A Survey on Texture Image Retrieval

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Abstract Retrieving images from the large databases has always been one challenging problem in the area of image retrieval while maintaining the higher accuracy and lower computational time. Texture defines the roughness of a surface. For the last two decades due to the large extent of multimedia database, image retrieval has been a hot issue in image processing. Texture images are retrieved in a variety of ways. This paper presents a survey on various texture image retrieval methods. It provides a brief comparison of various texture image retrieval methods on the basis of retrieval accuracy and computation time with the benchmark databases. Image retrieval techniques vary with feature extraction methods and various distance measures. In this paper, we present a survey on various texture feature extraction methods by applying variants of wavelet transform. This survey paper facilitates the researchers with background of progress of image retrieval methods that will help researchers in the area to select the best method for texture image retrieval appropriate to their requirements.

Keywords Image retrieval · Texture image · Multimedia database

1 Introduction

Texture image retrieval has been an emerging issue due to the big volume of multimedia data. Texture image retrieval is a type of content-based image retrieval. Texture images are different from the natural images. In general, texture images are characterized by the surface properties and appearance of an object such as shape,

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density, and arrangement. Texture may be hard or soft, coarse or grain, and smooth or rough. So analysis of texture images is different from non-textured images. Texture image retrieval mainly focuses on the texture properties of an object such as repeated patterns in an image, local periodicity, global periodicity, etc. Image analysis for texture feature extraction must be done from various orientations or angles to make it rotation invariant.

1.1 Requirements of a Good Texture Analysis Scheme

A good texture analysis must satisfy following two requirements:

1. Image retrieval should be rotation invariant. It means if the same type of images are stored in the databases with different rotating angles, then the system should retrieve the relevant one with any rotation angle. So texture feature analysis must be done at different angles. Some approaches like curvelets [1], contourlets [2], and directionlets [3] are wavelet systems with more directional sensitivity.
2. Scaling and translation invariant property must be maintained by the texture feature extraction methods. Fourier transform provides these properties. Basically, a texture is a surface property of an object. Each object is textured at certain scales. In [4], a new feature descriptor is used for image retrieval, which is also called oppugnant color space extrema pattern. Both color and texture features are used to index the images. This work is also having directional sensitivity in four directions. VisTex database [5] of 40 images is used as a benchmark database for experimental purpose in this work.

1.2 Performance Measure

Texture image retrieval performance is measured in terms of precision and recall. If any retrieval system is having higher precession and recall values, then it is up to the mark. Computational time is another measure for a retrieval system:

$$\text{Precision}: P_{I_c} = \frac{\text{Number of relevant images retrieved}}{\text{Total number of images retrieved}} \tag{1}$$

$$\text{Recall}: R_{I_c} = \frac{\text{Number of relevant images retrieved}}{\text{Total number of relevant imagesin the database}}. \tag{2}$$

The computational time depends on feature extraction time and searching time and also partially depends on the distance measure method:

$$\text{Computational time } = \text{feature extraction time} + \text{Searching time.}$$

Feature extraction time solely depends on the method used to extract the features, while computational time depends upon the distance measure formula.

2 Wavelet-Based Texture Image Retrieval

The wavelet transform is widely used for extracting texture features. Wavelet transform and its variants decompose the image into one low-pass and three high-pass subbands at each decomposition level. Texture features are extracted by taking only high passes at each subband. There are some variants like Gabor wavelet, complex wavelet transform, dual-tree complex wavelet transform, dual-tree rotated complex wavelet transform, Haar wavelet, and tetrolet which is a special case of Haar wavelet, which are used for extracting texture features. In [6], wavelet transform is used for extracting the bit planes from a complete plane. After decomposition of an image into wavelet subbands, bit plane extraction is performed at each subband separately. In this approach, the image signature is formed by combining the bit planes on the basis of the occurrence probability of bit planes: three-pass layer probability (TPLP) and Bit plane (BP). Image signature formed in this way is smaller in size and thus reduces the storage requirement. Since BP and TPLP signatures do not use dequantization process, the computational cost of this method is also less due to optimized signature size. Due to low storage requirements and less computational cost, this method is particularly suitable for the video databases and large JPEG2000 image. In [3], a new concept of texture feature extraction is used. In this paper, dual-tree rotated complex wavelet filters are used. This transform provides the texture analysis in 12 different directions, which is helpful in improving the characterization of oriented textures. This paper used standard deviation and energy as texture features. These two features are calculated at each subband of decomposed image. Performance of retrieval is checked on Brodatz [7] and VisTex [5] image databases. Both of these databases are benchmark databases which are used by some other image retrieval methods. The combination of DT-RCWF and DT-CWT outperforms in achieving the higher accuracy in texture features.

