UNMIXING WITH SLIC SUPERPIXELS FOR HYPERSPECTRAL CHANGE DETECTION

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ABSTRACT

Change detection by unmixing has been shown to provide enhanced change detection performance for hyperspectral images with respect to more traditional approaches, especially when the temporal images contain sub-pixel level changes. In a recent paper, change detection by spectral unmixing was investigated in detail and the advantages that can be gained by using such an approach were systematically presented through various experimental studies. However, the utilized unmixing-based change detection approach relied solely on spectral information and disregarded the spatial distribution in the scene, which inevitably limits the performance that can be achieved. In this paper, superpixels are used to integrate the spatial information in the image into the unmixing process, which in turn enhances the change detection performance with respect to spectral unmixing based change detection.

***Index Terms*—** Change detection, hyperspectral imaging, multitemporal, superpixels, unmixing.

1. INTRODUCTION

Hyperspectral change detection is the process of detecting the changes between temporal hyperspectral images acquired from the same scene at different times. These changes may occur due to a seasonal / diurnal variations, human interaction such as deforestation or urban development, or as a direct result of a significant event such a natural disaster [1]. Change detection for hyperspectral images can be used for many applications, ranging from environmental monitoring to military surveillance.

There exists a large number of change detection methods in the hyperspectral imaging literature. Whereas a good performance can be obtained by traditional change detection methods on a variety of cases, most (if not all) of such methods operate on a purely pixel-level basis, and normally do not provide sub-pixel level change detection outputs. In addition, most methods provide only the locations of the changes in the scene, instead of providing any information on the changes themselves.

In contrast, hyperspectral change detection by unmixing not only provides sub-pixel level outputs, but also has the potential to provide easy to interpret information on changes that have occurred. Such information is provided in terms of endmembers and their abundance distributions in the temporal hyperspectral images. Unmixing based change detection is a relatively recent addition to the literature. A general framework for spectral unmixing based change detection is proposed in [2], sub-pixel level change detection by unmixing is presented in the scope of a case study in [3], and the use of unmixing based change detection for land-cover mapping is investigated in [4]. In a recent paper, unmixing based change detection, and the unique benefits it is able to convey, have been examined in detail through various experimental studies [5]. Sparse unmixing based change detection is proposed in [6].

In this work, unmixing based change detection with endmember extraction and linear unmixing is improved by including the spatial information contained in the temporal images, instead of relying solely on the spectral domain. For this purpose, an oversegmentation scheme is adopted. Integrating spatial-contextual information to spectral processing is now a well-established approach to increase the performance of various image processing tasks, such as classification [7]. However, whereas the fact that integrating spatial information enhances the performances is well known, automating the process of a spatial processing approach such as segmentation often requires challenging or time-consuming steps, which has recently led to popularity of oversegmentation approaches which do not require such steps.

Superpixels are a special case of oversegmentation, in which the segments are more or less similar size and regular shape, and are uniformly distributed over the image. In this work, simple linear iterative clustering (SLIC) algorithm is adopted as the method to construct the superpixels, as it has been shown that SLIC outperforms many superpixel generation methods in terms of computational complexity, memory efficiency, boundary adherence, under-segmentation error and boundary error [8]. In addition, SLIC is easy to use, flexible, and provides control of superpixel compactness and boundary adherence trade-off [8].

In this work, SLIC superpixels are used together with unmixing for change detection in multitemporal hyperspectral images.

2. METHODOLOGY

Our strategy for hyperspectral change detection by unmixing with SLIC superpixels involves detecting the dimensionality of the data, constructing the superpixels, reconstructing the data based on the superpixels, extracting the endmembers, calculating the abundance maps of the endmembers (followed by the optional step of recomputing the abundances based on the superpixels) and, at the last step, the change in the abundance maps of temporal images for each endmember is detected by simple differencing.

The dimensionality of the data, i.e. number of endmembers to be extracted, is established in this work by using the hyperspectral signal identification by minimum error (HySime). HySime is applied to the whole multitemporal hyperspectral series, obtained by merging the temporal images spatially (in conjunction), instead of on each temporal dataset separately. This way the dimensionality is kept constant in each temporal image.

After dimensionality detection, SLIC superpixels are constructed from the multitemporal dataset. The procedure is adapted directly from that proposed in [9], and an RGB image of the multitemporal hyperspectral data set is given as input to the SLIC algorithm. SLIC first transforms the RGB images to CIELAB space, and then SLIC superpixels are generated in this space. SLIC has a single parameter: k, which controls the desired number of superpixels.

