Method for Searching Similar Images Using Quality Index Measurement

Chin-Chen Chang[1,2] and Tzu-Chuen Lu[2]

[1] Feng Chia University, Taichung, Taiwan, 40724, R.O.C.
ccc@cs.ccu.edu.tw
[2] National Chung Cheng University, Chiayi, Taiwan, 621, R.O.C.

Abstract. Searching for similar images is an important research topic for multimedia database management. This paper uses a quality index model to search for similar images from digital image databases. In order to speed up retrieval, the quality index model is partitioned into three factors: loss of correlation, luminance distortion, and contrast distortion. The method is performed on three different image databases to test for retrieval accuracy and category retrieval ability. The experimental results show that the proposed method performs better than the color histogram method, the color moment method, and the CDESSO method.

1 Introduction

In image processing, the most commonly used measurements for estimating the difference between two images are mean squared error (MSE), peak signal-to-noise ratio (PSNR), mean absolute error (MAE), and so on. These measurement methods are usually easy and have lower computation complexity. Nevertheless, according to Wang and Bovik's experiments, most of the methods cannot be accurately applied in strict testing conditions or in a different image distortion environment [10]. In addition, the methods require human vision to incorporate perceptual quality measurements. Therefore, Wang and Bovik proposed another image quality measurement - a universal image quality index (quality index) to estimate the difference between two images. The method was independent of images and human vision. According to their experiments, the scheme outperformed the MSE significantly. The concept of the quality index can be applied to various image processing applications. One application is used to search for similar images from an image database. Because of the rapid advance in information technology has enabled us to access a large number of images in an instant from every corner of the world. However, the huge number of images available, finding the right image from a large number of image databases is difficult. Hence, searching for images has become an important research issue [1, 4, 5, 10]. In the beginning, keywords were used to search for desired images. Each image in an image database annotated with keywords. However, annotation-based methods have become impractical and inefficient, since more and more images are generated from the Internet and most of them do not include keywords. In

R. Khosla et al. (Eds.): KES 2005, LNAI 3682, pp. 1224–1230, 2005.
© Springer-Verlag Berlin Heidelberg 2005

addition, annotation is a subjective operation in that different people may use different keywords for the same image [8]. Therefore, some researchers have developed other similarity search methods to accurately access desired images. One popular method is content-based image retrieval (CBIR), which automatically extracts features, such as color, texture, shape, moment, distance, and so on, from an image [2, 6, 7].

In this paper, we adopt the concept of the quality index to represent the features of an image for searching similar images. In addition, in order to speed up retrieval in terms of comparing the similarity between two images, the quality index is partitioned into three different factors, loss of correlation, luminance distortion, and contrast distortion. The organization of the paper is as follows. Section 2 briefly presents Chan and Liu's CDESSO image retrieval method and Wang's quality index model. Section 3 describes the proposed method in more detail. Section 5 demonstrates the experimental results, and Section 6 provides the conclusions.

2 Related Works

In 2003, Chan and Liu proposed a CDESSO-based method to characterize color complexity and color differences among adjacent pixels for 24-bit full color image retrieval [1, 3]. First, they used the K-mean algorithm to reduce the color space of an image. They divided all pixels of database images into 64 clusters. Each cluster had its own bin to record the difference between two adjacent pixels. Second, each pixel in an image was fitted into the closest cluster. Then they scanned the reduced image in spiral order and computed the difference between any two neighboring pixels. The difference is then added to the corresponding bin of the current pixel. Chen and Liu used the final 64 bins, called a color histogram, as the features to represent an image. In terms of image retrieval, the histogram of a query image was compared to all the histograms of images in the image database using the Euclidean distance. According to their experimental results, their method not only provided a high accuracy rate for finding database images, but also resisted scale variants, such as shifting and rotation, of images. The CDESSO image retrieval method, as well as other color-based CBIR methods, uses the Euclidean distance to estimate the difference between two images. However, measurements such as MSE, PSNR, and Euclidean distance cannot be accurately applied in strict testing conditions or in a different image distortion environment. Therefore, Wang and Bovik proposed a mathematically defined universal image quality index to measure the quality of an image.

