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Convex Denoising of Hyperspectral Images Using Non-Convex Tight Frame Regularization for Improved Sparsity Based Classification

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Abstract : Hyperspectral images contain large spectral and spatial information's and hence it is widely used in the field of remote sensing for various application such as urban planning, disaster management and land use land cover classification. However, these images are usually corrupted by various kind of noises and which adversely affect the quality of images. In order to resolve thisissue, various preprocessing technique are exploited while dealing with hyperspectral images. convexdenoising using non-convex tight frame regularization technique is proposed as a preprocessing technique . After preprocessing, the images are classified using Orthogonal Matching Pursuit (OMP) algorithm. The classification results are evaluated interms of accuracy assessment measures. Also, the impact of the proposed preprocessing stageis compared with classification results of existing denoising techniques such as Total Variation(TV)denoising and wavelet based denoising.

Keywords : Denoising, Hyperspectral image classification, Convex denoising, Tight frame regularization, Orthogonal Matching Pursuit.

1. INTRODUCTION

Hyperspectral Imagecapturing involves obtaining of detailedinformation in form of image with both spatial and spectral information. It is an n-dimensional data with 1D spectral information and 2D spatial resolution. The image arefwith the reflection, absorption or emission of the radiation illuminated. Every image or band represents a range of wavelength in electromagnetic spectrum. These images are stacked in layers to form a data structure for further process[1]. Hyperspectral sensors capturesnumber of wavelengths at a time, but it is not the number of wavelengths which makes it hyperspectral, it is the range and contiguousness of the measurements. A hyperspectral measurement will be narrow and contiguous in wavelength. Hyperspectral data can be used obtain sub-pixel information of the image. Multispectral image bands are discrete whereas the hyperspectral image bands are continuous. Multispectral sensors will not provide the spectrum of the object whereas hyperspectral sensor will provide the spectrum of the object[2]. Thus, hyperspectral images provide high details of the object which is not obtained using multispectral images. However these images are liable to various noises, which degrades the quality of images and reduces the accuracy of classification[3]. Therefore it is necessary to employ various preprocessing techniques like denoising to improve the quality of images and hence the classification accuracy [4].There are mainly two kinds of noises present in hyperspectral images: (1) signal dependent noise, (2) signal independent noise.

Hao yang et al.,[5]proposed a wavelet based denoising technique for hyperspectral images. In [6], a hyperspectral denoising using total variation algorithm is employed for both spatial and spectral view. In [7], the authors have proposed a preprocessing technique using AB filter denoising. Later the classification is done using

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Orthogonal Matching Pursuit(OMP) algorithm[7]. In [8],the author has proposed a preprocessing technique using sparse representation ,local redundancy and correlation denoising for both spatial and spectral domain[8] .In [9], the author proposed a sparsity based classification algorithm where hyperspectral data are represented as sparse by linear combination of training sample in a well-defined dictionary[9].

Recently, Ankit Parekh and Ivan Selensick proposed a fast algorithm for denoising sparse signals using non-convex tight frame regularization[10]. They have formulated the denoising problem in a convex framework by using non-convex tight frame regularization. In our paper, we have mapped this tight frame approach for hyperspectral image denoising. The papers is organized as follows; section II gives a brief description about the non-convex tight frame approach for denoising, section III explains the Orthogonal Matching Pursuits algorithm, Section IVdescribes the proposed methodology for sparsity based classification, section V explains experimental results and analysis and finally section VI concludes the work.

2. CONVEX DENOISING USING NON-CONVEX TIGHT FRAME REGULARIZATIONS

Consider the noisy hyperspectral data cube, $y \in \mathrm{R}^{n_1 \times n_2 \times n_b}$, where $n_1 \times n_2$ represents the number of pixels and n_b represents the number of bands. Now the problem of estimatingthe clean hyperspectral data cube, $z \in \mathrm{R}^{n_1 \times n_2 \times n_b}$ is formulated as a denoising problem with respect to over complete tight frame condition as follows,

$$\arg\min_{z} \left\{ \frac{1}{2} \| y - z \|_2^2 + \sum_{i=1}^{m_1} \lambda_1 \, \phi([\mathrm{Az}]_i \; ; a_1) \right\} \tag{1}$$

