SAR Images Change Detection based on Sparse Coding and NMF

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Abstract. There are many applications for SAR image change detection, from military and agriculture to detection and management. But in fact, there is the speckle noise in SAR images inevitably. Therefore, the difficulty to detect change is increased. For purpose of reducing the interference of noise, we propose an unsupervised feature learning method using the non-negative matrix factorization algorithm and an improved sparse coding algorithm. First, non-negative matrix factorization method is used to obtain a dictionary which contains spatial structure information. Then, in order to increase the discriminate ability, we extract features for each pixel and apply sparse coding. Finally, the result of SAR image change detection is generated by applying simple k-means clustering method to divide the learned features into two different clusters. The superior performance of the proposed method is verified on several real SAR image datasets through comparisons with several existing change detection techniques.

Keywords: Change detection, non-negative matrix factorization (NMF) algorithm, sparse coding.

1. Introduction
Synthetic aperture radar (SAR) image are generated by remote sensing techniques that allow obtaining images unaffected by night and day. Because of the independently of atmospheric and sunlight conditions, SAR have an important research value-Change detection (CD). CD could identify the differences of the same region at different times [1]. CD is applied to forest resource monitoring, disaster management, urban research, land surface materials [2], and so forth.

Recent years, many researchers are working on CD and have promoted the development of SAR technology. CD is by analysis two remote sensing images, which was registered and acquired from the same geographical location at two different times [3]. Generally, the key steps of CD methods are to obtain the difference image (DI) and then identify the changed pixels in the DI using unsupervised or supervised algorithms. When obtained using common techniques, SAR images are usually corrupt by the speckle, which makes complicates the application of CD to distinguish with changed and unchanged parts. Therefore, the removal of speckle noise is a key problem for the application of CD methods in SAR images.
To generate the DI, there are well-known techniques involving the subtraction and the ratio operators. The ratio operator is much robust than the subtraction in some way. The speckle of SAR images has the characteristics of multiplicative. Therefore, the log ratio operator is generally applied to generate the DI, because theoretically it suppresses the affect of speckle noise. In addition, there is a lot of well-known despeckling filters e.g., Lee and Gamma MAP filter [4]. These methods are generally used to restrain speckle noise. Although the noise is removed to a certain extent, the discriminative information which is very important for CD loss at the same time.

In fact, even after filtering there is a lot of noise remaining in the DI. Zhang [5] proposed the Mean shift clustering to suppress speckle noise in the DI. While it maintains the changed information to some degree, the marginal information be easily lost. Apart from clustering methods, some threshold-based methods had been put forward to generate the final change map, such as the thresholding algorithm [6]. It is effective, but results in inaccuracies because spatial information taken into account. In 2000, two excellent thresholding techniques [7] based on Bayes’ theory were presented in order to analyse the DIs by Bruzzone and Prieto. Although these methods achieved impressive results, they had high computational complexity.

Change detection based on feature extraction have been proposed and many methods can detect changes in SAR images using spatial neighborhood information. The principal component analysis (PCA) has been used to obtain the features for change detection [8]. The contextual information was taken into consideration with a low computational cost. Deep neural networks had been used to image understanding broadly in recent years. The deep belief network (DBN) was applied in [9] which combined with threshold methods. Due to the training set was necessary, a threshold method was applied to obtain the training samples at first. Then the training samples was sent to the DBN. The compressed sparse representation method was used to extract discriminative features in [10]. Besides the speckle noise was suppressed effectively. In [4], we proposed a feature extract method which make the best of sparse representation and non-local similarity. This algorithm restrain the speckle noise effectively, as well as enhances the discriminat of the obtained features. However, the spatial structure information is neglected.

Inspired by the early work, this paper comes up with a non-negative sparse coding method for change detection. The non-negative matrix factorization (NMF) method [11] is used to extract non-negative features. On account of the non-negativity constraint, NMF could make SAR image representation less redundant for feature extraction [11]. In order to increase the discrimination of the changed areas, we also apply the sparse coding algorithm [12] to obtain the non-negative features and create the features in the original data to generate an applicable representation using an unsupervised process. Every pixel of the DI is extracted as a feature vector through its $h \times h$ neighborhoods, so spatial information is preserved [3].

The paper structure is arranged like this. The second part expounds in detail the proposed method of unsupervised change detection. In the third part, the experimental results are discussed on some real SAR images data sets. Finally, the fourth part gives the conclusion.

