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Noisy Binary Texture Recognition Using the Coordinated Cluster Transform

Reconocimiento de Texturas Binarias Ruidosas Usando la Transformada de Cúmulos Coordinados

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Abstract

In this paper a technique using the coordinated cluster representation (CCR) is examined for recognition of binary computer generated and natural texture images corrupted by additive noise. A normalized local property histogram of the CCR is used as a unique feature vector. The ability of the descriptor to capture spatial statistical features of an image is exploited. The evaluation criteria is the recognition performance using a simple minimum distance classifier for recognition purposes. The experimental results indicate that the proposed technique is efficient for recognition of textures deteriorated by high level additive noise. Textures under test run through periodic up to random ones.

Keywords: Pattern recognition, binary texture analysis, image representation, coordinated clusters.

Resumen

En este artículo se estudia una técnica, basada en la representación de imágenes por cúmulos coordinados (RICC), para el reconocimiento de imágenes binarias tanto de texturas naturales como aquellas generadas por computadora, las cuales fueron corrompidas por un ruido aditivo. El histograma normalizado de RICC es usado como vector único de características de la imagen. Se explota la habilidad del descriptor de captar las características estadísticas espaciales de una imagen. Como un criterio de evaluación usamos la eficiencia de reconocimiento usando un clasificador simple de distancia mínima para el reconocimiento. Se muestra que la técnica propuesta es eficiente para el reconocimiento de texturas deterioradas por el ruido aditivo. Se prueba la eficiencia del método en un rango amplio de texturas, siendo éstas desde puramente periódicas hasta completamente aleatorias.

Palabras clave: Reconocimiento de patrones, análisis de texturas binarias, representación de imágenes, cúmulos coordinados.

1 Introduction

One of the purposes of any pattern recognition technique is to carry out the classification of test images using a set of attributes extracted from pattern images. The problem is to establish a set of significant attributes that can be efficiently used in the classification. The set of features should obey the following requirements: they should be independent and the cardinality of the set should be minimal to facilitate computer manipulation. Feature extraction techniques can be classified into four major categories: statistical, model based, signal processing and structural (Tuceryan and Jain, 1993). After the attributes are chosen, textures can be classified using one of the well-known pattern classification methods (Duda *et al.*, 2001; Kahil and Bongard, 1970; Chen *et al.*, 1996; Fukunga, 1990; Servin and Cuevas, 1993)

Images of natural textures are difficult to classify or recognize due to the presence of statistic component in the intensity and/or color distribution of an image. In real experiments, one can find both full-periodic and random textures (Tuceryan and Jain, 1993; Haralick, 1979; Berry and Goutsias, 1989; Ohanian and Dubes, 1992). The well-known techniques of random, natural and artificial textures classification are mainly based on correlation moments and co-occurrence matrices, both approaches are time consuming (Haralick, 1979; Berry and Goutsias, 1989; Ohanian and Dubes, 1992; Elfadel and Picard, 1994; Soh and Tsatsoulis, 1999; Goon and Rolland, 1999; Chetverikov, 1999). Some techniques are based on Markov random fields (Chellappa and Chatterjee, 1987) and others on window transforms (Turner, 1986; Azencott y Wang, 1997; Wang and He, 1990; Ojala *et al.*,1996; Valkealahti and Oja, 1998; Randen and Husøy, 1999).

Recently a model for binary image representation called the coordinated cluster representation (CCR) was proposed in (Kurmyshev and Cervantes, 1996; Kurmyshev and Soto, 1996). In this model a binary image is characterized by a histogram of the occurrence of pattern units. The aim of this work is to evaluate the use of the histogram as a descriptor of textures. A simple minimum distance classifier using the unique attribute, a local property histogram generated by the coordinated cluster transform, is examined. We report the results when the CCR technique is applied to the recognition of a set of binary texture images degraded by noise. The CCR technique is based on binary images and, thus, they are of special interest to determine the limitations of the technique. In addition, it is well known that the results obtained with simulated images can differ from that for real images where the texture can be irregular and a noise has to be estimated or supposed. In experiments with simulated images we have total control over texture and, in particular, over a noise. Thus, experiments of this work have been implemented with binary simulated texture images on purpose. The paper is organized as follows. Section 2 describes briefly the coordinated cluster transform of binary images and its mathematical background. In Section 3 we outline an approach to binary texture image classification and recognition. The classification setup and experimental results for binary texture images are given in Section 4. Conclusions and directions of future work are given finally in Section 5.

