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A Robust Image Matching Using FDCT and Local Textures for Image Retrieval Application

Sheela S.*, V. Subashini and A. Karunakaran*****

ABSTRACT

Image retrieval is the important technique in image processing. The paper presents the robust object recognition using texture and directional feature extraction. The system proposes texture descriptors such as fast discrete Curvelet transform based entropy feature and local directional pattern. The category recognition is to classify an object into one of several predefined categories. The Fast discrete Curvelet transform is used here to decompose the image into structural and textural details at different scale and orientation. It represents an object texture and Curvelet edge information from all orientation which is utilized to extract the entropy feature from each textural band. Entropy is a texture feature describes complexity pattern of an object. Second descriptor called Local directional pattern describes local primitives including different types of curves, corners and junctions. LDP computes the edge response values in all eight directions at each pixel position and generates a code from the relative strength magnitude. The performance measures such as precision and recall rate are measured to evaluate the system performance.

Keywords: Discrete Wavelet Transform, Fast Discrete Curvelet Transform, Local Directional Pattern, Local Binary Pattern, Local Ternary Pattern, Mean Square Error, Peak Signal Noise Ratio.

1. INTRODUCTION

In many image-processing applications, image retrieval technique plays a vital role. Content-based image retrieval systems works with entire images and searching is based on comparison of the query. Generally features like color, texture and shape are used for image retrieval. The various resolutions of the images, size and spatial color distribution are not concerned in these image retrieval techniques. Hence all these methods are not suitable for the art image retrieval. Even though, Global features like color, texture and shape is used by many other image retrieval systems whose results shows that there are too many false positives while using those global features to search for similar images. Hence, we introduce an effective image retrieval technique using both content and metadata.

2. EXISTING METHODOLOGY

Most of the existing methods use Discrete Wavelet Transform.

2.1. Wavelets

The general way to represent and analysis of multi resolution image is using wavelets. By applying translation and scaling on the mother wavelet $\psi(x)$, the basis can be constructed. A function $\psi(x)$ can be called a wavelet if it possesses the following properties: [1][3][4][9]

* Assistant Professor, Dept. of Electronics & Communication Engineering, Rajalakshmi Institute of Technology, Chennai, India, *Email:ssheela97@gmail.com*

** Assistant Professor, Dept. of Electronics & Communication Engineering, Rajalakshmi Institute of Technology, Chennai, India, *Email:ssheela97@gmail.com*

*** Assistant Professor, Dept. of Electronics & Communication Engineering, Rajalakshmi Institute of Technology, Chennai, India, *Email:ssheela97@gmail.com*

2.2. Types of wavelet

There are different types of wavelets. There are,

Haar wavelet: It is a bipolar step function. The Haar wavelet is discontinuous in time and it has good localization property in time and frequency domain.[2][4]

Morlet wavelet: The Morlet wavelet is obtained by multiplying the Fourier basis with a Gaussian window.[3]

Mexican-hat wavelet: Mexican-hat wavelet is a second-order derivative of the Gaussian function. The two-dimensional Mexican-hat is popularly known as the Laplacian operator. The Laplacian operator is widely used in edge detection.[6]

Daubechies wavelet: The Daubechies wavelet bases are a family of orthonormal, compactly supported scaling and wavelet functions that have maximum regularity for a given length of the support of the Quadrature mirror filters.[5]

Shannon wavelet: The Shannon wavelet has poor time resolution, but its frequency localization is excellent.[9]

2.3. Local Binary Pattern

In computer vision, Local Binary Patterns (LBP) is a type of feature used for classification. Texture Spectrum model's particular case is LBP .For texture classification, it has been found to be a powerful feature. When LBP is combined with the histogram of oriented gradient (HOG) descriptor, the detection performance considerably improved on some datasets. The LBP feature vector in its simplest form is created in the following manner.[2][4][7][8]

i. The examined window is divided into cells (e.g. 16 × 16 pixels for each cell). The pixel to each of its 8 neighbors (on its left-top, left-middle, left-bottom, right-top, etc.) is compared for each pixel in a cell. Along a circle, i.e. clockwise or counter-clockwise, the pixels are followed.

ii. Write "1" when the center pixel's value is greater than the neighbor's value,. Otherwise, write "0". An 8-digit binary number (which is usually converted to decimal for convenience) is obtained.

iii. The histogram, over the cell, of the frequency of each "number" occurring (i.e., each combination of which pixels are smaller and which are greater than the center) is computed.

iv. Normalizing the histogram is optional.

v. Histograms (normalized) of all cells are computed. This results in the feature vector for the window.

