Research Article

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Landslide site delineation from geometric signatures derived with the Hilbert–Huang transform for cases in Southern Taiwan

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Abstract: Landslides are a frequently occurring threat to human settlements. Along with global climate change, the occurrence of landslides is the forecast to be even more frequent than before. Among numerous factors, topography has been identified as a correlated subject and from which hillslope landslide-prone areas could be analyzed. Geometric signatures, including statistical descriptors, topographic grains, etc., provide an analytical way to quantify terrain. Various published literature, fast Fourier transform, fractals, wavelets, and other mathematical tools were applied for this parameterization. This study adopts the Hilbert–Huang transform (HHT) method to identify the geomorphological features of a landslide from topographic profiles. The sites of the study are four “large-scale potential landslide areas” registered in the government database located in Meinong, Shanlin, and Jiasian in southern Taiwan. The topographic mapping was conducted with an airborne light detection and ranging instrument. The resolution of the digital elevation model is 1 m. Each topographic profile was decomposed into a number of intrinsic mode function (IMF) components. Terrain characterization was then performed with the spectrum resulting from IMF decomposition. This research found that the features of landslides, including main scarp-head, minor scarp, gully, and flank, have strong correspondence to the features in the IMF spectrum, mainly from the first and the second IMF components. The geometric signatures derived with HHT could contribute to the delineation of the landslide area in addition to other signatures in the terrain analysis process.

1 Introduction

Landslides could create many hazards leading to catastrophic loss. As a part of sustainable land-use planning and hazard mitigation, landslide prediction is highly desired. Both the forewarning system [1] and the spatial susceptibility [2] have been found valuable. This prediction includes several aspects such as geomorphology, geology, land use/land cover, and hydrogeology. Landslide mapping is truly an old problem but with new tools. Guzzetti et al. [3] provided a comprehensive review on this subject. Lazzari et al. [4,5] utilized computer-assisted packages implemented on the platform of geographic information system. In addition to the new technology obtaining detailed topographic data, such as airborne light detection and ranging (LiDAR), and the direct observation of deformation time series, such as InSAR, information analysis schemes are also enriched by the newly developed mathematical tools. The geomorphological features could then be observed through another “lens.” The strategy of the computer-assisted landslide extraction scheme currently under development is to build knowledge models based on the geometric signatures from the investigated sites. Through the decision tree and/or other learning schemes, the built interpretation machine could be applied to other areas that have not been fully investigated. This interpretation machine is also envisaged to be able to assist the manual interpretation scheme.

For the delineation and characterization of landslides, the concept of geometric signatures has been applied to two shallow landslides with slow slide and fast flow in Marin County, California, that show different surficial processes. This use of geometric signatures can

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result in successful diagnostic modeling in the field [6]. Along this line of thought, different approaches could be applied to the geometric signature. Evans et al. [7] stated that altitude, gradient, aspect, profile convexity, and plan convexity are fundamental, while spectra and fractal analyses could also be applied. Glenn et al. [8] analyzed the landslide morphology in South Idaho with LiDAR and proposed that the main body of landslides has a relatively lower roughness than the toe, while fissures and scarps have higher roughness. It is also possible to adopt the approaches of non-stationary spectra analysis, such as the wavelet theory [9,10] or the Hilbert–Huang transform (HHT) [11], to characterize the morphological features along a landslide slope.

The wavelet theory has been adopted to extract geomorphic features from digital elevation/terrain models and to improve the quality of the models. In the past, the wavelet theory has been utilized to retrieve time-dependent information for various problems in geosciences, e.g., climate change [12,13], volcanic activities [14–16], and so on. In the field of geomorphology, Zhu et al. [9] used multiband wavelets to zoom out (reduce) the remote sensing images and to simplify digital elevation model ([DEM]; remove clutter). Bjørke and Nilsen [10] proposed a threshold wavelet coefficient to identify the topographic relief on DTM. Although the wavelet theory can be used to localize the wave in both time and frequency, the selection of its mother wavelet function affects the resolution of energy in time domain or frequency domain.

In view of the HHT proposed by Huang in 1998 [11], the signal is decomposed into approximately sinusoidal wave signals and trend functions, which is called the intrinsic mode function (IMF). IMF is one type of signal decomposition from high frequency to low frequency. Using the Hilbert transform, one could present the signal in frequency domain with variable periods. In brief, HHT consists of two parts: the empirical mode decomposition (EMD) and the Hilbert transform. Researchers have attempted to apply the EMD or HHT to the analysis and classification of spatial data. The feasibility of applying EMD for smoothing lines of spatial linear features and line simplification was also explored [17,18], where EMD serves as a low-pass filter. Line features could be obtained from each IMF. Liu et al. [19] performed the instantaneous vibration analysis of Zhaohou Bridge in China using the extreme-point symmetric mode decomposition. Although the results showed that the instantaneous frequencies of the first IMF (IMF1) changed from 2.49 to 3.37 Hz, the bridge was

in a steady state when the car passed over it. While positive applications of EMD have been realized for a variety of subjects, the present study intends to explore the feasibility of deriving a family of geometric signatures for landslides from EMD.

