Fusion of Difference Images for Change Detection over Urban Areas

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Abstract—As a result of urbanization, land use/land cover classes in urban areas are changing rapidly, and this trend increased in the recent years. Change information detected from multi-temporal remote sensing images can thus help to understand urban development and to effectively support urban planning. Differences in reflectance spectra, easily obtained by multi-temporal remote sensing images, are important indicators to characterize these changes. Although many algorithms were proposed to generate difference images, the results are usually greatly inconsistent. In order to integrate the merits of different algorithms to recognize spectral changes, fusion techniques merging multiple difference images are proposed and implemented in this paper. Feature and decision level fusion are used to combine simple change detectors, and to build an automatic change detection procedure. The proposed approach is tested with multi-temporal CBERS and HJ-1 images, and experimental results demonstrate its effectiveness and reliability. By integrating different change information, the appropriate fusion method can be selected according to the specific application in order to minimize the omission or the commission errors.

Keywords: change detection, difference image, fuzzy set theory, D-S evidence theory, fuzzy integral, majority voting

I. INTRODUCTION

Remote sensing images are widely used for monitoring urban expansion and land use/cover changes at a medium or large scale, to help better observe and understand the evolution of urbanization and advance the sustainable development process. Usually two schemes are adopted for such studies: post-classification comparison and direct change detection. Change detection from multi-temporal remote sensing images play especially an important role in urban remote sensing. The basic assumption is that it is possible to extract relevant change information by processing multi-temporal remotely sensed images over the same area. To this aim, change detection techniques have been widely used for land use/cover change [1,2], urban growth [3,4], forest and vegetation dynamics [5] and disaster monitoring [6,7]. For decades, a lot of change detection techniques have been designed and tested on a variety of data sets. Generally, for binary change detection, change detection algorithms can be divided into two categories: supervised and unsupervised. The former is similar to supervised classification where the prior knowledge about the study area is necessary for training the detection module, such as post-classification comparison (PCC) [8], support vector machine (SVM) [3] and artificial neural network (ANN) [9]. The latter group performs analysis and processing directly or indirectly on the original multi-temporal images to obtain change information in case that the prior knowledge is unavailable, such as image differencing [10], principal component analysis (PCA) [11], change vector analysis (CVA) [12], spectral ratioing [13] and so on. In [14], supervised and unsupervised change detection techniques were applied to flood area detection using multi-modal remote sensing data, which is a good example of change detection to real disaster monitoring. These change detection algorithms have shown to be effective in various applications. However, no existing approach is optimal and applicable to all cases, so it is always a
big challenge to select a suitable algorithm for a specific application [15-17]. Usually, supervised change detection methods based on multi-temporal image classification are used to detect temporal change and spatial distribution of land surface in urban areas. They are limited however by the availability of prior knowledge, and their accuracy and stability are strongly affected by those of the selected classifiers. Moreover, classification of remote sensing data on geographically wide areas may increase the computation burden and training cost time, working against the goal of a quick monitoring and detecting routine. Therefore, it is an important research topic to select and build an appropriate unsupervised change detection model to process multi-temporal remotely sensed images and implement a fast and efficient monitoring scheme for urban expansion and land cover change where no or little prior knowledge is available.

Being one of the easiest approach, spectral change difference (SCD) provides change information reflected by the pure radiance changes of the original images. A series of studies and applications about SCD algorithms have been proposed and experimented, and some examples have been reported above. Despite the methodological strengths of different methods, their robustness and applicability are still not quite satisfactory. For different data sources and study areas, there is no universally applicable approach suitable in all cases to obtain a high-precision change detection result. 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.

A solution to this problem has been proposed by fusion of differencing and ratiing images, in order to combine the characteristics of these two change detection approaches [18-20]. In the same line, and in order to address the aforementioned problems, in this work more refined information fusion strategies are applied to the change detection process. Feature and decision level fusion strategies are introduced and implemented by integrating information extracted from multiple SCD methods. The results are compared with those obtained using a single SCD approach to explore the feasibility and applicability of the proposed procedure. By combining different SCD images and the corresponding change 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.

