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Segmentation of Multi-scale Images via Multi-scale Texture 'Tuned' Masks

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ABSTRACT Using a multi-resolution texture 'tuned' mask, we have realized a multi-scale texture classifier based on Laws' texture energy term, able to work under a large range of Brodatz textures with various scales. A tuning scheme has been developed to produce the mask for image segmentation by introducing a guided random search to optimize the suggested performance index, using a double-linked list data structure.

***Key words:* Multi-scale, texture discrimination, image segmentation, texture energy, tuned mask, convolution, classifier.**

1. INTRODUCTION

Image segmentation is a basic approach in image analysis whereby the image is partitioned into meaningful regions of common property. Image features, often referred to as texture features, provide a higher-order description of the local image content, and image segmentation by texture property has been studied by many researchers121, [41, [5]. Historically, approaches to texture discrimination have been the analysis of the two-dimensional Fourier power spectrum of the image, co-occurrence matrices, and the use of various local property measurements.

Convolution masks have been used with considerable success for the task of texture discrimination[3] *be*cause they are computationally less expensive and more in keeping with human intuition relating to texture perception than Fourier methods and co-occurrence matrices. Previously we have developed a texture classifying scheme that is a generalization of the method devised by Laws[3]. In Laws' approach a set of fixed feature sensitive masks are available; one mask sensitive to spots, another to waves, one edge sensitive, one described sensitive to ripples. The image is convolved with each of these masks in turn, and a classifier is determined for each pixel based on the variance within a small(15 * 15 or 17*17) window. We showed17] that in the Laws' approach the variance of the classifier is very high. Benke and Skinner[1] introduced the idea of using a single tuned mask in Laws' scheme. However, their method as described is not properly extendable to the discrimination of many textures, as the textures are constrained to be in a fixed order. In our approach, we use a single tuned zero sum mask, and use as classifier the mean square pixel value within a sampling window. In our tuning process the mask parameters are adjusted so that the one parameter classifier has the properties most suitable for the application; a dynamic re-ranking scheme is used to reorder texture number to maximize the differences between all pairs of textures.

In this paper we are concerned with the development of a multi-scale texture classifier based on using convolution masks. New performance indexes are proposed as the desired property for tuning the mask to capture the multi-scale features of the given texture, and those that differentiate from other textures. We both segment and identify regions of common textures of unknown scale using our multi-scale texture 'tuned' mask

This paper describes a texture classifier function that can be applied to segment collages of different textures, so that pixels within the same texture, at a different scale, are assigned the same label. The problem arises in remote sensing, particularly in aerial reconnaissance, and has application to ambulatory robotics. The method is an extension of the mask tuning procedure previously developed by us[8], involving training over pure texture samples, utilising a single-linked data structure, and a tuning index that minimised the standard deviation *SDV* of the classifier within pure texture while maximising the dispersion for different textures. The extension has involved tuning over equal size pure texture samples of different scales, the utilization of a double-linked data structure, the further development of a guided random search procedure for optimising the performance index.

2. DISCRIMINATION STRATEGY

A texture is a distribution in a pattern space. The discrimination task contains feature extraction and classifier function design. For an adaptive system, the feature extractor will be adaptive wits adjustable weights. The discriminant function will have no weights, but will be dependent on the extractor output_

In this section we describe, by replacing Laws' fixed masks with our 'tuned' mask, an adaptive texture feature extractor for the discrimination task with simple classifier function.

2.1 Adaptive texture feature extraction

In designing an optimal feature extractor, the primary aim is to execute tra.:1-2::=z..:iczs pa.:t--n space in order to produce greater inter-class separation in feature space.

The statistical approach to texture segmentation pioneered by Laws[3) is notable for its computational simplicity. Laws' approach might be compared with co-occurrence matrix methods, where the pairwise distribution of gray-scale is determined(at high cost) in a local window. In contrast, in Laws' approach, one of the set of attribute masks is applied to the input textured image, and the classifier for each pixel in the input image is determined from those of the corresponding pixel in the convolved image. For Laws, the classifier used was the local variance, computed in a 15* 15 or 17*17 window about each pixel of the convolved image. Laws computed such a classifier for each of four masks, shown in Figure 1.