2. Proposed Approach

Suppose there are two co-registered SAR images $I_{m1}$ and $I_{m2}$. The DI of two SAR images is achieved using the log ratio operator [3]. The final result is expressed as $CM$ which represented the change map of the original images $I_{m1}$ and $I_{m2}$. The presented method involves three key stages as illustrated in Fig. 1. NMF is applied to learn a dictionary according to the DI for the first step. In the second stage, sparse coding which is constrained by non-negativity is used to generate the discriminative features. In the last step, k-means clustering algorithm is used to obtain a change detection map.
2.1. Learning Dictionary

NMF could decompose a matrix into two matrices whose all its elements are non-negative [11]. The DI is split into non-overlapping image blocks of size \( h \times h \). Suppose there are \( n \) original image blocks \( Q = [q_1, q_2, \ldots, q_n] \in \mathbb{R}^{m \times n} \), where \( m \) represents the dimension of each block, and \( n \) represents the number of training data. This purpose of NMF is to generate two non-negative matrix \( M \) and \( N \) to estimate the original matrix such that

\[
Q_{m \times n} = M_{m \times k}N_{k \times n}
\]  

(1)

Where \( N \) is the weight matrix, and \( M \) is the basis matrix. There is no exact method to determine \( k \). It is usually determined experimentally or empirical evidence and is set to be smaller than \( m \) and \( n \), which satisfies \( (m+n)k < mn \) [11].

Every column of the matrix \( Q \) is approximately represented by a weighted linear combination of the columns of the \( M \) matrix. The matrix of \( N \) contains the weights [16]. A more compact representation of the DI could be achieved by applying the basis vectors obtained through the NMF. These basis vectors include local spatial structure information [11], which are identical with the non-negative features.

The NMF of the original matrix \( Q \) is achieved by solving a nonlinear optimization problem. In order to measure this approximation, the convergent objective function is defined. The cost function [11] to be minimized is as follows:

\[
\min \| Q - MN \|_F^2
\]

s.t. \( M \geq 0, \quad N \geq 0. \)

Where \( \| \cdot \|_F \) is the Frobenius norm. There are many methods to obtain the non-negative matrices \( M \) and \( N \). In this paper, the iterative transition is used to realize NMF by means of changing the beginning values of \( M \) and \( H \) . The iterations will be ended in two cases. One is the error of approximation is convergent. Another case is the iterations reaching to a preset value [11]. The iterative updating equations are as follows:

\[
M_{m} \leftarrow M_{m} \frac{\sum \frac{N_{m}V_{m}^{i} / (MN)_{m}}{\sum N_{m}}}{N_{m}}
\]

(3)
\[ N_{a+} \leftarrow N_{a+} \sum_{i} \frac{M_i V_{m+}/(MN)_{m+}}{\sum_i M_{ka}} \]  

(4)

Each iteration results new values of \( M \) and \( N \), which are obtained by multiplying the current value by a factor. These factor is depended on the quality of the approximation in equation (2). In order to converge to a locally optimal matrix, repeated iteration of the updated regulation are needed [11].

In the unsupervised change detection method, only unlabeled data are available. We use NMF to learn the codebook. A codebook from the original pixels \( G \) is obtained. In consideration of the computation, the number of elements in the codebook is set to 10. The feature matrix of \( M \in R^{n \times k} \) is the learned codebook, where \( k = 10 \).

The local spatial structure information of the DI could be obtained in the non-negative features. However, the features do not have the discriminability, which is important to generate the changed features from the original pixels. On behalf of increasing the discrimination, the sparse coding algorithm is used to utilize the learned non-negative features.

2.2. Feature Vectors via Non-negative Sparse Coding

In order to capture higher-level features in the data, a class of algorithm were proposed for sparse coding to find compact representations [12]. To a certain extent, the spare coding can also restrain the negative effects of noise. Because speckle noise is a common occurrence in SAR image analysis, in this section, the sparse coding method is used to study the features of changed parts and unchanged parts in DI. The initial feature vector is produced by overlapping its \( h \times h \) neighborhood pixles. The DI is enlarged by repeating boundary data to avoiding errors at the image margin. In this manner, \( H \) \((H = L \times W)\) original vectors: \( F = \{f_1, f_2, \ldots, f_H\} \) were obtained, where \( L \) and \( W \) is the size of the image.

In the sparse coding algorithm, the codebook uses the learned \( M \in R^{n \times k} \) matrix, which includes non-negative features extracted from the original pixels. The optimization problem is as hereunder mentioned:

\[
\arg \min_\mathbf{c} \| f_i - M\mathbf{c}_i \|_2 + \lambda \| \mathbf{c}_i \|_1 \\
\text{s.t.} \quad \mathbf{c}_i \geq 0
\]  

(5)

where \( M \) is the learned dictionary, \( f_i (i = 1, 2, \ldots, H) \) is the original feature of the ith pixel, \( \lambda \) is a parameter that balances reconstruction error and sparsity, and the sparse coding feature vector is \( \mathbf{c}_i \), which with the non-negative constraint. The loss function is robust to irrelevant features, and the property augment the sensibility for different areas. The dual Lagrange and feature-sign algorithms [12] were applied to calculate the sparse coefficients \( \mathbf{c}_i \). After attained the features, their discriminatory ability augment and the changed pixels were much more suitable to be identified.

