ADAPTIVE MASKS FOR TEXTURE DISCRIMINATION

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Abstract

A new method which extends and improves the texture statistical classification scheme of Laws is presented for texture discrimination and image segmentation. Unlike Laws' set of fixed attribute masks, our adaptive masks are 'tuned' during a training stage to optimize the certain figure of merit which is suggested in this paper. Maximum texture energy difference of all the different similar texture samples is chosen as the required criteria in our training procedure for texture discrimination, while the minimum standard deviation of the energy image is for the texture composite image segmentation, and a dynamic data structure is applied to build up a large texture sample set. Experiment results are provided to show the advantage of our method and compare with the previous work.

Keywords and phrases: adaptive mask, texture discrimination, image segmentation, texture energy, standard deviation, convolution.

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

R5R5

-1	0	2	0	-1
-2	0	4	0	-2
0	0	0	0	0
2	0	-4	0	2
1	0	-2	0	1

E5S5

-1	0	2	0	-1
-4	0	8	0	-4
-6	0	12	0	-6
-4	0	8	0	-4
-1	0	2	0	-1

L5S5

-1	-4	-6	-4	-1
-2	-8	-12	-8	-2
0	0	0	0	0
2	8	12	2	2
1	4	6	1	1

E5L5

Figure 1. Laws four most powerful masks

1 Introduction

Image segmentation plays a fundamental role in picture recognition and scene analysis. There are two basic approaches to segmentation. One is edge detection, the other is what we call pixel labelling. Edge detection is based on abrupt transitions between regions and mapping the given picture to a segmented picture with a high rate of change in grey levels. What is here termed pixel labelling is usually a two step operation. In the first step, a classifier function is evaluated at all pixels of an image. The classic such texture classifier is the average grey scale in a window centered on each pixel (Rosenfeld et al [14]). In the second step, various global considerations are applied to finally label each pixel as belonging to a particular class. For example, when Rosenfeld discriminated simple textures distinguished by average gray scale, simple thresholding after window averaging was sufficient [14]. Because of the limitations of the classifiers they have used, most workers have been obliged to developed various elaborate schemes, such as region growing, to finally label each pixel according to texture.

Our work is related to that of Laws [1] who introduced the concept of a texture energy defined at each pixel after a series of operations (see below) involving particular convolutions. Laws used several different texture energies as classifiers in conjunction (usually four) for pixel labelling. Because of the use of several classifiers, each of which by itself has poor reliability, Laws method is complex to apply, especially for more than a very few textures.

In this paper we introduce and evaluate improved classifier functions, also based on texture energy. But whereas Laws used several classifiers, each related to different fixed masks, we used a single classifier for each discrimination task, based on the use of "texture tuned masks" [16]. For the task of optimally discriminating between a large number (here fifteen) of different textures using just one classifier function, we have determined a "tuned" mask. For the task of most reliably classifying the pixels of a given we have an adaptive scheme for tuning the masks used in accordance with the desired properties of the classifier. here we have explored the possibility of using a single classifier that can disciminate as many as fifteen different textures. Our classifier is simply the texture energy, but evaluated using a mask tuned to the particular discrimination task. We examine two different problems. Firstly developing a classifier that will optimally distinguish between fifteen textures. Secondly developing a classifier that has minimum dispersion on a single texture.

There are a great range of classifier functions in texture segmentation [7], [9], [11], [12], [13], [14], [15]. Co-occurrence matrix methods have been used with some success especially in the application to satellite imagery featuring [13]. Local property measurement is another approach to texture analysis, and different derivative operators are suggested to extract the information on direction [6], [7]. However, the reliability of these classifier is generally poor, so that various schemes have been tested to more reliably segment.

