Remote Sensing of Environment 187 (2016) 76–90

Contents lists available at ScienceDirect

Remote Sensing of Environment

journal homepage: www.elsevier.com/locate/rse

Landslide mapping from aerial photographs using change detection-based Markov random field

Zhongbin Li[a,b,*], Wenzhong Shi[a], Ping Lu[c], Lin Yan[b], Qunming Wang[d], Zelang Miao[a]

[a]Department of Land Surveying and Geo-Informatics, The Hong Kong Polytechnic University, Hong Kong
[b]Geospatial Sciences Center of Excellence, South Dakota State University, Brookings, SD, USA
[c]College of Surveying and Geo-Informatics, Tongji University, Shanghai, China
[d]Lancaster Environment Center, Lancaster University, Lancaster, UK

ARTICLE INFO

Article history:
Received 27 May 2016
Received in revised form 16 September 2016
Accepted 2 October 2016
Available online xxxx

Keywords:
Aerial photographs
Change detection
Landslide mapping (LM)
Markov random field (MRF)
Region-based level set evolution (RLSE)

ABSTRACT

Landslide mapping (LM) is essential for hazard prevention, mitigation, and vulnerability assessment. Despite the great efforts over the past few years, there is room for improvement in its accuracy and efficiency. Existing LM is primarily achieved using field surveys or visual interpretation of remote sensing images. However, such methods are highly labor-intensive and time-consuming, particularly over large areas. Thus, in this paper a change detection-based Markov random field (CDMRF) method is proposed for near-automatic LM from aerial orthophotos. The proposed CDMRF is applied to a landslide-prone site with an area of approximately 40 km^2 on Lantau Island, Hong Kong. Compared with the existing region-based level set evolution (RLSE), it has three main advantages: 1) it employs a more robust threshold method to generate the training samples; 2) it can identify landslides more accurately as it takes advantages of both the spectral and spatial contextual information of landslides; and 3) it needs little parameter tuning. Quantitative evaluation shows that it outperforms RLSE in the whole study area by almost 5.5% in *Correctness* and by 4% in *Quality*. To our knowledge, it is the first time CDMRF is used to LM from bitemporal aerial photographs. It is highly generic and has great potential for operational LM applications in large areas and also can be adapted for other sources of imagery data.

1. Introduction

Landslide hazards cause annual economic losses of nearly US$4 billion in Italy, over US$3 billion in Japan, more than US$1 billion in China (Klose et al., 2016), and at least US$2 billion in the United States (http://landslides.usgs.gov/). In Hong Kong, there are more than 100000 landslides on natural terrain, with almost 500 people killed in the past six decades (Choi and Cheung, 2013). The annual average expenditure over the last decade incurred by landslide prevention measures was about US$124 million (Choi and Cheung, 2013). Thus, landslide mapping (LM), including the date, spatial distribution, size, number, type, and morphological features of landslides, is essential for hazard prevention, mitigation, and vulnerability assessment. In recent years, the progress of LM has been considerably facilitated by the development of remote sensing techniques (Ardizzone et al., 2007; Ciampalini et al., 2015; Guzzetti et al., 2012; Metternicht et al., 2005; Scaioni et al., 2014; Tofani et al., 2013). To date, numerous LM methods using optical remote sensing images have been developed and they are briefly reviewed in the following subsection.

1.1. Prior work

Prior LM methods can be roughly classified into five groups: visual interpretation-based, feature-based, change detection-based, topographic model-based, and machine learning-based methods. Related review articles can be referred to Guzzetti et al. (2012) and Corominas et al. (2014). The studies of LM using synthetic aperture radar (SAR) data are not included in this section.

1.1.1. Visual interpretation-based methods

In Saba et al. (2010), Sato et al. (2007), and Xu et al. (2015), earthquake-triggered landslides were visually interpreted from high resolution satellite images. Three different LM techniques using

* Corresponding author at: Geospatial Sciences Center of Excellence, South Dakota State University, Brookings, SD, USA.
E-mail address: zhongbin.li@sdstate.edu (Z. Li).

http://dx.doi.org/10.1016/j.rse.2016.10.008

visual interpretation of aerial photos were compared in Galli et al. (2008). Similar comparisons can be found in Xu et al. (2014). Nearly 60000 landslide scarps were mapped from remote sensing images via visual interpretation in Gorum et al. (2011). In Ghosh et al. (2012), three types of landslides, i.e., shallow translational rockslides, shallow translational debris slides and deep-seated rockslides, were mapped by human interpretation of multitemporal remote sensing images. In Althuwaynee et al. (2015), a 12-year rainfall-induced landslide inventory map in the metropolitan area was visually delineated from aerial photos and SPOT-5 images. In Borrelli et al. (2014), rainfall-triggered landslides were mapped from aerial photos using visual interpretation which is aided by field surveys. In a different context Brunetti et al. (2014), landslides on Mars were visually interpreted from optical images. In Murillo-García et al. (2015), visual analysis of stereo pairs of GeoEye-1 images was applied to map rainfall-triggered landslides. A recent study found that visual interpretation of aerial photos is still the widely used LM method (Pellicani and Spilotro, 2015). In practice, however, visual interpretation is often labor-intensive and time-consuming.

