A Review on Hyper Spectral Imaging for Remote Sensing Applications

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Abstract: **Hyper spectral remote sensing has experienced various exploitation. Conventional methods are being prevailed by many advanced methods or approaches and also many new techniques are still being under research. An integrative review and comparison of HSI is being presented here to explore recent progress which are applied to HSI for classification, compression and detection. Actually a solid survey of various techniques used for HSI analysis is necessary for researches and practitioners for their evaluation purposes. HSI is the thrust area that enables one to distinctly identify the objects from space.**

Keywords: **Hyper Spectral Image (HSI), classification, compression, anomaly or target detection**

I. INTRODUCTION

A picture is worth thousand times and satellite image is worth infinite times. Once satellite image is acquired, extracting information from the image is the challenging task as the image constitutes of various noises. In the field of remote sensing, hyper spectral imaging plays a life-sustaining role, it consists of hundreds of spectral bands with narrow bandwidths and so it can produce contiguous spectral band when compared to multispectral. Hyper spectral imaging is a combination of imaging and spectroscopy. With this complete reflectance spectra can be obtained. Hyper spectral overcomes the multispectral in providing complete observation compared to the latter one. Also there is no spectral gap in hyper spectral which makes it efficient in identifying the objects on earth just by reading the spectrum of each pixel of a scene from the space. HSI is a representation of high-dimensional vector providing rich information of spectral bands and thereby helps to get accurate interpretation of data's collected.

ISRO has designed a chip "**Optical Imaging Detector Array**" with which the satellite can identify 55 spectral or colour bands from 630km above the ground. Normally HSI gives detailed information as it goes narrow and measures the feature. Various sensors are used for the observations and each sensor has its own characteristic features.

Hyper spectral sensors have the capability of collecting hundreds of narrow and contiguous spectral bands with fine spectral resolution for each pixel in the image. Usually the sensors are mounted on the aircrafts and satellites for imaging the geographical area to detect, locate and understand the physical properties and the details are later extracted using different algorithms. The main goal of HSI is to obtain the spectrum of each pixel for identifying, detecting and finding objects. Push broom scanners and snapshot hyper spectral imaging are the two commonly used branches of spectral imagers, where push broom scanner reads the images with respect to time and snapshot generates the image in an instant.

HSI is used by wide variety of applications for identification and monitoring of land cover, land use, disaster, urban, forestry, rural, water bodies, mineralogy, agricultural, eye care, food processing, surveillance, physics, astronomy, chemical imaging, environment, vegetation, snow grain size studies, aerial sensing recycling, etc,.

A: HYPER SPECTRAL DATA PROCESSING

HSI data processing is broadly categorized into (i) pre-processing, (ii) end member selection and (iii) classification. HSI data are usually acquired by spectral, spatial, spectral-spatial and non-scanning methods. Pre-processing is the first step in data processing. Here radiometric/atmospheric/geo corrections are done using special filters or models. In feature extraction the dimensionality is reduced using various techniques such as PCA, ICA, and SPCA, projection pursuit, orthogonal subspace projection and wavelet transformation. In some applications instead of reducing the dimensions their discriminant features are selected certain specific analysis like neural network, divergence analysis using transformed divergence, bhattacharaya distance and jeffrie matisuta distance.

II. SURVEY OF APPROACHES AND METHODS

The literature survey of various hyper spectral imaging techniques and algorithms are prescribed here. This paper aims in providing various ideas and approaches related to HSI which may be useful for the researchers and practitioners for further evaluation.

