ANADOLU ÜNİVERSİTESİ BİLİM VE TEKNOLOJİ DERGİSİ
ANADOLU UNIVERSITY JOURNAL OF SCIENCE AND TECHNOLOGY
Cilt/Vol.:2 - Sayı/No: 1 : 219-225 (2001)

TEKNİK NOT/**TECHNICAL NOTE**

A NEW WINDOWING TECHNIQUE IN TEXTURE CLASSIFICATION

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ABSTRACT

Texture classification is an important task in scene analysis, remote sensing, defect recognition from images for quality control and other industrial application areas. Recently, wavelet-based methods e.g.: DWT (Discrete Wavelet Transform), CWT (Continuous Wavelet Transform), Wavelet Packets, Wavelet frames have been proposed for texture features extraction. In this note, a new windowing algorithm is proposed, which forms variable sizes texture sub-images randomly rotated between 0° and 360° for training neural networks classifier with fast adaptive backpropagation algorithm. Non-subsampled wavelet frame transform has been used for feature extraction of 16 textures from a set of Brodatz' album, by means of various wavelet families. Very good classification performance has been obtained with the new windowing technique, when compared with that of the classical non-overlapping windowing method.

Key Words: Texture Classification, Rotational-invariance, Wavelet Transform, Neural Networks.

DOKU SINIFLANDIRMASINDA YENİ BİR PENCERELEME TEKNİĞİ

ÖZ

Doku sınıflandırma, Senaryo analizi, Uzaktan algılama, Kalite kontrolünde resimlerdeki bozuklukları tanıma ve diğer endüstriyel uygulama alanlarında önemli bir işlemdir. Yakın tarihlerde, dalgacık tabanlı metodlar, örneğin; DWT (Ayrık Dalgacık Dönüşümü), CWT (Sürekli Dalgacık Dönüşümü), Dalgacık Paketleri, Dalgacık Çerçeveleri, Doku Öznitelik çıkarımı için teklif edilmiştir. Bu makalede, hızlı adaptif geriye yayınımlı algoritmalı yapay sinir ağını eğitmek için, 0° - 360° arasında rastgele döndürülmüş ve değişken boyutlarda doku altörnekleri oluşturan yeni bir pencereleme algoritması teklif edildi. Alt-örneklemesiz dalgacık çerçeve dönüşümü, değişik dalgacık aileleri vasıtasıyla, Brodatz albümünden 16 dokunun öznitelik çıkarımı için kullanıldı. Klasik, örtüşmeyen pencereleme metodununkiyle mukayese edildiğinde, bu yeni pencereleme tekniği ile çok daha iyi bir sınıflandırma performansı elde edildi.

Anahtar Kelimeler: Doku Sınıflandırması, Döndürmeye Duyarsızlık, Dalgacık Dönüşümü, Yapay Sinir Ağları.

1. INTRODUCTION

Texture can be defined as a structure composed of many of more or less ordered similar elements or patterns without one of these drawing special attention. Texture classification is a pattern recognition process starting from the selection of texture descriptors and from the choice of training and classification. A large number of approaches for texture analysis has been suggested and reviewed, for the purpose of texture classification and segmentation (Pham and Cetiner, 1996; Mao and Jain 1992). An important aspect of texture is scale. Psycho-visual studies indicate that the human visual system processes images in a multiscale way (Daugman, 1990). This multiscale processing is a strong motivation for texture analysis methods based on these concepts. There are many applications for texture

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Received: 05 October 1999; **Revised:** 23 March 2000; 26 October 2000; **Accepted:** 02 November 2000.

