A Rule-based Approach for Landscapes Retrieval

Chiunhsiun Lin

Office of Research and Development Affairs, National Taipei University, Taipei, Taiwan, 104

Abstract

An accurate rule-based approach for landscapes retrieval scheme is developed to retrieve landscapes efficiently. We transfer each landscape to a color chain using only 8 rules. Afterwards, we utilize the color chains for comparing the landscapes, namely color chains comparison (CCC). We succeed in transferring the landscapes retrieval problem to the color chains comparison. In other words, we create a bridge between a content-based retrieval system and a text-based retrieval one. Thus the computational complexity is decreased significantly. Our new system offers both the advantages of the content-based landscapes retrieval system (similarity-based retrieval) and the text-based landscapes retrieval system (very rapid and mature).

Keywords -- **Color chains comparison (CCC), Content-based images retrieval (CBIR), Content-based videos retrieval (CBVR), Rule-based approach; Images retrieval.**

----

* Corresponding author: 2010allpass@gmail.com
DOI：10.3966/2223448920191000902004

I. INTRODUCTION

Since the digital images increase very speedy, 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 of digital images. 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 Fig. 1. Hence content-based retrieval approach instead of text-based retrieval one plays a very important role in multimedia system [1] and [9]. "Content-based" represents that the search will analyze the actual contents of the image rather than the annotation, such as keywords, tags, or descriptions associated with the image. The term "content" in the context may refer to colors, shapes, textures, or any other information that can be derived directly from the image itself. The content-based images retrieval (CBIR) was proposed in the early 1990s. CBIR systems retrieve similar images in a database directly using the content of the images [11]. Color features include the color histogram, the color coherence vector, the color co-occurrence matrix, the vector quantization, and the color moments [12]. Texture features are derived from the gray-level co-occurrence matrix, the Tamura feature, the wavelet coefficients, and the Gabor filter-based features [4]. The use of shape features are the normalized inertia, the Zernike moments, the histogram of edge direction and the edge map [9]. A feature descriptor can be dense or discrete. The dense feature is computed on all pixels, but the discrete one is computed on a subset of pixels [2]. Generally, the feature reduction can be divided into two main categories, namely feature transform and feature selection. (1) Feature transform creates new features by projecting the original feature space to a lower dimensional one. Principal component analysis and independent component analysis [5] are two broadly employed feature transform methods. Although feature transform can obtain the fewer dimensions, its major drawbacks are that its computational cost is sometimes high and the output is difficult to be understood for users. (2) Feature selection is the process of choosing a subset of the original feature spaces according to discrimination capacity. Unlike feature transform, the fewer dimensions obtained by feature selection facilitate the exploratory of results in images analysis. Because of the superiority, feature selection has now been widely applied in many domains, such as text categorization [3] and image retrieval [10]. Some more recent papers can be found from [16] to [21].

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 different sizes, various color saturation, dissimilar illumination conditions, the defocus and noise problems, and partial occlusion at the same time. In our investigation, we present a landscapes retrieval system that can handle above-mentioned problems at the same time. The overview of our system is shown in Fig. 2. The designed system contains three phases. Firstly, we resize all landscapes to decrease the effects of difference in size, and expedite the speed. Secondly, we convert each landscape to a color chain. Finally, we compare the color chains. We compare ch1 and ch2 firstly (ch1 is the color chain of the query landscape and ch2 is the color chain of the landscape in the database). Afterwards, we return the matching weight. Secondly, we compare ch1 and ch3 (ch3 is another color chain of landscape in the database), and return the matching weight, and so on. The rest of the paper is organized as follows. In section 2, rule-based color chain coding and color chains comparison are illustrated. Experimental results and discussions are demonstrated in section 3. Finally, conclusions are given in section 4

II. THE RULE-BASED APPROACH

A list of rules (rule base), which is a specific type of knowledge-base. A rule-based system consists of a set of IF-THEN rules. The rules are used to translate the high-level query given by the users to a low-level query that can directly utilize the extracted features. Since the landscapes are allowed having different size, all landscapes are normalized to a standard size (i.e., 20 × 20 pixels) firstly. Although resizing will lose some information of landscapes, it can obtain the power of toleration of different size, the defocus and noise problems, and accelerate the speed.

2.1. RULE-BASE COLOR CHAIN CODING

The RGB color space representation a good choice since that representation was designed to match the input channel of the eyes. RGB-representations are in wide-spread use. 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 or diverse color saturation. However, the relative relation between r (i), g (i), and b (i) are almost unchanged. For example, the values of r (i), g (i), and b (i) will become higher simultaneously when the illumination becomes superior. On the other hand, the values of r (i), g (i), and b (i) will become lower concurrently when the color saturation becomes lesser. Therefore, we can utilize the relative relation between r (i), g (i), and b (i) to transfer each image to a color chain to overcome the altered illumination conditions and diverse color saturation. Moreover, the number of the permutations of R, G, and B is only 6 (RGB, RBG, GRB, GBR, BRG, and BGR). Since pure white and pure black colors are very particular, we append pure white color series and pure black color series to let them become 8 series. The 8 rules are listed as below:

(1)	if a pixel 235 =< r (i) =< 255, 235 =< g (i) =< 255, and 235 =< b (i) =< 255 , then assigns the pixel as 'W'; (Pure white color)
(2)	if a pixel 0 =< r (i) =< 20, 0 =< g (i) =< 20, and 0 =< b (i) =< 20, then assigns the pixel as 'K'; (Pure black color)
(3)	if a pixel r (i) > g (i) >= b (i), then assigns the pixel as 'R'; (the first series of "Red" colors)
(4)	if a pixel r (i) >= b (i)> g (i), then assigns the pixel as 'S'; (the second series of "Red" colors)
(5)	if a pixel g (i) > r (i) >= b (i), then assigns the pixel as ' G'; (the first series of "Green" colors)
(6)	if a pixel g (i) >= b (i) > r (i), then assigns the pixel as 'H'; (the second series of "Green" colors)
(7)	if a pixel b (i) > r (i) >= g (i) , then assigns the pixel as 'B'; (the first series of "Blue" colors)
(8)	if a pixel b (i) >= g (i) > = r (i), then assigns 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 landscapes should be enough. An example demonstrates the 20 X 20 pixels 32 bits color map and its color chain is shown as Fig. 3. We use purple color letter ″W″ instead of white color letter ″W″ to able to be seen clearly by readers. We can observe the "R" and "S" present two series of red colors. The "G" and "H" show the two series of green colors. The "B" and "C" demonstrate two series of blue colors. The "W" represents the pure white color, and "K" displays the pure black color. An instance illustrates how to obtain a 2D color chain is shown as Fig. 4. Fig. 4 (a) An original frame of landscape (320X 240 pixels); (b) Resize the landscape (20 X 20 pixels); (c) Resize the 20 X 20 pixels landscape to 320 X 320 pixels to be seen clearly by readers; (d) Transfer the landscape (20 X 20 pixels) to a 2D color chain array. From the 2D color chain array, you can see the outline of the landscape. You can obtain the impression of the characters "C" presents the second series of "blue" colors. For instance, we can see the blue color of the landscape that is transferred to "C" (the second series of "blue" colors), and the green color of the landscape that is transferred to "G" and "H" (the first and second series of "Green" colors). Subsequently, each landscape will become a 2D color chain array, and then we will convert the 2D color chain array to a 1D color chain as below:

KKKKKKKK…CCCCCCCCCC…GGGGGGGGGG…KKKKKKKK

2.2. COLOR CHAINS COMPARISON

In mathematics, chain comparison (also known as similarity comparison) are a class of textual based comparison resulting in a similarity score between two text chains for approximate matching or comparison. For example, the chains of "research" and "researcher" can be considered to be similar. The most widely known chain metric is a rudimentary one called the Levenshtein Distance (also known as Edit Distance). It operates between two input chains, and returns a score. Simplistic chain comparisons such as Levenshtein distance have expanded to include phonetic, token, grammatical and character-based methods of statistical comparisons. A widespread example of a chain comparison is DNA sequence analysis and RNA analysis, which are performed by optimized chain comparison to identify matching sequences. Chain comparisons are used heavily in information integration and are currently used in fraud detection, fingerprint analysis, plagiarism detection, ontology merging, DNA analysis, RNA analysis, image analysis, evidence-based machine learning, database data deduplication, data mining, etc.

Firstly, we compare each element of ch1 to the same position element in ch2 (ch1 is the color chain of the query landscape image and ch2 is the color chain of the landscape image in the database), and return the matching weight. Then, we compare each element of ch1 to the same position element in ch3 (ch3 is another color chain of landscape 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 landscape images are the same one, the matching weight is 400. If the matching weight is 400, the distance is 0. The more similar landscapes should have higher matching weight and lower distance.

