A Survey on Hyperspectral Imaging for Mineral Exploration using Machine Learning Algorithms

S. Sudharsan[1], R. Hemalatha[2], and S. Radha[3]

[1]Assistant Professor, Department of ECE, AGNI College of Technology, Chennai, India
[2]Associate Professor, Department of ECE, SSN College of Engineering, Chennai, India
[3]Professor and Head, Department of ECE, SSN College of Engineering, Chennai, India
[1]sudharsan013@gmail.com [2]hemalathar@ssn.edu.in [3]radhas@ssn.edu.in

***Abstract*—Economic growth of the country mainly depends on the mineral and energy sources. In recent years, there is an increased pressure to reduce the environmental and social impact through the mineral exploration. The data from remote sensing satellite play a vital role and is capable of detecting minerals resources. Hyperspectral remote sensing is an effective tool for mineral exploration applications, as it has been providing significant development over the past three decades. In this paper, an up-to-date and focused review of mineral mapping techniques using the Hyperspectral Imaging (Hyperion data) is provided. A key factor on the success of hyperspectral imaging is the spatial, spectral and temporal resolution and the capability of covering large surfaces of earth using the modern sensor technologies. This review mainly focuses on the fundamentals of hyperspectral imaging and Analytical Imaging & Geophysics (AIG) techniques for mineral mapping. The procedures to be followed in the ENVI software, which is used to analyse and process the Hyperion data, determine the exact locations of different minerals using AIG classification techniques are provided. This review can be a useful baseline for future research in mineral exploration using hyperspectral image analysis.**

***Index Terms*—Hyperspectral Imaging, Multispectral Imaging, Resolution, Mineral Mapping, AIG Techniques.**

I. Introduction

India is a mineral rich country and ranks fourth amongst the mineral potential countries. However, the full mineral potential is yet to be explored and assessed, leading to good opportunities for mineral exploration development. Fig. 1. shows the minerals in India. Remote sensing technique was developed in 1880. It has been used in multispectral and uses Hyperspectral scanners, images to construct a complete reflectance spectrum of each pixel in the image. It is used for geological mapping and mineral exploration from 1970.

Remote Sensing techniques have been used for identifying potential areas of mineral occurrences in the country. Remotely sensed imagery generally describes the location or the condition of formation of mineral deposits. Fig. 2. describes the classification of minerals. Interpretation of Satellite data involves the basics of spectroscopy to identify and map minerals, as different minerals have unique reflectance and absorption pattern across different wavelengths, which act as their identifying signatures [1]. Mineral mapping is the method used to identify, classify and map the minerals using

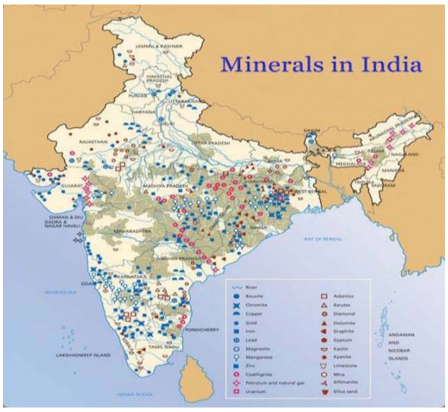

Fig. 1. Minerals in India.

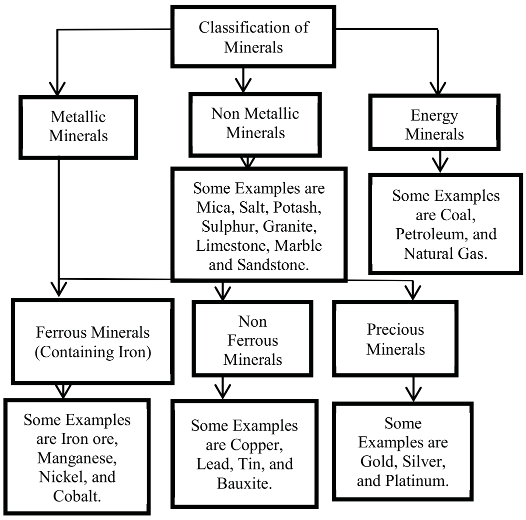

Fig. 2. Classification of minerals.

the Hyperspectral and Multispectral data. Generally, minerals in India are found in three regions they are

1) The North-Eastern Plateau Region;
2) The South-Western Plateau Region;
3) The North-Western Region.