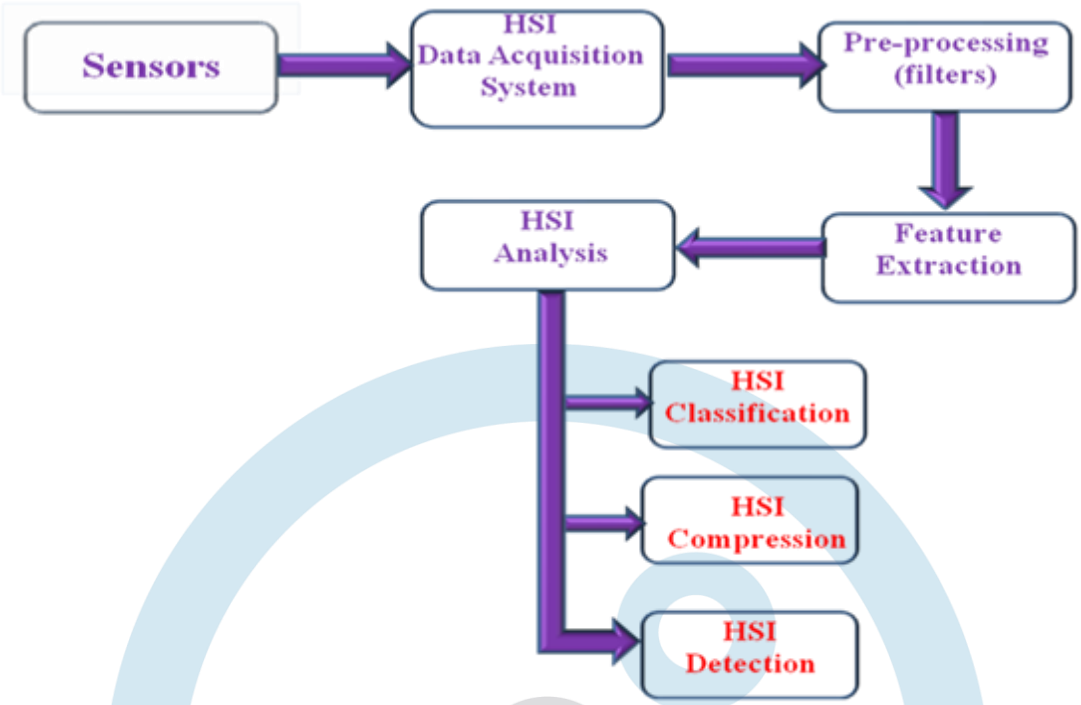

Fig: Basic Block Diagram of Hyper Spectral Imaging and processing

S.no	Author Paper-Year	Title	Algo/Method	Problem	Solution	Review
1	Chunyan Yu Journal-2018	Iterative Target-Constrained Interference-Minimized Classifier for Hyperspectral Classification	*ITCIMC(Iterative target constrained interference minimization classifier) *Otsu's method	*to improve HSI classification for multiple classes at one-shot operation	*Mixed pixel classifier is revived by using this TCIM filter *This filter is improved by ITCIMC which makes use of Gaussian filtered feedback process to capture the spatial information in a iterative manner by fixing threshold using otsu's method *Additional strategy measures like misclassification rate(MC), precision rate(PR) and accuracy rate(AR) are used using priori and posteriori concepts	*otsu's method used for fixing threshold is not optimal, this can be improved by using another technique *sigma value used by Gaussian filter can be selected optimally *though Gaussian filter reduce noise it takes more time and sometimes reduces the detail so a better filter can be replaced
2	Amirabbas Davari Journal-2018	GMM-Based Synthetic Samples for Classification of Hyperspectral Images With Limited Training Data	* PCA(principal component analysis) *EMAP(extended multi attribute profile) *DR(dimensionality reduction) *GMM(Gaussian mixture model) *RFC(random forest classifier) *EM(expectation max..)	*to perform multiclass classification with a few training data points using gaussian maximum likelihood classifier	*With limited training data the feature matrix is enriched by augmenting synthetic samples by reducing dimensions *Spectral bands are reduced by PCA and EMAP and then subject to DR *The feature points are drawn from GMM that is fitted to training samples and finally classified with RFC	*synthetic samples are alone added to the DR features, this can be extended *GMM cannot be estimated with few samples in high dimensional spaces. *GMM which are estimated using EM is replaced by Kmeans, this can further be modified better estimation
3	Peijun Du Trans-2018	Multikernel Adaptive Collaborative Representation for Hyperspectral Image Classification	*CRC(collaborative representation based classifier) *MKL(multiple kernel learning) method *PCA(principal component analysis) *EMP(extended morphological profile)	*to capture useful information from different pixel distributions using multiple kernel patterns	*to enhance the power of CRC, multikernel(MKCRC) framework is adopted for classifying HSI data *This framework first employs PCA and extends to EMP for features and then the 3 kernel patterns are selected followed by coding and updating of kernel thus yielding robust	*The proposed 3 kernel patterns can be increased for improving classification performance *The performance of multiple kernel CRC can be enhanced by applying dictionary learning methods to the framework

