A NEW DESCRIPTOR FOR IMAGE RETRIEVAL USING CONTOURLET CO-OCCURRENCE

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ABSTRACT: *In this paper, a new descriptor for the feature extraction of images in the image database is presented. The new descriptor called Contourlet Co-Occurrence is based on a combination of contourlet transform and Grey Level Co-occurrence Matrix (GLCM). In order to evaluate the proposed descriptor, we perform the comparative analysis of existing methods such as Contourlet [2], GLCM [14] descriptors with Contourlet Co-Occurrence descriptor for image retrieval. Experimental results demonstrate that the proposed method shows a slight improvement in the retrieval effectiveness.*

Keywords: *content-based image retrieval, CBIR, Contourlet Co-occurrence, Contourlet.*

1. INTRODUCTION

Content-based image retrieval (CBIR) becomes a real demand for storage and retrieval of images in digital image libraries and other multimedia databases. CBIR is an automatic process for searching relevant images to a given query image based on the primitive low-level image features such as color, texture, shape and spatial layout [15].

In other researching trend, transformed data are used to extract some higher level features. Recently, wavelet-based methods which provide better local spatial information in transform domain have been used [10, 8, 9, 6, and 7]. In [10], the variances of Daubechies wavelet coefficients in three scales were processed to construct index vectors. In SIMPLIcity [8], the image was first classified into different semantic classes using a kind of texture classification algorithm. Then, Daubechies wavelets were used to extract feature vectors. Another approach called wavelet correlogram [9, 6, 7] used the correlogram of high frequency wavelet coefficients to construct feature vectors.

1.1. Our Approach

In this paper, we propose a new descriptor for image retrieval called the *contourlet co-occurrence descriptor.* The highlights of this descriptor are: (i) it used Contourlet transform with improved characteristics compared with wavelet transform [11, 12], (ii) it used Grey Level Co-Occurrence Matrix that considers the spatial relationship of pixels [14], (iii) the size of the feature is fairly small. Our experiments show that this new descriptor can outperform the contourlet method [2] and the GLCM method [14] using individual for image retrieval.

The Contourlet transform based on an efficient two-dimensional multiscale and directional filter bank that can deal effectively with images having smooth contours. The main difference between contourlets and other multiscale directional systems is that the contourlet transform allows for different and flexible number of directions at each scale, while achieving nearly critical sampling. Specifically, contourlet transform involves basis functions that are oriented at any power of two's number of directions with flexible aspect ratios [4].

The co-occurrence probabilities provide a second-order method for generating texture features [14]. These probabilities represent the conditional joint probabilities of all pair wise combinations of grey levels in the spatial window of interest given two parameters: interpixel distance (δ) and orientation (θ) [3].

The *contourlet co-occurrence* descriptor extract co-occurrence matrix features from subband signals of the images are decomposed using contourlet transform. First, contourlet coefficients are quantized to different levels for each subbands and scales. The quantized *codebooks* are generated to reduce the computation time correlation. Second, co-occurrence matrix features are calculated on interpixel distance (δ) and orientation (θ) compatible with the direction of subbands that are quantized. Finally, the extracted feature vectors are constructed from 4 common co-occurrence features.

The similarity measure using for the feature vectors that are extracted from this descriptor is also designed. Details are presented in the following sections.

1.2. Related Works

The computation of co-occurrence matrix features from image to describe their second order statistics is proposed in [14]. To conjecture the statistical properties with multiscale representation, the feature sets called *wavelet co-occurrence signatures* are introduced in [16]. Authors found that some textures are best characterized using these wavelet co-occurrence signatures.

The wavelet correlogram is other approach for image indexing / retrieval [7, 13]. According to this approach, wavelet coefficients are computed first to decompose space-frequency information of the image. These directional sub-bands enable computing the image spatial correlation in a more efficient way, while taking into consideration the semantic image information. A quantization step is then applied before computing directional autocorrelogram of the wavelet coefficients. Finally, index vectors are constructed using these wavelet correlograms [9].

Our methodology compared with wavelet correlogram have some differences in the following ways:

• Contourlet transform is used in our method. This transform allows flexible number of directions at each scale compared with wavelet transform that have only horizontal, vertical, and diagonal directions.

- Co-occurrence matrices (with 6 orientations) is computed instead of wavelet correlogram (only computing on LH, HL subbands).
- Co-occurrence matrix features is extracted (their second order statistics) instead of computing autocorrelogram to construct feature vectors.