A typical human eye is able to view a limited range of electro-magnetic spectrum (390-700nm). Electromagnetic

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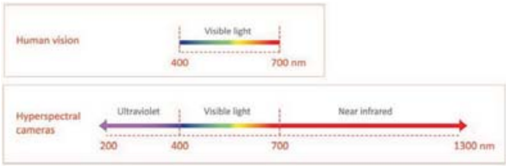


Fig. 3. Range of operation of normal and hyperspectral cameras.

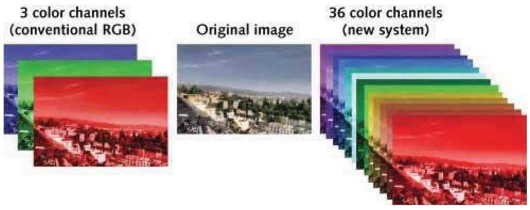


Fig. 4. Multispectral, normal and hyperspectral image for a specific place.

radiation in this range of wavelengths is called visible light or visible spectrum. Human can distinguish between objects based on their different spectral responses in that narrow spectral range. Fig. 3. shows range of operation of normal and hyperspectral cameras. However, the hyperspectral imaging sensors and multispectral imaging sensors have been developed to acquire an image in infrared and visible segments of electromagnetic spectrum. Fig. 4. indicates the multispectral, normal and hyperspectral image for a specific place.

Hyperspectral imaging, also known as imaging spectrometry or imaging spectroscopy, has become established as a critical technique in which an object is photographed using several well defined optical bands in broad spectral range for earth observation since it was first proposed by A. F. H. Goetz in the 1980s. It is made possible to acquire several hundred spectral bands of observational scene in a single acquisition. It was implemented on satellite and airborne platforms for remote sensing applications but during last two decades, HIS has been applied to numerous applications including agricultural and water resources control, military defense, medical diagnosis, forensic medicine, food quality control and mineralogical mapping of earth surface [1].

Multispectral imaging technology has been used as the data source for environment mapping and land observational remote sensing from satellite and airborne systems since late 1960s. It acquires data in a small number of spectral bands by using parallel sensor arrays. Spectrum of each pixel in a multispectral image provides information about surface of the material. Some remote sensing applications for multispectral data are environmental observation, defense and security and other earth observation applications [1]. Fig. 5. Shows the plot between the wavelength vs. intensity for the hyperspectral and multispectral data.

The rest of the paper is organized as follows. In Section II, survey on mineral mapping and feature extraction methods for HIS are reviewed. In Section III, the concept of hyperspectral imaging and hyperspectral sensors are discussed. In Section IV, importance of resolution & its types are given in detail are discussed. In Section V, hyperspectral techniques for mineral exploration are introduced. In Section VI, the

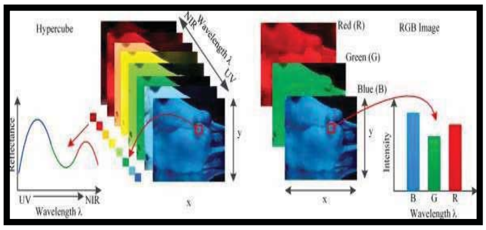


Fig. 5. Shows the plot between the Wavelength vs. Intensity for the hyperspectral and multispectral data.

concept of self-taught learning used for hyperspectral imaging is discussed. Conclusion and future work are presented in Section VII.