1.1.2. Feature-based methods

Generally, the spectral, textural, morphological and topographic features are combined for LM. For example, landslides were mapped using the spectral, spatial contextual information and morphometric features in Aksoy and Ercanoglu (2012), Lahousse et al. (2011), Martha et al. (2010) and Rau et al. (2014). In Lu et al. (2011) and Martha et al. (2012), object-oriented change detection methods were developed for LM from multitemporal satellite images. In Martha et al. (2011), optimal segments generated by object-based image analysis (OBIA) and terrain curvature derived from DTM were combined for landslide detection and classification in mountainous areas. In Van Den Eeckhaut et al. (2012), landslides in forested areas were identified by using multiple types of features derived from LiDAR data. Results in Moosavi et al. (2014) showed that OBIA outperforms pixel-based methods in LM from high resolution remote sensing images. In a recent study (Pradhan et al., 2015), landslides in a tropical urban area were detected using OBIA which combines airborne LiDAR data and Quickbird images.

1.1.3. Change detection-based methods

In some studies, landslides were mapped by differencing co-registered images or digital elevation models (DEMs) acquired over the same geographical position at different times. In van Westen and Getahun (2003), landslide evolution maps in Tessina, Italy were obtained via multitemporal aerial photographs interpretation and landslide volumetric changes were estimated by multitemporal DEMs analysis. In Hervás et al. (2003), landslides in the same area were mapped using bitemporal change detection of aerial photographs. In Tsutsui et al. (2007), multitemporal DEMs derived from SPOT-5 imagery were used to detect earthquake- and typhoon-triggered mountainous landslides and estimate their volumes. The similar application can be found in Pesci et al. (2011). In Yang and Chen (2010), LM was converted into the change analysis of the multitemporal normalized difference vegetation index (NDVI) from Landsat TM image and Advanced Spaceborne Thermal Emission and Reflection Radiometer image. In Mondini et al. (2011a,b), four different types of change detection techniques, i.e., dNDVI, spectral angle, principal component analysis, and independent component analysis, were combined to map shallow landslides from 8 m bitemporal satellite images. In Ventura et al. (2011), multitemporal LiDAR-derived digital terrain models (DTMs) were used to track the evolution of active rock landslides. More recently, change vector analysis (CVA) and level set method were integrated to map shallow debris flows from bitemporal aerial photos in Hong Kong (Li et al., 2016). Results indicated that region-based level set evolution (RLSE) outperforms edge-based LSE in LM.

1.1.4. Topographic model-based methods

In recent years, digital topographic models have been widely used for LM as they can provide detailed geomorphological features. In Giordan et al. (2013), Glenn et al. (2006), McKean and Roering (2004), Razak et al. (2013), Tarolli et al. (2012), and Trevisani et al. (2012), DEM derived from LiDAR was used to analyze the landslide surface geomorphological features. In Bichler et al. (2004), DTM derived from remote sensing images was used to map 3D landslides on a plateau in Canada. LiDAR-derived DEMs were used to identify rainfall-induced landslides in a hilly area (Ardizzone et al., 2007) and forested landslides in a mountainous area (Chen et al., 2014). In Booth et al. (2009), LiDAR-derived DEM combining signal processing techniques was exploited to map deep-seated landslides. In Kurtz et al. (2014), landslide morphological features (e.g., slope and curvature) derived from DTM were utilized for mapping shallow and slow-moving landslides. The application of LiDAR-derived DEM for LM has been comprehensively reviewed in Jaboyedoff et al. (2012) and Tarolli (2014).

1.1.5. Machine learning-based methods

In Borghuis et al. (2007), maximum likelihood classifier was used to map typhoon-triggered landslides in rugged area from 10 m SPOT-5 images. In Chang et al. (2007), a generalized positive Boolean function-based classifier was trained using spectral and morphological features for landslide classification. Probabilistic latent semantic analysis was applied to LM in semi-arid regions from GeoEye-1 images in Cheng et al. (2013). In Mondini et al. (2013), the inventory maps of rainfall-induced shallow landslides were produced using Bayesian inference. In Chen et al. (2014), random forest was trained using features derived from DTM to identify forested landslides. Support vector machine trained using backscatter and texture features was applied to detect slough slides along earthen levees in Mahrooghy et al. (2015).

The above brief review suggests that LM, despite the past efforts, remains a challenging task. There is significant demand for improvement in the accuracy and the degree of automation of LM (Guzzetti et al., 2012; van Westen et al., 2006). Although field surveys and visual interpretation of remote sensing images generally can provide reliable results, they are highly labor-intensive, time-consuming Galli et al. (2008), and sometimes impractical. Thus, this paper attempts to propose a more accurate and automated LM method.

1.2. Our work

This paper is a further development of our previous work (Li et al., 2016), in which landslides were mapped from bitemporal aerial photos using LSE (Li et al., 2015). Despite the decent performance of LSE, it has constraints regarding accuracy, automation and robustness considering large-area LM applications. In particular, LSE only utilizes the spectral information of landslides, which is sometimes not adequate to obtain reliable results. In addition, there are many free parameters in LSE that need to be tuned in practical applications, and however, it is not easy to obtain the optimal parameter values. Therefore, in this paper we propose a new change detection-based Markov random field (CDMRF) for near-automatic LM. Compared with the existing LM methods, CDMRF has the following attractive characteristics: 1) it takes into account both the spectral and spatial contextual information of landslides; 2) it has a great level of automation; and 3) it requires little parameter tuning.

2. Study area and dataset

The study area, with a total land area of approximately 40 km^2, is located on western Lantau Island, Hong Kong (Fig. 1). It is characterized by steep terrain, 40% of which is steeper than 25°. The highest point in the study area is Ling Wui Shan with a height of 490 m. There