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Performance Enhancement of Minimum Volume based Hyper Spectral Unmixing Algorithms by Variational Mode Decomposition

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Abstract

Hyper spectral unmixing of data has become an indispensable technique in remote sensing zone. Spectral Unmixing is defined as the source separation of a mixed pixel. The fundamental sources are termed as endmembers and percentage of the source content is known as abundances. This paper demonstrates the effect of Variational Mode Decomposition (VMD) on hyper spectral unmixing algorithms based on geometrical minimum volume approaches. The proposed method is experimented on standard hyper spectral dataset namely, cuprite. The effectiveness of the proposed method is subjected to evaluation, based on the standard quality metric namely, Root Mean Square Error (RMSE). The experimental result analysis shows that, the proposed technique enhance the performance of hyper spectral unmixing algorithms based on the geometrical minimum volume based approaches.

Keywords: Endmember Signature, Hyperspectral Imaging (HI), Hyperspectral Unmixing (HU), Variational Mode Decomposition (VMD)

1. Introduction

Hyper Spectral Imaging is a pioneering technique introduced into remote sensing technology. Since its inception the fields of astronomy, geology and meteorology strategic ideologies were enlightened. Hyper spectral scanning or Imagery[7] collects and processes information from the electromagnetic spectrum unlike other spectral imaging techniques which limits their expertise around the visible light spectral bands. One of the primary goals of Hyper Spectral Imaging is to generate a spectrum for each pixel and thereby close analysis would reveal earth's composition and mineral layout. The merits are numerous as the technology expands over more precise transducers and sensors which can help you pick out a needle from a haystack. Hyper spectral sensors scan a vast portion and collects 3 dimensional images. Alike normal image analysis which is divided into pixels, Hyper spectral image shades each image with specific spectral bands and which further divided into pixels. The information content in each pixels will be high, this in turn helps us to obtain an accurate and detailed information analysis/extraction. Typically, hyper spectral imaging is of low spatial resolution. A mixture of different substances is present in each pixel, called as endmembers, which possesses a characteristic hyper spectral signature[2]. Some objects leave a unique fingerprint while scanned through the electromagnetic spectrum, for instance petroleum or oil fields can be easily isolated using the HSI technology. Since the recorded image will be stashed with a lot of spectral bands, unmixing is recommended to accurately estimate the abundance of each endmember in the pixel. Hyperspectral Unmixing (HU) is defined as the separation of spectral content of each pixel into various constituent spectral signatures, termed as endmembers and their abundances. The materials without any mixture are known as endmembers and the percentage

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content of each material is called as abundances[1]. The mixing models can either be linear or nonlinear[16,17] according to its mixing scale and interaction of incident light with the materials. Geometrical approaches[3] are used to derive linear mixing models. The scattering is not taken into account in these geometrical approaches. In geometrical analysis the spectral vectors of the dataset can be plotted as a simplex, whose vertices refer to the endmembers. This type of mixing occurs because the spatial resolution of the sensor is low. These geometrical based unmixing algorithms are mainly pure pixel based and minimum volume based approaches. Relevant algorithms under pure pixel category are Vertex Component Analysis(VCA)[9], Alternating Volume Maximization (AVMAX)[18], Successive Volume Maximization (SVMAX)[18], Alternating Decoupled Volume Max-Min (ADVMM)[19], Successive decoupled volume max-min SDVMM[19], N-finder[20] etc. Pure pixels may not be available in all the scenes. To avoid this problem, minimum volume based approaches are used, which works violating the pure-pixel assumption. The examples for this type are the very popular methods for unmixing namely, RMVES[5], MVSA[8] and SISAL[11], based on Craigs criterion.

In this paper, we propose a method to unmix the highly mixed hyper spectral data using Variational Mode Decomposition (VMD)[7] followed by minimum volume into a number of bands with relevant details, the well-known reconstruction technique known as, Variational Mode Decomposition (VMD) is applied to the hyperspectral dataset. The most informative mode is given as input to the minimum volume unmixing approaches such as, RMVES, MVSA and SISAL. The results of the proposed method based on Variational Mode Decomposition (VMD) enhance the performance of unmixing techniques.

The paper is structured as follows. Section 2 describes the overview of Variational Mode Decomposition (VMD). Section 3 presents the minimum volume based geometrical approaches namely, RMVES, MVSA and SISAL. The proposed method and experimental result analysis of the proposed technique is described in section 4 and 5 respectively. The concluding statements derived from this paper and future research opportunities are presented in section 6.

