Implementation of an Image Retrieval System Using Wavelet Decomposition and Gradient Variation

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Abstract: - Texture gradient is a popular operation for extracting features used for content-based image retrieval (CBIR) of texture images. It is useful for depicting gradient magnitude and direction of adjacent pixels in an image. In this thesis, we proposed two methods for retrieving texture images. In the first method, discrete wavelet transform (DWT) and gradient operation were combined to extract features of an image with principal component analysis (PCA) used to determine weights of individual extracted features, while in the second method, only gradient operation without involvement of discrete wavelet transform was used to extract features. The Brodatz Album which contains 112 texture images, each has the size of 512×512 pixels, was used to evaluate the performance of the proposed methods. Before experiment, each image was cut into sixteen 128×128 non-overlapping sub-images, thus creating a database consisting of 1792 images. Regarding the number of features, a total of 126 features were extracted in the first method by calculating gradients after discrete wavelet transforms of the texture image, while in the second method only 54 features were extracted from each gradient image. By integrating useful features, image retrieval systems for retrieving texture images have been designed. The results show that the two proposed methods have been demonstrated to be able to achieve better retrieval accuracy than the method proposed by Huang and Dai. Additionally, our proposed systems, especially the second proposed method, use fewer features which significantly decrease the retrieval time compared to the previous investigation.

Key-Words: - Content-Based Image Retrieval, Texture, Gradient Operation, Entropy, Discrete Wavelet Transform (DWT), Principal component analysis

1 Introduction

Color [1-4], shape [5,6] and texture [7-12] are useful features widely used for content based image retrieval (CBIR). Color is simply manifested by the pixel intensity, while texture is delineated by variations in frequency and direction of pixel colors in an image. Although color and texture features have been shown to be powerful in retrieving texture images [13,14], which, however, do not describe the spatial distribution of the pixel colors in an image and greatly degrade the retrieved efficacy. Therefore, representing the spatial relation among pixels is important for image content description and retrieval. Color has been widely used in CBIR since it is easy and fast in computation [2,3]. For

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example, color histogram [15-18] is one of the most commonly used features in designing image retrieval system. The advantages of color histogram include simple in operation and fast in calculation. In addition, color histogram can resist noise and rotation variations of an image. However, it can describe only the principle colors rather than the texture of an image. Texture property of an image plays an important role in CBIR [7,11]. For example, Haralick et al. [19] proposed the co-occurrence matrix for delineating the texture features of an image, whereas Tamura et al. [20] used six features, including coarseness, contrast, directionality, line-likeness, regularity and roughness, obtained from the co-occurrence matrix for describing the texture of an image. In our daily living environment, texture-like objects and scenes exist everywhere, such as mountains, trees, flowers, clothes, sea, and so forth. Because the definition of texture is fuzzy that it is not easy to describe its property. Hence, extracting the texture attributes of an image by computer is not an easy task. Moreover, the shape of a texture image is even harder to detect that the restriction makes the retrieval of texture images more difficult to achieve with satisfactory efficacy.

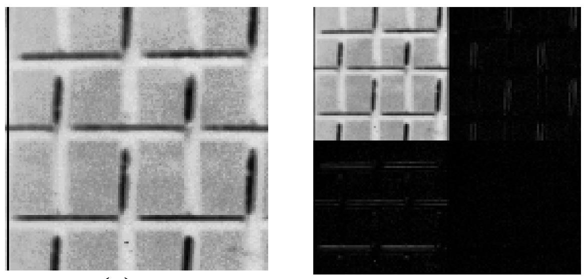
1.1 Motivations and goals

Recently, Huang and Dai [9] proposed an image retrieval method by evaluating texture similarity using features obtained from wavelet decomposition [21,22] and gradient operation [23]. They adopted this rigorous criterion to prevent any possible influence due to subjective factors. In this prototype system, there are coarse and detail feature descriptors associated with each image. Both features are derived from the discrete wavelet transform of the original image. The coarse feature descriptor was used at the first stage to quickly screen non-promising images in image retrieval, while the detail feature descriptor was subsequently used at the second stage to find the truly matched images.

The first motivation of this study is that since each feature vector is derived from wavelet decomposition and gradient operation, which one takes more important impact at the stage of similarity comparison is extremely important. In this paper, we improve Huang and Dai's approach by adopting the wavelet decomposition and gradient operation used by them and by considering the weighting factors for the coefficients in both HH and LL. For this reason, this study proposes a scheme for feature vector selection and weight generation using principal component analysis (PCA) which is believed to be able to reveal the importance of each feature vector and produce suitable weighting values for each one. Therefore, in addition to properly selected image feature vectors, weight generator is also considered for improving the efficacy of the texture image retrieval system.

