CHANGE DETECTION WITH MANIFOLD EMBEDDING FOR HYPERSPECTRAL IMAGES

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ABSTRACT

This paper proposes a manifold based approach for change detection in multitemporal hyperspectral images. Manifold representation, using Laplacian Eigenmaps, is applied for dimensionality reduction on stacked temporal datasets and change detection on the reduced datasets. The resulting latent vectors are utilized to cluster the changed vs. unchanged regions. A semi-supervised scheme is also proposed which circumvents the challenging thresholding issue and enables satisfactory binary change detection outputs. The proposed approach is validated on two real bitemporal hyperspectral datasets.

Index Terms— Change detection, hyperspectral, Laplacian Eigenmaps, manifold

1. INTRODUCTION

Change detection is the process of detecting the variations between multiple remote sensing images acquired from the same geographical region at different times. Multitemporal analysis of remote sensing images has a wide range of applications ranging from environmental monitoring to precision agriculture and urban studies. There is a large number of supervised and unsupervised change detection methods in the literature, and in-depth reviews on the subject can be found in [1-3].

Change detection can be categorized as binary, multiclass, or time-series change detection. The most typical category, binary change detection, aims to distinguish the pixels in the temporal images in terms of changed and unchanged. A simple, yet still prevalent, method for binary change detection is change vector analysis (CVA) [4], based on a simple comparison operator. An evaluation into the use of different comparison operators, distance and similarity metrics for change detection may be found in [5].

Whereas most change detection methodologies utilize the whole spectral range and size of the multitemporal remote sensing images, it is nevertheless possible to utilize band selection and dimensionality reduction (DR) techniques in the change detection process. Band selection-based DR techniques have been investigated for change detection in [6]. Transformation-based DR techniques have also been utilized for change detection in the literature [7-9]. However, none of these transformation-based methods have proved effective across the board in a robust manner.

For transformation-based DR techniques, nonlinear manifold learning methods have proven to be very useful compared to linear counterparts, especially in dimensionality reduction, image fusion, and multi-temporal image analysis [10]. Manifold learning has been previously utilized in the literature for the classification of temporal images, but their use in change detection is still severely limited. The clustering assumption on the data manifold is combined with kernel machines in the form of manifold regularization to classify multitemporal hyperspectral images in [11]. As the spectral shifts between multitemporal hyperspectral images pose difficulties, similar local manifolds of temporal images are aligned in a common latent space for multitemporal classification in [12]. Inspired by locally linear embedding, an automatic change-detection method through an offline learning approach is proposed for multitemporal SAR images in [13].

This paper proposes a manifold-based change detection approach for hyperspectral images. The proposed approach utilizes Laplacian Eigenmaps (LE) [14] on the spectrally stacked temporal hyperspectral datasets. The manifold extracted by LE is used for DR and change detection. A simple semi-supervised scheme on the first two output latent vectors is also proposed to provide the final binary change map. This scheme, although has the drawback of requiring a, albeit simple, decision from the user, has the benefit of circumventing a challenging issue in change detection, i.e., the thresholding or discrimination, of the changed vs. unchanged regions. Although older approaches often utilized a decision threshold based on one of two assumptions, either that only a few changes have occurred between the temporal images or that a threshold may be detected by analysis of simple image statistics such as histogram, the increase in the number of available sensors and modalities has created the need for more advanced solutions [15, 16]. However, the proposed method and scheme circumvents the thresholding issue by the contribution of the semi-supervised scheme.

2. LAPLACIAN EIGENMAPS

LE is a nonlinear dimensionality reduction method based on graph embedding. Given a set of samples $X = [x_1, \cdots, x_m]$, where $x_i \in R^n$, and m is the number of samples, the LE aims to preserve the samples' local neighborhoods lying on a manifold in the high-dimensional space when embedding the samples in a low-dimensional space. The resulting coordinates in the low dimensional space are denoted as $y_i \in R^d$ where $d \ll n$. The neighborhood relations are ensured by an adjacency matrix W that is typically constructed based on the samples' pairwise distances. To obtain the coordinates of the samples in the low-dimensional space, the following objective function is minimized:

$$\sum_{ij} \left| y_i - y_j \right|_2 W_{ij} = Tr(Y^T L Y) \tag{1}$$

under the constraint

$$Y^T D Y = I \tag{2}$$

with $Y = [y_1, \cdots, y_m]$. L is a graph Laplacian matrix and is calculated as $L = D - W$. The degree matrix D is defined as the diagonal matrix whose entries are the sum of the row or the column of the adjacency matrix. The solution of Eq. (1) yields the following generalized eigenvalue problem.

