Fusion of Difference Images for Change Detection in Urban Areas

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Abstract—**Land cover in urban areas in China is changing rapidly during the past years as a result of urbanization. Changes detected from multi-temporal remote sensing images may help significantly in understanding urban development and supporting urban planning. Indeed, differences in reflectance spectra, easily obtained by satellite sensors, are important indicators for characterizing these changes. Although many algorithms were proposed to generate difference images, the results are usually greatly inconsistent. In this work, a complete procedure for land cover change detection by fusing change information obtained from multiple difference images is designed and implemented. Measurement and decision level fusion techniques are used to combine multiple difference images, and support vector machine (SVM) is selected to detect the changes. Multi-temporal CBERS images acquired in 2002 and 2008 are used to detect land cover changes and urban expansion in Shanghai, and experimental results confirm the effectiveness of the proposed approach. Using more change information, both the omission error and commission error could be reduced.**

I. Introduction

Change detection is an important research field in remote sensing information processing. The main assumption is that, it is possible to extract relevant change information remotely by processing multi-temporal remotely sensed images for the same scene. To this aim, change detection techniques have been widely used for land use/cover change, urban growth, forest and vegetation dynamics and disaster monitoring [1, 2]. For decades, a lot of change detection techniques have been designed and tested, on a variety of data sets. Some methods, including principal component analysis (PCA) [3, 4], change vector analysis (CVA) [5, 6], support vector machine (SVM) [7] and object-oriented (OO) classification [8, 9] have shown to be effective in various applications. But there is no existing approach is optimal and applicable to all cases [1, 10].

Among all above mentioned approaches, the simple difference image is one of the main sources of potential change information, because it contains clues about spectral changes as well as spatial changes by means of textural, edge, gradient, and direction differences. Obtaining the difference information and selecting the appropriate threshold to extract the change feature and change information are the key steps in change detection from multi-temporal remote sensing images. A series of studies and applications about difference images in change detection have been proposed. For example, original spectral differencing [11] and ratioing [12,13], texture ratioing [14], combination of differencing and ratioing [15], integration of spectral, texture and shape change results [16], decision fusion of different change indices [17, 18] have been discussed. Despite the methodological strengths of all these methods, their robustness is still not enough. Moreover, different difference images are diversified in their meanings, bands and volume of change information. Therefore, change detection based on a single difference image usually does not allow reducing at a reasonable level both the omission and the commission errors. At the same time, for different data sources and study areas, there is no universally applicable difference image suitable to all cases to obtain a high-precision change detection result.

Aiming at addressing the aforementioned problems, in this work information fusion strategies are applied in change detection using different Spectral Change Difference (SCD) images. Measurement and decision level fusion strategies are designed and implemented by integrating the multiple SCD information or change detection results by SVM detector. The results are compared with those obtained using a single SCD image to explore the feasibility and applicability of the proposed procedure. Combining different types of SCD images or their detection results, the proposed approach can take full advantage of their merits to improve the ability to identify and extract changes, and reduce the uncertainty remaining after using a single difference image.

II. Methodology

Spectral change difference images indirectly reflect the change features and change information among multi-temporal remote sensing images due on the change in pixel spectral reflectance values. In this work, five main SCD images are used in the process of change detection, according to the techniques available in literature [6, 12, 19-21]. Measurement and decision level fusion is then implemented to exploit these multiple difference images. By comparing with the results obtained using each single SCD image in a real test case, the feasibility of the proposed approach is tested and proved.

The algorithms to obtain the above mentioned five SCD images are listed here. Note that N is the band number and that X_{T1}^{i} and X_{T2}^{i} represent the pixel reflectance spectra of ith band at time T1 and T2, respectively.

- Simple Differencing :

$$SD_{SCD}{}^{i} = X_{T2}^{i} - X_{T1}^{i}, \quad i = 1, 2, ..., N \qquad (1)$$

- Simple Ratioing :

$$SR_{SCD}{}^{i} = \frac{X_{T2}^{i}}{X_{T1}^{i}}, \quad i = 1, 2, ..., N \qquad (2)$$

- Absolute Distance :

$$AD_{SCD} = \sum_{i=1}^{N} \left| X_{T2}^{i} - X_{T1}^{i} \right|, \quad i = 1, 2, ..., N \qquad (3)$$

