A Review of Some Information Extraction Methods, Techniques and their Limitations for Hyperspectral Dataset

Suresh Merugu and Dr. Kamal Jain

Abstract: It is common to represent the remote sensing images in true and false color composites in various parts of electromagnetic spectrum. Visualising color images provide a crude view of the terrain and that too at the three selected wavebands. In order to derive detail and accurate information about the earth surface, more spectral information contained with an extended range of wavelengths is necessary. Hyperspectral image cube contains of different ground truth objects which have numerous, narrow and in close proximity spectral band information centering on equally distributed wavelengths ranging from visible to near infrared spectrum. This narrow wavelength helps in identifying various vegetation classes, mineral types, small military targets and many more objects on the surface of earth.

This paper presents existing conventional methods, issues, and their limitations of information extraction from hyperspectral imagery dataset. This review helps that designing and implementation of a suggestible digital image analysis approach is a prerequisite to get a better classification accuracy of optically sensory data into a thematic map layer i.e., from dimensionality reduction, perpixel, subpixel to super resolution mapping (SPM) based on the spatial dependences of fractional abundances and the anomaly detection is the case when one ca not know the signature member of the target which try to find pixels that deviate from the background. exact use of various feature information of optically sensory data and the usage of best required approach of classification method are effectively significant for producing better classification accuracy.

Keywords: Perpixel, Subpixel Classification, Super Resolution Mapping, Hyperspectral Dataset, Colorimetry and Advance Image Processing Techniques.

I. INTRODUCTION

To extract accurate information from plethora of hyperspectral datasets, efficient and intelligent image processing tasks are required. These tasks range from image pre-processing and feature reduction to image classification and many more. A number of algorithms have been and are being developed to carry out these tasks.

A number of air and space borne hyperspectral sensors have been providing data about the earth surface now at many different spectral and spatial resolutions on regular basis. Some of the airborne hyperspectral sensors are AVIRIS, TRWIS III, HYDICE, HYMAP, HyperCam whereas the space borne sensors are Hyperion EO-1.

Suresh Merugu, *Research Scholar, Indian Institute of Technology-Roorkee. Roorkee, India,*

Dr. Kamal Jain*, Professor, Indian Institute of Technology-Roorkee.*

The pre-processing includes radiometric and geometric calibration. Radiometric calibration includes the radiance calculation and the surface reflectance calculation. The radiance calculation from the digital numbers is done by the radiometric calibration coefficients or functions, both instruments specific and related to the viewing and illumination conditions.

The reflectance calculation uses standard or measured atmospherical parameters to calculate the ground surface reflectance from the top of atmosphere (TOA) reflectance.

In the wavelength area from 400 nm to 2500 nm, the reflection is highly affected by the particles of the atmosphere, the sun zenith and the climate. The atmosphere does not transmit all wavelengths similarly. The absorption and scattering due to the occurring particles of different size modify the distribution of the spectrum. A strong decline in the intensity of the radiation can be seen in the absorption bands. The strongest absorption bands of water vapour occur in 820 nm, 940 nm, 1140 nm, 1380 nm and 1880 nm (Gao et al, 1991). Oxygen absorbs in the bands 760 nm and 1270 nm, carbon dioxide at 1600 nm and 2080 nm, and methane at 2350 nm. Outside these absorption areas, also the fog and clouds disturb the measurements.

Since radiometric & geometric accuracy of hyperspectral data vary significantly from one sensor to other, these can be done by data producing centre (Varshney et al. 2004). While the pre-processing procedures related to hyperspectral data have fairly been stabilized, there is enormous scope to develop and testify a range of algorithms in processing of hyperspectral data to derive useful information about the earth surface.

II. DIMENSIONALITY REDUCTION

Due to large spectral dimension of the order of 10s of wavelength bands of hyperspectral data, the processes of information extraction such as object and target detection/identification, segmentation and classification, have generally been inefficient in two ways. First, in case of supervised classification, the number of training pixels is proportional to the number of bands involved in classification. As the spectral dimension increases, requirement for the number of training pixels also increases, which at times is difficult to fulfil. Thus, this may also lead to the curse of feature reduction or Hughes phenomenon. Secondly, the nearby wavebands in the hyperspectral datasets also show high correlation with each other. Therefore, some of the wavebands may provide redundant information. This redundancy may also be eliminated without any effective loss of information content within the hyperspectral dataset.

Reducing the high dimension data set into lower dimension without sacrificing significant information of interest is thus one of the significant steps in hyperspectral image processing. In the classification of hyperspectral images, concerned feature information's are those which are most capable of restoring class separability (Hsu, 2000). After feature reduction, a subset of features is obtained. But, preserving the useful information from hyperspectral sensor is the key issue in feature reduction, which demands for development of appropriate algorithms.

