IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

PRE-PROCESSING OF E0-1 HYPERION DATA

[1] Kaushik M, [2]Nishan R, [3]R Jayanth, [4]Krishan Rao, [5]Dr. H S Prasantha
[1]Student, [2]Student, [3]Student, [4]Student, [5]Professor
Department of Electronics and Communication Engineering
Nitte Meenakshi Institute of Technology, Bangalore, India

Abstract: Hyperspectral Classification is one of the most emerging technologies where input image plays important role as that of the processing that takes place so the pre-processing stages are an important step before the image can be used for classification or any other analysis. The stages of the pre-processing done for the image include Bad-band removal, vertical De-stripping, Radiometric calibration, Atmospheric correction, and Dimensionality reduction (MNF) and End member extraction. Since hyperspectral image can be used in variety of fields such as agriculture, mining, food quality, soil type, defense etc.

***Keywords*- Image processing, Hyperspectral Imaging, pre-processing, Feature Extraction and reduction**

1. Introduction

The process of detecting and monitoring the physical features of an area from a distance without physical contact is known as remote sensing (typically from satellite or aircraft). The technique of obtaining digital imaging of earth materials in several small contiguous spectral bands is known as hyperspectral remote sensing. Since the late 1980s, when airborne sensors were first introduced, and subsequently in the 1990s, it has been a frontier of geospatial technology. The Hyperspectral Imagery is a technology that involves imaging the land surface at many spectral bands. Hyperspectral Images (HSI) have a high spectral resolution, enabling for detailed classification of land cover and land use classes. However, the spectral redundancy of HSI and the quantity of training samples frequently limited its classification accuracy. Although increasing the spectral resolution in the HSI can capture more details, significant correlations between neighbouring bands cause considerable redundancy, which means that the hyperspectral data can be condensed into a subspace with reduced dimensions. To lower the dimension of HSI, two main procedures have been used: feature selection and feature extraction. The goal of feature selection is to generate a simpler feature subspace by using the most discriminative bands. Feature extraction is concerned with producing a new subspace by transforming the underlying spectral space mathematically, as in subspace-based projection. However, because of the presence of mixed pixels, the performance of this method is easily influenced by the training sample selection. Because an entire spectrum is acquired at each point, the operator does not need prior knowledge of the sample, and postprocessing allows all available information from the dataset to be mined. The spatial relationships between different spectra in a neighbourhood can also benefit hyperspectral imaging, allowing for more elaborate spectral-spatial models for more accurate image segmentation and classification.
The wide range of applications, freely available software for image processing, and significant number of relevant publications demonstrate the maturity of hyperspectral remote sensing today. Mineral detection, environmental monitoring, and defence can all benefit from hyperspectral photos with hundreds of spectral bands and a wealth of spectral information.

1.1 Hyperspectral image processing

For a hyperspectral image to be used for further processing for performing segmentation and classification the image must undergo pre-processing such that it gives accurate spectral profile and expected and desired pixel value. As the image is captured from an airborne device the captured image will undergo distortion

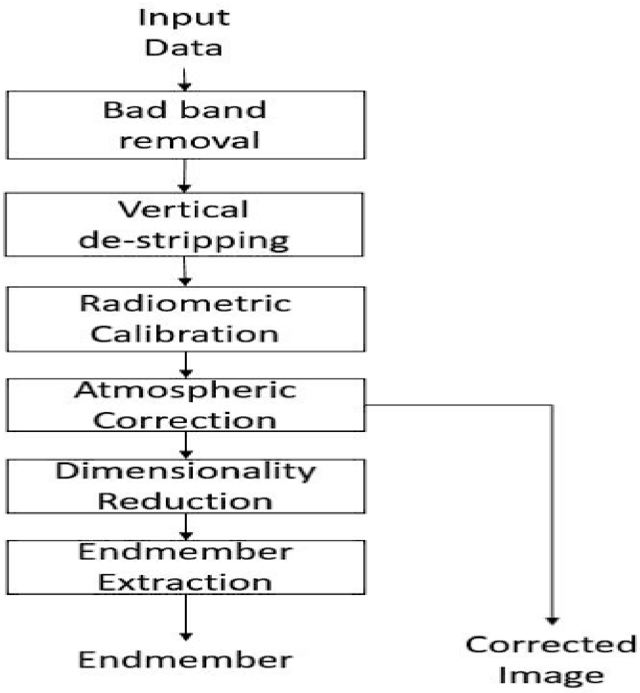

Fig 1: Block diagram for pre-processing.

