a triple comprising the RGB values of the color that it represents. Hence, the image has three color components:

$$\{I(R)_{W\times H}, I(G)_{W\times H}, I(B)_{W\times H}$$

Feature extraction in RGB

Selecting gradient-based features makes the scheme robust to illumination variations whereas use of orientation information to define features provides robustness against contrast variations. Basic idea behind these features is to split an image into tiles called cells and then extract a weighted histogram of gradient orientations for each cell. Following subsections provide details of each step.

Defining multiple resolutions

Since there may be difference in resolution between images used for training the classifier, and those of new target images, features should be extracted from an image at multiple levels of resolution. Resolution level is found by a shrinkage factor

$\gamma(\gamma = 0.95)$ that describes the amount by which the image size is reduced in each dimension, as compared to the size in previous level. Consequently, the size of an image in level l is $\omega(l) \times h(l)$ such that, $\omega(l) = \gamma^l W$ and $h(l) = \gamma^l H$ Features are extracted from cells at each resolution level from 0 to an upper limit L. An image is represented at level l as which comprises three color channels I_R^l, I_G^l, I_B^l

Gradient computation

For image at each level *l*, a gradient image Gl is determined as follows:

$$G^l = \{G^l_{mag}, G^l_\theta\}$$

such that

$$G^l_{mag}(x,y) = \sqrt{\begin{matrix}(I^l_{c*}(x+1,y) - I^l_{c*}(x-1,y))^2 + \\ (I^l_{c*}(x,y-1) - I^l_{c*}(x,y+1))^2\end{matrix}}$$

And

$$G^l_\theta(x,y) = \frac{\pi}{2} + arctan\frac{I^l_{c*}(x,y-1) - I^l_{c*}(x,y+1)}{I^l_{c*}(x+1,y) - I^l_{c*}(x-1,y)}$$

$$\arg min_{c\in(R,G,B)} \sqrt{\begin{matrix}(I^l_c(x+1,y) - I^l_c(x-1,y))^2 + \\ (I^l_c(x,y-1) - I^l_c(x,y+1))^2\end{matrix}}$$

Here, (x, y) represents the location of a pixel such that $1 < x < w(l)$ and $1 < y < h(l)$. Gradient values for all pixels available at the boundary of the image are defined to be zero (both magnitude and orientation).

It should be noted that Gl mag(x, y) has only one component as it retains the maximum gradient magnitude value amongst all color components at pixel (x,y). Similarly, G^l_θ(x, y) retains the orientation value for that color component for pixel (x, y).

Computing Histogram of Gradient Orientations

Gradient orientation values lie between [0 Π]. This range can be discretized into 9 bins of size $\frac{\pi}{9}$ each. Now, the image at each level is split into non-overlapping cells of size pxp. For each cell (cx; cy), a 9 element array is computed f(cx; cy). Each of the elements belongs to one of the bins in which the orientation of a pixel in a cell falls. Thus, each pixel is supposed to vote for one of the bins in the histogram. At that pixel, this vote is weighted by the magnitude of the gradient. The following equation shows this:

$$f(cx,xy)[b] = \sum_{x=cx\times p+1}^{(cx+1)\times p}\sum_{y=cy\times p+1}^{(cy+1)\times p}[I\left\{\left\lceil\frac{G^l_\theta(x,y)}{\frac{\pi}{9}}\right\rceil = b\right\} \times G^l_{mag}(x,y)]$$

Here $1 \le b \le 9$ and I{.} is the identity function. Energy of a cell (cx; cy) as defined

$$E(cx,xy) = \sum_{x=cx\times p+1}^{(cx+1)\times p}\sum_{y=cy\times p+1}^{(cy+1)\times p}(G^l_{mag}(x,y))^2$$

Now, in order to retain spatial information between neighboring cells, features of neighboring cells are appended to each cell features and also normalize all these features with the sum of energies of all neighboring cells. This neighborhood of cells is called a block. 2x2 block are considered such that the top, left and top-left cells are included in the neighborhood of a cell. Hence, an overall HOG feature vector is defined (at level l) for a cell (cx; cy) as follows:

$$HOG^l_{cell}(cx,cy) = \frac{\begin{matrix}[f(cx-1,cy-1)|f(cx,cy-1)| \\ f(cx-1,cy)|f(cx,cy)]\end{matrix}}{\begin{matrix}E(cx-1,cy-1)+E(cx,cy-1)+ \\ E(cx-1,cy)+E(cx,cy)\end{matrix}}$$

Here, j denotes concatenation of features. It should be noted here that the final HOG feature vector has a dimension of 4x 9 = 36. It should also be noted that image at each level generates $(\left\lfloor\frac{\omega(l)}{p}\right\rfloor - 1) \times (\left\lfloor\frac{h(l)}{p}\right\rfloor - 1)$ number of cell features, as features from cells in the topmost row and in the leftmost column in image cannot be generated because their left and top neighbors are not defined.