II. Survey on Mineral Mapping and Feature Extraction Methods for HSI

The mineral mapping and feature extraction for HSI is one of the important research area in the 21^{st} century for the mineral exploration. Ines Dumke *et al.* [2] proposed methods like Support Vector Machine (SVM) and Spectral Angle Mapper (SAM) are used to find Manganese in seafloor. It is a new method for high-resolution mapping, high potential for habitat mapping & environmental monitoring and classification of seafloor composition interms of mineral deposit quantification. Mapping using Underwater Hyperspectral Imager (UHIs) is limited to small areas of up to a few 1000 m^2, it can be increased by increasing the altitude to upto 7m (approximately 7m swath width) and by providing stronger illumination sources to ensure sufficient seafloor illumination. Ying Zhang *et al.* [8] proposed the algorithm of Mean Square Cross Prediction Error-Based Blind Source Extraction (MSCPE_BSE) for extracting the minerals like high-Al muscovite, med-Al muscovite, Calcite and Chlorite. It provided good results when compared to conventional mineral mapping methods. BI Xiaojia *et al.* [9] proposed a new automatic matching algorithm to find the minerals using SAM. The main advantage is that it can be applied on a wider area for mineral extraction compared to other methods. Eventhough using short-wave infrared spectrum is beneficial, few alteration and mineralization in the research area can only be detected in far-infrared emission spectroscopy, such as 0_2, $S0_4$ and other atom groups. Qiaoqiao Sun *et al.* [6] described about the classification of deep learning methods based on Principle Component Analysis (PCA) and Deep Belief Network (DBN) for hyperspectral data. PCA is used to reduce the dimension of HSI. DBN has good performance in big data classification. The proposed PCA-DBN can help to improve the HSI classification and it is mainly used in the application of target detection and un-mixing in HSI. The compound nature of HSI in both spatial and spectral domain like intra-class differences, strong connection among bands and less training samples etc., needs the classification results from traditional methods to be improved. Radhesyam Vaddi *et al.* [5] did the comparative study of feature extraction methods for hyperspectral imaging like dimensionality reduction, multilayer process and image fusion methods. It provides easy way to correctly classify

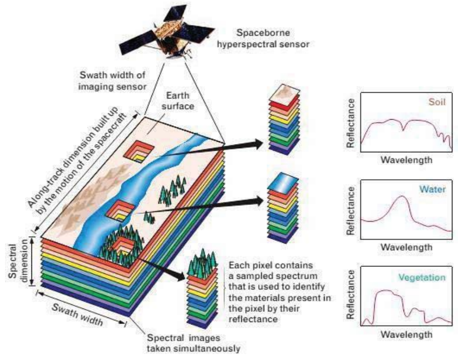


Fig. 6. Mapping of soil, water & vegetation using HSI technique [1].

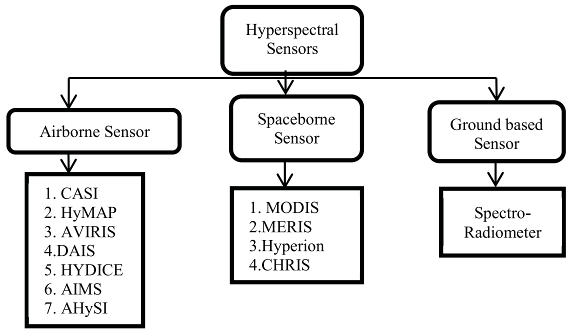


Fig. 7. Types of hyperspectral sensors.

TABLE I
HYPERSPECTRAL SENSORS PROVIDING ABOVE 100 SPECTRAL BANDS FOR THE SATELLITE DATA

Sensor	Organization /Country	Optical Subsystem	Spectral Bands	Spectra l Range (μm)	Spectral Resoluti on	Spatial Coverag e
Hyperion	NASA, US.	VNIR-SWIR	242	0.40-2.500	30	Region al
AVIRIS	NASA, US.	VNIR	224	0.38-2.500	4–20	Local
HyMap	Integrated Spectronics Pty Ltd, Australia.	VNIR-SWIR	128	0.45-2.480	2–10	Local
ROSIS	DLR, Germany.	VNIR	115	0.42-0.873	2	Local
AISA	SPECIM, Finland.	VNIR	286	0.45-0.9	2.9	Local
CASI	Itres Research, Canada.	VNIR	288	0.43-0.87	2	Local

and identify the different objects by using the feature extraction methods. Besides extraction methods like Scale Invariant Feature Transform (SIFT), MOtion SIFT (MOSIFT), Bag of features trajectory are improved, they work like handcrafted features specifically and visual features are not reliable for HSI. The survey forms the in-depth knowledge about the mineral detection algorithm and feature extraction of hyperspectral data using machine learning with their importance.

