ROBUST PCANET FOR HYPERSPECTRAL IMAGE CHANGE DETECTION

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ABSTRACT

Deep learning is an effective tool for handling high-dimensional data and modeling nonlinearity, which can tackle the hyperspectral data well. Usually deep learning methods need a large number of training samples. However, there is no labeled data for training in change detection (CD). Considering these, this paper develops an unsupervised Robust PCA network (RPCANet) for hyperspectral image CD task. The main contributions of this work are twofold: 1) An unsupervised convolutional neural networks named RPCANet is proposed to handle the hyperspectral image CD; 2) An effective CD framework using the RPCANet and change vector analysis (CVA) is designed to achieve better CD performance with more powerful features. Experimental results on real hyperspectral data sets demonstrate the effectiveness of the proposed method.

Index Terms— Hyperspectral image, change detection (CD), Robust PCA network (RPCANet), change vector analysis (CVA).

1. INTRODUCTION

Change detection (CD) has been a hot topic in recent years, which provides timely and accurate information for the global change. Among various remote sensing images, hyperspectral image characterized by high spectral resolution is able to detect finer changes than traditional multispectral images. A complete hyperspectral image CD process contains three steps: (1) Hyperspectral image preprocessing. Multitemporal images should be preprocessed to ensure that they are spatially and radiometrically comparable. (2) Difference image generation. Difference image obtained from different algorithms shows the changed and unchanged regions. This is a key step for it aims at how to design an effective CD algorithm. (3) Evaluation. In this step, evaluation measures are presented to evaluate the performance of algorithms.

In recent years, deep learning achieves great performance in the field of image analysis [1], [2]. It is an effective tool to handle high-dimensional data problem and model nonlinearity. By exploring which part of data is critical, deep learning learns a series of powerful features and tackles the hyperspectral data well. Specifically, deep convolution neural network (CNN) is able to model spatial context information inherently by receptive field. Overall, deep CNN is well-suited for processing hyperspectral data in CD task.

Usually, deep CNN need a large number of training data to learn the parameters of nonlinear function. However, obtaining labeled samples in hyperspectral image is not very practical. Thus, unsupervised method of deep CNN becomes more popular when dealing with hyperspectral image CD task. Chan et al. proposes PCANet [3], which is a very simple unsupervised convolutional deep learning network for extracting useful information. PCANet is easily and efficiently designed and has competitive even superior performance over some other deep networks. Considering these, this paper develops a Robust PCANet (RPCANet) to extract discriminative features for CD task. First, due to speckle noise in multitemporal images, PCANet is extended to RPCANet to improve the performance of CD task. Moreover, RPCA filters are taken as convolutional filters in deep CNN. Not only hierarchical features are learned by deep CNN, but also no labeled sample is required. The main contributions are summarized as follows.

(1) Robust PCANet (RPCANet) is proposed to learn the discriminative features effectively from the multitemporal hyperspectral images. To the best of our knowledge, it's the first time PCANet is used in hyperspectral image CD task.

(2) CVA works seamlessly with the powerful feature vectors extracted from RPCANet to achieve the final change result. With respect to different datasets, the proposed method improves the CD performance.

2. RPCANET CHANGE DETECTION

The high-dimensional hyperspectral image contains redundant spectral information, which always leads to huge computational complexity and Hughes phenomenon. In addition, the

