MVA2000 IAPR Workshop on Machine Vision Applications, Nov. 28-30, 2000, The University of Tokyo, Japan

8—5 Edge-Based Segmentation of Textured Images Using Optimally Selected Gabor Filters

Bertin R. Okombi-Diba*, Juichi Miyamichi†, and Kenji Shoji‡
Department of Computer Science
Faculty of Engineering
Utsunomiya University

Abstract

In this paper, we propose a technique for segmenting visual textures using features extracted from the reponses of Gabor filters, appropriately selected to be tuned to texture components of the input image. In the proposed method segmentation is achieved by detecting boundaries between adjacent textured regions, and this segmentation algorithm works as follows. The input image is first filtered using a small set of Gabor filters, each tuned to one of the textures composing the original image. Abrupt changes in the obtained Gabor filter output images are found by detecting the underlying local extremas. For this purpose, a gradient operator is applied to output image of each Gabor filter, yielding a set of gradient images. The *texture gradient* is subsequently obtained by grouping gradient images from all channels. Thresholding the *texture gradient* and thinning the result yields the expected texture boundaries. Experimental results on synthetic and natural textures, demonstrate the efficacy of the proposed technique.

1 Introduction

Texture segmentation is one of the most fundamental issues in image analysis and pattern recognition. The goal is to partition an image into distinct regions with *homogeneous* textural content. The homogeneity constraint signifies that each region of the input image is perceptually homogeneous. In other words, within each region, the arrangement of *texture elements* composing each region may be constant, periodic, pseudo-periodic, or gradually varying. In this paper, we limit our consideration to cases when textures in the input image are *spatially invariant*, and thus, covering the first three cases.

*Address: Youtou 7-1-2 Utsunomiya-shi, Tochigi-ken 321-8586 Japan. E-mail: bertin@is.utsunomiya-u.ac.jp
†E-mail: miya@is.utsunomiya-u.ac.jp
‡E-mail: miya@is.utsunomiya-u.ac.jp

In this paper, a spectral peak detection technique has been proposed for selecting Gabor filters. The underlying idea is the detection of dominant spectral components of the considered textured image. Theses dominant spectral components are thought to describe all textures within the image of interest. Using the exact location of these spectral peaks, a small set of Gabor filters is selected. Each selected filter is tuned to a specific component texture in the original image. The method presented here is an edge-based technique, detecting boundaries between adjacent regions in the image. Texture boundaries are induced by the presence of abrupt changes in the computed feature images, obtained by filtering the original image using the small set of Gabor filters previously obtained. Local extremas are detected by computing the gradient images of the output of each selected filter. The overall *texture gradient* is then obtained by grouping individual gradient images from all selected channels. A subsequent application of a thresholding operation, followed by a thinning operation yields the expected texture boundaries.

The remainder of this paper is organized as follows. In section 2, we show how feature extraction is achieved using Gabor filters. In section 3, the adaptive filter selection method used in our approach is presented. In section 4, our proposed texture boundary detection technique is presented. Experiments are conducted on synthetic and natural textures, and results presented in section 5, to demonstrate the effectiveness of the proposed technique. The paper is concluded in section 6.

2 Feature Extraction

A 2-D Gabor Elementary function (GEF), is defined in its general form as a complex sinusoid modulated by a Gaussian envelope

$$h(x,y) = \frac{1}{2\pi\lambda\sigma^2}\, e^{-\frac{(x'/\lambda)^2+(y')^2}{2\sigma^2}}\, e^{2\pi jFx'} \qquad (1)$$

where x' and y' are rotated spatial domain coordinates by angle θ: $x' = x\cos\theta + y\sin\theta$, $y' = -x\sin\theta + y\cos\theta$. The orientation of the complex sinusoid is characterized by its center frequency (U, V) and the angle $\phi = \tan^{-1}(V/U)$. The radial center frequency is defined by $F = \sqrt{U^2 + V^2}$. The spatial-frequency response of GEF is given by.

