DISCRIMINATING LINEAMENTS FROM THE ASTER IMAGE BY ANALYZING THE OBJECT PROPERTIES

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ABSTRACT

Lineament analysis constitutes an interesting approach in the geological mapping and mineral exploration. Classification of manmade lineament features like road, rail road, pipe line etc from the ASTER image using the suitable object properties. Feature extraction is the method of capturing the visual content of images for indexing and retrieval. A feature reduction is the method of Reduce the dimensionality of a data set by finding a new set of variables, smaller than the original set of variables. To extract the object of interest, Gray Level Co occurrence matrix (GLCM) and, Principal Component Analysis (PCA) algorithms have been considered. Object oriented segmentation and classification methods are a new development in this direction. Here, the Image is decomposed into non-overlapping regions. In addition to the spectral properties, shape and textural properties of the regions are taken into consideration for classification of the regions in lieu of the individual pixels.

Keywords: Feature extraction, GLCM , Object Based Image Analysis, Principal Component Analysis.

I. INTRODUCTION

Remote sensing is the science (and to some extent, art) of acquiring information about the Earth's surface without actually being in contact with it. This is done by sensing and recording reflected or emitted energy and processing, analyzing, and applying that information [1]. Recent researches on image classification made by chain code method and polygonal Approximation for detecting edge features in the image [2].

II. BACKGROUND AND RELATED WORK

In geology and hydrology applications, linear features regularly reflect the geological lineaments such as faults or fractures and hydrological structures such as river or shoreline [3]. The mapping of lineaments (fracturing) is a necessary part of the mineral exploration research. The lineaments are the linear or curvilinear discontinuities which dealt with the faults and folds; and are related with geo morphological features and/or a various tectonic formation [4]. Various image enhancement techniques use directional filters (Sobel) and non-directional (gradient) filters which are allowed to map a larger number of lineaments [5]. Extraction of linear features can be achieved in a satisfactory level through proper segmentation and appropriate definition & representation of key parameters of image objects [6].The faults and contacts from geological map and gravity data analysis are striking mainly in NNE-SSW, which is the direction of the Kabul block trending fault structure [7]. Landsat 7ETM+ image successfully differentiating fractures in different geological environment and the result is almost similar with the high spatial resolution image [8].The extracted lineaments, based on subjective assessment, from each dataset correlates lineament density and intersections with ore deposits occurrences. The aim of the study is to determine the relationship between ore deposits and lineaments by plotting their geospatial data on suitable maps [9]. Remotely sensed data frequently used to study about the terrain surface, thus unique geomorphic and geologic features can be identified. It looks like linear features on the satellite images usually represent fractures, faults or lithologic boundaries [10]. In this study, automatic lineament analysis is performed in high resolution satellite imagery for identifying discontinuites in rocks. Manual digitized lineament map is formed and it automatically extracted the lineaments [11]. In this paper canny algorithm offered perfect information about lineaments with 3D image visualization which reconstructs using SRTM. 3D image visualization provides excellent information about lineaments and geological features [12]. Canny edge detector is one of the tool for features extraction and also an enhancement tool for remote sensing images, thus results a very high enhancement level [13]. The detection of strong linear features on different scales from a level of ground information compared to that obtained from aerial photographs. For detecting geological lineaments from the aerial photographs, a new hough counter has been used. The new counter counts grey levels and operates on both a pictures and its inverse, then combine the results of line / peak detection [14]. For feature extraction, this paper presents an application of gray level co-occurrence matrix to extract second order statistical texture features. The results show that these features have high discrimination accuracy [15]. In this paper, a new method for color GLCM textures and computing with other good known methods is presented. Extracting color texture features with the help of RGB and HSV color spaces [16]. In this paper, in order to classify the plants by applying on the leaves images; the Gray-Level Co-occurrence matrix (GLCM) and Principal Component Analysis (PCA) algorithms have been considered [17]. In this paper, various image feature extraction algorithms are specified with architectural models with internal modules. Textural properties can be calculated from GLCM to understand the details about the image content [18]. This paper approaches segmentation of the scene with Multi-resolution Object Oriented segmentation. The step main focuses on exploiting both spatial and spectral characteristics of the target feature extraction system. The road regions are automatically identified using a soft fuzzy classifier based on a set of predefined membership functions. The detected road segments are further refined using morphological operations to form final road network, which is then evaluated for its completeness, correctness and quality [19]. The most important stage of OBIA is the image segmentation process applied prior to classification. Multi-resolution image segmentation technique was employed with the optimal object parameters like scale, shape and compactness that were defined after an extensive trail process on the data sets. Nearest neighbor classifier was applied on the segmented images, and then the accuracy assessment was applied. Results show that segmentation parameters have a direct effect on the classification accuracy, and low values of scale-shape combinations produce the highest classification accuracies [20].

