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Mobile Image Mining for Granite Quality Detection

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***Abstract*—Image Processing has a vital role in quality analysis of objects and presumably is one of the best ways of non destructive techniques. The project aims at detecting flaws if any in the granite blocks by analysis of their digital images. Two common defects, Crack and Mica contamination is studied by using hyper spectral image sensors. The unique characteristics of the defects are studied in hematite and geothite. To detect the mica contamination k-means segmentation algorithm is used. For crack detection, linear edge detection algorithm is applied and further processing is done to discriminate edges of cracks. Thus the algorithm categorizes the granite as defect less or defected granite.**
***Keywords*— non-destructive, crack detection, mica contamination, hyper spectral imagery, k-means segmentation,**

I. INTRODUCTION

Image Processing has a vital role in quality analysis of objects and presumably is one of the best ways of non destructive techniques. Imaging spectrometers have been used to acquire information about the geology and mineralogy of the Earth's surface .During this time, new analytical approaches have been developed to identify and map minerals in hyper spectral imagery by matching their spectral. Classical geologic mapping and mineral exploration utilize physical characteristics of rocks and soils such as mineralogy, weathering characteristics, geochemical signatures, and landforms to determine the nature and distribution of geologic units and to determine exploration targets for metals and industrial minerals. Subtle mineralogical differences, often important for making distinctions between rock formations, or for defining barren ground versus potential economic ore, are often difficult to map in the field. Hyper spectral remote sensing, the measurement of the Earth's surface in up to hundreds of spectral images, provides a unique means of remotely mapping mineralogy. A wide variety of hyperspectral data are now available, along with operational methods for quantitatively analyzing the data and producing mineral maps. This review paper serves to illustrate the potential of these data and how they can be used as a tool to aid detailed geologic mapping and exploration.

Detecting the quality of the Granite stone, mobilised is the challenge one to perform. Initially hyper spectrum imaging is used to detect the properties of the granite stones. The raw granites acquired from the mine were processed with several stages which provide its own market value. A fault in the production of stone will affect the major market rate. Generally the granite stone is exposed to several environmental damage which increases more vitality to generate more fault in the production of the solid stone. For several years imaging spectrometer is the only method to analyse the mineral content of the geological materials. An Ariel image of the granite rock is processed using the spectrum image to detect the quality and mineral composition of the rock. Many new techniques in processing spectral image is introduced in several years which compares the spectral details of the captured image with the digital library of spectral curves to generate the mineral contents of the rock. Probably many natural images capture using spectrum analyser will not show any regularity even though the normal vision can identify the difference in texture areas. Many techniques have been introduced to solve the problems faced by the spectrum analysis like texture analysis to detect the random texture defect detection all the techniques involved in detecting the quality analysis are not more flexible to make it as mobile one all the methods required a simple lab environment to perform the action. The techniques are K-means segmentation algorithm to identify the mineral contamination in the granite rock and linear edge detection method is introduced along with the k- means algorithm to detect the cracks presented in the rock. Both this techniques along with the image processing procedure we identify and separate the unqualified rock material from the production unit in the basis of mineral containment and crack presence in the surface of the stone. These are the important properties of the rock to maintain the market value of its type. This method provides the independence of mobility which does not need any laboratory setup to perform the analysis.

A. Hyper spectral imaging

The hyper spectral images provide more narrow spectral bands which help to provide the ability to differentiate community levels and the land cover feature imaging spectrometers are used to produce hyper spectral images. This development of image spectroscopy leads to two distinct technologies: Spectroscopy and remote imaging. A study about the reflected or emotion of the

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light from the materials and difference in the wavelength is called as Spectroscopy.

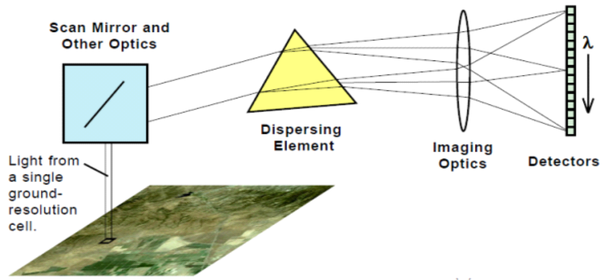

Fig 1. Hyperspectral imaging

When applying spectroscopy in optical remote sensing field it analyses the spectrum of sunlight that reflected by the material at the earth surface. The reflected light beamof the testing material are tested using instruments (spectrometers) to measure the labouratory measurement of the light reflection. An optical instruments like grating or prism is used to split the different wavelength of the light of narrow and adjacent band. The bands are measured using optical detectors. A narrow bandwidth as 0.01 micrometer can be made by using thousands of optical detectors. Averagely we can detect 0.4 to 2.4 micrometers which lies at middle of infrared wavelength.