In [8], the authors have proposed a new concept, which performs well for rotated images. It is the improvement of the work [9]. This work provides rotation invariant texture image retrieval from a set of DT-RCWFs and DT complex wavelet transform (DT-CWT). Invariance is achieved by calculating robust isotropic rotationally invariant features on the combination of DT-RCWF and DT-CWT.

2.1 Variants of Wavelet Transform for Texture Feature Extraction

Texture features are extracted from various ways. Wavelets are most used texture feature extraction approach. There are some variants like Gabor, Haar, Standard wavelet, complex wavelet, rotated complex wavelet filter, dual-tree complex wavelet filter, etc. These variants are used by various methods. Some methods used only one type of wavelet, while some used a combination of these as used in [8, 9]. Wavelets are the only core technology which provides the facility to the CBIR system to work directly in the compressed domain, which directly creates the impact on retrieval speed and also on storage requirement. So they reduce both the time and space complexity. Some methods used for feature extraction, based on wavelets, used for texture image retrieval, are as follows:

1. Standard DWT
2. DT-CWT
3. Gabor
4. DT-RCWF
5. DT-CWT and RCWF

- Standard DWT [10, 11] is also called traditional wavelet transform. The only advantage of using it is simplicity. But it is having some serious disadvantages such as poor directional selectivity, since it works only in two directions. This is insufficient to make a difference in analysis of object geometry, and it also does not provide shift invariance property.
- To overcome the deficiencies of DWT, complex wavelet transform is used. In CWT, limited amount of redundancy is introduced. But it is also not able to reconstruct the original signal from the decomposed one after one level.
- To make a perfect reconstruction possible along with the other advantages of complex wavelet, dual-tree complex wavelet transform is used. In DT-CWT [12], two parallel fully decimated trees, having real filter coefficients, are used. This combination provides the perfect reconstruction of the decomposed signal. It provides the directional selection ability in six directions{+15°, +45°, +75°, −15°, −45°, −75°}.
- Gabor wavelet is another wavelet variant, which has been widely used for texture feature extraction. Gabor wavelet provides minimum standard deviation both in frequency and time domain. Mainly, Gabor filters are a set of wavelets, with each wavelet capturing energy at a particular frequency and direction. Texture features are extracted from this group of energy distributions, but they are also having serious problem of non-orthogonality, so due to this, perfect decomposition into the basis is hard and complex.
- 2D-RCWF is another method to extract the edge information from an image in six different directions. It works jointly with complex wavelet filters by taking edges 45 apart from the cwt. For this, initially directions of the edges are extracted from the original image, and then it is rotated by 45. Since edge plays

a key role in texture feature, it is necessary to characterize the texture in different directions. So in many texture image retrieval systems, characterization of texture using directional information improves retrieval performance

- Combination of 2D-RCWF with DT-CWT improves the directional selectivity in 12 different directions: six directions from DT-CWT and six directions from 2D-RCWF. So this combination improves the retrieval performance of the system due to analysis of image in 12 directions. The 2-D RCWFs are non-separable and oriented, which improves characterization of oriented textures. RCWF in combination with DT-CWT performs better than other retrieval methods. This combination performs the texture analysis in 12 directions. A comparison of various feature extraction techniques is shown in Table 1.

In [13], a new texture image retrieval system is developed, which takes human visual system and stochastic behavior of texture into account. Point-by-point deviation of texture is performed that also relates the human judgmental behavior with the system analysis for texture. This work extends the idea of structural similarity. Two different types of databases Corbis [14] and CURET [15] are used in this work. This work for texture image retrieval outperforms by achieving average precision and recall values.

In [16], shearlet, which is a new variation of wavelet, is used for image texture characterization. However, traditional wavelets do not deal well with the distributed discontinuities such as edges. This paper proposed a texture image retrieval system

Table 1 Performance of various texture feature extraction methods

S. no.	Method	Merits	Demerits
1	Standard DWT [10]	Works well both in frequency and time domain, less complex, simple in use, no redundancy	Poor directional sensibility, less shift invariant, time-varying problem
2	CWT [12]	Average shift invariant	Redundant and complex, efficient reconstruction from the decomposition is not provided
3	DT-CWT [12]	Nearly shift invariant and directionally selective in two and higher dimensions	Redundant information is high, each time complex part is also processed with real part
4	2D-RCWF [9]	Rotation invariant, shift invariant, more directional selectivity	Slower than DT-CWT
5	DT-CWT + 2D-RCWF [9, 8]	Directional selectivity in 12 directions, better texture feature extraction, produces less redundant features as compared to Gabor wavelet, computational complexity is less	Space complexity is high

that deals with adjacent shearlet subband dependencies using linear regression. A simple linear regression model consists of the mean function and the variance function. Two energy features are used to represent texture classification instead of complex numbers. Regression residuals are used as a distance measure. This texture retrieval system has two subprocesses. The first subprocess is based on contourlet domain, while the second subprocess is feedback mechanism based on regression modeling of shearlet subband dependences.