The feature reduction can be achieved either through feature selection (selecting few original bands from the whole datasets by some mathematical modeling) and feature extraction (projecting the original data set onto adequate sub-spaces) through a number of mathematical tools.

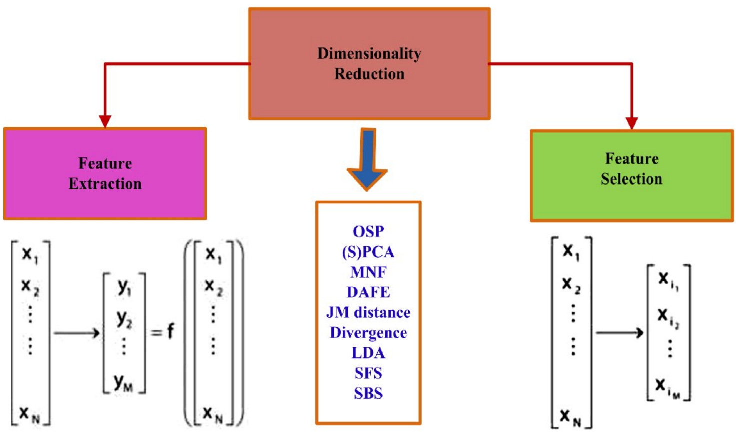


Figure 1: Showing various feature extraction and feature selection methods for dimensionality reduction.

Restoring the exact ground truth information from the image is the main advantage of feature selection. Some of these methods used for reducing hyperspectral data are sequential forward selection (SFS), sequential backward selection (SBS), distance measures (Bhattacharya distance, Mahalanobis distance, JM distance, etc.,), divergence analysis, etc. The standard and well known feature selection methods such as divergence, JM distance and transformed divergence may not be used effectively as a result of several considerations (Chang, 2007) especially for feature class separability measures.

The ultimate aim of dimensionality reduction is to minimise the number of band information substantially without sacrificing relevant information (Hsu, 2007). Feature extraction may require the most of the original data representation to extract the new features, forcing to always obtain and deal with the whole initial representation of the data. In addition, since the data are transformed, some critical information may have to be compromised and distorted as mention in this (Martínez-Usó, 2007). But feature extraction methods are more effective than feature selection methods (Serpico and Moser et al. 2007).

Some of the standard feature extraction techniques are principal component analysis (PCA) and minimum noise fraction (MNF). Others include segmented PCA (SPCA), orthogonal subspace projection (OSP), singular value decomposition subset selection, discriminant analysis feature extraction (DAFE), prototype space feature extraction (PSFE), penalized discriminant analysis, kernel Fisher discriminant, Fisher's canonical transform projection pursuit, decision boundary feature extraction (DBFE), independent component analysis (ICA), etc, are given in (Serpico and Moser et al. 2007).

The PCA utilise the eigen vector value analysis of the co-variance matrix obtained from the given data (Cheriyadat et al. 2003, Gonzalez et al. 2001) the popularity of PCA is due to its simplicity and ease of use. However, the PCA is not the optimal method for feature extraction in classification and target detection applications. The highest value of principal components (PC) does not always guarantee retention of the discriminatory fruitful information present in the original feature space.

When these feature extraction techniques are applied to hyperspectral image dataset, the principal components analysis (PCA) outperforms those feature extraction techniques that are based on class statistics. **But there are limitations in using PCA. First, it requires high computing load. Second, if the data are not calibrated the spectral band variances in the shorter wavelength areas are much greater than the remaining bands**. Finally, PCA always works on global statistics and thus it may overlook the local spatial variances that are useful for the detection of targets and anomalies.

The discriminant analysis feature extraction (DAFE) method uses the ratio of between-class covariance matrices to within-class covariance matrices as a criterion function. A transformation matrix is then determined to maximize the ratio, that is, the separability of classes will be maximized after the transformation which was given by (Hsu, 2007).

For solving the required features in so many situations and circumstances the discriminant process analysis is an effective and ground truth freehand algorithm, from (Hsu, 2007) there are several disadvantages in this method. First, maximum number of feature classes extracted from DAFE is equal to the number of classes minus one. Secondly, the derived feature class vectors are not that trusty when the mean values of various classes are closing to each other. Thirdly, if a feature class has a mean vector totally different from the other classes, the between-class covariance matrix will be biased toward this class and will result in ineffective features. Finally, in order to estimate the between-class and within-class scatter matrices reliably, the number of training samples should be large enough.