					classification	
4	Xiangyong cao Journal-2018	Hyperspectral Image Classification with Markov Random Fields and a Convolutional Neural Network	*Bayesian framework *MRF(markov random field) *SGD(stochastic gradient descent) algo *min-cut-based algo	*integrating spectral and spatial information in a unified bayesian framework	*spectral-spatial classification method is proposed *here hyperspectral image is classified in a Bayesian framework with simultaneous operation of deep learning and MRF	*hyperspectral image can be classified with unsupervised settings *hyperspectral dataset can be performed with other deep learning models like VAE(variational autoencoder),GAN(generative adversarial network)
5	Binge Cui Journal-2018	Superpixel-Based Extended Random Walker for Hyperspectral Image Classification	*SVM *multiscale segmentation algo. *EPF(edge preserving filtering) *IFRF(image fusion recursive filtering) *SnEPF(image segmentation and EPF) *GCK(generalized composite kernel) *ERW(extended random walker) *SPERW(superpixel based random walker)	*to encode the spatial information among and within the superpixels in a weighted graph	*super-pixel technique is used to solve all the problems over traditional classifiers *multiscale segmentation algo is used to generate super-pixel *pixel-wise classifier (SVM) is used to approximate superpixels and later optimized by ERW algo *super-pixel leads to high classification accuracy as the spectrum of superpixel is highly stable and less affected by noise	*semi supervised classification can be used to generate super-pixels *different other methods for generating super-pixel classification can be proposed

6	Leyuan Fang Trans-2018	Extinction Profiles Fusion for Hyperspectral Images Classification	*EP(extinction profile) *EPs-F(extinction profile fusion) *SVM	*to exploit the extinction profile function to get the information among the stacks for classification	*composite kernel based SVM are used to generate spectral and spatial info *EP method delivers better recognition and removes unwanted details *Eps-F method is used to create composite kernel and effective decision fusion method is applied to further improve the classification method	*other kinds of features can be used along with EPs to improve the classification accuracy
7	Leyuan Fang Journal-2018	A New Spatial–Spectral Feature Extraction Method for Hyperspectral Images Using Local Covariance Matrix Representation	* SVM *maximum noise fraction method *cosine distance measurement *local covariance matrix rep method	*to characterize the correlation among different spectral bands and spatial contextual information in the scene	*unsupervised feature extraction method is used to overcome the hughes and dimensionality pbm	*super-pixel based segmentation method can be combined with CMR to get spatial information
8	Wei Fu Trans-2018	Contextual Online Dictionary Learning for Hyperspectral Image Classification	*SR(sparse representation) *CODL(contextual online dictionary learning)	*learning the dictionary for the whole image to perform classification	*CODL learns the dictionary over the whole image rather few labeled pixels so that SR is complete *traditional classifier(SVM) is finally applied to SR for accuracy improvement	*training of SVM in DL can be done for future classification *simultaneous classification and dictionary learning can be performed to improve the accuracy
9	Qishuo Gao Journal-2018	Hyperspectral Image classification Using Joint Sparse Model and Discontinuity Preserving Relaxation	*JSM(joint sparse model) *DPR(discontinuity preserving relaxation method) *SOMP(simultaneous orthogonal matching pursuit)	*to detect the discontinuity of an image and smoothen the result in advance	*to avoid noisy appearance in the image, both spatial and spectral info are integrated by many traditional methods like MRF and kernel methods. *joint sparse representation overtakes the other traditional methods as it can be represented by a subset of atoms in the dictionary	*more testing and validation can be done to investigate over-smoothing

