J. of Basic Sciences, Cheju Nat'l Univ.
16(2), 83~92, 2003

기초과학연구 제주대학교
16(2), 83~92, 2003

Texture Classifications using second-order neural networks

Bong Kyu Lee[1], Gyung-Leen Park[2] and Chul Soo Kim[3]
[1,2,3]*Dept. of Computer Science & Statistics, Cheju National University*

Abstract

In this paper, we present a new method that combines the characteristics of edge informations and second-order neural networks for the classification of structural textures. The edges of a texture are extracted using an edge detection approach. From the edge information, classification features called *second-order features* are obtained. These features are fed into a second-order neural network for training and subsequent classification. It will be shown that the main disadvantage of using structural methods in texture classifications, namely, the difficulty of the extraction of texels, is overcome by the proposed method.

1. Introduction

In image analysis, texture is broadly classified into two main categories, statistical and structural [1]. Textures that are random in nature are well suited for statistical characterization, for example, as realizations of random fields. They do not have easily identifiable primitives (e.g., bark, sand etc.). Structural textures, on the other hand, are characterized by a set of primitives (*texels*) and placement rules. The placement rules define the spatial relationships between the *texels* and these spatial relationships may be expressed in terms of adjacency, closet distance or periodicities. And the *texel* may be defined by its gray level, shape or homogeneity of some local property. Many real-world textures have thestructural characteristic. A large number of woven fabrics and commercial furniture are good examples of purely structural or semi-deterministic textures. Also microscopic images of electron beam textures in steel surface and human endothelium [2] have structural characteristics. Thus, structural texture classification has many industrial applications, such as automatic fabric inspection, steel surface test and electronic catalog. For these reasons, structural texture classification is an important task in pattern recognition applications.

Texture classification approaches can be also described in two main categories: statistical and structural approaches [3]. Statistical approaches consider textures as complicated pictorial patterns on which sets of statistics can be defined to characterize these patterns. In the structural methods, the texture is considered a cellular and an ordered phenomenon. Hence the purpose of the first stage of the analysis is to define the *texel*. Since structural methods involve a lot of image pre-processing procedures to extract *texels* so that they are time-consuming, statistical approaches are the more efficient approach for texture matching [4]. Thus, almost of the former methods used statistical approaches regardless the class of textures. In the classification of structural textures, however, structural approaches are superior to statistical methods since the spatial structure is more strongly emphasized in the structural approach [5]. Liu *et al.* [6] observed that the MRSAR proposed in [7] (it belongs to statistical approaches) is incapable of distinguishing images where structural textures are involved. This result showed limitations of statistical methods and the effectiveness of the structural methods in measuring perceptual similarity.

Although structural approaches are well suited for structural textures, not many researchers have developed texture analysis techniques using structural methods since it is difficult to find an appropriate *texel* in an input texture during the classification. The difficulty of the extraction of *texels*is due to two major problems. Since the image textures to be analyzed generally have *texels*of different sizes, it is difficult to automatically determine the size of *texel*of each input texture during the recognition. The other is that it is difficult to define the correct *texel* since textures with the same *texel* may have more than one configuration. Also various types of subimages can be extracted in a texture.

In this paper, we present a new method that combines the characteristics of edge informations and second-order neural networks that achieves a high classification rate with structural textures. Several studies [8,9] had shown that using edge information in the texture features can achieve good classification performance. The edges of a texture are extracted using an edge detection approach. From edge informations, classification features called *second-order feature spaces* are obtained. These features are fed into a multilayer perceptron (MLP) for training and subsequent classification. The network can overcome the difficulty of the extraction of *texels* by the second-order features and the modified recognition step. And it requires just one learning sample per each texture. Thus the proposed method has simpler architecture and faster learning capability compared to the existing methods. Experiments were performed with structural textures extracted from Brodatz texture database [10]. The results were compared with another neural-based model proposed in [11]. Although the proposed method is limited to the classification of periodic textures, the underlying principles will provide an important foundation for ongoing researches to develop more general methods for designing models to classify textures.

