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Analysis of Band Selection Algorithms for Endmember Extraction in Hyperspectral Images

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Abstract: *This paper presents a novel approach of band selection for dimensionality reduction in Hyperspectral images (HSI). There are several methods of dimensionality reduction which can be further categorized into two groups; feature extraction and feature or band selection. Due to transformation in feature extraction, the critical information may have been distorted. Hence feature selection is preferable for dimensionality reduction because it preserves the relevant original information. Despite many algorithms exist for dimensionality reduction; it is even now a challenging task of selecting informative bands from the large volume data. The number of bands is estimated with the concept of Virtual Dimensionality (VD), because it provides reliable estimate. Bands are selected from hyperspectral images using Exemplar Based Band Selection (EBBS). End members are extracted from the selected bands using Simplex Growing Algorithm(SGA). The performance of EBBS is compared with the existing band selection techniques such as Constrained Band Selection (CBS) and Similarity Based Band Selection (SBBS) using the spectral angle distance as a measure.*

Keywords: *Hyperspectral images, Virtual Dimensionality, Simplex Growing Algorithm, Exemplar based band selection, Spectral angle distance.*

I. Introduction

The hyperspectral images can now concurrently capture hundreds of image band with wavelength range from the visible spectrum to the infrared region, due to the great improvement in current decade [3]. Even though the large number of hyperspectral bands provides sufficient information to distinguish resources, they may bring some problems, like Hughes phenomena [4]. Besides, the development of the mass data also stress significant calculation power. As an outcome of the dimensionality reduction is one of the most essential preprocess steps in hyperspectral data analysis to deal with these issues. Band selection (BS) is an efficient approach for hyperspectral dimensionality reduction, which has been rewarded an increasing attention in current years. The existing BS method [1] [2] consist of two broad types, namely supervised and unsupervised methods respectively. The supervised methods have need of training samples that may be virtually not available [5]. Thus, this paper mainly focus on unsupervised BS method. The unsupervised technique can be implicited as the development of selecting a skilled division from a larger set of bands, without any prior knowledge. Various unsupervised BS methods are based on information estimate resources. Their aim is to decide the subset with huge information [9]–[11], low similarity [5].

In order to choose the representative instead of extreme bands, currently, the researchers take BS as a clustering problem, i.e., a process of partitioning the bands into group of similar clusters. In these conditions, the cluster centers are generally considered preferable to insignificant bands. Based on different distant measures, like interquartile range, correlation coefficient and covariance, Ahmad estimated cluster and select the bands by corresponding different k-means version. These clustering-based methods can be hidden as the direct application of the clustering methods to hyperspectral bands. Though the centers of the clusters seem to be a best option these methods undergo from large computation complexity. Moreover, these methods may be greatly inclined by many clusters. Finally, these clustering methods require spherical distribution of the data since a data point is assigned to the closest center. In this paper, we choose the cluster centers without the actual clustering. Particularly, for each band, we use a pointer termed exemplar score (ES) to measure the possibility of a band to be an exemplar.

The ES utilizes two reasonable assumptions namely, the exemplars contains maximum local density and they are at a comparatively great distance from points of higher density. Based on ES, we here represent a fast BS method, i.e., Exemplar Based Band Selection (EBBS), which aims to select the bands with high chance to be exemplars (or high ES). EBBS does not involve actual clustering; as a substitute, it prioritizes the bands according to their ESs. EBBS has quite low computation complexity since it is actually a band-ranking method,. In accumulation, it is verified in the experiment, EBBS is able to identify nonspherical clusters. And also, EBBS has no distribution requirements of the data points.

II. Exemplar Based Band Selection

BS has its source in the fact that hyperspectral bands have high correlation. For a highly correlated subset of bands, we may need only the most representative one. As a result, BS is associated with data clustering. In this paper, each band of hyperspectral data are regarded as a data point in high-dimensional space. The main purpose of this paper is to present an algorithm that can determine the exemplars of these points accurately and efficiently. This method utilizes two reasonable assumptions: First the cluster centers must have the highest local density (ρ_i) , and the second is that they have comparatively larger distance (δ_i) to the points of gretaer density. In the following, we first demonstrate the computation of ρi and δi in detail.

