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Dimension Reduction Methods for Hyperspectral Image: A Survey

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Abstract: ***Hyperspectral imaging (HSI) is one of the progressive remote sensing techniques. HSI captures data in large number of continuous spectral bands with the spectral range from visible light to (near) infrared, so it is capable of detecting and identifying the minute differences of objects and their changes in temperature and moisture. But its high dimensional nature makes its analysis complex. Various methods have been developed to reduce the dimension of hyperspectral image by feature extraction. This paper highlights the advantages and drawbacks of number of classical dimension reduction algorithms in machine learning communities for HSI classification.***

Key Words: ***Hyperspectral imaging, dimension reduction, feature extrction, classification***

I. INTRODUCTION

HSI is a foremost research area in Remote Sensing. Hyperspectral remote sensing, which provides very high spectral resolution image data with hundreds of contiguous and narrow spectral bands, has been widely used for discriminating the various land–cover types in HSIs. [1]. It is also referred as imaging spectroscopy, which partition the spectral regions into abundant bands and generates visible images from them. Hyperspectral data usually consists of the spectral bands depicting the ultraviolet (200-400 nm), visible (400-700 nm), near infrared (700-1000 nm), and short-wave infrared (1000- 4000 nm).HSI are generally preferred over typical images for applications like environmental monitoring, forestry and crop analysis, thin films, remote sensing, security and defense, medical diagnose, mineral exploration, food analysis and surveillance. [2].

Recently, there is a noticeable increase in the number of Hyperspectral sensors on-board various satellites/airborne platforms. The data can be collected from different hyperspectral sensors like Airborne Visible Infrared Imaging Spectrometer (AVIRIS), Hyperspectral Digital Imagery Collection Experiment (HYDICE), Hyperspectral Imager (HySI), HYMAP, Compact Airborne Spectrographic Imager (CASI), Digital Airborne Imaging Spectrometer (DAIS), Reflective Optics System Imaging Spectrometer (ROSIS), Airborne Imaging Spectrometer for Applications (AISA) and Hyperion.[3] Key to feature identification from space imagery depends on the characteristic changes in the properties of the electromagnetic spectrum reflected or emitted from the target surface, spectral signatures could be inferred through spectral variations, polarization change, thermal inertia and temporal variations. HSI, gather and progress the information obtained from the entire electromagnetic spectrum. By means of the spectrum of each pixel in the image, HSI finds the objects, identifies materials, or detect the processes. Thus HSI captures data in very large number of spectral bands and forms hyperspectral data cube. Hyperspectral remote sensing furnish rich spectral resolution and the potential for discrimination of subtle differences in ground covers. However, the high-dimensional nature of hyperspectral image affords new challenges in the progression of data analysis techniques

As a result, there is a need for dimensionality reduction by feature extraction methods without losing the original information.[4] In other words, by dimension reduction data is transformed from a high order dimension to low order dimension.

II. NEED FOR DIMENSION REDUCTION

Dimensionality reduction is a branch of mathematics that deals with the complexities of huge data sets and enterprise to reduce the dimensionality of the data while capturing its important features. As the complexity of sensors have increased the ability to store enormous amounts of data, reduction algorithms are becoming more essential today. Hyperspectral sensors captures roughly a hundred times the amount of information compared to typical optical sensor. The number of bands as well as the correlation between the bands in HSI data is plentiful and strong. Copious of the data brings difficulties to data storage as well as for data processing. This somewhat limits the applying of the HSI data in some degrees. Also traditional methods which have been designed for multi-spectral image data cannot be easily applied to HSI. So, dimensional reduction in HSI without losing significant information about objects of interest is much essential. [5]. Basic idea of dimensionality reduction in hyperspectral image is shown in Fig.1.