analysis in which rotation-invariance is important, but a problem is that many of the existing texture features are not invariant with respect to rotation. e.g., co-occurrence matrix based on second-order statistics (Haralick, et.al. 1973) and Auto-correlation method (Chen and Pavlidis 1983). Gauss-Markov random fields (Kashyap, et.al. 1982), local linear transforms (Laws, 1980; Unser 1986) are restricted to analysis of spatial interactions over relatively small neighbourhoods (Haralick,1979; Van Gool et.al. 1983). Multiresolution techniques intend to transform images into a representation in which both spatial and frequency information is present. To accomplish this, a lot of multiresolution techniques have been developed, including Gabor, Haar, Walsh-Hadamard expansions, Gaussian and Laplacian pyramids, subband filtering. In the last decade wavelet theory emerged and became a mathematical framework which provides a more formal solid and unified approach to multiresolution representation (Julesz, 1981; De Valois and De Valois, 1988).

2. WAVELET TRANSFORM

Wavelet transform is the decomposition of a signal (image) into a family of functions $\psi_{a,b}(t)$ which are the translation and dilation of a unique function $\psi(t)$ called "mother wavelet" (Meyer 1993);

$$\psi_{a,b}\,(t) = \frac{1}{\sqrt{a}}\, y\left(\frac{t-b}{a}\right) \qquad (1)$$

where a and b are dilation *(scale)* and translation *(shift)* parameters, respectively. These may be continuous or discrete. In the latter case, usually $a=2^j$ and $b=k.2^j$, where j and k are integers which permit to constitute an orthonormal basis:

$$\psi_{j,k}\,(t) = 2^{-j/2}\,\psi(2^{-j}t - k) \qquad (2)$$

For specially chosen mother wavelet, the collection of $\{\ \psi_{j,k}\ (t)\ \}$ for all integers j,k forms an orthonormal basis for various function spaces. This means that wavelets can represent functions much in the same way as a Fourier or orthogonal polynomal series. The functions for which wavelets do better include those that have sharp jumps or discontinuities; for example, images where intensity may undergo sharp changes across an edge boundary. There exists different types of wavelet transforms which can be classified (Chan, 1996) broadly as :

1. The Continuous Wavelet Transform

$$\Psi[f]\,(a,b) = \int_{-\infty}^{\infty} f(t)\,\psi_{a,b}(t)\,dt \qquad (3)$$

2. The Discrete Wavelet Transform

$$\Psi[f]\,(j,k) = \frac{1}{\sqrt{N}} \sum_{t=-N/2}^{N/2-1} f(t)\ \psi_{j,k}(t) \qquad (4)$$

The 2D Fast (*Discrete*) Wavelet Transform, or *Mallat Pyramid*, of an image represents original image by a hierarchy of detail and average images, corresponding to different quality or resolution levels. The image pyramid structure is generated by repeatedly filtering and subsampling the preceding image level, starting from the input image. The 2D filtering for each level is performed by combining a *1D* lowpass filter L(n) and a highpass filter H(n) of first horizontally and then vertically, as shown in *Figures* 1 *and* 2, where "A" is lowpass approximation subbands, D^x, D^y and D^{xy} are vertical, horizontal and diagonal detail subbands, respectively.

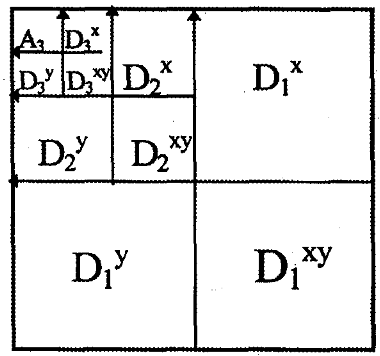

Figure 1. Data Flow Graph of The 2D-DWT With Separable Filters.

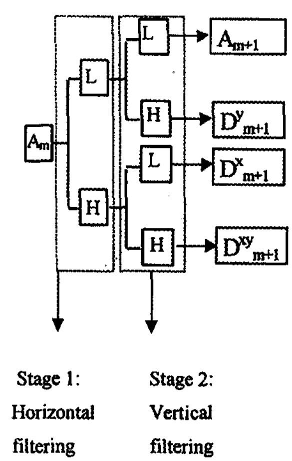

Figure 2. Wavelet Sub-bands.