$$H(u, v) = e^{-2\pi^2\sigma^2[(u'-F)^2\lambda^2+(v')^2]} \tag{2}$$

where $(u - U)'$ and $(v - V)'$ are rotated and shifted spatial-frequency domain coordinates: $(u - U)' = (u-U)\cos\theta+(v-V)\sin\theta$, $(v-V)' = -(u-U)\sin\theta+(v - V)\cos\theta$. $H(u, v)$ is then a bandpass Gaussian with center frequency (U, V) and rotated by an angle θ from the positive u-axis, with bandwith in the frequency domain defined by $\sigma_f = 1/(2\pi\sigma)$, and aspect ratio $1/\lambda$. Generally, the orientation of the Gaussian θ differs from the orientation ϕ of the complex sinusoid. For simplicity, we consider in this paper only GEF whose Gaussian envelop and complex sinusoid have the same orientation $\phi = \theta$. The asymmetry of the GEF is measured by its aspect ratio λ. The aspect ratio is constrained to 1 in this work. The input textured image is filtered by convolving it with the real and imaginary parts of a Gabor function of the above form.

3 Adaptive Filter Selection

A spectral peak detection technique has been used in this work for selecting Gabor filters. First, the power spectrum of the original image is computed using an FFT. The input image is devided by 9×9 subimages. Then, for each subimage, the global maximal value of the power spectrum is detected. Next, this peak detection is applied iteratively by searching among peaks found in each subimage, and the process terminates when the ratio of the current peak to that of the first one is smaller than a preset threshold. The threshold is empirically selected and its value is chosen depending on the original image. Because of the symmetry of the power spectrum, the search is limited to the upper half of the spatial-frequency plane. Robustness to noise may be achieved by first smoothing the input image with a Gaussian filter prior to power spectrum computation.

The number of peaks can be further reduced by checking if periodicity and/or directionality occurs among a set of peaks. For the case of texture periodicity, the peak corresponding to the lower fundamental frequency is selected. When texture directionality is detected, the peak corresponding to the fundamental frequency along the angle of orientation is selected.

An example of filter selection is illustrated in Fig.1. The original image on Fig.1(a) is a tex-