III. EXPERIMENTAL RESULTS AND DISCUSSIONS

Since the conventional image database is often taken by digital camera, it is very hard to say how similar between the query image and the retrieval results. Therefore, our landscapes/images are extracted from videos that are taken from Internet (about 70% from youtube). The original/normal extracted rate of the frames of videos is 30 frames per second (30 fps), but these extracted frames are too similar. Therefore, we extract the landscapes with 3 frames per second (3 fps). We also use different dataset (from photo collection, such as INRIA Holidays dataset [14] and ImageCLEF Datasets [15].) Since it is very difficult to find enough similar landscapes with different color saturation, blur, noise and partial occlusion, we add these conditions to the landscapes using Photoshop 7.0.1. SP denotes "increase color saturation to the landscapes", we raise 5% color saturation each time. SM symbolizes “reduce color saturation to the landscapes", we decrease 5 % color saturation each time. Therefore, the color saturation is from -40 % to + 40 %. BP presents "raise blur the landscapes", we increase 5% blur each time. Therefore, the blurred condition is from 0 % to + 45 %. NP implies “raise noise to the landscapes", we increase 10 % salt-and-pepper noise each time. Therefore, the salt-and –pepper noise is from 0 % to + 90%. OC presents “the partial occlusion of the landscapes", we amplify about 5 % occlusions each time. Therefore, the partial occlusion of the landscapes is from 0 % to 45 %. Accordingly, in our database, we collect 133,000 landscapes with noise, blur, partial occlusion, different size, dissimilar illumination conditions, and diverse color saturation. We have 12,160 different landscapes, and 10 to 13 samples for each kind of landscape. Moreover, we compare our new system with R. P. Kumar’s system [7] and K. Konstantinidis’s approach [6]. 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 [7]. 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 [6].

The first example is shown as Fig. 5. Fig. 5 (a) and (d) exhibit our approach is perfect in various illumination conditions. Fig. 5 (b), (e) (the R. P. Kumar’s system), and Fig. 5 (c), (f) (K. Konstantinidis’s method) demonstrate their systems are not work well for different lighting circumstances. The second illustration is displayed as Fig. 6. Fig. 6 (a) and (d) illustrate ours is ideal for various color saturation circumstances. Fig. 6 (b), (e) (the R. P. Kumar’s system), and Fig. 6 (c), (f) (K. Konstantinidis’s method) display their systems are not faultless for different color saturation situations. The third exhibition is displayed as Fig.7. Fig. 7 (a) and (d) illustrate ours is outstanding in blurred situations. Fig. 7 (b), (e) (the R. P. Kumar’s system), and Fig. 7 (c), (f) (K. Konstantinidis’s method) demonstrate their systems are deficient in blurred circumstances. The fourth exposition is demonstrated as Fig. 8. Fig. 8 (a) and (d) illustrate ours is wonderful in noise conditions. Fig. 8 (b), (e) (the R. P. Kumar’s system), and Fig. 8 (c), (f) (K. Konstantinidis’s method) demonstrate their systems are inadequate in noise circumstances. The fifth show is exhibited as Fig. 9. Fig. 9 (a), (d) illustrate ours is marvelous in partial occlusion situations. Fig. 9 (b), (e) (the R. P. Kumar’s system), and

Fig. 9 (c), (f) (K. Konstantinidis's method) exhibit their systems are not good enough in partial occlusion circumstances.

From the above 10 examples, the R. P. Kumar's system has 45 faults from 100 retrieval results, and the K. Konstantinidis's method has 46 faults from 100 retrieval results, . On the other hand, ours has 0 faults from 100 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 landscapes/images.

The quantitative evaluation of the proposed scheme is measured using standard evaluation benchmarks, such as, precision and recall rates. For a given query, let T be the total number of retrieved images, Rr be the number of retrieved relevant images, and Tr be the total number relevant images. Precision and recall are defined as:

Precision = Rr / T

Recall = Rr / Tr

In pattern recognition and information retrieval, precision is the fraction of retrieved instances that are relevant, while recall is the fraction of relevant instances that are retrieved. Both precision and recall are therefore based on an understanding and measure of relevance. When a search engine returns 10 images only 8 of which were relevant while failing to return 12 relevant images, its precision is 8/10 = 80% while its recall is 8/12 = 66.67%. Since both precision and recall are based on an understanding and measure of relevance, we offer each kind of landscapes contains 10 to 13 different samples in our database. Subsequently, we obtain the precision as 9.8/10 = 98% and the recall as 9.8/11 = 89.1%.

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. We use a P4 CPU 3.0 GHz PC. The training time and retrieval time of our approach is both superior than the others. The comparison is shown as Table 1.

The major differences between our proposed method and existing ones are:

1. We consider the spatial information (our color chains comparison is permutation comparison). Most of the existing ones (color quantization-based methods) are combination comparison.

2. We resized the images to 20 X 20 pixels. Therefore, our approach can handle diverse sizes, defocus and noise problems. Moreover, our approach is very fast.

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.

IV. CONCLUSIONS

One of the main differences between a content-based landscapes/images system and a text-based landscapes/images retrieval system is the capability of the previous one can rank landscapes/images by the degree of similarity with the query landscapes/images in the database, namely, similarity-based retrieval. Conversely, a text-based image retrieval system typically process queries based on precise match. Most established and common platforms of images retrieval utilize some processes of adding metadata such as captioning, keywords, or descriptions to the images. Afterward retrieval can be performed over the annotation words. However, manual landscapes/images annotation is time-consuming, laborious and expensive. The text-based retrieval methods could be retrieved if the images are well-annotated. In other words, the landscapes/images without annotation make them incapable of being retrieved. Since we transfer each landscape/image to a color chain, the landscapes/images retrieval system becomes an analogous text-based retrieval system. Since each character/letter of a chain contains a series of colors (e.g., white, black, red, green, or blue), our system can conquer different brightness conditions, various color saturation and tolerate some other dissimilarity between the query and the result image at the same time. Moreover, the chains comparison is very fast in computer; accordingly, our approach is very speedy. In other words, we create a bridge between content-based retrieval system and a text-based retrieval system. Moreover, 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 do improve landscapes searching by insertion of spatial information. Our approach makes landscapes/images searching simple and comfortable. 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.

V. REFERRENCES

[1] Antani, S., Kasturi, R., Jain, R. 2002. A survey on the use of pattern recognition methods for abstraction, indexing and retrieval of images and video, *Pattern Recognition*, Volume: 35, Issue: 4, pp. 945-965.

[2] Deselaers, T., Keysers, D. and Ney, H. 2008 Features for image retrieval: an experimental comparison, *Information Retrieval*, Volume: 11, Number 2, pp. 77–107.

[3] Forman, G. 2003. An extensive empirical study of feature selection metrics for text classification, *Journal of Machine Learning Research*, Volume: 3, pp. 1289–1305.

[4] Han, J. and Ma, K. K. 2007. Rotation-invariant and scale-invariant Gabor features for texture image retrieval, *Image and Vision Computing*, Volume: 25, Issue: 9, (2007), pp. 1474–1481.

[5] Khaparde, A., Deekshatulu, B. L., Madhavilatha, M., Farheen, Z., Kumari, S. V. 2008. Content-based image retrieval using independent component analysis, *International Journal of Computer Science and Network Security* (IJCSNS), Volume: 8, Number 4, pp. 327-332.

[6] Konstantinidis, K., Gasteratos, A., Andreadis, I. 2005. Image retrieval based on fuzzy color histogram processing, *Optics Communications*, Volume 248, Issues 4–6, pp. 375–386.

[7] Kumar, R. P. and Nagabhushan, P. 2007. An Approach Based on Regression Line Features for Low Complexity Content-based Image Retrieval, *Proceedings of the International Conference on Computing: Theory and Applications, IEEE*, pp. 600 - 604.

[8] Liu, G. H. and Yang, J. Y., 2013. Content-based image retrieval using color difference histogram, *Pattern Recognition*, Volume: 46, Issue: 1, pp. 188-198.

[9] Liu, Y., Zhang, D. Lu, G., Ma, W. Y. 2007. A survey of content-based image retrieval with high-level semantics, *Pattern Recognition*, Volume: 40, Issue: 1, pp. 262-282.

[10] Ozden, M. and Polat, E. 2007. A color image segmentation approach for content-based image retrieval, *Pattern Recognition*, Volume: 40, Issue: 4, pp. 1318-1325.

[11] Qiu, G., Morris, J., Fan, X. Visual guided navigation for image retrieval, *Pattern Recognition*, Volume: 40, Issue: 6, (2007), pp. 1711–1721.

