Debris Flow Detection Using a Video Camera

Ko-Fei Liu, Ting-lu Kuo, and Shih-Chao Wei

Abstract

The early warning of natural hazards is an important issue that was raised by the 2015 Sendai Framework for Disaster Risk Reduction. However, early warning systems need complimentary monitoring systems that themselves may be combined with automatic identification and prediction systems. For debris flows, once a disaster has been confirmed to have occurred in an upstream area, early warning of the hazard further downstream may be predicted with relatively good accuracy in time and space. In this study, we use video cameras to identify the arrival times of debris flows using a simple average grey-level method. We show that this method can automatically detect the arrival of debris flow events. This method is tested with both real events video and indoor experiments during the night with moonlight only illumination. All tests have an error of less than 1.3 s. The method is fast and therefore ideal for real-time monitoring and warning.

Keywords

Debris flow • Camera • Monitoring

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Introduction

Debris flows are among the most hazardous natural disasters that can occur on sloping land. To provide safety in debris-flow-affected areas, an early-warning system is vital.

The most commonly used early-warning systems are based on indirect warnings using rainfall or hydrology indices with calibrated thresholds (Jan and Lee 2004; Baum and Godt 2010; Thiebes 2012). These rainfall-based methods can issue warnings in an early stage and on a regional scale. This kind of warning indicates there may be debris flows within a large area containing many potential debris-flow streams. However, the specific location of an occurrence cannot be predicted. Confirmation of a debris flow still requires *in situ* monitoring devices or disaster records.

In recent years, debris-flow detection methods have been developed based on direct monitoring systems, such as geophones, video cameras, wire sensors, ultrasonic gauges, radar, etc. (Itakura et al. 2005). These direct detection methods can give precise warnings to affected areas. Among these devices, geophones and cameras have been used most often for debris flows. However, there is currently no automatic detection and warning system using geophones or cameras because the event detection threshold changes in time and still cannot be determined automatically.

Wei and Liu (2019) used the accumulated energy method combined with the characteristic frequency of debris flows to resolve the threshold determination problem and detect debris-flow arrivals. However, since only energy variation was considered, the events detected through geophones could be of a range of types, including granular flow, debris flow, or floods with a high sediment concentration. In these events, the flow energies may be approximately the same but the sediment contents to be very different. Thus, additional information from cameras is essential.

Our research uses a total grey-level method to identify changes in images. The method is based on identifying large

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changes in an image's grey level that indicate large changes to the objects in the images. Thus, information from a monitoring video camera can indicate changes in flow conditions and thus the detection of a debris-flow event. This information can in turn be used as part of an early-warning system.

Event Identification Method

Common Image Processing Methods

Past research using camera adopted the particle-tracking method to extract information from the video (Arattano and Grattoni 2000). The same concept has been applied to tracking surface bubbles, debris, and artificial particles in large-scale particle image velocimetry (Fujita et al. 1998; Theule et al. 2018). Many studies used the optical flow method (Horn and Schunck 1981; Lucas and Kanade 1981; Farnebäck 2003) to calculate the velocities of particles in images. After obtaining velocity or particle information, one can use the information to identify debris flows. Chang and Lin (2007) used the movement of a specific target for event detection. They also introduced discrimination of debris flows and floods by using features of contrast, entropy, energy, and homogeneity.

However, these methods usually do not produce accurate results for natural disaster detection, owing to the resolutions of the images and the fact that particles in video are very difficult to identify because of mud/water coverage. The most critical problem is the fundamental assumption used in particle tracking that the same point maintains the same grey level in consecutive images, which is normally not true. Furthermore, tracking analysis is computationally time-consuming, but time is critical for real-time warning.

Therefore, in this research, rather than use a method that is sensitive to variation of particular particles, we will develop a method that does not need to identify particles. Moreover, this method should be usable in the field and in night-time when there is otherwise insufficient illumination.

Therefore, we propose the total grey-level method to identify debris-flow events. We calculate the total grey level in the region of interest (ROI) and if it changes, this indicates there are events occurring within the ROI. This can be used to identify debris flow. After an event is identified, a geophone can be used to confirm if it is debris flow or high-concentration flow. However, the combination of geophones will not be discussed in the present paper.