The geomorphology of a slope that experienced slide failure may include some of the following landslide features: crown, main scarp, head, main body, foot, toe, minor scarp, flank, depleted mass, accumulation, etc. [20]. To use HHT to explore geomorphic features of landslides, DEM data can be considered as random signals in the space dimension. Therefore, these random parameters such as elevation, slope, and curvature could be decomposed into several IMF components, where the parameters are in terms of distance instead of time. The results of every IMF component may reflect different physical meaning. Then topographic features of landslides may be explored from these IMF components.

2 Materials and methods

This study extracts the elevation of landslides from the 1 m DEM, and then the Hilbert spectrum of elevation is obtained with HHT. First of all, the signal de-noising process is applied to the elevation data from the profile, and then space series (distance) is used instead of time series [21]. Thus, each elevation parameter could be decomposed into a number of pseudo-IMFs (IMF components). Furthermore, the frequency and amplitude domain signals of the data set could be obtained through Hilbert transform, and the energy distribution of the spectrums also calculated, providing a complete time–frequency distribution of energy. It is then possible to extract the topographic features of landslides and their locations on the profile by Hilbert transform. This method is expected to be able to provide a complementary set of geographic signatures to efficiently evaluate the landslide.

The data set used in this study is obtained from a topographic mapping mission executed with airborne LiDAR instruments. The grid resolution of this DEM is 1 m and the specification for the raw data collection is no less than two points for each square meter. Nominal height accuracy is 15 cm. The study sites are selected from the large potential landslide zones identified by this data set in a government project. Both the study sites and the analysis procedures are briefly described in the following sections.

2.1 Study area

Three sites with four landslides in southern Taiwan, namely, D004, D014, D044, and D047, are selected as examples. The topographic features of the landslides

include crown, main scarp, head, minor scarp, gully, reverse slope, and colluvium (Figure 1). D004, located in Meinong district, Kaohsiung City, shows a valley-like topography, covering about 0.42 km², with an average slope of 15.6° (Figure 1a). The crown has multiple ridges

Figure 1: Maps of landslide features and locations of the study areas, (a) D004, (b) D014, and (c) D044 and (d) D047. The profiles of A–A' and B–B' were identified by the Forestry Bureau, Taiwan in their analysis. C–C' profile is additionally selected for this study.

(a)

(b)

Figure 2: D004 A–A' profile and its IMFs from the original EMD. (a) The profile and its IMFs. IMF9 represents one residual component. (b) The waveforms of the first and the second IMFs. It can be seen that there are some asymmetric waveforms and two adjacent extrema which do not cross zero crossing.

with several arc-shaped scarps in the middle of the landslide. The upper part of the landslide site is a flat slope, and the lower concave part of the landslide is

covered by colluvial deposits, i.e., the deposit of a landslide with certain run-out distance downward from the original source of a previous landslide. The rocks at

D004 are composed of Miocene sandstone, shale, and their interbeds. The colluvial deposits in the area are originated from paleo shallow landslides induced by gully erosion. In the future, deep-seated landslides with circular failure surfaces may occur in the weathered rocks or colluvial deposits as shown in Figure 4a.

D014, located in Shanlin district, Kaohsiung City, exhibits a dip-slope and valley-like topography, covering about 0.475 km^2 , with an average slope of 25.2° (Figure 1b). The middle of the landslide deposits has several arc-shaped scarps and two significant reverse slopes. This presents a feature of gravitational slope deformation. The main scarp has an upward-sign shape. As the body of the landslide deposits is incised by a gully, the area is divided into the east and west sides [22]. The profile shape of the scarp is generally an arc. The rocks at D014 are composed of Miocene sandstone, shale, and their interbeds. Deep-seated landslides with plane failure surfaces along beddings and circular failure surfaces in the colluvial deposits may occur in the future as shown in Figure 5a.

D044 and D047 are located adjacently in Jiasian district, Kaohsiung City (Figure 1c). D044 covers about 0.67 km^2 , with an average slope of 20° . The topography can be divided into three parts: the upper part is a steep ridge with a dip-slope rock, the middle is a flat slope with a scarp of jointed sandstone, and the lower part has a clear scarp with steeper terrain. D047 covers about 0.84 km^2 , with an average slope of 17° . The topography can be divided into two parts: the upper part a dip-slope rock and the lower part a stepped-flat slope surface. The surface of the scarp is an arc shape with multiple ridges. The characteristics of the local failure are apparent, with the toe clearly delineated as a river terrace. The rocks at D044 and D047 are composed of Miocene sandstone, shale, and their interbeds. Yang *et al.* [23] presented the landslide as a sliding phenomenon with a buckling-induced rockslide model in dip-slope of interbedded sandstone and shale to explain the geomorphological evolutionary process of these two landslide areas. The failure of the slope in D004 was probably due to nonplanar sliding in weathered rocks (Figure 6a). The failure of the slopes in D014, D044, and D047 was likely due to a plane slide. It is possible that this plane slide failure was preceded by buckling of rock strata.

2.2 The HHT

The implementation of HHT is based on EMD. EMD decomposes the data series into a finite number of IMFs

and trend functions, with a mean value. Each of the IMF outcomes satisfies two conditions: (1) in the whole data set, the number of extrema and the number of zero crossings must either equal or differ at most by one and (2) at any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero [11].