Assume the hyperspectral data set is $\mathbf{X}_{NXL} = [\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_L]$ where $\mathbf{x}i = [x_{1i}, x_{2i}, \ldots, x_{Ni}]\ T$ represents vector constructed by the *i*th band, *N* represents the number of pixels and *L* represents the number of total bands. First the distance matrix of bands wants to be computed. Let *dij* denote the Euclidean distance between the *i*th band $\mathbf{x}i$ and *j*th band $\mathbf{x}j$, then

$$d_{ij} = || \mathbf{x}_i - \mathbf{x}_j ||_2 \qquad (1)$$

where $\|\bullet\|$ is the 2-norm operator. $\boldsymbol{\rho i}$ is defined as the number of points that are adjacent to point *i*, which can be implicit as using a hard threshold to define neighbors. In this paper, we utilize a soft threshold, known as Gaussian heat kernel function, to define $\boldsymbol{\rho i}$ as follows:

$$\rho_i = \sum_{j=1}^{L} \exp\left(-\frac{d_{ij}}{2\sigma^2}\right) \qquad (2)$$

where σ is a adjusting parameter. The calculation of δi is quite simple, as its definition is the closest distance to the points of greater density from point *i*, as follows:

$$\delta_i = min_{j:\rho_j > \rho_i}\left(d_{ij}\right) \qquad (3)$$

For the point with the maximum local density, we simply let $\delta i = \max_j (dij)$. From the definition of δi , only the points with local or global maxima density have a relatively large δi. In reality, δi plays an important role in the repression of extremely correlated bands.

These two indicators can suitably characterize the location of the bands in data clouds and play a very important role in the presentation of our method. Particularly, when ρi is large and δi is small, then the *i*th band is close but not the cluster center since there is a point which is in the same cluster having a larger ρi. When ρi and δi are small, this point lies about the edge of the clusters and if ρi is small and δi is large, the point is away from the entire data cloud,which indicates that the point is most likely an outlier. It is possible only when both ρi and δ_i are relatively large that the point can be exemplars.

Based on this, we utilize the product of ρ_i and δ_i to measure the probability of the bands to be exemplars. In this paper, the indicator is termed ES as follows:

$$ES_i = \rho_i * \delta_i \qquad (4)$$

When ρ_i and δ_i are both of large values then the *i*-th band have large ES*i*, which indicates a high possibility to be exemplars. Once the ES for the bands have been calculated, the BS for ECA is simple, ranging the bands according to their ESs from high to low and selecting the peak value. Therefore, EBBS is fundamentally a band prioritization method.

The existing band BS methods, suffer from the high correlation between the selected bands since the similar bands have similar values. Although EBBS is a band-prioritization-based method, it gives full concern of the correlation between the bands. Suppose the order of ES is $ESm1 > ESm2 > \cdots > ESmL$, $1 \leq m1, m2, mL \leq L$. The first band, named *m*1, correspond to the center of the large cluster since it has the highest ES. Then, band *m*2, which has the second largest ES, must contain huge distance from band *m*1. Suppose, if band *m*2 is close to band *m*1, then it will lead to a small $\delta m2$ and therefore a small ES*m*2 . Similarly, for any band *mi*, it must have a greater distance to the bands of larger ES. Since EBBS considers the local density and correlation between bands concurrently, it is likely to select more logical subset of bands.

III. Simplex Growing Algorithm

The simplex growing algorithm (SGA) was developed as an alternative to the N-finder algorithm (N-FINDR)and shows potential endmember extraction technique., SGA can efficiently address the following four major issues which arise in the practical implementation for N-FINDR: 1) use of random initial endmembers which causes unpredictable final results; 2) high computational complexity which results from an comprehensive search for finding all endmembers simultaneously; 3) requirement of dimensionality reduction because of large data volumes; and 4) lack of RT capability.