2 Coordinated Cluster Transform

In order to avoid some complicated mathematical notations, we describe coordinated cluster transform in an algorithmic way. Let $S^{\alpha} = [s^{\alpha}_{lm}]$ be a matrix of binary image intensities (binary pixels) where $l = 1,2,\ldots,L$ and $m = 1,2,\ldots,M$, $W = L \times M$ and $\alpha = 1,2,\ldots,2^{W}$ is the binary image index. In order to calculate the CCR of a binary image S^{α} one needs first to establish a rectangular window of $N = I \times J$ pixels ($I \le L$ and $J \le M$) and then scan sequentially by means of this window all over the image S^{α} with one pixel step. Given a binary image S^{α}, the coordinated cluster transformation generates the histogram of occurrence of pixel patterns that the scanning window has detected. The binary number of pixel configuration is used as a code for the configuration found by the window. Because pixels are binary units, the number of all possible states of a window of the size $N = I \times J$ is equal to 2^{N}. This number determines the "length" of a primary histogram that can be reduced if one discards all the states with zero of occurrence while scanning an image. Thus, the coordinated cluster transformation assigns to each binary image S^{α} a histogram $H^{\alpha}_{(I,J)}(b)$ that represents the occurrence of window pattern, here α is the index of an image, the subscript (I,J) indicates the size of the scanning window and the variable $b = 1,2,\ldots,2^{N}$ is the code number of window states. It is clear that the total number of occurrences, that is the total area of the histogram, is equal to $A = (L - I + 1) \times (M - J + 1)$. The coordinated cluster transform belongs to the kind of window transforms with no information preserved over the scanning window position. When a histogram $H^{\alpha}_{(I,J)}(b)$ is normalized, it is considered as a distribution function of occurrences

$$F^{\alpha}_{(I,J)}(b) = \frac{H^{\alpha}_{(I,J)}(b)}{A}. \qquad (1)$$

The distribution function can also be interpreted as an image spectrum in terms of the texture units; those were originally called coordinated clusters, in order to outline some statistical properties of the transform. The texture units of CCR are conceptually and mathematically different from those introduced by Wang and He (1990) and Ojala *et al.* (1996) where a binary code is used for the gray level pattern description.

An example of 3×3 window patterns and their binary codes are shown in Figure 1, where the binary coded decimal (BCD) corresponds to the index in the CCR histogram (and also in the distribution function).

Pattern	Binary Code	BCD
	000001011	11
	001011001	89
	011001000	200

Figure 1: Window binary pattern and its binary coded decimal as the index of CCR histogram.

The fundamental properties of the CCR were established in the two theorems (Kurmyshev and Cervantes, 1996; Kurmyshev and Soto, 1996) that are given here in a modified form. The first theorem establishes the structure of the CCR of periodic images.

Theorem 1. If a texel (primitive cell) of a transnational invariant binary image S^{α} has the size $\tau_1 \times \tau_2$ pixels, τ_1 in one and τ_2 in other direction, then any CCR distribution function $F^{\alpha}_{(I,J)}(b)$ takes no more than $T = \tau_1 \times \tau_2$ non-zero values. If the CCR scanning window has the size equal to or larger than the texel size, $I \ge \tau_1$ and $J \ge \tau_2$, then $F^{\alpha}_{(I,J)}(b)$ takes exactly $T = \tau_1 \times \tau_2$ non-zero values.

The second theorem establishes the relation between $H^{\alpha}_{(I,J)}(b)$ and spatial correlation moments of n-th order (n-th order statistics) of a binary image S^{α}. According to the second theorem, the histogram $H^{\alpha}_{(I,J)}(b)$ contains all information about the n-point correlation moments of the image S^{α} if and only if the separation vectors between n pixels fit into the scanning window, that is a distribution function $F^{\alpha}_{(I,J)}(b)$ provides sufficient information about n-point joint probability functions.