To verify whether the IMF meets this basic definition, the following sifting process is taken:

- (1) Find the extrema of the original signal.
- (2) Use the cubic spline to find separately the extrema including the defined upper envelope of local maximum $u_k(t)$ and the defined lower envelope of local minimum $l_k(t)$.
- (3) Compute the local mean of envelope $m_k(t) = [u_k(t) + l_k(t)]/2$ to take out the component

$$h_k(t) = x(t) - m_k(t).$$

- (4) Repeat steps 1–3 until $h_k(t)$ can be satisfied by the definition of IMF recording $c_n(t) = h_k(t)$.
- (5) Calculate the residual $r_n(t) = x(t) - c_n(t)$.
- (6) If $r_n(t)$ is identified as a trend component, the algorithm is stopped. This study takes the standard deviation computed from the two consecutive sifting results of components as the stop criterion; otherwise, steps 1–3 need to be repeated in order to find other IMFs.

From the above process, the original signal $x(t)$ can be interpreted as the combination of n IMF components and a mean trend component $r_n(t)$ according to equation (1)

$$x(t) = \sum_{k=1}^n c_k(t) + r_n(t) \quad (1)$$

Since this IMF is about twice the periodic characteristic of the previous one [24], a condition is included with the stop criteria of the EMD process in addition to the standard deviation: both must be satisfied. In practical experiments of this study, the threshold for standard deviation was set to 10^{-6} , and the periodic ratio limited to a range of 1.5–2.5.

However, on the process of the elevation profile from the landslide site by HHT, we found that IMFs of the elevation data could not meet our expectation. It seemed that the existence of noises in the data might have influenced the process. Taking the IMFs of D004 AA' elevation profile as an example (Figure 2a), we decomposed the profile into nine IMFs with the last one the residual component (IMF9 in Figure 2a). The sequence from IMF1 to IMF9 explains how the elevation is decomposed by short to long waveforms. Illustrating this problem with the first IMF (IMF1) and the

(a)

(b)

Figure 3: D004 A–A' elevation profile and its IMFs from the improved EMD. (a) The elevation profile and its IMFs. IMF10 represents one residual component. (b) The waveforms of the first and the second IMFs. The results show the waveforms have symmetric characteristics and that there is always zero crossing between two adjacent extrema.

second IMF (IMF2; Figure 2b), it is observed that there are some asymmetric waveforms as marked by the double-

headed arrows and two adjacent extrema which do not cross the zero crossing as annotated by the single arrows.

(a)

(b)-1

(b)-2

(c)

Figure 4: (a) The geomorphological features of profile D044 A–A' annotated in black come from the profile report of the Forestry Bureau, and in red for those from the map report. (b) The IMF1 and the IMF2 spectra, respectively. (c) The spectra assembled from IMF1 and IMF2. The height is in green with an arbitrary scale.

(a)

(b)-1

(b)-2

(c)

Figure 5: (a) The geomorphological features of profile D014 A–A' annotated in black come from the profile report of Forestry Bureau, and in red for those from the map report. (b) The IMF1 and the IMF2 spectra, respectively. (c) The spectrum assembled from IMF1 and IMF2. The height is in green with an arbitrary scale.

From the above observations, the asymmetric waveforms may be caused by the local mean in the EMD process, which is not zero. The waveforms that have not crossed the zero crossing may be affected by the extrema not being correctly estimated. In short, processing the original height series of the profile directly generates noise due to the numerical process of EMD. In order to mitigate this problem, the DI-EMD method proposed by Kopsinis and McLaughlin in 2008 [25] is introduced.

According to the sifting process step (3), the k th IMF can be obtained from the expression:

$$h^{(k)}(t) = x^{(k)}(t) - m_n^{(k)}(t) \quad (2)$$

where $h^{(k)}(t)$ is the temporal estimate of the k th IMF and $m_n^{(k)}(t)$ is an estimate of the local mean of $h^{(k)}(t)$ after N sifting iterations. From equation (2), it can be inferred that EMD considers the signals $\langle x^{(k)}(t) \rangle$ as fast oscillations $\langle h^{(k)}(t) \rangle$ superimposed on slow oscillations $\langle m_n^{(k)}(t) \rangle$, and the sifting process aims to iteratively estimate the slow oscillating signals. As a consequence, the k th IMF is an estimate of the fast oscillating component of the signal $x^{(k)}(t)$ from the signal $x(t)$. For the estimation of the extrema, we take the first derivative of $h^{(k)}(t)$, i.e., $D^1x^{(k)}(t) = D^1h^{(k)}(t) + D^1m_n^{(k)}(t)$; therefore, the extrema and the local mean of a signal can be efficiently estimated through a sifting process. That is, when a predefined number of sifting iterations is given, an estimate of $D^1m_n^{(k)}(t)$, which in turn can be subtracted from $D^1x^{(k)}(t)$, is produced and leads to an estimate of the first derivative of $h^{(k)}(t)$.

