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Feature Extraction from Multispectral Satellite Images Using GLCM and Back Propagation Technique

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Abstract— **This study presents the integration of discrete wavelet transform (DWT) derived contexture (macro-texture) and grey-level co-occurrence matrices (GLCM) (micro-texture) in the recognition and extraction of the following selected urban land cover information from very-high spatial resolution Quickbird imagery: buildings object, vegetation. The DWT filters capture the high and low -frequency texture information, whereas the GLCM captures the very high-frequency image components, for the same scene features. Besides the commonly used micro-texture (GLCM), the macro-texture (DWT) is modelled here to take care of the contextual information defined as feature edge (size and shape). This edge information is derived from multispectral components of the DWT. From the statistical image testing of the per-pixel classification accuracy with the z-score, it was found that the integrated feature sets comprising the Quick bird spectral bands, 3 × 3 mean-GLCM and the first level of the vertical-DWT sub-band outperformed all the other tested input primitives, with a z-score value of 2.0. The accuracy showed that all the three feature primitives were essential in improving the recognition and extraction of tested urban land cover in very-high spatial resolution Quickbird imagery.**

Then the features are extracted from the filtered image using Gray Level Co-occurrence Matrix (GLCM).Finally, Extracted features are classified using Back Propagation Artificial Neural Network (BPANN) and the performance is analyzed based on its image accuracy, very low error rate and sensitivity of image.

I. INTRODUCTION

Remote sensing is an important technique to obtain information of earth resources and environment. Remotely sensed images consist of spectral, spatial and temporal resolution. Spectral information is the foundation of remotely sensed image classification. Spatial resolution is the main factor which influences the recognition accuracy of ground object [1]. Application of urban land cover maps include environmental planning, land use change detection, transportation planning and water quality management. Analysis of urban areas using medium resolution remote sensing imagery is mainly focused on identification of built up areas or discrimination between residential, commercial and industrial zones [2]. For detailed observation on urban land cover, high spatial resolution remote sensing provides more information than medium resolution imagery. Increasingly, smaller spatial resolution does not necessarily improve classification performance and accuracy [3]. However, high resolution multispectral satellite imagery is possible to produce more detailed urban land cover maps by identifying features such as roads and buildings in urban environment.

This study has been focused on use of texture and contextual information in classification of high resolution satellite imagery of urban areas. Classification of urban areas is one of the most challenging tasks for remotely sensed data because of high spectral and spatial diversities due to its surface materials like asphalt, concrete, water, glass and soil [4]. Performance of a classifier depends directly on the choice of feature extraction and feature selection method employed on the data. So, the feature extraction stage is one of the important components in any pattern recognition system. The feature extraction stage is designed to obtain a compact, non-redundant and meaningful representation of observations. It is achieved by removing redundant and irrelevant information from the data. These features are used by the classifier to classify the data. It is assumed that a classifier that uses smaller and relevant features will provide better accuracy and require less memory, which is desirable for any real time system. Besides increasing accuracy, the feature extraction also improves the computational speed of the classifier. Intention of this paper is to recognize and extract the urban features using Gray Level Co-occurrence Matrix (GLCM) and then the extracted features are classified using Back Propagation Artificial Neural Network (BPANN).

II. LITERATURE REVIEW & RELATED WORK

Currently commercially available high spatial resolution multispectral (HSRM) images, obtained from Quick Bird, IKONOS, and SPOT-5, etc., can provide a large amount of detailed ground information in a timely manner. However, the availability of this type of data poses challenges to image classification. Due to the complex spatial arrangement and spectral heterogeneity even within the same class, conventional spectral classification methods are inadequate for HSRM imagery. It is well known that combining spatial and spectral information can improve land use classification from HSRM data. Therefore, many effective spatial features concerning the structure, shape, and geometric characteristics have been proposed. One commonly applied statistical procedure for interpreting texture is the gray level co-occurrence matrix (GLCM), which is a widely used texture and pattern recognition technique in the analysis of satellite data, and has been successful to a certain extent. A method based on straight lines to assess land development in high resolution satellite images is introduced in where a set of statistical measures are extracted based on the regional line distribution. A Markov random- field -based method using both contextual information and a multi-scale fuzzy line process for classifying HSRM imagery is investigated in. In and, the structural information is extracted by applying the extended morphological profiles with a multi-scale approach. Some algorithms that focus on contextual spectral similarity have been proposed. In a length–width extraction algorithm (LWEA) is developed to extract the length and width of spectrally similar connected groups of pixels from the HSRM imagery. These values of length and width are found by searching along a pre- determined number of equally spaced lines radiating from the central pixel. In a pixel shape index (PSI) is introduced, which sums the length of all the radiating lines to describe the structure around the central pixel.