[12] Teng, S. W. and Lu, G. 2007. Image indexing and retrieval based on vector quantization, *Pattern Recognition*, Volume: 40, Issue: 11, pp. 3299–3316.

[13] Zhang, D. and Lu, G. 2004. Review of shape representation and description techniques, *Pattern Recognition*, Volume: 37, Issue: 1, (), pp. 1–19.

[14] http://lear.inrialpes.fr/~jegou/data.php#holidays

[15] http://www.imageclef.org/photodata

[16] Wankhede, V. A. and Mohod, P. S. 2015. Content-based image retrieval from videos using CBIR and ABIR algorithm, Global Conference on Communication Technologies (GCCT 2015)

[17] Rashno, A. and Sadri, S. 2017. Content-based image retrieval with color and texture features in neutrosophic domain, 2017 3rd International Conference on Pattern Recognition and Image Analysis (IPRIA 2017)

[18] Anwar, S. M., Arshad, F., Majid, M. 2017. Fast wavelet based image characterization for content based medical image retrieval, 2017 International Conference on Communication, Computing and Digital Systems (C-CODE2017)

[19] Shinde, S., Desai, M., Gupte, M. ; Racha, D. 2018. Content Based Image Retrieval Using Multi-Sequential Search, 2018 Second

International Conference on Inventive Communication and Computational Technologies (ICICCT 2018)

[20] Sabahi, F., Ahmad, M. O., Swamy, M.N.S. 2018. Perceptual Image Hashing Using Random Forest for Content-based Image Retrieval, 2018 16th IEEE International New Circuits and Systems Conference (NEWCAS 2018)

[21] Daoud, M. I., Saleh, A., Hababeh, I., Alazrai, R. 2019. Content-based Image Retrieval for Breast Ultrasound Images using Convolutional Autoencoders: A Feasibility Study, 2019 3rd International Conference on Bio-engineering for Smart Technologies (BioSMART 2019)

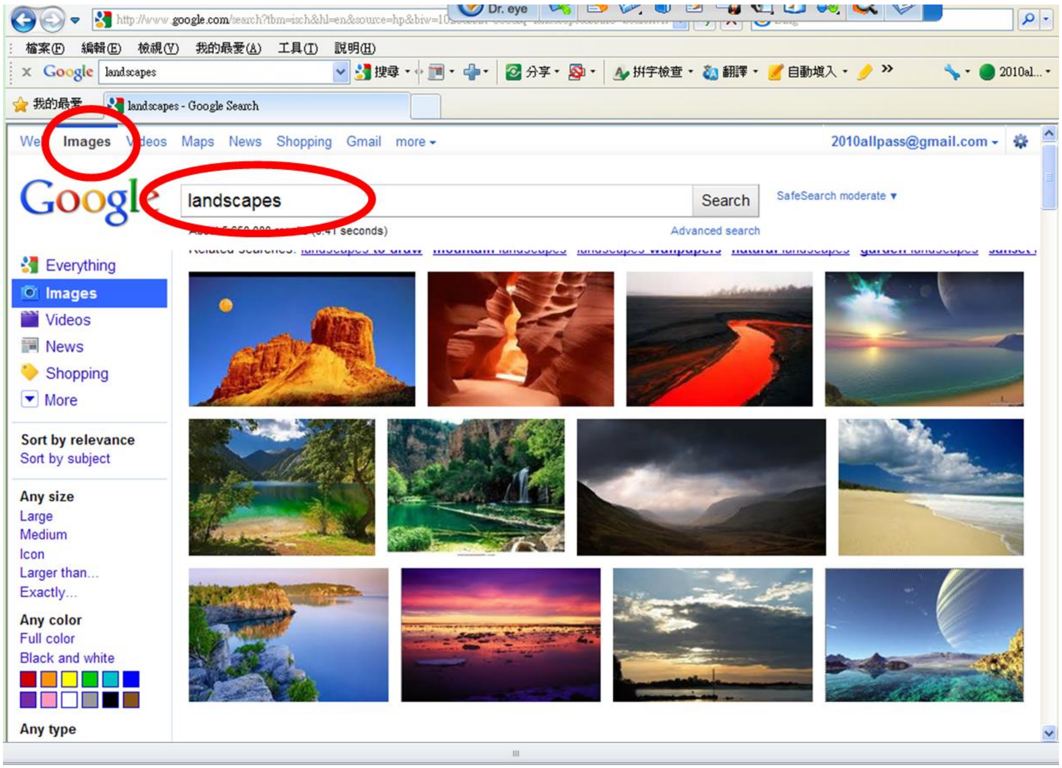


Fig. 1. Searching by keywords (e.g., landscapes) on the World Wide Web in Google, and the results.

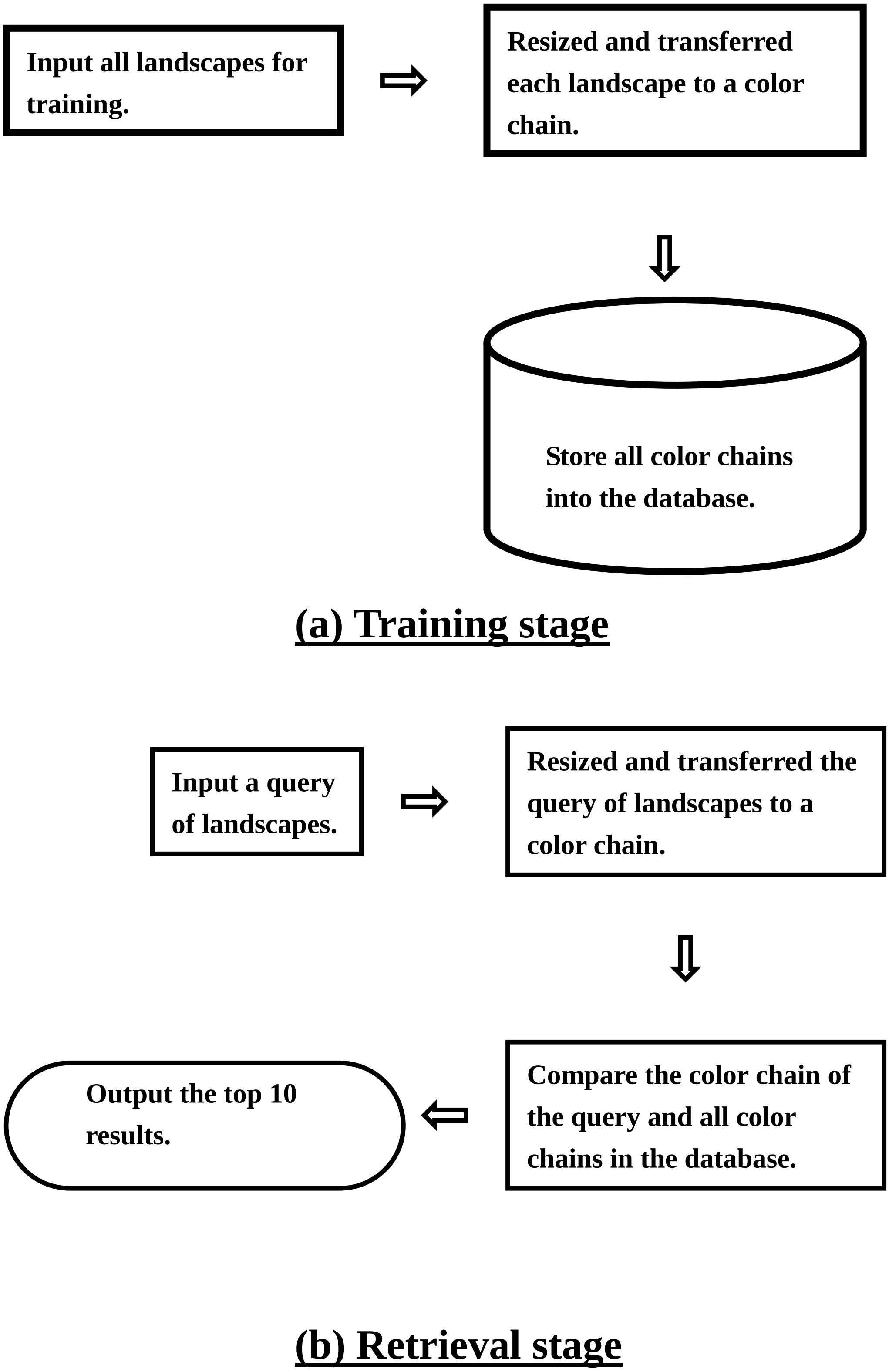
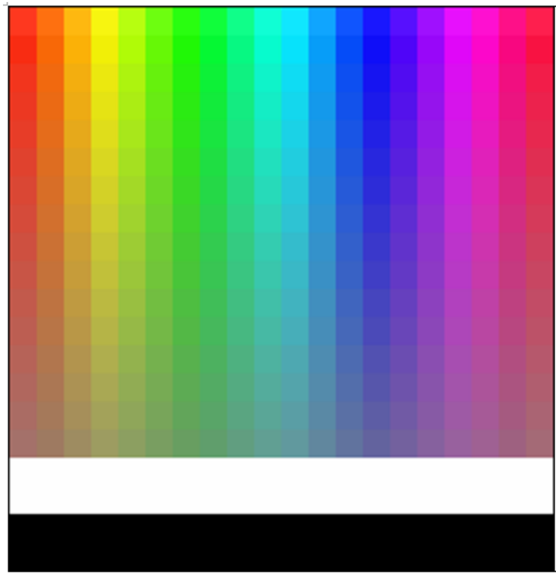


Fig. 2. Overview of our system.