1	-4	6	-4	1		-1	0	2	0	-1
-4	16	-24	16	-4		-2	0	4	0	-2
6	-24	36	-24	6		0	0	0	0	0
-4	16	-24	16	-4		2	0	-4	0	2
1	-4	6	-4	1		1	0	-2	0	1
		R5R5						**E5S5**		
-1	0	2	0	-1		-1	-4	-6	-4	-1
-4	0	8	0	-4		-2	-8	-12	-8	-2
-6	0	12	0	-6		0	0	0	0	0
-4	0	8	0	-4		2	8	12	8	2
-1	0	2	0	-1		1	4	6	4	1
		L5S5						**E5L5**		

Figure 1. Laws four most powerful masks

Basically, Laws' scheme has two steps. The first step involves convolving the whole image with a zero sum mask. After convolving, the (signed) image has zero mean. The second step involves labelling the difference between the convolved image and the real image. Laws studied the power of different convolutions and concluded that the masks in Figure 1 are the most useful.

Although individually Laws' masks can be used in isolation as a texture discriminator, a possible limitation of Laws' approach *lies* in the definition of the convolution masks, each of which contains the fixed elements. We extend Laws' approach by replacing constants of the traditional masks with variables which can be 'tuned' to meet the appropriate performance index. Such a new mask is called 'tuned' or adaptive mask. Our aim is to create an adaptive mask to capture the feature of the given texture dynamically, that is, the mask must be capable of being trained on a representative sample of the texture. In order to reduce the number of parameters to be determined, the 5 * 5 tuned masks A evaluated are constrained to be zero sum in each column. Therefore there are 20 parameters to be determined.

The 5 * 5 'tuned' mask can be interpreted as a transition matrix that is iteratively adjusted in order to maximize a performance index. Here the texture energy term *TE* via the mask(the statistical feature of the texture) is introduced as the adaptive texture feature. After the completion of a given number of trials, the parameter matrix will have been tuned to extract the texture feature by producing a strong response to the required performance index.

2.2 Mask tuning criteria

By introducing the *TE* via 'tuned' mask as adaptive texture feature extractor, we require a discriminant function to maximize the dispersion amongst an arbitrary set of textures scale independently.

Assume that we have defined a simple discriminant function $f(z)$, and that the texture energy $E(x,s)$ of texture x at scale s, via 'tuned' mask is introduced as the adaptive texture feature measure of certain scale s. The training procedure is to optimize the mask coefficients to maximize the texture feature dispersion of different textures with high feature convergence of the same texture with various scales. This is achieved via a carefully tailored performance index used in training. Traditionally, one requires that the discriminant be a least squares best fit to the data, so that

$$e = \sum_{x=1}^{N} \left(E(x) - kf(x)\right)^2$$

is minimal. For simplicity, we assume that the discriminant function $f(x)$ is linear, so that the least squares fitting requirement amounts to the maximization of

$$d = \frac{\left(\sum_{x=1}^{N} xE(x)\right)^2}{\sum_{x=1}^{N} E^2(x) \sum_{x=1}^{N} x^2}$$

In order to maximize dispersion of the TE, we should also seek to maximize the function d'

$$d' = \mathrm{minimum}\{ABS(E(x) - E(y))/(E(x) + E(y))\},$$

where *x, y* refer to different textures in the given texture set, and *E(x)*, E(y) represent their texture energy respectively with a certain mask.

A trade-off is required between good linearity - achieved by maximizing *d*, and good dispersion, *achieved* by maximizing *d'*. In previous work we used the product d* d' as the performance index which is optimized in training.

In the work reported here, we also needed to minimize the texture energy difference computed within each class of scaled textures, while maximizing the difference between texture classes. Our multi-scale performance index *D* is computed in term of d_1 and d_2, where d_1 represents the texture energy dispersion of different textures in the form of

$$d_1 = minimum(\mathrm{ABS}(E(x,sx) — E(y,sy))/(E(x,sx)+ E(y,sy))\},$$

and d_2 represents the texture energy convergence of the multi-scale texture in the following form:

$$d_2 = maximum\{ABS(E(x, sx) — E(x,sy))1(E(x,sx)+ E(x,sy)\},$$

where *sx*, sy refer to different scales while *x*, y refer to different textures in the given texture set, and *E(x, sx), E(y, sy), E(x, s3y)* represent the texture energy with certain scale.

