Automatic Change Detection from High-Resolution Satellite Imagery

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Abstract Change detection using remote sensing data is one of the most essential processing steps for monitoring urban and forest areas. And it provides an invaluable tool for archaeological sites in times of war or natural disasters. However, until now the visual interpretation is still the main technique in analyzing changes from these images. In this chapter, the state of the art of the change detection on archaeology applications and the latest change detection techniques in 2D and 3D are introduced.

Keywords Change detection · Stereo imagery · Culture heritage

Introduction

Following the 11th Europae Archaeologiae Consilium Heritage Management Symposium in 2010, in 2016 a technique session named cultural heritage data acquisition and processing has drawn special attention in the 23rd International Society for Photogrammetry and Remote Sensing (ISPRS) congress, which is one of the most influential international conferences in remote sensing. Remote sensing technology is helping and influencing the archaeology research since long time (van Genderen 1976; Osicki 2000). Change detection is an invaluable remote sensing technique for the archaeology site monitoring, especially during the war time and after natural disasters. Normally two kinds of changes are of interest in archaeology sites: one is the changes of the archaeology constructions, and the other is the changes of the environments, mainly the vegetation cover changes like crops. In 2016, experts of the German Aerospace Center (DLR) have processed and analyzed the remote sensing images from the Temple of Bel, Palmyra's Valley in Syria, and Nimrud archaeological site in Iraq to check the cultural heritage status (Cerra et al. 2016). Besides war,

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the natural disasters like earthquake and tsunami are also non-negligible threats to the cultural heritage. After the earthquake in Emilia-Romagna and Lombardy, Italy, a status survey of the important culture heritage constructions was performed using the remote sensing technologies (Adami et al. 2016). For the second kind of changes, the main goal is to detect the potential threats to the archaeology sites, thus to further protect the culture heritage. The regrowth and reforestation in the coastal area of north Norway were analyzed by comparing the Normalized Difference Vegetation Index (NDVI) applied to Landsat images (Barlindhaug et al. 2007). Nevertheless, in the archaeological operative practice, the use of remote sensing is still underexploited and in particular reduced to a mere visual interpretation exercise. Jahjah et al. (2007) analyzed the pre-postwar situation of Babylon archaeological site. Eighteen aerial photos were digitized and inserted to a GIS system to analyze the changes. In Fig. 1, the red circle has highlighted the location of some disappeared archaeological objects (segments, roads, and ruins).

In case of change monitoring of large heritage regions, visual interpretation is time-consuming, and the quality is difficult to control. Therefore, introducing the latest remote sensing change detection technologies to archaeological site monitoring is of great values. In this chapter, change detection approaches have been categorized into 2D change detection and 3D change detection. In Section "2D Change Detection," an overview of the existing 2D change detection and their applications

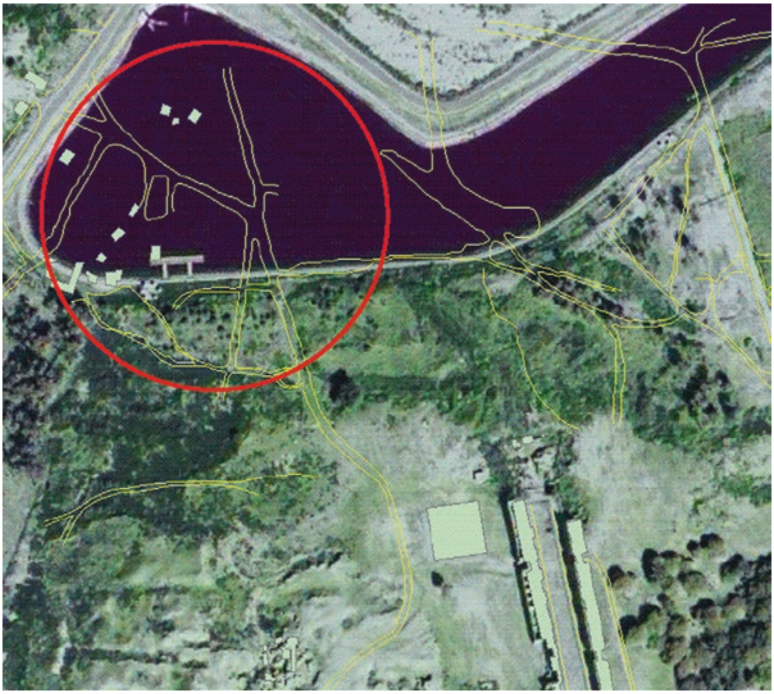

Fig. 1 Location of disappeared archaeological features using GIS technique. (Jahjah et al. 2007)