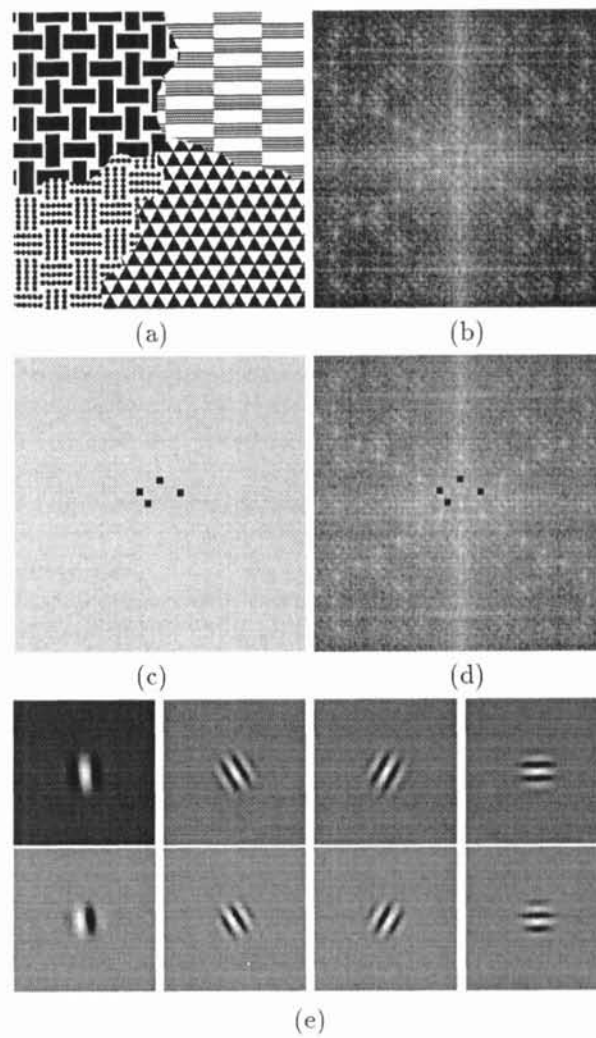

Figure 1: Filter selection scheme: (a) Original image; (b) Power spectrum of the original image; (c) Position of detected peaks for a threshold set to 30% of the highest peak; (d) Detected peaks overlaid on the power spectrum image; (d) Selected Gabor filters: On the first row are represented the real parts of selected Gabor filters, and on the second row are respresented the imaginary parts. The correponding optimal center frequencies are $(U_1, V_1) = (-0.043, 0.004)$, $(U_2, V_2) = (-0.070, 0.043)$, $(U_3, V_3) = (0.070, 0.039)$ and $(U_4, V_4) = (0.000, 0.082)$. For all filters, a fixed width $\sigma = 6.0$ was used.

ture mosaic consisting of four regions with synthetic textures. Only Gabor filters tuned to selected spatial-frequencies are used for further feature extraction. The scale parameter of each Gabor filter is selected as a trade-off between filter output variance and texture boundary localization. The former requires a large spatial extent and the later is achieved by filters with small spatial extent. A pratical method consists in succesively applying filters of size $\sigma = 2, 4, 6$ and 8, and select the size giving the best segmentation result.

4 Texture Boundary Detection

After the filter selection stage, the original image is filtered with a bank of adaptively selected Gabor filters, followed by a post-filtering with a Gaussian function having the same shape as the previously considered channel filter. Local extremas in feature images are detected by applying a gradient operator to each of them. The *texture gradient* is obtained by grouping gradient images from each channel. The resulting image is then thresholded. The value of this threshold is selected depending on the input image. For two-class textured images, this threshold was automatically selected by using the histogram of the gradient image. This thresholded image is more than one pixel wide and thus, should be thinned to obtain single pixel width texture boundaries. In this work, we have used Zhang-Suen's thinning algorithm [8]. To improve the quality of generated boundaries, it has been modified to receive input images from a pre-processing stage using Stentiford's pre-processing method [7]. Post-processing is performed using Holt's stair removal method [5]. This process leads to an image depicting the boundaries between adjacent regions in the original image.