2. Overview of Variational Mode Decomposition (VMD)

Empirical Mode Decomposition (EMD) and Empirical Wavelet Transform (EWT) are very popular methods in the area of signal and image decomposition. Like all other decomposition methods these methods also possess some drawbacks. Empirical Mode Decomposition (EMD) has a major disadvantage of being affected by noise. However, Empirical Wavelet Transform (EWT) has replaced EMD in various applications due to its effectiveness. In EWT, wavelet filters are designed in a well-chosen boundary and the Intrinsic Mode Functions (IMF) are extracted. Here, the filters satisfy the need for perfect reconstruction. Variational Mode Decomposition (VMD) can outrun all these methods. VMD is a well-known method which decomposes an image into N number of intrinsic mode functions. This is a non-recursive model where the modes are extracted concurrently. 1D VMD is based on Wiener filtering in which an input signal is decomposed into finite number of modes (sub signals), where each mode is band limited about a central frequency[7]. These modes are called intrinsic modes.

The bandwidth of a mode is determined by means of the Hilbert transform, which gives a unilateral frequency spectrum. The frequency spectrum is shifted to baseband. The bandwidth is then estimated through the H^1 smoothness of the demodulated signal[7]. The 1D VMD is mapped to 2D in order to apply for images.

In 1D, the analytic signal is acquired by avoiding the negative frequencies. In 2D one half plane of the frequency domain is set to zero relative to $\vec{\omega}_k$. Thus initially the 2D analytic signal of interest is defined in the frequency domain.

The function to be minimized is,

$$\min_{u_k,\vec{\omega}_k}\left\{\sum\left\|\nabla\left[U_{A,S,K}(\vec{x})e^{-i\langle\vec{\omega}_k,\vec{x}_k\rangle}\right]\right\|_2^2\right\} s.t. \sum_k u_k = f$$

We can optimize for u_k and by ω_k Alternating Direction Method of Multipliers (ADMM). i.e., Minimization w.r.t. the modes u_k and minimization w.r.t. the centre frequencies $\vec{\omega}_k$ can be done. The resulting solutions after minimization are the first moments of the modes power spectrum on the half plane ω_k. 2D-VMD is superior in accuracy to manual boundary identification and separating patterns that are very close and yet distinct in spectrum. Initialization of variables is the formidable advantage of this algorithm. Qualitatively, a high leads to better separation of constituent sub signals as Wiener filtering is greatly concentrated around the centre frequency. The modes are updated by Wiener filtering, directly in Fourier domain with a filter tuned to the current centre frequency. These modes reproduce the original image. The number of modes are selected manually. Initialize the ω_k^0 for k = 1, 2,..K, randomly on any half plane. A high value of α is used while running VMD algorithm and recorded the final values of ω_k^N [7]. By repeatedly performing this for a number of times a histogram of the convergent ω_k^N is created and the K values are observed. This histogram of convergent modes captures the location of the consistent modes, and the outcome is an excellent initialization for a final clean iteration. The detailed explanation of the mathematics behind this concept is explained in[7].

3. Minimum Volume based Hyper Spectral Unmixing Approach

Under linear mixing model, hyper spectral data belongs to a simplex where the vertices become endmembers. Geometrical approach exploits the above fact and hence identifying the vertices is equivalent to finding out the endmembers. This section extend the overview of three minimum volume based, geometrical approaches specifically RMVES, MVSA and SISAL. Robust Minimum Volume Enclosing Simplex analysis (RMVES)[5] is a well-organized, non-pure pixel based algorithm proposed by ArulMurugan Ambikapathi et al[8]. This comes under geometrical algorithms[10] and works on the support of minimum volume assumption. Craig developed an unmixing technique, based on an instinct, which does not require the pure-pixel assumption. The endmembers are estimated using a minimum-volume simplex which includes all the observed pixels in the given data set. And identifying the vertices is just like finding out the endmember. Minimum Volume Simplex Analysis (MVSA)[8] and Simplex Identification via Split and Augmented Lagrangian (SISAL)[11] are two non-pure pixel based unsupervised unmixing algorithms proposed by Jose M. Baoucas-Dias et al. In MVSA the hard nonconvex optimization problem, to fit a minimum volume simplex to the unmixed data is solved. A good initialization is done here with Vertex Component Analysis (VCA)[9], since it is fastest method among other pure pixel-based methods. Using Sequential Quadratic Programming (SQP) methods, the optimization problem is solved, and is described in[8]. In SISAL, hinge type soft constraints replaces the positivity hard constraints. The strength of the soft constraint is controlled by regularization parameter. According to this approach the advantages of replacements are like robustness to noise, outliers, poor initialization and it also deal with large problems. To solve the hard non convex optimization problem, i.e, to obtain a constraint formulation, variable splitting is used followed by an augmented Lagrangian technique. The mathematics behind this problem is explained in[11] Regularization parameter $\lambda > 0$ controls the amount of regularization. The soft constrained formulation results are robust to outliers, noise and poor initialization[12]. Replacement of $n \times p$ equality constraints with a regularizer, solves the large scale problems. Thus SISAL[11] is a modified version of MVSA, explained above and an efficient method that solves the problem of spectral unmixing.