The definition of Wang and Bovik's quality index model is given below. Let $\alpha = \{\alpha_i, 1 \leq i \leq N \times N\}$ be an original image of size $N \times N$, where δ_i is the i-th pixel of α and $\beta = \{\beta_i, 1 \leq i \leq N \times N\}$ is a test image of size $N \times N$. The difference between α and β is measured by

$$Q = \frac{4 \times \sigma_{\alpha\beta} \times \mu_\alpha \times \mu_\beta}{(\sigma_\alpha^2 + \sigma_\beta^2) \times (\mu_\alpha^2 + \mu_\beta^2)}, \tag{1}$$

where μ_α is the mean of α that is given by $\mu_\alpha = \frac{\sum \alpha_i}{N \times N}$, μ_β is the mean of β that is given by $\mu_\beta = \frac{\sum \beta_i}{N \times N}$, σ_α^2 is the variance of α, σ_β^2 is the variance of β, $\sigma_{\alpha\beta}$ is the correction between α and β that is given by $\sigma_{\alpha\beta} = \frac{\sum(\alpha_i - \mu_\alpha) \times \sum(\beta_i - \mu_\beta)}{N \times (N-1)}$. The range of Q is from -1 to 1. If the value of Q is close to 1, then we can say that the test image is almost the same as the original one. If the value of Q is equal to -1, then the two images are absolutely different. In the paper, we adopt the concept of quality index to search for similar images from an image database.

3 The Proposed Method

Suppose A is a digital image of size $N \times N$ in an image database. Most digital images are represented in RGB color space, such that each pixel can be interpreted as a value in the 3-dimension, red, green, and blue, color space. However, the RGB color space is unsuitable and inconvenient for image analysis. Therefore, the first step of the proposed method is to transform a 3-dimension color space into a 1-dimension gray space. Let $\alpha = \{\alpha_i, 1 \leq i \leq N \times N\}$ be the transformed image of A. Let B be a query image. The first step in searching for images similar to B from an image database is to transform B into 1-dimension gray space image $\beta = \{\beta_i, 1 \leq i \leq N \times N\}$. The next step is to use Equation 1 to calculate the quality index between β and each image α in the database. The image with the largest quality index is the image most similar to the query image. Since the range of Q is from -1 to 1, when the value of Q between β and α is 1, then we can say that images A and B are the same image. In the quality index model, the value of Q is computed using means and variances of β and α, and the correlation between β and α. The means and variances can be preprocessed independently. Nevertheless, the correlation still needs to be dynamically computed in terms of images comparison. That may requires a lot of comparison. Therefore, we recombine the formula of the quality index in Equation 1. The new formula can filter out non-matching images in advance to speed up image retrieval.

According to the definition of the quality index model, the quality index can be recombined by three factors: loss of correlation, luminance distortion, and contrast distortion. The recombined equation of the quality index is given by

$$Q = \gamma \times \ell \times \partial, \tag{2}$$

where $\gamma = \frac{\sigma_{\alpha\beta}}{\sigma_\alpha \times \sigma_\beta}$ is the correlation coefficient, $\ell = \frac{2 \times \mu_\alpha \times \mu_\beta}{\mu_\alpha^2 + \mu_\beta^2}$ is the luminance distortion, $\partial = \frac{2 \times \sigma_\alpha \times \sigma_\beta}{\sigma_\alpha^2 + \sigma_\beta^2}$ is the contrast distortion. The range of γ is from -1 to 1; the range of ℓ is from 0 to 1; and the range of ∂ is from 0 to 1. We can see that only the value of γ is concerned with each pixel of α and β. The parameters $\mu_\alpha, \mu_\beta, \sigma_\alpha, \sigma_\beta$ can be preprocessed before image comparison. Let $\theta = \ell \times \partial$ be the product of ℓ and ∂. Hence, the quality index Q can be represented by $Q = \gamma \times \theta$. Since the maximum value of γ, any value of γ would decrease the value of Q except $\gamma = 1$. Hence, we can predefine a threshold T to filter out unlikely images whose value of θ is lower than T. In other words, only the candidate image whose value of θ is greater than T needs to be compared. The features used to represent an image in an image database are mean, variance, and the set of central pixels, $C = \{\alpha_k, k \in Centralregion\}$, of the transformed image α. Since the most important objects in an image are usually located in the central region, we only record the transformed pixels in the central region of an image for further correlation coefficient analysis to save storage space.