					*finally DPR method is used to smoothen the result to be more finer	
10	Siyuan Hao Journal-2017	Two-Stream Deep Architecture for Hyperspectral Image Classification	*SdAE(stacked denoising autoencoder) *two stream deep architecture *CNN	*the spectral values of input pixels are encoded by stacked denoising encoder and finally the image patches are fused by adaptive class specific weights	*Two stream deep architecture is employed to extract both spectral and spatial info to enhance the classification *the processed image patches are fused by adaptive class specific weight regulizer to prevent overfitting	*the proposed method is time consuming and so this can be overcome by efficient computational methods *semi-supervised classification can be used to analyze the accuracy level of classification
11	Hong Huang Journal-2018	Fusion of Weighted Mean Reconstruction and SVMCK for Hyperspectral Image Classification	*WMR(weighted mean reconstruction) *SVMCK(support vector machine based on composite kernel)	*pixels are reconstructed by spatial neighbour using reconstruction weights	*with spatial neighbouring pixels, the extracted discriminating features are free from noise and thereby improves the classification accuracy	*in real time application effective computational algorithms can be implemented
12	Jiaojiao Li Journal-2018	Hyperspectral Image Classification With Imbalanced Data Based on Orthogonal Complement Subspace Projection	*OCSP(orthogonal complement subspace projection) *SMOTE(synthetic minority oversampling technique)	*create artificial samples to solve the imbalance of training samples	*the algo splits the classes into large and small sizes and creates an artificial samples for small ones *for small size sets SMOTE algo is used	*for algo which are sensitive to large training site other conventional methods can be employed to analyze the accuracy *SMOTE can be replaced by Near Mis for small size dataset
13	Atif mughees Conf-2017	Hyperspectral image classification based on deep auto-encoder and hidden markov random field	*deep auto-encoder *HMRF	*segmentation and merging of spectral and spatial information is done by maximum vote based criteria	*spectral features are extracted by stacked auto-encoder *spatial features are extracted by hidden markov random field	*AVIRIS and ROSIS sensors can be replaced

14	Yushi chen Journal-2014	Deep learning based classification of hyperspectral data	*auto-encoder *stacked auto-encoder *SVM *logistic regression	*spatial and spectral deep features are extracted by stacked auto-encoder and merged	*the eligibility of stacked auto-encoder is verified and spatial dominated information is classified *hybrid framework of PCA, deep learning architecture and logistic regression is performed	*the number of hidden layers can be increased from the proposed 6layer
15	Hamidullah Binol Journal-2016	Kernel Fukunaga–Koontz Transform Subspaces for Classification of Hyperspectral Images With Small Sample Sizes	*kernel Fukunaga–Koontz transform (KFKT)	*solve the multiclass problem by taking one class as target(OAA) approach to improve the accuracy	*the transform uses small size training sets for target detection *the method is the extension of multiclass classification	*as kernel plays the major role it can be modified to improve the performance of the classification accuracy
16	Erchan aptoula Journal-2016	Deep learning with attribute profiles for hyperspectral image classification	*AP(attribute profiles)	*attribute filtered images are stacked and feed as input to CNN	*geometric and spectral properties are captured efficiently with attribute profile thereby producing strong features even from raw samples *threshold is fixed for by attribute filters and patch is extracted for every pixel	*hyperspectral datasets can be increased from the proposed one *different deep network types can be tried instead of CNN
17	Weiwei Song Journal-2018	Hyperspectral Image Classification With Deep Feature Fusion Network	*CNN *DFFN(deep feature fusion network)	*to optimize convolution layers as identity mapping through residual learning	*the method helps to extract deeper features and obtain state of art performance	*for feature fusion only three layers have been taken and by modifying these layers classification performance can be increased
18	Vanika Singhal Journal-2017	Discriminative Robust Deep Dictionary Learning for Hyperspectral Image Classification	*DL(deep learning) *DL(dictionary learning)	*minimize absolute deviations in place of euclidean norm.	*each level of dictionary is learned and thier coefficients are used for next level *final level coefficients are used for classification	*different datasets can be used for this dictionary learning
19	Hao Wu Trans-2018	Semi-Supervised Deep Learning Using Pseudo Labels for Hyperspectral Image Classification	*CRNN(convolutional recurrent neural networks) * C-DPMM (constrained Dirichlet process mixture model)	*abundant unlabeled data are utilized along with thier pseudo labels(cluster labels)	*semi-supervised deep learning method is used where with CRNN for spectral info and C-DPMM for spatial info.	*pseudo labels can be generated in alternative way as it decides the quality of the feature extracted

20	Mengmeng Zhang Journal-2018	Diverse Region-Based CNN for Hyperspectral Image Classification	*DR-CNN(diverse region based CNN) *deep learning *pattern recognition	*to encode semantic content aware representation to obtain promising feature	*spectral and spatial info is connected to network and label of each pixel is predicted by softmax layer	*multi-scale summation can be replaced for improving the performance

A: HSI CLASSIFICATION

The most challenging task in analysis of hyper spectral imaging is the classification. Researchers use three broad classifications such as supervised, unsupervised and semi-supervised classification. This review paper focuses on various algorithms and methods which help in processing the hyper spectral images.