Total Grey-Level Method

First, video taken in the field is separated into images. Within each image, the ROI is defined and all calculation will be done within the ROI. For each pixel in the ROI, color is transformed to grey level according to the standard from the International Telecommunication Union (ITU-R 1990) code with:

$$Grey = 0.229 \times Red + 0.587 \times Green + 0.114 \times Blue, \tag{1}$$

where each pixel has a grey level from 0 to 255. Then the total grey level for one ROI is calculated as:

$$Total\ Grey\ Level = \sum_{All\ points\ in\ a\ frame} Grey. \tag{2}$$

This total grey level is then divided by the total number of pixels in the ROI to give the average grey level. If it is very dark, the average grey level will be close to 0. If it is very bright, the average grey level will be close to 255. Normal clear water flow will produce very bright and shining images, so the average grey level is around 150 or more. When debris flow or flood occurs, there is granular material and mud and the whole image becomes darker. As one of the characteristics of debris flows is a large amount of granular material concentrated at the front, the average grey level will become darker in a short period of time. An example of real video images taken at Ai-Yu-Zi creek is shown in Fig. 1.

There are boulders of diameter 1 m on top of the flow. A wave of muddy material can be seen in the third photo. There are usually 30–60 frames per second for a standard field camera. Each frame is an image like in Fig. 1, and one average grey level can be calculated. By plotting the variation of average grey level over time, the change can be seen and the rate of change of the average grey level can be calculated. The temporal variation of average grey level for Typhoon Mindulle (the case shown in Fig. 1) is plotted in Fig. 2. For cross referencing, the times corresponding to the three images in Fig. 1 are marked. It can be seen that average grey level remains roughly constant before the debris flow arrives. When the front of the debris flow arrives, average grey level decreased quickly (from brighter to darker). After debris flow passed out of the ROI (time 45–50 s), the grey level roughly returned to its original level. Later than 50 s, there was flood which increased the grey level.

With the temporal variation of average grey level obtained, a condition is required to determine the detection of debris flows. Since average grey level changes for different lighting conditions (sunlight, moonlight, rain), materials, and flow conditions, it seems impossible to find a fixed threshold to determine the arrival of an event (a debris flow or flood). However, before any event, the flow conditions should be steady or slowly varying, so the grey level should remain roughly the same for a long period of time. Hence, the "normal" average grey level for the stable state should be considered as the reference level. Any normal signals have

