

Hyperion Image Analysis for Iron Ore Mapping in Gua Iron Ore Region, Jharkhand, India

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Abstract

The paper introduces the concepts and application of hyperspectral remote sensing technology in mineral identification over Gua Iron Ore Mine, Jharkhand, India. Reflectance and emittance spectroscopy in the VNIR and SWIR regions offer an effective way in mineral identification and possible localized mapping. EO-1 Hyperion hyperspectral data has been used for the identification of Fe ore minerals. The first requirement is to compensate for the atmospheric effects. Hyperspectral image processing technology for mineral identification is based on spectral classification which comprises of three basic steps: i. MNF transformation to reduce noise and spectral data dimensionality, ii. the PPI for spatial dimension reduction and extraction of pure pixels and iii. n-D Visualization and endmember collection. These extracted endmembers are then compared using a mineral spectral library distributed from USGS as a reference and are used in Spectral Angle Mapping (SAM) to classify the image for identifying the occurrences of same minerals. The results revealed the potential use of Hyperion data in mineral identification.

Keywords: Hyperspectral remote sensing, gua iron ore mine, Hyperion, spectral angle mapping (SAM).

Introduction

The hyperspectral remote sensing is one of the most popular technological trends in surface feature identification and mapping in modern remote sensing. Hyperspectral remote sensing or imaging spectroscopy is analysis of the reflectance data recorded by a hyperspectral sensor from a region or part of the earth surface. Hyperspectral remote sensors images the earth surface features in hundreds of narrow contiguous spectral bands, provides higher accuracy for terrain features mapping compared to multispectral remote sensing. Practically, remotely sensed data represent values or DN value of the pixel¹ which is the surface reflectance value or radiance value of surficial features. Hyperspectral imaging spectrometers collect these radiance value sampled around ten nanometer intervals and with hundreds of spectral bands that used to construct the reflectance spectra similar to the laboratory spectra. Different minerals have a unique reflectance and absorption pattern across different wave-length. So, minerals can be uniquely identified². Thus constructs a unique spectral reflectance curve for each feature, that's why the signature curve also known as signature curve. This criterion is used in mineral identification using hyperspectral remote sensing in open cast mine.

Study area: The present study area (Gua iron ore mine and its surroundings) is located in Pashchimi Singhbhum district, Jharkhand, India. The plateau region constitutes a part of the Precambrian shield of the Indian peninsula. Gua is located at 22.12° N / 85.13° E. The average elevation of the study area is 435m and falls in the Toposheet no. 73 F/7, 8 as per Survey of India.

Banded Iron Formation (BIF) is found extensively in Jharkhand. The Gua iron ore deposit comprising the rocks belonging to Iron Ore Group (IOG) is overlain by "Kolhan group of rocks"³.

Hematite with minor quantity of Goethite, Siderite, Specularite and Limonite are found in the study area with Banded Jasper Quartzite as basement rock. The ores are intercalated with Chert and Shale. Hematite is located in the ridges formed of banded hematite quartzite/jasper (BHJ/BHQ) in the central and western part trending NE-SW.

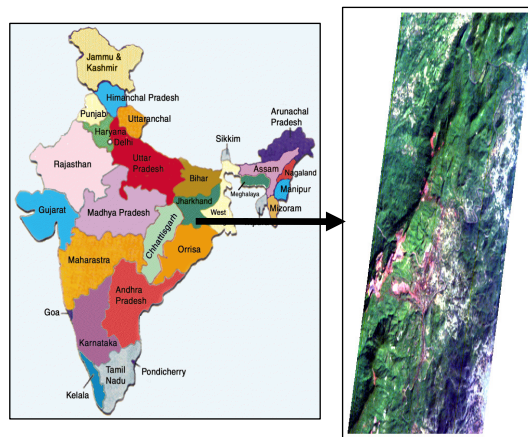


Figure-1
True Color view of Hyperion DATA of Gua Iron Ore mine and its surroundings

Application of Hyperspectral Image Analysis in Mineral Exploration:

Hyperspectral images have been used to identify and map surficial features depending on their reflectance characteristics. In mineral exploration or identification hyperspectral data have a great potential. The processing of hyperspectral data has different approach in comparison to multispectral data. Few basic steps of hyperspectral data analysis include atmospheric correction, feature identification and their mapping. The atmospheric correction algorithms like Cross-Track Illumination, FLAASH, etc are quite different from that of the algorithms used for multispectral data. The identification of surficial objects based on their spectral response in the wavelength range 400 nanometers to 2500 nanometers in hundred of narrow spaced spectral bands. For this purpose, a comparison is done in between the unknown image pixel's spectral signature and the spectral signature of known materials, in order to establish quantitatively how similar an image pixel compared to the reference materials⁴. Spectral Angle Mapper (SAM), Spectral Feature Fitting (SFF) etc algorithms are used in hyperspectral Image classification. Depending on this idea the image data is analyzed to identify and map the similar distributions of the minerals or mineral ores and assemblages.

Material and Methods

Freely downloadable Hyperion sensor data from USGS Earth Explorer Website, which was acquired on January 16, 2006 is used in the present study⁵. The Hyperion is a push-broom imager having 242 spectral bands with 10 nanometer band gaps covering the spectrum from 400 nanometers to 2500 nanometers in 30m spatial resolution. Areal coverage of each standard Hyperion scene is approximately 7.5 km by and 42 km. The whole image processing operation was done in ENVI 4.5 software.

Atmospheric Correction of Hyperspectral Data: Radiance value recorded in the sensor for each pixel represents the reflectance or emittance property of all the surface features covered by the pixel. This recorded value is different from the actual reflectance or emittance of the objects due to factors like: sun's azimuth angle and elevation of the target area, atmospheric conditions, viewing geometry and other sensor characteristics etc. Thus, prior to analyze the data Atmospheric correction is required to remove errors. Radiometric correction is required to obtain the actual reflectance/ emittance of surface features. Cross-Track Illumination correction and FLAASH are two most common and efficient tools used for atmospheric correction of hyperspectral data. Cross-Track Illumination Correction algorithm removes the illumination variation along the cross track direction of an image, which arises due to vignetting effects, instrument scanning, or other non-uniform illumination effects⁶. FLAASH atmospheric correction tool is used to remove errors from the bands in the visible range through NIR and SWIR regions, up to 3 μm and converts the DN value into spectral reflectance value.

Hyperspectral data analysis: The section includes the steps of hyperspectral image analysis for mineral identification. Prior to atmospheric correction, it is necessary to check whether the bad bands are removed or not for further image analysis. After the atmospheric correction, the hyperspectral data requires spectral and spatial dimension reduction for further processing. These two steps include i. the Minimum Noise Fraction and ii. the Pixel Purity Index. The spectrally and spatially reduced data is used in the iii. n-Dimensional Visualizer for determining the endmember classes, where n is the number of bands iv. the Spectral Analyst is used for endmember class identification using a standard spectral library (such as USGS spectral library) as reference, finally iii. the different classification methods such as Spectral Angle Mapper (SAM), Spectral Feature Fitting (SFF) etc are employed to map similar mineral occurrences in the image scene. The procedure of mineral identification and mapping is shown in the figure 2.

Minimum noise fraction (Mnf) transformation: MNF transformation segregates noise from data and determines the inherent data dimensionality, which indicates the number of bands to be taken for further data analysis. This is a two steps process. First transformations compute the covariance matrix to decorrelate and rescale the noise in the data and its breaks the band to band correlation. Then a second transformation computes the Eigen values, where bands having Eigen values much greater than one contains coherent image and having Eigen values near one contain noise. Using the coherent portion, noise is removed from data. These coherent images will be taken only for further data analysis, this way MNF reduces the spectral dimension of the data.

Pixel Purity Index (PPI): Pixels that contain radiance values more than one feature type called mixed pixels and those contain only one feature type called pure or spectrally pure pixels. PPI tool only identifies the spectrally pure pixels in a hyperspectral image scene. Thus it is one kind of spatial dimension reduction technique. This is done by repeatedly projecting data into n-Dimensional scatter plots on a random unit vector, where n is the number of bands. In each projection, the extreme pixel is marked as the purest pixel in that dimension. Pixel Purity Image is created where each pixel value corresponds to the number of times that pixel was recorded as extreme⁷.

n-D Visualizer: The coordinates of the points in n-space consist of "n" values that are simply the spectral radiance or reflectance values in each band for a given pixel. The distribution of these points in n-space can be used to estimate the number of spectral endmembers and their pure spectral signatures⁸. PPI only extracts the spectrally pure pixels, but the numbers of unique spectral classes are determined by the n-D Visualizer, where the pure pixels are rotated in n-D vector space, clustered and marked as the most extreme pixels as end member classes.

