Extraction of Change Information based on Multi-sequence Image Objects

Haitao Zhang* and Xinwen Cheng

Department of Information Engineering, China University of Geosciences, No. 388 Lumo Road, 430074, Wuhan, China
*Corresponding author, e-mail address: zht_410728@126.com

Abstract
For identification of change information, most studies focus on pixel-based techniques for low-resolution images, while few studies have examined object-based techniques for high-resolution images. Moreover, most of the techniques are complex and have a high requirement for the segmentation scale. This paper proposes a change detection method based on multi-sequence image objects and introduces the use of arithmetic progression to generate the set of segmentation scales. Pre-event and post-event images are segmented with multi-scales, respectively, and sub-objects are obtained based on the division of the minimum segmentation scales of bi-temporal images. Change feature vectors are constructed for each associated object of sub-object and vectors’ magnitude is computed. After the determination of change threshold values, the change feature vectors are used to confirm whether sub-objects have changed, providing final change information. This method was tested using the bi-temporal World View 2 images taken before and after a landslide. The results confirm the feasibility of the method presented in this paper, and show its high accuracy through a comparison with the changing vector analysis method and the post-classification comparison method based on object-oriented theory. The approach outlined herein would be helpful for extraction of change information in high-resolution images.

Keywords: Change detection, arithmetic progression, segmentation scale, sub-objects, feature vector.

Introduction
In recent years, remote sensing technology has shown rapid development and image resolution has also improved [Blaschke, 2010; Gomez-Chova et al., 2013; Hussain et al., 2013]. With the launch of high-resolution remote sensing sensors such as IKONOS and QuickBird, spatial resolution has reached levels better than 1 m. Change detection technology plays an important role in resource surveys, environmental monitoring, basic geographic database update applications, etc. [Blaschke, 2010; Chen et al., 2012; Hussain et al., 2013]. However, in earlier studies, change detection methods based on
remote sensing images were mainly conducted using low-resolution images. In traditional methods using high-resolution image data, the “salt and pepper” effect is very obvious and the rich textural information will be incorrectly considered as noise. This has a great impact on the extracted change information [Blaschke, 2010; Yang et al., 2013; Li et al., 2014]. Therefore, research into change detection methods based on high-resolution images is valuable [Klemas, 2013].

At present, research on change detection using high-resolution images can be divided into two categories [Dong and Shan, 2013]: post-classification comparisons and image similarity measurements (ISMs). The post-classification comparison method obtains change information, as well as information about the type of change of the ground surface. However, its detection accuracy is largely dependent on the accuracy of the image classification, and a key issue is improving the accuracy of the classification results of bi-temporal images. This shortcoming has limited the use of this method [Im et al., 2008; Li et al., 2014]. The ISM method can be approximately divided into pixel-based and object-based techniques.

The pixel-based method is mainly designed for use with low-resolution images, but has also been successfully applied to high-resolution images. Gomez-Chova et al. [2015] presented a combined object-based and pixel-based land cover classification method that improved land cover change detection accuracy using Landsat Enhanced Thematic Mapper (ETM+) images of a mountainous area in Mexico. Moosavi et al. [2014] presented a change detection method that combined the Taguchi method and a Support Vector Machine (SVM) to research landslide extraction. Vorovencii [2014] assessed the change vector analysis (CVA) technique using Landsat TM images and monitored the land cover changes caused by pollution in Copsa Mica. He applied CVA to the tasseled cap greenness and tasseled cap brightness indices, as well as to the normalized difference vegetation index and bare soil index. However, the change information extracted using the pixel-based ISM generally includes a significant “salt and pepper” effect [Blaschke, 2010; Chen et al., 2012; Hussain et al., 2013]. Moreover, a series of image transformation operations destroys some of the information contained in the images. Therefore, the pixel-based method is not considered effective for extracting change information from high-resolution images [Blaschke, 2010; Chen et al., 2012; Hussain et al., 2013; Willis, 2015].