in archaeology applications is given. In Section "3D Change Detection," the latest 3D change detection approaches are introduced. Section "Summary" concludes the chapter. Unlike fire or in some cases even flooding events (Alexakis et al. 2014), earthquakes cannot be prevented and cannot be controlled. For this reason the focus of emergency management strategies in these cases is on phases of preparedness and response, i.e., on measures aimed at (i) reducing the risk, (ii) enhancing earthquake resistance, (iii) improving earthquake detection and monitoring, and (iv) developing a response plan (Stovel 1998). In case of an earthquake in fact, the phase regarding damages evaluation is highly important for the first emergency response for securing of people, animals, and structures and during the recovery phase in order to support assistance and inspection teams. Furthermore, such evaluations can be valuable also to reconsider the phases preceding the event (such as prevention, mitigation, and preparedness) providing inputs to evaluation of economic damage and future urban planning and resilience strategies.

2D Change Detection

Recently, many advanced change detection algorithms and techniques have been presented and investigated in literature, most of which are based on satellite images, benefiting the large cover region and short revisit time. Change detection algorithms are built on features which can be extracted from multi-temporal images or digital surface models. They can also be generated with statistical methods by using information from multispectral or hyperspectral channels. Numerous approaches have been developed for change detection using only the 2D satellite images. Many articles reviewing the existing change detection methodologies can be found, such as Coppin and Bauer (1996), Lu et al. (2004), Macleod and Congalton (1998), Mas (1999), and Singh (1989). Recent developments in change detection can be divided into pixel-based and region- based methods. Both require that the multi-temporal remote sensing images are properly co-registered.

Pixel-Based 2D Change Detection

Pixel-based change detection methods are based on features extracted by combining images at pixel level, e.g., pixel-based subtraction, rationing, and image regression. When multispectral information is available, a feature vector can be obtained for each pixel. In addition to the pixel spectrum, more features, such as features after color transformation or texture features, can be extracted. To reduce data redundancy between bands and to emphasize the difference between objects and background, image transformations can be performed, such as color space transformation or principal component analysis (PCA) (Lillesand et al. 1987), Gram-Schmidt (Laben and Brower 2000), and chi-squared transformation. Paper (Fung 1990)

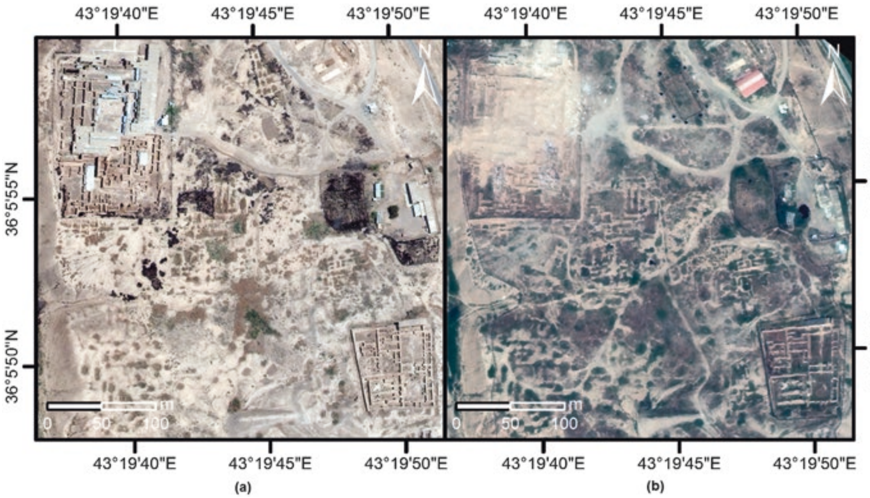

Fig. 2 (**a**) Nimrud pre- (GeoEye-1, 11th July 2011) and (**b**) post-event image (WorldView-2, 20th April 2015) (Cerra et al. 2016)