Laws [1] pioneered a computationally inexpensive approach for which a reasonable approximation to a classifier function is the texture energy TE calculated for particular mask and window size, or a linear combination of various such TE functions. Various classification trials and segmentation exercises have been reported for their superior discrimination when compared with co-occurrence matrices and gradient techniques [1]. Laws introduced the notion of a local 'texture energy', evaluated at each pixel location (i,j) in the convolved image over a large window size 15 * 15. For a zero-sum mask, such local texture measure is determined as statistical variance of the filtered image by computing the sum of the squared signal values in the filtered image. It is obvious that the approach developed by Laws is based on the use of a set of convolution masks to filter the image followed by the local population statistic calculation. Laws' four most powerfule 5 * 5 masks are depicted in Figure 1.

Though an individual Laws mask 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. In fact images of natural scenes are often complex and highly textured, and none of the single masks will be powerful enough to distinct all the unpredictable natural textures. Improvements to this method have been done by some researchers. In [6], a new texture measure based on a set of orientation-sensitive windows is introduced. The basic idea is to measure the non-uniformity of the intensity within a set of local directed neighboubhoods around a pixel, followed by the computation of a first order statistic of the variance measure within a large (macro) window. Though an effort was made to take into account global orientation sensitivities of the individual texture measures and improvement over Laws' method was shown by the classification result, only a certain texture samples are involved and selected by the author.

Benke modified Laws' fixed convolution mask to an adaptive mask by introducing the machine learning process [4]. The mask is considered as a general operator and the elements of the mask are adjustable parameters. The mask can be tuned to respond strongly to a particular feature by optimizing the elements to suit the task in hand. In [10], texture energy is chosen as such feature for training, but computation expense is increased to adjust the mask elements in the segmenting procedure.

Though improvements to Laws' method have been reported previously, no previous work has determined the basic statistic characteristic such as the standard deviation as the classifier for pixel labelling. Besides, the evaluation of image segmentation has traditionally been of a simple image, eg. Laws [1]. We have done this for comparison, but we have also determined the standard deviation SD of the classifier further and no modification process is required for segmentation after simple thresholding. In this paper a new approach to generate an adaptive convolution mask for texture discrimination and image segmentation is described. Unlike Laws' fixed mask, such mask is tuned on the image samples by optimizing the certain figure of merit suggested in our training procedure for different purposes. Maximum texture energy difference of the different texture samples is the new figure of merit suggested to classify 13 very similar texture samples in our test, and the minimum standard deviation of the energy image is used to segment the texture composite image by simple thresholding. The generation of the adaptive mask tuned through the training stage according to the above figures of merit is presented in the next section, and followed is the discription of the training system. At last the experiment results are provided.

2 The Generation of the Adaptive Mask

We require a systematic search procedure to produce the adaptive convolution mask for the texture discrimination and segmentation. This task is equivalent to the problem of defining optional masks subject to specified performance criteria. Conceptually, this means discarding traditional masks with fixed coefficients and replacing them with convolution masks containing variables as coefficients.

The adaptive mask is such a mask in which all coefficients are variables instead of constants. It is required that this mask should be able to adapt to a non-ideal system and it must produce the best possible response to a complex input pattern according to a given figure of merit. In other words, the mask must be capable of being trained on a representative sample of the texture by adjusting its coefficients in order to respond optionally to the training pattern. The generation procedure of the adaptive mask can be described in Figure 2.

In the texture discrimination and image segmentation task, the energy term, a property of the filtered image is useful. In order to scale the energy to be independent of the image size and multiplicative changes to mask values, we define the energy $E(A,I)$ passed by the mask A when convolued with the image I as:

$$E_{ij}^2 = \frac{1}{MNP}(\sum_{ij\epsilon W} G_{ij})$$

where the MN window W is centred about the pixel G_{ij}, both M and N are odd, G is the filtered image obtained by convolving the mask A with the original image I:

$$G = A * I$$

and P is the normaliser for the convolution mask A:

