Research Journal of Applied Sciences, Engineering and Technology 7(24): 5258-5263, 2014
DOI:10.19026/rjaset.7.922
ISSN: 2040-7459; e-ISSN: 2040-7467
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Submitted: February 28,2014 Accepted: April 08, 2014 Published: June 25, 2014

Research Article

A Gray Texture Classification Using Wavelet and Curvelet Coefficients

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Abstract: This study presents a framework for gray texture classification based on wavelet and curvelet features. The two main frequency domain transformations Discrete Wavelet Transform (DWT) and Discrete Curvelet Transform (DCT) are analyzed. The features are extracted from the DWT and DCT decomposed image separately and their performances are evaluated independently. The performance metric used to analyze the system is classification accuracy. The standard benchmark database, Brodatz texture images are used for this study. The results show that, the curvelet based features provides better accuracy than wavelet based features.

Keywords: Brodatz album, curvelet transform, nearest neighbor classifier, texture classification, wavelet transform

INTRODUCTION

In the field of pattern recognition and image processing, the one of the most important task is texture classification. Extensive researches have been made for texture image classification over the last two decades. An approach for texture image classification by modelling joint distributions of local patterns with Gaussian mixtures is presented in Lategahn *et al*. (2010). The local texture neighborhoods are first filtered by a filter bank. Then the joint probability density functions of the filter responses are described parametrically by Gaussian mixture models. A Completed Local Binary Pattern (CLBP) approach for texture classification is developed in Guo *et al*. (2010). It represents a local region by its center pixel and a local difference sign-magnitude transforms. The center pixels represent the image gray level and they are converted into a binary code. The sign component is more important than the magnitude component in preserving the local difference information.

An approach for texture image classification by contrasting the local energy histograms of all the wavelet sub-bands between an input texture patch and each sample texture patch in a given training set is implemented in Dong and Ma (2011). The contrast is conducted with a discrepancy measure defined as a sum of the symmetrized Kullback-Leibler divergences between the input and sample local energy histograms on all the wavelet sub-bands and then the one-nearest-neighbor classifier is used. A new approach to extract global image features for the purpose of texture classification based on Dominant Neighborhood Structure (DNS) is described in Khellah (2011). The DNS features are robust to noise and rotation-invariant. In order to exploit both the local and global information in texture image, the proposed global features are combined with local features obtained from the Local Binary Patterns (LBPs) method.

A novel Bayesian texture classifier based on the adaptive model-selection learning of Poisson mixtures on the contourlet features of texture images for texture classification is presented in Dong and Ma (2012). In order to classify the textures more efficiently, texture image is decomposed into sub-bands by the contourlet transform and extract features from each sub band to represent it. A texture classification system based on random projection, suitable for large texture database applications is described in Liu and Fieguth (2012). A small set of random features is extracted from local image patches. The random features assume no prior information about the texture image, whereas the conventional texture feature extraction methods make strong assumptions about the texture. A bag-of-words model is used to perform texture classification.

A novel local operator of Local Binary Count (LBC), for rotation invariant texture classification is described in Zhao *et al*. (2012). The LBC method can extract the local binary gray scale difference information that distinguishes different distributions of local pixels. Thus, the statistics of the LBC features can also be used to represent the macroscopic textural structures. A statistical histogram-based representation based on local energy pattern is implemented in Zhang *et al*. (2013). The normalized local oriented energies are used to generate the local feature vectors which are less sensitive to the imaging conditions and use the N-nary coding for the vector quantization.

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A new texture descriptor named wavelet based multi-fractal spectrum is developed in Ji *et al.* (2013) for both static and dynamic textures. In order to improve the robustness of certain statistical measurements of regular wavelet coefficients, additional wavelet-based measurements called wavelet leaders are used. The box-counting fractal dimension is used for this approach for its implementation simplicity and computational efficiency. A novel rotation invariant method for texture classification based on local frequency components is described in Maani *et al.* (2013). Three sets of rotation invariant features are extracted from the low frequency components, two based on the phase and one based on the magnitude.

