

This item is the archived peer-reviewed author-version of:

Fusion of hyperspectral and Lidar images using non-subsampled shearlettransform

Reference:

Soleimanzadeh Mohammad Reza, Karami Azam, Scheunders Paul.- Fusion of hyperspectral and Lidar images using non-subsampled shearlettransform IEEE International Geoscience and Remote Sensing Symposium - ISSN 2153-6996 - (2018), p. 8873-8876 Full text (Publisher's DOI): https://doi.org/10.1109/IGARSS.2018.8519547

uantwerpen.be

Institutional repository IRUA

FUSION OF LIDAR AND HYPERSPECTRAL IMAGES USING NON-SUBSAMPLED SHEARLET TRANSFORM

Mohammad Reza Soleimanzadeh¹, Azam Karami¹, Paul Scheunders²

¹Faculty of Physics, Shahid Bahonar University of Kerman, Kerman, Iran ²Visionlab, University of Antwerp, Belgium

ABSTRACT

In this paper, a new fusion method for merging the spectral and spatial contents of hyperspectral images (HSI) with the height information of light detection and ranging (LiDAR) for increasing the classification accuracy of HSI is introduced. First, 2D non-subsampled shearlet transform (NSST) is applied to each band of hyperspectral and LiDAR data separately in order to extract the spatial features. Second, principal component analysis (PCA) is applied to all shearlet subbands of HSI in order to reduce their dimension. Third, the spectral information of HSI and obtained spatial features are integrated and classified using subspace multinomial logistic regression (MLRsub). We evaluate the performance of the proposed method over University of Houston, USA and a rural one captured over Trento, Italy. The obtained results show that the proposed method can efficiently classify the joint hyperspectral and LiDAR images.

Index Terms— Fusion, Hyperspectral Images, LiDAR, Classification, Shearlet transform.

1. INTRODUCTION

Recently, hyperspectral image classification has significantly considered in different practical applications [1]. The HSI usually have high spectral resolution, however the spatial resolution is not adequate due to the sensor limitations . The lower spatial resolution of HSI causes difficulty for discriminating complex classes especially for urban areas [2]. For example, roof and roads, which are made by the same material, demonstrate the similar spectral characteristics. If data from the other sources such as LiDAR of the same scene is available, it could be fused with HSI in order to improve the results of classification. In fact, the LiDAR data provides the detailed information about the height of objects. It is noteworthy to mention that the classification of objects with the same elevation in the LiDAR data could not create reasonable results.

In recent years, many techniques have been developed for fusion of HSI and LiDAR data for classification. In these methods, first the spatial features are extracted from the HSI and LiDAR data. After that, the spectral information of HSI are fused with spatial features [2, 3, 4, 5, 6]. In [3], first PCA is applied to the HSI. Then, the attribute profile (AP) is used in order to extract the spatial features from the reduced HSI and LiDAR data respectively. Finally, the obtained spatial features and spectral information of HSI are combined and classified by random forest (RF) classifier. In [4, 5], by use of extinction profiles (EPs), the spatial features of HSI and Li-DAR data are extracted. EP in comparison with AP has better performance. It is exterma oriented instead of threshold oriented, which makes it less sensitive to image resolution, and it can be executed automatically. Then, the obtained spatial features are integrated with spectral feature of HSI using sparse and low rank analysis [2], graph based feature-fusion [5] and orthogonal total variation analysis [4]. Finally, the fused data are classified by SVM or RF [2, 4] and a learning based classifier [5] respectively. A flexible strategy based on morphological features and MLRsub was proposed in [6], for jointly classifying HSI and LiDAR data without the need for regularization parameters. In this paper, we also use the MLRsub for fusion, but instead of using AP, a new spatial feature extraction from HSI and LiDAR data is introduced based on the shearlet transform (ST). This transform has been significantly considered in many practical application such as denoising, classification, etc. [7, 8]. In this article, the spatial features are extracted using NSST. It is applied to each band of HSI and LiDAR data. Then, the shearlet sub-bands of HSI are reduced using PCA. Finally, the MLRsub technique fuses the multiple features.

The remainder of this paper is organized as follows: the proposed method is introduced in Section 2. Experimental results are shown in Section 3. In Section 4 some concluding remarks are provided.

2. PROPOSED METHOD

2.1. NSST

In this paper, a special type of discrete shearlet transform is applied, called non-subsampled shearlet transform (NSST). The implementation of the NSST includes two main steps: the application of non-subsampled pyramid (NSP) filter banks and non-subsampled shearing (NSS) filter banks. A nonsubsampled filter bank does not include down/up-sampling filters. NSP filter banks decompose the original image into high-frequency and low-frequency sub-bands which are of the same size as the original image. NSS executes the directional filtering in the spatial domain instead of the frequency domain. The NSS filter banks divide the high-frequency subbands into directional sub-bands. These filter banks are iteratively applied. At each iteration, the obtained low-frequency sub-band is again divided into a lower scale high-frequency and low-frequency sub-bands (see [8] for more details).