$$Ly = Dy \tag{3}$$

The y_i's corresponds to eigenvectors of Eq. (3) associated with the smallest eigenvalues. The second smallest eigenvector is called the Fiedler vector [17, 18], which has a strong connection to spectral clustering (graph partitioning) [19]. According to the spectral graph theory, graph Laplacian matrices are the primary tool for spectral clustering and approximate the graph mincut problem, which is identical to Laplacian Eigenmaps under some relaxations [20]. The related solution to the mincut problem refers to the Fiedler vector, which holds the structural properties of data regarding the graph's connectivity, forming the basis for spectral clustering. Therefore, to obtain a graph partitioning, the real-valued solution of the eigenvectors is transferred to discrete values using the sign function as below, where the clusters are denoted as A and $\bar{A}$:

$$\begin{cases} y_i \in A & if\ y_i > 0 \\ y_i \in \bar{A} & if\ y_i < 0 \end{cases} \tag{4}$$

3. METHODOLOGY

The proposed methodology starts by stacking the temporal hyperspectral images in the spectral dimension. This simple premise ensures that a joint manifold may be obtained for the entire multitemporal dataset. Another approach could be to obtain separate manifolds for each of the temporal datasets and analyze the differences between separate manifolds, but such an approach would necessitate the alignment of separate manifolds. Another reason behind a joint manifold is that "changed" and "unchanged" pixels vectors would be located in separate sections of this manifold and hence relatively easy to distinguish. Separate manifolds would represent the pixel vectors of temporal datasets instead of representing and enabling easier discrimination of changed/unchanged temporal pixels.

Although potentially any manifold approach may be used in this work, this work prefers the use of LE. This is because the resulting representation is easy to interpret in terms of eigenvector analysis. LE is applied to the stacked multitemporal dataset. The method involves two parameters, which have been simply selected as k = 13 for the number of neighbors, and σ = 1 for width of the heat kernel. A crude experimental analysis was used to check whether the method was robust in selecting these values, and the result was satisfactory.

Following manifold representation, DR is conducted, simply by taking the first two latent vectors of the resulting representation. The method then progresses to the semi-supervised scheme, which circumvents thresholding and results in a binary output. In this stage, the method simply asks the user to select the negative or positive values in each of the two latent vectors, and disregard the other values. The resulting two binary outputs are combined with a simple AND or OR logic operation for the binary change output.

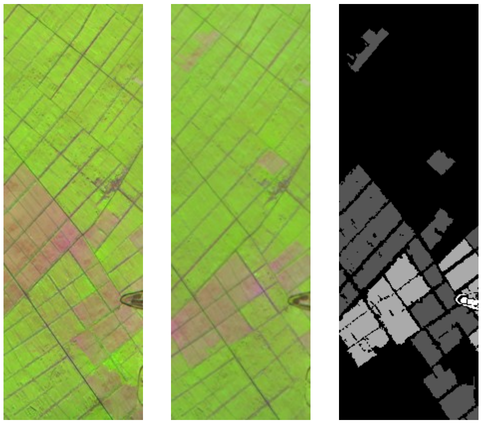
4. EXPERIMENTAL RESULTS

The proposed method is evaluated in two real bitemporal hyperspectral datasets. As the proposed method provides a binarized output, quantitative results are presented in terms of true positive (TP) and false positive (FP) ratio. The performance of CVA is also provided as a benchmark method. In order to disregard the effect of any threshold selection approach, CVA output is evaluated for all possible thresholds in terms of a receiver operating characteristics (ROC) curve. Minimum FP ratio, for the same TP rate, and maximum TP ratio, for the same FP rate as the proposed method is also provided.

5.1. Dataset 1 - Yuncheng

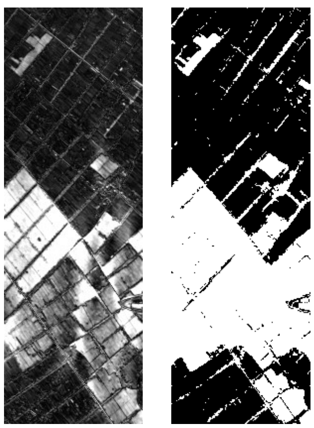
The first bitemporal dataset consists of two HS images acquired by the Hyperion sensor over Yuncheng, Jiangsu province, China, on the dates of 3 May 2006 and 23 April 2007. The images have 420 × 140 pixels, and 154 spectral bands are used. False color composites of the temporal datasets, and the ground truth change detection map are provided in Fig. 1. Note that as the proposed method is aimed towards, and evaluated based on, binary change detection, this ground truth map is binarized in terms of changed vs. unchanged.

Qualitative results, i.e. change detection outputs for the benchmark CVA, and the proposed method are presented in Fig. 2. ROC curve for CVA, and the TP and FP rate for the proposed method are provided in Fig. 3.