III. STUDY AREA

The study area is based on ASTER San Gabriel River (USACE, 1949) which covers 60.6 miles (97.5 km). The San Gabriel River in the San Gabriel Mountains and San Gabriel Valley in the Los Angeles Basin, Southern California (Fig.1). This image covers an area of 39.5 by 45.4 kilometers, and is located near 34.1 degrees North latitude, 117.9 degrees West longitude. For geologic epochs the river ran freely across dry grasslands and through riparian zones and wide marshes to the Pacific Ocean, flooding in the winter and spring then running nearly dry in the summer and fall. In this image, primary source that have many location in north fork fish contain mount san Antonio,san Gabriel mountains in the elevation of 7,500 ft(2,286 m) and it coordinates $34^{0}20'35''$N $117^{0}43'30''$W. In secondary source contains 4,800 ft (1,463 m) elevation & it have 34^{0} 15'29"N $118^{0}06'13''$W coordinates. This site is small town area and contains various land use types (residential areas, agriculture, forest, etc).

Fig. 1: ASTER image of San Gabriel, Los Angeles, California.

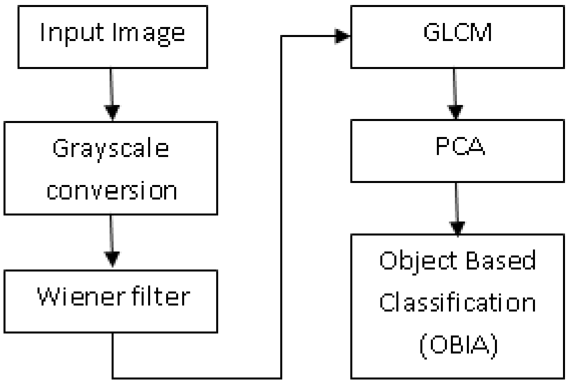

Fig 2. Object based Image Classification

IV. METHODOLOGY

Feature extraction is used to denote the piece of information which is relevant for solving the computational task is related to certain application system. At first, the image is preprocessed with the help of wiener filter which is used to remove noise from the original image. Wiener filter has been chosen because of its superior performance.

GLCM is used for extracting features that involves simplifying the amount of resources to describe a large set of data accurately. PCA is used for selecting particular features from the image. The main objective is to identify the pattern (input vectors are correlated with the given data) which reduces the dimensionality of data to get most favorable space wherever they are linearly distinguishable. Finally classification can be done with help of Object based classification. It was performed as the user friendly, multi scaled, and fully functional application. It is not directly access the single pixels. In this classification the image segmentation is the important preliminary step.

V. PROPOSED SYSTEM

5.1 Pre-Processing

Here the main focus is classifying the image using object information which leads to accurate classification from high resolution Satellite images. In Pre-Processing, Multispectral image is converted in to Gray scale image which eliminates hue, saturation information while retaining the luminance.

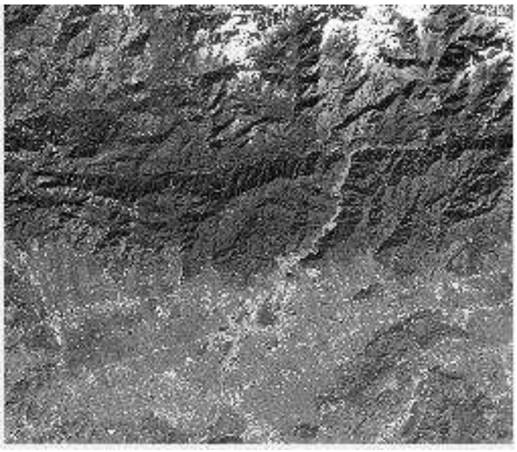

Fig. 3 Gray scale Image

Apply wiener filter to the image which for removing adaptive noise and produces an estimate of a desired or target random process by linear time-invariant filtering of an observed noisy process. The Wiener filter minimizes the mean square error between the estimated random process and the desired process. The wiener Filter has a variety of applications such as System Identification, Noise Reduction, and Signal Detection.

5.2 Gray Level Co-occurrence Matrix

In statistical texture analysis, texture features are computed from the statistical distribution of observed combinations of intensities at specified positions relative to each other in the image. According to the number of intensity values of the pixels in each combination, statistics are classified into first-order, second-order and higher-order statistics. The Gray Level Co-occurrence Matrix (GLCM) method extracts second order statistical texture features. The approach has been used in a number of applications, Third and higher order textures consider the relationships among three or more pixels.