1.2 Discrete wavelet transform

Discrete Wavelet Transform (DWT) [21,22] is widely used to transform an image from the spatial domain to frequency domain. The features extracted from the frequency domain of an image can be further utilized for image retrieval [7–9]. The coefficients of the image obtained from DWT transformation possess some useful characteristics for image retrieval. As shown in Figure 1, the image is decomposed into four bands as detailed later.



(a) **(b)**

Fig.1 (a) The original image and (b) the image performed using discrete wavelet transform.

Traditionally, a two-dimensional discrete wavelet transform can be accomplished in two steps, including horizontal and vertical operations. In this work, the simplest operation, Haar discrete wavelet transform, was used to obtain the image of frequency domain. Figure 2 shows the row and column operations.

A	B	C	D
E	F	G	H
I	J	K	L
M	N	O	P

Row operation

A+B	C+D	A-B	C-D
E+F	G+H	E-F	G-H
I+J	K+L	I-J	K-L
M+N	O+P	M-N	O-P

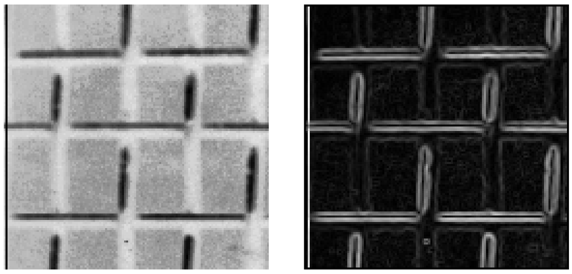
Column operation

(A+B)+(E+F)	(C+D)+(G+H)	(A-B)+(E-F)	(C-D)+(G-H)
(I+J)+(M+N)	(K+L)+(O+P)	(I-J)+(M-N)	(K-L)+(O-P)
(A+B)-(E+F)	(C+D)-(G+H)	(A-B)+(E-F)	(C-D)-(G-H)
(I+J)-(M+N)	(K+L)-(O+P)	(I-J)-(M-N)	(K-L)-(O-P)

Fig.2 Row and column operation of a two-dimensional Haar discrete wavelet transform.

1.3 Gradient operation

In general, gradient operation [23] has been used for detecting the edge in an image. Edge is the place where the pixel intensity changes obviously. An image can be sharpened or smoothened by applying different types of gradient operators. The gradient image not only shows the direction of the edge, it also reflects the magnitude of pixel color variation of an image. It is useful for representing the color complexity of an image. The operators such as Roberts, Sobel [24] and Prewitt have been widely used for gradient calculation. Images after gradient operation could be used for further analysis, such as histogram or statistical operation. Figure 3 shows an original image and its gradient image obtained using Sobel mask. The histogram of a gradient image is useful for describing the magnitudes of edge direction and color variation. By measuring the difference between the histograms of any two images, one can retrieve the database images which have greater similarity to the query. For example, if a gradient image possesses high value in 90 degree direction, which means that there must be a great amount of horizontal edges in the original image. As a consequence, retrieval system can differentiate images by measuring the difference between the histograms of gradient directions and magnitudes associated with them. The vertical and horizontal Sobel masks are shown in Figure 4.



(a) (b)

Fig.3 (a) The original image and (b) its gradient image performed using Sobel mask.

1	0	-1
2	0	-2
1	0	-1

1	2	1
0	0	0
-1	-2	-1

Fig.4 (a) Vertical and (b) horizontal Sobel masks.

1.4 Principal Component Analysis Based Weight of Feature Vector

Generally, there were many useful features which can be extracted after feature extracting process from the image database. To decide which features have greater influence on the efficiency of image retrieval is an important subject needed to be investigated. Principal Component Analysis (PCA) has been widely used for dimension reduction [25]. Basically, the first principal component is the axis passing through the centroid of the feature vectors that has the maximum variance. Therefore, this component can explain a large part of the underlying feature structure. The next principal component tries to maximize the variance that has not been embedded in the first one. Through this approach, consecutive orthogonal components can be extracted. By applying PCA to each vector, we can easily find out which vectors have greater influence on characterizing the image based on their coefficients, which in turn, will be used as the weights of individual features contained in the feature vector. Suppose that there are D images in the database and each one is represented as an n-dimensional random feature vector. Let S be the covariance matrix of feature matrix OI and W be a matrix whose columns are the orthogonal eigenvectors of the matrix S:

$$S = W \Lambda W^T \tag{1}$$

where

$$S = \begin{bmatrix} S_{1,1} & S_{1,2} & \cdots & S_{1,n} \\ S_{2,1} & S_{2,2} & \cdots & S_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ S_{n,1} & S_{n,2} & \cdots & S_{n,n} \end{bmatrix} \quad (2)$$

and

$$S_{i,j} = \frac{1}{D-1} \times \sum_{l=1}^{D} \left[\frac{OI_i^l - \mu_{OI_i}}{\max OI_i - \min OI_i} \right] \left[\frac{OI_j^l - \mu_{OI_j}}{\max OI_j - \min OI_j} \right] \quad (3)$$