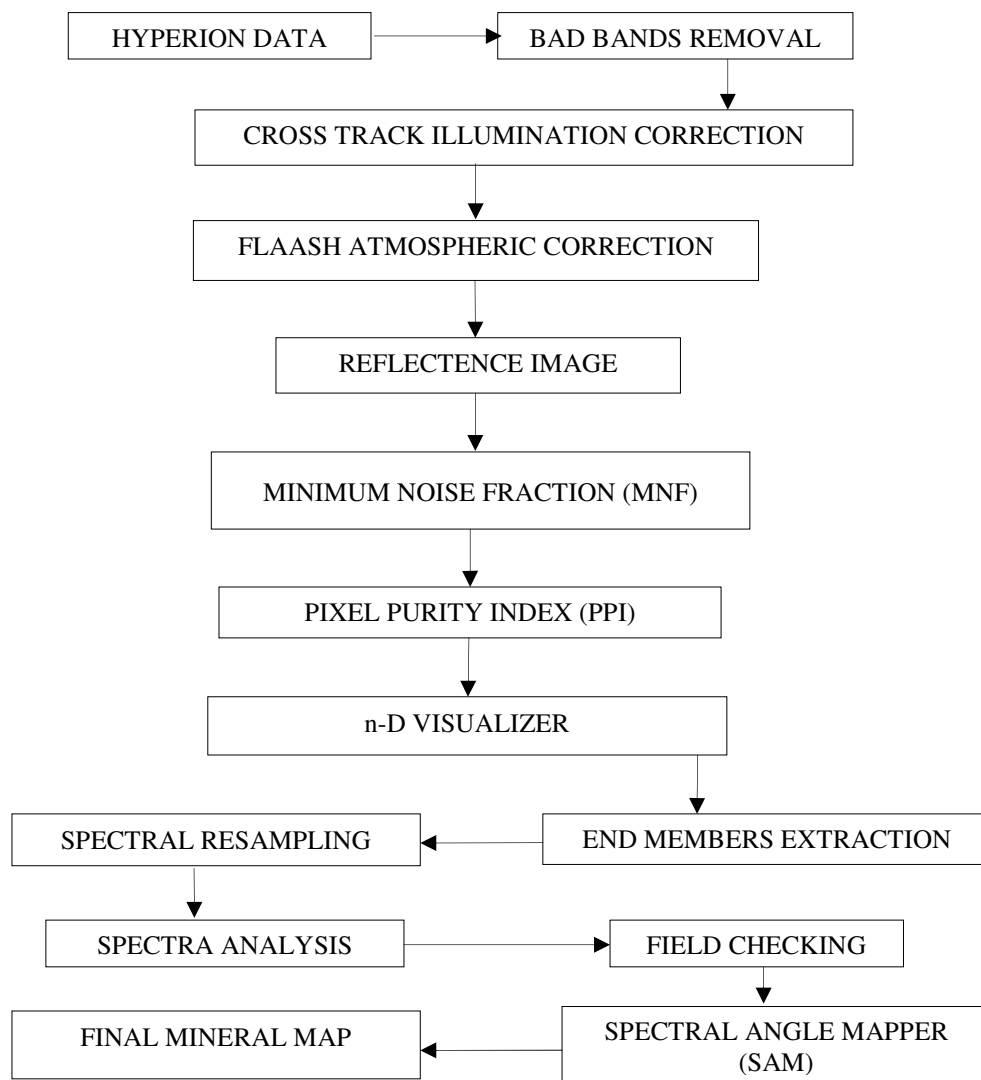


Figure-2
Processing flow for mapping iron deposits

Spectral Resampling: The numbers band in the input image data may or may not equal to the spectral library. Spectral Resampling is to resample spectral data files to match one of the following: The response of a known instrument (for example, AVIRIS) or An ASCII wavelength file, with or without full-width-half-maximums or the wavelengths of a specific image input file⁹. Basically it rescales the input spectral library according to the input image data to equalize the number of spectral bands, which will be the reference spectral library for features identification.

