Neural Network-Based Image Texture Classification Using Gabor Filter Bank

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1- Introduction

Texture analysis is important for many applications such as content-based image retrieval and scene analysis. Research on the subject has been active for decades. An image can be considered as the combination of different texture regions, and the image features associated with these texture regions can be used for searching and retrieving the image data. In order to make this practical, one need to address issues that involve both image feature extraction for texture analysis and efficient indexing structure design for data management. If want to address some utility of texture analysis, we must offer to:

- Shape from texture is a problem in which estimates of the surface orientations of planar curved surfaces are obtained. This work focuses on the estimation of a planar surfaces inclination from a monocular perspective point of view [2]. Perspective projection causes similar surface properties at different depths to appear with different scales in the projected image.

- Texture is a surface property that can be used for object classification and recognition. Orientation is one of the features that humans use in differentiating textured regions. Texture analysis methods are applied to model the variety of coarse to fine or hierarchically ordered image-structures typical for the surface quality. Since synthetic surfaces are often manufactured in the form of band material with high speeds, the time constraints to inspection algorithms are very strict.

- With the restriction to a set of known textures, retrieval and segmentation problems are essentially reduced to a supervised classification task, which is amenable for standard techniques from pattern recognition and statistics.

- Classification of texture in microwave imagery

2 - Texture

We recognize texture when we see it but it is very difficult to define. The number of different texture definitions demonstrates this difficulty. Coggins has compiled a catalogue of texture definitions in the computer vision literature and we give some example here:

- Its structure is simply attributed to the repetitive patterns in which elements or primitives are arranged according to a placement rule.
- A region in an image has a constant texture if a set of local statistics or other local properties of the picture function are constant, slowly varying, or approximately periodic.
- Texture is an apparently paradoxical notion.
- Texture is defined as an uncounted primary image.
- Texture is defined for our purpose as an attribute of a field having no components that appear enumerable.

This collection of definitions demonstrates that the definition of texture is formulated by different people depending upon the particular application and that there is no generally agreed upon definition. The fact that the perception of texture has no many different dimensions is an important reason why there is no single method of texture representation, which is adequate for a variety of textures.

2-1 Statistical methods
Image texture, defined as a function of the spatial variation in pixel intensities. The use of statistical features is therefore one of the early methods proposed in machine vision literatures.

2-1-1 Co-occurrence Matrices
Texture information is assumed to be contained in the overall, or average, spatial relationship among gray levels for a particular image. Of primary importance to this work, this spatial relationship is considered to be the covariance of pixel values as a function of distance between pixels (First order statistics). Such textural information can be extracted from an image using gray-tone spatial –dependence matrices or co-occurrence matrices. [14].
Spatial gray level co-occurrence estimates properties related to second-order statistics. This matrix P_d for a displacement vector $\vec{d} = (dx, dy)$ is defined as equation 1:

$$P_d(i,j) = \left| \{(r,s),(t,v); I(r,s) = i\} \right| \ I(t,v = j) \right| \qquad [1]$$
$$(t,v) = (r + d_x, s + d_y)$$

The entry (i,j) of P_d is the number of occurrence of the pair of gray levels i and j which are a distance d apart. Harlick has proposed a number of useful texture features that can be computed from the co-occurrence matrix. For this method, five most popular textural features namely standard deviation, contrast, correlation, entropy and homogeneity, were calculated and used to form the feature vector for each image block. Table 1 lists some of these features. As we know, the limitation of this matrix is on selecting the displacement vector d.

Energy: $\sum_i \sum_j P_d^2(i,j)$ Homogeneity: $\sum \sum \dfrac{P_d(i,j)}{1 + |i - j|}$

Entropy: $-\sum\sum P_d(i,j).\log P_d(i,j)$ Contrast : $\sum\sum(i-j)^2 P_d(i,j)$

Correlation : $\dfrac{\sum\sum(i-\mu_x)(j-\mu_y)P_d(i,j)}{\sigma_x \sigma_y}$

Table 1. Some textures features extracted from co-occurrence matrix

2.1.2 Spatial Autocorrelation: The Semi-Variogram

An important property of many textures is the repetitive nature of the placement of texture elements in the image. The autocorrelation or semivariogram function of an image can be used to assess the amount of regularity as well as the fineness/coarseness of the texture present in the image.

