

AN IMAGE RETRIEVAL SYSTEM BASED ON THE COLOR COMPLEXITY OF IMAGES*

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Manuscript received 28 June 2004; revised 16 April 2005
Communicated by Michael M. Richter

Abstract. The fuzzy color histogram (FCH) spreads each pixel's total membership value to all histogram bins based on their color similarity. The FCH is insensitive to quantization errors. However, the FCH can state only the global properties of an image rather than the local properties. For example, it cannot depict the color complexity of an image. To characterize the color complexity of an image, this paper presents two image features – the color variances among adjacent segments (CVAAS) and the color variances of the pixels within an identical segment (CVPWIS). Both features can explain not only the color complexity but also the principal pixel colors of an image. Experimental results show that the CVAAS and CVPWIS based image retrieval systems can provide a high accuracy rate for finding out the database images that satisfy the users' requirement. Moreover, both systems can also resist the scale variances of images as well as the shift and rotation variances of segments in images.

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Keywords: Image retrieval, color-based image retrieval, color histogram, fuzzy color histogram

1 INTRODUCTION

“Image Search Engine” is most often used of Web-based services that collect and index images from other sites on the Internet. Image searching is offered by some general search engines, like Google or Yahoo, but there are also specialized image search engines – services devoted to indexing images or multimedia. Besides, there are meta-search engines, which pass on search requests to more than one search engine and then bring back the results. “Image Search Engine” is also used to refer to collection-based search engines – services that index a single or small number of image collections.

Large digital libraries or commercial stock photo collections, like Corbis, typically offer their own search engine-like facilities. Medical images are produced in ever-increasing quantities and used for diagnostics and therapy. Cardiology is currently the second largest producer of digital images, especially with videos of cardiac catheterization. Endoscopic videos can equally produce enormous amounts of data [13].

All of these types of image search engines are text-based – their indexes are created from words associated with the images. The CBIR (content-based image retrieval) uses visual features extracted from images for indexing and querying. Content-based access to medical images for supporting clinical decision-making has been proposed that would ease the management of clinical data and scenarios for the integration of content-based access methods into picture archiving and communication systems have been created [13].

Because of their simplicity and robustness, color, texture, shape and spatial relationships [13] are frequently selected as part of the set of visual features. Various approaches have been proposed to extract different types of image features to support CBIR. Many proposed techniques provide query by color [2–5, 7–12], because of their insensitivity to noise and image resolution. Color histogram [8–10, 12] is one of the most frequently used image features in the applications of color-based image retrieval [2, 10, 16]. The advantages of color histogram include simple procedure and quick calculation. In addition, the feature is indifferent to the rotation and shift variances of segments in images. In a particular image, moving the position of its segments and rotating its segments in certain degree are separately called the shift variances and rotation variances of segments in this image. Figure 5 exactly shows the image pairs containing the rotation variances of segments, and Figure 6 demonstrates other image pairs with the shift variances of segments.

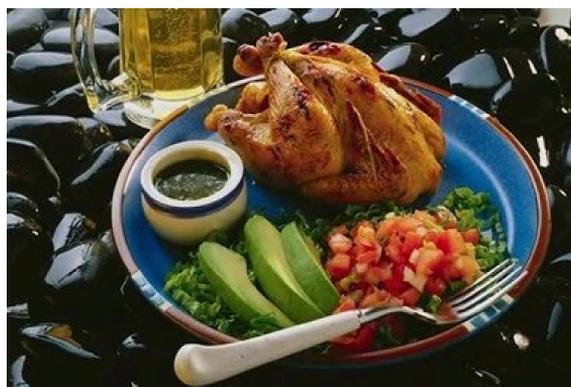
However, a conventional color histogram (CCH) [2] considers neither the color similarity across different bins nor the color dissimilarity in the same bin. Therefore, it is sensitive to quantization errors. To address these concerns, Ju et al. presented

a color histogram representation, called fuzzy color histogram (FCH) [10]. The FCH considers the similarity of each pixel's color associated to all the histogram bins through a fuzzy-set membership function [1, 6]. It computes the membership values based on a fuzzy c-means algorithm [14]. The FCH is further exploited in the application of image retrieval. The FCH is less sensitive and more robust than the conventional color histogram (CCH) on dealing with lighting intensity changes and quantization errors [10].