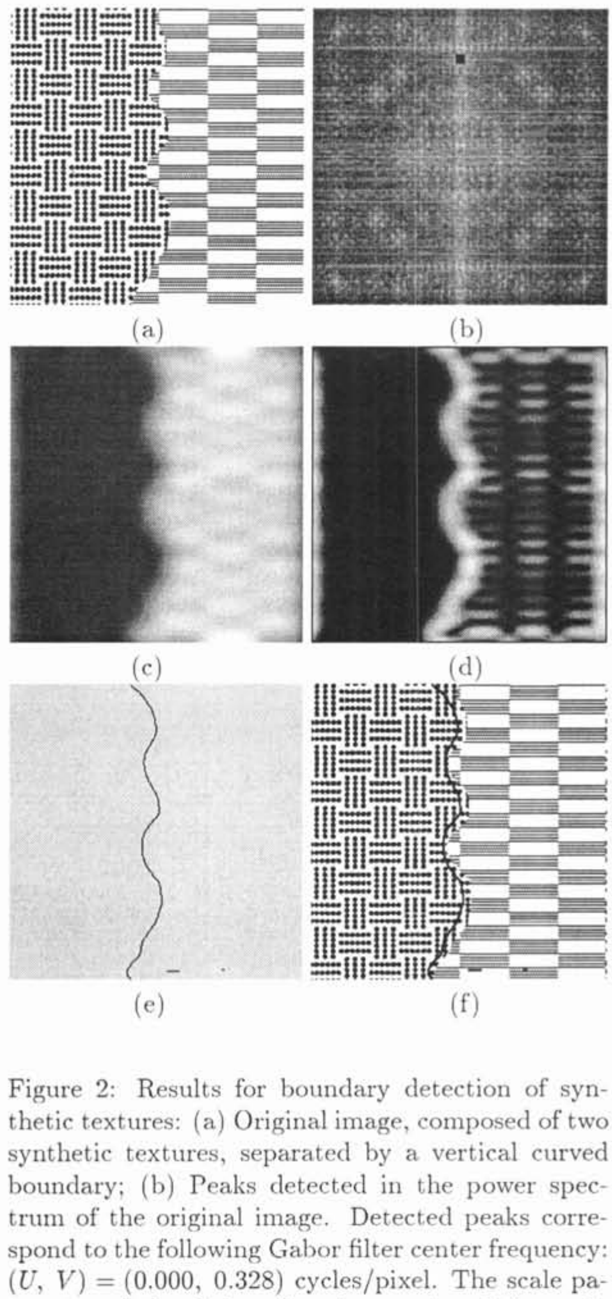

Figure 2: Results for boundary detection of synthetic textures: (a) Original image, composed of two synthetic textures, separated by a vertical curved boundary; (b) Peaks detected in the power spectrum of the original image. Detected peaks correspond to the following Gabor filter center frequency: $(U, V) = (0.000, 0.328)$ cycles/pixel. The scale parameter of the Gabor filter is $\sigma = 4$ and the scale parameter of the Gaussian post-filter is $\sigma_p = 8$; (c) Gabor filter magnitude response; (d) *Texture gradient*; (e) Detected texture boundary; (f) Texture segmentation result depicting detected boundary superimposed on the original image.

5 Experimental Results

First, we applied our texture segmentation system to a synthetic texture. Obtained results are presented in Fig.2. The original image is shown in Fig.2(a). It is a 256×256 pixel 8-bit gray-scale image. The threshold in our filter selection algorithm was set to 90% of the highest peak, to allow the selection of only one filter. The reason is that, the response of one filter, tuned to one of the two textured regions, is sufficient to achieve segmentation. The texture gradient image was first converted into a binary image by thresholding and then, the texture boundary was obtained after edge thinning.

The next experiment was performed using the original image shown of Fig.3(a). It is a bipartite image made of texture D68 "wood grain" on the left and texture D17 "herringbone weave" on the right side. These textures were taken from the Brodatz album of natural textures [2]. To enforce the selection of only one filter, the threshold was set to the value of the highest peak. The texture boundary, obtained after thresholding and thinning is shown of Fig.3(e). The resulting segmentation result is depicted overlaid on the original image on Fig.3(f). The slight displacement from the true boundary is due to the smoothing introduced by the post filtering operation which is necessary to reduce variance in the Gabor filter output. .

