# A STUDY ON APPLICATION OF VARIATIONAL MODE DECOMPOSITION ON HYPERSPECTRAL IMAGE CLASSIFICATION

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**Abstract**
**Interpretation of information from hyperspectral images is difficult because of its huge volume of data. The difficulty in analysing the data accounts for the presence of distortion from atmosphere and the impure pixels which occur during the acquisition of data.Many denoising techniques have been introduced to reduce the dimensionality of the data as well as removing the distortions.The work proposes the application of two dimensional Variational Mode Decomposition(VMD) to the acquired image.VMD decomposes the image into different intrinsic mode functions(IMFs). The lower order modes are removed and the higher ones are combined to reconstruct the original image. The modes are used as features for classification using Orthogonal Matching Pursuit. Comparison of accuracy is made using a single mode as feature and using 4 modes as the features.**
**Index Terms: Hyperspectral image,Intrinsic Mode Functions(IMFs), Orthogonal Matching Pursuit, Variational Mode Decomposition(VMD).**

## I. INTRODUCTION

Remote sensing is the acquisition of information about an object or phenomenon without making physical contact with the object. Hyperspectral sensors measure reflected radiation at a series of narrow and contiguous spectral bands typically hundreds of bands. This characteristic of hyperspectral imagery provides for potential for more accurate and detailed information extraction.

Hyperspectral imagery consists of a wealth of data, but interpreting it is a difficult task for its large data volume, atmospheric distortion and impure pixels. The analysis process is characterized by data that contain a high degree of redundancy. Thus it is necessary to compress the hyperspectral data set without significant losses in the spatial and spectral features. The dataset is then subjected to classification.

The proposed work aims to improve the accuracy of the hyperspectral image classification by using bidimensional variational mode decomposition (VMD) on the data set.

In [1], noise reduction using hybrid spatial-spectral derivative domain wavelet shrinkage is proposed. It uses soft thresholding to reduce noise in hyperspectral data cube. In [2], hyperspectral image denoising employed a spectral-spatial adaptive variation model. The work could realize the spectral-spatial adaptive mechanism in the denoising process, and superior results were produced. [3] demonstrated superior performance on simulated and measured data.

In [4], hyperspectral image denoising was done by means of sparse representation and low rank constraint. Good denoising results were produced. However, the method was slow in computation time. [5] contained denoising hyperspectral imagery using PCA and wavelet shrinkage. In this paper principal component analysis(PCA) was used to preprocess data cubes and then reduce the noise in the noisy PCA components but keep the first few PCA components untouched. The inverse PCA generates the denoised data cube. In [6] hyperspectral image processing by jointly filtering wavelet component tensor was performed. Here, after noise whitening, a multi-dimensional wavelet packet transform in tensor form is presented to find different component tensors. A multi-way Weiner filter is introduced to jointly filter a component tensor in each mode. To determine the best transform level and the basis of multidimensional wavelet packet transform, a risk function is proposed.

In [7], a survey on hyperspectral image denoising methods based on tensor decompositions was presented. It showed that multi-dimensional wavelet packet transform ad multiway weiner filter is a suitable tool for denoising especially when there exists small targets in hyperspectral images. Analysis and denoising of hyperspectral remote sensing image in the curvelet domain was presented in [8]. The proposed algorithm effectively removed the common speckle noise and strip noise and at the same time, maintained more fine features during denoising process.

[9] introduced noise removal from Hyperspectral images by multidimensional filtering. Comparative studies with dimensional weiner filtering, wavelet thresholding, and channel-by-channel weiner filtering showed that the algorithm provides better performance while restoring impaired HYDICE hyperspectral images. In [10], denoising and dimensionality reduction in hyperspectral images using wavelet packets, neighbour shrinking and Principal Component Analysis(PCA) is proposed.[11] performed hyperspectral image denoising using a spatial-spectral Monte-Carlo sampling approach. The method was tested on both simulated and measured hyperspectral images.The results demonstrated that the proposed method is capable of largely removing the noise while also preserving image details very well. Spectral-spatial kernel regularized for hyperspectral image denoising was presented in [12]. It was inspired by the observations that the spectral-spatial information is highly redundant in hyperspectral images, which is sufficient to estimate their clear images. The method maintained the spectral correlations in spectral dimension and matches the original structure between two spatial dimensions. It suppressed noise in the high noise band and preserved information in low noise band. [13] proposed enhanced unmixing based hyperspectral image denoising using spatial preprocessing. It used spatial-spectral preprocessing prior to spectral unmixing guide the endmember extraction process to spatially homogeneous regions. Enhanced end member extraction performance leads to enhaced denoising performance.