which can be caused by the sensors and/or by the atmosphere, the transmitted signal must hit the ground and reflect back such that the sensor captures this reflected signal but the signal must travel through the atmosphere which contains various gases and material in the air which might cause the signal to diffract or scatter because of which there might be loss of data. This lose can be minimized by making use of atmospheric models to simulate the environment and obtain an approximate value for the pixel which undergoes this distortion. Processing of the image is an important step as this determines the accuracy of the system we use to classify or segment the image. As part of the processing stage of HSI the dimension of the image can be reduced by making use of feature reduction techniques along with the extraction of unique classes present in the given image like buildings, farms, water bodies etc.

1.2 Data set

Dataset is obtained from USGS Earth Explorer, which is a data portal for obtaining geo-spatial datasets. The hyperspectral images obtained from USGS Earth Explorer are taken by Earth Observing-1 (EO-1) Hyperion satellite. Hyperspectral images contain 242 bands with bandwidths ranging from 400 to 2500 nm having a pixel resolution of 30 meters, swath of 7.5 km by 100 km, and provide detailed spectral mapping across each band. The satellite makes use of a push broom sensor that is it scans the area of earth at one shot over the specified swath area. The data set obtained is radiometrically corrected that is instrumentation error and distortion in brightness along with geometric correction where the pixels are arranged in a proper manner to view the image as it was captured where this is caused because of satellite and earth's rotation.

2. Method

For classification of the image, it must undergo a set of pre-processing stages the flow diagram for the pre-processing is as shown in the block diagram

2.1 Bad Band Removal

Generally, different ground objects have different spectral characteristics, which is the physical basis for target detection or land cover mapping. From the perspective of target detection/image classification, some band combinations are considered to be more informative than others when detecting or separating one specific target, and for different targets, those informative band combinations may be different, and even for the same target, the informative band combination will vary when the background changes. Therefore, there are no universal rules to determine which band is more important than others. Yet the opposite is definite. That is, a band that provides little information to help to improve the detection/classification accuracy of all the objects can be considered as a bad one. Therefore, the bands which cannot provide useful information to detect any target in the scene. Based on the definition of bad bands, some preliminary conclusions can be drawn as the band within or near the water absorption ranges is a bad band, the band with a low SNR value is usually a bad band and the number and locations of bad bands change in different scene and the region of study

2.2 Vertical de-stripping

In this stage of pre-processing the vertical strips present in the image is removed where the value of the strips is set to 0 as there is no date being recorded by the sensor. This error occurs when the sensors used to capture a particular area overlaps the swath area hence that particular strip of pixels are zero as 2 or more sensors scan the same area. Since the images are a high resolution, the particular pixels do not hold much information when compared to the whole image hence the values of these pixels are approximated to an average of the neighbouring pixels or by making use of average mean and standard deviation of the neighbouring set of pixels the new pixel values are estimated.

2.3 Radiometric calibration

Radiometric calibration is required to obtain the spectral profile in the desired parameters that is in terms of Radiometric or reflectance so that we can get the radiance/reflectance plot for each of the classes present in the image. The scanned image will be saved in terms of signed integer called digital number (DN) which ranges from −32,768 through 32,767 which has to be converted in terms of radiance which is done with the help of the sensors offset and gain of the sensor. Once the image is in terms of radiance which has the value greater than zero, we can estimate the approximate reflectance of the pixel values of the image. With the acquired radiance value, the image can undergo atmospheric correction.

2.4 Atmospheric correction

Once the image is in terms of radiance, atmospheric correction can be applied on it. This correction is applied so that it can be expressed in reflectance value and temperature value, these corrections are needed in order to remove atmospheric distortion, dark pixels, to compare images from different sensors and/or dates of the same area, to perform environmental, ecological or geophysical analysis and to improve the classification results. The different methods available are Empirical methods are scene-based approaches that estimate relative surface reflectance values. Empirical methods are computationally efficient and does not require a priori measurements and the Model-based methods are dependent on in situ atmospheric data and are useful for accurate estimation of surface reflectance values. We have made use of the model-based approach specifically FLAASH algorithm which takes in the required atmospheric data that's the atmospheric conditions when the image was captured which has been extracted from the meta data. The other algorithms used to perform this include QUAC and SHARC which both yielded good results but comparatively FLAASH presented better results in terms of the spectral profile that was obtained at the end of this step.