Semivariogram functions are compared to co-occurrence matrices for classification of digital image texture [14]. Let the gray levels comprising a given digital image be represented as G (x, y). Then the variogram for these gray levels is written as 2:
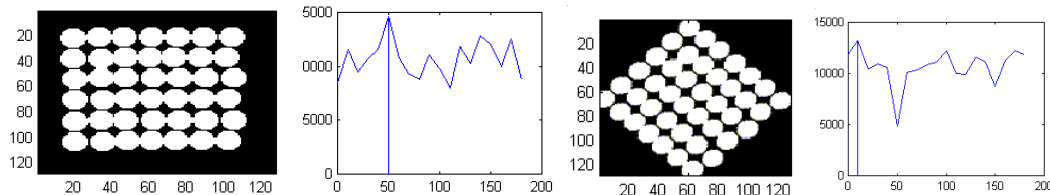
$$2\gamma(h) = \int_x \int_y \left[G(x,y) - G(x',y') \right]^2 dydx \qquad [2]$$
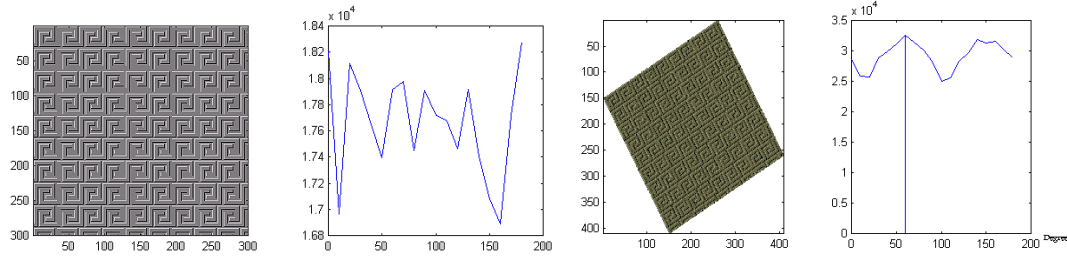
in which *h* is the Euclidean distance between the pixel value *G* as row *x*, pixel *y*, and the pixel value *G* at row *x'*, pixel *y'*. Note that the value of the semivariogram increase as h increase. This is the anticipated behavior if image pixels are spatially correlated pixels located closer together are more similar in value than pixels spaced farther apart. This change in semivariogram with increasing h is the statistical signature that is relied upon for classifying texture.

The autoregressive model and its various extensions are linear models and have been popular for some time. Many real-world images, especially textures, contain long-range and nonlinear spatial interaction (correlation) that often can only be adequately captured by high-order models. The basic idea here is that the correlation lengths in the lower-resolution tend to be smaller than that in the original fine resolution image.

The autocorrelation function is also related to the power spectrum of the Fourier transform [4].

$$f_{r1,r2} = \int_0^{2\pi} \int_{r_2}^{r_1} |F(r,\theta)|^2 dr.d\theta \qquad , f_{\theta_1,\theta_2} = \int_{\theta_1}^{\theta_2} \int_0^{R} |F(r,\theta)|^2 dr.d\theta$$

$$r = \sqrt{u^2 + v^2} \qquad , \theta = Tg^{-1}\frac{u}{v}$$

The position of the peak indicates rotation angle and scale rate.

2.2 Model Based Methods

Model based textures analysis methods are based on the construction of an image model that be used not only to describe texture, but also to synthesize. The Random Field Models and Fractal have been popular for modeling images [16].