According to N-FINDR, for a given positive integer *p*, a simplex formed by *p* endmember produces the maximum volume among all possible simplexes formed by any set of *p* data sample vectors. Using this principle, SGA grows the current k-vertex simplex S ($\mathbf{e}^{(0)}$, $\mathbf{e}^{(1)}$, . . . ,$\mathbf{e}^{(k-1)}$) to a (k +1)-vertex simplex S($\mathbf{e}^{(0)}$, $\mathbf{e}^{(1)}$, . . . , $\mathbf{e}^{(k-1)}$, $\mathbf{e}^{(k)}$) by finding a new (k + 1)th vertex $\mathbf{e}^{(k)}$ so that the new (k + 1)- vertex simplex S($\mathbf{e}^{(0)}$, $\mathbf{e}^{(1)}$, . . . , $\mathbf{e}^{(k-1)}$, $\mathbf{e}^{(k)}$) produces its volume no less than the volumes of all possible (k + 1)-vertex simplexes S($\mathbf{e}^{(0)}$, $\mathbf{e}^{(1)}$, . . . , $\mathbf{e}^{(k-1)}$, $\mathbf{r}$) increased by any other data sample vector $\mathbf{r}$. The implementation of simplex process is based on the following algorithm:

1) Initialization:

a) Let p be the number of endmembers to be generated.

b) There are two ways to generate random initial endmembers for SGA.

i. Select data sample random vector as an initial endmember $\mathbf{e}^{(0)}$ and set k = 0. In this case, the SGA is referred to as 1-SGA.

ii. Randomly select a pair of two data sample vectors ($\mathbf{e}^{(0)}$, $\mathbf{e}^{(1)}$) to form a random degenerate 2-D simplex which is a line segment connecting $\mathbf{e}^{(0)}$ and $\mathbf{e}^{(1)}$. Set k= 1. In this case, the SGA is referred to as 2-SGA.

2) At $k \geq 0$ and for each sample vector $\mathbf{r}$, we calculate V ($\mathbf{e}^{(0)}$, . . . , $\mathbf{e}^{(k)}$, $\mathbf{r}$) defined by

$$V\left(\mathrm{e}^{(0)}\ ,\ \ldots, \mathrm{e}^{(k)}\ , \mathrm{r}\right)=\frac{\det\begin{bmatrix} 1 & 1 & \cdots & 1 & 1 \\ \mathrm{e}^{(0)} & \mathrm{e}^{(1)} & \ldots & \mathrm{e}^{(k)} & \mathrm{r} \end{bmatrix}}{\mathrm{k}!} \qquad (5)$$

which is the volume of the simplex specified by vertices $\mathbf{e}^{(0)}$, $\mathbf{e}^{(1)}$, . . . , $\mathbf{e}^{(k)}$, $\mathbf{r}$, denoted by S($\mathbf{e}^{(0)}$, $\mathbf{e}^{(1)}$, . . . , $\mathbf{e}^{(k)}$, $\mathbf{r}$). Since the matrix $\frac{det\begin{bmatrix} 1 & 1 & \cdots & 1 & 1 \\ e^{(0)} & e^{(1)} & \ldots & e^{(k)} & r \end{bmatrix}}{k!}$ in (5) is not necessarily a square matrix, a DR technique such as principal components analysis (PCA) or maximum noise fraction (MNF) is required to reduce the original data dimensionality L to the dimension k + 1.

