Texture Recognition Based on DCT and Curvelet Transform

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Abstract: *This paper presents a proposed technique for texture recognition which depends on the combination of Discrete Cosine Transform (DCT) with Fast Discrete Curvelet Transform (FDCvT) via Wrapping.The proposed technique includes two stages, the first stage is implemented by taking individual natural textures (wood, stone and grass) with several positions and calculation of the features vector (Mean and standard deviation) by using many methods: DCT, FDCvT via Wrapping, and both FDCvT via Wrapping and DCT. The second stage is implemented by taking several samples of new textures for testing the work.The results show that the texture recognition rate by the DCT is 52%, and the FDCvT via Wrapping is 88%. But the new technique of (FDCvT via Wrapping and DCT) achieves better recognition rate (92%). This combination leads to efficiency in texture recognition because the DCT added some qualities that strengthen the work of the Curvelet Transform.*

Keywords: ***Texture Recognition, DCT, Curvelet Transform..***

1. Introduction

The Texture is a commonly used feature in the analysis and interpretation of images, Texture can be described by uniformity, density, coarseness, roughness, regularity, linearity, directionality, frequency and phase [1,2]. The Recognition of objects based on their images is one of the central problems in modern computer vision and the Analysis of texture in images provides an important cue to the recognition of objects [3,4]. Texture analysis techniques are recognized into four ways: statistical approaches, structural approaches, filter based approaches and model based approaches [5].The different types of textures can be classified by using the texture analysis, so that we must find the features that may recognize the types of texture. The transformation is a process that transforms an object from a given domain to another which can be used for its recognition, and it is very important to extract the features of texture image. One of the transformations methods is the Fourier transform which usually transforms the signal from its time domain to the frequency domain. Due to the Fast Fourier Transform (FFT) it finds a wide area of application. This transform extends two-dimension fields with its fast algorithm; hence it is used for image processing [6]. Discrete Cosine Transform (DCT) has mostly used in the area of image processing, its basic operation is to take a signal and transforms it from one type of representation to another, in this case the signal is a block of an image [7].

Curvelet Transform allows representing edges and other singularities along curves in a more efficient way when it is compared with other transforms and Curvelet Transform is one kind of new multi-scale transforms and non-adaptive transforms, which possess directionality and anisotropy [8,1]. The structural elements of Curvelet Transform include the parameters of scale, location, and orientation parameters [9].

Two separate digital (or discrete) curvelet transform (FDCvT) algorithms are introduced. The first algorithm is Unequispaced Fast Fourier Transform (USFFT), where the curvelet coefficients are found by irregularly sampling the Fourier coefficient of an image. The second algorithm is the Wrapping transform, using a series of translations and wraparound technique, both algorithms have the same output, but the Wrapping Algorithm gives both a more intuitive algorithm and faster computation time [10,11].

In this paper, a new texture recognition technique based on both DCT and Curvelet Transform is proposed. The FDCvT via Wrapping is one type of Curvelet Transform. By combining the two methods: FDCvT via Wrapping and DCT for access, a new technique and efficiency in Texture Recognition are obtained.

The structural activity extracted from the FDCvT via Wrapping and DCT of the texture image can be analyzed statistically to generate a texture feature vector used in the classifier create classification rules.

The statistical measures used are (Mean and Standard Deviation).

2. Discrete Cosine Transform

Before describing the method I used in conducting this research, The Discrete Cosine Transform is one of the extensive family of sinusoidal transform [12].The concept of this transformation is to transform as set of points from the spatial domain into an identical representation in frequency domain [7]. The two dimensional DCT then can be written in terms of pixel values f(i,j) for i,j =0,1,…………N-1 and the frequency-domain transform coefficients F(u,v) would be[13,14] :

$$F(u,v)=\frac{1}{\sqrt{2N}}c(u)c(v)\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}f(i,j)\times\cos\left[\frac{(2i+1)u\pi}{2N}\right]\cdot\cos\left[\frac{(2j+1)v\pi}{2N}\right] \quad \text{.....(1)}$$

for u,v =0,1,…,N-1

Where

$$C(u),c(v) = \begin{cases} \frac{1}{\sqrt{2}} & \text{For u,v=0} \\ 1 & \text{otherwise} \end{cases}$$

The inverse DCT transform is given by

$$f(i,j)=\sum_{u=0}^{N-1}\sum_{v=0}^{N-1}c(u)c(v)F(\times\cos\left[\frac{(2i+1)u\pi}{2N}\right]\cdot\cos\left[\frac{(2j+1)v\pi}{2N}\right] \quad \text{.......(2)}$$

for i,j =0.1,…, N-1.

f(i,j) is the i,jth element of the image(intensity of the pixel) represented by the matrix f. N is the size of block that the DCT is done on. u,v are frequency coordinates in the transform domain.