2.3 Signal Processing Methods

Visual system operates in a combined frequency-position space, where the operators can be well describe by localized frequency descriptors. The importance of phase in image representation was previously demonstrated in the context of a global (Fourier) transformation. In vision where processing is accomplished by signal decomposition into localized elementary functions in the combined frequency-position space, there exist mechanisms (cortical cells) which exhibit sensitivity to localized phase relationship. These finding have motivated out study of image representation by localized phase; a representation, which we call Phasogram. [7]

2.3.1 Spatial Domain Filters

Earlier attempts at defining such methods concentrated on measuring the edge density per unit area. Fine textures tend to have a higher density of edges per unit area than coarse textures. Simple edge masks such as the Robert's operator or the Laplacian operator usually compute the measurement of edgeness. (Gonzalez; 1993). Another set of filters is based on spatial moments. The (p+q) th moments over an image region R are given by the formula:

$$m_{pq} = \sum_{(x,y)\in\Re}(x-\mu_x)^p(y-\mu_y)^q.I(x,y)$$

2.3.2 Gabor Models

The Gabor transformation is a biologically inspired transformation, which may be used to transform raw input data that encodes the pattern for further classification. Biological visual systems, in particular the simple cells of the visual cortex, employ localized frequency signature similar to those obtained from Gabor operations.

The Fourier transform representation, which expresses the image in terms of sine's and cosines, provides only frequency domain information. It gives the spatial periodicity of the image belonging to a given frequency but loses all measured of locality. Gabor filters perform a local Fourier analysis and exhibit excellently discrimination properties.

$$F_w(u,\xi) = \int_{-\infty}^{+\infty} f(x)\overline{g(x-\xi)}e^{-j2\pi ux}$$

The precision to which a function can be specified is limited by an uncertainly principal. It turns out that the minimum uncertainly is achieved when the spatial term, $g(x)$, is a Gaussian window, leading to the definition of a one-dimensional Gabor function.

Filters such as Gabor filter, which are localized and tunable in both frequency and orientation have been generally accepted as good approximation for the behavior of simple cells. While many functions may be used for multiresolution space-frequency analysis, Gabor functions are particularly well suited since they achieve the theoretical minimum space-frequency bandwidth (minimum uncertainly) product. As filters, they provide optimal spatial resolution for a given bandwidth.

Gabor filters can be also described in terms of a sinusoidal plane wave of some frequency and orientation within a two-dimension Gaussian envelope in the spatial domain or shifted Gaussian functions in the spatial frequency domain. *2D* Gabor function $h(x, y)$ centered at frequency (u_0, v_0) is given by:

$$h(x, y) = g(x, y)e^{-2\pi j(u_0 x + v_0 y)} \qquad\qquad [3]$$

where: $g(x, y)$ is a symmetric Gaussian of the form: $g(x, y) = \exp\left\{\dfrac{-1}{2}\left(\dfrac{x^2}{\sigma_x^2} + \dfrac{y^2}{\sigma_y^2}\right)\right\}$

and σ_x, σ_y are the standard deviation of the Gaussian envelope along the x and y directions, respectively, which can be expressed in the polar form (f, θ), where,

$$f = \sqrt{u_0^2 + v_0^2}\ ,\ \theta = \tan^{-1}(\frac{v_0}{u_0})$$

In effect the convolution represents the sum of the product of each picture element in a window that is the size of the filter with a corresponding filter values. A 2D Gabor filter works as a band pass filter for the local spatial frequency distribution, achieving an optimal resolution in both spatial and spatial-frequency domains[6]

The frequency domain representation of a Gabor filter is a Gaussian of the two dimensional spreads given by:

$$\sigma_u = \frac{1}{2\pi\sigma_x}, \sigma_v = \frac{1}{2\pi\sigma_y}$$

The standard deviation of the Gaussian spread domain, $\sigma_x, and \sigma_y$, are calculated correspondingly. The function in *(3)* can be split into an odd and even part, known as the anti symmetric and symmetric filter respectively, in the frequency domain:

$$H_e(u, v) = e^{s\left[(u-u_0)^2 + (v-v_0)^2\right]} + e^{s\left[(u+u_0)^2 + (v+v_0)^2\right]}$$
$$H_o(u, v) = e^{s\left[(u-u_0)^2 + (v-v_0)^2\right]} - e^{s\left[(u+u_0)^2 + (v+v_0)^2\right]} \qquad\qquad \text{where } s = -2\pi^2\sigma^2$$