Spectral Analyst: This tool uses one or more than one algorithms such as Spectral Angle Mapper, Spectral Feature Fitting and Binary Encoding to measure the similarity between the unknown endmember image spectra and object spectra of the resampled spectral library.

Spectral angle Mapper (SAM): The Spectral Angle Mapper Classification (SAM) is an automated method for directly comparing image spectra to known spectra (usually determined in a lab or in the field with a spectrometer) or an endmember¹⁰. SAM treats the spectra as vectors in n-Dimensional space, where n is the number of bands and computes similarity between unknown and reference spectra within angle between 0° and 90° (or as cosine of the angle). SAM is one of the best methods for hyperspectral image classification and it is quite resembled to supervised classification method used in multispectral image classification. It deals equally with all possible illumination. As the spectra is transformed into vector, therefore the direction of vector is taken into consideration not their length, hence ignores associated unknown gain factor.

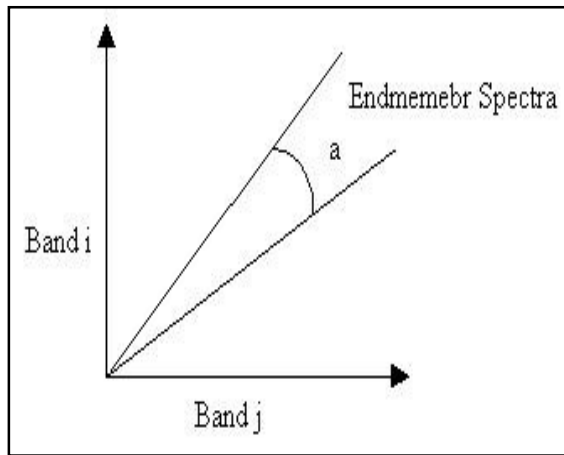


Figure-3
Spectral Angle Mapper (SAM) concept

$$a = \cos^{-1} \left[\frac{\vec{t} * \vec{r}}{\|\vec{t}\| * \|\vec{r}\|} \right] \quad a = \cos^{-1} \left[\frac{\sum_{i=1}^{nb} t_i r_i}{(\sum_{i=1}^{nb} t_i)^{1/2} (\sum_{i=1}^{nb} r_i)^{1/2}} \right]$$

where, t = Unknown spectra; r = Reflectance spectra; nb = number of bands

Results and Discussion

Before going to atmospheric correction, the scale and Metadata/Template files were created by ENVI open external file option. The bad band list was checked using ENVI edit header file option, will be excluded from further data analysis. To compensate the atmospheric effects, first the Cross-Track Illumination Correction tool was used. The FLAASH atmospheric correction tool was used to remove others atmospheric errors and to convert the DN value to its equivalent surface reflectance value. Prior to FLAASH atmospheric correction, the data was converted into BIL format, as the input file format for FLAASH have to be either in BIL or BIP format. The scale factor file and image Meta-data/Template files were used also during FLAASH atmospheric correction for data scaling and to define the scene, sensor information, atmospheric, aerosol model to be used in MODTRAN model which is used in FLAASH. The final atmospherically corrected image is shown in figure 4.

The calibrated reflectance image was linearly transformed using MNF transformation. From the eigen value plot shown in figure-5, it can be easily inferred that top 10 MNF bands contain the spectral information required for further analysis and rest of bands contain high amount of noise. Thus these top 10 bands were used as input for the PPI to identify the pure pixels in the scene with threshold value 2 and 10000 iteration. Figure 6 shows the pure pixels obtained by PPI in the study area.