Discrete Wavelet Packet Transform (DWPT) constitutes a multi-band extension of *DWT*, and allows for more flexibility by providing an adaptive basis. Unfortunately, both decompositions are not translation invariant. A possible solution is achieved by using FIR Filter Bank Multiresolution analysis on overcomplete wavelet decomposition called Discrete *Wavelet Frame (DWF)*, in which the output of the FIR filter banks is not subsampled. In general, omission of subsampling will improve results, but at the expense of increased CPU time (Unser, 1995; Laine, and Fan, 1996; Randen, and Husoy, 1994) . There are different types of wavelet families whose qualities vary according to several criteria. The main criteria are the support, symmetry, the number of vanishing moments and the regularity. Wavelets which are zero outside of some interval (compactly supported) have good time localisation. Compact support enables the use of fast recursive FIR filter-bank algorithms using filters with a finite number of coefficients. Vanishing moments property permits extremely efficient approximation of low-order polynomials. Many different orthogonal or biorthogonal families have been developed, e.g: Haar, Symlets, Battle-Lemarie etc. Very few wavelets have an explicit analytical expression. Notable exceptions are wavelets that are piecewise polynomials (Haar, Battle-Lemarie, Morlet, or Mexican hat). Wavelets are usually defined by dilation (5) and wavelet (6) equations;

$$\phi(t) = \sum_{k=0}^{N} 2h(k)\ \phi(2t-k) \qquad (5)$$

$$\psi(t) = \sum_{n=0}^{N} 2g(k)\ \phi(2t-k) \qquad (6)$$

where $\phi(t)$ is the father wavelet or scaling function.

The simplest orthogonal wavelet is the Haar mother which can be defined on [0,1) by

$$\psi(t) = \begin{cases} 1 & \text{for } t \in [0,1/2) \\ 1 & \text{for } t \in [1/2,1) \end{cases}, \qquad (7)$$

Haar father wavelet is defined to be;

$$\phi(t) = 1 \ \ for\ t \in [0,1]. \qquad (8)$$

Daubechies wavelets depend on an integer $N \geq 1$, the number of vanishing moments, that defines the support [0,2N-1]. These wavelets have no explicit expression except for Daubechies(2) which is a Haar wavelet. Their regularity increases with N. The algorithm to construct this family of wavelets has been proposed by Daubechies (1992). The Battle-Lemarie wavelets are associated with multiresolution analysis ladders consisting of spline function spaces.

3. FEATURE EXTRACTION

Various features have been proposed for texture analysis, but no general conclusion in favour of a particular feature can be drawn from them. (Laine and Fan, 1993) compared energy and entropy features and found the latter to be less suitable. Energy feature is additive and its total is conserved by the transformations. The energy of a wavelet channel is given simply by the mean magnitude of its wavelet coefficients;

$$e = \frac{1}{p \cdot q} \sum_{i=1}^{p} \sum_{j=1}^{p} |x(i,j)| \qquad (9)$$

where the channel is of dimensions p by q and x is a wavelet coefficient within the channel. In general, the anisotropy is an important aspect of most textures and a rotation will result in completely different features. In classification tasks, one usually wants results that are independent of the orientation of the texture.

The filter outputs of discrete schemes represent only 3 different directions, which is a very coarse representation of directional information. Continuous transforms, on the other hand, have a continuous representation of directional information, which offers better possibilities for constructing rotation invariant features.

The classification of textures with reduced number of features is a very important point for real-time applications where high processing speed is necessary. There is, however, another important reason to do so. Although more features may carry more information, they increase feature extraction time.