This paper is organized into five sections. Section II briefly describes the adopted algorithms for computing SCD data sets. In Section III, the proposed fusion procedure for change detection is investigated. Section IV presents two experiments and analyzes the corresponding results. Finally, Section V concludes the paper with some remarks and further research directions.

II. SPECTRAL CHANGE DIFFERENCE ALGORITHMS

The spectral characteristics of the ground surface, including reflectance and radiance features, and the difference of radiance energy received by the sensor cause the difference of gray-scale expression values of for different pixels in the same image and determine the spectral information recorded by passive optical systems. Usually, land cover objects should have their own different reflectance and radiance represented by peculiar representative spectral features (in some cases, due to the quality of the image or the complication of land surface cover, this may lead to the phenomena of ‘same spectral from different materials’ and ‘same material with different spectral’ are quite common) captured by these sensors, so various features can be extracted according to its the original spectral information. To the aim of change detection from multi-temporal remote sensing images, spectral changes on difference images indirectly reflect the change features and change information due to the change of pixel spectral reflectance values usually and provide hints to land cover changes during the observation time. This work attempts to find the potential capabilities of SCD approaches for change detection, and to improve the performances by using appropriate fusion strategies.

In this research, five basic algorithms to extract information based on spectral changes are implemented [21-23]. These algorithms are briefly introduced in the following paragraphs, where $N$ is the band number and $X_i^T$ and $X_i^U$ represent the pixel reflectance spectra of $i$-th band at time $T_1$ and $T_2$, respectively.
The $Y_{SD}$ image is the most direct indicator of a spectral change in reflectance [21].

The $Y_{SR}$ image reflects the change information through the ratioing of two images. After the absolute value operation, the pixels with larger values correspond to higher possibilities of change, and those pixels with a value close to 0 are hints to no-change areas. Ratioing is immune to false positives caused by sun elevation angle, shadows and terrain, at least to some extent.

The $Y_{SD}$ image integrates the change information on each band into a single band through simple addition. However, this process may also cause amplification and accumulation of detection errors.

The $Y_{SD}$ image describes the change information according to the pairs of spectral vectors in the multi-temporal images, and generates an intensity map of change vectors, where larger values represent higher probability of change, and the opposite for small values [22].

Chi Square Transformation:

$$Y_{CST} = \sqrt{\sum_{i=1}^{N} \left( \frac{X_{i}^{t} - X_{i}^{r}}{\sigma_{i}^{SD}} \right)^{2}}, \quad i = 1, 2, ..., N$$

where $\sigma_{SD}^{i}$ represents the standard deviation value on the $i$-th band of the simple difference image. This transformation is based on the assumption that the value distribution for each band of the difference image may be modeled by a normal distribution, so that the $N$ multi-spectral difference follows as a chi square distribution with $N$ degrees of freedom [23]. By weighting pixel by pixel the spectral differences according to the variance of each band of the difference image, $Y_{CST}$ becomes more objective and comprehensive as a single band difference image for representing the spectral changes.

Following these methods, it is always possible to extract from a pair of multi-spectral images five typical spectral difference images. It should be noted that their capabilities for representing temporal changes are different from each other.

Let’s take a simple example for $Y_{SD}$ and $Y_{SR}$, two common used difference images, and two kinds of digital number changes: 1) from 30 to 60; 2) from 60 to 120. Choosing the $Y_{SR}$ method, both cases will result into a value of 2, and cannot be effectively separated. In the $Y_{SD}$ image, instead, the corresponding values will be 30 and 60, which can be found as different. In contrast, if the changes are 1) from 15 to 45; 2) from 30 to 60, the $Y_{SR}$ image values will be with value 3 and 2, respectively, while in the $Y_{SD}$ image failed due to the same volume of change values will be equal obtained. So as a consequence, it makes sense to aim at combining more change information from different SCD images by using fusion strategies and improve the final result.

### III. CHANGE DETECTION BASED ON FUSION OF DIFFERENCE IMAGES

According to technical literature [24], remote sensing image fusion may be performed at three levels: data level,
feature level, and decision level. Fusion strategies at different levels have their own merits for specific applications. In this research, after building multiple SCD datasets able to provide hints to various change features, information fusion techniques are introduced into the change detection process to improve the reliability of the final detection result. Some advanced and popular fusion schemes have been therefore selected to combine the advantages of the various detectors, further improving the accuracy of detection results based on each single method alone. In the following, two different fusion schemes are tested, at the feature and decision levels. The flowchart of the whole procedure is shown in Figure 1.