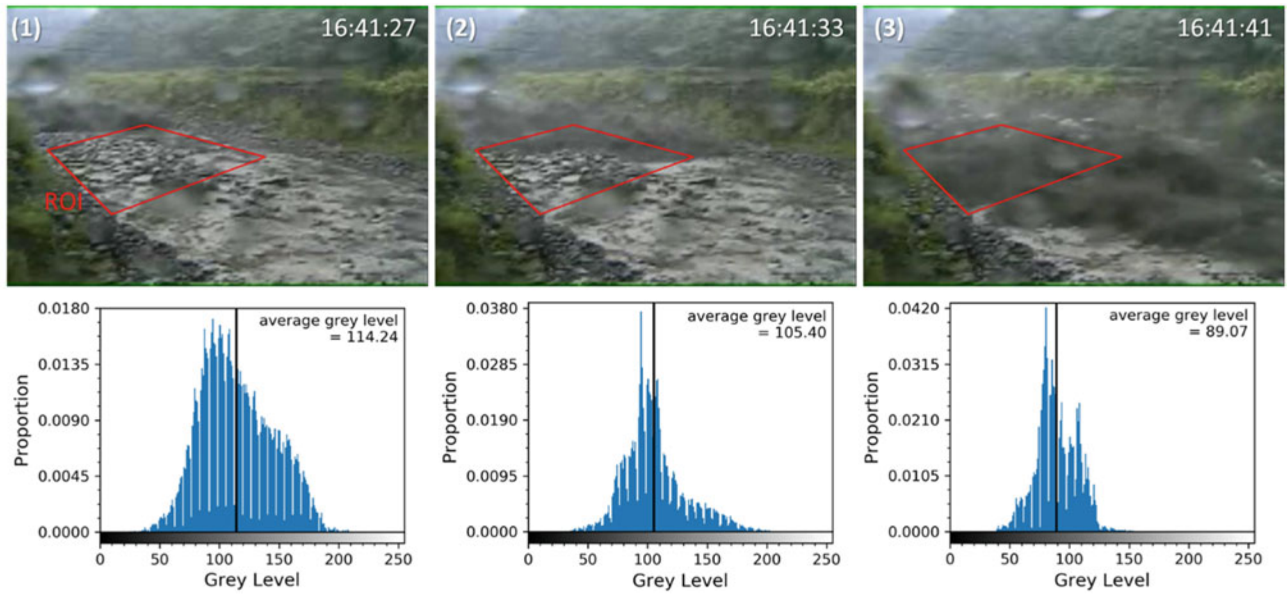

Fig. 1 Grey-level distributions from video of the Typhoon Mindulle debris flow. 'Proportion' denotes the ratio of the number of pixels of a given grey level to total number of pixels in the ROI (region of interest). Next to the grey-level axis, the corresponding brightness is plotted as a grey-level bar. The vertical line indicates the position of the average grey level for that image. (1) Debris flow just entering ROI (from top corner of ROI). The average grey level of the ROI is 114.24. (2) Front of the debris flow reaches the centre of the image. The average grey level of the ROI is 105.4. (3) The front of the debris flow just reaches the boundary of the image. The average grey level of the ROI is 89.07

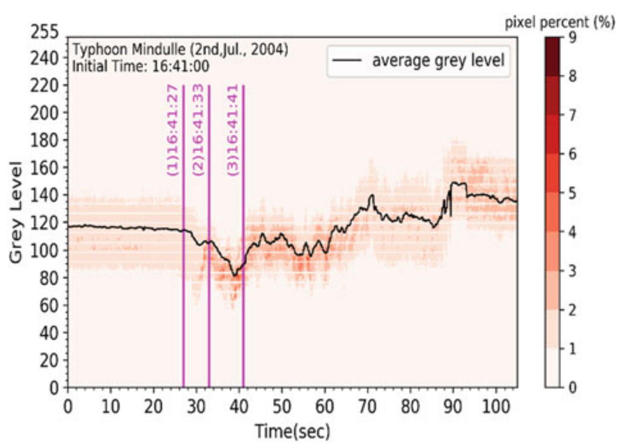

Fig. 2 Temporal variation of average grey level in Ai-Yu-Zi creek for Typhoon Mindulle. The first 25 s is noise before the debris flow arrives. The black line is the average grey level. Darker color indicates a larger proportion of pixels at that grey level. Pink lines indicate the time locations for images in Fig. 1

fast-varying "noises". Therefore, a time average should be taken to remove these noises. Thus, we average the total grey level for every 11 frames (frame from $t_0 - 5$ to $t_0 + 5$) to produce one dataset at each time t_0. These averaged values can effectively remove all pulse irregularities.

To detect a change in average grey level, we use the slope of Fig. 2. The rate of change of the grey level is calculated as:

$$S(t) = \frac{\mathrm{Ave.Grey}(t + \Delta t) - \mathrm{Ave.Grey}(t - \Delta t)}{2\Delta t} \tag{3}$$

For every 10 s, we choose the maximum slope S_{max} within that 10 s as the representative parameter of flow condition. While S_{max} is small, the flow conditions remain the same. However, if at any moment the calculated slope is greater than twice the S_{max} value obtained 2 s before, and this continues to be true for consecutive a 5 points (1.5 s), this indicates something happened within the ROI. Then a debris flow warning will be issued after this detection process.

This simple procedure is tested through laboratory experiments. In practice, the warning triggered by video camera can be checked with detection of geophone or other sensors but this discussion is excluded in this study.

In this paper, the warning given by the proposed detection method will be checked with manual tracking of video images by eyes.

Laboratory Tests

The setup of the experiment is depicted in Fig. 3. The flume is 5 m long and 60 cm wide. A video camera is mounted on top of the flume. Lighting is provided from above.

White Styrofoam balls with a density of 21.4 kg/m^3 are used. We mixed 170 balls of diameters from 1.5 to 10 cm.