For the DI-EMD method, the sifting iterations used for the desired extrema estimates will be referred to as internal, and the normal EMD sifting iterations used for the current IMF estimate will be called external. Both the number of sifting iterations (it) for the desired extrema estimates and the number of sifting iterations (ex) for the original EMD are required [25]. Based on the experiments conducted in this study, the best result was achieved by two cascading DI-EMD processes. The first time, ex equals 2.5 times it; and the second time ex equals to 3.5 times it. This result is obtained in an empirical way with ratios tested ranging from a value of 1 to 3 with increments of 0.1.

Besides, to resolve the problem that two adjacent extrema (such as two adjacent local maxima or two adjacent local minima) do not have zero crossing, the EMD-based de-noising method of Kopsinis and McLaughlin in 2009 [26] is applied. The rationale is that if there are noises in the signal, when the signal is decomposed, the noises are also decomposed into finite

IMFs. That is, the signal $x(t)$ is equal to $x'(t) + s(t)$, where $x'(t)$ is the noiseless signal and $s(t)$ is the noise. Assuming that the energy of all noises is captured by IMF1 (the first IMF), then the noise variance of the IMF1 E_1 may be estimated. This would mean that the thresholds of other IMFs T_i as well as the extrema of two adjacent zero crossings may likewise be estimated. All the IMF samples that correspond to zero-crossing intervals with extremum exceeding the threshold must be smoothly reduced in order for the extremum to be reduced exactly by an amount equal to the threshold. The values of β and ρ parameters in equation (4) are specifically proposed by Flandrin *et al.* in 2005 [27].

This can be presented as equations (3)–(6).

$$E_1 = (\text{median}|IMF1|/0.6745)^2 \quad (3)$$

$$E_i = \sqrt{(E_1/\beta)\rho^{-1}}, \quad (4)$$

$$E_i = \text{IMF1 the noise variance of IMF,} \\ i = 2, 3, \dots,$$

In which $\beta = 0.719$ and $\rho = 2.01$.

$$T_i = \sqrt{2 \ln N} = \sqrt{E_i} \times 2 \ln N \quad (5)$$

$$i = 1, 3, \dots, N, \quad N \text{ is sampling number}$$

$$z'_i{}^j = z_i{}^j, |r_i{}^j| > T_i \text{ or } z'_i{}^j = 0, |r_i{}^j| \leq T_i \quad (6)$$

Here $z'_i{}^j$ shows the threshold interval, where $r_i{}^j$ indicates the j th extrema of the i th IMF, $j = 1, 2, \dots, (M_i - 1)$, and M_i indicates the zero crossing number of the i th IMF.

From the above approach, the noise from the original signal may be removed. The results are shown in Figure 3a and b, where waveforms of symmetric characteristics and zero crossing between two adjacent extrema could be observed. The IMFs have been improved to more closely meet the characteristics of the narrow band. In other words, the unwanted noises in the elevation data have been removed for subsequent spectrum analysis.

Finally, through the Hilbert transform, the instantaneous amplitude and frequency in the IMFs are derived and a complete time–frequency distribution of energy is obtained.

For the de-noised signal $X(t)$, the Hilbert transform can be given as equation (7):

$$Y(t) = P \int_{-\infty}^{\infty} X(t')/(t - t') dt' \quad (7)$$

Equation (7) is the convolution of $X(t)$ and $1/t$; P is the Cauchy principle value, so Hilbert transform can identify

Figure 6: (a) The geomorphological features of profile D044 A–A' annotated in black come from the profile report of the Forestry Bureau, and in red for those from the map report. (b) The IMF1 and the IMF2 spectra, respectively. (c) The spectrum assembled from IMF1 and IMF2. The height is in green with an arbitrary scale.

the local properties of $X(t)$. The analytical signals are obtained from the conjunction of $X(t)$ and $Y(t)$ as equation (8):

$$Z(t) = X(t) + iY(t) = a(t)e^{i\theta(t)} \quad (8)$$

In which

$$a(t) = [X(t)^2 + Y(t)^2]^{1/2}$$

$$\theta(t) = \tan^{-1}[Y(t)/X(t)]$$

Here $a(t)$ indicates the instantaneous amplitude of the de-noised signal $X(t)$, $\theta(t)$ indicates the instantaneous phase angle of $X(t)$, and the instantaneous frequency, $\omega(t)$ of $X(t)$ as delineated by equation (9).

$$\omega(t) = d\theta(t)/dt \quad (9)$$

The de-noised signal $X(t)$ can also be expressed as n IMFs and a residual by the abovementioned EMD method as in equation (10).

$$X(t) = \sum_{j=1}^n c_j + r_n \quad (10)$$

For IMFs by Hilbert transform, the same data if expanded in Fourier representation would be in the form of equation (11).

$$X(t) = \text{Re} \sum_{j=1}^n a_j(t) e^{i \int \omega_j(t) dt} \quad (11)$$

Residual component $r_n(t)$ can be omitted.

Equation (11) can be expressed in three dimensions on the amplitude and frequency as functions of time, showing the distribution of amplitude on the frequency and time, known as the Hilbert amplitude spectrum, $h(\omega, t)$. In addition, on the time–frequency plane, it can show the amplitude or energy of the original signal to form the high or low relief of the surface.