3) Find $\mathbf{e}$(k+1) that yields the maximum of (5),i.e.,

$$\mathrm{e}^{(\mathrm{k}+1)} = \arg\left\{\underbrace{\max}_{\mathrm{r}} \quad \left[\mathrm{V}\left(\mathrm{e}^{(0)}, \ldots, \mathrm{e}^{(\mathrm{k})}, \mathrm{r}\right)\right]\right\} \quad (6)$$

4) Stopping rule:If $k < p - 1$, then $k \leftarrow k + 1$ and gostep 2). Otherwise, the final set of {$\mathbf{e}^{(0)}$, $\mathbf{e}^{(1)}$, .$\mathbf{e}^{(p-1)}$} is the desired p endmembers.

IV. Proposed Methodology

In this proposed method, the hyperspectral image is first read and the dimension is roughly reduced. Virtual Dimensionality (VD) estimates the number of endmembers present in the HSI image. Virtual dimensionality (VD) also provides an effective alternative.A new band selection method is proposed using the Exemplar Based Band Selection (EBBS) for selecting the exemplar bands respectively. It prioritizes the bands according to their exemplar score, which is an easy-to-compute. Then a new algorithm, called SGA, is proposed for endmember extraction to find a set of desired endmembers by growing a sequence of simplexes. It starts off with two vertices and begins to grow a simplex by increasing its vertices one at a time. Finally, the performance of the different band selection methods are analyzed with SGA as endmember extraction algorithm and evaluated that EBBS with SGA is indeed superior in endmember extraction by deriving most informative bands compared to the other band selection methods. The steps involved in our proposed method are clearly depicted below and the block diagram is shown in Fig 1.

1. Read Hyperspectral Image
2. VD is estimated to know the number of bands required for band selection algorithm.
3. Exemplar Component Analysis is used for selecting the exemplar bands.
4. SGA is used for endmember extraction to detect a set of desired endmembers by growing a sequence of simplexes.
5. The performance are compared between different band selection algorithm and evaluated that EBBS with SGA is indeed superior in endmember extraction.

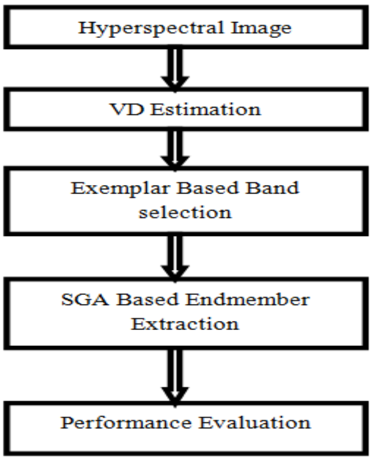

Fig 1. Block Diagram of proposed method

V. Experimental Results

Here, we estimate the number of bands to be selected using VD estimation and also identify the efficient band selection method by comparing various band selection algorithms. The SGA is analyzed as endmember extraction algorithm for the performance of various band selection methods. The other images can also be used to analyze the band selection algorithm for endmember extraction in hyperspectral images. The performance of the different band selection methods are analyzed with SGA as endmember extraction algorithm. For comparison we choose three different types of band selection method :Constrained Band Selection (CBS), Exemplar Based Band Selection (EBBS), Similarity Based Band Selection (SBBS). To evaluate their performance, Spectral Angle Distance (SAD) is used. The endmembers from the selected bands using simplex growing algorithms are extracted.

A. Cuprite Image

The hyperspectral image cuprite is being considered for experimentation as shown in Fig 2.