The processing steps and detailed fusion models are as follows.

The first stage is the computation of the aforementioned five SCD data sets (Y_{SD}, Y_{SR}, Y_{AD}, Y_{ED}, Y_{CST}), where Y_{SD} and Y_{SR} images are multi-band, and the others are single-band images. We perform principal component analysis (PCA) on the multi-band differencing and ratioing images, and only the most important components from each PCA transformed dataset are further selected. It should be noted that, in this work, more than 90% of the change information is concentrated in the first principal component (PC1), that is thus selected in order to make all SCD images single-band and comparable. In other cases, when change information is concentrated in more components, different fusion strategy, like fuzzy set, can still be used to combine the components into a single one.

Multiple SCD images are then normalized according to Equation (6) in order to assign appropriate weight to every SCD image, and to avoid the instability and inconsistency among the data sets.

\[ Q_i = \frac{Y_i - \text{Min}(Y_i)}{\text{Max}(Y_i) - \text{Min}(Y_i)} \] (6)

where \( Y_i \) is the \( i \)-th SCD image, \( Q_i \) its corresponding normalized result, and the Max() and Min() operators generate the maximum and minimum values of the \( Y_i \) data set.

In feature level fusion, the aim is to build a higher quality difference image with stronger contrast between “change” and “no-change” areas by merging the five SCD data sets. To this aim, a fuzzy set theory (FS) [21, 25] fusion model is selected. Through the uncertainty analysis of every SCD image, FS can describe and redefine the “probability of change” of each pixel. Therefore, the inconsistency of detection performances in different feature data could be reduced to a great extent by fuzzy fusion. A brief description of the FS algorithm is listed in Table 1.

Please note that in Step 3 the modified Kittler-Illingworth (KI) segmentation algorithm [26] is applied, and in Step 4 the Sigmoid fuzzy membership function is used to compute the degrees \( H_i \) and \( H_o \) [25] (see Equation (7) and (8)).
\[ H_i(x_i) = \begin{cases} 0, & x_i \leq a_i \\
\frac{1}{2} \left( \frac{x_i - a_i}{b_i - a_i} \right)^2, & a_i \leq x_i \leq b_i \\
\frac{1}{2} \left( \frac{x_i - c_i}{b_i - c_i} \right)^2, & b_i \leq x_i \leq c_i \\
1, & x_i \geq c_i \end{cases} \quad (7) \]

\[ H_0(x_i) = 1 - H_i(x_i) \quad (8) \]

where \( x_i \) is the value of a generic pixel in the \( i \)-th band of \( V^n_i \), \( a_i = 0.8 T_i \), \( c_i = T_i \) and \( b_i = (a_i + c_i)/2 \), with \( H_0(h_i) = 0.5 \).

The final degree \( H'_i, t \in \{c, u\} \) in Step 5 is computed according Equation (9), where we assume that \( w_i = \frac{1}{N} \), and at last the final change map is obtained by looking for the larger value (Equation (10)).

\[
H'_i(x_i) = \sum_{i=1}^{N} w_i \times H(x_i)
\]

\[
H'_0(x_i) = \sum_{i=1}^{N} w_i \times H_0(x_i)
\]

\[
F = \arg \max_{t \in \{c,u\}} (H'_t)
\]

Table 1. Fuzzy set feature level fusion algorithm.

**Input:** original remotely sensed images at time \( T_1 \) and \( T_2 \)

**Output:** change map \( F \).

**Step1:** build the SCD dataset \( Q \) (\( i=1, 2, \ldots, n \)) from the original bi-temporal images.

**Step2:** build a SCD multi-band data set \( V^n \).

**Step3:** identify the optimal segmental threshold \( T_i \) for each band of \( V^n_i \).

**Step4:** compute the value of \( H_i \) (degree of change) and \( H_0 \) (degree of no-change) for every pixel in each dimension according to the fuzzy membership function.

**Step5:** apply fuzzy weighted fusion to the results in each band to generate the final degree \( H'_i \) and \( H'_0 \).