2.3.3 Wavelet Models

Wavelet transform, possess many of the properties, which make this transform unique for non-stationary signal/image processing. It provides the capability of zooming into any desired frequency channel of the signal/image. In the *WT* textural analysis, the image is iterviavley decomposed through the dyadic multi-resolution framework. In each decomposition level, the image is separated into one low pass approximation and three added detail images, which contain high frequency information (edge information) in three directions including horizontal, vertical and diagonal. (Fig. 2)

In the case of two-dimensional input data, this algorithm yields to a pyramidal structure. For each level, we obtain three detail images, which contain fine structures with horizontal, vertical and diagonal orientation, and a smoothed residual image, which is a coarse approximation of the original. Due to sub sampling the volume of the original data is not increased [9].
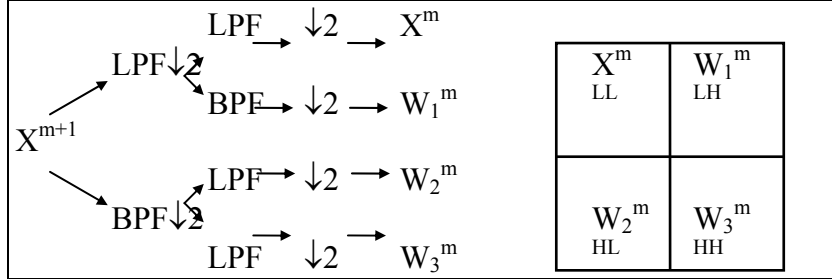

Fig.2

The low pass output is an approximation of the input signal at a lower resolution and the high pass output contains the details needed to reconstruct the original signal. Taking the approximation as new input to the filters leads to a multi scale representation of the original signal. The most important information for classification is often in the middle bands. However, it is observed that the energy in different bands is more stable for classification than the structure itself. The wavelet transform consist of computing coefficients that are inner products of the signal and a family of wavelets, each wavelet generated by scaling and shifting a mother–wavelet ψ, which has a compact support (4). For the continuous wavelet transform the scale parameter a and the position parameter b vary continuously.

$$\omega_{x(t)}[a,b] = \frac{1}{\sqrt{a}} \int x(t) \Psi^* (\frac{t-b}{a}) dt \qquad\qquad [4]$$

$$\psi(x,y,k_x,k_y) = \exp\left(\frac{k_x^2 k_y^2}{2\sigma^2}(x^2+y^2)\right)\exp\left(i(k_x x + k_y y)\right)$$

To fully specify the wavelet based filter set values of orientation angle, θ, frequency, ω and the Gaussian spread, σ, must all be chosen.
The wavelet transformation involves filtering and sub-sampling.
To summarize the observations [5]:
- In general feature components corresponding to higher frequency have better discrimination performance.
- At any given level of the wavelet decomposition, the LH, HL, and HH bands have better performance than the LL band.
- The orthogonal wavelet texture features are slightly better than bi-orthogonal ones. [Reference]

The conventional orthogonal and bi-orthogonal wavelet transforms have many advantages such as lower feature dimensionality and image processing complexity.
By investigation the performance of different types of wavelet transform based texture features. In particular, we consider:

- Orthogonal wavelet transform ***OWT***

- Bi-orthogonal wavelet transform ***BWT***
- Gabor wavelet transform ***GWT***

We must remember that first, since images are mostly smooth, analysis should be performed with a smooth mother wavelet. On the other hand, to achieve fast computation, the filters have to be short, affecting the smoothness of the associated wavelet, second the filters should be symmetric, and so they can be easily cascaded without any additional phase compensation.

3. Texture Analysis

Various studies of human visual system have shown that concept of frequency and scale is fundamental for texture description. Therefore, in the past decade, multichannel and multiresolution algorithms for texture analysis have gained a lot of interest.