The proposed descriptor and the algorithm for CBIR were test on the database of 1000 color image including 10 different image categories. Experimental results demonstrated slightly improvement in the retrieval effectiveness of the *contourlet co-occurrence* method compared with the methods based on contourlet transform or GLCM.

1.3. Overview of Paper

Next sections of the paper are structured as follows: the Contourlet Co-occurrence descriptor and algorithm for CBIR is reviewed in Section II. Section III introduces similary measure using for the proposal algorithm. Experimental results and performance comparing with relative algorithms are given in Section IV. Finally, Section V is devoted to concluding remarks.

2. CONTOURLET CO-OCCURRENCE

2.1. The Parameters for Contourlet Transform

Contourlet transform are implemented through a double filter bank structure to decompose images on a number scales and directions. This is done by a combination of the Laplacian Pyramid decomposition with filter banks at each scale. Because of the structure of stage (level), number of direction in each level of multiscale decomposition in contourlet transform independent each other. Characteristics make contourlet transform achieve the high flexibility in image decomposition.

In our descriptor, the images are decomposed by Contourlet transform with 2 levels. The parameters as following:

- Decomposition level: *[0, 2]*,
- Pyramidal filter: ‘*pkva*’,
- Directional filter: ‘*pkva*’.

Figure 1 illustrates a image is decomposed by contourlet trasform with parameters as was stated above.

In level 1, all 4 directional subbands are used in quantization step and computing co-occurrence matrix. With level 2, only horizontal and vertical subbands are used for next steps.

2.2. Quantization of Subbands in Each Level

Since contourlet coefficients in subbands are real numbers with a large dynamic, a quantization step is required before computed co-occurrence matrices. In each level, contourlet coefficients have the dynamic range variation. So that, 2 quantized levels (2 codebooks) is used corresponding to each level. Subband of the same level is quantized the same codebook.

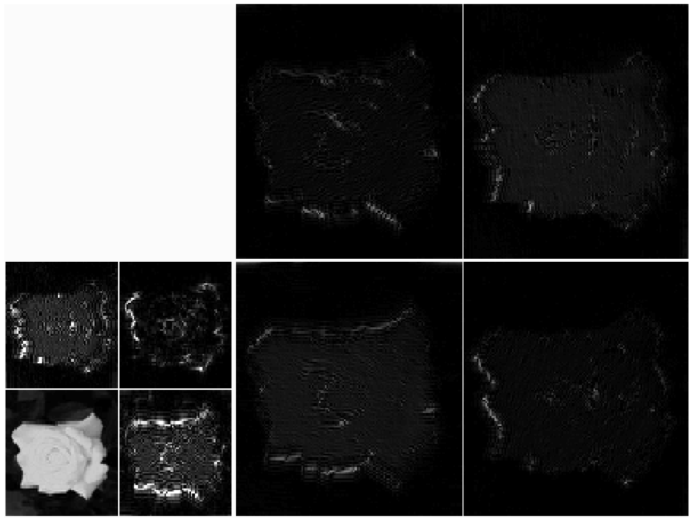

Figure 1. The illustration of contourlet transform of a image with parameters are defined.

Figure 2 shows the quantization procedure performed on 2 levels.

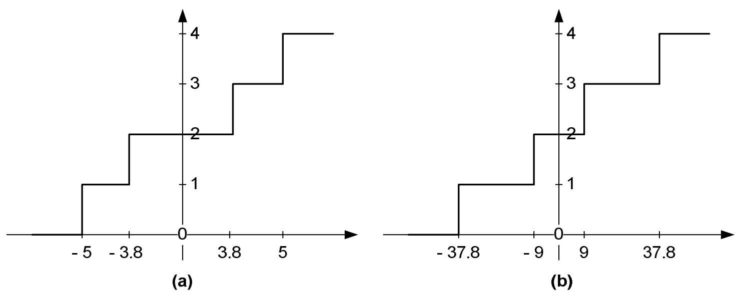

Figure 2. Quantized levels used corresponding to level 1 (a) and level 2 (b)

2.3. Grey Level Co-occurrence Matrix (GLCM)

The Grey Level Co-occurrence Matrix (also called the Grey Tone Spatial Dependency Matrix) is a spatial dependence matrix of relative frequencies in which two neighboring pixels that have certain grey tones and are separated by a given distance and a given angle; occur within a moving window [14].