**Step6:** extract the change and no-change pixels.

As for decision level fusion, the aim is to integrate the results from all single SCD data sets and obtain a more precise change map. Popular decision level fusion approaches, including Majority Voting (MV) [27, 28], Dempster-Shafer evidence theory (D-S) [29, 30], and fuzzy Integral (FI) [3, 31] are adopted.

**Majority Voting (MV)** is a basic and simple decision integration method, designed to combine the output results by multiple processors. The main idea of MV is to arrange the identified results according to some specific voting rules, for example, simple majority voting and weighted voting rules. In this work, majority voting rule is selected to integrate the results from SCD datasets, and the final change map is obtained by voting each pixel with its labels on multiple outputs.

**Dempster-Shafer (D-S) evidence theory** is an important extent to the traditional Bayes theory, and allows the modeling of both imprecision and uncertainty through the definition of two functions: plausibility (pls) and belief (bel), deriving from a mass function (m). \( \Theta \) is the space of hypothesis, \( 2^\Theta \) is the set of subsets of \( \Theta \). In a change detection problem, \( \Theta = \{C, \overline{C}\} \), where \( C \) denotes “change” and \( \overline{C} \) denotes “no-change”. For any hypothesis \( A \) of \( 2^\Theta \), \( m(A) \in [0,1] \) and
\[
\begin{align*}
&\sum_{A \subseteq \Phi} m(A) = 1 \\
&Bel(B) = \sum_{A \subseteq \Phi} m(A)
\end{align*}
\]  

where \( \Phi \) is the empty set. \( A \) and \( B \) consists of several or all the elements in \( \Phi \), denote nonempty subsets of \( \Phi \), and \( A \subseteq B \). \( Bel(.) \) is the belief function which assigns a value in \([0,1]\) to every nonempty subset \( B \) of \( \Phi \).

A new evidence is computed according to the orthogonal sum of the different source evidences (outputs).

\[
m(F) = m_1 \oplus m_2 \oplus \ldots \oplus m_n(F) = \frac{1}{1 - k} \sum_{X \subseteq \Phi, X \neq \emptyset} \prod_{i=1}^{n} m_i(X_i)
\]

where \( m_1, m_2, \ldots, m_n \) are independent basic probability function, and \( m_i = p_i \), where \( p_i \) is the class accuracy from the \( i \)-th band of \( V^D \). Particularly, for the “change” class, \( p \) equals to the ratio of the corrected detected change pixels to the number of actual changes. Also, for the “no-change” class, \( p \) is the accuracy value from the ratio of the detected unchanged pixels to actual unchanged samples. \( m(F) \) is the computed new evidence about the two classes. \( n \) represents the number of source evidence and \( X_i \) is the \( i \)-th one. Finally, \( k \) represents the degree of the conflict between different evidences: when \( k \) equals 1, the orthogonal sum doesn’t exist, indicating a total contradiction of two evidences.

When the D-S evidence combination is completed, the final decision is made according to the larger evidence value:

\[
E(x) = \begin{cases} 
1, & m(F_i) > m(F_j) \\
0, & \text{otherwise}
\end{cases}
\]

where the value “1” represents a change and the value “0” represents a no-change.

The Fuzzy Integral (FI) approach evaluates the performances of different processors by a fuzzy measurement. A set function \( g \) is defined in a finite space \( S = \{s_1, s_2, \ldots, s_n\} : 2^S \rightarrow [0,1] \), with the following properties:

1) \( g(\emptyset) = 0 \);
2) \( g(S) = 1 \);
3) \( g(s_i) \leq g(s_j) \) if \( s_i \subseteq s_j \).

As a popular fuzzy integral approach, Sugeno integral uses a fuzzy measure \( g \), depending on a \( \lambda \) parameter indicating the degree of interaction between two elements [32].

\[
g(s_i \cup s_j) = g(s_i) + g(s_j) + \lambda g(s_i)g(s_j)
\]

