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Low dimensional variational mode features for hyperspectral image classification

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ABSTRACT

High Dimensionality is always a great concern while working with hyperspectral images. The high dimension of hyperspectral image increases the computational complexity, creates data storage issues and decrease the performance and accuracy of hyperspectral image analysis algorithms. This paper focuses on low dimensional Variational Mode features for hyperspectral image classification. The proposed method consist of three stages: preprocessing using Inter Band Block Correlation (IBBC) technique, feature extraction using Variational Mode Decomposition (VMD) and dimensionality reduction using Singular Value Decomposition (SVD). The efficiency of the proposed method based on the low dimensional feature extraction using VMD is evaluated by one of the sparsity based classification algorithms namely Orthogonal Matching Pursuit (OMP). The proposed work is experimented on the standard dataset namely Indian pines acquired by the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS). The experimental analysis shows that our proposed technique produces 90.88% overall accuracy with 40% of training which is greater than the classification accuracy obtained without feature extraction.

KEY WORDS: Inter Band Block Correlation, Variational Mode Decomposition, Singular Value Decomposition, Band Selection, Classification, Orthogonal Matching Pursuit.

1. INTRODUCTION

Increased use of hyperspectral images in wide area of application increases the need for various processing techniques on the data. The high dimensionality of the hyperspectral images makes this task further difficult by computational complexity and data storage issues. Also, there is likely to be high correlation between the neighboring bands of the hyperspectral image and few of the bands doesn't contain significant information. These problems are avoided by making use of efficient dimensionality reduction techniques or proper band selection methods. Dimensionality Reduction techniques include Principal Component Analysis (PCA), Kernel Principal Component Analysis (KPCA) etc. Here, the high dimensional data is transformed to a low dimensional space without any loss in the data or, it can also be considered as summarizing of the high dimensional data in a low dimensional space. Band selection methods include the extraction of independent bands from the hyperspectral data cube. There are various band selection algorithms based on Singular Value decomposition, Wavelet, Independent component analysis (ICA), Mutual Information, Constraint energy, Support Vector Machines etc. One of the commonly preferred algorithms among these is the Singular Value Decomposition which effectively extracts the independent bands. But, the calculation of the covariance matrix makes the algorithm a complex technique.

The Mutual Information based band selection method measure the statistical dependence between two random variables and therefore evaluates the relative utility of each band to classification. It heavily relies on the availability of a reference map usually obtained by ground surveys, which can be reviewed as the significant weakness of the method. In Independent Component Analysis (ICA) method, the average absolute weight coefficients of individual spectral bands are compared to select the bands that contain maximum information. The constrained energy based band selection relies on the concept of Constrained Energy Minimization (CEM). The Singular Value Decomposition method overlies all these methods as it deals the band selection in the multivariable fashion whereas, other methods uses greedy approach for the same.

In this paper, we focus on low dimensional Variational Mode features for hyperspectral image classification. In our proposed method, we have incorporated the preprocessing technique known as Inter Band Block Correlation (IBBC), Variational Mode Decomposition (VMD) is used as a feature extractor followed by dimensionality reduction by Singular Value Decomposition method. IBBC is a preprocessing algorithm used to automatically remove the noisy bands and water absorption bands in hyperspectral images. This approach is based on the average inter band block wise correlation coefficient measure with a simple thresholding strategy. Variational Mode Decomposition decomposes the input hyperspectral band into a number of two dimensional (2D) modes based on their respective center frequencies, such that the band limited modes reproduce the input band. Singular Value Decomposition (SVD) finds a subset of the hyperspectral image by extracting the best bands from the hyperspectral data cube. The efficiency of the proposed method is validated using one of the sparsity based classification method known as Orthogonal Matching Pursuit.

Variational mode decomposition (VMD): Variational Mode Decomposition focuses on decomposing an input signal into discrete number of sub-signals (modes) that have specific sparsity properties while reproducing the input.

The modes are compact around a center pulsation ω_k, and is determined during the decomposition. The VMD algorithm can be summarized as:
a) The unilateral frequency spectrum is obtained by computing the associated analytic signal for each mode using Hilbert transform.
b) The mode's frequency spectrum is shifted to the baseband. This is achieved by mixing the mode's frequency spectrum with the exponential which is tuned to the estimated center frequencies.
c) The H1 Gaussian smoothness of the demodulated signal estimates the bandwidth.