In the formulation defined in (1), it is assumed that the underlying image is considered to be sparse with respect to an over complete tight frame matrix, $\mathrm{A} \in \mathrm{R}^{\mathrm{m}_1 \times n_2}$, $m_1 \geq n_2$. The tight frame condition need to be satisfied is defined as,

$$\mathrm{A}^{\mathrm{T}}\mathrm{A} = v\mathrm{I}, \; v > 0 \tag{2}$$

In formulation (1), $\lambda_i > 0$ represents the regularization parameter and $\phi : \mathrm{R} \rightarrow \mathrm{R}$ represents the non-convex sparsity inducing penalty function. Usually, λ_1 norm regularization is used in formulation for inducing sparsity. In the proposed Method λ_1 norm is replaced by non –convex regularization function 'atan' for inducing more sparsity than norm .In formulation (1) the convex penalty function have been replaced by non convex penalty functions,:. However while using a non-convex regularizer in an objective function the whole objective function becomes non-convex. Hence in the formulation, a restricting parameter is introduced for controlling the degree of non-convexity and the final solution is obtained by convex optimization algorithms [10].

A. Algorithm

The problem defined in (1) has been solved via the proximal algorithm [14][15] and Alternating Direction Method of Multipliers (ADMM) [13][14]. By variable splitting method, (1) can be rewritten as,

$$\arg\min_{u,z} \left\{ \frac{1}{2} \| y - z \|_2^2 + \sum_{i}^{m_1} \lambda_1 \, \phi(u_i \; ; a_1) \right\} \tag{3}$$

$$stu = \mathrm{Az}$$

The objective function is separable into in and . Now by applying ADMM to (3), the update equations and the corresponding solutions can be obtained as follows,

$$z \leftarrow \arg\min_{z} \left\{ \frac{1}{2} \| y - z \|_2^2 + \frac{\gamma}{2} \| u - \mathrm{Az} - d \|_2^2 \right\} \tag{4}$$

This can be solved explicitly as,

$$z = (\mathrm{J} + \gamma \mathrm{A}^{\mathrm{T}} \mathrm{A})^{-1} \, (y + \gamma^{\mathrm{AT}} (u - d)) \tag{5}$$

$$z = \frac{1}{1+\gamma v}(y + \gamma^{AT}(u-d)) \tag{6}$$

Now the update for can be obtained as,

$$z \leftarrow \arg\min_{u} \left\{ \sum_{i=1}^{m_1} \lambda_1 \phi(u, ; a_i) + \frac{\gamma}{2} \| u - \mathrm{A}z - d \|_2^2 \right\} \tag{7}$$

and the solution for this can be obtained via the proximal algorithm as,

$$u_i \leftarrow \mathrm{prox}_{\phi}([\mathrm{A}z + d]_i ; \lambda_1/u_i, a_i) \tag{8}$$

Finally updated equtaion for as follows.

$$d \leftarrow d–(u - \mathrm{A}z) \tag{9}$$

Refer [10] for more details about the algorithm derivation part.

B. Penalty Functions Used

In the problem defined in (2), two penalty functions are used such as norm and arctangent penalty (atan). The λ_1 norm is defined as, $\phi(z ; 0) = |z|$, [10][11]. Now to induce more sparsity, the λ_1 norm is replaced by the non-convex arctangent penalty (atan) function. The atan penalty function is defined as,

$$\phi(z) = \frac{2}{a\sqrt{3}}\left(\tan^{-1}\left(\frac{1+2az}{\sqrt{3}}\right) - \frac{\pi}{6}\right), \forall z > 0 \tag{10}$$

3. OMP BASED HYPERSPECTRAL IMAGE CLASSIFICATION

Orthogonal Matching Pursuit (OMP) is a sparsity based algorithm used for the classification of hyperspectral images[9]. In this algorithm, the test pixel vectors are selected randomly from the entire data using few numbers of training samples. The dictionary matrix is formed by combining the randomly selected training pixels from each class, $\mathrm{B} = [\mathrm{B}_1, \mathrm{B}_2, \mathrm{B}_3 \ldots \mathrm{B}_\mathrm{M}]$, where M represents the total number of classes. The sub directory belongs to the dictionary matrix, B_i is defined as, $\mathrm{B}_i = [b_1, b_2, \ldots b_{mi}]$where B_i represents the training pixel vector belonging to the i^{th} class. Now, the problem formulation is given by,

$$\begin{aligned} \bar{u} &= \arg\min \|u\|_0 \\ \text{subject to } \mathrm{B}u &= t \end{aligned} \tag{11}$$