R	R	R	R	G	G	G	H	H	H	C	C	C	C	B	B	B	S	S	S
R	R	R	R	G	G	G	H	H	H	C	C	C	C	B	B	B	S	S	S
R	R	R	R	G	G	G	H	H	H	C	C	C	C	B	B	B	S	S	S
R	R	R	R	G	G	G	H	H	H	C	C	C	C	B	B	B	S	S	S
R	R	R	R	G	G	G	H	H	H	C	C	C	C	B	B	B	S	S	S
R	R	R	R	G	G	G	H	H	H	C	C	C	C	B	B	B	S	S	S
R	R	R	R	G	G	G	H	H	H	C	C	C	C	B	B	B	S	S	S
R	R	R	R	G	G	G	H	H	H	C	C	C	C	B	B	B	S	S	S
R	R	R	R	G	G	G	H	H	H	C	C	C	C	B	B	B	S	S	S
R	R	R	R	G	G	G	H	H	H	C	C	C	C	B	B	B	S	S	S
R	R	R	R	G	G	G	H	H	H	C	C	C	C	B	B	B	S	S	S
R	R	R	R	G	G	G	H	H	H	C	C	C	C	B	B	B	S	S	S
R	R	R	R	G	G	G	H	H	H	C	C	C	C	B	B	B	S	S	S
R	R	R	R	G	G	G	H	H	H	C	C	C	C	B	B	B	S	S	S
R	R	R	R	G	G	G	H	H	H	C	C	C	C	B	B	B	S	S	S
R	R	R	R	G	G	G	H	H	H	C	C	C	C	B	B	B	S	S	S
W	W	W	W	W	W	W	W	W	W	W	W	W	W	W	W	W	W	W	W
W	W	W	W	W	W	W	W	W	W	W	W	W	W	W	W	W	W	W	W
K	K	K	K	K	K	K	K	K	K	K	K	K	K	K	K	K	K	K	K
K	K	K	K	K	K	K	K	K	K	K	K	K	K	K	K	K	K	K	K

Fig. 3. the 32 bits color map with the size of 20 X 20 pixels, and its color code (We use purple color word (e.g., W) instead of white color word to be seen clearly by readers).

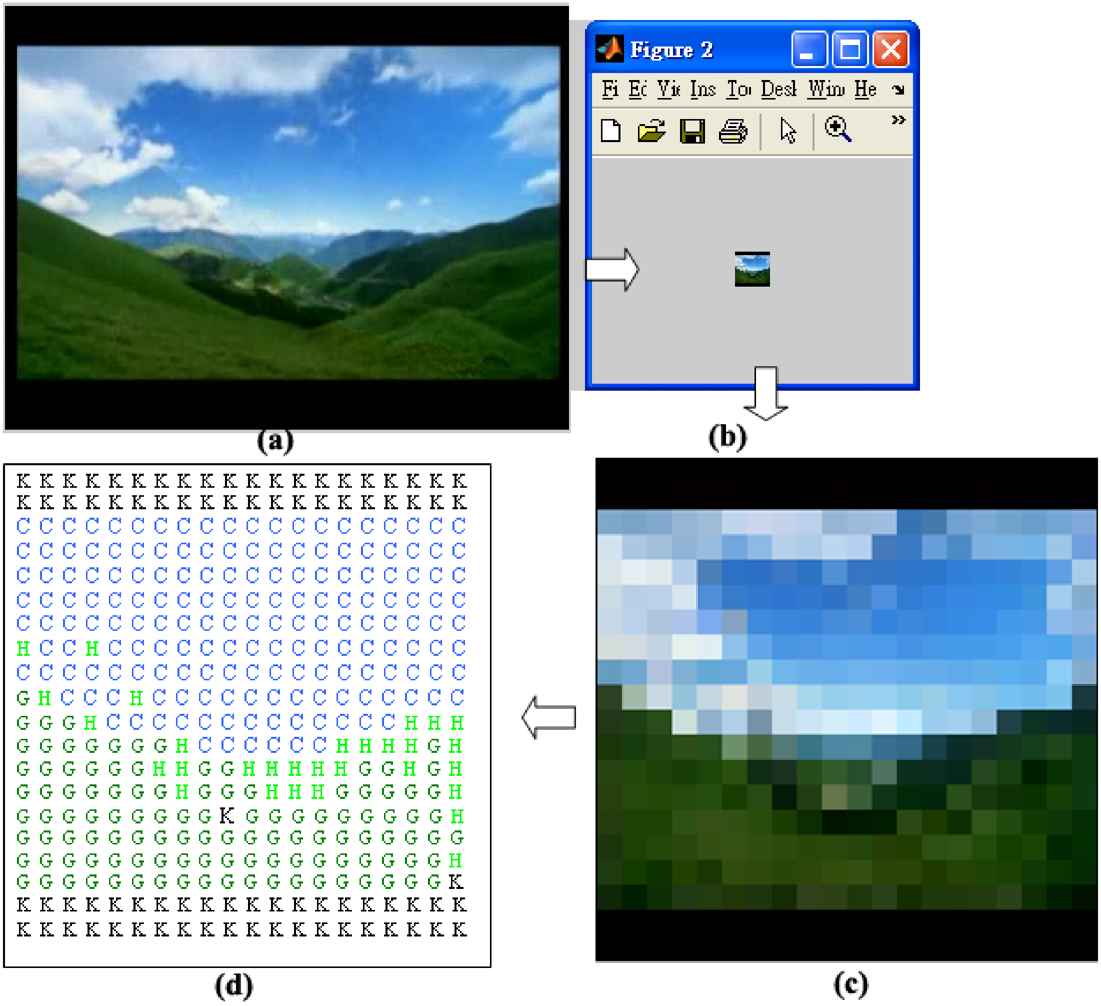
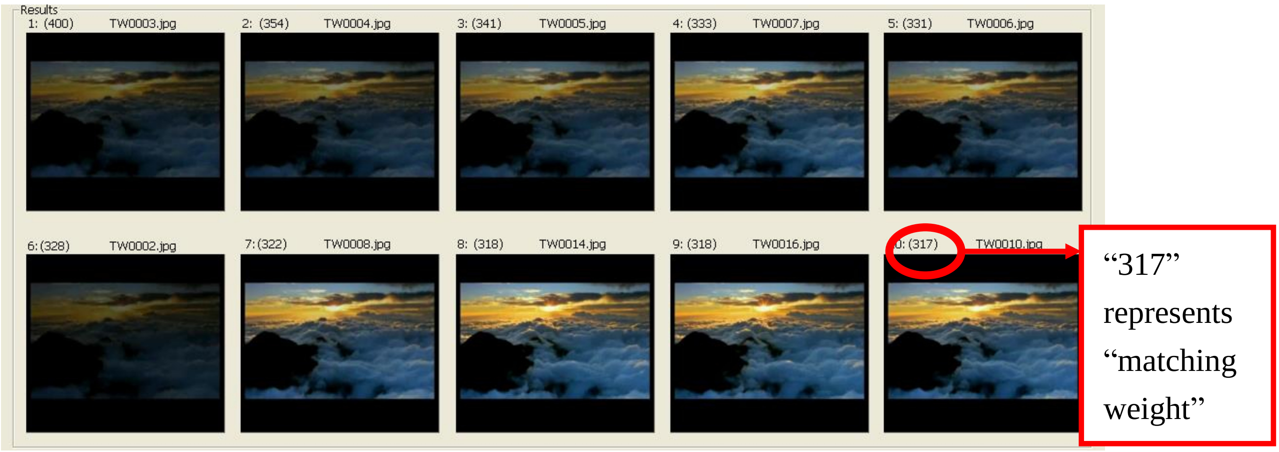
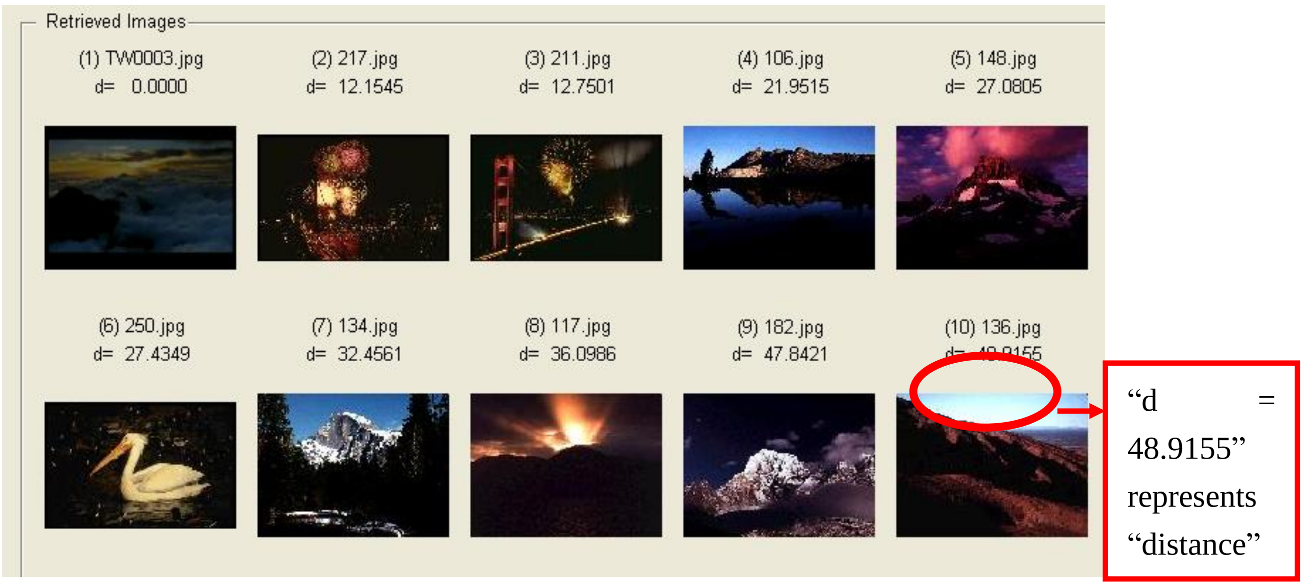


