Development of a method to assess runout distance of debris

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Abstract: In order to predict the runout distance of debris, this study performed a detailed field survey, laboratory soil tests and analysis of runout distance at three pilot sites with different lithologies in Korea. The purpose of the field survey was to acquire the geometric data on debris flow such as length, width, slope angle, orientation, depth to failure plane or thickness of deposited debris, volume and flow trajectory of debris as well as lithology. Laboratory soil tests were conducted to get physical and geotechnical properties of in-situ soil and of the sliding material.

Based on the results of the field survey and of the laboratory tests, an artificial neural network approach was used to assess the runout distance of debris. Because the factors affecting runout distance are too complex to analyze one by one in a deterministic manner, a back analysis approach was used to characterize runout distance based on the topographic and geologic properties gathered during the study. The training data for runout distances were derived from 24 landslides that were not affected by adjacent landslides in natural terrain. The input parameters used were: slope gradient, length of landslide, permeability, dry density and porosity. Values were selected by the logistic regression analysis that had been utilized to develop landslide probability. Using the artificial neural network method, it was possible to determine runout distance from two models with the error rate of inference lower than 5% and 2%.

Résumé:. Afin de prévoir la distance de fin de bande des débris, cette étude a exécuté une enquête détaillée de champ, des essais de sol de laboratoire et l'analyse de la distance de fin de bande à trois emplacements pilotes avec différentes lithologies en Corée. Le but de l'enquête de champ était d'acquérir les données géométriques sur l'écoulement de débris tel que la longueur, la largeur, l'angle de pente, l'orientation, la profondeur à l'avion d'échec ou l'épaisseur de la trajectoire déposée de débris, de volume et d'écoulement des débris aussi bien que la lithologie. Des essais de sol de laboratoire ont été effectués pour obtenir les propriétés physiques et géotechniques du sol in-situ et du matériel coulissant.

Basé sur les résultats de l'enquête de champ et des essais en laboratoire, une approche artificielle de réseau neurologique a été employée pour évaluer la distance de fin de bande des débris. Puisque les facteurs affectant la distance de fin de bande sont trop complexes pour analyser un d'une façon déterministe, une approche arrière d'analyse a été employée pour caractériser la distance de fin de bande basée sur les propriétés topographiques et géologiques recueillies pendant l'étude. Les données de formation pour des distances de fin de bande ont été dérivées de 24 éboulements qui n'ont pas été affectés par des éboulements adjacents dans le terrain normal. Les paramètres d'entrée utilisés étaient : gradient de pente, longueur d'éboulement, perméabilité, densité sèche et porosité. Des valeurs ont été choisies par l'analyse logistique de régression qui avait été utilisée pour développer la probabilité d'éboulement. En utilisant la méthode artificielle de réseau neurologique, il était possible de déterminer la distance de fin de bande de deux modèles avec le taux d'erreur de l'inférence plus bas que 5% et 2%.

Keywords: landslides, mapping, terrain analysis, numerical models, risk assessment, laboratory tests

INTRODUCTION

In Korea, most landslides are closely related to periods of intensive rainfall during the summer rainy season and typhoon period.. The precipitation in the summer contributes over half of the mean annual precipitation and can be as much as 1,200mm. The most important type of landslides in Korea are debris flows that comprise 90% of landslides (Kim *et al.*, 2003; Chae *et al.*, 2004 a).

An accurate prediction of landslides contributes to the mitigation and prevention of landslide damage. However, landslides do not always cause a large amount of damage. The runout distances of debris from landslides of a similar size differ and vary dependent on the geomorphology of slopes and geologic conditions of the material comprising the debris flow. Because the runout distance of debris is directly related to the magnitude of damage, it is necessary to assess the runout distance of debris as part of the prediction of landslide risk.

The existing research on runout distance and the characteristics of debris flow fall largely into two groups namely field survey or observation and laboratory models. Most of the field survey and observation studies record measurements of rainfall, pore pressure, displacement of foundation and runout distance of debris and classification of debris. They try to find a relationship between the geomorphologic characteristics, kind of sliding material and runout distance of debris based on the analyses of results of transportation mechanisms, velocity and energy of debris (Suwa, 1988; Suwa and Sumaryono, 1995; Iverson, 1997; Sassa, 1998). However, the field observation and measurement approach has difficulties because the studies need to identify the weighting value and the role of each factor related to the transportation of debris because the factors are mixed in the field. To help overcome some of the problems of the field survey, laboratory based tests can be undertaken to understand the characteristics and distance over which debris transportation can occur. The laboratory tests usually use large or intermediate sized flumes filled with soils of various characteristics and analyze the flow characteristics of debris runout for different combinations of rainfall intensity and slope angles (Moriwaki, 1987; Okura *et al.*, 2002; Wang and Sassa, 2003; Moriwaki *et al.*, 2004).