Following the SLIC superpixel generation, the spectral pixel vectors of the original multitemporal hyperspectral dataset are assigned to their corresponding superpixels. Then, for each superpixel, the average of pixel vectors in the superpixel are assigned as the new value of each of those pixels, resulting in a new, smoothed, multitemporal dataset.

After this step, the endmembers are extracted from the whole multitemporal data series. This ensures that there will be a single endmember pool, instead of endmembers varying temporally. Hence, multiple pixels will not be selected for the same endmember.

There are various endmember extraction algorithms (EEAs) in the literature, and any EEA can be used with the proposed approach. In this work, experimental results with N-FINDR and vertex component analysis (VCA) are provided. Endmember extraction is followed by fully constrained least squares (FCLS) used to obtain the abundances in each pixel for each endmember, in each temporal dataset. After this, as an optional step, the abundances may be smoothed so that for each superpixel, the abundances are reassigned as their average, for each endmember.

In a last step, the change in each abundance map for each endmember is calculated by means of a simple difference operation between the corresponding abundance maps of different temporal datasets. The total change map can be obtained by the summation of the change maps for each endmember.

3. EXPERIMENTAL RESULTS

3.1. Synthetic Dataset 1

For the first experimental study on synthetic datasets, a synthetic multitemporal hyperspectral dataset is simulated from the AVIRIS Salinas image. The original dataset and ground truth information are available online at [9]. The dataset has 224 spectral bands, but water absorption bands have been eliminated, resulting in 204 spectral bands. The original dataset also is sized 512 × 217 pixels, but a subset of the image in the size of 217 × 217 pixels is selected as the first temporal hyperspectral dataset in this work. The second temporal dataset is simulated from the first dataset by modifying pixels of the data that are in the "grapes_untrained" class, and the modification is done by changing each pixel to a randomly selected pixel from the "vineyard_untrained" class. The change is purely at pixel level, but is quite challenging, as the pixels are modified to pixels of a very similar class, both in terms of RGB values, and spectrally. RGB images of the temporal datasets, and the ground truth change map are presented in Fig. 1. Before processing for change detection, additive Gaussian white noise is added to each temporal dataset in 30dB SNR to make the problem more challenging.

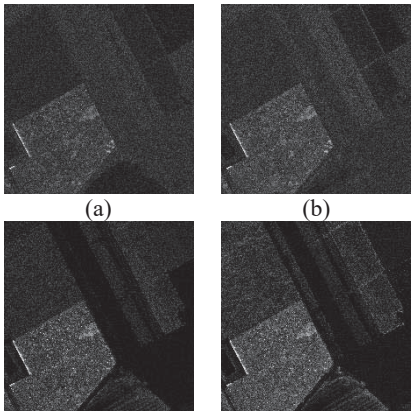
The performance of the proposed approach is compared with spectral unmixing based change detection without the superpixel enhancement. A comparison of unmixing based change detection with traditional change detection methods can be found in [5, 6] and is not provided here.For the endmember extraction process, two EEAs, namely N-FINDR and VCA, have been selected. For the proposed approach, the number of superpixels to be constructed by the SLIC algorithm is selected as (rounded) N / 128, where N is the total number of pixels in the multitemporal data stack, i.e. 217 × 217 × 2. Hence, in this case study, the number of superpixels is 736.

The overall change maps obtained for a single run are presented in Fig. 2. These change maps are obtained by the summation of abundance change maps obtained for each endmember. ROC curves based on the ground truth change map obtained for this run are provided in Fig. 3. It can be observed that a significant performance enhancement can be gained by the proposed SLIC superpixel based approach with respect to spectral unmixing based change detection.

The average area under curve (AUC) values derived from the ROC curves for 10 runs of the algorithms are presented in Table I. It can be observed that the proposed approach provides higher AUC values.

(a) (b) (c)

Fig. 1. *Salinas* dataset, (a) First temporal dataset RGB, (b) Second temporal dataset RGB, (c) Change ground truth map



(a) (b) (c) (d)

Fig. 2. Change maps for *Salinas* by (a) spectral unmixing (N-FINDR), (b) spectral unmixing (VCA), (c) proposed with N-FINDR, (d) proposed with VCA