2. Texture classification

Texture is observed in the structural patterns of surfaces of objects such as wood, grain, grass and cloth. The term texture generally refers to repetition of basic texture elements called *texels* [11]. A *texel*contains several pixels, whose placement could be periodic, quasi-periodic or random. Natural textures are generally random, whereas artificial textures are often deterministic or periodic. Texture may be coarse, fine, smooth, granulated, rippled, regular, irregular or linear.

A large number of approaches for texture feature extraction and classification have been developed [12,13]. Methods using markov random field (MRF) models were proposed [14,15,16,17]. Gimel *et al.* [17] proposed a MRF model with a Gibbs probability distribution for describing particular classes of uniform stochastic textures. Mao *et al.* [7] proposed simultaneous auto-regressive models to perform texture classification and segmentation. Haralick [12] and others [18,19] gray tonedependence co-occurrence matrices to represent texture. Unser *et al.* [4] and others [20,21,22] proposed methods using adaptive spatial filters. Gabor filter based methods were also proposed [23,24,25]. The use of Gabor filters in extracting textured imagefeatures is motivated by the fact that the Gabor representation has been shown to be optimal in the sense of minimizing the joint two-dimensional uncertainty in space and frequency [24]. Chen *et al.* [3] used statistical geometrical features for textures. Wavelet based feature extraction methods [26,27], neural network based filtering methods [11,28,29,30,31] and methods using Fourier power spectrum [32] were also proposed for texture classification and segmentation. Liu *et al.* [6] and others [33,34] used Wold transform to represent textures. The structural approaches use the geometrical features of texture primitives as the texture features. Several edge-based methods have been proposed [35,36], these generally attempt to locate texture edges based on the computation of a multifeature gradient-like operator. Patel *et al.* [37] calculate edged direction using 3×3 masks then used rank order statistics to produce the texture features. Hierarchical approaches using pyramid node linking [38] or applying the split-and-merge algorithm to the co-occurrence matrix [39] have been also described.

Since statistical methods characterize the interaction among neighboring image pixels, they are appropriate for modeling random fields with continuous spectra and random textures. When compared to statistical approaches, structural approaches have some advantages where deterministic textures are considered. Rao *et al.*[40] has indicated that the three most important perceptual dimensions in natural texture discrimination can be described as "repetitiveness," "directionality," and "complexity". Among them "repetitiveness" is the most important dimension of human perception for structural textures. Since structural approaches try to find an elementary region of a texture and use this for classification, they can measure the preceptual similarity well. To deal with structural textures efficiently, we propose a new second-order neural network using *second-order feature spaces* in section 3.

3. Second-order Neural Networks

The output of a node *i*, denoted by y_i in a general higher-order neural network is given by

$$\begin{aligned} y_i &= \Theta(h_i) \\ &= \Theta(\textstyle\sum_j W_{ij} x_j + \sum_j \sum_k W_{ijk} x_j x_k + \ldots\ldots) \end{aligned} \tag{1}$$

where Θ is a nonlinear threshold function, h_i is the net input of node *i*, the values of x are the values of input nodes, and the interconnection matrix elements *W*. The second-order neural network uses only the second-order term in the activation function of a higher-order neural network. Thus the output for a second-order network is given by

$$y_i = \Theta(h_i) = \Theta(\textstyle\sum_j \sum_k W_{ijk} x_j x_k) \tag{2}$$

The inputs are first combined in pairs and then output is determined from a weighted sum of these products. Figure 1 shows the architecture of a strictly second-order neural network. Giles *et al.*[41] showed that the invariances achieved using this network depend on the constraints placed on the weights. The most severe limitation of second-order neural networks is that the number of input nodes required for an $m \times n$ image is $O((mn)^2)$. This makes the implementation difficult. Spirkovska *et al.* [42] solved this problem using coarse coding which involves the use of overlaying fields of coarser pixels in order to represent smaller pixels.