Theorem 2. Let $S^{\alpha} = [s^{\alpha}_{lm}]$ be the matrix of a binary image and $F^{\alpha}_{(I,J)}(b)$ be the CCR distribution function of the image. If $\max\{l_i\} \le I$ and $\max\{m_i\} \le J$ $(i = 1,2,...,k-1)$ and $k \le I \times J$, then any autocorrelation function of *k-th* order

$$\langle s^{\alpha}(l,m)s^{\alpha}(l+l_1,m+m_1)...s^{\alpha}(l+l_{k-1},m+m_{k-1})\rangle =$$

$$\lim_{L,M\to\infty} W^{-1}\sum_{l,m=1}^{L',M'} s^{\alpha}(l,m)s^{\alpha}(l+l_1,m+m_1)...s^{\alpha}(l+l_{k-1},m+m_{k-1})$$

can be uniquely reconstructed from $F^{\alpha}_{(I,J)}(b)$, where $W = L \times M$ is the image size, $L' = L - \max\{l_i\}$, $M' = M - \max\{m_i\}$.

It is well recognized that the second and higher order joint probability density functions provide structural information about a gray level image, being the correlation moments a set of significant attributes for the classification of images (Liu and Jernigan, 1990; Thomson and Foster, 1997). On the other hand, there is a structural correspondence between a gray level image and its binarized analog. A binarized image keeps quite enough structural information about a primary gray level image to be classified. Thus, the CCR of a binary image, which preserves extremely well its structural information, is highly suitable for recognition and classification of gray level texture images having statistical properties in a wide range, from totally periodic to totally random textures included (Kurmyshev and Sánchez-Yáñez, 2001). The CCR of each image can be implemented in a bitwise-oriented algorithm, allowing a fast computation of each number representing the local binary pattern.

In order to preserve structural information of an image it is necessary to choose a CCR scanning window with a side approximately equal to or larger than the correlation distance between pixels. When a correlation distance is large, the scanning window has to be proportionally large too. Then the CCR histogram becomes rather large and complicated for computer management. One practical way to reconcile the two contradictory requirements (information preservation and manageability of CCR) is to reduce the scale of images to be classified.

3 Texture Pattern Recognition

In this work a set of noisy binary texture images was used to test the performance of the proposed recognition technique (see also Liu and Jernigan, 1990). We proceed in the following way. For a given set of binary texture images $S^p = [s^p_{lm}]$ $(p = 1,2,...,P)$, we generate a set of noisy images $\mathbf{B} = \{S^p(k,\alpha_p) = [s^p_{lm}(k,\alpha_p)]\}$ by adding a noise to these pattern textures. In this work we use particularly a uniform additive noise. Several images are generated for each *k-th* noise level (SNR value). If Δ is the difference between the two nearest noise levels, then the images $S^p(k,\alpha_p) = [s^p_{lm}(k,\alpha_p)]$ for the *k-th* noise level can be calculated as follows:

$$s^p_{lm}(k,\alpha_p) = \begin{cases} s^p_{lm} & \text{if } rand < 1 - k\Delta \\ 1 - s^p_{lm} & \text{otherwise} \end{cases} \tag{2}$$

where α_p indicates the $\alpha_p - th$ seedling of noise to be added to S^p, $k = 0,1,2,..., K < \mathrm{int}(1/\Delta)$ and *rand* is the random number generator function with uniform distribution in the range (0,1). When $k = 0$, the image generated by the Eq. (2) coincides with the original pattern texture, $S^p(0,\alpha_p) = S^p$. After the set **B** is generated, the coordinated cluster transform is used to calculate the histograms $H^p_{(I,J)}(k,\alpha_p;b)$ corresponding to each $S^p(k,\alpha_p)$.

