ORIENTED TEXTURE CLASSIFICATION BASED ON SELF-ORGANIZING NEURAL NETWORK AND HOUGH TRANSFORM

A. N. Marana, L. da F. Costa†, S. A. Velastin and R. A. Lotufo*

Unesp, R. Claro, SP, Brazil
nilceu@ifqsc.sc.usp.br

Usp, S. Carlos, SP, Brazil
luciano@olive.ifqsc.sc.usp.br

King's College London - UK
s.velastin@kcl.ac.uk

Unicamp, Campinas, SP, Brazil
lotufo@dca.fee.unicamp.br

ABSTRACT

This paper presents a technique for oriented texture classification which is based on the Hough transform and Kohonen's neural network model. In this technique, oriented texture features are extracted from the Hough space by means of two distinct strategies. While the first operates on a non-uniformly sampled Hough space, the second concentrates on the peaks produced in the Hough space. The described technique gives good results for the classification of oriented textures, a common phenomenon in nature underlying an important class of images. Experimental results are presented to demonstrate the performance of the new technique in comparison with an implemented technique based on Gabor filters.

1. INTRODUCTION

The special importance of straight line segments to the primate visual system has been investigated, amongst others, by Blasdel and Salama [1], who have suggested that representation of the visual information in terms of patches of oriented lines play a major role in vision processing. In their pioneering studies, Hubel and Wiesel [2] also demonstrated the existence of cells in the primary visual cortex (Broadmann's area 17), presenting receptive fields specialised for the detection of straight stimuli. In addition to the motivation provided by such biological insights, oriented straight patterns (oriented textures) are relatively common in nature. It is thus hardly surprising that one of the goals in computer vision is to develop techniques for extracting meaningful information from the straight features present in images [3, 4].

The technique for oriented texture classification presented in this paper is based on straight line information extracted from the images by means of the Hough transform [5]. Image classification is carried out by a neural network based on Kohonen's model [6].

This paper starts by briefly reviewing, in Sections 2 and 3, the Hough transform principles and the Kohonen's self organising neural network model, respectively. Section 4 describes the proposed technique for texture classification. Experimental results are presented in Section 5.

*Supported by a grant from the CNPq (Proc.No.200823/95-7).

†Thanks FAPESP (Procs.94/3536-6 and 94/4691-5) and CNPq (Proc.301422/92-13) for financial help.

2. HOUGH TRANSFORM

The Hough transform (HT) [5] provides an effective means for detecting curves, particularly straight lines. The basic principle underlying the HT consists in mapping all points of a specific curve into a single point or *"peak"* in the parameters space.

The normal parametric equation of straight lines used to compute the normal HT is given by: $\rho = x\cos\theta + y\sin\theta$, where ρ is the normal distance from the line to the origin of the Cartesian co-ordinate system, and θ is the normal angle with respect to the horizontal axis. Assuming this parametrisation, each image space point (x_i, y_i) is transformed by the HT into the sinusoidal curve $\rho = x_i\cos\theta + y_i\sin\theta$, $S(x_i, y_i)$, in the (θ, ρ) parameter space. The most important property of the HT, assuming continuous image and parameter spaces, is that all the sinusoidal curves $S(x, y)$ corresponding to the aligned points $R(\theta, \rho)$ in the image space, intersect at a same point in the parameter space. The (θ, ρ) co-ordinates at such an intersection point define the line in the image space which contains the aligned points.

3. KOHONEN'S SELF ORGANISING MAP

Kohonen's self organising map (SOM) [6] is a neural network model that implements a non-linear projection from a high-dimensional space X onto a low-dimensional map M. The two-dimensional mapping (frequently adopted in Kohonen's model) is a function $f : X \rightarrow M$, where $X \subset R^n$ and $M \subset R^2$, which assigns to each element $x \in X$ a pair $(i, j) \in M$. The elements m_{ij} of the map M, as well as the input data, are n-dimensional vectors which hold the values of the synaptic strengths of the neural network.

For a given input stimulus $x \in X$, the winner node $(i, j) \in M$ is determined by the following conditions: $\|m_{ij} - x\| = min\|m_{kl} - x\|$, for $0 \leq i, j, k, l \leq D$ (D is the size of M) and $(k, l) \in M$.

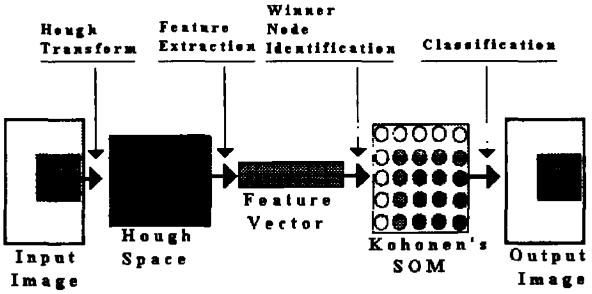

Figure 1: Diagram of the oriented texture classification technique.