Recently, researchers tried to solve the problem of the “salt and pepper” effect using object-oriented methods for high-resolution remote sensing images. Multi-feature and multi-method fusions, were chosen to deal with some of the problems [Im and Jensen, 2005]. A change detection method based on random forest was proposed by Stumpf and Kerle [2011]. This method segments images and obtains multi-features of objects. The results were extracted by classifying objects using random forest. Behling et al. [2014] presented a change detection method that analyzes temporal NDVI-trajectories using RapidEye time series data to extract landslide-related changes. They combined the pixel-based multiple thresholds and object-based analysis to discriminate landslides. Sandric et al. [2010] improved the change detection method using images, Digital Elevation Model (DEM), and daily meteorological data combined with spectral and morphometric properties of landslides using object-based analysis to landslide inventory. Im et al. [2008] introduced a change detection model based on Neighborhood Correlation Images (NCIs), which relies on the hypothesis that images are highly correlated if small changes occur, but uncorrelated
when significant changes occur. The accuracies of several methods were compared, and using the object-based NCI and the Object Correlation Image achieved good results. A semi-automatic approach, based on object-oriented change detection for rapid landslide mapping, was introduced by Lu et al. [2011]. This approach achieved good landslide extraction using high-resolution optical images and other auxiliary data. Li and Shao [2014] generated a land cover change map with an object-based approach, which identified land cover types using 1-m resolution aerial orthophotography and a 5-foot DEM. A fuzzy-knowledge-based method within an object-based image analysis system for automatic change detection of buildings was introduced by Argialas et al. [2013]. It assigns each object to a category using fuzzy classification, and is able to perform change detection for buildings. The common problem of these methods is that the selected image segmentation scale has a significant influence on the analysis of the results [Lu et al., 2011; Gianinetto et al., 2014; Tewkesbury et al., 2015]. Determining the optimal segmentation scale is therefore a critical problem in such studies.

The purpose of this paper is to introduce a new change detection method for bi-temporal high-resolution remote sensing image datasets using an object-oriented technique. The paper also introduces the arithmetic progression in the change detection process used to generate a set of segmentation scales, and the concept of multi-sequence image objects to determine the changed sub-objects. Section "Study area and data sources" presents the study area and spatial database. In Section "Methods" the newly developed approach for bi-temporal change information extraction based on multi-sequence objects is described. The results obtained by applying this approach to the study area are presented in more detail in Section "Application and analysis", which also shows the accuracy assessment and comparison of accuracy with other methods. In Section "Conclusions", we discuss the advantages and limitations of the proposed method for the extraction of change information exploiting high-resolution remote sensing images.

**Study area and data sources**

The study area is located in Xinjiang Province, China, and is an area where landslides, mudslides, and other geological disasters often occur. Rain erosion and disasters provide obvious visual evidence. The image data for this study were collected by the WorldView 2 satellite, and include data from red, green, and blue bands with a resolution of 0.5 m. The acquisition dates for the images were 4 March 2014 and 9 June 2014. The post-event image was registered to the pre-event image using a 2nd order polynomial rectification transformation and 14 ground control points that were collected uniformly in the study area, with a root mean square error of 0.8 pixels.

To verify the proposed method, two sets of high-resolution images were used and named as Site A and Site B. An image of Site A is shown in Figure 1 covering an area 405 × 343 meters. The first image shows flourishing vegetation and a large amount of bare soil. Because the vegetation was just beginning to grow, some areas (e.g., the bottom right area) show sparse grass not yet fully covering the ground. The second image shows the effects of rainfall and other factors, including some landslides (e.g., the area outlined by the blue box) that seriously damaged the growing vegetation. Both sides of the road show evidence of damage, showing as bright white areas.
Site B images are shown in Figure 2 covering an area 499 × 251 meters. The images mainly show growing vegetation, some bare soil, and a road. The main change information comes from both sides of the tunnel exit, showing landslides and rain erosion (e.g., the area outlined by the blue box). In addition, there are some changes caused by rainfall-related destruction of vegetation.
Methods
Image objects were structured from bi-temporal images using the eCognition commercial software, and average gray value (AGV) of objects was extracted. The image segmentation was executed $n$ times and the segmentation scales were from a scales set (SS). The descriptions of the scales set (Section “Obtaining Image Segmentation Scales”) is based on arithmetic progression, which is a common sequence of numbers in mathematics. The sub-objects were structured from the $n$-th segmentation layer in pre-event image and the $n$-th segmentation layer in post-event image. The proposed algorithm is based on the fact that pairs of the AGV from the same geographic area (e.g., an object) between bi-temporal
images tend to be highly approximated and that the differences will be very small when
the sub-object has little change, owing to a high degree of heterogeneity within-object.
In contrast, AVG of objects may differ significantly. The proposed algorithm, which uses
object-based detection rather than pixel-based detection, can reduce the data processing
time. In addition, the basic unit of the algorithm is object rather than pixel, which can
effectively avoid the impact of the “salt and pepper” effect. The algorithm flowchart is
shown in Figure 3.

