Image classification using textures

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Abstract: Textures play an important role in the field of image classification. It is one among the significant features used for identifying regions of interest in an image. There are various methods of classifying images based on textures. This work presents a method in which textures of an image are discriminated by edge detection technique with the help of Gabor filter. Once the textures are identified, the output image is processed in iGIS image processing software for image classification, as desired.

Keywords: Image classification, Texture, Gabor filter, Edge detection, Minimum distance algorithm

1. Introduction

FImage classification is the methodology wherein thematic labels are assigned to each pixel in the image. This process is frequently used to generate land cover maps from satellite images. Using the texture information of an image for categorization is an effective form to classify image. Important information about the structural arrangement of surfaces is contained in textures. Such approach has been used in different areas of image processing such as plant leaf recognition (Chaki and Parekh, 2012), medical imaging and quality inspection. The purpose of this paper is to examine the usability of textures in the classification of satellite images used for remote sensing and GIS.

2. Basic concepts

2.1Image classification

Image classification refers to the task of extracting information classes from a multiband raster image. The primary objective of image classification is to detect, identify and classify the features occurring in an image in terms of the type of class (land cover) these features really represent on the field.

Depending on the interaction between the analyst and the computer during classification, there are two types of classification: supervised and unsupervised.

2.1.1 Supervised classification

It is a technique by which a user provides sample training data to a computer, which in turn is used by the computer to generate the spectral response signature and to classify pixels on the basis of this spectral response pattern.

2.1.2 Unsupervised classification

It is a type of classification where various unknown pixels are categorized by clustering into spectral classes solely on the basis of image statistics without any prior knowledge of the location. The spectral classes are classified into information classes based on training sites. Images are classified in such a manner that, in a particular class, pixel values are quite close to each other, whereas values in different classes are well-separated.

2.2 Texture

An important property of any image is the spatial structure, or arrangement, of bright and dark tones. Spatial information can be expressed in terms of spatial autocorrelation, a measure of the similarity between a pixel and its neighbours. Texture is another expression of the local spatial structure in digital images. Texture can be defined as the spatial distribution of tones of the pixels in remotely sensed images, i.e. tonal or grey level variation of an image (Baulkani and Ganesan (2007).

3. Research methodology

3.1 Relevance of textures in image classification

Texture is an integral property of virtually, all images. Essential information regarding the structural arrangement of surfaces is contained in textures. It is easy for humans to identify and describe textures in empirical terms, but it has been extremely difficult to perform digital analysis on them.

There have been many suggested texture discrimination techniques, most of which lie in one of the following classes: feature extraction, pattern sampling, template matching, geometrical moments and spatial transforms.

Most of the classification methods have a two-stage process. The first stage is the learning phase or the feature extraction, which returns a characterisation of each texture class in terms of feature measures. These features, which can be discrete histograms or scalar numbers or empirical distributions, characterize given properties of the textures such as contrast, orientation, spatial structure, roughness, etc. Ideally, quantitative measures of the selected features ought to be close for similar textures. The second stage is the recognition phase or the classification, in which a classification algorithm is used to compare the textural features of the sample data with those of the training images. The sample is then assigned to the closest match.

3.2 Identifying textures in an image

The textures are being identified using the edge detection method. The whole process of edge detection can be subdivided into two stages. In the first stage, intensity changes in the image are detected and described. Following which, physical properties of edges in the image are inferred from this description, in the second stage. The first stage process has been carried out by convolving the input image with Gabor signals and transforming it into a representation image that allows differentiating the features on the basis of intensity differences. If the background and target regions contain different features, they will have different intensity levels. Hence their segregation can be done easily on this basis. In the next stage, a Laplacian of Gaussian operator is used for finding the edges between areas of dissimilar textures. This algorithm responds to energy differences, spatial frequency and rotation and is not sensitive to local translation.

