ADAPTIVE WINDOWS FOR TEXTURE DISCRIMINATION

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ABSTRACT

The application of image processing operators known as adaptive windows to the task of complex texture discrimination is reported. Comparisons are made with the ability of the pre-attentive human visual system for the same tasks. A modification to the standard adaptive window is presented which has several advantages for this type of image processing task. The performance of the adaptive windows is reported with reference to texture described in terms of statistical parameters, textons and periodicity radii.

I INTRODUCTION

There is now a large body of knowledge about the human visual system, the functions of which can be partitioned into the attentive and pre-attentive systems. An important function of the pre-attentive visual system is that of texture discrimination. The limitations of the visual system for texture discrimination have been widely reported and several theories have been proposed. This paper is concerned with the capabilities and limitations of artificial vision operators known as adaptive windows for the same task of textural discrimination. The background to texture discrimination and some associated theories are presented along with the basic structure and function of adaptive windows. A modification to these adaptive window operators is proposed which have several advantages, in particular for complex texture discrimination. Experiments on textures defined using two important concepts of statistical parameters and textons are reported in which adaptive windows are shown to have similar capabilities and limitations as the pre-attentive human visual system.

II BACKGROUND

A. The Adaptive Window

The adaptive window has previously been described in several papers, especially in (Aleksander and Wilson 1985) and (Wilson 1985). Briefly, it consists of a window of $x \times y$ pixels each connected at random to the address inputs of a set of RAMs known as a discriminator. The outputs of the RAMs are summed to produce a response value of the window to an input pattern. The window can of course be scanned across an image or randomly sample an image. The basic structure is illustrated in Figure 1, where the discriminator consists of $(x \times y)/N$ RAMs each with N inputs. N is also referred to as the connectivity of the adaptive window. During training, a '1' is written into the location in each RAM which is addressed by the sample of the window and thus each RAM will output a '1' during testing if it has previously seen the same input combination during training. For several training patterns $T_1, \ldots, T_{|T|}$ the most likely relative response of the window to a test pattern X is

$$R_U = \sum_{j=1}^{|T|} (-1)^{j+1} P(j)$$

where

$$P(j) = \sum \left(\prod_{k=1}^{j} A_{a_k} \right)^N$$

$$\forall \{a_1, a_2, \ldots, a_j \mid 1 \leqslant a_j \leqslant |T| \}$$

and A_{a_j}

represents the relative overlap similarity between

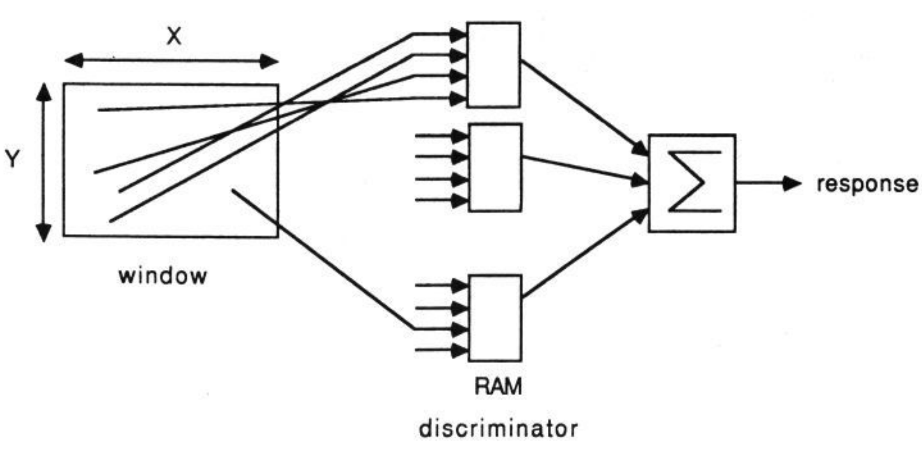


Figure 1. The Adaptive Window

patterns X and T_{a_j}. N is the number of inputs to each RAM.