Nomenclature of Classification

- Point, per pixel, hard, crisp classification
- Sub-pixel, soft, fuzzy classification
- Textural, contextual, spatial classification
- Supervised, unsupervised classification
- Parametric, non-parametric classification

Each nomenclature in turn uses various classifiers, for instance the parametric classifiers are performed using parallelepiped, minimum distance to mean and maximum likelihood classifiers. Similarly some of the common non-parametric classifiers include neural networks, SVM, fuzzy set based methods, evidential reasoning, decision trees and expert systems.

Generally the factors which influence the performance of classification are data, cost, complex spectral libraries, classifier problems, selection of features and analysing methodology. These have to be overcome to attain the accuracy at the end result. Some of the common tools used for extracting the features for the classification purposes include MATLAB, ENVI, ERDAS, HyperSpy, Opticks, Scyllarun, Gerbil, Grass, OpenCV, Arcgis, MIA toolbox, etc,.

Hyper spectral image is broadly classified into SAM and MTMF. SAM (Spectral Angle Mapper) is the algorithm which works based on the characteristics of image and the training data. It also helps to calculate the spectral similarity between the reference spectrum (ASD-Analytical Spectral Device and Image spectrum). MTMF (Mixed Tuned Matched Filtering) performs partial unmixing to find the abundances of user defined endmembers. It also suppresses the unknown background and produces series of gray-scale images from 0 to 1 to get perfect degrees of match.

Chunyan Yu [2018], the author uses TCIM filter which makes use of Gaussian filtered feedback to capture the spatial information in an iterative manner by fixing threshold using Otsu's method. Later this filter is improved by Iterative target constrained interference minimization classifier (ITCIMC). With this additional strategy measures such as misclassification rate, precision rate and accuracy rate are used.

Amirabbas Davari [2018], here with limited training data the feature matrix is enriched and dimensions are reduced by augmenting synthetic samples. Also the spectral bands are reduced by PCA and EMAP before subjecting to dimension reduction. The features points are drawn from GMM fitted to training samples and are finally classified with RFC.

Peijun Du [2018], the author enhances the power of CRC, multikernel framework adopted for classifying HSI data. Later this framework employs PCA and extends to EMP for features and 3 kernel patterns are selected followed by coding and updation of kernel is performed which yields robust classification

Xiangyong cao [2018], here the hyper spectral image is classified in a Bayesian framework with simultaneous operation of deep learning and markov random field. Also pure classification methods like PCA, ICA, LDA ignores the spatial correlations and leads to poor classification so to overcome this spectral-spatial classification method is proposed here.

Binge Cui [2018], the author uses super-pixel technique to solve all the problems over the traditional classifiers and multi scale segmentation algorithm is used to generate the super-pixel technique. Apart pixel-wise classifier is used to approximate super-pixels optimized by ERW algorithm. Super-pixel leads to high classification accuracy as the spectrum of super-pixel is highly stable and less affected by noise.

Qishuo Gao [2018], proposed discontinuity preserving relaxation method to smoothen the result to be more finer. Actually the joint sparse representation overtakes the other traditional methods by a subset of atoms in the dictionary and also to avoid the noisy appearance in the image both spatial and spectral information are integrated by many traditional methods like MRF and kernel.

Siyuan Hao [2018], in this paper various traditional classifiers which suffers from extracting deep features are solved by using two stream deep architecture which helps to employ both spatial and spectral information for enhancing the classification. Also the architecture employs stacked encoder for the input pixel in the initial stage and then these image patches are processed by deep CNN.

Hong Huang [2018], this paper overcomes the noisy images as some of the traditional classifiers fails to consider the spatial relationship between the pixels. The author proposes weighted mean reconstruction and SVM based composite kernel which reconstructs the spatial neighbouring pixels by weights and fuse both the spectral and spatial information. Finally the discriminating features are extracted to remove the noise and thereby the accuracy is maintained.

Jiaojiao Li [2018], some classifiers achieves accuracy only for equal size classes. In this paper the author uses orthogonal complement subspace projection (OCSP) algorithm to overcome the problem of imbalanced training classes. Here the algorithm splits the classes into large and small sizes and further it creates an artificial sample for the smaller size classes. Synthetic minority oversampling technique (SMOT) is used for creating artificial samples.

