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PERFORMANCE ANALYSIS OF GLOBAL AND LOCAL BASED DIMENSIONALITY REDUCTION IN HYPERSPECTRAL IMAGES

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ABSTRACT

Hyperspectral images possess abundant and fine spectral details compared to other remote sensing images. Hyperspectral images have several hundreds of bands leading to more complexity, issues in handling the images with vast dimension, the need of immense storage and transmission, high correlation between the bands and moreover automatically processing time also becomes high. This makes the need of dimension reduction methods as a pre-processing step in hyperspectral image analysis. An overview of state of art dimension reduction methods and its application in end member extraction stage of spectral unmixing were discussed in this paper. The performance analysis of Scale Invariant Feature Transform (SIFT) based dimension reduction is analysed in two ways by extracting endmembers from a single pixel and from endmember bundles. Also the performances of dimension reduction methods were investigated with the help of spectral angle distance. Further, spectral unmixing can be utilized as a post-processing technique in classification, target detection and identification.

Keywords: *Hyperspectral image, Endmember Extraction, Dimension Reduction, Scale Invariant Feature Transform, Spectral Unmixing.*

1. INTRODUCTION

In current decades, processing of images in spectral domain plays a prime role with vast applications. Since 1960's, multispectral images are acquired and used to observe earth surface or for any application. Early sensor technologies collect spectral data of less than 20 bands due to its insufficient storage data capability [1]. Imaging spectrometers is a major advancement in sensor technology which can collect and store thousands of spectral bands. This leads to a hyperspectral image acquisition and analysis. Hyperspectral image collect narrow and continuous spectral bands and gives spectra of all pixels in the scene captured [2]. An image with 20 bands can be considered as hyperspectral when it is captured in the visible range of electromagnetic spectrum 500nm to 700nm with 10nm wide between the bands [3]. Nowadays ultraspectral images also emerging with very fine spectral resolution than hyperspectral image with wide application. Hyperspectral images find applications in almost all fields such as agriculture, eye-care, food processing, mining and geology, environmental monitoring and astronomy [4].Hyperspectral image analysis includes enhancement, restoration, denoising [5], unmixing [6], classification [7]. Among these, spectral unmixing is an emerging technique as a post-processing step with application in classification [8], change detection [9], fusion, target detection and identification [10], PAN sharpening and medical diagnosis [11].Spectral unmixing is the procedure of separating distinctive materials in an image with the help of spectral signature plot [12]. Spectral signature plot is a graph of spectral pixel values in the y-axis and wavelength of image in the x-axis. A vast research in detail about spectral unmixing were discussed in [13] with challenges and future directions. Although many methods are available for multispectral image analysis and the same cannot be extended for hyperspectral images due to its high dimension. The complexity of the algorithm increases with the increase in the number of bands. This leads to the need of dimension reduction in hyperspectral images. In this paper, we discuss on dimension reduction methods applied in hyperspectral images to realize its importance in attaining accurate results [11].Dimension reduction can also be imagined as reducing hyperspectral data cube from its high dimension to low dimension or eliminating redundant information between the bands as shown in Fig.1. Transform based dimension reduction methods [4] includes Minimum Noise Fraction(MNF),Principal Component Analysis, Kernel Principal Component Analysis, ,ISOMAP, Independent Component Analysis and locality preserving Projections[14,15].

The various examples of band selection or feature selection based methods incorporate linear discriminant analysis (LDA), Laplacian Eigen maps and locally linear embedding techniques [16]. In this paper, the need of dimension reduction is tested with proposed feature extraction [17] based dimension reduction methodology with existing Principal Component Analysis (PCA) and LDA based dimension reduction methods with application in Endmember Extraction(EME) of spectral unmixing. Therefore this paper discusses the importance of dimension reduction methods in the extraction of endmembers in hyperspectral images.

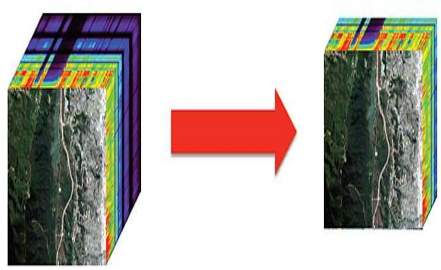

Figure 1:.Schematic Diagram-Dimension Reduction

2. PROBLEM STATEMENT

In real world, datas are of various dimensions like speech, image, video, multispectral, hyperspectral and ultraspectral images. Further, with advancement in sensor technology, enormous informative datas are captured for a scene and increased the memory needed to store and process those datas. Hyperspectral sensors capture data nearly hundred times greater than ordinary optical sensors. Moreover, hyperspectral images are abundant in spectral information with fine spatial resolution. This leads to the need of dimension reduction to reduce the complexity of huge data and capturing only its important features in reduced data. High correlation between the bands and ample data initiates the trouble in handling the data for storage and may cause problem in processing phase and inversion phase. Also, it may limit the application of hyperspectral data to some extent. Further the conventional methods designed for multispectral images cannot be easily applied in hyperspectral images. Moreover dimension reduction plays a vital role in post-processing applications like classification, unmixing and change detection. In the case of classification, higher the dimension of the data higher the training samples needed. The complexity of the algorithm becomes high if the original huge dimension data is directly processed in unmixing process to find different materials and thereby increases computation time. In change detection applications where multi-temporal images are utilized dimension reduction is an essential one to reduce the dimension and processed to find the changes occurred in different places.