The attraction of adaptive windows over standard window operators is that no mathematical algorithm is required; indeed any arbitrary logical operation can be learned by the window. This implies that adaptive windows should be capable of performing poorly defined image processing tasks such as arbitrary texture discrimination.

The investigation of the use of adaptive windows for edge detection, stereopsis and simple texture discrimination has previously been reported (Aleksander and Wilson 1985, Wilson[2] 1985, Wilson[3] 1985).

B. Texture discrimination

Further experiments on two simple textures of horizontal and vertical bars attempted to repeat the experiments on the human visual system of Green et al. (1959) to test the ability of the windows to discriminate between the two textures in the presence of varying amounts of noise. The results of these experiments produced discrimination curves having the same form as those reported by Green et al. but the confidence levels were lower for the adaptive windows. These confidence levels were raised significantly by the use of response feedback which is described in Section III.A.

The main experiments reported in this paper concern the use of adaptive windows to discriminate much more complex textures, based on the concepts of order statistics and textons.

Julesz (1962) reported a series of experiments on the discrimination by the human visual system between pairs of textures defined statistically. Textures which had identical first- and second-order statistical parameters but differed in their third- and higher-order parameters were found to be indistinguishable. This led to the conjecture that the pre-attentive visual system cannot process statistical parameters of third- or higher-order.

Marr (1976) suggested that perhaps only the first-order statistics of conspicuous local features are used in human pre-attentive texture perception and Caelli et al. (1978) reported the existence of iso-second-order texture pairs which could be discriminated. Thus, the earlier conjecture of Julesz was disproved and was modified to the conjecture that the pre-attentive visual system cannot compute statistical parameters higher than second-order.

Later work by Julesz (1980) presented a theory of pre-attentive texture discrimination based on local first-order statistical parameters. This theory is based on the concept of localised features called textons which Julesz proposes as being responsible for the ability to discriminate iso-second-order textures.

III MODIFICATIONS TO THE STANDARD ADAPTIVE WINDOW

A. Response Feedback

A frequent problem encountered in applying adaptive windows is that of poor confidence levels of discrimination.

A typical example might be where several adaptive windows are required to discriminate between several textures, each window having been trained on a particular texture. The confidence

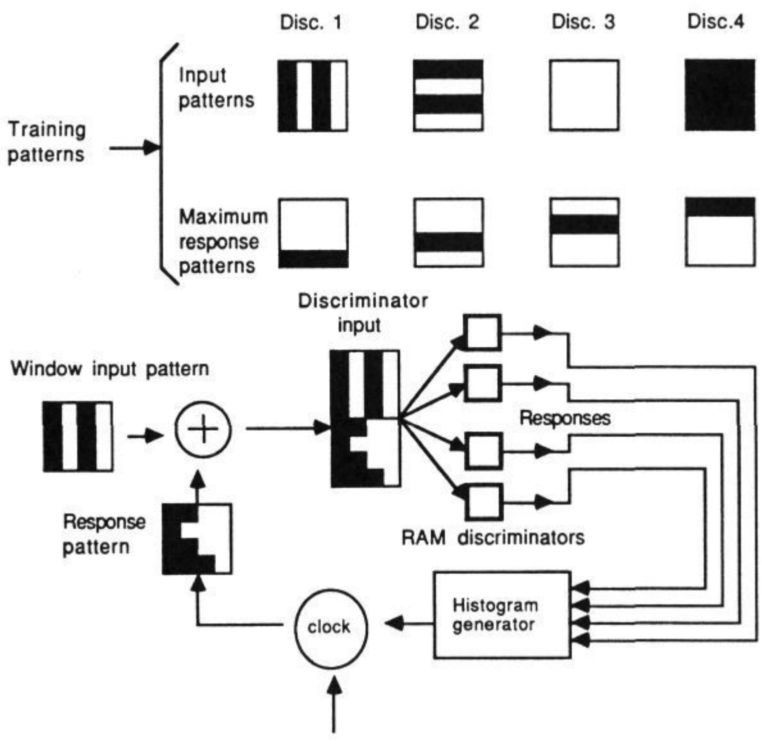


Figure 2. Response Feedback over Several Adaptive Window Operators

level achieved for a particular test texture depends essentially on the dissimilarity of the two trained textures to which the test texture is most similar. One way in which the confidence level can be increased is by the use of a technique called response feedback.

