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A study on the use of Planarity for quick identification of potential landslide hazard

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Abstract. In this study we focused on identifying geomorphological features that control the location of landslides. The representation of these features is based on a high resolution DEM (Digital Elevation Model) derived from airborne laser altimetry (LiDAR) and evaluated by statistical analysis of axial orientation data. The main principle of this analysis is generating eigenvalues from axial orientation data and comparing them. The Planarity, a ratio of eigenvalues, would tell the degree of irregularity on ground surface based on their ratios. Results are compared to the recent landslide case in Korea in order to evaluate the feasibility of the proposed methodology in identifying the potential landslide hazard. The preliminary landslide hazard assessment based on the Planarity analysis well discriminates features between stable and unstable domain in the study area in the landslide initiation zones. Results also show it is beneficial to build the landslide hazard inventory mapping, especially where none of information on historical records of landslides is existed. By combining other physical procedures such as geotechnical monitoring, the landslide hazard assessment using geomorphological features will promise a better understanding of landslides and their mechanisms, and provide an enhanced methodology to evaluate their hazards and appropriate actions.

1 Introduction

Landslides, reflecting the geomorphological process of the natural landscape, become a threat only when they interfere with our societies (Pestrong, 1976). They annually cause losses of many lives and have enormous economic impacts. There is a considerable attention about landslides since they usually make significant casualties and property damages (Aleotti and Chowdhury, 1999). Increasing costs are closely related to the expansion of population and development which result in residential areas near slopes. Through urban expansions, cities transform their surrounding environments and produce new risks (UNDP, 2004). Constructing residences, industrial structures, transportation routes, and lifelines around the slopes may decrease their stability. Therefore, landslides became disastrous events and, in turn, disturb and affect the well being of society. In developing countries, these impacts are even more severe (Schuster and Highland, 2007).

Once landslides occur, they usually leave features such as scarps, cracks, and displaced materials on the ground. Identifying these geomorphological features in order to determine the potential landslide hazard area based on historical evidences would provide valuable information in assessing the landslide hazard. The identification of locations potentially susceptible to landslides is a long debated topic and a large variety of methods has been proposed to map those areas (Soeters and van Westen, 1996; Guzzetti et al., 1999, and references therein). Although many studies proved that a large number of explanatory variables has to be combined to obtain the best possible landslide susceptibility assessments (Nefeslioglu et al., 2011; Catani et al., 2013), sometimes a preliminary assessment is needed and a single terrain attribute easily derivable from DEM could be used as an indicator of potential landslide areas.

Recent distinct characteristic in this field is utilizing recent remote sensing technologies. For example, Kimura and Yamaguchi (2000) used a synthetic aperture radar interferometry (InSAR) with precipitation data for modeling landslide movements in northern Japan. They noted that the model powered by InSAR technology can account for the complex landslide movements showing either shallow or deep seated landslide behaviours when ground surface measurements observed at the same location are difficult to recognize the overall movement mechanisms. Catani et al. (2005) also discussed the capability of the SAR interferometry technique for quantifying landform attributes. While InSAR technologies are focused on the recognition of dynamic behaviours of geomorphological landslide controlled features on ground surfaces in order to identify landslide movement mechanisms, the static quantification of landslide control attributes is carried out by a high resolution topographic information, which is obtained from LiDAR (Light Detection and Ranging) technique (Glenn et al., 2006). LiDAR can generate high resolution models which differentiate distinct landslide features such as steep scarps at the top, fan shaped lobes at the toe, and an irregular hummocky topography between top and bottom. These features can be evaluated based on their evolution by natural processes over time. The landslide inventory mapping enhanced by the LiDAR derived digital elevation model (DEM) can provide not only the exact boundary of previous landslides but also an insight on the internal deformation of the landslide body (McKean and Roering, 2004). Other applications augmented by LiDAR derived DEM, from detection to modeling and monitoring, are well described by Jaboyedoff et al. (2012). However, approaches to find these remnants of landslides have several limitations (Kim et al., 2012). Major issues are insufficient compilation of key features and changes of topography by other processes such as weathering. Implementing landslide hazard assessments with incomplete information would lead to erroneous decisions about ongoing and future developments of landslides (Kim, 2012).

In this study, therefore, we focus on identifying locations which are potentially susceptible to landslides by using a geomorphological landslide controlled feature. For this scope, this work proposes the use of a measure of the irregularity in the terrain, defined by a statistical analysis of axial orientation data in a three dimensional space performed on a high resolution DEM. Results are applied to identify locations of the recent landslide and compared other terrain attributes whether the proposed methodology assures the potential landslide hazard or not.