B: HSI COMPRESSION

HSI compression is the other challenging task next to classification. Feature reduction decides the end result as the performance metrics highly depends on the discriminant features selected. When the training samples are very limited, classifying the image becomes complicated and this is overcome by reduction technique which reduces the number of bands essential for HSI interpretation. End member selection represents a class that have to spectrally classify or identify in the image and the process of end member selection from the image data is classified as MNF (Minimum Noise Fraction), PPI (Pixel Purity Index) and N-dimensional visualize.

Feature extraction or dimensionality reduction approach and feature selection or selecting discriminant features are used to extract the necessary information. Some traditional used linear methods are principal component analysis (PCA), local preserving projection (LPP), fisher linear discriminant analysis (FLDA) etc, now recent approaches like tensor PCA, LPP, FLDA are used. In non-linear methods local linear embedding (LLE), isometric feature mapping (ISOMAP), laplacian eigenmaps (LE) is used.

Lena Chang [2011], here the author uses two specific algorithms where initially the image is divided into various regions using clustering signal subspace projection (CSSP) and finally merged by maximum correlation band clustering (MCBC). The author also proposes parallel computing techniques to get better efficiency compared to earlier algorithms.

Bruno Aiazzi [1999], this paper is based on 3D fuzzy prediction where the author uses space-spectral varying prediction of pixel using fuzzy switching and further classifies the outcome so as to minimize the mean-squared error. Since relevant multispectral characteristics of data's are collected, decoding becomes faster.

Loredana Pompilio [2004], here the hyper spectral image is preserved in the reduced space. Normally huge data with single observation may reflect a limitation in giving out better data exploitation, so this is overcome by feature reduction technique which preserves the spatial information for better classification. Exponential Gaussian Optimization (EGO) and Spectral Angle Mapper (SAM) and SVM are used.

Massimo Selva [2015], the author clearly explains about pan sharpening by using two hyper sharpening methods. For this the author takes two steps to perform the technique, the whole datacube is sharpened in order to enhance each band at the resolution of PAN where SWIR data is fused with VNIR resolution.

C: HSI DETECTION

Detection of target or anamoly is yet another important parameter in HSI techniques. Commonly used dimension reduction methods are Constrained Band Selection (CBS), Divergence Measure (DM), Mutual Information (MI), Affinity Propagation (AP), Laplacian Eigenmaps (LE), Kernel Principal Component Analysis (KPCA), and Progressive Band Selection (PBS). Generally Overall Accuracy (OA), Kappa Coefficient (KC), Average Accuracy (AA) is some of the metrics used to assess the performance of dimensionality reduction.

Ye ZHANG [2004], here the author uses kernel based invariant subspace detection method and he proposed the combination of Kernel Principal Component Analysis (KPCA) and Linear Mixture Model (LMM). Further he proposed that these combination can overcome the spectral variability in the target detection thereby he concludes that the proposed method is better than the earlier one.

Zhou Jun [2012], this paper is based on Non Sub sampled Pyramid Decomposition (NSPD) where the hyper spectral image is mouldered into sub-band under different scale using NSPD algorithm. Here image background is suppressed using kernels unsharp masking method and the disturbance affecting the background is overcome by enhancing the anomaly signal.

Xiaodan Zhang [2015], conventional methods levy the rigorous assumption on spectrum distribution of both target and background but that cannot adjudge for all practical situations. Here the author averts this problem by sparsity-based method where each test pixel is represented by few samples from over complete dictionary Locality-constrained Group Sparse Representation (LGSR) method thereby preserving the multiplex structure of hyper spectral data.

III. CONCLUSION

Today hyper spectral imaging techniques have been fascinated to wide range due to amount of information and the range of potential applications. We have presented a brief review on comparative study of the various processing methods of hyper spectral image ranging from traditional to recent learning methods. The difficulty arises in the generation and availability of training samples. Each method and algorithms vary with their efficiency and accuracy. Hyper spectral image is thousand times more than a picture and so researchers are widely using this imaging technique for various applications as we discussed above.

IV. REFERNCES

[1] S. Prasad, J. Chanussot, J. E. Fowler, J. Bioucas-Dias and C. D. Creuserre, "Introduction to the Issue on Advances in Hyperspectral Data Processing and Analysis," in IEEE Journal of Selected Topics in Signal Processing, vol. 9, no. 6, pp. 961-963, Sept. 2015.

