A colour image retrieval scheme based on Z-scanning technique

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Abstract: This paper proposes a new colour image retrieval scheme using Z-scanning technique for content-based image retrieval (CBIR). In recent years, the CBIR is a popular research topic for image retrieval. This paper proposes a scheme which employs the Z-scanning technique to extract directional intensity features for measuring the similarity between query and database images. In the multiple channel images, each colour channel can be processed individually or combined into a grey channel Y. In order to extract the features by Z-scanning technique from all images, each channel of all images must be divided into several $N \times N$ blocks. In each block, F pairs of pixels are scanned by a 'Z' direction to obtain the texture features. Each colour channel can be obtained an $M \times M$ Z-scanning co-occurrence matrix (ZSCM) for storing the probability of each relationship of all closest blocks. At the similarity measure stage, the ZSCMs of query image and database images are compared to measure their similarity. The experimental results show that the proposed scheme is beneficial for image retrieval when the images include the same texture or object. On the other hand, the proposed scheme also can get better retrieval results and more efficiency than colour correlogram (CC) technique for colour texture images. Another technique uses motif co-occurrence matrix (MCM) as the feature in similarity measurement. The experimental results show the proposed ZSCM can get better retrieval results and higher recall and precision values than the CC and MCM techniques for public image databases.

Keywords: image retrieval, content-based image retrieval (CBIR), Z-scanning, co-occurrence matrix, Z-scanning co-occurrence matrix (ZSCM)

1 INTRODUCTION

In recent years, the multimedia systems and research are becoming increasingly popular and progressive. They include words/texts, sounds/music, images/photos and videos. The images belong to a very general type of the multimedia and can carry more information, and are understood more easily than texts for users. Hence, they are generally used in many applications, for example, web pages, medical images, teaching materials, digital photos, geographic information systems and weather information etc. In many applications, their images are increasing daily and usually have a large number of images in the image databases. Hence, how to find correct or similar images in an image database has become a very important and popular research topic.[12,13] It is usually called 'image retrieval' or 'image indexing' and includes two types of retrieval ways. One is to perform the image retrieval by the file names or metadata of images. Another uses the content features of images, and it is usually called 'content-based image retrieval (CBIR).' Because the CBIR techniques retrieve images by the contents of images, the images are very useful and necessary for people.

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Nowadays, the CBIR has become an important and popular research topic on multimedia.

A general CBIR system can be divided and considered as three parts. The first part is the image database that can be constructed by many images with different objects, lights, illuminations, colours, etc. Generally speaking, these images can be classified into several classes and the images of each class have the same or similar features understood and defined by humans. In some research papers, in order to increase their confidence, some public and general image databases are used in their experiments, for example, Vistex database of the MIT Media Lab and the Corel photo database are used to evaluate the performance of many CBIR techniques. The second part of CBIR is the query images, which are usually provided by the users to be the input of a CBIR system, and the outputs are the similar images of the image database. For example, a user takes a building image for the query image, and inputs the image into a CBIR system. The CBIR system then inputs the image into a CBIR system and outputs top N images which are similar to the buildings to the user. The second part of CBIR is the feature extraction and similarity measurement. The feature extraction is used to extract some features to measure the similarity between query and database images. Generally speaking, the features includes: spatial relationships or shape of objects,[14–20] spatial colour distributions,[21–23] texture characteristics,[24] etc. How to extract the correct features for similarity measuring is a very important and interesting topic of most CBIR research. A general structure of CBIR is shown in Fig. 1. The flowchart of a general colour CBIR system is shown in Fig. 2. In many colour CBIR systems, in order to gain more accuracy, the features are extracted from each colour channel independently. Some CBIR researches also consider the conditions that images or objects with shifting, rotating and resizing. Otherwise, in order to gain more accuracy, too many features may be extracted. It will increase the computing complexity of similarity measurement. Hence, how to decide the quantity of features is also very important for CBIR research.

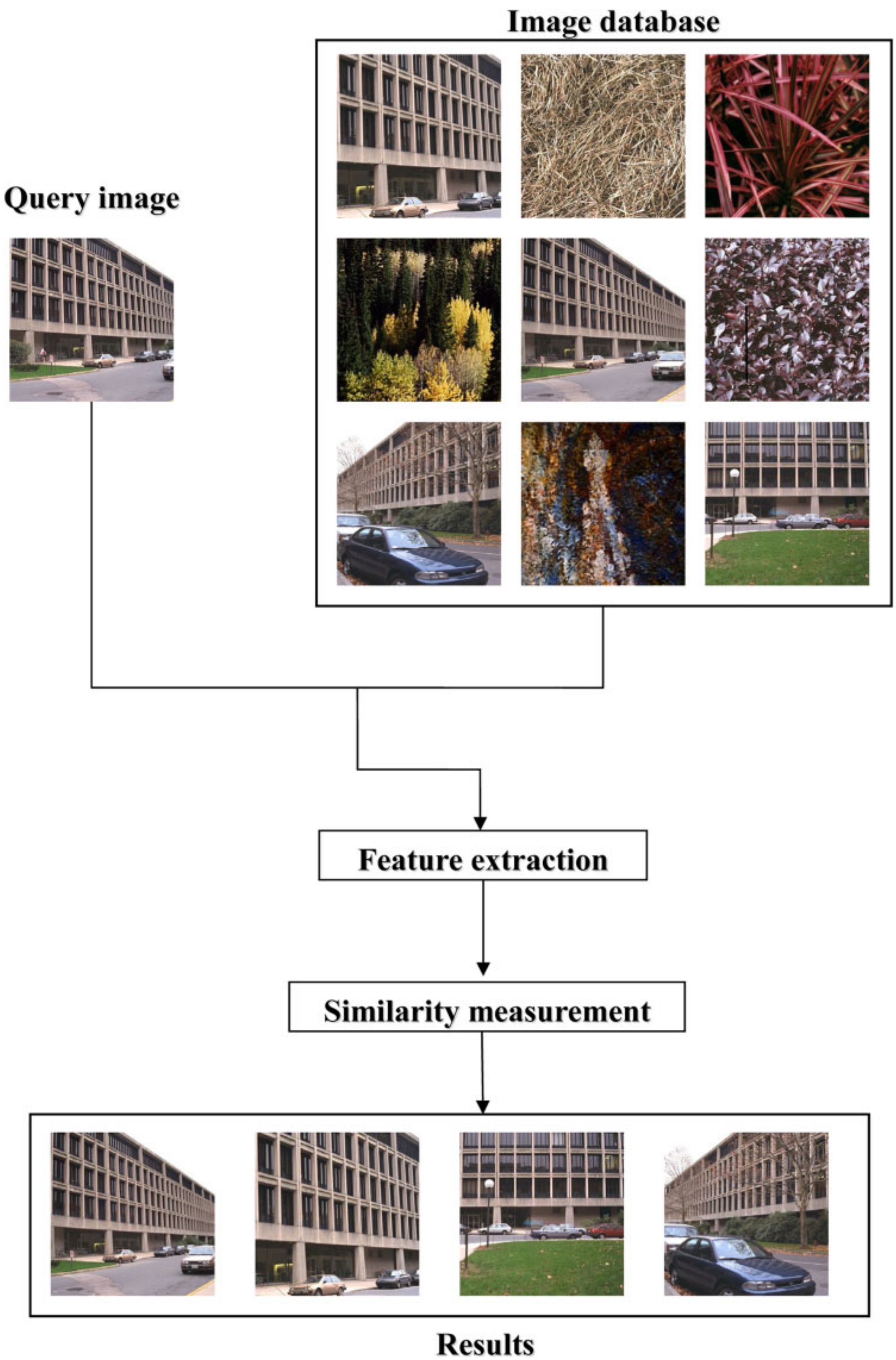
In order to perform the image retrieval by the content of image, some features have to be extracted from images. In this paper, a Z-scanning feature extracting scheme is proposed for image retrieval, and it is used to extract some direction intensity features to measure the similarity of query images and database images in our scheme. In this scheme, Z-scanning co-occurrence matrix (ZSCM) is created by computing the probability of different intensity direction features existing in all pairs of closest $N \times N$ blocks of an image. When the block size is 2×2, ZSCM is only created as an 8×8 matrix, and it can be used to gain more efficiency for similarity measurement.