First, we propose some new statistical measures to extract the structural features of direction lines, such as weighted mean (w-mean), length–width ratio, and standard deviation (SD), which overcome the inadequacy of the previous algorithms (PSI and LWEA). Second, some dimension reduction approaches, including feature extraction and feature selection, are tested and compared in order to reduce information redundancy. Third, different classifiers including maximum- likelihood classifier (MLC), back propagation neural network (BPNN), probability neural network based on expectation– maximization training(EM-PNN), and support vector machine (SVM) are used to process the hybrid spectral-structural features after the steps of spatial feature extraction and dimension reduction.

When using morphological features for the classification of high resolution hyper spectral images from urban areas, one should consider two important issues. First one is that classical morphological openings and closings degrade the object boundaries and deform the object shapes. Morphological openings and closings by reconstruction can avoid this problem, but this process leads to some undesirable effects. Objects expected to disappear at a certain scale remain present when using morphological openings and closings by reconstruction. The second one is that the morphological profiles (MPs) with different structuring elements and a range of increasing sizes of morphological operators produce high-dimensional data. These high-dimensional data may contain redundant information and create a new challenge for conventional classification methods, especially for the classifiers which are not robust to the Hughes phenomenon. In this project work, we first investigate morphological profiles with partial reconstruction and directional MPs for the classification of high resolution hyper spectral images from urban areas. Secondly, we develop a semi-supervised feature extraction to reduce the dimensionality of the generated morphological profiles for the classification. Experimental on real urban hyper spectral images will be used to demonstrate the efficiency of the considered techniques.

III. ANALYSIS OF PROBLEM

In this project, we are trying to gain the pixels value so that they can provide us with better resolutions of the cropped image which can be achieved by classical morphological openings and closings. With the help of GLCM algorithm, the pixel value can be maintained. Two steps to generate spatial features. First, spatial information of a satellite image is window defined by moving window of given size. This type of matrix contains frequencies of any combination of gray levels occurring between pixel pairs separated by a specific distance and angular relationship within the window. After this, it will compute the statistics from the GLCM to describe the spatial information according to relative position of matrix elements extracted by a co- occurrence matrix calculated on a pixel window defined by moving window of given size. This type of matrix contains frequencies of any combination of gray levels occurring between pixel pairs separated by a specific distance and angular relationship within the window. Finally, compute the statistics from the GLCM to describe the spatial information according to relative position of matrix elements

IV. PRAPOSED WORK

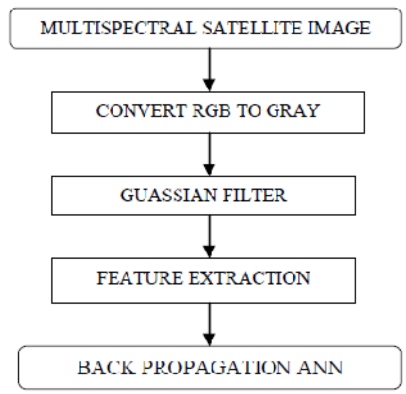

Fig.1 method of image processing

A. Multispectral Satellite Image

Multispectral Satellite Image is an RGB image which can be converted into Gray Scale Image for further processing.

Gaussian filter is used for filtering the noise which is present in the gray scale image.

Fig.2 Multispectral satellite image in RGB

B. Gaussian Filter

Images are corrupted by random variations in intensity values called noise due to non perfect camera acquisition or environmental conditions. To filter the noise Gaussian filter is used. Gaussian filters are a class of linear smoothing Correlation filters with the weights chosen according to the shape of a Gaussian function. The Gaussian smoothing filter is a very good filter for removing noise drawn from a normal distribution and it is used to avoid the overshoot of step

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function while reducing the rise and fall time [5]. The two dimensional Gaussian function is given by

$$G(X.Y) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{-x^2+y^2}{2\sigma^2}}$$

Gaussian filter performs the convolution between input and Gaussian factors. Here in the pre-processing the Variance unwanted noise components are reduced from the input image while passing through Gaussian filter. It is mainly used to enhance the image quality than the original image.

