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Texture Classification Using SVM Classifier Based on Feature Fusion

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Abstract:

Texture classification using SVM classifier based on feature fusion is proposed in this paper. There are many image transform approaches are applied to image enhancement, restoration, encoding, description and feature extraction. All image processing techniques can be categorized into two, namely spatial domain and frequency domain. The two main special domain techniques, discrete wavelet transform and discrete curvelet transform are used in the proposed system. Both the transforms are applied to 111 image textures of Bradatz album to extract features and the extracted features are sorted and stored in data base as energy vector for classification. The SVM classifier is employed for classification and the maximum accuracy 99.19% is achieved.

***Keywords* — discrete wavelet transform, discrete curvelet transform, support vector machine, texture classification.**

I Introduction

Texture analysis and classification is an active topic in image processing which plays an important role in most of the applications. The application include image retrieval, remote sensing, inspection systems, face recognition, medical image processing, etc. Texture analysis approaches are usually categorised into structural, statistical, model-based and transform.

There are many approaches to extracting texture features in gray-level images such as local binary patterns, gray level co-occurrence matrices, statistical features, skeleton, scale invariant feature transform, etc. These methods can be classified into four categories, namely statistical approaches, structural approaches, model based approaches and filter based approaches. [1]statistical approaches do not attempt to understand explicitly the hierarchical structure of the texture. Instead, they represent the texture indirectly by the non-deterministic properties that govern the distributions and relationships between the grey levels of an image. More complex measures are based on multiresolution analysis. The structural approach provides a good symbolic description of the image; however, this feature is more useful for synthesis than analysis tasks. . In this paper, we review most efficient and state-of-the-art image texture analysis methods. SVM classifier for classification also reviewed.

The proposed approach uses discrete wavelet transform and discrete curvelet transform, 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 levels. The energy is calculated as a feature vector from the decomposed sub-band images. Similarly , DCT is applied to input gray texture images at various scales. This decomposition produces a number of sub-bands which depend on the number of decomposition levels and then energy is calculated like in DWT. The energy coefficients of DWT and DCT are sorted. Then, the obtained features from DWT and DCT transformations are fused together and stored in database for classification.

The second step of the proposed system is classification. For classification, a hyperplane is constructed by the SVM which separates the feature optimally into two categories. The reason to choose SVM as a classifier is its fast convergence rate and superior generality in high dimensionl data[5]. In general, SVM creates high dimension space by plotting the training samples

II Feature Extraction Stage

Feature extraction is a critical pre-processing step for pattern recognition and machine learning problems. In the proposed approach, 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 wavelet features is shown in figure 1.

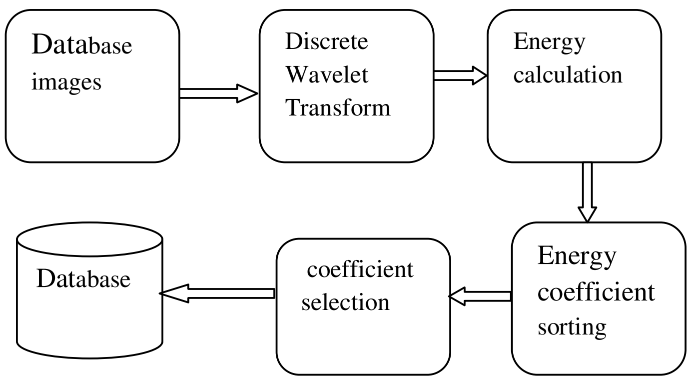

Figure1. Feature extraction stage of the proposed system based on DWT

At first, texture image is decomposed by DWT at various decomposition levels. 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 [1]:

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

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). 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 figure 2.

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.

1) Convolve each row in the input image with the low pass filter followed by the high pass filter to obtain row wise decomposed image
2) Down sample the row wise decomposed image by 2
3) 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
4) 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
5) Apply steps 1-4, for higher level decomposition to the approximation sub-band which is

obtained from the previous level of decomposition[3].

