

## FLAGS RETRIEVAL USING COLOR STRINGS

CHIUNHSIUN LIN<sup>1,\*</sup>, HSUAN SHU HUANG<sup>2</sup> AND KUO-CHIN FAN<sup>2</sup>

<sup>1</sup>National Taipei University

No. 69, Sec. 2, Chian\_Kwo N. Road, Taipei 10433, Taiwan

\*Corresponding author: 2010allpass@gmail.com

<sup>2</sup>Department of Computer Science and Information Engineering

National Central University

Chung-Li 32054, Taiwan

Received November 2012; revised March 2013

**ABSTRACT.** *The difference between a content-based flag image system and a text-based flag image retrieval system is the capability that the previous one can rank flag images by the degree of similarity between the query flag image and flag images in the database, namely similarity-based retrieval. Conversely, a text-based flag image retrieval system is based on precise match. Our flags retrieval scheme is developed to retrieve flags efficiently. Firstly, we transfer each flag to a color string using only 8 rules automatically. Secondly, we utilize the color strings for comparing the flags, namely color strings comparison (CSC). Our system offers both advantages of the content-based flags retrieval system (similarity-based retrieval) and a text-based flags retrieval one (very rapid and mature). The major differences between our proposed method and existing ones are shown as follows. 1) We consider the spatial information (our color strings comparison is permutation comparison). Most color quantization-based methods are combination comparison. 2) We resized the images to 20\*20 pixels. Therefore, our approach can handle diverse sizes, defocus and noise problems. 3) We adopt the concept of the relative relation of RGB. Consequently, our system can deal with dissimilar lighting conditions, partial occlusion, and various color saturation at the same time. We succeed in transferring the flags retrieval problem to the strings comparison. 4) We create a bridge between a content-based retrieval system and a text-based retrieval one. Therefore, the content-based flags retrieval system becomes an analogous text-based retrieval system. Thus, the computational complexity is decreased significantly.*

**Keywords:** Contents-based flags retrieval (CBFR), Content-based images retrieval (CBIR), Rule-based approach, Color strings comparison (CSC)

**1. Introduction.** Since the digital images increase very speedily, various systems for storing, browsing, searching, and retrieving images have been presented in the past 20 years. It would be impossible to cope with the rise of the World Wide Web and the spread of digital information unless those data could be retrieved efficiently. An images retrieval system is a computer system for browsing, searching and retrieving images from a huge database. Unfortunately, most images retrieval methods now are only text-based methods. The traditional methods of images retrieval utilize some processes of adding metadata, such as captioning, keywords, or descriptions to the images. Consequently, retrieval can be performed over the annotation words. In other words, the text-based retrieval techniques can only retrieve the images that are well-annotated. The images without well-annotation make them incapable of being retrieved. Moreover, manual images annotation is time-consuming, laborious and expensive. Enormous images are stored in digital format now and can only be searched by keywords on the World Wide Web (e.g., Google or Yahoo) as shown in Figure 1. Hence, content-based retrieval approach instead of text-based retrieval

one plays a very important role in multimedia system. For a state-of-the-art review, please see [1,3,16,18,20]. We can classify CBIR systems into two types according to the techniques. 1) Global-based category: all features are obtained from the entire image. Many global-based approaches are utilized in the literature, e.g., gray level histograms [21], average intensity measures [11], pair-wise comparisons [26], and color histograms [8]. However, most global-based methods fail in the various lighting conditions, the partial occlusion, the defocus and noise problems, and the diverse color saturation. Furthermore, images with totally dissimilar spatial outline cannot be considered differently. These are the common shortcomings for global-features based techniques. For more information, please see [6,12-15,17]. 2) Region-based category: the image is divided into segments and then the features are extracted from each segment. Numerous region-based techniques are utilized in the literature, e.g., region-based color histograms [5], segmenting the focused region [25], the SIMPLIcity system [24]. Regions are characterized by color, texture, shape, and location. However, most region-based methods also fail in the various lighting conditions, the partial occlusion, the defocus and noise problems, and the diverse color saturation. For more information, please see [2,4,7,9,19,22,23]. Although color plays a very significant role in the most CBIR systems, the potential of color is not yet completely employed. For example, if the illumination is dissimilar between the query images and the images in the database, the retrieval problem will happen. Most previous CBIR systems cannot consider the different sizes, the various color saturation, the dissimilar illumination conditions, the defocus and noise problems, the partial occlusion, and the spatial information at the same time. In our investigation, we present a flags retrieval system that can handle above-mentioned problems at the same time. The overview of our system is shown in Figure 2. The designed system contains three phases. Firstly, we resize all flag images to decrease the effects of variation in size, and expedite the speed. Secondly, we convert each flag to a color string. Finally, we compare each element of  $str1$  to the same position element in  $str2$  ( $str1$  is the color string of the query flag image and  $str2$  is the color string of one flag image in the database), and return the matching

