A Survey on Textured based CBIR Techniques

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ABSTRACT
Content based image retrieval (CBIR) is a method of retrieving images from large image resource, which has been found to be very effective. To represent images in terms of their features, CBIR involves the use of low-level image features like, colour, texture, shape, and spatial location, etc. To improve existing CBIR performance, it is very important to find effective and efficient feature extraction mechanisms.

Texture effectively describes the distinguishing characteristics between images. It is one of the most important and prominent properties of an image. A variety of techniques have been developed for extracting texture features, broadly classified into the spatial and spectral methods. Though many works on texture classification and representation have already been done, it is still an open issue. Vector Quantization (VQ) is an efficient and simple approach for data compression. Therefore, the computational cost of CBIR system can be reduced by using vector quantization.

In this paper we have provided the overview of different methods for textured based CBIR system and also discussed how its performance can be improved by vector quantization.

General Terms
Image Processing, image retrieval

Keywords
CBIR**,** texture, special, spectral, vector quantization

1. INTRODUCTION
Content Based Image Retrieval (CBIR) is a technique which uses visual contents to search images from large scale image databases according to users' requests in the form of a query image. Its goal is to support image retrieval based on content properties (e.g., shape, color, texture), usually encoded into feature vectors [5]. One of the main advantages of the CBIR approach is the possibility of an automatic retrieval process, instead of the traditional keyword-based approach, which usually requires very laborious and time-consuming previous annotation of database images [1]. There are many large resources, which people can use to create and store images. This has created the need for a means to manage and search these images. Therefore, finding efficient image retrieval mechanisms has become a wide area of interest to researchers. CBIR depends on several factors, such as, feature extraction method, suitable features to use in CBIR, similarity measurement method, mathematical transform chosen to calculate effective features, user feedback, etc. All these factors are important in CBIR. An improvement to any of these influencing factors can result in a more effective retrieval mechanism [6].

Texture is an important and prominent visual property of an image. Low-level texture features play a vital role in CBIR and texture classification. Texture has qualities such as periodicity and scale. Besides this, it can be described in terms of direction, coarseness, contrast and so on. Similar images are expected to have similar texture patterns, so texture features are important for content based image retrieval [3]. Basically, there exist two types of texture features extraction approaches, such as spatial domain and spectral domain methods.

The spatial approaches mostly rely on statistical calculations on the image. Unfortunately, these statistical techniques are sensitive to image noise and have insufficient number of features. As a result, small changes in the image due to noise affect the total feature extraction process. When the same image with and without noise is compared, the values of their texture features vary significantly. Therefore, similar but noisy images may not be retrieved in a CBIR method using spatial features. On the other hand, spectral domain methods like multiresolution wavelet, Gabor filters, discrete cosine transform, and the multiresolution simultaneous autoregressive model have the advantage of being insensitive to noise. Therefore, these transforms have widely been used to represent image textures. A new multiresolution method, discrete curvelet transform, has been developed by Candès and Donoho, which is effective in representing the edges in an image [5]. Due to the advantages of spectral domain texture features over spatial methods, they have been widely used in content based image retrieval.

When processing images one is always faced with the problem that information on the one hand needs to be quantized as compactly as possible and on the other hand must be represented with sufficient accuracy. VQ (Vector Quantization) can provide a way of better way for compacting exploiting the spatial information.

2. MULTIRESOLUTION TECHNOLOGIES
Multiresolution methods or hierarchical approaches attempt to find a specific frequency at a specific location, which is the main shortcoming of Fourier Transform (FT) and Short Time Fourier Transform (STFT). However it is not possible to find a specific frequency at a specific location simultaneously. Therefore, as a trade off between time-frequency representations, multiresolution methods are created. Multiresolution methods are designed to obtain a good time resolution but less accurate frequency resolution at high frequencies and a good frequency resolution but lessaccurate time resolution at low frequencies. This approach is useful when the signal contains high frequency components for

short durations and low frequency components for long duration. This effectively overcomes the window size problem of STFT

The multiresolution method is similar to image zooming process. When the image is zoomed out, we get a global view of the image, whereas, a detailed view of the image is obtained when it is zoomed in. Using the multiresolution approach, we can get a complete picture of the image consisting of its low frequency components. Meanwhile, high frequency components of the image at low scales provide the detailed and discriminatory structures of the image, which is important when using content based image retrieval based on texture features.

A set of coefficients are obtained from a multiresolution transform. These coefficients correspond to the frequency information at a different resolution, location and sometimes the orientation of the image. In multiresolution approaches, such as discrete wavelet, Gabor filters and discrete curvelet transforms, the frequency information at different scales, orientations and locations are obtained.