4. A NEW WINDOWING TECHNIQUE

In texture classification, the training of the neural network classifier are accomplished by means of feature vectors of sub-images formed (windowing) from each texture sample. Windowing is a poorly investigated area in texture classification literature. According to classical windowing schemes, non-overlapping windows of equal sizes are obtained. Meanwhile, these methods are far from guaranteeing rotation invariance, as also revealed by our experience. The better way seems to extract feature vectors from windows of rotated textures. (Chen and Kundu, 1994) have tried to incorporate rotation-invariance in the classification strategy by including rotated examples in the learning data. Other strategies have been proposed for dealing with rotation invariance. (Greenspas et al 1994) tried to solve the problem by employing 4 angular filters and interpolate their responses. An approach by Wu and Wei 1996) performs a spiral resampling of the data to obtain

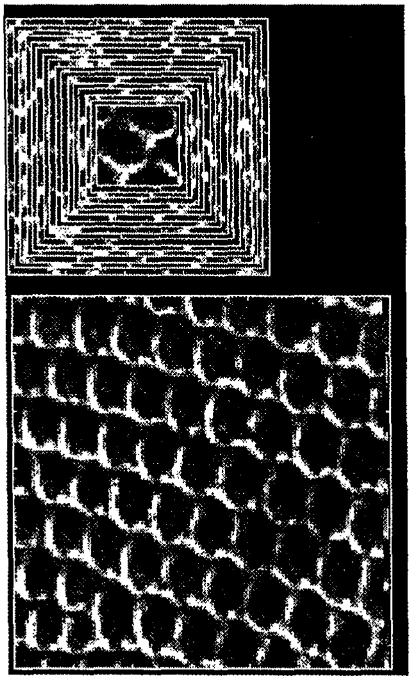

Figure 3. Pyramidal Windowing Method Used In This Study.

a *1*-dimensional signal, where rotation-invariance is reflected as translation-invariance. (Porter and Canagarjah 1996) proposed a method to obtain rotation-invariant features by grouping the pairs of diagonally opposite LH and HL wavelet sub-bands in each level of decomposition.

In this study, a new *"pyramidal"* windowing method has been proposed *(See Figure 3).*

The motivation of this new windowing technique is to combine useful effects of "image rotation", "overlapping" and the using variable size windows in a convenient way to obtain better performance. Sixteen overlapping sub-images (window) of variable sizes, shrinking toward the centre of the texture by fixed increment, and rotated randomly at an angle between 00 and 3600 were formed from each texture as training and test examples. As known, digital images are represented conveniently by a two dimensional array, the elements of which are image pixel values. Thus, the following matrix notation may be used to summarise our windowing algorithm;

$$\begin{bmatrix} (1,1). & . & . & . & .(1,m) \\ & \begin{bmatrix} (n_1,n_2) & . & . & . \\ . & & & \\ . & . & . & . & (n_3,n_4) \end{bmatrix}_W & & & \\ (m,1) & . & . & . & . \; (m,m) \end{bmatrix}_Y \qquad (1)$$

Row and column numbers, $n_1,....,n_4$ are calculated by the following formulas

$$\begin{pmatrix} n_1 = m + j^* \; delv \\ n_2 = m - j^* \; delv \\ n_3 = m + j^* \; delv \\ n_4 = m - j^* \; delv \end{pmatrix} \qquad (11)$$

Where $j=1:16$; W is texture window, Y is randomly rotated square texture image of pixel sizes $m*m$, and *delv* is fixed increment adjusted to obtain *16* windows from each texture image of pixel sizes 128**128*, the smallest window being of pixel sizes *28*28*.

5. TEXTURE CLASSIFICATION BY NEURAL NETWORKS

Neural networks gained a great deal of interest in texture classification over the past decade (Visa, 1990). Multilayer Perceptron Neural network trained by back-propagation algorithm (Pao, 1989) has been found very effective for classifying Brodatz textures in this work. Learning in an MLP model involves using an iterative gradient descent algorithm to minimise the mean square error between the actual outputs of the network and the desired outputs in response to given inputs. Training in an MLP network is performed by forward and backward operations. In the forward operation, the network produces its actual outputs for a certain input pattern using the current connection weights. Subsequently, the backward operation is carried out to alter the weights to decrease the error between the actual and desired outputs. The alteration of weights are affected by two parameters namely learning rate and momentum coefficient. The learning rate defines the range of the changes in the connection weights, the larger the learning rate, the larger the changes in the connection weights. The momentum coefficient, as stated earlier, is introduced to improve the learning process and it works by adding a term to the weight adjustment that is proportional to the previous weight change.