**Figure 3 - Flowchart of the proposed algorithm.**
Obtaining image segmentation scales

At present, commonly used segmentation methods include the watershed algorithm, the fractal net evolution approach, the region growing method, etc. [Lu et al., 2011]. However, these methods use trial and error to optimize the segmentation scale. Moreover, optimizing the segmentation scale for one land cover type does not always improve the segmentation quality for other features [Lu et al., 2011; Gianinetto et al., 2014]. Considering these challenges, this paper presents a new concept of multi-sequence segmentation, in which objects are obtained by segmenting bi-temporal images at various scales. It also introduces the use of arithmetic progression to generate the sequential segmentation scales. Arithmetic progression is a common sequence of number in math. In a sequence of numbers, if the difference between any element and its front element is a constant, then the sequence of numbers will be called an arithmetic progression, and the constant will be called tolerance. The basic expression of an arithmetic progression is:

\[ a_n = a_1 + (n-1) \cdot d \]  

where \( a_n \) and \( a_1 \) are the last and first elements, respectively, and \( d \) is the tolerance. In the expression, \( a_n \) and \( a_1 \) should be determined after a considerable number of pre-segmentations for the bi-temporal images, after which the proper maximum and minimum segmentation scale is selected for \( a_1 \) and \( a_n \). Here, \( d (d < 0) \) is determined in accordance with the requirements of the segmentation number. After a number of experiments, we found that extraction will show better results if the number of segmentations is not more than eight. Therefore, the set \( S \), which consists of a sequence of segmentation scales, is generated by arithmetic progression:

\[ S = \{ a_i | a_i = a_1 + (i-1) \cdot d, i \in [1, n] \} \]

The pre-event image will be segmented with scales \( a_1, a_2, \ldots, a_n \) and the results are layers \( L_1, L_2, \ldots, L_n \). The same operation is used for the post-event image, and the results are \( L_1', L_2', \ldots, L_n' \). The segmentation scales \( a_1, a_2, \ldots, a_n \) obtained from arithmetic progression are varied regularly, so the evolution of objects in the segmentation processes can be observed.

However, compared with the commonly used segmentation methods, the maximum and minimum segmentation scale selected here is not the optimal segmentation scale for images or the optimal segmentation scale for a land cover type. The maximum scale can be used to segment the maximum features in images and the minimum scale can be used to segment most of features in images. Therefore, the selection of the maximum and minimum scale in this paper will not require very often for pre-segmentation. In addition, the bi-temporal images are often acquired during the same season. Therefore, both the maximum and minimum segmentation scales for bi-temporal images generally differ little. However, in order to prevent the selected scale value from being located near the critical value, the scales are selected as follows:
\[
\begin{align*}
\text{max Scale} &= \max \{\text{max Scale}T1, \text{max Scale}T2\} \\
\text{min Scale} &= \min \{\text{min Scale}T1, \text{min Scale}T2\}
\end{align*}
\] [3]

In this work, the eCognition commercial software was employed for multi-sequence segmentation of bi-temporal images. The objects in layer \(L^n_i, L^n_2\) are the most broken compared with objects in all the segmented layers \(L^n_1, L^n_2, \cdots, L^n_i, L^n_1, L^n_2, \cdots, L^n_2\).

**Retrieving associated objects**

There is an object \(objX\) in layer \(L_1\) and an object \(objY\) in layer \(L_2\). If \(objY\) would contain or equal to \(objX\), then we will called that \(objY\) is a associated object for \(objX\). We ask that the object and associated object can not be located in a same layer. For example, in Figure 2, \(obj11\) in layer \(L^n_i\) would contain \(obj1\) in the sub-object layer and \(obj21\) in layer \(L^n_2\) is equal to \(obj1\), so \(obj11\) and \(obj21\) are the associated objects for sub-object \(obj1\). Objects in bi-temporal images at the same scale, for a same feature, may be different owing to the influence of co-registration error and radiation difference. This will cause some objects in \(L^n_i (i = 1, 2, \cdots, n)\) to have no associated object in layer \(L^n_1, L^n_2, \cdots, L^n_2\) and some objects in \(L^n_i (i = 1, 2, \cdots, n)\) to have no associated object in layer \(L^n_1, L^n_2, \cdots, L^n_2\). Considering these challenges, we propose generating sub-objects using \(L^n_i, L^n_2\) and units by sub-object for data processing. Sub-objects are generated by the Union operation. The method for generating sub-objects is shown in Figure 4.

| \(L^n_i\): The \(n\)-th segmented layer in pre-event image | \(L^n_2\): The \(n\)-th segmented layer in post-event image |
|-----------------|-----------------|
| \(obj11\) | \(obj12\) |
| \(obj13\) | \(obj14\) |
| Union | \(L_{sub-object}\): The sub-object layer |
| \(obj1\) | \(obj2\) |
| \(obj3\) | \(obj4\) |
| \(obj5\) | \(obj6\) |
| \(obj7\) | \(obj8\) |
| \(obj9\) | \(obj10\) |
| \(obj11\) | \(obj12\) |

**Figure 4 - Method for generating sub-objects.**

In this study, it is assumed that the number of bands of an image is \(m\) and that the segmentation number is \(n\).