In this technique, the response values of each of a group of adaptive window operators (discriminators) are converted into a bit pattern and fed back via a delay to form part of the input to each discriminator as shown in Figure 2 a. The bit pattern generated takes the form of a histogram of the response values of each discriminator. The total input to each discriminator is therefore a composite image of the window input and the response histogram. During training, the feedback loop is cut and each discriminator is trained on a window input pattern plus a response histogram corresponding to a maximum response from that discriminator and zero response from all others as shown in Figure 2 b. The output of the system consists of several response values and the discrimination confidence is determined by the difference between the two highest responses. It is this response difference which is to be amplified by the response feedback.

It is relatively straightforward to define the time incremental behaviour of the feedback system. The relative response at time, t+1, of a discriminator, i, is determined by the total relative overlap, $OV_i(t+1)$, between the composite pattern formed by the window image and the system response histogram for time t and the composite training pattern for that discriminator. The actual relative response value, $R_i(t+1)$, is then given simply by :

$$R_i(t+1) = (OV_i(t+1))^N.$$

The total relative overlap, in a four discriminator system, for discriminator 1 is given by :

$$OV_i(t+1) = [\ W^2A_1 + W^2R_1(t)/4 + W^2(1 - R_2(t))/4 + W^2(1 - R_3(t))/4 + W^2(1 - R_4(t))/4\ ]/2W^2$$

where,
W = window area, x y = response histogram area;
A_1 = relative overlap for just the window pattern for discriminator 1.

For the general case of D discriminators, the response of discriminator i at time t+1 is given by :

$$R_i(t+1) = (1/2^N).[\ A_i + (1/D)(D-1 + R_i(t) - \sum_{j\neq i} R_j(t)\ ]^N$$

The confidence of discrimination of such a system can be related to confidence without response feedback. If the highest and next highest responses are produced by discriminators j and k, respectively, then the confidence without feedback (open-loop confidence) is given by :

$$1 - (A_k/A_j)^N$$

With response feedback, the closed-loop confidence is given by :

$$1 - (R_k(t)\ /\ R_j(t)) \text{ as } t \to \infty$$

The confidence improvement factor, I, is therefore given by :

$$I = (A_k/A_j)^N - (R_k(t)/R_j(t))/(1 - (A_k/A_j)^N)$$

With feedback, the responses are asymptotic and stabilise in tens of cycles.

For the case of a single discriminator system, the definition of confidence is slightly modified, such that it now defines the difference in response of a single discriminator to two different window input patterns. The above expressions still apply, but with j and k referring to window input patterns such that $R_j(t)$ is the response of the single discriminator with pattern j in the window and A_j is the relative overlap between pattern j and the window training pattern.

Figure 3 shows typical relationships between the connectivity N and the confidence improvement factor, I, with the number of discriminators D as a parameter. The maximum improvement is obtained when N = 2D. It can be seen from Figure 3 that the confidence improvement achieved by the method becomes insignificant for large groups of adaptive window operators and would therefore appear to have limited utility in any practical texture analysis system. However, it may be possible to apply response feedback to many small groups of adaptive windows in a hierarchical manner.

