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# Texture image retrieval using adaptive tetrolet transforms

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ABSTRACT

This paper proposes a novel technique for texture image retrieval based on tetrolet transforms. Tetrolets provide fine texture information due to its different way of analysis. Tetrominoes are applied at each decomposition level of an image and best combination of tetrominoes is selected, which better shows the geometry of an image at each level. All three high pass components of the decomposed image at each level are used as input values for feature extraction. A feature vector is created by taking standard deviation in combination with energy at each subband. Retrieval performance in terms of accuracy is tested on group of texture images taken from benchmark databases: Brodatz and VisTex. Experimental results indicate that the proposed method achieves 78.80% retrieval accuracy on group of texture images D1 (taken from Brodatz), 84.41% on group D2 (taken from VisTex) and 77.41% on rotated texture image group D3 (rotated images from Brodatz).



## 1. Introduction

During last few years, use of multimedia especially in digital image libraries has been increasing very rapidly. Therefore there is a need of effective access of an image from a database. There are two basic approaches for image retrieval: text based image retrieval and content based image retrieval. Text based search becomes ineffective in various image search applications because it creates a huge semantic gap between human perception and system understanding. Digital image databases are continuously growing in size, therefore, traditional text based search methods are inappropriate to retrieve the image from the large databases. Image annotation cannot be performed on large databases to increase the retrieval performance. Similarly, it is also difficult to express features of an image like color, texture, shape and object within the image perfectly. Another problem with text based search is that it increases linguistic problem to share images worldwide. To overcome these problems associated with text based search, content based image retrieval (CBIR) is used.

Content based image retrieval plays a vital role in digital image processing. Mostly CBIR techniques use the visual features like color, texture and shape for image search. Indexing of images is performed on the basis of these visual features. Main advantage of using CBIR is its ability to deal with visual queries.

In development of a CBIR system, main issue is to achieve higher accuracy. Various approaches to CBIR have been developed but an approach having high precision with minimum computation time is considered to be best. The technique proposed in this paper performs texture image retrieval is based on CBIR. Texture characteristics are present in many real world images like clouds, trees, fabrics, bricks, hairs, etc. Basically texture represents the roughness of the image surface and it is a low level visual feature which deals with the surface properties of an image.

This paper employs the concept of 'Tetrolet' which is a special case of 'Harr' wavelet. An image is analyzed for all possible rotations and reflections. A strategy is designed using tetrolet transforms which makes image retrieval process rotation invariant.

Image retrieval performance of proposed algorithm is measured in terms of average retrieval precision and average retrieval recall rate:

$$\text{Precision:} \quad P_i = \frac{N_r}{T_r} \tag{1}$$

where $N_r$ is number of relevant images retrieved and $T_r$ is total number of images retrieved from the database.

$$\text{Average Retrieval Precision:} \quad ARP = \frac{1}{|DB|} \sum_{i=1}^{|DB|} P_i \tag{2}$$

where $DB$ is the total number of images in the database and $P_i$ is precision of $i$th image.

$$\text{Recall:} \quad R_i = \frac{N_r}{T_{ri}} \tag{3}$$

where $T_{ri}$ is total number of relevant images in the database.

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$$\text{Average Retrieval Recall:} \quad ARR = \frac{1}{|DB|}\sum_{i=1}^{|DB|} R_i \tag{4}$$

where $R_i$ is recall value of $i$th image.

An effective image retrieval system must have high precision and recall values for getting better performance.

## 2. Related work

Wavelet transforms provide multiresolution analysis of an image with color and texture features [5]. This approach provides higher retrieval accuracy while having a low dimensional feature vector. In this work, multiresolution analysis is performed with the help of wavelets. RGB to HSV conversion is performed and the converted image is decomposed. The feature vector of decomposed image is constructed using color and texture features. For color feature autocorrelogram is used [7]. The color autocorrelogram captures the spatial correlation between identical colors only. In [2], an interactive genetic algorithm is used to minimize the semantic gap in combination with relevance feedback technique. With the help of explicit feedback technique used by this approach, higher precision and low recall value are achieved.

An approach given by Shrivastava and Tyagi [1] uses selective region codes matching. In this approach the images are divided in the regions and regions are assigned codes on the basis of their distance from central region. Similarity measure is performed on the basis of these region codes. An approach by Ja-Hwung Su et al. [9] uses the navigation based relevance feedback which reduces the number of iterations in feedback process and high precision is achieved in comparatively less computational time. A survey of CBIR techniques is given in [8,22].

Manjunath and Ma [11] proposed a texture feature extraction technique using Gabor filter. In this work, authors have used an adaptive filter selection strategy, which reduces the computation time and provides satisfactory retrieval performance.