2.3 Data preparation and processing scheme

The steps for preparing the data with HHT analysis are as follows:

1. Delimit the interested region from the 1×1 m digital elevation model based on the results of field geology.
2. Determine the location of the likely sliding direction of the landslide. The profile of parallel sliding direction is chosen first. The cross profile is perpendicular to the sliding direction, roughly passing the center of the landslide mass. The height profiles are generated from DEM both along and across this direction.
3. After preparing the data, HHT analysis is performed in the Matlab environment.

4. HHT and the signal de-noising analysis include three parts: (1) decompose signals at different scales to get IMFs, (2) remove the noise in elevation data and then reconstruct the de-noised elevation signals, and (3) undergo HHT to obtain the Hilbert spectrum.

The scheme of the proposed process is carried out step by step as follows:

1. collect 1×1 m DEM from LiDAR;
2. construct 1-m resolution discrete data points for elevation within the profile of interest;
3. decompose the discretized series of elevation data into IMFs via EMD;
4. de-noise the elevation data by reconstructing the de-noised elevation data;
5. pick the first two IMFs, i.e., IMF1 and IMF2; and
6. obtain the Hilbert spectrum of IMF1 and IMF2, individually, by the Hilbert transformation.

3 Results

As shown in Figure 1, there are seven profiles in total. In each site, the along slope profiles (A–A' and B–B') have been investigated by the Forestry Bureau, Taiwan, for identifying the geomorphological features. These could be applied for cross validation. The across slope profiles are manually investigated by this team with geological maps and studied on-site. In order to avoid repetition, four distinct profiles from the seven studied are selected for this article as representative cases.

The profiles are selected across the entire landslide range. Both ends of the profile are extended 250 m further from the intersection of the A–A' and B–B' profiles with the landslide boundary. We aim to include the crown, toe, and flank of the landslide in order to holistically analyze the characteristics of the landslide and reduce the influence of other topographical factors. In addition, each profile has its own unique landslide characteristics, i.e., D004 A–A' passes through the main scarp, sag, reverse slope, head, colluvium, and toe, with the toe bound by the gully; D014 passes through the main scarp, head, and then through the sag, reverse slope, and the middle part of the landslide is the colluvium, with the toe bordered by the gully; D044 A–A' has a 200-m distance between the main scarp and head; and, finally, D047 B–B' passes through the main scarp, head, and has a sag, reverse slope in the middle of the landslide.

The purpose of spectrum analysis is to describe the change in the spectral content of the signal, so that the energy or intensity of a signal can be expressed simultaneously in time and spectrum [11]. That is, the Hilbert spectrum, which is an energy–frequency–time distribution, informs us which frequencies appear at what time, showing the time variation of the signal. In this study, the time dimension is replaced by the distance. In observing equation (9), the instantaneous frequency becomes the differential of phase to distance, representing a signal where the frequency changes with the distance. Therefore, the characteristics of spatial variation in the elevation signal could be understood from which frequency on the spectrum fulfills the condition of strong energy at that location. As a landslide is a mass movement and the result of material sliding down, the rapid change in height can be considered as a phenomenon of high frequencies or short wavelengths. Subsequently, we pick high-frequency parts of the spectrum (IMF1 to IMF2) of each profile A–A' and B–B' to analyze the correlation with the topographical features of the landslide.

In the drawing of spectra, the y-axis represents the frequency and the x-axis the distance of the profile. The color bar on the right side represents the code for energy intensity. In order to clearly show both height and energy, the scale of the height is adjusted “arbitrarily” but consistently for each profile (Figures 4b, 5b, 6b and 7b). The corresponding analysis of landslide features and spectrum is described in the following sections.

3.1 Elevation profile of landslide, D004 A–A'

The length of this profile is about 950 m. The landslide features from the main scarp to the toe are followed by two minor scarps, soil and weathered stratum, gully, minor scarp, colluvium, and gully (Figure 4a). The colluvium in the profile ranges horizontally from about 470 to 910 m. The distance between the main scarp and the head is about 60 m, in which there are the sag and reverse slope.

The landslide features annotated in Figure 4b are identified from the energy distribution patterns of the spectrum, where relatively obvious changes in energy are consistent with the location of the landslide features, as shown in Table 1. Generally, the Gaussian filter is used to enhance the spectrum for identifying features. In the process, the center point of each spectral feature is used for the correspondence analysis.

Figure 7: (a) The geomorphological features of profile D047 B–B' annotated in black come from the profile report of the Forestry Bureau, and in red for those from the map report. (b) The IMF1 and the IMF2 spectra, respectively. (c) The spectrum assembled from IMF1 and IMF2. The height is in green with an arbitrary scale.

The spectral features observed from IMF1 and IMF2 of A–A' (Figure 4b) with stronger energy (>0.1) are summarized as follows:

- (1) The energy–frequency variation from the main scarp, sag, reverse slope to the head shows a concave distribution.
- (2) The toe is bound by the colluvium and the gully. The energy–frequency variation near the distance from 890 to 910 m is relatively strong.
- (3) The upper boundary of the colluvium is about 470 m and divides the zone of depletion and the zone of accumulation. The frequency varies from 0.04 to 0.09 and the energy distribution presents a band-shaped pattern.
- (4) For the gully, the frequencies of 0.24 and 0.26 and the energy concentration show a sparse pattern.