Where u is the sparsevector used to evaluate the class label of the test pixel vector. The residue is calculated as $r_i = \|t - \mathrm{B}_i u\|_2$ where $i \in$ M.Now the class of each test vector is given by,

$$\text{class}(t) = \arg\min_{t = 1, \ldots \mathrm{M}} (r_i) \tag{12}$$

4. PROPOSED METHOD

A novel hyperspectral image denoising method is proposed which uses non-convextight frame regularizations and then denoised image are subjected to OMP based classification to validate the results. The proposed method involves two process spatial processing and hyperspectral image classification. Fig 1 shows the flow chart for proposed Method.

A. Spatial Processing

Noise affected hyperspectral images produces low PSNR values and reduces the classification accuracy. To address this problem images are subjected to band wise denoising using non-convex tight frame regularization to produce better accuracy results. Non-convex regularization 'atan' function estimates all the non zero valuesthan non-convex regularization function. Therefore images are denoised properly without losing any edge information.

B. Hyperspectral Image Classification

Classification involves segregating hyperspectral image into training and testing pixels. Trainingsamples are selected randomly from the data and rest of the other data is used for testing pixels. Classification is carried out using sparsity based Orthogonal Matching Pursuit algorithmwhere hyperspectral data are represented as sparse by linear combination of training sample in a well-defined dictionary.

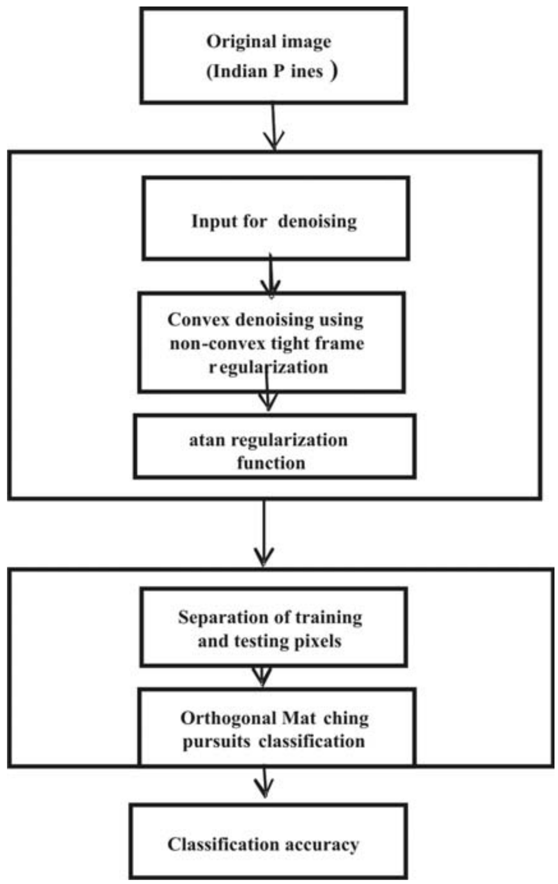

Fig. 1. Flow chart for proposed method.

5. EXPERIMENTAL RESULTS AND ANALYSIS

A. Dataset Description

The analysis is carried out on hyperspectral dataset - Indian Pines. Dataset is acquired by AVIRIS sensor over Indiana Pines test center in North western Tippecanoe Country Indiana on 1992 [17]. The dataset consist 224 spectral reflectance bands in the wavelength of 0.4 to 2.5.In 224 four bands are removed because it does not contains any useful information. Each band contains 145X145 pixels. Fig 2 shows the AVIRIS Indian pines dataset. Ground truth data contains 16 classes.

