Int. J. of GEOMATE, June, 2015, Vol. 8, No. 2 (Sl. No. 16), pp. 1226-1231
Geotech., Const. Mat. and Env., ISSN:2186-2982(P), 2186-2990(O), Japan

IDENTIFICATION OF SLOPES WITH HIGHER RISK TO SLOPE FAILURES BASED ON INFORMATION PROCESSING TECHNIQUES

Shinichi Ito[1], Kazuhiro Oda[2], Keigo Koizumi[3] and Yohei Usuki[4]

[1,2,3,4] Osaka University, Japan

ABSTRACT: In recent times, the sediment disasters, such as slope failures, debris flows, and landslides, caused by typhoons or cloudbursts have occurred in Japan. The progression of global warming will increase the scale of typhoons and cloudbursts striking the Japanese Islands, and there is a concern that the frequency of sediment disasters may increase. Therefore, it is important to identify slopes with a higher risk to sediment disasters to prevent future disasters. In this study, a method based on artificial neural networks and mathematical statistics was used to identify such slopes. In the proposed method, the self-organizing map (SOM), cluster analysis, and Hayashi's second method of quantification are combined. The proposed method was applied to the data gathered from periodical inspections of road slopes. In the results, slopes with a higher risk to slope failure were identified and ranked according to their risk.

Keywords: Sediment disasters, Data from periodical inspections, Self-organizing map (SOM), Cluster analysis, Hayashi's second method of quantification

1. INTRODUCTION

In Japan, where mountainous districts occupy 70% of the land, sediment disasters, such as slope failures, debris flows, and landslides have occured each year [1]. With the progression of global warming, the intensity of rainfall brought by typhoons and cloudbursts has become more severe, and correspondingly, the number of sediment disasters in Japan has also increased. Therefore, disaster prevention planning for future sediment disasters should be established.

In Japan, periodical inspections of road slopes are conducted to prevent future sediment disasters [2]. These periodical inspections are performed about every 5 years, and the data are gathered and integrated into a database. However, the data are, as yet, not used effectively and should be further used to identify slopes with a higher risk to sediment disasters.

There are endogenous and exogenous factors related to the occurrence of sediment disasters. Endogenous factors refer to the characteristics of slopes such as topographical and geological features. Exogenous factors refer to those that trigger the occurrence of sediment disasters such as rainfall and ground water. It is difficult to forecast the time, location, and quantity of rainfall that is expected, and therefore, it is useful to identify slopes with a higher risk to sediment disasters based on endogenous factors.

As there are innumerable slopes in Japan, the amount of data gathered from periodical inspections of road slopes is enormous. In addition, the time and expense needed to analyze this data are limited. Thus, a method for analyzing the characteristics of these slopes as efficiently and effectively as possible to identify slopes with a higher risk to sediment disasters is necessary. The method must be able to treat a large amount of data, and therefore, methods using artificial neural networks and mathematical statistics should be applied.

The authors proposed a new method for identifying slopes with a higher risk to deep-seated catastrophic landslides by applying the proposed method to topographical information [3]. In the proposed method, the self-organizing map (SOM) (an artificial neural network technique) [4], cluster analysis (a mathematical statistics) [5], and Hayashi's second method of quantification (a quality determination method) [6] are combined.

In this study, we applied the proposed method to data gathered from periodical inspections of road slopes to identify slopes with a higher risk to slope failure. The purpose of this study is to identify slopes with a higher risk to slope failure and to prioritize these slopes.

2. ANALYTICAL METHOD

2.1 Self-organizing map (SOM)

The SOM is an artificial neural network technique. The SOM is known to be an effective technique for analyzing high-dimensional data. In other words, high-dimensional vectors can be mapped to two dimensional space for visual understanding. The two-dimensional representation can then be used to observe patterns and correlations present in the high-dimensional data. In addition, vectors with similar characteristics are placed closer on the two-dimensional map and dissimilar vectors are located farther apart. Therefore, high-dimensional vectors can be automatically classified into several clusters when SOM is applied to them. Fig.1 shows an example of an analytical result of SOM. There are several parts with warm colors with certain vectors gathering at each warm color part. A set of vectors gathering at a warm color part is a cluster.