III. HYPERSPECTRAL IMAGING

The purpose of the hyperspectral imaging is to identify the material required and to obtain the spectral of each pixel in the image. The Hyperspectral image is obtained from the solar radiation that is scattered from the Earth's surface, which after interaction with the atmosphere reaches the sensor. The Hyperspectral image is obtained from EO-I (Earth Orbiting) satellite. Hyperion provides high resolution hyper spectral images capable of resolving 220 spectral bands and resolution of 30m. The Instrument covers an area upto 7.5km by 100km land per image [4]. This provides a precise spectral mapping over 220 channels with very high radiometric accuracy. Analytical Spectral Devices (ASD) Spectrometer can be used to record and measure the spectral data from the study area. Airborne Imaging Spectrometers (AIS) are widely used to collect the hyperspectral remote sensing data. Spectroradiometric Instruments are used to gather the consecutive ground data collection. To evaluate the remotely sensed data with the ground reference, the following steps has to be carried for the better understanding of the data. Fig. 6. Shows the mapping of soil, water & vegetation using HSI technique.

1) Accurate calibration in terms of radiance of the received signals (the calibration problem);
2) A sufficiently precise assessment of all alterations of the object inherent spectral radiance induced by atmospheric effects (the atmospheric correction problem);
3) Better understanding of the object– and illumination geometry and the objects non–Lambertian behaviour [the Bidirectional Reflectance Distribution Function (BRDF) problem];
4) Full understanding and quantification of the relations between nature and status of the object and its electromagnetic emittance– and/or reflectance spectrum (the signature problem).

A. Hyperspectral Sensors

Hyperspectral Sensors (also known as Imaging Spectrometers) typically collect 200 or more bands enabling the construction of an almost continuous reflectance spectrum for every pixel in the scene. Some important characteristics of hyperspectral sensors are Contiguous and narrow bandwidths. They represent the next step in the spectral dimension. But the evolution of multispectral sensors in satellite such as the Landsat Thematic Mapper which collects data in seven simultaneous bands. Fig. 7 shows the types of hyperspectral sensors. Table I shows Hyperspectral sensors providing above 100 spectral bands for the satellite data.

IV. RESOLUTION

Resolution is defined as the number of pixels displayed on a display device (or) the area on the ground that a pixel represents in an image file. For describing the remotely sensed data the following types of resolution are considered,

1) Spatial Resolution;
2) Spectral Resolution;
3) Temporal Resolution;
4) Radiometric Resolution.

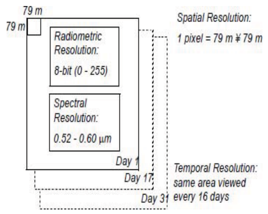
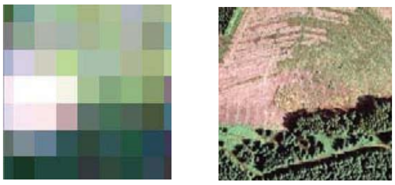


Fig. 8. Types of resolution in single image.



(a) (b)

Fig. 9. (a) Low spatial resolution. (b) High spatial resolution.

Hyperspectral images are characterized by spatial and spectral resolutions. The spatial resolution measures the geometric relationship of the image pixels to each other while the spectral resolution determines the variations within image pixels as a function of wavelength. Fig. 8. Shows the types of resolution in single image.

A. Spatial Resolution

Spatial resolution is defined as the minimum discernible detail in an image which can be described as the measure of smallest object in an image that can be distinguished as a separate entity in the image [1]. Spatial features of an image are based on the design of imaging sensor in terms of its field of view and altitude. Finite patch of the ground is captured by each detector in a remote imaging sensor. Spatial resolution is inversely proportional to the patch size. Fig. 9. (a) shows low spatially resolution and (b) shows the high spatially resolution.

B. Spectral Resolution

Spectral resolution is defined as the number of spectral bands and range of electromagnetic spectrum measured by the sensor [1]. If a sensor is sensitive to lower frequency range it will capture large number of spectral bands has high spectral resolution, due to its ability to distinguish between scene elements having close or similar spectral signatures. Multispectral images have a low spectral resolution, thus unable to resolve finer spectral signatures present in the scène. Table II.Shows the main Hyperspectral Sensors on Satellite and Aircrafts.

The spectral range of hyper spectral sensors on aircraft work is 380–12700 nm and for those on the satellites is 400–14400 nm. The number and width of bands varies from one system to another in the range of 1–288 and widths ranging from 2–2000 nm.

C. Temporal Resolution

Temporal resolution in hyperspectral imaging is dependent on orbital characteristics of remote sensors [1]. It is defined as the time needed by the sensor to revisit data from the same location. Temporal resolution is said to be high when revisiting frequency of the sensor platform for the exact same location is high and is said to be low if revisiting frequency is low. Temporal resolution is mainly used in the application of change detection studies.