The figure 3 illustrates the spatial relationships of pixels that are defined by this array of offsets, where δ represents the distance from the pixel of interest.

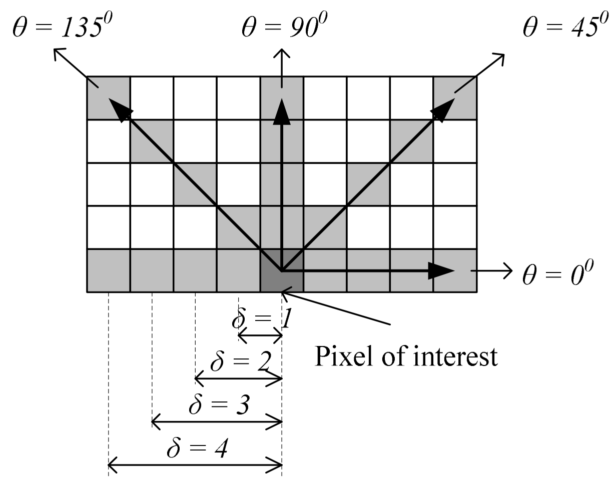

Figure 3. Four Orientations (θ) and distances (δ) in Co-occurrence matrix

The probability measure can be defined as:

$$\Pr = \{C_{ij} \mid (\delta, \theta)\} \quad (1)$$

where C_{ij} (the co-occurrence probability between grey levels i and j) is defined as:

$$C_{ij} = \frac{P_{ij}}{\sum_{i,j=1}^{G} P_{ij}} \quad (2)$$

where P_{ij} represent the number of occurrences of grey levels i and j within the given window, given a certain (δ, θ) pair; and G is the quantized number of grey levels. The sum in the denominator thus represents the total number of grey level pairs *(i,j)* within window.

Although many statistics exits [14], four grey level shift invariant statistics that are commonly applied are used in our method. Statistics (Table 1) were applied to the co-occurrence probabilities to generate the features as following:

Table 1. Textural Features Extracted from GLCM

Description	Formula
Contrast (CON)	$\sum C_{ij}(i-j)^2$
Correlation (COR)	$\sum \frac{(1-\mu_x)(1-\mu_y)C_{ij}}{\sigma_x \sigma_y}$
Uniformity (UNI)	$\sum C_{ij}^2$
Inverse difference (INV)	$\sum \frac{C_{ij}}{1+\lvert i-j \rvert}$

In our method, the images are decomposed by the Contourlet transform with decomposition level: [0, 2]. Six directional subbands are quantized and calculated GLCM as in figure 4.

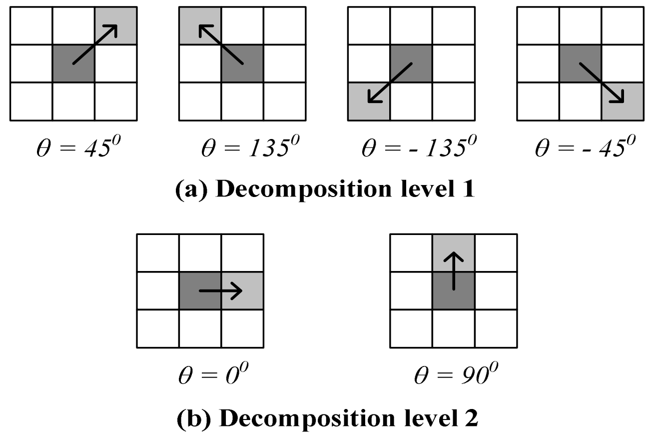

Figure 4. Orientations are used to calculate GLCMs for subbands

With decomposition level 1, all four directional subbands are quantized as in Fig. 2 (a) and calculated GLCMs as following:

- In first subband, the GLCMs are calculated with $\delta = \{1,2,3,4\}$ and $\theta = 45^0$.
- In second subband, the GLCMs are calculated with $\delta = \{1,2,3,4\}$ and $\theta = 135^0$.
- In third subband, the GLCMs are calculated with $\delta = \{1,2,3,4\}$ and $\theta = -45^0$.
- In fourth subband, the GLCMs are calculated with $\delta = \{1,2,3,4\}$ and $\theta = -135^0$.

With decomposition level 2, only horizontal and vertical subbands are quantized as in Fig. 2 (b) and calculated GLCMs as following:

- In horizontal subband, the GLCMs are calculated with $\delta = \{1,2,3,4\}$ and $\theta = 0^0$.
- In vertical subband, the GLCMs are calculated with $\delta = \{1,2,3,4\}$ and $\theta = 90^0$.