The GLCM calculation based on following table:

Neighbour pixel value → Ref pixel value:	0	1	2	3
0	0,0	0,1	0,2	0,3
1	1,0	1,1	1,2	1,3
2	2,0	2,1	2,2	2,3
3	3,0	3,1	3,2	3,3

A GLCM is a matrix where the number of rows and columns is equal to the number of gray levels, G, in the image. The matrix element P (i, j | Δx, Δy) is the relative frequency with which two pixels, separated by a pixel distance (Δx, Δy), occur within a given neighborhood, one with intensity 'i' and the other with intensity 'j'. The matrix element P (i, j | d, θ) contains the second order statistical probability values for changes between gray levels 'i' and 'j' at a particular displacement distance d and at a particular angle (θ). Using a large number of intensity levels G implies storing a lot of temporary data, i.e. a G × G matrix for each combination of (Δx, Δy) or (d, θ). Due to their large dimensionality, the GLCM's are very sensitive to the size of the texture samples on which they are estimated. Thus, the number of gray levels is often reduced.

5.3 Entropy

Entropy shows the amount of information in the image that is needed for the image compression. Entropy measures the loss of information or message in a transmitted signal and also measures the image information.

$$Entropy = \sum_{i,j=0}^{N-1} -\ln(P_{ij})P_{ij}$$

5.4 Energy

Energy provides the sum of squared elements in the GLCM. Also known as uniformity or the angular second moment. Angular Second Moment is high when image has very good homogeneity or when pixels are very similar

$$Energy = \sum_{i,j=0}^{N-1} (P_{ij})^2$$

5.5 Correlation

Correlation-Measures the joint probability occurrence of the specified pixel pairs.

$$Correlation = \sum_{i,j=0}^{N-1} P_{ij} \frac{(i-\mu)(j-\mu)}{\sigma^2}$$

5.6 Contrast

Measures the local variations in the gray-level co occurrence matrix.

$$Contrast = \sum_{i,j=0}^{N-1} P_{ij}(i-j)^2$$

5.7 Inverse Difference Moment

Inverse Difference Moment (IDM) is the local homogeneity. It is high when local gray level is uniform and inverse GLCM is high. IDM weight value is the inverse of the Contrast weight.

$$Homogeneity = \sum_{i,j=0}^{N-1} \frac{P_{ij}}{1+(i-j)^2}$$

The results of feature extraction methods are:

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Feature Extractions are

Entropy       -        1.058964e+02
Energy        -        1.038964e+02
Correlation     -        1.008964e+02
Contrast        -        9.689642e+01
Homogenity      -        1.018964e+02
Auto Correlation       -        9.589642e+01
Variance        -        1.028964e+02
```

Fig 4. GLCM Calculation

5.8 Feature Selection Process

The reduced Principal Components are then sorted in ascending order. The reduced matrix of PCA features has been arranged as

$PC1 \geq PC2 \geq PC3 \ldots\ldots\ldots \geq PCN$

Principle component and N is the number of features for an image. Left side of the matrix contains most significant features and right side of the matrix has least significant features after PCA calculation. Least important features can be useless as these hold very fewer information and have no impact on precision. Features on the left side hold more important information because left side of the matrix having very high variation. The aim of our research is to choose smallest amount of features that can give best precision. At last, from PCA features we have selected first L columns of matrix M. Though, we have chosen first few columns of PCA reduced feature that have high variations.

$PC1 \geq PC2 \geq PC3 \ldots\ldots\ldots\ldots \geq PCL$

L is the number of columns in above equation. The results of feature selection calculation are

```
Feature reductions are

Energy        -        1.058964e+02
Correlation     -        1.038964e+02
Contrast        -        1.008964e+02
Homogenity      -        9.689642e+01
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Fig 5. PCA Calculation

VI. CONCLUSION & FUTURE ENHANCEMENTS

The basic elements of an object-oriented approach are image objects. Image objects are contiguous regions in an image. Image objects can be linked to a hierarchical network, where they are attributed with a high-dimensional feature space. Segmentation parameters for multi resolution segmentation are: scale, color, shape, compactness, smoothness. Now, features in the ASTER image are extracted with the help of GLCM and PCA. It reduces the essential features of objects of interest. Furthermore, this method results efficient retrieval of object properties from the image. Further it will be applied to the object oriented segmentation and classification techniques to extract the objects of interest. Object based classification was performed as the multi scaled, and fully functional application. It is not directly access the single pixels if the segmentation will produce the accurate result means the classification performance is automatically increase. The main advantage of using object based classification it gives better performance than the pixel-based classification.

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