In Eq. (3), OI^d_k is the k-th feature in the d-th image; i=j=1,2,…,n; μ_{OI} indicates the mean value of i-th feature vector of image in all the database images; $\max_{OI}$ and $\min_{OI}$ represent the maximum and the minimum values of the i-th feature vector of texture image in all the database images, respectively; and Λ is a diagonal matrix whose diagonal elements are the eigenvalues of S with $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_n$. Let W_q be the first q columns of W and let $W_1, W_2, \ldots, W_n \in \Re_q$ be the rows of the matrix W_q. Each vector W_i represents the projection of the i-th feature (variable) of the vector OI_i to the lower dimensional space, that is, the q elements of W_i correspond to the weights of the i-th feature on each axis of the subspace. The key observation is that the features which are highly correlated or have high mutual information will have similar absolute values of weight vectors W_i. For example, regarding two extreme cases, two independent variables have maximally separated weight vectors; while two fully correlated variables have identical weight vectors (up to a change of sign). To find the best subset, we used the structure of the rows W_i to first find the subsets of features that were highly correlated and choose one feature from each subset. The chosen features represent each group optimally in terms of high spread in the lower dimension.

2 Materials and Methods

In this work, two proposed approaches which were used to extract texture features of an image are described. The first presents the method which combines techniques, including wavelet decomposition, gradient operation, and principal component analysis (PCA), for extracting image features. Another method using gradient and statistics operation for feature extraction is discussed.

2.1 The Method Based on Wavelet Decomposition and Gradient Variation

In the first proposed method, discrete wavelet transform (DWT) and gradient operation were combined for texture image retrieval with the significance of individual features was determined using principal component analysis (PCA). In Figure 6, the block diagram of image retrieval system based on DWT and gradient operation is shown. Each feature was multiplied by its corresponding weight determined using principal component analysis (PCA) for calculating distance between any two feature vectors obtained from two texture images.

2.1.1 Selection of Gradient Angle

In the method proposed by Huang and Dai [9] who used 1-level discrete wavelet transform to transform a textual image into 4 bands (LL, HL, LH, and HH) before feature extraction. After the wavelet transform, gradient operation was performed on each band, and then the frequency of every successive 10^o directions were grouped together to make a bin, which in turn each band consists of a total of 36 bins. Hence, the feature vector of an image for the method proposed by Huang and Dai consists of 4×36=144 bins [9]. However, we consider that the number of bins for each band might have great influence on the retrieval efficiency. Table 1 lists the number of features in a feature vector and the recall rates for different bin size of gradient directions. As shown in this table, we can observe that fewer features (72) and better accuracy (56.78%) can be obtained at 20^o bin size compared to 10^o used in the previous investigation [9]. Although greater bin sizes have smaller number of features, the recall rate, however, decrease accordingly for the bin size greater than 20^o.

In the first proposed method, 2-level wavelet transform and 20^o bin size of gradient directions were adopted for feature extraction based on the previous investigation [9]. A texture image is represented as a feature vector consisting of 7×18=126 features.

2.1.2 Two-level Discrete Wavelet Transform

As mentioned before, in the first proposed method, 2-level DWT (Figure 5) was used to transform an image from its spatial domain to frequency domain before gradient operation. Therefore, an image can be separated into 3×2+1=7 bands after wavelet transform.

2.1.3 Adopt PCA Weights for Image Retrieval

In addition to decreasing the number of features in a feature vector, the weights for individual features were obtained using PCA analysis to improve retrieval efficiency. Afterwards, the procedures described in Section 1.4 were utilized to extract PCA weights for texture images stored in the database. The obtain weight vector which is consisted of 126 weights is shown in Figure 6.

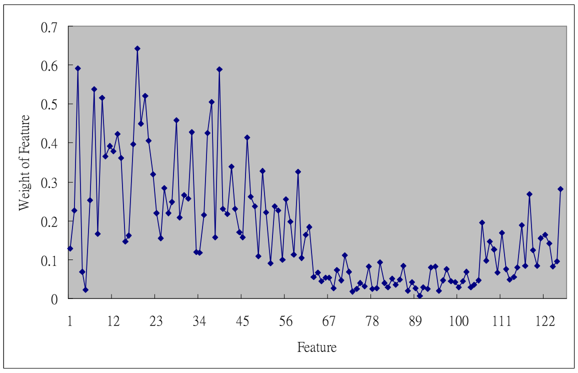


Fig.6 Weights for individual features obtained using PCA analysis based on the database texture image.