In the proposed method, 2D NSST is applied to each band of HSI and LiDAR data separately. Let $\mathbf{X}^H \in \mathbb{R}^{(I_1 \times I_2 \times I_3)}$ denotes the HSI where $(I_1 \times I_2)$ is the number of pixels and I_3 is the number of spectral bands. The LiDAR data is denoted by $\mathbf{X}^L \in \mathbb{R}^{(I_1 \times I_2)}$. After applying 2D NSST, we have:

$$\mathbf{X}_{NSST}^{H}(:,:,j) = NSST(\mathbf{X}^{H}(:,:,j)), j = 1, ..., I_{3}$$
(1)

$$\mathbf{X}_{NSST}^{L} = NSST(\mathbf{X}^{L}) \tag{2}$$

After that, PCA is applied to \mathbf{X}_{NSST}^{H} as follows:

$$\mathbf{X}_{PCA}^{H} = PCA(\mathbf{X}_{NSST}^{L}) \tag{3}$$

In the next step, MLRsub is applied to multiple spectral and spatial features ($\mathbf{X}^{H}, \mathbf{X}_{NSST}^{L}, \mathbf{X}_{PCA}^{H}$). The MLRsub classifier is briefly explained in the next subsection.

2.2. MLRsub

The spectral and spatial features are considered as $\mathbf{Z} \equiv (\tilde{\mathbf{Z}}_1, \tilde{\mathbf{Z}}_2, \tilde{\mathbf{Z}}_3)$ where $\tilde{\mathbf{Z}}_1 = \mathbf{X}^H, \tilde{\mathbf{Z}}_2 = \mathbf{X}^L_{NSST}$ and $\tilde{\mathbf{Z}}_3 = \mathbf{X}^H_{PCA}$. The MLR classifier is given by [6]:

$$p_m(y_i^{(c)} = 1 \mid (\tilde{\mathbf{Z}}_i)_m, \boldsymbol{\omega}_m) = \frac{exp(\boldsymbol{\omega}_m^{(c)}\mathbf{h}((\tilde{\mathbf{Z}}_i)_m))}{\sum_{k=1}^c exp(\boldsymbol{\omega}_m^{(c)}\mathbf{h}((\tilde{\mathbf{Z}}_i)_m))}$$
(4)

 p_m denotes the posterior probability of feature $\tilde{\mathbf{Z}}_m$ for m = 1, 2, 3. $Y = (y_1, ..., y_n)$ shows the labels of groundtruth, n is the number of pixels $(I_1 \times I_2)$.

the number of pixels $(I_1 \times I_2)$. $y_i = [y_1^{(1)}, y_2^{(2)}, ..., y_i^{(k)}]^T$ where k is the number of classes. $y_i^c = \{0, 1\}$ for c = 1, ..., k and $\sum_c y_i^c = 1$. $\boldsymbol{\omega}_m^{(c)}$ is the set of logistic regressor for class c and $\boldsymbol{\omega}_m \equiv [\boldsymbol{\omega}_m^{(1)T}, ..., \boldsymbol{\omega}_m^{(c-1)T}]$. $\mathbf{h}((\tilde{\mathbf{Z}}_i)_m) \equiv [h_1(\tilde{\mathbf{Z}}_i)_m, ..., h_l(\tilde{\mathbf{Z}}_i)_m^T]$ is a vector of l nonlinear function of the input feature. The MLRsub projects the training samples of each class into lower dimension. This projection could improve the classification accuracy (see [6] for more details). After calculating p_m for each features, they are combined and the maximum value for c = 1, ..., k shows the class number.

The pseudo-code for the proposed method is shown in Algorithm1. Algorithm 1 PROPOSED ALGORITHM (NSST-MLRsub)

Input: Original HSI $(\mathbf{X}^H \in \mathbb{R}^{(I_1 \times I_2 \times I_3)})$, LiDAR $(\mathbf{X}^L \in \mathbb{R}^{(I_1 \times I_2)})$, Groundtruth $(\mathbf{G}_{th} \in \mathbb{R}^{(I_1 \times I_2)})$, NSST Parameters.

1- Apply 2D *NSST* to $(\mathbf{X}^{H}, \mathbf{X}^{L})$ 2- Apply *PCA* to \mathbf{X}_{NSST}^{H} 3- Apply *MLRsub* to $(\mathbf{X}^{H}, \mathbf{X}_{NSST}^{L}, \mathbf{X}_{PCA}^{H})$

Output: Classification Map

3. EXPERIMENTAL RESULTS

3.1. Datasets

Two real hyperspectral and LiDAR datasets were used in the experiments.

