The acceleration algorithm was also tested in the presence of noise. The image was corrupted by additive Gaussian noise with unit variance. Fig. 3 shows the MSE between the original and restored image, and occurs after 201 unaccelerated iterations or 19 accelerated iterations, a speedup of 10.6 times.

An analysis of the MSE curves for several different images and PSFs, shows if an unaccelerated restoration requires N iterations then the equivalent accelerated restoration requires O(N/√N) iterations. In the example presented a restoration with N0 unaccelerated iterations is equivalent to Nα accelerated iterations with

\[ N_A = 1.5\sqrt{N_I} - 1 \]  

Conclusion: The acceleration of the convergence of the iterative R-L restoration algorithm has been investigated. A conjugate gradient technique with an MMSE criterion has been used to accelerate the convergence of the R-L image restoration algorithm. The acceleration method is simple to calculate and produces significantly higher levels of acceleration than previous methods.

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Genetic-based fuzzy hit-or-miss texture spectrum for texture analysis

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Indexing terms: Genetic algorithms, Texture (image processing)

A new method using a fuzzy hit-or-miss transform recognition procedure, which measures degrees of fit of specified patterns within an image, is proposed for texture analysis. For a given texture, three optimal texture patterns (structuring elements) dynamically generated by genetic algorithms are used to inspect the degrees of fit by using the fuzzy hit-or-miss transform, respectively. The distribution of these degrees of fit, converted into a texture spectrum, is used as the texture feature for texture analysis.

Introduction: Texture analysis is one of the important techniques in image processing. The major problem of texture analysis is the extraction of texture features. The general methods for feature extraction are to estimate local features at each pixel in a texture image, and then derive a set of statistics from the distributions of the local features. The surveys and comparisons of different methods for feature extraction can be found in [1, 2].

A new method for texture feature extraction based on fuzzy theory is presented. Fuzzy set theory [3] is a mathematical tool in modelling ambiguity or uncertainty and has been applied to texture analysis [4]. In texture analysis, we define the 'fuzzy hit-or-miss transform', which ranges from 0 to 1, for a block B in the texture as the degree of fit to a given specified structuring element (SE). Therefore, we can transform a gray-scale image into a fuzzy image by using the transform. The fuzzy image membership distribution, denoted as the fuzzy hit-or-miss texture spectrum (FHMTS), is then used as a distinguishing feature for texture analysis. For texture classification, the selection of the SE is important since the size and content of the employed SE for input texture determines the accuracy of texture classification. To gain a superior accuracy rate of texture classification, we use genetic algorithms (GAs) to dynamically generate three optimal SEs according to the characteristics of input texture.

Fuzzy hit-or-miss texture spectrum: The fuzzy hit-or-miss transform [5] is difficult to apply in gray-scale images. Therefore, thresholding for gray level texture images into binary images is necessary in our application and the following procedure is used: if \( f(x, y) > \mu \) then \( f(x, y) = 1 \) otherwise \( f(x, y) = 0 \), where \( f \) is the gray level image, \( \mu \) is the mean value of \( f \), and \( g \) is the output binary image. Let \( g^x(x, y) = 1 - g(x, y) \) be the dual template of \( g \); the fuzzy hit-or-miss transform is defined as

\[ [f \oplus (g, y)](x, y) = \psi[a(x, y), b(x, y)] \]

where \( \psi \) is a real-valued function (here, average operator is used) such that \( \psi(0, x, y) = 0 \), and \( \psi(a, x, y) = 2a + f \oplus g \) where \( g(x, y) = 2(2a + f \oplus g) \) where the operator \( \ominus \) is the morphological erosion [6] and \( \oplus \) is the complement of binary image \( f \). \( A_g(x, y) \) and \( A_g^+(x, y) \) are the area (number of pixels) of the template \( g \) and \( g^+ \), and \( D_g \) are the domains of \( g \) and \( g^+ \).
The fuzzy hit-or-miss transform can be considered as a pattern matched degree filter. It allows both for partial and exact occurrence of the dual templates $g^*$. Therefore, we use the fuzzy hit-or-miss transform to analyse textures in our experiments. In a fuzzy image, the member with fit value 0 represents the corresponding subimage being the complement of the $SE$. I represents the corresponding subimage being the same with the $SE$. The greater the fit value, the more a given pattern is revealed.

To analyse a texture image, we transform it into its corresponding fuzzy image using eqn. 1. As the value in the fuzzy image represents the local aspect, the statistics of these values in the fuzzy image should reveal its texture information. The occurrence distribution of these values is the FHMTS, with the abscissa indicating the degree of fit and the ordinate representing its frequency occurrence. To evaluate the performance of the extracted feature by using the proposed method, we calculated and compared the FHMTS for two Brodatz textures D54 and D77 [7]. The two textures are shown in Fig. 3 (f) and (g) and their corresponding FHMTS are displayed in Fig. 1. From Fig. 1, we find that the measured FHMTS are distinguishable from each other so they can serve as a good discriminating tool in texture classification. The FHMTS of D54 shows a higher frequency than D77 when the measured degree of fit is close to unity, so that the texture image D54 contains more $5 \times 5$ square patterns than D77.

