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Smart monitoring system with multi-criteria decision using a feature based computer vision technique

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Abstract. When natural disasters occur, including earthquakes, tsunamis, and debris flows, they are often accompanied by various types of damages such as the collapse of buildings, broken bridges and roads, and the destruction of natural scenery. Natural disaster detection and warning is an important issue which could help to reduce the incidence of serious damage to life and property as well as provide information for search and rescue afterwards. In this study, we propose a novel computer vision technique for debris flow detection which is feature-based that can be used to construct a debris flow event warning system. The landscape is composed of various elements, including trees, rocks, and buildings which are characterized by their features, shapes, positions, and colors. Unlike the traditional methods, our analysis relies on changes in the natural scenery which influence changes to the features. The "background module" and "monitoring module" procedures are designed and used to detect debris flows and construct an event warning system. The multi-criteria decision-making method used to construct an event warring system includes gradient information and the percentage of variation of the features. To prove the feasibility of the proposed method for detecting debris flows, some real cases of debris flows are analyzed. The natural environment is simulated and an event warning system is constructed to warn of debris flows. Debris flows are successfully detected using these two procedures, by analyzing the variation in the detected features and the matched feature. The feasibility of the event warning system is proven using the simulation method. Therefore, the feature based method is found to be useful for detecting debris flows and the event warning system is triggered when debris flows occur.

Keywords: debris flow; natural disaster; feature based; computer vision; natural disasters detection; event warning system

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1. Introduction

Over the past twenty years, global climate change has been more extreme. This has led to an increase in the incidence of occurrence and worsening in the consequences in a variety of natural disasters such as earthquakes, tsunamis, and debris flows brought about by severe storms. Natural disasters cause impact society, causing damage to infrastructure destroying buildings and crops, leading to huge economic losses and even human casualties. Van Aalst (2006) has described the factors that influence climate changes and the relationship between climate change and extreme weather phenomena. Such knowledge can be used to reduce the risk of natural disasters. It is particularly important for developing countries to develop and apply strategies for the prevention and mitigation of the effects of natural disasters (Alcántara-Ayala 2002). Generally, the need for the disaster risk assessment, disaster detection and devising disaster warning systems has become more important in recent years. There have been several recent works investigating the process of risk assessment, analyzing the types of damage that can be caused by natural disasters and proposing different types of the models to assess the damage (see for example, Douglas 2007, Ellingwood 2001, Erdik *et al*. 2003, Faber and Stewart 2003, Hsu *et al*. 2011, Hsu *et al*. 2012, Jaffe and Gelfenbaum 2002, Lugeri *et al*. 2010, Markus *et al*. 2010, and Pandey *et al*. 2010. Other studies have focused on the disaster detection and the construction of warning systems (Heaton 1985, Kanamori *et al*. 1997, Kanamori 2005, Wu *et al*. 1998, Wu *et al*. 2000, Wu *et al*. 2002, He *et al*. 2014, and Khajehzadeh *et al*. 2014). Many methods have been employed to analyze the conditions that lead to the occurrence of debris flows, the extent of the damage they can cause and the components that make up the debris flows. Unlike the traditional methods, in this study, we developed a debris warning system which uses the feature based computer vision technique. The feature based method which is characteristics of repeatability, distinctiveness and robustness can overcome challenges such as changes in illumination to find stable feature points such as the corners and edges of objects. The effectiveness of this method is verified in simulations based on information about real debris flows captured by different devices. A debris flow event warning system is also proposed. The rest of this paper is organized as follows. First, the related works in the literature are discussed, followed by a discussion of the architecture of the proposed system and its modules. Next, the debris flows detection method is used with real case examples and the feasibility of the debris flow event warning system is demonstrated. Last, we present our conclusions and possibilities for future works.

2. Related works

Natural disasters can be classified into four categories based on type: geological, climatic, ecological, and astronomical. In Taiwan, the most frequently occurring natural disasters are earthquakes, tsunamis, and debris flows which are classified as geological and climate disasters. Numerous studies of earthquakes have been carried out over the last few decades. Nakamura (1988) constructed the UrEDAS earthquake warning system which includes two steps: the quick warning and the accurate warning. The quick warning is given after arrival of the P waves and the accurate warning is given after arrival of the S waves. Allen *et al*. (2003) proposed an earthquake alarm system (ElarmS) which uses the frequency of the arriving P-waves to determine the magnitude of the earthquake, utilizing this information to warn of damaging ground motion. Wu and Zhao (2006) estimated the magnitude of an earthquake for early warning by using the P-wave amplitude. On the other hand, Nakamura (1988), Allen and Kanamori (2003), Wu and Zhao (2006), and Stramondo *et al*. (2006) used remotely sensed satellite remote data to detect the damage caused by earthquakes. They discovered that the process of damage classification can be significantly improved by combining optical data and some SAR features. Others investigated tsunamis, and found interesting results. For example, Okal *et al*. (1999) utilized altimetry captured by satellites to judge the severity of a tsunami. They discussed seven cases, with only two being successful because of the influence of Kuroshio. Greidanus *et al*. (2005) used medium (25 meter) resolution satellite radar imagery to detect damage from tsunamis. Their approach is useful to detect the coastal damage. In other studies related to debris flows, Arattano and Marchi (2008) built a debris flow monitoring and warning system that includes an advance warning system and event warning system with an ultrasonic sensor network. Jin (2011) used high frequency radar to detect water content underneath the ground surface which can trigger a debris flow. Jiann *et al*. (2007) and Liliet *et al*. (2010) performed regular monitoring and assessment of debris flows by using the FORMOSAT-2 and HJ-1-B (Environment and Disaster Monitoring Constellation 1) satellites, respectively. Wireless sensors are another type of device which can be used to detect the natural disasters. Cho *et al*. (2008) combined a waterproof pyramid-like capsule with a wireless sensor to detect debris flows. The radio signals and the light are allowed to cross the capsule. Lee *et al*. (2009) and Lee *et al*. (2010) also used wireless sensors including the COORDINATOR sensor and the INSIDER sensor. The INSIDER sensor is used to collect data on debris flows and the COORDINATOR sensor is the receiver which receives the information from the INSIDER sensor. Lin *et al*. (2013a) used a dual camera to construct a wide-angle, high-resolution monitoring system, which could observe detailed information. Several methods have been proposed to address the problem of the natural disasters detection and construct a warning system for the natural disasters. Different types of disasters can be detected by using the same device. For example, it is undisputed that high-resolution satellite imagery can be used to assess damage and also can be used to detect earthquakes. However, there has been a lack of integration. Therefore, we propose a novel computer vision technique which is feature based that can be used for the detection of natural disasters and take a debris flow as an example.

