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Contour Connection Method for automated identification and classification of landslide deposits

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A B S T R A C T

Landslides are a common hazard worldwide that result in major economic, environmental and social impacts. Despite their devastating effects, inventorying existing landslides, often the regions at highest risk of reoccurrence, is challenging, time-consuming, and expensive. Current landslide mapping techniques include field inventorying, photogrammetric approaches, and use of bare-earth (BE) lidar digital terrain models (DTMs) to highlight regions of instability. However, many techniques do not have sufficient resolution, detail, and accuracy for mapping across landscape scale with the exception of using BE DTMs, which can reveal the landscape beneath vegetation and other obstructions, highlighting landslide features, including scarps, deposits, fans and more. Current approaches to landslide inventorying with lidar to create BE DTMs include manual digitizing, statistical or machine learning approaches, and use of alternate sensors (e.g., hyperspectral imaging) with lidar.

This paper outlines a novel algorithm to automatically and consistently detect landslide deposits on a landscape scale. The proposed method is named as the Contour Connection Method (CCM) and is primarily based on bare earth lidar data requiring minimal user input such as the landslide scarp and deposit gradients. The CCM algorithm functions by applying contours and nodes to a map, and using vectors connecting the nodes to evaluate gradient and associated landslide features based on the user defined input criteria. Furthermore, in addition to the detection capabilities, CCM also provides an opportunity to be potentially used to classify different landscape features. This is possible because each landslide feature has a distinct set of metadata – specifically, density of connection vectors on each contour – that provides a unique signature for each landslide. In this paper, demonstrations of using CCM are presented by applying the algorithm to the region surrounding the Oso landslide in Washington (March 2014), as well as two 14,000 ha DTMs in Oregon, which were used as a comparison of CCM and manually delineated landslide deposits. The results show the capability of the CCM with limited data requirements and the agreement with manual delineation but achieving the results at a much faster time.

1. Introduction

A landslide, as defined by Cruden (1991) is a movement of a mass of rock, debris, or earth down a slope. This geo-hazard can result in severe consequences, including economic and infrastructural impacts and casualties, in the worst cases. Therefore, identifying hazardous locations, determining the magnitude of risk, understanding causative factors, and mitigating the impacts of this phenomenon have been a critical area of research. Typically, previous studies focus on evaluating the specific details of individual landslides and understanding the causative mechanism. Beyond these case studies, large inventories of landslides are being collected by geologists and remote sensing professionals in an effort to mitigate landslide impacts. For example, the United States Geological Survey (USGS) has an open access database on their web site reporting the landslides that occur around the world since 1994 (USGS, 2014) as well as other state and local organizations also work on establishing hazard databases (e.g., Burns et al., 2013 and Puget Sound lidar Consortium, 2014).

Landslides manifest in a variety of morphologies and magnitudes (Burns and Madin, 2009). For example, recently in March

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and April in 2014, the media has reported several landslide events that ranged significantly in magnitude and location. The first major landslide reported was in Steelhead Haven, 6.5 km east of Oso, Washington (The Pacific Northwest of the United States). The footprint of the landslide covered an area approximately 2.6 km^2 and 41 people have lost their lives (Seattle Times, 2014). At the end of April, a large landslide in Afghanistan's Badakhshan region covered about 300 homes with mud and debris and more than 350 people reported to have lost their lives with an additional 2000 people missing BBC (2014).

In general, the combination of geometry of the slope/hillside, vegetation, soil and rock properties, rock mass structure, precipitation and water conditions (including both groundwater and surface water) have direct effects affecting slope instability (Cornforth, 2005; Ling et al., 2009; Leshchinsky, 2013). Understanding these factors enables scientists and engineers to evaluate potential hazards for particular areas, a critical step for prevention or minimization of damage. However, geotechnical evaluation of slope stability is often on an individual basis, and often only in consideration of two-dimensional conditions (ignoring three-dimensional effects) with idealized soil and rock properties. DTM-based mechanistic are mainly dependent on the infinite slope method (translational failure with assumed soil strength) for highlighting regions of instability Dietrich et al. (2001). Currently, the USGS has a specific landslide hazards program that includes seven monitoring sites along the west coast where particular landslides are monitored with an aim on developing methodologies geared towards predicting the behavior of the landslide (USGS, 2014). A similar interest in characterizing and mitigating of landslides also exist within the transportation agencies in the United States. The Transportation Research Board has developed a special report particularly focusing on landslide investigations and mitigations (Turner and Schuster, 1996) and more recently National Research Council (NRC) has developed guidelines for assessment of national landslide and rock fall hazards NRC (2004). Mitigation of landslides is a benefit for a variety of reasons, including safety and development of infrastructure and environmental concerns, yet the most ideal way of mitigating the impacts of landslides is simple – avoiding them. However, avoidance of these features is not trivial as it requires adequate mapping and inventorying – a daunting task over large, vegetated landscapes.