Denoising techniques in adaptive multi-resolution domains with application to biomedical images was presented in [14]. It presented a comparative study of a wide range of image denoising techniques when applied to biomedical images in empirical mode decomposition (EMD) and variational mode decomposition (VMD) domains. It was observed that several denoising techniques performed better in EMD domain. However, a single denoising technique gave better results in VMD domain. In [15], empirical mode decomposition of hyperspectral images for SVM classification is presented. EMD is used to increase the classification accuracy using SVM classification. It decomposes the hyperspectral images to intrinsic mode functions and a final residue. EMD performs a decomposition that is spatially adaptive with respect to intrinsic features. In [16], composite kernels are used to combine spatial and spectral features of hyperspectral images to provide higher accuracy compared with that of using spectral information only. In [17] classification of hyperspectral data from urban areas based on extended morphological profiles is presented.Initially. theprincipal components of hyperspectral data are obtained.Morphological profiles are constructed by opening and closing operations on principal components. They are directly used for classification with a neural network. In [18], spectral and spatial classification of hyperspectral data using support vector machines and morphological profiles are presented. Here, morphological features are fused with original features for SVM classification.

## II. VARIATIONAL MODE DECOMPOSITION

Variational Mode Decomposition is an adaptive and variational method for signal decomposition.This method was proposed by Dragomiretskiy and Zosso in 2013. The one dimensional VMD is used to decompose a sign Variational Mode Decomposition is an adaptive and variational method for signal decomposition.This method was proposed by

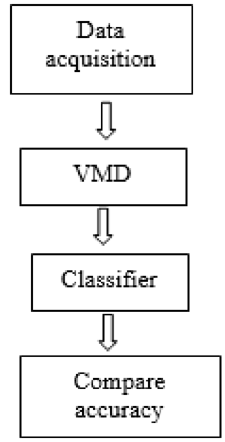
Dragomiretskiy and Zosso in 2013. The one dimensional VMD is used to decompose a signal in the time domain into discrete number of sub signals, also called al in the time domain into discrete number of sub signals, also called modes.There are also called Intrinsic Mode Functions(IMFs)[19] or AM-FM signals. Each mode has limited bandwidth in the spectral domain and is compact around a center frequency. The main goal of VMD is to decompose a real valed input signal f into discrete number of modes,uk,which have speci_c sparsity while reproducing the input.The sparsity property is chosen to be the bandwidth of each mode in its spectral domain.The center frequency of each mode is to be determined along with decomposition.

For images, two dimensional variational mode decomposition is adopted. 2D VMD adaptively decomposes an image into few different modes of separate spectral bands.These modes have limited bandwidth around their center frequencies.These modes are amplitude-frequency modulated(AM-FM) 2D signals.Such a mode has limited spatial support[20] [21].

## III. METHODOLOGY

The flowchart of the proposed work is shown .It consists of acquiring the data and then application of VMD on the image. The dataset used is the Indian Pine image acquired from the AVIRIS sensor. The hyperspectral AVIRIS Indian Pine image with ground truth reference is available from [22]. The area comprises one third forest and two third agricultural land and is composed of 145x145 pixels and 220 bands. VMD is an adaptive technique that decomposes the original image into two dimensional bandlimited modes. These modes upon reconstruction provides the original image.

These modes are then used as features for classification. The classifier used is orthogonal matching pursuit(OMP)[23]. Results are compared by taking a single mode as feature and all the modes as features.