2.4. Local Ternary Pattern (LTP)

LTP is a three-valued code, in which zero are quantized to the gray values in the zone of width $\pm T$ around Gc, + 1 are quantized to those above ($Gc + T$), –1 are quantized to those below (Gc-T). Local Ternary Patterns are an added feature of Local Binary Pattern. It uses a threshold constant 'T" to threshold pixels into three values, unlike LBP; it does not threshold the pixels into 0 and 1 rather. Here, LTP code is more resistant to noise as "T" is a user specified threshold.[2][4][5]

3. PROPOSED METHODOLOGY

By using Fast Discrete Curvelet Transform and Local Directional Pattern, the category recognition system will be developed for image retrieval applications. The category recognition is to classify an object into one of several predefined categories. The concept of Discrete Ridgelet Transform is the first approach of Curvelet transform. The Ridgelet based Curvelet transforms creation is an effective tool and successfully used in

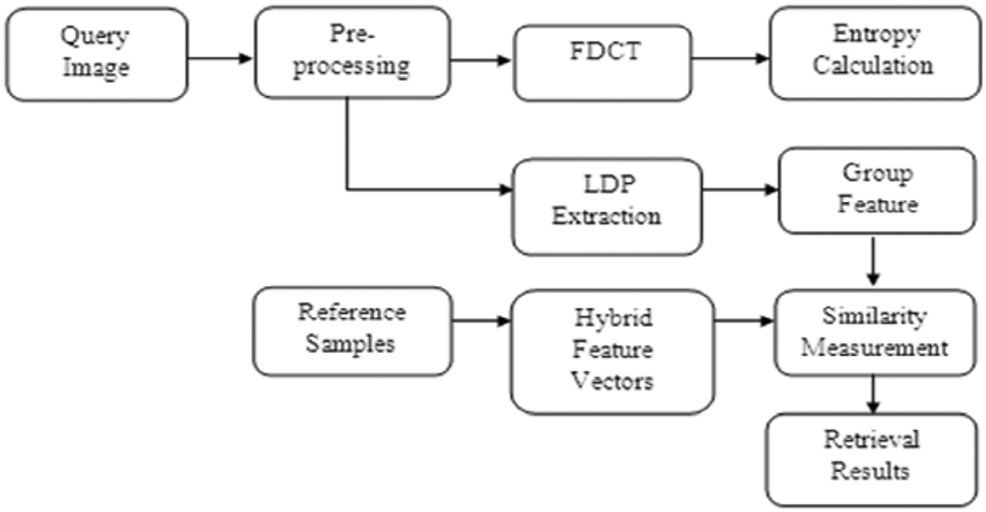

Figure 1: Block Diagram of Proposed Methodology

image de noising, image decomposition, texture classification, image de-convolution and contrast enhancement, etc. Since it uses complex Ridgelet transform, it is not very efficient. Compared to Ridgelet and USFFT Curvelet transforms, wrapping based Curvelet transform is more robust and its computation time is faster. In CBIR there hasn't been any work done on unsystematic evaluation of Curvelet and wrapping based Curvelet transform has not been used.[2][3][4]

Concept: The àtrous wavelet transform and the Radon transform combines to form Ridgelet based Curvelet transform. The input images are at first decomposed in Curvelet and then they are partitioned in Ridgelet analysis. In Ridgelet transform, a Radon transform and the 1-D wavelet transform are used in which one of the processes is spatial partitioning. Here the spatial partitioning involves overlapping of windows for avoidance of blocking effects which results in large amount of redundancy. For larger database, the texture feature analysis is less feasible and this process is very time consuming.[5][6][10]

3.1. Fast Discrete Curvelet Transform

The concept of Discrete Ridgelet Transform is the first approach of Curvelet transform. FDCT has less computational complexity, which is based on wrapping of Fourier samples. Instead of complex Ridgelet transform it uses FFT. To reduce data redundancy in frequency domain, a tight frame has been introduced as the Curvelet support. The Ridgelet has fixed length and variable width but Curvelet had both variable width & length and it represents more anisotropy. Comparing Ridgelet based Curvelet transform; the wrapping based Curvelet transform is simpler, less redundant and faster in computation. Let us discuss about discrete Curvelet transform based on wrapping Fourier samples which is the most promising approach of Curvelet that we intend to use it for texture representation in our CBIR research.