Fig. 4. (a) An original landscape (320 X 240 pixels); (b) Resized landscape (20 X 20 pixels); (c) Resized the 20 X 20 pixels landscape to 320 X 320 pixels to be seen clearly by readers; (d) Transfer the resized landscape (20 X 20 pixels) to a 2D color chain array. From the 2D color chain array, you can easy to see the layout of the landscape.



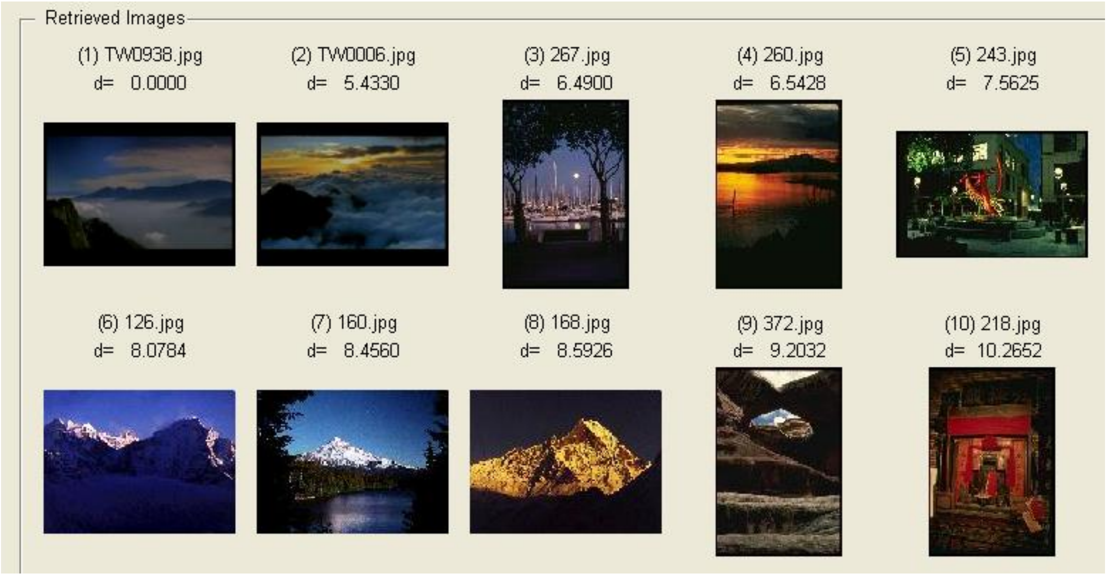
The 10 results of our approach and the precision is 10/10. The first landscape image is also the query image. The images are presented in descending matching weight from left to right and from top to bottom.



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

The 10 results of K. Konstantinidis's approach and the precision is 2/10. The first landscape image is also the query image. The images are presented in descending similarity ratio from left to right and from top to bottom.

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

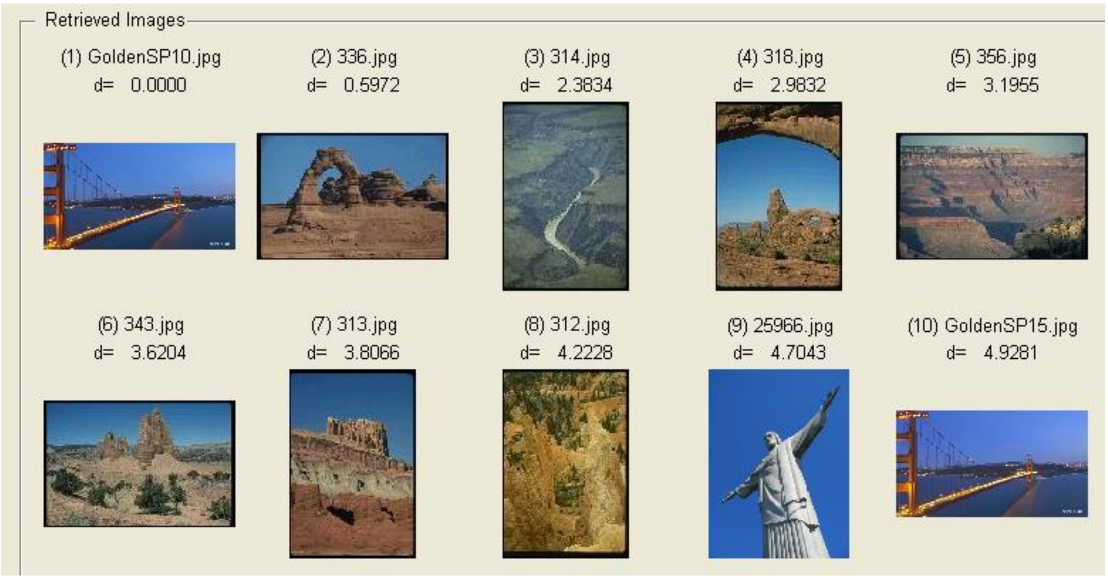


The 10 results of R. P. Kumar's system and the precision is 1/10. The first landscape image is also the query image. The images are presented in ascending distance from left to right and from top to bottom.

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

Fig. 5 exhibits ours is perfect in various lighting conditions.

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



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

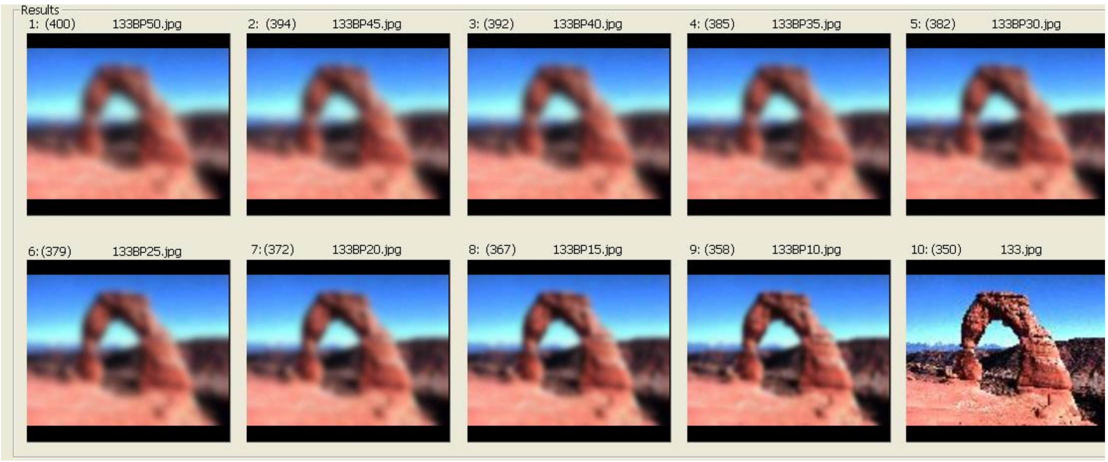
The 10 results of K. Konstantinidis's approach and the precision is 6/10. The first landscape image is also the query image. The images are presented in descending similarity ratio from left to right and from top to bottom.