3.3 Use of Gabor filter in context of our paper

In most of the texture classification works, the intermediate features obtained by passing the input image through 2-D Gabor filters are used to establish the relation to the local spectrum (Ferro, 1998).

3.3.1 About Gabor filter

A Gabor filter is a local and linear filter. The convolution kernel of this filter is a product of a cosine and a Gaussian function. The filter is characterized by a desired spatial frequency and a desired orientation. A 2-dimensional Gabor filter behaves as a local band-pass filter in the spatial domain as well as in the spatial frequency domain. Typically, an image is convolved with a set of Gabor filters of different orientations and frequencies (Ferro, 1998). A feature vector field is formed by the features thus obtained, which can further be used for classification, segmentation, or analysis.

3.3.2 Mathematical significance of Gabor filter

Typically, an input image *I(x,y), (x,y)* $\in \Omega$ (Ω — the set of image points), is filtered with a two dimensional Gabor function *g(x,y), (x,y)* $\in \Omega$, to obtain a Gabor feature image *r(x,y)* as follows (Grigorescu et al., 2002) :

$$r(x,y) = \iint_{\Omega} I(\xi,\eta)\, g(x-\xi, y-\eta)\, d\xi\, d\eta$$

In this paper, the following filter family of Gabor functions is used:

$$g\lambda,\Theta,\varphi(x,y) = e^{-((x'^2+\gamma^2 y'^2)\sqrt{2\sigma^2})} \cos\left(2\pi\frac{x'}{\lambda}+\varphi\right)$$

Where

$x' = x\cos\Theta + y\sin\Theta, \quad y' = -x\sin\Theta + y\cos\Theta$

and $\gamma = 0.5$.

We are using two filter banks in our experiments, one with anti-symmetric ($\varphi = \pi/2$) and the other with symmetric ($\varphi = 0$) Gabor kernels. Both the banks consist of 24 Gabor filters that are formed by using eight different equidistant orientations ($\theta = k(\pi/24)$, k = 1, 2, 3…8). The implementation has been done using MATLAB and the values of all the above parameters can be defined by the user, these values are only the test values.

3.3.3 Attributes of Gabor filter

Gabor filter banks can decompose an image into suitable texture features for classification. Multi-channel filtering mimics the Human Visual System's (HVS) sensitivity to spatial-frequency and orientation. This ability led to development of an HVS model. The model consists of independent detectors which are preceded by NBFs (narrow band filters) tuned to different frequencies.

For texture discrimination we needed a filter which could detect the edges in an image. Keeping this in mind we designed a Gabor filter to which Fig. 1 was fed as input and the corresponding output is given in Figure 2. It can be seen that the edges are prominent in the output image; therefore the filter is efficient in edge detection.

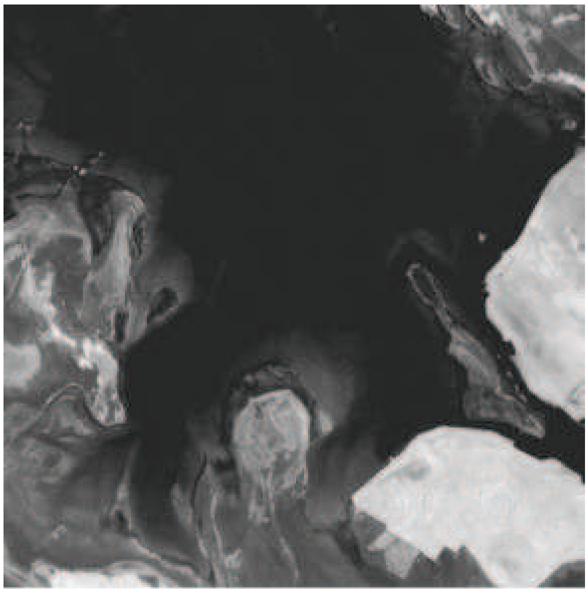

Figure 1: Original input image

3.3.4 Change in Gabor filter response for change in different parameters

In the simulations we have convolved Figure 3 with the Gabor filter with different values of parameters. The parameters are as follows: (Figure 4).