3. LITERATURE SURVEY

David Ruiz et al [18] proposed unsupervised method based on Kohonan self-organizing maps which works automatically by selecting input patterns to directly work on some special features of hyperspectral images in reducing the dimension of the data .The main advantage of the proposed method is it performs specifically good for image classification compared to other popular methods such as principal component analysis and wavelet transform based dimension reduction methods.

Zhenhua Wang et al [19] suggest a decision system in which feature parameters are selected based on information entropy. The stability of the suggested rough set theory based method is tested on different datasets and compared with existing state of art methods in terms of computational complexity.

Liangpei Zhang et al [20] present an overview about various graph based representative methods such as manifold learning, sparse learning and hypergraph learning methods. The basic algorithms were discussed and concluded that spatial-spectral combined graph learning method need to be devised in future for better results.

Hong Huang et al [21] recent article proposed a graph embedding based dimension reduction method. Existing graph based dimension reduction uses only spectral features and ignores spatial features. A new dimension reduction is presented in this paper combining spatial spectral features named as regularized sparse hypergraph embedding (SSRHE). Indian pines and Pavia real datasets are used to prove the results in comparison with existing graph based embedding methods. The running time of the proposed method is high, so optimizing the algorithm in future and to be extended for different application like gene expression, face images and radiometric features.

Omprakash Saini et al [22] present an overview about dimension reduction used for computational engineering and intelligent systems in reducing complexity for analyzing data. A comparative analysis of different dimension reduction method also discussed in terms of data type, training time and concluded that a combination of methods may overcome the disadvantage of one method over another.

Giorgio Licciardi et al [23] suggested nonlinear principal component analysis method to reduce the dimension of hyperspectral images. This method provides lower dimension data with fewer features compared with standard PCA and tested with different real hyperspectral datasets.

K. Thilagavathi et al [24] This article discusses various dimension reduction methods such as PCA, Information Gain(IG),global-local linear discriminant analysis and Fisher LDA.A brief explanation about the methods were discussed. Non-parametric feature extraction method is also presented and performance results are compared with LDA.

Bharath Damodaran et al [25] presents kernel based feature extraction method to overcome the curse of dimension reduction by taking into account the non-linearities present in the data. To approximate the kernel value, random Fourier feature transform is applied. The proposed randomized method performs well in comparison with the existing methods discussed in the paper.

Reshma.Ra et al [26] This article presents the importance of dimension reduction and discusses Inter-band block correlation coefficient method in detail. Methods were implemented with application in hyperspectral image classification and proved that the use of dimension reduction improves classification accuracy.

Shuangting Wang et al [27] proposed a non-linear global mixture coordination analysis based dimension reduction method. The method is implemented in three steps. The end member maximization algorithm is utilized to obtain a local maximum of the data and parameters of linear low dimensional manifold from original huge hyperspectral data. The global coordinated factor analysis is applied to align the manifold to a global parameterization and low dimension image is obtained. The proposed method retains maximum spectral information and eliminates redundant data among bands than PCA, LDA techniques.

Aloke Datta et al [28] suggests a unsupervised band selection dimension reduction for classification applications .From the hyperspectral image, characteristics or attributes are calculated for each band and then redundancy between the bands were removed using clustering algorithm. In the last step, rank for each band based on discriminating capability is calculated and bands were selected. The proposed method is compared with four existing state of art methods and highlighted its performance in terms of entropy, classification accuracy, kappa coefficient.

Aloke Datta et al [29] presented an unsupervised band elimination method. This method iteratively eliminates band with the help of correlation depending on discriminating capability of band image. Compared with three popular state of art methods and demonstrated the performance of proposed method in terms of qualitatively and quantitatively.

Karthick.V et al [30] proposes a band selection method using numerous statistical measures such as variance, standard deviation, mean absolute deviation. End member extraction algorithm is applied to prove the effectiveness of the band selection method.

Muhammad Sohaib et al [31] discuss a band selection based dimension reduction method. A spread value for each band is calculated and clustered using K-means while minimizing intra-cluster variance and maximizing inter-cluster variance. Spectral unmixing is applied to examine the accuracy of proposed band selection method.

Ashish Ghosha [32] presents a supervised feature selection technique guided by evolutionary algorithm. The method is tested on three datasets and compared with four other evolutionary based state of art feature selection techniques in terms of kappa coefficient.

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Zhuo Zang et al [33] discusses the effects of different data transformation and dimension reduction by PCA and ICA.PCA performs better than ICA and has no advantage than PCA. Also the cost of ICA is 4 to 5 times more than PCA.

