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Hazard analysis and monitoring for debris flow based on intelligent fuzzy detection

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Abstract. This study aims to develop the fuzzy risk assessment model of the debris flow to verify the accuracy of risk assessment in order to help related organizations reduce losses caused by landslides. In this study, actual cases of landslides that occurred are utilized as the database. The established models help us assess the occurrence of debris flows using computed indicators, and to verify the model errors. In addition, comparisons are made between the models to determine the best one to use in practical applications. The results prove that the risk assessment model systems are quite suitable for debris flow risk assessment. The reproduction consequences of highlight point discovery are shown in highlight guide coordinating toward discover steady and coordinating component focuses and effectively identified utilizing these two systems, by examining the variety in the distinguished highlights and the element coordinating.

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

1. Introduction

Since then debris flows have often occurred after heavy rains, leading to serious damage. Especially in the recent years, several typhoons have struck southeast Asia bringing high rainfall accumulations. These are all key factors affecting the occurrence of debris flows. There are many rivers and streams considered to have the potential for debris flows. It is obvious that the risk of debris flows has become more and more significant. To develop a risk assessment model for debris flows to verify the accuracy of risk assessment would help related organizations reduce losses caused by landslides (Gucunski *et al*. 2015). The established models should help us to assess the likelihood of the occurrence of debris flows using computed indicators, to verify modeling errors, and make comparisons between the models to determine the best one to use in practical applications. In the establishment of a debris flow risk assessment model, the major factors affecting landslides include the average terrain slope, rainfall, watershed area, effective watershed area, rainfall intensity, and geological conditions.

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Van Aalst (2006) has depicted the variables that impact atmosphere changes and the connection between environmental change and outrageous climate marvels. It is especially essential for creating nations to create and apply procedures for the counteractive action and alleviation of the impacts of cataclysmic events (Alcántara-Ayala 2002). There have been a few ongoing works exploring the procedure of hazard evaluation, examining the sorts of harm that can be brought about by cataclysmic events and proposing diverse kinds of the models to survey the harm (see for example, Douglas (2007), Lin *et al.* (2013), Huynh *et al.* (2017), and Yu *et al*. (2018). Numerous strategies have been utilized to examine the conditions that lead to the event of hazards. Debris flows are a very common type of natural disaster. There are many conditions affecting the occurrence of debris flows, but some are very difficult to investigate. Fuzzy theory is the most commonly-used tool to predict the probability of debris flows. Lu *et al.* (2007) proposed a GIS-based decision support system, which incorporated local topographic and rainfall effects on debris flow vulnerability. Lin *et al.* (2009) argued that the proposed SVM-based (support vector machines) models offer better performance, and are more robust, and efficient than the existing BPN-based models. Fleissner *et al*. (2009) also presented a new approach that can aid the design of protective barriers. An uncertainty analysis of the flow around a debris barrier is carried out using a chute flow laboratory model of the actual debris flow.

Various investigations of seismic tremors have been completed in the course of the most recent couple of decades. Allen and Kanamori (2003) proposed a quake caution framework which utilizes the recurrence of the arriving P-waves to decide the extent of the tremor, using this data to caution of harming ground movement. Also, they utilized remotely detected satellite remote information to distinguish the harm brought about by tremors. Remote sensors are another sort of gadget which can be utilized to identify the catastrophic events. Lin *et al*. (2013) utilized a double camera to build a wide-edge, high-goals checking framework, which could watch itemized data. A few strategies have been proposed to address the issue of the cataclysmic events recognition and to develop a notice framework for the catastrophic events.

