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Classification of Textures using Patch Based Energy Features of Selected Wavelet Coefficients

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Abstract: In this study, a method for classification of texture images using patch based energy features is proposed. The ability of Discrete Wavelet Transform (DWT) to capture the texture properties of given image is exploited. First, the texture image is decomposed by using DWT. Then the proposed patch based energy features are extracted from the selected wavelet coefficients in each sub-band based on the edge intensities. The performance of the system is evaluated by varying the decomposition level, No. of selected wavelet coefficients and size of the patch used to extract the energy features. Brodatz album is used for the proposed classification task. The performance of the system is analyzed with other state of art techniques and the results are tabulated. Experimental results show the efficiency of the proposed system in terms of classification accuracy and better accuracy of over 99% is obtained.

Key words: Texture, image classification, wavelet transform, nearest neighbor classifier

INTRODUCTION

Texture classification is the most important task in image processing and pattern recognition. Over the years, extensive researches have been made for the classification of texture images. It has been widely used in industrial, biomedical, remote sensing areas and target recognition. Approaches to texture feature extraction can be categorized as statistical, structural and model based. Statistical approaches are based on definitions such as smooth, coarse, grainy, regular, directional, etc. that include standard deviation, variance, skewness and kurtosis of the gray levels. The structural approaches are based on the spatial arrangement of basic primitives. The texture feature extraction can then be done by obtaining measurements of the primitives and their spatial arrangements. The model based approaches are based on random fields and fractal parameters. In this study, classification of Brodatz texture images based on DWT is proposed.

Li *et al*. (2010) have presented an approach for texture classification by modelling the wavelet sub band detail coefficients based on Refined Histogram (RH) and the associated RH signature. The RH model makes use of the step function with exponentially increasing intervals to approximate the detail histogram and to capture the histogram characteristics. Also, RH signature is extracted efficiently using the coefficient-counting technique that involves only multiplication and counting. Dong and Ma (2011) have reviewed supervised texture classification using one-nearest neighbour classifier. The contrast of local energy histograms is calculated from input texture patch and each sample texture patch in a given training set. The various wavelet families are used for feature extraction and an efficient one-nearest-neighbour classifier is used for classification task.

Liu and Fieguth (2012) have implemented a simple and powerful approach for texture classification based on random projection. An effective random feature in the compressed patch domain is obtained. The random features are embedded into a bag-of-words model to perform texture classification and support vector machine is used as a classifier. Lategahn *et al*. (2010) have proposed an efficient texture classification based on joint Probability Density Functions (jPDFs) to reduce information loss. Local texture neighborhoods are first filtered by a filter bank. Without further quantization, the jPDF of the filter responses is described parametrically by gaussian mixture models.

Zhao *et al*. (2012) has proposed Local Binary Count (LBC) for rotation invariant texture classification. LBC features are effectively represented by the local texture.

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The micro-structure can improve the classification rate sometimes but the micro-structure is not absolutely invariant to rotation, especially when the illumination conditions or the textural scales change a lot. Riaz *et al.* (2013) have developed a novel texture descriptor that is invariant to rotation and scale changes in the images. Gabor filters are used for feature extraction task. Homogeneous texture features mean and variance are calculated from two distinct matrices and support vector machine is used for classification purpose.

Huh and Lee (2010) have implemented signature Linear Discriminant Analysis (signature-LDA) as an extension of LDA that can be applied to signatures. Several good properties including avoiding the rank deficiency problem of classical LDA and requiring no parameter tuning. Dong and Ma (2012) have reviewed a novel Bayesian texture classifier based on the adaptive model selection learning of poisson mixtures on the contourlet features of texture images. The contourlet decomposition sets up an efficient representation of the image for texture classification.

Zhang *et al.* (2013) have presented a local descriptor which models texture image as histogram over statistical local feature vectors. These features are less sensitive to the imaging conditions. The pyramid analysis makes the feature more robust to scale changes. N-nary coding is used for the vector quantization. Maani *et al.* (2013) have analyzed rotation invariant method for texture classification based on local frequency components. A set of features are extracted from the low frequency components, two based on the phase and one based on the magnitude.

DISCRETE WAVELET TRANSFORM

The proposed texture classification approach is based on Discrete Wavelet Transform (DWT). In this section the theoretical background of DWT is introduced. 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 in Eq. 1 (Mallat, 1989):

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

where, the $U_{m,n}(x) = 2^{-m/2}U(2^{-m}x\text{-}n)$ 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

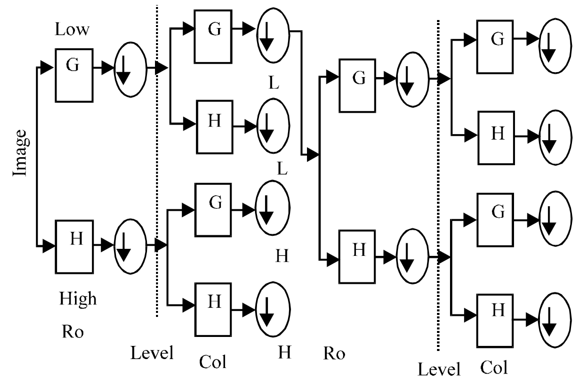

Fig. 1: 2 Level discrete wavelet transform

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) (Mallat, 1989). 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).