However, color histogram can explain only the global properties of an image rather than its local properties [9]. It cannot depict the color complexity of an image. For example, an image that depicts blue sky would have minor pixel color variations, but a multiple color image that presents scenery would have greater changes in pixel colors. We define the degree of pixels' color variations in an image as the color complexity of the image. The FCH cannot distinguish the images in Figure 1 with similar color histograms, but with different color complexities.



a)



b)

Fig. 1. Two different images with similar color histogram

In order to solve the problem above, this paper proposes two image features – CVAAS and CVPWIS. A segment is a region consisted of adjacent pixels with identical or similar colors. The CVAAS writes down the color variances among adjacent segments in an image, and the CVPWIS portrays the color variances of the pixels within identical segments in an image. Both features can characterize the principle colors and color complexity of an image, regardless of the influences from the rotation and shift variances of segments, as well as the scale variance in the image.

This paper still applies both above features to the field of image retrieval. In the CVAAS and CVPWIS based image retrieval systems, a user can input a query image into the system with a tool such as a scanner. The systems then compares the color features of database images that were previously extracted and stored in a database, with those of the query image, and then delivers the user the database images which are most similar to the query image.

The remainder of this paper is organized as follows. Next section will briefly review the FCH based image retrieval system proposed by Ju et al. [10]. Section 3 introduces both CVAAS and CVPWIS in detail. Section 4 describes the CVAAS and CVPWIS based image retrieval systems. Section 5 presents the experimental results in this paper. The conclusions will be given in the last section.

2 RELATED WORKS

Ju et al. [10] proposed a fuzzy color histogram (FCH) which associates the color similarity of each pixel's color to all the histogram bins through fuzzy-set membership function. The FCH $F(I) = [f_1, f_2, \dots, f_n]$ of an image I with N pixels can be defined as

$$f_i = \sum_{j=1}^N \mu_{ij} P_j = \frac{1}{N} \sum_{j=1}^N \mu_{ij},$$

where n is the number of color bins in the FCH; P_j is the probability of a pixel selected from image I being the j^{th} pixel; μ_{ij} ($0 \leq \mu_{ij} \leq 1$) is the membership value of the j^{th} pixel in the i^{th} color bin.

To speed up the computation, Ju et al. [10] perform fine uniform quantization in RGB color space by mapping all pixel colors to n' histogram bins. n' must be large enough so that the color difference between two adjacent bins is small enough. Then, they transform the n' colors from RGB to CIELAB color space. Finally, they classify these n' colors in CIELAB color space into n clusters by using FCM clustering technique, with each cluster representing an FCH bin.

During image retrieval, the FCH of a query image can be extracted by the above approach; then the system compares this FCH with the FCHs of all database images. The similarity between two images with the FCHs F_Q and F_T can be measured by the following formula:

$$d_E^2(F_Q, F_T) = [F_Q - F_T]_{n \times 1}^T [F_Q - F_T]_{n \times 1}.$$

Ju et al. [10] uses a fuzzy c-means (FCM) clustering algorithm [16] to compute the FCH. They employ the FCM clustering algorithm to classify the n' fine colors to n , and to compute the membership matrix at the same time. The algorithm minimizes the objective function J_m which is the weighted sum of squared errors within each group:

$$J_m(U, V; X) = \sum_{k=1}^n \sum_{i=1}^c \mu_{ik}^m \|x_k - v_i\|_A^2 \tag{1}$$

The algorithm stops when J_m is less than a given threshold ε . Here $V = [v_1, v_2, \dots, v_c]^T$ is a vector of unknown cluster prototypes, and the weighting exponent m controls the extent of membership shared by c clusters. The value of μ_{ik} represents the membership of the data point x_k from the set $X = \{x_1, x_2, \dots, x_n\}$ with respect to the i^{th} cluster, and the membership matrix is represented as $U = [\mu_{ik}]$, which satisfied:

$$\mu_{xk} \in [0, 1]; \quad \sum_{k=1}^n \mu_{xk} = 1; \quad \sum_{k \in X} \mu_{xk} > 0; \quad 1 \leq k \leq n; \quad x \in X \tag{2}$$