compared image differencing, principal component analysis, and tasseled-cap transformation based on Landsat TM data. These combinations can improve the mathematical combination result, and the original images can be filtered or transformed to achieve a better change map. For the research project applications of geomatics for long-term archaeological settlement pattern analysis, Jahjah et al. (2007) have analyzed the pre-postwar changes in Babylon archaeological site, Iraq. Both historic maps and satellite imagery have been collected for this research. Changes were analyzed with visual interpretation of the historic dataset. In Cerra et al. (2016), a change vector analysis is applied to the GeoEye-1 (Fig. 2a) and WorldView-2 images (Fig. 2b). The destroyed temples were well highlighted in the final result (Fig. 3).

Region-Based 2D Change Detection

The increasing high resolution of satellite images allows the extraction of more detailed changed objects with higher accuracy but also introduces some false alarm that are not related to the changes of interest. The main drawback of pixel-based change detection, called the salt-and-pepper effect, is a result of these false alarms. Therefore, region-based change detection methods have gained more interest in recent years (Blaschke 2005). Instead of analyzing pixels independently, region-based approaches take the pixels inside one meaningful homogeneous region. Some papers refer to this method as object-based change detection (OBCD) (Blaschke 2005; Hall and Hay 2003), as one feature of OBCD is to extract meaningful objects from images. Initially, these meaningful objects were obtained from Geographic

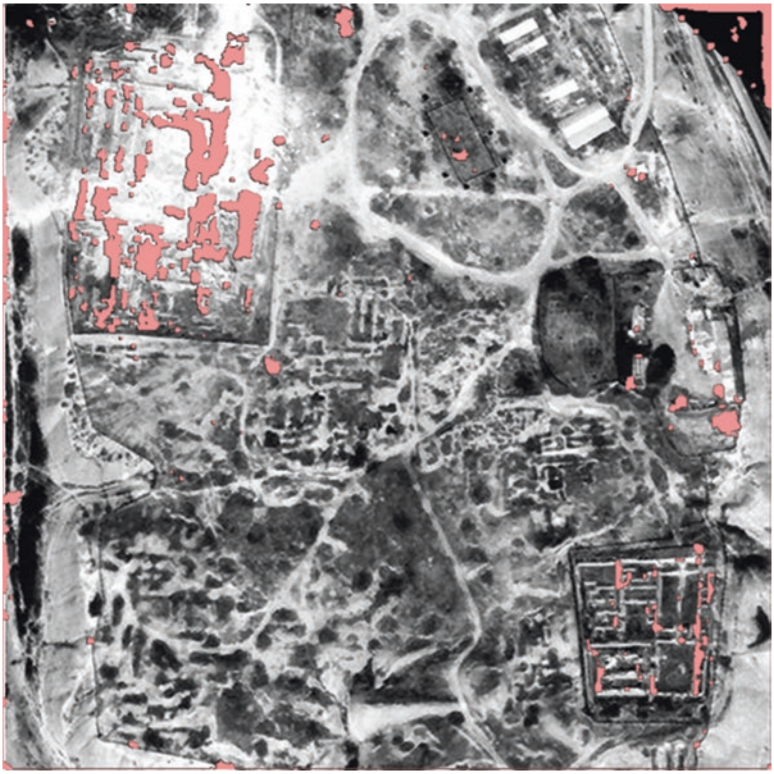

Fig. 3 3D change detection (Cerra et al. 2016)