2 Methodology

Analyzing a terrain, whether rough or smooth, is an important part for landslide studies, in which understanding a terrain is essential for future development of landslides. Finding geomorphological features which are generated by landslides is the main purpose of the landslide inventory mapping that gathers information from various sources such as aerial photographs and archives. However, the limited time span and evolution of topography by natural processes may have restricted any meaningful progress using terrain attributes. Various approaches were examined to overcome these limitations (Glenn et al., 2006; Kaplan, 2006; Delacourt et al., 2007; Sappington et al., 2007; Schulz, 2007; van Den Eeckhaut et al., 2007; Teza et al., 2008; Grohmann et al., 2009).

One promising methodology describing geomorphological landslide controlled features is the statistical analysis of axial orientation data in a three dimensional space. Obtained from the orientation tensor, they are useful to analyze the randomness in directional data (Woodcock, 1977; Woodcock and Naylor, 1983).

Based on the spherical distribution of directional and non-directional data, it is shown that typical characteristics of spherical distribution are equivalent to the determination of eigenvalues and eigenvectors especially of a symmetric three by three matrix which comprises direction cosines (Watson, 1966). Consider N points of the unit mass of (l_i, m_i, n_i), where $N = 1, 2, ..., N$ and suppose that $\boldsymbol{u}$ is a true or preferred direction through the centre of the sphere, the moment of inertia I of the set of N points of unit observation data about $\boldsymbol{u}$ can be described as follows (Watson, 1966):

$$I = N - \boldsymbol{u}'\boldsymbol{M}\boldsymbol{u} = N - \sum_{j=1}^{3}\sum_{k=1}^{3} u_j M_{jk} u_k \tag{1}$$

where $\boldsymbol{M}$ is an orientation matrix, a three by three matrix consisting sums of the cross products of direction cosines of the unit mass, (l_i, m_i, n_i). It is given by:

$$\boldsymbol{M} = \begin{pmatrix} \sum l_i^2 & \sum l_i m_i & \sum l_i n_i \\ \sum m_i l_i & \sum m_i^2 & \sum m_i n_i \\ \sum n_i l_i & \sum n_i m_i & \sum n_i^2 \end{pmatrix} \tag{2}$$

The eigenvalues of the orientation matrix are calculated from roots of the characteristic equation. Therefore:

$$\text{det}(\boldsymbol{M} - \lambda \boldsymbol{I}) = 0 \tag{3}$$

where det is the determinant of $\boldsymbol{M}$, $\boldsymbol{I}$ is the identity matrix. Roots of the characteristic equation are eigenvalues, λ_i (i = 1, 2, 3; $\lambda_1 > \lambda_2 > \lambda_3$), and corresponding vectors are eigenvectors, $\boldsymbol{v_i}$ (i = 1, 2, 3). Three eigenvalues are always positive and add to N while three eigenvectors are always perpendicular to each other (Watson, 1966). A normalized form of the eigenvalues can be obtained from dividing by the number of unit observation points, N:

$$S_j = \frac{\lambda_j}{N}, \quad j = 1, 2, 3 \tag{4}$$

The determination of the typical distribution of eigenvalues and eigenvectors are dependent of the spherical location of the axial orientation data. Watson (1966) proposed two distinct distributions on a spherical surface: (a) a clustered distribution and; (b) a girdle distribution, which are represented by the different magnitude and direction of eigenvalues and eigenvectors (Fig. 1). If the unit mass are clustered at both ends of the great circle in a sphere (Fig. 1a), indicating either uni or bimodal distributions, the moment of inertia in Eg. (1) along this axis would be small and therefore, large eigenvalue and eigenvector are induced from the small value of the moment of inertia. Two other small values of eigenvalue and eigenvector are comparable and located along the diameter of the great circle. Obviously fairly equal eigenvalues would represent no preferred direction which having the uniform distribution in observation data. For the clustered distribution, therefore, one large eigenvalue and other two small eigenvalues are usually observed.

On the other hand, a girdle distribution, where the unit mass are positioned around the great circle (Fig. 1b) would require the greatest moment of inertia which leads to a minimum eigenvalue at the axis perpendicular to the great circle. Other two moments of inertia along the diameter of the great circle have the least values and they cause large eigenvalues and eigenvectors both of which have similar values. The girdle distribution, therefore, is generally indicated by one small eigenvalue with two large eigenvalues. Detailed types of the spherical distributions based on eigenvalues and eigenvectors of the orientation matrix $\boldsymbol{M}$ are summarized in Table 1.