Gabor filters based rotation and scale invariant texture image classification is presented in Riaz *et al.* (2013). The shift invariance property of discrete Fourier transform is used to propose rotation and scale invariant image features. Homogeneous texture is extracted from the images and support vector machines are used for classification purposes. A rotation invariant descriptor based on the shearlet transform for texture classification is presented in He *et al.* (2013). This method consists of four steps. The shearlet transform is first employed on the images. The local shearlet-based energy features are then calculated. After that, the local features quantized and encoded to obtain the rotation invariant description. The energy histograms are finally concatenated into one histogram and used to describe texture images.

Discrete wavelet transform: Wavelets are families of basis functions generated by dilations and translations of a basic filter function. The wavelet functions construct an orthogonal basis and the discrete wavelet transform is thus a decomposition of the original signal in terms of these basis functions (Mallat, 1989):

$$f(x) = \sum_{m=0}^{\infty} \sum_{n=0}^{\infty} C_n^m U_{m,n}(x). \tag{1}$$

where, $U_{m,n}(x) = 2^{-m/2} U(2^{-m} x-n)$ are dilations and translations of the basic filter function $U(x)$. Unlike Fourier bases which are composed of sines and cosine that have infinite length. Wavelet basis functions are of finite duration. The discrete wavelet transform coefficients C_n^m are the estimation of signal components centered at $(2^m\ n.2^{-m})$ in the time frequency plane and can be calculated by the inner products of $U_{m,n}(x)$ and $f(x)$. It is obvious that the wavelet transform is an octave frequency band decomposition of the original signal. The narrow band signals then can be further down-sampled and provide a multi-resolution representation of the original signal.

The discrete wavelet coefficients C_n^m can be efficiently computed with a pyramid transform scheme using a pair of filters (a low-pass filter and a high-pass filter) (Riaz *et al.*, 2013). For images which have two dimensions, the filtering and down sampling steps will be repeated in rows and columns, respectively. The procedure for two levels is shown in Fig. 1. At each level the image can be transformed into four sub-images: LL (both horizontal and vertical directions have low frequencies). LH (the vertical direction has low frequencies and the horizontal has high frequencies). HL (the vertical direction has high frequencies and the horizontal has low frequencies) and HH (both horizontal and vertical directions have high frequencies).

The algorithm for DWT for an image is as follows: Let us consider G and H is the low pass and high pass filter, respectively:

- Convolve each row in the input image with the low pass filter followed by the high pass filter to obtain row wise decomposed image.
- Down sample the row wise decomposed image by 2.