The Major Limitations of Dimensionality Reduction:

1. First, especially for hyperspectral image dataset this should be impractically larger because the number of permutations of various band subsets to be rechecked.
2. Second, for feature reduction the resulting subsets may not be as information-rich as the features consisting of linear combinations of bands generated by transformation-based methods.

The classical feature extraction techniques contribute little to class separability. Canonical analysis and discriminant analysis feature extraction, while often useful when this is applied to multispectral images, but have disadvantages when applied to hyperspectral images. These include difficulty in calculating covariance matrices with high dimensional data, and unreliability of extracted features when the classes have similar means or when a class has a very different mean from other classes (Hsu, 2007).

Wavelet transforms have been introduced for image analysis of hyperspectral image datasets as an efficient means of feature extraction. A wavelet is a mathematical function used to divide a function into different frequency components, affording analysis of each component with scale dependent resolution. A wavelet transform is the representation of a function by a packet of wavelets in an image. The strength of the wavelet transform for hyperspectral feature extraction lies in this ability to analyze signal at different resolution or scales. The advantages of multi-scale representation of hyperspectral data are twofold. First, subtle variation in spectral features in the original hyperspectral data may be detected at different scales (Hsu, 2007). Second, the useful information is represented by fewer wavelet features, effectively compressing the data (Peng et al. 2009, and Banskota, 2011).

Further some discrete wavelet-based methods, such as the matching pursuit, the nonlinear wavelet feature extraction (WFE) and the best basis approaches are based on the best approximation for image data representation, the results of these experiments showed that they are still efficient for classification. Especially, the nonlinear wavelet feature extraction methods are more effective for classification than linear methods. In particular circumstances, the matching pursuit basis had better results than the best wavelet packet basis given by (Hsu, 2007).

However, it has been demonstrated that the reduction of features will be in powers of two may lead to either reducing more features with loss of some useful information or taking more features for further processing.

III. IMAGE CLASSIFICATION AT PERPIXEL

In hyperspectral image analysis, especially in classification and detection applications, spectral characterization plays an important role. To derive the spectral variability, similarity, discrimination, and divergence, different spectral measure criteria that calculate various distance metrics have been proposed and used over the past few decades. These include maximum likelihood decision metric, spectral angle mapper (SAM), spectral correlation mapper (SCM), and spectral information measure (SIM), Euclidean minimum distance (EMD), spectral gradient angle (SGA), and band add-on spectral angle mapper (BAO-SAM). Suitable distance metrics employed in hyperspectral image data processing for classification and detection application can be obtain the best result through describing spectral characteristics in mathematical or physical meaning properly (Ying Wang et al. 2009).

With the large number of bands in hyperspectral data sets, the availability of training members in pixels per class to perform better estimates of class statistics may not be there (Chang, 2007). The mean vector and covariance matrix are usually estimated from the training samples. When the training sample size is small compared to the dimensionality, the sample estimates, especially the covariance estimate become highly variable and consequently, the classifier performs poorly. The problem of limited training samples is prevalent in remote sensing applications.

In N dimensional multi/hyper spectral space, a training pixel vector x has both magnitude and an angle to be measured with respect to the axes that defines the coordinate system of the space. In the Spectral Angle Mapper (SAM) technique for identifying pixel spectra, only the angular information is used. SAM is based on the idea that an observed reflectance spectrum can be considered as a vector in a multidimensional space, where the number of dimensions equals the number of spectral bands. If the overall illumination increases or decreases (due to the presence of a mix of sunlight and shadows), the length of this vector will increase or decrease, but its angular orientation will remain constant as mention in (Wang et al. 2009).

The Major limitations of Spectral Angle Mapper are:

1. The SAM algorithm may not distinguish between positive and negative correlations because a spectral angle value measured by SAM may be generated from two spectral vectors with random interrelation (Wang et al. 2009)
2. Further, due to sensitivity to the additive factor in the feature space, the SAM holds high false alarm rate generally (Wang et al. 2009).
3. The SAM may also fail if the vector magnitude is important in providing discriminating information, which it will in many instances.

Therefore, during last decade or so, **a number of machine learning algorithms have become popular in producing image classification from hyperspectral data**. These include ANN (Foody et al. 2005) and decision tree classification, support vector machines (Brown et al. 2000). **These techniques are attractive as they do not suffer from the problem of dimensionality as observed in many statistical classifiers.** There are several studies conducted on the use of ANN for per pixel classification (Foody et al. 2005).