Information System (GIS) databases (Coppin and Bauer 1996; Durieux et al. 2008; Walter 2004). However, in more recent work, these objects are often extracted using segmentation: thus, the obtained regions might not always be a whole object, such as a complete building or bridge, but very probably only one part of it. Therefore, referring to these methods as region-based is more suitable. Region-based change detection evolved from region-based image analysis, which combines spectral images with segmentation or GIS data for image understanding or land cover classification. The GIS database can also be used as training data, since it includes not only the boundary but also the attributes of each region (Walter 2004). As the use of GIS data is limited to the available data sources, object-based change detection using image data is usually preferred, along with the development of automatic segmentation techniques. After segmentation, the images can be divided into a number of homogeneous regions. The research in this direction is thus focused on obtaining an appropriate segmentation level for all land covers of interest. Bruzzone and Prieto (2000) stated that the original segments that can be used for change detection should be elementary homogeneous regions. However, it is difficult to provide an ideal definition of homogeneous when various objects are of interest: for example, the cars on the road, the cars in car parks, etc. Multilevel segments are preferred for detecting changes to various classes of objects (Bovolo 2009).

In Jahjah et al. (2007), a region-based classification on the very high-resolution satellite images was performed. The results could be used to update the Geographic Information System (GIS) database.

3D Change Detection

Even though 2D multi-temporal satellite images can already provide plenty of useful information, it is usually insufficient when dealing with changes in the vertical direction. Moreover, if only one class of changes, such as the buildings in archaeology site, is of interest, it is often difficult to distinguish between relevant and irrelevant changes. In such cases, the information provided by digital surface models (DSMs) is crucial, as it provides additional height information, which can be indispensable when analyzing changes.

DSMs can assist 3D change detection in a variety of approaches. Limited to the quality of the DSMs generated from stereo imagery, it is hard to reach precise change detection results using only the DSMs. Therefore, DSMs should be used in combination with the spectral information from the original stereo images. As the DSMs are generated using stereo images, spectral information of the same time and area is always available. After orthorectification of these images using the generated DSM, the orthophoto and DSM are well co-registered, and pixel-wise fusion is applicable. Many methods have been proposed to fuse data from two or more kinds of sources. The main difference of these methods is how and when the DSM content is fused with the original images. Three classes of data fusion techniques are summarized in Hall and Llinas (1997) and Pohl and Van Genderen (1998) and named as pixel/data level fusion, feature level fusion, and decision-level fusion approaches, as shown in Fig. 4. For our purpose, the selected fusion method should be able to resolve the quality restriction of DSMs by using the additional information available in the corresponding spectral images. Depending on the quality of the DSMs,

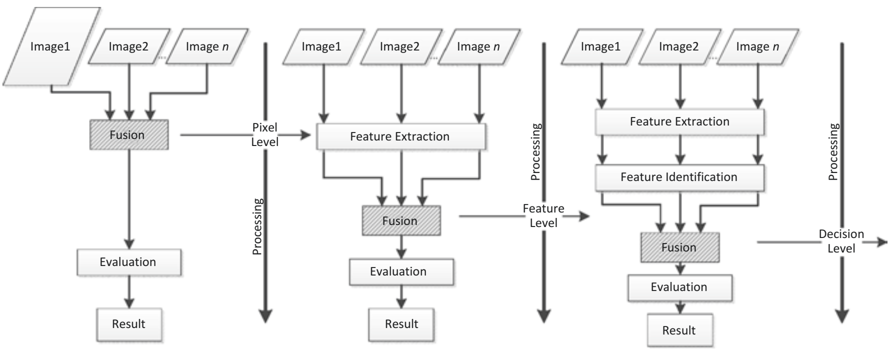

Fig. 4 Processing levels of image fusion

the availability of multispectral channels, and the requirements of the individual change detection task, proper 3D change detection methods have to be developed.