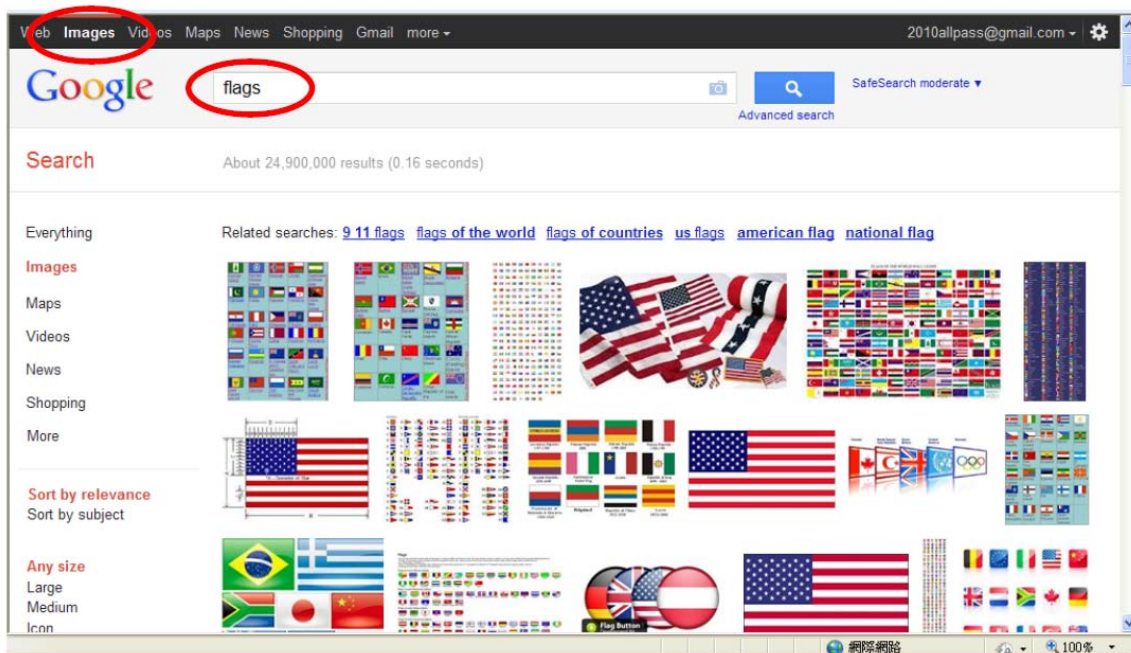


FIGURE 1. Searching by keywords (e.g., flags) on the World Wide Web in Google, and the results

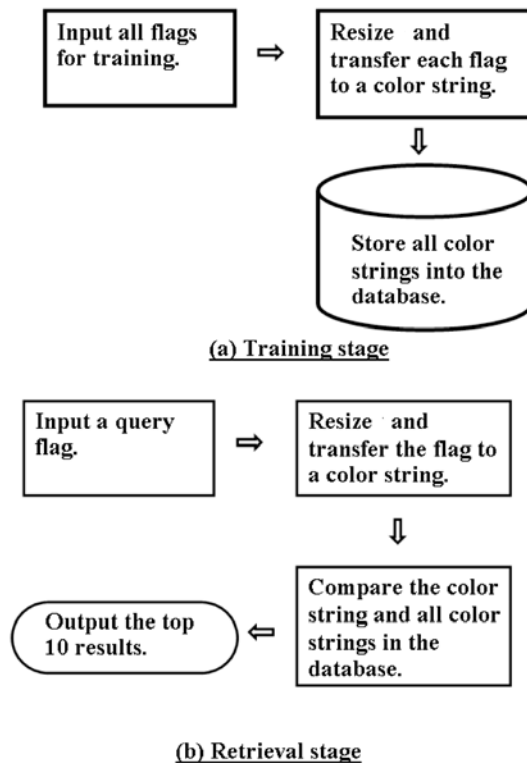


FIGURE 2. Overview of our system

weight. Then, we compare each element of  $str1$  to the same position element in  $str3$  ( $str3$  is another color string of another flag image in the database), and so on. The rest of the paper is organized as follows. In Section 2, color string coding and color strings comparison are illustrated. Experimental results and discussions are demonstrated in Section 3. Finally, conclusions and future work are given in Section 4.

**2. Color String Coding and Strings Comparison.** The leading principle for our approach is simplicity and speed. Since the flags are allowed having different sizes, all flags are normalized to a standard size (i.e.,  $20 \times 20$  pixels) in the first step. Since resizing will lose some information of flags, it can get the power of toleration of the different sizes, the defocus and noise problems, and expedite the speed. In other words, losing some information is sometimes helpful for content-based flags retrieval system. Otherwise, the template matching should become the best approach to retrieve images. Therefore, all flags are resized by the bicubic interpolation technique. In mathematics, bicubic interpolation is an extension of cubic interpolation for interpolating data points on a two dimensional regular grid. The interpolated surface is smoother than corresponding surfaces obtained by bilinear interpolation or nearest-neighbor interpolation. Bicubic interpolation can be accomplished using “Lagrange polynomials”, “cubic splines”, or “cubic convolution algorithm”. In image processing, bicubic interpolation is often chosen over bilinear interpolation or nearest neighbor in image resampling, when speed is not an issue. Images resampled with bicubic interpolation are smoother and have fewer interpolation artifacts. For more information, please see Gonzalez and Woods [10].

**2.1. Color string coding.** Since RGB color space is a 3-dimensional vector space, and each pixel,  $p(i)$ , is defined by an ordered triple of red, green, and blue coordinates,  $(r(i), g(i), b(i))$ , which represent the intensities of red, green and blue light color respectively. We realize that the values of  $r$ ,  $g$  and  $b$  are totally different with the altered

illumination conditions and diverse color saturations. However, the relative values between  $r(i)$ ,  $g(i)$  and  $b(i)$  are very similar. Therefore, we can utilize the relative values between  $r(i)$ ,  $g(i)$  and  $b(i)$  to transfer each image to a color string for overcoming the altered illumination conditions and diverse color saturations. The 8 rules are listed as below.