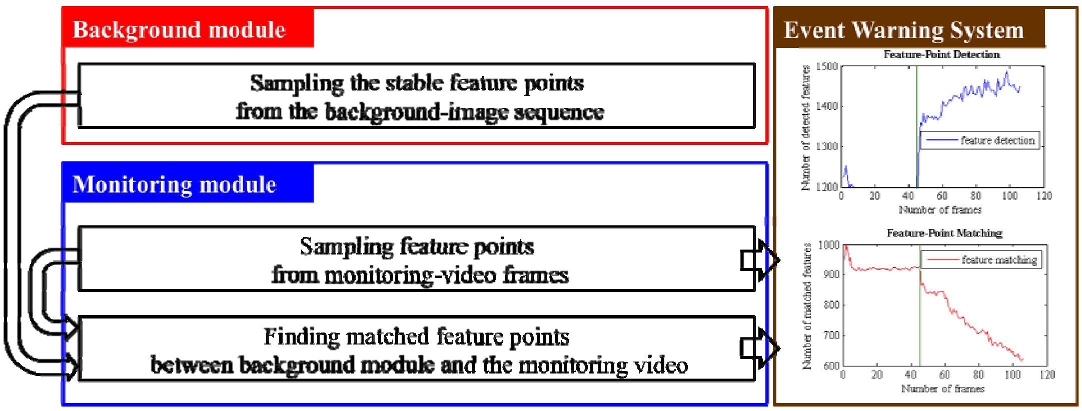


Fig. 1 The work flow of the proposed system

3. System architecture

The proposed system aims to detect debris flows and alert of the danger. In order to construct an event warning system, several important tasks must be considered. As shown in Fig. 1, the proposed system includes three main technical components: the background module, the monitoring module, and the event warning system. First, we determine the stable feature points for the background module by using the feature detection method. In this procedure, a sequence of scenes from before the occurrence of debris flow is used to find the stable feature points which are combined for the background module. Next, the monitoring module is generated by using the feature-point detection method and feature-point matching method. The feature-point detection method is used to find the feature points on the current scene, and the feature-point matching method is used to match feature points between the background module and the current scene. The number of detected and matched feature points show drastic fluctuations. Finally, we integrate the information from the monitoring module to construct the event warning system.

4. Background module

The background module aims to build stable feature points for the monitored scene before the occurrence of a debris flow which can then be used to detect the variation in the environment. In this study, we used the SURF (Speeded up Robust Features) mechanism designed by Bay *et al*. (2006) to detect the feature points in the background and monitoring modules. This mechanism has the advantages characteristic of SURF which are repeatability, distinctiveness and robustness. In the SURF mechanism, the Hessian matrix H is used for detecting features and is scaled to achieve the characteristic of scaling invariance as shown in the following equation

$$H(\mathbf{x},\sigma)=\begin{bmatrix} L_{xx}(\mathbf{x},\sigma) & L_{xy}(\mathbf{x},\sigma) \\ L_{xy}(\mathbf{x},\sigma) & L_{yy}(\mathbf{x},\sigma) \end{bmatrix} \tag{1}$$

where $\mathbf{x}=(x,y)$ in an image I, σ is the scale which is the standard Gaussian deviation, and $L_{xx}(\mathbf{x},\sigma)$ is the Gaussian second order derivative at point x. The expression of $L_{xx}(x,\sigma)$ is shown as follows: $L_{xx}(\mathbf{x},\sigma)=G(\sigma)*I(x,y)$

$$G(\sigma)=\frac{\partial^2 g(\sigma)}{\partial x^2} \tag{2}$$

where $G(\sigma)$ is a Gaussian kernel function and $g(\sigma)$ is a Gaussian distribution function. The other symbols, $L_{xy}(\mathbf{x},\sigma)$ and $L_{yy}(\mathbf{x},\sigma)$, are similar to $L_{xx}(\mathbf{x},\sigma)$.

The interesting features are selected from an image and are scaled according to the determinant of the Hessian matrix as shown in the following equation

$$\det(H)=L_{xx}L_{yy}-(L_{xy})^2\,. \tag{3}$$

Bay *et al*. (2006) used the difference of Gaussian (DoG) to approximate the Laplacian of the Gaussian (LoG) and this is used with the integral images to reduce the computational cost. Therefore, the determinant of the Hessian matrix can be rewritten by using the following equation

$$\det(H_{approx}) = D_{xx}D_{yy} - (\omega D_{xy})^2 \tag{4}$$

where ω is a parameter used to verify the errors cause by the DoG which is used to approximate LoG.

Each feature is described as a vector of 64 dimensions including the orientation assignment and the descriptor components. Finally, the robust feature points are detected from the different scales of the image.

5. Monitoring module

Once the background module is built, we begin to monitor the environment with the monitoring module. There are two stages to constructing the monitoring module: feature-point detection and feature-point matching. In feature-point detection, we use the SURF mechanism described above to detect the features from the scene. In feature-point matching stage, we find the matching feature points between the results of feature-point detection and the background module by using the nearest neighbor search method. The matching process can be time consuming, therefore, the trace of the Hessian matrix is utilized to reduce the computational time. For a more detailed description of the methodologies including "feature-point detection" and "feature-point matching" please refer to our previous study Lin *et al*. (2013b).