$\theta = 0^\circ, 45^\circ, 90^\circ, 135^\circ$.

$\varphi = 0^\circ, 90^\circ$. $\lambda = 4, 8, 16, 32$,

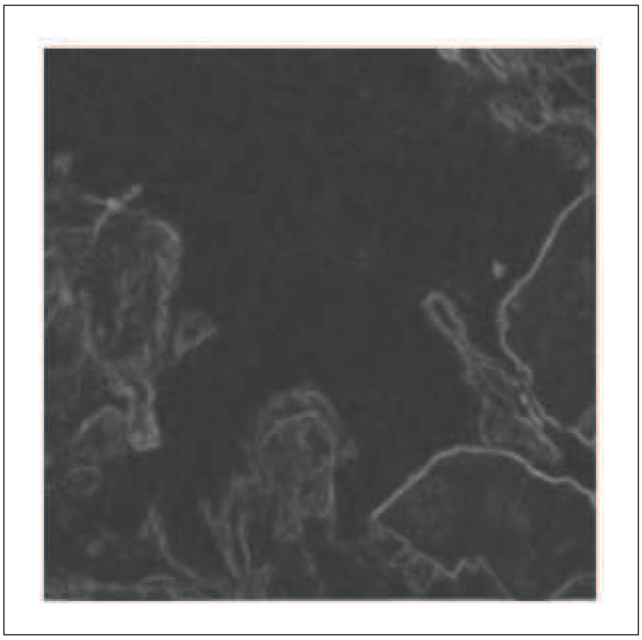

Figure 2: Output of Gabor Filter (Example of edge detection)

Figure 3: Input image

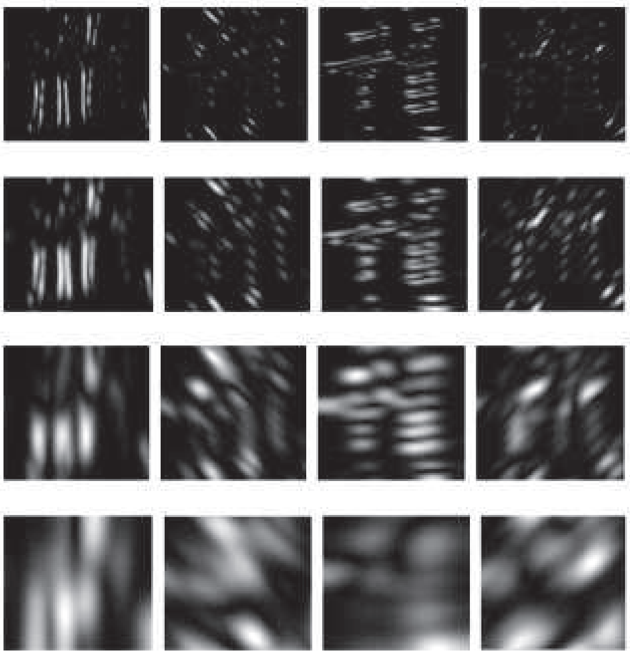

Figure 4: Top row to bottom row - λ (4,8,16,32) respectively and for each λ, θ(0˚, 45˚, 90˚, 135˚)

3.4 Image classification using minimum - distance algorithm

Pixels are assigned to different classes based on their closeness to the class mean vectors:

$c_i = x \;\; iff \; d_i(x) < d_j(x)$

The distance (d) of a particular pixel from different class mean vectors (x) is usually calculated using Euclidean distance:

$$d_{cx} = \sqrt{\sum_{i=1}^{N} (c_i - x_i)^2} \equiv \sqrt{\{c_1 - x_1\}^2 + \{c_2 - x_2\}^2 + \ldots + \{c_N - x_N\}^2}$$

This results in a feature space that is shown in figure 6.