There have been other approaches based on the invariant features for solving the problem. Schmidt

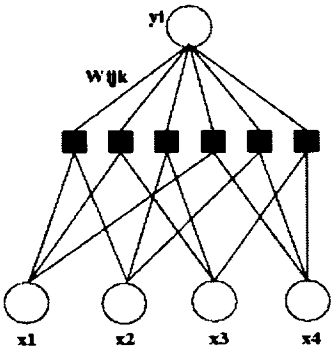

Figure 1. A strictly second-order neural network

et al.[43] showed that the constraints placed on the weights in a second-order network can be implemented using the summations of products of each pair of input pixels. This summation of the product at given relative positions or prescribed positions is called SOP (*Summation Of Products*). They concluded that a second-order neural network to a specific deformation can be considered as a standard MLP using second-order features that are invariant to a deformation. Using this scheme, Lee *et al.* [44] and Kwon *et al.* [45] proposed second-order neural networks invariant to types B and C in Figure 2, which have $O(mn)$ input nodes.

Now, we consider a two-dimensional image B of size $m \times n$ as an input. In this case, we extend the notion of distance windows to two dimensions. Since we allow all kinds of wrap-translated patterns in this paper, we consider four copies of B to compute second-order features as shown in Figure 2-G. Using this schemem, we can correctly compute the second-order features of image B after performing the algorithm.

4. The architecture of the proposed model

The proposed classification scheme is comprised of a structure of edge extraction and a second-order neural network. First, an edge map of the size $m \times n$ of an input image is generated, where $m \times n$ is the dimensionality of an input image. Then the second-order neural network receives the

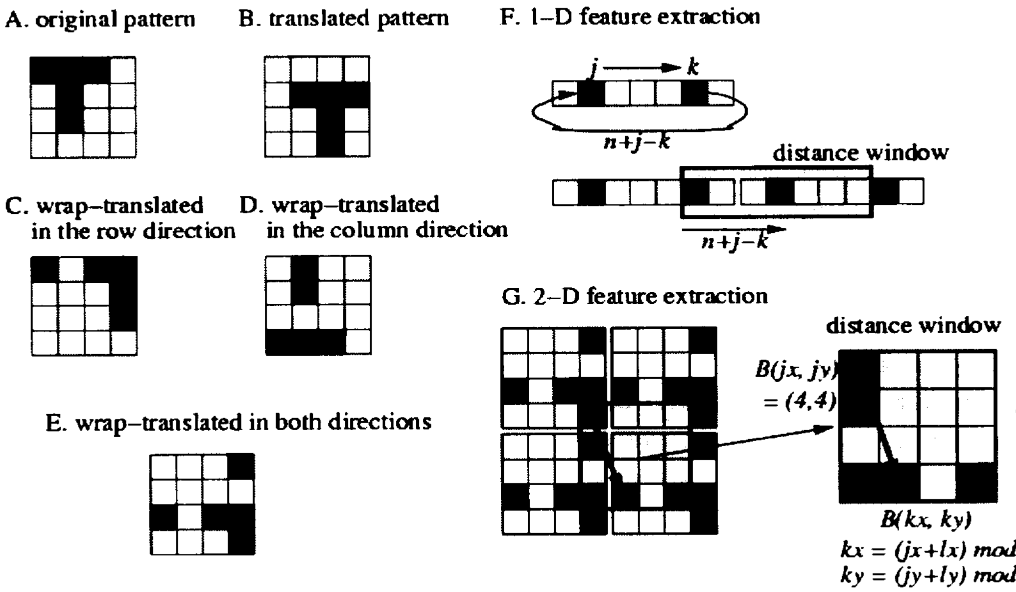

Figure 2. Translation invariances in a second-order neural network

edge map from the edge extraction stage and extracts $m \times n$ dimensional feature spaces, which are called *second-order feature spaces*in this paper. The transformed feature vectors are fed into the MLP for classification.

The MLP has two consecutive phases, the training and the recognition. In the training phase, two different strategies were adopted in contrast to the traditional MLP training. The number of input nodes were defined by the dimension of the largest *texel*, since the MLP may receive *texels* with various sizes. If three sample *texels* with 3×3, 5×5 and 3×5 sizes are considered, then the MLP has 25(5×5) input nodes. In order to apply the network to smaller *texels*, outsized vector components are filled with zero. The other is that all pairs (m,n) of sample *texels* are recorded in the internal table of the network, where m is the row size of a *texel* and n is the column size. This record will be used to solve the size variance of *texels*in the recognition phase. The contents of the table can be shown in the right side of the Figure 8 after *texels* of sizes 10×10, 15×10 and 30×30 were trained.