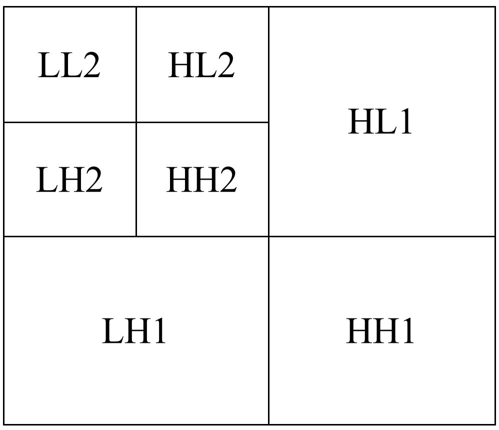


Fig.5 Two-level DWT decomposition

2.2 Proposed Method Based on Features Obtained from Gradient Variation

Although wavelet decomposition approach achieves satisfactory efficacy in the retrieval of texture images, the dimensionality of the feature vector and the computation time increases significantly. In order to overcome this problem, before feature extraction, a less-complicated scheme applying only gradient operation to the original texture image without doing wavelet decomposition. By using this scheme, fewer extracted features, thereby less time needed for computation, with better retrieval efficiency and accuracy can be achieved compared to the wavelet-based method.

2.2.1 Decision of Number of Regions

Figure 7(b) demonstrates an example of the scatter-plot of the gradient image obtained from an original image shown in Figure 7(a). Each point in the scatter-plot represents the corresponding *Delta* and *Theta* of a pixel.

The scattering plot illustrating the relationship between magnitudes and directions of pixels in each gradient image was obtained before feature extraction. The number of regions in a gradient image was calculated by 360/D with D representing the direction range. Since the decision of direction range is crucial in affecting retrieval performance, the value of D should be fine-tuned to achieve greatest performance. Based on a series of experiments, the value of D was set to 40^{o} which has the greatest retrieval performance.

Table 1. Number of features and corresponding recall rates for different bin sizes of gradient directions obtained from Huang and Dai's method.

Bin size (deg)	10	15	20	30	40	45	60	90
Feature	144	96	72	48	36	32	24	16
Recall rate	56%	57%	57%	57%	56%	55%	54%	46%

2.2.2 Features Extraction

After the gradient operation, three features, including mean, standard deviation, and entropy shown in Eqs. (4)–(6), have been calculated from the gradient image.

$$Mean = \frac{1}{N}\sum_{i=1}^{N}\delta_i \quad (4)$$

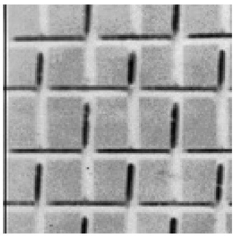
$$Std = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(\delta_i - Mean)^2} \quad (5)$$

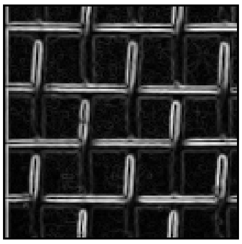
$$Entropy = H(D_j) = \sum_{i=1}^{n} P_i \log\left(\frac{1}{P_i}\right) \quad (6)$$

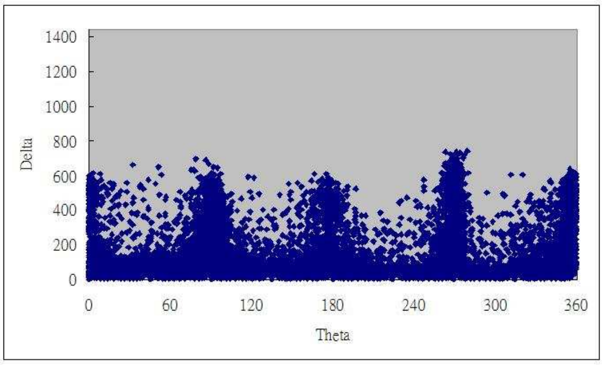
where N is the number of pixels in a region and δ_i indicates the magnitude of the pixel. For calculating the direction of each pixel, δ is replaced with θ in Eqs. (1)-(3). Hence, there are 6 features, including $Theta_{mean}$, $Theta_{std}$, $Theta_{entorpy}$, $Delta_{mean}$, $Delta_{std}$ and $Delta_{entorpy}$, will be extracted from each region which accounts to 54 features in total for an image. Entropy is a measure of histogram uniformity. The closer a histogram to a uniform distribution, the lower the entropy is. In Eq. (3), $D_j=\{a_1, a_2,\ldots, a_n\}$ in which n indicates the number of bins for quantifying parameters δ and θ; and P_i represents the probability of a_i. In this study, n was set to 360 for θ and 1443 for δ.