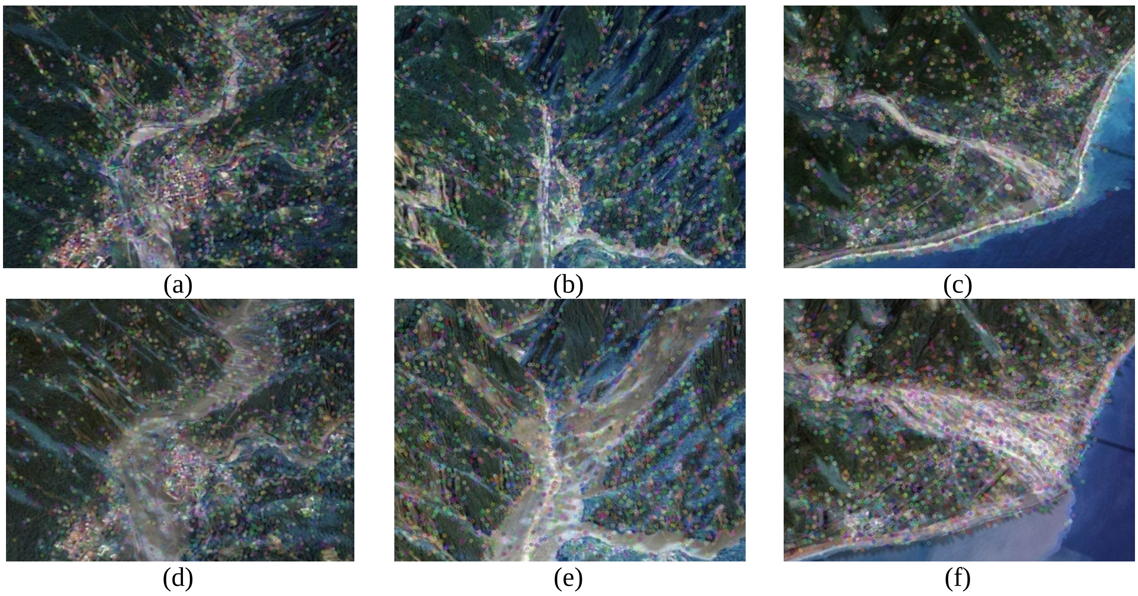


Fig. 2 The results of the feature-point detection for debris flows from satellite images: before the occurrence of the debris flow (a) in Jiasian; (b) in Shiaolin; (c) in Taimali; after the occurrence of the debris flow (d) in Jiasian; (e) in Shiaolin; (f) in Taimali

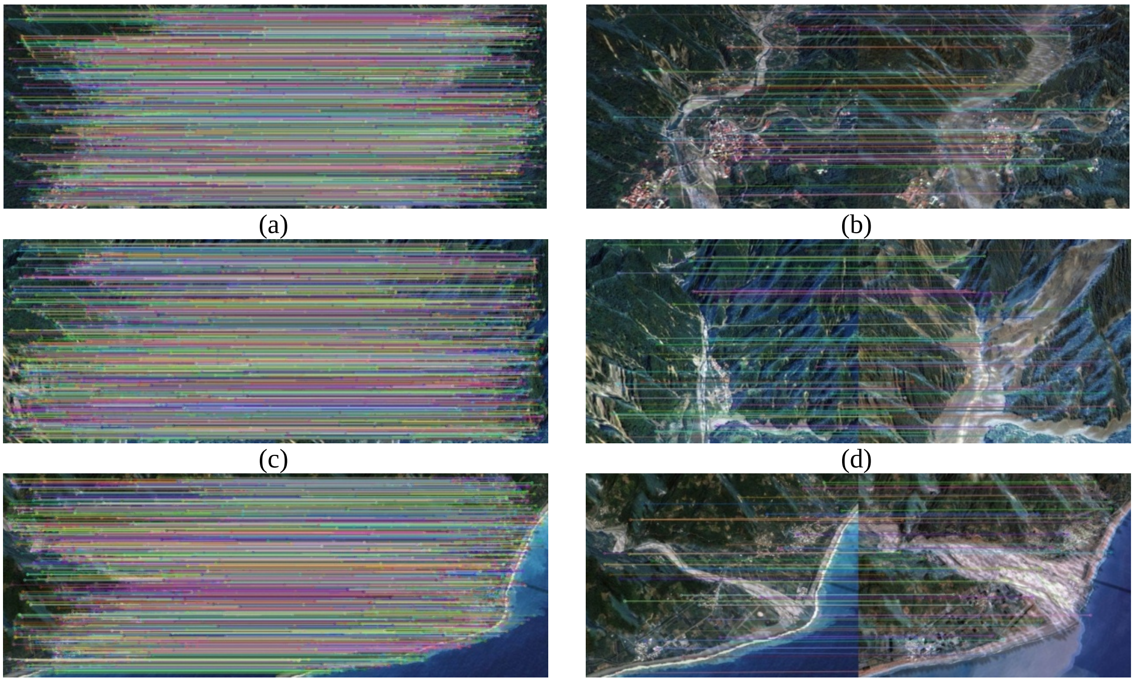
6. Debris flow detection

The physical environment is constructed of many different types of features, both natural (trees, mountains, water) and manmade. The features in the natural scenery change because of changes in the landforms caused by the natural disasters. In recent years, the occurrences of debris flows have increased because of the neglect of soil and water conservation and the occurrence of more extreme climatic changes and this has caused extreme damage to the environment.

The feasibility of the proposed method which combines feature-point detection and feature-point matching for the detection of debris flows is discussed. Two kinds of static images are analyzed, the satellite and surveillance images captured by satellites and surveillance cameras. In the images below, the detected features are indicted by colored circles, and the matched features are connected with straight colored lines.

6.1 Satellite images

The satellite images (obtained from the National Applied Research Laboratories (2013)) show actual cases of debris flows that occurred in Taiwan, as shown in Fig. 2. The cases of Jiasian, Shiaolin and Taimali are shown on the left, middle, and right of Fig. 2. The cities of Jiasian and Shiaolin are located in Kaohsiung and Taitung Counties. Figs. 2 (a)-2(c) show the results of feature-point detection from the background module captured before the debris flows occurred and



(a) (b) (c) (d) (e) (f)

Fig. 3 The results of feature-point matching for debris flows from satellite images: (a) before the debris flow in Jiasian; (b) between before and after the debris flow in Jiasian; (c) before the debris flow in Shiaolin; (d) between before and after the debris flow in Shiaolin; (e) before the debris flow in Taimali; (f) between before and after the debris flow in Taimali.