- Euclidian Distance :

$$ED_{SCD} = \sqrt{\sum_{i=1}^{N} \left(X_{T2}^{i} - X_{T1}^{i} \right)^2}, \quad i = 1, 2, ..., N \qquad (4)$$

- Chi Square Transformation :

$$CST_{SCD} = \sum_{i=1}^{N} \left(\frac{X_{T2}^{i} - X_{T1}^{i}}{\sigma_{i}^{diff}} \right)^2, \quad i = 1, 2, ..., N \qquad (5)$$

In order to improve the detection effect and increase the detection precision, different level fusion strategies are introduced. Supervised SVM binary detector is selected for labeled all the pixels into changed and unchanged areas, according to its merits and advantages in solving the problem of two classes separation. The methodology for gaining the final change map consists of the following four steps:

(1) initially, Fuzzy set theory (FS) [19] is used to combine the multi-band SCD image (differencing and ratioing) into a single-band SCD, which is consistent with the other three SCD images;

(2) a set of change and unchanged samples are then selected according to field visits and visual analysis for training the SVM detector to obtain detection results from each SCD;

(3) measurement level fusion of the five original SCD images by means of Fuzzy Set theory is implemented using the same training samples in (2) for training the SVM detector.

(4) finally, three decision level fusion techniques, i.e. Majority Voting (MV) [22, 23], Dempster-Shafer evidence theory (D-S) [17, 24] or Fuzzy Integral (FI) [7, 25], are exploited to merge the single SCD image SVM detection results into the final result.

The complete methodology of the proposed change detection approach is shown in Fig.1.

III. EXPERIMENTS AND ANALYSIS

Two CBERS (China Brazil Earth Resource Satellite) multi-spectral images with 19.5m spatial resolution acquired in June 5, 2002 (CBERS-01) and June 3, 2008 (CBERS-02B) are used for change detection. The study area is in Shanghai City, China's largest commercial and financial center, which is located in the Yangtze River Delta alluvial plain. With the rapid urbanization and modernization, the urban area of Shanghai has been grown more quickly than any other cities in china. The case study area with the size of 2000*1600 pixels is selected to perform the change detection, mainly including the Pudong New Area and downtown area of Shanghai. Construction and building areas, vegetation and the coastal land are the main land cover changes in the study area during the period from 2002 to 2008 (see Fig.2).