Kitti Koonsanit et al [34] presents an integrated PCA and IG (Information Gain) method. The results from PCA and IG are combined by intersection and bands were selected. The integrated approach has been examined on real hyperspectral datasets.

Jihan Khodr et al [35] discusses numerous techniques like PCA, Kernel PCA, ISOMAP, multidimensional scaling, local tangent space alignment, local linear embedding, locality preserving projections. Based on different quantitative measures such as entropy, variance it has been concluded that sammon mapping and ISOMAP provides better results.

Wei Li et al [36] presents local fisher's discriminant analysis to reduce dimension of data while preserving multimodal structure .In general, dimension reduction leads to ill-conditioned formulations and most popular dimension reduction methods PCA, LDA assumes Gaussian distribution.

L.J.P. van der Maaten et al [16] presents an overall review about non-linear dimension reduction techniques. A detailed explanation regarding weakness of existing non-linear techniques are identified and suggestions to improve the same are discussed. Non-linear techniques works well for artificial datas but traditional PCA only works good for real world tasks.

Shen-En Qian et al [37] proposes a new non-linear technique combining locally linear embedding(LLE) with laplacian eigen maps. The proposed method finds same number of end members as PCA, LLE and performs good than existing in terms of identifying more pure end members.

Jiang Li et al [38] this paper investigates four dimension reduction methods and how it improves abundance map generation using least square estimation. The four methods discussed are discrete wavelet transform (DWT),discrete cosine transform(DCT),PCA and LDT. In terms of abundance estimation error, it is concluded that DWT and LDT based dimension reduction greatly improves the unmixing process.

A. Mathur et al [39] presents how the performance of unmixing process can be improved through feature extraction using wavelet transform. Quantitative parameters used to show the accuracy of proposed method are root mean square error and confidence of abundance estimation.

Each of the methods discussed in the literature has own advantages and disadvantages. Hyperspectral images are of high dimension with rich spectral information. Therefore there is still a need of dimension reduction technique to be designed by incorporating spatial and spectral information with less complexity in minimum processing time.

4. CHALLENGES AND ISSUES IN DIMENSION REDUCTION

The dimension reduction methods are categorized in different ways. It may be classified as supervised or unsupervised, linear or non-linear, Transform based or Feature extraction based dimension reduction and Clustering based dimension reduction. Principal Component Analysis is an example for linear supervised dimension reduction technique and works well for linear datasets. With the help of neural network, non-linear PCA also has been developed. ICA is an example for unsupervised dimension reduction technique. But the method has highly complicated strategy in reducing dimension of the data. Most of the unsupervised dimension reduction methods are based on clustering and they perform faster compared to conventional methods. Feature extraction based dimension reductions obtain features through transforms and minimizes the data dimension. Each of the existing approaches has its own merits and demerits. In summary, some of the issues are

- Linear methods works well for steady datasets. An integrated approach of these methods may produce superior results.
- Non-linear methods works well for artificial data and need to be extended for the use in real world datas.
- A reduction method with highly discriminating capability between the bands need to be designed to achieve satisfactory results.
- Graph based methods produce better results, but it ignores spatial features. So, a method incorporating spatial features in graph based dimension reduction improves the performance more compared to other traditional methods.

- Transform based methods extracts features and selects bands for further processing preserving the spectral data and ignoring spatial features.
- A method which works well for small datasets fails to work for more datasets resulting error in sub-pixel classification. An algorithm need to be developed which works for different applications like classification, unmixing, face recognition etc.
- In general, combination of methods improves results by mitigating the negative effects of one method by another. An integrated spatial-spectral approach incorporating noise method need to be developed to reduce the dimension.

Dimension reduction step is an optional one but it reduces the computational complexity of the subsequent processing. The choice of a dimension reduction algorithm relies on whether it incorporates noise or not and how much it reduces dimension of the original data with adequate important information. As a consequence, new methods of reducing dimension without dropping remarkable information is greatly needed today for any application of hyperspectral images.

5. PROPOSED METHODOLOGY

The dimension reduction plays a major role in subsequent processing of hyperspectral image analysis. In this paper, various dimension reduction methods are implemented and their performances were analysed. Three different dimension reduction methods such as Principal Component Analysis(PCA) a linear based algorithm, Linear Discriminant analysis(LDA) a non-linear based algorithm and Scale Invariant Feature Transform (SIFT) a features extraction based algorithms were implemented[40].The input hyperspectral image $'H'$ with $'R'$ bands is taken and the number of endmembers $'e'$ is calculated using virtual dimensionality algorithm [41].Then dimension reduction is performed and endmembers are extracted.