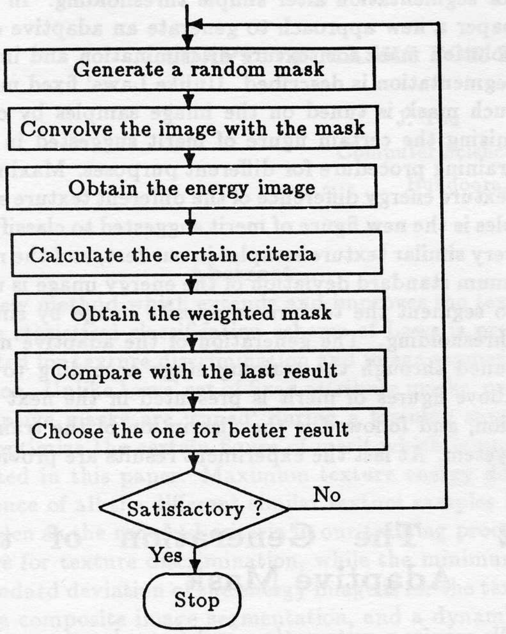


Figure 2. The main step to generate the adaptive mask

$$P^2 = \sum_{i,j} (A_{i,j})^2$$

In our experiment, the $15 * 15$ window size is used to calculate the energy term of the $512 * 512$ image.

Note that all Laws' masks are zero sum and axially symmetric, we also apply such constraints to our adaptive masks in order to reduce the number of parameters to be determined. In texture discrimination procedure, the adaptive mask is assumed to possess axial symmetry

$$A_{i,j} = A_{i,5-j}$$

Thus each row of the mask is of the form $(a\ b\ c\ b\ a)$, where $2a - 2b + c = 0$ Therefore there are 10 parameters to be determined through the training procedure. In image segmentation procedure, the adaptive mask is constrained to be zero row sum only. Therefore, for a $5 * 5$ 'tuned' mask A there are 20 parameters to be determined and the mask is in the form of $(a\ b\ c\ d\ e)$, where $a + b + d + e - c = 0$.

3 The Training System

The key improvement of our approach lies in the fact that the mask is obtained through the training procedure. In this section a special data structure and the suggested new figure of merit are described.

3.1 The Link List

As the goal is to obtain an adaptive convolution mask to separate different texture sample, the training pro-

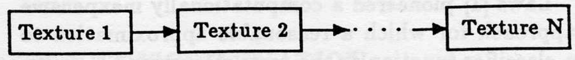


Figure 3. The link list of the texture samples

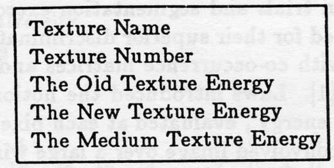


Figure 4. The data field of one texture

cedure should be dynamic, which means the different ideal masks can be generated among different textures sets, while the texture samples are chosen and determined by the user. The previous research performed by others [5] was focused on training the mask on a fixed texture data base. The disadvantage of this lies in that the number and type of texture samples should be known beforehand and can not be changed. However, it is constract to what happens in practice. Actually during the discrimination procedure the number and type of texture is unpredictable. A new data structure is used to improve this. In our experiment a link list of different textures is set up dynamically by the user. The number of the samples and the textures are determined by the user and each texture is linked for later training, shown in Figure 3.

For each texture element there will be five fields to hold different data for comparison in training procedure, shown in Figure 4.

3.2 Re-ranking the link-list

From the simple point of view, linear function $f(x) = kx$ is suggested for texture discrimination, where x refers to the order number of the samples in the texture set. In this case all the texture samples should be restricted in the monotonically increasing sequence. Considering the fact that the texture will respond differently to different masks because different mask will capture their different features. We suggested a so-called re-ranking step in the training procedure. As the training procedure is based on the random mask generation system and the learning, the link list must be re-ranked first according to its energy term and then learning procedure applied.

The effect of the re-ranking procedure is shown in Figure 5. Two different random masks are convolved with 13 samples and the texture samples are sorted according to their energy terms. The orders are different corresponding to the different masks.