2.5 Dimensionality Reduction

Since the input image is a high-resolution image with a large number of bands the size of the image must be reduced such that there isn't loss of information for further processing of the image. This is achieved by making dimensionality reduction algorithms such as Principal Component Analysis (PCA) but since we are processing a hyperspectral image, PCA did not give accurate compression but with the help of Minimum Noise Fraction (MNF) we are able to reduce the size of the image by using Eigen values and Eigen vectors where there are 10,000 iterations for each image containing 196 bands. Where Minimum Noise Fraction Rotation (MNF-Rotation) is used to identify the intrinsic dimension (the number of bands) of image data, segregate the noise in the data, and reduce the computational demand for further processing. It is a two-tiered main component transformation. The MNF transformation can help to reduce noise in data. To do so we must calculate the covariance matrix CN of the noise in the hyperspectral image, and then diagonalizable CN into the matrix DN.

$$D_N = U_T . C_N . \mathrm{U} \tag{1}$$

Minimal Noise Fraction (MNF), it consists of 2 cascaded PCA the first step is to minimizes the noise followed by the second step where a standard PCA transformation is applied to the noise whitening. The data is divided into two parts: one part is associated with large Eigen vector matrix and Eigen values and the other part stores noise co-variance data.

2.6 Endmember Extraction

Endmembers are the pure spectra or pixel of a data cube corresponding to particular classes. The endmember signatures can be extracted from a hyperspectral data cube using the Pixel Purity Index (PPI) algorithm. Its idea is to use Orthogonal projection (OP) to determine whether a data sample vector is an endmember. If a data sample is a potential endmember, its OP on a random vector should be very likely to yield either maximal or minimal projection (projections in the extreme ends). In order to produce such a vector, a random unit vector is generated by PPI, referred to as a skewer.

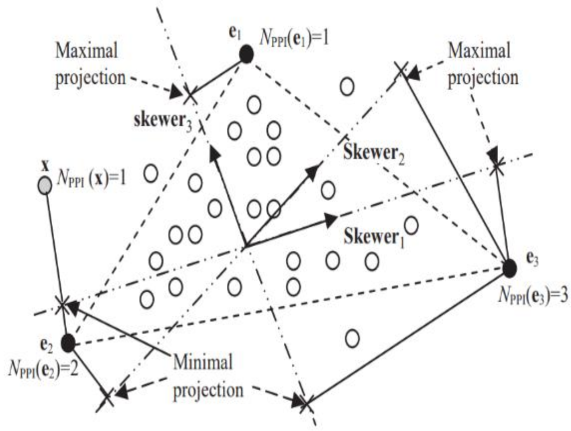

Fig-2 Illustration of PPI with 3 endmembers e1, e2, and e3

The three skewers, skewer1, skewer2, and skewer3, are randomly generated unit vectors where data sample vectors are denoted by open circles and as per figure 1 three endmembers e1, e2, and e3 by solid circles located at three vertices of the triangles and a maximal or a minimal projection of an endmember on a skewer is indicated by a cross "x." Orthogonal projection (OP): The criterion of OP is to orthogonally project data samples on a set of selected vectors so that the data samples whose orthogonal projections fall at the end (extreme) points of these selected vectors will be considered as endmember candidates.

This indicates that e1, e2, and e3 are the three desired endmembers. Because of convexity, all the sample vectors in Figure 1 inside the triangle are supposed to have their PPI counts = 0, which implies that they are mixtures of the three endmembers at the vertices of the triangle indicated by dashed lines. It should be noted that a projection can be positive or negative depending on whether the projection occurs in the same or opposite direction of a skewer. A data sample with its maximal or minimal projection that occurred at a skewer is the one that is a potential candidate for an endmember.

Finally, PPI extracts endmembers according to their PPI counts, with a threshold value t that must be determined a priori. As a result, all sample vectors whose PPI counts are higher than t will be extracted as endmembers. In this case, many endmembers representing the same pure signature may also be extracted.