The vast majority of techniques developed to date assume that textures are acquired from the same viewpoint. This is an unrealistic assumption for most practical applications. Texture analysis methods should ideally be invariant to viewpoints. Obtaining viewpoint invariant texture features as a very difficult task. Rotation and scale invariance are important aspects of the general viewpoint invariance problem.

Several methods of rotation invariant texture classification have been proposed. Of spatial domain techniques those based on Markov Random Field models predominate. We can consider two usual approach, one that transforms a Gabor filtered image into rotation invariant feature and the other of which rotates the image before filtering; however neither utilizes the spatial resolving capabilities of the Gabor filter. The paper investigates the use of Gabor filters for rotation, scaling and viewpoint invariant texture analysis.

Gabor filtering and the wavelet transform have been used which not only extract the salient features of the data efficiently but also reduce the dimensionality of data to a manageable size.

3.1 Gabor Filter Bank Design

In image segmentation using texture, 2D Gabor filters are being widely used for extraction of local texture information. The merit of employing Gabor filters is that it provides maximum spatial resolution in characteristics, while keeping the filters as narrow bands as possible for discrimination of the spectrally neighboring feature of textures. It is possible to use a bank of Gabor filters so as to represent a certain texture with a feature vector whose elements are the amplitude of each filter response. This approach is known as multichannel texture classification. Selection of the filter bands for efficient characteristics of the texture within image is one of the major issues in multichannel filtering.

The differential structure of an image $I(\vec{x})$ is completely extracted by the classical scale-space representation. But in much application it is convenient to use filters, which are tuned to the features of interest, e.g., a particular spatial frequency.

Gabor filters perform a local Fourier analysis and exhibit excellently discrimination properties over a broad range of texture. The Gabor multi-scale image representation is especially useful for unsupervised texture processing. [6]

In this work, a image I is represented by a set of filtered images I_r, defined by the modules of the filter outputs, $I_r(\vec{x}) = \left| I(\vec{x}) * G(\vec{x}, \sigma_r, \vec{k}_r) \right|$.

$$G(\vec{x}, \sigma, \vec{K}) = \frac{1}{\sqrt{2\pi}} \exp(\frac{-\vec{x}\vec{x}^T}{2\sigma^2}) \exp(j\vec{K}^T \vec{x})$$

We have chosen 12 Gabor filters at 4 orientation and 3 scales separated by octaves with $\sigma_r = \dfrac{3}{\|k_r\|}$ in our experiments. For simplicity we consider squared area around the center point, where the size of the window is chosen proportional to the scale parameter σ_r of the Gaussian filter.

In term of texture segmentation it has been established that multichannel filter banks, provide well suited feature extraction tool for the ensuring pattern classification process. Therefore, we employ in our approach a filter bank that consist of a set of fixed complex value Gabor filters with n_r radial center frequencies and n_a orientations as the basic image preprocessing step to construct a feature space from an input image of size N*M pixel. The feature images $f(x, y; n_r, n_a)$ are generated by computing the local magnitudes of the quadrature filter images according to:

$$f(x, y; n_r, n_a) = \left\lfloor \left(\Re\{s(x, y) * h(x, y; n_r, n_a)\}\right)^2 + \left(\Im\{s(x, y) * h(x, y; n_r, n_a)\}\right)^2 \right\rfloor$$

where $h(x, y; n_r, n_a)$ is the impulse response of a Gabor filters and $s(x, y)$ is the input image. Hereby, n_r denotes the index for the center frequency and n_a the index for the orientation of a certain filter. These feature images compare closely to Fourier invariant descriptors, since texture rotations in the image space are transform into shifts in the n_r-direction of the feature images.

The reference images are computed by filtering images of reference textures with the same filter bank as used for the input images and averaging the local amplitudes of all aquardture filter images. Thus, we get for the reference feature images of size n_r * n_a. Comparing the largest amplitudes of the matched filter outputs performs labeling of the pixels.

A generalized filter or a bank of filters responsive to several texture properties will be needed to fully simulate the human visual system. Filter bank performing the *DWT* is one form of the local linear transform approach for the texture characteristics.