In the segmentation task described here *D* alone is used as performance index in training, which is defined as

$$D = d_1/d_2$$

However, for the training of a mask that discriminated between 15 different textures, the product of *D * d* was used as the required performance index.

2.3 Parameter optimization

A search procedure is required to find an optimal mask subject to specified performance index. Many of the traditional search procedures use gradient approaches, which are based on differential calculus. Though such methods are simple, they are highly susceptible to entrapment at a local extremum, so that the result achieved can be dependent on the starting point.

Random search techniques are a standard optimization strategy in the design of adaptive control systems[11J. However, a conventional search strategy does not use its past experience to modify the search strategy, and as a consequence, it can be highly computationally expensive. Note that heuristic approaches utilize information gained from the problem domain in order to influence the search process, we propose a guided search strategy based on gradient and random search guided by the heuristic learning.

Assume that we have a positive figure of merit, *f*, which is a function of a large number of variables expressed as a vector V = (v(1), v(2), ..., v(n)) in an n-dimensional space. The problem is to find the set of variables which will maximize *f* subject to a given set of constraints. Similar to the random search, we begin the search with two random guesses, V_1 and V2, for the required vector, with corresponding values f_i and f_2 for the figure of merit. Base on the gradient search approach and the heuristic learning algorithm, we propose that a further estimate for the vector could be

$$\mathbf{V}_3 = k(\mathbf{V}_1 + \alpha * (\mathbf{V}_2 - \mathbf{V}_1))$$

where the multiplier k may be necessary to keep $\mathbf{V}_3$ within the the coefficient α is a learning coefficient, whicl is defined as

$$\alpha = | f_2 - \bar{f} \,| / \bar{f} \qquad \text{when } f_1 \neq f_2$$

where $\bar{f}$ is the average of f_1 and f_2.

In order to avoid the local minimum, the above formula is modified by introducing a weight coefficient δ which is represented in the following form:

$$\delta = \begin{cases} 0 & \text{if } f_1 = f_2 \\ 1 & \text{otherwise} \end{cases}$$

Therefore the final estimate for a new vector which we use is:

$$\mathbf{V}_3 = k(\mathbf{V}_1 + \tfrac{f_2 - \delta * f_1}{f_1 + f_2}(\mathbf{V}_2 - \mathbf{V}_1))$$

By using the above guided estimation, our aim is to maximize f by heuristic search, which will be detailec in the following section.

3. TRAINING SYSTEM

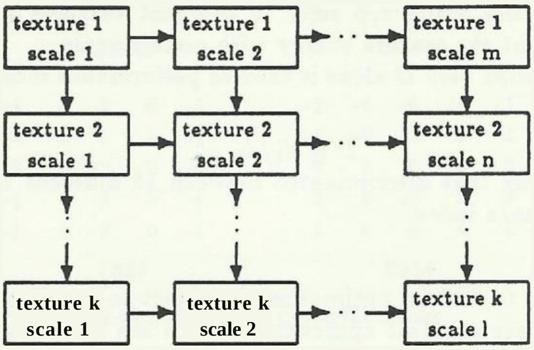
Previously we have used a single linked list so that the textures, whose discrimination function *f(x)* has been assumed to be linear, can be dynamically re-ordered to achieve both maximum linearity with minimum dispersion. In order to be able to impose the requirement of minimum dispersion between the same (class) textures of different scale, a double-linked data structure(see Figure 2) has been developed. This section **describes** the special data structure and re-ranking scheme.

3.1 Dynamic texture database via link list

In texture discrimination, the more the textures can be separated, the more powerful the classifier is. It is necessary to create a large and dynamic texture data set for tuning the mask for multi-scale texture discrimination.

For experimental purposes, Brodatz textures have been chosen as the natural texture samples by the researchers in this area such as Laws, Pietikainen, Rosenfeld and Benke, *etc.* However, the number of the textures involved is very limited. By introducing a two dimension link list in which each texture in different scale is linked by column while different textures are linked by row, we create a dynamic texture data set of large size. The structure is shown in Figure 2, in which each texture sample is a node in the list:

Figure 2. Two dimension link *list*



3.2 Learning procedure

In a training system, a search procedure is required to find the particular parameter set that optimizes the objective functions. Since heuristic approaches utilize information gained from the problem domain to influence the search process, the heuristic random walk is applied in our training procedure and results in a guide search strategy based on experience or discovery. It makes use of the history of the calculation to refine the estimate of the optimum parameter set. This heuristic method suggests the following algorithm:

(a) Generate a random parameter set, the current set, and compute its merit function.