B. Enhanced Adaptive windows

A significant factor in the performance of adaptive windows to texture discrimination is that the occurrence frequencies of sub-patterns in any given texture are not taken into account. Thus, an adaptive window treats a single occurrence of a particular sub-pattern in a texture in exactly the same way as many occurrences. A major distinguishing feature of textures is the occurrence frequency of the constituent sub-patterns and it is therefore essential to modify the adaptive window to recognise this. This

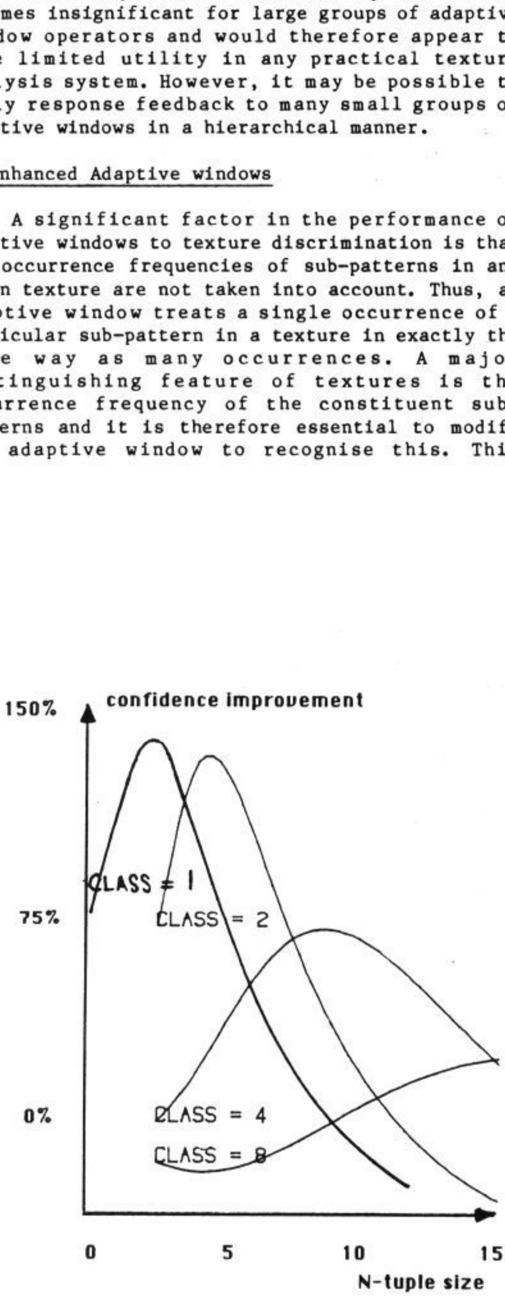


Figure 3. Confidence Improvement

involves a relatively straightforward change in the structure of the adaptive window. In the standard adaptive window, each location in a RAM consists of a single bit which can therefore indicate whether the particular input pattern to the RAM which selects that location has been seen zero or one times. In order to store occurrence frequencies of particular input combinations each RAM location in the enhanced adaptive window must be m bits wide. The maximum number of training patterns is therefore limited to 2^{m-1} in order to guarantee non-saturation, but in practice will normally be much higher. In order to train the adaptive window, the contents of RAM locations selected by the training pattern are now incremented rather than simply set to one.

The response of the enhanced adaptive window can be calculated in several ways. However, in the experiments reported here a very simple method is adopted which first of all, before any testing can take place, requires the calculation of the absolute maximum possible response. This is determined by finding, for each RAM, the highest value in any location. A summation of these highest values yields the maximum possible response value. Then, in testing, the output values from each RAM are summed to give the actual response, which can be divided by the maximum response to give the relative response.

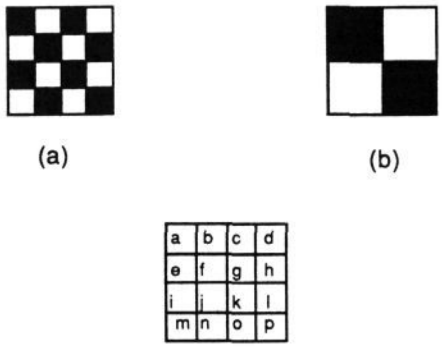
The enhanced adaptive window described here obviously addresses the problem of occurrence frequencies in textures, but also has several other advantages over the standard adaptive window. Standard adaptive windows are easily saturated when diverse training patterns are employed (as is indeed the case in complex textures) whereas even moderately sized enhanced adaptive windows would greatly improve upon this situation. Two further advantages of the enhanced window are its tolerance of noisy and erroneous (misclassified) patterns in the training set.