However, SOM has a disadvantage. It is difficult to classify high-dimensional vectors into several groups objectively. For example, from the result of Fig.1, some users may classify them into five groups bounded by the white circles as shown in Fig.2. On the contrary, users may classify them into five groups bounded by the black circles. The subjective judgment of the user controls the clustering based on visual mapping.

2.2 Cluster analysis

Cluster analysis is one of the representative techniques in mathematical statistics. It can objectively divide a set of high-dimensional vectors into several clusters that are fixed previously according to the similarity between the high-dimensional vectors. However, cluster analysis also has a disadvantage. It is necessary to determine previously the number of clusters before conducting the cluster analysis. The number of clusters cannot be determined automatically unlike SOM. It is difficult to determine the number of clusters without preliminary analysis.

2.3 Combination of SOM and cluster analysis

In this study, both SOM and cluster analysis were combined to overcome the two disadvantages of objective clustering in SOM and determination of the number of clusters in cluster analysis. The analytical process is follows. First, the number of clusters is visually determined by SOM. Then the number of clusters is applied to cluster analysis, and the objective clustering is performed. The results of cluster analysis are plotted on the map of SOM. If the number of clusters is wrong, the analytical results of SOM and cluster analysis are not matched as shown in Fig.3. However, if the correct number of clusters is applied to cluster analysis, the analytical results of SOM and cluster analysis are matched as shown in Fig.4.

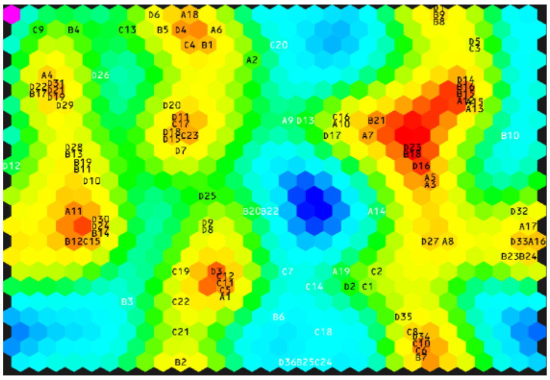

Fig.1 Example of analytical result of SOM

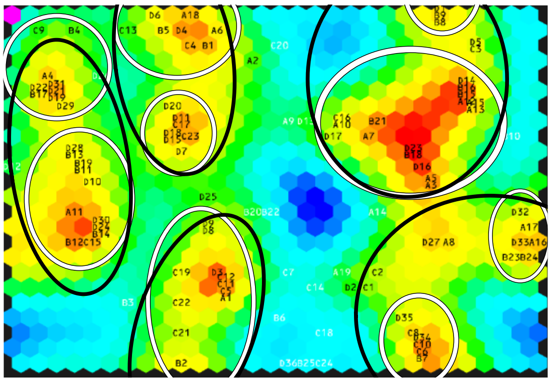

Fig.2 Different clusters of SOM by individual difference

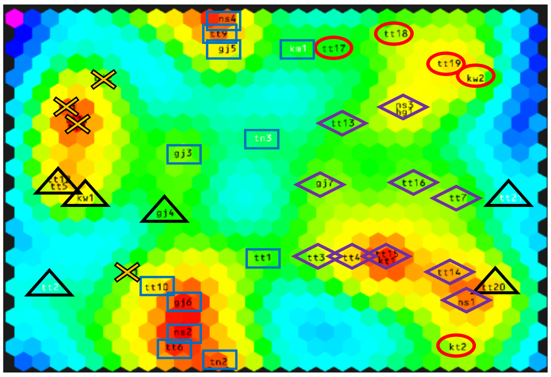

Fig.3 Analytical result of SOM and cluster analysis in case of applying wrong number of clusters

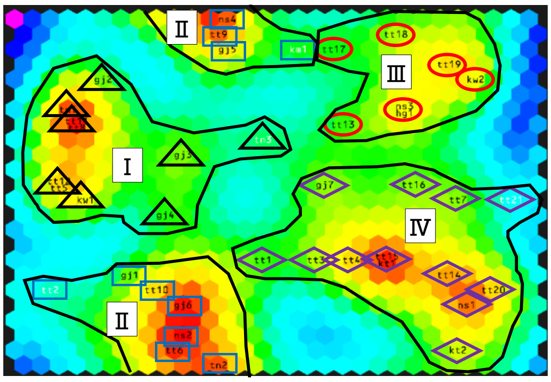

Fig.4 Analytical result of SOM and cluster analysis in case of applying correct number of clusters

2.4 Hayashi's second method of quantification

Hayashi's second method of quantification is a method of mathematical statistics. It is known as a representative technique of the discrimination analysis. This method treats categorical data and derives dependent variables from an explanatory variable. In other words, Hayashi's second method of quantification can divide one group into two groups.