Feature extraction of HSV

Color Features of HSV

Because of a broad range of HSV each component that the computation is very difficult to ensure rapid retrieval in the time of directly calculates the characteristics for retrieval image [8, 9]. So to reduce computation and improve efficiency by quantify HSV space component to. With this to, doesn't need to calculate all segments by the limitation of the distinguish color of the human eye. Unequal interval quantization applied on H, S, and V components based on the human color perception. Color is divided into eight parts based on the color model of substantial analysis. Based on the distinguish of the human eye saturation and intensity is divided into three parts separately [10]. In accordance with the different colors and subjective color perception quantification, quantified hue (H), saturation (S) and intensity (V) are showed in equation below.

$$H = \begin{cases} 0 \ if \ h \in [316,20] \\ 1 \ if \ h \in [21,40] \\ 2 \ if \ h \in [41,75] \\ 3 \ if \ h \in [76,155] \\ 4 \ if \ h \in [156,190] \\ 5 \ if \ h \in [191,270] \\ 6 \ if \ h \in [271,295] \\ 7 \ if \ h \in [296,315] \end{cases}$$

$$S = \begin{cases} 0 \ if \ s \in [0,0.2) \\ 1 \ if \ s \in [0.2,0.7) \\ 2 \ if \ s \in [0.7,1) \end{cases}$$

$$V = \begin{cases} 0 \ if \ v \in [0,0.2) \\ 1 \ if \ v \in [0.2,0.7) \\ 2 \ if \ v \in [0.7,1) \end{cases}$$

That the quantified level for each H, S, V are discussed previously based on this one-dimensional feature vector named G are formed by using of three-dimensional feature vector of H, S, V for different values of with different weight to form:

$$G = Q_s Q_v H + Q_v S + V$$

Where Q_S is quantified series of S, Q_V is quantified series of V.
Here $Q_S = Q_V = 3$ is set, then

$$G = 9H + 3S + V$$

One-dimensional vector are formed in this way by using of three-component vector of HSV form, which quantize the whole color space for the 72 kinds of main colors. So it can grip 72 bins of one-dimensional histogram. By this type of quantification effectively reducing the images by the effects of light intensity and also reducing the computational time and complexity.

As the components of feature vector may have different physical meaning entirely, their rate of change may be very different. It will be much of the deviation of the calculation of the similarity if it is not normalized, so the components are normalized to the same range. The process of normalization is to make the components of feature vector equal importance.

A. Texture Primitive

Supposed I is a M × N image. The image is divided into m×m pixel non-overlap blocks. For each block, the mean value μ and the standard deviation σ of gray in an image block is calculated according to

$$\mu = \frac{\sum_{\forall i,j} p(i,j)}{4}$$

$$\mu = \frac{\sum_{\forall i,j} ||p(i,j) - \mu||}{4}$$

where p (x, y) is the gray value of the pixel located in (x, y) for image I . By the principle of BTC, for those pixels in each block whose gray value is bigger than μ, we make them equal to “1”, otherwise, “0”. In this way, a series of binary blocks are gained and the shape distribution is also expressed by these binary blocks to some extent. In the experiment, the similar texture structure leads to the similar binary blocks.

In the extraction, we found that the different blocks may be lead to same texture value. As shown in figure 3.1 (d) and figure 3.1 (e). Therefore, in this paper, a threshold β is adopted to avoid the question. Those image blocks whose standard deviation is smaller than β are regard as even blocks and make the primitive value as “0”. Otherwise, the primitive value is calculated according to above method. In the experiment, we adopted the statistical methods. We found that it did not affect the performance of method when β = 0.0025σ. where, σ is the mean value of gray for image block.

Image block	$\begin{bmatrix}20&22\\8&7\end{bmatrix}$	$\begin{bmatrix}9&19\\11&20\end{bmatrix}$	$\begin{bmatrix}17&11\\18&9\end{bmatrix}$	$\begin{bmatrix}8&7\\6&8\end{bmatrix}$	$\begin{bmatrix}20&7\\6&23\end{bmatrix}$
Binary block	$\begin{bmatrix}1&1\\0&0\end{bmatrix}$	$\begin{bmatrix}0&1\\0&1\end{bmatrix}$	$\begin{bmatrix}1&0\\1&0\end{bmatrix}$	$\begin{bmatrix}1&0\\0&1\end{bmatrix}$	$\begin{bmatrix}1&0\\0&1\end{bmatrix}$
Binary codes	1100	0101	1001	1001	1001
Texture primitive codes	12	5	10	9	9
	(a)	(b)	(c)	(d)	(e)