IV. DISCRIMINATION OF ISO-N^{TH}-ORDER TEXTURES

A. Order-Statistics and Connectivity

The ability of adaptive windows to discriminate textures on the basis of their n^{th} order statistical parameters has been studied. It would appear to be a reasonable conjecture that an adaptive window of connectivity n is capable of discriminating between textures which differ in the window area in their n^{th} order statistics. This of course introduces an idea of locality slightly different from that described in the literature. However, it will be shown here that the ability of an adaptive window of connectivity 2 to discriminate between textures which differ in their second-order statistics is not guaranteed and is dependent on the relationship between (random) connection mapping and the textures. Furthermore, increasing the connectivity of the window does not result in certainty of discrimination.

As an example, consider the two textures of Figure 4 a and b which have identical first-order statistics and differ in their second and higher orders. Figure 4 c describes possible connection mappings for three adaptive windows with connectivity N=2, 4 and 8. It can be shown that each of these windows, when scanned across areas of the above two textures, cannot discriminate between them. This is because if the window is trained on all possible positions in the texture of Figure 4 a, then, when scanned over an area of the texture of Figure 4 b, each RAM in the window will see a combination of bit values which it saw at some time during training. Thus, the response



Connections to each RAM

N=2 {a,f}{k,p}{d,g}{j,m}b,e}{l,o}{c,h}{i,n}
N=4 {a,f,k,p}{d,g,j,m}{b,e,l,n}{c,h,i,n}
N=8 {a,f,k,p,d,g,j,m}{b,e,l,o,c,h,i,n}

(c)

Figure 4. Two Textures and Connection Mappings which Result in their Non-discrimination

of each of the windows described will be a maximum everywhere in the two textures. This is in fact an extreme case where there is never a difference between the response to the two textures. For several other connection mappings, non-discrimination may occur in a few or perhaps just one position in a texture; this, however, still constitutes non-discrimination. Thus, it can be seen that there is no guarantee of discrimination between textures described by order statistics.

An analysis of the probability of non-discrimination between two textures follows.

B. Analysis

The total number of different connection mappings is S!, where S is the window size in pixels. We wish to establish the number of connection mappings which will result in non-discrimination, these being the mappings in which each RAM is entirely connected to the overlap area between a training pattern and a testing pattern. The overlap area between a testing pattern and a training pattern is defined as the set of pixels which have the same value in both patterns.

It is worth noting that from this a necessary but not sufficient condition for non-discrimination is that for a given test pattern the union of the overlap areas of that pattern with each training pattern must be the full window. This is obvious, as a single pixel which is outside any overlap area will have a different pixel value during testing than at any time during training, thus ensuring a degree of discrimination.

It is possible to calculate the number of connection mappings which will result in non-discrimination between a given set of testing and training patterns. For the above example textures, the training set consists of Figure 4 a and its inverse, whilst the testing set can consist simply of Figure 4 b as it can be shown that the overlap areas remain constant as the window is moved over the texture of Figure 4 b. In general, for two training patterns T_1 and T_2, and a single testing pattern X we define the exclusive overlap areas to be

$$A_1 = T_1 \cup X - T_1 \cup T_2 \cup X$$

$$A_2 = T_2 \cup X - T_1 \cup T_2 \cup X$$

$$A_{12} = T_1 \cup T_2 \cup X$$

and the number of pixels in these areas to be a_1, a_2, a_{12}, respectively. Each pixel in area A_{12} can be considered to be a potential contributor to T_1 or T_2 and yet must not be considered twice when enumerating the connection mappings. An approach to this problem is to define three new exclusive overlap areas a_1', a_2', a_{12}' where pixels are removed from A_{12} and added to A_1 and A_2 to ensure that a_1' and a_2' are multiples of N, the number of inputs to a RAM. This must by definition result in a_{12}' also being a multiple of N. All possible ways of achieving this situation must be accounted for.