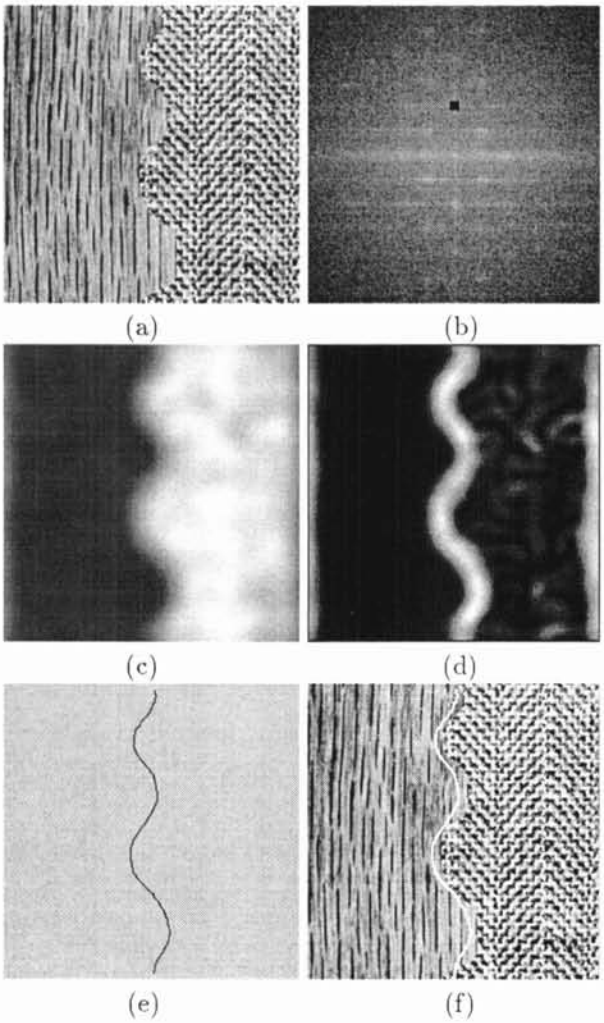

Figure 3: Results for boundary detection of natural textures: (a) Original composite image made of two textures: D68 "wood grain" on the left and texture D17 "herringbone weave", separated by a vertical curved boundary; (b) Peaks detected in the power spectrum of the original image. Detected peaks correspond to the following Gabor filter center frequency: $(U, V) = (0.00, 0.164)$ cycles/pixel. The scale parameter of the Gabor filter is $\sigma = 4.0$ and the scale parameter of the Gaussian post-filter is $\sigma_p = 8.0$; (c) Magnitude response of Gabor filter tuned to selected center frequency; (d) *Texture gradient* computed from Gabor response; (e) Detected texture boundary; (f) Texture segmentation result depicting detected boundary superimposed on the original image.

6 Conclusion

A segmentation technique for textured images was presented along with an efficient adaptive selection method. The proposed method was demonstrated to work on both synthetic and natural textures, and does not require *a priori* knowledge of the number and type of textures in the input image. In contrast to other multi-channel filtering techniques, the proposed approach uses only a small number of channel filters, tailored to considered component textures. The method is quite fast and thus, could be implemented in practical machine vision systems.

References

[1] A. C. Bovik, M. Clarck and W.S. Geisler, "Multichannel Texture Analysis Using Localized Spatial Filters," IEEE Trans. Pattern Anal. Machine Intell., vol. PAMI-12. no.1, pp.55-73, 1990.

[2] P. Brodatz, "Texture: A Photographic Album for Artists and Designers," Dover, N.Y., 1966.

[3] J.G. Daugman, "Uncertainty relation for resolution in space, spatial-frequency, and orientation optimized by two-dimensional visual cortical filters," Jounal of Optical Society of America, vol.2, no.7, pp.1160-1169, 1985.

[4] D. F. Dunn and W. E. Higgins, "Optimal Gabor filters for texture segmentation," IEEE Trans. Image Proc., vol.4, no.7, pp.947-964, 1995.

[5] C. M. Holt, A. Clint and R. H. Perrott, "An improved parallel thinning algorithm," Communications of the ACM, vol.30, no.2, pp.156-160, 1987.

[6] A. K. Jain and F. Farrokhnia, "Unsupervised texture segmentation using Gabor filters," Pattern Recognition, vol.23, pp.1167-1186, 1991.

[7] F. W. M. Stentiford and R. G. Mortimer, "Some new heuristics for thinning binary handprinted characters for OCR," IEEE Trans. Syst, Man, Cybern., vol.13, no.1, pp.81-84, 1983.

[8] S. Zhang and K. S. Fu, " A thinning algorithm for discrete binary images," Proc. Intern. Conf. Computers and Applications, Beijing, China, pp.879-886, 1984.