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

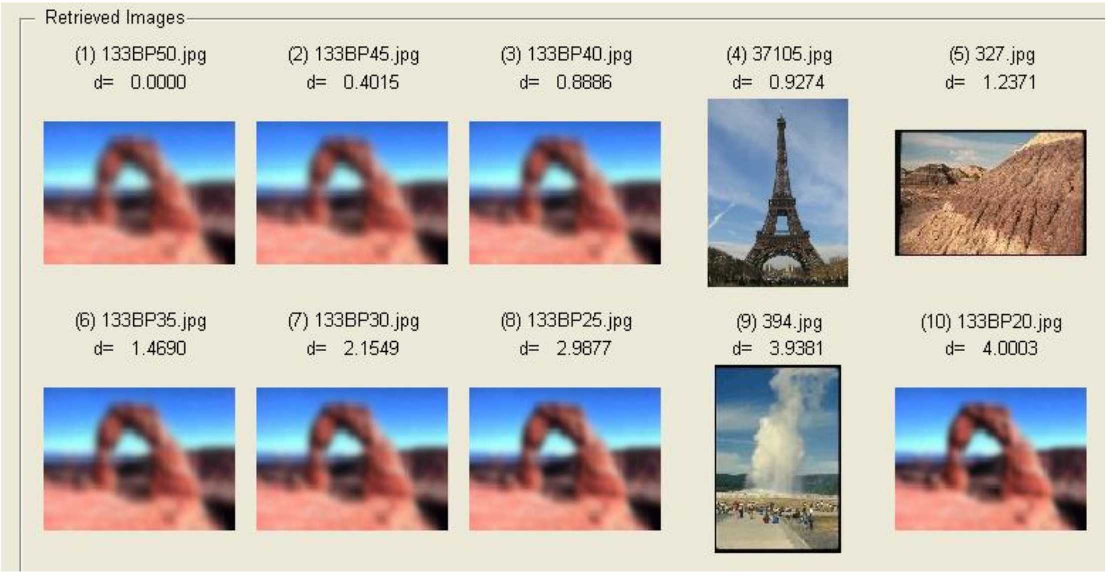
The 10 results of R. P. Kumar's system and the precision is 5/10. The first landscape image is also the query image. The images are presented in ascending distance from left to right and from top to bottom.

(The 10 results of K. Konstantinidis's approach and the precision is 6/10. The first landscape image is also the query image. The images are presented in descending similarity ratio from left to right and from top to bottom.

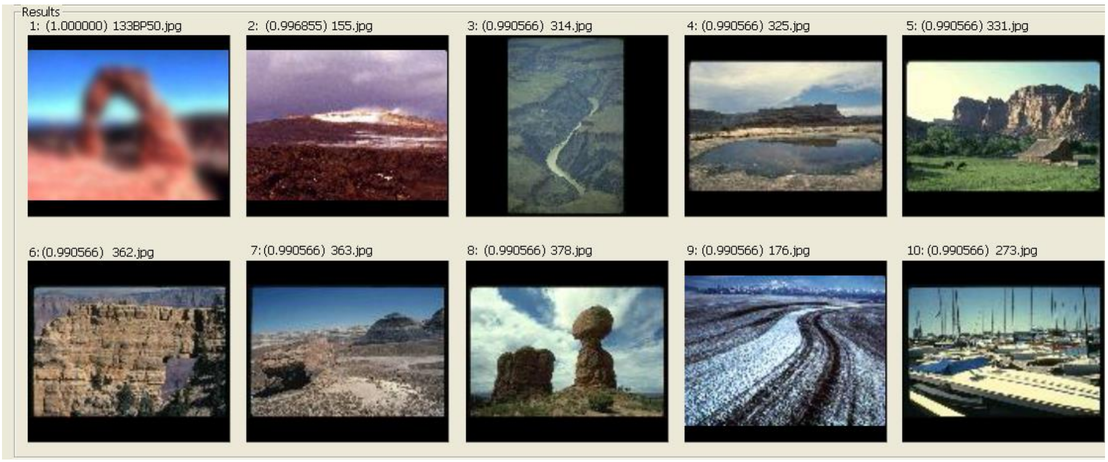
Fig. 6 illustrates ours is remarkable in dissimilar color saturation conditions.



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

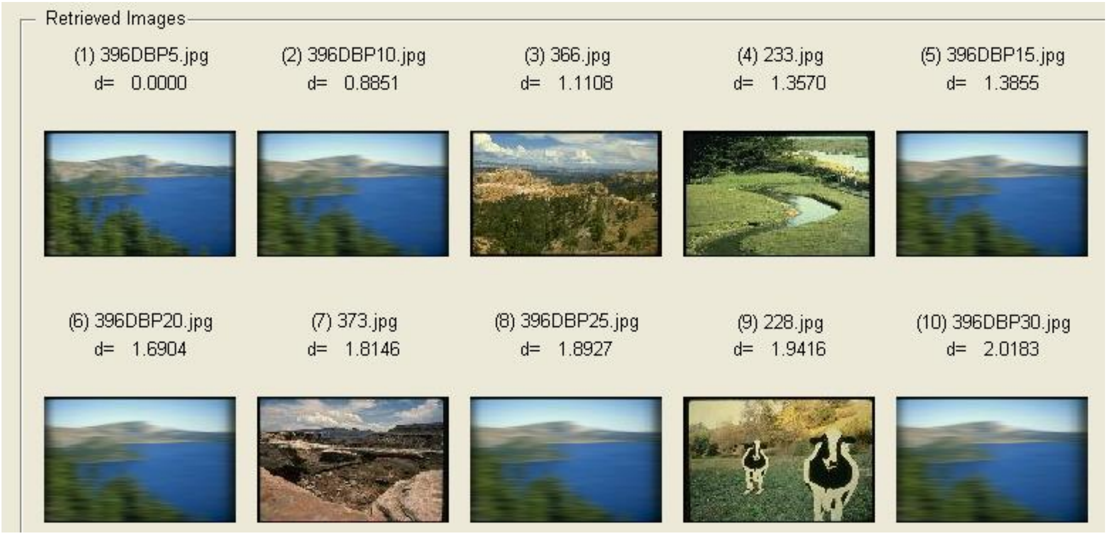


The 10 results of R. P. Kumar's system and the precision is 7/10. The first landscape image is also the query image. The images are presented in ascending distance from left to right and from top to bottom.



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

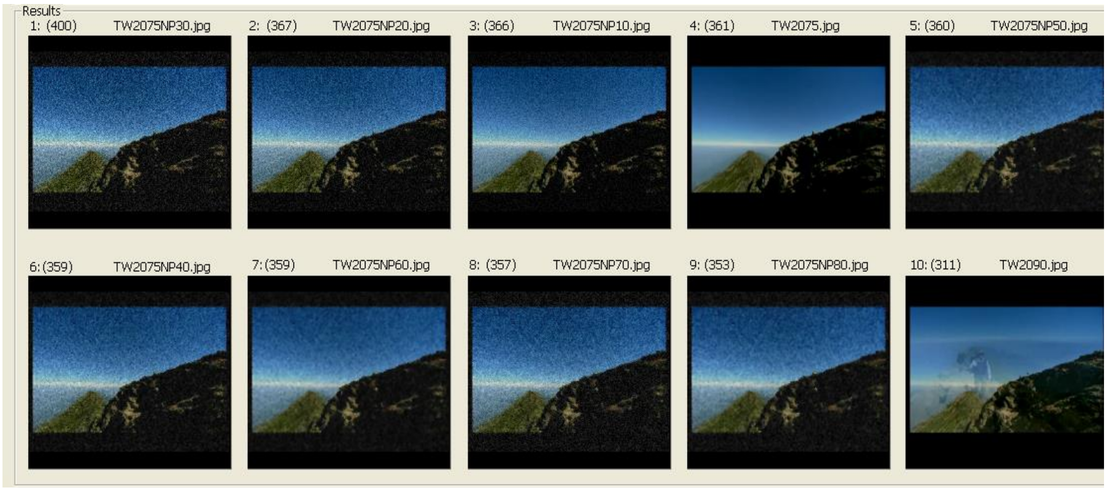
The 10 results of our approach and the precision is 10/10. The first landscape image is also the query image. The images are presented in descending matching weight from left to right and from top to bottom.