Figure 4c is reassembled from IMF1 and IMF2 spectra. It appears that there are three notable zones with relatively strong energy in the spectra: the first zone is near the main scarp, the second zone is on the middle of the slope, and the third zone is on the toe. The energy between the middle of the slope and toe is higher than the energy between the main scarp and the middle of the slope, indicating the depleted mass and accumulation of the landslide body. In addition, the energy–frequency distribution from the main scarp to the head has a concave upward shape.

3.2 Elevation profile of landslide, D014 A–A'

The length of the profile is about 800 m. Figure 5a shows the landslide features of the main scarp, three minor scarps, colluvium, three gullies, and weathered stratum on the profile. In addition, from Figure 1b, it can be seen that the distance between the main scarp and the head is about 15 m, and approximately 45 m below the head of the colluvial deposit. The colluvium in the profile ranges from about 350 to 680 m bound by the gully. The minor scarp located about 580 m in the profile seems to be the active scarp (in red color in Figure 5a). The toe is bound by the terrace.

Table 2 shows the landslide characteristics corresponding to the strong energy zones (>0.05) in Figure 5b. Observation are as follows: (1) the frequency at the main scarp varies from 0.1 down to 0.052, and the frequency at the head varies from 0.09 down to 0.025 (IMF2 spectrum in Figure 5b). (2) The energies for the sag and reverse slope are relatively high in this spectrum. (3) At the toe, on the adjacent terrace, the energy is also relatively strong. (4) The frequency for the minor scarp is about 0.05. (5) For the junction of gully and colluvium at about

Table 1: Landslide features of the D004 A–A' profile relative to changes in frequency and energy in the IMF1 and IMF2 spectra.

Spectrum	IMF1			IMF2		
	Frequency	Energy (>0.1)	Location (m)	Frequency	Energy (>0.1)	Location (m)
Main scarp	—	—	—	0.05	0.25–0.3	0
Sag	—	—	—	0.036	>0.5	15
Reverse slope	0.05	0.3–0.32	40	0.027	0.45–0.5	40
Head	0.052	0.33–0.35	60	0.039	0.35–0.4	60
Minor scarp	—	—	—	0.05	0.1–0.15	280, 595
Gully	0.26, 0.24	0.1–0.15	620, 910	—	—	—
Colluvium boundary	0.08–0.17	0.25–0.3	450–470	0.04–0.09	0.25–0.32	450–470
				0.06–0.07		890–910

460 and 680 m in the spectrum along the horizontal axis, the frequency variation from about 0.05 to 0.12 and energy distribution shows a band-shaped pattern. (6) For the gully, the frequencies of 0.2 and 0.24 and the energy concentration present a parse pattern.

In Figure 5c, there are three distributed zones with relatively strong energy level, including the main scarp, the colluvium (350–680 m), and the toe. The energy between the main scarp and the reverse slope is higher than the energy between the middle and the toe. In addition, the distance between the main scarp and head is approximately 15 m, so the energy–frequency distribution presents a slight concave upward pattern.

3.3 Elevation profile of landslide, D044 A–A'

The length of the profile is about 1,150 m. Figure 6a shows the landslide features of the main scarp, two minor scarps, two colluviums, and weathered stratum on the profile. Measured from Figure 1c, the distance between the main scarp and the head is about 210 m,

and the head is bound by the colluvium. The range of the two colluvia is about 210–480 m and 550–850 m, respectively. There is a gully at the toe.

The correspondence observed between the IMF1 and IMF2 spectra to landslide characteristics is as follows (Table 3 and Figure 6b): (1) the highest energy of the spectrum is located at the toe, which is adjacent to the river terrace. (2) The energy of the main scarp is greater than that of the surrounding area. The frequency at the main scarp varies from about 0.03 to 0.06. (3) The energy of the minor scarp, which is about 90 m behind the head, is very high. The phenomenon of high energy could be explained by the findings of Yang *et al.* [23]: this minor scarp is formed by the deposit of the run-out rock mass after plane sliding over the original slope surface. (4) In the boundary of the colluvium, which is located at a horizontal distance from 470 to 480 m and 840 to 850 m in the profile, the frequency varies from 0.025 to 0.11 and the spectrum of the energy shows a band-shaped pattern.

In Figure 6c, there are three distributed zones with relatively high energy in the energy–frequency spectra, including the main scarp, minor scarp, and the

Table 2: Landslide features of D014 A–A' profile that can relate to changes in frequency and energy in the IMF1 and IMF2 spectra.

Spectrum	IMF1			IMF2		
	Frequency	Energy (>0.05)	Location (m)	Frequency	Energy (>0.05)	Location (m)
Main scarp	0.1	0.13–0.15	45	0.052	>0.25	45
Head	0.09	0.15–0.17	60	0.025	>0.25	60
Sag	—	—	—	0.051	>0.3	95
Reverse slope	—	—	—	0.05	>0.3	105
Minor scarp	—	—	—	0.05	0.15–0.17	430
Gully	0.24, 0.2	0.1–0.15	460, 680	—	—	—
Colluvium boundary	0.09–0.14	0.07–0.1	350–360	0.05–0.12	0.15–0.17	350–360
	0.05–0.1		650–660	0.055–0.08		650–660

Table 3: Landslide features of D044 A–A' profile that related to changes in frequency and energy in the IMF1 and IMF2 spectra.