The principle of the statistical analysis proposed by this study is generating eigenvalues that represent typical values for the degree of irregularity. For more clear identification, we introduce one non-dimensional parameter, composing the ratio of eigenvalues (Woodcock, 1977; Woodcock and Naylor, 1983):

$$Planarity = \ln\left(\frac{S_1}{S_2}\right) \qquad (5)$$

The Planarity (P), the natural logarithmic proportion of the eigenvalue S_1 relative to S_2, can be a good indicator in describing the level of irregularity on ground surface (Kim et al., 2012). The evaluation of the Planarity is especially beneficial when large amounts of field data are acquired and compared, which contain the directional characteristic of materials.

The procedure to identify geomorphological features for landslides is performed as follows. First, the DEM of 1 by 1 metre spatial resolution is used for the calculation. It is taken from 2009 LiDAR dataset. Direction cosines are then calculated from the slope and aspect values. Each element of the orientation matrix shown in Eq. (2) is then represented by these direction cosines.

All cell-based (i.e., raster based) calculations such as summation of elements in the orientation matrix by the moving window (3 by 3) and their geographical representations augmented by the Spatial Analyst tool embedded in ArcGIS®. A cubic equation is employed to determine three eigenvalues. These are then normalized by N total cells. Finally, Planarity (P) is introduced by a ratio of eigenvalues. Thresholds of each Planarity are based on appropriate representation of characteristics of different units consisting the study area such as major valleys, secondary tributaries, gently rolling surfaces, and smooth surfaces. High planarity may indicate a smooth ground surface that has a preferred direction while low one may have a less preferred direction, describing a rough ground surface, and after all, may reflect previous landslides that contain related features such as scarps, cracks, and displaced materials (McKean and Roering, 2004; Kasai et al., 2009).

3 Overview of the study area

Mt. Umyeon, located in the south of Seoul Metropolitan City, Republic of Korea, is a part of major mountains traversing the southern part of Seoul in the direction of north-northeast (Fig. 2). It is consisted by relatively lower hilly reliefs, which is based on a variety of gneisses by tectonic movements and weathering processes (Jeong et al., 2011). Major geological characteristic in the study area is dominated by the biotite banded gneiss and small parts are covered by augen gneiss, granitic gneiss, leuco-cratic gneiss, and fine-grained gneiss (Hong and Lee, 1982). Due to characteristics of gneisses such as severe weathering and multiple faults, and geomorphological defects such as many trails and military bases, the study area would have a high susceptibility to landslides. Fig. 3 described distinct geological aspects of the study area.

The 2011 landslide disasters in the study area were initiated on July 27, 2011. Major landslide areas, which indicated in Fig. 2, are: a) Ramian and Sindonga A.P.Ts. (Site A); b) Jeonwon-maul (Site B); c) Hyungchon-maul (Site C). Table 2 summarizes general information on landslide initiation zones and detailed descriptions of individual site are given in the following sections.

3.1 Site A (Ramian and Sindonga APTs.)

Site A is located in the north of Mt. Umyeon and was affected by two major landslides in different time span. The first landslide initiated at 8:40 AM and second one occurred at 10:00 AM on July 27, 2011. Both started their movement around roof areas of the mountain and flowed rapidly along the previous drainage channels. Finally, displaced materials destroyed the ground surface in their routes, overflew the road, and hit the residential areas opposite to Mt. Umyeon (Fig. 4). These resulted five casualties in total. Fast movement of displaced materials and existence of scars in slopes made us to classify those landslides as open slope debris flow (Evans, 1982; Hungr et al., 2014).

The elevation of major initiation and deposition zones are around 260 m and up to 80 m, respectively. It leads to 180 m of vertical elevation difference. The largest trace of major debris flows is about 620 m and their cross sections showed a gentler descending channel gradient from around 40 to 10 degrees (Yoo et al., 2014). Also, there was no evidence that displaced materials were preserved in the deposition zone, which may cause the catastrophic impact on residential areas opposite to landslides. Average depth of surface erosion along the landslide profile was 1.6 m and a maximum depth of 4 m was observed around 320 m from the initiation zone. Based on the existence of thick colluvial layers, at least one or composite historical landslides were recorded in this area and their debris was deposited on bedrocks (Jeong et al., 2011).

3.2 Site B (Hyungchon-maul)

Site B sat on the southeast of Mt. Umyeon and have a major gully and eight small tributaries over the area. Total 30 landslides started their movements on July 27, 2011, flooded most residences within the site, and finally made one casualty (Fig. 5). There was a reservoir located on the middle of the mountain and failed by overflowing of water due to heavy rainfall intensity of over 85.5 mm/h. As similar to other sites, the types of landslides are debris flows, especially progressing along a major gully with a help of other small tributaries. These characteristics believed them as the channelized debris flow (Evans, 1982).