Some related works about CBIR are shown in Section 2. The detail of the proposed scheme are shown in Section 3 and some experimental results are presented to confirm the proposed scheme can get well performance for colour texture image retrieval in Section 4.

2 RELATED WORKS

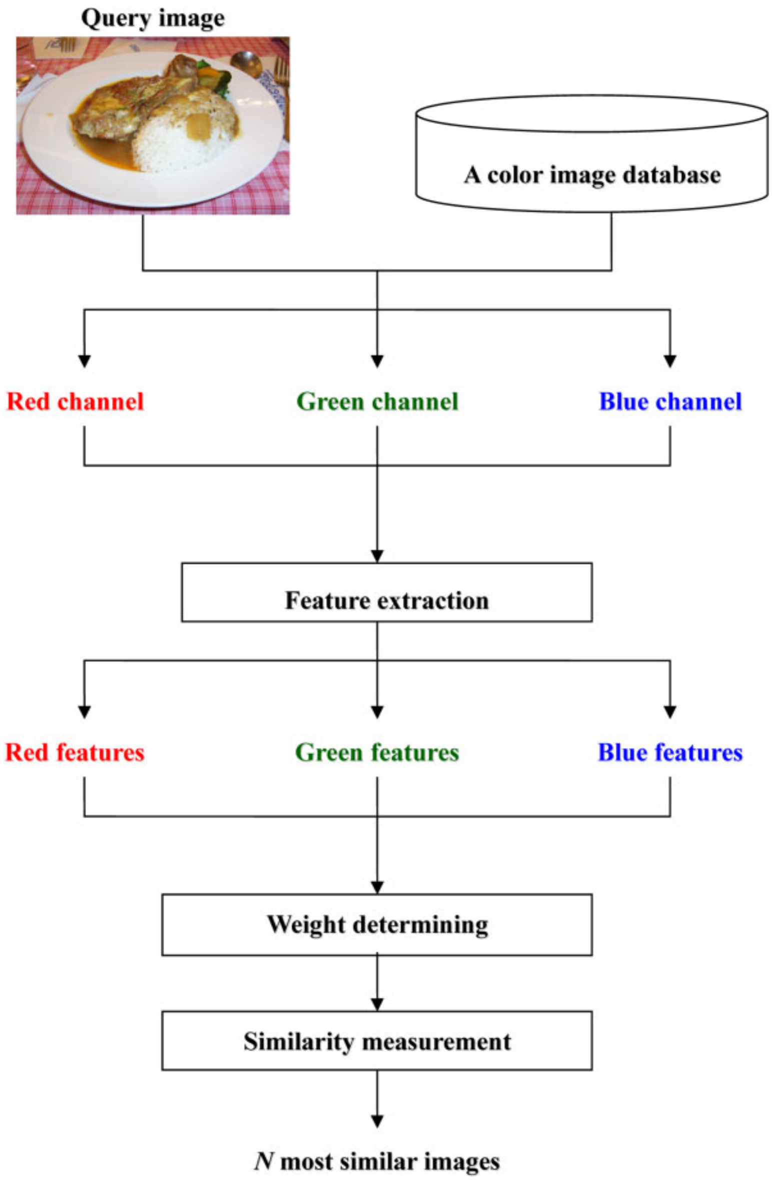
Since the 1990s, the colour of images is employed to acquire some features for content-based image retrieval.[1–8] The feature of images on vision is apparent and helpful to achieve a better retrieval result. In 1991, Swain and Ballard proposed a colour histogram analysis technique to extract features used in CBIR.[6] Each colour image can be used to obtain a colour histogram to present the colour distribution features. Generally speaking, a colour histogram has N bins to accumulate the probability of J colours occurring in an image, but N may be too large to increase computing complexity for measuring similarity between any two images. A flowchart of an image retrieval technique which uses colour histogram is shown in Fig. 3. In Ref. 6, the authors used k-means clustering technique to cluster J colour into K clusters for all images. In each cluster, the centre colour is obtained by computing the mean of colours to be the representative colour, and a colour histogram is created by accumulating the probability of K colours occurring in an image. In colour histogram technique, the similarity between the two images is measured by comparing their colour histograms. The advantages of this technique are that the computing complexity is very low and can extract the global features of an image to reduce the affects when the objects shift, rotate and distort in the different images.