There is only one associated object in a segmented layer for a sub-object, owing to the non-overlapping characteristics of objects in a layer.

Based on the above analysis, we can sum up three basic criteria of associated objects: 1) the number of sub-objects is not less than the number of objects in each segmented layer. 2) for a sub-object, there is only one associated object in a segmented layer, and 3) each object in multi-sequence segmented layers \(L^n_1, L^n_2, \cdots, L^n_i, L^n_1, L^n_2, \cdots, L^n_2\) will be associated at least once.

The steps for retrieving associated objects are as follows. All the sub-objects must be traversed and associated objects searched for in segmented layers \(L^n_1, L^n_2, \cdots, L^n_i, L^n_1, L^n_2, \cdots, L^n_2\). The search procedure is not halted until each sub-object has retrieved \(2n\) associated objects.
Building multi-scale spectral feature change vectors

The AGV of an object in every band is computed during image segmentation and sub-object acquisition. After completion of the associated object retrieval, there are $2n$ associated objects for each sub-object, named $obj_1^1, obj_1^2, \ldots, obj_n^1, obj_2^1, obj_2^2, \ldots, obj_n^2$. The differences in the AGV for each associated object are computed in every band. The expression of the change vector for each sub-object can be written as follows:

$$P(x_1) = (f(b_1^1), f(b_1^2), \ldots, f(b_1^n))$$
$$P(x_2) = (f(b_2^1), f(b_2^2), \ldots, f(b_2^n))$$
$$\ldots$$
$$P(x_m) = (f(b_m^1), f(b_m^2), \ldots, f(b_m^n))$$  \[4\]

where $P(x_i)$ is the current sub-object’s change vector for spectral characteristics in the $i$-th band, and $f(b_j^k)$ is its difference in gray value for the $j$-th band, when the $k$-th segmentation is executed.

Change information extraction

After the above process, there are $m$ change vectors for each sub-object named $P(x_1), P(x_2), \ldots, P(x_m)$. In this paper, the change intensity is defined as the total change in the $m$ change vectors. The change intensity for each sub-object is defined as

$$R = \sqrt{|P(x_1)|^2 + |P(x_2)|^2 + \cdots + |P(x_m)|^2} \quad [5]$$

The selection of the change threshold has important implications for the final extraction results. This study adopts the method of iterative selection in a change interval. The sub-objects standard deviation is $\sigma$ and the average change intensity is $\bar{R}$, so the change interval is $[\bar{R} - 3\sigma, \bar{R} + 3\sigma]$. The change threshold selection process is as follows.

1). Some samples are selected from image objects;
2). The start threshold is defined as $\bar{R} - 3\sigma$, the final threshold as $\bar{R} + 3\sigma$, and the step length as $\Delta R$;
3). A threshold $R_i$ is selected to extract the change information and to compute the extraction precision. If $R_i \geq \bar{R} + 3\sigma$, then the focus shifts to Step 5;
4). $R_i = R_i + \Delta R$ is defined and then the focus shifts to Step 3;
5). The extraction precision obtained from each threshold is compared and the threshold associated with the highest precision is selected as the final threshold.

Accuracy assessment

In this study, there are many change positions as well as sporadic changes in the two sets of experimental data. However, these change positions and sporadic changes are difficult to
quantify accurately. In order to evaluate the accuracy of the proposed method quantitatively, small portions of the images were taken from the bi-temporal images (blue boxes in Figures 1 and 2) as experimental areas to quantify the extracted information. In subset images area, the change information is very concentrated and significant, mainly showing landslides and destruction of vegetation. These subset images are shown in Figures 5 and 6. In the referenced change information map of the study area, the landslide information was completed using the collected landslide inventory data, extensive fieldwork, and visual interpretation of images. However, the other change information mainly resulted from the visual interpretation. Producer accuracy, user accuracy, overall accuracy, and Kappa accuracy were calculated to quantitatively evaluate the effectiveness of the proposed method.

Figure 5 - Subset images of Site A.