The neural network consists of a set of simple processing units which are inter-connected by weighted channels in a manner defined by the network architecture (Foody et al. 2010). There are a range of different network architectures and a range of potential applications in remote sensing. Feed-forward artificial neural networks can be trained to learn by example and are attractive for supervised classification. They also can readily accommodate multisource data acquired at different levels of measurement precision, are free of distribution assumptions, and can process data rapidly once trained. Such networks have been used for image classification.

ANN has two limitations particularly in reference to Hyperspectral data:

1. First, as in any neural network, to generate a minimum network that will solve the problem at hand, the number and sizes of the hidden layers need to be set. Generally, the problem is over specified and some form of pruning is used. Nevertheless, the issue is not straightforward (Chang, 2007).
2. Second, a large number of back iterations are often required to find a solution which leads to computation overload.

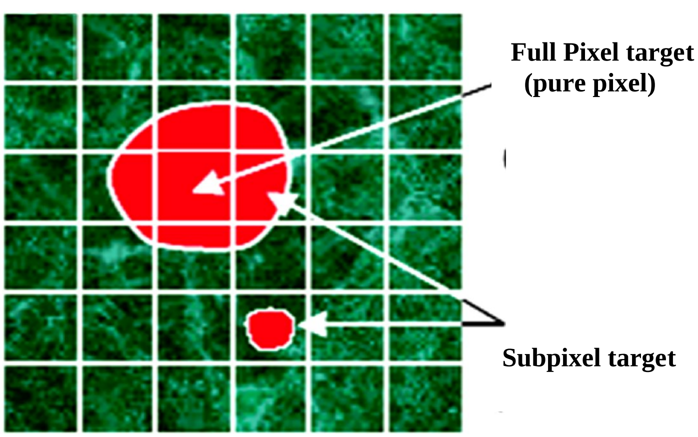
Support Vector Machines (SVMs) are large margin classifiers that exploit the principles of the statistical learning theory. If an L2-norm regularizer is used, the optimization problem related to the learning of SVMs can be represented as a quadratic convex optimization problem with inequality constraints. For such optimization problems in nonlinear optimization theory, duality is preferred. Thus, SVMs are often solved in dual representation by introducing Lagrange multipliers. However, this is not mandatory since one can also implement SVMs in the primal representation (Chapelle, 2007).

SVM appears to be the most appropriate classifier for any hyperspectral image classification problem. However, **its major limitation lies in the selection of appropriate kernel function**, selection of the suitable multiclass method and the choice of appropriate value of the parameters for the selected kernel function. Moreover, **SVMs also have high algorithmic complexity and extensive memory requirements due to quadratic programming** in applications requiring a large datasets. **The computational complexity also increases in case of non-linear SVM when the data are projected into higher dimension it's computationally expensive.**

IV. IMAGE CLASSIFICATION AT SUB-PIXEL LEVEL

In classification of per-pixel, every pixel is assigned to one and only one class, whereas in case of sub-pixel classification the fraction abundance tells the proportion of available classes in each pixel. The hyperspectral sensors which are efficient to collect fine details from the ground, are useful to identify the type of vegetation, the type of mineral and the objects present in the image. Various researchers have used hyperspectral image dataset to find fine details (Shah et al. 2004). Some algorithms for sub-pixel classification of hyperspectral data are linear mixture model (Lu et al. 2003), orthogonal subspace projection (Kwon et al. 2005), independent component analysis mixture model (Shah et al. 2004), etc.

The linear mixture model (LMM) algorithm assumes that the spectrum measured by a sensor is a basic linear combination of the spectra of all components within the pixel. The linear mixing model has been widely used due to its strong point i.e., tie between the required mathematics of the model and the physical processes of mixing that result in much of the variance seen in hyperspectral image dataset. Further, problems exist where the basic assumptions of the model are violated and it fails to accurately represent the nature of hyperspectral imagery dataset. One such situation is nonlinear mixing. Another reason is the assumption that mixtures of a few numbers of deterministic spectra should be used to represent all of the non-noise variance in hyperspectral imagery dataset.



The end member spectra are generally assumed to be pure. Further, these are somewhat difficult to obtain in practice. This is particularly true when the spectral signatures are extracted directly from an image data with no prior knowledge of actual ground truth. So the orthogonal subspace projection tackles some of these limitations.

The idea of orthogonal subspace projection is to divide the p substances into two classes, desired substance class and undesired substance class. Without loss of generality one can assume that the desired substance class contains only one single substance and undesired substance class consists of the remaining p–1 substance.

The OSP algorithm is particularly based on improving the signal-to noise ratio (SNR) in the orthogonal subspace projection to the background subspace and only depends on the noise second-order statistics. It should not be directly provide an estimation of the abundance measures for the desired end member in the subpixel portion. However, (Settle et al. 1996) has shown that the output of the OSP operator is related to the unconstrained least squares estimate or the maximum-likelihood estimate of the unknown signature abundance of the desired endmember by a scaling factor (so-called normalization). Therefore, normalized OSP provides a measure of the abundance for the desired target spectral signature as given by (Kwon et al. 2005).