As Figure 1.a and 1.b,indicate each sub block contains one DC coefficients and other AC coefficients show lower frequency coefficients that contain(useful data for the image) gather at the top-left corner and higher frequency ones that (contain less useful information) at the bottom-right corner of the transformed matrix[14,15].

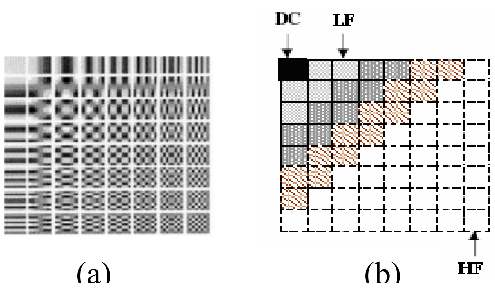


Figure 1: (a) DCT basis pattern.
(b) Vector element from frequency components [16]

3. Curvelet Transform

Curvelets as proposed by E. Candes and D. Donoho are developed to overcome inherent limitations of traditional multiscale representations [11]. There are two generations of the curvelet transform, first generation curvelet (1999) which used complex series of steps involving ridgelet analysis of the radon transform of an image, the performance is exceedingly slows [17]. The second generation curvelet (2003), which does not use ridgelet transform thus reducing the mount of redundancy in transform and increasing the speed considerably [18].

The structural elements of curvelet transform include the parameters of dimension, location and orientation parameter more, which let it have good orientation characteristic [9].

In 2003, Emmannel Candes and David Donoho proposed a simplified implementation of second generation curvelet directly in the frequency plane that relied on interpolation by means of the USFFT, and Wrapping of Fourier samples instead of interpolation [11]. In this research, Fast Digitial Curvelet Transform via Wrapping is used because the wrapping is much faster than the USFFT. Fast Digital Curvelet Transforms (FDCvT) can be implemented via two methods [11,19]:

1-Unequispacee FFTs.
2-Wrapping.

These digital transformations are input Cartesian arrays of the form f[t1, t2], 0 ≤ t1, t2 < n, which allows us to think of the output as a collection of coefficients cD(j,ℓ,k) obtained by

$$c^D(j,\ell,k) := \sum_{0\le t_1,t_2<n} f[t_1,t_2]\,\overline{\varphi^D_{j,\ell,k}[t_1,t_2]}, \quad \text{.................(3)}$$

The two implementations essentially differ by the choice of spatial grid used to translate curvelets at each scale and angle [9].Both methods have the same output, but the wrapping method gives both amore intuitive algorithm and faster computation time [10].

The FDCvT via Wrapping Algorithm involved four steps [19,11,20]:

1- Apply the 2D FFT and obtain Fourier samples f^

[n1, n2], where −n/2 ≤ n1, n2 < n/2.

2- For each scale j and angle ℓ, form the product Ũj, ℓ

[n1,n2] f^ [n1, n2] .

3- Wrap this product around the origin and obtain

Class

f`j,ℓ [n1, n2]=W(Ũj,ℓ f^)[n1,n2],…………(4)

where the range for n1 and n2 is now $0 \le n1 < L1,j$ and

$0 \le n2 < L2,j$ and θ in the range $(-\pi/4, \pi/4)$.

4-Apply the inverse 2D FFT to each f~j,ℓ, hence

collecting the discrete coefficients C^D (j, ℓ , k).

The proposed technique enters texture image to the FDCvT via Wrapping and the output is coefficients matrix, this coefficients matrix enter into feature extraction to compute feature vector such as (Mean,STD).

It is clear that this algorithm has computational complexity O(n2 log n) and in practice, its computational cost does not exceed that of 6 to 10 two-dimensional FFTs [19].