The recently published 3D change detection review paper (Qin et al. 2016a) has classified the 3D change detection approaches into geometric comparison and combined geometric and spectral analysis. The geometric comparison relies mainly on the height information. This kind of approaches performed better on DSMs with higher quality. However, directly subtracting two DSMs does not always result in an ideal change map due to multisensor and co-registration problems (Tian 2013). Shown in Fig. 5 are several newly constructed buildings located in the middle of Fig. 5b. Figure 5c features the direct subtraction results of the corresponding DSMs, showing only the positive values: all the negative values have been set to 0 for better display. As can be seen from this difference image, some unchanged buildings around them also show quite high positive change values. Moreover, some false height values exist in the middle of the rightmost building. However, after the robust difference measure, the noise in the background is successfully reduced, while the yellow and green areas as shown in Fig. 5d, which are more likely to be real changed areas, are not influenced significantly, especially in the building boundary area.

Advanced denoising and distance measurements enable improved change detection results (Akca 2007; Tian et al. 2010; Qin et al. 2016b). But the improvement is negligible in many cases. Under the framework of satellite stereo imagery, spectral information is always available and could lead to enhanced change detection results.

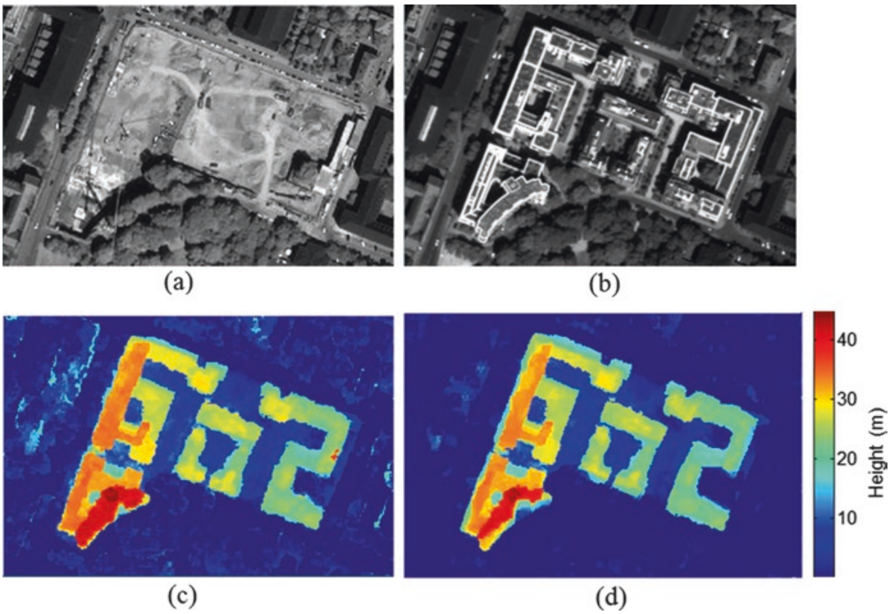

Fig. 5 DSM subtraction results of a building site: panchromatic images from Date1 (**a**) and from Date2 (**b**); DSMs subtraction result (**c**) and the robust height difference result with a window size of 15 × 15 (**d**) (Tian 2013)

When only one or some specific objects of changes are of interest, both of the height information and spectral information bring advantages and false alarms. Thus, the main challenge in fusing spectral and height information is to appropriately address the advantages of each information sources without bringing additional false alarms. In general, the available fusion approaches can be categorized into three groups: (1) post-refinement, (2) direct feature fusion, and (3) decision fusion.

Post-refinement

The post-refinement approach starts by extracting change candidates using the height information (Jung 2004). With DSM subtraction, it is computationally easy to obtain the initial change map, which can be improved to a more precise building change map using additional spectral information.