Therefore, when Hayashi's second method of quantification is applied to slopes, the slopes can be estimated to fail or not fail.

2.5 Method for identifying slopes with higher risk to slope failures

In this study, the proposed method was applied to data gathered from periodical inspections of road slopes to identify slopes with a higher risk to slope failure. Fig.5 shows the flowchart of the proposed method. The proposed method has three stages.

In the first stage, only failed slopes are grouped into several clusters through a combination of SOM and cluster analysis. There are all sorts of failed slopes and all failed slopes do not necessarily have the same characteristics. Therefore, the failed slopes are grouped into several clusters in which the failed slopes have almost similar characteristics in order to effectively perform the following discriminant analysis.

In the second stage, Hayashi's second method of quantification, one of the representative methods of discriminant analysis, is applied to the set of slopes that includes the failed slopes in a cluster and all the not-failed slopes to identify slopes with a higher risk to slope failure. Slopes with a higher risk to slope failure can be identified this way.

In the third stage, slopes with a higher risk are given a rank according to the sample score of Hayashi's second method of quantification. The sample score indicates the risk of slopes; slopes with a higher sample score have a higher risk to slope failure. Additionally, Hayashi's second method of quantification also gives the score of the boundary between slopes that fail and those that do not. In this study, the rank of slopes was determined by the difference between the sample score and the score of the boundary. In other words, the slopes having a higher difference between the sample score and the score of the boundary were given a higher rank.

In this way, the proposed method, which is based on SOM, cluster analysis, and Hayashi's second method of quantification, can identify slopes with a higher risk to slope failure and rank these slopes.

3. APPLICABLE DATA

From the data gathered from periodical inspections of road slopes, that for the year 1996 was used. The data contains 128 slopes along expressways and 89 slopes along national roads. There are eight failed slopes along expressways and 29 failed slopes along national roads in the data gathered from periodical inspections of road slopes. Table 1 shows the parameters used to estimate the risk of each slope, and the categorical data corresponding to each parameter.

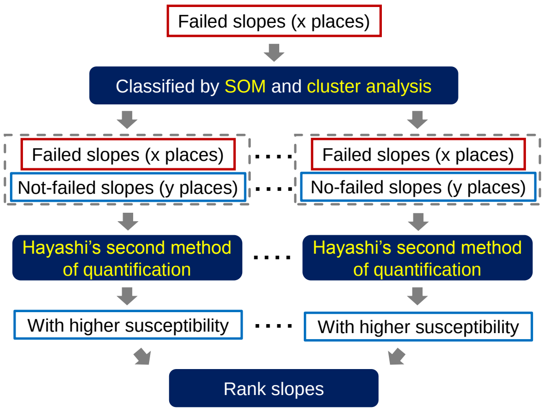

Fig.5 Method of identifying slopes with higher risk

Table 1 Parameters and categorical data

parameters		categorical data
talus cone	0	0
	1	0.5
	2 or more	1
soil	stable	0
	medium	0.5
	fragile	1
lithology	stable	0
	medium	0.5
	fragile	1
formation	opposite slope	0
	dip slope	1
difference of permeability	small	0
	medium	0.5
	large	1
topsoil, loose part rock, boulder stone	stable	0
	medium	0.5
	unstable	1
spring water	without spring	0
	leakage	0.5
	spring	1
covering condition	construct	0
	compound	0.5
	vegetation, bare land	1
height of slopes	$H < 15$	0
	$15 \leqq H < 30$	0.333
	$30 \leqq H < 50$	0.666
	$50 \leqq H$	1

4. ANALYTICAL RESULTS

4.1 Analytical results of the first stage

The proposed method was applied to 217 slopes (37 failed slopes and 180 not-failed slopes). At first, only the failed slopes were classified into several clusters by SOM and cluster analysis. Fig.6 shows the analytical result of clustering. The result of SOM and cluster analysis was matched as shown in Fig.6, so that the failed slopes could be classified into five clusters. The characteristics of the failed slopes in each cluster were checked and the distribution conditions of the failed slopes in each cluster with respect to each parameter are shown in Table 2.