6. RESULTS AND DISCUSSION

In the study, the influences of wavelet type, the scale of wavelet transform and the windowing technique on the classification performance and time for feature extraction using non-subsampled FIR filter bank have been investigated. Sixteen 128x128 classical "Brodatz textures" shown in Figure 4 were used in classification study; These more or less similar textures have been especially selected so as to make the classification task difficult.

The basic scheme of the texture classification is shown in Figure 5.

The training and tests were performed using Multi-Layer Perceptron Neural networks with back propagation algorithm. The input layer of neural network consisted 4 inputs corresponding to feature vector obtained through wavelet transform, 140 processing elements in hidden layer and 16 output neurons in output layer for

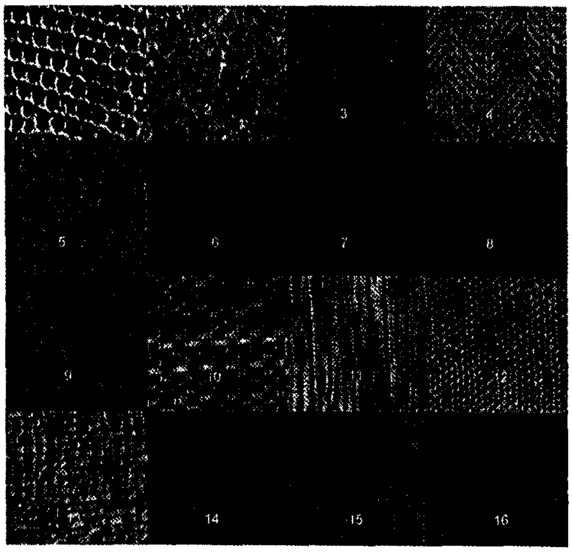

Figure 4. Brodatz Textures [Brodatz, 1966] (from top-left) 1. Reptile Skin (D03) 2. Grass Lawn (D09) 3. Tree Bark (D12) 4. Herringbone Weave (D17) 5. Calf Leather (pressed) (D24) 6. Beach Sand (D29) 7. Pressed Cork (D32) 8. Water (D38) 9. Beach Pebbles (D54) 10. Straw Matting (D55) 11. Wood Grain (D68) 12. Canvas Cotton (D77) 13. Raffia Looped to a High Pile (D84) 14. Ceiling Tile (D86) 15. Clouds (D90) 16. Fur of Unborn Calf (D93).

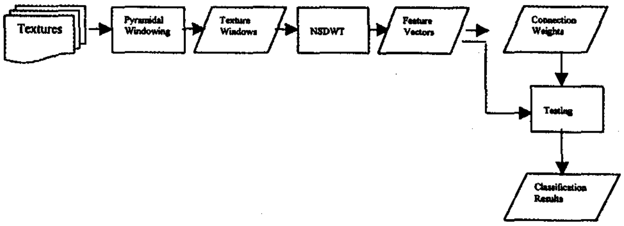

Figure 5. Basic Scheme of Texture Classification.