TABLE II
MAIN HYPERSPECTRAL SENSORS ON SATELLITE AND AIRCRAFTS

Hyperspectral Sensors on Satellite			
Types of sensors	**Producer**	**Number of bands**	**Spectral range (μm)**
FTHSI on Mighty Sat II	Air Force Research	256	0.35-1.05
Hyperspectral Sensors on Aircrafts			
HYDICE	Naval Research Lab	210	0.40-2.50
PROBE-I	Earth Search Science Inc.	128	0.40-2.50
HyMap	Integrated Spectronics	100-200	Visible to thermal infrared
DAIS 7915 (Digital Airborne Imaging Spectrometer)	GER Corporation(Geophysics and Environmental Research Imaging Spectrometer)	VIS/NIR (32), SWIR1(8), SWIR2(32), MIR(1), TIR(12)	VIS/NIR (0.43-1.05), SWIR1(1.50-1.80), SWIR2(2.00-2.50), MIR(3.00-5.00), TIR(8.70-12.30)
DAIS 21115 (Digital Airborne Imaging Spectrometer)	GER Corporation	VIS/NIR (76), SWIR1(64), SWIR2(64), MIR(1), TIR(6)	VIS/NIR (0.40-1.00), SWIR1(1.00-1.80), SWIR2(2.00-2.50), MIR(3.00-5.00), TIR(8-12.00)
EPS-H (Environmental Protection System)	GER Corporation	VIS/NIR (76), SWIR1(32), SWIR2(32), TIR(12)	VIS/NIR (0.43-1.05), SWIR1(1.50-1.80), SWIR2(2.00-2.50), TIR(8-12.50)

Fig. 10. Different radiometric resolutions of same image.

D. Radiometric Resolution

Radiometric resolution is defined as the dynamic range or numbers of possible data file values in each band. This is referred to the number of bits into which the recorded energy is divided. Fig. 10. shows the different radiometric resolutions of same image.

V. HYPERSPECTRAL TECHNIQUES FOR MINERAL MAPPING

Interpretation of Hyperspectral data has been developed by Analytical Imaging and Geophysics (AIG). These approaches are implemented in the "Environmental for visualizing Images". AIG scientists developed ENVI system software. The Hyperspectral anatomization methodology includes [11]

1) Data pre-processing;
2) Atmospheric correction is necessary for finding the apparent reflectance of the data;

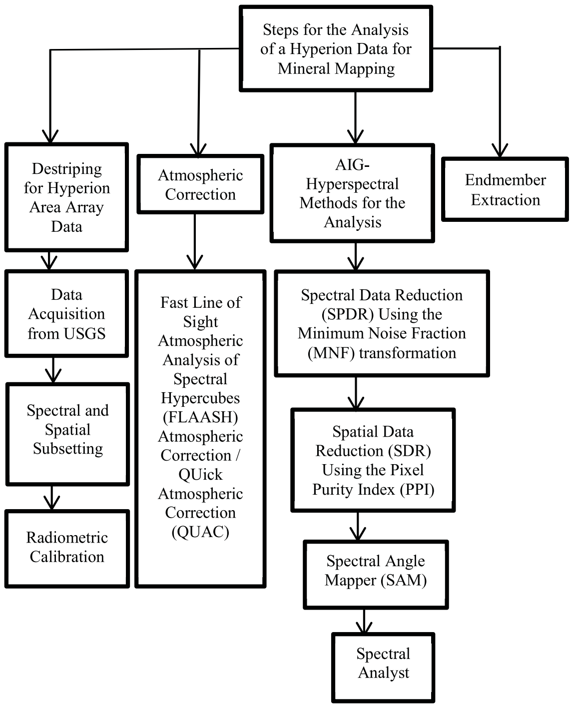


Fig. 11. Steps for the analysis of hyperion data for mineral mapping.

3) Linear transformation of the reflectance data to reduce noise and determine data dimensionality;
4) Location of the most spectrally pure pixels;
5) Extraction and automated identification of end member spectra;
6) Spatial mapping and abundance estimates for specific image end members.

The following are the steps to be performed for the analysis of a Hyperion data.Fig. 11. Shows the steps for the analysis of Hyperion Data for Mineral Mapping.