2.3. Obtaining Change Map

This section applies the k-means clustering algorithm to allocate a learned features into changed cluster and unchanged cluster to generate the change map. Similarly to [8], we set the \( ME_c \) as mean feature of the changed category, and \( ME_u \) as the mean feature of the unchanged category. The binary change map \( CH = \{cm(l,w), 1 \leq l \leq L, 1 \leq w \leq W\} \) is created in accordance with the Euclidean distance. The formula is shown as follows:

\[
ch(l,w) = \begin{cases} 
1, & \| v(l,w) - ME_c \|_2 \leq \| v(l,w) - ME_u \|_2 \\
0, & \text{others}
\end{cases}
\]  

(6)

Where the unchanged sector is denoted as “0”, and the changed sector is denoted as “1”[3].
3. Experimental Results

3.1. Data Sets

This section provides three SAR images to evaluate the availability of the presented algorithm in this paper. Meanwhile, this section demonstrates the performance of the presented approach by means of comparing with four other related approaches.

The three SAR images are shown as Fig. 2 to Fig. 4, respectively. Fig. 2 is with 10m resolution, whose size is 290×350 pixels. The two images were obtained near the city of Ottawa, Canada, in May and August 1997, respectively. Fig. 2(c) shows a reference map. There are 101500 changed pixels, and the white parts represent changed areas. The second pair of data set is with 30m resolution and C-band and VV polarization, which are shown in Fig. 3(a) and (b) [3]. The two images were the city of Bern, Switzerland. They were respectively obtained in April and May 1999. The reference image which was defined with 1155 changed pixels by scientists is shown in Fig. 3(c). The images in Fig. 4 are obtained from the farmland near the Yellow River of China [8]. Its size is 257×289 pixels. Fig. 4 (c) is the reference image. This data set with different look, which are respectively single-look and four-look. Therefore, there are much more difficulty than the last two data sets.

![Fig. 2 Ottawa. (a) Image acquired in July 1997. (b) Image acquired in August 1997. (c) Reference.](image)

![Fig. 3 Bern. (a) Image acquired in April 1999. (b) Image acquired in May 1999. (c) Reference.](image)

![Fig. 4 the Yellow River. (a) Image acquired in June 2008. (b) Image acquired in June 2009. (c) Reference](image)

3.2. Quantitative Analysis

The used quantitative analysis of the results is set up like this: false alarms (FA, the amount of real unchanged pixels), missed alarms (MA, the amount of real changed pixels), overall error (OE, the sum of the FA and MA), the percentage of the accuracy of detection (PCC) and Kappa index. The value of
kappa index is between zero and one. When the kappa index is higher, the reference image and change map are more consistent [13].

3.3. Quantitative Results and Analysis

In this session, four advanced methods were carried out for comparisons: generalized minimum-error thresholding (GKI-LN) method [9], principal component analysis and K-means clustering (PCA-K) [8], compressed sampling sparse representation (CS-KSVD) method [10], neighborhood-based ratio approach (NR) [13]. For our proposed method, we set the parameter $\lambda$ to be 0.1 in the experiments.

Fig. 5 shows the results acquired by the methods mentioned above for the first SAR images. We can see that all of the methods can detect most changes. However, the result of NR method has much more FA pixels than the another four algorithms. Because it is sensitive to the speckle noise. From the result, we can see that the result of GKI-LN has many missed detection. Fig. 5 shows that the proposed method achieves better result than the another four algorithms in the upper left corner.

Fig. 5 Results of Ottawa. (a) GKI-LN, (b) PCA-K, (c) CS-KSVD, (d) NR, (e) proposed method.

Fig. 6 Results of Bern. (a) GKI-LN, (b) PCA-K, (c) CS-KSVD, (d) NR, (e) proposed method.

Fig. 6 is the experimental results of the second data set. The results of the other four methods present much more scattered points. The proposed method can removed the single-point as shown in Fig. 6(e). The results of the proposed method obtains the minimum FA as shown in Table II.
Fig. 7 Results of Yellow River. (a) GKI-LN, (b) PCA-K, (c) CS-KSVD, (d) NR, (e) proposed method

Table 1. Results of Ottawa

| Methods    | FA  | MA  | OE  | Kappa   | PCC  |
|------------|-----|-----|-----|---------|------|
| GKI-LN     | 68  | 4183| 4251| 0.8244  | 95.81%|
| PCA-K      | 955 | 1515| 2470| 0.9073  | 97.57%|
| CS-KSVD    | 558 | 1929| 2487| 0.9047  | 97.55%|
| NR         | 1366| 760 | 2126| 0.9224  | 97.91%|
| Proposed method | 403 | 1507| 1910| 0.9273  | 98.12%|