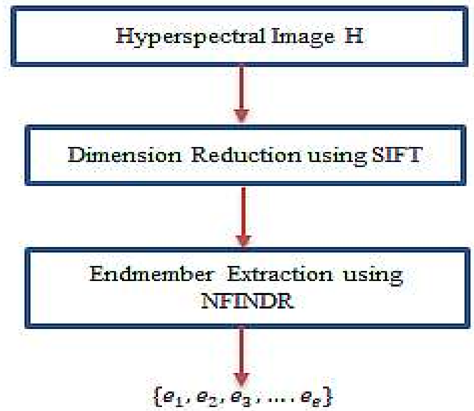

Figure 2: Endmember Extraction Using SNFINDR Algorithm

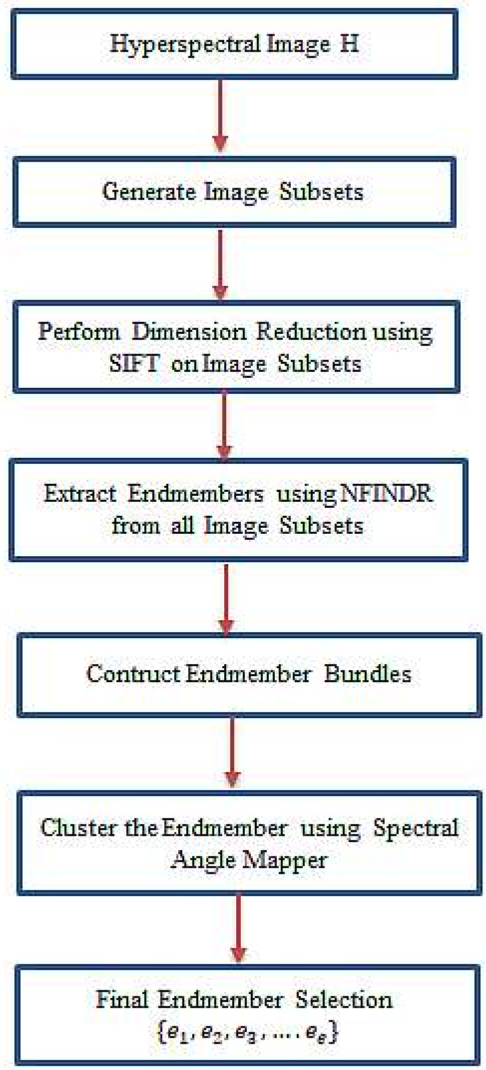

Figure 3: Endmember Extraction Using SIFTDC Algorithm

Scale invariant feature transform based endmember extraction is analysed in two ways by

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performing the operation globally and locally on input hyperspectral image. The first method named as SNFINDR performs dimension reduction on original data and extracts endmembers as in Fig.2. Scale invariant feature transform on input image results in a matching score between any two bands. Using the matching score, non-redundant bands are chosen. Endmember extraction algorithm NFINDR [42] is applied on dimension reduced data to extract endmembers. Another method named as SIFTDC is implemented on sub-images obtained from original image. The original hyperspectral image is divided into sub-images of size 20 bands. By trial and error the number of bands in one sub-image is fixed as 20.For each sub-image, SIFT is applied and endmembers are extracted. The endmember from sub-images are collected as endmember bundles. Finally, the endmembers are clustered and final endmember is chosen from endmember bundles using spectral angle mapper (SAM). Let $'e_g'$ be the extracted endmember and $'g_b'$ be the ground truth endmember then SAM is given by

$$\mathrm{SAM} = \cos^{-1}\left(\frac{\sum_{b=1}^{n} e_b g_b}{\left(\sum_{b=1}^{n} {e_b}^2\right)^{1/2}\left(\sum_{b=1}^{n} {e_b}^2\right)^{1/2}}\right) \quad (1)$$

SNFINDR extracts endmembers by performing the operation globally whereas SIFTDC is based on local operation. The main advantage of SIFTDC is it performs operation in parallel and uses cache memory. The flowchart of SIFTDC is depicted in Fig.3. The complete algorithm is shown in Table 1.

5.1 Steps to Implement

The steps to implement the endmember extraction process in generating spectral signature plots in SNFINDR method are as follows.

(1). Hyperspectral image $'H'$ with $'R'$ number of bands is taken as input.

(2).The number of end members $'e'$in the original data is calculated using virtual dimensionality algorithm [41]. These number of end members indicate the number of unique materials in an image.

(3). Dimension reduction methods PCA, LDA and SIFT are applied on original hyperspectral data and reduced to only $'e'$ number of bands. The detailed description of the algorithm is explained in Table.2.

(4). NFINDR is employed on original data and on dimension reduced data to extract spectral signature of end members.

(5). With the use of ground truth data, end members or materials are identified and SAD error values are obtained.

The same procedure is repeated for sub-images to extract endmembers in SIFTDC method.