The elevation of initiation zone in this area is 250 m and has a gradient of up to 40 degrees. On the other hand, the bottom zone only has 50 m of elevation and 5 degrees of gradient. The debris flow traveled about 980 m with 200 m of vertical elevation changes. The average erosion along the streambed was 1.5 m and a 3.5 m of maximum erosion was found at 180 m from the initiation zone (Yoo et al., 2014). There was a distinct interface between colluvial layer and bedrock. The composition of colluvium at this area is dominated by silt with pebble size gravels up to 0.2 m diameter and piled 1 m high at average. Thick colluviums deposits, average of 1 m, were often found in this area and up to 5 m of these were located where gullies are merged each other (Jeong et al., 2011).

3.3 Site C (Jeonwon-maul)

Located in the west of Mt. Umyeon, landslides in Site C initiated in the morning of July 27, 2011 and resulted six casualties (Fig. 6). Landslides were classified as channelized debris flows because of their typical characteristics such as a fast downward movement of displaced materials along the existing gullies. Numbers of landslides in this site were reported as 22 and their average slope angles at initiation and transition zones of landslides were 27 and 15.6 degrees, respectively (Yoo et al., 2014). These are closely related to what VanDine (1996) described on debris flow with typical slope angles of greater than 25 and 15 degrees for each individual zone. Average length of transition zone was recorded as 454.4 m (Yoo et al., 2014).

Most foliations in gneiss were observed southeast direction, which are the opposite to slope gradient and severe weathered strata were found up to 1 m thick. Silty soil and maximum depth of 0.1 m diameter pebble size gravels formed colluvial layers in this area (Jeong et al., 2011).

3.4 Rainfall information

The main cause of the landslides in the study area, even though the main causal factor of this disastrous event is still unclear, was precipitation, which classifies into two different domains based on the temporal variation: a. antecedent rainfall; b. daily rainfall. Firstly, an antecedent rainfall of 463.0 mm fell within two weeks before the landslide events were occurred. This made the ground surface fully or almost fully saturated. Secondly, a heavy daily rainfall amounting 342.5 mm fell into the study area. It took about 74 percent of antecedent rainfall. The rainfall intensity of the first impacted landslide areas was 68.5 mm/h (Fig. 7). Based on the rainfall records, the landslides in the study area may be initiated by the high intensity daily rainfall with the help of the saturated condition of the ground surface by long-term antecedent rainfall.

4 Results and discussion

In this study we employed a statistical analysis using axial orientation data in order to identify the geomorphological features of landslides. The main principle of this analysis is generating eigenvalues from axial orientation data and comparing their values. The Planarity (P) would tell the degree of irregularity on ground surface based on their ratios. The extent of the area for analysis is defined by LiDAR dataset acquired in 2009 before landslides occurred. The topographic overview of the study area is shown in Fig. 2.

Fig. 8 shows the spatial distribution obtained from the Planarity over the study area. The distribution is limited to steep slope areas more than 15 degrees in slope values and Planarity beyond this extent is ignored since it could not describe a natural topography but an anthropogenic effect on ground profile. Based on the Planarity analysis shown in Fig. 8, the lowest Planarity (less than three), defined by this study as "Very rough" areas, can be found in major valleys, secondary tributaries, and upper mountain areas near the army base and take 0.9 percent of the total evaluated area. Results also indicate the "Moderately rough (Planarity is less than five)" areas would cover 14.3 percent of the effective study area and these are usually wrapping the very rough areas. On the other hand, "Relatively flat" areas, the Planarity is less than seven, can be found in most gentle slopes. Majorities (about 50.6 percent) of the evaluated area are included in this category. High Planarity of less than nine usually covers the other parts of gentle slopes. These areas, "Mostly flat", take 28.4 percent of the evaluated study area. Finally, the "Completely flat" areas, over the value of nine, are concentrated on the few anthropogenic places where constructed within or boundary of the mountain and usually combined with "Mostly flat" areas (5.7 percent of the evaluated study area). Table 3 shows a detailed distribution of Planarity on individual initiation zones. We assumed the boundary of each initiation zone as a circle which has a radius of 5 m. Planarity is divided by same intervals noted in Fig. 8. Table 3 also describes designated slope values within the boundary.