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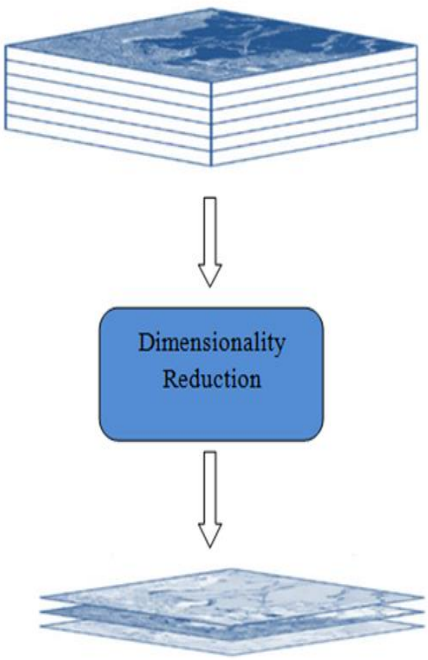

Fig.1.Dimension reduction of hyper spectral image

III. DIMENSIONALITY REDUCTION METHODS

HSI data processing consist of several pre-processing steps including sensor error correction, atmospheric correction and dimensionality reduction. Emphasis is given to techniques that circumvent the curse of dimensionality in order to discard superfluous features and excerpt needed information. In projection-based strategy, the original data is projected into a lower dimensional subspace by finding optimal mapping matrix. This scheme enclose supervised methods like linear discriminate analysis (LDA), and local Fisher discriminate analysis (LFDA) [6] [7] as well as unsupervised methods such as principal component analysis (PCA) [8] and the maximum-noise-fraction (MNF) transform.

Lori Mann Bruce et al [9] proposed a method based on wavelet transform for hyperspectral feature extraction and classification. Synthetic aperture radar (SAR), multispectral, and panchromatic data use wavelet transform for image compression, edge detection, and image fusion. Its inherent multiresolution nature makes the wavelet transform an important tool for feature extraction. Wavelet functions when applied to hyperspectral signal separate the fine-scale and large-scale information. This is done in an iterative fashion using the discrete wavelet transform (DWT). A varying width operator which is not restricted to being derivative is used for wavelet transform. The operator is referred to as the mother wavelet. Once a mother wavelet is selected, the wavelet transform can be used to separate the fine-scale information from the large-scale information. DWT based feature extraction method is compared with conventional feature extraction methods. It is found that the classification accuracy is high compared to dimensionality reduction methods such as best spectral band selection and PCA. Also, the DWT method outperformed[40] techniques, such as FFT- and DCT-based feature extraction that consider only frequency content of the signal and not localized information. The data obtained after applying wavelet based reduction technique has spectral distribution similar to the original distribution, but in a compressed form. Thus this method yields better classification accuracy than PCA. The system architecture is shown in figure 2.

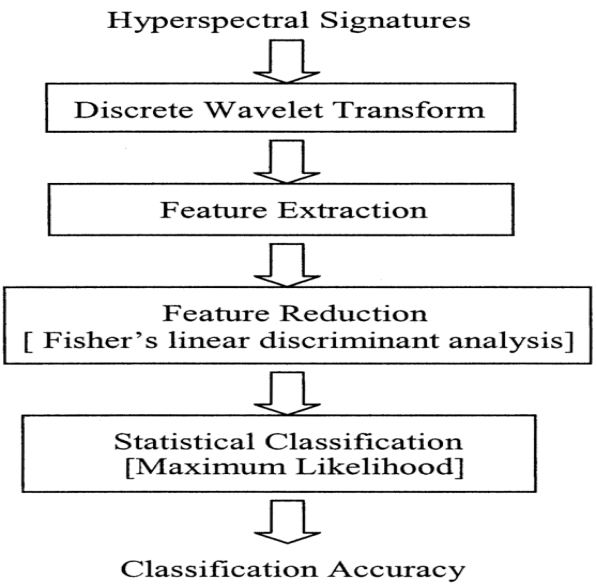

Fig 2: System block diagram for the wavelet based system

The DWT based method is a lossy compression as only the approximation after Wavelet transform is kept for analysis and for the class separation and identification eliminated high frequency signal will also be considered as it contains significant information. When this method is used for land-cover classification, feature extraction is performed in the absence of spatial information on the adjacent data.

Antonio Plaza et al [10] presented design of multichannel filters for analyzing spatial and spectral patterns simultaneously. Three morphological filtering techniques are explained in this paper: extended differential morphological profiles, extended alternated sequential filters, and scale-orientation morphological profiles. In the first method an extended differential morphological profile (EDMP) is defined as a vector where a measure of the spectral variation of the multichannel

opening-closing profile is stored for every step of an increasing series. Maximum derivative score in the opening series is obtained for pixels that are spectrally pure, whereas the maximum derivative score in the closing series is obtained for mixed pixels.