3.3 New Figure of Merit in Learning

There are two figures of merit suggested to improve the performance of the texture discrimination and

Random Mask M1		Random Mask M2	
-34 -71 -96 -71 -34		33 -10 -46 -10 33	
4 -4 -35 -4 4		-25 -7 64 -7 -25	
-41 30 63 30 -41		45 -26 -38 -26 45	
46 -39 -71 -39 46		81 -62 -38 -62 81	
44 100 69 100 44		-49 37 24 37 -49	
texture name	**texture energy**	**texture name**	**texture energy**
strawd15	1021.34	pebbd57	308.96
canvd20	2245.04	sandd28	442.58
canvd21	2251.11	raffd84	540.03
sandd28	2952.96	canvd20	638.51
calfd24	3092.53	canvd21	690.20
wired14	3171.48	papd57	738.77
wired6	3312.73	pigd92	894.99
pebbd54	3398.97	sandd29	974.56
pigd92	3737.06	wired14	1041.51
raffd84	4235.17	grassd9	1148.56
grassd9	4741.23	wired6	1288.29
sandd29	4935.31	calfd24	1431.04
papd57	5137.37	strawd15	1724.84

Figure 6. The effect of re-ranking procedure

texture image segmentation respectively, the maximum texture energy difference of different texture samples and the minimum standard deviation of the texture energy image.

The maximum texture energy difference is the proposed new figure of merit for texture discrimination. In the learning step, there are usually two ways to judge the generated masks whether they can maximize the dispersion among the texture set. One is to minimize the total square errors

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

by mixmizing the following function.

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

The other is to maximizing the minimum of difference between each texture samples, that is

$$d' = mimimum(\frac{ABS(E(x) - E(y))}{(E(x) + E(y))})$$

These two figure of merits were used by some researchers [5], however they have their own disadvantage. In the first case though it is simple and fast for the calculation, it can not avoid the circumstance in which the d value is large enough and the difference between the samples may be very small, which will cause the certain mask fail in texture discrimination. In the second case the numbers of pair-wise comparisons per trial is given by $N!/(N-2)!2!$, the total number of different textures in the sample should not be too large because of the computational overload caused by the combinatorial explosion. In order to avoid the above disadvantages of the old figure of merit, a new figure of merit is suggested. It can be represented in the following form:

$$D = (\frac{\sum_{x=1}^{N}(E(x)f(x))^2}{(\sum_{x=1}^{N}E^2(x))(\sum_{x=1}^{N}f^2(x))})min$$

where

$$min = minimum(difference\ between\ d)$$

So now the goal in training procedure is to seek the mask which can maximize the value of D. Since the textures are already ranked, it is fast to calculate the minimum difference between d and only the mask which produce large d and d' are the satisfactory one. With such mask the textures are well separated. The test results are shown in Section 6.

As to the texture image segmentation task, the minimum standard deviation of the texture energy image can be used as the new figure of merit for 'tuning' the mask. If the texture energy term of the different texture image samples is well separated and only few textures are involved for the segmentation, the texture energy term of the filtered image itself can be used as the required criteria for the training. In this case an adaptive mask can be determined by tuning it on the basis of the maximum energy term. The authors have done some work on this subject and for more details see [16]. In that paper , the mask optimization problem is explained as seeking a 5*5 mask M which maximizes the energy response E of one of the texture samples. The idea is based on the fact that if few texture samples involved and the mask produce the maximum response to one texture, it should be easier to discriminate other texture samples because their responses to that mask are different. However, it is not always true in real world. Actually there will be quite a lot of different textures involved and their texture energy terms are quite close , and meanwhile the texture energy standard deviation is quite large, the above method for training the mask will lose its advantages since several samples may produce the similar energy responses and it is difficult to separate them. And also even if the energy terms are well separated but the standard deviation is large, the energy terms of different textures will overlap and it will be impossible to segment the mixed textures by texture energy only. Thus a new criteria for tuning the mask is suggested.

From the simple operation for segmentation view of point, texture energy term will still be used as a key texture measure for the segmentation task. In order to make such method successful, the maximum texture energy is replaced by the minimum texture energy standard deviation for the training procedure. The segmentation result is shown in section 6.

