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Comparative analysis of surface roughness algorithms for the identification of active landslides

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ABSTRACT

Parameters correlated to surface roughness are quite commonly used to describe landslide activity in quantitative geomorphology. Previous studies proved that topographic roughness is closely related to both landslide mechanics and features. A number of different techniques have emerged over the years to describe quantitatively the great variety of landforms and processes that affect unstable slopes. In this work we perform a comparative analysis of several methods used in literature to compute surface roughness (root mean square applied to elevation and slope grids, eigenvalue ratios, semivariance, discrete Fourier transform, continuous wavelet transform and wavelet lifting scheme) in order to evaluate quantitatively which algorithms are best suited to discriminate active landslides and to predict them for automated mapping purposes. A first test was carried out on artificial surfaces simulating different roughness patterns encountered in nature, so to highlight advantages and limits in controlled conditions. Then, the algorithms were applied to LiDAR datasets of two earth flow case studies in the Northern Apennines, Italy.
Results obtained by using "effect-size" statistical test to objectively quantify the capability of the different algorithms of discriminating active landslide slopes from other slope types showed that most algorithms perform reasonably well and that simple techniques (RMS-based and wavelet lifting scheme) achieve equal or sometimes even better results that more complex ones. Results from the use of roughness indexes for the prediction of landslide slopes in automated mapping showed that non-forested active slopes could be predicted by most methods with an accuracy greater than 85% and that most methods had a 15% drop in prediction accuracy in forested active slopes. Results also proved that increasing the size of the moving window has minor beneficial effects in predictive capability, suggesting that small size of pixels and moving windows should be used to retain a full resolution of surface conditions in slopes.

1. Introduction

In quantitative geomorphological analysis, the classification of terrain types requires the use of statistical parameters to define the topographic signature of specific processes and landforms (Pike, 1988; Bishop and Shroder, 2004; Hengel and Reuter, 2009). However, since landforms vary in size and shape according to a variety of factors (e.g. the causal geomorphic process, climate, lithology, vegetation, and tectonic activity) many different statistical parameters have been proposed in literature to provide a quantitative description of topography (Bishop et al., 1998; Wallace et al., 2004; Miska and Hjort, 2005). In the specific case of landslides, some recent studies have shown that surface roughness can be successfully used to delineate landslide features, to analyze past landslide activity or to create maps of active landslides (McKean and Roering, 2004; Van Den Eeckhaut et al., 2005; Booth et al., 2009). The growing availability of high-resolution LiDAR (Light Detection And Ranging) topographic data and the increase of computational capacity, provide new opportunities for the statistical analysis of terrain roughness. Such analysis could contribute to the development of routines for semi-automatic mapping of landslides from large regional datasets and for the objective evaluation of their degree of activity.

A number of methods have been proposed to quantify topographic roughness. The most commonly used methods are based on the statistical dispersion of heights, slopes and normal vectors to slopes (Shepard et al., 2001; Guth, 2003; Grohmann, 2004) or on the ratio between the surface area of an object and its planar area (Hobson, 1972; Troiani and Della Seta, 2011). Alternatively, more advanced spectral techniques can also be used. Booth et al. (2009) suggest that landslides features can be recognized using automated, frequency-domain-based procedures. However, they admit that such a classification must be backed-up by classic photo interpretation and field analysis. Fractal dimension is also used as a measure of

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surface complexity (Mandelbrot, 1983; Tate, 1998; Wilson et al., 2007). Other studies suggest the use of semivariograms (Glenn et al., 2006; Trevisani et al., 2009) or second-generation wavelets (Hani et al., 2011).

Such a variety of methods indicate that it is difficult to characterize topographic roughness by one specific algorithm. The question is whether some methods are better-suited than others in terms of discriminatory capability and in terms of their usage for automated mapping of topographic features such as landslides. To our knowledge, a quantitative comparative analysis including all major methods for roughness analysis has never been done.

The objective of this paper is therefore to compare the performance of several roughness computation algorithms in discriminating active landslides and in producing accurate automated maps of landslide activity. For this purpose, the methods are tested on sample synthetic surfaces as well as on two LiDAR datasets acquired for two study areas located in the Northern Apennines (Italy). To measure the ability of the algorithms to discriminate between unstable and stable slopes, a simple and efficient technique based on effect-size statistics (Cohen, 1988) is adopted (Section 4.1). Moreover, we propose a method for the automated mapping of active landslides based on surface roughness computation (Section 4.2). To evaluate the accuracy of predictive maps obtained with different algorithms, predicted landslides are compared to the observed landslides by using the ROC curve (Green and Swets, 1966).

2. Background on roughness computation

A number of different algorithms have been proposed in the literature to quantify surface roughness. Most of these methods, however, have not been developed to describe topographic roughness and show some deficiencies when applied to this purpose. According to Hani et al. (2011), an ideal algorithm suitable for a distributed analysis of surface morphology should:

i) provide a local, pixel-level measure of the surface, not a global measure of the whole DEM;
ii) be simple enough so to run on large datasets with a reasonable computational time and memory usage;
iii) return indexes that are representative of an intrinsic property of the surface, invariant with respect rotation or translation;
iv) take into account the scale dependency characteristics of natural surfaces; and
v) have an intuitive or physical meaning.