(Suresh M and K Jain, 2012&13) Colorimetry, the numerical specification of the color of visual stimuli, is related to the spectral sensitivities of the three cone photoreceptors. Colorimetry is more intuitive when defined in terms of cone excitations than when defined in terms of imaginary primaries, such as the CIE XYZ primaries. Color-matching data and CMFs tell us which spectral distributions will match under a given set of viewing conditions for a given observer. However, they tell us little about the actual color appearance of the match, which can vary enormously with the viewing conditions. It has been quantitatively evaluated and outperforms the classical gray world algorithm. As a future research they plan to improve the multi domain analysis that drives the automatic white balancing, considering more features, related to objects whose reflectance have the most perceptual impact on the human visual system, such as skin, vegetation or sky. They also intend to introduce the influence of the device in the illuminant estimation, investigating the role of the sensor profiling.

It is also well-known that linear classifiers fail when the data are not linearly separable. However, by transforming the original data into a much higher dimensional space (feature space) by using an appropriate nonlinear mapping, the mapped data will probably become linearly separable in the high-dimensional feature space where a linear classifier can be applied (Sebastiano et al. 2001).

In real imagery, when light reflects off surfaces that are composed of an intimate mixture of various material components that cause multiple bounces, spectral mixing tends to become nonlinear (Keshava, 2002). But both LMM & OSP are linear algorithms based on a linear mixture model, which do not exploit the higher order correlations between the spectral bands nor it addresses the nonlinear mixing of the spectral signatures that are encountered in real data. Therefore, LMM & OSP are not flexible enough to fully exploit the complex data structure encountered with real hyperspectral imagery. **The higher order statistics which are useful in discriminating classes is not possible by LMM & OSP. So ICAMM which exploits the higher order statistics came into existence.**

The ICA mixture model (ICAMM) algorithm views the observed data as a mixture of several mutually exclusive classes. Each of these classes is described by a linear combination of independent components with non-Gaussian densities. The ICAMM algorithm finds independent components and the mixing matrix for each class using an extended information-maximization learning algorithm and computes the class membership probability for each pixel. The pixel is allocated to the class with the highest posterior class probability to produce the classification map (Hyvärinen & Oja, 2000, Shah et al. 2004).

The Major Limitations of Independent Component Analysis mixture model (ICAMM):

1. The independent components may have at most one non-gaussian distribution.
2. It requires lots of computation in finding the fraction abundance, particularly if the number of bands is more than the number of classes.
3. We cannot determine the variances (energies) of the independent components.
4. We cannot determine the order of the independent components (Hyvärinen & Oja, 2000). Since the extraction of mixing matrix starts from random initialization of mixing matrices, the clusters permute with respect to the other clusters. The order of fraction abundance values need not same for every run.

The fractional abundance images classified from the soft classification can provide more useful land cover information as compared with that derived from hard classification technologies. However, the spatial distribution of each class in these mixed parts of the pixels may not be ascertained from sub-pixel classification outputs. Only the urban areas could be estimated more precisely using sub-pixel classification methodologies, whereas the boundary edges of the urban buildings could not be determined (Ling et al. 2009). To find details upto that level, super resolution mapping may be helpful. The art of producing fine spatial resolution map form a coarse spatial resolution is called super resolution mapping.

V. SUPER RESOLUTION MAPPING

The sub-pixel classification gives the proportion of classes available in each of the mixed pixels, but fails to locate the classes at sub-pixel level. Super resolution mapping is a promising algorithm for prediction of the spatial distributions of each class at the mixed pixel scale. This distribution is often determined based on the principle of spatial dependence and from fraction images classified with sub-pixel classification approaches. This method uses the fraction maps derived with soft classifications as input and converts them into high resolution maps based on the land cover spatial pattern, which is often described with the maximum spatial dependence principle. The super resolution mapping has its origin by converting a single gray scale image into finer by simply dividing the pixels and rearranging according to the neighbouring pixels. Current super-resolution mapping methods include the Hopfield neural network (HNN), linear optimization (Verhoeye & Wulf et al. 2002), pixel swapping (Atkinson et al. 2009, Thornton et al. 2007), simulated annealing (Makido et al. 2007) and geostatistical methods.