Let $\quad d_1 = a_1' - a_1$

$$d_2 = a_2' - a_2$$

and thus the total number of ways of performing this redistribution is given by :

$$\binom{a_{12}}{d_1} \cdot \binom{a_{12}-d_1}{d_2}$$

The number of ways of permuting the connections of the RAMs inside a given area A_x is simply $A_x!$. Finally, the number of ways of assigning the RAMs to the areas is :

$$\binom{S/N}{a_1'/N} \binom{S/N-a_1'/N}{a_2'/N}$$

Thus, the total numbet of connection mappings which result in non-discrimination is given by the expression :

$$M = \binom{a_{12}}{d_1} \binom{a_{12}-d_1}{d_2} \cdot a_1'! a_2'! a_{12}'! \binom{S/N}{a_1'/N} \binom{S/N-a_1'/N}{a_2'/N}$$

For the specific case here,

$a_1 = a_2 = 8$ and $a_{12} = 0$

Thus, $a_1' = a_1 = a_2' = a_2$, $a_{12} = 0$ and

$$M = 8!8! \binom{16/N}{8/N}$$

The probability, P, of non-discrimination is therefore simply

$$P = M/(S!)$$

giving, for various values of N, the following results :

N	2	4	8
P	5.4×10^{-3}	4.6×10^{-4}	1.5×10^{-4}

These are of course rather small probabilities, but increase with increasing similarity between the test pattern and one or more of the training patterns. For more than two training patterns, the method of calculating the probability of non-discrimination is essentially the same but rather more complex.

V TEXTURE DISCRIMINATION BASED ON FIRST-ORDER STATISTICS OF TEXTONS

The objective here was to investigate the ability of adaptive windows to discriminate textures in comparison with the pre-attentive human visual system using the concept of textons as described by Julesz (1981). Textons are local conspicuous features such as line segments and line end points and Julesz shows that pre-attentive texture discrimination is based on first-order statistics (density) of textons and that indeed even second-order statistical parameters cannot be processed by the visual system. Figure 5 shows various 'micropatterns' used by Julesz who superimposed these micropatterns in a regular array over a section of a field of completely random black and white dots and investigated the efficiency of pre-attentive texture discrimination between the area containing micropattrens and the remaining area. We have repeated these experiments with both standard and enhanced adaptive windows with varying connectivity using exactly the same test data as Julesz. The micropatterns of size 4 x 4 pixels are repeated at a pitch of 8 pixels both horizontally and vertically, whilst those of 8 x 8 pixels are repeated at a pitch of 16 pixels. The micropatterns of Figure 5 a, b and e are relatively free of textons, whilst those of Figure 5 c, d, f and g are texton-rich. As an example of the use of micropatterns Figure 5 h shows four of the micropatterns of Figure 5 c towards the left of a random field.

Each texture pair formed by an area containing micropatterns and a completely random area have identical first-order statistics and different second-order statistics. Julesz found that several of these texture pairs could not be discriminated (Figure 5 a,b,e) whilst texture pairs formed using micropatterns of Figure 5 c,d,f and g could all be discriminated and in addition discrimination was found to be easier with the larger micropatterns. The micropattern in Figure 5 b does not have the same first-order statistics as noise, i.e., is more dense and yet was still not discriminated. The conclusion was therefore that the degree of discrimination is solely dependent on the richness of textons used in the texture.

In our experiments both standard and enhanced adaptive windows of 24 x 24 pixels in size were trained on randomly selected points in an area of periodic micropatterns on a white background. The test image is then constructed by replacing the white backgroud with noise generated using a particular random seed and the response of the adaptive window observed when scanned over the entire image of 256 x 256 pixels. The average response was then used to define a discrimination confidence level :

$$\text{confidence} = 100\% \times (P - F)/P$$

where P is the average response in the micropattern populated area and F is the average response in the micropattern free area.

For each texture pair this procedure was repeated 20 times with a different value of random noise seed to achieves a reliable result. Both the standard and the enhanced adaptive windows were trained on 50 randomly selected points, this being an arbitrarily chosen figure which, for the enhanced adaptive window, may easily be increased without risk of saturation.