The recognition phase of the trained network was modified compared to the traditional recognition phase of the neural network. Using each entry of the internal table, the output of the network is computed with second-order features from $m \times n$ pixels from a random position of a test image. Then the node with the maximum value is selected for the recognition result for each entry. If *(10,10)*, *(15,10)* and *(30,30)* are the current entries of the internaltable, three nodes are selected for all entries. Each selected node represents the result for each window size. From all the selected nodes, the node with the maximum value is considered as the final recognition result of a test image. Figure 3 shows the algorithm recognition.

5. Experimental results

The performance of the proposed scheme was analyzed using a variety of structural textures, including the Brodatz photo album [10]. Twenty deterministic textures of size 128×128 were used for experiments. These images were categorized in four sets according to the size of *texel*, which are *15×15, 15×20, 20×20 and 30×30*. For the training of the network, *texels* within images were extracted manually and applied tothe network. The MLP adapted its weights according to the learning rule (backpropagation) and recorded the size of applied *texel*. Since the proposed network is a second-order neural network, the network needs to be trained on just one *texel* of each texture, not on numerous distorted views. Such generalization

```
Algorithm: Recognition
for each entry $(m,n)$ in the internal table do
    extract features from $m \times n$ pixels from an arbitrary position of a test image
    select one node with maximum output from all nodes
    save the number of node, the window size and the value of the node
od
for all selected node $i$ do
    final result $\leftarrow$ $max$ (output($i$))
od
end
```

Figure 3. The algorithm for the recognition phase

has been demonstrated in numerous simulations [42]. In the recognition phase, the trained network extracted a pattern from a random position of each texture and classified it using the algorithm Recognition. This recognition test was performed 20 times for one image. Thus the total number of recognition tests was 400 (20 times per texture).

The performance of the proposed scheme was compared with the model proposed in [11], which belongs to the statistical approach. This model used a set of Gabor filters for extracting texture features and a structure that combined the characteristics of SOM(Self Organizing Map) and first-order MLP for classifications. It was trained using features from 400 (20×20) pixels from the center of each texture. Then the classifications were performed by the same way used in the proposed system. The comparison between two systems will show the superiority of the proposed system to statistical systems in the classification of deterministic textures.

The simulation results are listed in Table 1. Both of the systems did not achieve 100% accuracy on experiments. However, the proposed system produced better recognition results than the compared system. Since it can not be predicted which type of translation has occurred, the first-order MLP needs more training patterns[41,42,43], while the second-order MLP using second-order feature spaces did not require more than one pattern. We also observed that errors can be eliminated by some parameters of the edge detection. Various edge images can be obtained by changing three parameters of the edge detection algorithm.

From the evaluation results, it can be seen that the proposed method has good characteristics for deterministic texture classification compared to the existing models. These characteristics are due to capabilities of *second-order feature spaces.*

Table 1. Recognition results of the experiments

Pattern id	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12	T13	T14	T15	T16	T17	T18	T19	T20
The proposed (# of correct recognitions)	20	20	19	20	20	19	20	20	19	20	20	19	20	20	20	20	17	20	20	18
The compared (# of correct recognitions)	15	14	15	13	16	10	12	17	19	8	20	18	20	7	16	15	18	16	6	16

6. Conclusion

In this paper we have proposed a new two-stage model for the classification of deterministic textures. The model used *second-order feature spaces* of edge map of each *texel* for feature extraction. The results were achieved by a second-order neural network trained by the backpropagation algorithm. The evaluation of the model with a set of deterministic textures was performed and compared to another neural-based method proposed in [11]. As a result, our method showed better classification results than the compared model.

It was found that *second-order feature spaces* solved the basic problem which occurs in the deterministic texture recognition, the translation variance of *texel.* And modified learning and recognition phases solved the size variation of *texels.* Also it can be implemented more easily than the existing methods because of its simplicity. Finally, the proposed model is size limited since the dimension of *second-order feature spaces* is also of the size $m\times n$ for an $m\times n$ input image.

Further research will be conducted for recognizing textures which consist of more than one *texel*. Researches for classification of deterministic textures with noise distortions will be also conducted.