4 The learning strategy

As has been illustrated, our adaptive mask is obtained by a so-called training procedure through learning. In that procedure the problem is to find an optimal mask subject to specified performance criteria. A search procedure is required to find the particular parameter set that optimizes the objective function. 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 result 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 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.

By applying this algorithm to the training procedure with appropriate figure of merit according to the task in hand, satisfactory result of texture discrimination and segmentation is obtained and shown in section 6 for demonstration.

5 Texture Composite Image Segmentation

In this section the adaptive convolution mask is applied to the image segmentation task. Usually computation efforts have been made to modify the final segmentation results. In [18], the algorithm consists of three stages: First the image is decomposed into a number of blocks of equal size as a preliminary segmentation, adjacent blocks having common textual characteristics are then merged to form larger connected regions, finally, the boundaries between connected regions are refined to produce more precise edges between regions. Since the second stage, region merging, is performed iteratively, it is the most expensive task of the algorithm. In [6], though the iteration operation is not required and the computation expense is reduced, extra texture measures referred to as LDSD and MLDSD have to be calculated and the image has to be convolved twice by 7*7 window size followed by two successive 7*7 averaging operation. In [10], the approach developed for texture segmentation can be summarized as the the sequential application of filtering and smoothing for pixel labelling, followed by automatically thresholding for pixel classification.

Since our adaptive mask is tuned on the samples to produce large difference of the texture energy term between different samples and the small texture energy standard deviation for each sample, it will be a promising approach to segment the composite texture image by simple energy term threshsolding. No further modification is required because such mask avoids the different energy overlapping and thus the computation expense is reduced. The outline of such procedure is described as follows:

Step1: Generate a convolution mask which minimizes the texture energy standard deviation of the texture samples.

Step2: Convolve the different texture images with this optimized mask and calculate their texture energy terms respectively.

Step3: Convolve the composite texture image with this optimized mask.

Step4: Convert the convolved mixed texture image into a so-called energy image by calculating the energy term by 15*15 window size.

Step5: Considering the texture energy term of the original texture composite, choose the energy threshold value to separate different textures in the mixed texture image.

Step6: Assign the pixels in the energy image of the mixed texture image into different groups, i.e, object or background, according to the selected energy threshold value.

6 Experiment Results

In this section we demonstrate the performance of our algorithm on 512*512 texture images. All the textures are carefully chosen from Brodatz [3] which are visually similar. There are 15 textures involved. They are calfd24, canvd20, canvd21, corkd4, grassd9, papd57, pebbd54, pigd92, raffd84, sandd28, sandd29, strawd15, wired6, wired14 and woold19, shown in Figure 7 respectively. All these texture images are digitised with pixel grey levels in the range 0 - 255 and histogram equalized.

Figure 8 lists two optimized masks M1 and M2 which are obtained by maximizing d and $d * minimum(difference\ among\ all\ the\ samples)$ respectively for texture discrimination.

Figure 9 is a data diagram to show that different mask will produce different energy term and it is important to re-rank the link list during the training procedure.

From this example we can see that different mask will cause different energy term and the importance of re-ranking during the training procedure.

For M1 the minimum difference between the textures is 1.03%, and for M2 it is 8.18%, which shows the improvement of the new figure of merit.

Laws four most powerful masks R5R5, L5E5, E5S5 and L5S5 are applied to the same texture database for compare. The minimum difference between the textures is 1.42%, 0.23%, 3.09% and 2.91% respectively. Thus the optimized mask M1 produced lower standard deviation value of the texture energy image. In Figure 10 some great standard deviation values are chosen from the texture sample database as the worst case for compare with Laws' masks. TE refers to texture energy and SDV to the standard deviation.