![Fig. 1 FHMTS of textures of D54 and D77](image)

Genetic-based structuring elements and texture classification: To obtain a superior accuracy rate in texture classification, three optimal $SE$s, which are dynamically generated by GAs [8] according to the input testing texture, are used to compute the FHMTS. To demonstrate the discrimination performance of the GA-based FHMTS, we use a supervised classification with minimum distance rule to classic nature images, extracted from the Brodatz album. Eight $256 \times 256$ natural images with $256$ grey-levels are used for the texture classification (see Fig. 3). Each texture image is divided into $16$ nonoverlapping $64 \times 64$ subimages.

In the training phase, we randomly select a $64 \times 64$ block from each texture image for GAs training cycle to generate three optimal $SE$s and prototype texture spectra. The representation scheme is to encode a $5 \times 5$ square into a gene string raw by raw sequentially and a $25$-length gene string is obtained. Three different fitness functions and a two-point crossover method are employed since three optimal $SE$s are used in our experiments. The three fitness functions are defined as follows:

$$ fit_1(g_m) = \inf D(S_{m_i}^l, S_{m_j}^l) $$

for $i, j = 1, 2, \ldots, K$ and $i > j$ \hspace{1cm} (2)

$$ fit_2(g_m) = \frac{2}{K(K-1)} \sum D(S_{m_i}^l, S_{m_j}^l) $$

for $i, j = 1, 2, \ldots, K$ and $i > j$ \hspace{1cm} (3)

$$ fit_3(g_m) = \sup D(S_{m_i}^l, S_{m_j}^l) $$

for $i, j = 1, 2, \ldots, K$ and $i > j$ \hspace{1cm} (4)

where $S_{m_i}^l$ is the spectrum of texture $j$ by using structuring element $g_m$, where $m = 24$ is the size of the population, $K$ is the number of texture type and $D(S_{m_i}^l, S_{m_j}^l)$ is the Hamming distance between $S_{m_i}^l$ and $S_{m_j}^l$. The Hamming distance is defined as

$$ D(S_{m_i}^l, S_{m_j}^l) = \frac{1}{L} \sum_{k=1}^{L-1} |S_{m_i}^l(k) - S_{m_j}^l(k) | $$

where $L$ is the uniformly quantised levels of the degree of fit values (range from 0 to 1) in a fuzzy image and 25 levels are used in our experiments to reduce the calculation time for the pursuit statistics. By iterative running of the evolution cycle, gene strings are updated and the performance is gradually improved. The cycle terminates when all gene strings no longer change, i.e. the gene strings converge. The constructed three optimal $SE$s according to the input eight texture images are displayed in Fig. 2.

![Fig. 2 Three optimal $SE$s obtained from different fitness functions](image)

Conclusion: A new method using GAs and FHMTS has been proposed for texture analysis. In this method, the local texture feature for a given block is characterised by its corresponding degree of fit, and the global texture aspect of an image is revealed by its texture spectrum. Promising results have been obtained with an accuracy classification rate of 96.9% by using three optimal basic $SE$s. From the experimental result, we conclude that the GA-based FHMTS is an excellent discriminating tool in texture analysis and classification.

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Improved discrete cosine transform picture coding by utilising extended Hamming codes

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Indexing terms: Discrete cosine transforms, Hamming codes, Image coding

Introduction: The quality of received DCT coded pictures drops when the channel becomes noisy. A number of approaches to the enhancement of the transform coding method have appeared in the literature [1, 2]. In this Letter, to combat the channel errors, the extended Hamming codes are utilised.

New approach: Consider an \((n,k)\) Hamming code and its extended version \((n+1,k)\). Let \(d_{can}\) and \(d_{mem}\) denote the minimum distances of the codes, respectively. It is known that \(d_{can} = d_{mem} + 1\) [3]. The extended Hamming code is superior in terms of error detection capability, it can correct all patterns of \(d_{can}/2\) errors and simultaneously detect all patterns of \(d_{mem}/2\) errors. In our approach, once an error is detected, the value of the coded coefficients is replaced with the average of the same coefficient in the horizontal and vertical directions. This is possible because the low-order DCT coefficients (such as \(X(0,0), X(0,1), X(1,0)\) and \(X(1,1)\), where \(X(n_1,n_2)\) is the DCT of image \(x(n_1,n_2)\)) vary slightly on a block to block basis.

Results: In the simulations, images were compressed at the rate of 1 bit/pixel. Fig. 1 demonstrates that the use of an \((8,4)\) extended Hamming code is superior to the use of parity or a \((7,4)\) Hamming code when the error rate is >0.01. At an error rate of 0.03, the system employing \((8,4)\) is >7dB superior to the uncodded system.

Conclusions: The use of extended Hamming codes for error protection of DCT coded images results in a larger picture SNR compared to the use of Hamming codes.