4. Proposed Method

In to account, the idea of the proposed method depends on both DCT and FDCvT, the texture image enters to the FDCvT via Wrapping and the output is coefficients matrix, this coefficients matrix enter into DCT. The output of DCT is coefficients matrix that has real values. It is noted that all coefficients are not taken because they are useful. The coefficient matrix contains one DC and another AC coefficient. The final coefficients matrix will enter to the feature extractor process to compute feature vector such as (Mean, STD) which is used to determine the class of texture.As shows in Figure 2.

There are two stages of implementation, the first stage called Learning Stage and the second stage called Testing Stage.

In the learning stage (31) texture images have been taken, each texture is taken in several positions (angles) which are (45,90,135), and then we divide them into three groups of texture images, all these textures with (256*256) gray-level. First group is Wood texture contains 13 textures. Second group is Stone texture which contains 7 textures. Third group is Grass texture which contains 11 textures, as shown in Figure 3.One applies the steps of the proposed technique to these textures for the extraction of features vector (Mean, STD).

One can put the values of the same group as a range which consists of the Min value and Max value for each feature extraction of the same group. These values are used in classification, for example if the unknown texture has value from the Mean=15 and the group A has the range from 12 to 15, the type of texture is group A. Table 1 illustrates the range for each group from the feature extraction in three methods.

Figure 2: Recognition Procedure Diagram.

Table 1: Ranges of Mean and Standard Deviation for Three Texture Groups Using DCT, FDCvT and both FDCvT & DCT

Group	DCT		FDCvT		FDCvT & DCT	
	Mean	STD	Mean	STD	Mean	STD
Wood	18-60	114-447	83-97	14-75	24-31	218-256
Stone	25-44	241-330	58-86	50-142	19-27	155-226
Grass	18-44	122-251	54-74	79-187	13-22	148-196

5. Results and Discussion

Different unknown textures images are used in learning stage to calculate the feature vector (Mean, STD).The feature vector obtained from the unknown texture image is compared with the features vector (for learning stage) using (IF….Then) statement to classify the texture into the class to which it belongs. To evaluate the performance of any texture recognition system, the rate of the system result should be calculated as follows:

*Recognition Rate= (Number of correctly classified textures / Total number of textures) * 100 …. (5)*

The recognition rates of over 92% were obtained for combination of FDCvT via Wrapping and DCT. The results indicate that combination between FDCvT via Wrapping and DCT is the most effective for texture recognition. because that DCT added some qualities that strengthen the work of the Curvelet Transform.

Table 2 illustrates the results of three methods with different testing new texture images.The recognition rate by DCT is 52%,by (FDCvT via

Wrapping) is 88% and by technique of (FDCvT via Wrapping and DCT) is 92%.

Table 2: The Comparison of Texture Recognition Rate.

Method	Recognition Rate
DCT	52%
FDCvT via Wrapping	88%
DCT & FDCvT via Wrapping	92%

The results indicate the improvement of data entering the DCT (the information that come out from the FDCvT via Wrapping is useful information). They also indicate the reduction of overlapping between the three groups by the combination between the FDCvT via Wrapping and DCT. Finally, the most important thing is access to a new and efficient technique for texture recognition.

6. Conclusion

In this paper the new technique proposed depends on the combination of (DCT with FDCvT via Wrapping). Depending on the results of the experiences, the following points are concluded:

1- This work is applied to a set of nature texture images, which is divided into three groups, each texture is taken in several (angles),which are (450,900,1350), because the unknown texture can come in any angle. It is concluded that the use of rotation leads to obtaining a high accuracy of discrimination, as well as reducing the overlap.

2- The results show that the texture recognition rate by the DCT is 52%, and the FDCvT via Wrapping is 88%.But the new technique of (FDCvT via Wrapping and DCT) achieves better recognition rate (92%).This combination leads to efficiency in Texture Recognition.

3- Using of these methods reduces the rate of overlap, but each method reduces certain rates. In the new technique (FDCvT via Wrapping and DCT) the lowest overlap rate is noted. And then the rate of overlap in the FDCvT via Wrapping increases until one reaches the highest level of overlap in the DCT. But it is difficult to get rid of them permanently, because the overlap always exists.