## IV. EXPERIMENTS AND RESULTS

Variational mode decomposition is applied on the Indian Pines dataset which consist of 224 spectral bands collected by the AVIRIS instrument on June 12th 1992. The image size is 145 x 145 and the ground truth of the scene provides information about 16 mutually exclusive classes. VMD decomposes the image into 4 modes. The following results are obtained:

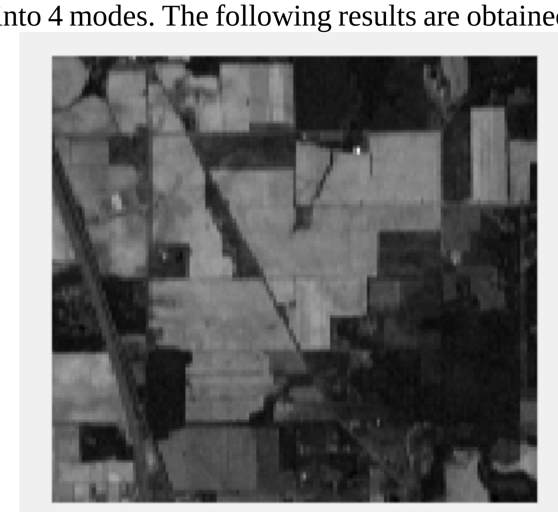


Fig.1 Input Image

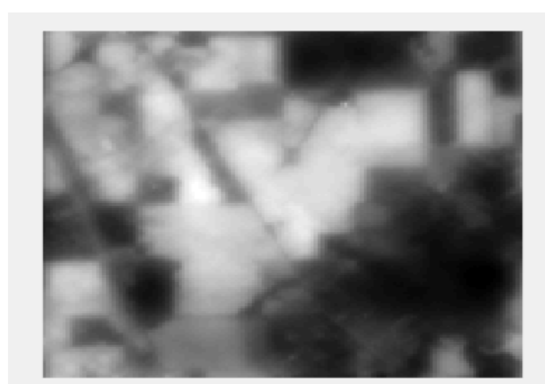
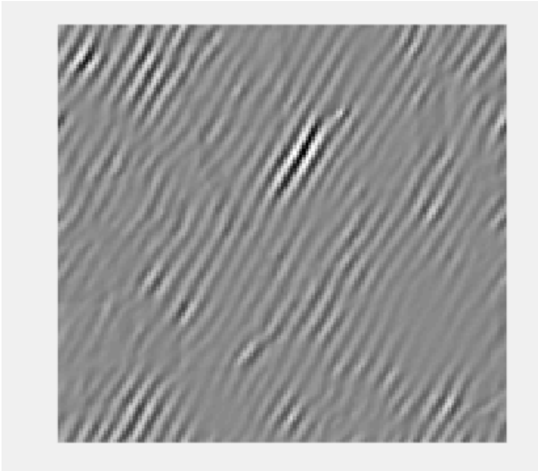
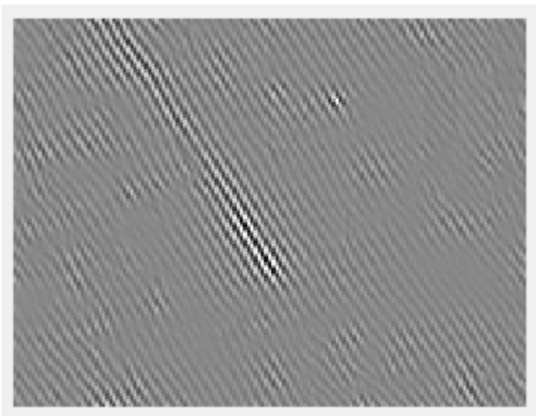


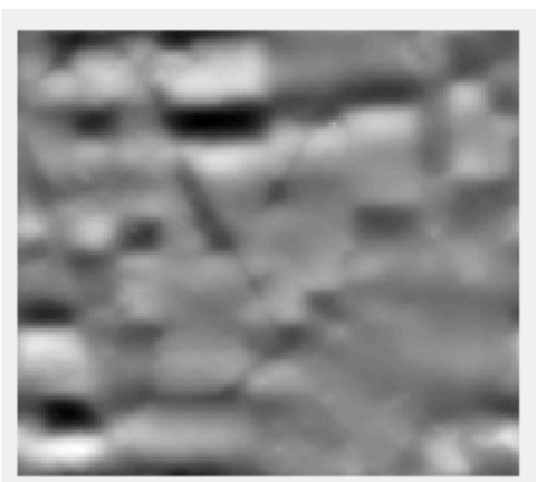
Fig 2.(a) Mode1



(b)Mode2



(c)Mode3



(d)Mode4

The modes are then used as features for classification. The modes are given to the OMP classifier. The dataset is classified into 16 classes. The accuracy for each class is found. Also, the overall accuracy is found.