Many 3D change detection methods can be categorized into this approach. Hong et al. (1999) and Zhifang et al. (2003) detected house changes based on DSMs from airborne images. DSMs were computed on the digital photogrammetry workstation VirtuoZo. These potential changed areas were generated based on DSM subtraction. The candidate regions obtained were classified into newly built, demolished, and rebuilt buildings using gradient direction histograms. These histograms were extracted from the original airborne images. In Jung (2004), DSMs generated from airborne stereo imagery were employed to obtain an initial change map. The change regions from subtracted DSMs are used as candidates. Subsequently, these candidate regions from four images (two stereo pairs) are classified into building and no-building areas based on graph features. Regions which have building within one dataset and no-building in the other dataset are considered changed buildings. This method will fail if one building is only partly changed or if buildings are rebuilt. Also in high-density building areas, several buildings might exist in one candidate region. A false alarm will be produced if only a part of these buildings have changed. Zhu et al. (2008) detected building changes based on ADS 40 airborne stereo imagery. In their change detection procedure, initial change candidates were derived from the height difference of the two DSMs. Height thresholding followed by low-pass morphological filtering was used to reduce the noise level. These change candidates were combined with the extracted building masks from two dates. The building masks were extracted separately for two DSMs by combining the building extraction result of two methods: local surface normal angle transform and marker-controlled watershed segmentation. Height change was analyzed only for the regions detected as buildings. Tian et al. (2010) tried to refine the building change map using a box-fitting algorithm. To remove the false alarms within the initial change candidate map, in the work of Chaabouni-Chouayakh et al. (2010), post-processing steps such as morphological operations and contextual knowledge introduction have been proposed. These methods help to remove virtual changes and to preserve the real ones. When only building changes are of interest, shape features can also be used to refine the change map (Tian et al. 2011). However the post-refinement approaches have mainly employed to remove false alarms in the change candidate data. Therefore, the false negatives in the initial step can be hardly recovered with these refinement approaches.

Direct Feature Fusion

Under the category of direct feature fusion, various features were extracted from images and DSMs, respectively. Height difference from DSMs is normally used as change/no-change features or more detailed negative/positive/no-change features. This feature can be directly fused with change features from spectral images to enhance the change detection accuracy. They can be fused either at feature level or at decision level. In the feature fusion level, the 2D change detection approaches can be directly applied by taking height changes as one feature vector. For instance, Sasagawa et al. (2008) combined the pixel changes generated from least square fitting of two images and height changes detected by DSM subtraction, to generate the final change map containing three channels (green, pixel change; red, positive DSM change; blue, negative DSM change). This change map was provided together with spectral imagery for manual interpretation. As an automatic change detection approach, Tian et al. (2013) fused the height and spectral intensity changes of Cartosat-1 data based on change vector analysis (CVA). As a subsequent work, focusing on forest changes, the kernel minimum noise fraction (kMNF) was adopted to transform the change vector matrix that was composed with height change and radiometric changes. As well as feature fusion in pixel-level, the object-level change detection can be performed. In this approach the object map can be produced through image segmentation (Kranz et al. 2017; Tian et al. 2013) and classification (Vögtle and Steinle 2004). In addition, the available GIS database can also be used as object map (Champion 2007).

Tian et al. (2014) have introduced the belief function-based decision fusion to the 3D change detection. The belief function integrated changes that were extracted separately from images and DSM. Images were assumed to highlight all kinds of changes, while height changes were indicating only changes of high-level objects. The fusion model has been further revised in their later publications (Tian et al. 2015).

Post-classification

Land use and land cover classification is a task of great importance in remote sensing. Post-classification approach proposes to detect changes by comparing the classification results or object extraction results. A widely used building change extraction procedure is building detection+change detection (Champion et al. 2008; Olsen 2004; Matikainen et al. 2010). Thus the 3D change detection is actually a follow-up step of 3D building extraction. A main advantage of this approach is to use the existing classification/object extraction method or the existing GIS data. In addition, a more detailed from-to change map can be delivered. However, in most cases, the change detection performance of this method highly depends on the classification accuracy and efficiency.

Summary

The chapter has presented an exhaustive review of the available literature in the field of change detection, especially 3D change detection. Many practical 2D change detection approaches have been presented, and several applications using these techniques have also been reported. These 2D change detection techniques have recently been adopted for 3D change detection purposes. Previous studies have demonstrated that 3D change detection that works by fusing DSM and spectral imagery is possible and relatively good results can be achieved. However, until now, most of the change detection methods have been carried out only for one or two representative test regions. The 2D/3D change detection approaches are so disparate; thus there is no universally best method/strategy that outperforms others. Further investigation of the existing change detection approaches on archaeology applications could be of interest.

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