References

[1] A.K. Jain. Fundamentals of digital image processing. Prentice Hall (1989).

[2] W. Zhang. A. Hasegawa. K. Itoh and Y. Ichioka. Image processing of human corneal endothelium base on a learning network. Applied Optics. 30. 4211-4217 (1991).

[3] Y.Q. Chen. M.S. Nixon and D.W. Thomas. Statistical geometrical features for texture classification. Pattern Recognition. 24(4). 537-552(1995).

[4] M. Unser and M. Eden. Multiresolution feature extraction and selection for texture segmentation. IEEE Trans. on PAMI 11(7). 717-728(1989).

[5] O.D. Faugeras and W.K. Pratt. Decorrelation Methods of Texture Feature Extraction. IEEE Trans. on PAMI 2(2). 323-332(1980).

[6] F. Liu and R.W. Picard. Periodicity. Directionality and Randomness : Wold features for image modeling and retrieval. IEEE Trans. on PAMI 18(7). 722-733(1996).

[7] J. Mao and A.K. Jain. Texture Classification and segmentation using multiresolution simultaneous autoregressive models. Pattern Recognition 25(2). 173-188(1992).

[8] H. Tamura. S. Mori and T. Yamawaki. Texture features corresponding to visual perception. IEEE Trans. on System. Man and Cybernetics 8(6). 460-473(1978).

[9] L.S. Davis. S.A. Johns and J.K. Aggarwal. Texture analysis using generalized co-occurrence matrices. IEEE Trans. on PAMI 1(3). 251-259(1979).

[10] P. Brodatz. Textures. Dover. New York (1996).

[11] P.P. Raghu. R. Poongodi. B. Yegnanarayana. A combined neural network approach for texture classification. Neural Networks 8(6). 975-987 (1995).

[12] R.M. Haralick. Statistical and Structural Approaches to Texture. Proc. IEEE 67(5). 786-804(1979).

[13] T.R. Reed and J.M. Hans Du Buf. A review of recent texture segmentation and feature extraction techniques. CVGIP: image understanding 57. 359-372(1993).

[14] G.R. Gross and A.K. Jain. Markov random field texture models. IEEE Trans. on PAMI 5(1). 25-39(1983).

[15] R. Chellapa. S. Chatterjee and R. Bagdazian. Texture synthesis and compression using Gaussian Markov random field models. IEEE Trans. on System. Man and Cybernetics 15. 298-303(1985).

[16] B.R. Povlow and S.M. Dunn. Texture Classification using noncausal hidden markov models. IEEE Trans. on PAMI 17(10). 1010-1014 (1995).

[17] G.L. Gimel'farb. Texture modeling by multiple pairwise pixel interactions. IEEE Trans. on PAMI 18(11). 1110-1114(1995).

[18] R.W. Conners and C.A. Harlow. A theoretical comparison of texture algorithms. IEEE Trans. on PAMI 2(3). 204-222(1980).

[19] M. Unser. Sum and difference histograms for texture classification. IEEE Trans. on PAMI 8(1). 118-125(1986).

[20] A.C. Bovik. M. Clark and W.S. Geisler. Multichannel texture analysis using localized spatial filters. IEEE Trans. on PAMI 12(1). 55-73(1990).

[21] A.C. Bovik. Analysis of multichannel narrowband filters for image texture segmentation. IEEE Trans. on Signal Processing 39(9).

2025-2043(1991).

[22] T.N. Tan. Rotation Invariant Texture Features and their use in automatic script identification. IEEE Trans. on PAMI 20(7). 751-756(1998).

[23] A.K. Jain and F. Farrokhnia. Unsupervised texture segmentation using Gabor filters. Pattern Recognition 24(12). 1167-1186(1993).

[24] B.S. Manjuath and W.Y. Ma. Texture fetaures for browsing and retrieval of image data. IEEE Trans. on PAMI 18(8). 837-842(1996).

[25] G.M. Haley and B.S. Manjuath. Rotation invariant texture classification using modified Gabor filters. Proc. IEEE ICIP95. 262-265 (1995).