- (1) If a pixel  $235 \leq r(i) \leq 255$ ,  $235 \leq g(i) \leq 255$ , and  $235 \leq b(i) \leq 255$ , then assign the pixel as ‘W’; (Pure white color)
- (2) If a pixel  $0 \leq r(i) \leq 20$ ,  $0 \leq g(i) \leq 20$ , and  $0 \leq b(i) \leq 20$ , then assign the pixel as ‘K’; (Pure black color)
- (3) If a pixel  $r(i) > g(i) \geq b(i)$ , then assign the pixel as ‘R’; (the first series of “Red” colors)
- (4) If a pixel  $r(i) \geq b(i) > g(i)$ , then assign the pixel as ‘S’; (the second series of “Red” colors)
- (5) If a pixel  $g(i) > r(i) \geq b(i)$ , then assign the pixel as ‘G’; (the first series of “Green” colors)
- (6) If a pixel  $g(i) \geq b(i) > r(i)$ , then assign the pixel as ‘H’; (the second series of “Green” colors)
- (7) If a pixel  $b(i) > r(i) \geq g(i)$ , then assign the pixel as ‘B’; (the first series of “Blue” colors)
- (8) If a pixel  $b(i) \geq g(i) \geq r(i)$ , then assign the pixel as ‘C’; (the second series of “Blue” colors)

Since 400 characters present  $8^{400}$  ( $= 2^{1200}$ ) permutations, we can realize the power of discrimination between different flags should be enough. An example demonstrates the  $20 \times 20$  pixels 32 bits color map, and its color string [We use purple color letter “W” instead of white color letter “W” to be able to be seen clearly by readers.] is shown as Figure 3. We can observe the “R” and “S” present two series of red colors, the “G” and “H” show the two series of green colors, and the “B” and “C” demonstrate two series of blue colors. The “W” represents the pure white color, and the “K” represents the pure black color respectively. An instance illustrates how to obtain a 2D color string is shown

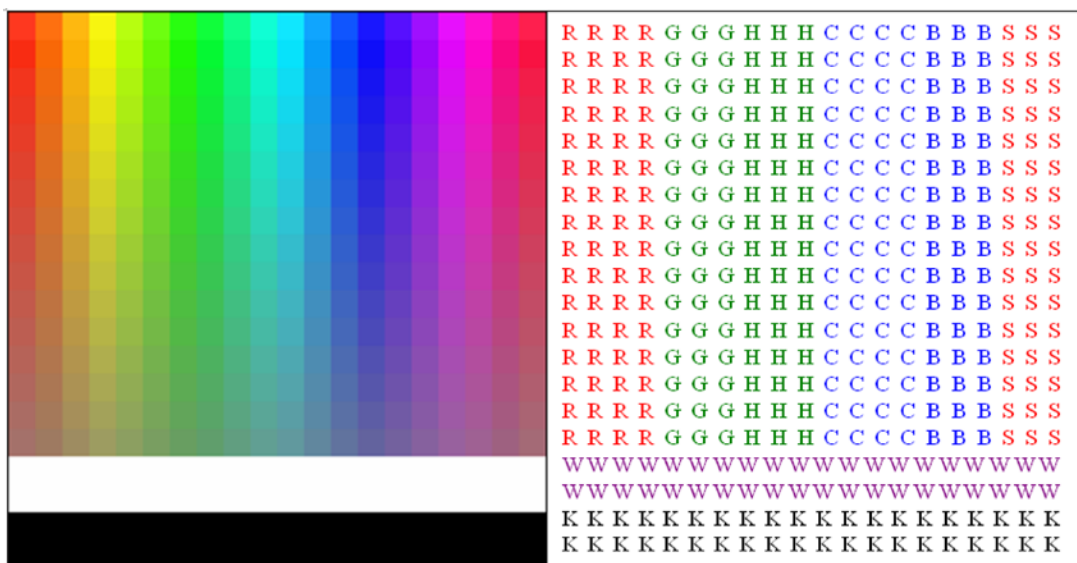


FIGURE 3. The 32 bits color map with the size of  $20 \times 20$  pixels, and its color code [We use purple color word (e.g., W) instead of white color to be seen clearly by readers.]

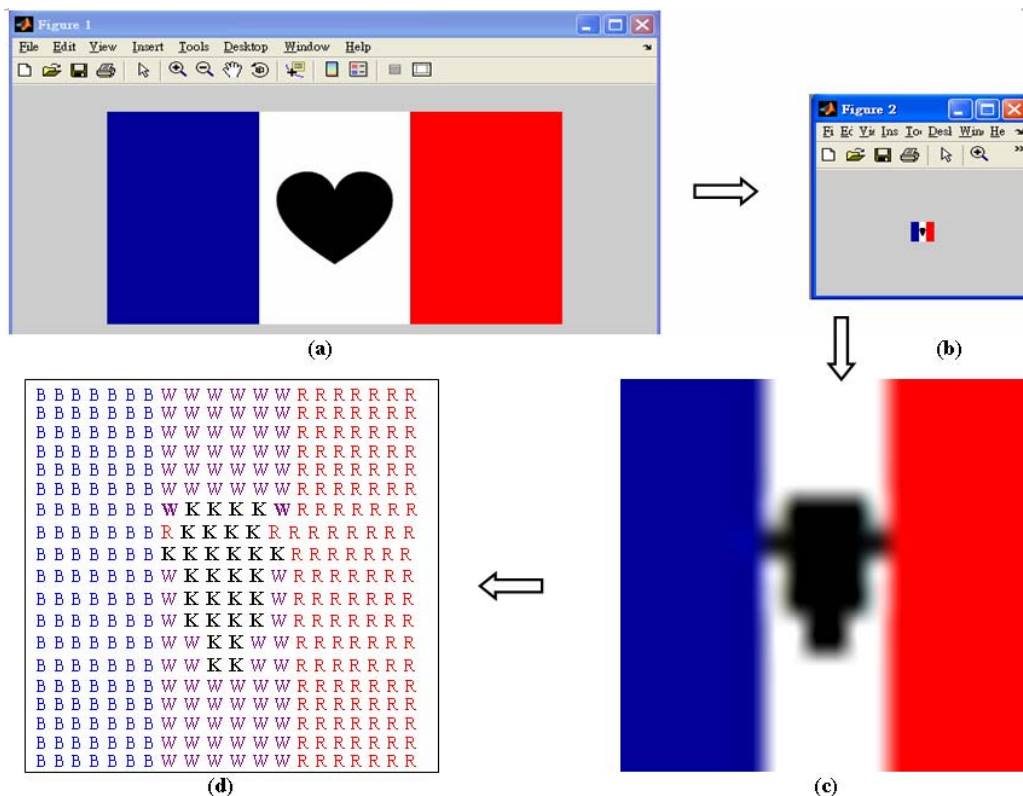


FIGURE 4. (a) An original flag (352 × 240 pixels); (b) resized flag (20 × 20 pixels); (c) resize the 20 × 20 pixels flag to 322 × 322 pixels to be seen clearly by readers; (d) transfer the resized flag (20 × 20 pixels) to a 2D color string array. From the 2D color string array, you can see the layout of the flag.

as Figure 4. Since the 8 rules as above, we can obtain the impression of the characters “B” presenting a series of blue colors. For instance, we can see the blue color in the flag that is transferred to “B” (the first series of “blue” colors) and the red color in the flag that is transferred to “R” (the first series of “Red” colors) as demonstrated as Figure 4. Subsequently, each flag will become a 2D color string array, and then we will convert the 2D color string array to a 1D color string as below.