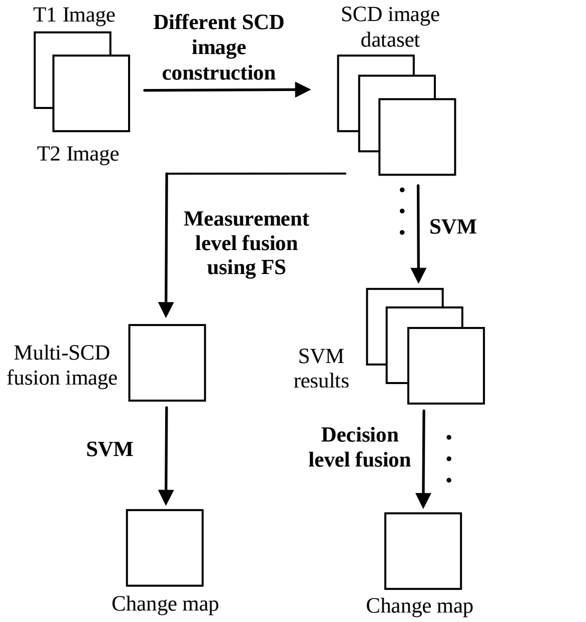


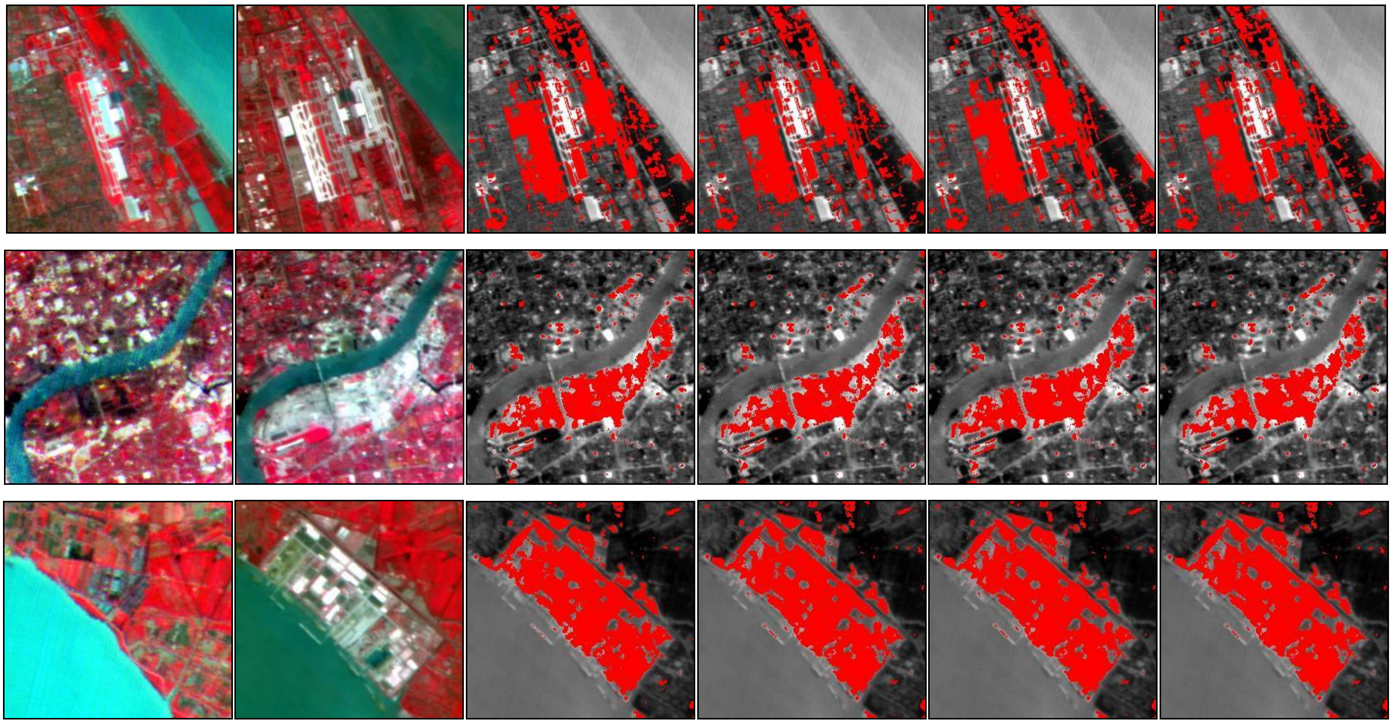
Figure 1. Flowchart of change detection based on fusion of Multi-SCD Images

(a) (b)

Figure 2. False colour composite images of the study area in 2002 and 2008.

After radiometric correction, image co-registration is implemented, achieving a mean displacement pixel errors of 0.4 pixels. Then, five SCD images are computed, and a training samples (1519 changed pixels and 3278 unchanged pixels) as well as test samples (3546 changed pixels and 5893 unchanged pixels) are selected after field visits and visual analysis.

Measurement and decision level fusion strategies as mentioned above are applied to the SCD images and single-SCD SVM results, respectively. Three typical and important case areas are further selected for comparing the experimental results (Fig.2 (b)). Image block A is in the Pudong International Airport, block B is the area around the Expo Park of World Expo 2010, block C is the Jiangnan Shipyard located in Changxin island, Shanghai. In Fig.3, the three image blocks and corresponding change maps using different fusion method are shown in row 1~3, and SVM change detection results after measurement or decision level fusion are shown in (c)~(f). The accuracy and errors of different single SCD image using SVM detector and their fusion results under different level fusion strategies are summarized in Tab. I.



Row1: Pudong International Airport. Row2: Expo Park. Row3: Jiangnan Shipyard. (a) 2002 (b) 2008 (c) FS (d) MV (e) DS (f) FI

Figure3. False colour composite images and change detection results for different fusion strategy (detailed analysis on three image blocks)

TABLE I. ACCURACY AND ERRORS OF CHANGE DETECTION

Fusion Level	***SVM Results/ Fusion Method***	***Overall Accuracy (%)***	***Kappa***	***Omission Ratio (%)***	***Commission Ratio (%)***
Single SCD Image	***SD***	85.07	0.6945	21.72	13.24
	SR	85.48	0.7036	20.19	13.58
	AD	89.07	0.7767	16.27	9.10
	ED	88.20	0.7594	16.52	10.78
	CST	86.67	0.7257	22.79	8.60
Measurement Level	***FS***	91.11	0.8186	12.38	8.25
Decision Level	***MV***	91.43	0.8248	15.22	4.43
	DS	90.78	0.8121	14.50	6.65
	FI	91.78	0.8318	14.90	3.88

From the experimental results and the above table, we can summarize that:

(1) Fusion strategies are effective to integrate the change information of multiple difference images, and most of the actual changes are detected by using the fusion strategy and SVM detector. With the information fusion techniques, their detection accuracies are higher than any single SCD image, which increase the overall accuracy by 2~6 % with respect to single SCD image SVM results.