B. Spectral Libraries

Several libraries of reflectance spectra of natural and man-made materials are available for public use. These libraries provide a source of reference spectra that can aid the interpretation of hyperspectral and multispectral images.This library has been made available by NASA as part of the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) imaging instrument program. It includes spectral compilations from NASA.s Jet Propulsion Laboratory, Johns Hopkins University, and the United States Geological Survey (Reston). The ASTER spectral library currently contains nearly 2000 spectra, including minerals, rocks, soils, man-made materials, water, and snow. Many of the spectra cover the entire wavelength region from 0.4 to 14 μm.

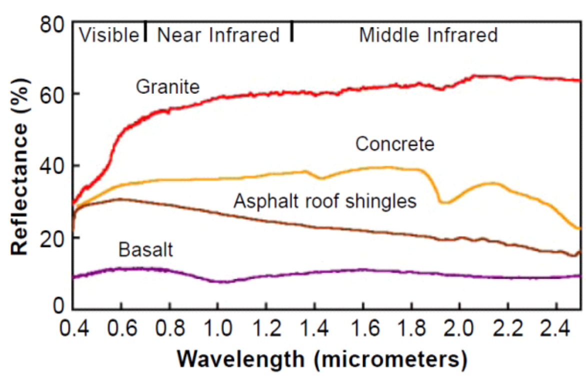

Fig 2. ASTER Spectral Library

II. RELATED WORK

Hyperspectral imaging offers the possibility of characterizing materials and objects in the air, land and water on the basis of the unique reflectance patterns that result from the interaction of solar energy with the molecular structure of the material. In this paper, we provide a seminal view on recent advances in techniques for hyperspectral data processing. Our main focus is on the development of approaches able to *naturally* integrate the spatial and spectral information available from the data. Geologists have used remote sensing data since the advent of the technology for regional mapping, structural interpretation and to aid in prospecting for ores and hydrocarbons. This paper provides a review of multispectral and hyperspectral remote sensing data, products and applications in geology.

During the early days of Landsat Multispectral scanner and Thematic Mapper, geologists developed band ratio techniques and selective principal component analysis to produce iron oxide and hydroxyl images that could be related to hydrothermal alteration.

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The data owner establishes the public system parameter via Setup and generates a public/master-secret3 key pair via KeyGen. Messages can be encrypted via Encrypt by anyone who also decides what ciphertext class is associated with the plaintext message to be encrypted. The data owner can use the master-secret to generate an aggregate decryption key for a set of ciphertext classes via Extract. The generated keys can be passed to delegates securely (via secure e-mails or secure devices) Finally, any user with an aggregate key can decrypt any ciphertext provided that the ciphertext's class is contained in the aggregate key via Decrypt.

The Center for the Study of Earth from Space (CSES) at the University of Colorado, Boulder, has developed a prototype interactive software system called the Spectral Image Processing System (SIPS) using IDL (the Interactive Data Language) on UNIX-based workstations. SIPS are designed to take advantage of the combination of high spectral resolution and spatial data presentation unique to imaging spectrometers. It streamlines analysis of these data by allowing scientists to rapidly interact with entire datasets.

The objective of this continuing effort is to develop operational techniques for quantitative analysis of imaging spectrometer data and to make them available to the scientific community prior to the launch of imaging spectrometer satellite systems such as the Earth Observing System (EOS) High Resolution Imaging Spectrometer (HIRIS). we consider how we may determine the relative proportions of ground cover components in a mixed pixel. We assume the usual linear model for signal mixing and examine a number of methods, closely related, for estimating the proportions. We also show how the precision of our estimates can be defined. We introduce a new estimator which is based on regularisation principles and which produces a smoother set of images than other methods, and gives more accurate estimates. The methods are compared on a simulated data set.