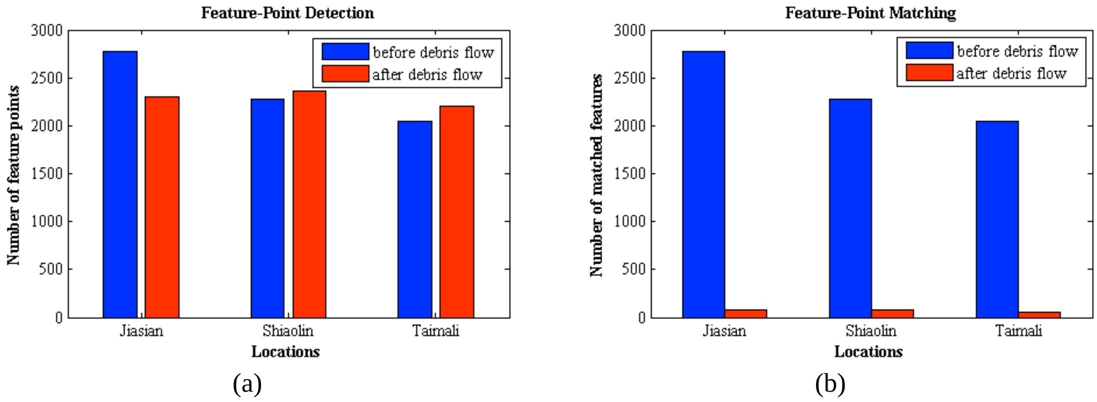


Fig. 4 Statistical chart for satellite image comparison: (a) number of detected feature points; (b) number of matched features points

Figs. 2 (d), 2(e) and 2(f) show the results after the occurrences of debris flows caused by Typhoon Morakot which happened in 2009. In Fig. 2, it can be seen that parts of the mountainside, watercourse, and the adjacent area have been demolished with great variation in the feature points because of the debris flows.

Given the results from Fig. 2, the matched feature points between the before and after the debris flow can be computed using the "feature-point matching" procedure. When a debris flow occurs, the terrain is altered and features in the scenery are changed. The feature-point matching method is used to find stable features which exist both before and after the debris flows. The results of the feature matching method are shown in Fig. 3.

The straight colored lines indicate stable feature points which exist before and after the debris flow. Figs. 3(a), 3(c) and 3(e) show the results of feature-point matching between the background models and the monitored scenes captured before the debris flows. There are a number of matched lines because a lot of stable feature points are detected. Figs. 3(b), 3(d) and 3(f) show the matching results of comparison between the background models and the monitored scenes captured after the debris flows. There is an obvious decrease in the number of matched feature points because the terrain has been significantly altered and features are destroyed.

Fig. 4 charts statistics for feature-point detection and feature-point matching at these three sites showing variance in the number of feature points because of changes in the terrain. Fig. 4(a) shows a change in the number of detected feature points because of debris flows and it can be seen that the number of feature points in Jiasian decreased because of the occurrence of the debris flow; however, this did not happen at Shiaolin or Taimali. The destruction of landforms changed the terrain before and after the debris flows. This change is the criterion that is used to judge the event of a debris flow. Fig. 4(b) shows a statistical chart of the number of the matched feature points at Jiasian, Shiaolin and Taimali. There is a substantial decline in the number of matched feature points because the terrain has been completely altered, which causes significant changes to features. Comparison of the statistical results in Fig. 4(a) with Fig. 4(b) shows the difference in the trends of the number of detected features before and after the occurrence of a debris flow at these three sites. The results show decay (see Fig. 4(b)) at all three different sites, because the terrain has been altered and many stable features have disappeared as a result.

(a)

(b)

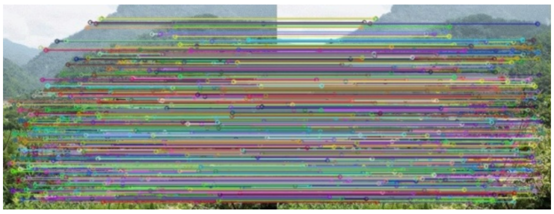
Fig. 5 The results of feature detection of a debris flow captured by a surveillance camera at Shiaolin: (a) before the debris flow; (b) after the debris flow

The results of "feature-point detection" and "feature-point matching" show detectable debris flows from the satellite images. Next, we give an example of the analysis of the images captured by surveillance cameras to prove the feasibility of the proposed process.

6.2 Surveillance images

As part of efforts to prevent terror attacks, different kinds of cameras, including the wide-angle fixed and pan-tilt-zoom (PTZ) cameras, have been erected to monitor abnormal events. We utilize the existing camera devices to monitor debris flows. Fig. 5 illustrates a real case of feature detection in Shiaolin village (using images obtained from the Department of Civil Engineering, National Taiwan University (2013) captured by a surveillance camera). Figs. 5(a) and 5(b) show the results of feature-point detection before and after a debris flow, respectively. In Fig. 5(a) the feature points are uniformly distributed throughout the scene, but after the debris flow, the feature points are concentrated in the lower half of the scene, as shown in Fig. 5(b). The results of feature-point matching captured by the surveillance camera are shown in Fig. 6. Fig. 6(a) shows the results before the debris flow, and Fig. 6(b) shows the results after the debris flow. Clearly, the landforms have been completely destroyed which induces large changes in the distribution of the features in the scene and as a result there are few matched features, as shown in Fig. 6(b).

The statistical results for Fig. 5 are shown in Fig. 7 (a). In this case, there is a drastic decrease in the number of detected feature points because the environment has been completely altered. There is an obvious gap between before and after the debris flow. The variation in the number of matched feature points from Fig. 6 is obvious; the exact statistical results of feature-point matching are shown in Fig. 7 (b).



(a)

(b)

Fig. 6 The results of feature matching captured by a surveillance camera at Shiaolin: (a) before the debris flow; (b) between before and after the debris flow

There is a substantial decline in the number of matched feature points because the environment has been so drastically altered that many of the original and stable feature points have disappeared.

From the above comparisons it is clear that variation in the number of detected and matched feature points can be successfully used to pinpoint debris flows. When a debris flow occurs, the number of detected and matched feature points will change. Both processes are utilized to judge the magnitude and location of the debris flows.

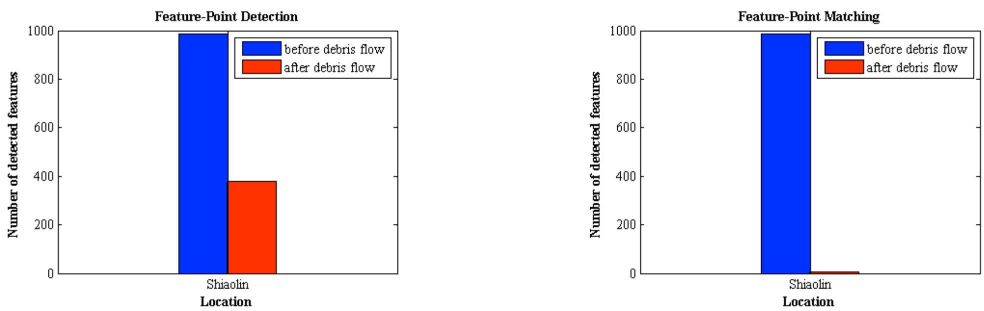
7. Debris flow warning system

In section 6, we proved that the feature based method could be used to detect debris flows in static images. In this section, we utilize the phenomena of obvious gaps and changes in the number of detected and matched feature points before and after the debris flow to construct an event warning system. However, since it would be very difficult to construct an actual full-scale experimental environment in the real world, 3D computer graphics software is utilized to construct a simulation environment of the Hua-Shan area and the Fong-Ciou area in Taiwan for examination of debris flows. A debris flow event warning system is constructed using the feature based method in the simulation environment to prove the feasibility of the proposed method.