Table.1 Complete algorithm

Input: Hyperspectral image $'H', 'e'$	
SNFINDR Algorithm	**SIFTDC Algorithm**
$H_{DR} = \{H_1, H_2 \ldots . H_e\} = SIFT\{H\}$	Image subsets H_M=$\{H_1, H_2 \ldots . H_m\}$
$\{e_1, e_2 \ldots . e_e\} = NFINDR\{H_{DR}\}$	$H_{DR} = SIFT\{H_M\}$=[SIFT$\{H_1\} + SIFT\{H_2\} + \cdots . SIFT\{H_m\}$]
Output: $\{e_1, e_2 \ldots . e_e\}$	$endmembers\{e\} = NFINDR\{H_{DR}\}$=[NFINDR$\{H_1\}$ + $NFINDR\{H_2\} + \cdots . NFINDR\{H_m\}$]
	$\{e_1, e_2 \ldots . e_e\} = \min[SAM\{e\}]$
	Output: $\{e_1, e_2 \ldots . e_e\}$

NFINDR Algorithm: Input $'e'$

Step 1: Let $'e'$no.of end members be

$$\left\{m_1^{(0)}, m_2^{(0)}, \ldots m_e^{(0)}\right\}$$

Step 2: Volume calculation,

$$vo\left\{m_1^{(k)}, m_2^{(k)}, \ldots m_e^{(k)}\right\} = \frac{\det(m_1^{(1)}, m_2^{(1)}, \ldots m_e^{(1)})}{(e-1)!}$$

Step 3: Volume recalculation for the sample vector 's',

$$vo\left\{s, m_2^{(k)}, \ldots m_e^{(k)}\right\}, vo\left\{m_1^{(k)}, s, \ldots m_e^{(k)}\right\} \ldots vo\left\{m_1^{(k)}, m_2^{(k)} \ldots s\right\}$$

If the volume calculated for sample's' is greater than the volume calculated in step2, then that vector is selected as the final end members. The same process is repeated until all spectral signatures are obtained.

Output: $\{e_1, e_2 \ldots . e_e\}$

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RESULTS AND DISCUSSION

The need of dimension reduction is examined with the help of endmember extraction of spectral unmixing process. Using only the dimension reduced data, different end members present are extracted from the huge original data. In this paper, we investigate 2 existing state of art dimension reduction methods namely PCA and LDA with proposed SIFT (Scale invariant feature extraction) [17] based dimension reduction in extracting end members of spectral unmixing process [43]. Two variant methods from SIFT namely SNFINDR and SIFTDC are implemented to analyse its performance. The algorithms were implemented in MATLAB 2020a software and two hyperspectral datasets used for testing are Jasper Ridge image and Samson image. Both the datasets have same spatial resolution (9.4nm per pixel) and wavelength range (380nm-2500nm).The image size of Jasper Ridge is 100X100 with 224 bands and Samson image is of size 95X95 with 156 bands. Quality measures used to analyze the results are Spectral Angle Distance (SAD) and Average Spectral Angle Distance (A-SAD) [44]. Spectral unmixing involves 2 stages. In the first stage, particular materials or end members are extracted and in the second stage the area covered by the material or abundance maps are generated. The distinct matter present in image is called end member. The graph of pixel values versus wavelength of band is called as spectral signature.

The spectral signatures are analysed using performance measure to validate the dimension reduction methodology.

Endmember extraction is utilized in this paper to investigate dimension reduction methods. Many end member extraction algorithms exist in the literature namely Pixel purity index(PPI)[45],Simplex Growing Algorithm(SGA)[46], NFINDR[42], Vertex Component Analysis(VCA)[47],Non-negative matrix factorization(NMF)[43].In this paper, NFINDR algorithm is implemented to examine the effectiveness of dimension reduction methods employed in endmember extraction stage of unmixing process.

Table.2. Dimension Reduction Methods

Parameter	**PCA**	**LDA**	**SIFT**
Input	Two dimensional data	Two dimensional data	Three dimensional data
Algorithm	1.$\in = \frac{1}{m} * R' * R$; 2.$[E \ \in V] = PCA(\in)$; 3.$E_{reduce} = E(:,1:p)$; 4. Band reconstructed $Z = E'_{reduce} * R$;	1. Convert the hyperspectral image into 2-dimensional matrix and compute the $'d'$-dimension mean vectors. 2. Compute the scatter matrices In-between class $S_B = \sum_{i=1}^{c} N_i(m_i - m)(m_i - m)^T$ Within class scatter matrix $$S_W = \sum_{i=1}^{c} S_i$$ $S_i = \sum_{i=I_i}^{n} (X - m_i)(X - m_i)^T$ Where N and m_i denotes the sample size and overall mean. 3. Compute the Eigen vectors and Eigen values. 4. Sort in the decreasing order of Eigen values and generate $d \times k$ dimensional matrix$W$. 5. Generate 'e' number of new samples or bands using $Y = X.W$ Where X is $n \times d$ dimensional matrix representing the 'n' samples and Y is the transformed $n \times k$ dimensional samples in new subspace.	1. Scale space $$L(x,y,\sigma) = G(x,y,\sigma) * I(x,y)$$ where $$G(x,y,\sigma) = \frac{1}{2\pi\sigma^2} e^{-(x^2+y^2)/2\sigma^2}$$ 2. Difference of Gaussian(DOG) $$D(x,y,\sigma) = (G(x,y,k\sigma) - G(x,y,\sigma)) * I(x,y)$$ $$D(x,y,\sigma) = L(x,y,k\sigma) - L(x,y,\sigma)$$ 3. Locate DOG extraction Comparing with all neighboring points (include scale) and identify min and max value. 4. Sub-pixel localization $$D(x) = D + \frac{\partial D^T}{\partial x} x + \frac{1}{2} x^T \frac{\partial^2 D}{\partial x^2} x$$ 5. Orientation assignment $$m(x,y) = \sqrt{(L(x+1,y) - L(x-1,y))^2 + (L(x,y+1) - L(x,y-1))^2}$$ $$\theta(x,y) = \tan^{-1}((L(x,y+1) - L(x,y-1))/(L(x+1,y) - L(x-1,y)))$$ 6. Key point descriptors

