Land Cover Change Detection Using Gabor Filter Texture

Fen Yang and Roly Lishman

Abstract— **We wish to detect land cover change for environment management. Gabor filters are used to correlate with original land cover images to derive texture information. This paper investigates a texture based image description in which the standardised MPEG-7 Homogeneous Texture Descriptors (HTD) of Gabor filters are used as the textural feature vector. Then this vector is input to a discriminant classifier using linear regression analysis. This paper presents the result of possible change detection of arable land. Experiment results show that the MPEG-7 texture descriptor gives an efficient and effective classification rate on land cover images.**

Index Terms— **change detection, discriminant analysis, Gabor filters, remote sensing, texture classification.**

I. Introduction

Land use and land cover are important aspects in studying environmental changes. Since it is a large burden for human photo-interpreters to classify landscape or detect change from remotely sensed images, many automatic and semi-automatic methods have been applied to this area. As a kind of spatial information, texture provides context information of pixels which can be used as local information to describe images. Various kinds of texture measures are applied to the land cover classification and change detection. Statistical features based on second-order grey level statistics, grey level difference statistics and co-occurrence statistics have been studied extensively since the early 1970s [6], [7]. Markov random field (MRF) and Gibbs distributions are investigated in [16]. Separate information at different scales is analysed through wavelet or Gabor filters in [2], [4], [11], [13], [17], [18]. Since landscape objects are stochastic in nature, the local properties of objects are important for discriminating different objects. Gabor filters are a kind of operator that can capture the local information in an image optimally. And Gabor filters mimic the biological perception of texture and share many properties with the human visual system [14]. This property of Gabor filters makes them capable of reaching the minimum bound for simultaneous localisation in the spatial and spatial/frequency domains [10]. Moreover a Gabor filter bank comprising filters with different parameters of Gabor functions provides a complete cover of spatial frequency domain so that it can generate a versatile model for texture description. Gabor functions are applied in [1], [3], [5] to transform texture differences into detectable filter-output discontinuities at texture boundaries.

While Gabor filters are a good choice their parameter design is rather difficult. References [9], [15] show the qualification of MPEG-7 texture descriptors for the retrieval of images. MPEG-7 texture descriptors and a discriminant classifier making use of linear regression are investigated in this paper for potential "ecological" changes of arable lands.

This paper is organised as follows: Gabor filter and MPEG-7 texture descriptor are reviewed in part two. A discriminant classifier is introduced as well in this part. Experiment design is described in detail in part three. In the last part the result are summarised and possible future work is discussed.

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II. Method

A. Gabor filters

Biological research shows simple cells in the primary visual cortex of primates play an important role in the perception of texture. Since Gabor filters are closely related to the function of simple cells a mathematical model of this function could be expressed as follows [5]:

$$r = \chi(\int\int_{\Omega} f(x,y)g(x,y)dxdy) \qquad (1)$$

where r denotes the response of a simple cell. This can be represented by the correlation between a receptive field function $g(x,y)$ and an image $f(x,y)$, $(x,y) \in \Omega$ (Ω represents the visual field domain). Here $\chi(z) = 0$ for $z < 0$, $\chi(z) = z$ for $z \geq 0$. So if receptive field function could be chosen appropriately, the response of a simple cell could be derived. Then various responses from various objects could be discriminated by using an appropriate classifier for land cover classification.

A Gabor function is a complex sinusoid modulated by a Gaussian envelope. Its general form in Cartesian co-ordinate is:

$$g(x) = \frac{1}{\sqrt{2\pi}\sigma} exp(\frac{-x^2}{2\sigma^2}) exp(i2\pi\frac{x}{\lambda}) \qquad (2)$$

where σ, the standard deviation of the Gaussian function, determines the size of the receptive field. λ is the wavelength of the complex sinusoid. $\frac{2\pi}{\lambda}$ determines the preferred spatial frequency of the receptive field function.

The 1-D Gabor function in the spatial frequency domain is as follows:

$$G(u) = exp[\frac{-\sigma^2(u-u_c)^2}{2}] \qquad (3)$$

where u is the spatial frequency. u_c is the preferred spatial frequency with value $\frac{2\pi}{\lambda}$ as defined above.