| CLASS | SINGLE MODE | 4 MODES |
|---|---|---|
| ALFALFA | 100 | 97.83 |
| CORN-NOTILL | 61.76 | 50.63 |
| CORN-MIN | 44.34 | 29.28 |
| CORN | 89.45 | 78.90 |
| GRASS/PASTURE | 79.50 | 54.87 |
| GRASS/TREES | 66.58 | 36.44 |
| GRASS/PASTURE-MOWED | 100 | 100 |
| HAY-WINDROWED | 94.98 | 56.07 |
| OATS | 100 | 100 |
| SOYABEANS-NOTILL | 78.09 | 65.33 |
| SOYABEANS-MIN | 60.77 | 31.16 |
| SOYABEAN CLEAN | 73.69 | 47.05 |
| WHEAT | 91.71 | 73.17 |
| WOODS | 86.96 | 31.62 |
| BLDG-GRASS-TREE-DRIVES | 91.71 | 70.73 |
| STONE STEEL TOWERS | 90.32 | 88.17 |
| OVERALL | 71.17 | 45.17 |
| AVERAGE | 81.87 | 63.2 |

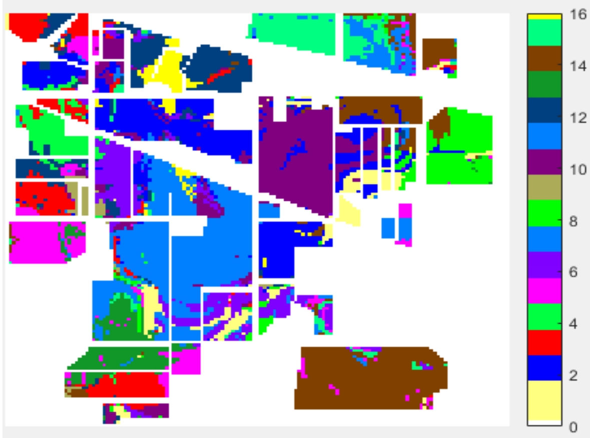


Fig. 3 Classified image for single mode.

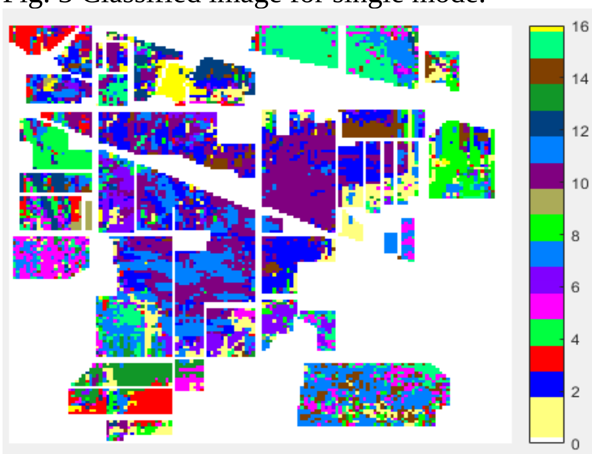


Fig.4 Classified image for all the modes

It is observed that the overall accuracy and average accuracy are higher when a single mode,preferably the first mode is selected as feature for classification. The first mode has higher information content compared to other modes.

## V. CONCLUSION

In this paper Variational Mode Decomposition is applied to hyperspectral image dataset of Indian Pines acquired by the AVIRIS sensor.The extracted modes are used as features for classification.The classification accuracy is compared for classification using a single mode and all the modes. It is observed that greater accuracy is achieved for classification using a single mode,preferably the first mode.Future works may include improving accuracy using other classifiers.

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