4. Feature Extraction

The basic idea adopted in this work is to combine the time-frequency approach with orientation and scale-invariant texture recognition techniques in order to analyze multi-invariant scene. The proposed method is explained in the following chapter.

For a given radial frequency *f* multiple filter locations are locations are obtained by sampling the circle of radius *f* at an interval of *Δθ*; sampling is only taken between 0° and 180° due to the conjugate symmetry. This results in *180/ Δθ* filters and the same number of filtered images. The sequence of these filtered images energy measure forms a period function of *θ* with period *π*. A rotation of the input image corresponds to a translation of this function. The magnitude of the period function's Fourier coefficient are therefore invariant to image rotations. The first *n* magnitude result in *n* feature and are represented as an *n*-dimensional feature vector.

A major purpose of this paper is to investigate the effects of different frequency combinations, the influence of the sampling interval *Δθ* and the noise robustness of the rotation invariant features. Such studies are of great importance to practical application. [10]

Numerous experiments were performed in order to discover the optimum parameters setting in terms of accuracy and efficiently. The minimum number of features,

optimum sampling interval and frequency combinations were investigated. The first six power of two (i.e. 2,4,8,16,32,64) were selected as radial frequencies for the frequency analysis in which all possible combinations were examined.

5. Neural Network Classifies

PNN, on the other hand, is a kind of supervised network, which is closely related to Bayes classification rule. Comparing with the well-known back-propagation network, *PNN* has a very fast one-pass learning scheme while it has comparable generalization ability. There are three feed-forward layers in PNN: input layer, pattern layer, and summation layer. In input layer accepts the features vectors and supplies them to all the neurons in the pattern layer.

In the summation Layer, the *kth* neuron will sum up all the outputs from the *kth* pool in the pattern layer. The weights of the summation layer are determined by the decision cost function and a prior class distribution.

For the input pattern *X*, the final decision will be made by a simple comparison of all the outputs. If the Gaussian mixture model is assumed for the distribution of each class, the structure of *PNN* can be greatly simplified.

6. Experiment Results

A basic texture classification was carried to test whether the Gabor layer can capture the appropriate spectral features through training. The texture image used for this experiment is shown in Fig.
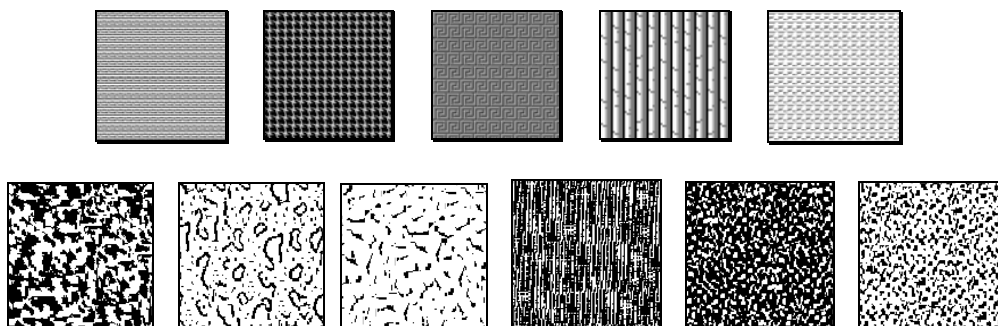

Fig.3

For each image a sub-grid of 128*128 sites and a window size of 16x16 pixels was selected. The size of the network used for this experiment was (40,25,2), which is a minimal configuration for this problem. After training, the texture map was made by scanning the input region through the whole image and classifying them into the three classes. In the produced texture map in Fig.3, The regions used as the training sets for classes A and B are correctly classified, as well as the other parts of the image having the same textures.

When tried with the minimum network size, there were cases when the training could not be accomplished even with 10000 training epochs. Such cases were due to the network parameters being caught in a local minimum of the error potential function.

From each of the texture classes 12 training sub images were selected for training. The classification map in Fig.4,was obtained by a network of a configuration of (40,25,2), trained for 8885 epochs to achieve the MSE per output unit of 0.01.