Existing methods fall short to meet all these requirements which may explain why many different algorithms were developed. Basically all algorithms can be implemented for analyzing a DEM on a pixel basis by using a moving window (or kernel) roving over the dataset. Moving window techniques work like spatial filters which replace the central value in the window with some function of neighboring pixel values, including that central value. One known limit of moving window methods is that they cannot provide values at the boundaries of the analyzed raster dataset.

The key characteristics of methods considered in this work are summarized in Table 1. Their applicability to complex topographic surfaces was tested on synthetic surfaces (Fig. 1a) representing different combinations of smooth background, random noise and deterministic sine waves. Such components are representative of natural topographic surfaces, which can be described as a complex mix of self-affine Brownian noise and pseudo-deterministic landforms with dominant spatial harmonics (Shepard et al., 1995; Malamud and Turcotte, 1999; Booth et al., 2009).

RMS-based algorithms are probably the most commonly adopted methods for roughness computation. These methods are simple to implement and can describe random, deterministic and composite surface roughness (Fig. 1b, c). Data detrending is required in order to remove the general sloping trend and it is usually carried out by subtracting the elevation of a best fit plane to the elevation of pixels in the computation window. RMS methods are quite sensitive to outliers,

Table 1
Surface roughness algorithms. N = width of the moving windows (number of cells); z_i = cell elevation; $\bar{z}$ = mean elevation within the moving window; z_c = elevation of the central cell; z_b = elevation of the cells along the border; Δx_b = distance from the central cell to a border cell; $\Delta X = d(N-1)/2$, where d is the cell size; m_i = slope of the i-th cell; $\overline{m}$ = mean slope within the moving window; S_1, S_2 = normalized eigenvalues of the 3×3 orientation matrix (given by the sums of cross products of direction cosines); x_i, y_i = spatial coordinates of the i-th cell; h = lag distance; K = number of iterations (k) of the wavelet lifting scheme; $A(k)$ = cumulative difference in elevation within the moving window between iteration k and iteration $k-1$; $f1, f2$ = characteristic frequency range (see text); V_{DFT} = two-dimensional discrete Fourier transform periodogram; V_{CWT} = two-dimensional continuous wavelet transform periodogram. The field "Detrending" indicates the need of data detrending.

Method/parameter	Algorithm	Detrending	Reference
RMS height	$\mathrm{RMSH} = \left[\frac{1}{N^2-1}\sum_{i=1}^{N^2}(z_i-\bar{z})^2\right]^{1/2}$	Yes	Shepard et al. (2001)
RMS deviation	$\mathrm{RMSD} = \left[\frac{1}{4(N-1)}\sum_{b=1}^{4(N-1)}(z_c-z_b)^2\right]^{1/2}$	Yes	Shepard et al. (2001)
RMS slope	$\mathrm{RMSS} = \left[\frac{1}{4(N-1)}\sum_{b=1}^{4(N-1)}\left(\frac{z_c-z_b}{\Delta x_b}\right)^2\right]^{1/2}$	Yes	Shepard et al. (2001)
Absolute slope	$\mathrm{AS} = \left[\frac{1}{4(N-1)}\sum_{b=1}^{4(N-1)}\frac{\lvert z_c-z_b\rvert}{\Delta X}\right]$	Yes	Kreslavsky and Head (1999)
Standard deviation of slope	$\mathrm{SDS} = \left[\frac{1}{N^2}\sum_{i=1}^{N^2}(m_i-\overline{m})^2\right]^{0.5}$	No	Frankel and Dolan (2007)
Direction cosine eigenvalue	$\mathrm{DCE} = [\ln(S_1/S_2)]^{-1}$	No	McKean and Roering (2004)
2D semivar.	$\gamma = \frac{1}{2n}\sum_{i=1}^{n}[z(x_i,y_i)-z(x_{i+h},y_{i+h})]^2$	Yes	Glenn et al. (2006)
Wavelet lifting scheme	$\mathrm{WLS} = \sum_{k-1}^{K}\frac{A(k)}{N^2}$	Yes	Hani et al. (2011)
Discrete Fourier transform	$\mathrm{DFT} = \sum_{f-f1}^{f2}V_{\mathrm{DFT}}(f)$	Yes	Booth et al. (2009)
Continuous wavelet transform	$\mathrm{CWT} = \sum_{f-f1}^{f2}V_{\mathrm{CWT}}(f)$	No	Booth et al. (2009)

which are common in high-resolution DEMs in areas characterized by the presence of fractures, trenches and isolated rock blocks. To mitigate this problem Kreslavsky and Head (1999) introduced the absolute slope (AS) index.

The standard deviation of slope (SDS; Frankel and Dolan, 2007) is a slope-based roughness index which uses the cell slope m instead of the cell elevation z (see Table 1). Data detrending is not required in this method, as the general trend of the surface is removed by computing the difference between the mean slope in the moving window and the slope of individual pixels inside it.

The same applies to the direction cosine eigenvalue ratios (DCE; McKean and Roering, 2004), which measures the variability in slope and aspect using the normalized eigenvalues (S_1, S_2) of the slope orientation matrix (Davis, 1986). Theoretically, this method is unable to describe random roughness because the two eigenvalues become equal ($S_1 \approx S_2$) and the roughness index tends to infinite. In the case of topography, however, random roughness is always superimposed to a deterministic sloping (or horizontal) surface. Slope vectors are