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. Figure 3.4 shows a texture image decomposed by DWT at 2, 3 and 4 level of decomposition. 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. The dominant wavelet features are selected based on the energy in each wavelet Coefficients[3].

classification system. Non parametric statics b SVM classifier is employed as classifier and it assign a target class to an unknown texture image by using the database created in the training stage. Figure 3 shows the proposed gray texture classification system model.

Figure 3. Performance of SVM Classifier

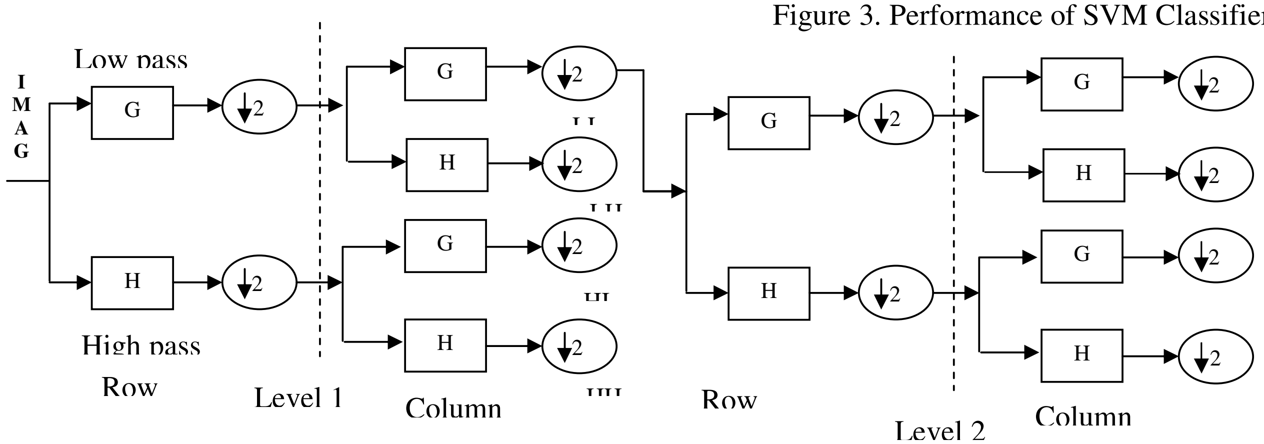

Figure 2 2-level DWT [3]

Energies can be measured by either magnitude or squaring the coefficients in the decomposed image. After energy calculation, the wavelet coefficients in each sub-band are sorted in descending order and predefined number of coefficients is selected from the sorted list. Hence, the selected coefficients have higher energies. The proposed features are extracted for all training texture samples in the same way, and stored in the database for classification.

III Classification Stage

The second stage of the proposed system is classification or validation stage. However in addition to good feature extraction technique an efficient classifier is needed to establish appropriate texture

The performance of the proposed system is analyzed by using SVM classifier in this section. The main advantages of SVM classifier over Artificial Neural Network are given below:

SVM can be mathematically derived and simpler to analyze theoretically compared to ANN.

It also provides a clear intuition of what learning is about. SVM work by mapping training data for learning tasks into a higher dimensional feature space using kernel functions and then find a maximal margin hyper plane, which separates the data.

The major difference between SVM and ANN is in the error optimization.

In ANN, the aim of learning is to obtain a set of weight values which minimize the training error while in SVM the training error is set to minimum while training adjust the capacity of the machine. During training, SVM learned the parameters and the number of support vectors which is equivalent to the number of hidden units in ANN[6].

Based on the advantages of SVM, the proposed method uses SVM classifier to classify the textures. The mathematical derivation of SVM classifier is discussed briefly. SVMs are a set of related supervised learning methods that analyze data and recognize patterns, used for classification and regression analysis. The standard SVM is a non-probabilistic binary linear classifier, i.e. it predicts, for each given input, which of two possible classes the input is a member of. A classification task usually involves with training and testing data which consists of some data instances. Each instance in the training set contains one "target value" (class labels) and several "attributes" (features). SVM has an extra advantage of automatic model selection in the sense that both the optimal number and locations of the basic functions are automatically obtained during training. The performance of SVM depends on the kernel [2].