3. Results and Discussions

This section presents the results obtained along with delated discussion for each individual stage of pre-processing.

3.1 Pre-processing of hyperspectral image

The pre-processing was done in ENVI 5.1 software with the system specification of 4gb ram and on AMD Ryzen-3 3200g processor.

3.1.1 Bad-band Removal

The uncalibrated data product consists of redundant bands which are irrelevant called bad-bands and are of no use for processing of the image which are removed by making use of BBL mask which holds the data regarding the bad bands that are acquired during the scan. The list of bad-bands is shown in table-1 along with their spectral range.

Tabel-1: Bad-Bands

Bad-Bands	Spectral range
1-7	355–417 nm
58-70	936-1058nm
71-76	852-902nm
225-242	2406–2578 nm

Once the bad bands in the hypercube is removed the number of bands is reduced from 242 bands to 196 calibrated bands the 46 bad bands are set to 0 and removed.

3.1.2 Vertical De stripping

Vertical de-stripping to remove strips and smears from the data product as show in fig 3a and 3b.

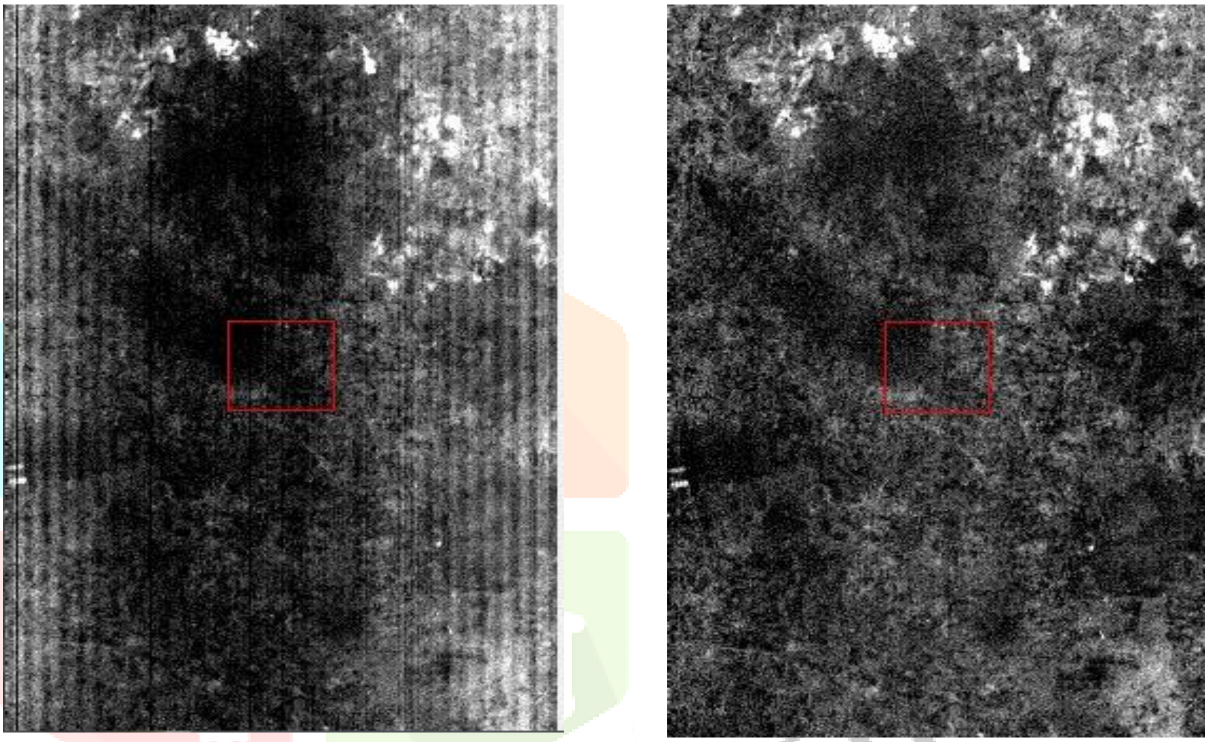

Fig 3: a) Before De-stripping there is presence of strips which are redundant, **b**) After De-stripping the image is free of strips and is ready for processing further.