The 1-D Gabor function may be extended to 2-D as follows:

$$g(x,y) = \frac{1}{2\pi\sigma^2} exp[-\frac{1}{2}(\frac{x^2+y^2}{\sigma^2})] exp[i2\pi(\frac{x+y}{\lambda})] \quad (4)$$

where σ and λ are defined as above. Its spatial frequency domain in Cartesian co-ordinate is given by:

$$G(u,v) = exp[\frac{-\sigma^2(u-u_c)^2}{2}] exp[\frac{-\sigma^2(v-v_c)^2}{2}] \quad (5)$$

where u and v are spatial frequencies along the x and y axis. u_c and v_c are the central spatial frequencies along the x and y directions respectively.

If we let f denote the radial frequency and θ denote orientations the 2D Gabor function in the spatial frequency domain could be expressed in polar coordinate. [3] pointed that compared with the standard form, the Gabor function in polar form has a narrower response at low frequencies and a wider response at high frequencies. This makes a more uniform coverage of the frequency domain with less overlap at low frequencies and smaller gaps at high frequencies. Also the polar form is more suitable for rotation invariant analysis which is a requirement to describe natural objects in landscape images. Another advantage of the polar form is that the parameters of Gabor function are more easily determined than the standard form. The Gabor function in polar form will be described in next part.

B. MPEG-7 Homogeneous Texture Descriptor

MPEG-7, the Multimedia Content Description Interface, is an ISO/IEC standard for describing the multimedia content, developed by MPEG (Moving Picture Expert Group) [12]. It describes three texture descriptors, a homogeneous texture descriptor (HTD), an edge histogram descriptor (EHD), and a perceptual texture browsing descriptor (PBD).

The HTD provides a precise quantitative representation of texture that is useful for similarity analysis. The descriptor is derived from filtering with the original image using scale and orientation selective kernels which create a filter bank. Gabor functions in the spatial frequency domain in polar form make them convenient to generate the parameters of Gabor kernels. The spatial frequency domain in polar co-ordinate could be partitioned into 30 channels with equal divisions in the angular direction (at 30° intervals) and octave division in the radial direction (five octaves), as shown in Fig. 1 taken from [9]. The channel index i can be denoted as $i = 6 * s + r + 1$. Here s is the radial index with $s \in \{0,1,2,3,4\}$ and r is the angular index with $r \in \{0,1,2,3,4,5\}$.

Every feature channel in the spatial frequency domain is modelled using a 2-D Gabor function of polar form as follows:

$$G_{p_{s,r}}(f,\theta) = exp[\frac{-(f-f_s)^2}{2S_{f_s}^2}] exp[\frac{-(\theta-\theta_r)^2}{2S_{\theta_r}^2}] \quad (6)$$

where f is the frequency in radial direction. θ is the angular direction. Center frequency of octave bandwidth $f_s = \frac{3}{4}(max(f) - min(f)) \cdot 2^{-s}$, where radial index $s \in$

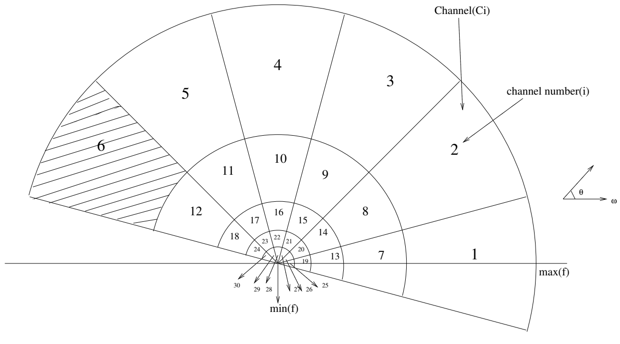

Fig. 1. Frequency partition of the Gabor filter bank with ID's of feature channels C in spatial frequency domain. $max(f)$ and $min(f)$ denote the maximum and minimum frequency in the spatial frequency domain respectively.

$\{0,1,2,3,4\}$. $max(f)$ is the maximum frequency of the image and has wavelength 2 pixels/cycle. $min(f)$ is the minimum frequency of the image and has wavelength 1 picture/cycle. Angular direction $\theta_r = 30° * r$, where angular index $r \in \{0,1,2,3,4,5\}$. S_{f_s} and S_{θ_r} are the standard deviations of the Gabor function in the radial direction and the angular direction respectively. In the angular direction, S_{θ_r} has a constant value as follows:

$$S_{\theta_r} = \frac{15°}{\sqrt{2ln2}} \quad (7)$$

In the radial direction, S_{f_s} depends on the octave bandwidth as follows:

$$S_{f_s} = \frac{B_s}{2\sqrt{2ln2}} \quad (8)$$

where B_s is the octave bandwidth whose value is $(max(f) - min(f)) \cdot 2^{-(s+1)}$.