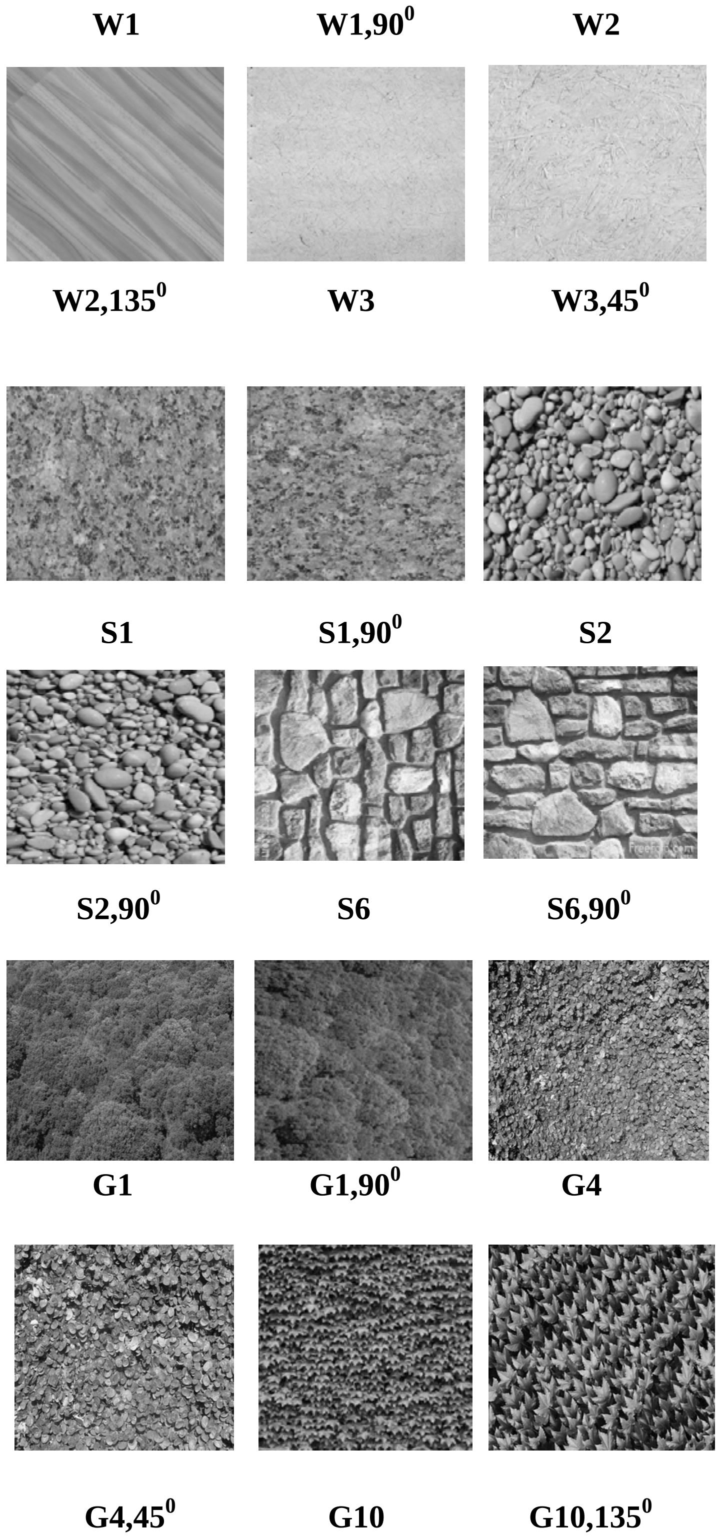
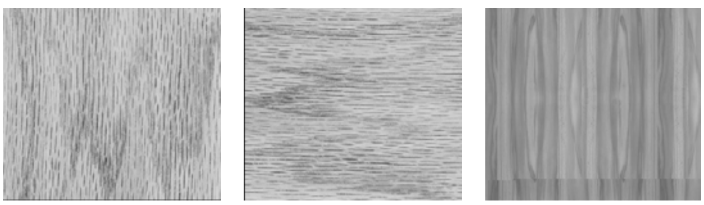


Figure (3):Some samples of 3 types of textures (wood,stone and grass).



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