Tables 1 and 2 show average discrimination confidence versus micropattern type and N-tuple size using standard and enhanced adaptive windows respectively.

N-tuple size	2	3	4	6	8
periodic(4x4)	0.00	0.02	0.17	2.34	6.14
dense periodic(4x4)	0.00	0.01	0.29	2.89	7.61
periodic bars(4x4)	0.00	0.01	0.30	4.75	10.85
diagonal(4x4)	0.00	0.04	0.50	5.89	14.59
noise(8x8)	0.00	0.01	0.06	1.40	2.52
perodic bars(8x8)	0.00	0.04	0.69	6.91	18.00
diagonal(8x8)	0.00	0.00	0.68	6.63	16.87

Table 1 : Average discrimination confidence for the standard adaptive window

N-tuple size	2	3	4	6	8
periodic(4x4)	0.42	0.97	2.07	4.69	8.57
dense periodic(4x4)	0.61	1.02	1.92	4.73	9.55
periodic bars(4x4)	0.46	1.12	2.30	5.92	10.48
diagonal(4x4)	0.78	2.28	4.38	9.88	18.64
noise(8x8)	0.09	0.14	0.29	0.95	0.35
perodic bars(8x8)	0.71	2.43	4.55	10.21	18.00
diagonal(8x8)	0.81	2.62	4.62	11.25	20.12

Table 2 : Average discrimination confidence for the enhanced adaptive window

The results show clearly the need for a fairly high connectivity in order to achieve reasonable confidence, indeed the standard adaptive windows with connectivity 2 and 3 were seen to be saturated. The adaptive windows were clearly able to discriminate between all texture pairs except for the pair using the ′noisy′ micropattern of Figure 5 e, in agreement with Julesz. Contrary to Julesz′s findings, the adaptive windows were able to discriminate the textures of Figure 5 a and b almost as well as the texture of Figure 5 c and the confidence for the small diagonal micropattern of Figure 5 d was superior to that for the vertical micropattern of Figure 5 c. The results for the large micropatterns of Figure 5 f and g are however consistent with those of Julesz. These results would tend to suggest that adaptive windows can perform superior texture discrimination to the pre-attentive human visual system, though of course further work in this area is necessary to confirm this.

VI TEXTURE DISCRIMINATION BASED ON RADIUS OF PERIODICITY OF TEXTONS

Different textures can be discriminated where it is not the structure of the micropattern which is important but the periodicity of the micropatterns in the textures. We have shown that adaptive windows can be applied to this type of texture discrimination operation. The method essentially consists in training the window at a particular point in the image and then scanning in a given direction until a maximum response is obtained or a radius limit reached. This is repeated for directions North, South, East and West and an average distance recorded. This can be repeated over an entire image either systematically or at random in order to produce a map of the micropattern periodicity radii in the image. Figure 6 a shows a 256 x 256 input image containing three areas of periodic micropatterns with radii of periodicity 4, 8 and 12 pixels along with an area of random noise. Figure 6 b shows the result of applying a 16x16 adaptive window as described above with the measure of periodicity represented as a grey scale. This method has proved successful, its only drawback being a finite width border between correctly identified textures in which unreliable measurements are produced. The width of the border between two areas with radii of periodicity R1 and R2 is