2. System architecture

Fuzzy concepts can generate uncertainty because they are imprecise (especially if they refer to a process in motion, or a process of transformation where something is "in the process of turning into something else"). In that case, they do not provide a clear orientation for action or decision-making; reducing fuzziness, perhaps by applying fuzzy logic, might generate more certainty. With the development of fuzzy logic, some mathematical models have been developed based on fuzzy theories and elaborated on to achieve greater accuracy, dimensionality and also to simplify the structure of the model. Compared with conventional mathematical models, the main advantage of the fuzzy model is the possibility of elaborating them on the basis of far less information concerning a real system and in addition, the information can be of an uncertain, fuzzy or inexact character. These fuzzy models include Mamdani, relational, T-S types etc. Fuzzy Logic Systems Architecture (shown in Fig. 1) include fuzzification module to transforms the system inputs, knowledge base to store IF-THEN rules provided by experts, inference engine to simulate the human reasoning process and defuzzification module to transform the fuzzy set into a crisp value. The average slope, catchment area, effective catchment area, accumulated rainfall, rainfall intensity, and geological conditions are used as system inputs. Membership functions of these parameters are defined first. Then these membership functions are used to fuzzify the input values. Output values are obtained

after defuzzification is performed by applying Mamdani's fuzzy inference method. The output values are used to determine the result of categorization.
This study defines 6 factors according to the parameter information in Table 1. These weighting factors are used for the highlight the strength of the measure spots. We define three levels of the weighting values by 0, 1, and 2. That means the fuzzy variables are classified in three levels, low, medium and high with 0, 1, and 2. Debris flows often occur in terrains with slopes of 15-22 degrees. Terrains with slopes of over 22 degrees often directly collapse due to unstable earth. Therefore, before the occurrence of debris flows, they often collapse to form gentler slopes. Thus, the gradient criterion for a middle risk of debris flow is set to 22 degrees. This means that larger values of parameters do not necessarily mean higher risk (e.g., average gradient). A value of w_i is given to each of the other factors in ascending order. Finally, all the values of w_i are added up to determine the resultant output by the system.
This study selects 6 influential factors and, because there are interactions between them, the fuzzy system rules are built using “and”. Considering the completeness of the system rules, we assign degrees of belonging to the categories (w) to each parameter. The values of w for the variables are listed in table 1. There are 3 w values for each parameter, and there are 6 parameters. Therefore, there are a total of 729 rules with all the combinations. The rules are constructed with the Malab Fuzzy Toolbox as in figure 2. The rules include low-risk, middle-risk, and high risk rules. The fuzzy rules constructed for this study are shown in table 2. The sum of weighing ranges from 0-3 is sorted in low riskiness, 4-8 in medium riskiness, and 9-12 in high riskiness.

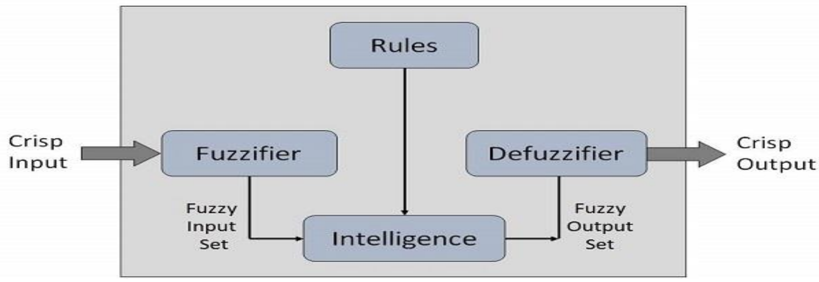


Fig. 1 The system architecture of the fuzzy-rule-based decision system

Table 1 Parameter settings for fuzzy variables

Variable	w_i	W=0	W=1	W=2
Average gradient (∘)	W_1	15	22	18.5
Catchment area (ha)	W_2	30	65	100
Effective catchment area (ha)	W_3	42	71	100
Accumulated rainfall (mm)	W_4	238	369	500
Rainfall intensity (mm/hr)	W_5	27	43.5	60
Geological conditions	W_6	1	2	3