KKKKKKKKBBBBBBBWWRRRRR...BBBBBBBWWWWWRRRRRRRKKKKK

**2.2. Color strings comparison.** In mathematics, string comparison (also known as similarity comparison) is a class of text-based comparison resulting in a similarity score between two strings. For example, the strings of “teach” and “teacher” can be considered to be similar.

After we obtain the 1D color string, firstly, we compare each element of str1 to the same position element in str2 (str1 is the color string of the query flag image and str2 is the color string of one flag image in the database), and return the matching weight. Then, we compare each element of str1 to the same position element in str3 (str3 is another color string of another flag image in the database), and so on. If the same location character is the same one (e.g., both are “C”), we will increase 1 to the matching weight. If the same location character is not the same one (e.g., one is “C”, and the other is “R”), we will increase 0 to the matching weight. For example, if two flag images are the same one, the matching weight is 400. If the matching weight is 400, the distance is 0. The more similar flags should have higher matching weight and lower distance.

**3. Experiment Results and Discussions.** The experimental database contains 30,000 flags that are taken from Internet mostly (about 90%). Since it is very difficult to find enough similar flags with dissimilar illumination conditions different color saturation, blur, noise and partial occlusion, we add these conditions to the flags using Photoshop 7.0.1. LP denotes “increase light to the flags”, and we raise 10% light each time. SM symbolizes “reduce light to the flags”, and we decrease 10% light each time. Therefore, the light is from  $-40\%$  to  $+40\%$ . SP denotes “increase color saturation to the flags”, and we raise 10% color saturation each time. SM symbolizes “reduce color saturation to the flags”, and we decrease 10% color saturation each time. Therefore, the color saturation is from  $-40\%$  to  $+40\%$ . BP presents “raise blur the flags”, and we increase 5% blur each time. Therefore, the blurred condition is from 0% to  $+45\%$ . NP implies “raise noise to the flags”, and we increase 10% salt-and-pepper noise each time. Therefore, the salt-and-pepper noise is from 0% to  $+100\%$ . OC presents “the partial occlusion of the flags”, and we amplify about 5% occlusions each time. Therefore, the partial occlusion of the flags is from 0% to 45%. Therefore, in our database, we collect flags with noise, blurred, partial occlusion, different sizes, dissimilar illumination conditions, and diverse color saturations.

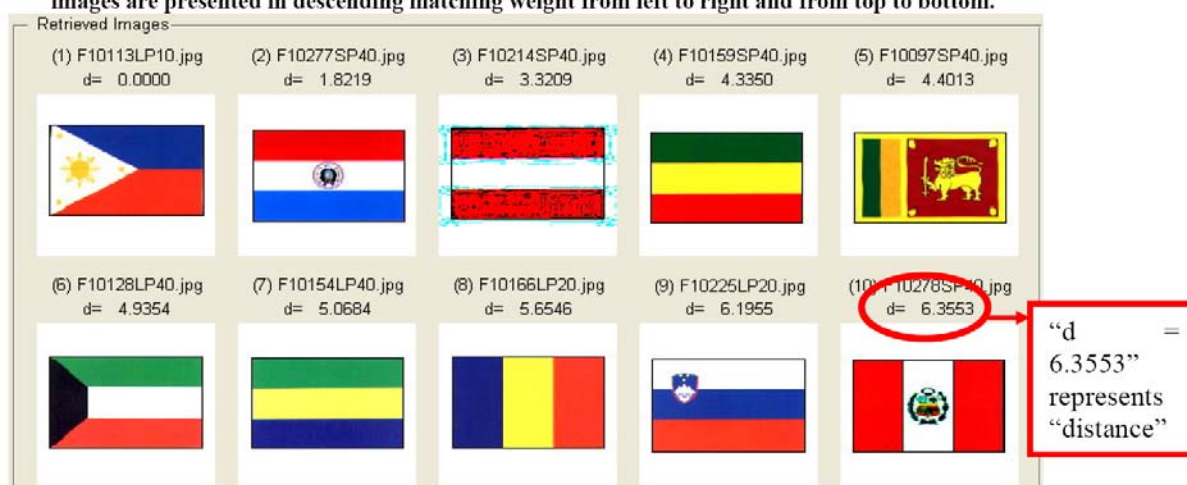
Furthermore, we compare our new system with R. P. Kumar’s system [15] and K. Konstantinidis’s approach [27]. The R. P. Kumar’s system proposed a methodology based on regression line features for further reducing the computational complexity of these multiresolution histogram based techniques. The details can be found in [15]. The K. Konstantinidis’s approach presented a fuzzy linking method of color histogram creation that is based on the  $L^*a^*b^*$  color space and provides a histogram which contains only 10 bins. The histogram creation method in hand was assessed based on the performances achieved in retrieving similar images from a widely diverse image collection. Their method is claimed less sensitive to various changes in the images (such as lighting variations, occlusions and noise) than other methods of histogram creation. The details can be found in [27].