There were seven failed slopes in cluster 1. All of them were along the slopes of expressways, and almost all of them had parameters associated with relatively lower risk to slope failures. However, the failed slopes in cluster 1 had higher slopes heights.

There were seven failed slopes in cluster 2. All of them were dip slopes. In addition, almost all of them were associated with fragile lithology. However, their other parameters had relatively lower risk to slope failures.

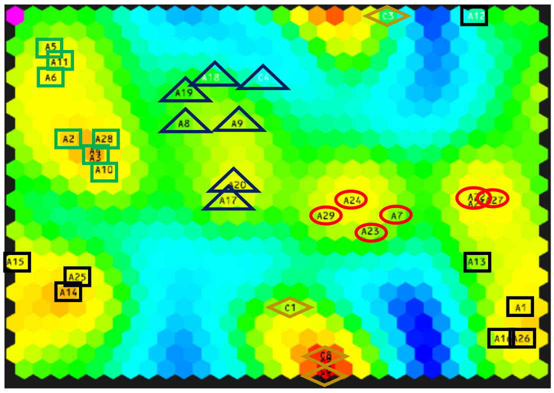

Fig.6 Analytical result of SOM and cluster analysis

Table 2 Distribution condition of failed slopes in each cluster with respect to each parameter

(a) Cluster 1

parameters		number of slopes	parameters		number of slopes
talus cone	0	5	topsoil, loose part rock,	stable	7
	1	2		medium	0
	2 or more	0		unstable	0
soil	stable	6	spring water	without spring	1
	medium	1		leakage	6
	fragile	0		spring	0
lithology	stable	7	covering condition	construct	1
	medium	0		compound	6
	fragile	0		vegetation, bare	0
formation	opposite slope	7	height of slopes	$H<15$	0
	dip slope	0		$15\leqq H<30$	0
difference of permeability	small	7		$30\leqq H<50$	5
	medium	0		$50\leqq H$	2
	large	0			

(b) Cluster 2

parameters		number of slopes	parameters		number of slopes
talus cone	0	2	topsoil, loose part rock,	stable	4
	1	2		medium	3
	2 or more	3		unstable	0
soil	stable	4	spring water	without spring	2
	medium	3		leakage	2
	fragile	0		spring	3
lithology	stable	0	covering condition	construct	4
	medium	1		compound	3
	fragile	6		vegetation, bare	0
formation	opposite slope	0	height of slopes	$H<15$	2
	dip slope	7		$15\leqq H<30$	1
difference of permeability	small	3		$30\leqq H<50$	2
	medium	4		$50\leqq H$	2
	large	0			

(c) Cluster 3

parameters		number of slopes	parameters		number of slopes
talus cone	0	1	topsoil, loose part rock,	stable	1
	1	2		medium	5
	2 or more	4		unstable	1
soil	stable	2	spring water	without spring	5
	medium	2		leakage	2
	fragile	3		spring	0
lithology	stable	0	covering condition	construct	7
	medium	0		compound	0
	fragile	7		vegetation, bare	0
formation	opposite slope	7	height of slopes	$H<15$	1
	dip slope	0		$15\leqq H<30$	3
difference of permeability	small	1		$30\leqq H<50$	1
	medium	6		$50\leqq H$	2
	large	0			

(d) Cluster 4

parameters		number of slopes	parameters		number of slopes
talus cone	0	0	topsoil, loose part rock,	stable	0
	1	2		medium	4
	2 or more	6		unstable	4
soil	stable	0	spring water	without spring	1
	medium	0		leakage	4
	fragile	8		spring	3
lithology	stable	0	covering condition	construct	1
	medium	1		compound	4
	fragile	7		vegetation, bare	3
formation	opposite slope	8	height of slopes	$H<15$	6
	dip slope	0		$15\leqq H<30$	2
difference of permeability	small	1		$30\leqq H<50$	0
	medium	6		$50\leqq H$	0
	large	1			