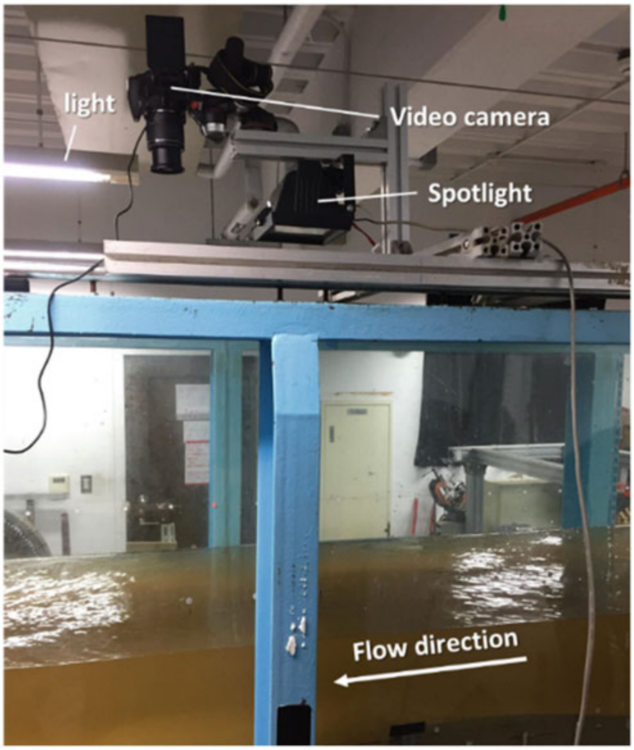

Fig. 3 Flume test setup. Water flow is 20 cm/s to the left. There is strong lighting from the top and normal room lighting

Then we dropped them as a whole into the flume from upstream. The balls flowed down the flume with the water flow at a speed of 20 cm/s. Because the balls float, this is used to simulate granular material on top of the debris flow front. The video camera captured images from directly above. To control the lighting conditions, experiments were conducted at night. We used four different lighting methods to test the influence of lighting: strong artificial lighting (100 W) from on top of the flume, only normal room lighting (two 60 W from 3 m above), no artificial lighting but with all windows open to admit moonlight and starlight, and finally no artificial lighting with all windows closed and curtains blocking all possible light sources. The corresponding sample photos are shown in Fig. 4.

The resulting average grey levels and the calculated slopes are depicted in Fig. 5. The solid blue lines are the average grey levels and the dotted orange lines are the corresponding slopes. In all cases, the grey-level variation before arrival of the balls is small. The slope increases are sufficient to identify the fast change of grey level when the balls arrive. As lighting becomes weaker, the maximum grey level becomes smaller, as do the slopes. For strong lighting, the grey level actually keeps changing, while only the slope remains the same. However, twice the maximum slope for previous 10 min gives a good arrival time.

With no lighting, the maximum grey level is only 2.7 (and cannot be identified by human eyes). However, the slope is still detectable.

The time that the Styrofoam balls enter the ROI is marks the beginning of event detection. The differences between the times determined using the total grey-level method are compared with those identified by eye are listed in Table 1.

The accuracies in all four cases are very good. Since the time difference between two frames is 0.03 s, these values indicate the error is between 1 and 7 frames. The most significant result is for Case 4, where there is no light at all. The human eye can barely distinguish objects in these conditions, yet this method can identify the arrival of the balls. This means that using slope variation enables this method to work under almost no light and still provide an automatic early warning.

Application to Ai-Yu-Zi Creek

Test Area

Ai-Yu-Zi Creek located at Shenmu Village, Nantou County, Taiwan, was selected as the test area. It was identified as having a high potential for debris flow torrents by the Soil and Water Conservation Bureau of Taiwan. The length of the stream is 3.731 km and the watershed area is 405.02 ha. Stream elevation extends from 1200 to 2500 m with an average slope of 39.3°. The river width at the monitored location is approximately 50 m. The study area is mainly located in the Nanchuang and Nankang formations. These formations are composed of sandstone, siltstone, shale, and alternations of sandstone and shale. The landslide area occupies 12–34.2% (1996–2009) of the whole watershed area, and it has had an increasing trend in recent years (Chen et al. 2012). The average annual rainfall is 3054.7 mm with 87% (2644.5 mm) concentrated in the rainy season from April to October. The observed debris flow events in the are involve large boulders of typically 1 to 2 m in diameter, and occasionally boulders of up to 5 m can be observed. All debris flows have high concentration of granular material, but concentration changes from event to event.