The HTD generates a feature vector TD constituted by the mean value f_{DC} and standard deviation f_{SD} of the original image as well as the energies e_i and their standard deviations d_i of the Gabor filtered images.

$$TD = [f_{DC}, f_{SD}, e_1, e_2, e_3, \cdot\cdot\cdot, e_{30}, d_1, d_2, d_3, \cdot\cdot\cdot, d_{30}] \quad (9)$$

C. Discriminant Analysis

Discriminant analysis (DA) is a supervised classification method, which is used to build a predictive model of group membership based on observed characteristics of each case. A discriminant function, or a set of discriminant functions if there are more than two groups, is generated based on linear combinations of the feature vectors.

The discriminant functions are generated from a sample of cases for which group memberships are known, and the functions can then be applied to new cases with measurements for the independent variables but unknown group membership. The discriminant function is defined as follows:

$$L = B \cdot TD_1' \quad (10)$$

where $B = [b_1, b_2, b_3, \cdot\cdot\cdot, b_{62}, c]$. Elements in B are discriminant coefficients and c is a constant. Discriminant coefficients try to maximise the distance between the means of the criterion (dependent) variables. TD_1' is the transpose of TD_1 which is from the feature vector TD. Here $TD_1 =$

$[f_{DC}, f_{SD}, e_1, e_2, e_3, \cdots, e_{30}, d_1, d_2, d_3, \cdots, d_{30}, 1]$. So how to find an effective way to decide discriminant coefficients?

Linear regression explores the relationship between independent variables and what you want to predict. So it can be used to distinguish two groups. Thus discriminant functions are estimated by linear regression. The linear regression coefficients become the discriminant coefficients and are derived by least square minimisation. Group membership can then be determined by the discriminant score calculated with the linear regression function. There is a dividing point $\bar{D}$ to determine the membership of new case.

$$\bar{D} = \frac{\bar{D_1} + \bar{D_2}}{2} \tag{11}$$

where $\bar{D_1}$ and $\bar{D_2}$ are means of discriminant scores of cases which have known the group memberships in group 1 and group 2 respectively.

If discriminant score is less than $\bar{D}$, the new case has to be assigned to the first group, otherwise it is assigned to the other group.

III. Experiments

Six kinds of land cover types, i.e. arable land, good rough grassland, poor rough grassland, bracken, mixed woodland, and scrub have been tested as, according to experts [8], these land cover types are ecologically "similar". Arable land is likely to transfer into good rough grassland and possibly transfers to poor rough grassland, bracken, mixed woodland, and scrub. More detailed land cover types may be found under these six categories. In this experiment some samples of these six land cover types first used to train a discriminant classifier which makes use of the homogeneous texture descriptor TD derived from images filtered with Gabor filters. And then the efficiency of this discriminant classifier was tested using the discriminant functions derived from the training stage.

A. Description of the Used Image Data

The data in this experiment is from aerial images covering the Elgin area in north-east Scotland. The image has been manually segmented into different land cover types by expert interpreters who gave every pixel in the image a land code representing the land cover type of the pixel [8]. To detect land cover changes we have to design a classifier which can discriminate various land cover types. Therefore first we have to prepare many images each containing just one land type so that different information from different land cover types could be compared and analysed without the influence of other land cover types. According to the given code many polygons are obtained by using the floodfill method and the image has been split into many polygons. Fig. 2 shows two examples of polygons produced by floodfill method. Each polygon corresponds to a land cover code so each polygon is composed of the same land cover type. There may exist many polygons associated with one land cover code because polygons with the same land cover code may not be adjacent. Thus it is reasonable to derive land cover texture information from these different individual land covers for further analysis.

