Feature Extraction and Classification of High Resolution Satellite Images using GLCM and Back Propagation Technique

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Abstract- Remote sensing data provides much essential and critical information for monitoring many applications such as image fusion, change detection and land cover classification. This paper proposed about the classification and extraction of spatial features in urban areas for high resolution multispectral satellite image. Spectral information is the foundation of remotely sensed image classification. Initially, Preprocessing is done for multispectral satellite image using Gaussian filter. 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 accuracy, error rate and sensitivity.

Keywords- **Multispectral Satellite Image, Gaussian filter, GLCM, Back Propagation Artificial Neural Network, Feature Extraction.**

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).

Organization of paper as follows section II describes about proposed methodology and section III we present the result and discussion. Finally, section IV conclusion of the paper.

II. PROPOSED METHODOLOGY

Fig.1 shows the representation of proposed methodology. The proposed methodology consists of four steps. In step I, Multispectral Satellite Image is an RGB image which can be converted into Gray Scale Image for further processing. Step II, Gaussian filter is used for filtering the noise which is present in the gray scale image. Step III, Extracting the features of filtered image using Gray Level Co-occurrence Matrix. Step III, classifying the extracted features using Back Propagation Artificial Neural Network.
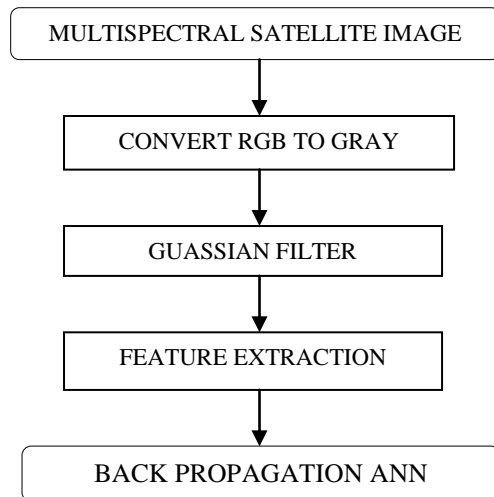
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┌─────────────────────────────────────────┐
│      MULTISPECTRAL SATELLITE IMAGE        │
└─────────────────────────────────────────┘
                     │
                     ▼
┌─────────────────────────────────────────┐
│           CONVERT RGB TO GRAY             │
└─────────────────────────────────────────┘
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                     ▼
┌─────────────────────────────────────────┐
│             GUASSIAN FILTER               │
└─────────────────────────────────────────┘
                     │
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┌─────────────────────────────────────────┐
│            FEATURE EXTRACTION             │
└─────────────────────────────────────────┘
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┌─────────────────────────────────────────┐
│          BACK PROPAGATION ANN             │
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Fig. 1: Proposed Methodology

A. 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 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 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 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.

B. 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.

i. 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

Homogeneity	$\displaystyle\sum_{i,j=1}^{N} \frac{P(i,j)}{1+\lvert i-j\rvert}$
Entropy	$\displaystyle\sum_{i,j=1}^{N} P(i,j)\log P(i,j)$
Angular Second Moment	$\displaystyle\sum_{i,j=1}^{N} \{P(i,j)\}^2$
Dissimilarity	$\displaystyle\sum_{i,j=1}^{N} P(i,j)\lvert i-j\rvert$
Correlation	$\displaystyle\sum_{i,j=1}^{N} \frac{(i-\mu_i)(j-\mu_j)P(i,j)}{\sigma_i\sigma_j}$
Mean	$\displaystyle\mu_i = \sum_{i,j=1}^{N} iP(i,j)$ $\displaystyle\mu_j = \sum_{i,j=1}^{N} jP(i,j)$
Variance	$\displaystyle\sigma_i = \sum_{i,j=1}^{N} (i-\mu_i)^2 P(i,j)$ $\displaystyle\sigma_j = \sum_{i,j=1}^{N} (j-\mu_j)^2 P(i,j)$
Contrast	$\displaystyle\sum_{i,j=1}^{N} P(i,j)\,(i-j)^2$

Where, i,j - Co-ordinates in the co-occurrence matrix.
P(i,j) - Co-occurrence matrix value at the coordinates i,j.
N- Dimension of the Co-occurrence matrix

of different texture features can be found in Table I.

TABLE I

TEXTURE MEASURES

This study involves two steps to generate spatial features. First, spatial information of a satellite image is 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.

C. 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:

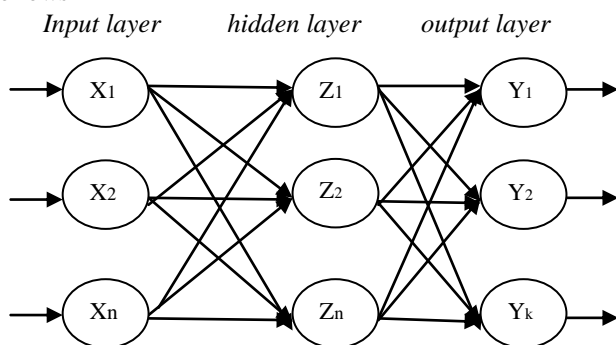*Input layer*   *hidden layer*   *output layer*

Fig.2: Back propagation feed forward multilayer 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 of the resulting sum. 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.

III. RESULT AND DISCUSSION

The multispectral satellite image is shown in Fig.3 which can be converted into gray scale image for further processing which is shown in Fig.4.The gray scale image is filtered with the Gaussian filter to remove the noise which is present in the image and the output of filtered image is shown in Fig.5. Then the texture features are extracted from the filtered image. The extracted features are classified by using Back Propagation Artificial Neural Network which is shown in Fig.6.

Fig.3: Multispectral Satellite Image

Fig.4: Gray level Image
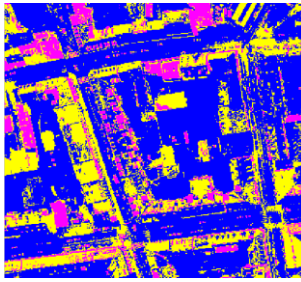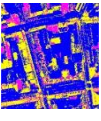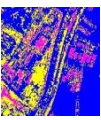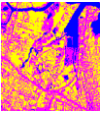
Fig.5: Filtered Image
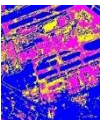
Fig.6: classified image

A. Performance Evaluation

In this section, the performance evaluation of proposed technique is discussed. Here, the performances of various multispectral satellite images are evaluated based on its accuracy, error rate and sensitivity. The Back Propagation output of different satellite images are shown in TABLE II.

TABLE II
STATISTICAL ANALYSES

Satellite images	Classified image	Accuracy (%)	Error rate	Sensitivity
		94.54	0.11	0.921
		91.89	0.08	0.9459
		87.84	0.12	0.8919
		94.59	0.05	0.9459

IV. CONCLUSION

An efficient image classification technique is proposed with the help of neural network classifier. Here, proposed technique is made of three phase namely pre-processing, feature extraction and final classification using Back Propagation Network classifier (BPN). First the multispectral satellite image is subjected to set of pre-processing steps, which are used to transform an image into suitable form that is easier for extracting the features and classification. Subsequently, the pre-processed image is extracted by using Gray level Co-occurrence Matrix. This

result in the image is extracted into number of features. Then, the training data for Back Propagation is chosen from extracted output. The chosen data is given to the input of trained BPN. Finally the multispectral image is classified into multiple regions based on the training data. The experimental results demonstrated the effectiveness of the proposed classification techniques. This analyse ensures that the classification has good accuracy in all type of multispectral satellite images.

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