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THE SEGMENTATION OF IMAGES OF UNKNOWN SCALE USING MULTI-SCALE TEXTURE 'TUNED' MASKS

H.A. Cohen J. You

Department of Computer Science and Computer Engineering
La Trobe University, Bundoora, Victoria, Australia 3083

Abstract

A method is outlined for segmentation by texture of images comprising texture regions of unknown scale. The method involves (a) convolving the image with a specially prepared multi-scale texture tuned mask, (b) computing a local window-based texture energy that is closely related to Laws texture energy, and (c) simple thresholding of the energy image. Examples of scale-invariant segmentation of collages of Brodatz textures illustrate the method.
The mask tuning scheme outlined involves training over samples of the 'pure' textures involved, with samples for each texture being supplied over a range of scales. Special data structures, and performance index are required. The tuning process involves a 'guided' random search combining a gradient descent with random search.

Key words and phrases: Multi-scale, scale-invariant, texture discrimination, image segmentation, texture energy, tuned mask, Convolution, classifier.

I. Introduction

The segmentation of textured images involves demarcating regions of common texture within an image. Such a process can be usefully considered as a two stage process. In the first stage each pixel is tentatively classified, with each pixel gaining the label of a classifier function. In the second stage, relaxation methods, including region growing, which embody region smoothness heuristics are applied. Hence a simple but efficient classifier function is required for texture pixel classification in the first stage.

Laws[3] has documented and tested a general approach for texture discrimination which is based on convolution masks. We have been concerned with extensions of Laws approach, using multi-scale texture 'tuned' masks rather than the scale-dependent fixed masks of Laws. We have developed and experimentally verified a scheme for segmenting images composed of regions of textures of different scale with the range of $(2:1)^2$, $(1:1)^2$, and (1:2). Using this scheme regions of the same texture are classified as the same irrespective of scale.

The experimental results reported are based on 15 Brodatz textures at three scales. Statistical analysis is provided by a determination of ration of standard deviation to mean value, SDV/AV, of the classifier over pure texture, over the range of scales (2:1) to (1:2). which are contrasted Much larger SDV/AV values are also reported for a Laws fixed mask classifier.

Despite the known significance of texture in human vision, there has been little application of texture analysis other than in such simple cases as where average gray-scale can effect a reasonable segmentation. Other approaches to texture have been very much scale-dependent, and/or limited in the number of textures involved. This study, in which 15 distinct textures were involved over a range of scales, points the way to more effective utilisation of texture analysis in image analysis. In the examples shown, simple thresholding of the texture energy has yielded a satisfactory segmentation, without the usual 'stage 2' of region growing and the like. Thus while mask tuning is computationally expensive, not only has scale invariance over a significant range been achieved for a significant number of textures, but application time is minimal.compared to other compuationally more expensive approaches to texture such as Fourier power spectrum, co-ocurrence matrices, MRF etc. This suggests that in addition to applications in medical imagery and in manufacturing, our approach has scope for real-time application especially in ambulatory robotics in which the actual scale of the images varies.

2. Texture Discrimination Strategy

2.1 Adaptive Texture Feature Extraction

The statistical approach to texture discrimination pioneered by Laws is notable for its computational simplicity. He applied two-dimensional digital filtering techniques followed by a computation of the texture statistics. He proposed the texture energy TE as a texture classifier function, where laws TE was defined as the local variance of the image after convolving with certain fixed zero sum masks. As the mean over a sufficiently large window will be zero, we have replaced Laws definition by a simpler definition. Our definition of TE is simply as the

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window sum $\Sigma (I_{ij})^2$ where I.- is the pixel gray scale after convolution with a zero sum texture selective mask. Laws used 15*15 and 17*17 masks, the work described here involves 16*16 mask. An example of one of the Laws fixed masks is provided by the 5*5 mask R5R5 shown in Table 1.

Benke and Skinner 111 greatly improved Laws' approach by replacing Laws fixed masks by adaptive masks, but provided no statistical evaluation. This work was for a small number of textures at a fixed scale.

Our aim is to create an adaptive mask with variables to capture the feature of the given texture dynamically and scale-invariantly.

In [2], we have shown that adaptive masks 'tuned' to maximize the TE for various textures give markedly lower standard deviation for the TE than do Laws' fixed masks. In [4] we showed that our extension of the Benke-Skinner approach could be effectively applied to as many as 15 different Brodatz textures.

In this paper we both segment and identify regions of common textures of unknown scale using our multi-scale texture 'tuned' mask, which has not been done by previous researchers.