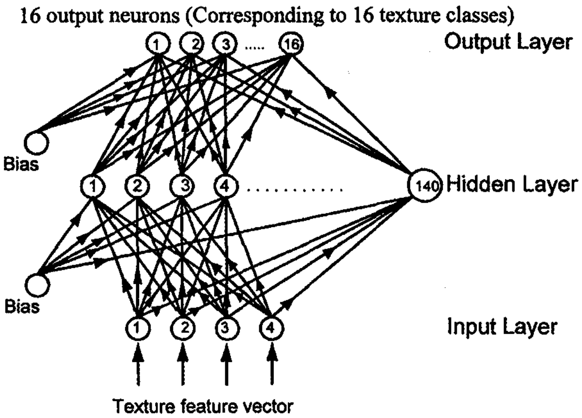

Figure 6. Topology of The MLP Neural Network Used In This Study.

representing 16 different texture images. The number 140 in hidden later was decided experimentally in Figure 6.

Preliminary tests with low 16 grey levels gave relatively low test performances. Therefore, remaining tests have been performed with 256 grey levels. The feature extraction program based on non-subsampled FIR filter bank has been written using "Matlab" program. The wavelets namely Haar, "4-16" Symlets, and "4-16" Battle-Lemarie wavelets were compared to each other with regard to the classification performance.

Table 1 shows the results obtained with four features extracted at 2 scale transform. The best performance, with a classification accuracy of 99.9%, has been obtained with Haar wavelet.

Moreover, except Lemarie(16), the test performances are all over 99%. By increasing the scale of transform from 2 to 3; test performances decrease and feature extraction time increases, as seen in Table 2, where only Haar is the best performing wavelet.

Table 1. Train and Test Performance Results With Various Wavelets And Relative CPU Time of Feature Extraction Number of Features = 4, Number of Scale = 2.

Wavelet	Train %	Test %	* RelativeFeature Extraction time
Haar	100	99.9	1
Symlets(4)	100	99.86	0.99
Symlets(6)	100	99.86	1.26
Symlets(8)	100	99.73	1.18
Symlets(12)	100	99.21	1.24
Symlets(16)	100	99.08	1.44
Lemarie(4)	100	99.5	0.99
Lemarie(6)	100	99.51	1.04
Lemarie(8)	100	99.59	1.13
Lemarie(12)	100	99.6	1.56
Lemarie(16)	100	98.72	1.49

* Relative Feature Extraction time was computed by dividing the feature extraction times for all methods by the feature extraction time of the method giving maximum performance.

Table 2. Train and Test Performance Results With Various Wavelets and Relative CPU Time of Feature Extraction Number of Features = 4, Number of Scale = 3.

Wavelet	Train %	Test %	* RelativeFeature Extraction time
Haar	100	98.72	1.06
Symlets(4)	99.6	97.65	1.14
Symlets(6)	99.6	97.35	1.49
Symlets(8)	99.6	97.06	1.69
Symlets(12)	99.6	97.06	2.47
Symlets(16)	99.6	97.45	3.22
Lemarie(4)	98.04	95.31	1.12
Lemarie(6)	100	96.67	1.32
Lemarie(8)	100	96.67	1.67
Lemarie(12)	99.6	96.09	2.27
Lemarie(16)	99.6	97.45	3.24

Table 3: Train and Test Performance Results With Two Windowing Method Wavelet : Haar , Number of Features = 4, Number of Scale = 3

Windowing Method	Train %	Test %
Non overlapping	97.65	78.38
Pyramid	100	**98.72**

Table 4: Train and Test Performance Results With Two Windowing Method Wavelet : Haar , Number of Features = 4, Number of Scale = 2

Windowing Method	Train %	Test %
Non overlapping	93.22	85.43
Pyramid	100	**99.9**

Comparison results obtained with classical non-overlapping and the new pyramid windowing techniques are given in Tables 3 and 4. As seen clearly, the new method surpassed the classical one as regard with test performances.

7. CONCLUSION

A new pyramid windowing technique for training neural network classifier is proposed by rotating randomly variable sizes textures sub-images. Texture features have been extracted by non-subsampled wavelet frame decomposition at 2 and 3 scales using various wavelet families. The best results have been obtained with Haar wavelet at 2 scale. It has been found that the new windowing technique is superior to the classical method as regard with test performances.

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