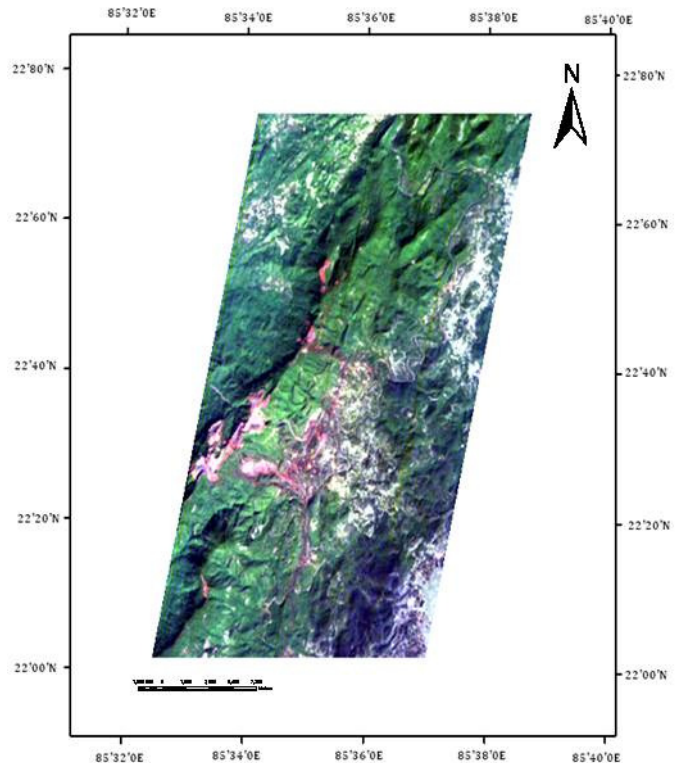


Figure-4
Atmospherically corrected image

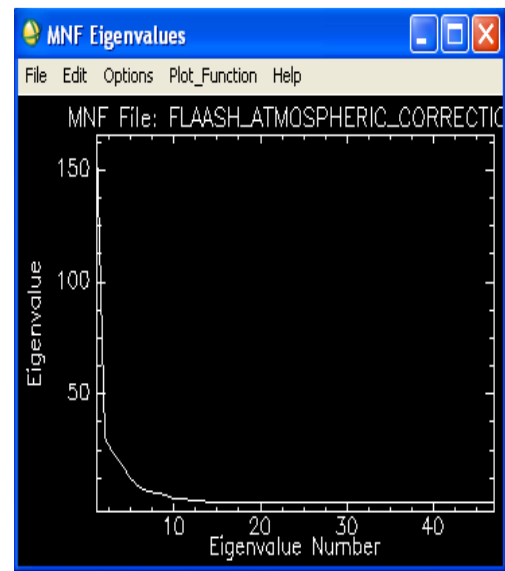


Figure-5
MNF eigen value plot

PPI-derived pixels were rotated in 10 dimensional spaces to extract the end members using n-D Visualizer. The extreme pixels or end members were extracted as Region of Interest (ROIs) to extract their spectral reflectance curve from the image data cube.

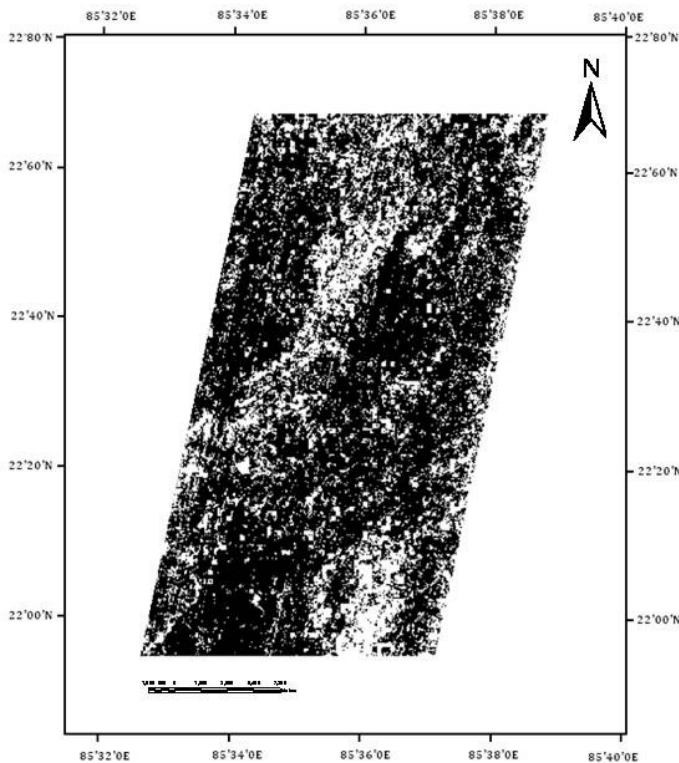


Figure-6
 Pure pixels computed by PPI

Spectral resampling was done using the atmospherically corrected image over the USGS mineral spectral library, due to lack of field spectrometer data. Thus the resulted library spectra respond as the image spectral information. This spectral resampled library was used as a reference to identify the endmember spectra using Spectral analyst tool. Nontronite, Sphalerite and Opal have been identified in the study area, and their spectral signatures are shown in Figure 7.