Fang Liu et al. [10] suggested a model for texture feature extraction that represents most prominent harmonic structures in a texture and also used the robust statistical models to deal with relatively unstructured patterns. Brodatz texture database is used in this work.

J. Mao and A.K. Jain [13], described a color and texture image retrieval mechanism for extracting texture feature using wavelet decomposition. This work uses the higher frequency components and texture classes are characterized only by the variances in high frequency components. For similarity measure, Bhattacharya distance is used. Performance is measured for both texture and colored images. VisTex and Brodatz databases are used as texture databases. Retrieval performance is checked against Wold model [10] and Gabor [11] transforms. These techniques do not perform well on the rotated images.

In Manesh Kokare et al. [4], a new concept in texture image retrieval is proposed which is rotation invariant. Dual tree complex wavelets and dual tree complex rotated wavelets are used, which make texture image retrieval invariant in twelve directions $\{0°, +15°, +45°, +75°, -15°, -45°, -75°, +30°, +60°, +90°, +120°, -30°\}$. Extracted features are rotationally invariant due to decomposed subbands. Standard deviation and energy is used as texture features. Brodatz and VisTex databases are used for experiments.

Ming Hong Pi et al. [3], adopted a new method for constructing image signatures from the bit planes of decomposed wavelet subbands. This work employs three-pass layer probability (TPLP) and bit plane signature, which provides low computational complexity, because these signatures do not require dequantization and feature extractions from wavelet coefficients.

Reddy A.H. and Chandra N.S. [14] proposed an approach that uses a combination of RGB and HSV color spaces. This technique integrates the color and texture features. Directional local extrema pattern is used to extract the directional information in four directions i.e. $\{0°, +45°, +90°, +135°\}$ directions. In this approach image is converted into RGB and HSV color spaces then oppugnant is generated with color-texture feature.

Roland Kwitt et al. [15] used copulas in a Bayesian Framework for extracting texture images. This approach gives good retrieval accuracy, and runtime behavior, which enables the deployment even on large image databases. This work also includes a systematic computational analysis of runtime measurements, storage requirements and main building blocks.

Nour-Eddine Lasmar and Yannick Berthoumieu [12] proposed an approach, Gaussian copula multivariate modeling, for texture image retrieval. It separates dependence structure from marginal behavior. Authors have introduced two new multivariate models using generalized Gaussian and Weibull densities respectively. They have combined Gaussian copula based modeling and Jeffrey divergence as a similarity measure.

Manesh Kokare & P.K. Biswas in [21] proposed a texture image retrieval technique based on rotated complex wavelet filters, which improved the performance of image retrieval both in time and accuracy.

## 3. Texture image retrieval using tetrolets

Conventional 2D wavelet transforms prefer only horizontal and vertical directions. Discrete wavelet transform (DWT) is applied only on rows and columns so analysis is done only in two directions. Whole image geometry cannot be represented in two directions only therefore it fails to achieve the optimal representation of the image after decomposition. Few methods have been proposed to improve the local geometry representation of an image such as, curvelets [16], contourlets [17] and directionlets [18] with more directional sensitivity. In proposed work, we have used tetrolets to represent an image in an efficient way. Tetrolet is a special case of Haar wavelets. Tetrominoes were introduced by Golomb in [19]. The concept of tetrolets to represent an image was introduced by Jens Krommweh [6].

The low-pass subband component of the image $a^{r-1}$ is divided into blocks $Q_{i,j}$ of size $4 \times 4$, $i, j = 0, \ldots, \frac{N}{4} - 1$. For each block $Q_{i,j}$ all 117 possible coverings $c = 1, \ldots, 117$ are applied and for each tiling $c$, 4 low-pass coefficients and 12 high pass coefficients are obtained. Low pass part at each decomposed level is extracted as follows:

$$A^{r,(c)} = \left(a^{r,(c)}[S]\right)_{s=0}^{3}$$
$$a^{r,(c)}[s] = \sum_{(m,n)\in I_s^{(c)}} \epsilon\left[0, L(m,n)\right] a^{r-1}[m,n] \tag{5}$$

For further decomposition, only low pass component is taken into consideration while high pass components are collected separately at each level for texture analysis. Three high pass components at each level of decomposition are extracted using:

$$W_l^{r,(c)} = \left(w^{r,(c)}[s]\right)_{s=0}^{3}$$
$$w^{r,(c)}[s] = \sum_{(m,n)\in I_s^{(c)}} \epsilon\left[l, L(m,n)\right] a^{r-1}[m,n] \tag{6}$$

$$W = \left(\epsilon[l,m]\right)_{l,m=0}^{3} = \frac{1}{2}\begin{pmatrix} 1 & 1 & 1 & 1 \\ 1 & 1 & -1 & -1 \\ 1 & -1 & 1 & -1 \\ 1 & -1 & -1 & 1 \end{pmatrix} \tag{7}$$



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