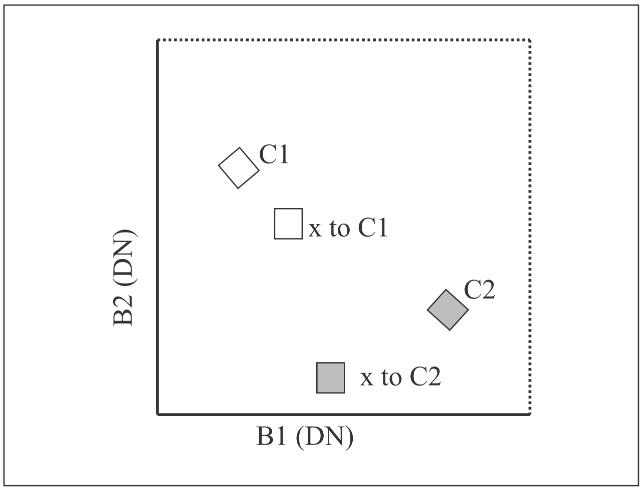

Figure 5: Assigning pixels to closest class mean vector

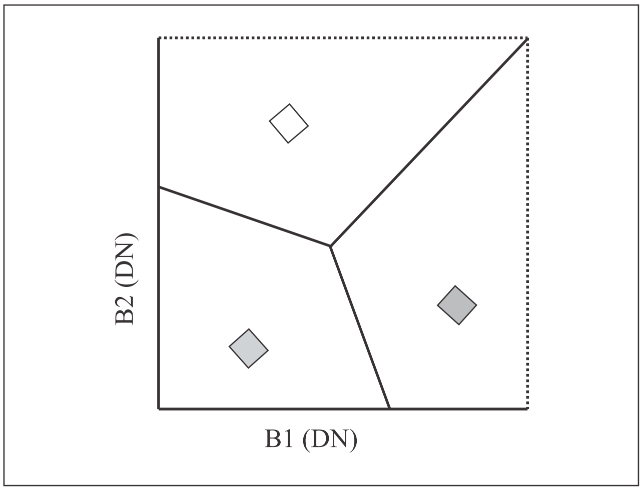

Figure 6: Class mean vectors of three defined classes

When spectral distance is calculated for all values of c, the class of the unclassified candidate pixel is assigned to the class with the lowest spectral distance (see Figure 5). As shown in Figure 6, if the candidate pixels lie in the limits of a class feature space, based on feature space, then they are assigned to that class.

The advantage of the minimum distance algorithm is that no unclassified pixels are produced and it is computationally efficient. However, the disadvantage of this algorithm is its unaccountability for class variability: for example, an urban land cover, which is a high variance class, may wrongly classify some urban pixels which are on the edges of urban area and a low variance class such as a water-body may be over-classified by those pixels which are in proximity to the water class mean.

We have used an input image for use with Gabor filter which in turn gave an image as output. minimum distance classifier was then applied on both input and output images for 4-class classification of the image. Classification of the image was done using image processing software, namely IGIS.

4. Results and discussion

We have used a set of two images with different characteristic features for classification. One is a satellite image of an urban-dominated area and the other is an image of a village-side. We have taken two images with different characteristic features in order to test our hypothesis that a texture image is better than original image in both the situations.

4.1 Case 1

The classification algorithm was applied on Figures 7 & 8, and Figures 9 & 10 were obtained as classified output. The legend of the image, i.e. which colour represents which class, is mentioned under the caption of the figure itself. The image processing software provided us with the output statistics which contained the area occupied by each class on the scene.