For a binary change detection task as in our research, change maps \( s_i(CM) \) from \( i \)-th SCD data set need to be integrated, and thus a fuzzy measure \( g_i(s_i) \) is used to describe the measurement in class \( t \), \( t \in \{c, u\} \), while \( h_i(s_i) \) represents the accuracy from the \( i \)-th detection result \( s_i \) in class \( t \). Fuzzy density \( g \) can be built according to the following equation:

\[
g_i(s_i) = \frac{h_i(s_i)}{\sum_{i=1}^{n} h_i(s_i)}
\]

\[
\sum_i = \sum_{i=1}^{n} h_i(s_i)
\]
where $\sum_t$ is the sum of $i$-th class accuracy from all change maps, and $d_i$ denotes the expected sum of $i$-th class fuzzy density from single SCD detectors. It should be noted that in this work we assume that each class has the same sum of fuzzy density, so $d_i = \sum_{t=1}^{n} h_t(s_i)/\text{total}_t$, where $\text{total}_t$ is the number of classes, 2 in our case.

When $h_t(s_i) \geq \ldots \geq h_t(s_n) \geq 0$, the fuzzy measure can be reconstructed with the new sequence of elements $A_i = \{s_i, s_2, \ldots, s_n\}$, and $A_i = A_{i-1} \cup s_i$:

$$g_i(A_i) = g_i(s_i)$$  \hspace{1cm} (19)

$$g_i(A_i) = g_i(A_{i-1}) + g_i(s_i) + \lambda g_i(A_{i-1}) g_i(s_i)$$  \hspace{1cm} (20)

where $\lambda$ is determined by:

$$\lambda + 1 = \prod_{i=1}^{n} (1 + \lambda g_i(s_i))$$  \hspace{1cm} (21)

and $\lambda \in [-1, \ldots, +\infty]$, $\lambda \neq 0$ as the unique root of a $n-1$ degree equation.

The final decision can be computed by means of the maximization of the fuzzy integral rules (Equation 22), and the result is obtained according to Equation 23.

$$FI_i = \max_{i=1}^{n} \left[ \min(h_t(s_i), g_i(A_i)) \right]$$  \hspace{1cm} (22)

$$F = \arg \max_{i=1}^{n} (FI_i)$$  \hspace{1cm} (23)

The procedure for decision level fusion is listed in Table 2. According to the previous procedure, the modified KI algorithm is used for auto-thresholding each SCD data set. Then, three decision level fusion schemes, i.e. Majority Voting (MV), Dempster-Shafer evidence theory (D-S) and Fuzzy Integral (FI), are applied.

Table 2. Decision level fusion strategy

| Input: original remotely sensed images in time $T_1$ and $T_2$ |
| Output: change map $F$ |
| Step1: build the SCD image dataset $Q_i$ ($i=1, 2, \ldots, n$) from original bi-temporal images. |
| Step2: extract change maps $s_i(CM)$ from each SCD data set by auto-thresholding |
| Step3: select a specific decision fusion model to fuse multiple $s_i(CM)$ |
| Step4: generate the final change map $F$ according to the decision rules |

IV. EXPERIMENTS AND ANALYSIS

In order to prove the effectiveness of the proposed procedure, two datasets acquired by Chinese domestic satellite are used as experimental data source. The assessment of the proposed method is provided by looking at land cover change detection in urban areas.

IV.A. Change detection in Shanghai City using CBERS data

The first test aims at analyzing two CBERS (China Brazil Earth Resource Satellite) multi-spectral images acquired on March 7, 2005 (CBERS-02) and May 7, 2009 (CBERS-02B) over the Shanghai area. The two multi-band data sets, with a spatial resolution of 19.5 m, were radiometrically corrected and co-registered to a mean displacement error of 0.5 pixels.

As well known, Shanghai is China’s largest commercial and financial center, located in the Yangtze River Delta alluvial plain. With the rapid urbanization and modernization, the urban area of Shanghai grew more quickly than any other cities...
in China. The case study area, with the size of 2920×2720 pixels, includes the main downtown area, Pudong new area and Changxing island. Construction and building areas, vegetation and coastal land are the main land cover classes affected by changes during the study period. To visually assess the point, Figure 2 shows false color composite images of the study area in 2005 and 2009, respectively.

![Figure 2](image)

Figure 2. False color composites of 2005 and 2009 CBERS images for the first test site (Shanghai).