7.1 Simulation environments

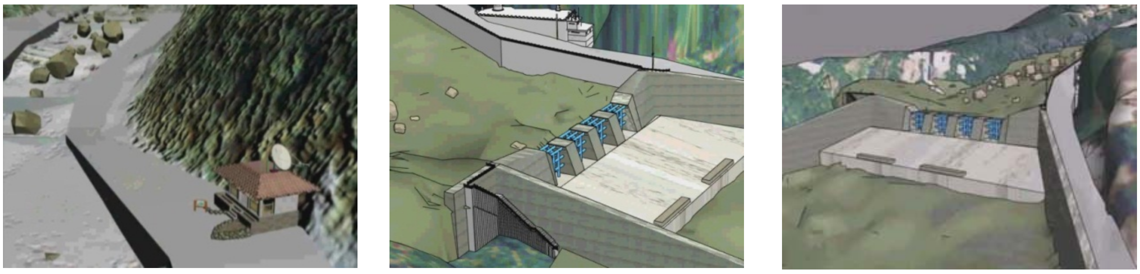
There is a variety of well-known 3D computer graphics software such as 3DS MAX and MAYA which can be used to construct a simulated environment for the model of natural disasters. The user-friendly interface provided by the existing 3D computer graphics software can help programmers to create programs easier and faster.

The simulation environments discussed in this subsection which include different terrains, ranges and velocities of debris flows are easily simulated using 3D computer graphics software. The environments of the Hua-Shan and the Fong-Ciou areas are constructed (using information from the Soil and Water Conservation Bureau and the GIS research Center of Feng-Chia University (2013)). Different perspective views of the simulation environments are shown in Fig. 8. Fig. 8(a) shows the scenario in the Hua-Shan area, and Figs. 8(b) and 8(c) are the different perspectives of the scenario for the Fong-Ciou area.



(a) (b)

Fig. 7 The statistical chart for the surveillance images: (a) number of detected feature points; (b) number of matched feature points



(a) (b) (c)

Fig. 8 Simulation environments: (a) Hua-Shan area; (b)perspective 1 of Fong-Ciou area; (c) perspective 2 of the Fong-Ciou area

In the next section, we discuss the results of feature-point detection and feature-point matching for these two areas, including three cases, one for the Hua-Shan area and two perspectives for the Fong-Ciou area.

7.2 Feature-detection detection in simulation environments

Simulation environments are constructed for simulation of debris flows using 3D computer graphics software. The technique of feature-point detection is used to detect stable features in the observed views and detected feature points which are represented as colored circles. The scenarios in the simulated environments are shown in Fig. 8. The results of feature-point detection in the simulation environments for the Hua-Shan area and the Fong-Ciou area (two perspectives) before the debris flows are shown in Figs. 9 (a)-9(c), respectively.

The behavior of the debris flows was simulated as described in section 6. The number of feature points changed because of the destruction of the terrain when the debris flows happened. The results of feature-point detection in the simulation environments of the Hua-Shan area and the Fong-Ciou area after the debris flows are shown in Figs. 10 (a)-10(c), respectively.

A lot of feature points created by the debris flow appeared. The statistical results for the simulations in Figs. 9 and 10 are illustrated in Fig. 12(a). The blue and the red bars indicate the statistical results for feature-point detection before and after the debris flows, respectively. There is an increase in the number of detected feature points in the different areas after the debris flows, because of changed in the terrain. Newly created features can be detected after the debris flows. The change in the images from before and after the event assists in judging the extent of the debris flow.

7.3 Feature-point matching in the simulation environment

When a debris flow occurs, the distribution of feature points in the environment is altered because the terrain is changed; however, certain stable features can be extracted from the monitoring stream for matching between background module and the current frame even as a debris flow occurs. We use the results of the feature-point detection as shown in Fig. 9 and Fig. 10 in the feature-point matching procedure. The results of the feature-point matching are shown in Fig. 11. Figs. 11 (a), 11(c) and 11(e) show the results of feature-point matching before the debris flows, and Figs. 11 (b), (d) and (f) show the results after the debris flows. The stable features are matched between background module and current frame in this procedure, and the colored lines connect the stable features between the two images.

When debris flows happen, the original features disappear and new features are created, which causes the sudden decrease in the number of matched features. The statistical results for Fig. 11 are shown in Fig. 12(b). As seen in this figure, there is a clear gap between before and after the debris flow. The results of feature-point detection and feature-point matching produced in the simulation environments conform to the results obtained in the real cases described in section 6.

7.4 Debris flow event warning system with multi-criteria decision analysis

In section 6, section 7.2 and section 7.3, we proved that the phenomena of sudden changes in the number of detected feature points and matched feature points occur in both real cases and simulation environments. Now, we integrate "feature-point detection" and "feature-point matching" to construct a debris flow event warning system. In order to increase the accuracy of the debris flow warning system, we propose using a multi-criteria decision system that includes gradient information and the variation of the percentage of feature-points. For each criteria, three simulated cases are used, one for the Hua-Shan area and two perspectives for the Fong-Ciou areas, to prove the feasibility of the proposed system.

