Land Classification and Crop Identification Using Gabor Wavelet Transform on Satellite Images

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***Abstract*-- The aim of this research is to evaluate crop discrimination using satellite data based on textural information. This paper illustrates the use of Gabor wavelet transform on satellite images to classify the land in to crop land and non-crop land and to classify different crops. The input image is enhanced first using Colour Space Transform and Discrete Cosine Transform, and then a filter bank consisting of Gabor wavelets is used to extract texture features from the satellite image. The feature formation process models the texture features from Gabor filter bank as a Gaussian distribution. The use of Gabor filters is driven by the potential they have to isolate texture according to particular frequencies and orientations. The parameters that define a Gabor filter are its frequency, standard deviation and orientation. By varying these parameters, a filter bank is obtained that covers the frequency domain almost completely. A texture image database of different crops is created. The texture features of the input image are then compared with texture features obtained from the image database of different crops and the different types of crops are identified. Finally, the implementation of classification method for multicrops is explained.**

Keywords- Remote sensing, Discrete Cosine Transform, Colour space transform, Gabor Wavelet transform, Feature extraction

I. INTRODUCTION

The current process of crop estimation in India is manual survey by regional state government officers in which selected farmers or village officials are interviewed regarding their crops. By comparison with the results of previous years, this information is then extrapolated to generate data and predictions on a regional basis. This means that these traditional surveys are time-consuming. In addition, the information collected is often imprecise and unreliable, leading to inaccurate crop-yield forecasts and subsequent difficulties for agricultural planners and managers on both regional and national scale.

In case of natural calamities also; such as flood or draught or pest infection, the survey to find out damage to crops takes several months and; the finical or any other aid may not reach timely to the needy farmers. Therefore, there is need for sophisticated methods which are accurate enough for crop estimation and such surveys to avoid delays so that timely action can be taken.

The satellite image processing is becoming increasingly available for vegetation mapping and to decision makers for future growth and development. Remote sensing identified as a tool to assess performance more than a decade ago [1] [2]. In the last decade, remote sensing has been increasingly identified an objective, standardized, possibly cheaper and faster methodology for crop production surveys than conventional field investigation [3] [4].

In this paper the use of satellite imaginary is proposed. The very first thing is the image enhancement. In this paper we used a technique for colour enhancement in the compressed domain. The used technique is simple but more effective than some of the existing techniques reported earlier. Also for the land classification an appropriate feature extraction algorithm and classification algorithm are very important. These classification algorithms include Multiple Classifiers [5] [6], Neural Network [7] [8], Support Vector Machine [9], fuzzy classification [10] and other biologically inspired algorithms [11]. These classifications were based on various features such sub-pixels, wavelet functions and texture features etc.

In this paper the use of Gabor wavelet transform for obtaining features from satellite images is demonstrated for land classification as crop and non-crop area. Gabor wavelet transform is one of the most effective feature extraction techniques for textures. As the Gabor wavelets are believed to be rather consistent to the response of Human Vision System (HVS). It provide a comprehensive experimental evaluation of feature extraction as compared with other multi-resolution texture features indicating that the Gabor features provide the best pattern retrieval accuracy [13].

The paper is organized as follows: Section 2 contains the image enhancement problem. Section 3 contains a feature extraction using Gabor wavelet transform. Finally, Section 4 classification of Land and section 5 gives the results and conclusions drawn from the work with the proposed system. General flow of the work is as shown in Figure 1.

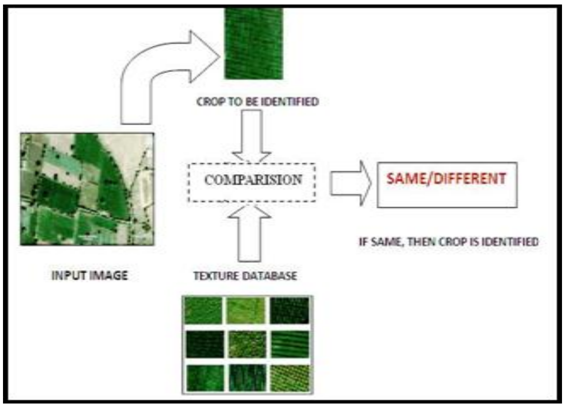

Fig.1 Overview of the methodology used

II. IMAGE ENHANCEMENT

Image enhancement techniques are designed to improve the quality of an image as perceived by a human being to improve the interpretability of the information present in images. It can be done both in spatial as well as in the frequency domain. The spatial domain method operates directly on pixels, whereas the frequency domain method operates on Fourier transform of an image and then transforms it back to the spatial domain.