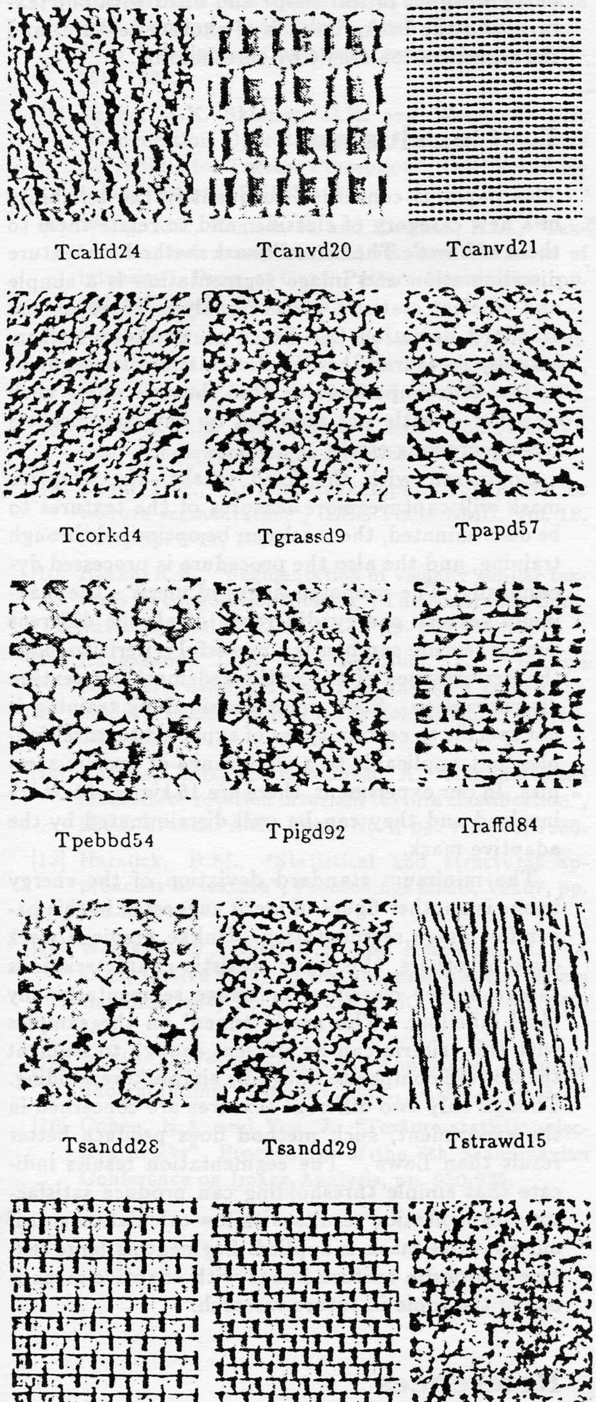


Figure 7. 15 texture samples

-32	-16	96	-16	-32	33	-10	-46	-10	33
-25	21	8	21	-25	-25	-7	64	-7	-25
-21	21	0	21	-21	45	-26	-38	-26	45
58	-64	12	-64	58	81	-62	-38	-62	81
-7	-17	48	-17	-7	-49	37	24	37	-49
		M1					M2		

Figure 8. Two Adaptive Masks

M1		M2	
texture name	texture energy	texture name	texture energy
pebbd54	296.77	pebbd54	308.90
sandd28	453.38	sandd28	442.58
raffd84	494.46	raffd84	540.03
canvd20	566.61	canvd20	638.51
papd57	769.29	canvd21	690.20
pigd92	892.04	papd57	738.77
canvd21	970.41	pigd92	894.99
sandd29	980.22	sandd29	974.56
wired14	1091.53	wired14	1041.51
grassd9	1141.93	grassd9	1148.56
calfd24	1366.17	wired6	1288.29
wired6	1435.94	calfd24	1431.04
strawd15	1594.96	strawd15	1724.84

Figure 9. The difference of the two optimized masks

Figure 8 lists two optimized masks M1 and M2 which are obtained by maximizing d and $d * minimum(difference\ among\ all\ the\ samples)$ respectively for texture discrimination.

Figure 9 is a data diagram to show that different mask will produce different energy term and it is important to re-rank the link list during the training procedure.