Four textural features (Table 1) is extracted from each GLCM. In each subband, GLCMs are calculated with $\delta = \{1,2,3,4\}$ and a θ, total have four GLCMs. So that, feature vector structure of a gray level image is: 4 features/each GLCM x 4 GLCMs/each subband x 6 subbands/image = 96 features that corresponding to 96 real numbers, equivalent to 384 bytes per feature vector.

In case of the color image, feature vector structure is extracted from three color components of image so the feature vector of color image is larger than three times of gray image.

2.4. Contourlet Co-occurrence Descriptor and Algorithm for CBIR

The *Contourlet Co-occurrence descriptor* extracts feature vectors in some steps as shows in the block diagram of Figure 5.

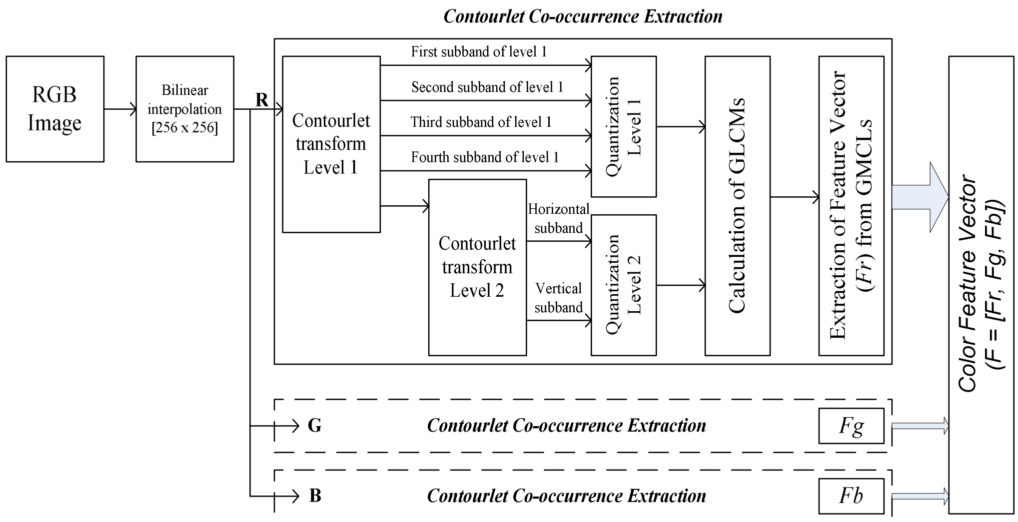

Figure 5. Contourlet Co-occurrence extraction

In this block diagram, images are without color space conversion that using R, G, B channels to calculate image features for channel separation. First, images are converted to 256x256 sizes by bilinear interpolation. This size appropriates to contourlet transform in second step. The parameters of contourlet transform are selected as above introduction. Four subbands of level 1 are quantized as in Fig 2(a). Horizontal and vertical subbands of level 2 are quantized as in Fig 2(b). Third, quantized subbands are calculated the GLCM with orientations *(θ)* and distances *(δ)* as presented in the above. Finally, the feature vectors are extracted from GLCMs on three channels.

3. SIMILARITY MEASURES

The image retrieval problem is following: let D be an image database and q be the query image. Obtain a permutation of the images in D based q, i.e., assign rank of images in D using some notion of similarity to q. This problem is usually solved by sorting the images $r \in D$ according to $|F(r) - F(q)|$, where $F(.)$ is a function computing feature vectors of images and $|.|$ is some distance measure defined on feature vectors.

Let $F(r) = [f_{rj}]_{j=1}^{p}$ and $F(q) = [f_{qj}]_{j=1}^{p}$ be the vectors of two different images where p is the feature vector length. For similarity matching, the distance measure is selected as follows:

$$D(r,q) = \sum_{j=1}^{p} w_j \left| \frac{f_{rj} - f_{qj}}{1 + f_{rj} + f_{qj}} \right| \quad (3)$$

where w_j (j = 1,2,…,p) specifies the weight of each component of the feature vector.

4. RESULTS OF WORK

Programs are written in Matlab version R2006a and use with multiple formats of images such as GIF, JPEG, PPM, TIFF, PNG.