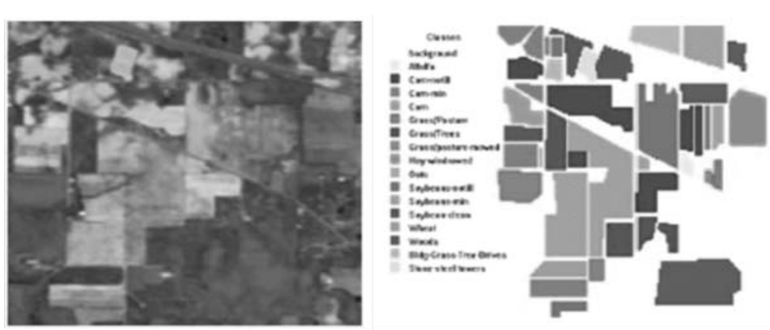

Fig. 2. AVIRIS Indian Pines dataset (I) color composite image (II) ground truth dataset

B. Experimental results and analysis

In the proposed hyperspectral image classification, a convex denoising using non-convextight frame regularization is been applied to the all the bands as preprocessing. Experiment is carried for both the λ_1 convex and atan non-convexregularization for various values λ in the range of (1 to 10) and γ value in the range of (1 to 2). To show the significance of the proposed method, results are compared with the standard denoising techniques such as TV denoising and wavelet based denoising. Figure 3 shows the preprocessing results of different kind of denoising techniques of a single noisy band165. On evaluation, the atan based denoising produces better results than norm based denoising.

The classification is done using OMP algorithm on 10%, 20%, 30% and 40% training pixels. Table 1 shows the classification accuracy for without processing, TV denoising, wavelet based denoising, convexnorm regularization and non-convexatan regularization for various training pixels taken. From table 1, it is clear that the atan based non-convex denoising has the highest accuracy when compared with other denoising techniques.

The overall accuracy of atan based denoising method increases by 1% -10% when compared with T.V, wavelet and λ_1 based denoising methods for 10% training pixels. Similarly for increasing the percentage of training pixels, the overall accuracy increases in the order of 2% - 6% for atan based denoising. Also, the Kappa coefficient for proposed atan denoising technique is around 0.8098-0.9273 for various training pixel percentage. While the Kappa coefficient for T.V denoising, wavelet based denoising and based denoising are in the range of 0.7628, 0.7849, 0.08017 respectively. Figure 4 shows the OMP classification map forwithoutprocessing, T.Vdenoising, wavelet based denoising and convex regularization function with 10% training pixels. Figure 5 shows the OMP classification map for atan based denoising for 10%, 20%,30% and 40% training pixels respectively.

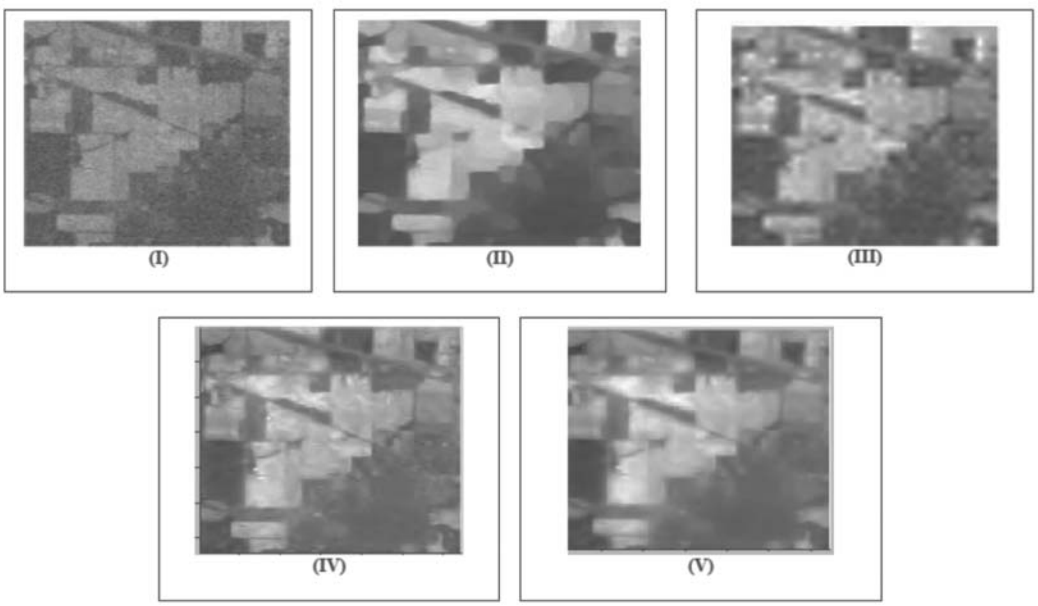

Fig. 3. Preprocessing results for noisy band 165 of Indian pines dataset for various methods (I) noisy band 165 (II) denoising using TV algorithm (III) denoising using wavelets (IV) denoising using λ_1 norm regularization (V) denoising using atan regularization function