Thus the information about the spectral purity of the pixel and the spatial distribution of the object in the scene are attained. Alternated sequential filters (ASFs) depend on reconstruction-based morphological operations.

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Image features are preserved in this method. EDMP approach ensures self-duality property. In ASF method the property may be lost based on whether the sequence is started with an opening or a closing by reconstruction filter.

Scale-orientation morphological profiles represent (SOMP) a line segment with minimal length and the analysis is based on the slope of the line. Rose of directions (ROD) is used to analyze the SOMP at a given pixel by plotting the opened and closed values versus the orientation of the line segment by using a polar diagram.

A drawback in the proposed approach is a heavy computational difficulty when processing high-dimensional data. This is caused by the need to have morphological filters with increasing scale and orientation feature.

Anish Mohan et al [11] introduced the spatially coherent nonlinear dimensionality reduction technique called locally linear embedding (LLE). The proposed method is critical for accurate classification and segmentation of hyperspectral image. Hyperspectral image consists of numerous continuous spectral bands. Each pixel is represented in the form of a vector called spectral vector. The high correlation among these spectral vectors is considered in LLE. The first step in the algorithm is to calculate the neighbors [41]of a pixel in a spatially coherent way. Then the pixel is represented as a linear combination of its local neighbors. The linear approximation in the neighborhood is based on the calculation of weights that linearly reconstruct the data point from its spatial neighbors. LLE is called spatially coherent because the same spatial local neighborhoods exist in the original high and lower projected dimensions. LLE follow Euclidean distance calculation. An alternative approach to calculate the distance between pixel vectors is also introduced in this paper. This is based on a distance matrix whose entries are proportional to the spatial (Euclidean) distance between pixels. This method has a problem if objects of the same class are spatially separated. The limitation of LLE is its poor efficiency when used with natural images.

In paper [12] independent component analysis (ICA) approach to dimensionality reduction (DR), to be called ICA-DR is studied. The number of dimensions needed to be retained is estimated based on virtual dimensionality.In the dimensionality reduction techniques, PCA and MNF plays a vital role and generally referred to as PCA-DR and MNF-DR, respectively. There are two major issues for these methods are the measurement of data that exceeds second-order statistics and the determination of number of dimensions to be retained. These issues are addressed by ICA-DR and for the components generated by the ICA-DR, prioritization is negligible as the independent components are generated using random initial projection vectors.Three algorithms are developed in this paper to introduce component prioritization. First algorithm called ICA-DR1 is based on virtual dimensionality. Second one is known as ICA-DR2,the function of this is to implement ICA as a random algorithm with randomness represented by random initial projection vectors. The third algorithm called ICA-DR3 which ousts the random projection vectors used by ICA along with the use of a custom-designed initialization algorithm in combination with the virtual dimensionality by generating an appropriate set of initial projection vectors. The biggest disadvantage of ICA is that scale of resulting signal is not same as original data as it cannot estimate energy of result.[13].

Linear mixing and best band selection are the general methods for spectral analysis. These approaches do not consider the inherent nonlinear characteristics of hyperspectral data. An algorithm called Isometric mapping (ISOMAP) exploits the nonlinear structure of hyperspectral image. Charles M. Bachmann et al [14] presented ISOMAP which provides globally optimal solution. However, computational burden is dominant in this algorithm. This paper introduces a hybrid technique to avoid ISOMAP's computational cost by applying scaling to large-scale remote sensing datasets. The approach here is to divide a large dataset to small tiles and manifold is derived from each tile. These results are aligned and stitched together to reconstruct the original scene. The second approach described involves random sampling of original data cube in order to generate small data cubes.

The limitations of ISOMAP are graph discreteness overestimates the geodesic distance (Shortest curve along the manifold connecting two points) and the dimension must be high to avoid "linear shortcuts" near regions of high surface curvature.