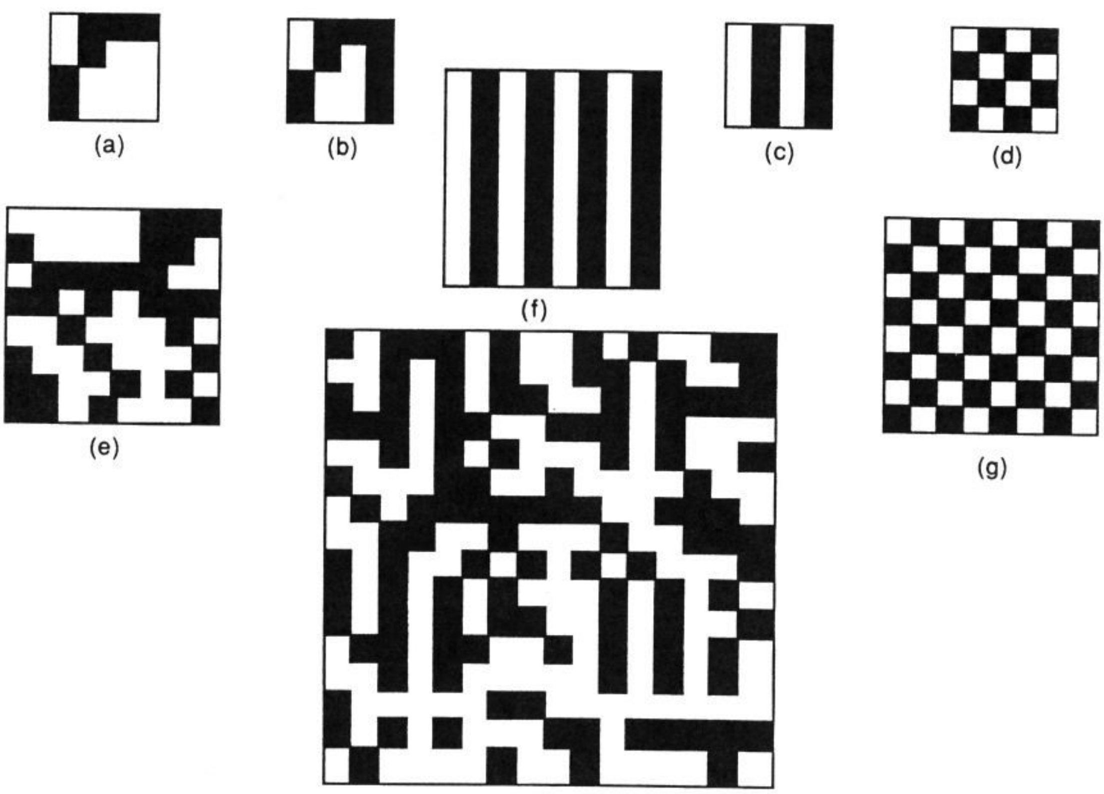


Figure 5. (a) to (g) Micropatterns Used in the Experiments
(h) Example of Micropatterns Embedded in Noise

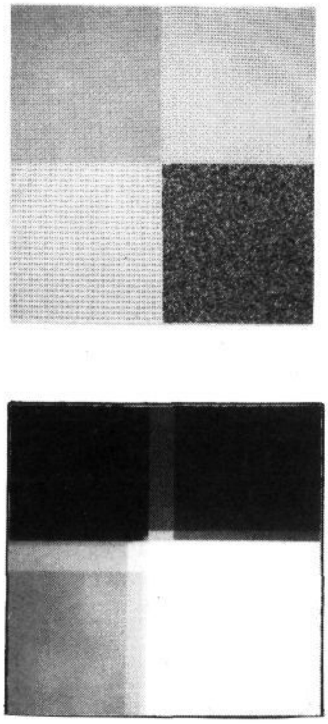


Figure 6. Micropattern Periodicity Radius Discrimination

simply given by :

window width + R1 + R2.

This border could possibly be removed by further adaptive window processing.

Combining the output of texton discriminating adaptive windows with the periodicity radii discriminating adaptive windows would produce a powerful texture discriminating system.

VII CONCLUSIONS

As adaptive window operators depend solely on training by example and not a formal mathematical description, they are completely general purpose and are especially useful in poorly defined image processing tasks such as texture discrimination. Our aim in this work has been to assess their capabilities and suitabilities for texture discrimination and to compare their performance with the natural vision system. The results of our experiments show adaptive windows to be, in fact, superior to the pre-attentive visual system in discriminating between textures. A modification to the adaptive window described previously has been presented which has several definite advantages and all indications are that an artificial vision system based on adaptive windows will be capable of sophisticated texture discrimination tasks.

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