[2] D Chutia, D K Bhattacharyya,† KK Sarma, R Kalitaˇ and S Sudhakar, "Hyperspectral Remote Sensing Classifications: A Perspective Survey" in Transactions in GIS, vol. 20, no. 4, pp. 463- 490, 2016.

[3] L. G. Olmanson, P.L. Brezonik, M.E. Bauer, "Airborne hyperspectral remote sensing to assess spatial distribution of water quality characteristics in large rivers: The Mississippi River and its tributaries in Minnesota", Remote Sensing of Environment, vol. 130, pp. 254- 265, 2013

[4] Amini S, Homayouni S, and Safari A 2014 Semi-supervised classification of hyperspectral image using random forest algorithm. In Proceedings of the IEEE International Geoscience and Remote Sensing Symposium (IGARSS), Quebec City, Quebec: 2866-69

[5] Adam E, Mutanga O, and Rugege D 2010 Multispectral and hyperspectral remote sensing for identification and mapping of wetland vegetation: A review. Wetlands Ecology and Management 18: 281–96

[6] D. Qian and E. James, “Hyperspectral image compression using JPEG2000 and principal component analysis,” IEEE Geosci. Remote Sens. Lett., vol. 4, pp. 201–205, April 2007.

[7] L. Chang, Y.-L. Chang, and C.-M. Cheng, “An efficient hierarchical hyperspectral image classification using binary quaternion-momentpreserving thresholding technique,” in Proc. Int. Geoscience and Remote Sensing Symp. (IGARSS’09), Jul. 2009, vol. 2, pp. 294–297.

[8] R. E. Roger and J. F. Arnold, “Reversible image compression bounded by noise,” IEEE Trans. Geosci. Remote Sensing, vol. 32, no. 1, pp. 19–24, 1994.

[9] W. B. Pennebaker and J. L. Mitchell, JPEG: Still Image Compression Standard. New York: Van Nostrand, 1993

[10] A. F. X. Goetz, G. Vane, J. E. Solomon, and B. N. Rock, “Imaging spectrometry for Earth remote sensing,” Science, vol. 228, no. 4704, pp. 1147–1153, Jun. 1985.

[11] F. F. Sabins, “Remote sensing for mineral exploration,” Ore Geol. Rev., vol. 14, no. 3, pp. 157–183, Sep. 1999

[12] B. Aiazzi, S. Baronti, F. Lotti, and M. Selva, “A comparison between global and context-adaptive pansharpening of multispectral images,” IEEE Geosci. Remote Sens. Lett., vol. 6, no. 2, pp. 302–306, Apr. 2009.

[13] S. Baronti, B. Aiazzi, M. Selva, A. Garzelli, and L. Alparone, “A theoretical analysis of the effects of aliasing and misregistration on pansharpened imagery,” IEEE J. Sel. Topics Signal Process., vol. 5, no. 3, pp. 446–453, Jun. 2011.

[14] B. Aiazzi, L. Alparone, S. Baronti, A. Garzelli, and M. Selva, “25 years of pansharpening: A critical review and new developments,” in Signal and Image Processing for Remote Sensing, 2nd ed. Boca Raton, FL, USA: CRC Press, New York, NY, USA: Taylor & Francis, 2011, pp. 503–548.

[15] D.Manolakis and G.Shaw. Detection Algorithms for Hyperspectral Imaging Applications. IEEE Signal Processing Magazine, pp. 29-43, January 2002.

[16] D.Manolakis, C.Siracusa and G.Shaw. Hyperspectral Subpixel Target Detection Using the Linear Mixing Model. IEEE Trans. Geosci. Remote Sensing, Vol. 39, No.7, pp. 1392-1408, July 2001.

[17] C. I. Chang, S. S. Chiang, and I. W. Ginsberg, "Anomaly Detection in Hyperspectral Imagery," Proc. Geo-Spatial Image and Data Exploitation II, SPIE, Jun. 2001, 4383, pp. 43-50, doi: 10.1117/12.428250.

[18] Y. Chen, N. M. Nasrabadi, and T. D. Tran. Simultaneous joint sparsity model for target detection in hyperspectral imagery. IEEE Geoscience and Remote Sensing Letters, 8(4):676–680, 2011.