Both the data and decision level fusion procedures proposed in this paper were applied to the original five SCD data sets, and a pair of final land cover change detection results, overlapped on band 2 of the original 2005 CBERS image, are shown in Figure 3. In this image four typical and important case areas, which represent the urbanization process of Shanghai during the study period, are further selected for comparison, and are marked by blue rectangles in Figure 3 (a).

![Figure 3](image)

Figure 3. Change detection results (in red) for the Shanghai test site using two level fusion schemes: (a) feature level fusion; (b) decision level fusion using Majority Voting. In blue the areas highlighted in Figure 4: A - Pudong International Airport; B - Expo Park of World Expo 2010, C - Jiangnan Shipyard located in Changxing Island, and D - Hongqiao International Airport.

In Figure 4, the false color composite images of the above mentioned image blocks and their corresponding change results are shown. Change maps by means of both feature and decision level fusion strategies are reported. According to a first visual assessment in these two figures, a few comments may be of interest.

1) The proposed change detection methods based on fusion of spectral difference images effectively detect most of the land cover changes in the first test site, indicating the successful use of remote sensing satellite images and change detection techniques for monitoring urbanization process on wide geographical areas.

2) From the whole detection result, during the study period, land cover changed obviously because of human activities, mainly connected to the constructions due to key projects like international airports, the 2010 World Exposition Park and new shipyards.
3) From the detailed detection results, it may be found that the change regions and change targets are detected successfully by using the proposed method. Although there are still some errors, the results are quite promising. Different individual change detectors produce different commission or omission errors and contain incomplete target information, which can be reduced by using fusion strategies.

A more quantitative analysis of the results have been obtained by selecting 2824 samples of change areas and 4294 samples of no-change areas, according to field work and image interpretation. These samples are used to compute the accuracy values reported in Table 3. Moreover, in order to compare the statistical significance of the difference between two individual SCD detectors or fusion strategies, a statistical z-test [33] has been computed among the \( K \) coefficients, and the results are reported in Table 4. The z-test is defined as

\[
z = \frac{K_2 - K_1}{\sqrt{\sigma^2_{K_1} + \sigma^2_{K_2}}}
\]

where \( K_1 \) and \( K_2 \) are two selected kappa coefficients, \( \sigma^2_{K_1} \) and \( \sigma^2_{K_2} \) are their variances. Under the assumption of normal distribution, if the absolute z value exceeds 1.96, the difference is significant at the 95% confidence level.

<table>
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<tr>
<th>Fusion Level</th>
<th>Fusion Method</th>
<th>Overall Accuracy (%)</th>
<th>Kappa Coefficient</th>
<th>Omission Ratio (%)</th>
<th>Commission Ratio (%)</th>
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<td>1.8362</td>
<td>-1.4862</td>
<td>-0.0225</td>
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<td>4.3651</td>
<td>2.5606</td>
<td>2.1064</td>
<td>1.8362</td>
<td>-1.1119</td>
<td>0.3433</td>
<td>0.3657</td>
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</tbody>
</table>

Table 3: Accuracy values for the Shanghai test site

Table 4: Statistical significance of the difference between kappa coefficients (z-test)
Figure 4. False color composite images and change detection results from different level fusion strategies for each of the four image blocks identified in Figure 3 (a): (a) 2005 false color composite; (b) 2009 false color composite; (c) \( Y_{SD} \); (d) \( Y_{SR} \); (e) \( Y_{AD} \); (f) \( Y_{ED} \); (g) \( Y_{CST} \); (h) FS feature level fusion; (i) MV decision level fusion; (j) DS decision level fusion; (k) FI decision level fusion.


Figure 7. False color composite images and change detection results from different level fusion strategies for each of the four image blocks identified in Figure 6 (b): (a) 2009 false color composite; (b) 2011 false color composite; (c) \( Y_{SD} \); (d) \( Y_{SR} \); (e) \( Y_{AD} \); (f) \( Y_{ED} \); (g) \( Y_{CST} \); (h) FS feature level fusion; (i) MV decision level fusion; (j) DS decision level fusion; (k) FI decision level fusion.