The closeness of the test texture to one of the pattern textures is calculated using the Hamming distance in the CCR space. The Hamming distance between two images S^{α} and S^{β} is defined as follows:

$$d_{(I,J)}(S^{\alpha},S^{\beta}) = \sum_{b=0}^{2^N-1} \left| H^{\alpha}_{(I,J)}(b) - H^{\beta}_{(I,J)}(b) \right|, \tag{3}$$

where the index *(I,J)* indicates the scanning window size of the CCR and $N = I \times J$. Given a pattern texture $S^p = [s^p_{lm}]$ $(p = 1,2,...,P)$, the class corresponding to the texture S^p is defined as the set of images S^{α} such that

$$d_{(I,J)}(S^{\alpha},S^p) = \min_{p'}\left[d_{(I,J)}(S^{\alpha},S^{p'})\right] \quad (p' = 1,2,...,P). \tag{4}$$

It is clear that the distance rule assigns an image S^{α} to the pattern class S^{p} if and only if the CCR histogram of S^{p} is the most similar to that of S^{α}. Thus, it is declared that the noisy texture image $S^{p}(k,\alpha_{p})$ belongs to the class S^{p} if the following equation is valid:

$$d_{(I,J)}\left(S^{p}(k,\alpha_{p}),S^{p}\right)=\min_{p'}\left[d_{(I,J)}\left(S^{p}(k,\alpha_{p}),S^{p'}\right)\right]\quad (p'=1,2,\ldots,P). \tag{5}$$

If the noisy texture image $S^{p}(k,\alpha_{p})$ is assigned to the class S^{p}, then the recognition is considered to be correct. When the noise level is high enough, the last condition is not satisfied and the noisy texture is not recognizable.

4 Experiments

In order to test the technique we applied it to the recognition of $P=20$ different binary pattern textures S^{p} $(p=1,2,\ldots,P)$. Each pattern texture was computer generated by reproducing a 5×5 random bitmap window (texel) periodically. The image resolution was 100 x 100 pixels. Consequently, the generated pattern textures are random locally and periodical in total. A set of six computer generated pattern textures is shown in Figure 2.

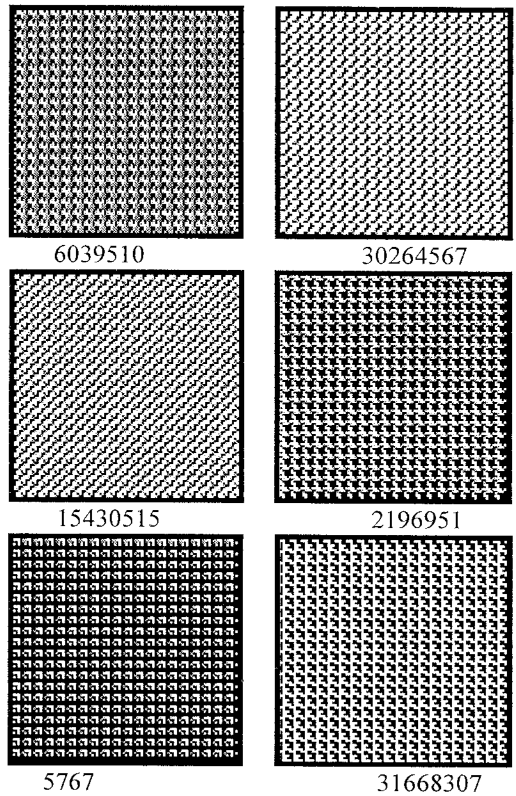


Figure 2: A subset of six sample textures that were computer generated by using a 5×5 texel and the binary coded decimal of respective texels.

The test texture database **B** was generated by adding to each pattern texture S^{p} an uniform noise of different levels $k=0,1,\ldots,20$, starting from 0 % noise until reaching the 100 % noisy image. For this purpose we take $\Delta=0.05$ and $\alpha_{p}=1,2,\ldots,10$ (see Eq. (2)). Thus, in each recognition test for a given noise level k, a set of 200 test texture images is formed by $P=20$ groups of 10 noisy texture images $S^{p}(k,\alpha_{p})$.