Table 2. Results of Bern

| Methods    | FA  | MA  | OE  | Kappa   | PCC  |
|------------|-----|-----|-----|---------|------|
| GKI-LN     | 291 | 86  | 377 | 0.8480  | 99.58%|
| PCA-K      | 158 | 146 | 304 | 0.8674  | 99.66%|
| CS-KSVD    | 161 | 147 | 308 | 0.8657  | 99.66%|
| NR         | 110 | 199 | 309 | 0.8596  | 99.66%|
| Proposed method | 72  | 209 | 281 | 0.8691  | 99.69%|

Table 3. Results of Yellow River

| Methods    | FA  | MA  | OE  | Kappa   | PCC  |
|------------|-----|-----|-----|---------|------|
| GKI-LN     | 172 | 6902| 7074| 0.6006  | 90.48%|
| PCA-K      | 2137| 2663| 4800| 0.7785  | 93.54%|
| CS-KSVD    | 2215| 2697| 4912| 0.7736  | 93.39%|
| NR         | 2344| 2802| 5146| 0.7630  | 93.07%|
| Proposed method | 2338| 2083| 4421| 0.8005  | 94.04%|

4. Conclusion
This paper proposed a change detection technique based on non-negative sparse coding was presented. The discrimination dictionary is applied to the NMF algorithm, which can make the image representation less redundant. In consideration of the interference of speckle noise, we applied sparse coding with the learned dictionary. Meanwhile, the discriminative change information was acquired. Several data sets was applied to proof the presented method. Through experimental results, the proposed method acquired smaller overall errors and better visual quality.
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References
[1] B. Aiazzi, L. Alparone, S. Baronti, A. Garzelli and C. Zoppetti, “Nonparametric change detection in multitemporal SAR images based on mean-shift clustering,” IEEE Trans. Geosci. Remote Sens., vol. 51, no. 4, pp. 2022-2031, April. 2013.
[2] N. Gupta, G. V. Pillai and S. Ari, “Change Detection in Optical Satellite Images Based on Local Binary Similarity Pattern Technique,” IEEE Geosci. Remote Sens. Lett., vol. 15, no. 3, pp. 389-393, March. 2018.
[3] S. Wang, L. Jiao and S. Yang, “SAR Images Change Detection Based on Spatial Coding and Nonlocal Similarity Pooling,” IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens., vol. 9, no. 8, pp. 3452-3466, Aug. 2016.
[4] A. Lopes, E. Nezry, R. Touzi, and H. Laur, “Structure detection and statistical adaptive speckle filtering in SAR images,” Int. J. Remote Sens., vol. 14, no. 9, pp. 1735-1758, 1993.
[5] Zhang, X., Le, W., and Jiao, L. C.. (2011, Jan). An unsupervised change detection based on clustering combined with multiscale and region growing. International Workshop on Multi-Platform/Multi-Sensor Remote Sensing and Mapping (M2RSM), pp. 1-4.
[6] G. Moser and S. B. Serpico, “Generalized minimum-error thresholding for unsupervised change detection from SAR amplitude imagery,” IEEE Trans. Geosci. Remote Sens., vol. 44, no. 10, pp. 2972-2982, Oct. 2006.
[7] L. Bruzoneand and D. F. Prieto, “Automatic analysis of the difference image for unsupervised change detection,” IEEE Trans. Geosci. Remote Sens., vol. 38, no. 3, pp. 1171-1182, May. 2000.
[8] T. Celik, “Unsupervised change detection in satellite images using principal component analysis and k-means clustering,” IEEE Geosci. Remote Sens. Lett., vol. 6, no. 4, pp. 772-776, Oct. 2009.
[9] Zhao, J., Gong, M., Jia, L, and Jiao, L.. (2014, Jul). Deep learning to classify difference image for image change detection. Proc. Int. Joint Conf. Neural Netw., pp. 411–417.
[10] Fang, L., Li, S., and Hu, J.. (2011, Sep). Multitemporal image change detection with compressed sparse representation. Proc. 18th IEEE Int. Conf. Image Process., pp. 2673-2676.
[11] Cao, Z., Feng, J., Rui, M. and Pi, Y.. (2012, Jun). “NMF and FLD based feature extraction with application to synthetic aperture radar target recognition. 2012 IEEE International Conference on Communications (ICC), pp. 6416-6420.
[12] Vidya, R., Nasira, G. M., Priyanka, R. P. J. (2014). Sparse coding: A deep learning using unlabeled data for high-level representation. World Conference on Computing Communications Technologies (WCCCT), pp. 124-127.
[13] M. Gong, Y. Cao, and Q. Wu, “A neighborhood-based ratio approach for change detection in SAR images,” IEEE Geosci. Remote Sens. Lett., vol. 9, no. 2, pp. 307-311, Mar. 2012.