The first example is shown as Figure 5. Figure 5(a) exhibits our approach is perfect in various illumination conditions. Figure 5(b) R. P. Kumar’s system and Figure 5(c) K. Konstantinidis’s method demonstrate their systems do not work very well for various lighting circumstances. The second illustration is displayed as Figure 6. Figure 6(a) illustrates ours is ideal for various color saturation circumstances. Figure 6(b) R. P. Kumar’s system and Figure 6(c) K. Konstantinidis’s method display their systems are not spotless for different color saturation situations. The third exhibition is displayed as Figure 7. Figure 7(a) exhibits ours is outstanding in blurred situations. Figure 7(b) R. P. Kumar’s system and Figure 7(c) K. Konstantinidis’s method demonstrate their systems are incomplete in blurred circumstances. The fourth exposition is demonstrated as Figure 8. Figure 8(a) displays ours is wonderful in noise conditions. Figure 8(b) R. P. Kumar’s system and Figure 8(c) K. Konstantinidis’s method demonstrate their systems are inadequate in noise circumstances. The fifth show is exhibited as Figure 9. Figure 9(a) shows ours is marvelous in partial occlusion situations. Figure 9(b) R. P. Kumar’s system and Figure 9(c) K. Konstantinidis’s method exhibit their systems are not good enough in partial occlusion circumstances.

From the 15 examples, the R. P. Kumar’s system has 32 faults from 50 retrieval results, and the K. Konstantinidis’s method has 19 faults from 50 retrieval results. On the other hand, ours has 0 faults from 50 retrieval results. Therefore, we can profess our new system is superior to R. P. Kumar’s system and the K. Konstantinidis’s method. Our new system not only can handle diverse size, the defocus and noise problems, a dissimilar lighting condition, partial occlusion, and various color saturation simultaneously, but also consider the layout/spatial relation of the flags/images.



(a) The 10 results of our approach and the precision is 10/10. The first flag image is also the query image. The images are presented in descending matching weight from left to right and from top to bottom.



(b) The 10 results of R. P. Kumar’s system and the precision is 1/10. The first flag image is also the query image. The images are presented in ascending distance from left to right and from top to bottom.



(c) The 10 results of K. Konstantinidis’s approach and the precision is 8/10. The first flag image is also the query image. The images are presented in descending similarity ratio from left to right and from top to bottom.

FIGURE 5. Ours is perfect in various lighting conditions.





(a) The 10 results of our approach and the precision is 10/10. The first flag image is also the query image. The images are presented in descending matching weight from left to right and from top to bottom.



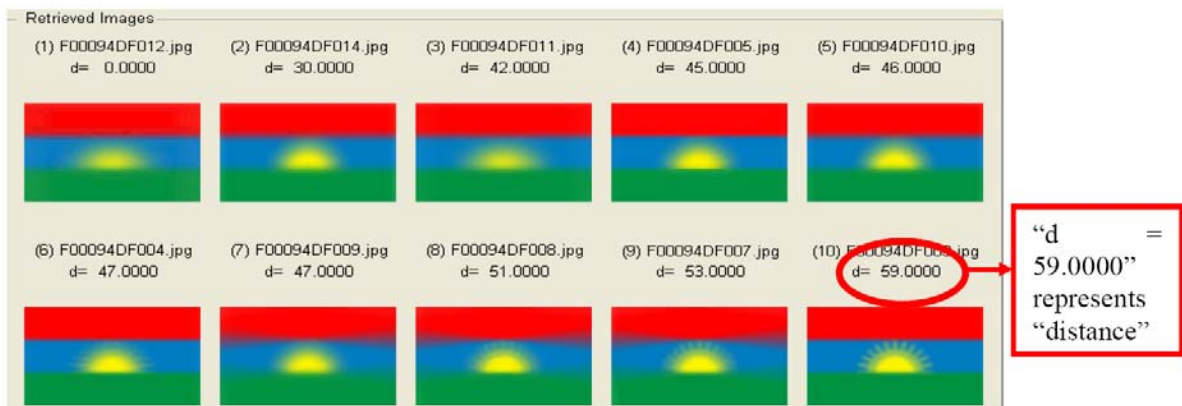
(b) The 10 results of R. P. Kumar’s system and the precision is 1/10. The first flag image is also the query image. The images are presented in ascending distance from left to right and from top to bottom.



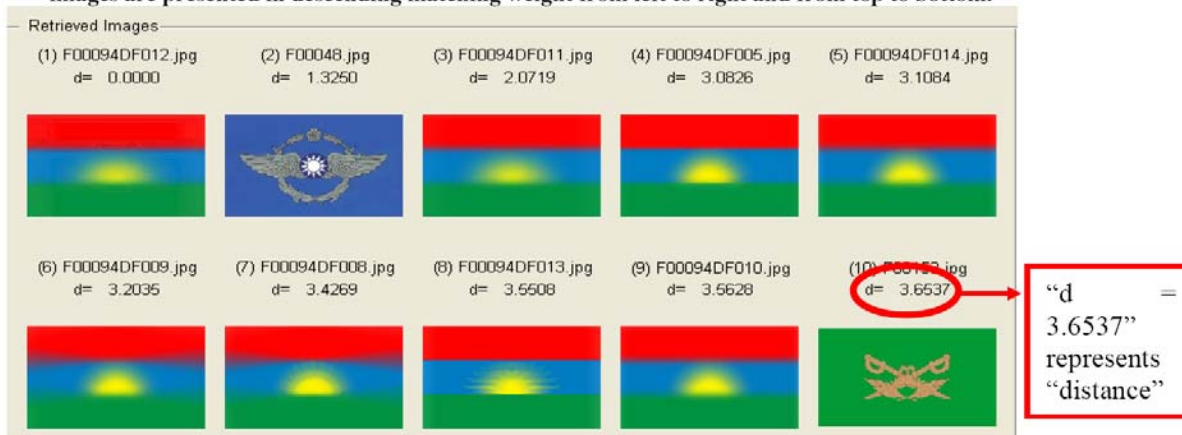
(c) The 10 results of K. Konstantinidis’s approach and the precision is 1/10. The first flag image is also the query image. The images are presented in descending similarity ratio from left to right and from top to bottom.