(2) Measurement level fusion combines the change information from original image data, which efficiently reduce the omission errors. So, it has the lowest omission rate (12.38%) among all methods, reducing by 4~10% with respect to single SCD image results. Decision level fusion integrates the change features and change results by all SCD images, not only preserving the main changes, but also restraining the false alerts occurred in single SCD image, so it reduces the commission rate by 2~10%. Therefore, the experimented information fusion techniques have their own merits, according to the practical needs of the specific applications.

(3) In all fusion methods, the FI fusion approach at the decision level outperforms others in terms of detection accuracy (overall accuracy 91.78%, Kappa coefficient 0.8318) and the lowest commission error (3.88%).

(4) The performance of the five single SCD images alone is not as good as the fusion results, but they can still detect most of the real changes. Absolute Distance (AD) has the highest detection accuracy, whose overall accuracy and Kappa coefficient are 89.07% and 0.7767, and next is Euclidian Distance (ED). Chi Square Transformation (CST), Simple Ratioing (SR) and finally Simple Differencing (SD). All these five SCD images are therefore providing a valuable result for multi-temporal and multi-band remote sensing image change detection.

IV. CONCLUSION

A novel change detection approach based on the fusion of multiple difference images is proposed and experimented in this paper. CBERS remote sensing images of Shanghai City in two different years are used in an experiment in order to test its feasibility and applicability in urban land cover change detection and urban expansion monitoring.

Through this work, we can conclude that:

(1) the proposed change detection method based on fusion of multiple spectral change difference images is feasible and effective for land cover change detection because the change information in different single SCD images and the advantages of different fusion strategies can be integrated. The constructed SCD image dataset makes the final detection results more complete and closed to the actual changed areas

(2) The different fusion strategies implemented and compared in this work have different advantages. Measurement level fusion can effectively reduce omission errors, and decision level fusion is good at restraining commission errors, which both of them increased the overall accuracy of change detection. However, this conclusion is case specific in some extent, according to the specific practical change detection applications, the appropriate strategy should be selected to obtain the most valuable change information.

(3) Land cover changed a lot in the study area of Shanghai urban area during 2002 and 2008 because of the urbanization process. The three image blocks selected in our experiment for the more detailed analysis represent three obvious change areas in Shanghai during the study period, corresponding to the construction of Pudong International Airport, Expo Park 2010 and Jiangnan Shipyard. The construction of these key projects always changed the land surface a lot and can be obviously observed from the multi-temporal remote sensing images. More subtle changes need to be considered to further validate the change detection and fusion technique.

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REFERENCES

[1] D S. Lu, P. Mausel, E. Brondi Zio, E. Moran, “Change Detection Techniques”, International Journal of Remote Sensing, Vol. 25, No. 12, 2004, pp. 2365-2407.

[2] A. Singh, “Digital change detection techniques using remotely sensed data”, International Journal of Remote Sensing, 10, 1989, pp. 989-1003.

[3] T. Fung, E. LeDrew, “Application of principal components analysis change detection”, Photogrammetric Engineering and Remote Sensing, 53, 1987, pp, 1649-1658.

[4] T. Celik, “Unsupervised Change Detection in Satellite Images Using Principal Component Analysis and k-Means Clustering”, IEEE Geoscience and Remote Sensing Letters, Vol.6, No.4,2009, 772-776.

[5] F. Bovolo, L. Bruzzone, “A theoretical framework for unsupervised change detection based on change vector analysis in the polar domain”, IEEE Transactions on Geoscience and Remote Sensing, Vol.45, No.1, 2007, pp. 218-236.

[6] E. F. Lambin, A. H. Strahler, “Change-vector analysis in multitemporal space-a tool to detect and categorize land-cover change processes using high temporal resolution satellite data”, Remote Sensing of Environment, 48, 1994, pp. 231-244.