From the numbers reported in two tables, a few further observations can be summarized:

a) The detection performance is different for each SCD data set, as expected, showing the need to design fusion strategies. At the same time, differences between two kappa coefficients show the potentials for improving the performance of single detectors. After feature or decision level fusion, since the hints to changes coming from multiple SCD data sets are merged, the detection results are always providing a more accurate change map. Accuracy values for both the overall accuracy and the kappa coefficient have increased, between 2% and 5% for the overall accuracy, showing the effectiveness of the proposed method. According to the z-test value, kappa coefficients before and after fusion are significantly different, and the consistent performances from different fusion strategies can be proven by the low level of z-test values, indicating the effective implementation of a general fusion idea rather than a specific selection of a fusion method.

b) As for the different fusion strategies, feature level fusion reduces the omission errors, which occur when using single difference data sets, to a minimum of 11.4%, with a reduction between 5% and 12% compared with the results of any single SCD image. Instead, decision level fusion works better on commission errors, which decrease by 1%-4%. From this test, it is therefore apparent that these two schemes have different merits. For the feature level fusion, change/no-change probabilities are computed according to the fuzzy fusion model, which relies more on the original SCD detector capabilities to represent the change information. Thus, omission errors can be effectively controlled by uncertainty analysis and fusion. For the decision level fusion, the results from every single SCD detector become the fusion objects, described by label rather than data value or probabilities. Therefore, a more reliable result with low level of commission errors can be generated through reducing the conflicts and comparing the various performances among multiple outputs.

c) Looking at the results of single difference data sets, three multi-band change detectors produce similar and higher values than other two single-band detectors, where Y_{CST} has the highest score, followed by Y_{ED} and Y_{AD}. As expected, data sets integrating change information from multiple bands in one index perform better because they average the errors in each band. Moreover, according to the weighted combination, Y_{CST} controls both the omission and commission errors at a reasonable level, whereas Y_{AD} and Y_{ED} produce more errors due to the simple integration process using equal weights. The first principal component (PC_1) of simple differencing or ratioing includes most of the change information, but may lose something related to the sub-dominant or subtle changes, incorporated in other principal components. For example, the first PC of the simple difference detects changes in brightness, and consequently may ignore changes resulting in negligible brightness change, such as those from bright vegetation to bright urban land. Due to this limitation, a little bit larger omission errors occurred in the results of Y_{SD} and Y_{SR}.

IV.B: Change detection in Xuzhou using HJ-1A/B data
The second test was performed using HJ-1A/B (Environment and Disaster Monitoring and Forecasting Small Satellite) multi-spectral data, including RGB and near infrared bands, captured on April 30, 2009 (HJ-1B CCD1) and April 19, 2011 (HJ-1A CCD2). The test site is Xuzhou, in the Jiangsu province. The test area, with a size of 1000x1000 pixels, includes the whole urban area, because Xuzhou is definitely smaller than Shanghai. A detailed radiometric correction was performed on the data by linear regression analysis, and a fine geometric correction reduced coregistration errors to an average value of 0.5 pixels. False color composite images of the study area in 2009 and 2011 are shown in Figure 5. According to the field work and manual interpretation, new built-up areas and vegetation re-growth are the main land cover changes during the study period.
Figure 5. False color composite images of the second test site (Xuzhou): (a) 2009 HJ-1/B data; (b) 2011 HJ-1/A data.

Change detection results exploiting the two proposed fusion strategies are shown in Figure 6. Three image blocks representing the typical urban expansion regions during the years from 2009 to 2011 are selected for a more precise analysis and visual comparison in Figure 7. This figure shows from Row 1 to Row 11 the false color composite images and corresponding detection results for these three blocks. According to field work and visual data interpretation, 851 test samples for the “change” class and 1536 samples for the “no-change” class were selected. The accuracy values are reported in Table 5, while Table 6 lists the z-test between every two kappa coefficients.