Ju et al. [10] use the following algorithm *Fuzzy-C-Means* to compute the approximate solutions of equations (1) and (2):

Algorithm Fuzzy-C-Means()

- Step 1)** Input c , m , and ε .
- Step 2)** Initialize the cluster centers v_i , for $1 \leq i \leq c$.
- Step 3)** Input data $X = \{x_1, x_2, \dots, x_n\}$.
- Step 4)** Calculate the c cluster centers $\{v_i^{(l)}\}$ by

$$v_i = \frac{\sum_{k=1}^n (\mu_{ik})^m x_k}{\sum_{k=1}^n (\mu_{ik})^m}$$

- Step 5)** Update $U^{(l)}$ by

$$\mu_{ik}^{(l)} = \frac{1}{\sum_{j=1}^c \left(\frac{\|x_k - v_i\|^2}{\|x_k - v_j\|^2} \right)^{\frac{1}{m-1}}}, \text{ for } 1 \leq i \leq c \text{ and } 1 \leq k \leq n.$$

- Step 6)** If $\|U^{(l)} - U^{(l-1)}\| > \varepsilon$, $l = l + 1$, and go to Step 4; otherwise, stop.

3 THE CVAAS AND CVPWIS FEATURES

In a full color image, a pixel color is generally described by a 24-bits memory space, so there are a total of 2^{24} different possible pixel color values. In the real world, there

are a lot of images containing a group of large regions with a uniform color when the pixel colors of the images are quantized down to a small subset of representative colors. Especially, many synthesized images like trademarks, cartoons, and flags possess this property.

Segmentation of objects is very important for extracting the shape attributes of an image [11]. However, extracting objects from an image is very difficult because of discretization, occlusions, poor contrasts, viewing conditions, noises, etc. [11]. An image with a limited color palette is generally composed of a set of unicolor regions. In this case, the segmentation of unicolor regions is less difficult and always possible. Figure 2b) shows the segments A , B , C , and D on the image in Figure 2a). In this paper, we call each unicolor region a segment. Figure 2b) shows the segments A , B , C , and D contained on the image in Figure 2a).

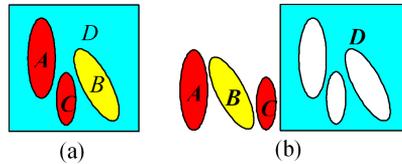


Fig. 2. A color image and its segments

Before extracting the CVAAS and CVPWIS of an image, all the pixels of the database images are categorized into k clusters by using the K-means algorithm [15] according to the similarity of their colors. The mean of all the pixel colors in each cluster is considered to be one color value in a color palette. In order to make image matching easier, the color palette containing the k different colors is used as the common color palette CP for all images.

To extract the CVAAS and CVPWIS of an image I , each pixel color C in I is replaced by one color in CP that is most similar to C so as to create an image I' , which is as large as I and uses the k colors in CP as possible. This image I' is called the color-reducing image of I .

For each color C_h in CP , two corresponding variables a_h and w_h are calculated during a scanning process that starts at the top-left pixel of the image I' in the order from left to right and top to bottom. Let $P'_{i,j}$ be one of pixels in I' , and let $P_{i,j}$ be its corresponding pixel in I . Here, (i, j) are the coordinates of $P'_{i,j}$ and $P_{i,j}$ on I' and I , respectively; $C'_{i,j}$ and $C_{i,j}$ are the pixel colors of $P'_{i,j}$ and $P_{i,j}$, respectively. For the CVAAS, during the scanning process, a color difference d is computed for each currently scanned pixel $P'_{l,m}$, and d is added to the variable a_h which $C'_{l,m}$ corresponds to. d can be calculated by the following statements:

$$\begin{aligned} &\text{for } (i, j) = (l, m + 1), (l + 1, m + 1), (l + 1, m), \text{ and } (l + 1, m - 1) \\ &\text{if } (C'_{l,m} \neq C'_{i,j}) \text{ then} \\ &\quad d = d + \sqrt{(R_{l,m} - R_{i,j})^2 + (G_{l,m} - G_{i,j})^2 + (B_{l,m} - B_{i,j})^2} \end{aligned}$$