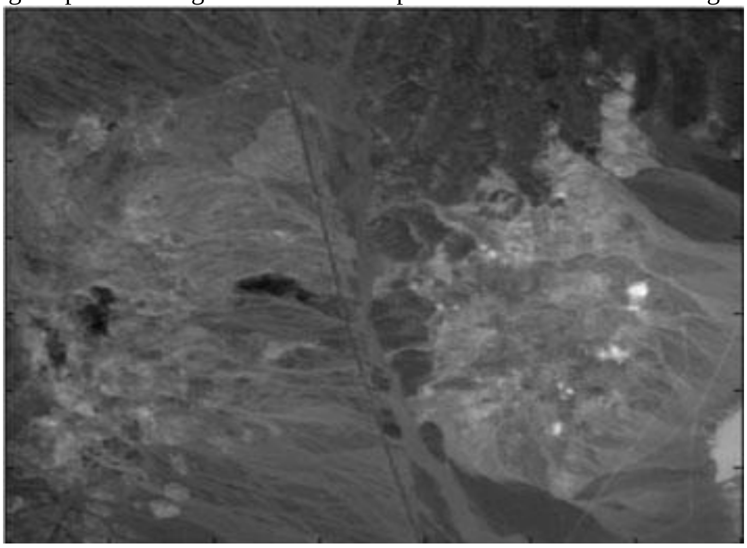

Fig 2. Hyperspectral image CUPRITE**.**

B. Groundtruth Spectral Signatures

The groundtruth spectral signatures of five minerals – Alunite, BuddingTonite, Calcite, Kaolinite, Muscovite are shown in Fig 2..

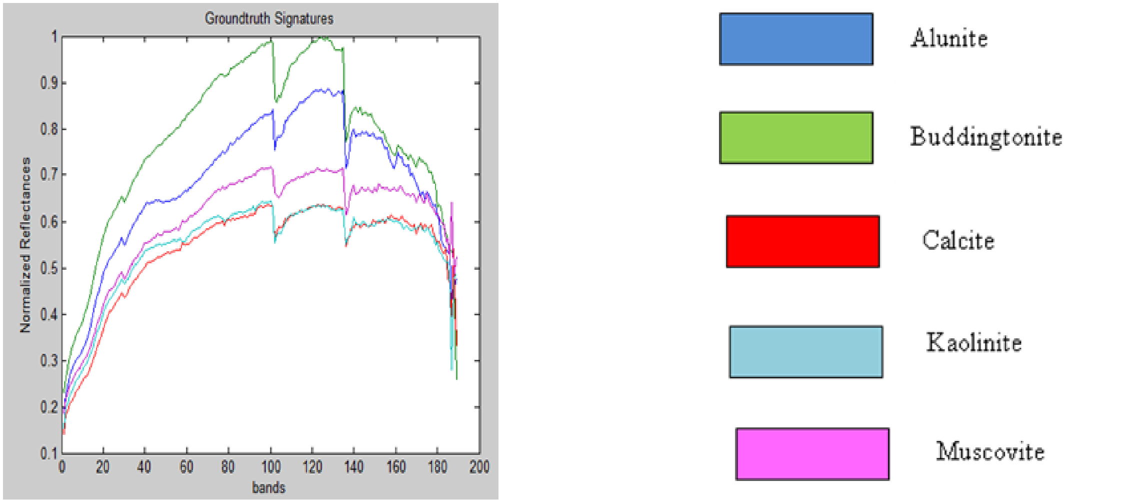

Fig 2. The groundtruth spectral signatures of five minerals

C. VD Estimation

Virtual Dimensionality (VD) estimates the number of endmembers present in the HSI image. The VD estimation with different false alarm rate for cuprite is tabulated in Table I. It is shown that the VD estimation can also be used as the number of endmembers that are to be generated.

Table I: VD Estimation With Different False Alarm Rate For Cuprite

P_F	10^{-1}	10^{-2}	10^{-3}	10^{-4}
VD	35	28	25	22

D. Band Selection

The comparison of selected bands using different techniques and the performance comparison between different band selection algorithms were shown in Table II and Table III.