Rouhollah Dianat et al [15] introduced dimension reduction techniques called minimum change rate deviation (MCRD). It considers the spatial relation among neighboring pixels. The resulted components after PCA are uncorrelated with each other and the error decreases with the increasing number of components. These properties are preserved in minimum change rate deviation and it is shown that MCRD outperforms PCA in retaining the required information for classification purposes. Thus the main objective of this paper is to develop a linear – spatial oriented dimension reduction method. The main steps of the proposed MCRD methods are:

- First, apply a linear spatial-oriented image operator to the image.
- Rearrange the selected features by assigning some priority.
- Calculate the ith reduced image so that its related features for each point are as close as possible to the ith initial feature image.
- To improve the results, assign some conditions such as uncorrelatedness of reduced components and linear relationships between each reduced component and the initial data.

Some quadratic objective functions are obtained by presenting the above mentioned steps in mathematical form. Standard quadratic equation and can be optimized using the well-known quadratic programming algorithms.

In paper [16] [17], present band selection technique based PCA and information gain (IG) for HSI such as small multi-mission satellite (SMMS) are introduced. For identification of optimal spectral for different satellite applications, band selection tool is required. [18].

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Processing of hyperspectral image is crucial due to the curse of dimensionality. So dimension reduction is a meaningful pre-processing step in HSI data analysis. The general steps involved in PCA are: [19][20]

1) Find mean vector in x-space
2) Find covariance matrix in x-space
3) Compute Eigen values and corresponding eigenvectors
4) Form the components in y-space

In this method, the components in the direction of maximum variation are considered as first principal component. Thus only the first few components which are in the direction of maximum variation are considered. Figure 3 shows the PCA approach to dimensionality reduction.

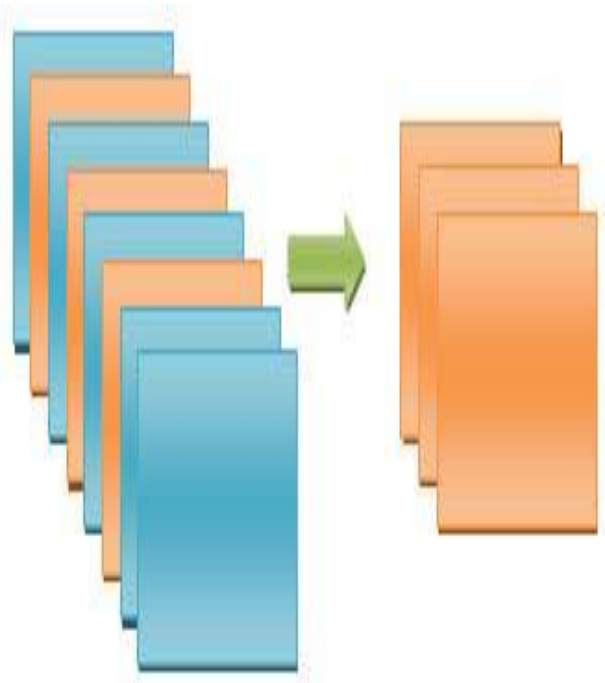

Fig 3. PCA dimension reduction technique

One more technique called information gain is discussed in this paper. Information gain is a measure of relevance between the feature and the class label. IG is calculated using the following formula:

$IG(X, Y) = H(X) - H(X|Y)$

Where H(X) is entropy of the random variable X and H (X|Y) is the entropy of band X and the entropy of band X after observing Class Y. The maximum value of information gain is 1 and it is calculated independently for each feature and the features with the top-k values are identified as the relevant features. Information Gain does not eliminate redundant features. [21]. Thus an integrated PCA and IG method is proposed. PCA and IG are integrated as:

X Band Selected = PCA of Band ∩ IG of Band

Figure 4 shows the overall structure of integrated PCA and IG method.

The disadvantage of this method is that spatial information is not taken into account as PCA is not a spatial oriented technique. [22]