Super resolution mapping of a hyperspectral image was done by artificially multiple sub-pixel shift of the original data. Also, by fusion of multi-observation images by sub-pixel shifted to get more accurate image of higher spatial resolution than the original observations. This can be done by iteratively back propagation algorithm and interpolation based super resolution for land cover mapping (Peleg et al. 2002, Lu et al. 2010 and Ling et al. 2013). The performance of different SRM algorithms was assessed by calculating the Kappa coefficient through a comparison of the reference land cover map and the resulting fine resolution land cover map. Moreover, an adjusted Kappa coefficient that is calculated only for mixed coarse resolution pixels was also applied to further assess the accuracy of these SRM algorithms (Jin et al. 2012).

To map a certain features alone like roads, water bodies, by giving the characters of that particular feature the super resolution map was obtained (Foody et al. 2005, Ling et al. 2008). Super resolution mapping algorithm based on an MRF model was also proposed. It is assumed that a super-resolution map (SRM) has MRF properties, i.e., two adjacent pixels are more likely to belong to the same land cover class than different classes. By integrating this fact into the model, a large number of misclassified pixels, which often appear as isolated pixels, are removed from the resulting SRM (Kasetkasem et al. 2005). By using multiple subpixel shifted remotely sensed images super resolution map will be obtained (Ling et al. 2010 and 2013). Low-resolution pixels in these remotely sensed images contain different land-cover fractions that can provide useful information for super-resolution land cover mapping.

The Major Limitations of Super Resolution Mapping:

(i) The information on accurate boundary feature (i.e., the reference data) may not be readily available.
(ii) It does not consider the spatial dependence within and between pixels.

A spatial-spectral data fusion technique was discussed by (Mianji et al. 2010). In this algorithm, the four main steps used are endmember extraction, spectral unmixing, training of the SRM algorithm and super resolution mapping. Here training data are taken from high spatial resolution hyperspectral image. Based on the assumption of spatial correlation of the land cover classes, simulated annealing is used to optimize a function where spatial proximity of pixels belonging to the same land cover class is preferred (Villa et al., 2011).

VI. DETECTION OF ANOMALIES/TARGET

The anomaly detection is the case when we do not know the spectral signature of the target which we try to find pixels that deviate from the background. When the target signatures are known then it comes under target detection. Anomaly detection can be done in the following ways:

1. Anomaly Detector based on Gaussian Mixture Model (GMM based anomaly detector (Stein et al. 2002)).
2. OSP based anomaly detector (Matteoli et al. 2010), selective KPCA based anomaly detector (Gu et al. 2008)). Non Linear Anomaly Detectors (Kernalized RX anomaly detector (Kwon & Nasarbadi et al. 2005).
3. Recently few anomaly detectors were introduced namely, anomaly detection using LTSA (Li et al. 2010), advances in local normal model based anomaly detector (Matteoli et al. 2010, 2011), random selection based anomaly detector (Zhang et al. 2011).

But these detectors are not capable of identifying anomalies present in the sub-pixel level. Hyperspectral target detection is based on exploiting the fact that most targets/materials in nature can be uniquely characterized using their spectral signatures. Multi-pixel target detection can exploit both the spatial and the spectral properties. The spectrum of the subpixel target is mixed with the spectrum of the background in a given pixel.

VII. SUMMARY

Image classification has made great progress over the past decades in the following three areas (1) development and use of advanced classification algorithms, such as per-pixel, subpixel, and super resolution mapping at subpixel level based on fractional abundances (2) use of multiple remote sensing features, including spectral, spatial, multitemporal, and multisensor information and (3) incorporation of ancillary data into classification procedures, including such data as topography, soil, road, and census data. Accuracy assessment is an integral part in an image classification procedure.

A number of feature selection and feature extraction algorithms have been developed each having its limitations. The efficacy of these on hyperspectral data has yet to be established. There appears to be no work conducted in the direction of evaluating the quality of features obtained from any feature selection and feature extraction technique. The learning of kernel functions in classification of hyperspectral data by using SVM is required until its computation load is reduced. The independent component analysis mixture model has generally been implemented by assuming that the number of bands is same as that of the number of clusters. But in case of hyperspectral images due to its large spectral dimension, mis-classifications may result. While producing super resolution map from a single hyperspectral image, the basic assumption is that the spatial proximity of pixels belonging to the same land cover class is preferred. But classes may fall in the center of the pixel also, which has not been studied earlier.

Hence, spatial dependences information is efficiently useful for fine spatial resolution data, how this effectively solves to derive and use it in image subpixel classification remains a research topic. Still more research, however, is needed to identify and reduce uncertainties in the image processing chain to improve classification accuracy.