Discrete Curvelet transform is implemented by using the wrapping based fast discrete Curvelet transform, where its multi resolution in spectral domain utilizes the advantages of FFT. Here in FFT, the image and the Curvelet at given scale and its orientation are transformed into the Fourier domain. The product in the Fourier domain is obtained by the convolution of the Curvelet with the image in the spatial domain. For the spectral product, we apply the inverse FFT to it and obtain the set of CURVLET coefficients at the end of computation process.[1][2][5][7]

3.1.1. Implementation

Based on the original construction, the Curvelet transform uses a pre-processing step which involves a special partitioning of phase-space followed by thr ridglet transform. Here it is applies to the well localized

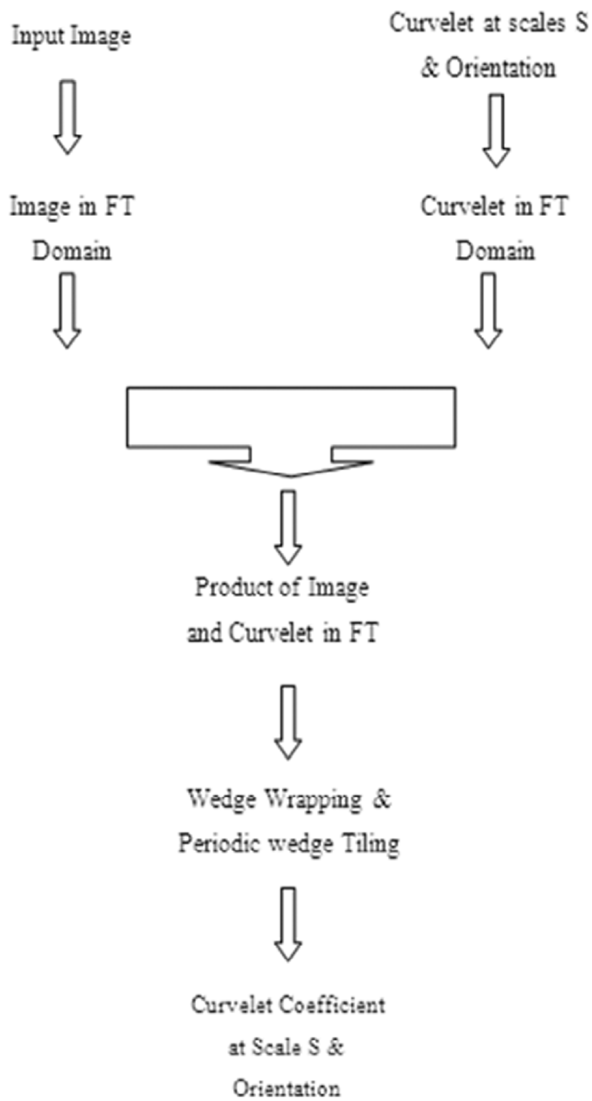

Figure 2: FDCT Wrapping

blocks of data in the space and frequency.The redesign of Curvelet results the new construction to be simpler and totally transparent and also made then easier to use and understand. One of the interesting fact here is the new mathematical architecture suggests innovative algorithmic strategies. It also provides the opportunity to improve upon earlier implementations. Compare to the existing proposals, there are two new FDCTs which are simpler, faster and less redundant. They are Curvelet via USFFT and Curvelet via Wrapping.[2][4][7]

3.1.2. Advantages of FDCT

DCT has the advantages of both color feature. The existing texture features are outperformed by the Curvelet feature in accuracy and efficiency. The Curvelet captures edge information and anisotropic elements such as the edges of an image more accurately than wavelet. The frequency plane of an image is covered by the Curvelet spectra. In image retrieval, the more accurate texture features are used which are extracted by the Curvelet transform.

Also the detailed information of the image in the spectral domain using more orientation is provided by the Curvelet transform. The database images using low order statistics for retrieval are represented by wrapping based DCT, at each scale. Curvelet texture features are used to retrieve images from a large database consisting of original and scale distorted images, which helps in the study of robustness of this feature.