2.2 Improved Performance lndex

We use a figure of merit D = XY where X is the well-known expression for the least squares error of the least-squares line of best fit line (x,f(x)) through the points (x,E(x))

$$X = \frac{\sum_{x=1}^{N} (E(x)f(x))^2}{\sum_{x=1}^{N} f^2(x) \sum_{x=1}^{N} E^2(x)} \text{ while we define}$$

$$Y = \frac{\text{minimum texture energy difference}}{\text{max texture energy standard deviation}}$$

Thus f(x) is the discriminant function and E(x) is the texture energy via the 'tuned' mask. We assume that f(x) = kx.

2.3 Parameter Optimization

We have formulated a particular way of combining random search with gradient search which we call 'guided random search'. We use guided random search to tune the parameters of the single mask used for texture discrimination.

The search procedure is as follows:

Assume we have a positive figure of merit f, which is a function of a large number of variables expressed as the n-vector
V = (v(1),v(2),...,v(n)) The problem is to find the set of variables which will maximize f subject to a given set of constraints.

Suppose that the 'best' location so far found is the n-vector Vb. As in 'pure' random search, a guess location V_g can be found at random, assuming a uniform distribution in the search space. The corresponding values f_b and f_c for the figure of merit. To combine the idea of gradient search with random search procedure, a further estimate for the vector is computed, viz

$$V_c = k(V_b + a(- V_g - V_b) \text{ where } \alpha = \frac{f_g - \delta f_b}{f_g + f_b}$$

and $\delta = 0$ when $f_g = f_d$, otherwise $\delta = 1$ Note that our a is essentially the Newton formula.The delta factor is introduced so that there is always a distinct V_c. By comparing the three values, f_b, f_g, and f_c a new V_b is determined.

Benke [1] performs similar multi-variate optimization, but uses the centroid of V_b and V_g, to determine a V_c lying between these two vectors

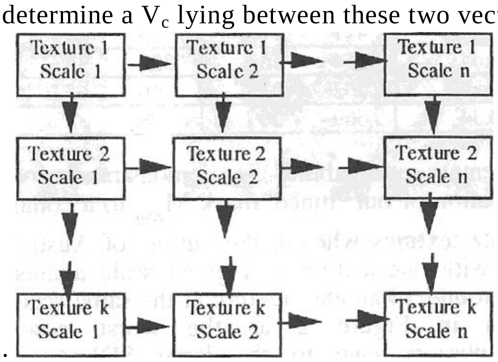

Figure 1. Two dimension linked list

3. Training System

In this section, a two-dimension linked list (shown in Figure 1) of different textures (up to 15 carefully selected very similar Brodatz textures) with various scales is set up dynamically for the scale-invariant texture classification purpose. The calculation of the improved performance index D is simplified by introducing a re-ranking procedure. Meanwhile the learning strategy for training is also detailed.

4. Experimental Results

All the textures used in our experiment are carefully selected from Brodatz which are visually similar. Contrast to the previous research, up to 15 textures

With $(1:2)^2$, $(1:1)^2$, and $(2:1)^2$ scale range are used to verify our scheme.

As an example of our method, adaptive mask M_{seg} listed below is obtained by 'tuning' on two different textures referred to as corkd4 and raffiad84 with 3 different scale $(1:2)^2$, $(1:1)^2$, and $(2:1)^2$. The texture energy TE of each sample and its standard deviation captured by this mask are shown in Table I for comparison with the effect of one of Laws' masks R5R5.

M_{seg}

-11	60	-6	-21	-22
-41	58	-57	-26	66
-27	-27	62	35	-43
87	-68	-81	44	18
-77	5	66	-45	51

R5R5

1	-4	6	-4	1
-4	16	-24	16	-4
6	-24	36	-24	6
-4	16	-24	16	-4
I	-4	6	-4	1

Table 1 Texture Energy Dispersion using tuned mask M_{seg} and Laws R5R5 (above).

	Tuned Mask M_{seg}		Laws Mask R5R5	
Texture	TE	SDV/TE	TE	SDVITE
slraffiad84	1331	18%	131	29%
slcoekd4	2677	18%	486	51%
s2raffiad84	447	17%	5	30%
s2corkd4	1154	16%	320	37%
s3raffiad84	2 0 2	21%	'6	65%
s3corkd4	569	20%	28	38%

Segmentation capability is demonstrated for the application of our 'tuned' mask M_{seg} to a collage of Brodatz textures wherein the outline of Australia is filled with one texture at a given scale against the background of another texture at the same scale. are shown in Figure 2 as the worst case for segmentation. Due to the large SDV/AV ratio indicated in table above the Laws R5R5 is totally impractical. for this task.