C. Discrete Wavelet Transform

The decomposition of images into various frequency ranges permits the isolation of the frequency components introduced by "intrinsic deformations" or "extrinsic factors" into certain subbands [7]. This process isolating small changes in an image mainly in low-frequency sub band images. The 2-D wavelet decomposition of an image is performed by applying 1-D DWT along the rows of the image first, and, then, the image are decomposed along the columns. This Decomposition image in four decomposed subband images referred to as low–low (LL), low high (LH), high–low (HL), and high–high (HH). We have proposed a new method for satellite image equalization which is an extension of Histogram Equalization, and it is based on the PCA of an LL subband image obtained by DWT. DWT is used to separate the input low-contrast satellite image into different frequency subbands, where the LL subband has approximation co efficient . For that, LL subband takes for Histogram Equalization process, which preserves the high-frequency components (i.e., edges). Hence, after inverse DWT (IDWT), the resultant image will have sharper edges with high-quality contrast. In this letter, the proposed method has been compared with the various histogram equalization like conventional GHE technique as well as LHE and some state-of-the-art techniques such as BPDHE and SVE.
Extracting the features of filtered image using Gray Level Co-occurrence Matrix.

Fig.3 Gray level image

D. Feature Extraction

Texture is the main feature to characterize the surface and structure of a given object or region. As image is made up of pixels, texture can be defined as an entity consisting of mutually related pixels and group of pixels. Texture can be characterized into two categories as structural and statistical approach. For analyzing and evaluating the performance of texture features these methods are consider. Statistical method characterize the texture by statistical distribution of image intensity and structural method describes texture by identifying structural primitives and it is suitable for textures where their spatial size can be described using a variety of properties. Structural method proposed for extracting the features is Gray Level Co-occurrence Matrix

E. Gray Level Co-occurrence matrix (GLCM)

Gray level co-occurrence matrices have been used extensively in remote sensing applications for land-use classification and texture analysis. Human visual system uses second order distribution of gray levels as a discriminator in identifying textures. The features based on co-occurrence matrices should capture some characteristics of textures, such as homogeneity, entropy, contrast and others. Paper [6] elaborate about the extraction of 14 textural features based on GLCM. The detailed descriptions .
glcm = graycomatrix(I) creates a gray-level co-occurrence matrix (GLCM) from image I. graycomatrix creates the GLCM by calculating how often a pixel with gray-level (grayscale intensity) value *i* occurs horizontally adjacent to a pixel with the value *j*. Each element (*i,j*) in glcm specifies the number of times that the pixel with value *i* occurred horizontally adjacent to a pixel with value *j*.

F. Classifying the extracted features using Back Propagation Artificial Neural Network.

Back propagation is a common method for training artificial neural networks. It is a supervised learning network, and is a simplification of the delta rule. Back propagation requires the activation function used by The artificial neurons (or nodes) be differentiable. The data in the network flow from the input layer to the output layer crossing the intermediate layers (called hidden layers) without feedbacks, then the network is called "feed forward". This type of neural network has been widely used in supervised image classification of remotely sensed data. It requires dataset of the desired output for many inputs, for making the training set. The back propagation algorithm trains a network for a given set of input patterns with known classifications. When each entry of the sample input pattern is presented to the network, the network examines the output response to the sample input pattern. The output response is then compared with the known and desired output and the error value is calculated. Based on the error value, the connection weights are adjusted. Back propagation Feed-forward multilayer network depicted as follows:

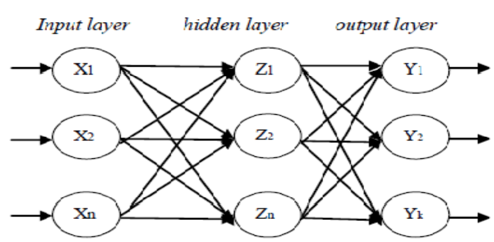

Fig.4 Neural Network

The Neural Network contains three layers: input, hidden, and output Layer. During the training phase, training data is fed into the input layer and it propagates to the hidden layer and then to the output layer is known as the forward pass. In forward pass, each node in hidden layer gets input from the input layers, which are multiply with appropriate weights and then added. The output of the hidden node is the non-linear transformation. In the same way each node in output layer gets input from hidden layer, which are multiplied with suitable weights and then added. The output of this node is the non-linear transformation of the ensuing sum. Output values from the output layer are compared with the target output value. The target output values are those that attempt to train our network. The error between actual output values and target output values is calculated and propagated back to hidden layer. This is called the backward pass. The error is used to update the connection strength between nodes, as weight matrices between input hidden layers and hidden-output layers are updated. During the testing phase, learning does not takes place because of no change in the weight matrices. Each test vector is fed into the input layer and the feed forward of the testing data is similar to the training data.

CONCLUSION

An efficient image classification technique will be proposed with the help of neural network classifier Here proposed technique will be made up of three phases namely pre-processing, feature extraction and final classification using back propagation network classifier Finally the multi spectral image will be classified in to multiple region based on training data

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