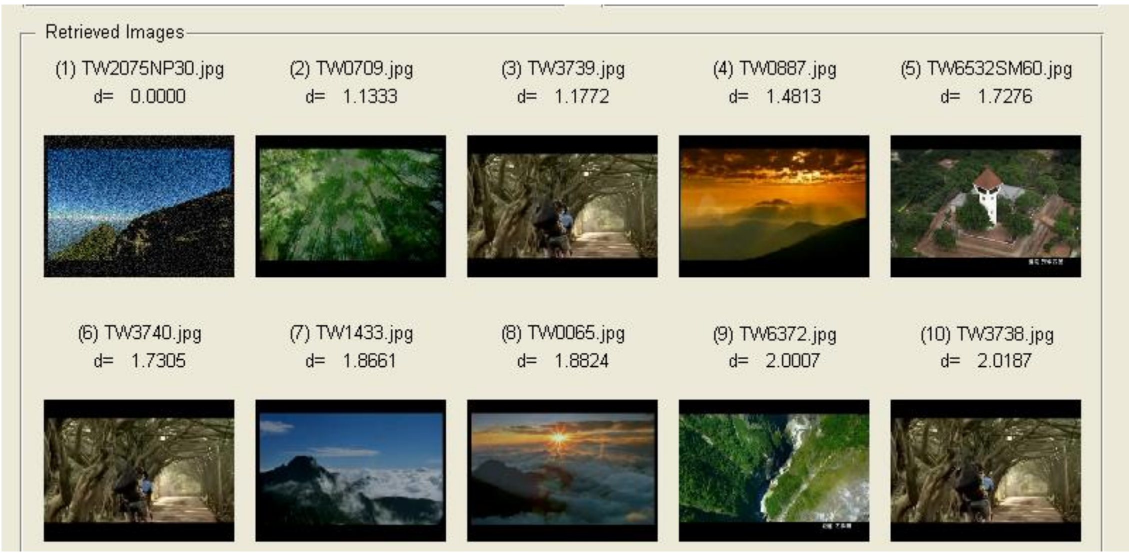
The 10 results of R. P. Kumar's system and the precision is 6/10. The first landscape image is also the query image. The images are presented in ascending distance from left to right and from top to bottom.

(The 10 results of K. Konstantinidis's approach and the precision is 4/10. The first landscape image is also the query image. The images are presented in descending similarity ratio from left to right and from top to bottom.

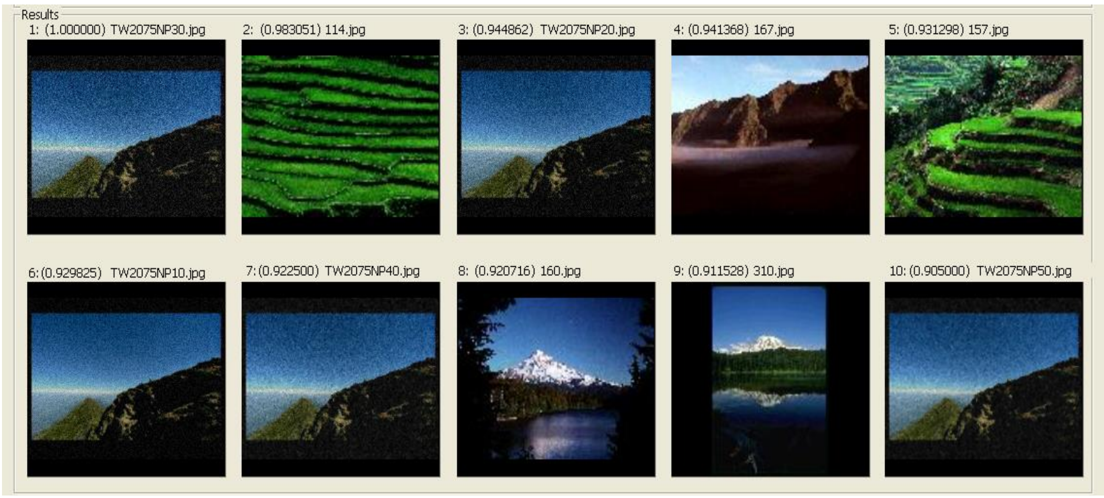
Fig. 7 demonstrates ours is outstanding in blurred situations.



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



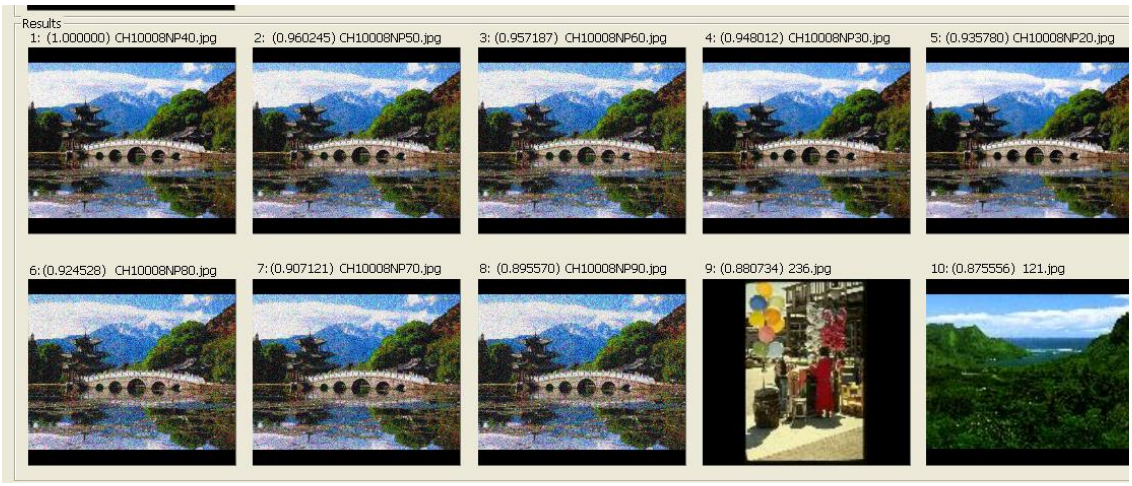
The 10 results of R. P. Kumar's system and the precision is 1/10. The first landscape image is also the query image. The images are presented in ascending distance from left to right and from top to bottom.



The 10 results of K. Konstantinidis's approach and the precision is 5/10. The first landscape image is also the query image. The images are presented in descending similarity ratio from left to right and from top to bottom.

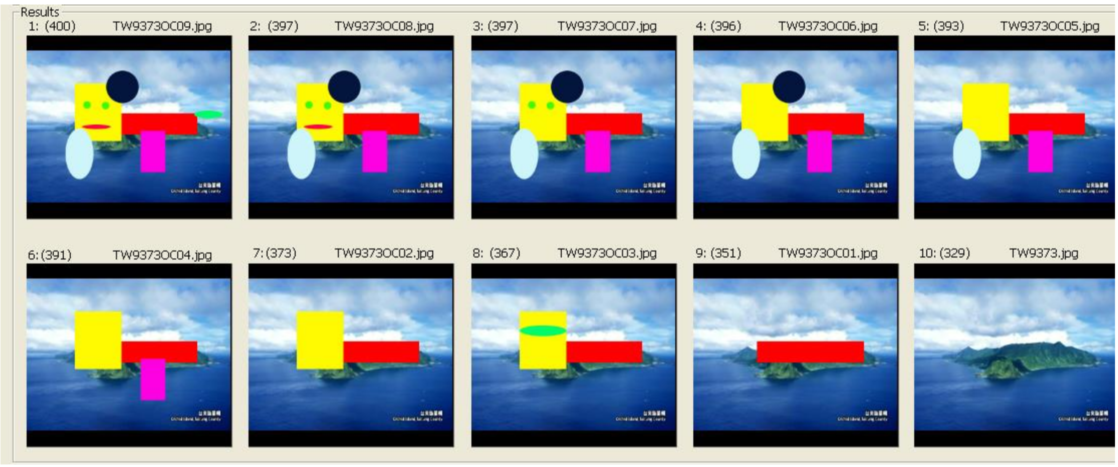
The 10 results of our approach and the precision is 10/10. The first landscape image is also the query image. The images are presented in descending matching weight from left to right and from top to bottom.