SVM is a linear learning machine. For the input training sample set

$$(x_i, y_i), i = 1 \ldots. n, x \in R^n, y\{-1, +1\} \quad)$$

Let the classification hyperplane equation is to be

$$(\omega . x) + b = 0$$

Thus the classification margin is 2 / |ω| .To maximize the margin, that is to minimize |ω| ,the optimal hyperplane problem is transformed to quadratic programming problem as follows,

$$\begin{cases} min\emptyset(\omega) = \frac{1}{2}(\omega, \omega) \\ s.t. y_i\big((\omega . x) + b\big) \geq 1, \;\; i = 1,2 \ldots. l \end{cases}$$

After introduction of Lagrange multiplier, the dual problem is given by,

$$\begin{cases} max\ Q(\alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} y_i y_j \alpha_i \alpha_j K(x_i . x_j) \\ s.t \sum_{i=1}^{n} y_i \alpha_i = 0, \;\; \alpha_i \geq 0, i = 1,2 \ldots, n \end{cases}$$

According to Kuhn-Tucker rules, the optimal solution must satisfy

$$\alpha_i(y_i\big((w . x_i) + b\big) - 1 = 0, i = 1,2, . . n$$

That is to say if the option solution is

$$\alpha^* = (\alpha_1^*, \alpha_2^*, \ldots . , \alpha_i^*)^T, \qquad i = 1,2, \ldots n$$

Then

$$w^* = \sum_{i=1}^{n} \alpha_i^* y_i x_i$$

$$b^* = y_i - \sum_{i=1}^{n} y_i \alpha_i^* (x_i . x_j) \;\; , j \in \{j | \alpha_i^* > 0\}$$

For every training sample point x_i , there is a corresponding Lagrange multiplier. And the sample points that are corresponding to $\alpha_i = 0$ don't contribute to solve the classification hyperplane while the other points that are corresponding to $\alpha_i > 0$ do, so it is called support vectors. Hence the optimal hyperplane equation is given by,

$$\sum_{x_i \in SV} \alpha_i y_i (x_i . x_j) + b = 0$$

The hard classifier is then,

$$y = sgn\left[\sum_{x_i \in SV} \alpha_i y_i (x_i . x_j) + b\right]$$

For nonlinear situation, SVM constructs an optimal separating hyperplane in the high dimensional space by introducing kernel function $K(x . y) = \emptyset(x) . \emptyset(y)$, hence the nonlinear SVM is given by,

$$\begin{cases} min\emptyset(\omega) = \frac{1}{2}(\omega, \omega) \\ s.t. y_i\left(\left(\omega.\emptyset(x_i)\right) + b\right) \geq 1, i = 1,2, \dots . l \end{cases} \quad (3.17)$$

And its dual problem is given by,

$$\begin{cases} maxL(\alpha) = \sum_{i=1}^{l} \alpha_i - \frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l} y_i y_j \alpha_i \alpha_j K(x_i.x_j) \\ s.t. \sum_{i=1}^{n} y_i \alpha_i = 0, \ \ 0 \leq \alpha_i \leq C, i = 1,2, \dots, l \end{cases} \quad (3.18)$$

Thus the optimal hyperplane equation is determined by the solution to the optimal problem. The proposed approach uses LIBSVM package for SVM classification. LIBSVM is integrated software for support vector classification, regression and distribution estimation. It also supports multi-class classification.

IV Experimental results and discussion

The texture database is derived from the Brodatz album. It has 111 different original 8 bit texture images. As the classification system requires training images to train the classifier, the proposed approach subdivides the original Brodatz texture images of size 640x640 pixels into small sized sub-images of size 128x128 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 128x128 pixels. Among the 256 images, 81 images are randomly selected and 40 and 41 images are used for training and testing respectively. Moreover, the tested images usually exhibit strong homogeneity within each class as well as visual and semantic dissimilarity between classes[7].