Spectrum	IMF1			IMF2		
	Frequency	Energy (>0.1)	Location (m)	Frequency	Energy (>0.1)	Location (m)
Main scarp	0.04	0.2	20	0.03	>0.8	20
Minor scarp	0.04, 0.06	0.3–0.35	300, 625	0.04, 0.03	>0.8, >0.6	300, 625
Gully	0.12	0.13	1,020	—	—	—
Colluvium boundary	0.04–0.09	0.35–0.4	470–480,	0.03–0.04	0.47–0.5	470–480
	0.04–0.11		840–850	0.025–0.04	0.57–0.6	840–850

colluvium with a distance of about 600 m to the toe. Due to the distance of 210 m between the main scarp and the head, the energy distribution is not obvious, but the energy–frequency distribution between the main scarp and head also shows a concave upward pattern.

3.4 Elevation profile of landslide, D047 B–B'

This profile is about 1,450 m long. Figure 7a shows the landslide features of the main scarp, two minor scarps, sag, reverse slope, two colluviums, and weathered stratum on the profile. Figure 1c shows that the distance between the main scarp and the head is about 15 m, and there are two gullies. In addition, there are two parts of the colluvium, ranging from about 400 to 540 m and from 670 to 1,320 m in the horizontal axis of the profile.

The landslide characteristics identified and corresponding spectral features are summarized in Table 4 and presented in Figure 7b. In sum, the following observations are made: (1) the energy from the highest point of the profile goes down to the head, showing a concave upward trend in IMF1 (Figure 7b-1). But the characteristic of this concave upward trend is not significant in IMF2 (Figure 7b-2), likely resulting from the short distance between the main scarp and head,

which is only 15 m. (2) At the toe, the energy is relatively strong, in contrast to the boundary of the terrace. (3) The frequency at the minor scarp is 0.06. (4) For the junction of gully and colluvium at the distance of 790 m, the frequency variation from about 0.04 to 0.1 shows a band-shaped pattern. (5) For the gully, the frequencies from 0.15 to 0.24 and the energy concentration present a sparse pattern.

In Figure 7c, it can be seen that the energy–frequency distribution presents two zones, including the main scarp to the reverse slope, and the colluvium at the distance of about 970 m to the toe. The energy distribution for the reverse slope is the strongest in the spectrum.

4 Discussion

A comparison of the spectra with the landslide features along the profile, such as the main scarp-head, the minor scarp, the colluvium, the gully, the boundary of the terrace, and the toe, indicates a general correspondence could be established. The findings are as listed below:

1. The energy–frequency variation between the main scarp and the head presents a concave upward

Table 4: Landslide features of D047 B–B' profile that correspond to changes in frequency and energy in the IMF1 and IMF2 spectra.

Spectrum	IMF1			IMF2		
	Frequency	Energy (>0.05)	Location (m)	Frequency	Energy (>0.05)	Location (m)
Main scarp	—	—		0.06	0.25–0.3	35
Head	0.035	0.15–0.17	50	—	—	—
Minor scarp	—	—		0.06	0.3–0.32	540
Sag	—	—		0.06	>0.5	600
Reverse slope	—	—		0.05	>0.4	650
Gully	0.24	0.15–0.17	1,320	0.15–0.22	0.15–0.17	1,320
Colluvium boundary	0.05–0.1	0.25–0.3	530–540	0.04–0.06	0.32–0.35	530–540

distribution, with the frequency of the main scarp as generally approximately 0.05.

2. The spectral presentation of the minor scarp's frequency seems to be around 0.05.
3. The sag and reverse slope reflect the strongest energy in the profile.
4. The gully in the spectrum presents the high frequency, which varies from 0.1 to 0.3, and shows a sparse distribution.
5. At the boundary of the colluvium, the frequency varies from 0.04 to 0.15, and the energy–frequency distribution shows the band-shaped energy concentration or energy concentration in this small range.
6. For the toe adjacent to the terrace, the energy response is relatively high.

According to the characteristics summarized above, this study extracts three profiles of D004 C–C', D014 C–C', D044, and D047 C–C' to identify the features of landslides by the spectrum once again (Figure 1). The C–C' profiles are approximately orthogonal to the profile A–A'. From the spectrums of the three profiles, we can delineate the landslide features of the gully, the minor scarp, the boundary of colluvium, and the flank (red arrows symbol in Figures 8–10). The landslide characteristics on the profiles are represented by white arrows on the graph. This comparison shows that the features of landslides have strong correspondence with energy–frequency variation in the IMF spectrum.

As verified by experiments, the Hilbert amplitude spectrum is able to show the amplitude levels at a wide range of frequencies at various distances along a slope profile. Each frequency in the spectrum stands for a specific wave number per unit length along the analyzed cross section. In the Hilbert amplitude spectrums of the first two IMFs, the amplitude level corresponding to the zones covering the scarps, depletion, accumulation, and toe of a landslide is significantly much higher than other zones' energy levels.