Following the scheme represented in Section 3, we then calculate the CCR histogram for each noisy test texture from database **B**. A 3×3 scanning window was used, so that each histogram $H^{p}_{(3,3)}(k,\alpha_{p};b)$ ($p=1,2,\ldots,20$; $k=0,1,\ldots,20$; $\alpha_{p}=1,2,\ldots,10$; $b=1,2,\ldots,2^{9}$) demonstrates the occurrence of $2^{3\times 3}=512$ possible states of the scanning window. The recognition was accomplished using Eq. (5). Figure 3 shows a set of histograms corresponding to the sample texture 5767 degraded by different level noise. As an example, six different texture images used for classification are shown in Figure 4. In this case, the noise added to each sample texture is 30 % ($k=6$ and $\Delta=0.05$). These were classified successfully in spite of high-level noise.

We define the recognition efficiency, for a given noise level k, by the following expression:

$$R=\frac{N_{k}}{10P}\times 100\%, \tag{6}$$

where $10P$ is the total number of test textures with noise level k, N_{k} is the number of noisy textures with noise level k that were correctly recognized. In terms of the recognition efficiency, the final recognition results are shown in the figure 5. This graph shows the recognition efficiency against noise level. From figure 5 we can see that, in the experiments described above, 100% recognition was achieved in all cases of textures degraded up to 30% by additive uniform noise.

In addition, figure 5 shows an interesting phenomenon of recognition revival for textures with the noise level above 60%. The explanation of the phenomenon as follows. First, note that each primary binary texture under the test S^{p} is the periodic translation of a random texel. Second, from the equation (2) we see that the additive uniform noise used in this work changes the binary value of each pixel in accordance to the noise level k for a given Δ. A primary image is slightly degraded and well recognized when $k \leq 6$. Instead, when noise increases, $6 \leq k \leq 10$, the image is degraded strongly and recognition decreases to zero. Nevertheless, if noise level is higher, say $10 < k \leq 20$, then for the kind of noise used in this work most of pixels have to change their values and some textures are reconstructed partially. The level of reconstruction depends on the regularity of the primary texture. For example, the chessboard image is reconstructed completely. The CCR histogram senses this reconstruction, giving rise to the recognition of the pattern. Note that 100% noise means a negative texture that is not identical to the original positive texture but can have certain morphological similarity to that.

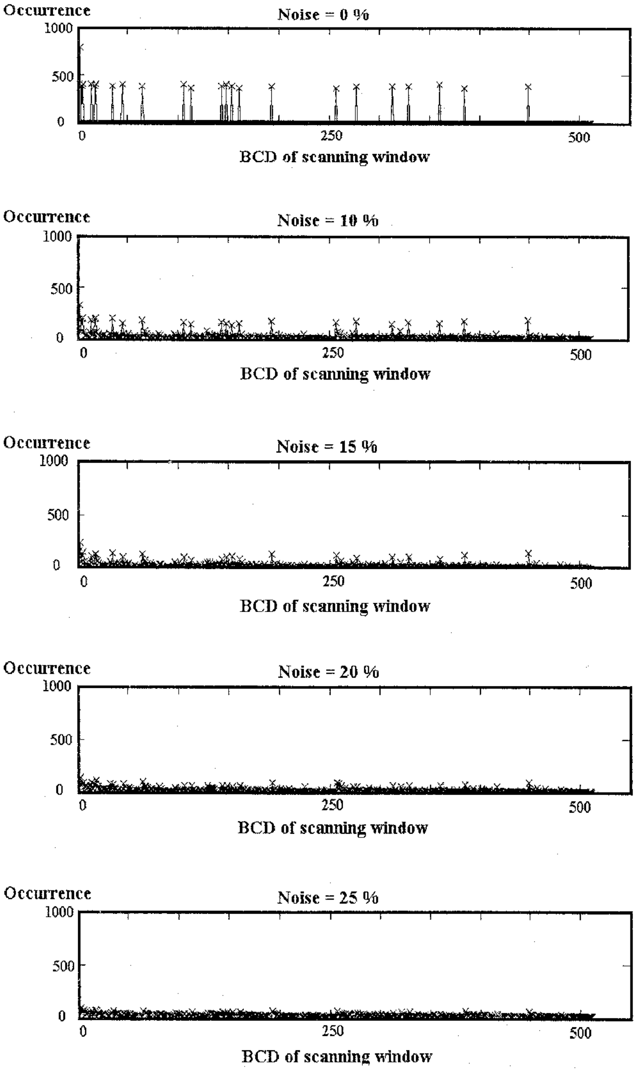


Figure 3: A set of five CCR histograms corresponding to the sample texture 5767 degraded by different level noise.