4 Experimental Results

Two different experiments were carried out to test the performance of the proposed method. The first experiment examined the retrieval accuracy, and another examined the category query ability. Three existing programs, color histogram, color moment, and CDESSO, were used to benchmark the proposed method. All the methods were implemented on an Intel Pentium III 500 MHz PC with 256 MB Ram in Java language. The methods were tested with three image databases. The first image database contained two image sets, D_1 and Q_1. Each image set contained 410 full color animations in JPEG format with different sizes [3]. Every image in Q_1 had one corresponding image in D_1 in pairs. The second image database contained two image sets, D_2 and Q_2. Each image set contained 235 full color images with size 384×256 or 256×384 [3]. Every image in Q_2 had one corresponding image in D_2. The third image database D_3 contained 10,235 full color images, which were collected from [5, 7, 9]. The 235 images in D_2 were also embedded into D_3. Let $\|D_i\|$ and $\|Q_i\|$ be the total numbers of images in the image sets D_i and Q_i, respectively.

4.1 The Retrieval Accuracy Experiments

The first experiment tested the retrieval accuracy of the proposed method with D_1 and Q_1. The benchmark used in this experiment was the CDESSO method. We used each image in the sets Q_1 and Q_2 as the query image to retrieve N_R images from D_1 and D_2. The retrieved images were ranked according to the quality index values, which are given by Equation 4, in descending order. If the corresponding image of a query image is one of the N_R retrieved images, then we can say that the query image was accurately used to retrieve the target image. The measurement used to estimate the retrieval accuracy of a method using D_i is given by

$$R_i = \frac{C_i}{\|Q_i\|}, \tag{3}$$

where C_i is the total number of the query images in Q_i, which can be accurately used to retrieve the target image from D_i. Table 1 shows the retrieval accuracies of the CDESSO method and the proposed method using D_1 and D_2. For $N_R = 1$, the retrieval accuracies of the proposed method were 95.34% and 55.13% using Q_1 and Q_2, respectively, while the retrieval accuracies of the CDESSO method were 93.72% and 40% using Q_1 and Q_2, respectively. According to the results, as

Table 1. The retrieval accuracies from the first experiment.

	Q_1		Q_2	
N_R	CDESSO	Our's	CDESSO	Our's
$N_R = 1$	93.72	95.34	40.00	55.13
$N_R = 2$	97.09	97.67	47.23	63.68
$N_R = 3$	97.09	98.19	51.49	67.52
$N_R = 4$	97.76	98.45	52.77	68.80
$N_R = 5$	97.98	98.70	54.47	68.80
$N_R = 10$	99.33	99.48	60.43	71.37
$N_R = 20$	99.55	99.74	70.21	77.78

shown in Table 1, the proposed method would have had better retrieval accuracy than the CDESSO method using both Q_1 and Q_2.

The second experiment examined the retrieval accuracy of the proposed method with a large number of images from the image set D_3. In this example, we also used Q_2 as the query image set and retrieved N_R images from D_3. The benchmarks used in this experiment were the color histogram and the color moment methods. The experimental results are shown in Table 2.

Table 2. The retrieval accuracies from the second experiment.

Methods	$N_R \leq 10$	$N_R \leq 100$	$N_R \leq 500$	$N_R \leq 1000$	$N_R > 1000$
Color histogram	0.00	3.03	8.08	12.12	87.88
Color moment	46.46	70.71	85.86	88.89	11.11
Our method	61.80	74.68	89.27	94.85	5.58

4.2 The Category Retrieval Precision

The third experiment evaluated the categorizing ability of the proposed method. In this experiment, we formed the subset images of D_3 using ten image categories (architecture, city, dog, eagle, elephant, leopard, model, mountain, pyramid, and royal), each containing 100 images. Every image in these ten categories was used as the query images, and the corresponding images for each query image were the other images belonging to the same category. The measurement used to evaluate the precision of the category of a method is given by: $P = \frac{N_{Cr}}{N_R}$ where N_{Cr} is the number of N_R retrieved images that belong to the same category as the query image. The N_R set in this experiment was 30. Table 3 shows the experimental results of the proposed method, the color histogram, and the color moment. For the category Eagle, the number of target images found by the proposed method was 23, while no target image was found by the color histogram, and only 3 target images were found by the color moment. The corresponding precisions were 63%, 0%, and 10%, respectively. Fig. 1 shows the aggregated results over all ten categories. According to the results, we can see that our proposed scheme is indeed better than others in most cases in terms of the categorizing ability.

Table 3. The experimental results for the ten categories for $N_R = 30$.

