ISPRS Journal of Photogrammetry and Remote Sensing 67 (2012) 105–119

Contents lists available at SciVerse ScienceDirect

ISPRS Journal of Photogrammetry and Remote Sensing

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

Object-oriented analysis of multi-temporal panchromatic images for creation of historical landslide inventories

Tapas R. Martha [a,b,*], Norman Kerle [b], Cees J. van Westen [b], Victor Jetten [b], K. Vinod Kumar [a]

[a] *National Remote Sensing Centre (NRSC), Indian Space Research Organisation (ISRO), Hyderabad 500625, India*
[b] *Faculty of Geo-Information Science and Earth Observation (ITC), University of Twente, Hengelosestraat 99, 7500 AE, Enschede, The Netherlands*

ARTICLE INFO

Article history:
Received 14 June 2011
Received in revised form 8 October 2011
Accepted 9 November 2011
Available online 17 December 2011

Keywords:
Feature extraction
OOA
GEOBIA
Cartosat-1
Landslide hazard and risk
Disaster

ABSTRACT

Object-oriented analysis (OOA) has been demonstrated to produce more accurate results than pixel-based image processing. Studies carried out by previous researchers have shown how landslide inventories can be prepared from multispectral satellite images using OOA. However, panchromatic images are frequently the only data available after a landslide event. Furthermore, preparation of historical inventories relies on the analysis of satellite images and aerial photographs acquired over past few decades that are also mostly only available in black and white. In such cases the methodology developed using multispectral data cannot be used directly due to limited spectral information, in particular in near-infrared bands. In this paper we present a new methodology that addresses some of these issues. Using high resolution panchromatic images from Cartosat-1 (2.5 m) and IRS-1D (5.8 m), and a 10 m gridded DTM extracted from Cartosat-1, we developed a new approach which uses change detection techniques and a global contextual criteria in an object-based environment to detect and classify landslides into five different types. Continuous time series images from 1998 to 2006 were used to prepare annual landslide inventories in a highly rugged Himalayan terrain. The maximum and minimum detection percentages achieved for all landslides are 96.7% and 71.5%, respectively, with corresponding quality percentages of 88.1% and 55.3%, respectively. However, the lack of spectral information proved to be a hurdle resulting in a high branching factor that indicates that further work is required to eliminate false positives. Nevertheless, the method was able to create much needed historical landslide inventories, which are critical for landslide hazard and risk assessment studies.

1. Introduction

Fast detection of landslides is vital for rapid damage assessment and supporting disaster management activities. Segmentation-based object-oriented analysis (OOA) provides an alternative to detect landslides automatically from remote sensing images in comparison to traditional pixel-based approaches that mainly use spectral and texture information (Townshend et al., 2000; Walter, 2004; Mallinis et al., 2008; Xie et al., 2008). OOA mimics the human cognitive interpretation process and has the potential to identify meaningful geomorphic processes, such as landsliding, using criteria based on shape, colour, texture and context, and produces result that are verifiable and can easily be converted to GIS data (Benz et al., 2004; Navulur, 2007; Blaschke, 2010). Although rapid inventorisation of new landslide occurrences is crucial for planning of immediate disaster response, historical landslide inventories play an important role for the preparation of landslide susceptibility and hazard maps required for setting up long term landslide management strategies (Guzzetti et al., 2005; Devoli et al., 2007). Previous workers (e.g. Barlow et al., 2003, 2006; Moine et al., 2009; Martha et al., 2010a, 2011; Lu et al., 2011; Stumpf and Kerle, 2011) have shown how to detect landslides from multispectral images by OOA. However, panchromatic images are frequently the only data available after an event (van Westen and Lulie Getahun, 2003; van Westen et al., 2008), where these methodologies cannot be used directly, since they rely on thresholds derived from spectral information during the detection process. In particular infrared information has been playing a critical role, for example to distinguish vegetation, water or shadow. Also, satellites such as from SPOT, LANDSAT and IRS-1C/1D, all useful sources of Earth Observation (EO) data for the preparation of historical landslide inventory databases, have panchromatic cameras with higher spatial resolution than their multispectral counterparts. For example, both IRS-1C and 1D carry a multispectral LISS-III (23.5 m) camera,

* Corresponding author. Address: Geosciences Division, National Remote Sensing Centre, Department of Space, Government of India, Balanagar, Hyderabad 500625, India. Tel.: +91 40 23884276; fax: +91 40 23772470.
E-mail addresses: trmartha@rediffmail.com, tapas_martha@nrsc.gov.in (T.R. Martha).

0924-2716/$ - see front matter © 2011 International Society for Photogrammetry and Remote Sensing, Inc. (ISPRS) Published by Elsevier B.V. All rights reserved.
doi:10.1016/j.isprsjprs.2011.11.004

the data from which if used for preparation of historical landslide inventory will miss smaller landslides. Those, however, can be detected if data from the panchromatic (5.8 m) camera onboard the same satellite were used. Although PAN-sharpening can help, availability of both (panchromatic and multispectral) data on the same day of acquisition, preferable for data merging, is often limited. Therefore, an object-oriented landslide detection method for the preparation of historical landslide inventories from panchromatic images only is desirable.