Two dimensional variational mode decomposition: The Two Dimensional (2D) Variational Mode Decomposition is non recursive 2D decomposition model. The method extracts the modes concurrently [10]. The input hyperspectral band is decomposed into a number of 2D modes and respective center frequencies by the model. In 2D, one half-plane of the frequency domain is set to zero and the analytical signal is chosen relative to the vector ω_k, the center pulsation. Whereas, in ID, the analytic signal is achieved by suppressing the negative frequencies. The 2D analytic signal, $u_{AS,k}(\vec{x})$ can be defined as,

$$\hat{u}_{AS,k}(\omega) = (1+\mathrm{sgn}(\vec{\omega}.\vec{\omega}_k))\hat{u}_k(\vec{\omega}) \quad (1)$$

redefining based on the Fourier properties as,

$$\hat{u}_{AS,k}(\vec{x}) = \hat{u}_k(\vec{x}) * (\delta(<\vec{x},\omega_k>) + \frac{j}{\pi<\vec{x},\omega_k>})\delta(<\vec{x},\omega_k>) \quad (2)$$

Where, $u_k(\vec{x})$ denotes each mode and * denotes convolution. From this definition of 2D analytic signal, the functional to be minimized can be defined as,

$$\min_{u_k,\vec{\omega}_k}\left\{\sum_k \left\|\nabla\left[u_{AS,k}(\vec{x})e^{-j<\vec{\omega}_k,\vec{x}}\right]\right\|_2^2\right\} \quad (3)$$
$$st, \sum_k u_k = f$$

Where, *f* is the original image. Proceeding with Alternate Direction Method of Multiplier optimization to address the reconstruction constraint, u_k and ω_k are optimized by considering the 2D analytic signal. In fourier domain, the functional with the augmented Lagrangian can be written as,

$$\hat{u}_k^{n+1} = \underset{\hat{u}_k}{\arg\min}\, \alpha\left\| j(\vec{\omega}-\vec{\omega}_k)\left[(1+\mathrm{sgn}(\vec{\omega}.\vec{\omega}_k))\hat{u}_k(\vec{\omega})\right]\right\|_2^2 + \left\|\hat{f}(\vec{\omega}) - \sum_k \hat{u}_i(\vec{\omega}) + \frac{\hat{\lambda}(\vec{\omega})}{2}\right\|_2^2 \quad (4)$$

Which yields the Wiener filter result,

$$\hat{u}_k^{n+1}(\vec{\omega}) = \left(\hat{f}(\vec{\omega}) - \sum_{i\neq k}\hat{u}_i(\vec{\omega}) + \frac{\hat{\lambda}(\vec{\omega})}{2}\right)\frac{1}{1+2\alpha\left|\vec{\omega}-\vec{\omega}_k\right|^2} \quad (5)$$
$$\forall \vec{\omega}\in\Omega_k : \Omega_k = \{\vec{\omega}\,|\,\vec{\omega}.\vec{\omega}_k \geq 0|\}$$

Optimizing for $\vec{\omega}$ is similar to the one dimensional (1D) VMD case, except that now we are considering the domains to be the half-planes (that is, we have two components). The update goal is:

$$\hat{\omega}^{n+1} = \underset{\vec{\omega}_k}{\arg\min}\left\{\alpha\left\| j(\vec{\omega}-\vec{\omega}_k)\left[1+\mathrm{sgn}(\vec{\omega}.\vec{\omega}_k)\hat{u}_k(\vec{\omega})\right]\right\|_2^2\right\} \quad (6)$$

Where, α is the bandwidth constraint. The minimization is solved by letting the first variation w.r.t. $\vec{\omega}_k$ vanish. The resulting solutions are the first moments of the mode's power spectrum $|\hat{u}_k(\vec{\omega})|^2$ on the half-plane Ω_k :

$$\vec{\omega}_k^{\,n+1} = \frac{\int_{\Omega_k} \vec{\omega}_k\left|\hat{u}_k(\vec{\omega})\right|^2 d\vec{\omega}}{\int_{\Omega_k}\left|\hat{u}_k(\vec{\omega})\right|^2 d\vec{\omega}} \quad (7)$$