2.2.3 The Image Retrieval System

In general, decreasing the number of features will accompany with a reduction in retrieval accuracy for an image retrieval system. Our proposed method can achieve better performance while still keeping the number of features lower than Huang and Dai's method. As described in the previous section, the number of features used for image retrieval is only 54 in this proposed method. Figure 8(a) shows the block diagram of the proposed system. The steps of feature extraction, consisting of Sobel gradient operation, magnitude and direction calculation, and SD, mean, and entropy computation are depicted in Figure 8(b).

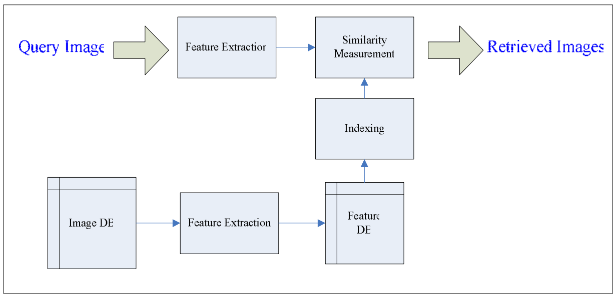

(a)


(b)

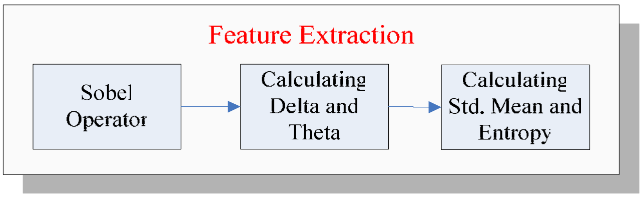


(c)

Figure.7 (a) The original image, (b) gradient image, and (c) scatter-plot of the gradient image.



(a)



(b)

Fig.8 (a) Block diagrams of image retrieval based on features obtained from gradient variation and (b) the block diagram of feature extraction

3 Experimental Results

The Brodatz Album [27] containing 112 texture images were used to evaluate the performance of the proposed methods. The size of each texture image is 512×512 pixels and each one has been cut into sixteen 128×128 non-overlapping sub-images, thus creating a database of 1792 images. In Figure 9, examples of texture images used for the experiment are shown.

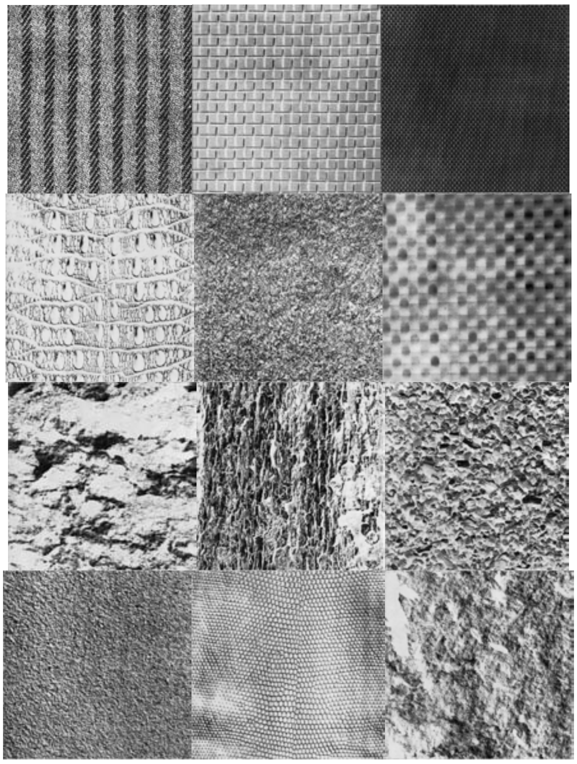


Fig.9 Examples of texture images

Table 2. A comparison of recall rates with and without PCA analysis being applied for the method proposed by Huang and Dai [9].

Without PCA	With PCA
56.29%	58.18%

Two sets of images, database $D=\{I^1{}_d, I^2{}_d, I^3{}_d, \ldots, I^p{}_d\}$ and query $Q=\{I^1{}_q, I^2{}_q, I^3{}_q, \ldots, I^p{}_q\}$ that each consists of p gray-level images. For each query, there are a set of 16 corresponding images in the database similar to the query image are expected to be retrieved by the system, although variations such as shifting, rotation, scaling, color, texture, etc. existed among these images. If at least one image in D corresponding to a query image $I^i{}_q$ in Q has been retrieved, the system is said to have a successful retrieval; otherwise, it is an incorrect retrieval. The dissimilarity measure (Euclidean distance) between two images, I_q and I_d, is defined as:

$$dist = \sqrt{\sum_{i=1}^{k}\left(W_i \times I_i^q - W_i \times I_i^d\right)^2} \tag{7}$$