Now days images are being represented in the compressed format for efficient storage and transmission. Therefore the processing in the DCT domain has attracted significant attention of researchers.

The display of a colour image depends upon three fundamental factors, namely i) its brightness, ii) contrast, and iii) colours.

In this work we have used the method of Enhancement Color Images by scaling the DCT Coefficients which consider all three fundamental factors while enhancing the image [12]. The simplicity of the proposed algorithm lies in the fact that the computation requires only scaling of the DCT coefficients mostly by a factor which remains constant in a block. The used algorithm uses the same scale factor for both the DC and AC coefficients, and also scales the chromatic components with the same factor.

The proposed method performs the colour image enhancement operation in three steps. First, it adjusts the background illumination. The next step preserves the local contrast of the image and the last one preserves the colours of the image. Figure 1 shows an example of input image and figure 2 shows the DCT enhanced image.

Fig 2: Input Satellite Image

Fig 3: DCT enhanced image

III. FEATURES EXTRACTION

In Land classification appropriate feature selection from satellite images is important. Wavelet analysis is an advanced feature extraction algorithm which is a based on windowing technique with variable-sized regions. In wavelet analysis use of long time intervals is possible to get more precise low frequency information and shorter regions where high frequency information is required.

A discrete wavelet transform (DWT) is the wavelet transform process in which the wavelets in numerical analysis and functional analysis are discreetly sampled. Temporal resolution is a key advantage of wavelet transform over Fourier transform in which it captures both frequency and location information. In this study single level 2-D wavelet transform decomposition is used for features extraction.

The objective of this paper is to study the use of texture as an image feature for identification of different types of crops. An image can be considered as a mosaic of different texture regions, and the image features associated with these regions can be used for search and retrieval. The input information in our case is an intensity pattern or texture within a rectangular window as shown in Figure 4.

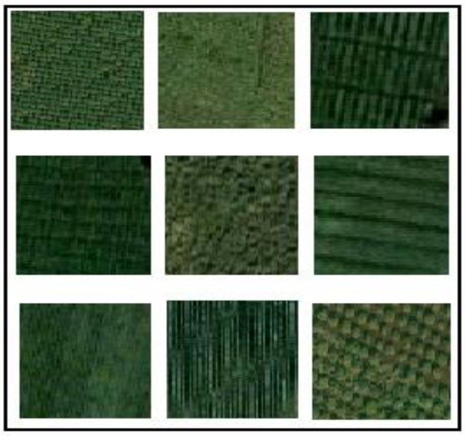

Fig. 4: Textures of different crops

A. *Gabor Functions and Wavelets*

A two dimensional Gabor function g(x, y) and its Fourier transform G (u, v) can be written as:

$$g(x,y) = \left(\frac{1}{2\Pi\sigma_x\sigma_y}\right) exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2}\right)+2\Pi j W_x\right] \quad (1)$$

$$G(u,v) = exp\left\{-\frac{1}{2}\left[\frac{(u-W)^2}{\sigma_u^2}+\frac{v^2}{\sigma_v^2}\right]\right\} \quad (2)$$

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

Gabor functions form a complete but nonorthogonal basis set. Expanding a signal using this basis provides a localized frequency description. A class of self-similar function, referred to as *Gabor wavelets* is used in the following discussion. Let g(x, y) be the mother Gabor wavelet, then this self-similar filter dictionary can be obtained by appropriate dilations and rotations of g(x, y) through the generating
function:

$$g_{mn}(x,y) = a^{-m} g(x',y'), \text{ a >1, } m, n = \text{integer}$$

$$x' = a^{-m}(x\cos\theta + y\sin\theta),$$

and

$$y' = a^{-m}(-x\sin\theta + y\cos\theta) \quad (3)$$

Where, $\theta = {}^{n\pi}/_{K}$ and K is the total number of orientations.

The scale factor a^{-m} in (3) is meant to ensure that the energy is independent of m.