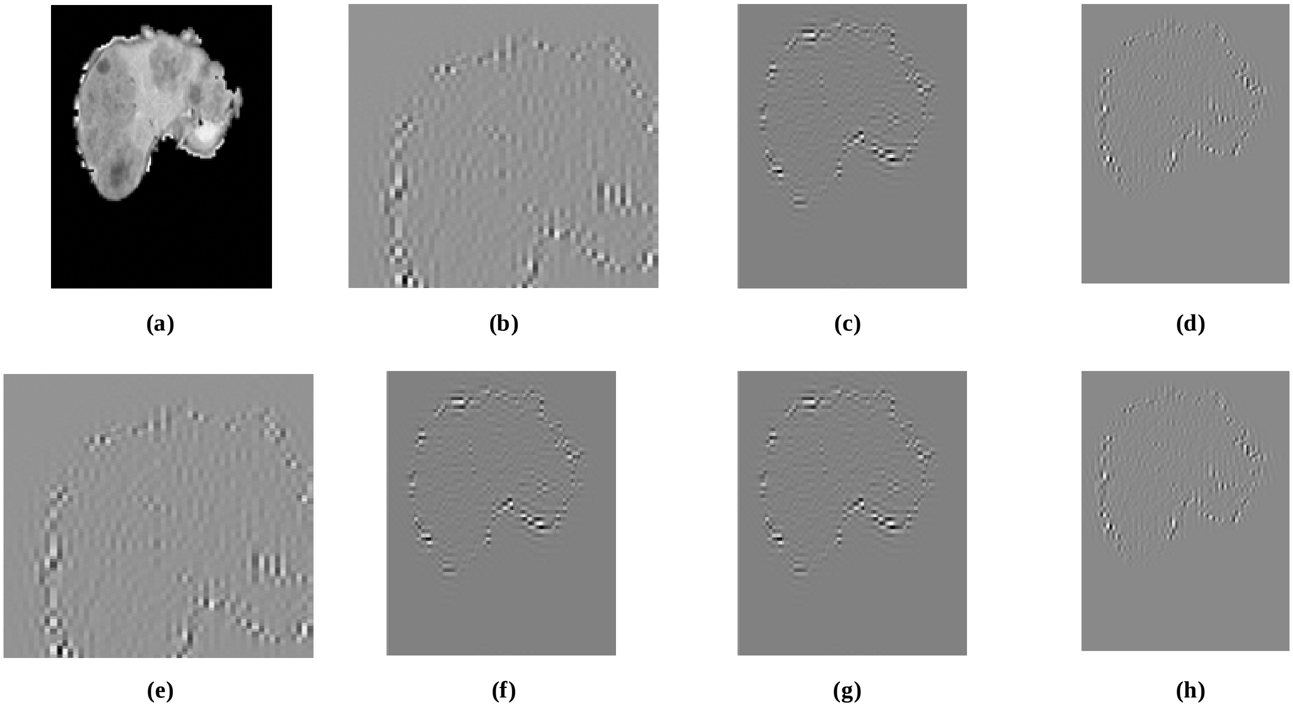

Fig 3. FDCT Decomposition. (a). D1 (b). D11 (c). D12 (d). D13 (e). D14 (f). D15 (g). D16 (h). D17

The limitations of wavelet and Gabor filters paved the way for the development of the Curvelet transform. The wavelet transform fails to represent objects containing randomly oriented edges and curves, in spite of being widely used in various branches of image processing. And also it is not good at representing line singularities. To overcome this Gabor filters are found. Due to its multiple orientation approach, it gave better performance than wavelet transform in representing textures and retrieving images. However the spectral loss of information made Gabor filter to represent images ineffectively and also it affects the CBIR performance. So because of this, the Curvelet transform has been developed to achieve a complete coverage of the spectral domain and to capture more orientation information.[2][4]

3.2. Local Directional Pattern

LDP is the characterization of the spatial structure of a local image texture in a gray-scale texture pattern. The edge response values in all eight directions at each pixel position are computed by LDP operator and generates a code from the relative strength magnitude. The local primitives including different types of corners, curves

-3	-3	5
-3	0	5
-3	-3	5

(a)