To remove the vertical strips the neighbouring pixels are made use of to estimate the values of the missing pixels and standard deviation and mean of the pixels are used to estimate the values of those pixels.

1.3 Atmospheric correction

Atmospheric correction is performed using FLAASH algorithm where the atmospheric conditions when the image was captured must be fed into the model such that it simulates a model based on the parameters which includes radiance value(L), earth sun distance in astronomical units(d), sun elevation angle(Θ_s) and the mean solar irradiance each band ($ESUN_\lambda$) which is given to equation 2 which gives the reflectance of each pixel.

$$Reflectance, p = \frac{\pi . L_\lambda . d^2}{coscos\, \theta_s \cdot ESUN_\lambda} \qquad (2)$$

The outputs after performing atmospheric correction are as shown in the following fig-4

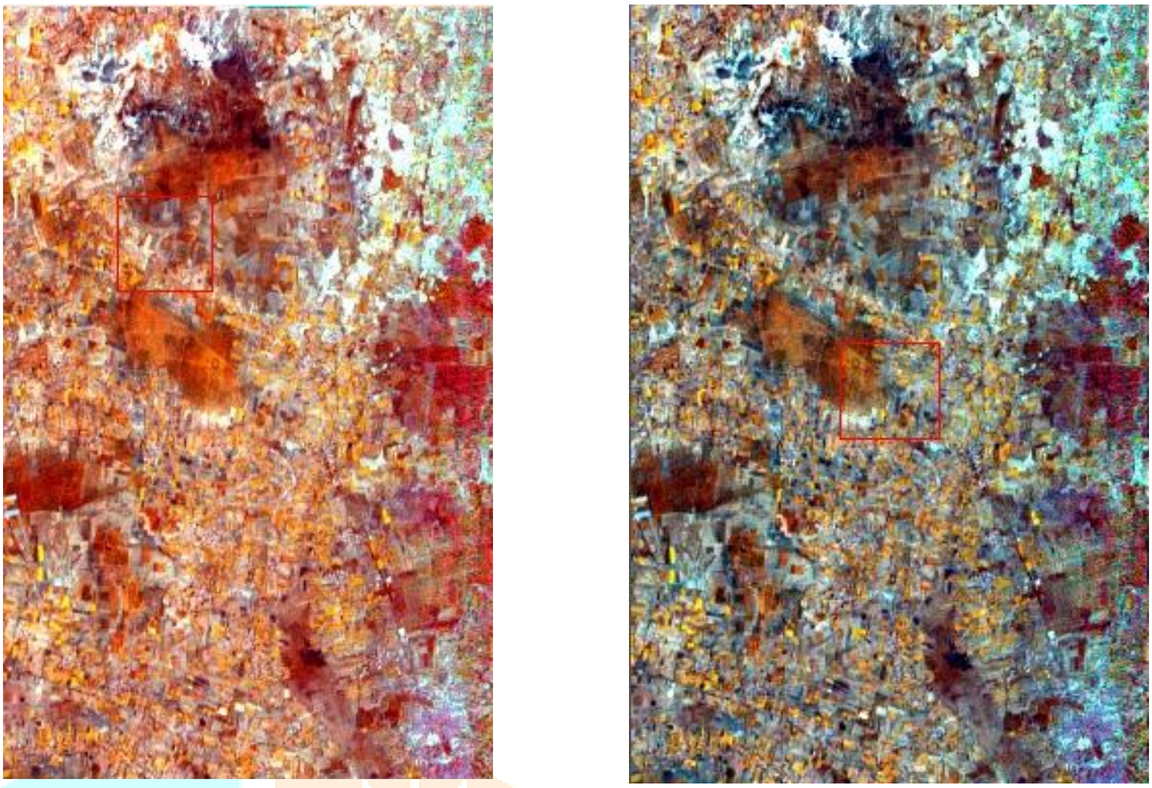

Fig 4: a) performing FLAASH there are certain features that are missing, **b)** After FLAASH the image is more detailed

3.1.4 Dimensionality Reduction

Dimensionality Reduction of the hyperspectral data is done using Minimum Noise Faction (MNF) to reduce the number of bands. To select good bands, we compare Eigen values of the MNF bands. MNF bands with Eigen value (>1.0) contain signal are selected and MNF bands with Eigen value (<1.0) contain noise are discarded.