A co-occurrence matrix (CM) is a popular technique for analysing the variation of image features in spatial domains. In CBIR research area, the CM is generally performed to help achieve the relationship of a feature changing between a pair of pixels and



1 A general structure of CBIR

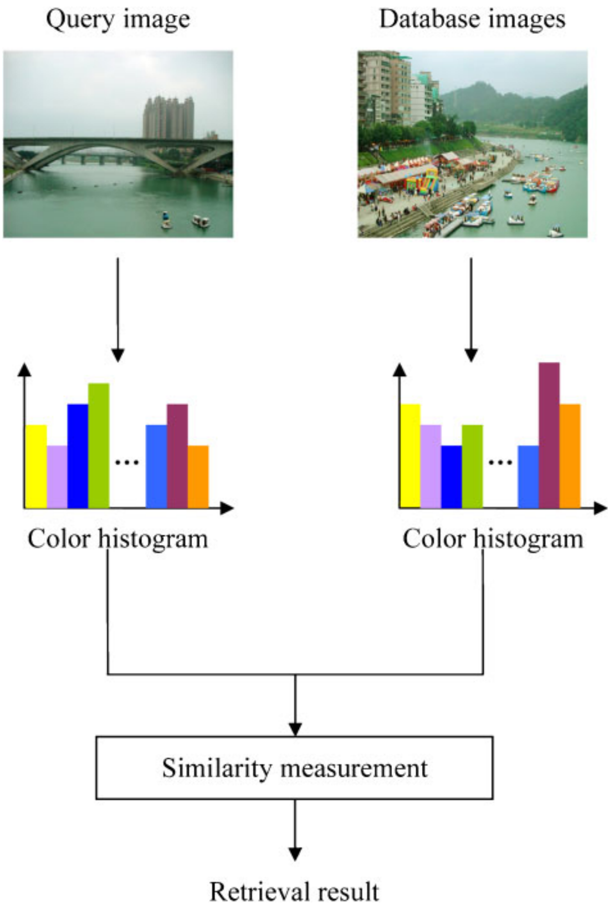
regions of images. Generally speaking, the attributes between rows and columns of CM are symmetrical, and its elements are used to record the probability of each mapping relationship of rows and columns co-occurring in the spatial domain of a whole image. In an image, when a pair of pixels is mapped closer to the diagonal region of CM, it has a higher possibility to be the smoother region of the image. Hence, the diagonal elements of CM are the homogeneous regions of an image, but the far diagonal elements are more possible to be the shape regions (see Fig. 4). The attributes of CM are determined by the features which



2 The flowchart of general structure of colour CBIR technique

are extracted for analysing and computing in the similarity measurement of CBIR. When the closer diagonal elements of a CM, it means that the features have a smaller variation in a spatial domain of an image; hence, it is very helpful for extracting the features variation of images in CBIR research.

Colour correlogram (CC) technique[5,8] analyses the colour relationship between any two closed pixels of an image. It quantifies all colours into J colours C_1, C_2, …, C_J; thus, $J \times J$ kinds of colour relationship can be obtained to cumulate their probability in a certain image. The $CC(i,j,k)$ of an image $Z(x,y)$ is defined in equation (1).[11] Colour co-occurrence matrix (CCM) is created to store the probability of all colour relationships. In multiple colour channel images, the colour relationship is analysed in each colour channel independently. Hence, a multiple dimension CCM must be created for each colour image. CC has some disadvantages which does not consider the edge or shape features, so it is weaker for objects or texture image queries. Otherwise, the size of CCM depends on the level of colour quantification, for example, a 256-colour image must create a 256×256 CCM. It causes the size of CCM to be greater in a multi-tone image and takes more computing time in the similarity measure stage.



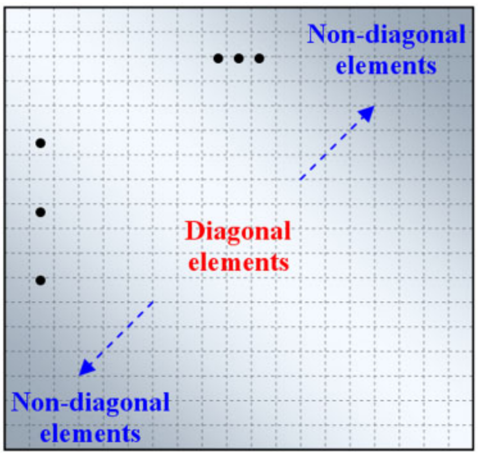
3 The flowchart of the image retrieval technique using colour histogram

$$CC(i,j,k) = \Pr[Z(x_1,y_1) \in C_i | Z(x_2,y_2) \in C_i; \quad k = \max(|x_1 - x_2|, |y_1 - y_2|)] \quad (1)$$

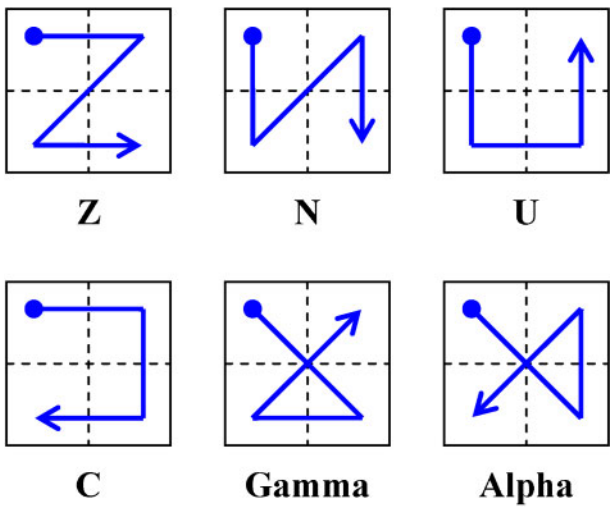
where $C_i\{C_1, C_2, \ldots, C_J\}$, and k is the distance between two pixel of an image.

Shim and Choi[9] proposed a modified colour co-occurrence matrix (CCM) image retrieval technique with modifying CCM. In general, the pixel values that exist in edge or non-homogeneous regions are more different from the neighbours than existing homogeneous regions. Hence, the non-diagonal elements of CCM may be obtained from the pixels of edge regions. The authors considered that the pixels of edge regions carry more important feature information. Hence, they added the weights of non-diagonal elements of CCM to emphasise the edge information. Their experiments confirmed modified CCM can improve the traditional CC technique to gain a better performance for CBIR.

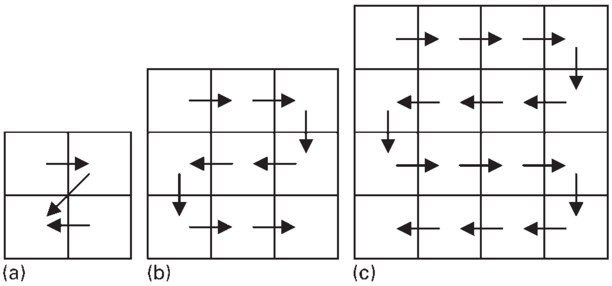
Jhanwar *et al.*[10] divided the original image into 2×2 blocks. They referred Peano scanning technique to scan each block to locate the scanning path which can achieve the minimum pixel variation. In each block, a scanning path can be found and is called 'motifs' here. The authors set the scanning always starting at the top-left pixel of each block and can find six kinds of motifs. The six motifs include 'Z', 'N', 'U', 'C', gamma and alpha, and they are shown in Fig. 5. In non-overlapping block case, an $N \times N$ image can obtain $N/2 \times N/2$ motifs. They considered and analysed each block to find its motif to be the local feature and computed the probability of each motif to create a motif co-occurrence matrix (MCM) for similarity measure. Their experimental results show that this technique can achieve a better



4 The diagonal and non-diagonal elements of a co-occurrence matrix



5 Six possible motifs[10]



6 The examples of scanning directions for different sizes of blocks

efficiency and retrieval results than CC in the Vistex database from the MIT Media Lab.