Figure 6 - Subset images of Site B.
Application and analysis

Results and qualitatively accuracy assessment

In this study, Visual Studio 2010 (VS2010) and Geospatial Data Abstraction Library (GDAL) were used to implement the algorithm described in Section “Methods”. Figure 7 shows the change information for Site A. From this figure, it can be seen that the proposed method is highly accurate overall for the extracted information, and has achieved seamless recognition of the landslide (area outlined by the blue box in Fig. 1). In addition, it also effectively detected minor changes in other locations. However, owing to the influence of season, time difference, and other factors, there are some small and sporadic changes in the results that need to be addressed.

Figure 7 - Change information results for Site A overlapping the original images.
Figure 8 shows the extracted change information overlaying the bi-temporal images for Site B. Based on a comparison of the images in Figures 8, highly accurate change information was extracted from the images of Site B. Complete extraction was achieved for the landslide and in the alluvial vegetation change areas; in addition, vehicles on the road were extracted. However, there is some isolated and scattered change information caused by co-registration errors, or by differences in the season in which the images were acquired.

The two experiments show that the detection accuracy of the proposed method is high overall, especially for the change border positions, and that there were few false or missed detections.
Comparison with other methods

To verify the reliability of the proposed method, we used the C++ and GDAL to implement the commonly used algorithm of pixel-based CVA and object-oriented post-classification method, respectively.

Change vectors were constructed using pixels as the basic unit, and the change intensity was calculated. Change information for the two study sites was obtained after threshold selection; the results are shown in Figures 9 and 10.

Figure 9 - Change information results based on pixels for Site A overlapping the original images.
As shown in Figures 9 and 10, large ranges of change information can be extracted using the method of pixel-based change vectors, but the results are broken and incomplete. Moreover, the method is not sensitive to small changes. For example, as visible in Figure 10, the vegetation destruction located inside the rectangle was not identified and the “salt and pepper” effect was particularly evident. These issues seriously affect the accuracy of the change detection. Additionally, the pixel-based method cannot use the change threshold from the proposed method, but uses a smaller threshold compared with the proposed method. A possible reason is that the spectral information used in image objects is based on the average spectrum. However, owing to the high homogeneity of the pixels within an object, the threshold should be set to a slightly larger value.

Figure 10 - Change information results based on pixels for Site B overlapping the original images. Vegetation destruction is not identified and “salt and pepper” effect is evident in the blue box.
We also obtained the change information using the post-classification comparison method, by which the sub-objects of bi-temporal images are classified. Figures 11 and 12 show the classified image overlaid over post-event image. The change information was divided into two categories: red areas refer to changes from vegetation to bare soil, while green areas refer to changes from bare soil to vegetation. Figures 11 and 12 show that the accuracy of the detected change information is poor because of low classification accuracy. For example, there is a certain degree of inaccurate identification at the boundary of the landslide location in the rectangular area in Figure 11. There is also some missed detection (the left-hand rectangle) in the landslide area and some false detection (the right-hand rectangle) due to sparse vegetation growth seen in Figure 12.

Figure 11 - Change detection results using an object-oriented post-classification comparison method for Site A. The change information is presented in two categories: red color represents change from vegetation to bare soil, while green color represents change from bare soil to vegetation. The two blue boxes indicate inaccurate identification.
Figure 12 - Change detection results using an object-oriented post-classification comparison method for Site B. The change information is presented in two categories: red color represents change from vegetation to bare soil, while green color represents change from bare soil to vegetation. The big box contains some missed detection; the small box indicates some false detection.

Quantitative Accuracy Assessment
To quantitatively evaluate the extraction accuracy of the proposed method, we used the subset images of the two experimental areas and obtained the change information. In addition, we extracted change information for the subset images using pixel-based CVA and object-oriented post-classification comparison separately. Figures 13 and 14 are the change information maps and Tables 1 - 6 show the quantitative assessment of the results of the three methods for the two subsets of images.
Figure 13 - Change information results for subset images of Site A.
Figure 14 - Change information results for subset images of Site B.

Table 1 - Detection accuracy based on the proposed method for Site A.

| Reference | Change detection |
|-----------|------------------|
|           | Change | No change | Total | Producer accuracy (%) |
| Change    | 3890.756 | 1424.744 | 5315.5 | 73.20 |
| No change | 635.570  | 8454.930 | 9090.5 | 93.01 |
| Total     | 4526.326 | 9879.674 | 14406 | ——     |
| User accuracy (%) | 85.96 | 85.58 | —— | —— |

Overall accuracy: 85.70%, Kappa coefficient: 0.68

Table 2 - Detection accuracy based on the proposed method for Site B.