where k represents the number of features, W_i indicates the weights of individual feature contained in a feature vector, and $I^q{}_i$ and $I^d{}_i$ represent the feature vectors for query and database images, respectively. Recall rate and precision rate [26] have been widely used as a measure of retrieval performance. For a query, the recall rate is defined as the percentage of the ground-truth images in the database that have been retrieved by the system. For example, for a query q with a set of images $S(q)$ relevant to q, if a set of images $A(q)$ have been retrieved, the recall rate $R(q)$ and precision rate $P(q)$ rate are given below:

$$R(q) = \frac{|A(q) \cap S(q)|}{|S(q)|} \tag{8}$$

$$P(q) = \frac{|A(q) \cap S(q)|}{|A(q)|} \tag{9}$$

Since the number of $S(q)$ is 16 in this study, therefore recall rate will be used for calculating the retrieval accuracy if the number of retrieved image $A(q)$ is less or equal to 16. On the other hand, precision rate will be used for calculating the retrieval accuracy if the number of retrieved image $A(q)$ is greater than 16.

Traditionally, the weighting scheme was frequently used to obtain additional improvement of performance in an image retrieval system. In this experiment, we compared the method proposed by Huang and Dai [9] with and without applying PCA analysis for obtaining weights for individual features. The results are shown Figure 10 and Table 2. Adopting PCA analysis for obtaining weights for individual features based on Huang and Dai's method [9] can slightly improved the retrieval accuracy for 1.89% or so.

A comparison of the number of extracted features for a texture image and the retrieval accuracy by using the methods proposed in this thesis and by Huang and Dai [9] are shown in Table 3. The second proposed method uses only 54 features with a decrease of 90 features and an increase of 9.41% retrieval accuracy compared to the method proposed by Huang and Dai [9]. In contrast, the first proposed method adopts 126 features with a decrease of 18 feature and an improvement of 3.51% retrieval accuracy. Figure 11 compares the retrieval accuracy with different retrieval images for three different methods.

Table 3. Comparisons of number of features and retrieval accuracy for three methods.

	Huang and Dai's Method	The First Proposed method	The Second Proposed method
Number of Feature	144	126	54
Retrieval Accuracy	56.29%	61.51%	65.70%

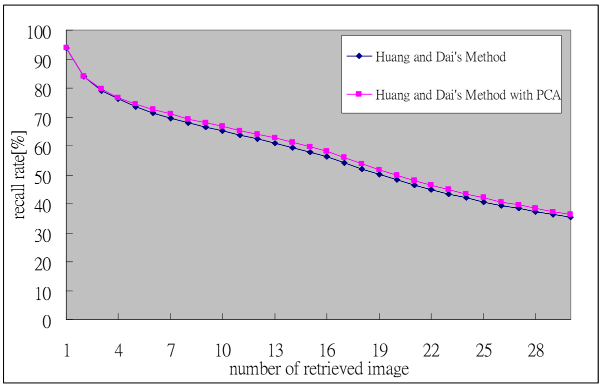


Fig.10 Using PCA and without PCA weighting performance of Huang and Dai's method.

4 Conclusion

The query image and its related retrieved images are demonstrated in Figure 12(b), 12(c) and 12(d) show the retrieved images for the two proposed methods, respectively. Although, the first proposed method and the method proposed by Huang and Dai [9] have similar retrieval accuracy, the former uses only 126 features compared to 144 features used in the latter. Regarding the second proposed method, 12 texture images related to the query image have been retrieved while there are only 6 related images have been retrieved for the method proposed by Huang and Dai [9].

In conclusion, in this paper, two methods have been proposed to improve the retrieval accuracy for the method proposed by Huang and Dai [9]. The proposed methods have been demonstrated to be able to achieve better performance than the previous investigation. Additionally, our proposed systems use fewer features which significantly reduce the retrieval time during the image retrieval stage. In the future, genetic algorithm will be used to replace PCA to determine weights of individual features.