The computer calculates these experiments that have the CPU speed is 2 x 1.83GHz and 1GB of RAM. The image database used for experiments is WANG database [5] including 1000 images that are categorized in 10 classes (including *africans, beaches, buildings, buses, dinosaurs, elephants, flowers, horses, mountains, food*) and each class contains 100 pictures in JPEG format.

4.1. Search Effectiveness

The most common evaluation measure used in Information Retrieval is *recall rate* and *precision rate* [1]. *Precision rate* is the probability of retrieving a image that relevant to query, and *recall rate* is the probability of relevant being retrieved. Let n_1 be the number of images retrieved in top 20 positions that are close to the query. Let n_2 represent the number of images in the database similar to the query. Evaluation standards *recall rate* and *precision rate* are defined as follows:

$$\mathrm{Re}\,call\ rate = \frac{n_1}{n_2} \times 100\% \quad (4)$$

$$\mathrm{Pr}\,ecision\ rate = \frac{n_1}{20} \times 100\% \quad (5)$$

WANG database includes 1000 natural images that are divided into 10 different categories, each including 100 images. So that, $n_2 = 100$.

4.2. Experimental Results

To evaluate the performance of algorithm using the *Contourlet Co-occurrence feature* in image retrieval, two relative algorithms are used to compare with it. First algorithm is based on extracting features from coefficients in subbands of contourlet transform [2] (hereinafter call this feature is the *contourlet feature*). Second algorithm is based on co-occurrence signatures [14] (hereinafter call this feature is the *co-occurrence feature*). The computation of co-occurrence matrix features from the images use δ and θ parameters as follow: $\delta = \{1,2,3,4\}$ and $\theta = \{45^0, 135^0, -45^0, -135^0\}$.

A retrieved image will be considered a match if it belongs to the same class of the query image. Figure 6 illustrates a query result using *Contourlet Co-occurrence* CBIR with query image is also the image displaying on the upper left of the figure. The retrieved result include 20 images have smallest similarity measures of the *flowers* image category in the WANG database. Average processing time for each query in experiments is: 4.72 (sec).

Table 2 compares the performance of CBIR using the contourlet co-occurrence feature with the co-occurrence feature and the contourlet feature. In each category of the WANG database, two image queries is used to retrieval and calculate *recall rate* (*R*) and *precision rate* (*P*). Total averages of *R_ave.* and *P_ave.* is also calculated with the best matched retrieved images is achievable using contourlet co-occurrence method.

Table 2. Evaluation of CBIR Algorithms Using Contourlet Co-occurrence Feature with Co-occurrence Feature and Contourlet Feature

	Contourlet Co-Occurrence			Co-Occurrence			Contourlet		
Category	Q1	Q2	Ave.	Q1	Q2	Ave.	Q1	Q2	Ave.
Africans	*q = 0*	*50*		*0*	*50*		*0*	*50*	
	R (%) = 10	10	**10**	5	9	**7**	9	8	**8.5**
	P (%) = 50	50	**50**	25	45	**35**	45	40	**43**
Beaches	100	150		100	150		100	150	
	3	8	**5.5**	3	10	**6.5**	1	2	**1.5**
	15	40	**28**	15	50	**33**	5	10	**7.5**
Building	*200*	*250*		*200*	*250*		*200*	*250*	
	10	8	**9**	8	5	**6.5**	9	1	**5**
	50	40	**45**	40	25	**33**	45	5	**25**
Buses	*300*	*350*		*300*	*350*		*300*	*350*	
	18	11	**15**	17	8	**13**	12	14	**13**
	90	55	**73**	85	40	**63**	60	70	**65**
Dinosaurs	*400*	*450*		*400*	*450*		*400*	*450*	
	20	20	**20**	20	20	**20**	9	16	**13**
	100	100	**100**	100	100	**100**	45	80	**63**
Elephants	*500*	*550*		*500*	*550*		*500*	*550*	
	8	8	**8**	7	6	**6.5**	3	6	**4.5**
	40	40	**40**	35	30	**33**	15	30	**23**
Flowers	*600*	*650*		*600*	*650*		*600*	*650*	
	20	19	**20**	20	19	**20**	20	20	**20**
	100	95	**98**	100	95	**98**	100	100	**100**
Horses	*700*	*750*		*700*	*750*		*700*	*750*	
	3	13	**8**	3	14	**8.5**	6	12	**9**
	15	65	**40**	15	70	**43**	30	60	**45**
Mountains	*800*	*850*		*800*	*850*		*800*	*850*	
	6	9	**7.5**	2	7	**4.5**	3	16	**9.5**
	30	45	**38**	10	35	**23**	15	80	**48**
Food	*900*	*950*		*900*	*950*		*900*	*950*	
	3	10	**6.5**	7	4	**5.5**	13	8	**11**
	15	50	**33**	35	20	**28**	65	40	**53**
TOTAL AVE.:		R_ave (%)	***11***			***10***			***9***
		P_ave (%)	***54***			***49***			***47***