B. Gabor Filter Design

The non orthogonality of the Gabor wavelets implies that there is redundant information in the filtered images, and the following strategy is used to reduce this redundancy. Let u_l, and u_h, denote the lower and upper center frequencies of interest. Let K be the number of orientations and S be the number of scales in the multi resolution decomposition. Then the design strategy is to ensure that the half-peak magnitude support of the filter responses in the frequency spectrum touch each. This results in the following formulas for computing the filter parameters σ_u and σ_v.

$$a = \left({}^{u_h}/_{u_l}\right)^{\frac{1}{S-1}}, \sigma_u = \frac{(a-1)u_h}{(a+1)\sqrt{2ln2}}$$

$$\sigma_u = tan\left(\frac{\pi}{2k}\right)\left[u_h - 2ln\left(\frac{2\sigma_u^2}{u_h}\right)\right]\left[2ln2 - \frac{(2ln2)^2\sigma_u^2}{u_h^2}\right]^{-\frac{1}{2}} \quad (4)$$

Where W=u_h and m = 0,1,…,S-1. In order to eliminate sensitivity of the filter response to absolute intensity values, the real (even) components of the 2D Gabor filters are biased by adding a constant to make them zero mean .This can also be done by setting *G(0,0)* in (2) to zero.

C. Feature Representation

Given an image I(x, y), its Gabor wavelet transform is then defined to be

$$W_{mn}(x,y) = \int I(x_1,y_1)g_{mn} * (x - x_1, y - y_1)dx_1dy_1 \quad (5)$$

Where * indicates the complex conjugate. It is assumed that the local texture regions are spatially homogeneous, and the mean μ_{mn} and the standard deviation σ_{mn} , of the magnitude of the transform coefficients are used to represent the region for classification and retrieval purposes:

$$\mu_{mn} = \iint |W_{mn}(xy)|dxdy \quad \text{and}$$

$$\sigma_{mn} = \sqrt{\iint (|W_{mn}(x,y)| - \mu_{mn})^2 dxdy} \quad (6)$$

A feature vector is now constructed using, μ_{mn} *and* σ_{mn} as feature components. In the experiments, we use four scales S = 4 and six orientations *K* = 6, resulting in a feature vector

$$\bar{f} = [\mu_{00}\sigma_{00}\ \mu_{01}\sigma_{01} \dots\dots \mu_{35}\sigma_{35}] \quad (7)$$

Consider two image patterns i and *j*, and let $\bar{f}^{(i)}$ *and* $\bar{f}^{(j)}$ represent the corresponding feature vectors. Then the distance between the two patterns in the feature space is defined to be

d (i,j) = $\sum_m \sum_n d_{mn}(i.j)$

Where

$$d_{mn}(i,j) = \left|\frac{\mu_{mn}^{(i)} - \mu_{mn}^{(j)}}{\propto(\mu_{mn})}\right| + \left|\frac{\sigma_{mn}^{(i)} - \sigma_{mn}^{(j)}}{\propto(\sigma_{mn})}\right|$$

(8)

$\alpha(\mu_{mn})$ *and* $\alpha(\sigma_{mn})$ are the standard deviations of the respective features over the entire database, and are used to normalize the individual feature components.

IV. Classification of Land

In this paper, the classification is conducted in the following order: separation of land and non-crop land only by extracting the green colors within the enhanced image. Then the texture database is used in the experiments which consist of 12 different texture classes. A query pattern in the following is any one of the image in the database. This image is then processed to compute the feature vector as in Eq.(7). The distance *d(i, j)*, where *i* is the query pattern and *j* is a pattern from the database, is computed. The distances are then sorted in increasing order and the closest set of patterns are then retrieved and grouped together. Figure 5 and figure 6 shows a texture image of wheat crop and an identification of wheat crop in an input image respectively.

Fig. 5: Textures of wheat crop

Colour	Meaning
	Wheat Crop
	Non-Crop Land

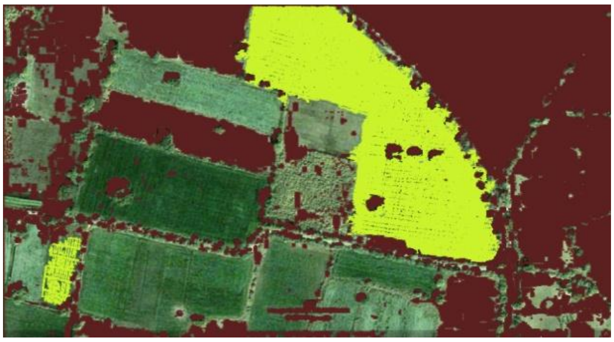

Fig. 6: Identification of wheat crop

V. Conclusion

In this study we have used techniques such as Color Space Transform and Discrete Cosine Transform, and the Gabor wavelet transform. A texture based classification method will be used for the classification of land as well as for the classification of different crops and then the method can be applied for the monitoring of the different crops throughout the year. Some difficulties, such as mixing and overlapping of crop differentiation were encountered; however these problems can be eliminated by the statistical averaging of training areas in different seasons. The results of this study can provide on economic means to apply remote sensing data for agriculture management.

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