[7] H. Nemmour, Y. Chibani, “Multiple support vector machines for land cover change detection: An application for mapping urban extensions”, ISPRS Journal of Photogrammetry & Remote Sensing, Vol.61, No.2, 2006, pp. 125-133.

[8] F. Bovolo, “A multilevel parcel-based approach to change detection in very high resolution multitemporal images”, IEEE Geoscience and Remote Sensing Letters, Vol.6, No.1, 2009, pp. 33-37.

[9] Sicong Liu, Peijun Du, “Object-oriented change detection from multi-temporal remotely sensed images”, Proceedings of GEOBIA 2010 - Geographic Object-Based Image Analysis. Ghent University, Ghent, Belgium, ISPRS XXXVIII-4/C7, 2010, Archives ISSN No 1682-1777.

[10] Deren Li, “Remotely sensed images and GIS data fusion for automatic change detection”, International Journal of Image and Data Fusion, Vol.1, No.1, 2010, pp.99-108.

[11] T. Sohl, “Change analysis in the United Arab Emirates: an investigation of techniques”, Photogrammetric Engineering and Remote Sensing, 65, 1999, pp. 475-484.

[12] C. J. Riordan, “Change detection for resource inventories using digital remote sensing data”, Proceedings of the Workshop on In-Place Resource Inventories: Principles and Practices, University of Maine, Orono, ME, USA (Bethesda, MD: SAF), 1981, pp, 278-283.

[13] Puqian Tang, Jianyu Yang, Chao Zhang, Dehai Zhu, Wei Su, “An object-oriented post-classification remote sensing change detection after the pixel ratio”, Remote Sensing Information, No.1, 2010, pp. 69-72.

[14] Song Li, Yiqiu Li, Yulun An, “Automatic recognition of landslides based on change detection”, Remote Sensing Information, No.1, 2010, pp. 27-31.

[15] Guori Ma, Pingxiang Li, Qianqing Qin, “Based on fusion and GGM change detection approach of remote sensing images”, Journal of Remote Sensing, Vol.10, No.6, 2006, pp. 847-853.

[16] M Wang and X Y Zhang. “Change detection using high spatial resolution remotely sensed imagery by combining evidence theory and structural similarity”, Journal of Remote Sensing, Vol.14, No.3: 564-577.

[17] S. Le Hegarat-Mascle, R. Seltz, “Automatic change detection by evidential fusion of change indices”, Remote Sensing of Environment, 91, 2004, pp. 390-404.

[18] S. Le Hegarat-Mascle, R. Seltz, L. Hubert-Moy, S. Corgne,N. Stach, “Performance of change detection using remotely sensed data and evidential fusion: comparison of three cases of application”, International Journal of Remote Sensing, Vol.27, No.16, 2006, pp. 3515-3532.

[19] P. Gong, “Change detection using principal component analysis and fuzzy set theory”, Canadian Journal of Remote Sensing, Vol. 19, No.1, 1993, pp.22-29.

[20] Weiwei Qiao, Chengmao Wu, “A new image thresholding segementation algorithm based on absolute distance”, Computer Application and Software, Vol.27, No.8, 2010, pp. 259-262.

[21] A. D'Addabbo, G. Satalino, G. Pasquariello, P. Blonda, “Three different unsupervised methods for change detection: an application”, In: Proceedings of Geoscience and Remote Sensing Symposium 2004. IGARSS '04, 2004, 3, pp.1980-1983.

[22] Yanchen Bo, Jinfeng Wang, “Combining multiple classifiers for thematic classification of remotely sensed data”, Journal of Remote Sensing, Vol.9, No.5, 2005, pp.555-563.

[23] Yue Lu, Pengfei Shi,Yuming Zhao, “Voting principle for combination of multiple classifiers”, Journal of Shanghai JiaoTong University, Vol. 34, No.5, 2000, pp.680-683.

[24] S. Le Hegarat-Mascle, I. Bloch, D. Vidal-Madjar, “Application of Dempster-Shafer evidence theory to unsupervised classification in multisource remote sensing”, IEEE Transactions on Geoscience and Remote Sensing, Vol.35, No.4, 1997, pp.1018-1031.

[25] M. Fauvel, J. Chanussot, J. A. Benediktsson, “Decision fusion for the classification of urban remote sensing images”, IEEE Transactions on Geoscience and Remote Sensing, Vol.44, No.10, 2006, pp.2828-2838.