In the Kohonen's SOM neural network model, the neurons in the output layer are connected to every cell in the input space and have lateral interactions, which are defined by a function $h_{ijkl}(t)$ of the distance between the winner node (i,j) and any other node (k,l) in the winner node's neighbourhood. Usually, a Gaussian function is used to determine the spatial influence amongst the nodes around the winner node.

The learning is unsupervised and carried out in the training stage according to the following incremental adjustments in the synaptic weights: $m_{kl}(t+1) = m_{kl}(t) + h_{ijkl}(t)[x - m_{kl}(t)]$, where $h_{ijkl}(t) = \alpha(t)exp\left[-\frac{\|r_{kl}-r_{ij}\|^2}{\delta(t)^2}\right]$, (i,j) identifies the winner node for the stimulus x, $\|r_{kl}-r_{ij}\|$ is the spatial distance between the winner node and the node (k,l) belonging to the winner node's neighbourhood N_{ij}, and $\delta(t)$ is the Gaussian's variance which defines the interaction level around the winner node. The function $N_{ij}(t)$, the learning rate $\alpha(t)$ and the Gaussian's variance $\delta(t)$ are adjusted during the training stage as a function of time [6].

After the training stage the network nodes are labelled by presenting a number of input vectors with known classification and assigning the nodes to different classes by majority voting, according to the frequency with which such nodes are closest to the calibration vector of a particular class.

4. ORIENTED TEXTURE CLASSIFICATION

Figure 1 presents a diagram of the oriented texture classification technique proposed in this paper. First, a moving window is centred at a position (x,y) in the input image and then the HT of the sub-image under this window is calculated. Next, the texture feature vector is determined from the Hough space and a winner node in the SOM is found. Finally, the label corresponding to the winner node is used to label the (x,y) pixel in the output image. The window is then moved to the next pixel and so on until the complete image has been processed. When the window is moved, the HT of the sub-image under the new window can be quickly computed from the last HT, since it is not necessary to compute again the HT for the pixels belonging to the intersection area between the old and the new sub-images.

4.1. Texture Features from the HT Domain

The HT is a powerful technique for finding oriented texture features, since particularly relevant orientation information can be extracted from the (θ,ρ) domain. Although the ideal feature vector based on HT is the whole Hough space, this is unfeasible because of the demanded computer storage and computational time. For this reason, a more realistic feature vector must be determined by sampling the Hough space or by considering HT properties.

4.1.1. Feature Vector by Hough Transform Operating over a Non-Uniformly Sampled Hough Space - NUSHS

In the first strategy, the N_ρxN_θ-dimensional Hough space is uniformly sampled on the θ direction by m Δ_θ-spaced columns (where $m < N_\theta$). Next, the Hough space's envelope is found for each column. Then, each extracted column is divided in n equal parts (where $n < N_\rho$) and the maximum value of the each such part is stored. Therefore, the N_ρxN_θ Hough space is sampled by a smaller nxm vector. The oriented texture feature vector is obtained by putting the columns of the sampled HT arranged one after the other, making up a feature vector with nxm elements. This strategy has been used by Chan to perform pattern recognition [7].

4.1.2. Feature Vector from Hough Space Peaks - HSP

The second strategy describes texture features such as: orientation, spacing between lines (spatial frequency) and the length of the segments.[1] The feature vectors are defined in the following way: two 180-dimensional vectors v_1 and v_2 are created to store, respectively, the mean distance from the peak to peak detected in each direction and the amount of pixels in each direction determined by the detected peaks. Then, the feature vector is determined by merging and normalising the vectors v_1 and v_2, which are compacted before the merging operation by computing the average of their n to n entries (n is a parameter which depends on the adopted feature vector's length).

5. RESULTS

The efficiency of the proposed technique for oriented texture classification has been assessed through several tests. The obtained results have been compared with those produced by applying a technique based on Gabor filters [9, 10].

Figures 2(a) and 3(a) show two examples of 256x256-images used in our tests. The first is a mixture of D15 and D68 Brodatz's textures and the second is the D17 Brodatz's texture [11]. To perform the tests on these two images, sets of 100 25x25 samples for each different textured region were collected from the edge detected input images and randomly presented 10000 times to the network in the training stage. Next, for the SOM's node labelling, new sets of 100 25x25 classified samples for each different textured region were again collected and presented to the network. The feature vectors extracted from the Hough space were set up to 60 elements (in the NUSHS strategy, the Hough spaces were

[1] Orientation and length are examples of Julesz's textons [8].