III.ARCHITECTURE DESIGN

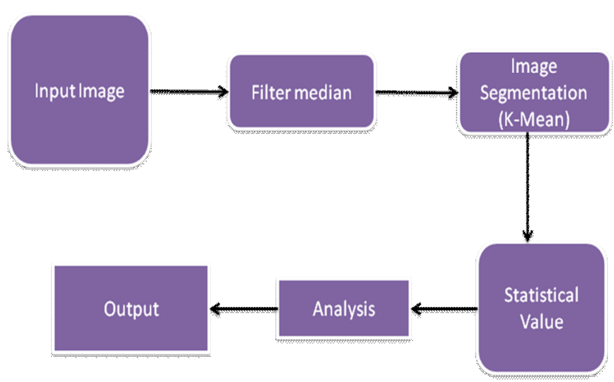

Fig 3.Block Diagram

In the proposed system, Mobile image Processing is used. Cost is low. High speed to detect the quality of stone cracks in the stone Cloud based image processing. Data mining is used for the storage of statistical values and image segmentations-pso, dpso is used for detection . Image filtering allows you to apply various effects on photos. The trick of image filtering is that you have a 2D filter matrix, and the 2D image. Every pixel of the image, take the sum of products. Each product is the colour value of the current pixel or a neighbour of it. Two types of filtering are: convolution & correlation. If the sum of the elements is larger than 1, the result will be a brighter image, and if it's smaller than 1, a darker image. If the sum is 0, the resulting image isn't necessarily completely black. Statistical values of each stone is found using pso coding in matlab and the mean, variance, standard deviation of each stone is stored and retrieved using data mining. Image enhancement is to modify attributes of an image to make it more suitable for a given task and a specific observer. During this process, one or more attributes of the image are modified.There exist many techniques that can enhance a digital image without spoiling it. The enhancement methods can broadly be divided in to the following two categories: 1. Spatial Domain Methods 2. Frequency Domain Methods image enhancement techniques provide a multitude of choices for improving the visual quality of images.

A. Algorithm details

There are mainly three algorithms used in this paper are PSO, DPSO, K-MEANS segmentation algorithm.

1) *K-means Segmentation Algorithm:* A collection of objects into K groups is one of the least-squares partitioning method. There are one or more steps: 1. to compute the cluster mean. 2. To compute the distance between each cluster to each point and its corresponds to cluster mean. 3. the sum of squared within group errors cannot be lowered over the above two steps to be iterated. To Random the points to clusters as initial assignment to be done. The distances between the points to the respective groups by means of iterations, to minimize the sum of algorithm, all over the groups within the errors have

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been coursed. Lower the objective function can reached in convergence. To compact the geometrical groups by means of possible groups. A feature vector is construct each pixel ($[e_1(a,b)$, $e_2(a,b)$, , $e_d(a,b)]$), where d is the number of feature images used for the segmentation process.We add one more additional cluster. The important feature is to calculate a different weight we assigned. K-means algorithm to segment in distance between two vectors to be computed.

If the cluster is wrongly assigned, but we re-correct the related pixels means

$$V = \sum_{i=1}^{k} \sum_{x_j \in S_i} (x_j - \mu_i)^2$$

Various steps in the algorithm are as follows:

a) To calculate the more intensities.
b) To initialize the centroids with k random intensities.
c) The image of cluster labels does not change until the following steps done repeatedly.
d) The centroid intensities of cluster points based on their distance intensities.

$$c^{(i)} := \arg\min_j ||x^{(i)} - \mu_j||^2$$

e) The new centroid for each of the clusters.

$$\mu_i := \frac{\sum_{i=1}^{m} 1\{c_{(i)} = j\} x^{(i)}}{\sum_{i=1}^{m} 1\{c_{(i)} = j\}}$$

Where k is a parameter of the algorithm
i iterates over all or centroid the intensities.
j iterates over all the centroids.

2) *Linear Edge Detection*: Edge detection is mathematical methods are identify the image brightness changes sharply discontinuous. The feature detection and extraction for edge detection is a fundamental tool using image processing (i.e., machine vision and computer vision).

To capture the important events and changes in properties of the world of detecting the sharp changes in image brightness. The general assumptions for an image formation model, discontinuities in image brightness are likely to correspond to

a) Discontinuities in depth.
b) Discontinuities in surface orientation.
c) Changes in material properties.
d) Variations in scene illumination.

The result of edge detector is to lead a set of connected curve indicate the boundaries of objects and surface markings to discontinuities in surface orientation. An edge detection algorithm to reduce the amount of data to be processed and as less relevant to important structural properties of an image. To understand the information about original image as sampled through edge detection step. It is not possible in real life images. The edge curve is not connected to non-trivial images through the missing edge segments in images, the subsequent task to interpret the data. The edges extracted to three dimensional image scenes for two dimensional scenes are classified as either viewpoint dependent or viewpoint independent. The inherent properties of three dimensional objects reflect the independent edge of viewpoint as surface markings and shape. A typical view point reflects the geometry scene of viewpoint changes.

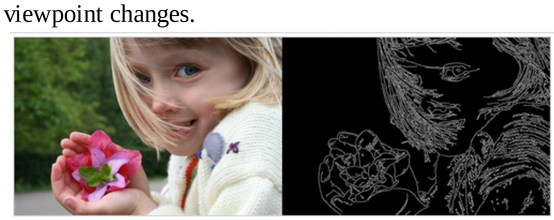

Fig 3.Edge Detection

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A number of researchers have used a Gaussian smoothed step edge (an error function) as the simplest extension of the ideal step edge model for modeling the effects of edge blur in practical applications. Thus, a one-dimensional image f which has exactly one edge placed at $x = 0$ may be modeled as:

$$f(x) = \frac{I_r - I_l}{2}\left(\operatorname{erf}\left(\frac{x}{\sqrt{2}\sigma}\right) + 1\right) + I_l.$$

At the left side of the edge, the intensity is $I_l = \lim_{x\to-\infty} f(x)$, and right of the edge it is $I_r = \lim_{x\to\infty} f(x)$. The scale parameter σ is called the blur scale of the edge.