The 10 results of R. P. Kumar's system and the precision is 5/10. The first landscape image is also the query image. The images are presented in ascending distance from left to right and from top to bottom.



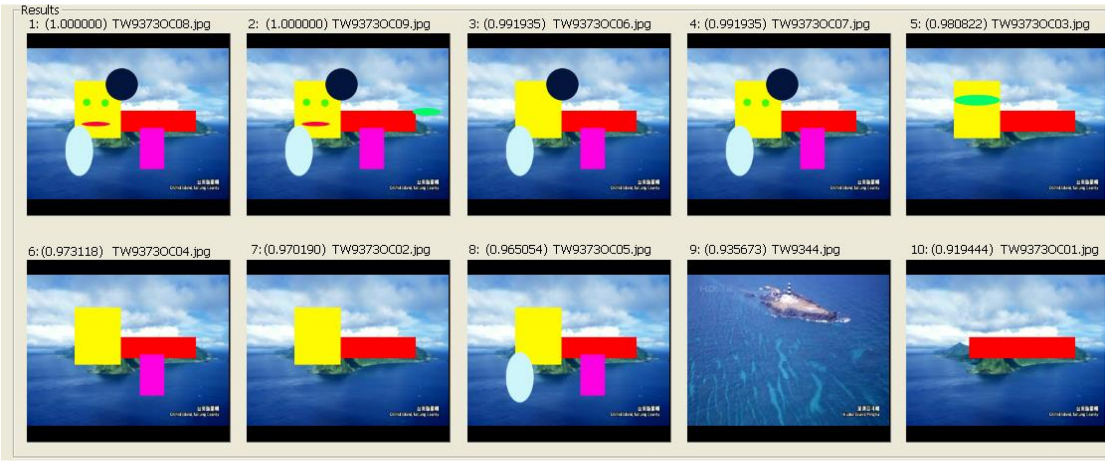
(The 10 results of K. Konstantinidis's approach and the precision is 8/10. The first landscape image is also the query image. The images are presented in descending similarity ratio from left to right and from top to bottom.

Fig. 8 displayed ours is marvelous in noise conditions.

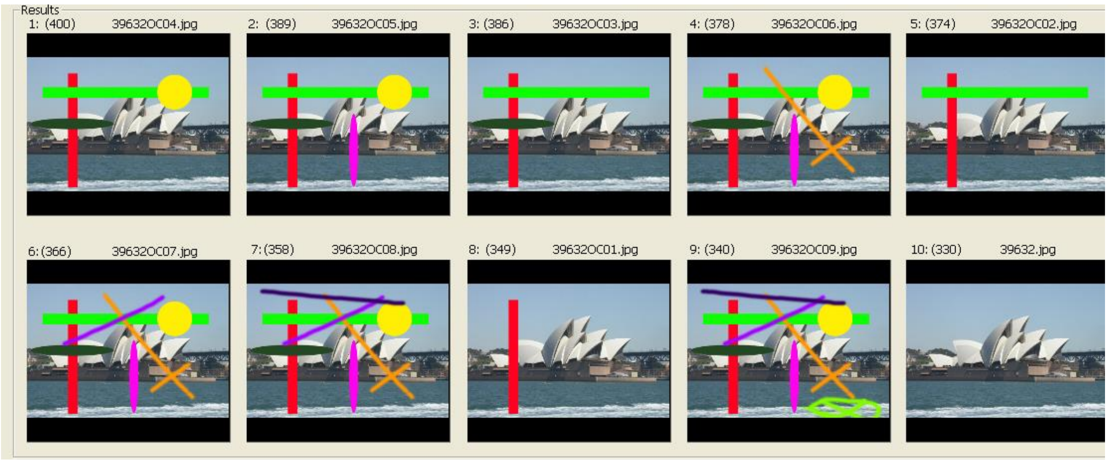


The 10 results of our approach and the precision is 10/10. The first landscape image is also the query image. The images are presented in descending matching weight from left to right and from top to bottom.

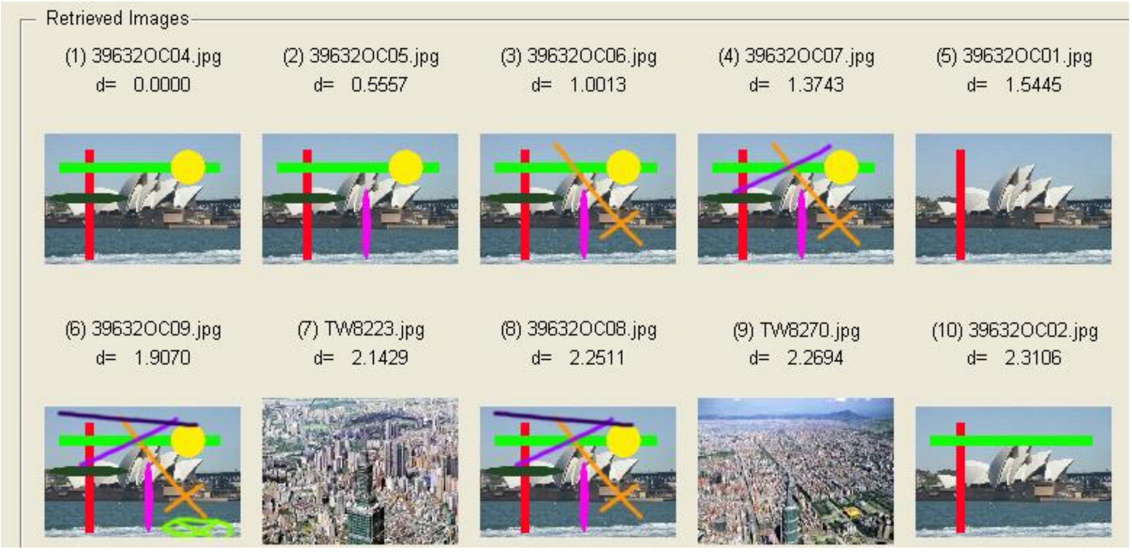
The 10 results of R. P. Kumar’s system and the precision is 9/10. The first landscape image is also the query image. The images are presented in ascending distance from left to right and from top to bottom.



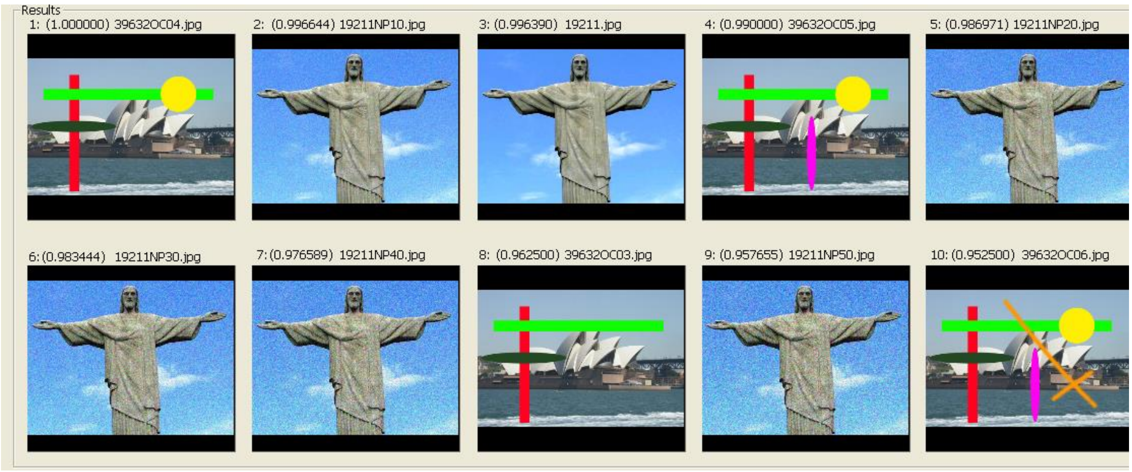
The 10 results of K. Konstantinidis's approach and the precision is 9/10. The first landscape image is also the query image. The images are presented in descending similarity ratio from left to right and from top to bottom.



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



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



(The 10 results of K. Konstantinidis's approach and the precision is 4/10. The first landscape image is also the query image. The images are presented in descending similarity ratio from left to right and from top to bottom.

Fig. 9 shows ours is remarkable in partial occlusion situations.

Table 1

The training time and retrieval time of our approach is superior than the others.

Time / Approach	Training time (seconds) / landscapes	Retrieval time (seconds) / average
Our approach	38.313000/133,000	0.7810
R. P. Kumar's system	289.107005/133,000	1.2830
K. Konstantinidis's approach	79.109001/133,000	0.9380