This study developed a method to assess the runout distance of debris on natural terrain. The runout distances of three debris flows with different lithologies were measured in the field. The selected flows were chosen to ensure that the debris flows that were not affected by other nearby debris flows and that the measurements taken accurately reflected the distance of debris transportation for a single landslide. The field measurement results together with the geomorphology and geotechnical properties of debris were used to determine optimal models for assessment of runout distance of debris using an artificial neural network.

METHODOLOGY OF THE STUDY

Study area

The sites selected needed to be in areas where recent debris flows had occurred and where there was an obvious trace of debris transportation. The sites also needed to have different physical properties of debris. Based on the site selection criteria, three pilot sites in the Sacheon, Macheon and Gabuk areas were chosen for the study.

The Sacheon area was selected as a pilot site to identify the characteristics of flows and runout distance in an area composed of sandy material with gentle slopes and rounded topography. The soils typically comprise equigranular sand formed from the decomposition and weathering of granite. The area has a large number of debris flows which occurred during typhoon 'Rusa' in 2002. The area was also damaged by an extensive fire in the spring of 2000.

The Macheon area was chosen as a pilot site to analyze the characteristics of flows and transportation of debris composed of a mixture of grain sizes, ranging from large corestones to sand and silt, down steep mountain slopes. The area is composed of gabbro which forms mountainous steep slopes. The corestones are well developed in the weathered soil layers and the area has large debris flows that occurred during the typhoon 'Maemi' in 2003.

The Gabuk area is formed from gneiss and has extensive debris flows which occurred during the typhoon 'Maemi' in 2003. The area still has the traces of debris deposition on the bottom of mountain slopes.

Detailed field survey and laboratory soil tests

In order to accurately measure the runout distance of debris and to analyze the transportation mechanism from the head of a debris flow it was important to trace the progress of a single debris flow that had not been affected by other adjacent debris flows. For this reason, the authors only selected debris flows for the study that had developed as a single landslide, without interference from adjacent debris flows and that did not converge with other debris flows.

A detailed field survey covering a total area of $99km^2$ was conducted for the three pilot sites to investigate the geology and geometry of debris flows, to track the debris transportation and measure runout distance and to collect soil samples. The geometry of the whole debris flow was measured from the head of the flow to its toe. The measurements recorded were: change of slope angle, width, orientation, and erosion depth or deposition thickness. These measurements were taken along longitudinal and lateral cross sections across the flows. From these data it was possible to identify geometric changes in the shape of the debris flows and characteristics of debris transportation dependent on geomorphologic and geologic conditions.

Thirteen different soil laboratory tests were performed to understand the relationship between the geotechnical properties of the debris flow and runout distances. Soil samples were collected as undisturbed samples from the undisturbed soil layer and as disturbed samples in the soil deposited near the toe of debris flow. An in-situ density test was also conducted to determine the density of soil layers composed of larger rock fragments and boulders (Kim et al., 2004).

An assessment of the runout distance of debris, based on the field survey and the laboratory soil tests, cannot be made using a deterministic method because the relationship between the data is very complex. Therefore, the study applied an artificial neural network method to assess the runout distance of debris. The artificial neural network method is a useful method to identify the relationship between different data and factors. The data from the detailed field survey and the laboratory tests were analyzed to find inter-relationships between the transportation characteristics, the runout distance of debris, geomorphology and geologic conditions using the artificial neural network.

ASSESSMENT OF RUNOUT DISTANCE OF DEBRIS USING THE ARTIFICIAL NEURAL NETWORK

In order to select optimal models for assessment of runout distance of debris, twenty two out of a total of twenty four debris flows were used for the inference simulation by the artificial neural network.

Analyses of model structures

The analyses to select optimal artificial neural network models used six input factors known to influence the transportation of debris. The six input factors were the change in rate of slope angle, permeability coefficient, dry density, porosity, proportion of sand and volume of debris. The output factor was the runout distance of the debris flow. The evaluation computations were performed with the following four groups.

Group A: changing rate of slope angles, permeability coefficient, dry density, porosity, volume of debris
Group B: changing rate of slope angles, permeability coefficient, dry density, porosity, volume of debris, sand proportion
Group C: changing rate of slope angles, permeability coefficient, dry density, porosity, sand proportion
Group D: changing rate of slope angles, permeability coefficient, dry density, porosity

The learning theory used a multi-layer back propagation theory which is composed of an input layer, hidden layer and output layer. The artificial neural network has large changes of learning reliability and inference capacity dependent on the structure of the input layer, output layer and hidden layer. It is also influenced by the learning factors such as learning constant, momentum constant and the number of learning. Therefore, this study performed the learning with values for the learning constant of 0.6 and 0.9 and fixing the momentum constant as 0.7. The model structure changes with the number of hidden layers and the number of layer items varied between two and four.