Table 2 Fuzzy system rules

Sum of w_i	Low risk	Medium risk	High risk
$\sum_{i=1}^{6} Wi$	0~3	4~8	9~12

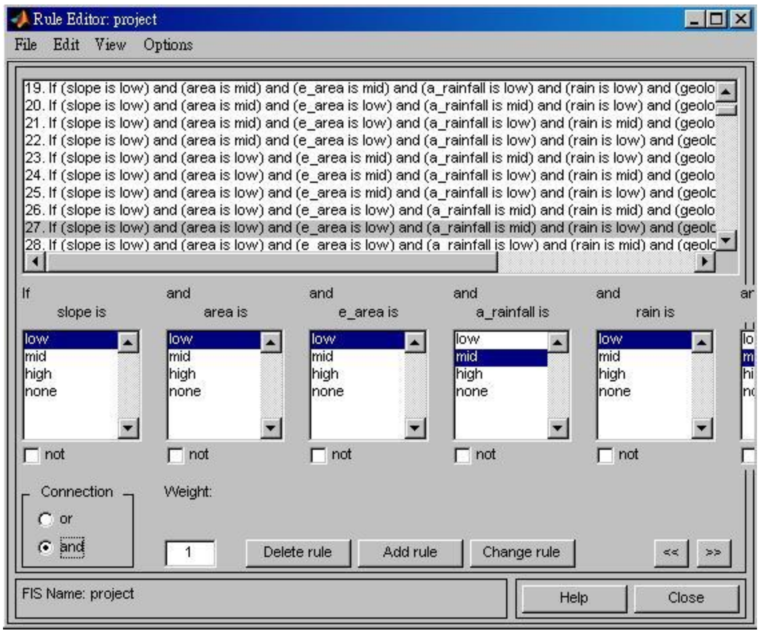


Fig. 2 User interface of the fuzzy rule editor

The w values of each input variables are added up to obtain the output w value. By referencing table 2, the risk category of debris flow can be inferred.

The proposed framework plans to distinguish avalanches and caution of the peril. So as to build an occasion cautioning framework, a few imperative assignments must be considered. The proposed framework incorporates three principle specialized segments: the foundation module, the observing module, and the occasion cautioning framework. To start with, we decide the steady element focuses for the foundation module by utilizing the element discovery technique. In this technique, a grouping of scenes from before the event of avalanche is utilized to locate the steady component focuses which are joined for the foundation module. Next, the observing module is created by utilizing the component point identification strategy and highlight point coordinating technique. The component point location technique is utilized to discover the element focuses om the present scene, and the element point coordinating strategy is utilized to coordinate element focuses between the foundation module and the present scene. The quantity of recognized and coordinated element focuses show extreme variances. At long last, we incorporate the data from the checking module to develop the occasion cautioning framework.

If the numerators of the output value ratios are close to the ones of the actual value ratios and the same is true for the denominators, then the adaptation of normalized relative errors becomes meaningful, and the required relative errors can be further obtained. The formulas (1) used to calculate these values are listed below

$$E = \frac{\sqrt{\frac{1}{n}\left[\ (a_1 - b_1)^2 + (a_2 - b_2)^2 + \ldots + (a_n - b_n)^2\ \right]}}{\sqrt{\frac{1}{n}\left(\ a_1{}^2 + a_2{}^2 + \ldots + a_n{}^2\ \right)}} \tag{1}$$

n : Number of terms; a : Actual value ratio; b : Output value ratio.

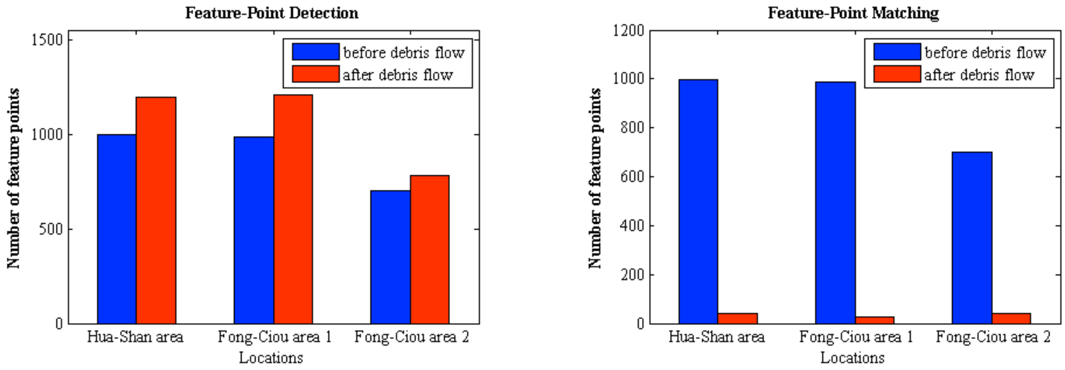
Both ratios are unitless, satisfying the unit consistency. This means that when the numerators and denominators of the fuzzy system output values and actual values are very close.