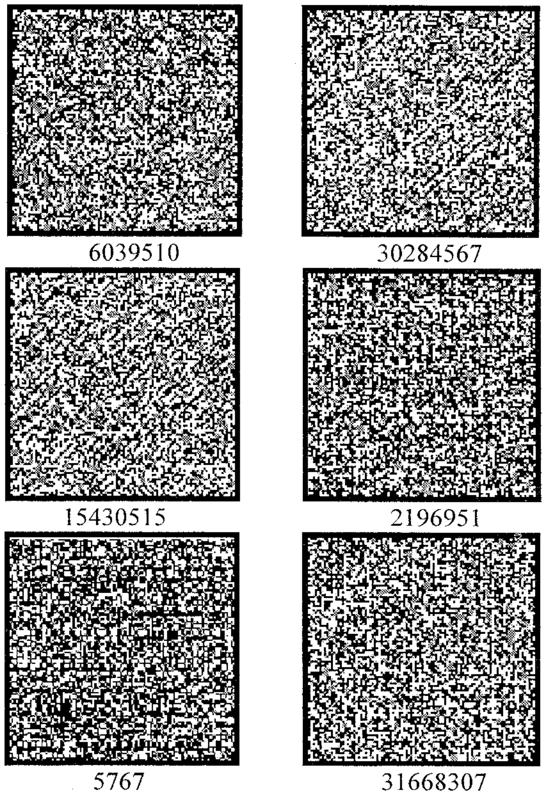


Figure 4: Texture images degraded by 30% noise, those have been correctly classified by the CCR technique.

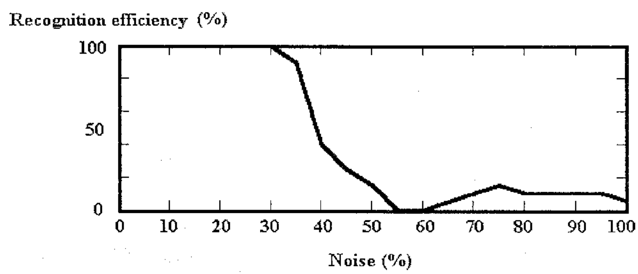


Figure 5: Recognition efficiency versus noise (computer generated textures).

In the second experiment, just the same classification technique was evaluated using ten binarized subimages from the Brodatz album (Brodatz, 1966) corrupted by uniform noise. To prepare prototype database we have scanned gray level images D9, D16, D32, D68, D77, D78, D79, D92, D93 and D112. Ten binarized subimages of 100 x 100 pixels, S^p ($p = 1,2,\ldots,10$), are used in the experiment as the reference set. They are shown in Fig. 6. A test texture database **B** is generated by adding to each of ten binary textures S^p a uniform noise by Eq. (2). In each recognition test for a given noise level k, a set of 100 test texture images is used. That is formed by $P = 10$ groups of 10 noisy texture images $S^P(k, \alpha_p)$, where $\alpha_p = 1, 2, \ldots, 10$. A 3×3 scanning window is used to calculate the CCR histograms.