REFERENCES

[1] Apan, A., Held, A., Phinn, S. & Markley, J., 2004, detecting sugarcane ‘orange rust’ disease using EO-1 Hyperion hyperspectral imagery. *International Journal of Remote Sensing*, 25, pp. 489–498.

[2] Banerjee, A., Burlina, P., and Diehl, C. 2006, “A support vector method for anomaly detection in hyperspectral imagery”, *IEEE Transactions on Geoscience and Remote Sensing*, 44(8), pp. 2282-91.

[3] Banskota, A., 2011, Improving within-genus tree species discrimination using the discrete wavelet transform applied to airborne hyperspectral data., *International Journal of Remote Sensing*, 32(13), pp. 37-41.

[4] Brown, M., Lewis, H., & Gunn, S., 2000, Linear spectral mixture models and support vector machines for remote sensing. *IEEE Transactions on Geoscience and Remote Sensing*, 38, pp. 2346–2360.

[5] Chang, C., 2007, Hyperspectral *Data Exploitation, A John-Wiley & Sons, Inc., Publications.*

[6] Chapelle. O., 2007, Training a support vector machine in the primal, *Journal of Machine Learning Research*, *Neural Computation*, 19(5), pp. 1155–1178.

[7] Di, W., Pan, Q., He, L., and Cheng, Y. 2008, “Anomaly detection in hyperspectral imagery by fuzzy integral fusion of band-subsets”, *Photogrammetric Engineering & Remote Sensing*,74(2), pp. 201-213.

[8] Du, B., and Zhang, L. 2011, “Random-selection-based anomaly detector for hyperspectral imagery”, *IEEE Transactions on Geoscience and Remote sensing*, 49(5), pp. 1578-1589.

[9] Foody, G. M., Muslim, A. M., & Atkinson, P. M., 2005, Super-resolution mapping of the waterline from remotely sensed data. *International Journal of Remote Sensing*, *26*(24), pp. 5381-5392.

[10] Gonzalez. R & Woods. R., 2001, Digital Image Processing, 2nd Edition, Addison-Wesley.

[11] Govender, M., Chetty, K., & Bulcock, H., 2007, A review of hyperspectral remote sensing and its application in vegetation and water resource studies. *Water SA*, *33*(2), pp. 145-152.

[12] Hsu, P. (2007). Feature extraction of hyperspectral images using wavelet and matching pursuit. *ISPRS Journal of Photogrammetry and Remote Sensing*, *62*(2), pp. 78-92.

[13] Hughes, G. F., 1968, on the mean accuracy of statistical pattern recognizers. *IEEE Transactions on Information Theory*. (1), pp. 55-63

[14] Hyvärinen, a, & Oja, E., 2000, Independent component analysis: algorithms and applications. *Neural networks: the official journal of the International Neural Network Society*, *13*(4-5), pp. 411–430.

[15] Keshava, N, 2003, A survey of spectral unmixing algorithms, Lincoln *Laboratory Journal*, 14(1), pp. 55-78.

[16] Keshava, N and Mustard, J F, 2002, Spectral unmixing, *IEEE Signal Processing Magazine*, 19(1), pp. 44-57.

[17] Kwon, H., and Nasrabadi, N. M. (2005), “Kernel RX-algorithm: a nonlinear anomaly detector for hyperspectral imagery”, *IEEE Transactions on Geoscience and R S*, 43(2), pp.388-397.

[18] Li, M., Crawford, M. M., and Jinwen, T. (2010), “Anomaly detection for hyperspectral images using local tangent space alignment”, *Proceedings, IEEE International Geoscience and Remote Sensing Symposium*, IEEE, Honolulu, HI, pp. 824-827.

[19] Ling, F., Du, Y., Xiao, F., Xue, H. & Wu, S., 2010, Super resolution land cover mapping using multiple sub-pixel shifted remotely sensed images, International Journal of Remote Sensing, 31(19), pp. 5023-40.

[20] Ling, F. & Fu, B., 2009, Super-resolution mapping of urban buildings with remotely sensed imagery based on prior shape information, *IEEE Conference on Urban Remote Sensing Joint Event.*

[21] Suresh Merugu, Kamal Jain, 2013, colorimetrically resolution enhancement method for satellite imagery to improve land use 14th ESRI User Conf. id: UCP0046, New Delhi, India, 11-12th Dec, 2013.

[22] Suresh Merugu, Kamal Jain, 2013, to generate high resolution images (conventional subpixel) from low resolution satellite images: colorimetry concept” ISG & ISRS, Visakha, India, 4-6th Dec, 2013.