Here, $(R_{l,m}, G_{l,m}, B_{l,m})$ and $(R_{i,j}, G_{i,j}, B_{i,j})$ represent the three color components R, G, and B in $C_{l,m}$ and $C_{i,j}$. By repeating the above procedure till the end, the values of the k variables (a_1, a_2, \dots, a_k) are the CVAAS of I ; each a_h maps to one certain color in CP .

For the CVPWIS, a color difference d' is similarly calculated for each currently scanned pixel $P'_{l,m}$; then d' would be added to the variable w_h to which $C'_{h,k}$ corresponds. Here d' can be obtained by executing the following statements:

$$\begin{aligned} &\text{for } (i, j) = (l, m + 1), (l + 1, m + 1), (l + 1, m), \text{ and } (l + 1, m - 1) \\ &\text{if } (C'_{h,k} \neq C'_{i,j}) \text{ then} \\ &\quad d' = d' + \sqrt{(R_{l,m} - R_{i,j})^2 + (G_{l,m} - G_{i,j})^2 + (B_{l,m} - B_{i,j})^2} \end{aligned}$$

Finally, the values of the k variables (w_1, w_2, \dots, w_k) are the CVPWIS of I .

When using a tool like a scanner to input an image, the image may be enlarged or shrunk because of different scanner resolution setups. We call this phenomenon the scale variance of images. The image pair in Figure 4 shows the scale variance images. Let I be an image with $H \times W$ pixels. To remedy the problem of scale variances, this paper divides each variable a_i by $H + W$, and each variable w_i by $H \times W$. Hence, the features CVAAS and CVPWIS are very robust with respect to scale variant images.

The proposed CVAAS and CVPWIS belong to the color histogram, too. The CVAAS is the histogram of the gaps among the colors of adjacent segments in the image I ; the CVPWIS is the histogram of the color differences of the pixels within identical segments. Both features can state the principle colors of I as well. Besides, they are insensitive to the shift and rotation variances of segments in images.

Since sketching the color discrepancy among adjacent segments in an image, the CVAAS can distinguish the segments with inconsistent contours. The CVPWIS can delineate the color variances within identical segments in an image. The CVPWIS can characterize the textures of segments in an image. Thus, the two features can interpret different kinds of color complexities of an image.

4 THE CVAAS AND CVPWIS BASED IMAGE RETRIEVAL SYSTEMS

The CVAAS and CVPWIS can state not only the principle pixel colors, but also the color complexities among or within segments, or in an image. The CVAAS can detect the discrepancies in the contours of the segments, and the CVPWIS can perceive the differences of textures in images. This paper uses these two features to develop two image retrieval systems, which are called CVAAS and CVPWIS based image retrieval systems. In these systems, a user may input a query image into the system with a tool such as a scanner. The systems find out the database images that have the minimal image matching distances with the query image, and then deliver them to the user.

Let $(a_1^q, a_2^q, \dots, a_k^q)$ and $(a_1^d, a_2^d, \dots, a_k^d)$ be the CVAASs of the query image Q and a certain database image D . The CVAAS based image retrieval system defines the image matching distance D_{CVAAS} between Q and D as follows:

$$D_{CVAAS} = \sum_{i=1}^k |a_i^q - a_i^d|.$$

The smaller the value of D_{CVAAS} , the more similar Q is to D . Finally, the system delivers those images from the database which have the lowest D_{CVAAS} values.