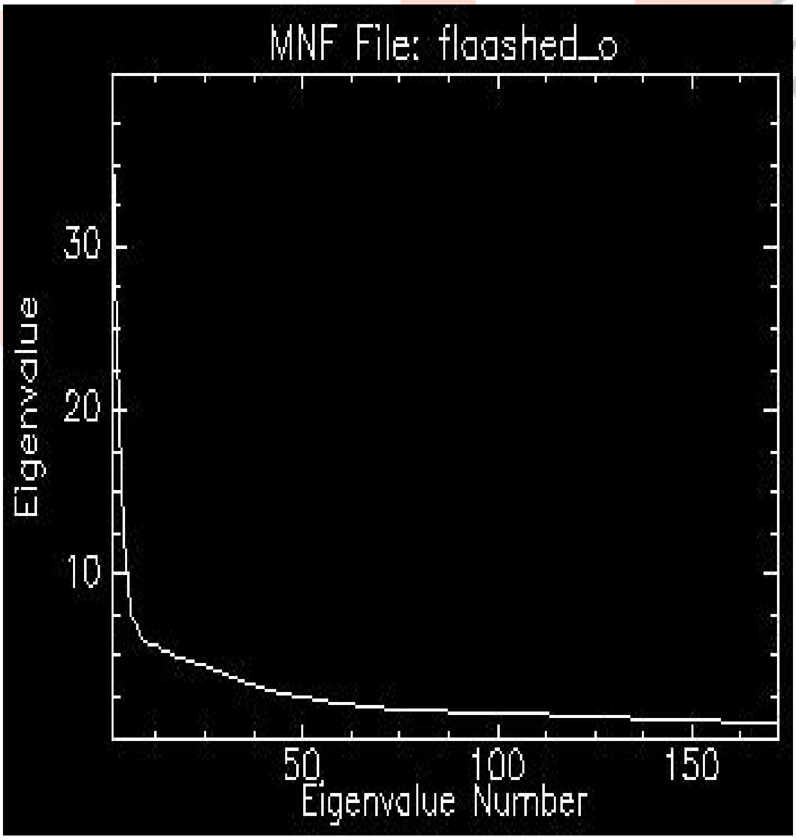

Fig 5: Selecting informative bands based on eigenvalue and band numbers.

3.1.6 Endmember Extraction

End member is extracted from a hyperspectral data cube using the Pixel Purity Index (PPI) algorithm in order to get the purest spectral signature among other spectra extracted from the data cube. This spectrum can be used to find the different classes present in the whole image. The accuracy of this spectral profile totally depends on the corrections that are done on the image to get the accurate profile in terms of reflectance from which we can extract the reflectance properties of the classes are present.

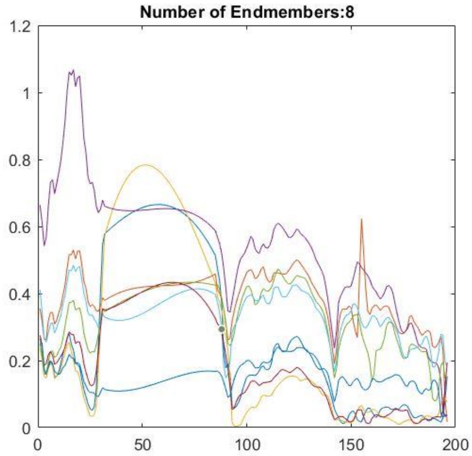

Fig 5: Extracted spectral profile using PPI.

4. Conclusion

In this study, we went over various pre-processing steps to be performed on a hyperspectral image acquired from a Hyperion sensor. We utilized MATLAB 2021a and the Envi 5.1 tool to perform bad band removal, vertical de-stripping, atmospheric correction, dimension reduction of the hyperspectral data, and end member extraction so that the image obtained at the end of the process is ready to undergo classification or analysis of the area under study.