[23] Suresh Merugu, Kamal Jain, 2013, to detect infrastructural damages caused by natural disaster using low resolution images” Joint International Workshop of ISPRS & INCOIS WGVIII/1&WGIV/4on Geospatial Data for Disaster and Risk Reduction, Hyderabad, India, 21-22nd Nov, 2013.

[24] Suresh Merugu, Kamal Jain, 2013, sub pixel analysis on hypothetical image by using colorimetry International Journal of Recent Technology and Engineering (IJRTE), ISSN: 2277-3878, Vol. 2, Issue-4, Sep, 2013.

[25] Suresh Merugu, Kamal Jain, 2013, change detection and estimation of illegal mining using satellite images at 2nd International Conference on Innovation in Electronics & Communication Engineering ICIECE–2013, organized by GNIT, Hyderabad, during August 9-10, 2013.

[26] Suresh Merugu, Kamal Jain, 2013, change detection and estimation of change analysis using satellite images at 2nd International Conference on Innovation in Electronics & Communication Engineering ICIECE–2013, organized by GNIT, Hyderabad, during August 9-10, 2013.

[27] Suresh Merugu, Kamal Jain, 2013, development of sub-pixel data based on colorimetric approach" at National Symposium on Space Technology for Food & Environmental Security at Annual Convention of ISRS & ISG, New Delhi, during December 5-7, 2012.

[28] Mianji, F. A., Zhang, Y., Babakhani, A., 2009, Super resolution of hyperspectral images using back propagation neural network, 2nd International Workshop on Nonlinear Dynamics and Synchronization, 2009, INDS '09.

[29] Mianji, F. A., Zhang, Y., & Babakhani, A., 2010, Key information retrieval in hyperspectral imagery through spatial-spectral data fusion, *Radio Engineering* 19(4), pp. 734-744.

[30] Mojaradi, B., Abrishami, M. H., Javad, M., Zoej, V., & Duin, R. P. W., 2009, Dimensionality reduction of hyperspectral data via spectral feature extraction. *Jet Propulsion*, *47*(7), pp. 2091-2105.

[31] Pu, R., 2004, Wavelet transform applied to EO-1 hyperspectral data for forest LAI and crown closure mapping, *Remote Sensing of Environment*, *91*(2), pp. 212-224.

[32] Serpico, S. B., Member, S., & Moser, G., 2007, Extraction of spectral channels from hyperspectral images for classification purposes, *IEEE Transactions on Geoscience and Remote Sensing*, *45*(2), pp. 484-495.

[33] Shah, C., Arora, M. K., Robila, S., & Varshney, P. K., 2002 a, unsupervised classification of hyperspectral data: an ICA mixture model based approach, International Journal of Remote Sensing, 25(2), pp. 481-487.

[34] Taylor, P., Nguyen, Q. M., Atkinson, P. M., & Lewis, H. G., 2011, Super-resolution mapping using Hopfield Neural Network with panchromatic imagery, *International Journal of Remote Sensing*, 32(21), pp. 6149–6176.

[35] Tsai, F., Lin, E. K., & Yoshino, K., 2007, Spectrally segmented principal component analysis of hyperspectral imagery for mapping invasive plant species, *International Journal of Remote Sensing*, *28*(5), pp. 1023-1039.

[36] Villa, G. C. & Bruzzone, L., 2005, Kernel-Based Methods for Hyperspectral Image Classification, *IEEE Transactions on Geoscience and Remote Sensing*, *43*(6), pp. 1351-1362.

[37] Varshney, P. K., & Arora, M. K., 2004, advanced image processing techniques for remotely sensed hyperspectral data, Springer.

[38] Wang, Y., Guo, L., & Liang, N., 2009, improving the classification precision of spectral angle mapper algorithm. *Proc. of SPIE*, *7498*.

Suresh Merugu, Research Scholar, Indian Institute of Technology (IIT) Roorkee, Uttarakhand, and Associate Professor in the Deptt. of ECE, CMRCET, Hyderabad India. He received his Master of Science (Electronics and Computers) degree from Jawaharlal Nehru Technological University, Hyderabad in 2003 and M.Tech (Spatial Information Technology) degree from JNT University, Hyderabad in 2009. He is currently working in the area of Colorimetry to improve Classification Accuracy and has a research interest in Advances in Satellite Image Processing, Super Resolution, and Colorimetry.

Dr. Kamal Jain, Professor, Indian Institute of Technology (IIT) Roorkee, Uttarakhand, India. He received his Master of Engineering and PhD from Indian Institute of Technology (IIT) Roorkee. His research and teaching interest include advanced applications of DIP, GPS, Digital Photogrammetry, Remote Sensing and GIS. He is having 20 years experience in above fields and he is active member for many National and International [redacted]

ISSN: 2278 – 1323