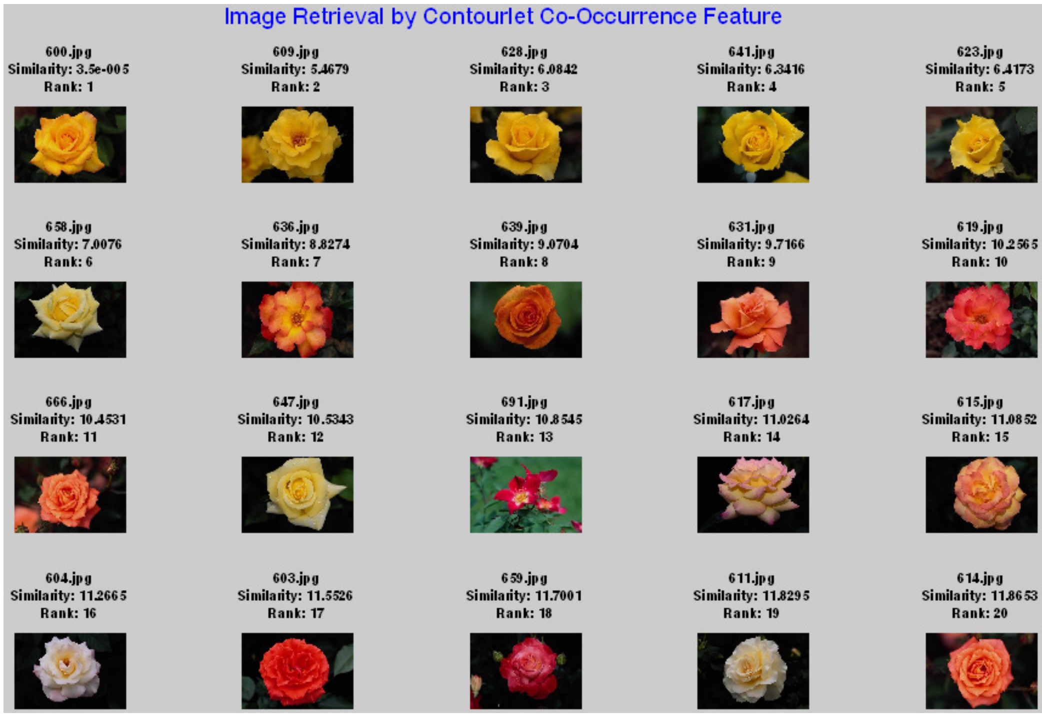

Figure 6. Results obtained from the query image 600.jpg.

5. CONCLUSION

In this paper, a new descriptor in CBIR was presented. Contourlet transform and GLCM matrix were combined to build a new descriptor called *Contourlet Co-occurrence descriptor*. The CBIR algorithm using new descriptor demonstrated higher performance compared to two relative algorithms based on contourlet feature and co-occurrence feature.

BỘ MÔ TẢ MỚI ỨNG DỤNG TRONG TRUY VẤN ẢNH DÙNG CONTOURLET CO-OCCURRENCE

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Tóm tắt: *Trong bài báo này, một bộ mô tả mới dùng để trích đặc điểm của ảnh trong các cơ sở dữ liệu ảnh được giới thiệu. Bộ mô tả mới này, gọi là Contourlet Co-Occurrence, được thiết kế dựa trên sự kết hợp của biến đổi contourlet và ma trận co-occurrence mức xám (GLCM - Grey Level Co-occurrence Matrix). Để đánh giá hiệu quả của bộ mô tả đề xuất, chúng tôi thực hiện các so sánh giữa phương pháp dùng các bộ mô tả đặc điểm đã giới thiệu như Contourlet [2], GLCM [14] với bộ mô tả đặc điểm Contourlet Co-Occurrence trong ứng dụng truy vấn ảnh. Kết quả thực nghiệm đã chứng minh phương pháp đề xuất có hiệu quả được cải thiện hơn.*

Từ khóa: *CBIR, Contourlet Co-occurrence, Contourlet.*

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