Figure 6: Change detection results (in red) in the Xuzhou test site using two level fusion schemes: (a) feature level fusion; (b) decision level fusion using Majority Voting. In blue the areas highlighted in Figure 7: A- Xuzhou Economic Development Zone, B- anew district of Xuzhou, C- Tongshan new area

<table>
<thead>
<tr>
<th>Fusion Level</th>
<th>Fusion Method</th>
<th>Overall Accuracy (%)</th>
<th>Kappa Coefficient</th>
<th>Omission Ratio (%)</th>
<th>Commission Ratio (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single SCD Image</td>
<td>$Y_{sd}$</td>
<td>87.32</td>
<td>0.7265</td>
<td>18.11</td>
<td>16.61</td>
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<tr>
<td></td>
<td>$Y_{sr}$</td>
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<td>0.7233</td>
<td>10.17</td>
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<tr>
<td></td>
<td>$Y_{sd}$</td>
<td>88.96</td>
<td>0.7620</td>
<td>15.78</td>
<td>14.42</td>
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<td></td>
<td>$Y_{ed}$</td>
<td>87.99</td>
<td>0.7386</td>
<td>19.28</td>
<td>14.19</td>
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<td></td>
<td>$Y_{ext}$</td>
<td>90.52</td>
<td>0.7938</td>
<td>15.78</td>
<td>10.57</td>
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<tr>
<td>Feature Level</td>
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<td>0.8307</td>
<td>7.99</td>
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<td>Decision Level</td>
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<td></td>
<td>$DS$</td>
<td>92.11</td>
<td>0.8267</td>
<td>13.16</td>
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<tr>
<td></td>
<td>$FI$</td>
<td>92.58</td>
<td>0.8355</td>
<td>13.51</td>
<td>8.91</td>
</tr>
</tbody>
</table>

Table 5: Accuracy values for the Xuzhou test site.
Yu actively reduces an expansion, the necessity inside of the Chinese.

To this aim, tested two different test sites. To this aim, we conclude that:

1) The behaviors are the same in the two tests, so we can stress the robustness of the proposed approach. For the single SCD detectors, $Y_{SD}$ and $Y_{SR}$ have the higher difference with three distance measure method ($Y_{AD}$, $Y_{ED}$, $Y_{CST}$) with $z$ values exceeding 1.96, which show the necessity to combine their capabilities in representing the change information. Better performance is straightforward for the fusion outputs than the single SCD results, according to the increased overall accuracy and decreased omission and commission errors. Moreover, the results of both tests are consistent even if the two urban areas, the two sensors and the change typologies are different. This further confirm the effectiveness of the multi-SCD fusion procedure.

2) The feature level fusion approach implements the fusion operation from the inside of the SCD dataset using single pixels as fusion objects, and the original change information is reflected in the form of fuzzy values. Therefore, we can get a more precise and complete change map than the one in any single SCD result, which effectively reduces the omission errors. Decision level fusion strategies take every identified pixels (pixels already labelled as change or no-change) as processing objects, combine the detected results, emphasize the general observation results and average the errors occurred in single SCD data set. Therefore, commission errors are reduced and this improves the overall accuracy.

3) The most accuracte values are obtained using fuzzy methods, since the fuzzy set fusion and the fuzzy integral fusion provides the best results in test 1 and test 2 respectively, indicating the effectiveness of the fuzzy integration process between the uncertain values and the certain ones.

V. CONCLUSIONS

A novel change detection approach based on fusion of multiple spectral change difference images is proposed and tested in this paper. Feature and decision level fusion techniques were implemented and their performance evaluated in two different test sites. To this aim, CBERS and HJ-1 images were used as experimental data source for urban expansion monitoring and land cover change detection task in the urban areas of Shanghai and Xuzhou, respectively, to test the feasibility and applicability of the proposed method.

Thanks to this work, we may conclude that:

(1) the proposed change detection method based on fusion of multiple SCD data set is feasible and more effective for urban expansion monitoring and land cover change detection over urban areas than the change information extracted by single SCD algorithms. From the experimental results in two different study areas, it is confirmed that the limitation and uncertainties caused by a single SCD image can be reduced using suitable fusion techniques.
(2) Fusion methods at different levels have their own advantages and merits. Feature level fusion can effectively reduce omission errors, and decision level fusion is good at restraining commission errors, but both of them lead to an increase of the overall accuracy.

(3) The most important land cover changes in the two considered test areas are connected with human activities and the urbanization process. Shanghai and Xuzhou represent the typical super and medium city in China, respectively. The urban constructions due to key projects in China are the most obvious land cover changes detected from the multi-temporal remote sensing images.

Further research will focus on fusion of multiple change indices in very high-resolution data to better delineate the urban change areas. Moreover, the spatial distribution of change/no-change pixels will be considered to improve the final result.

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REFERENCES