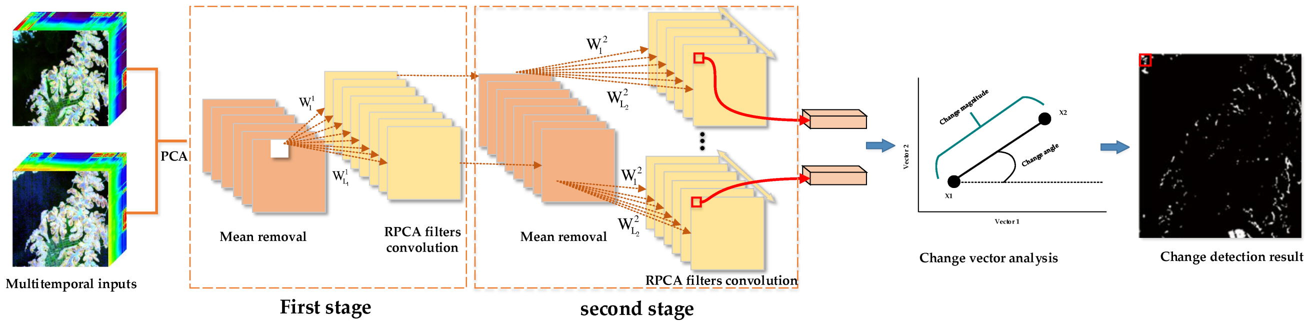

Fig. 1. The RPCANet change detection workflow.

dimension of feature obtained by PCANet will increase exponentially with deeper network. Thus, it is necessary to reduce the high-dimension of hyperspectral image. PCA is a simple and effective method for feature extraction. In this work, PCA is used to linearly transform each hyperspectral image into a new K-dimensional image for dimensionality reduction. Given two input hyperspectral images acquired at the same position from different times, and each size of image is $m \times n$. After dimensionality reduction, each K-dimensional image is divided into K single-band images. Specifically, there are K input training samples of hyperspectral image at time 1. In the whole network, only Robust PCA (RPCA) [4] filters demand to be learned from the K images. The overview of RPCANet CD method for multitemporal Hyperspectral images is shown in Fig. 1.

2.1. Robust PCA

Supposing that the number of RPCA filters in the i-th stage is L_i, given a data matrix $X = [X_1, X_2, ..., X_K] \in R^{d \times K}$,where K is the number of data point and d is the dimensionality of data point. RPCA is to minimize the following reconstruction error:

$$\min_{rank(Z)=L_i} \|X - Z\|_{2,1}, \tag{1}$$

where Z is an approximation of X and the $rank\,(Z)$ is L_i. The problem (1) can be described as to solve the following problem:

$$\min_{U \in R^{d \times L_i}, U^T U = I} \sum_{i=1}^{K} \left\| \left(I - UU^T\right) \mathrm{X}_i \right\|_2, \tag{2}$$

$$H_d = D - \frac{D11^T D}{1^T D1}, \tag{3}$$

where $U = [u_1, u_2, ..., u_{L_i}] \in R^{d \times L_i}$ consists of eigenvectors of XH_dX corresponding to the L_i largest eigenvalues; u_l denotes the l-th eigenvector; H_d is a weighted centering matrix. By an iterative re-weighted method to solve the problem (2). The detail of the algorithm is illustrated in Algorithm 1.

Algorithm 1 Algorithm to solve Robust PCA

Initialize D as an identity matrix W

While not converge **do**

1. Using k right singular vectors of X$(\mathrm{D}^{\frac{1}{2}} - \frac{D11^T D^{\frac{1}{2}}}{1^T D1})$ corresponding to the k largest singular values to update U.
2. Update the i-th diagonal element of D by $d_{ii} = \frac{1}{2\|(I - UU^T)(X_i)\|_2}$

end While

Output: U

2.2. Structures of RPCANet

1) The First Stage (RPCA): With respect to each pixel, we take a $p \times q$ patch and obtain all vectorized patches of the i-th image. Then the patch mean is subtracted from each patch. Generally, the i-th single-band image can be expressed as $\overline{X}_i = [\overline{x}_{i,1}, \overline{x}_{i,2}, ..., \overline{x}_{i,mn}]$, where $\overline{x}_{i,j}$ denotes the j-th mean removed patch. By performing the same operation on all the K input images, we obtain $X = \left[\overline{X}_1, \overline{X}_2, ..., \overline{X}_K\right] \in R^{pq \times Kmn}$. According to abovementioned RPCA, RPCA filters can be expressed as

$$W_l^1 = mat_{pq}\,(u_l) \in R^{p \times q}, \qquad l = 1, 2, ..., L_1, \tag{4}$$

where $mat_{pq}\,(v)$ is a function which maps $v \in R^{pq}$ to a matrix $W \in R^{p \times q}$; u_l is the l-th eigenvector of XH_dX; L_1 is the number of filters in the first stage. Then the l-th filter output of the first stage is

$$H_i^l = H_i * W_l^1, \qquad i = 1, 2, ..., K, \tag{5}$$

where $*$ denotes 2-D convolution. After achieving the L_1 filter outputs, the first stage is completed.