Test Result

The total grey-level method was used for the video recordings made during Typhoon Mindulle. The images were those shown in Fig. 1. With the total grey-level method and twice the reference level as the warning criterion, the time of the warning is marked in Fig. 6.

The time differences for this method applied at Ai-Yu-Zi creek are listed in Table 2. We tracked frame by frame and

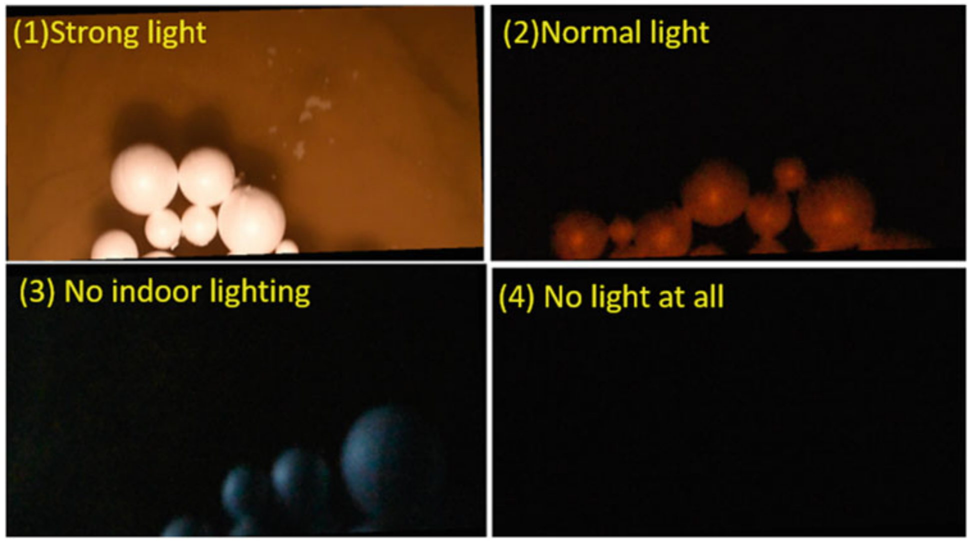

Fig. 4 Images of balls flowing down the flume. The white Styrofoam balls have different grey levels under different lighting conditions: (1) strong lighting provided from on top of the flume, (2) only normal room lighting, (3) no indoor lighting with room lights turned off and only natural moonlight from one small window, and (4) curtains used to block all natural light and no indoor lighting provided

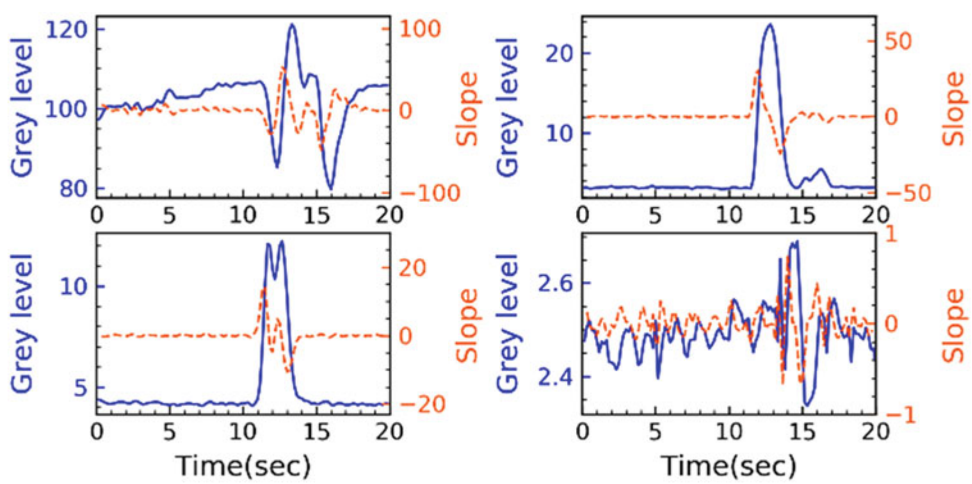

Fig. 5 Temporal variation of average grey level. Solid blue lines are average grey-level variations. Dotted orange lines are slope variations. Graphs correspond to the lighting conditions in Fig. 4