In the CBIR systems, features are extracted from the content of original images. However, it is possible to extract features from the image compression code. Qiu[11] proposed a CBIR scheme for black truncation coding (BTC) images. BTC is an image compression technique. It compresses images by blocks, and each block can gain a bit pattern and two means. In this scheme, the author took two features from each image for similarity measure. The first feature is the block colour co-occurrence matrix, and another is block pattern histogram. The first feature is created by computing the concurrent probability of different pair means, and the other feature is obtained by counting the concurrent probability of different bit patterns. In their experiment, the two features had the same weight in image similarity measure. The scheme extracts features from the BTC code directly. Hence, it can improve the performance of image retrieval when the images are compressed by BTC.

In this paper, a new image retrieval scheme is proposed. A known Z-scanning technique is used to determine the scanning order of extracting features of directional strength from each $N \times N$ block of an image, and all probability of all kinds of directional strengths are recorded in a ZSCM used for similarity measure of colour images.

3 PROPOSED SCHEME

CBIR is an image retrieval technique that uses the content of images to perform the similarity measure. In order to perform the image retrieval according to the content of image, some features must be extracted from images. Many methods were proposed and used to obtain some useful features from spatial or frequency domain of images. In the images that include different textures and objects, some features must exist and can be extracted to use in comparing similarity of any pair images. In this chapter, a scheme is proposed to extract the feature of the occurrence frequency of different edges in each image. In our proposed method, the Z-scanning technique is a useful tool to determine the scanning direction for extracting features from spatial domain of images. The intensity relationships are obtained from comparing each pair pixel of blocks using the Z-scanning technique. They are computed statistically to be the features and used to structure a ZSCM for each query and database image. The ZSCMs between query and database images are the basis of evaluating their difference in similarity measure. The details of the proposed scheme are shown as follows.

In most cases, colour images are stored in RGB space, and it is also the most well-known colour space in human visual system. Hence, the proposed scheme only considers this colour space for all colour images in this paper. The RGB space is structured by red $I_r(x,y)$, green $I_g(x,y)$ and blue $I_b(x,y)$ colour channels, where x and y are the coordinates of each pixel in a colour image. In human vision, people have different kinds of sentience in red, green and blue. In order to allow the retrieval results to be closer to human vision, each colour channel is processed and analysed independently, and each owns its different own weight (λ_r, λ_g and λ_b). In the proposed scheme, all channels are considered as a grey image and can be considered in two-dimensional domains.

Generally speaking, each object is a part of an image; in addition, the texture of an image is composed of many smaller motifs. Hence, in order to extract and analyse the feature more precisely, each colour channel is divided into several $N \times N$ blocks B. Each block can be analysed to achieve a feature value. The pixels of each block are defined as $b_{i,j}$, where i and j are the coordinates of B.

In each block, all pixels are scanned by a 'Z' direction and the first scanned pixel is the top-left one. For example, in the case of 2×2 block, the scanning order is that: first, the top-left pixel; second, the top-right pixel; third, bottom-right pixel; and final, the bottom-left pixel. Some examples of scanning directions for 2×2, 3×3 and 4×4 blocks are shown in Fig. 6. In each scanning, a comparison of the current pixel and the next pixel must be performed. The comparison can get two possible results: one is the current pixel that is larger than the next pixel or is equal to the next pixel; another is the current pixel that is smaller than the next pixel. To consider whole $N \times N$ blocks, F comparisons must be performed, and 2^F possible sets can be obtained, where F can be computed from equation (2). For example, a 2×2 block must be compared three times and eight possible sets can be got.

$$F = (N-1) \times N + (N-1) = (N-1) \times (N+1) \quad (2)$$

When all blocks have performed the scan and comparison procedures, the relationship between each two closed blocks is considered in a whole colour channel. In order to analyse the intensity relationship between each pair of closed blocks in spatial domain, a co-occurrence matrix is employed in our scheme. The co-occurrence matrix is a very useful tool for feature storing and analysing. In our scheme, the co-occurrence matrix is a two-dimensional matrix created by the possible sets of all pairs of blocks. In this paper, it is called ZSCM. The size of the ZSCM is $2^{(N-1)\times(N+1)} \times 2^{(N-1)\times(N+1)}$ when the size of the blocks is $N \times N$. Each value $ZSCM_C(i,j)$ of the ZSCM is a probability and can be obtained from equation (3). After each colour channel created its ZSCM, in order to reduce the cost of similarity measure, the ZSCMs of all colour channels can be combined into one matrix $ZSCM_T(i,j)$ by equation (4).

$$ZSCM_C(i,j) = \Pr\left[I_C(x_1,y_1) \in P_i \middle| I_C(x_2,y_2) \in P_j\right] \quad (3)$$

where $I_C(x,y)$ is the current pixel in the C channel of image I, $I_C(x_2,y_2)$ is the next pixel of $I_C(x_1,y_1)$, and P_i and P_j is the ith and jth possible sets.

$$ZSCM_T(i,j) = \frac{\lambda_r \times ZSCM_r(i,j) + \lambda_g \times ZSCM_g(i,j) + \lambda_b \times ZSCM_b(i,j)}{3} \quad (4)$$

where $ZSCM_r(i,j)$, $ZSCM_g(i,j)$ and $ZSCM_b(i,j)$ are the ZSCMs of red, green and blue channels; λ_r, λ_g and λ_b are the weights for the colour channels.

Considering a 2×2 block, the scanning directions are shown in Fig. 6a and the definition of each pixel is shown in Fig. 7. In Fig. 7, the four pixels are PTL (pixel of top-left), PTR (pixel of top-right), PBL (pixel of bottom-left) and PBR (pixel of bottom-right). In this case, each block has three comparisons, which must be performed by each pair of close pixels. And the three comparisons can achieve eight possible combinations. The eight possible combinations P_i for the case using 2×2 blocks are shown in Fig 8. In this experiment, an 8×8 ZSCM can be constructed by accumulating the co-occurrence of the P_i between each pair of close blocks (B_i and B_{i+1}) in a complete image. In equation (4), in order to consider the significance of red, green and blue for human vision, the weights λ_r, λ_g and λ_b are set to 0.299, 0.587 and 0.114.