Band Selection using Singular Value Decomposition: The singular value decomposition (SVD) can be defined as the factorization of a real or complex matrix. Let 'M' be a matrix of size *m* x *n*, Singular Value Decomposition decomposes the matrix to the form $M = U\Sigma V^T$. Where, U is the real (complex) unitary matrix of size *m* x *m*, Σ is the rectangular diagonal matrix (non-negative real numbers on the diagonal) of size *m* x *n*, and V^T is a real (complex) unitary matrix of size *n* x *n*. The diagonal entries of Σ are the singular values of M.
The SVD based band selection method can be summarized as:

The hyperspectral image under consideration is ordered into a matrix form as explained below.
The matrix, M (m x n x b), the matrix with m rows, n columns and b bands is ordered to A (mn x b), mn is the total number of pixels in each image band.
The SVD of the matrix A is then calculated using the equation,

$$A = U \Sigma V^T \quad (8)$$

Where, U= [u_1,u_2,....,u_n] is the orthogonal matrix of the singular vector and V=[v_1,v_2,....,v_n] is the orthogonal matrix of the right singular vector. Σ =diag(σ_1, σ_2, ..., σ_n), σ_i is the ith-singular value of A.
The subset selection is formulated as the problem to find the permutation matrix P. The Permuted matrix is obtained by multiplying A with P.

The matrix A and the Permuted Matrix $\bar{A}$ can be related as,

$$\bar{A} = AP = U \Sigma V^T P \quad (9)$$

The Permutation matrix P is generated from the rank deficient QR decomposition of the matrix V_1^T, which can be written as,

$$V_1^T P = QR \quad (10)$$

The permutation matrix P reorders the columns of the original matrix A, with the desired independent bands available in first l columns of the Permuted matrix.
Orthogonal Matching Pursuit: Orthogonal Matching Pursuit is one of the most basic greedy algorithms which is widely used because of its simplicity to implement and analyze. The method seeks to update the estimate of the signal without taking into account the global structure. It exactly adds one atom to the signal at every iteration. Let b be the observation and A be the measurement matrix, start with $x=0$, and the residual $r=Ax-b$. Also, the hyperspectral data is b-dimensional. Every step of the algorithm consists of two parts: Selecting atom i, which is most correlated with the residual r and updating x by solving the least squares problem using the atoms that have been selected.
OMP based Classification: The two stages of the classification algorithm include the computation of the sparse vector using OMP algorithm and assigning the class labels to the test pixel by finding the residue. The inputs to the classifier include, the Dictionary matrix (matrix formed by concatenating randomly selected training samples from each class) A, the test pixel vector b of size $D \times 1$ and Sparsity level K. And, the output of the system is the sparse vector x_k with K non-zero entries. The implementation steps of the algorithm can be found in the paper.

2. METHODOLOGY

High Dimensionality is a major concern under consideration while working with hyperspectral images. We incorporate Singular Value Decomposition based band selection method to overcome this problem. The result of our proposed method is validated using sparsity based classification. The effectiveness of the proposed algorithm is proved by the classification accuracy parameters: Average accuracy, Overall accuracy and Classwise accuracy. The steps involved in the experiment can be summarized in four steps: preprocessing using Inter Band Block Correlation (IBBC) method, Feature Extraction using Variational Mode Decomposition (VMD), Band selection based on Singular Value Decomposition (SVD) and Validation using Classification. Fig. (1) Shows the flowchart being followed for the proposed work.