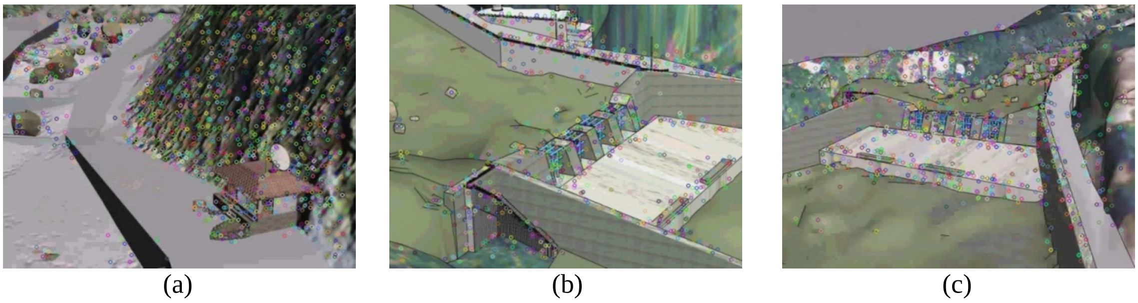


Fig. 9 Simulation environments: (a) Hua-Shan area; (b)perspective 1 of Fong-Ciou area; (c) perspective 2 of the Fong-Ciou area

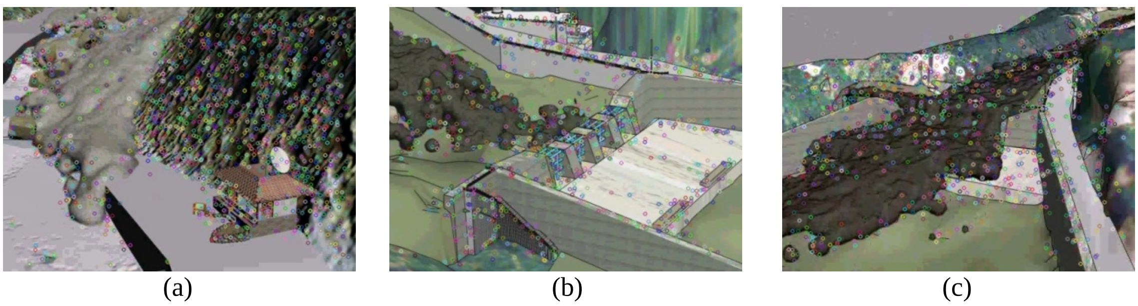


Fig. 10 Results of feature-point detection in the simulation environment after debris flows: (a) Hua-Shan area; (b) perspective 1 of Fong-Ciou area; (c) perspective 2 of Fong-Ciou area

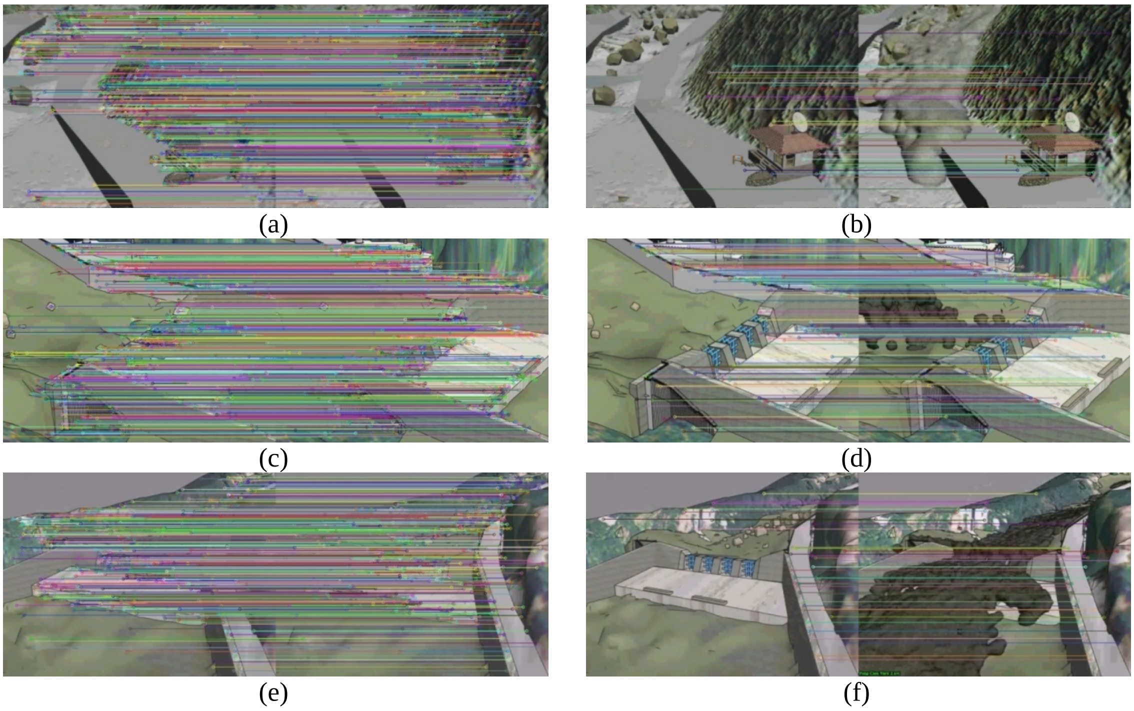


Fig. 11 The results of feature-point matching in the simulation environment. (a) before debris flow in Hua-Shan area; (b) between before and after debris flow in Hua-Shan area; (c) before debris flow in perspective 1 of Fong-Ciou area; (d) between before and after debris flow in perspective 1 of Fong-Ciou area; (e) before debris flow in perspective 2 of Fong-Ciou area; (f) between before and after debris flow in perspective 2 of Fong-Ciou area

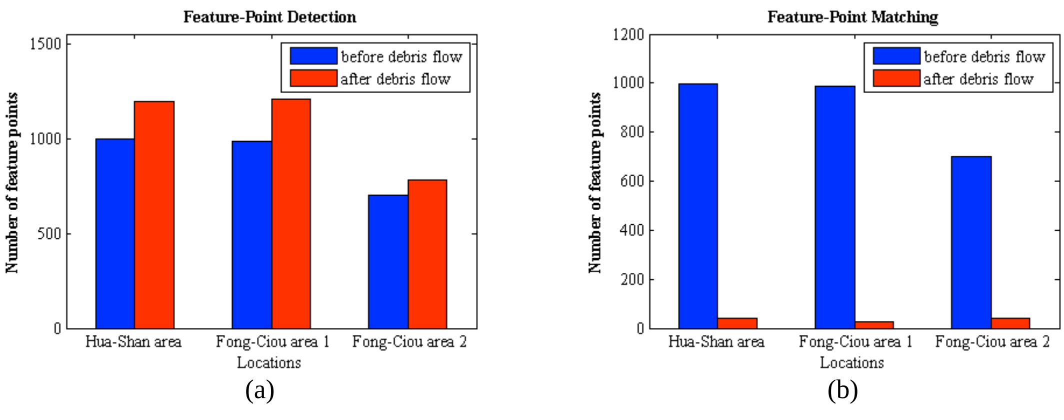


Fig. 12 The statistical chart for the simulation environment: (a) number of detected feature points; (b) number of matched features points