Consider the CVPWISs $(w_1^q, w_2^q, \dots, w_k^q)$ and $(w_1^d, w_2^d, \dots, w_k^d)$ of the query image Q and the database image D . Similarly, the CVAAS based image retrieval system computes the image matching distance D_{CVPWIS} between Q and D by the following formula:

$$D_{CVPWIS} = \sum_{i=1}^k |w_i^q - w_i^d|.$$

The CVAAS and CVPWIS can tell not only the principle colors of an image, which the FCH can describe, but also the color complexities of the image. Since the CVAAS and CVPWIS explain more properties than the FCH does, the CVAAS and CVPWIS based image retrieval systems can provide a greater capacity to recognize similar images.

5 EXPERIMENTS

The aims of this section are to investigate the performances of the CVAAS and CVPWIS based image retrieval systems, and to compare them with those of the FCH based image retrieval system. $Set_D = \{I_1, I_2, \dots, I_{500}\}$ and $Set_Q = \{I'_1, I'_2, \dots, I'_{500}\}$ are two image sets, each of which contains 500 full color images. They are used as the testing images in this paper. The images in Set_D are the database images, while those in Set_Q are the query images. Some parts of them are drawn out from animations, where this paper selects out one image pair (I_i, I'_i) from each animation. Most of the animations are downloaded from the websites <http://www.mcsh.kh.edu.tw> and <http://co25.mi.com.tw>. Some other images are downloaded from <http://wang.ist.su.du/IMAGE>. The rest are the copies acquired from natural images and trademark images by using a scanner.

In these experiments, each time an image I'_i would be used as the query image. During image retrieval, the system would respond to the user L database images whose image matching distances to I'_i are the shortest. If I_i is one of the L database images, we say the system finds out the desired image correctly. Otherwise, the system is considered to have failed to find out the desired image.

In these experiments, the FCH system performs the fine uniform quantization in RGB color space by distributing all pixel colors among 4096 histogram bins; then it transforms the 4096 colors from RGB to CIELAB color space. Finally, these

4096 colors in CIELAB color space are classified into 64 clusters by using FCM clustering technique, where $m = 1.9$.

On the average, the total time to execute the 500 queries is 42.67 seconds for the FCH based image retrieval system, 28.89 seconds for the CVAAS based image retrieval system, and 27.53 seconds for the CVPWIS based image retrieval system in these experiments. The FCH, CVAAS, and CVPWIS of an image separately include 64 dimensions, each with 4 bytes memory space. Hence, the memory space required to hold the whole image features of all the database images for the CVAAS and CVPWIS based image retrieval systems are 128 000 bytes. For the FCH, in the fine uniform quantization, all pixel colors are mapped to 4 096 histogram bins, and every histogram bin is classified into 64 clusters, each of which takes up a 4-bytes memory space. The FCH based image retrieval system needs to save this extra space. Therefore, the memory space required to keep the whole image features of the database images for FCH based image retrieval system is 1 176 576 bytes. Table 1 shows the accuracy rate of finding out the desired database images.

L	FCH	CVPWIO	CVAAS
1	79.0%	96.4%	95.0%
2	82.2%	98.0%	97.4%
3	84.4%	98.2%	98.6%
4	85.0%	98.4%	98.8%
5	86.0%	98.6%	99.0%

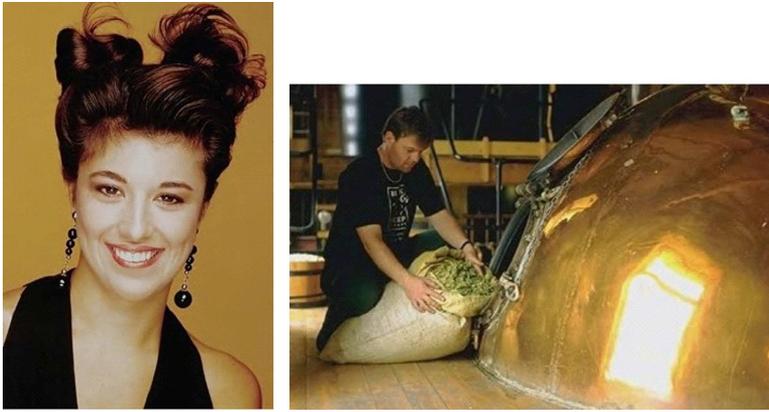
Table 1. The accuracy rates of the experiments

The experimental results indicate that the proposed CVAAS and CVPWIS based image retrieval systems indeed excel the FCH based image retrieval system in the aspects such as accuracy rate of finding out the desired images, memory space required to hoard the features of all the database images, and retrieving time.