2.1 Wavelet Transform

Wavelet transform is introduced with the advancement in multiresolution transform research. Discrete wavelet transform is one of the most promising multiresolution approaches used in CBIR. It has the advantage of a time-frequency representation of signals where Fourier transform is only frequency localized. The location, at which a frequency component of an image exists, is important as it draws the discrimination line between images. Unlike the FT and STFT, the window size varies at each resolution level when the wavelet transform is applied to an image. In discrete wavelet transform, the original image is high-pass filtered yielding three detail images, describing the local changes in horizontal, vertical and diagonal direction of the original image. The image is then low pass filtered yielding an approximation image which is again filtered in the same manner to generate high and low frequency subbands at the next lower resolution level. This process is continued until the whole image is processed or a level is determined as the lowest to stop decomposition. This continuing decomposition process is known as down sampling. The whole decomposition process provides us with an array of DWT coefficients obtained from each subbands at each scale. These coefficients can then be used to analyse the texture patterns of an image. The wavelet transform yields a much higher texture classification rate and retrieval accuracy than discrete cosine transform or spatial partitioning.

2.2 Gabor Filter

From the recent literature, the Gabor filters seem to be the most promising for texture representation as well as image retrieval based on texture features. Gabor filters perform better than other wavelet methods. Gabor filters is a good multiresolution approach that represents the edges of image in an effective way using multiple orientations and scales. Gabor filters have a spatial property that is similar to mammalian perceptual vision, thereby providing researchers a good opportunity to use it in image processing. Gabor filters creates a filter bank consisting of Gabor filters with various scales and orientations. Then the filters are convolved with the image. Gabor filters use multiple window size at different level of resolutions whereas STFT uses only one window. STFT obtains either a good frequency or good location resolution information but Gabor filters obtain both by applying multiresolution filter banks. Gabor filters outperform other wavelet transforms, including the orthogonal wavelet (OWT), bi-orthogonal wavelet (BWT) and tree-structured wavelet transform (TWT) at the cost of high computational expense.

2.3 Curvelet Transform

Curvelet transform has been developed to achieve a complete coverage of the spectral domain and to capture more orientation information. The initial approach of curvelet transform implements the concept of discrete ridgelet transform. In 2005, Candès et al. proposed two new forms of curvelet transform based on different operations of Fourier samples, namely, unequally-spaced fast Fourier transform (USFFT) and wrapping based fast curvelet transform [1]. Wrapping based curvelet transform is faster in computation time and morerobust than ridgelet. We'll see the curvelet transform in more details in the next section.

3. THE CURVELET TRANSFORM

Curvelet transform based on wrapping of Fourier samples takes a 2-D image as input in the form of a Cartesian array $f[m, n]$ such that $0 \le m < M, 0 \le n < N$ and generates a number of curvelet coefficients indexed by a scale j , an orientation l and two spatial location parameters (k_1,k_2)as output. To form the curvelet texture descriptor, statistical operations are applied to these coefficients. As explained in [1], the discrete curvelet coefficients can be defined as:

$$C^D(j,l,k_1,k_2) = \sum_{\substack{0<=m<M \\ 0<=n<N}} f[m,n]\phi^D_{j,l,k1,k2}[m,n]$$

Here, each $\phi^D_{j,l,k1,k2}[m,n]$ is a digital curvelet waveform. This curvelet approach implements the effective parabolic scaling law on the sub bands in the frequency domain to capture curved edges within an image more effectively.[2]

To achieve higher level of efficiency, curvelet transform is usually implemented in the frequency domain. That is, both the curvelet and the image are transformed and are then multiplied in the Fourier frequency domain. The product is then inverse Fourier transformed to obtain the curvelet coefficients. The process can be described as Curvelet transform = IFFT [FFT(Curvelet) × FFT(Image)] and the product from the multiplication is a wedge [1].

The trapezoidal wedge in the spectral domain is not suitable for use with the inverse Fourier transform which is the next step in collecting the curvelet coefficients using IFFT. The wedge data cannot be accommodated directly into a rectangle of size $2^j \times 2^{j/2.}$ To overcome this problem, Candes et al. have formulated a wedge wrapping procedure where a parallelogram with sides 2 j and 2 j / 2 is chosen as a support to the wedge data [5]. The wrapping is done by periodic tiling of the spectrum inside the wedge and then collecting the rectangular coefficient area in the center. The center rectangle of size$2^j \times 2^{j/2}$ successfully collects all the information in that parallelogram as shown in Fig. 1.

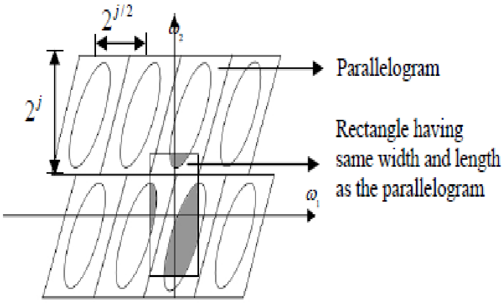


Fig. 1 : Wrapping wedge around the origin by periodic tiling of the wedge data.

Basically, multiresolution discrete curvelet transform in the spectral domain utilizes the advantages of fast Fourier transform (FFT). During FFT, both the image and the curvelet at a given scale and orientation are transformed into the Fourier domain. The convolution of the curvelet with the image in the spatial domain then becomes their product in the Fourier domain. At the end of this computation process, we obtain a set of curvelet coefficients by applying inverse FFT to the spectral product. This set contains curvelet coefficients in ascending order of the scales and orientations.