(b) Generate a new random parameter set, the randomised set, and compute its merit function.

(c) Generate a parameter set, the learned set, by averaging the current and the randomised set, weighted as their merit functions. Compute the merit function for the learned set.

(d) Define the current parameter set as the set having the highest merit function.

(e) If an arbitrary iteration count is not exceeded, return to step (b), otherwise consider the current set as an approximation to the optimum solution.

4. TEXTURE COMPOSITE IMAGE SEGMENTATION

Image segmentation is the division of an image into different regions, each having certain properties. The segmentation of the textured image can be usefully considered as a two stage process. In the first stage, referred to as pixel labelling, each pixel is tentatively classified by evaluating a classifier function at all pixels of an image. In the second stage, referred to as region modification, relaxation methods (including region growing), which embody region smoothness heuristics are applied. In this section we detail the first stage of segmentation using texture energy TE based on a multi-resolution 'tuned' mask.

Our adaptive mask is 'tuned' on the samples to produce a large difference of the texture energy term between different samples, high inner-class clustering of different scaled texture, and the low texture energy standard deviation for each sample, it will be a promising approach to segment the texture composite image by simple energy term thresholding. Such a procedure can be outlined as follows:

Step 1: Generate a convolution mask which optimizes the proposed performance index D on the set-up 2 — D multi-resolution texture sample link list.

Step 2: Convolve the different texture images with this optimized mask and calculate their texture energy terms respectively.

Step 3: Convolve the texture composite image with this optimized mask.

Step 4: Convert the convolved texture composite image into a so called energy image by calculating the energy term by 15*15 window size.

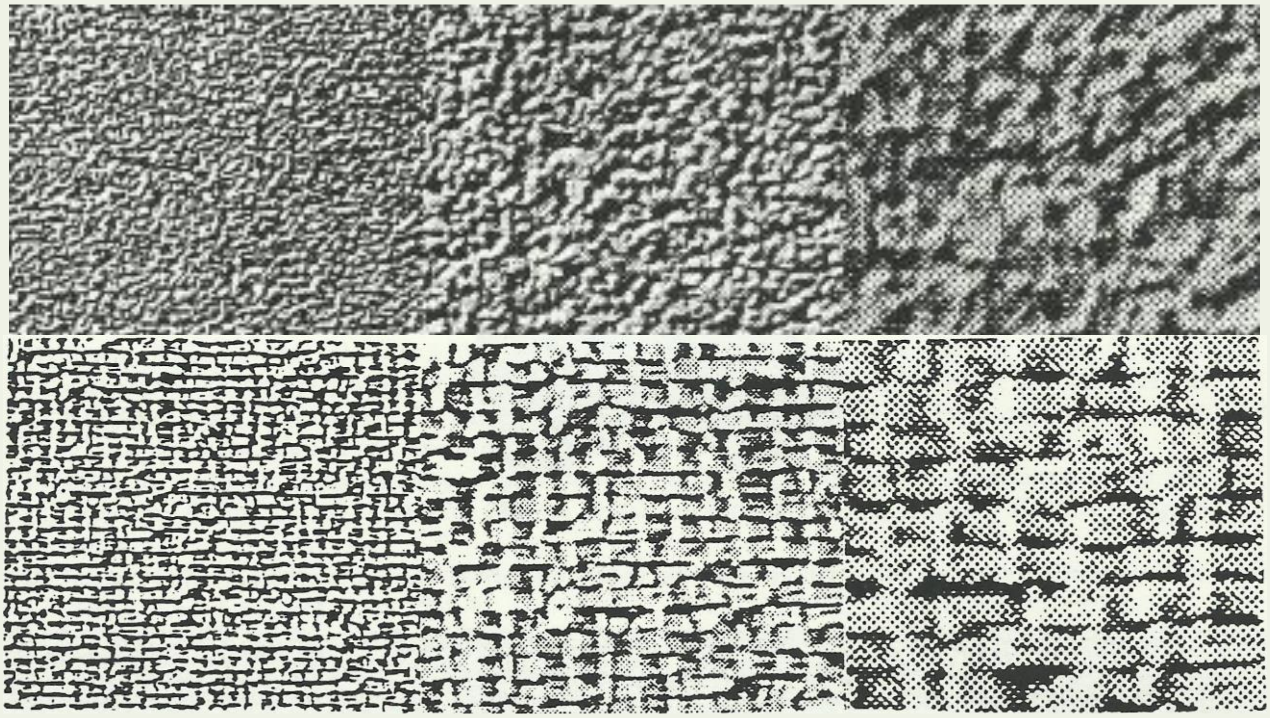
Step 5: Considering the texture energy term of the original texture composite, choose the energy threshold value to separate different textures in the texture composite image.