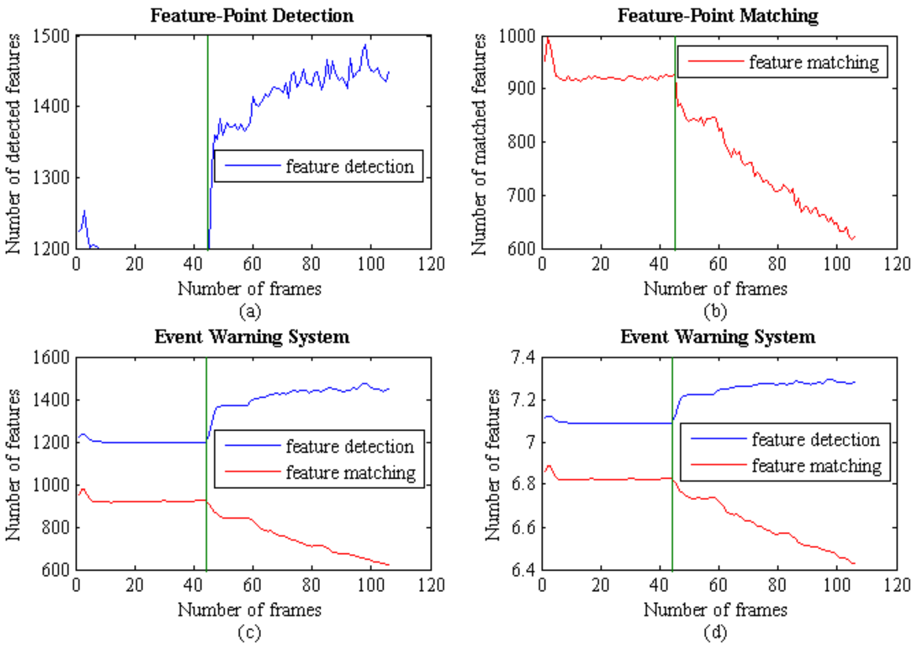


Fig. 13 The duration of the features in the debris flow sequence: (a) the number of detected features without smoothing; (b) the number of matched features without smoothing; (c) the combination of feature detection and feature matching with smoothing for the Hua-Shan area; (d) the combination of feature detection and feature matching with scaling using the log function for the Hua-Shan area

7.4.1 The event warning system using the gradient criteria

In the case of the Hua-Shan area, the number of detected feature points and the number of matched feature points are recorded, as shown in Fig. 13. Figs. 13(a) and 13(b) show the original detected features and the original matched features, respectively.

Figs. 13(a) and 13(b) show rapid changes as indicated by the green lines that identify that a debris flow is beginning to occur. However, using only the number of detected or matched features may cause a false alarm. Therefore, we integrate the results of “feature-point detection” and “feature-point matching” to create a debris flow event warning system that also uses gradient information, as shown in Fig. 13(c).

In order to easily observe sudden changes of gradient in Figs. 13(a) and 13(b), the scale of these two figures is adjusted by using the log function and integrate to produce Fig. 13(d). The green line indicates a sudden change in the number of detected and matched feature points which can assist in detecting the occurrence of debris flows. In this case, the fluctuation in the number of matched feature points is larger than the detected features. The results are combined to form one of the criteria for decisions in a debris flow event warning system.

In the last case, the simulation with the two perspectives of the Fong-Ciou area prove the feasibility of the debris flow event warning system. Figs. 14 and 15 show a combination of feature detection and feature matching for the Fong-Ciou area for the different perspectives. Figs. 14(a) and (b) respectively show the original signal for feature-point detection and matching for perspective 1 in the Fong-Ciou area. Figs. 15(a) and 15(b) are the same as Figs. 14(a) and 14(b), but for perspective 2. The green lines in Figs. 14(c) and 15(c) indicate the debris flow event, while Figs. 14(d) and 15(d) show the results after log function scaling. The phenomena of the sudden changes of gradient in the number of detected and matched features reflect the occurrence of a debris flow.

7.4.2 Event warning system using the percentage of feature variation

In the background module procedure, the average number of detected features and the average number of matched features is evaluated at the same time. The percentage of variation in the features for both feature detection and feature matching is calculated as follows

$$p_{fd_i} = \frac{N_{fd_i}}{Avg_{fd}} \quad \text{and}$$

$$p_{fm_i} = \frac{N_{fm_i}}{Avg_{fm}}, \tag{5}$$

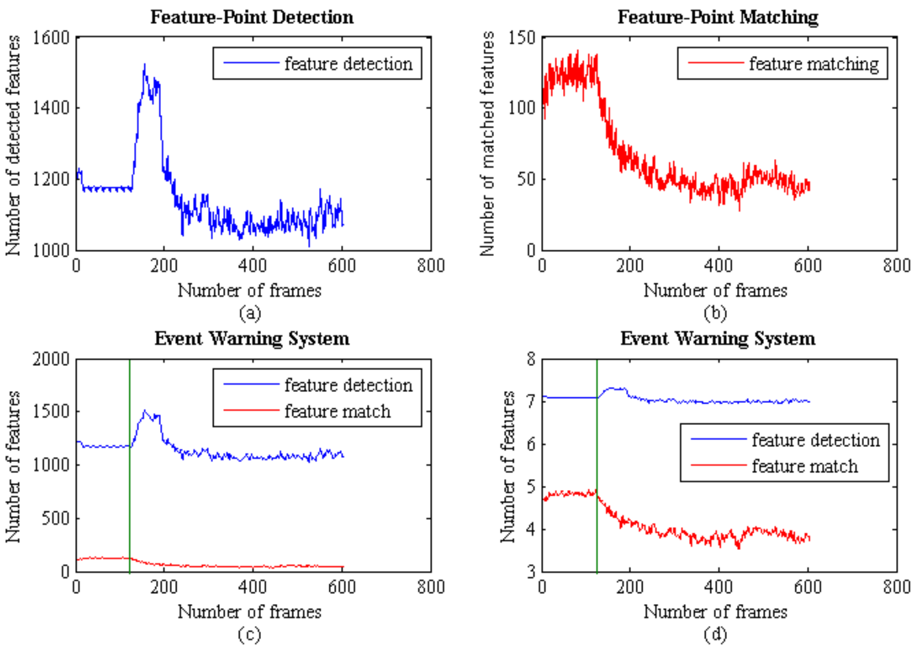


Fig. 14 The duration of features of debris flow sequence (a) the number of detected features without smooth; (b) the number of matched features without smooth; (c) the combination of feature detection and feature matching with smoothing in Fong-Ciou area with perspective 1; (d) the combination of feature detection and feature matching with scaling using log function in Fong-Ciou area with perspective 1