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			Separate the region in to sub regions and create histogram for each sub region with 8 bins. (4 * 4* 8)= 128 element vector 7. Repeat the above steps for all pair band images. 8. Generate the dissimilarity matrix using descriptors. 9. Select first $'e'$ number of bands.
Output	$'e'$ Number of bands.		

SAD value derived in Eq.(2) denotes error values how much the extracted spectral signature $'d_i'$is identical to ground truth data $'d_g'$.

$$SAD = \cos^{-1}\frac{(d_g . d_i^t)}{(\|d_g\| . \|d_i^t\|} \quad (2)$$

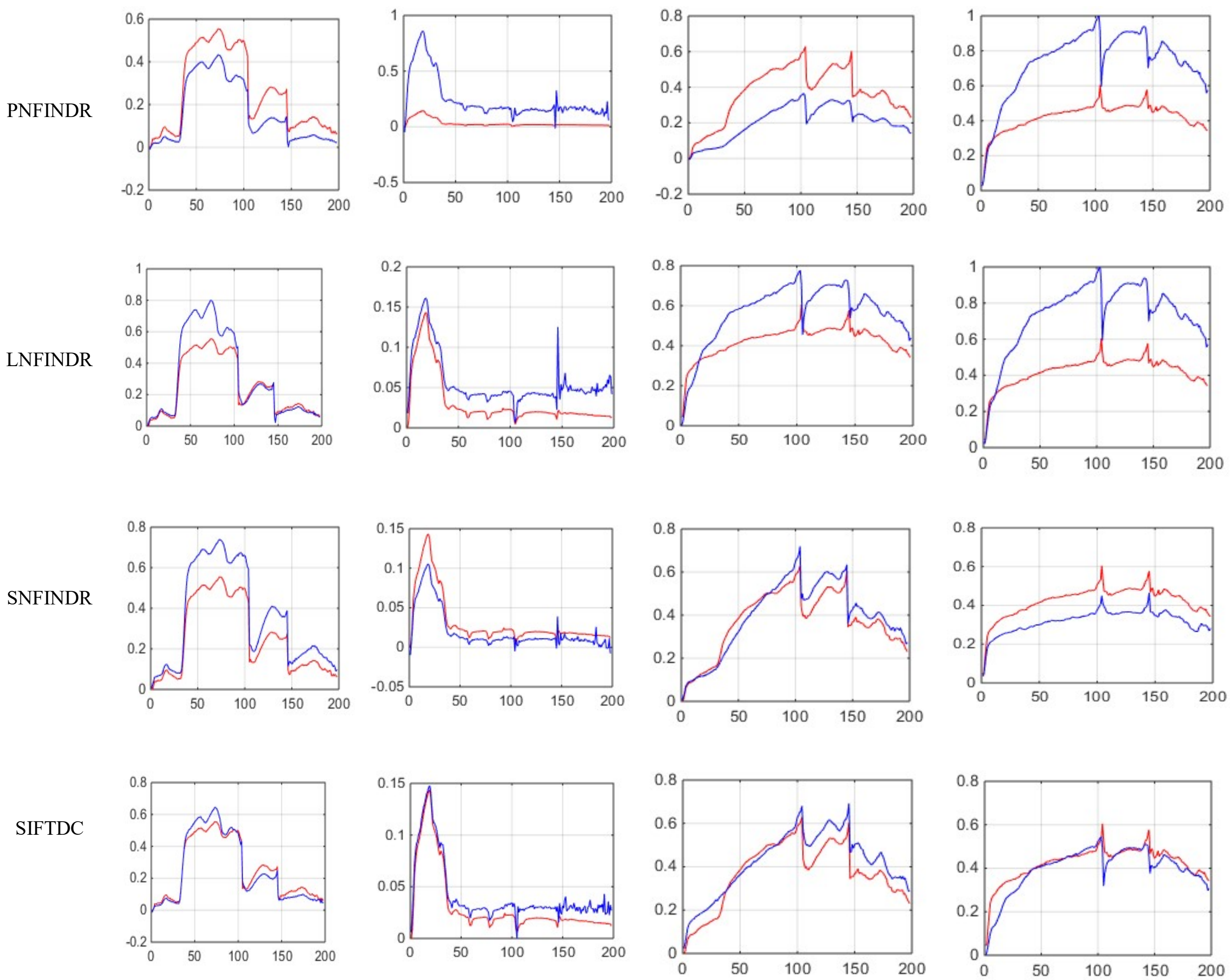

Figure 4: Extracted Spectral Signatures (from left to right)-Tree, Water, Road, Dirt-Jasper Ridge Image

In general, dimension reduction method reduces the number of operations need to be performed on $'H'$ with $'R'$ bands to only $'e'$ number of bands.