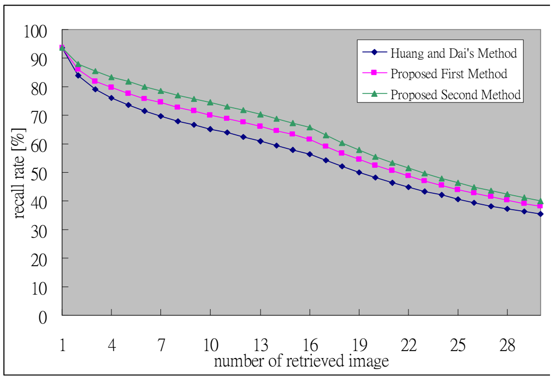
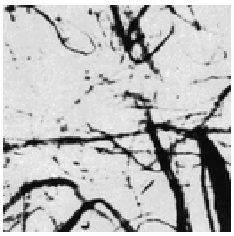
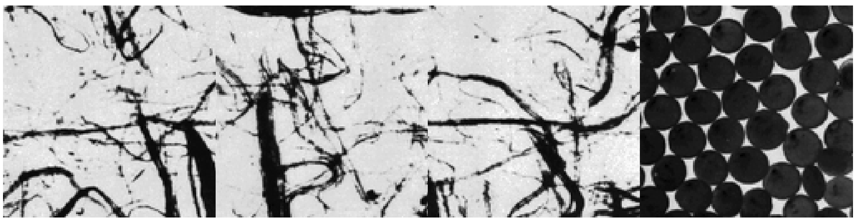
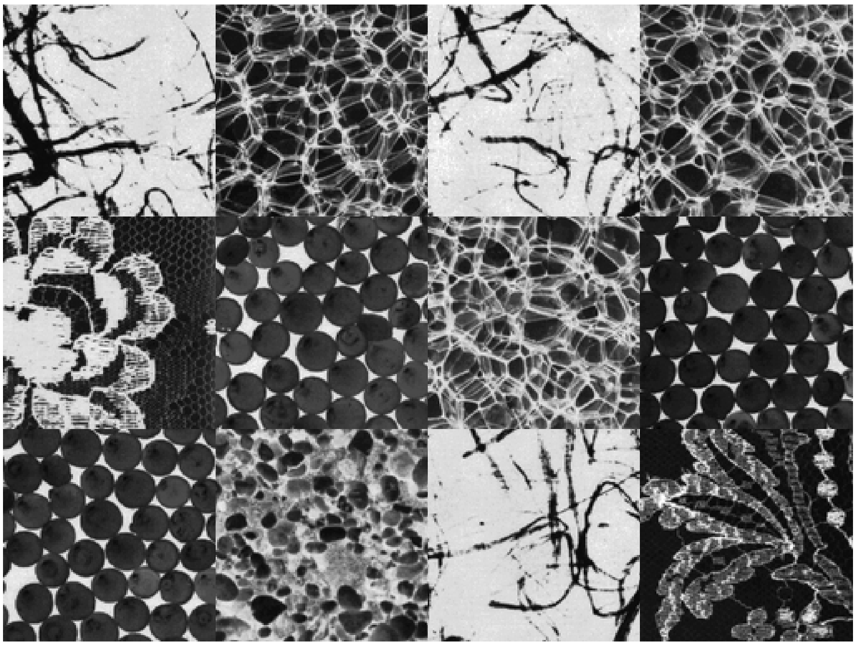


Fig.11 A comparison of retrieval accuracy with different retrieved images for three different methods.

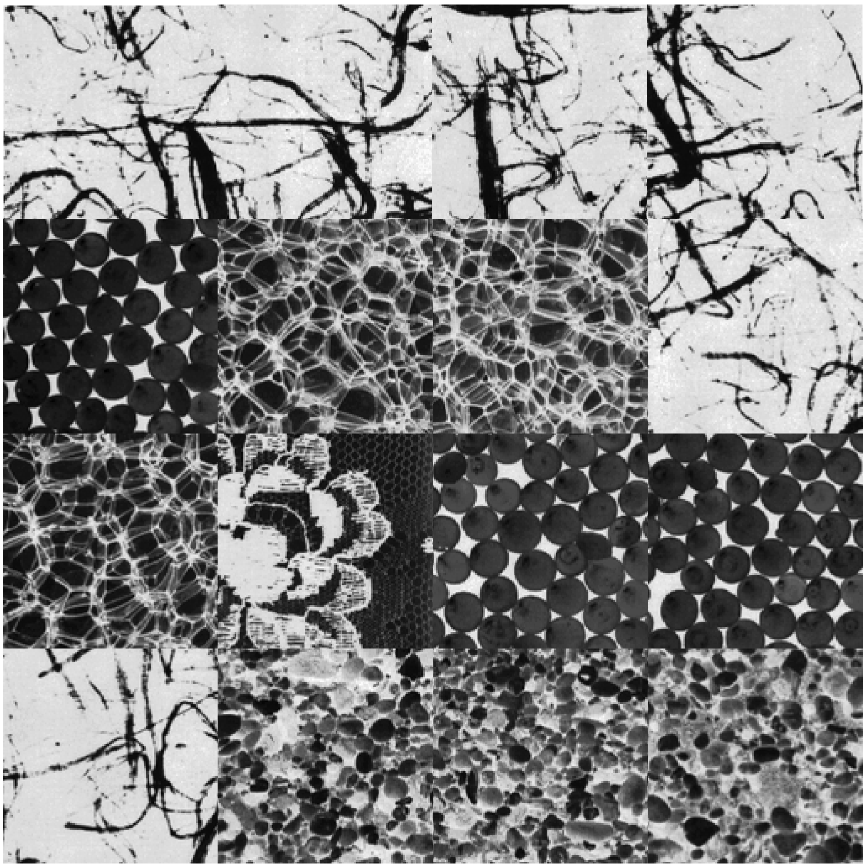


(a)