Category	Color histogram N_{Cr}	P (%)	Color moment N_{Cr}	P (%)	Our method N_{Cr}	P (%)
Architecture	1	3	2	6	7	22
City	0	0	2	6	20	66
Dog	1	3	1	3	13	43
Eagle	0	0	3	10	23	63
Elephant	0	0	2	6	21	69
Leopard	0	0	2	6	11	35
Model	1	3	1	3	12	41
Mountain	0	0	2	6	12	39
Pyramid	0	0	2	6	10	33
Royal	1	3	2	6	13	45

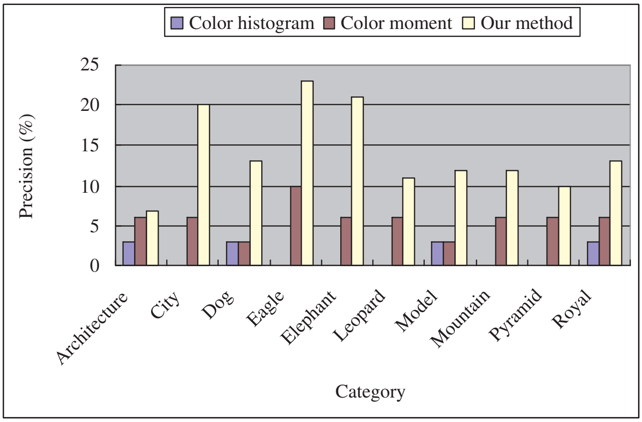

Fig. 1. Aggregated results over all ten categories.

5 Conclusions

In this paper, we proposed a method for searching for similar images based on the quality index measurement. In order to speed up image retrieval, we recombined the formula of the quality index for filtering impossible images. The proposed method was tested under different conditions to determine performance. The experiments were performed on three different databases. The results showed that the proposed method performs better than the color histogram, the color moment, and the CDESSO method, especially for retrieval of images in the city, eagle, elephant, leopard, mountain, pyramid, and royal categories. The total memory space for saving the image features of the proposed method is less than other methods.

References

1. Chang, C. C. and Chan, Y. K.: A Fast Filter for Image Retrieval Based on Color-Spatial Features. Proceedings of the Second International Workshop on Software Engineering and Multimedia Applications. **2**, Baden-Baden, Germany. (2000) 47–51
2. Chan, Y. K. and Chen, C. Y.: Image Retrieval System Based on Color-Complexity and Color-Spatial Features. Journal of Systems and Software. **71** (2004) 65–70
3. Chan, Y. K. and Liu, Y. T.: An Image Retrieval System Based on the Image Feature of Color Differences on Edges in Spiral Scan Order. International Journal on Pattern Recognition and Artificial Intelligence. **17** (2003) 1417–1429
4. Fuh, C. S., Cho, S. W. and Essig, K.: Hierarchical Color Image Region Segmentation for Content-Based Image Retrieval System. IEEE Transactions on Image Processing. **9** (2000) 156–162
5. Iqbal, Q. and Aggarwal, J. K.: CIRES- A System for Content-based Retrieval in Digital Image Libraries. Proceedings of the Seventh International Conference on Control, Automation, Robotics and Vision, Singapore. (2002) 205–210
6. Kokare, M., Chatterji, B. N. and Biswas, P. K.: Cosine-Modulated Wavelet Based Texture Features for Content-Based Image Retrieval. Pattern Recognition Letters. **25** (2004) 391–398
7. Li, J. and Wang, J. Z.: Automatic Linguistic Indexing of Pictures by a Statistical Modeling Approach. IEEE Transactions on Pattern Analysis and Machine Intelligence. **25** (2003) 1075–1088
8. Schettini, R., Ciocca, G. and Zuffi, S.: A Survey of Methods for Colour Image Indexing and Retrieval in Image Databases. Color Imaging Science: Exploiting Digital Media, (MacDonald, L. W. and Luo, M. R. Eds.), Wiley, J. & Sons Ltd., Chichester, England. (2001)
9. Wang, J. Z., Li, J. and Wiederhold, G.: SIMPLIcity: Semantics-Sensitive Integrated Matching for Picture Libraries. IEEE Transactions on Pattern Analysis and Machine Intelligence. **23** (2001) 947–963
10. Wang, Z. and Bovik, C.: A Universal Image Quality Index. IEEE Signal Processing Letters. **9** (2002) 81–84