Panchromatic images have previously been used for land use/land cover classification using the tonal variation, i.e. texture, in the high resolution imagery. The grey level co-occurrence matrix (GLCM) is by far the most commonly used tool in remote sensing to derive second order texture measures (Haralick et al., 1973). For example, Rao et al. (2002) used GLCM textures in addition to tone for land cover classification from IRS-1D PAN data. Similarly, Zhang et al. (2003) identified the spatial pattern of an urban area using GLCM texture features derived from SPOT PAN data. Change detection using time-series panchromatic images is another method that has been applied successfully for target identification (Smits and Annoni, 2000; Negi et al., 2002), and can effectively be used for preparation of historical landslide inventories from multi-temporal satellite images. Image differencing, principal component analysis, and post-classification comparison are the most common methods of change detection (Lu et al., 2004). Precise geometric registration and normalisation between time-series images are the key requirements for deriving accurate results by change detection (Lu et al., 2004). Negi et al. (2002) used PAN–PAN change detection for the identification of buildings and aircrafts, whereas Nichol and Wong (2005) used change detection to prepare a landslide inventory from grey level images. However, these workers essentially used panchromatic images in pixel-based classification, which has an inherent inability to address feature characteristics and context during image analysis.

Object-based land cover classification using panchromatic images has been attempted by previous workers (e.g. Elmqvist et al., 2008). However, object-based change detection with panchromatic images has so far not been used to its full potential. Only recently, Dissanska et al. (2009) used object-based post classification change detection and classified peat lands from recent high spatial resolution greyscale Quickbird images and old aerial photographs. They used GLCM textures to characterise and classify the peat lands and monitored the changes. One of the important properties commonly observed in the post-landslide panchromatic images is the increase in brightness of the area affected by landsliding due to loss of vegetation and exposure of fresh rock and soil (Martha et al., 2010a). This effect can be captured in an object-based environment to detect landslides by change analysis of pre- and post-landslide images. However, the increase in brightness due to land cover changes such as mining, forest fire and other anthropogenic causes has to be eliminated successfully.

In this study we developed a new approach by applying additional texture measures, the main property offered by high resolution panchromatic images, along with tone and context-based criteria to detect landslides. The methodology was developed using eCognition software. Multiresolution segmentation was used to derive image primitives with optimal segmentation parameters, determined by a plateau objective function (POF), which is a combination of intrasegment variance and spatial autocorrelation (Martha et al., 2011). Texture measures based on GLCM were used to identify false positives, such as roads, agricultural terraces and built-up areas. While an IRS-1D panchromatic image (5.8 m) was used for the segmentation and extraction of GLCM textures, a digital elevation model (DEM) derived from along-track stereoscopic Cartosat-1 data (2.5 m) was used to extract morphometric features of landslides. A combination of these diagnostic features was used in an object-based environment with a knowledge-based approach to detect landslides using panchromatic images from 1998 to 2006 (except for 2004) in parts of the highly rugged Himalayan terrain.

2. Materials and method

2.1. Study area

The Himalayas are one of the global hotspots for landslide hazard (Nadim et al., 2006). A test area was selected covering 81 km^2 in parts of the Mandakini river valley in the Western Indian Himalayas around Okhimath town (30° 30′ 48″ N and 79° 05′ 41″ E) in the Rudraprayag district of Uttarakhand state, India (Fig. 1). This area was selected because of the occurrence of many recent landslides of different types, and associated with a variety of land covers and litho units. Okhimath is situated at an average elevation of 1300 m at the confluence of the Mandakini and Madhyamaheshwar rivers. In August 1998, a total of 466 landslides were triggered by a major rainfall event, which killed 103 people and damaged 47 villages throughout the Mandakini valley (Naithani, 2002). Some of the landslides in the area are as much as a century old but permanently active.

2.2. Data sources

To prepare an annual historical landslide inventory by OOA, and taking the landslide super event of August 1998 as a starting point, cloud free panchromatic data (one scene per year) from 1998 to 2006 were procured from archives (Table 1). High sensor tilt angles during data acquisition create geometric distortion in mountainous areas and are generally problematic for change detection using time series images. Therefore, only images acquired with <5° tilt angle, which are generally available in archives, were procured and used in this study. A 10 m digital surface model (DSM) derived from Cartosat-1 stereoscopic images, having a vertical and planimetric RMSE of 2.31 m and <1 m, respectively (Martha et al., 2010b), was converted to a digital terrain model (DTM) by applying vegetation height correction (Martha et al., 2010a). The DTM was used to extract morphometric layers such as slope, flow direction and relief. The DTM created using 2006 image forms an input to OOA together with the time-series panchromatic images.

2.3. Pre-processing of satellite data

2.3.1. Image geometric correction

Accurate geometric registration of satellite data to a common spatial framework is a principal requirement for image analysis involving multiple satellite images (Prenzel and Treitz, 2004). In this study, first the Cartosat-1 PAN-Aft image was orthorectified using the 10 m DTM, and subsequently used as reference for the geometric correction of IRS-1D PAN time-series images, using a projective transform model. During geometric correction, uniform projection (UTM) and datum (WGS84) were maintained. The maximum RMS error after the transformation was less than 3 pixels, and can be considered satisfactory given the problems of image registration in mountainous areas (Xu et al., 2010).

2.3.2. TOA reflectance calculation

Quantitative comparison of multi-temporal images requires conversion of DN values to reflectance (Lu et al., 2008). The conversion is essential for two reasons: (i) to compensate for the brightness difference due to image acquisition under different sun illumination conditions; and (ii) to adjust for the difference in DN values due to the seasonal adjustment of sensor parameters by the data provider. We calculated the top of atmosphere reflectance (ρ_{TOA}) to address these issues