IV. CONCLUSION

In this paper an approach is used as k-means segmentation technique to segment the stone an to detect if any crack in that stone. The statistical values are found using particle swan optimization (pso). Then the crack is detected by comparing the statistical values of crack stone and non-cracked stone. Finally the cracks are detected in the given granite.

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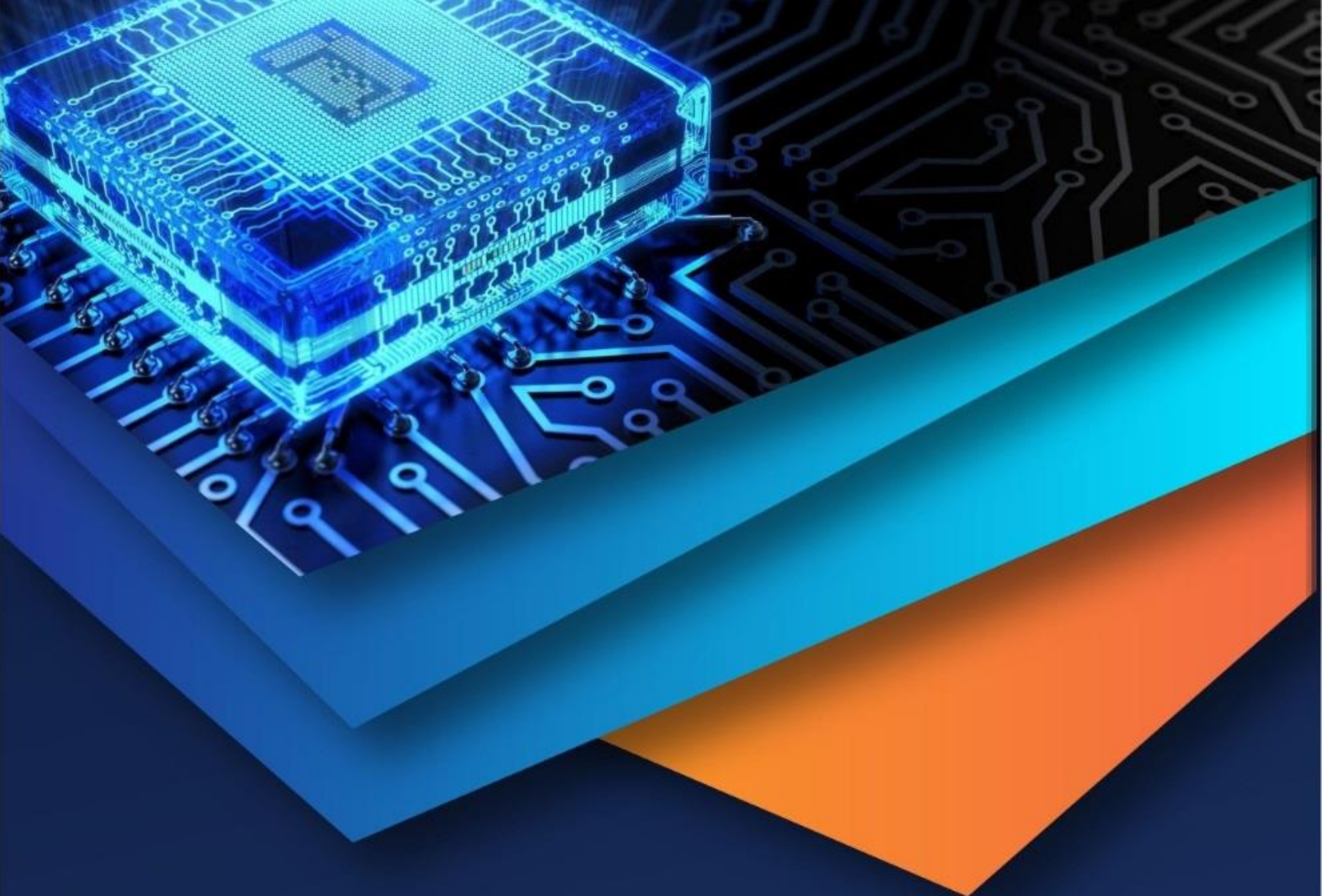

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