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# Semi-automated landslide inventory mapping from bitemporal aerial photographs using change detection and level set method

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ABSTRACT

Landslide inventory mapping (LIM) is an increasingly important research topic in remote sensing and natural hazards. Past studies achieve LIM mainly using on-screen interpretation of aerial photos, and little attention has been paid to developing more automated methods. In recent years, the use of multitemporal remote sensing images makes it possible to map landslides semi-automatically. Although numerous methods have been proposed, only a few methods are competent for some specific situations and there is large room for improvement in their degree of automation. For these reasons, a semi-automated approach is proposed for reliable and accurate LIM from bitemporal aerial orthophotos. Specifically, it consists of two principal steps: 1) change detection-based thresholding (CDT) and 2) level set evolution (LSE). CDT is mainly used to generate the initial zero-level curve (ZLC) for LSE, thus automating the proposed method considerably. It includes three substeps: 1) generating difference image (DI) using change vector analysis (CVA), 2) detecting landslide candidates using a thresholding method, and 3) removing errors using morphology operations. Then, landslide boundaries are detected using two types of LSE, i.e., edge-based LSE (ELSE) and region-based LSE (RLSE). Finally, the effectiveness and advantages of the proposed methods are corroborated by a series of experiments. Given its efficiency and accuracy, it can be applied to rapid responses of natural hazards. This study is the first attempt to apply LSE to LIM from bitemporal remote sensing images.



## 1. Introduction

Landslide hazard (natural or human-induced) often results in tremendous loss to human lives and properties (Hervas et al., 2003; Metternicht, Hurni, & Gogu, 2005; Keefer & Larsen, 2007; Huang & Fan, 2013; Qiu, 2014; Lu, Catani, Tofani, & Casagli, 2014). Over the past few decades, it has received considerable attention by disciplines such as geography (Guzzetti, Carrara, Cardinali, & Reichenbach, 1999; Lee & Choi, 2004; van Westen, Castellanos, & Kuriakose, 2008; Chang, Wan, & Lei, 2010; Van Den Eeckhaut & Hervas, 2012; Guzzetti et al., 2012; Battistini, Segoni, Manzo, Catani, & Casagli, 2013; Promper, Puissant, Malet, & Glade, 2014; Corominas et al., 2014; Xu, Xu, Yao, & Dai, 2014), natural hazards (Carrara, Guzzetti, Cardinali, & Reichenbach, 1999; van Westen, Rengers, & Soeters, 2003; Hong, Adler, & Huffman, 2006), and remote sensing (Nagarajan, Mukherjee, Roy, & Khire, 1998; Saha, Gupta, & Arora, 2002; Kaab, 2002; Metternicht et al., 2005; Tralli, Blom, Zlotnicki, Donnellan, & Evans, 2005; Joyce et al., 2009; Mondini et al., 2011; Stumpf & Kerle, 2011; Travelletti et al., 2012; Scaioni, Longoni, Melillo, & Papini, 2014; Lu et al., 2015). In particular, there has been an escalation of research into landslide inventory mapping (LIM), which records the attribute information of landslide, including the location, type, distribution, size or volume, date of occurrence, and sometimes the triggering factors (Guzzetti et al., 2012; Corominas et al., 2014). It is therefore the most essential information for landslide investigation (Brunsden, 1993; van Westen et al., 2008; Fell et al., 2008; Stumpf & Kerle, 2011; Corominas et al., 2014). Clearly, it is not only important to analyze and understand the causal factors of the past landslides, but also helpful for monitoring and predicting future hazards. However, it is currently still difficult to achieve LIM reliably and automatically in practical engineering applications. Although traditional field survey can obtain reliable results, it is often time-consuming, labor-intensive, and costly (Galli, Ardizzone, Cardinali, Guzzetti, & Reichenbach, 2008).