PTL	*PTR*
PBL	*PBR*

7 The definition of each pixel in a 2×2 block

During the similarity measurement stage, the distance $D(I_p,I_q)$ between the pattern image I_p and the query image I_q can be obtained from equation (5). The more similar pattern images for the query image have a less distance, and the distance between all pattern images and the query image will be sorted increasingly to be the similarity order.

$$D(I_p,I_q) = \sum_i \sum_j \left[\frac{|ZSCM_p(i,j) - ZSCM_q(i,j)|}{1 + ZSCM_p(i,j) + ZSCM_q(i,j)}\right] \quad (5)$$

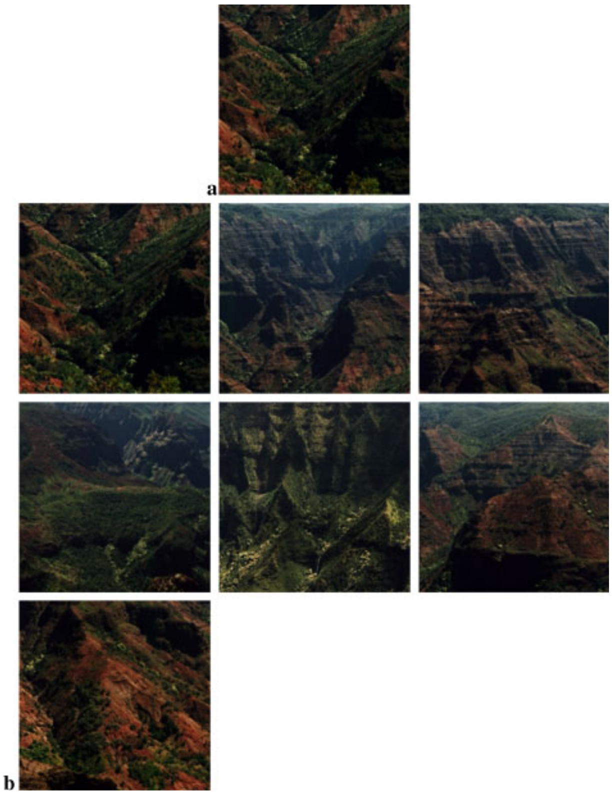
4 EXPERIMENTAL RESULTS

In order to evaluate the performance of the proposed scheme, some experiments are performed. These experiments use two public image databases to validate the performance of the proposed scheme. The first image database which is employed in this experiment is the Vistex database from the MIT Media Lab. VisTex database is assembled and maintained to help develop

$$P_1 : PTL > PTR \wedge PTR > PBR \wedge PBR > PBL$$
$$P_2 : PTL > PTR \wedge PTR > PBR \wedge PBR \leq PBL$$
$$P_3 : PTL > PTR \wedge PTR \leq PBR \wedge PBR > PBL$$
$$P_4 : PTL > PTR \wedge PTR \leq PBR \wedge PBR \leq PBL$$
$$P_5 : PTL \leq PTR \wedge PTR > PBR \wedge PBR > PBL$$
$$P_6 : PTL \leq PTR \wedge PTR > PBR \wedge PBR \leq PBL$$
$$P_7 : PTL \leq PTR \wedge PTR \leq PBR \wedge PBR > PBL$$
$$P_8 : PTL \leq PTR \wedge PTR \leq PBR \wedge PBR \leq PBL$$

8 The eight possible combinations for the case using 2×2 blocks

9 (a) The query image; (b) the query results for the *Buildings* images



11 (a) The query image; (b) the query results for the *Terrain* images

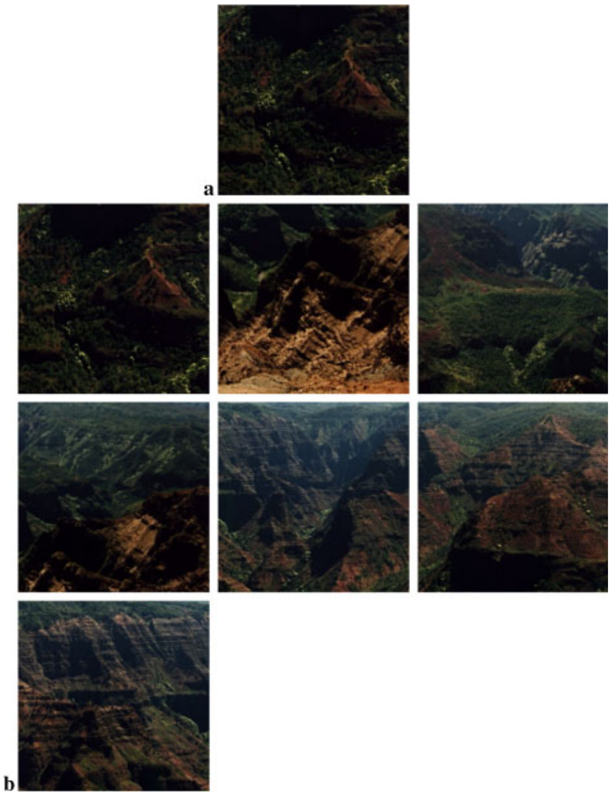
better computer vision techniques by comparing their performance on a common texture image database. It includes about 19 classes of texture images and each

10 (a) The query image; (b) the query results for the *Sand* images

class has one more image with similar texture and different rotation and lighting conditions.

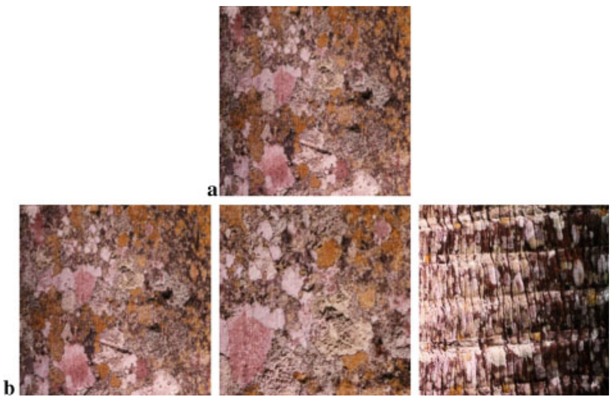
First, the VisTex database is used to test the performance of the proposed scheme for different topics or texture image and several experiments of different query images, and the retrieval results are shown as follows.

The first experiment uses an image about buildings. In the retrieval result, the first seven images all are about buildings. Although the least two images are not about buildings, they all still include a similar colour and the feature of grids. In Fig. 9, the similarity order is from left to right and from top to bottom. Following the first experiment, some other experiments are performed to show that the proposed method also can get good retrieval results for the images of other classes in image database. Some of these experiments are used to test the retrieval ability for some pairs of most similar images in the image database. The experimental results show that the proposed scheme has good retrieval ability for the images with similar topics, colours and textures. The retrieval results of all other experiments are shown in Figs. 10–21.