FIGURE 6. Ours is remarkable in dissimilar color saturation conditions.





(a) The 10 results of our approach and the precision is 10/10. The first flag image is also the query image. The images are presented in descending matching weight from left to right and from top to bottom.



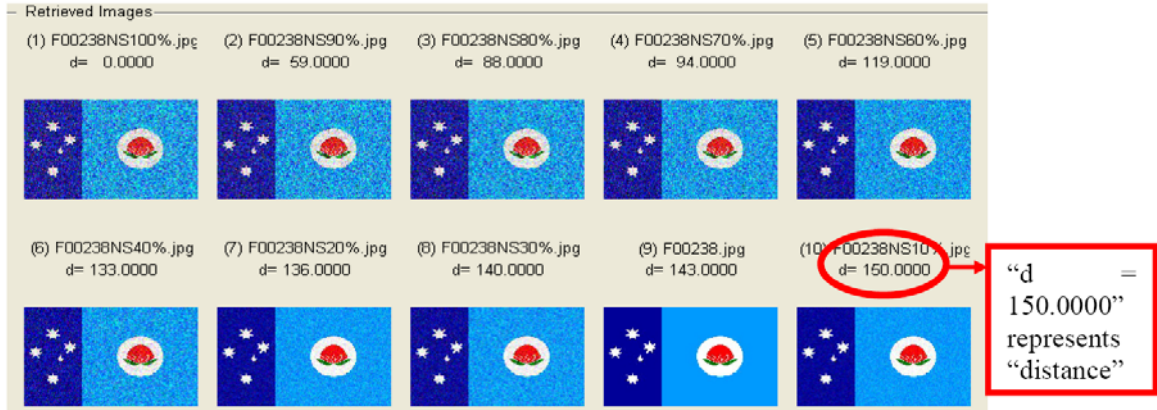
(b) The 10 results of R. P. Kumar’s system and the precision is 8/10. The first flag image is also the query image. The images are presented in ascending distance from left to right and from top to bottom.



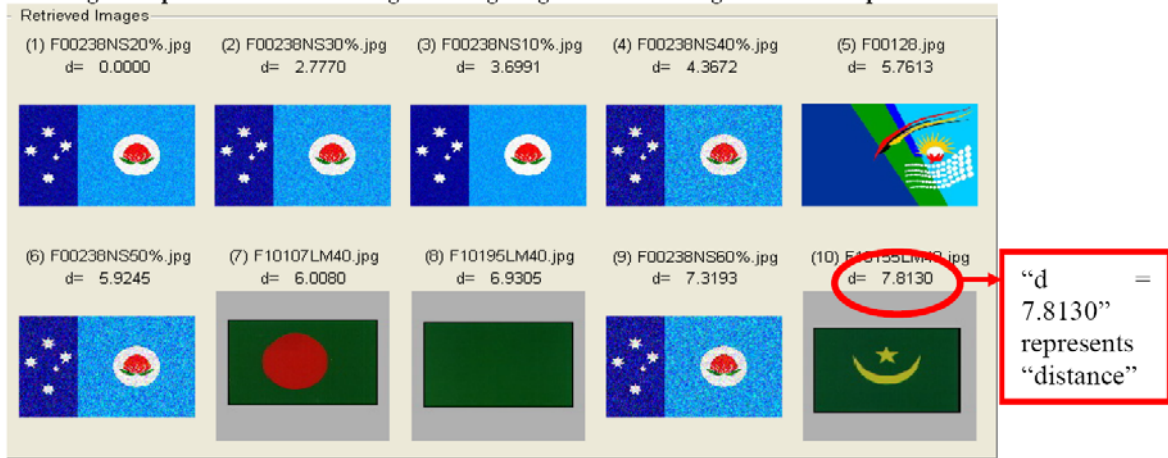
(c) The 10 results of K. Konstantinidis’s approach and the precision is 7/10. The first flag image is also the query image. The images are presented in descending similarity ratio from left to right and from top to bottom.

FIGURE 7. Ours is outstanding in blurred situations.

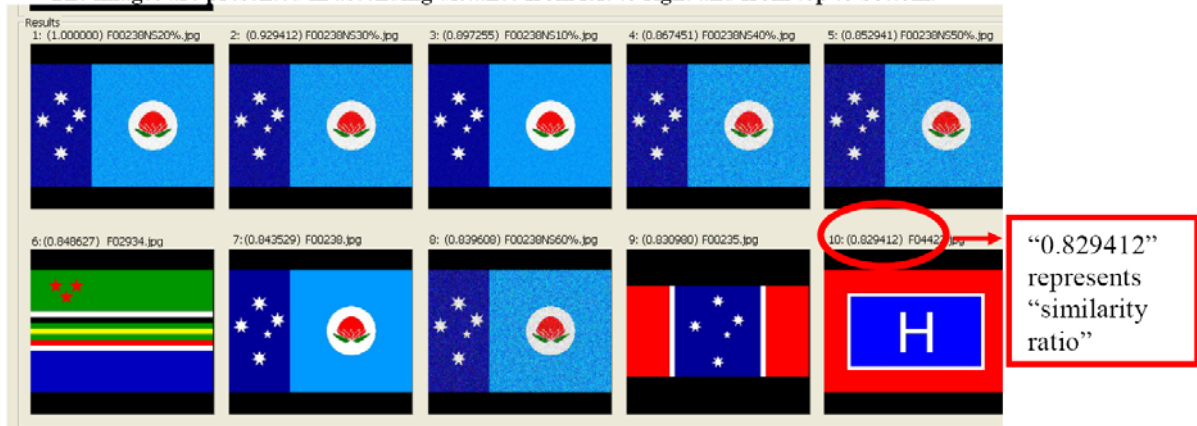
Retrieval results not only depend on strong feature representation, but also depend on suitable similarity measures or distance metrics. The measurement of image content similarity remains problematic [28]. We use a P4 CPU 3.0 GHz PC. The training time and retrieval time of our approach are both superior to the others. The comparison is shown as Table 1.