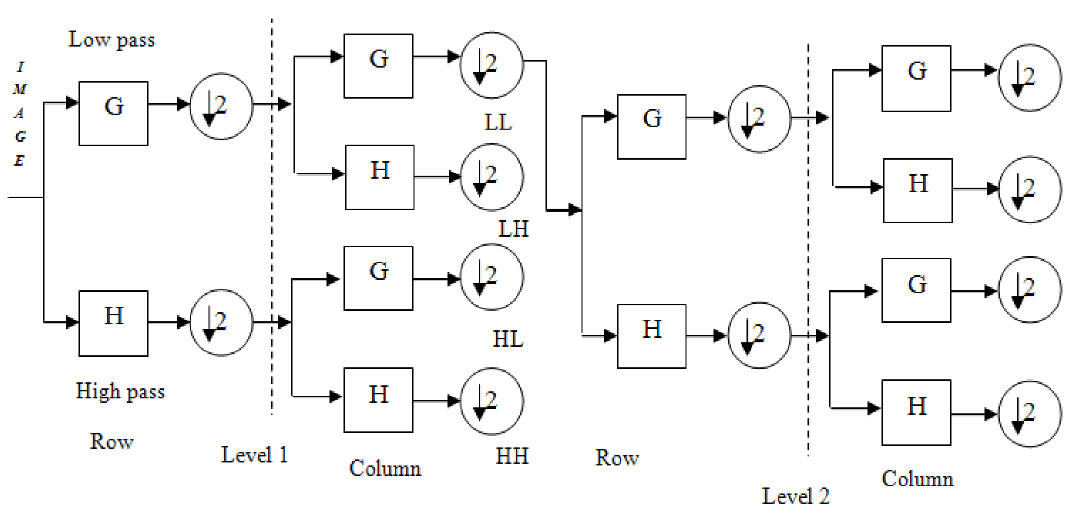

Fig. 1: 2-level DWT of images

- Convolve the column of the row wise decomposed image with the low pass filter followed by the high pass filter to obtain column wise decomposed image.
- Down sample the column wise decomposed image by that produces one approximation sub-band and three high frequency sub-band. This is called 1-level decomposition.
- Apply steps 1-4, for higher level decomposition to the approximation sub-band which is obtained from the previous level of decomposition.

Discrete curvelet transform: Donoho and Duncan (1999) introduced a new multi-scale transform named curvelet transform which was designed to represent edges and other singularities along curves much more efficiently than traditional transforms, i.e., using fewer coefficients for a given accuracy of reconstruction Donoho and Duncan (1999) and Starck *et al*. (2002). 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. Discrete curvelet coefficients can be defined by (Candès *et al*., 2005):

$$c^D(j,l,k_1,k_2) = \sum_{\substack{0 \le m < M \\ 0 \le n < N}} f[m,n]\varphi^D{}_{j,l,k_1,k_2}[m,n]$$

where, each $\varphi^D j, l, k_1, k_2 [m, n]$ is a digital curvelet waveform. With increase in the resolution level the curvelet becomes finer and smaller in the spatial domain and shows more sensitivity to curved edges which enables it to effectively capture the curves in an image. As a consequence, curved singularities can be well approximated with few coefficients.

Components of an image play a vital role in finding distinction between images. Curvelets at fine scales effectively represent edges by using texture features computed from the curvelet coefficients. If we combine the frequency responses of curvelets at different scales and orientations, we get a rectangular frequency tiling that covers the whole image in the spectral domain. Thus, the curvelet spectra completely cover the frequency plane and there is no loss of spectral information like the Gabor filters.

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. 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, a wedge wrapping procedure is described in Candès *et al*. (2005) where a parallelogram with sides 2^j and $2^{j/2}$ is chosen as a support to the wedge data.

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. Thus we obtain the discrete curvelet coefficients by applying 2-D inverse Fourier transform to this wrapped wedge data. The algorithm is as follows:

- Apply the 2D FFT and obtain Fourier samples $\hat{f}[n_1, n_2]$,$-n/2 \le n_1, n_2 < n/2$
- For each scale/angle pair (j, l), resample (or interpolate): $\hat{f}[n_1, n_2]$ to obtain sampled values $\hat{f}[n_1, n_2 - n_1 \tan \phi_l]$ for $(n_1, n_2) \in p_j$
- Multiply the interpolated (or sheared) object $\hat{f}$ with the parabolic window $\widetilde{U}_j$, effectively Localizing $\hat{f}$ near the parallelogram with orientation ϕ_l and obtain:

$$\widetilde{f}_{j,l}[n_1, n_2] = \hat{f}[n_1, n_2 - n_1 \tan \phi_l]\widetilde{U}_j[n_1, n_2]$$

Apply the inverse 2D FFT to each $\widetilde{f}_{j,l}$, hence collecting the discrete coefficients $c^D(j, l, k)$.

PROPOSED METHODOLOGY

The overall automated system for texture classification based on DWT and DCT is shown in Fig. 2. The two steps in the proposed approach are feature extraction and classification. The proposed approach uses two multi resolution transformations, which are applied to input texture images in order to extract features from their corresponding sub bands. The input gray texture image is initially decomposed by DWT at various decomposition levels. The energy is calculated as a feature vector from the decomposed sub band images. This process is as follows.