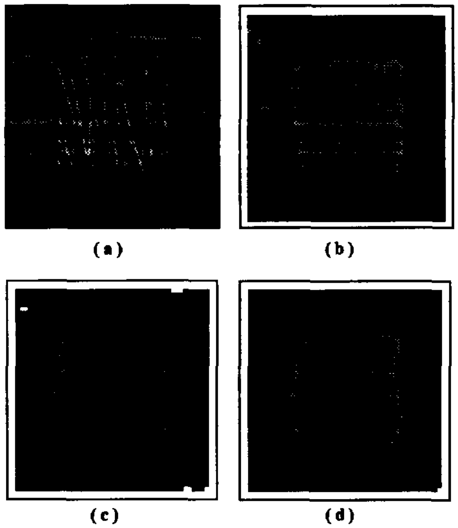

Figure 2: (a) D15 and D68 Brodatz's input image; (b) Classification using Gabor filters; (c) Classification using the NUSHS strategy; (d) Classification using the HSP strategy.

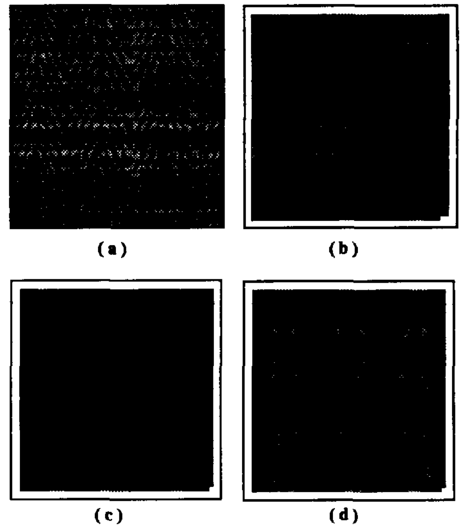

Figure 3: (a) D17 Brodatz's input image; (b) Classification using Gabor filters; (c) Classification using the NUSHS strategy; (d) Classification using the HSP strategy.

sampled by 15 columns and 4 elements per column). The features vectors used in the technique based on Gabor filters were set up to 28 elements, since 28 filters were used (4 orientations and 7 frequencies). The adopted SOMs were 7x7 arrays.

Figures 2(b) and 3(b) present the classification results for the application of the technique based on Gabor filters. Figures 2(c) and 3(c) present the classification results for the application of the NUSHS and Figures 2(d) and 3(d) present the classification results for the application of the HSP. The classifications were performed successfully in all situations, but the NUSHS strategy produced slightly better results (see Figures 2 and 3). In addition, the NUSHS was always faster than the HSP strategy and the technique based on Gabor filters. For the D17 image presented in Figure 3, for instance, the classification process based on the NUSHS strategy took 146 seconds (including the training stage), being 2.45 times faster than the HSP strategy and 6.08 times faster than the technique based on Gabor filters. The technique based on Gabor filter is so slow because it uses a large bank of filters, which must be convolved with the input image. The HSP technique is slow because it depends on the detection of local peaks in the Hough space, which is a time consuming process.

Considering such experiments, it is reasonable to conclude that, although been more restricts than techniques based on Gabor filters, which can be applied on a wider class of textures, techniques based on Hough transform provide an interesting alternative to texture segmentation in terms of straight texture features extraction. In addition, the technique based on the sampled HT is substantially faster than those based on Gabor filters.

6. REFERENCES

[1] G. G. Blasdel and G. Salama, "Voltage-sensitive dyes reveals a modular organisation in monkey striate cortex", *Nature*, 321(5), pp. 579-585, June 1986.

[2] D. H. Hubel and T. N. Wiesel, "Brain mechanisms of vision", *Scientific American*, pp. 130-144, Sept. 1979.

[3] A. R. Rao, "Computing Oriented Texture Fields", *CVGIP: Graphical Models and Image Processing*, vol. 53, No.2, March, pp. 157-185, 1991.

[4] Z. Lin, R. Rangayyan and C. Frank, "Directional Analysis of Images in Scale Space", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 13, No. 11, November, pp. 1185-1192, 1991.

[5] J. Illingworth and J. Kittler, "A survey of the Hough Transform", *Computer Vision, Graphics, and Image Processing*, 44, pp. 87-116, 1988.

[6] T. Kohonen, "The Self-Organizing Map", *Proceedings of IEEE*, vol. 78, No. 9, pp. 1464-1480, September 1990.

[7] C. K. Chan, "Hough Transform Techniques for Pattern Recognition", thesis submitted for the degree of Doctor of Philosophy in the University of London (King's College London), 1994.

[8] B. Julesz, "Texton Gradients: The Texton Theory Revisited", *Biol. Cyber.*, 54, pp. 245-251, 1986.

[9] A. K. Jain and F. Farrokhnia "Unsupervised Texture Segmentation Using Gabor Filters", *Pattern Recognition*, vol. 24, No. 12, pp. 1167-1186, 1991.

[10] P. P. Raghu, R. Poongodi and B. Yegnanarayana, "A Combined Neural Network Approach for Texture Classification", *Neural Networks*, Vol. 8, No. 6, pp. 975-987, 1995.

[11] P. Brodatz, *Textures: a Photographic Album for Artists and Designers*, Dover Publications, Inc., New York, 1966.