In recent years, with the availability of very high resolution (VHR) remote sensing images (spaceborne, airborne, and terrestrial), landslides can be mapped more accurately, completely, and rapidly than ever before (Metternicht et al., 2005; Keefer & Larsen, 2007; Kirschbaum et al., 2012; Qiu, 2014; Guzzetti et al., 2012). For example, simulated 1 m IKONOS images (Hervas et al., 2003), 0.6 m pan-

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sharpened Quickbird images (Kieffer, Jibson, Rathje, & Kelson, 2006), 6.6 m KOMPSAT-1 images (Lee & Lee, 2006), 2.5 m pan-sharpened ALOS images (Voigt et al., 2007), 10 m SPOT5 images (Joyce et al., 2009), and terrestrial laser scanning and Nikon reflex digital camera combined data (Travelletti et al., 2012) have been used for LIM. Also, point cloud or Light Detection and Ranging (LiDAR) data has proven effective at mapping landslides in forested areas (Razak, Straatsma, van Westen, Malet, & De Jong, 2011; Baldo, Bicocchi, Chiocchini, Giordan, & Lollino, 2009; Jaboyedoff et al., 2012; Travelletti, Malet, & Delacourt, 2014; Chen, Li, Wang, Chen, & Liu, 2014) and quantifying the volume changes of landslide over time (Ventura, Vilardo, Terranova, & Sessa, 2011; Pesci et al., 2011). In addition, Synthetic Aperture Radar (SAR) images and Interferometric SAR (InSAR) technology have been widely used for LIM because of their competitive advantages over optical images in slow-moving landslides monitoring and LIM in cloudy areas (Hilley, Burgmann, Ferretti, Novali, & Rocca, 2004; Liu et al., 2013; Cascini, Fornaro, & Peduto, 2009; Lu, Casagli, Catani, & Tofani, 2012; Herrera et al., 2013; Del Ventisette, Righini, Moretti, & Casagli, 2014; Ciampalini et al., in press).

In the next subsections, the previous pioneering works are briefly reviewed.

### 1.1. Previous work

In this paper, past LIM methods are classified into three general groups: pixel-based, object-based, and other approaches.

#### 1.1.1. Pixel-based approaches

The basic processing elements of pixel-based approaches are single pixels. Change detection (CD) is by far the most commonly used LIM method due to its simplicity and applicability (Hervas et al., 2003; Cheng, Wei, & Chang, 2004; Lee & Lee, 2006). A comprehensive review of CD techniques can be found in Lu, Mausel, Brondizio, and Moran (2004). From the perspective of CD, landslides can be regarded as land cover changes that occur over time. For instance, in Yang and Chen (2010), LIM is converted into the quantification of vegetation change, which is derived from Landsat and ASTER images automatically. Similar idea can be found in Zhang, Lin, Peng, and Lu (2010) for LIM from MODIS surface reflectance and ASTER images. Cheng et al. (2004) exploit band ratio for semi-automated LIM from SPOT images. In Nichol and Wong (2005), post-classification (PC) comparison is used for LIM from SPOT images. In Mondini et al. (2011), CD techniques are applied to LIM from bitemporal Quickbird images.

Although numerous CD approaches have been developed for LIM, few are competent enough for all situations due to the diversity of landslides. Thus, there is a tremendous need to develop more reliable and automated CD techniques (Bruzzone & Bovolo, 2013).

In addition to CD approaches, there have been many other methods proposed for LIM. For example, image correlation technique is used to LIM from images acquired by digital single-lens reflex camera in Travelletti et al. (2012) and SAR images in Raucoules, De Michele, Malet, and Ulrich (2013). A semi-automated method based on intensity threshold and maximum likelihood classification is applied to LIM from EO1 and SPOT5 images (Parker et al., 2011). More recently, Cheng et al. (2013) combine scene classification and machine learning for LIM from GeoEye images.