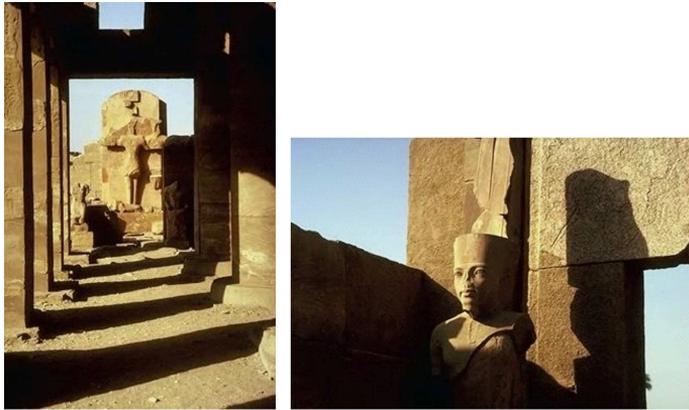
Since the FCH, CVAAS, and CVPWIS belong to color histogram, the image retrieval systems on the basis of these features can display the principal pixels' colors of an image. For instance, all of them regard the image pairs in Figure 3, which have the same shapes of pixel colors as the similar images. These three systems can still resist the scale variance of images, as well as the shift and rotation variances of the segments in images. Take the image pairs in Figures 4–6 as an example; they, respectively, consider each of the image pairs to be similar.

However, the FCH based image retrieval system cannot distinguish the color complexities of images. The images of each group in Figure 7 have similar color histograms, but differ in their color complexities, such as contours and textures. The FCH based image retrieval system cannot differentiate the images in each image group; however, the CVAAS and CVPWIS based image retrieval systems do well.

The FCH based image retrieval system is sensitive to the lightness variances of images. It even considers each image pair with slight lightness variance in Figure 8 as dissimilar images. However, both the CVAAS and CVPWIS based image retrieval systems view each image pair in Figure 8 as similar images. The CVAAS based



a)



b)

Fig. 3. Two image pairs with similar color histograms

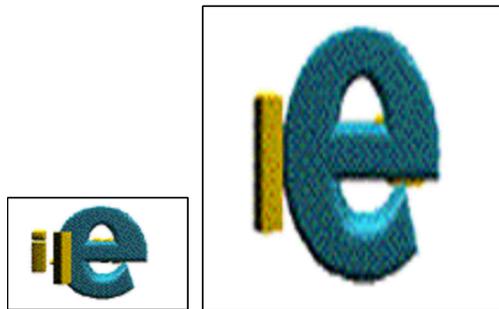


Fig. 4. Two scale variant images

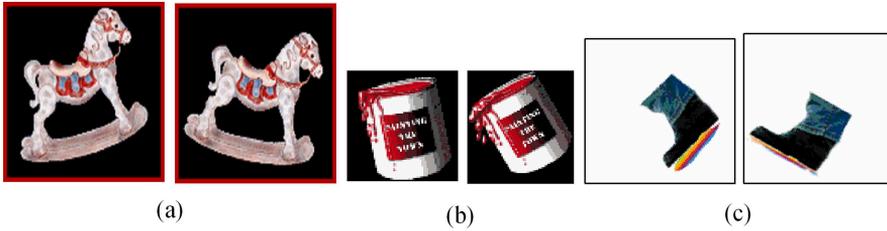


Fig. 5. Three image pairs with rotation variances of objects

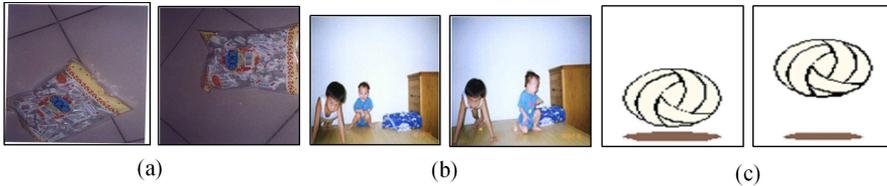


Fig. 6. Three image pairs with shift variances of objects

image retrieval systems still see the images of each image pairs in Figure 9 alike which are the lightness variant images but have the same segment contours.