2) The Second Stage (RPCA): The second stage is similar to the first stage. First, we collect all the patches of H_i^l and patch mean is subtracted from each patch. Then, the mean-removed patches form $\overline{Y}_i^l = \left[\overline{y}_{i,l,1}, \overline{y}_{i,l,2}, \cdots, \overline{y}_{i,l,mn}\right] \in R^{pq \times mn}$, where $\overline{y}_{i,l,j}$ denotes the j-th patch in H_i^l. The matrix $Y^l = \left[\overline{Y}_1^l, \overline{Y}_2^l, ..., \overline{Y}_K^l\right] \in R^{pq \times Kmn}$ collects all the mean-removed patches of the l-th filter output. After that we concatenate Y^l of all the filter outputs as

$$Y = \left[Y^1, Y^2 ..., Y^{L_1}\right] \in R^{pq \times L_1 Kmn}. \tag{6}$$

The RPCA filters are obtained as

$$W_\ell^2 = mat_{pq}\left(u_\ell\right) \qquad \ell = 1, 2, ..., L_2, \tag{7}$$

Each input H_i^l in second stage will generate L_2 output images with the size of $m \times n$, each convolves H_i^l with W_l^2:

$$S_i^l = H_i^l * W_\ell^2, \qquad \ell = 1, 2, ..., L_2. \tag{8}$$

The total number of output images of the second stage is $L_1 L_2$. In this way, each pixel in preprocessed hyperspectral image at time 1 is transformed into a vector $\tau_i^1 \in R^{L_1 L_2 \times 1}$. Similarly, $\tau_i^2 \in R^{L_1 L_2 \times 1}$ represents the corresponding pixel in hyperspectral image at time 2. τ_i^1 and τ_i^2 contain a series of discriminative features extracted from RPCANet, which can identify pixels whether they change or not effectively. Higher features will be extracted if more stages of RPCA filters is stacked.

2.3. Change vector analysis

After exploiting RPCANet, a series of discriminative features of multi-temporal hyperspectral data are obtained. The two feature vectors τ_i^1 and τ_i^2 represent the i-th pixel in hyperspectral images of time1 and time 2, respectively. The difference of a pair of corresponding pixels can be expressed as

$$\Delta\tau_i = \tau_i^2 - \tau_i^1. \tag{9}$$

The magnitude of τ_i is used to represent the magnitude of change. Now the magnitude of vector $\Delta\tau$ can determine whether the two input feature vectors change or not. Then double-window flexible pace search (DFPS) [5] is adopted for the selection of appropriate threshold T. In this work, CVA can work well with the representative feature vectors extracted from PCANet to obtain the final change result.

3. EXPERIMENTS

In this section, experiments are conducted in two real-world HSI data sets. Firstly, data sets used in experiments are introduced. Then the experimental performances of different methods are analyzed in detail.

3.1. Datasets Description

In this work, all the hyperspectral image data sets used in the experiments are from Earth Observing-1 (EO-1) Hyperion images. The first data set "farmland" is illustrated in Fig.4 (f), with 155 bands for CD after noise elimination. This data set covers farmland near the city of Yancheng, Jiangsu province,

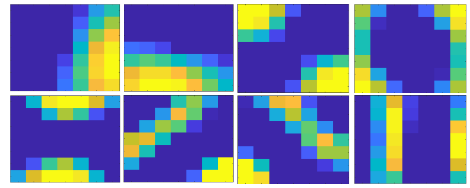

Fig. 2. Visualization of RPCANet filters.

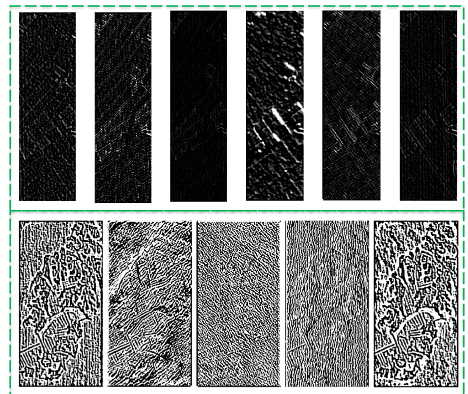

Fig. 3. Some selected convolution maps of the RPCANet.