Table II: Comparison Of Selected Bands Using Different Techniques

Criteria	Selected Bands
CBS	26/117/48/37/189/64/1/185/10/172/47/4/60/28/165/17/5/2/151/158/3/94
SBBS	8/14/26/39/53/71/91/106/114/132/149/153/157/163/172
EBBS	63/64/66/81/82/105/107/134/135/136/137/138/146/151/153/154/156/162/169/177/180/181

Table III: Performance Comparison Between Different Band Selection Algorithms

	CBS	**SBBS**	**EBBS**
		SAD(%)	
Alunite	5.62	4.82	4.54
Buddingtonite	5.25	3.88	5.76
Calcite	6.56	8.73	5.76
Kaolinite	4.90	9.22	6.35
Muscovite	6.73	7.39	4.73
Average	5.81	6.81	5.49

The bar chart for the performance comparison between different band selection algorithms are shown separately from Fig. 3 to Fig. 8

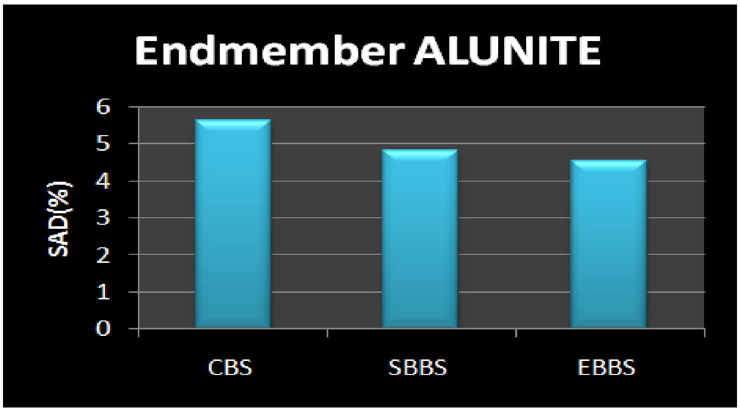

Fig. 3 Endmember ALUNITE

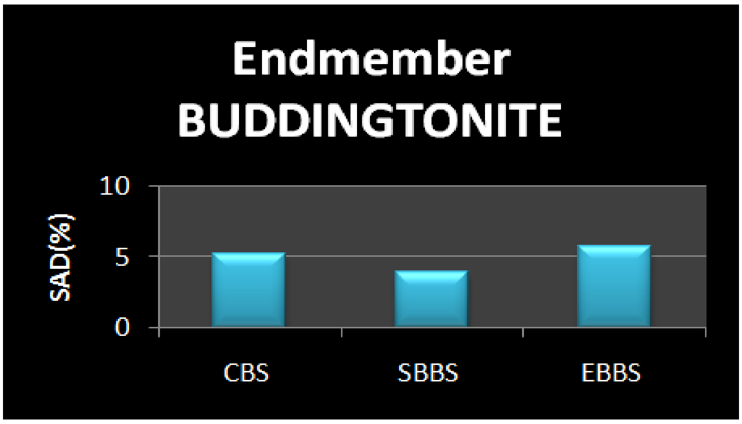

Fig. 4 Endmember BUDDINGTONITE

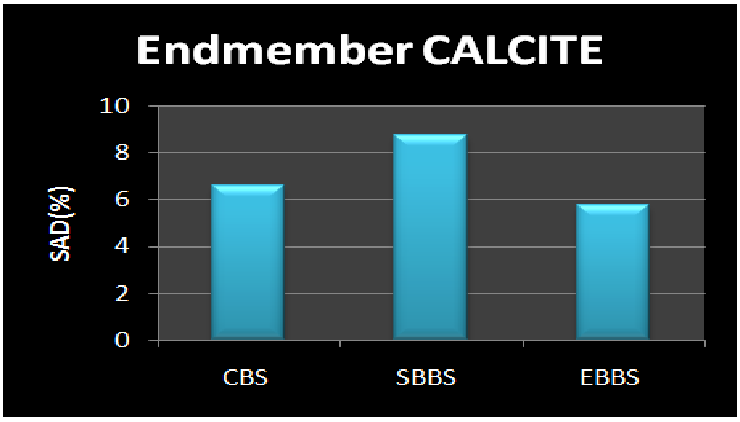

Fig. 5 Endmember CALCITE

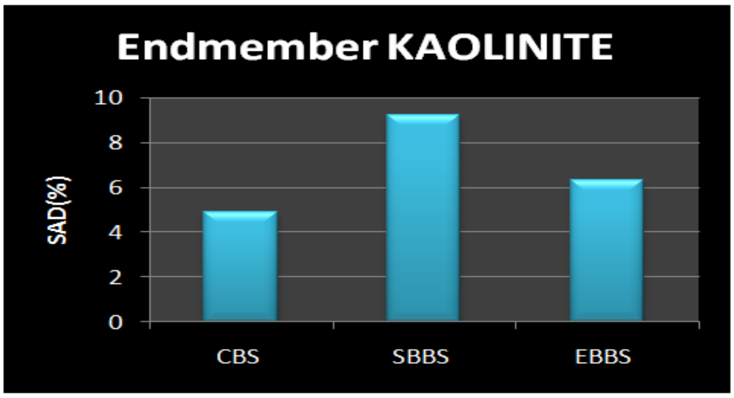

Fig. 6 Endmember KAOLINITE

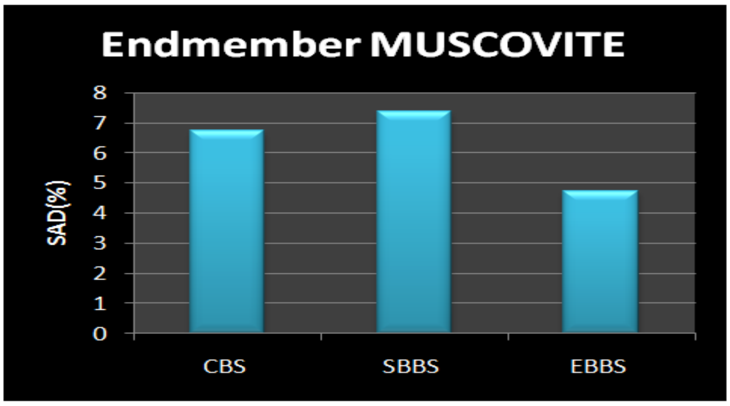

Fig. 7 Endmember MUSCOVITE