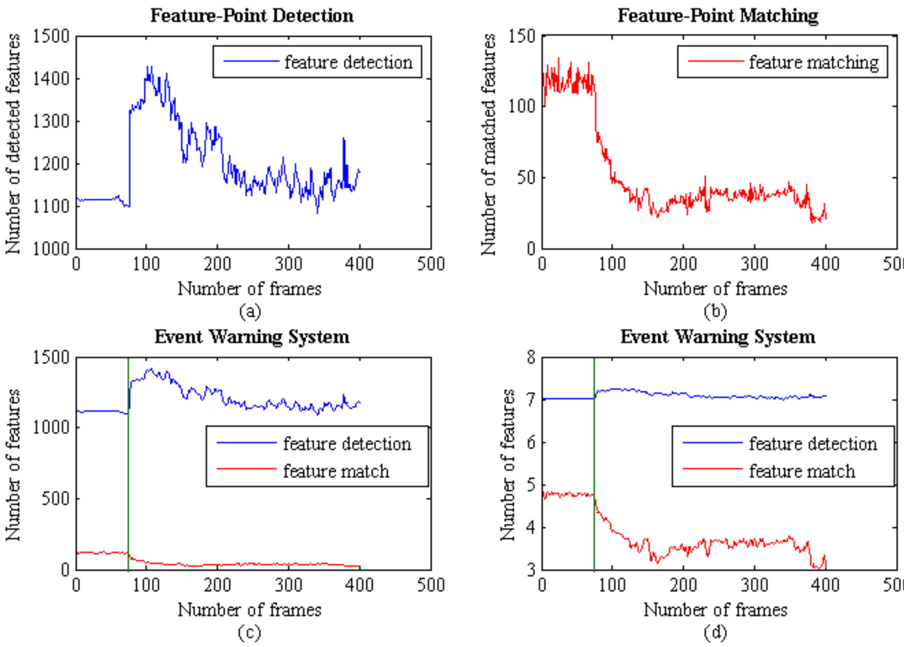


Fig. 15 The duration of features in the debris flow sequence: (a) the number of detected features without smoothing; (b) the number of matched features without smoothing; (c) the combination of feature detection and feature matching with smoothing for perspective 1 in the Fong-Ciou area; (d) the combination of feature detection and feature matching with scaling using the log function for perspective 1 in the Fong-Ciou area

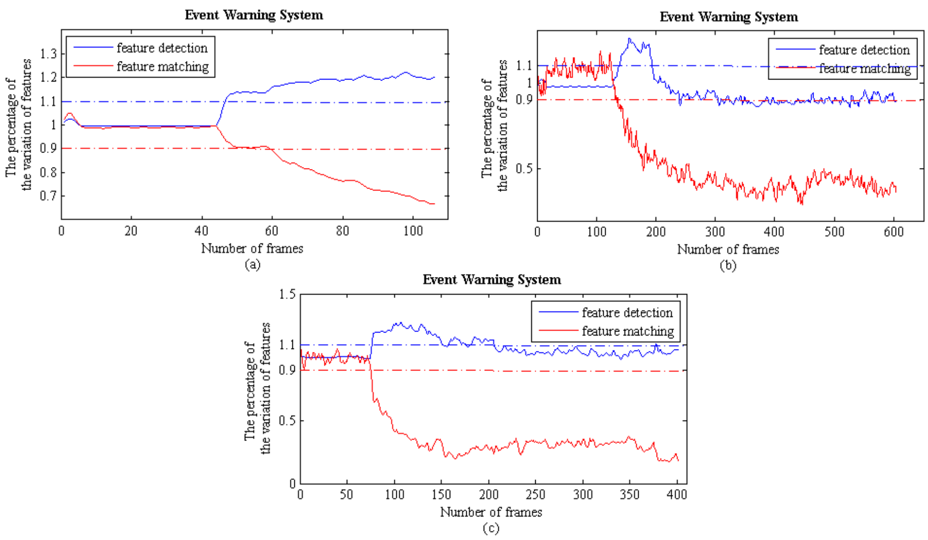


Fig. 16 The percentage of the variation of feature points for: (a) the Hua-Shan area; (b) the Fong-Ciou area, perspective 1; (c) the Fong-Ciou area, perspective 2

where p_{fd_i} and p_{fm_i} are the percentage of variation of features in feature detection and feature matching at time i, respectively; N_{fd_i} and N_{fm_i} are the number of detected feature points and matched feature points, respectively; and Avg_{fd} and Avg_{fm} are the average number of detected features and matched features, respectively, calculated in the background module procedure.

The results of the percentage of variation of feature points are shown in Fig. 16. Figs. 16(a)-(c) show the results for the Hua-Shan area, and Fong-Ciou area, perspective 1 and perspective 2. The red dashed line indicates the threshold of feature matching and the blue dashed line indicates the threshold of feature matching. In the experiments, the thresholds for feature matching and feature detection are set to be 0.9 and 1.1, respectively.

The debris flow event warning system will be triggered if two conditions are satisfied at the same time: a rapid change of gradient and a rapid change in the percentage of variation of feature points within a short period of time.

8. Conclusions

In this study, we utilized a feature based computer vision technique to detect the extent of debris flows and to construct an event warning system. The proposed process is comprised of two modules: a background module and a monitoring module. In the background module, the stable feature points are learned from a sequence of scenes using feature-point detection and the average number of feature points for feature detection and feature matching are detected. The feature-point detection process is used to detect the features from the observed view by using a feature based method. In monitoring module, both feature-point detection and feature-point matching are used. The results of feature-point detection are used in feature-point matching to find stable and matching feature points by comparison between the background module and the current scene. Debris flows are detected from the difference between the features detected and matched before and after the occurrence of a natural disaster.

A framework for constructing a debris flow event warning system is proposed that includes gradient information and the percentage of variation in the features. The background module and the monitoring module are combined, and the variation in the number of detected and matched features observed. The effectiveness of the detection and warning system is tested using 3D computer graphics software to simulate a debris flow as an example. The results of the debris flow detection in the simulation environment correspond to the results using real cases, and the event warning system is triggered when a debris flow occurs.

The current system utilizes images captured during the day. In the future, we will consider the effects of light and other weather conditions and apply the feature-based method to other types of structural damage analysis such as to buildings and bridges.

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