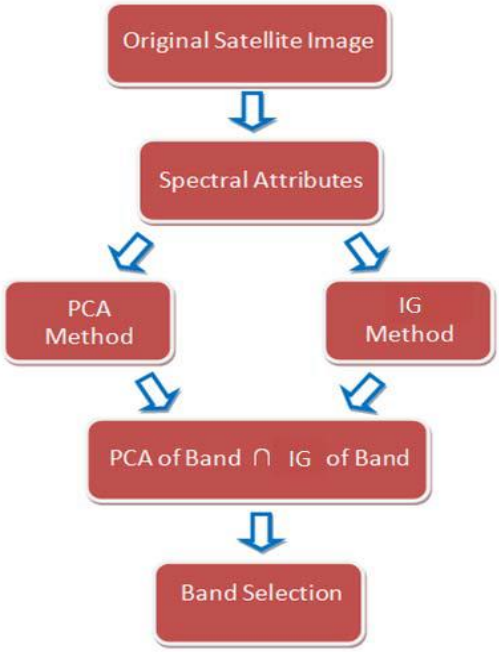

Fig.4. Overall band selection technique

Ufuk Sakarya [23] presented complete global-local linear discriminant analysis (CGLDA) based dimension reduction of hyperspectral image. This method considers both global and local pattern information for hyperspectral image processing. Unlike PCA, LDA is a supervised dimension reduction method. This method projects data into lower dimensions in such a way that members of the similar group are adjacent to each other whereas the members of distinct group are far from each other.

But LDA has limitation such as the singularity problem, the distribution assumption, the small sample size problem. Moreover LDA consider global structure and ignores local structure. Thus CGLDA, which focuses on both global and local structure, is an improved version of LDA. In this paper advantages of the usage of not only global pattern information, but also local pattern information are experimentally demonstrated by comparative analysis and an experimental strategy is proposed in order to tune the parameters of CGLDA [24] in hyperspectral application domain.

Hyperspectral data and training samples are the two inputs used in the system. There are two training processes. One of them is finding parameters of CGLDA and dimension reduction projection matrix WCGLDA. The other training is classification training. WCGLDA is used to reduce the dimension of the hyperspectral data.

The classification process is applied on dimension reduced data and then classification map is obtained.

CGLDA algorithm has some drawbacks. As CGLDA is a still linear technique for feature extraction it cannot be used for applications involving non-linear relationship.

The selection of balance coefficients for the proposed methods is a complex task.

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PCA and LDA assume that data are Gaussian. However, practical point of view observed data are often not Gaussian. Wei Li et al [25] proposed a classification method called local Fisher's discriminant analysis (LFDA) to exploit the statistical structure of the data. LFDA [26] is used to reduce the dimensionality of HSI data and Gaussian mixture-model (GMM) [27] classifier is employed. LFDA combines the properties of LDA and locality-preserving projections (LPP). LPP [28] is a technique that tries to find a linear map that retains the local structure of neighbouring samples in the input space. In other words, after an LPP mapping, neighbourhood points in the original input space remain neighbours in the LPP-embedded space, and vice versa. The spectral responsivity of remotely sensed data can be affected by many factors, including differences in illumination conditions, geometric features of material surfaces, and atmospheric effects. Hence classifiers based on GMMs are natural fit for remotely sensed data.

Jinn-Min Yang [29] presented nonparametric feature extraction algorithm called nonparametric fuzzy feature extraction (NFFE). The limitations of LDA can be overcome NFFE. In NFFE, fuzzification procedure is carried out and membership grades are estimated. Two remotely sensed hyperspectral image data sets are employed for testing purpose. Two classifiers are employed: 1-nearest-neighbor (1NN) and support vector machine (SVM) with RBF kernel function. The kernel function employed in SVM is RBF kernel function with a parameter σ.

In paper [30] dimensionality reduction using fract analysis is described. Complex non-linear systems are analyzed using fractal method. Both spectral and spatial characteristics are considered in this method. Fractal measurement based spectral domain feature analysis for hyperspectral image has been proposed. Fractal method is widely used in remote sensing applications because of its ability to analyze both spatial structure and spatial complex. The spectral domain fractal characteristic of hyperspectral image has been emphasized by three points. First point states that spectral imaging model is a non-linear complex system. As non-linearity is the unique characteristic of fractal phenomenon it is concluded that spectral curve has fractal characteristic. Second point considers the self-similar property of fractal phenomenon which states that local part of fractal is similar to whole model. Self-similar property of spectral curve is demonstrated in figure 5 for SPOT and TM image. The third point states that the length of spectral curve has exponential relation with band width. The methodology of fractal analysis involved three main steps: noise removal by spectral curve filtering, fractal dimension calculation of spectral curve and dimensionality reduction with the fractal dimension feature of the spectral curve. Qazi Sami ul Haq et al [31] presented a dimension reduction method based on the fusion of segmented principal component analysis (SPCA) and LDA.