Twenty Gabor filters and a classical layered network were used for feature extraction and classification. Initially, we allowed the center frequency and the bandwidth of the

Gabor filter to change so that the aliased energy could be kept small. Making such hard limits in the parameter domain however, typically caused the training process to be caught in an artificial local minimum in the error potential surface. Therefore, in the experiments, the filter bands were allowed to change freely in the 2D frequency domain with an iterative structure of a tours surface.

With wideband initial state, the training was accomplished in a relatively wideband state and the produces classification map included many speckle-like misclassified regions. Therefore, when the texture regions to be segmented are comparatively larger then the training so images, the resulting classification map will be much smoother when the training was stated from a relatively narrowband state, and gradually turning wider-band to accommodate the spectral instability of the texture class.

It was found that the bands of the Gabor filter sets were adequately modified through the *PNN* net's training, and it proved that the spectral features could be effectively extracted for the multichannel texture classification.
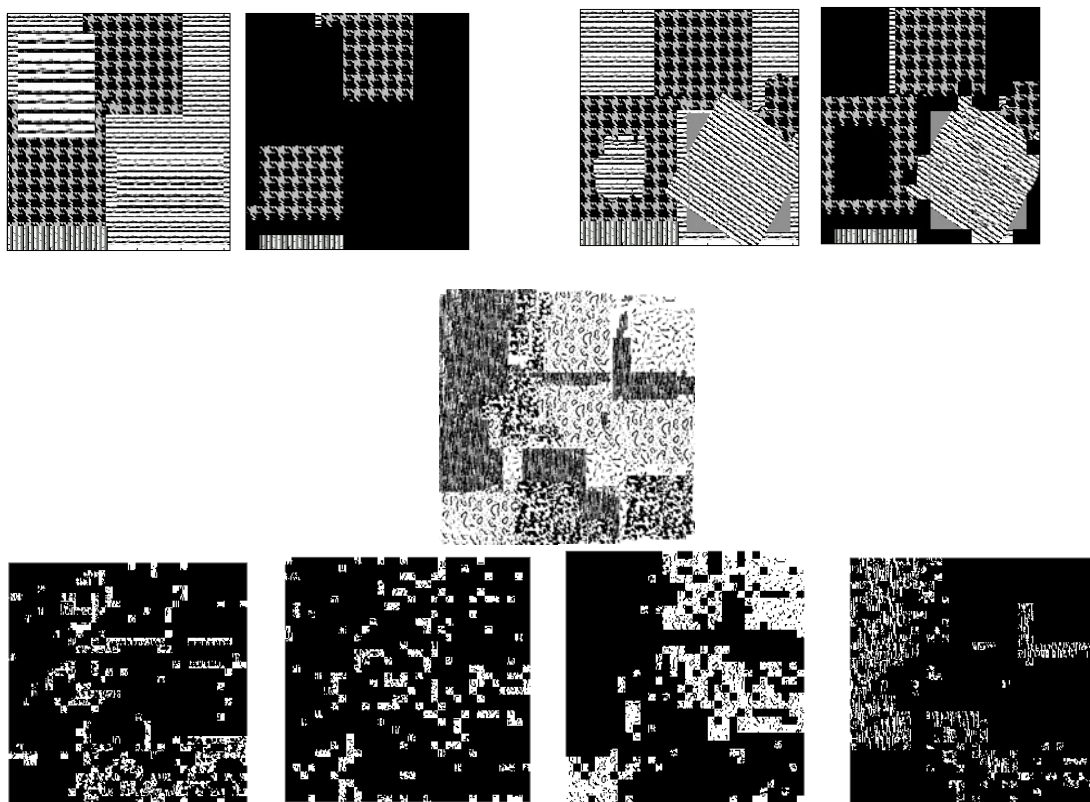