5. References

1. Chein-I Chang and A. Plaza, "A fast iterative algorithm for implementation of pixel purity index," in IEEE Geoscience and Remote Sensing Letters, vol. 3, no. 1, pp. 63-67, Jan. 2006, doi: 10.1109/LGRS.2005.856701
2. X. Wu, B. Huang, A. Plaza, Y. Li and C. Wu, "Real-Time Implementation of the Pixel Purity Index Algorithm for Endmember Identification on GPUs," in IEEE Geoscience and Remote Sensing Letters, vol. 11, no. 5, pp. 955-959, May 2014, doi: 10.1109/LGRS.2013.2283214.
3. C. Chang, Y. Li and Y. Wang, "Progressive Band Processing of Fast Iterative Pixel Purity Index for Finding Endmembers," in IEEE Geoscience and Remote Sensing Letters, vol. 14, no. 9, pp. 1464-1468, Sept. 2017, doi: 10.1109/LGRS.2017.2710219.
4. X. Wang, Y. Zhong, C. Cui, L. Zhang and Y. Xu, "Autonomous Endmember Detection via an Abundance Anomaly Guided Saliency Prior for Hyperspectral Imagery," in IEEE Transactions on Geoscience and Remote Sensing, vol. 59, no. 3, pp. 2336-2351, March 2021, doi: 10.1109/TGRS.2020.3001353.
5. Y. Duan, W. Chen, M. Wang and L. Yan, "A Relative Radiometric Correction Method for Airborne Image Using Outdoor Calibration and Image Statistics," in IEEE Transactions on Geoscience and Remote Sensing, vol. 52, no. 8, pp. 5164-5174, Aug. 2014, doi: 10.1109/TGRS.2013.228702
6. Hamadache, Zohra & Smara, Youcef. (2014). Destriping methods for EO-1 Hyperion Hyperspectral Sensor.
7. A.K. Singh, G. R. Kadambi, J. K. Kishore and J. Shuttleworth, "Performance evaluation for data reduction techniques of hyperspectral images," *International Conference on Circuits, Communication, Control and Computing*, 2014, pp. 64-68, doi: 10.1109/CIMCA.2014.7057758
8. M. D. Farrell and R. M. Mersereau, "On the impact of PCA dimension reduction for hyperspectral detection of difficult targets," in IEEE Geoscience and Remote Sensing Letters, vol. 2, no. 2, pp. 192-195, April 2005, doi: 10.1109/LGRS.2005.846011.
9. J. Wu, W. Yan, W. Ni and H. Bian, "Feature extraction for hyperspectral data based on MNF and singular value decomposition," 2013 IEEE International Geoscience and Remote Sensing Symposium - IGARSS, 2013, pp. 1430-1433, doi: 10.1109/IGARSS.2013.6723053.
10. Nisha Rani, Venkata Ravibabu Mandla and Tejpal Singh, " Evaluation of atmospheric corrections on hyperspectral data with special reference to mineral mapping" in ELSEVIER Journal of Geoscience
11. Dr. H S Prasantha, "NOVEL APPROACH FOR IMAGE COMPRESSION USING MODIFIED SVD", International Journal of Creative Research Thoughts (IJCRT), Volume 8, Issue 8, Page 2234-2243, Aug 2020
12. Dr. H S Prasantha, "IMPLEMENTATION OF IMAGE COMPRESSION USING FAST COMPUTATION OF SVD ON DM642", International Journal of Creative Research Thoughts (IJCRT), Volume 8, Issue 8, Page 2364-2368, Aug 2020

13. Prasantha, H, H Shashidhara, K N B Murthy, and M Venkatesh. "Performance Evaluation of H.264 Decoder on Different Processors." International Journal on Computer Science & Engineering. 1.5 (2010): 1768. Web. 7 Apr. 2013.
14. H. S. Prasantha, H. L. Shashidhara, and K. N. Balasubramanya Murthy. Image compression using SVD. In Proceedings of the International Conference on Computational Intelligence and Multimedia Applications, pages 143–145. IEEE Computer Society, 2007.
15. Gunasheela K S, H S Prasantha, "Compressive sensing for image compression: survey of algorithms", Proceedings of Emerging Research in Computing, Information, Communication and Applications, ERCICA, Springer publication, Bengaluru, 2018
16. K N Shruthi, B M Shashank, Y. SaiKrishna Saketh, H.S Prasantha and S. Sandya, "Comparison Analysis Of A Biomedical Image For Compression Using Various Transform Coding Techniques", IEEE, pp. 297-303, 2016