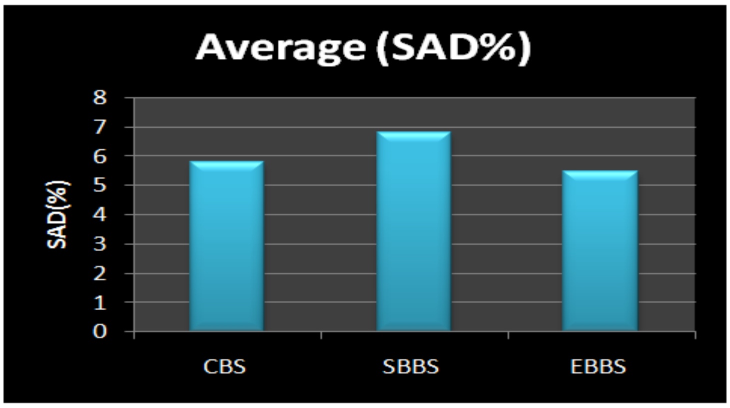

Fig. 8 Average SAD for CUPRITE

VI. Conclusion

The performance of the different band selection methods are analyzed with SGA as endmember extraction algorithm. The bands are selected using various comparisons such as constrained band selection, similarity based band selection and exemplar based band selection. And also the performance comparison between different band selection algorithms has been made using spectral angle distance. The proposed method of dimensionality reduction using exemplar based band selection method provides better band selection. The experimental results prove that the average SAD using EBBS is 0.32% lower than the average SAD using CBS and the average SAD using EBBS is 1.32% lower than the average SAD using SBBS. It has been proved that Exemplar Based Band Selection (EBBS) with Simplex Growing Algorithm (SGA) is indeed superior in endmember extraction by deriving most informative bands compared to the other band selection methods.

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