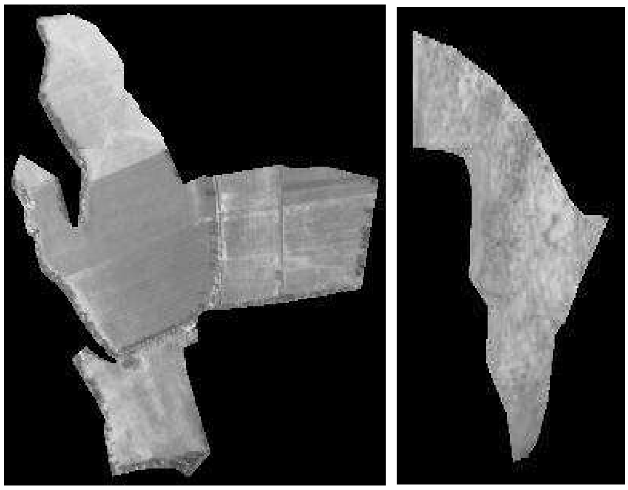

Fig. 2. Left polygon is labelled as arable field, and right polygon is labelled as smooth grass/rushes but no rock and no trees

B. Experiment Results

There are a total of 178 polygons of 6 land types used in the training stage. Fig. 4 shows an example of some polygons used in the training dataset. According to the method mentioned in part II these polygons are correlated with 30 Gabor filters of a filter bank. The parameters of Gabor filters are obtained by the partition of the space frequency domain in the way described in part II. The radial parameters are shown in Table I. The frequency range f_0 is chosen as 64 pixels/cycle since frequencies of most polygons are not bigger than it. The angle directions in Gabor filters are from $0°$ to $150°$. Six Gabor filters in scale of 3 changing with the whole angular directions are shown in Fig. 3.

As parameters of Gabor filters are determined in the spatial frequency domain in polar form these generated filters were described in the spatial frequency domain first. Then they have to be transformed back to spatial domain through inverse Fourier transform for further analysis. As mentioned in part II human texture perception is like response of original image with Gabor filter, these polygons representing land covers are correlated with these Gabor filters. Then homogeneous texture descriptor TD of these filtered polygons were extracted and input to the discriminant classifier. There are 62 features in each homogeneous texture descriptor TD.

We make use of the linear regression functions to discriminate the various land covers. As we try to detect the potential changes to arable land, it is necessary to discriminate arable land and any other potential land cover types. In this case as arable land is likely to transfer into good rough grassland and possibly transfers to poor rough grassland, bracken, mixed woodland, and scrub, a total of 5 discriminant functions have to be created through linear regression functions. The denotation of land cover types used in this experiment is shown in Table II. Training result of total 144 polygons is shown in Table III. Results show that the total successful rate is 98.3%. Then 34 polygons are used as testing data to predict their group memberships using the 5 discriminant functions. The classifying result is shown in Table III as well. The total

Ratial Index S	0	1	2	3	4
Center frequency f_s	$\frac{3}{4}f_0$	$\frac{3}{8}f_0$	$\frac{3}{16}f_0$	$\frac{3}{32}f_0$	$\frac{3}{64}f_0$
Octave bandwidth B_s	$\frac{1}{2}f_0$	$\frac{1}{4}f_0$	$\frac{1}{8}f_0$	$\frac{1}{16}f_0$	$\frac{1}{32}f_0$

TABLE I

PARAMETERS OF GABOR FILTER BANK IN RADIAL DIRECTION. FREQUENCY RANGE $f_0 = max(f) - min(f)$, f IS THE FREQUENCY VARIABLE OF THE ORIGINAL IMAGE.

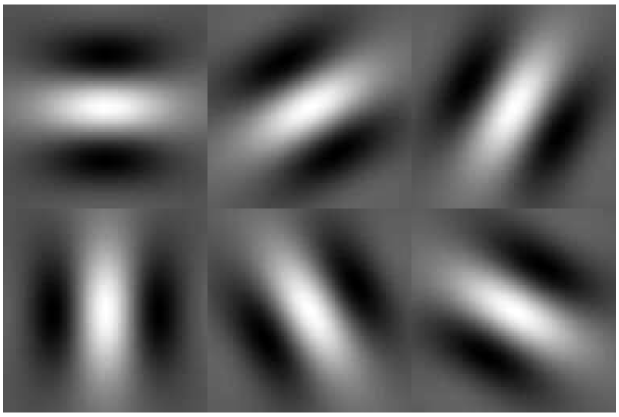

Fig. 3. Six $128 * 128$ Gabor filters in spatial space whose center frequencies are at $3/32 * f_0$. Bandwidth is $1/16 * f_0$ and angular directions are $0°$, $30°$, $60°$, $90°$, $120°$ and $150°$.

successful classifying rate is 91.8%. Overall these results are very encouraging.