(a) The 10 results of our approach and the precision is 10/10. The first flag image is also the query image. The images are presented in descending matching weight from left to right and from top to bottom.



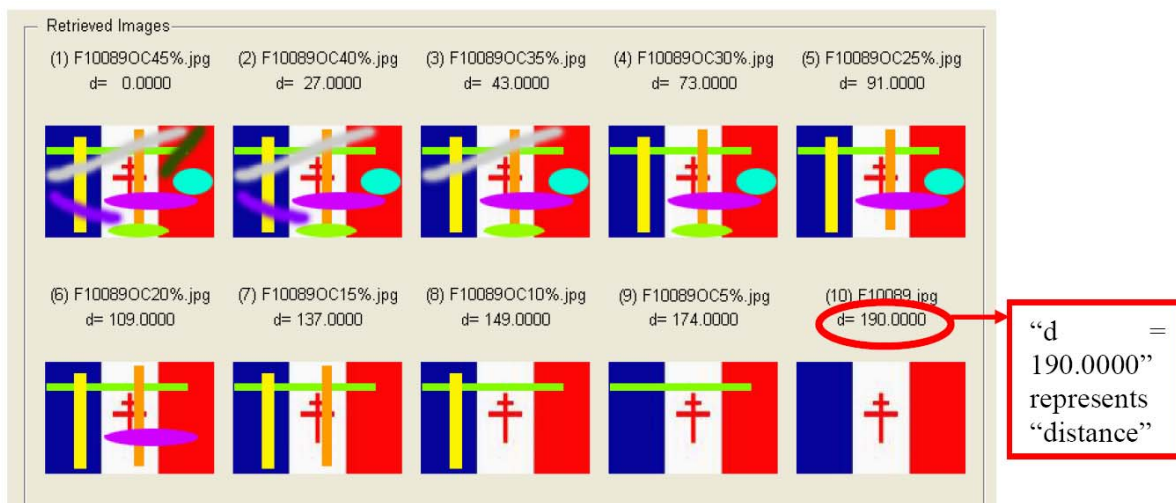
(b) The 10 results of R. P. Kumar’s system and the precision is 6/10. The first flag image is also the query image. The images are presented in ascending distance from left to right and from top to bottom.



(c) The 10 results of K. Konstantinidis’s approach and the precision is 7/10. The first flag image is also the query image. The images are presented in descending similarity ratio from left to right and from top to bottom.

FIGURE 8. Ours is marvelous in noise conditions.

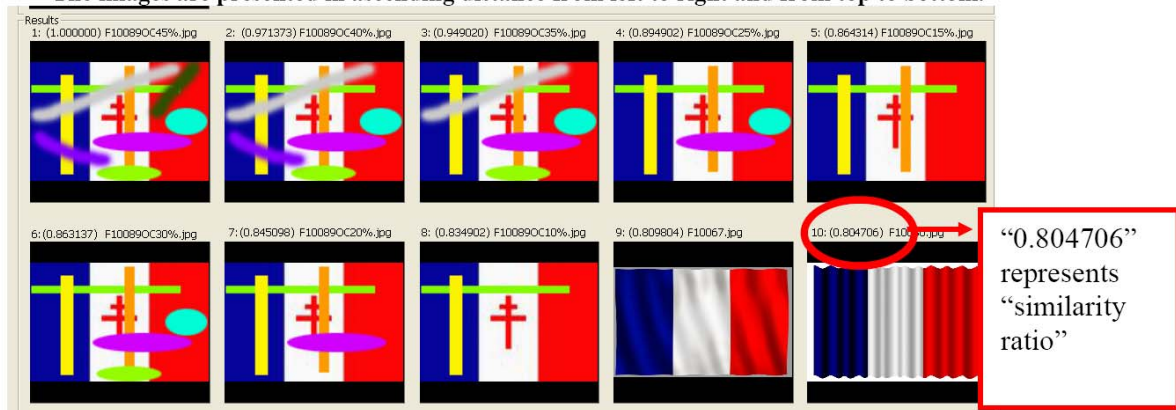
4. **Conclusions.** Since we transfer each flag to a color string by computer automatically (without manual annotation, e.g., captioning, keywords, or descriptions.), the content-based flags retrieval system becomes an analogous text-based retrieval system. Since the strings comparison is very fast in computer, our approach is very speedy. Each character/letter of a string contains a series of colors, e.g., white, black, red, green, or blue,



(a) The 10 results of our approach and the precision is 10/10. The first flag image is also the query image. The images are presented in descending matching weight from left to right and from top to bottom.



(b) The 10 results of R. P. Kumar’s system and the precision is 2/10. The first flag image is also the query image. The images are presented in ascending distance from left to right and from top to bottom.



(c) The 10 results of K. Konstantinidis’s approach and the precision is 8/10. The first flag image is also the query image. The images are presented in descending similarity ratio from left to right and from top to bottom.

FIGURE 9. Ours is remarkable in partial occlusion situations.

TABLE 1. The training time and retrieval time of our approach are superior to the others

Approach \ Time	Training time (seconds)/flags	Average retrieval time (seconds)
Our approach	19.525/30,000	0.393
R. P. Kumar's system	145.030/30,000	0.885
K. Konstantinidis's approach	38.053/30,000	0.486

so our system can conquer different brightness conditions, miscellaneous color saturation and tolerate some dissimilarity between the results and the query image at the same time. Our system offers both advantages of the content-based image retrieval system (similarity-based retrieval) and a text-based image retrieval system (very rapid and mature). We succeed in transferring the flags retrieval problem to strings comparison automatically. In other words, we create a bridge between content-based retrieval system and a text-based retrieval system. It will make images searching more ordinary, comfortable, and straightforward. In the future, we will adapt our approach to different domains, such as trademarks search, Internet queries, personal photo retrieval and retrieval of remote sensing images. We hope images searching will become more widespread as the way we currently search text information on the World Wide Web.