A. *Destriping for Hyperion Area Array Data*

It is necessary that preprocessing must be applied to the data prior to atmospheric correction. There was still a striking vertical striping pattern in the data, though radiometric corrections were implemented on the Hyperion data. Aspects such as detector non-linearities, movement of the slit and temperature effect may be caused by AIS. Destriping is necessary only for correcting the Pushbroom Hyperion data [11]. The destriping of a hyperion data has the following procedures they are given below.

1) Spectral and Spatial Subsetting: Eliminating some portions for foreshortening the size of the data which are contemplated useless is called sub setting a dataset or the information is just comparatively less or not present. Spectral subsetting is used to restrain the number of bands in the input images [4]. Bad bands are done based on eradicating or deselecting certain bands from input data. Spatial subsetting is done by selecting a small region in the input image of our interest for analysis.

2) Radiometric Calibration: Radiometric errors will entail any form of image. The sensors absorb emitted and reflected

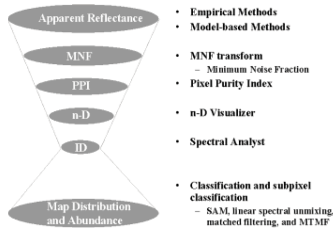


Fig. 12. AIG Hyperspectral Methods for Analysis [11].

waves. The error due to atmospheric condition causes absorbed wave may or may not coexist with the emitted wave, this result in improper irradiance values and radiometric correction is mandatory[4]. It calculates the radiance, reflectance and brightness of the data subset.

B. *Atmospheric Correction*

This analysis can be used for both Airborne & Satellite data. However, this method includes processing radiance calibrated data to apparent reflectance. Airborne and satellite Hyper spectral data is corrected and converted to apparent reflectance by using the Atmospheric CORrection Now (ACORN) [11].Appropriate model parameters used for each instrument are sensor altitude, date, time, seasonal atmospheric model, latitude/longitude and average elevation. The different methods of atmospheric corrections are given below.

1) FLAASH- Fast Line of Sight Atmospheric Analysis of Spectral Hypercubes: Nisha Rani *et al.* [12] FLAASH is a model approach that is based generally on radiative transfer model. It is rigorous atmospheric algorithm and involves various parameters to perform but it has ability to compensate the effects of atmospheric absorption. FLAASH provides smooth spectral curves which helps in accurate identification of composition of minerals.

2) QUAC- QUick Atmospheric Corrections: Nisha Rani *et al.* [12] QUAC is an empirical approach that is scene-based and determines atmospheric compensation parameters directly from the information contained within the scene without ancillary information. It uses the information within the scene. Radiometric calibration is not required for this method.

C. *AIG- Hyperspectral Methods for the Analysis*

Hyperion data are processed based on the following methods for the analysis given below. Fig. 12. Shows the AIG Hyperspectral Methods for Analysis.

1) Spectral Data Reduction Using the Minimum Noise Fraction (MNF) transformation.
2) Spatial Data Reduction Using the Pixel Purity Index (PPI).
3) Spectral Angle Mapper (SAM).
4) Identification of endmembers using their reflectance spectra in the Spectral Analyst.

1) Spectral Data Reduction Using the Minimum Noise Fraction (MNF) Transformation: To determine the image dimension Hyperspectral imaging data is used on Minimum Noise Fraction (MNF). MNF will separate the noise from signal and it is followed by inverse transform to produce spectral

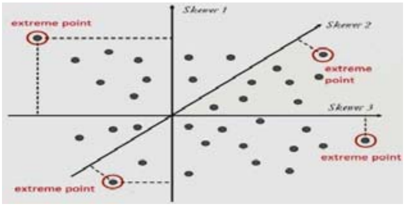


Fig. 13. SDR using pixel purity index [4].

images which is completely noise free [4].MNF transformation shows that the vast majority of unique spectral information will be contained within the first few bands of the data.

2) Spatial Data Reduction Using the Pixel Purity Index (PPI): Spectrally pure pixels out of the given hyperspectral images is the designate of PPI. To perform dimensionality reduction either PCA/MNF transform is indispensable by PPI algorithm. PCA or MNF are second order, statistics need not to be desiccate for higher order [4]. They produce large number of random vectors. Fig. 13 shows the purest pixels in different skews. A pixel is identified by an extreme of all the projections when it is presented by ultimate score. Spectrally high score and pure images are darker pixels over the output of the spectral image will be the brighter one.