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. 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 $\det(H_{approx}) = D_{xx}D_{yy} - (\omega D_{xy})^2$, where ω is a parameter used to verify the errors cause by the DoG which is used to approximate LoG.

3. Monitoring module and detection example

The physical condition is developed of a wide range of sorts of highlights, both characteristic (trees, mountains, water) and artificial. The highlights in the characteristic landscape change in light of changes in the landforms brought about by the cataclysmic events (Gattulli *et al.* 2016; Hiasa *et al.* 2016, You *et al.* 2014, Kim *et al*. 2014, Li *et al*. 2014). Lately, the events of avalanches have expanded as a result of the disregard of soil and water preservation and the event of increasingly extraordinary climatic changes and this has made outrageous harm the earth. The achievability of the proposed technique which joins highlight point discovery and highlight point coordinating for the recognition of avalanches is talked about. Two sorts of static pictures are breaking down, the satellite and observation pictures caught by satellites and reconnaissance cameras. From the above examinations plainly variety in the quantity of identified and coordinated component focuses can be effectively used to pinpoint avalanches. At the point when an avalanche happens, the quantity of distinguished and coordinated component focuses will change. The two procedures are used to pass judgment on the extent and area of the avalanches.

There is an assortment of understood 3D PC illustrations programming, for example, 3DS MAX and MAYA which can be utilized to develop a re-enacted domain for the displaying of catastrophic events. The easy to use interface given by the current 3D PC designs programming can assist software engineers with creating programs simpler and quicker. In the following segment, we talk



(a) (b)

Fig. 3. The statistical chart for the simulation environment: (a) number of detected feature points and (b) number of matched features points

about the aftereffects of highlight point discovery and highlight point coordinating for these two zones.

The results of the feature-point matching are shown in Fig. 3. The stable features are matched between background module and current frame in this procedure, and the coloured lines connect the stable features between the two images. When landslides 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. 3 are shown in Fig. 4(b). As seen in this figure, there is a clear gap between before and after the landslide. The results of feature-point detection and feature-point matching produced in the simulation environments conform to the results obtained in the real cases.

We incorporate "highlight point recognition" and "highlight point coordinating" to build an avalanche occasion cautioning framework. So as to build the exactness of the avalanche cautioning framework, we propose utilizing a multi-criteria choice framework that incorporates slope data and the variety of the level of highlight focuses. Figs. 4(a) and 4(b) show rapid changes as indicated by the green lines that identify that a landslide 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 landslide event warning system that also uses gradient information, as shown in Fig. 4(c).

In order to easily observe sudden changes of gradient in Figs. 4(a) and 4(b), the scale of these two figures is adjusted by using the log function and integrate to produce Fig. 4(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 landslides. 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 landslide event warning system.

In the last case, the simulation with the two perspectives prove the feasibility of the landslide event warning system. Figs. 4(a) and 4(b) are the same of indicate the landslide event, while Fig. 4 (d) shows 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 landslide.

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:

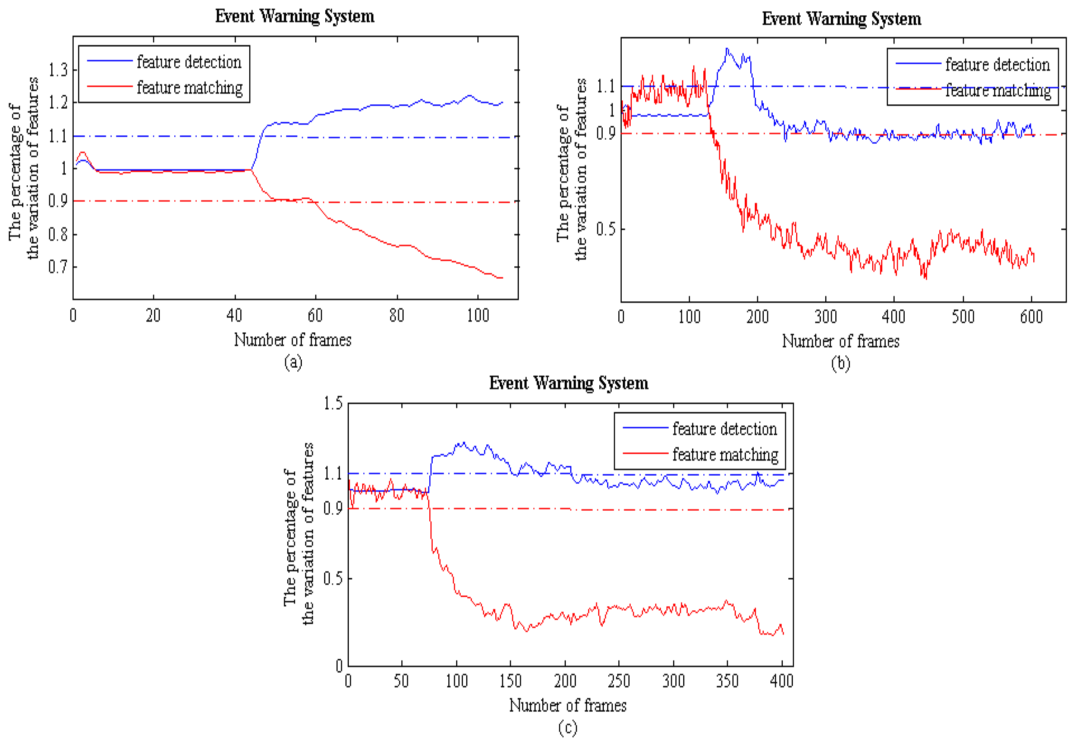


Fig. 4 The percentage of the variation of feature points for: (a) the Hua-Shan area, (b) the Fong-Ciou area, perspective 1 and (c) the Fong-Ciou area, perspective 2

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

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 landslide 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.

4. Conclusions

There is possible explanation for the traditional lack of use of fuzzy logic by social scientists is simply that, beyond basic statistical analysis (using programs such as SPSS and Excel) the mathematical knowledge of social scientists is often rather limited; they may not know how to formalize and code a fuzzy concept using the conventions of fuzzy logic. The standard software packages used provide only a limited capacity to analyze fuzzy data sets, if at all, and considerable skills are required. To simply and strengthen the merits of the artificial intelligent approaches, we used an element based PC vision method to identify the degree of avalanches and to develop an occasion cautioning framework. The proposed procedure is involved two modules: a foundation module and a checking module. Out of sight module, the steady element focuses are gained from a grouping of scenes utilizing highlight point identification and the normal number of highlight focuses for highlight recognition and highlight coordinating are recognized. The component point recognition process is utilized to distinguish the highlights from the watched view by utilizing an element based technique. In checking module, both component point discovery and highlight point coordinating are utilized. The consequences of highlight point identification are utilized in highlight direct coordinating toward discover steady and coordinating component focuses by examination between the foundation module and the present scene. Avalanches are distinguished from the contrast between the highlights identified and coordinated when the event of a cataclysmic event. A structure for developing an avalanche occasion cautioning framework is recommended that incorporates slope data and the level of variety in the highlights. The foundation module and the checking module are consolidated, and the variety in the quantity of recognized and coordinated highlights watched. The viability of the recognition and cautioning framework is tried utilizing 3D PC designs programming to reproduce an avalanche for instance. The consequences of the avalanche recognition in the re-enactment condition compare to the outcomes utilizing genuine cases, and the occasion cautioning framework is activated when an avalanche happens. The present framework uses pictures caught amid the day. Later on, we will think about the impacts of light and other climate conditions and apply the element based strategy to different sorts of basic harm investigation, for example, to structures and scaffolds.

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