Obviously the optimized mask M1 enlarge the difference of the texture energy terms with lower standard deviation values among all the samples. Therefore the new training strategy has its own advantages for texture discrimination.

As to the texture composite image segmentation, the adaptive mask M3 is obtained by minimizing the standard deviation of the energy image through training. In our experiment the optimized mask M3 is given in Figure 11.

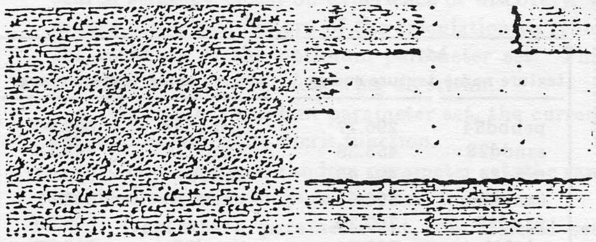
Both the block mixed texture image and the natural mixed texture image are considered for the segmentation test. By applying such mask to the texture composite images, satisfactory result is obtained by simple thresholding.

	M1		R5R5		E5S5		L5S5	
texture name	TE	SDV	TE	SDV	TE	SDV	TE	SDV
strawd15	1280	451	13	10	1013	540	9150	4190
pebbd54	376	140	6	3	644	268	2188	980
canvd21	826	162	58	22	475	201	5399	1358

Figure 10. Examples to compare with Laws' masks

-41	88	-23	-47	23
-14	47	-52	27	-8
-36	-61	77	2	18
-11	-18	-37	70	-4
-5	-54	13	-63	1

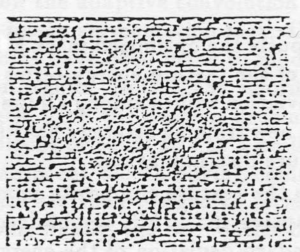
Figure 11. Optimized mask for image segmentation



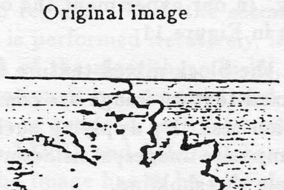
Original image After segmentation

Figure 12. Block Texture Composite Image And The Segmentation Result

Template



Original image



Segmentation result

Figure 13. Natural Texture Mixed Image And The Segmentation Result

Figure 12 shows a block texture composite image (such image can be made up by choosing different textures from our texture sample set and each block is of 64*64 size) and the segmentation result. Figure 13 is a natural mixed texture image (the forthground of the image is of leaf shape and filled with one texture, and the background is of another texture) and the segmentation result by thresholding.

7 Conclusion

This paper is concerned to quantify the reliability of a new category of classifier and to relate them to those of Laws'. The 'tuned' mask method for texture discrimination and image segmentation is a simple and efficient statistic texture analysis based on the standard deviation SD. Since no previous workers actually measured the SD of a classifier for segmentation, it is important to note that we apply such classifier directly not modified by any later process (region growing etc.).

Compared with the fixed masks, the adaptive mask will capture more features of the textures to be discriminated, the mask can be optimized through training, and the also the procedure is processed dynamically. The proposed figure of merit – the maximum texture energy difference of all the different similar texture samples is a powerful criteria to judge the performance of the optimized mask for texture discrimination. Such mask obtained by training is not specific to certain types of expected texture samples, but applicable to a wide range of texture samples. In our experiment, there are 15 types of texture involved and they can be well discriminated by the adaptive mask.

The minimum standard deviation of the energy image is another figure of merit suggested in this paper for image segmentation. Unlike previous work done by others, this basic statistic characteristic is chosen as the classifier for image segmentation by pixel labelling. The mask 'tuned' on the samples with this criteria can be efficient enough to segment the texture composite image by simple thresholding. Though only two different textures are concerned in the experiment, such method does produce better result than Laws'. The segmentation results indicate that simple thresholding can produce satisfactory segmentation results with low calculation cost if our adaptive mask is applied. Segmenting large texture composite texture image with adaptive mask is one of the topic in future research.

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