PROPOSED METHOD

The proposed method for texture classification based on DWT and KNN classifier is shown in Fig. 2. The proposed system incorporates a series of two stages that include feature extraction stage and classification stage.

In the first stage, the features that best discriminate the textures are extracted. The extracted features contain sufficient information to allow specific and correct classification of texture types. The process of extracting the proposed feature is as follows. At first, texture image is decomposed by DWT at various decomposition levels. The output of DWT based decomposition produces a collection of sub-images called sub-bands. Each sub-band represents the components of the original image at specific resolutions. The number of wavelet coefficients in the decomposed image is same as the size of the input texture image. This high dimensionality makes it difficult to extract salient features or produces high number of features. To overcome this, the dominant wavelet coefficients must be selected. As the high frequency sub-band in the wavelet decomposed image produces edge information in the horizontal, vertical and diagonal direction, the edge density is chosen as a parameter for the selection of wavelet coefficients in each sub-band.

Initially, the wavelet coefficients in each sub-band are sorted in descending order and predefined number of coefficients is selected from the sorted list. Then the proposed patch based features are extracted around the selected coefficients. The Patch Based Energy (PBE) is calculated by using Eq. 2:

$$PBE = \frac{1}{ps * ps} \sum_{i=1}^{ps} \sum_{j=1}^{ps} PB(i,j) \tag{2}$$

where, Ps is the patch size and PB is the patch block around the selected wavelet coefficients. This process produces patch based energies for the corresponding sub-band involved. This process is carried out for all the sub-bands of the wavelet decomposed image. The extracted patch based energies of all sub-bands are fused together to form the feature vector. The proposed features are extracted for all training texture samples in the same way and stored in the database for classification.

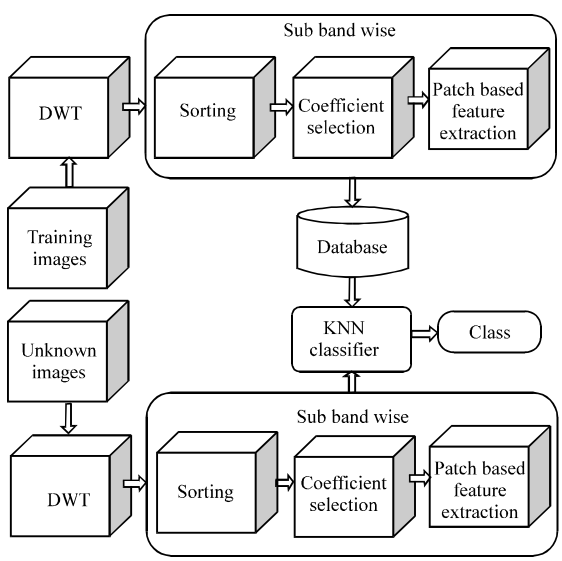

Fig. 2: Proposed texture classification system using discrete wavelet transform

The second stage of the proposed system is classification. In the classification stage, KNN classifier is used. The proposed patch based energy features from each sub-band are extracted for the unknown texture image. The distance between the extracted features to the feature database is calculated based on Euclidean distance metric. The minimum distance measure produced by the reference texture image is assigned to the class of unknown texture image. The euclidean distance measure in Eq. 3 is used in the proposed method. Let us consider $a = (x_1, y_1)$ and $b = (x_2, y_2)$ are two points. The Euclidean distance between these two points is given by:

$$D(a,b) = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \tag{3}$$

The proposed approach is evaluated by classification accuracy measured as the percentage of test set images classified into the correct texture class.

EXPERIMENTAL RESULTS

The proposed system presented for texture classification in section 3 is based on DWT which means that the proposed patch based energy features are extracted from the wavelet decomposed image. In this section, the accuracy of the proposed method is estimated on Brodatz texture images. The accuracy obtained by the system is analyzed with other techniques such as Linear Regression Modal (Wang and Yong, 2008)., TSWT (Chang and Kuo, 1993), Gabor and GLCM (Clausi and Deng, 2005), Wavelet with GLCM (Van de Wouwer *et al.*, 1999), Gabor transform (Manjunath and Ma, 1996), F16b (Randen and Husoy, 1999) and PSWT (Mallat, 2003). The size of the Brodatz texture image is 640×640 pixels and the images are gray scale images. Figure 3 shows the selected texture images for the classification task.