These are major geomorphologic signatures of a landslide. Among all, the depletion and the accumulation zones could be identified through Hilbert amplitude spectrums. The strong-amplitude zones of depletion and accumulation are always separated. Since the depletion zone is always in the upper slope while the accumulation zone is always in the lower slope, it would not be difficult to separate these two strong-amplitude zones in the spectrums. With the identification of the accumulation zone, the boundaries of colluvium over a previously occurred landslide may be estimated from the range of depletion zone. It is potentially possible to

Figure 8: The elevation profile, D004 C–C', and the IMF1 and the IMF2 spectra, respectively.

use Hilbert amplitude spectrums of IMF1 and IMF2 to lineate the depletion and accumulation zones of a landslide area. Regarding the other IMFs besides the first two, the frequency of the spectrum shows a longer

Figure 9: The elevation profile, D044 and D047 C–C', and the IMF1 and the IMF2 spectra, respectively.

Figure 10: The elevation profile, D014 C–C', and the IMF1 and the IMF2 spectra, respectively.

period. In this study, no convincing correspondence was identified.

Despite the successful correspondence established between the features of HHT spectrum and landslide, there are still some unexplainable phenomena. That is, the geomorphological features do not correspond to the IMF spectral features. In the D044 site shown in Figure 1c, there are active scarps (local failures) identified in the field. However, these features are not reflected in the IMF spectra. This may result from the complexity of geographical conditions in the landslide site and the diversity of the landslide patterns. Meanwhile, the proposed approach may be limited to slope-failure sites with notable landslide features, such as crown, main scarp, head, main body, foot, toe, minor scarp, flank, depleted mass, accumulation, etc.

At present, the correspondence between EMD-derived features and landslide features was established. The contribution of EMD-derived signatures in terms of classification accuracy is still too early to be assessed. Further study is required to collect more profiles of different types of landslides. With a library of the correspondence between topographic and HHT spectral features, the integration of Hilbert amplitude spectrums of IMFs with other geometric signature for landslide area delineation may be investigated further.

Conventional methods for the production of landslide maps rely chiefly on the visual interpretation of stereoscopic aerial photography, aided by field surveys [3]. With the new data acquisition technology such as airborne LiDAR, the same visual approach could be conducted in a digital environment with high-resolution DEM and orthoimages based on human interpretation. In addition to this, a computer-assisted scheme, even fully automated scheme, could be realized.

In the future, it is possible to apply the HHT-EMD method onto the automatic or semi-automatic mapping of landslides in a large region. A scenario of the potential approach is as follows: one can first generate a series of consecutive profiles at a constant interval in two mutual perpendicular directions (e.g., the x - and y -directions) from the high-resolution DEM over a large area. The Hilbert spectra for the first two IMFs (IMF spectra) of each profile can be produced by the method described in Section 2, one by one. Then local statistics of the frequency-dependent energy can be conducted to identify all possible locations of the geometric signatures for landslide features.

Landslide mapping can then be either fully automatic, tentatively through artificial intelligence learning, or semi-automatic, i.e., computer-assisted human operation. The geometric signatures, including the IMF spectra explored in this study, could be used as attributes in the geomorphological description. As a tentative implementation scheme, a model could be constructed with the fully investigated data set through learning schemes and then the knowledge transferred for application in other cases. Another scenario would be the computer-assisted approach, where the geometric signatures generated serve as a reference for the human operator. While the significance would be evaluated by the learning machine in the first case, a normality measure should be provided to the operator in the computer-assisted approach.

5 Conclusion

In this study, the topographic features of landslides for profiles extracted from three sites are analyzed with the HHT spectrum. In the HHT, the time dimension is replaced by the distance. The following conclusions are made:

1. This study suggests that the Hilbert amplitude spectrums of the first two IMFs are able to show the geomorphologic signature of a landslide. From the HP derived from HHT, major geomorphologic signatures of a landslide, especially the depletion and the

accumulation zones, are identified. The cases presented in this study are selected from many cases processed in the study as topography with no landslides would not show the spectra of landslides. In principle, the spectra of IMFs are related to the topographic changes but “projected” into different feature space. If there is no topographic feature, then there is no spectral feature.

2. The HHT spectrum of landslides essentially provides another view of the topographical features of the landslide. The use of HHT is potentially useful for the delineation of landslides with the use of a high-resolution DEM over a large area, in particular, by providing evidence and rules to construct a decision support system that integrates other geometric and geomorphologic signatures. No indoor terrain analysis could replace *in situ* investigation, but better decisions could be achieved with more evidence.
3. The proposed approach is reasonable for determining the notable landslide features, such as crown, main scarp, head, main body, foot, toe, minor scarp, flank, depleted mass, accumulation, etc.
4. Through a composition of geometric and morphological signatures, including those derived from EMD, a decision support system may be constructed. At present, the correspondence between EMD-derived features and landslide features was established.

The feasibility of deriving signatures from EMD for landslide boundary delineation has been explored in this study. Through a composition of geometric and morphological signatures, including those derived from EMD, a decision support system may be constructed.

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