Table 1 Accuracy of using the total grey-level method to detect events in the flume test. Cases are those shown in Fig. 4. Error is the time difference between detections from the total grey-level method and by eye. A negative value indicates detection earlier than the actual time (due to a shadow in front)

Case	1	2	3	4
Error (s)	−0.125	−0.041	−0.308	0.267

when the debris flow front reached the ROI, as judged by eye, we marked that frame as the arrival time for debris flows. Also listed in Table 2 are the results using a higher detection level (five times S_{max}) and averaging over more frames (31 frames). The results for criterion of twice the noise level have a detection time error of less than 1.3 s. This means that the total grey-level method is acceptable for use in the field.

Conclusion

In this study, we extracted a region of interest (ROI) from each frame captured from a video camera setup in both flume and field tests, conducted image processing and calculated the average total grey level of each image. We defined the slope of the temporal variation of the average

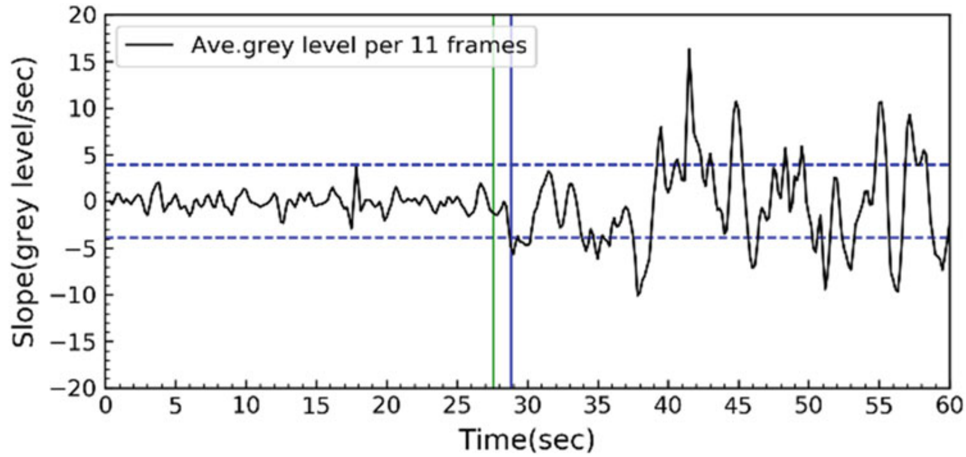

Fig. 6 Temporal variation of the average grey-level slope. The horizontal blue dashed line is twice the noise level S_{max}. The vertical blue solid line denotes warning time with respect to twice the noise level S_{max}. The vertical green line is the reference time estimated by eyes

Table 2 Accuracy of using the total grey-level method to detect debris flows at Ai-Yu-Zi creek during Typhoon Mindulle. Error is between the total grey-level method and estimation by eye. 2T indicates using two times the noise level and 5T is using five times the noise level. 11F denotes results from an average over 11 frames and 31F denotes an average over 31 frames

Case	2 T		5 T	
	11F	31F	11F	31F
Error (s)	1.28	0.95	10.28	1.95

total grey level as the main index for determining changes in flow conditions, and thus detection of debris flows. We adopted twice the reference level, S_{max}, of temporal slope change for detection of events in the video images. Using laboratory experiments and videos of debris flow in the field, we showed that the error of detection method is within 1.3 s of that made by viewing the same imagery with the human eye. Furthermore, in flume tests, we showed that the method can be used in even very dark environments without the need for artificial lighting. This is essential for field monitoring and early warning of debris flows, given that these events can occur at any hour of the day or night. The simple image-processing method used here requires very little computational time compared with other image-processing methods, which is also very desirable for real-time detection and monitoring.

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