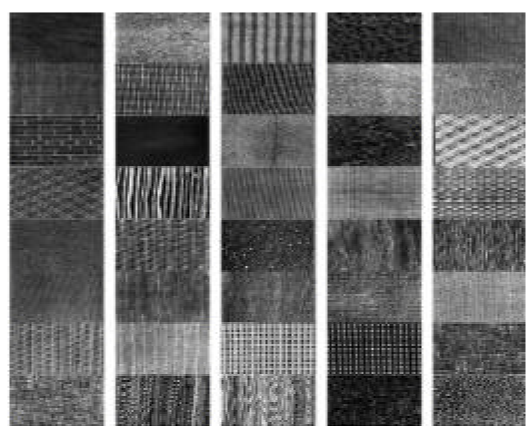

Fig. 3: Selected texture images from Brodatz album

Table 1: Overall classification accuracy achieved by the proposed system

level	Patch size	Selected wavelet coefficients (%)					
		10	20	30	40	50	60
1	3×3	97.62	96.94	97.62	97.31	97.62	97.37
	5×5	97.19	96.37	96.62	96.69	97.44	96.81
	7×7	93.81	96.00	96.69	96.50	97.56	97.56
2	3×3	98.81	98.25	98.25	98.19	98.44	98.44
	5×5	97.12	97.37	97.94	97.87	98.06	98.37
	7×7	98.44	98.37	98.50	98.81	98.56	98.44
3	3×3	97.75	98.44	99.00	98.75	98.94	99.00
	5×5	97.87	98.87	99.19	98.69	98.44	98.87
	7×7	97.94	98.50	98.75	98.87	98.69	98.69
4	3×3	90.12	97.25	98.25	97.87	98.37	98.37
	5×5	43.65	68.42	92.43	97.31	98.44	98.50
	7×7	94	82.61	82.61	80.18	80.49	80.30

Table 2: Classification accuracy of each texture classes achieved for 5×5 patch size with 30% coefficients at 3-level discrete wavelet transform

ID	Accuracy (%)	ID	Accuracy (%)
D6	100	D64	97.56
D9	100	D66	100
D11	100	D68	100
D16	100	D76	100
D17	100	D77	100
D20	100	D78	100
D21	100	D79	97.56
D22	100	D80	100
D24	100	D82	100
D26	100	D83	100
D34	100	D85	97.56
D36	100	D101	100
D41	100	D102	100
D46	100	D103	95.12
D47	100	D104	95.12
D51	92.68	D105	97.56
D53	100	D106	97.56
D55	100	D109	100
D56	100	D111	100
D57	97.56	Average	99.19

Table 3: Comparative analysis of the proposed system

Methods	Classification accuracy (%)
Gabor and gray level co-occurrence matrix (Clausi and deng, 2005)	49.00
Gabor (Manjunath and ma, 1996)	43.43
Pyramid structured wavelet transform (Mallat, 2003)	61.59
Tree structured wavelet transform (Chang and Kuo, 1993)	79.17
Wavelet and gray level co-occurrence matrix (Van de wouwer *et al.*, 1999)	96.71
F16b (Randen and Husoy, 1999)	90.06
Linear regression model (Wang and Yong, 2008)	97.15
Proposed method	99.11

As a preliminary step, the images in the Brodatz album are subdivided into 128×128 sub-images with an overlap of 32 pixels between vertical and horizontal direction from the original image resulting in a database of 256 samples per class. From the whole database, 81 images are randomly chosen and split into two disjoint subsets, one for training with 40 samples per class and another one for testing with 40 samples per class.

The performance of the proposed system is evaluated by varying the three parameters; decomposition level, number of selected coefficients and patch size for extracting the features.

From one-level to 3-level decompositions is used and 10-60% of coefficients are selected for each sub-band based on edge intensities. As the sub-band size varies for a particular decomposition level, the number of selected coefficients also varies. The patch sizes used to analyze the system are 3×3, 5×5 and 7×7. Table 1 shows the overall classification accuracy of the proposed system by changing the aforementioned parameters.

In the proposed approach, highest accuracy achieved for 5×5 patch size with 30% selected coefficients at 3-level decomposition level. Table 2 shows the classification accuracy of each texture classes achieved for the same. It is observed from the Table 2 that the classification accuracy of the proposed approach decreases for higher decomposition level. This is due to that the DWT produces redundant data at higher decomposition level. Table 3 shows the comparative analysis with state of art techniques.

CONCLUSION

In this study, texture classification of 40 Brodatz texture images using patch based energy features is presented. The multiresolutional representation of texture images are achieved by DWT. The proposed patch based features are extracted for only the selected wavelet coefficients in each sub-band. The proposed system achieves over 99% classification accuracy for 5×5 patch size with 30% selected coefficients at 3-level decomposition level. Experimental results indicate that the proposed patch based energy features can provide useful information for discriminating the texture classes considered and the proposed patch based energy features is a superior feature compared to other state of art techniques. It is also observed that the proposed system is able to classify the g iven texture image into one of the 40 predefined texture in the Brodatz album.

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