[26] T. Chang and C.-C.J. Kuo. Texture analysis and classification with tree structured wavelet transform. IEEE Trans. on Image Processing 2(4). 429-441(1993).

[27] W.Y. Ma and B.S. Manjuath. A comparison of wavelet features for texture annotation. Proc. IEEE Int'l Conf. Image Processing'95 II. 256-259(1995).

[28] N.R. Dupaguntla and V. Vemuri. A neural network architecture for texture segmentation and labeling. Proc. IJCNN'89 I. 127-133(1989).

[29] V. Ari. A texture classifier based on neural network principles. Proc. IJCNN'90 I. 491-496 (1990).

[30] F.A. DeCosta and M.F. Chouikha. Neural network recognition of textured images using third order cumulants as functional links. Proc. ICASSP'92 IV. 77-80(1992).

[31] A.K. Jain. K. Karu. Learning texture discrimination masks. IEEE Trans. on PAMI 18(2). 195-205(1996).

[32] J.O. Eklundh. On the use of fourier phase features for texture discrimination. Computer. Graphics and Image Processing 9. 191-201 (1979).

[33] J.M. Francos. A.Z. Meiri and B. Porat. A Unified texture model based on a 2-D Wold like decomposition. IEEE Trans. on Signal Processing . 2665-2678(1993).

[34] J.M. Francos. A. Narasimhan and J.W. Woods. Maximum likelihood parameter estimation of textures using a Wold decomposition based model. IEEE Trans. on Image Processing. 1655-1666(1995).

[35] S. Grinaker. Edge based segmentation and texture separation. ICPR80. 776-780(1980).

[36] A. Khotanzad and J.Y. Chen. Unsupervised segmentation of textured images by edge detection in multidimensional features. IEEE Trans. on PAMI 11(4). 414-421(1989).

[37] D. Patel and T.J. Stonham. Texture image classification and segmentation using rank order clustering. ICPR92). 92-95(1992).

[38] M. Pietikainen and A. Rosenfeld. Image segmentation by texture using pyramid node linking. IEEE Trans. on System. Man and Cybernetics 11. 822-825(1981).

[39] P.C. Chen and T. Pavlidis. Segmentation by texture using a co-occurrence matrix. Computer. Graphics and Image Processing. 172-182(1979).

[40] A.R. Rao and G.L. Lohse. Towards a texture naming system: identifying relevant dimensions of texture. Proc. IEEE Conf. Visualization. 220-227(1993).

[41] C.L. Giles. T. Maxwell. Learning. invariance. and generalization in high-order neural networks. Applied Optics 26. 2972-2978(1987).

[42] L. Spirkovska. M. B. Reid. Coarse-coded higher-order neural networks for PSRI object recognition. IEEE Trans. on Neural Networks 4(2). 276-283(1993).

[43] W.A.C. Schmidt. J.P. Davis. Pattern recognition properties of various feature spaces for higher order neural networks. IEEE Trans. on PAMI 15(8). 795-801(1993).

[44] B. Lee. S. Cho. Y. Cho. Translation. scale and

rotation invariant pattern recognition using PCA and reduced second-order neural network. Int. Journal of Neural. Parallel and Scientific Computation 3(3). 417-429(1995).

[45] H.Y. Kwon. B.C. Kim. H.Y. Hwang. Rotation and scale invariant pattern recognition using complex log mapping and augmented second-order neural network. IEE Electronics Letters 29(7). 620-621(1992).

이차신경망을 이용한 텍스쳐 분류기법

이 봉 규[1], 박 경 린[2], 김 철 수[3]
[1,2,3]제주대학교 자연과학대학 전산통계학과

요 약

본 논문에서는 구조적 texture를 효과적으로 인식할 수 있는 새로운 시스템을 제안한다. 제안된 시스템은 전처리과정과 이차신경망을 결합한 2단계 구조를 가진다. 입력된 texture로부터 얻어지는 윤곽선 정보는 인식을 위해 이차신경망에 입력한다. 이차신경망은 입력된 edge정보에서 이차특징을 추출하여 학습/인식을 수행한다. 제안된 시스템은 기존의 방법과 비교하여 구조적 texture를 보다 잘 인식할 수 있음을 보인다.