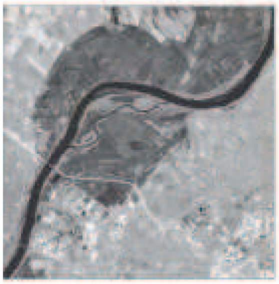

Figure 7: Original Image

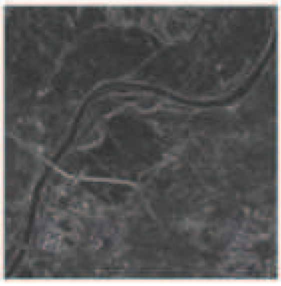

Figure 8: Gabor filter output

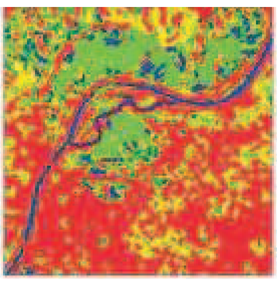

Figure 9: Classified output of Fig. 7

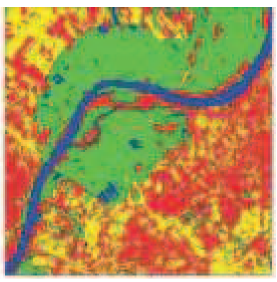

Figure 10: Classified output of Fig. 8

Legend for Figure 9& 10

(Blue = water, Green = vegetation, Yellow = fallow land, Red = urban area)

The actual area covered by the respective classes was recorded separately using Arc GIS software. Then, a confusion matrix was created for comparison of accuracy and reliability. In the confusion matrix, rows and columns represent classes in the test set and classification result set, respectively. The diagonal elements shows the number of pixels which are correctly classified. The off-diagonal elements state the classification errors, i.e. the number of test set pixels that were placed in wrong classes during classification. The last column and the last row show the accuracy and reliability (in percentage) respectively.

Table 1 represents the confusion matrix of the classified data for Figure 9. Similarly Table 2 represents the confusion matrix of the classified data for Figure 10.

Table 1: Contingency Table/Confusion matrix for Figure 9

ACTUAL (Area in $1000m^2$)	CLASSIFIED (Area in $1000m^2$)					
	Water Bodies	Urban Area	Vegetation	Fallow Lands	Total/ Avg.	Accuracy (%)
Water Bodies	18	0	0	0	18	100
Urban Area	0	68	0	24	92	73.9
Vegetation	0	17	67	0	84	79.7
Fallow Lands	0	24	0	41	65	63.1
Total/ Avg.	18	107	67	65	-	**79.2**
Reliability (%)	100	63.5	100	63.1	**81.5**	**80.3**

Average accuracy = 77.0%

Average reliability = 69.3%

Overall accuracy = 73.1%

Table 2: Contingency Table/Confusion matrix for Figure 10

ACTUAL(Area in $1000m^2$)	CLASSIFIED (Area in $1000m^2$)					
	Water Bodies	Urban Area	Vegetation	Fallow Lands	Total/ Avg.	Accuracy (%)
Water Bodies	18	0	0	0	18	100
Urban Area	0	72	2	18	92	78.2
Vegetation	7	12	60	5	84	71.4
Fallow Lands	5	17	5	38	65	58.4
Total/ Avg.	30	101	67	67	-	**77.0**
Reliability (%)	60.0	71.3	89.5	56.7	**69.3**	**73.1**

Average accuracy = 79.2%

Average reliability = 81.5%

Overall accuracy = 80.3%

The above results are for the satellite image showing a village-side area having a river, croplands, fallows and settlements around the river. The classification results of the texture segmented image are much more accurate than those of the original image.

Though the average accuracy for both the results is close, the reliability of the texture segmented image (81.5%) is far better than the original image (69.3%).

4.2 Case 2

Figure 11 is the original image and Figure 12 is the Gabor filtered output of the original image. Figures 13 and 14 are the classified outputs of the original and texture segmented images respectively.