1.1. Landslide mapping

Despite its challenges, landslide hazard mapping is a common practice in urban settings for planning purposes. There are three primary types of mapping:

1. **Inventory** – Mapping, classification and documentation of existing landslides, both historic and pre-historic based on geologic evidence; and
2. **Susceptibility** – Mapping based on soil and site conditions that indicate areas susceptible to landslides, and
3. **Hazard** – Mapping and evaluating the potential for damage, incorporating external factors. This differs from susceptibility in that the triggering sources are included in the analysis. In some literature, these are referred to generically as hazard maps. Further, potential mapping methodologies can be classified into deterministic and probabilistic.

Recently, there has been a drive to utilize new remote sensing technologies to identify, investigate, and map landslides as opposed to field visits (small coverage) or classical photogrammetry (susceptible to missing landslides in forested terrain). Several techniques include (but are not limited to) differential interferometric synthetic aperture radar (DInSAR) which can measure displacements (Belardinelli et al., 2005) at high (mm-level) accuracies, panchromatic QuickBird satellite images of the ground that can be used to evaluate changes in topography (Niebergall et al., 2007), airborne and terrestrial geodetic lidar-scans, which can create detailed, 3D point clouds used for monitoring changes in the terrain (Jaboyedoff et al., 2012; Olsen et al., 2012; Olsen, 2013; Conner and Olsen, 2014) at high resolutions, and unmanned aerial vehicles (UAVs) equipped with digital cameras to map and record spatial and temporal measurements (Niethammer et al., 2012).

Using remote sensing methods provide a significant advantage by facilitating landscape-scale hazard inventories without the practical challenges of physically verifying landslide features (Van Westen et al., 2008; Burns and Madin, 2009). Not only does the use of some new remote sensing technologies enable landscape-scale collection of topography; but also it can provide abilities to remove vegetation or forest canopies from the models, clearly exposing the scarred earth beneath. However, when data obtained from remote sensing is used to develop models to predict and forecast landslides, the models become very complex; therefore, inventorying of old landslides is the first major, yet exhaustive measure to evaluate potential hazards on a landscape.

1.2. Use of lidar in remote sensing

Light detection and ranging (lidar) technology is a line-of-sight technology that emits laser pulses at defined, horizontal and vertical angular increments to produce a 3D point cloud, containing XYZ coordinates for objects that return a portion of the light pulse within range of the sensor. This detailed point cloud is a virtual world that can be explored and analyzed for multiple uses long after the data are collected. Time series surveys enable damage and deterioration analyses at unprecedented detail across multiple scales. Currently, an initiative, the 3D elevation plan (3DEP) is underway to obtain airborne lidar data across the entire U.S. at meter level resolution (Snyder, 2012).

One of the key benefits of lidar data is its ability to model the ground surface and key geomorphological features covered by vegetation when a portion of the emitted light is able to penetrate the ground. A variety of processing techniques exist to filter ground points and create a Digital Terrain Model (DTM). These approaches depend on the type of terrain and vegetation characteristics. Common approaches including lowest elevations, ground surface steepness, ground surface elevation difference, and ground surface homogeneity are reviewed in Meng et al. (2010).

In the last decade, lidar has become a key tool for landslide delineation. Jaboyedoff et al. (2012) provides a detailed review of lidar usage for landslide studies. Lidar has been used to undertake detailed geological assessments of several landslides, enabling improved understanding of the processes and mechanisms contributing to landslide movement. Considerable work has also been undertaken in recent years to document the patterns of landslides and mechanisms for failure, particularly in forested environments where lidar provides detailed surface topography to delineate landslides that were previously undetectable. In general, there are three approaches to delineate landslides from lidar data:

1. **Manual** – Manually delineating landslide deposits and scarps from airborne lidar is the most common approach (see Fig. 1). Burns and Madin (2009) demonstrate a systematic methodology using airborne lidar to map landslides in northwest Oregon, ultimately creating landslide hazard maps that could be used by local government for planning purposes. Similarly, Schulz (2007) presents approaches for landslide susceptibility estimation from airborne lidar data.