Step 6: Assign the pixels of the energy image into different groups; *i.e*, foreground or background, according to the selected energy threshold value.

5. EXPERIMENTAL RESULTS

The textures used in this study were selected from Brodatz's well-known compilation. We chose the following 15 textures, including 8 Brodatz textures used by other workers augmented by 7 visually similar textures: In this section the segmentation results of different scaled texture composite images show the potential usage of our scale-invariant tuned mask in textured image segmentation with simple classifier and low computation cost. Being tuned on texture samples with different possible resolutions, the 'tuned' mask is capable of classifying different texture pixels of unknown scale by simple texture energy thresholding. 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 $(1 : 3)^2$ scale range are *used* to verify our scheme. They are calfd24, canvd20, canvd2l, corkd4, grassd9, papd57, pebbd54, pigd92, raffiad84, sandd28, sandd29, strawdl5, wired6, wiredl4 and woold19, as numbered in Brodatz texture set. All these texture images are digitised with pixel gray levels in the range 0 - 255 and histogram equalized. Figure 3 shows two texture samples corkd4 and raffiad84 with three different scales $(1 : 1)^2$, $(1 : 2)^2$ and $(1 : 3)^2$.

corkd4(scale $(1:1)^2$) corkd4(scale $(1 : 2)^2$) corkd4(scale (1:3)2)



raffiad84(scale $(1:1)^2$) raffiad84(scale $(1:2)^2$) raffiad84(scale $(1:3)^2$)

Figure 3. Texture samples at 3 different scales

The adaptive multi-scale mask M_d listed in Figure 4 is 'tuned' on the 15 texture sample set listed above at the three scales indicated, so as to maximize the performance index *D*. Using this mask, the corresponding texture energy *TE* was determined for each texture at each of the three scales. These results are presented in Table 1 in rank order of *TE*. The results in Table 1 show good dispersion of the *TE* for the 15 different textures over a range of values 261 — 1621, with the *TE* for the same texture at different scales being highly convergent.

As an example of our scheme in multi-scale textured image segmentation, we applied our 'tuned' mask *Md* to the texture composite image at three different scales for segmentation. Satisfactory results are shown in Figure 5 for collages of two textures differing in rank by 2.

M_d

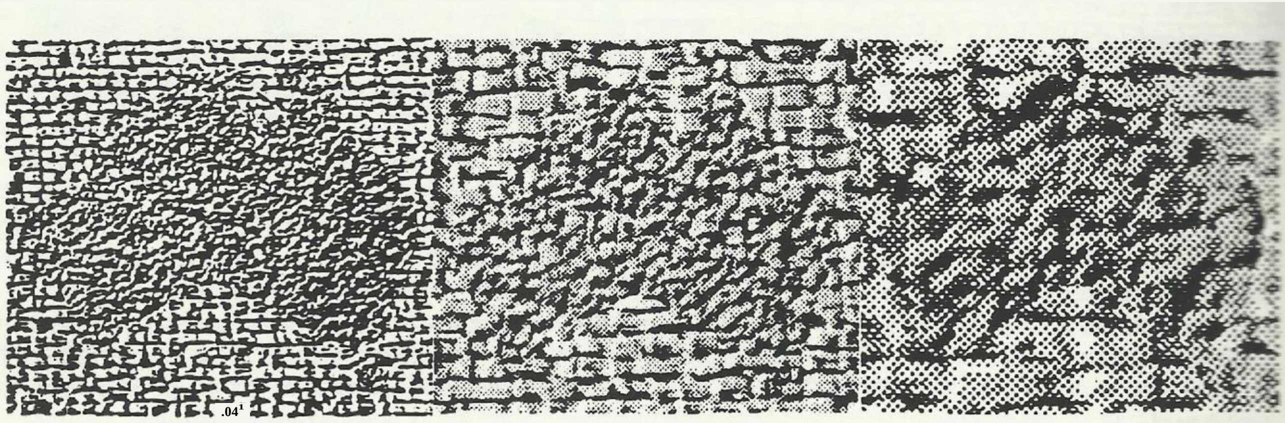
24	-9	-5	13	-23
-3	36	-25	22	-30
-15	26	-21	18	-8
31	-14	-24	42	-35
4	2	-8	16	-14