4. ANALYSIS OF EXISTING TECHNOLOGIES

From the recent literature, we find the texture features of an image are effective due to their fine discriminatory property. Therefore, we find spectral texture features are more suitable for content based image retrieval. From this discussion, multiresolution approaches are found to be the most effective in texture features representation.

To evaluate the retrieval performance, the most commonly used performance measurement; precision-recall pair is used. Recall measures the robustness of a retrieval mechanism whereas precision measures the accuracy. According to [4], when experiments were conducted on Brodatz database, we find that Gabor filters show 65.75% retrieval precision at full recall, Curvelet however, gives an average retrieval precision of 77.65%. Therefore, curvelet retrieval performance is significantly better than both the Gabor filters and wavelet methods.

Though wavelet transform has been widely accepted, it has several problems which results in a poor outcome for content based image retrieval. In 2-D space, wavelets cannot capture highly anisotropic elements like the curves of an image effectively as wavelets are not effective at representing line singularities. Images with a dense composition of highly anisotropic elements such as curves may not be well represented using wavelet texture representation. Images containing a high level of directionality will not be well represented by wavelet spectral domain.

Gabor filter performs better than wavelet but there is loss of spectral information. Thus the limitations of Gabor filters and wavelet transform leaves room for improvement in texture based image retrieval. Due to the above mentioned flaws, researchers have been trying to introduce spectral approaches which involve more directional information in an image for texture representation. Discrete curvelet transform is the result of this endeavour.

Discrete curvelet transform consists of more scales and orientations in the frequency domain than the Gabor filters and completely covers the spectral plane. The Gabor filters transform has less number of orientations at every scale whereas, in the curvelet transform, the number of orientations increases as the level of resolution increases so that more directional information from high frequency components can be captured.

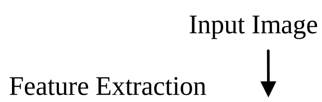
5. VECTOR QUANTIZATION

The curvelet transform outperforms other multiresolution methods but it has drawback of high computational costs. This higher cost is due to the large size of feature vector, which results in higher time and space complexity for our curvelet computations. These large sized feature vectors degrade the overall performance of the CBIR system. To overcome this, we have proposed to use vector quantization. But there is some more scope to improve the retrieval performance.

Vector Quantization is a technique of compressing data based on grouping blocks having similar data. These blocks are called code vectors and all the code vectors grouped together is called a Codebook. The key to VQ data compression is a good codebook. Vector Quantization (VQ) is a compression technique based on grouping blocks of information based on the similarity of their values. There is a loss of quality while using VQ, but this is duly compensated by the significant savings achieved by this compression method. [7]

VQ leads to formation of Codebooks. These codebooks are a subset of the blocks derived from the data. It is an iterative method of clustering data, where iteration involves increasing the number of clusters twofold and re-clustering the data till a finite desired number of clusters is reached. It is a three phase process involving Codebook Generation, Encoding and Decoding. The density matching property of vector quantization is powerful, especially for identifying the density of large and high dimensioned data. Since data points are represented by the index of their closest centroid, commonly occurring data have low error, and rare data high error. This is why VQ is suitable for lossy data compression. It can also be used for lossy data correction and density estimation

Vector quantization can be used with the existing system as shown in fig. 2. First an image is taken as an input and its curvelet transform is should be calculated to generate the curvelet coefficients. Followed by it, texture feature is extracted by the coefficients associated with each sub band. This results in generation of feature vector, which are then quantized using vector quantization scheme. These quantized feature descriptors can be then used to index images in the feature database.



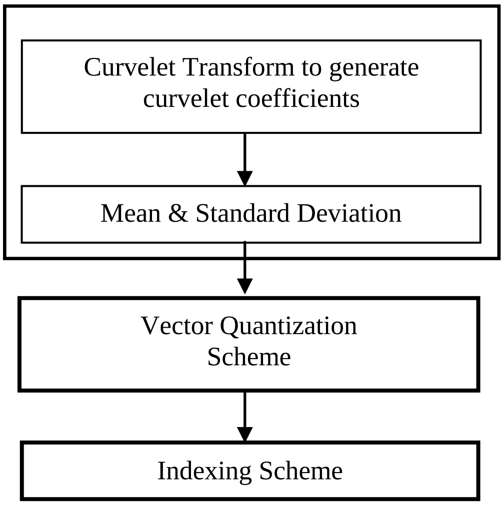


Fig 2. Curvelet Transformation with Vector Quantization

6. CONCLUSION

The results of the existing systems show that the curvelet transform obviously gives better results than the other methods. The reason behind this is curvelet transform with higher levels of decomposition contains more directional information at high frequencies, thereby representing edges of an image effectively. It can be observed that the size of feature vector for the curvelet is very large. This can degrade the performance and has a scope for improvement. Large size vectors can add to the computational cost of the CBIR system. One most probable solution to this problem would be to use vector quantization in the existing system.

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