(e) Cluster 5

parameters		number of slopes	parameters		number of slopes
talus cone	0	0	topsoil, loose part rock,	stable	1
	1	0		medium	4
	2 or more	8		unstable	3
soil	stable	0	spring water	without spring	1
	medium	0		leakage	5
	fragile	8		spring	2
lithology	stable	0	covering condition	construct	4
	medium	0		compound	2
	fragile	8		vegetation, bare	2
formation	opposite slope	0	height of slopes	$H<15$	6
	dip slope	8		$15\leqq H<30$	1
difference of permeability	small	1		$30\leqq H<50$	1
	medium	7		$50\leqq H$	0
	large	0			

There were seven failed slopes in cluster 3. All of them were associated with fragile lithology, but not with dip slopes. In addition, they were covered with concrete constructions.

There were eight failed slopes in cluster 4. All of them were associated with fragile soils, and almost all of them were associated with two or more talus cones and fragile lithology. However, they were not associated with dip slopes, and they had relatively lower heights.

There were eight failed slopes in cluster 5. All of them were associated with the highest risk categories of four parameters (talus cone, soil, lithology, formation). In addition, the other parameters had relatively higher risk categories. Therefore, the failed slopes in cluster 5 had the highest risk to slope failures in the five clusters.

4.2 Analytical results of the second stage

In this study, the characteristics of failed slopes were classified into five clusters according to their characteristics. Thus, the five clusters and not-failed slopes made five groups. Cluster 1 and all the not-failed slopes formed group 1, cluster 2 and all the not-failed slopes formed group 2, cluster 3 and all the not-failed slopes formed group 3, cluster 4 and all the not-failed slopes formed group 4, cluster 5 and all the not-failed slopes formed group 5. Hayashi's second method of quantification was then applied to each group, and these analytical results are shown in Table 3.

Hayashi's second method of quantification estimated 25 slopes to fail in group 1 that in reality did not fail. Similarly, 14 such slopes were identified in group 2, eight in group 3, and 10 in group 4. However, no failures were observed in group 5. Five not-failed slopes were estimated to fail in two groups, and therefore, 52 not-failed slopes were estimated to fail as shown in Table 4. In this study, the not-failed slopes estimated to fail by Hayashi's second method of quantification are those slopes that have a higher future risk to slope failure; they have a higher possibility of slope failure than the not-failed slopes estimated to not fail when heavy rain due to future typhoons or cloudbursts occur. On the contrary, the failed slopes estimated to not fail are regarded as mistakes, indicating that the proposed method cannot identify all the slopes that failed as a result of heavy rain in the past. In this study, there was only one failed slope estimated as not-failed, and therefore, the precision of this study can be regarded as high.

There were no not-failed slopes estimated to fail in group 5. As stated above, the failed slopes in cluster 5 have the highest risk to slope failures, so that there are no not-failed slopes in this study that have characteristics similar to the failed slopes in cluster 5. Thus, if there are not failed slopes that have the characteristics similar to the failed slopes in cluster 5, they can be identified as having the highest risk to slope failures without using the proposed method.

Table 3 Analytical results of Hayashi's second method of quantification of each group

(a) Group 1

		Real	
		Failed	Not-failed
Estimate	Failed	6	25
	Not-failed	1	155

(b) Group 2

		Real	
		Failed	Not-failed
Estimate	Failed	7	14
	Not-failed	0	166

(c) Group 3

		Real	
		Failed	Not-failed
Estimate	Failed	7	8
	Not-failed	0	172

(d) Group 4

		Real	
		Failed	Not-failed
Estimate	Failed	8	10
	Not-failed	0	170

(e) Group 5

		Real	
		Failed	Not-failed
Estimate	Failed	8	0
	Not-failed	0	180

Table 4 Final result of Hayashi's second method of quantification

		Real	
		Failed	Not-failed
Estimate	Failed	36	52
	Not-failed	1	128

4.3 Analytical results of the third stage

The priority of slopes with a higher risk to slope failure is given by the difference between the sample score and the score of the boundary that discriminates between failed slopes and not-failed slopes. As a result, not-failed slopes with higher risk can be prioritized as shown in Table 5.