Figure 4. The 'tuned' mask *Md* defined in the text

Table 1. Texture energy in rank order computed using Ma

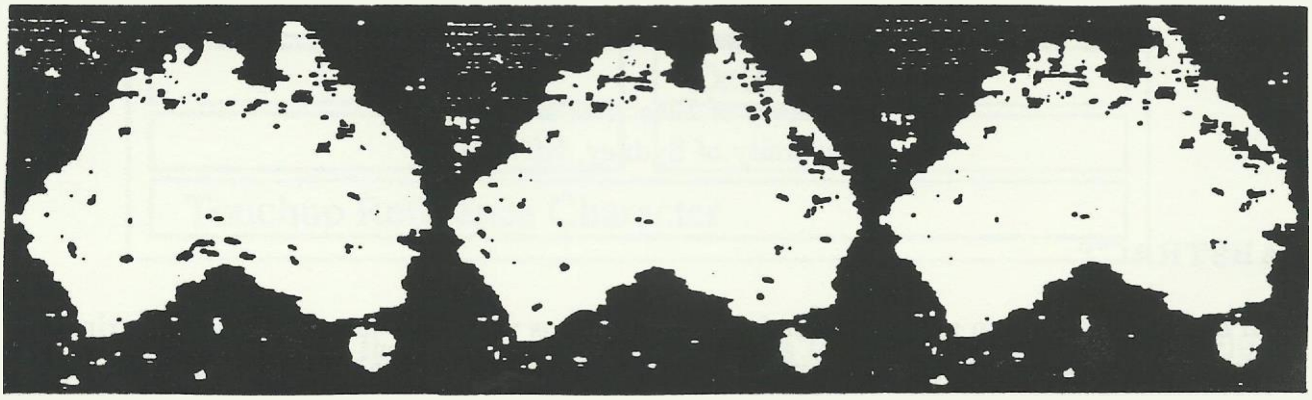
Texture	TE(scale $(1 : 1)^7$)	TE(scale $(1 : 2)^{-7}$)	TE(scale $(1 : 3)^2$)
canvd20	261	270	279
sandd28	378	385	396
calfd24	447	460	472
pebbled54	538	549	568
strawd15	6 2 6	640	665
canvd2l	737	748	767
wook119	817	831	850
wiredl4	907	922	934
pigskind92	992	1016	1031
sandd29	1071	1093	1123
paperd57	1 1 6 4	1181	1200
wired6	1286	1299	1316
rafEad84	1377	1401	1464
grassd9	1492	1525	1572
corkd4	1621	1657	1698

template



Original image Original image **Original image**

scale $(1 : 1)^2$ scale $(i :2)^2$ **scale $(1 : 3)^2$**



Segmented image Segmented image Segmented image

Figure 5. Examples of multi-scale image segmentation

6. Conclusion

We have shown that the mask tuning procedure previously developed by us can be extended to produce a mask that will classify a pixel as belonging to a particular texture irrespective of local image scale (over a scale range). Essentially the mask determined selects the scale invariant(over a certain range) statistical features of a texture that distinguish it from other textures in the training set.

In the experiments reported here mask tuning involved 15 Brodatz textures over the scale range $(1:1)^2$ to $(1:3)^2$. It was found that for all textures, the classifier function differs by only a few percent over the scale range, while the difference between different textures is of the order of 15 — 30 percent.

There is significant computational cost in the training process, but the application of the single mask so determined to distinguish a moderately large number of different textures is very computationally cheap, leading to potential application in materials handling, in remote sensing, in the handling of agricultural products, and in ambulatory robotics. In such applications, the convenience of scale insensitivity is often an advantage. A current limitation of the texture classification system described here is its sensitivity to orientation. This warrants further work which is currently in progress.

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