IV. RESULTS

SPOT image of Wuhan city

TM image of Wuhan city

Fig.5. Self-similar property of spectral curve

The bands are independently selected using SPCA and LDA and merged later. Fusion of SPCA [32] and LDA [33] preserve the properties of both algorithms: informativeness property of SPCA and information redundancy property of LDA. SPCA selects the principal components which contain the most informative features. These components are in the direction of maximum variation. LDA tries to eliminate the shared information by maximizing the rate of between-class scatter matrix. Figure 6 shows the correlation matrix of AVIRIS Indian Pines scene for the dimension compressed by fusion method. Dark cells represent lower correlation. The two methods have not shared much overlap. The constraints in the number of dimensions to be selected for SPCA and LDA are considered.

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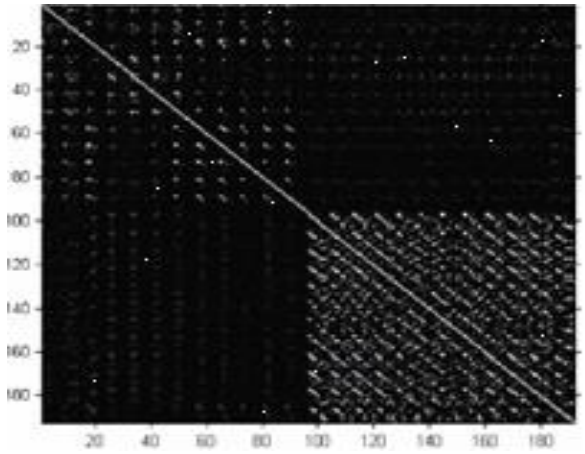

Fig.6. Correlation of the dimensions compressed by Fusion.

For SPCA, 3 or 4 bands are found to be enough for each segment. For LDA at most c-1 dimensions are found to be available. when the number of classes was c. By considering the dual criteria of informativeness and redundancy classification accuracy was improved.

Joseph et al [34], developed a reduction technique which simultaneously reduces the data dimensionality, suppresses undesired or interfering spectral signatures, and detects the presence of desired spectral signature. The idea behind this is to project each pixel vector onto a subspace which is orthogonal to the undesired signatures. This operation is an optimal interference suppression process in the least squares sense. Once the interfering signatures have been nullified, projecting the residual onto the desired signature maximizes the signal-to-noise ratio and results in a single component image that represents a classification for that desired signature. The orthogonal subspace projection (OSP) operator can be extended to k number of desired signatures, thus reducing the dimensionality of k and classifying the hyperspectral image simultaneously. This methodology is suitable for both spectrally pure pixels as well as mixed pixels.

It can be perceived as a mixture of two linear operators into a sole classification[39] operator. The two operators are: optimal interference rejection process in the least squares sense and optimal detector in the maximum SNR sense. The standard statistical classifiers and matched filtering/spectral signature matching techniques are suboptimal in the presence of multiple correlated interferers and the limitations of these will not affect the performance of the above mentioned approach.

Hong Huang et al [35] proposed a new method for dimensionality reduction using sparse manifold embedding (SME) which is on the basis of graph embedding and sparse representation. It constructs a similarity graph by employing the sparse coefficients of affine subspace and retains this sparse similarity in embedding space. A novel supervised learning method termed sparse discriminant manifold embedding (SDME) can be developed by utilizing the preceding label information. SDME inherits the virtues of the sparsity property of affine subspace and also it boosts the compactness of intra-manifold, which enhances selective features and further promotes the classification accuracy of HSI.

In [36], a new supervised dimensionality reduction method is proposed which is called sparse discriminant embedding (SDE), developed to combine the merits of both intermanifold structure and sparsity property. It is not only protects the sparse reconstructive relations through l1-graph [37] but also enhances the intermanifold separability of data, and the discriminating power of SDE is further improved than Sparsity Preserving Projections (SPP). [38].

V. CONCLUSION

This paper attempts to study and provides a brief knowledge about the different dimensionality reduction methods for hyperspectral image.ie, to remove the irrelevant and redundant data, different approaches are elaborated and analysed. Most common approaches for dimension reduction can be categories as supervised and unsupervised in which PCA plays a vital role. This review makes it potentially more suitable for the selection of dimension reduction method leading to further processing.

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