1- University of Houston data: This dataset were captured by the NSF-funded Center for Airborne Laser Mapping (NCALM) on June 2012 over the University of Houston campus and its neighboring urban area. The HSI dataset has 144 spectral bands. Both datasets have the same spatial resolution (2.5m). The whole scene of the data contains 349×1905 pixels. The existing groundtruth for this dataset includes 15 classes. The available numbers of training test samples are shown in Table.1. The LiDAR, false color image of HSI and groundtruth are depicted in Figs.1 (a), (b) and (c).

2- Trento data: It was captured over a rural area in the south of the city of Trento, Italy. The subset used in this experiment includes images of size 600×166 pixels. The Li-DAR DSM data were acquired by the Optech ALTM 3100EA sensor and the hyperspectral dataset captured by the AISA Eagle sensor, all with a spatial resolution of 1m. The hyperspectral data includs 63 bands, where the spectral resolution is 9.2nm. The groungtruth with six classes are considered. Figs. 2(a-c) show the LiDAR, false color of HSI and grandtruth respectively.

3.2. Results

In the proposed method (NSST-MLR), three level decomposition is used and the number of shearing directions is chosen [32, 32, 16, 16].

Tables.1 & 2 show the average accuracy (AA), overall accuracy (OA) and the kappa (κ) coefficient. SVM classifier applied to the LiDAR, HSI, NSST-PCA (LiDAR) and NSST-PCA (HSI) for University of Houston and Trento datasets respectively. Then the obtained classification results of different data using SVM are compared with the fusion method graph-based feature fusion (GBFF) [5], MLRsub-MRF (HSI+LiDAR) [6] and proposed method NSST-MLRsub (HSI+LiDAR). The fusion methods MLRsub-MRF and NSST-MLRsub have better performance in comparison with employing a single feature. It means that the fusion methods could significantly integrate the information of both datasets

class	train	test	SVM (HSI)	NSST-PCA- SVM (LiDAR)	NSST-PCA- SVM (HSI)	NSST-PCA -SVM (HSI+LiDAR)	GBFF	MLRsub -MRF	NSST-PCA- MLRsub
1	198	1053	82.05	23.17	82.43	83.03	78.73	81.67	87.31
2	190	1064	81.20	27.25	83.36	81.52	94.92	83.55	99.31
3	192	505	100	99.80	100	100	100	100	100
4	188	1056	91.95	62.21	92.23	95.64	99.34	91.09	95.81
5	186	1056	97.44	18.18	98.67	99.15	99.62	99.62	99.94
6	143	182	95.10	66.43	95.10	92.31	95.80	88.11	95.71
7	196	1072	76.39	72.76	80.59	87.59	87.87	92.72	92.46
8	191	1053	46.62	66.19	47.48	90.26	95.25	77.77	94.93
9	193	1059	76.48	13.12	80.54	91.78	89.71	89.80	92.33
10	191	1036	58.10	22.39	59.74	82.76	81.18	77.99	84.21
11	181	1054	76.18	51.80	81.11	96.58	86.34	97.72	97.34
12	192	1041	75.02	31.02	80.69	92.32	92.70	78.19	87.29
13	184	285	68.07	69.12	70.52	76.84	87.02	78.94	85.67
14	181	247	99.19	99.59	100	99.53	99.19	99.59	100
15	187	473	98.30	1.69	98.30	98.81	89.64	98.09	99.55
AA			78.54	42.22	80.81	90.51	91.02	88.10	92.61
OA			81.48	48.22	83.39	91.06	91.82	88.99	92.95
Kappa			76.89	38.72	79.34	89.85	90.33	87.07	91.54
Time(s)			25.95	13.01	740.82	754.3	861	217.49	945.51

Table 1: Classification Results (Houston)

(HSI+LiDAR). In fact, spectral feature of HSI discriminate the specific classes with distinctive spectral characteristics and the LiDAR data could classify the objects with the different elevation information well. The obtained classification results of proposed method are higher than GBFF [5] and MLRsub-MRF [6]. It can be concluded that the ST could extract spatial features more efficiently than AP and EP.

The classification maps obtained from SVM (HSI) and NSST-MLRsub (HSI+LiDAR) are depicted in Figs 1.(d-e) and Figs 2.(d-e) for both datasets. The proposed method could significantly preserve the structure and this characteristic is very important especially for urban areas. This is the result of using ST for extracting the spatial features of HSI and LiDAR data. In fact, NSST could create an optimal sparse representation.