Each image pair in Figure 10 owns similar contour and texture but distinct hue variances. The CVAAS and FCH based image retrieval systems see each pair of them as diverse images. In addition, since the image pairs in Figure 11 have homologous textures but different contours, the CVAAS based image retrieval system considers each of the image pairs to be unlike. However, the CVPWIS based image retrieval system regards each of the image pairs in Figures 10 and 11 as similar images.

When an image has a great number of noises added, its textures may be changed significantly. Hence, the CVPWIS based image retrieval system is susceptible to the noise variance in images. For example, the image pair in Figure 12 are regarded as similar images in the CVAAS based image retrieval system, but not in the CVPWIS based image retrieval system. Besides, the CVAAS can discriminate the contour variances of segments in images. Thus, the CVAAS based image retrieval system can recognize each of the image pairs in Figure 13 as resembling images; nevertheless, the CVPWIS and FCH based image retrieval systems see them unlike.

6 CONCLUSIONS

This paper presents two image features – CVAAS and CVPWIS. Both features can characterize not only the principle colors of images, but also the color complexities. The CVAAS tells the color variations among adjacent segments in an image. The CVAAS based image retrieval system can discriminate the images with different segment contours. The CVPWIS sketches the color variations of the pixels within

identical segments. One can tell two segments with distinct textures apart by their CVPWISs.



a)



b)



c)



Fig. 7. Some other image groups with similar color histograms

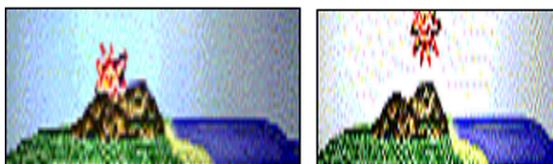
Furthermore, both features are indifferent to scale variance of images, as well as to shift and rotation variances of segments. In this paper, the experimental results demonstrate that the CVAAS and CVPWIS based image retrieval systems are better than the FCH based image retrieval system in the aspects such as the accuracy rate of finding out the desired images, the memory space required to store the features of all the database images, and the image retrieving time.



a)



b)



c)