China, having a size of 450×140 pixels. The second data set "Poyang lake" is illustrated in Fig. 5 (f), with 166 bands for CD after noise elimination. This data set covers the province of Jiangxi, China, having a size of 450×140 pixels.

3.2. Experimental results

We visualize the RPCANet filters learned from the farmland dataset in Fig. 2. It can be found that 8 filters with the size of 7×7 pixels capture different direction gradient features. Moreover, the convolution outputs of the RPCANet by exploiting the learned filters is shown in Fig. 3. It indicates the convolution results learn different direction and hierarchical features, which is more representative for hyperspectral image CD.

In this work, overall accuracy (OA) and Kappa coefficient are adopted to evaluate the performance of CD methods. The

Table 1. THE OVER ACCURACY OF RPCANET AND OTHER THREE CHANGE DETECTION METHODS ON TWO DATA SETS

	Farmland		Poyang Lake	
Methods	OA(%)	Kappa	OA(%)	Kappa
CVA	95.23	88.55	96.93	80.92
PCA-CVA	96.68	92.02	95.48	72.59
IR-MAD	96.04	92.31	89.63	86.32
RPCANet(ours)	**97.12**	**95.26**	**97.67**	**94.38**

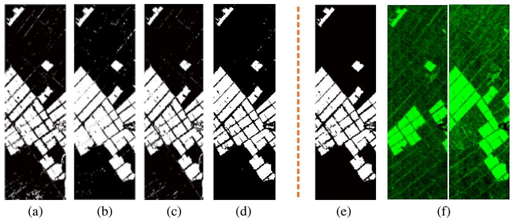

Fig. 4. (a) the difference image of CVA on the "farmland" data set, (b) the difference image of PCA-CVA, (c) the difference image of IR-MAD, (d) the difference image of RPCANet, (e) the ground truth and (f) The "farmland" data set

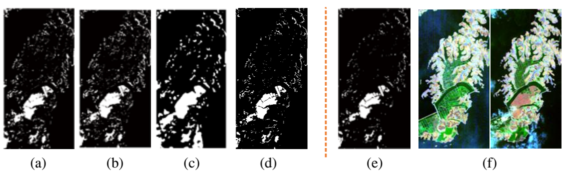

Fig. 5. (a) the difference image of CVA on the "Poyang lake" data set, (b) the difference image of PCA-CVA, (c) the difference image of IR-MAD, (d) the difference image of RPCANet, (e) the ground truth and (f) The "Poyang lake" data set.

higher value of OA and Kappa coefficient, the better result of CD will be. We compare it with other state-of-the-art methods, including change vector analysis (CVA) [6], principal component analysis- change vector analysis (PCA-CVA) [7], iteratively reweighed multivariate alteration detection (IR-MAD) [8], and Table 1 shows the details of them on two data sets. On the "farmland" data set, it can be obviously found that RPCANet is a very effective method for CD task, with the highest OA and Kappa coefficient. The performance of CVA is relatively poor, since it is a simple arithmetical operation without useful feature extraction. The difference images of "farmland" data set are shown in Fig. 4.

On the "Poyang lake" data set, RPCANet outperforms the other three CD methods, since it extracts a series of discriminative features. However, IR-MAD yields lower OA, mainly because it is insensitive to complicated changes. Though CVA and PCA have the high OA, the Kappa coefficient of either is relatively low. The difference images are shown in Fig. 5.

4. CONCLUSION

In this paper, RPCANet is proposed to learn the discriminative features effectively for hyperspectral image CD task. First, PCANet is extended to RPCANet for improving the performance on anti-noise. Specifically, its the first time PCANet is used in hyperspectral image CD task. Then, CVA is able to work seamlessly with the powerful feature vectors extracted from PCANet to achieve the final change result. In the end, the proposed method is evaluated on two data sets and shows its effectiveness.

5. ACKNOWLEDGMENT

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