Energies are evaluated by squaring the coefficients in the decomposed image. To account higher energies for classification, the higher valued energy coefficients are extracted by applying sorting techniques. After

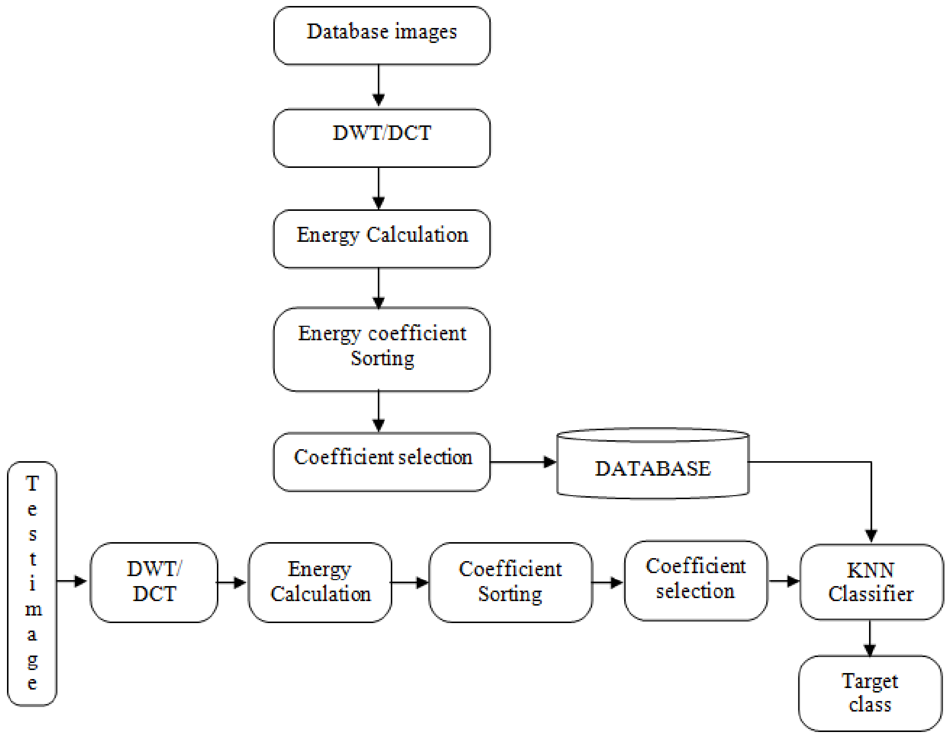

Fig. 2: Proposed automated system for texture classification based on DWT and DCT

sorting, predefined percentage of coefficients from each sub-band image are selected as features. Similarly, DCT is applied to input gray texture images at various scales. This decomposition produces sub bands and energy is calculated like in DWT. Then, the obtained features from DWT and DCT transformations are stored in database for classification separately.

The second step of the proposed system is classification. The efficient nearest neighbor classifier is employed for classification. The proposed feature extraction method is applied to unknown texture images and features are obtained from the texture image to be classified. Unknown texture class is computed by comparing the database and unknown image features based upon the minimum distance between them.

EXPERIMENTAL RESULTS

In this section, experiments on Brodatz album, a bench mark database is demonstrated. Figure 3 shows the texture images of Brodatz album taken for the proposed approach for classification. As the classification system requires training images to train the classifier, the original Brodatz texture images of size 640×640 pixels are subdivided into small sized sub-images of size 128×128 pixels. This is based on overlapping technique in order to capture the pattern in a texture image that are extracted with an overlap of 32 pixels between vertical and horizontal direction from the original image. This process produces 256 sub-images of 128×128 pixels. Among the 256 images, 81 images are randomly selected and 40 and 41 images are used for training and testing respectively.

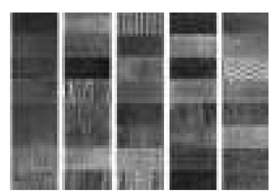

Fig. 3: Texture images used in this study

In the proposed approach, two frequency domain analyses such as DWT and DCT are considered. The main difference between DCT and DWT is that the degree of localization in orientation varies with scale for DCT. The performance is evaluated by decomposing texture images by different decomposition levels starting from 2 to 4. Also, the number of coefficients used as features in the analysis is varied from 10 to 50% of coefficients in each sub-band after sorting the coefficients in the descending order. In order to account the maximum energy coefficients the sorting technique is introduced.