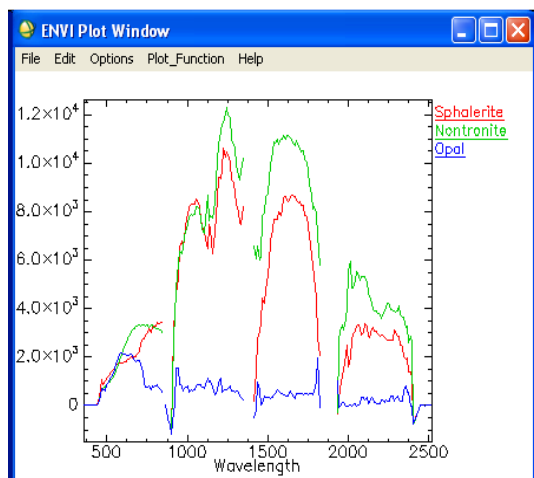


Figure-7
 Nontronite, Sphalerite, Opal minerals spectra

The SAM supervised classification technique was used to map Nontronite, Sphalerite and Opal minerals occurrences in the image scene. The spectral angle used in this study was 0.10 radian. SAM successfully identified most of the mineral deposited areas in the study area is shown in figure 8. Occurrences of Nontronite and Sphalerite were found higher in compared to Opal.

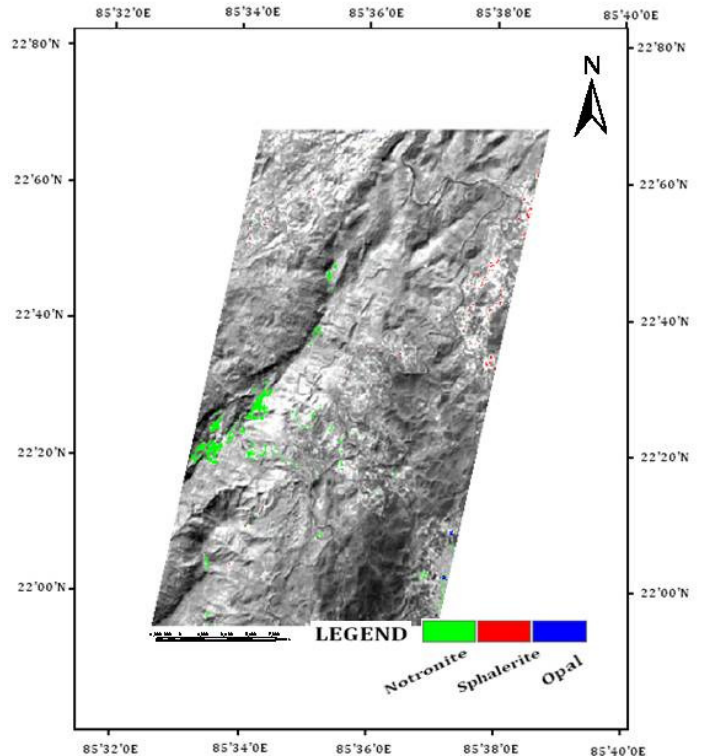


Figure-8
 Final mineral map in Gua Iron Ore region

Conclusion

Hyperion image data study over Gua iron ore mine, Jharkhand has established the viability of hyperspectral data for surface mineral zone identification and mapping. Having the same spatial resolution in compare to other multispectral data, the Hyperion data provided the advantage of high-quality reflectance spectra of the surficial features. This data has been analyzed using a standardized hyperspectral data analysis procedure consisting of atmospheric error removal, selection and identification of spectral endmembers and their spatial mapping in the image scene. Thus the obtained results show the potential uses of hyperspectral imagery for mineral mapping in areas where the minerals are exposed on the surface.

This study is not a new discovery or nor leads to new hematite discoveries in and around the Gua Iron ore mine, but it shows that it is possible to identify and map valuable minerals in the study area using hyperspectral remote sensing data.

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