5	-3	-3
5	0	-3
5	-3	-3

(b)

5	5	5
-3	0	-3
-3	-3	-3

(c)

-3	-3	-3
-3	0	-3
5	5	5

(d)

-3	-3	-3
-3	0	5
-3	5	5

(e)

-3	5	5
-3	0	5
-3	-3	-3

(f)

-3	-3	-3
5	0	-3
5	5	-3

(g)

5	5	-3
5	0	-3
-3	-3	-3

(h)

Figure 4: Kirsch edge mask in all eight directions

and junctions are described by the resultant LDP feature, more stably and retains more information. The kirsch template to extract the all orientation edge response for better texture representation, given the central pixel of the image is used. In all directions the response values are not equally important. High response values are caused by the presence of a corner or edge in some directions. Therefore, k most prominent directions is preferred to generate the LDP. Here, the value 1 is set to the top k directional bit responses bi(a). The value 0 is set to remaining (8-k) bits of the 8-bit LDP pattern. Finally, the LDP code is derived using equation.[2][4]

4. RESULT AND DISCUSSION

The required Query image is pre-processed so that the noise is removed by using the common filter 'Gaussian Filter'. The input image is decomposed in to its 10 sub bands and entropy features was extracted from the sub bands. The LDP assigns an 8 bit binary code to each pixel of an input image, the features are extracted and Histogram is plotted. Finally the performance measures such as Precision Rate and Recall Rate are calculated and showed in Table.1.

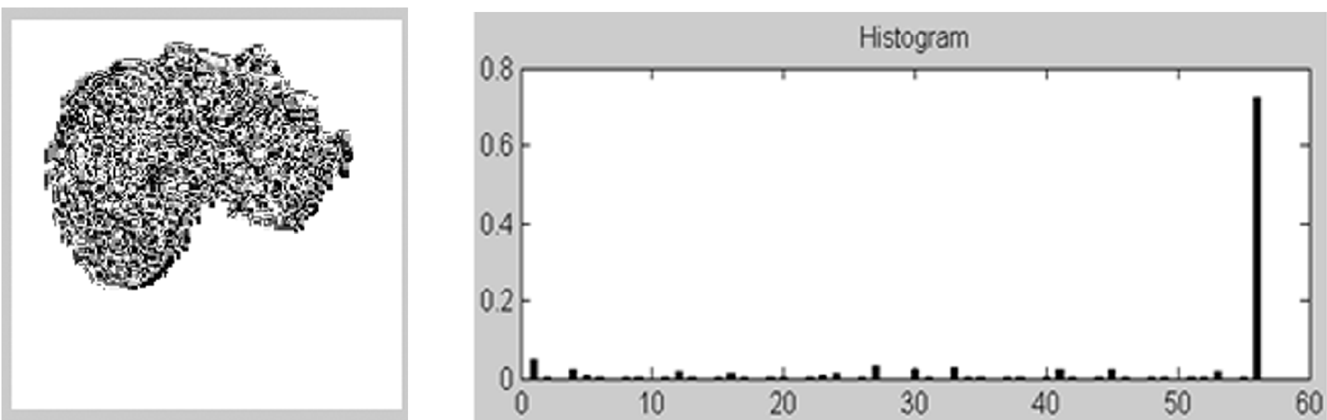

Figure 5: Local Directional Pattern. a) LDP Coded Image b) Histogram

Figure 6: Retrieved results

Table 1
Precision and Recall rate

No of Retrieved Images	*Precision*	*Recall Rate*
5	0.3125	0.3333
6	0.3750	0.4000
7	0.4375	0.4667
8	0.5000	0.5333
9	0.5625	0.6000

5. CONCLUSION AND FUTURE WORK

The project presents the robust object recognition using texture and directional feature extraction. The system proposes texture descriptors such as Fast Discrete Curvelet Transform (FDCT) based entropy feature which represents better texture and edges and Local Directional Pattern (LDP) which provides textural details about all eight directions. By using these methods, the category recognition system will be developed for application to image retrieval which proves Low computational complexity and high compatibility. An Evaluated features from FDCT and LDP are grouped and it is matched with already stored image samples for similar category classification. The simulated results will be shown that used methodologies have better discriminatory power and recognition accuracy compared with prior approaches. The performance measures such as precision and recall rate are measured to evaluate the system performance.

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