#### 1.1.2. Object-based approaches

The basic processing units of object-based image analysis (OBIA) are image objects that often consist of single pixels with similar spectral signatures (Benz, Hofmann, Willhauck, Lingenfelder, & Heynen, 2004; Blaschke, 2010). In this way, objects can be characterized by statistics (e.g., mean or variance value of all the bands), shapes (e.g., length, width, and area), texture, and contextual features (mutual relationships of image objects), which are often unavailable for traditional pixel-based approaches. In recent years, OBIA has been widely employed in remote sensing due to the release of the commercial software eCognition®.

In Martha, Kerle, van Westen, Jetten, and Kumar (2011), landslide boundaries are delineated using OBIA, which is enhanced by segment optimization. In Lu, Stumpf, Kerle, and Casagli (2011), CD technique and OBIA are combined for rapid LIM from Quickbird images. In Stumpf and Kerle (2011), OBIA and random forest are combined to achieve LIM from VHR satellite images, and some important object metrics have been summarized. More recently, Rau, Jhan, and Rau (2014) also employ OBIA for LIM from optical ortho-images and digital elevation model (DEM). Generally, panchromatic images can offer finer spatial details of landslides compared with lower resolution images. Thus, historical LIM is obtained from multitemporal panchromatic images using OBIA in Martha, Kerle, vanWesten, Jetten, and Kumar (2012). However, VHR images also increase the heterogeneity of landslides, which often complicates LIM substantially. To address this issue, Kurtz et al. (2014) exploit multiresolution optical images for LIM.

Although OBIA can take advantage of landslide features (Martha, Kerle, Jetten, van Westen, & Kumar, 2010), it suffers from limitations in real applications. For instance, 1) issues regarding feature selection and generic applicability still remain (Stumpf & Kerle, 2011), 2) to obtain the optimal parameter values, considerable human interactions are required, and thus, it is time-consuming and the degree of automation is very low, and 3) there are uncertainties such as scale selection in OBIA, which is still an open problem (Myint, Gober, Brazel, Grossman-Clarke, & Weng, 2011).

#### 1.1.3. Other approaches

For reliable LIM, most existing studies still exploit time-consuming and labor-intensive visual interpretation in practical applications. For example, in Lee and Pradhan (2007); Huang and Li (2009); Fiorucci et al. (2011); Gorum et al. (2011); Xu et al. (2014), considerable visual interpretation is employed to map landslides from various aerial orthophotos and satellite images. In contrast to traditional 2D data, some studies have achieved LIM via 3D data. For instance, DEM derived from aerial photos and ASTER images in Kaab (2002) and IKONOS stereo images in Nichol, Shaker, and Wong (2006) is exploited for LIM. In addition to field reconnaissance and remote sensing technique, Kirschbaum et al. (2009, 2010) have attempted to compile the global LIM from mass media sources such as academic articles and online news.

As LIM is currently an intensive research topic, it is hard to make an exhaustive review here. Related review articles can be found in Brunsden (1993); Guzzetti et al. (1999); van Westen et al. (2006, 2008); Joyce et al. (2009); Guzzetti et al. (2012); Van Den Eeckhaut and Hervas (2012); Corominas et al. (2014).

### 1.2. Our work

Numerous semi-automated or automated approaches have been developed for LIM over the past few years, as previously surveyed. However, their applicability needs to be further verified in different situations, and there is no single method and no single type of remote sensing data practical enough for all types of LIM (Joyce et al., 2009). In addition, it is currently still difficult to find an appropriate method that can be directly applied to rapid responses and emergency managements of natural hazards. Therefore, there is a need to propose more reliable and automated LIM methods (Lacroix, Zavala, Berthier, & Audin, 2013).

For these reasons, in this study a semi-automated approach is proposed for LIM from bitemporal aerial orthophotos. Specifically, it consists of two main steps: change detection-based thresholding (CDT) and level set evolution (LSE). The former is mainly used to generate the initial zero-level curve (ZLC) for the latter, thereby automating the proposed method considerably. CDT includes three substeps: 1) generating difference image (DI) using change vector analysis (CVA), 2) identifying landslide candidates using a thresholding method, and