A total 13 landslide initiation zones is analyzed based on the Planarity method. Each landslide zone has a wide range of Planarity, from 2.41 to 13.26, and the average is 6. This value is within the "Very rough" and "Moderately rough" categories and can be used as a threshold between stable and unstable domains. The unstable portion, i.e. less than 6, of the Planarity within all landslide initiation zones is 57 percent and ranges between 45 (C in Table 3) to 77 (G in Table 3) percent, respectively. This implies that landslide initiation zones have a Planarity which is relatively small values compared to other areas of consideration. Some limitations found in this analysis are that the boundary of landslide initiation zone is delineated as a circle which ignores the real extent of the zone. The second is the appropriate size of the moving window when the Planarity is calculated. Tarolli et al. (2012) introduced a logical assumption in determining the moving window size for the channel network recognition in order to reduce the noise and noted that a proper window sizes are critical element for extracting geomorphological features. In our case, the moving window used in this study was 3 by 3 which is relatively optimal for 1 m LiDAR-derived DEM. Nevertheless some defects related to complex geomorphological structures may affect the performance of Planarity.

The reliability of Planarity as an indicator to identify the potential landslide hazard is evaluated by a bivariate data analysis which correlates Planarity observed from landslide initiation zones with corresponding slope values (Table 3). Relationships of each parameter with the slope value are shown in Fig. 9 and summarized in Kim (2012) and Kim ea al. (2012). Relationships between slopes and Planarity give some uncertainties in applying it to the preliminary landslide hazard assessment. Uncertainties can be expressed as scatters in the plot when Planarity is related to the slope and treated as noise (Fig. 9). It may be generated at the time when the raw data was obtained.

Current studies have proposed and demonstrated the usefulness of orientation data in identifying previous landslide features. However, they satisfied specific local conditions only. These conditions are closely related to the site specific geometry itself such as the presence of preferred directions which are perpendicular to the unit terrain rather than contributions to landslide causal factors. Therefore, it is necessary to carry out more investigations to find physical contributions of the Planarity in order to make the potential landslide hazard assessment more comprehensive.

In order to show the benefit of the Planarity analysis in potential landslide hazards, the mean slope value is employed since ignoring gentle slope areas in the analysis would give clear understanding of landslide hazards in the study area. Kim et al. (2012) noted that combining the Planarity with slope values can improve a capability of the landslide hazard assessment. Figure 10 illustrates the Planarity where the individual cell has over the mean slope value of 19 degrees.

And finally, the modified Planarity is implemented to representative landslide areas in 2011, i.e., Sites A to C for evaluating its suitability as a potential landslide hazard assessment. Figures 11 to 13 show the typical landslide characteristics observed in each site.

Figure 11a shows the aerial photo in Site A, which is obtained before the landslide. There was a landslide that was in the relict state and might be generated prior to 2011. The upstream part covered by forests would give a clue of the temporal variation since the landslide has occurred. The modified Planarity was draped on this area (Fig. 11b). Very rough areas are located in upper mountain areas where we believed those are scarps and the landslide might be initiated from these zones. The other can be found along the valley bottom. The actual landslide in 2011 clearly showed that landslides initiated adjacent very rough areas determined by Planarity (Fig. 11c). This consistency can also be found in Sites B and C (Figs. 12 and 13).

Even though there are various limitations which might come from the visual observation, the proposed methodology, the Planarity analysis, can provide a useful framework to understand the initial state of landslides without any other conventional approach. It also provides a fundamental data for the landslide inventory mapping, which is the initial form of the landslide hazard assessment. Combined with other physical consideration such as geotechnical monitoring for ongoing landslide movements, its feasibility as an indicator of the landslide hazard assessment can be enhanced and also suggests appropriate mitigation measures.

5 Conclusions

In this study we have delineated geomorphological features of recent landslides observed in the recent landslide area. The usefulness of them in utilizing for the potential landslide hazard is also discussed. The Planarity, based on the statistical analysis of axial orientation data, provides benefits when landslide controlled features are identified by high resolution spatial data such as a LiDAR generated DEM.

The spatial distribution of Planarity would distinguish between stable and unstable domains in the study area especially in the landslide initiation zones. Within the study area the Planarity has various portions of occupied areas from less than one to 51 percent and these roughly represent characteristics of different units consisting slopes such as major valleys, secondary tributaries, gently rolling surfaces, and smooth surfaces. The three specific sites in the study areas also indicate that areas designated as "Very rough" and "Moderately rough" categories where the potential landslide hazard is relatively high are closely related to the actual landslide initiation zones.

Results are also useful in the landslide inventory mapping without information on historical records of landslides. By combining other physical procedures, the landslide hazard assessment proposed in this study will promise a better understanding of landslides and their mechanisms, and provide an enhanced methodology to evaluate their hazards and appropriate actions.

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