Figure 11: Original Image

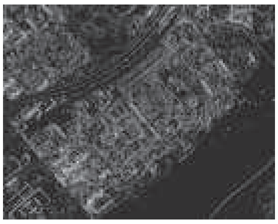

Figure 12: Gabor filter output

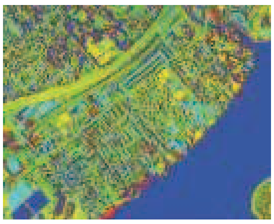

Figure 13: Classified output Fig. 11

(Blue = Water, Light blue = Urban, Green = Fallow, Yellow = Vegetation)

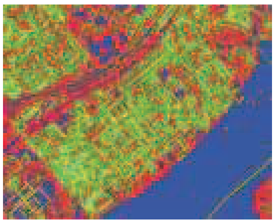

Figure 14: Classified output Fig.11

(Blue = Water, Red = Vegetation, Yellow = Fallow, Green = Urban)

The confusion matrix for Figure 13 is given in Table 3.

Table 3: Contingency Table/Confusion matrix for Figure 13

ACTUAL (Area in 10000m^2)	CLASSIFIED (Area in 10000m^2)						
		Water Bodies	Urban Area	Vegetation	Fallow Lands	Total/ Avg.	Accuracy (%)
	Water Bodies	15	0	0	0	15	100
	Urban Area	4	12	1	1	18	66.6
	Vegetation	11	0	14	0	25	56.0
	Fallow Lands	3	0	0	10	13	76.9
	Total/Avg.	33	12	15	11	-	**74.8**
	Reliability(%)	45.4	100	93.3	90.9	**82.4**	**78.6**

Average accuracy = 66.0%

Average reliability = 74.1%

Overall accuracy = 70.0%

Table 4 contains the details of the classified image of the Gabor filtered output (Figure 14).

Table 4: Contingency Table/Confusion matrix for Figure 14

ACTUAL (Area in 10000m^2)	CLASSIFIED (Area in 10000m^2)						
		Water Bodies	Urban Area	Vegetation	Fallow Lands	Total/ Avg.	Accuracy (%)
	Water Bodies	15	0	0	0	15	100
	Urban Area	2	7	7	2	18	38.8
	Vegetation	10	0	14	1	25	56.0
	Fallow Lands	0	0	4	9	13	69.2
	Total/ Avg.	23	7	25	12	-	**66.0**
	Reliability(%)	65.2	100	56.0	75.0	**74.1**	**70.0**

Average accuracy = 74.8%

Average reliability = 82.4%

Overall accuracy = 78.6%

The above results are for the satellite image in urban-dominated area. This is a special case, where shadows of trees and buildings are also present in the image. The spectral values of the shadows and water body are similar, because of which shadows were classified as water-bodies class. This led to a significant decrease in the accuracies of both urban (38.8%) and vegetation (56%) classes (Table 3). We can see that the decrease in the accuracies of the two classes has caused the average accuracy (66%) to fall significantly. Texture orientation and period estimator were successfully used for discriminating forest, orchard, vineyard, and tilled fields in high resolution aerial images obtaining 95.5 % accuracy (Trias-Sanz, 2006).

In the texture segmented image, although the accuracy of vegetation class (56.0%) remained the same, the average accuracy has increased due to the increase in accuracy of urban class (66.6%) (Tables 3/4).

We can also observe that the average reliability of the texture segmented image (82.4%) is much higher than that of the original image (74.1%) (Tables 3/4).

5. Conclusions

In both cases 1 and 2, the results of the classified output of texture segmented image are better than that of the original image.

Average overall accuracies of original images in case 1 and 2 are 71.55% and 79.45%, respectively.

This image classification technique is best suited for images where textural features are dominant. One limitation of this technique is that edge detection could prove to be difficult in areas with less intensity variation and more colour variation, as the edge detectors are working on intensity differences and not on tonal differences.

From the above study, we can conclude that the texture identification methods are practical for further usage. Different values of frequency and orientation in the filter design can be optimized to make the results even better. Some of the changes which are made may introduce the cost of calculation efficiency.

The research in the field of classifying images on the basis of textural features is still nascent and extensive research is being carried out in this field. We have achieved a decent level of accuracy in classifying images but there is still a lot of scope for improvement, better filters in future can achieve very high accuracy.

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