Figure 3.1: Image Blocks and corresponding Texture Primitive

B. The Spatial Feature of the Texture Primitive

After defining the type of texture primitive, an image of M × N is corresponding to a matrix of [M /m]×[N / m] expressed by P. P(x, y) is the index of the texture primitive which is located in (x, y) in P. To extract the spatial information of the texture primitive, for certain kind of texture primitive in P(x, y), we kept its value and make others equal to zero. The spatial distribution map of texture primitive is constructed. Based on the map, the spatial feature is proposed

Suppose

$$A_i = \{(x,y) | (x,y) \in P, P(x,y) = i, 0 \le i \le 2^{m\times m} - 1\}$$

be the set of points with index i in P and $|A_i|$ be the number of elements in i A . Let $C_i = (x_i, y_i)$ be the centroid . Moreover, x_i and y_i are defined as follows

$$x_i = \frac{1}{|A_i|}\sum_{(x,y)\in A_i} x \,;\, y_i = \frac{1}{|A_i|}\sum_{(x,y)\in A_i} y \qquad (3)$$

Let r_i be the radius of the point whose index is i. The definition is given by

$$r_i = \sqrt{(x - x_i)^2 + (y - y_i)^2} \qquad (4)$$

Therefore, the sum of the distance between all points whose index is i and centroid is defined as follow

$$R_i = \sum r_i = \sum_{(x,y)\in A_i} \sqrt{(x - x_i)^2 + (y - y_i)^2}$$

Integration of the color and texture feature

Assuming that images A, B, extracted the normalized feature as:

$$F_A = [f_{1A}, f_{2A}, \dots, f_{NA}]$$
$$F_B = [f_{1B}, f_{2B}, \dots, f_{NB}]$$

Here, N is the scale of the feature. Through the similarity computation by Euclidean distance, design this model:

$$D(A,B) = \omega_1 D(F_{CA}, F_{CB}) + \omega_2 D(F_{TA}, F_{TB})$$

Here 1 ω is the weight of color features, 2 ω is the weight of texture features, F_C* represents the 72-dimensional color features, F_T* on behalf of 8-dimensional texture features. For a more precise measure of the similarity between images, usually the calculated Euclidean distance has to be normalized, because Euclidean distance range is [0, 2], normalized Euclidean distance is as follows:

$$D(A,B) = \omega_1 \frac{\sqrt{2} - D(F_{CA}, F_{CB})}{\sqrt{2}} + \omega_2 \frac{\sqrt{2} - D(F_{TA}, F_{TB})}{\sqrt{2}}$$

The feature extraction methods for the RGB and HSV based images are explained. These features are used for the further processing in the content based image retrieval techniques.

Experimental Results

The dataset provided at webdocs.cs.ualberta.ca [11] is used to test the proposed method. Experimental images cover a rich of content, including landscapes, animals, plants, monuments, transport (cars, planes) and so on. Experiments show that $\omega_1 = \omega_2 = 0.5$, with better retrieval performance. Image retrieval based on texture feature, the use of the above-mentioned method of similarity measure to calculate the texture feature distance between the sample image and the library image. According to a similar distance from small to large with the image, the smaller the distance, that is, the more similar. Two typical image retrieval examples are done by means of the RGB and HSV. The result is displayed as follows.

Figure 2. Sample image given to test both RGB and HSV

Figure 3 gives the retrieved images when the RGB color space is used. The input image given is shown in figure 2. Figure 4 shows the retrieved images when HSV color space is used. When comparing the HSV color space used CBIR with RGB method, HSV have higher performance. The time consumed by RGB to retrieve similar images is around 0.95 seconds. When using the HSV the same images are retrieved within 0.8 seconds.