| Reference | Change detection |
|-----------|------------------|
|           | Change | No change | Total | Producer accuracy (%) |
| Change    | 2379.902 | 466.348 | 2846.25 | 83.62 |
| No change | 750.161  | 5281.089 | 6031.25 | 87.56 |
| Total     | 3130.063 | 5747.437 | 8877.5 | —— |
| User accuracy (%) | 76.03 | 91.88 | —— | —— |

Overall accuracy: 86.30%, Kappa coefficient: 0.69
### Table 3 - Detection accuracy based on pixel-based CV A for Site A.

| Reference     | Change detection |         |         | Producer accuracy (%) |
|---------------|------------------|---------|---------|-----------------------|
|               | Change           | No change | Total   |                       |
| Change        | 2725.447         | 1800.879  | 4526.326 | 60.21                 |
| No change     | 104.74           | 9774.934  | 9879.674 | 98.94                 |
| Total         | 2830.187         | 11575.813 | 14406   |                       |
| User accuracy (%) | 96.30         | 84.44     |         |                       |

Overall accuracy: 86.77%, *Kappa* coefficient: 0.66

### Table 4 - Detection accuracy based on pixel-based CV A for Site B.

| Reference     | Change detection |         |         | Producer accuracy (%) |
|---------------|------------------|---------|---------|-----------------------|
|               | Change           | No change | Total   |                       |
| Change        | 1263.524         | 1866.539  | 3130.063 | 40.37                 |
| No change     | 17.545           | 5729.892  | 5747.437 | 99.69                 |
| Total         | 1281.069         | 7596.431  | 8877.5   |                       |
| User accuracy (%) | 98.63         | 75.43     |         |                       |

Overall accuracy: 78.78%, *Kappa* coefficient: 0.46

### Table 5 - Detection accuracy based on post-classification comparison for Site A.

| Reference     | Change detection |         |         | Producer accuracy (%) |
|---------------|------------------|---------|---------|-----------------------|
|               | Change           | No change | Total   |                       |
| Change        | 2840.329         | 1685.997  | 4526.326 | 65.75                 |
| No change     | 1548.420         | 8331.254  | 9879.674 | 84.33                 |
| Total         | 4388.749         | 10017.251 | 14406   |                       |
| User accuracy (%) | 64.72         | 83.17     |         |                       |

Overall accuracy: 77.55%, *Kappa* coefficient: 0.47

### Table 6 - Detection accuracy based on post-classification comparison for Site B.

| Reference     | Change detection |         |         | Producer accuracy (%) |
|---------------|------------------|---------|---------|-----------------------|
|               | Change           | No change | Total   |                       |
| Change        | 2762.638         | 367.425   | 3130.063 | 88.26                 |
| No change     | 2223.863         | 3523.574  | 5747.437 | 61.31                 |
| Total         | 4986.501         | 3890.999  | 8877.500 |                       |
| User accuracy (%) | 55.40         | 90.56     |         |                       |

Overall accuracy: 70.81%, *Kappa* coefficient: 0.44
Figures 13 and 14 show that the proposed method is applicable to the information extraction over a wide range of changes. However, the extraction result is poor when the range of changes is small, although the results are still better than those using the other two methods. The extraction results using the pixel-based CVA are broken and contain numerous errors. In the extraction results using the object-oriented post-classification comparison, some changes from grass to soil were not recognized in the subset image of Site A and some changes from grass to soil were obviously wrong in the subset image of Site B.

The extraction criteria of the proposed method are largely dependent on the gray values of the sub-objects and parent objects in each band. Shadows in images will cause a change of the gray values and unchanged objects will be mistaken as changed objects. For example, the change information based on the proposed method shown in Figures 13 and 14 has some holes that require further processing.

Tables 1 - 6 show that the kappa accuracy and overall accuracy of the proposed method are higher compared to the other methods, reflecting the best extraction results of the proposed method.

Tables 1 and 2 indicate that the producer accuracy and user accuracy of the proposed method are high. The producer accuracy for Site A in the “change” category is 73.20% and the user accuracy for Site B in the “change” category is 76.03%. These results from the fact that the two lower values may be depicted at the boundaries of the larger change area, and the small “no change” portions in “change” area, and small “change” portions in the “no change” area, are ignored artificially. Overall accuracy and kappa accuracy are also good. In addition, the difference of the producer accuracy and user accuracy of the proposed method is small, which shows that the accuracy of the extraction results is uniform and that there is no single category with lower accuracy.