Table 6 shows the characteristics of the three slopes that were given the highest rank to slope failures. In other words, the three slopes had the largest difference between the sample score and the score of the boundary. B53 had characteristics such as fragile lithology and dip slope that were similar to the failed slopes in cluster 2. In addition, B53 was associated with two or more talus cones, and medium topsoil. B33 had characteristics such as fragile lithology that were similar to the failed slopes in cluster 3. Furthermore, B33 was associated with two or more talus cones, fragile soil, spring water, and other characteristics. These similarities were also identified in B11.

Therefore, the not-failed slopes that were given a higher rank have characteristics similar to the failed slopes in a certain cluster, and also have characteristics that increase their susceptibility to slope failures.

Table 5 Analytical results of ranking

ranking	slopes	group	difference
1	B53	2	2.1442
2	B33	3	1.9525
3	B11	4	1.9133
4	B54	2	1.9033
5	B23	3	1.6536
6	B5	4	1.5474
7	B33	4	1.2050
8	B26	2	1.1590
9	B28	2	1.1590
10	B16	4	1.0809
⋮	⋮	⋮	⋮

Table 6 Characteristics of three slopes with the highest risk

(1) B53

parameters	categories	parameters	categories
talus cone	2 or more	topsoil	medium
soil	stable	spring	without
lithology	fragile	covering	construct
formation	dip slope	height	15≦H＜30
difference	small		

(2) B33

parameters	categories	parameters	categories
talus cone	2 or more	topsoil	medium
soil	fragile	spring	spring
lithology	fragile	covering	construct
formation	opposite slope	height	30≦H＜50
difference	medium		

(3) B11

parameters	categories	parameters	categories
talus cone	2 or more	topsoil	medium
soil	fragile	spring	leakage
lithology	fragile	covering	compound
formation	opposite slope	height	15≦H＜30
difference	medium		

5. CONCLUSION

In this study, the proposed method, in which SOM, cluster analysis, and Hayashi's second method of quantification were combined, was applied to data gathered from periodical inspections of road slopes. The main conclusions of this study are summarized as follows.

1. All the failed slopes can be objectively divided into five clusters by applying the proposed method. In addition, the characteristics of the failed slopes in each cluster were elucidated.
2. The proposed method can identify slopes with a higher risk to slope failure and can rank these slopes according to slope failures susceptibility.
3. The not-failed slopes that had characteristics similar to the failed slopes in cluster 2, cluster 3, and cluster 4, and had characteristics associated with increased risk to slope failures were given a higher rank with respect to their risk to slope failures. Therefore, these slopes can be regarded as slopes with a possibility of undergoing future slope failure.

6. REFERENCES

[1] Yamamoto H. Kobayashi H. Yamamoto M. "Characteristics of heavy rainfall and landslides in Izu Oshima by Typhoon No.26, 2013", Japan Society for Natural Disaster Science, Vol.33, No.2, 2014. (in Japanese)

[2] Road Management Technology Center, "Manual of periodical inspection of road (heavy rain, heavy snow)", 2009, pp. 20-37. (in Japanese)

[3] Ito S. Oda K. Koizumi K. "Method for hazard assessment to deep-seated catastrophic landslides due to heavy rain with both artificial neural network and mathematical statistics", The 14th International Conference of the International Association for Computer Methods and Advances in Geomechanics, 2014.

[4] Okita M. Tokutaka H. Hujimura K. Gonda E. "Self-organizing Maps and Tools", Springer Japan, 2008, pp. 1-13. (in Japanese)

[5] Murase Y. Takada H. Hirose T. "Multivariate Analysis by SPSS", Ohmusha, 2012, pp. 273-298. (in Japanese)

[6] Kan T. "Practice of multivariate analysis vol. 2", Company of Modern Mathematics, 2007, pp. 44-116. (in Japanese)

Int. J. of GEOMATE, June, 2015, Vol. 8, No. 1 (Sl. No. 15), pp. 1226-1231.
MS No. 4154 received on July 31, 2014 and reviewed under GEOMATE publication policies.

Corresponding Author: Shinichi Ito