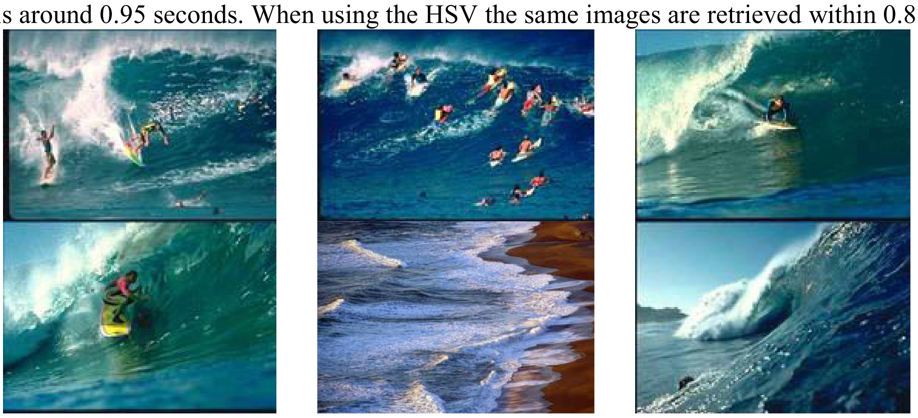

Figure 3. Retrieved images when RGB Color space is used

Figure 4. Retrieved images when HSV Color space is used

Conclusion

This paper presents an approach supported HSV color space and texture characteristics of the image retrieval and comparison with RGB color house. Through a range of statistics the experimental results will be finished that a feature extraction methodology cannot adapt to any or all the photographs. Supported the color feature, the made color images, like the sort of landscape pictures or planes, the color characteristics of the utilization of standard search colors will be the same as the image. The utilization of color and texture options of rippling rework is additional appropriate for segmentation of objects and classification of connected image from thousands of pictures. During which the retrieved pictures square measure a lot of similar once the HSV is employed and therefore the retrieval time is additionally less once scrutiny with the RGB methodology.

REFERENCES

[1] J. Feng, M. J. Li, H. J. Zhang, B. Zhang, “A unified framework for image retrieval using deyword and visual features,” IEEE Transactions on Image Processing, vol.14, no.7, 2005, pp. 979–989.
[2] Pentland, R. W. S. Picard, Sclaroff, “Photobook: Content-based manipulation of image databases,” In International Journal of Computer Vision, vol.18, no.3, 1996, pp. 233–254.
[3] Y. Rui, T. Huang, S. Mehrotra, “Content-Based image retrieval with relevance feedback in MARS, ” In Proc of the IEEE Int'1 Conf. on Image Processing, New York, vol.2, 1997, pp. 815–818.
[4] S. Sclaroff, L. Taycher, and M. La Cascia, ImageRover: A content-based image browser for the world wide web, IEEE Workshop on content-based access of image and video libraries (1997).
[5] J. Vogel and B. Schiele, On Performance Characterization and Optimization for Image Retrieval, 7th European Conference on Computer Vision, Springer, 49-63 (2002).
[6] Pentland, R. Picard, and S. Sclaroff, “Photobook: tools for content-base manipulation of image databases,” in Storage and Retrieval for Image and Video Databases II, vol. 2185, (San Jose, Califronia, USA), pp. 34–47, SPIE, February 1994.
[7] J. Wang, J. Li, G. Wiederhold, “Simplicity: Semantics-sensitive integrated matching for picture libraries,” Transactions on Pattern Analysis and Machine Intelligence, vol.23, no.9, 2001, pp.947–963.
[8] B S Manjunath, W Y Ma, “Texture feature for browsing and retrieval of image data,” IEEE Transaction on PAMI, vol.18, no.8, 1996, pp. 837–842.
[9] Y. Rui, C. Alfred, T. S. Huang, “Modified descriptor for shape representation, a practical approach,” In: Proc of First Int's workshop on Image Database and Multimedia Search, 1996.
[10] Cao Li Hua, Liu Wei, Li Guo Hui, “Research and Implementation of an Image Retrieval Algorithm Based on Multiple Dominant Colors,” Journal of Computer Research & Development, vol.36, no.1, 1999, pp.96–100.
[11] CBIR image data sets: http://webdocs.cs.ualberta.ca/~mn/CBIRone//A0004-soldiers/
[12] Ji-quan ma, “Content-Based Image Retrieval with HSV Color Space and Texture Features”, International Conference on Web Information Systems and Mining, 2009, Pp.61-63.

Lt. Dr. S. Santhosh Baboo, has around Seventeen years of postgraduate teaching experience in Computer Science, which includes Six years of administrative experience. He is a member, board of studies, in several autonomous colleges, and designs the curriculum of undergraduate and postgraduate programmes. He is a consultant for starting new courses, setting up computer labs, and recruiting lecturers for many colleges. Equipped with a Master degree in Computer Science and a Doctorate in Computer Science, he is a visiting faculty to IT companies. It is customary to see him at several national/international conferences and training programmes, both as a participant and as a resource person. He has been keenly involved in organizing training programmes for students and faculty members. His good rapport with the IT companies has been instrumental in on/off campus interviews, and has helped the post graduate students to get real time projects. He has also guided many such live projects. Lt. Dr. Santhosh Baboo has authored a commendable number of research papers in international/national Conference/journals and also guides research scholars in Computer Science. Currently he is Reader in the Postgraduate and Research department of Computer Science at Dwaraka Doss Goverdhan Doss Vaishnav College (accredited at ‘A’ grade by NAAC), one of the premier institutions in Chennai.

Sudhir Ramadass received his Bachelor Degree in Computer Science, Master Degree in Computer Applications from Bharathiar University, Coimbatore and Master of Philosophy in Computer Science from Manonmaniam Sundaranar University, Thirunelveli. He has around Eleven years of teaching experience in Computer Science & Applications. His research interest is in the field of image mining, digital image retrieval. He is currently working as Assistant Professor, Department of Computer Science, CMS College of Science & Commerce, Coimbatore, Tamilnadu, India.