4. Proposed Method

The hyper spectral image taken for the experiment is first given as the input for an adaptive decomposition algorithm called Variational Mode Decomposition (VMD). VMD decomposes the image into few different modes or sub-images of separate spectral bands. Here the number of modes is 3. Each modes are given as the input to the 3 minimum volume based unmixing algorithms namely RMVES, MVSA and SISAL. The result of the unmixing algorithms are validated using a standard quality metric called Root Mean Square Error (RMSE). Among the three modes the mode which gives the lowest RMSE is selected as the best mode.

5. Experimental Results and Analysis

The hyper spectral image data used in this experiment is the Cuprite data, acquired by Airborne Visible/IR Imaging Spectrometer (AVIRIS) sensor over NEVADA, U.S in 1997[13]. In this work, dataset containing 188 bands and 250191 pixels in the spectral range of 400-2500nm, which excludes the bands with low SNR are used to experiment the proposed method[14]. The effectiveness of the proposed method is evaluated based on the well-known quality metric called Root Mean Square Error (RMSE)[15]. A non-recursive characteristics extraction technique called Variational Mode decomposition (VMD) is applied prior to the unmixing techniques. It sparsely decomposes images in a well-founded manner with minimal parameters and no explicit interpolation. In VMD, an image is decomposed into an ensemble of band-limited intrinsic mode functions with limited bandwidth, here we took

Table 1. Perfomance evaluation of our proposed method based on RMSE values

p	RMVES	Proposed method (VMD+RMVES)	MVSA	Proposed method (VMD+MVSA)	SISAL	Proposed method (VMD+ SISAL)
3	0.0079	0.0039	0.8427	0.5254	1.0209	0.7104
4	0.0061	0.003	0.6564	0.5881	0.7391	0.5314
5	0.0061	0.0027	0.5110	0.5162	0.7391	0.5263
6	0.0047	0.0023	2.2762	0.5382	1.0079	0.5902
8	0.0035	0.0015	0.6043	0.5804	1.0740	0.7733

the number of modes equal to 3. The modes are updated by simple Wiener filtering. We have done the unmixing techniques with all the three modes and selected the best mode which gives least RMSE and finalizes the results. To enhance the performance of proposed methods, the balancing parameter $\alpha = 5000$, time step $\tau = 0.25$ tolerance tol = $K * 10-6$ where k=3 the number of modes here, are initialized. Table 1 shows the performance comparison of our proposed method with RMVES, MVSA and SISAL respectively based on RMSE values calculated for different number of endmembers (p). From the results, it is clear that the Root Mean Square Errors (RMSE) obtained after applying VMD (proposed method) is much better than the result without VMD. By our proposed methods the average RMSE obtained is reduced from 0.007892 to 0.0039 for p = 3 and from 0.0035 to 0.0015 for p = 8 (RMVES). Among the three hyper spectral unmixing algorithms (RMVES, MVSA and SISAL), our proposed method based on VMD enhance the performance of all the three algorithms for various endmembers. These results highlights the quality improvement of unmixing techniques by our proposed method based on Variational Mode Decomposition (VMD).

6. Conclusion

This paper presents an image segmentation and directional decomposition method called VMD, to improve the performance of minimum volume based unmixing techniques. In this work the three minimum volume based unmixing algorithms are used, specifically RMVES, MVSA and SISAL which have been tested on standard hyper spectral data. The standard quality metric, RMSE, is used to validate the results. The tabulated quality metric for the dataset used in this experiment shows that the performance of the proposed method outperforms the existing minimum volume hyper spectral unmixing methods. From the experimentation, it is noticed that the application of VMD enhances the performance of endmember identification algorithms. VMD can be used to enhance the performance of other existing geometrical spectral unmixing algorithms, as a future work.

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