Tables 3 and 4 show that using the pixel-based CVA method, the subset images of the Site A achieve better extraction accuracy, but the producer accuracy of the change category is low at only 60.21%. In addition, in the subset images of the Site B, the kappa accuracy is low and the producer accuracy of the change category is the lowest at 40.37%. Combined with the extraction maps in Figures 13 and 14, this indicates that the pixel-based CVA method is affected seriously by the gray values of images.

Tables 5 and 6 show that using the object-oriented post-classification comparison method, the overall extraction accuracy of the two subset images are little different and that the classification accuracy of a single category is low. This is demonstrated by a producer accuracy and user accuracy of the change category of 65.75% and 64.72%, respectively, in subset images of Site A. In the subset images of Site B, the user accuracy of the change category and the producer accuracy of the unchanged category are low at 55.40% and 61.31%, respectively. However, the producer accuracy of the changed category and the user accuracy of the unchanged category are high at 88.26% and 90.56%, respectively. The reason for these difference may be that the classification accuracy of the change category is very high but the classification accuracy of the unchanged category is very bad. This demonstrates that the post-classification comparison method is strongly affected by the classification accuracy.
Conclusions
In this paper, we proposed a new change detection method based on multi-sequence image objects, and introduced the use of an arithmetic sequence for creation of segmentation scales. Sub-objects were generated from the minimum scale segmentation objects of bi-temporal images, and the associated objects were retrieved. Multi-scale spectral feature vectors were built for each sub-object and the change intensity was calculated. Finally, an appropriate threshold was selected and the change information was extracted.
The proposed algorithm was implemented using VS2010 and GDAL, and its efficiency was tested using World View 2 images. The results show that the proposed method can achieve high accuracy for detection of changed information. We also compared the proposed method with the pixel-based CVA and the object-oriented post-classification comparison methods, and verified the reliability of the proposed method.
The proposed method has several advantages. (1) It can obtain better detection information if a smaller minimum segmentation scale is selected. However, the retrieval time for associated objects will increase and some “salt and pepper” effects will also be generated. (2) The data processing time is shorter than for the pixels-based CVA method, and the accuracy requirement for co-registration of images is relatively small. This is because the image co-registration error in this study was > 0.5 pixels. The proposed method also has some disadvantages. (1) Associated objects are retrieved using GDAL, which is relatively time-consuming, and the retrieval method requires further optimization. (2) Small amounts of “change” data were extracted in “no change” areas, and small amounts of “no change” data were extracted in “change” areas, which are often treated as artificial noise, without considering their impact. (3) A significant amount of manual intervention is required in the selection of the change threshold for sub-objects, which may affect the proposed method’s efficiency. All of these factors can help improve the transferability of the approach developed in this study.

Acknowledgments
This research was supported by the High Resolution Earth Observation Systems of the National Science and Technology Major Project (No. 07-Y30A05-9001-12/13).

Author contributions
Zhang Haitao conceived, designed, and performed the experiments and wrote the manuscript. Cheng Xinwen analyzed the data and revised the manuscript.

References
Argialas D.P., Michailidou S., Tzotsos A. (2013) - Change Detection of Buildings in Suburban Areas from High Resolution Satellite Data Developed Through Object based Image Analysis. Survey Review, 45: 441-450. doi: http://dx.doi.org/10.1179/1752270613Y.0000000058.
Behling R., Roessner S., Kaufmann H., Kleinschmit B. (2014) - Automated Spatiotemporal Landslide Mapping over Large Areas Using RapidEye Time Series Data. Remote Sensing, 6: 8026-8055. doi: http://dx.doi.org/10.3390/rs6098026.
Blaschke T. (2010) - Object-based Image Analysis for Remote Sensing. ISPRS Journal
Zhang and Cheng

of Photogrammetry and Remote Sensing, 65: 2-16. doi: http://dx.doi.org/10.1016/j.isprsjprs.2009.06.004.

Chen G., Hay G.J., Carvalho L.M.T., Wulder M.A. (2012) - Object-based Change Detection. International Journal of Remote Sensing, 33: 4434-4457. doi: http://dx.doi.org/10.1080/01431161.2011.648285.

Dong L.G., Shan J. (2013) - A Comprehensive Review of Earthquake-induced Building Damage Detection with Remote Sensing Techniques. ISPRS Journal of Photogrammetry and Remote Sensing, 84: 85-99. doi: http://dx.doi.org/10.1016/j.isprsjprs.2013.06.011.

Gianinnetto M., Rusmini M., Candiani G., Via G.D., Frassy F., Maianti P., Marchesi A., Nodari F.R., Dini L. (2014) - Hierarchical Classification of Complex Landscape with VHR Pan-sharpened Satellite Data and OBIA Techniques. European Journal of Remote Sensing, 47: 229-250. doi: http://dx.doi.org/10.5721/EuJRS20144715.