From the analysis shown in Table.3, in the case of Jasper Ridge image, the methods SNFINDR and SIFTDC results in minimum error compared to PCA and LDA. This means that spectral signature generated using SIFT based methods are more alike to ground truth data than PCA, LDA based end member extraction methods. Average-SAD indicates average SAD error values of all the materials given by Eq. (3).The dimension reduced methods are capable of selecting informative bands and produces results comparable to the results processed with full hyperspectral data as seen in Table.3. The spectral signatures extracted are shown in Fig.4. Average SAD is also minimum for SIFT based endmember extraction methods as shown in Fig.6.

$$A - SAD = \sqrt{\frac{1}{e}\sum_{i=1}^{e}(SAD)_i^2} \tag{3}$$

The average SAD error is also minimum for SIFT dimension reduced methods as compared to error produced by PCA and LDA based methods as shown in Figure.5.

From the analysis shown in Table.4, in the case of Samson image, 3 end members exist. For the 3 end members, 3 different methods have produced minimum SAD error values. For example, minimum error for rock has been obtained using PCA, minimum error for Tree observed in LDA and for water minimum error is observed in SIFTDC. In overall, SNFINDR and SIFTDC performance is good. The spectral signatures extracted are shown in Fig.6.

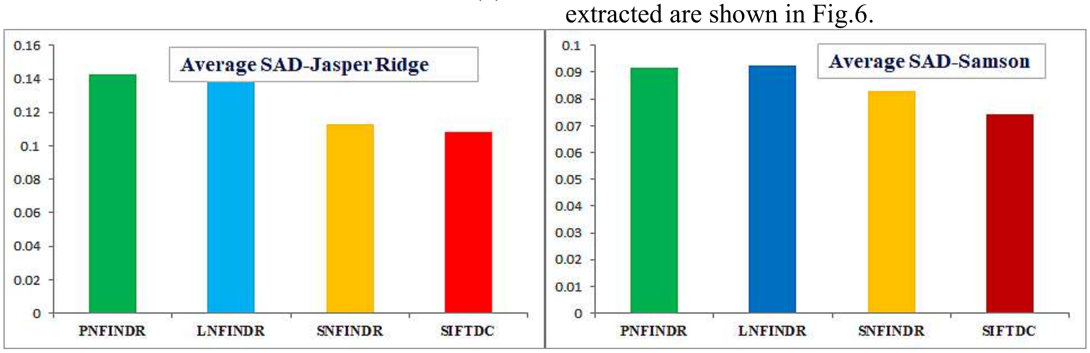

Figure 5: Average SAD Values-Jasper Ridge Image(Left),Samson Image(Right)

Table.3. SAD Values-Jasper Ridge Image

End Members	PNFINDR	LNFINDR	SNFINDR	SIFTDC
Tree	0.1554	0.1456	0.1243	0.1090
Road	0.1498	0.1142	0.1089	0.0254
Water	0.2856	0.2171	0.1066	0.1909
Dirt	0.1654	0.1345	0.1128	0.1058

Table.4. SAD Values-Samson Image

End Members	PNFINDR	LNFINDR	SNFINDR	SIFTDC
Rock	0.0645	0.0503	0.0499	0.0443
Tree	0.0598	0.0752	0.0529	0.0209
Water	0.1657	0.1611	0.1347	0.1419

6.1 Discussion

The Jasper Ridge image has microscopic variations among end members and Samson image has macroscopic variation among end members, therefore in both the cases SIFT feature extraction based end member extraction produces better results in comparison with PCA and LDA. SNFINDR and SIFTDC achieved minimum error value with ground truth data.

In summary, dimension reduction methods play a vital role in hyperspectral image analysis. The use of dimension reduction definitely reduces processing time, memory needed to storage and transmit, training samples needed for classification, number of band in the case of unmixing, change detection, target detection and identification. More efficient dimension reduction methods are capable of producing accurate results in comparison to processing full hyperspectral data as discussed above. Instead of processing the full hyperspectral data, informative and non-redundant bands are enough to yield better results. Specifically, from the unmixing process reviewed in this paper, the endmember characteristics or spatial information about end member plays a major role in choosing a dimension reduction method. Highly mixed data needs feature extraction based dimension reduction method to be employed to generate spectral signatures. SIFTDC is based on divide and conquer strategy which performs the operations in parallel and extracts endmember bundles compared to SNFINDR resulting in a minimum memory requirement compared to SIFTDC [48]. The

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extraction of endmember from endmember bundles also takes into account the spectral variability occurring due to illumination and atmospheric conditions [49].