Shrivastava et al. [17] presented a good survey on image retrieval techniques based on Region of interest. ROI-based techniques require a good representation of subregions which lies in an image. Feature extraction, query formulation, and similarity matching are performed with the help of region codes.

Jacob et al. [18] presented Local Oppugnant Color Texture Pattern, which is an enhancement of Local Tetra Pattern. Relationship is determined by the directional information and intensity between the referenced pixels and their oppugnant neighbors. It relates the human perception with system by harmonized link between color and texture. This technique is used for retrieving both texture and natural images. Results are tested on Brodatz texture database and Corel database. YCbCr, HSV, Lab, and RGB color models are also evaluated.

Mukhopadhyay et al. [19] proposed a texture image retrieval system. This system works in two stages. At first stage, using of neural network class membership is calculated for query image. Combination of simple and weighted distance metric is used to retrieval the texture images at the second stage. This system reduces the search space and increases the speed of retrieval.

Manisha et al. [20] proposed a retrieval technique based on local extrema co-occurrence patterns. HSv color space is used to utilize the color, intensity, and brightness of images. Local extrema occurrence patterns are used to extract the local directional information of an image. Corel, MIT, VisTex, and STex databases are tested by this method.

Kwitt et al. [21] used dual-tree complex wavelet transform for texture feature extraction. Constant similarity measurement is achieved with Kullback–Leibler divergences between the proposed statistical models. This work is aimed to focus on both retrieval time and accuracy. Statistical models are also presented with DT-CWT to get coefficient magnitudes. Choy et al. [22] presented a generalized Gamma density function with three parameters for texture image retrieval. Generalized gamma density is used to control on shape features of the model that cannot be achieved by histogram-based applications, because it provides an extra index to control on shape model and provides flexibility in calculating the histograms. This model can also be applied to the high-frequency coefficients also. Symmetrized Kullback–Leibler measure is used to calculate the distance between the features of the images.

Texture image retrieval is a process of extracting texture images from the database. These images exhibit different properties from natural images. So treatment of texture images is also different. Repetitive patterns present in texture images can only be identified and extracted by analyzing the image in different directions also, as performed in [9, 8]. Standard deviation, mean, entropy, energy, correlation, and variance are the numerical features of the texture. By taking more than one feature into account, a feature vector is created. The same process is applied to the stored database images and a new dataset is prepared, which contains all the feature vector of the database images. Various similarity measures like Euclidean distance, chi-squared, Bhattacharya distance, and Canberra distance Histogram intersection methods are used in many approaches for calculating the similarity between the query image and database images.

Pi et al. [23] proposed texture image retrieval based on the fractal parameters. Image signature is constructed using quantitative measurement of these fractal parameters and collage error. Histogram of joint histogram of contrast scaling and collage error, collage error, and joint histogram of range block mean and contrast scaling and collage error are constructed by taking fractal parameter and collage errors as input. Statistical properties inherent in the images can be extracted by applying these fractal signatures. Computational complexity can be reduced with the fractal signature consisting of histograms. Combination of histograms performs better than the Individual histograms of fractal parameters in texture image retrieval both in computational complexity and time.

Do et al. [24] proposed a wavelet-based texture image retrieval system. A generalized Gaussian density function is used to calculate the distribution of wavelet coefficients. Kullback–Leibler distance is used to calculate the distance between the query image and stored database images. Experimental results are tested on benchmark texture databases. After decomposition extraction, wavelet coefficients at each subband are collected and modeled by the Gaussian density function. In this paper, a combined classification and modeling scheme is presented on similarity measurement and feature extraction phase of image retrieval.

Nava et al. [25] presented log-Gabor filter method to retrieve the texture images. To overcome the distortion produced by Gabor filter, which results in poor accuracy in retrieving of patterns, log-Gabor filter is used. This filter is an enhancement in previous filter designed to prevent distortion. Kullback–Leibler and the Jensen–Shannon divergences are used on both Gabor and log-Gabor filters with the USC-SIP database to check the accuracy of the proposed system.

3 Conclusion

In this paper, we have surveyed various issues of texture image retrieval methods. A brief introduction of a texture image retrieval system is presented. The main purpose of this survey is to provide an analytical description of various wavelet-based texture feature extraction methods. Survey is done on some variants of wavelet-like Standard DWT, DT-CWT, RCWF, and Gabor filter. After the study of various methods, it is concluded that better results of texture image retrieval can be achieved only if feature extraction is done perfectly, i.e., rotation, scaling, and reflection of the image should be considered. Among all of the variants, combination of DT-CWT and 2D-RCWF performs well. The performance of this combination works for both rotated and non-rotated image databases. We hope that this survey will help researchers to select the best algorithm and feature extraction methods to meet their requirements.

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