Fig. 4. Classification map for 10 % (I) withoutprocessing (Overall accuracy- 71.72 %), (II) denoising using T.Valgorithm (Overall accuracy- 78.27 %), (III) denoising using wavelets (Overall accuracy- 81.12 %), (IV) denoising using λ_1 norm (Overall accuracy- 82.63 %),

Fig. 5. (I) Classification map for 10 % - denoising using atan regularization (Overall accuracy- 83.38 %), (II) Classification map for 20 %- atan regularization (Overall accuracy- 88.11 %), (III) Classification map for 30 % -atan regularization (Overall accuracy- 91.9 %), (IV) Classification map for 40 % -atan regularization (Overall accuracy- 93.63 %).

Table 1. OMP based classification results on Indian Pines dataset with various preprocessing techniques

Class	*Class title*	*Without processing*	*Denoising using TV algorithm*	*Denoising using wavelet*	*Denoising using λ1 norm*	*Denoising using atan*			
	Training percentage (%)	10	10	10	10	10	10	20	30
1	Alfalfa	47.83	93.48	91.3	76.09	80.43	93.48	93.48	97.83
2	Corn-notill	56.51	65.55	73.81	73.6	77.52	83.75	88.24	91.6
3	Corn-mintill	58.8	68.31	67.83	73.37	67.83	78.67	86.75	90.24
4	Corn	38.82	70.46	67.51	55.27	58.65	73	75.11	81.86
5	Grass-pasture	85.51	90.68	89.86	94.2	92.96	93.58	96.48	97.93
6	Grass-trees	94.38	94.93	96.58	98.08	98.63	99.18	98.63	99.32
7	Grass-pasture-mowed	71.43	100	100	99.16	82.14	82.14	89.29	96.43
8	Hay-windrowed	96.44	96.44	97.28	99.16	98.95	99.16	99.37	99.79
9	Oats	50	100	100	60	75	90	100	90
10	Soybean-notill	69.55	77.57	74.07	83.44	77.47	83.64	88.58	90.53
11	Soybean-mintill	74.99	76.74	83.38	83.71	86.6	87.62	89.94	94.3
12	Soybean-clean	48.74	60.2	54.81	69.81	67.62	80.1	81.45	87.18
13	Wheat	95.61	99.02	99.51	99.02	97.07	99.51	99.51	100
14	Woods	88.7	93.6	94.15	93.99	94.23	97.15	98.1	98.02
15	Buildings-Grass-Trees-Drives	37.31	50.52	69.95	57.51	67.62	74.09	82.64	85.75
16	Stone-Steel-Towers	87.1	98.92	92.47	92.47	94.62	94.62	100	98.92
overall accuracy (%)		**71.72**	**78.27**	**81.12**	**82.63**	**83.38**	**87.83**	**91.9**	**93.63**
average accuracy (%)		**68.86**	**83.53**	**84.53**	**76.95**	**82.33**	**88.11**	**91.72**	**93.73**
Kappa coefficient		**0.6771**	**0.7528**	**0.7849**	**0.8017**	**0.8098**	**0.8611**	**0.8962**	**0.9273**

6. CONCLUSION

This paper discusses about an effective preprocessing method based on convex denoising using non convex tight frame regularization function. Each bands of the dataset are denoised prior to the orthogonal matching pursuit based image classification. The denoising is performed based on λ_1 norm regularization function and non-convex atan regularization function. The analysis is carried out on Indian Pines hyperspectral imagery and the performance of the proposed method is evaluated interms of classification accuracy assessment measures. Also the performance of the proposed method is compared with other denoising techniques such as T.V denoising and wavelet based denoising. From the evaluation it is concluded that the proposed atan based denoising approach outperforms all other techniques and hence it is appropriate for noisy hyperspectral image classification.

7. REFERENCES

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