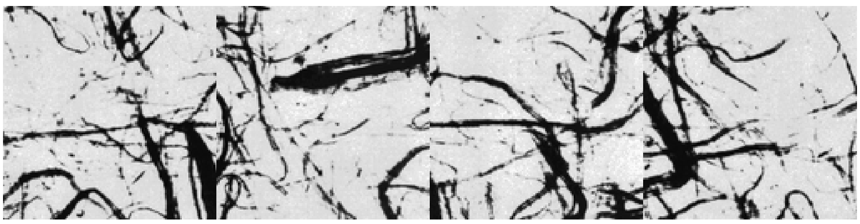


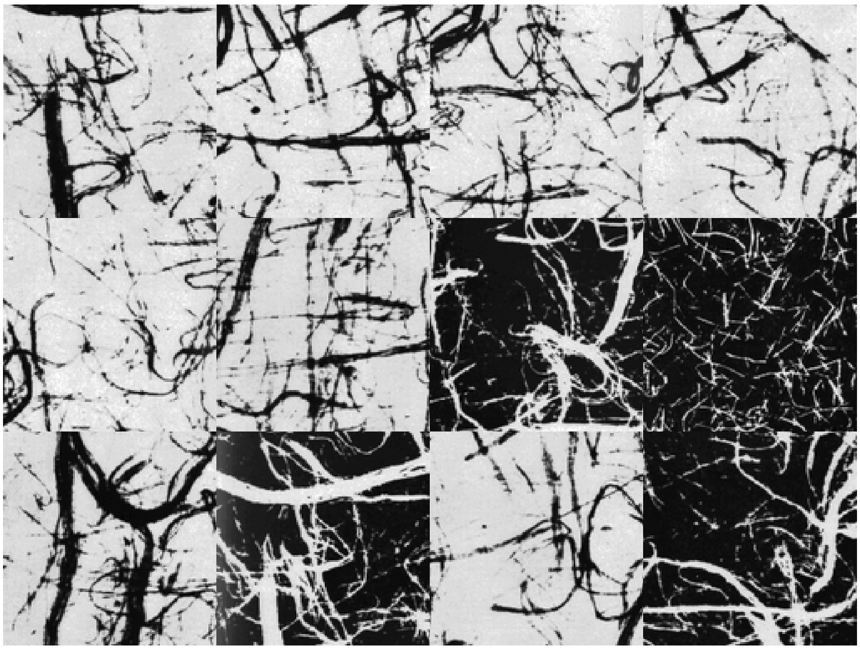


(b)



(c)





(d)

Fig.12 Comparison of retrieval results between Huang and Dai's method and our proposed method. (a) Query image. (b) The retrieval results using Huang and Dai's method. (c) The first proposed method. (d) The second proposed method.

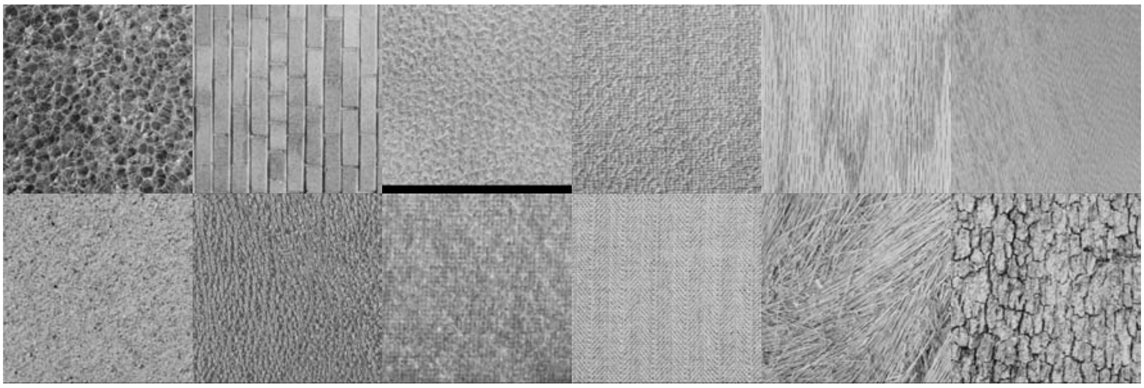


Fig13. Example for University of Southern California (USC) texture images to database.

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