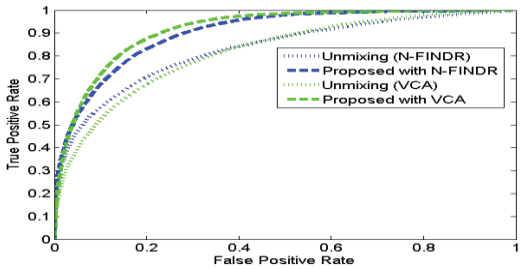


Fig. 3. ROC curves for the *Salinas* dataset

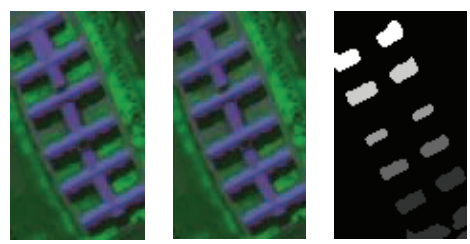
TABLE I
AUC VALUES FOR SALINAS

	Unmixing	Proposed
with N-FINDR	0.8267	**0.8651**
with VCA	0.8215	**0.9061**

3.1. Synthetic Dataset 2

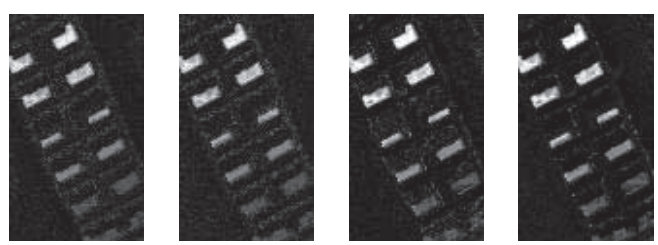
The second synthetic multitemporal hyperspectral dataset is simulated from the ROSIS Pavia University dataset. The original dataset, and ground truth information is available online [22]. Pavia University image has 103 spectral bands, and is originally sized 610 × 340 pixels. In this work, a subset of the Pavia University image, sized 120 × 70 pixels, is selected as the first temporal hyperspectral dataset. This subset contains a metal roofed building and the surrounding areas. For the second temporal dataset, the vegetation regions located between the parts of the building are modified to dirt such as those located around the building. This modification process is done in sub-pixel level and gradually such that, diagonally, the upper-left parts of the image are modified more significantly, whereas the lower-right parts are modified less significantly. False color images of the temporal datasets, and the ground truth with indication on their modification strength are visualized in Fig. 4.

Before processing, additive Gaussian white noise is added to each temporal dataset in 30dB SNR to make the problem more challenging. For the proposed approach, the number of superpixels to be constructed by the SLIC algorithm is selected as (rounded) N / 64, where N is 120 × 70 × 2. Hence, a total number of 263 superpixels have been constructed. The overall change maps obtained for a single run are presented in Fig. 5. ROC curves based on the ground truth map obtained for this run are provided in Fig. 6. It can be observed that a significant performance enhancement can be gained by the proposed SLIC superpixel based approach with respect to change detection based on spectral unmixing. Average AUC values for 10 runs are presented in Table II.



(a) (b) (c)

Fig. 4. *Pavia* dataset, (a) First temporal dataset RGB, (b) Second temporal dataset RGB, (c) Change ground truth map



(a) (b) (c) (d)

Fig. 5. Final change maps for *Pavia* by (a) spectral unmixing (N-FINDR), (b) spectral unmixing (VCA), (c) proposed with N-FINDR, (d) proposed with VCA

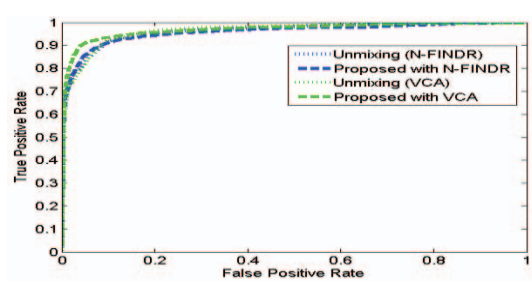


Fig. 6. ROC curves for the *Pavia* dataset

TABLE II
AUC VALUES FOR PAVIA UNIVERSITY

	Unmixing	Proposed
with N-FINDR	0.9631	**0.9637**
with VCA	0.9579	**0.9693**

4. CONCLUSIONS

The numerous potentials and advantages of change detection by unmixing for multispectral hyperspectral data, with respect to traditional methods, have only recently begun to be investigated in detail. Whereas regular spectral unmixing has the potential to outperform many traditional change detection methods, it relies solely on spectral information. In this work, the use of superpixels with unmixing based change detection is proposed to integrate the spatial information into the process. The proposed approach provides enhanced change detection performance with respect to regular unmixing based change detection, by extracting the endmembers from superpixels, and modifying abundances to obtain smooth abundance maps in correspondence with the superpixels.

5. REFERENCES

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