Fig. 8. Three image pairs with slight lightness variances

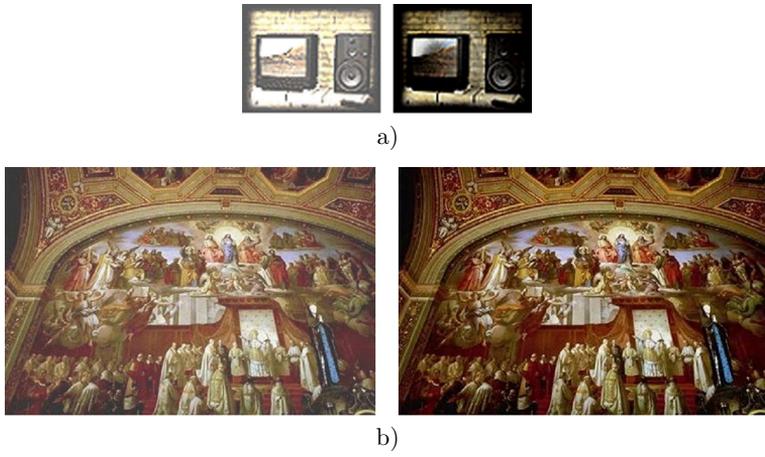


Fig. 9. Two image pairs with large lightness variance

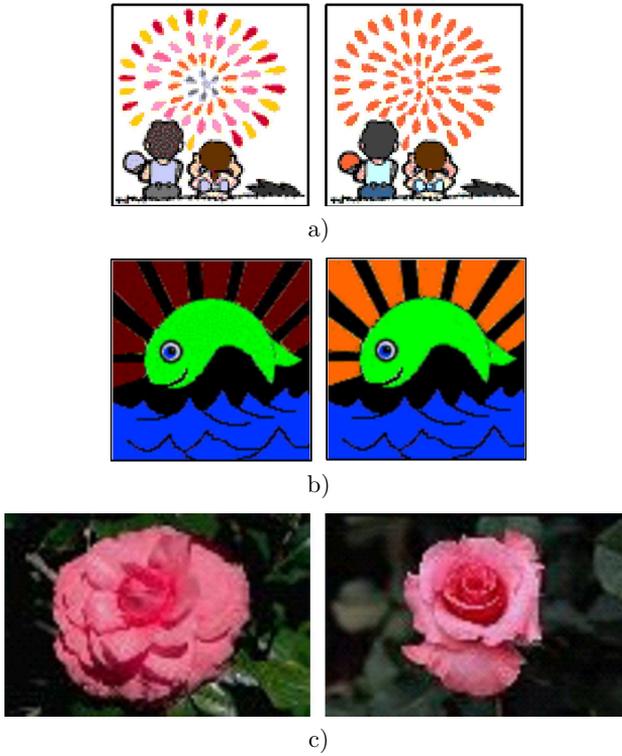


Fig. 10. Three image pairs with different hues but with similar textures

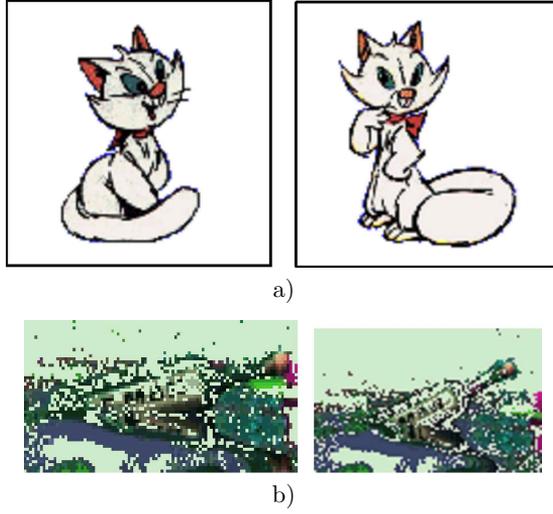


Fig. 11. Two image pairs with different contours but with similar textures

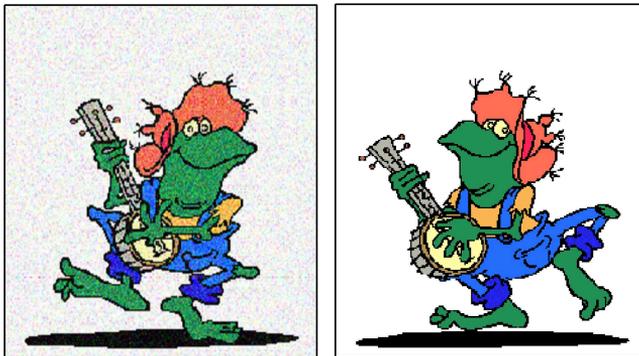


Fig. 12. Two images with noise variance

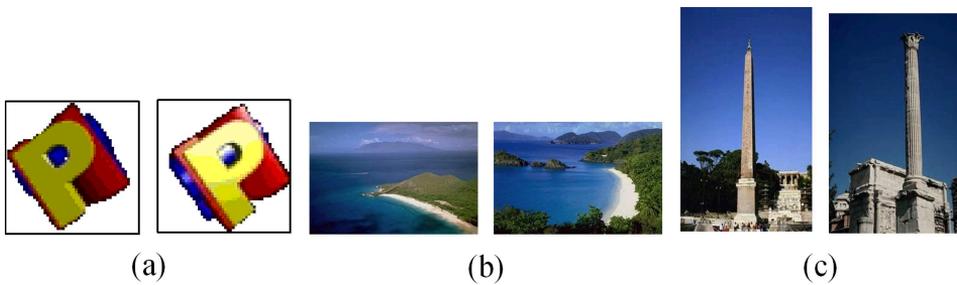


Fig. 13. Three image pairs with similar contours but with different textures

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