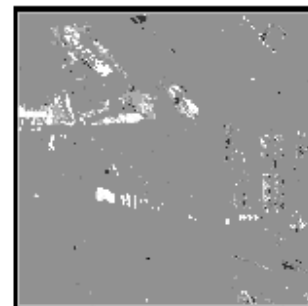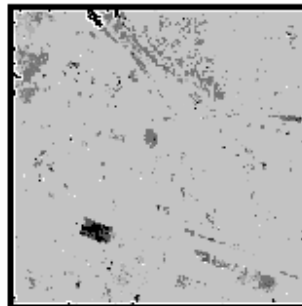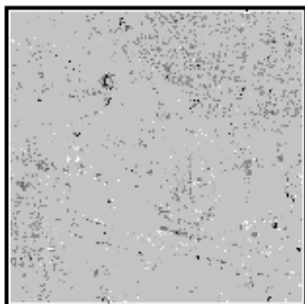Fig.4 Texture map produced by *PNN* for 2 and 4 classes

In second examination we try to implement the texture analysis on real world imaging (LANDSAT *TM (6 band)* Tehran 1999). In a successful experiment in order to fuzzy classification (Sh.Moafipoor, M.S.Seresht; 2000) of this image on three class (water, soil, city), we reach the below result:
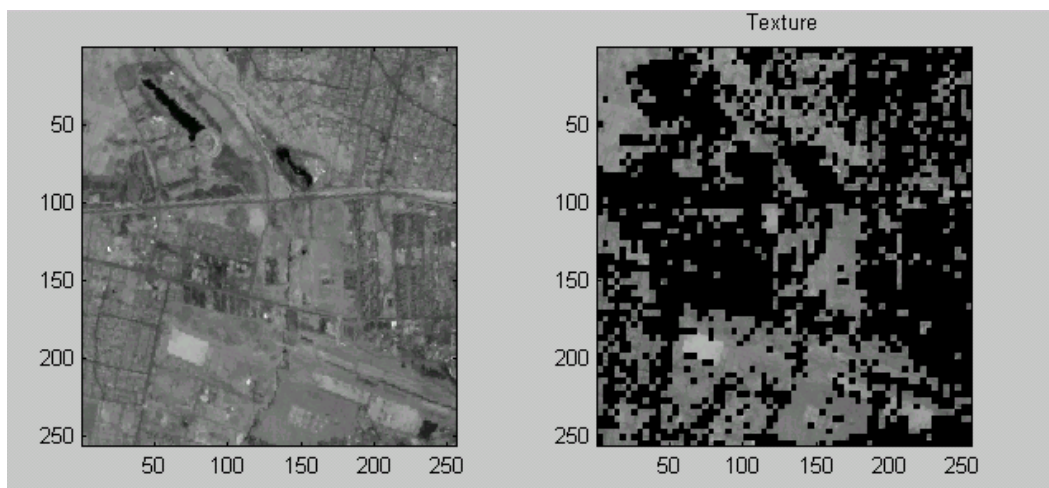
As we can see, the soil and city class have a same radiometric value and in fuzzy classification we have also a serious problem in distinction between them. Insert of texture parameters must resolve such these problem especially in change detection of urban region. Fig.6, shows the classify map which result from our algorithm.

6. Summary

Recent research on texture analysis has shown that algorithms using the multiresolution wavelet transform achieve very good performance.

The optimum frequency combinations discovered during parameter analyze were tested on the large database. (6 features per frequency were selected). The use of Gabor filters for rotation invariant texture analyze has been investigated.

A recognition rate of 95% is obtained using a database of 10 texture classes and over 10 images. The resolution was found to be 5 radial frequency, 2 features per frequency and a sampling interval of 10°.

The effect of different frequency combinations was analyzed in order to discover the relative significance of each frequency and to identify the most desirable frequency combination containing the least number of frequencies.

We tested the proposed method on 10 artificial textures shown in Fig.3. Using a filter bank consist\s of 20 Gabor filters with 5 different center frequencies and 4 orientations.

Recently multichannel/multisacle image modeling has become an active research area and most work attempts to capitalize on the computational power of the multiresolution models, i.e., faster algorithms and better convergence.

We proposed and analyzed a supervised method for scale and orientation invariant segmentation based on multi channel filtering. Segmentation is performed using a symmetric phase only matched filter where the detection of the largest peaks of the filter outputs are used to classify the pixels of the native image.

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