5. Conclusion

The results presented in this paper show the potential usage of our multi-scale 'tuned' mask in textured image segmentation. Applying the classifier directly, without a subsequent smoothing yields good results which further maintains the modest computation cost. Because it was 'tuned' on texture samples at different possible resolutions, a multi-scale 'tuned' mask is capable of labelling pixels in a demarcated region with a texture type of unknown scale by simple texture energy thresholding scale-invariantly.

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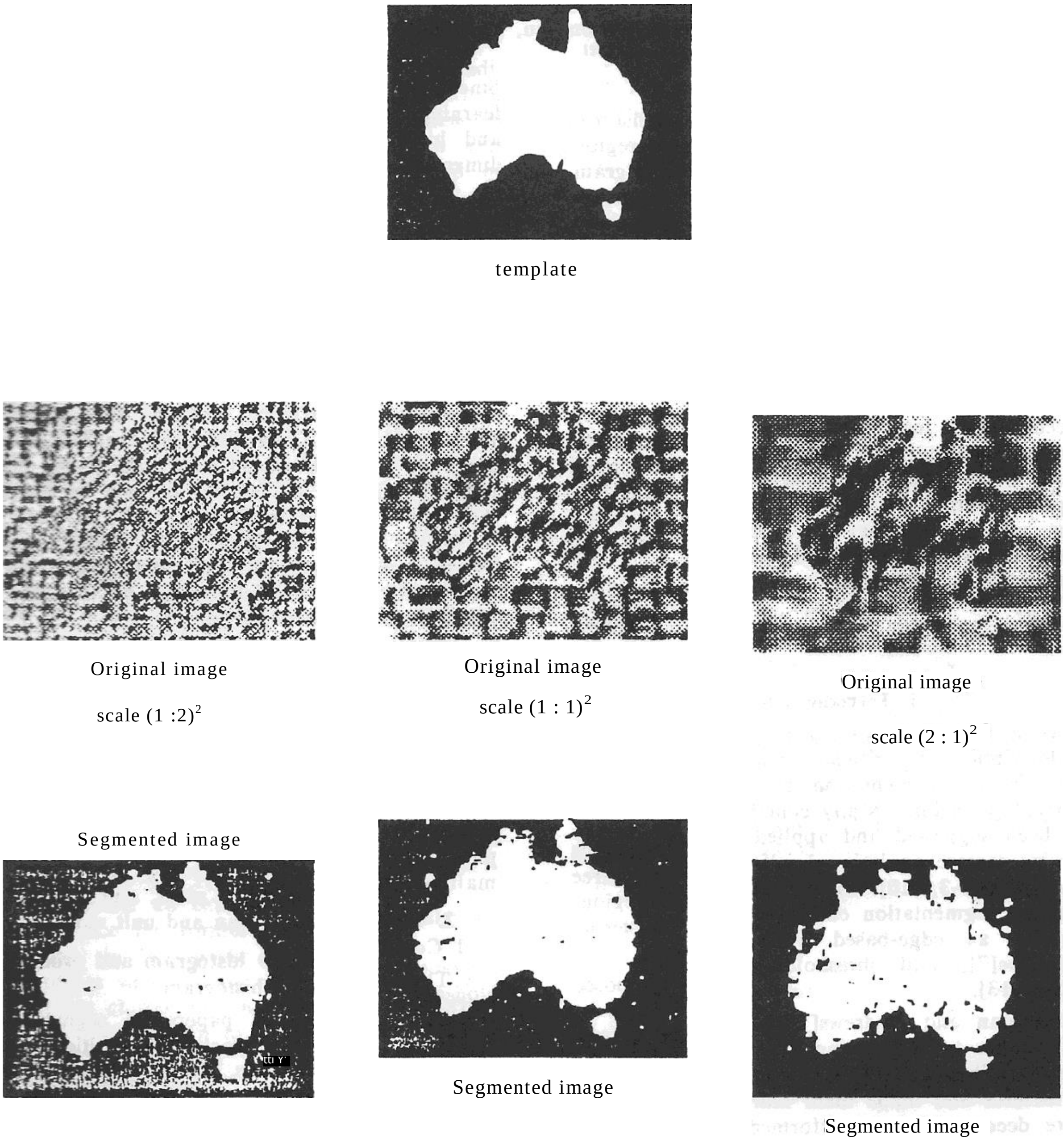

Figure 2. Examples of multi-scale image segmentation.

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