Table 1 shows the simulation models used to find optimal artificial neural networks. The number of items of input layer was changed from four to six on each group. The output layer, the runout distance of debris, was fixed as one. The structure of the hidden layer was set up as two layers and three layers.

Table 1. Structures of test models and learning constants

GROUP	Model No.	Input layer	Hidden layer	Output layer	Learning constant	Momentum constant	System error
A	1	5	2-2-2	1	0.6	0.7	0.94
	2	5	3-3	1	0.6	0.7	0.79
	3	5	3-3-3	1	0.6	0.7	0.54
	4	5	4-4	1	0.6	0.7	0.14
	5	5	4-4-4	1	0.6	0.7	0.27
B	6	6	2-2-2	1	0.6	0.7	2.14
	7	6	3-3	1	0.6	0.7	0.59
	8	6	3-3-3	1	0.6	0.7	0.92
	9	6	4-4	1	0.6	0.7	0.89
	10	6	4-4-4	1	0.6	0.7	0.19
C	11	5	3-3	1	0.6	0.7	0.97
	12	5	2-2-2	1	0.6	0.7	2.64
	13	5	4-4	1	0.6	0.7	1.36
	14	5	4-4-4	1	0.6	0.7	4.22
	15	5	2-2	1	0.6	0.7	2.04
	16	5	3-3-3	1	0.9	0.7	1.53
	17	5	2-2	1	0.9	0.7	2.98
	18	5	4-4	1	0.9	0.7	1.14
	19	5	3-3	1	0.9	0.7	0.99
D	20	4	3-3-3	1	0.6	0.7	2.54
	21	4	3-3	1	0.6	0.7	1.48
	22	4	2-2-2	1	0.6	0.7	2.07
	23	4	4-4	1	0.6	0.7	0.51
	24	4	3-3	1	0.9	0.7	1.48
	25	4	2-2-2	1	0.9	0.7	1.63
	26	4	2-2	1	0.9	0.7	1.91
	27	4	4-4	1	0.9	0.7	0.67
	28	4	3-3-3	1	0.9	0.7	2.57

Analyses of the computation results

In order to verify the learning reliability, the runout distance of the debris flow was inferred for the twenty four debris flows used to train the neural network. The average error rate of inference, $P_{avr.}$, was calculated as

$$P_{ave} = \frac{1}{n}\sum_{i=1}^{n} P_i$$

$$P_i = \frac{|R_m - R_i|}{R_m} \times 100$$

where, R_m is the measured runout distance, R_i is the inferred runout distance, and *n* is the number of data for the inference. The trend of convergence was classified as “good” where the average error rate of inference was lower than 20%, and classified as “poor” when it was between 20-50%, and “divergent” when higher than 50%.

The learning results of a total of twenty eight artificial neural network models are shown in table 2. In the case of Group A, model numbers 4 and 5 have good inference results with low average error rate of inference. The model number 10 of the Group B also shows good inference result with the average error rate of inference as 3.7%. For Groups C and D, the model numbers 18, 23 and 27 have relatively good inference results. The results show that the good models have two and three hidden layers and four items of each hidden layer. The higher average error rates of inferences for Groups C and D that those of Groups A and B imply that the volume of debris influences the runout distance of debris. These results need from further studies.

Table 2. Learning results of the test models

GROUP	Model No.	No. of learning iteration	Trend of convergence	Average error rate of inference (%)
A	1	146094	Poor	22.8
	2	304276	Poor	20.4
	3	49420	Good	15.4
	4	518334	Good	2.6
	5	391032	Good	6.9
B	6	192089	Divergent	62.4
	7	127215	Good	13.9
	8	112186	Good	13.9
	9	361525	Good	12.0
	10	149333	Good	3.7
C	11	261637	Poor	24.9
	12	124617	Divergent	77.9
	13	74507	Poor	29.8
	14	127788	Divergent	111.9
	15	17761	Divergent	57.9
	16	63566	Poor	39.6
	17	80564	Divergent	52.7
	18	101319	Good	18.6
	19	266463	Poor	25.4
D	20	121016	Divergent	71.7
	21	85015	Poor	36.4
	22	24445	Poor	48.3
	23	293607	Good	15.9
	24	69300	Poor	34.4
	25	196809	Poor	23.1
	26	207457	Poor	48.0
	27	323226	Good	14.3
	28	64818	Divergent	72.3

Tables 3 and 4 show the inference results of model numbers 4 and 5 that have the average error rates of inferences lower than 10% among the ten models of good inference results. Because the error rate of inference on each debris flow also has lower value as much as 10% the models are evaluated as excellent models to predict the runout distance of debris. However, in the case of model numbers 18, 23 and 27, they have large differences of error rates of inferences on the debris flows, although the average error rates of inferences are lower than 20%. It is thought to be due to small data number of the analyzed debris flows as 24. Therefore, the more number of debris flows and various test models are needed to draw more accurate inference models in the further studies.