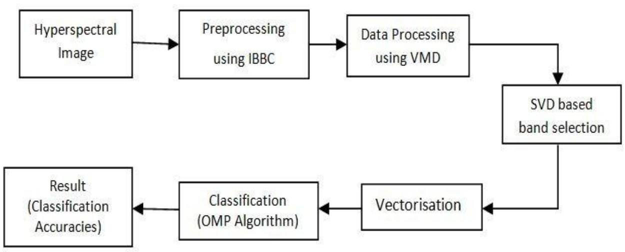
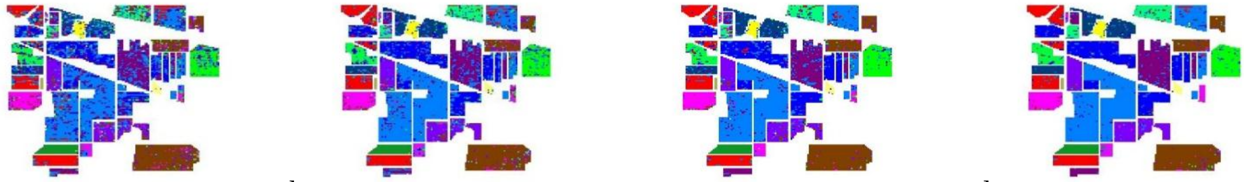


Fig.1.Flowchart of the proposed method



a b c d

Fig.2.Classification maps of the proposed method for Indian pines dataset

(a), (b): classifications results for 30%, 40% data used for training for the proposed method on 50 bands.

(c), (d): classifications results for 30%, 40% data used for training for the proposed method on 75 bands.

Preprocessing: Preprocessing is the processing performed on raw hyperspectral data. High dimensional image datasets are collected simultaneously by the hyperspectral remote sensors in dozens or hundreds of narrow, adjacent spectral bands. The preprocessing is an inevitable process while working with hyperspectral images, as the computational complexity is high. Here, the noisy bands and the water bands are removed automatically using Inter band block correlation (IBBC) method. IBBC, the preprocessing algorithm is defined based on the average inter band block wise correlation coefficient measure with a thresholding strategy. The noisy bands and the water absorption bands are removed by the process. The remaining bands are given as input to the Variational Mode feature extraction process.

Feature Extraction: The preprocessed data was given as input to the Variational Mode decomposition (VMD). VMD adaptively decomposes the experimental data set into few different modes of separate spectral bands, which are unknown. The number of modes to which each band has to be decomposed is specified by the number K. The parameter K is user defined. The generated modes are concatenated to reproduce a hyperspectral cube of dimension $m \times n \times (Kb)$ where, $m \times n$ is the dimension of each band and b refers to the total number of bands, (Kb) is the total number of bands obtained as a result of VMD. The Variational Mode Decomposition acts as a feature extractor during the process. Best bands are chosen from the hyperspectral cube which is feature extracted using VMD.

Band Selection: The Variational Mode Feature extracted data undergoes the process of band selection using Singular Value Decomposition (SVD) method which effectively reduces the dimensionality. The process involved in SVD based band selection/Dimensionality reduction includes the following steps. Conversion of the hyperspectral cube obtained as a result of Variational Mode decomposition to a 2D matrix representation. SVD of this matrix is computed to find the effective rank. The QR factorization is computed to obtain the permutation matrix P and this P matrix is used to reorder the columns of A by $\overline{A}=AP$. The first l columns of $\overline{A}$ will give the independent bands.

Classification: Identifying and classifying the constituent elements of a scene to their respective categories defines the classification process. Here, the scene is classified mainly into c classes. The background pixels are not considered for classification. Orthogonal Matching Pursuit is one of the widely used algorithms, as it is one of the simplest algorithms to implement and analyze. Initially, pixels of the hyperspectral data under consideration are separated into training and testing samples. Sparse representation of the test sample with respect to the training sample is obtained from the dictionary matrix generated by random selection of pixels from each class.

Experimental Results: The experiments were conducted on the standard hyperspectral dataset acquired by the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) sensor operated by the National Aeronautics and Space Administration Jet Propulsion Laboratory.

Dataset Description: The Indian Pines consists of 224 spectral bands with spectral bands defined in the wavelength range of 400-2500nm. Spatial resolution of these spectral bands is 20m per pixel and they have a nominal spectral resolution of 10nm. The image was collected by the AVIRIS instrument on June 12, 1992 over a 2x2 mile portion of Northwest Tippecanoe, Indiana. The image size is 145 x 145 pixels per band and the ground truth of the scene provides information of 16 mutually exclusive classes in which one class represent building, five classes represents vegetation types. The background pixels (represented as white) are not considered during classification. Figure 3(a) shows a band from the Indian pines dataset with 224 bands and 3(b) shows the ground truth of the Indian pines dataset.