(a) (b) (c)

Fig. 1. Bitemporal Yuncheng HS dataset, a) May 2006 false color, b) April 2007 false color, c) ground truth map



(a) (b)

Fig. 2. Change detection map for Yuncheng data, a) CVA, b) Proposed

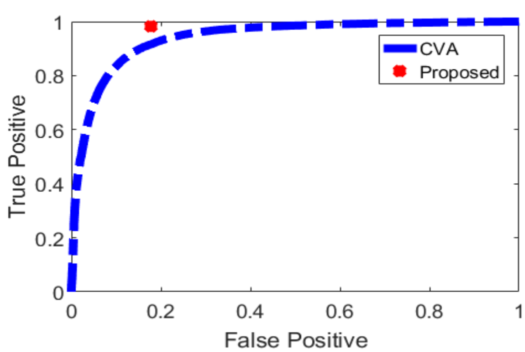
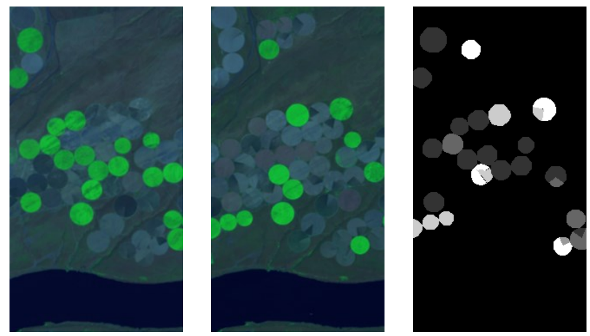


Fig. 3. ROC curve for CVA and TP-FP rates for the proposed approach

The proposed approach provides a TP rate of 0.9824 and FP rate of 0.1778. For the same TP rate with the proposed method, i.e., 0.0924, CVA results in a worse FP rate of around 0.45. Similarly for the same FP rate with the proposed method, i.e., 0.1778, CVA results in a worse TP rate of around 0.9157.

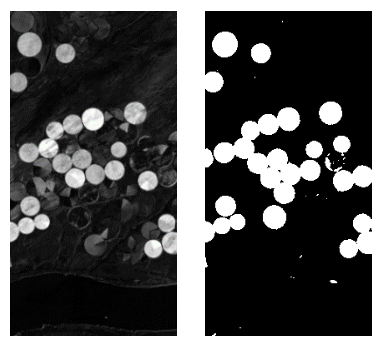
5.2. Dataset 2 - Hermiston

The second bitemporal dataset consists of two HS images acquired by the Hyperion sensor over Hermiston City, Oregon, USA, in 2004 and 2007. The images have 390 × 200 pixels, and 154 spectral bands are used in this work. False color composites of the temporal datasets, and the ground truth change detection map, are provided in Fig. 4.



(a) (b) (c)

Fig. 4. Bitemporal Hermiston HS dataset, a) 2004 false color, b) 2007 false color, c) ground truth map



(a) (b)

Fig. 5. Change detection maps for Hermiston data, a) CVA, b) Proposed

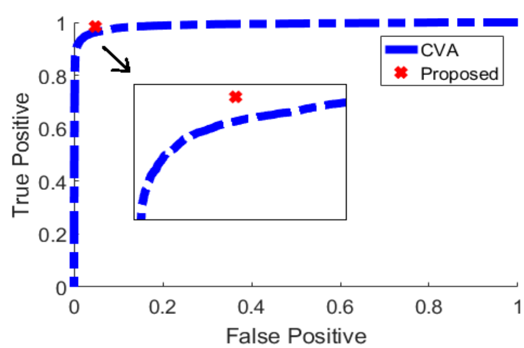


Fig. 6. ROC curve for CVA and TP-FP rates for the proposed approach

Qualitative results, i.e. change detection outputs for the benchmark CVA, and the proposed method are presented in Fig. 5. ROC curve for CVA, and the TP and FP rate for the proposed method are provided in Fig. 6.

The proposed approach provides a TP rate of 0.9842 and FP rate of 0.0482. For the same TP rate with the proposed method, i.e. 0.9842, CVA results in a worse FP rate of around 0.1382. Similarly for the same FP rate with the proposed method, i.e. 0.0482, CVA results in a worse TP rate of 0.9622.

It can be observed that the proposed manifold based DR and change detection approach with the semi-supervised output scheme results in overall satisfactory performance for both multitemporal datasets. The method has the added benefit of circumventing the challenge of thresholding. It should be noted that the proposed method has the drawback of significantly high computation time, due to manifold graph matrix computations. Although the methodology and the experimental validation presented in this paper are the result of preliminary work, they nevertheless showcase that this line of research shows promise.

5. CONCLUSIONS

This paper proposes a hyperspectral data change detection approach which utilizes manifolds extracted by Laplacian eigenmaps, and a very simple semi-supervised thresholding scheme. The proposed method is evaluated for two real bitemporal hyperspectral datasets for binary change detection, and the obtained performances validate the proposed approach. The method has also the added benefit of circumventing the very challenging issue of selecting a threshold, for binary outputs, for each multitemporal dataset. Future studies will aim to fully automate the methodology and get rid of the ambiguity in the last step, by possibly using manifold segmentation or including additional information using a simple method such as CVA. Another future line of research could be to address the major drawback of the significant computation time, which is caused by constructing the adjacency matrix.

6. REFERENCES

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