Initially, the performance of the proposed approach using DWT is analyzed. The decomposition levels are varied and predefined selected coefficients are used for classification using nearest neighbor classifier. Table 1 shows the classification accuracy obtained by the proposed approach using DWT. The distance measure used in the approach is Euclidean, correlation, cosine and city block.

Table 1: Classification accuracy obtained by using DWT

		% of coefficients				
Distance measure	Level	10	20	30	40	50
Euclidean	2	93.18	93.68	94.06	94.81	95.43
	3	93.00	92.87	92.25	92.75	93.00
	4	89.18	88.12	87.99	86.74	86.93
Cosine	2	96.00	97.56	97.25	97.69	97.56
	3	94.31	95.00	94.18	94.31	95.00
	4	91.31	90.43	90.49	90.12	89.93
Correlation	2	94.75	96.56	97.00	97.25	97.50
	3	93.62	94.12	93.68	93.50	94.62
	4	90.68	89.56	89.99	89.87	89.31
City block	2	97.75	98.69	98.81	98.94	99.00
	3	98.87	99.44	99.50	99.44	99.25
	4	99.25	99.25	99.37	99.12	99.31

Table 2: Classification accuracy obtained by using DCT

		% of coefficients				
Distance measure	Level	10	20	30	40	50
Euclidean	2	84.55	84.18	86.05	87.18	88.31
	3	84.30	85.80	87.68	88.68	90.18
	4	85.87	85.80	86.74	87.74	88.24
Cosine	2	85.49	85.55	87.18	87.93	88.49
	3	89.31	90.12	91.93	92.50	94.18
	4	87.62	88.93	88.12	88.49	88.81
Correlation	2	80.80	83.43	86.24	86.93	87.80
	3	87.93	89.24	91.24	92.31	94.12
	4	86.55	87.74	87.30	87.80	88.31
City block	2	94.56	92.62	92.43	93.00	93.25
	3	98.75	98.94	98.69	98.44	98.69
	4	99.12	99.62	99.56	99.50	99.44

Table 3: Maximum classification accuracy obtained by the proposed system

ID	Accuracy (%)	ID	Accuracy (%)	ID	Accuracy (%)	ID	Accuracy (%)
D6	100	D34	100	D64	100	D85	100
D9	100	D36	97.56	D66	100	D101	100
D11	100	D41	100	D68	100	D102	97.56
D16	100	D46	100	D76	100	D103	97.56
D17	100	D47	100	D77	100	D104	100
D20	100	D51	100	D78	97.56	D105	100
D21	100	D53	100	D79	100	D106	95.12
D22	100	D55	100	D80	100	D109	100
D24	100	D56	100	D82	100	D111	100
D26	100	D57	100	D83	100	Average	99.62

The experiments using DWT demonstrate the capability of DWT features for texture classification. The maximum classification accuracy obtained is 99.49% at 3^{rd} level of decomposition. Only 30% of wavelet coefficients are enough to achieve this maximum classification accuracy. The same technique is applied in order to analyze by using DCT. Table 2 shows the classification accuracy obtained by the proposed approach using DCT.

It is observed that the maximum classification accuracy obtained by curvelet features is 99.62% which is 0.13% higher than wavelet features. From the Table 1 and 2, the absolute distance between the test features and the database outperforms all other distance metrics used in the approach. Table 3 shows the classification accuracy of each texture while using 20% coefficients of DCT at level 4.

Further increase in the decomposition level and percentage of coefficients used in the proposed system does not affect the classification accuracy. Hence the evaluation of the proposed system is stopped at 4^{th} level and up to 50% coefficients.

CONCLUSION

In this study, wavelet and curvelet domain features for texture classification is analyzed. To effectively extract the wavelet and curvelet features, the given texture image is decomposed at various decomposition levels. The performance of the proposed approach is evaluated by selecting the coefficients based on their energy content. Experimental results show that the maximum classification accuracy achieved by DWT and DCT based features are 99.49 and 99.62% respectively. In order to increase the classification accuracy, feature fusion can be applied to wavelet and curvelet features in future.

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