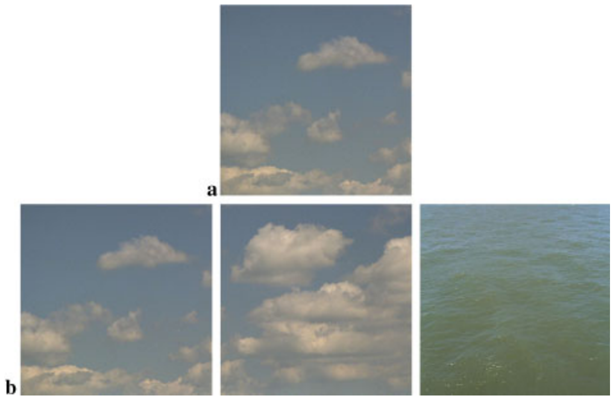


12 (a) The query image; (b) the query results for the *Terrain* images

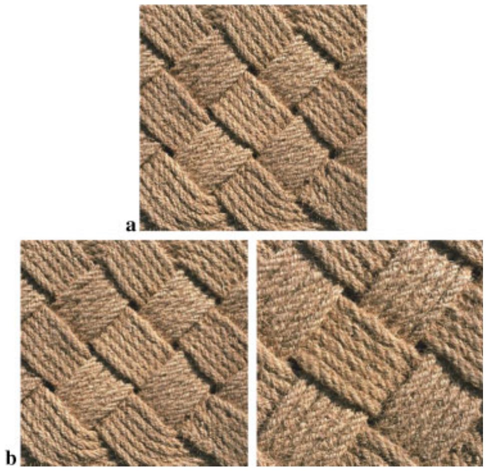
CC technique[7] is the most popular technique for image comparison in other related researches. Hence, it is also compared with our scheme in this section. In this comparison, the query image is the same as Fig. 9a, and the query results of CC are shown in Fig. 22b. In Fig. 22b, there are only four images which are correct in the top nine similar images and the other incorrect images are irrelevant to the query image. The query results of our scheme are shown in Fig. 22a: there are seven images which are correct in



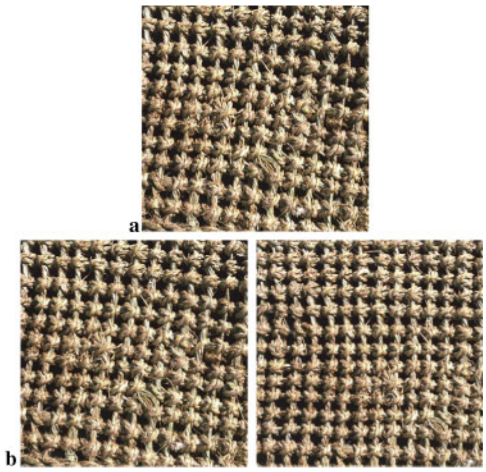
13 (a) The query image; (b) the query results for the *Bark* images



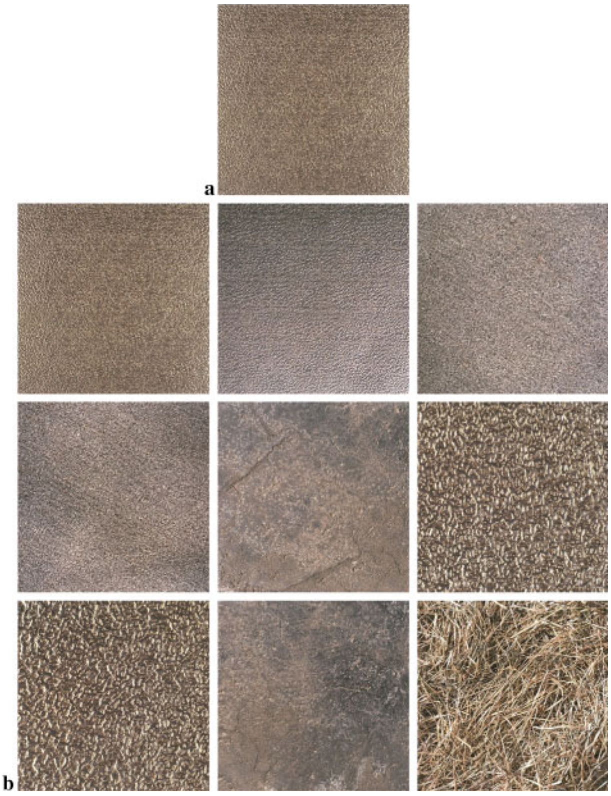
14 (a) The query image; (b) the query results for the *Clouds* images



15 (a) The query image; (b) the query results for the *Fabric* images

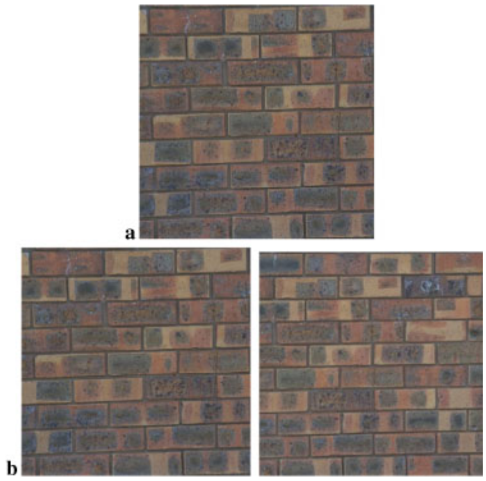


16 (a) The query image; (b) the query results for the *Fabric* images

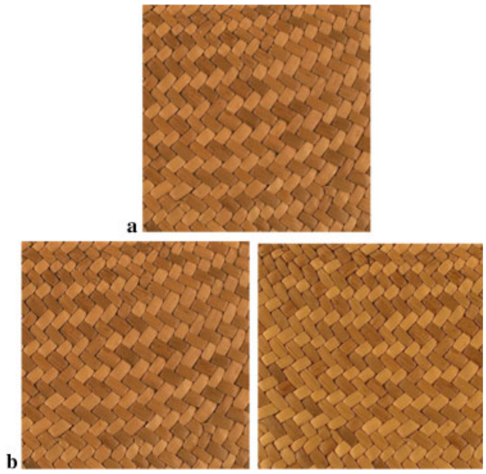


17 (a) The query image; (b) the query results for the *Metal* images

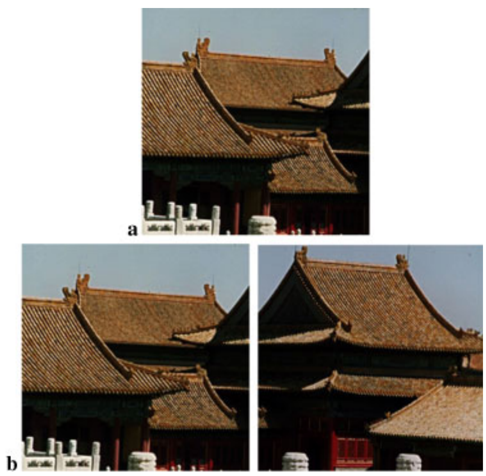
18 (a) The query image; (b) the query results for the *Metal* images