6. CONCLUSION

This paper aim to analyze and provides layout of state of art dimension reduction methods in the literature for hyperspectral image. Among the existing dimension reduction methods, feature extraction based method plays a paramount role with extended modification in the literature. Also, the combination of different methods may give rise to superior results compared to single method usage for any processing of hyperspectral data. Dimension reduction methods plays an essential pre-processing step for different application of hyperspectral images like classification, unmixing, change detection, target detection and identification and restoration. In spectral unmixing application discussed in this paper, local based dimension reduction performs better than global based dimension reduction.

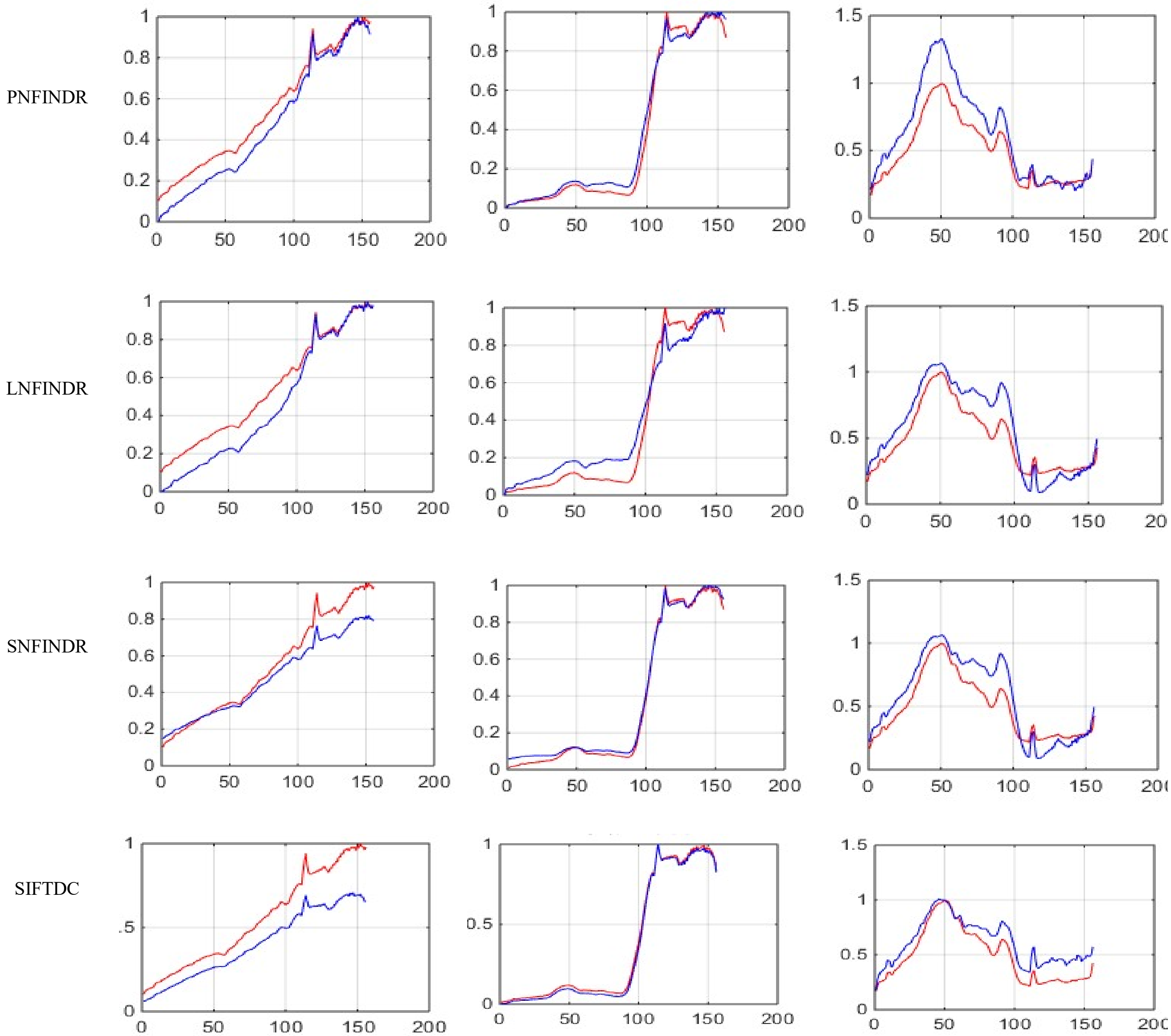

Figure 6: Extracted Spectral Signatures (from left to right)-Rock, Tree, Water - Samson Image (X axis-Wavelength, Y axis-Reflectance)

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