Gomez-Chova L., Tuia D., Moser G., Camps-Valls G. (2015) - Multimodal Classification of Remote Sensing Images: A Review and Future Directions. Proceedings of IEEE, 103 (9): 1560-1584. doi: http://dx.doi.org/10.1109/JPROC.2015.2449668.

Hussain M., Chen D.M., Cheng A., Wei H., Stanley D. (2013) - Change Detection from Remotely Sensed Images: From Pixel-based to Object-based Approaches. ISPRS Journal of Photogrammetry and Remote Sensing, 80: 91-106. doi: http://dx.doi.org/10.1016/j.isprsjprs.2013.03.006.

Im J., Jensen J.R. (2005) - A Change Detection Model based on Neighborhood Correlation Image Analysis and Decision Tree Classification. Remote Sensing of Environment, 99: 326-340. doi: http://dx.doi.org/10.1016/j.rse.2005.09.00.

Im J., Jensen J.R., Tullis J.A. (2008) - Object-based Change Detection using Correlation Image Analysis and Image Segmentation. International Journal of Remote Sensing, 29: 399-423. doi: http://dx.doi.org/10.1080/01431160601075582.

Klemas V. (2013) - Remote Sensing of Emergent and Submerged Wetlands: an Overview. International Journal of Remote Sensing, 34: 6286-6320. doi: http://dx.doi.org/10.1080/01431161.2013.800656.

Li M., Zang S.Y., Zhang B., Li S.S., Wu C.S. (2014) - A Review of Remote Sensing Image Classification Techniques: the Role of Spatio-contextual Information. European Journal of Remote Sensing, 47: 389-411. doi: http://dx.doi.org/10.5721/EuJRS20144723.

Li X.X., Shao G.F. (2014) - Object-Based Land-Cover Mapping with High Resolution Aerial Photography at a County Scale in Midwestern USA. Remote Sensing, 6: 11372-11390. doi: http://dx.doi.org/10.3390/rs61111372.

Lu P., Stumpf A., Kerle N., Casaglini N. (2011) - Object-Oriented Change Detection for Landslide Rapid Mapping. IEEE Geoscience and Remote Sensing Letters, 8: 701-705. doi: http://dx.doi.org/10.1109/LGRS.2010.2101245.

Moosavi V., Talebi A., Shirvivahomandi B. (2014) - Producing a Landslide Inventory Map using Pixel-based and Object-oriented Approaches Optimized by Taguchi Method. Geomorphology, 204: 646-656. doi: http://dx.doi.org/10.1016/j.geomorph.2013.09.012.

Sandric I., Mihai B., Chitu Z., Gutu A., Savulescu I. (2010) - Object-oriented Methods for Landslides Detection using High Resolution Imagery, Morphometric Properties and Meteorological Data. 100 Years ISPRS Advancing Remote Sensing Science, Vienna, pp. 486-491.

Stumpf A., Kerle N. (2011) - Combining Random Forests and Object-oriented Analysis
for Landslide Mapping from very High Resolution Imagery. Procedia Environmental Sciences, 3: 123-129. doi: http://dx.doi.org/10.1016/j.proenv.2011.02.022.
Tewkesbury A.P., Comber A.J., Tate N.J, Lamb A., Fisher P.F. (2015) - A Critical Synthesis of Remotely Sensed Optical Image Change Detection Techniques. Remote Sensing of Environment, 160: 1-14. doi: http://dx.doi.org/ 10.1016/j.rse.2015.01.006.
Vorovencii I. (2014) - A Change Vector Analysis Technique for Monitoring Land Cover Changes in Copsa Mica, Romania, in the Period 1985–2011. Environmental Monitoring and Assessment, 186: 5951-5968. doi: http://dx.doi.org/10.1007/s10661-014-3831-5.
Willis K.S. (2015) - Remote Sensing Change Detection for Ecological Monitoring in United States Protected Areas. Biological Conservation, 182: 233-242. doi: http://dx.doi.org/10.1016/j.biocon.2014.12.006.
Yang H.L., Peng J.H., Xia B.R., Zhang D.X. (2013) - Remote Sensing Classification Using Fuzzy C-means Clustering with Spatial Constraints Based on Markov Random Field. European Journal of Remote Sensing, 46: 305-316. doi: http://dx.doi.org/10.5721/EuJRS20134617.

© 2016 by the authors; licensee Italian Society of Remote Sensing (AIT). This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution license (http://creativecommons.org/licenses/by/4.0/).