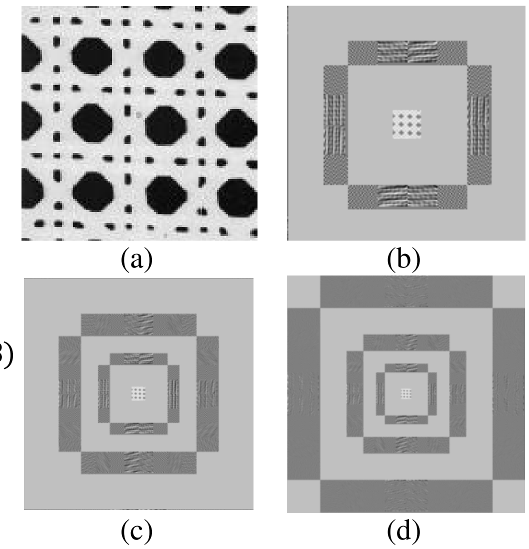

Figure 4: (a) sample image (b) 2-level DCT decomposed image

(c) 3-level DCT decomposed image (d) 4-level DCT decomposed image

V Performance of SVM Classifier

The performance of proposed system is analysed by using SVM Classifier. SVM can be mathematically derived and simpler to analyze theoretically compared to Artificial Neural Network. It also provides a clear intuition of what learning is about. SVM work by mapping training data for learning task into a higher dimensional feature space using kernel functions and then find a maximal margin hyper plane, which separates the data. The main difference between SVM and ANN is in the error optimization. SVM has an extra advantage of automatic model selection in the sense that both the optimal number and locations of the basic functions are automatically obtained during training. The performance of SVM largely depends on the kernel[6].

Based on the advantages of SVM, the proposed method uses SVM classifier to classify the texture. To obtain maximum average classification accuracy, SVM classifier requires 20% dominant coefficients extracted from the 3rd level decomposition of DWT and DCT whereas 40% dominant coefficients for 2nd and 4th level decomposition. Gray texture classification achieves maximum average **classification** accuracy 99.19% at 3rd level decomposition whereas 99.06 and 98.25 is achieved at 2nd and 4th level decomposition respectively. Table2. Shows the average classification accuracy obtained by SVM Classifier.

Table 2. Average Classification Accuracy by SVM

Features	Level	Classification accuracy (%)				
		10	20	30	40	50
Wavelet	2	98.31	98.62	99.06	98.75	99.06
	3	97.69	98.44	98.75	98.87	98.87
	4	97.19	97.37	97.69	97.81	97.56
Curvelet	2	95.75	92.25	92.43	92.87	93.43
	3	97.19	97.31	98.19	98.12	98.94
	4	97.31	98.12	97.81	98.12	98.06
Fusion	2	99.06	98.56	98.12	97	97
	3	98.87	99.19	99.12	99.12	99.00
	4	97.81	97.75	98.00	98.25	98.06

It is observed that DWT features provide maximum classification accuracy 99.06% at 2nd level of decomposition. Only 30% of wavelet coefficients are enough to achieve this maximum average classification accuracy. The maximum average classification accuracy obtained by the DCT approach is 98.94%, which is 0.12% lesser than the wavelet based performance. In order to get yet improved and reliable classification accuracy, wavelet and curvelet features are fused together. The maximum classification accuracy 99.19% is achieved from the fusion of wavelet and curvelet based analysis at 3rd level decomposition with 20% of maximum energy coefficients of wavelet and curvelet decomposed texture feature. Table 2. shows the comparison between the proposed approach and other state-of-art techniques. The proposed texture classification system based on the fusion of DWT and DCT is evaluated against Linear Regression Modal , Tree Structured Wavelet Transform (TSWT) , Gabor transform , Gabor and Gray Level Co-occurrence Matrix (GLCM) , Wavelet with GLCM, Pyramid Structured Wavelet Transform (PSWT) and F16b.

Table 2. Comparative analysis of the proposed system with state of art techniques

Methods	Classification Accuracy
Gabor	43.43
Gabor..	48.99
PSWT	61.59
TSWT	79.17
F16b	90.06
Wavelet	96.71
Linear	97.15
proposed	99.19

VI. Conclusion

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