## REFERENCES

- [1] P. Aigrain, H. J. Zhang and D. Petkovic, Content-based representation and retrieval of visual media: A state-of-the-art review, *Multimedia Tools and Applications*, vol.3, pp.179-202, 1996.
- [2] A. Anjulan and N. Canagarajah, Object based video retrieval with local region tracking, *Signal Processing: Image Communication*, vol.22, no.7-8, pp.607-621, 2007.
- [3] S. Antani, R. Kasturi and R. Jain, A survey on the use of pattern recognition methods for abstraction, indexing and retrieval of images and video, *Pattern Recognition*, vol.35, no.4, pp.945-965, 2002.
- [4] M. Banerjee and M. K. Kundu, Edge based features for content-based image retrieval, *Pattern Recognition*, pp.2649-2661, 2003.
- [5] M. Bressan, D. Guillaumet and J. Vitrià, Using an ICA representation of local color histograms for object recognition, *Pattern Recognition*, vol.36, no.3, pp.691-701, 2003.
- [6] R. Brunelli and O. Mich, Histograms analysis for image retrieval, *Pattern Recognition*, vol.34, pp.1625-1637, 2001.
- [7] C. Carson, S. Belongie, H. Greenspan and J. Malik, Blobworld: Image segmentation using expectation-maximization and its application to image querying, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, pp.1026-1038, 2002.
- [8] O. Cetin and A. T. Ozcerit, A new steganography algorithm based on color histograms for data embedding into raw video streams, *Computers & Security*, vol.28, no.7, pp.670-682, 2009.
- [9] F. Chevalier, J.-P. Domenger, J. Benois-Pineau and M. Delest, Retrieval of objects in video by similarity based on graph matching, *Pattern Recognition Letters*, vol.28, no.8, pp.939-949, 2007.
- [10] R. C. Gonzalez and R. E. Woods, *Digital Image Processing*, Addison-Wesley Publishing Company, 1992.
- [11] A. Hampapur, R. Jain and T. Weymouth, Digital video segmentation, *Proc. of the ACM Multimedia*, pp.357-364, 1994.
- [12] P. Jain and S. N. Merchant, Wavelet based multiresolution histogram for fast image retrieval, *Conference on Convergent Technologies for Asia-Pacific Region*, pp.581-585, 2003.
- [13] S. Jeong, C. S. Won and R. M. Gray, Image retrieval using color histograms generated by Gauss mixture vector quantization, *Computer Vision and Image Understanding*, vol.91-93, pp.44-66, 2004.
- [14] M. J. Kim, B. C. Song and J. B. Ra, A fast multiresolution feature matching algorithm for exhaustive search in large databases, *IEEE Transactions on Circuits and Systems for Video Technology*, vol.11, no.5, 2001.



- [15] R. P. Kumar and P. Nagabhushan, An approach based on regression line features for low complexity content based image retrieval, *Proc. of the International Conference on Computing: Theory and Applications*, 2007.
- [16] S. Lefèvre, J. Holler and N. Vincent, A review of real-time segmentation of uncompressed video sequences for content-based search and retrieval, *Real-Time Imaging*, vol.9, no.1, pp.73-98, 2003.
- [17] S. Liapis and G. Tziritas, Color and texture image retrieval using chromaticity histograms and wavelet frames, *IEEE Transactions on Multimedia*, vol.6, no.5, pp.676-686, 2004.
- [18] Y. Liu, D. Zhang, G. Lu and W.-Y. Ma, A survey of content-based image retrieval with high-level semantics, *Pattern Recognition*, vol.40, no.1, pp.262-282, 2007.
- [19] Y.-K. Chan, Y.-A. Ho, Y.-T. Liu and R.-C. Chen, A ROI image retrieval method based on CVAAO, *Image and Vision Computing*, vol.26, no.11, pp.1540-1549, 2008.
- [20] H. Müller, N. Michoux, D. Bandon and A. Geissbuhler, A review of content-based image retrieval systems in medical applications – Clinical benefits and future directions, *International Journal of Medical Informatics*, vol.73, no.1, pp.1-23, 2004.
- [21] A. Nagasaka and Y. Tanaka, Automatic video indexing and full-video search for object appearances, *Proc. of the Visual database Systems*, pp.113-127, 1992.
- [22] M. Ozden and E. Polat, A color image segmentation approach for content-based image retrieval, *Pattern Recognition*, vol.40, no.4, pp.1318-1325, 2007.
- [23] I. B. Özer, W. Wolf and A. N. Akansu, A graph-based object description for information retrieval in digital image and video libraries, *Journal of Visual Communication and Image Representation*, vol.13, no.4, pp.425-459, 2002.
- [24] J. Z. Wang, J. Li and G. Wiederhold, SIMPLIcity: Semantics-sensitive integrated matching for picture libraries, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol.23, no.9, pp.947-963, 2001.
- [25] Rajashekhara and S. Chaudhuri, Segmentation and region of interest based image retrieval in low depth of field observations, *Image and Vision Computing*, vol.25, no.11, pp.1709-1724, 2007.
- [26] H. J. Zhang, A. Kankanhalli and S. W. Smoliar, Automatic partitioning of full-motion video, *Multimedia Systems*, vol.1, pp.10-28, 1993.
- [27] K. Konstantinidis, A. Gasteratos and I. Andreadis, Image retrieval based on fuzzy color histogram processing, *Optics Communications*, vol.248, no.4-6, pp.375-386, 2005.
- [28] G.-H. Liu and J.-Y. Yang, Content-based image retrieval using color difference histogram, *Pattern Recognition*, vol.46, no.1, pp.188-198, 2013.