4. CONCLUSIONS

In this paper, a new method for fusion of HSI and LiDAR data based on shearlet transform is introduced. The proposed method improves all classification results in terms of the OA, the AA, the kappa coefficient (κ) and the quality of classification map. This clearly shows that the chosen sets of feature (especially spatial shearlet features) are efficiently selected. The spatial and spectral features could significantly improve the classification performance. In future, our aim is to reduce the computational complexity of the proposed algorithm.

5. REFERENCES

- P. Ghamisi, J. Plaza, Y. Chen, J. Li, and A. J. Plaza, "Advanced spectral classifiers for hyperspectral images: A review," *IEEE Geoscience and Remote Sensing Magazine*, vol. 5, no. 1, pp. 8–32, 2017.
- [2] B. Rasti, P. Ghamisi, J. Plaza, and A. Plaza, "Fusion of hyperspectral and lidar data using sparse and low-rank component analysis," *IEEE Trans. Geosci. Remote Sens*, vol. 55, no. 11, pp. 6354–6365, 2017.
- [3] P. Ghamisi, J. A. Benediktsson, and S. Phinn, "Fusion of hyperspectral and lidar data in classification of urban areas,," in 2014 IEEE Geosci. Remote Sens Symposium, 2014, pp. 181–184.
- [4] B. Rasti, P. Ghamisi, and R. Gloaguen, "Hyperspectral and lidar fusion using extinction profiles and total variation component analysis," *IEEE Trans. Geosci. Remote Sens*, vol. 55, no. 7, pp. 3997–4007, 2017.
- [5] P. Ghamisi, B. Hfle, and X. X. Zhu, "Hyperspectral and lidar data fusion using extinction profiles and deep convolutional neural network," *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens*, vol. 10, no. 6, pp. 3011– 3024, 2017.
- [6] M. Khodadadzadeh, J. Li, S. Prasad, and A. Plaza, "Fusion of hyperspectral and lidar remote sensing data using multiple feature learning," *IEEE J. Sel. Topics Appl.*

class	train	test	SVM (HSI)	NSST-PCA -SVM (LiDAR)	NSST-PCA -SVM(HSI)	NSST-PCA -SVM (HSI+LiDAR)	GBFF	MLRsub -MRF	NSST -PCA -MLRsub
1	129	3905	90.96	42.30	92.24	95.76	99.53	93.34	99.75
2	125	2778	83.87	92.08	88.48	98.32	98.79	93.26	98.75
3	105	374	96.52	44.11	43.31	92.34	99.79	93.31	95.45
4	154	8969	96.23	97.03	99.81	99.79	99.50	99.50	99.86
5	184	10317	77.40	83.16	97.68	98.26	99.76	95.20	98.91
6	122	3252	69.10	50.98	86.10	90.21	93.01	76.86	98.61
	AA			78.97	94.85	97.53	98.93	94.16	99.05
OA			85.68	68.28	84.61	96.14	98.48	91.92	98.61
Kappa			80.17	71.77	93.08	96.46	98.55	92.18	98.13
Time(s)			16.52	5.56	53.26	55.01	248	87.25	102.27

Table 2: Classification Results (Trento)

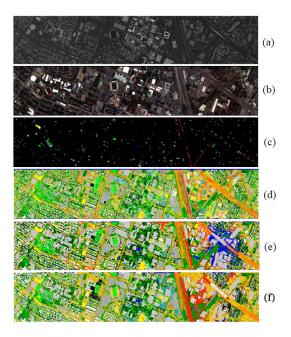


Fig. 1: (a) LiDAR data, (b) false color of the HSI, (c) Groundtruth, (d) Classification map of SVM (HSI), , (e) Classification map of GBFF, (f) Classification map of NSST-PCA-MLRsub (HSI+LiDAR).

Earth Observ. Remote Sens, vol. 8, no. 6, pp. 2971–2983, 2015.

- [7] A. Karami, R. Heylen, and P. Scheunders, "Bandspecific shearlet-based hyperspectral image noise reduction," *IEEE Trans. Geosci. Remote Sens*, vol. 53, no. 9, pp. 5054–5066, 2015.
- [8] M. R. Soleimanzadeh and A. Karami, "Hyperspectral image classification using nonsubsampled shearlet transform," in *Proc.SPIE*, pp. 10427–10427–11. 2017.

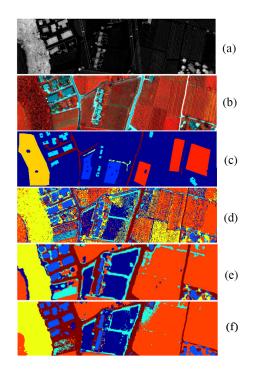


Fig. 2: (a) LiDAR data, (b) false color of the HSI, (c) Groundtruth, (d) Classification map of SVM (HSI), (e) Classification map of GBFF, (f) Classification map of NSST-PCA-MLRsub (HSI+LiDAR).