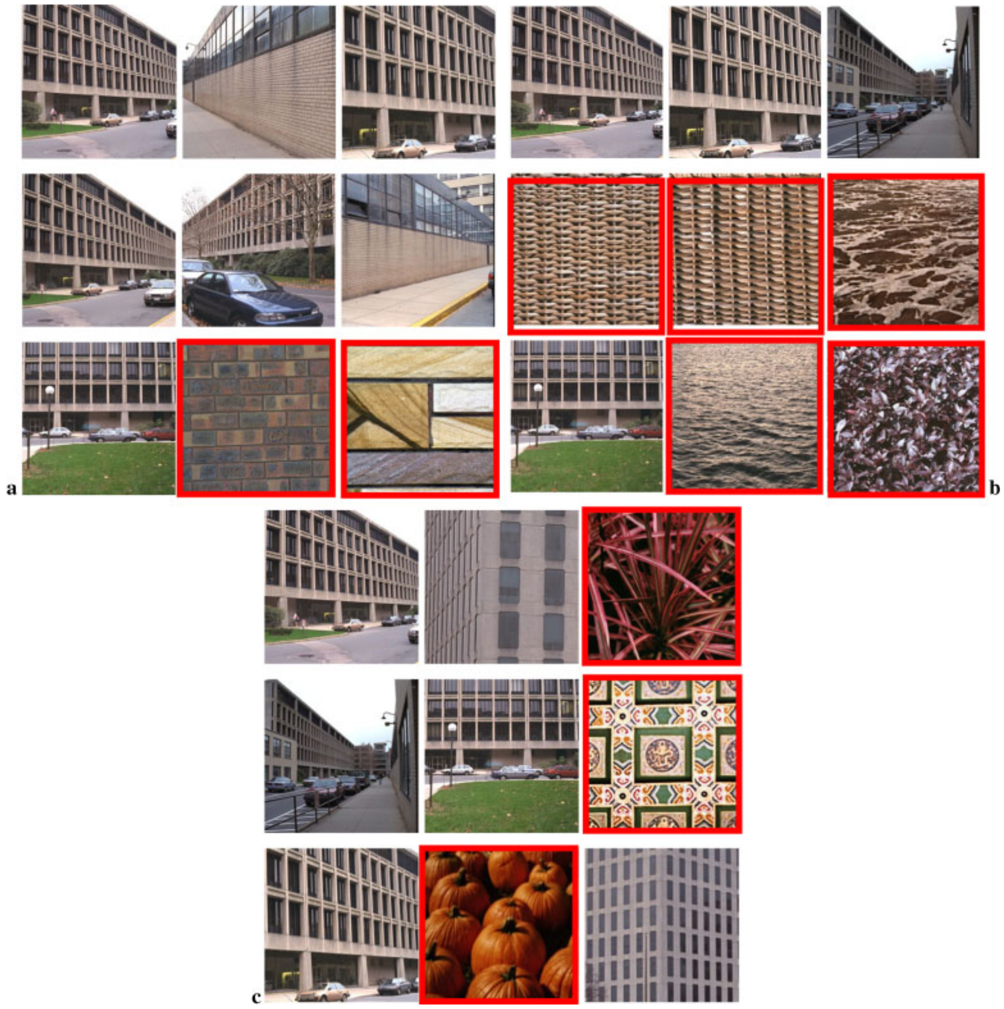
19 (a) The query image; (b) the query results for the *Brick* images



20 (a) The query image; (b) the query results for the *Fabric* images



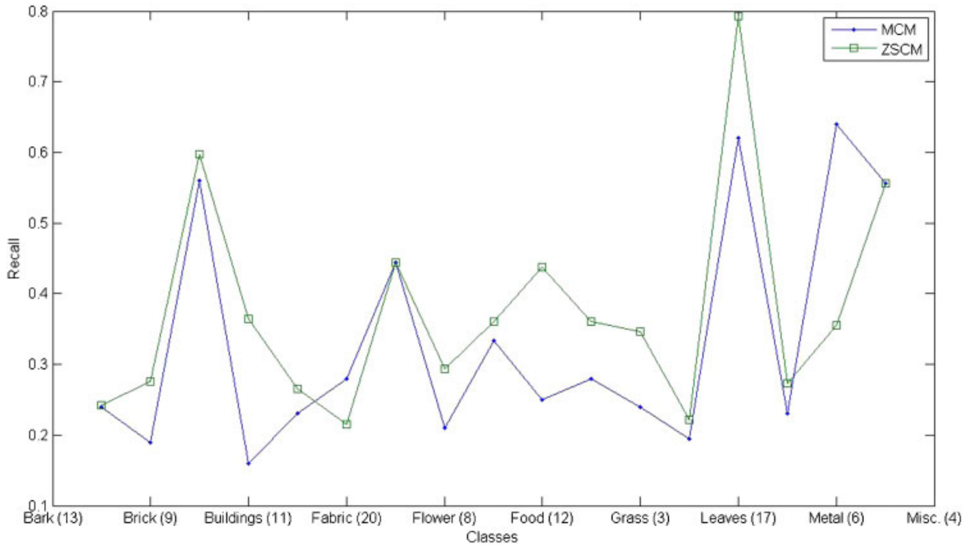
21 (a) The query image; (b) the query results for the *Tile* images



22 (a) The query results of the proposed scheme; (b) the query results of the CC technique;[7] (c) the query results of the MCM[10] technique

top nine similar images and the other incorrect images are similar to the query image. On the other hand, the proposed scheme only requires a 8×8 co-occurrence matrix in the case of using 2×2 blocks. It can gain more efficiency for CBIR. Another technique[10] uses MCM to be the feature for image retrieval. In MCM, the colour is transformed into a grey colour space and it is similar to our method. The same query image is used in this experimental (Fig. 22a), and the MCM is the feature in this experiment. And the results are shown in Fig. 22c. There are three incorrect images in the retrieval results. Two of them are the images of plants and they are far from the query image.

In order to compare the performances of the proposed ZSCM and the MCM, a popular measurement method is used to compute recall to show the retrieval rate of CBIR techniques. The recall r_j of the query image QI_j can be obtained from equation (6). This index can show the percentage of the retrieved images with the same class i of the query image QI_j in certain rank N_i. In this experiment, all images of the database are used to be query images to obtain a recall value r_j. The group average recall value each class is computed to show the retrieval performance of ZSCM and MCM in each texture class. The group average recall values of ZSCM and MCM. The number of images in each texture class is shown in Fig. 23. This experimental result shows that the proposed ZSCM can get better retrieval accuracy in most texture classes. The total average recall for whole database also is computed by considering the number of images of each class as weights to show the overall performance. In this experiment, the weighted total recall of the proposed ZSCM is about 119% of the weighted total recall of the MCM.