3) Spectral Angle Mapper (SAM): Matching of the spectral library to each of the image spectra is called spectral angle mapping. If identifies the parallelism between two spectra and is done by calculating the spectral angle between them. The vector in space is the spectral angle for the reference spectra no of classes or spectral library is taken from the SAM algorithm. SAM is used for calculating the angular distance between each of the image spectra and the reference spectra [4]. Graphical output is given by the SAM, darker pixels are represented by smaller spectral angles. Smaller spectral angles indicate greater similarity between the reference and the input spectrum. Ines Dumke *et al.* [2] provide the spectral classification difference between SVM and SAM. SAM method was able to distinguish these non-sediment pixels from the background sediment, it was often not able to classify them in the same way as SVM. SAM provides better accuracy for mineral mapping than SVM. BI Xiaojia *et al.* [9] SAM provides enhanced reflectance curve for carbonate altered minerals like calcite, dolomite, siderite and gypsum. T. J Cudahy *et al.* [13] proposed Mixture Tuned Marched Filtering (MTMF) algorithm instead of SAM. MTMF has an advantage of excellent spatial coherency and correlates well with the published geology.

4) Identification of Endmembers Using their Reflectance Spectra in the Spectral Analyst: Materials centered on their spectral characteristics are classified by spectral analyst tool. It uses techniques like Binary Encoding, Spectral Angle Mapper (SAM) and Spectral Feature Fitting (SFF) and the output will be in the form of weighted score comparing the fit of the image spectra with that of reference spectra using SFF, with the help of least square method [4]. Between these two spectrum high score denotes greater closeness or more similarity in the spectral features. The reference spectra are matched with the image spectra. Result of SFF in the RMS image output image is the measure of absorption feature depth.

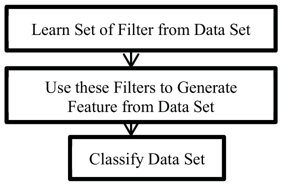


Fig. 14. Steps for self-taught training.

Rosa Maria Cavalli *et al.* [14] describes different spectral analyst methods like mineralogical composition and spectral characterization. Spectral analyst provides each endmember and output as on RMS error image.

D. Endmember Extraction

In both the spectral and spatial dimensions methodology is the limiting to locate, characterize and single out a few key spectral (endmembers) [11]. Once when the end members are handpicked using different techniques like Linearly transformation, SAM, Binary Encoding, the location and abundances can be mapped. By minimizing the dependency, these techniques drive the maximum information from the hyperspectral data.

VI. Self Taught Learning for Hyperspectral Imaging

In HSI one of the biggest challenges is determining what types of features should be extracted from pixels. Deep convolutional Neural Networks widely adopted computer vision but require large labelled data, otherwise it works poorly. So in HSI unsupervised learning is preferred instead of deep learning. Fig. 14. represents the steps for Self-Taught Training. Basically there are two self-taught learning techniques in the analysis of Hyperspectral image they are Multiscale Independent Component Analysis (MICA) and Stacked Convolutional Audio Encoder (SCAE) [3].

A. MICA

It learns the low level feature representation and extracting filters from the image. The input for this technique is contrast stretched image. Edges of home or Outline of a long road are the examples for this technique [3]. The low level features learned by MICA yields a superior result compared with the SCAE.

B. SCAE

SCAE is a deep Neural Network approach which can potentially learn higher level non-linear features than MICA. It is made up of several auto encoders. Auto encoder is also a type of neural network that can be trained by an unsupervised manner to learn an encoded representation of data[3]. SCAE model yielded the superior performance to MICA model, showing that higher level features can be advantageous in some cases.

VII. Conclusion and Future Work

This article surveys the use of hyperspectral remote sensing for mineral exploration and also it is an effective tool for the identification and mapping of minerals. Currently, there is an increasing number sensor technologies which have encouraged researchers to use hyperspectral imagery. This study discussed about the basics of Hyperspectral and Multispectral data with their different resolution types. It mainly focused on AIG based hyperspectral methods that can be used for the mineral mapping using the Airborne and Spaceborne hyperspectral platforms. This study may form the basis for future research ideas in the development of hyperspectral imaging for mineral exploration.

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