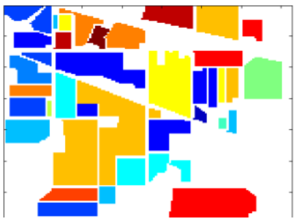


Fig. 3: (a): Sample band of Indian Pines dataset, (b): Ground truth of Indian Pines dataset

Accuracy Assessment Measures: The Classification Accuracy can be calculated using the statistical measurements obtained from the confusion matrix (classification error matrix). Confusion matrix is generated by comparing the results obtained by classification to a reference data (ground truth data). Confusion matrix is a square matrix with size max (class labels), with the main diagonal giving the correctly classified pixels and the non-diagonal elements giving the misclassified pixels. The analysis is carried out by considering the classification accuracies before and after applying Variational mode decomposition. The statistical parameters considered are Overall accuracy (OA), Average Accuracy (AA) and the Class wise accuracies.

Table.1.Classification accuracies of the proposed method for Indian pines dataset when 30%, 40% data is used for training on 50 bands and 75 bands

No of Bands	**50**				**75**			
Training Pixel (%)	**30**		**40**		**30**		**40**	
Class	**Without Feature Extraction**	**Proposed method**	**Without Feature Extraction**	**Proposed method**	**Without Feature Extraction**	**Proposed method**	**Without Feature Extraction**	**Proposed method**
1	93.48	91.3	89.13	97.83	86.96	93.48	91.3	97.83
2	68.7	83.89	75.21	87.68	70.03	82.14	74.93	90.41
3	69.64	88.67	72.89	92.05	76.02	89.28	81.2	91.93
4	62.03	82.7	73.42	81.43	71.31	82.28	79.32	88.19
5	93.79	84.68	96.27	89.65	94.41	85.3	95.86	90.27
6	97.12	83.84	97.81	90.96	96.99	81.78	97.81	93.15
7	96.43	96.43	92.86	92.86	100	89.29	100	96.43
8	97.07	84.52	98.54	88.91	97.49	88.49	98.12	91.63
9	100	100	100	100	100	100	100	100
10	73.46	80.25	78.09	89.4	78.19	83.02	82.92	90.23
11	81.47	92.3	84.48	95.48	81.14	92.55	85.38	95.48
12	66.1	73.19	72.01	83.98	65.77	81.79	75.55	87.86
13	99.02	99.51	98.54	97.56	99.51	99.51	99.02	100
14	95.02	93.04	96.92	94.15	96.36	93.44	95.65	93.68
15	66.84	77.46	67.62	84.97	68.39	72.8	73.32	86.53
16	97.85	87.1	100	87.1	95.7	86.02	96.77	90.32
OA	80.81	86.69	84.22	91.06	82.31	87.23	85.90	92.29
AA	84.88	87.43	87.11	90.88	86.14	87.57	89.20	92.74

3. RESULTS AND DISCUSSION

The experiments were carried out with the proposed method on the Indian pines dataset. The classification accuracy assessment parameters obtained by our technique is compared with the data which is not feature extracted using Variational Mode Decomposition. The classification is carried out with 30% and 40% data pixels for training. The Variational Mode feature extractor divides each band into two modes resulting a higher dimension. The SVD based band selection process extracts 50/75 (which is very low when compared with the original dimension of the dataset). Table I shows the classification accuracies obtained while 50 bands and 75 bands were chosen for classification from the Variational Mode feature extracted dataset. Fig.(2) shows the classification maps obtained for Variational Mode feature extracted dataset when 30% and 40% data pixels were used for training for 50/75 selected bands. From table I, it can be noted that, for 50 selected bands, the overall classification accuracy obtained is 91.06% when 40% data pixels are used for training (overall classification accuracy of 50 bands which is not subjected to feature extraction is only 84.22%). Similarly, 75 selected bands shows an improvement in overall accuracy from 85.90% to 92.29% when 40% data pixels are used for training.

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