23 The average recall of MCM[10] and ZSCM for each texture class

$$r_j = \frac{n_i}{N_i} \tag{6}$$

where n_i is the number of retrieved images which belong to the class of the query image QI_j in rank N_i, and N_i is the total number of class i.

Another image database is a public database called Corel. This public image database contains 1000 natural images with different topics, and some example images are shown in Fig. 24. In this experiment, the average precisions of ZSCM and

24 Some example images of the Corel image database

MCM are about 55.19% and 50.45% for each topic. The comparisons of MCM with other classical CBIR methods can be found in the corresponding SCI journal paper,[10] and the MCM can get better results than the classical methods.

5 CONCLUSION

In this paper, a ZSCM scheme is proposed. It can extract the features of objects and texture from colour images successfully. The experimental results show that the proposed scheme is useful to query images with the same objects or texture. In the comparison, a well-known CBIR technique: CC must use the CCM to store their features. In most cases, the colour images must be quantised to 256 colours in CC, and the size of CCM is 256×256. However, the proposed scheme can fixed the ZSCM in 8×8 when the images is in 2×2 block. Hence, the proposed can get more effective similarity measure in the general case. The experimental results show that the proposed scheme can get better retrieval results for colour texture images.

REFERENCES

1 Smeulders, A., Worring, M., Santini, S., Gupta, A. and Jain, R. Content-based image retrieval at the end of the early years. *IEEE Trans. Pattern Anal. Mach. Intell.*, 2000, **22**, 1349–1380.

2 Funt, B. V. and Finlayson, G. D. Color constant color indexing. *IEEE Trans. Pattern Anal. Mach. Intell.*, 1995, **17**, 522–529.

3 Gevers, T. and Semulders, A. W. M. PicToSeek: combining color and shape invariant features for image retrieval. *IEEE Trans. Image Porcess.*, 2000, **9**, 102–119.

4 Geusebroek, J. M., van den Boomgaard, R., Smeulders, A. W. M. and Geerts, H. Color invariance. *IEEE Trans. Pattern Anal. Mach. Intell.*, 2001, **23**, 1338–1350.

5 Kovalev, V. and Volmer, S. Color co-occurrence descriptor for querying-by-example, Proc. Int. Conf. on *Multimedia modeling: MMM '98*, Lausanne, Switzerland, October 1998, IEEE Computer Society, pp. 32–38.

6 Swain, M. and Ballard, D. Color indexing. *Int. J. Comput. Vis.*, 1991, **7**, 11–32.

7 Huang J., Ravi Kumar, S., Mitra, M., Zhu, W.-Jand Zabih, R. Image indexing using color correlograms, Proc. Conf. on *Computer vision and pattern recognition: CVPR '97*, San Juan, Puerto Rico, June 1997, IEEE Computer Society, pp. 762–768.

8 Chang, P. and Krumm, J. Object recognition with color co-occurrence histograms, Proc. Conf. on *Computer vision and pattern recognition: CVPR '99*, Ft Collins, CO, USA, June 1999, IEEE Computer Society, Vol. 2, pp. 498–504.

9 Shim, S.-O. and Choi, T.-S. Image indexing by modified color co-occurrence matrix, Proc. Int. Conf. on *Image processing: ICIP 2003*, Barcelona, Spain, September 2003, IEEE, Vol. 3, pp. 493–496.

10 Jhanwar, N., Chaudhuri, S., Seetharaman, G. and Zavidovique, B. Content based image retrieval using motif cooccurrence matrix. *Image Vis. Comput.*, 2004, **22**, 1211–1220.

11 Qiu, G. P. Color image indexing using BTC. *IEEE Trans. Image Process.*, 2003, **12**, 93–101.

12 Rui, Y., Huang, T. S. and Chang, S. F. Image retrieval: current techniques, promising directions and open issues. *J. Vis. Commun. Image Represent.*, 1999, **10**, 39–62.

13 Smeulders, A. W. M., Worring, M., Gupta, A. and Jain, R. Content-based image retrieval at the early years. *IEEE Trans. Pattern Anal. Mach. Intell.*, 2000, **22**, 1349–1380.

14 Kankanhalli, M. S., Mehtre, B. M. and Huang, H. Y. Color and spatial feature for content-based image retrieval. *Pattern Recogn.*, 2001, **22**, 323–337.

15 Chang, C. C. and Chang, Y. K. A fast filter for image retrieval based on color-spatial features, Proc. 2nd Int. Workshop on Software Engineering and Multimedia Applications: *SEMA 2000*, Baden-Baden, German, August 2000, pp. 47–51.

16 Carson, C., Thomas, M., Belongie, S., Hellerstein, J. M. and Malik, J. Blobword: a system for region-based image indexing and retrieval, Proc. 3rd International Conference on *Visual information systems: VISUAL '99*, Amsterdam, The Netherlands, June 1999, Universiteit van Amsterdam, pp. 509–516.

17 Hirata, K. and Kato, T. Rough sketch-based image information retrieval. *NEC Res. Dev.*, 1992, **34**, 263–273.

18 Hsu, W., Chua, T. S. and Pung, H. K. An integrated color-spatial approach to content-based image retrieval, Proc. ACM Multimedia Conf., San Francisco, CA, USA, November 1995, ACM Press, pp. 305–313.

19 Pass, G. and Zabih, R. Histogram refinement for content-based image retrieval, Proc. 3rd IEEE Workshop on *Applications of computer vision: WACV '96*, Sarasota, FL, USA, December 1996, IEEE Computer Society, pp. 96–102.

20 Mehtre, B. M., KanKanhalli, M. S. and Lee, W. F. Content-based image retrieval using a composite color-shape approach. *Inf. Process. Manage.*, 1998, **34**, 109–120.

21 Brunelli, R. and Mich, O. Image retrieval by examples. *IEEE Trans. Multimedia*, 2000, **2**, 164–171.

22 Fuertes, J. M., Lucena, M., Pérez de la Blanca, N. and Chamorro-martõânez, J. A scheme of colour image retrieval from databases. *Pattern Recogn.*, 2001, **22**, 323–337.

23 Fuh, C. S., Cho, S. W. and Essig, K. Hierachical color image region segmentation for content-based image retrieval system. *IEEE Trans. Image Process.*, **9**, 156–162.

24 Flickner, M., Sawhney, H., Niblack, W., Ashley, J., Huang, Q., Dom, B., Gorkani, M., Hafner, J., Lee, D., Petkovic, D., Steele, D. and Yanker, P. Querying by image and video content: the QBIC system. *IEEE Comput.*, 1995, **28**, 23–22.