IV. SUMMARY AND OUTLOOK

In this paper a method to detect land cover changes is analysed and discussed. A set of Gabor filters, whose parameters are determined in spatial frequency domain and in polar form, is correlated with original images to obtain MPEG-7 homogeneous texture descriptors as the discriminant feature base. Then a discriminant classifier making use of linear regression based on means statistics is used to discriminate different land cover types.

Compared with other methods the parameters of Gabor filters are determined in polar form of spatial frequency domain and the partition of spatial frequency is based on the human visual system. Texture descriptors, MPEG-7 homogeneous descriptor, is concise in representation regardless of image size and is shown to be effective in detection land cover changes. The method shows fast computation of texture descriptors and determination of parameters of Gabor functions. Experiment shows the result is promising and the Gabor filter is quite helpful to find the local information in images. But as discriminant classifier needs to train pre-known group data the quantity of training data plays a role in the discriminant result. Although potential changes to arable land could be detected which specified land cover type is more possible is still a question. Thus it is quite possible to use not only HTD but also other features in the classify process. So in the future more and more data would be tested. Besides statistical information of the filtered images geometrical and morphological information of filtered images could be applied as well.

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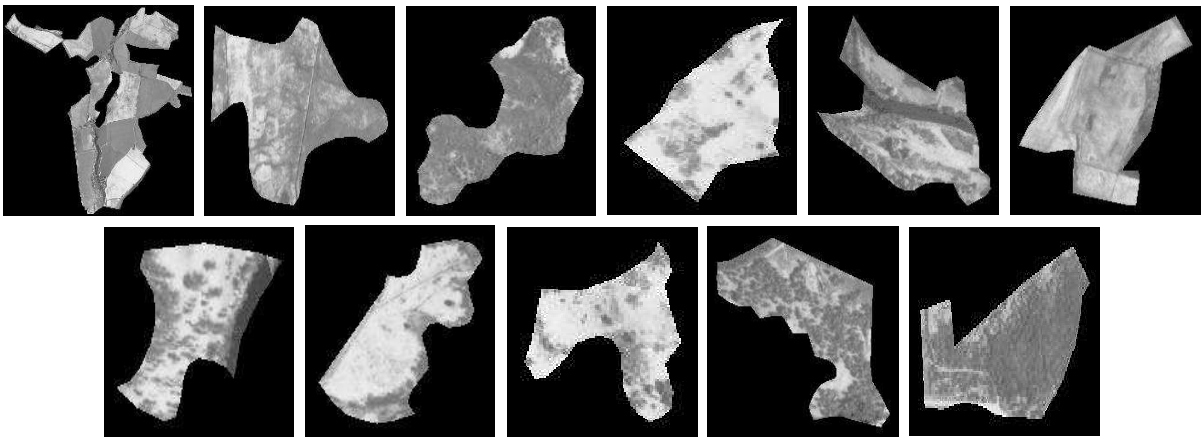

Fig. 4. An example of polygons in training data set. From left to right and up to down, the land cover code of there polygons are: 100, 150, 151, 155, 156, 160, 161, 140, 170, 79 and 82 as denoted in Table II

Land cover category	Land cover code	Main feature
Arable field	100	Arable field (no rock, no farms, no trees)
Good rough grassland	150	Smooth grass/rushes(no rock, no trees)
	151	Smooth grass/rushes(no rock, trees)
	155	Smooth grass/low scrub(no rock, no trees)
	156	Smooth grass/low scrub(no rock, trees)
	160	Undifferentiated smooth grass(no rock, no trees)
	161	Undifferentiated smooth grass(no rock, trees)
Poor rough grassland	140	Undifferentiated Nardus/Molinia(no rock, no trees)
Bracken	170	Undifferentiated bracken(no rock, no trees)
Mixed woodland	79	Undifferentiated mixed woodland(area)
Scrub	82	Undifferentiated low scrub

TABLE II

LAND-COVER TYPES DESCRIPTION.

Correct classification rate		Good rough grassland						Poor rough grassland	Bracken	Mixed woodland	Scrub
		150	151	155	156	160	161	140	170	79	82
Arable land(100)	Training	92.7%	100%	96%	96.7%	100%	100%	100%	100%	97.6%	100%
	Testing	100%	71.4%	87.5%	70%	100%	88.9%	100%	100%	100%	100%

TABLE III

TOTAL TRAINING CORRECT CLASSIFICATION RATE IS: 98.3%, TOTAL TESTING CORRECT CLASSIFICATION RATE IS: 91.8%.