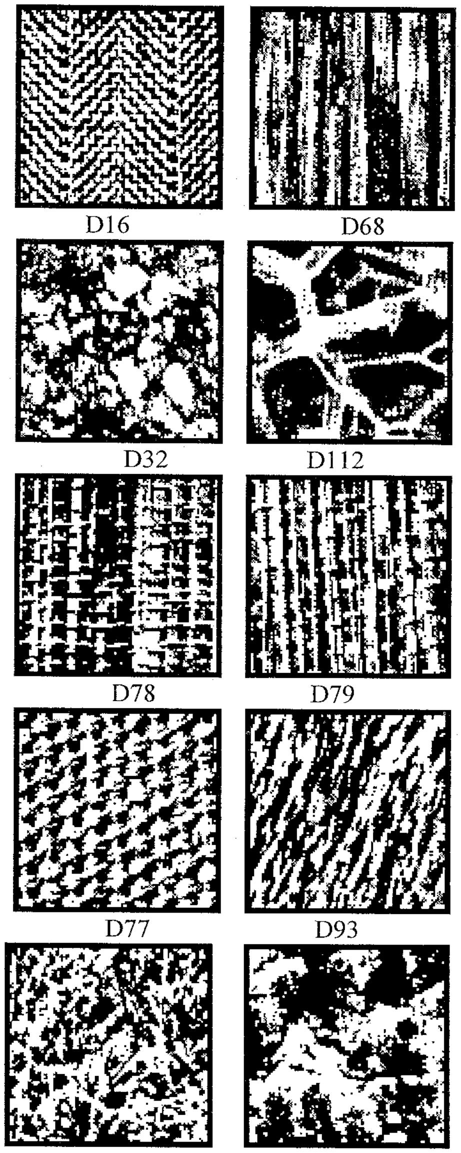
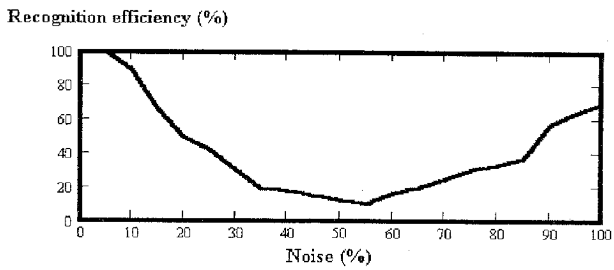


Figure 6: Binarized Brodatz images used to evaluate the CCR technique.

Figure 7 shows that the recognition efficiency of Brodatz natural textures versus noise decreases as compared to that of computer generated textures of Fig. 5. The 100% recognition was achieved for all textures degraded up to 5 % by additive noise. This is an expected result because artificial textures of Fig. 2, being periodical, have a narrower statistical distribution in the CCR feature space than that of Brodatz textures. In addition, figure 7 shows the phenomenon of recognition revival for textures with the noise level above 55%. The explanation of the phenomenon is just the same as for the computer-generated textures. Note that images of Fig. 6 are ordered, from left to right in line order, to follow from the best recognizable to the worse. That is the D92 has failed first to be recognized at the 10% noise, D9 and D93 failed at the 15% noise. Finally, the D16 have failed at 40% noise. That means a particular texture can be extremely robust to the uniform noise and can be recognized up to 35% noise.

Figure 7: Recognition efficiency versus noise (binarized Brodatz



textures).

5 Conclusions

A method for recognition and classification of binary texture images has been discussed and its application to recognition of texture images degraded by additive uniform noise has been evaluated. One of the available classifiers is used in the CCR feature space in order to assign an image to the category whose prototype it matches best. The CCR histogram is used as the unique attribute for recognition of a binary image. The capacity of the coordinated cluster representation to capture spatial statistical features of an image is exploited. In this paper, the simple minimum distance classifier is used.

Two kinds of class prototype images were used, computer generated and natural binary textures. Even though in this work the binary textures, the small 3×3 scanning window for the coordinated cluster transform and very simple (minimum distance) classification criteria were used in order to test the method for recognition of noise degraded binary images, the performance of the method is highly promising. 100% recognition was achieved for some binary test images degraded by uniform noise up to 30%. As shown in (Kurmyshev and Sánchez-Yáñez, 2001; Sánchez-Yáñez *et al.*, 2003; López and Castro, 2002), the combination of the binarization and CCR of textures characterizes the gray level images successfully. Thus, the technique exploited in this work is expected to be adequate for the recognition of real gray level images degraded by noise, for example, in medical imaging where the images used to be noisy.

Future work should be done to extend the method for gray level and color texture images, to analyze and improve the performance of this recognition method when it is used with different size of scanning windows and other classifiers for images degraded by different type of noise.

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