Table 3. Inference results of the model 4

Landslide ID	Changing rate of dip angle	Permeability coefficient (cm/sec)	Dry density (g/cm^3)	Porosity (%)	Volume (m^3)	Length (m) *measured	Length (m) *inferred	Error rate of inference (%)
KR-73-18	0.278	0.0210	1.38	81.00	245.2	100	101.46	1.46
KR-73-20	0.452	0.0240	1.35	74.80	103.2	47	47.12	0.26
KR-84-01	0.321	0.0224	1.39	85.00	130.6	43	43.82	1.90
KR-84-02	0.364	0.0138	1.52	74.70	16.6	39	36.94	5.29
GY-72-01	0.581	0.0053	1.31	68.62	252.0	74	80.00	8.11
GY-72-02	0.490	0.0135	1.41	69.62	323.4	132	129.46	1.92
GY-72-03	0.496	0.0155	1.33	67.03	256.7	139	141.18	1.57
GY-81-01	0.438	0.0035	1.49	74.52	653.1	305	297.88	2.33
GY-81-02	0.369	0.0076	1.41	76.77	153.2	270.5	269.16	0.49
MP-79-02	0.481	0.0034	1.25	83.17	1320.5	168	181.97	8.32
WB-27-01	0.587	0.0337	1.51	73.71	301.5	270	270.76	0.28
WB-36-01	0.362	0.0136	1.38	61.45	1401.0	168	175.75	4.62
WB-36-02	0.445	0.0053	1.16	64.72	1400.2	197	200.26	1.65
WB-37-01	0.547	0.0400	1.26	69.72	1238.7	322	318.21	1.18
WB-37-02	0.475	0.0030	1.22	68.65	3012.6	175	173.47	0.87
WB-46-01	0.528	0.1208	1.07	71.84	4003.7	483	488.72	1.19
WB-46-02	0.371	0.0504	1.07	69.52	1690.5	297	299.53	0.85
WB-46-03	0.402	0.0146	1.19	65.46	666.6	299	303.21	1.41
WB-46-04	0.402	0.0406	1.28	67.73	485.9	64	67.11	4.85
WB-46-05	0.544	0.0474	1.25	69.91	2240.5	491	491.32	0.07
WB-46-06	0.367	0.0390	1.28	70.58	426.5	56.5	49.62	12.18
WB-47-01	0.370	0.0075	1.29	64.77	870.9	244	240.33	1.50
WB-47-02	0.318	0.0152	1.26	64.17	5822.9	333	335.11	0.63
WB-47-03	0.582	0.0337	1.02	71.15	630.4	223	223.19	0.09

Table 4. Inference results of the model 5

Landslide ID	Changing rate of dip angle	Permeability coefficient (cm/sec)	Dry density (g/cm^3)	Porosity (%)	Volume (m^3)	Length (m) *measured	Length (m) *inferred	Error rate of inference (%)
KR-73-18	0.278	0.0210	1.38	81.00	245.2	100	88.81	11.19
KR-73-20	0.452	0.0240	1.35	74.80	103.2	47	44.48	5.36
KR-84-01	0.321	0.0224	1.39	85.00	130.6	43	47.05	9.43
KR-84-02	0.364	0.0138	1.52	74.70	16.6	39	45.26	16.06
GY-72-01	0.581	0.0053	1.31	68.62	252.0	74	63.09	14.74
GY-72-02	0.490	0.0135	1.41	69.62	323.4	132	118.87	9.95
GY-72-03	0.496	0.0155	1.33	67.03	256.7	139	126.30	9.14
GY-81-01	0.438	0.0035	1.49	74.52	653.1	305	276.71	9.27
GY-81-02	0.369	0.0076	1.41	76.77	153.2	270.5	276.77	2.32
MP-79-02	0.481	0.0034	1.25	83.17	1320.5	168	149.29	11.14
WB-27-01	0.587	0.0337	1.51	73.71	301.5	270	272.03	0.75
WB-36-01	0.362	0.0136	1.38	61.45	1401.0	168	154.12	8.26
WB-36-02	0.445	0.0053	1.16	64.72	1400.2	197	181.73	7.75
WB-37-01	0.547	0.0400	1.26	69.72	1238.7	322	319.29	0.84
WB-37-02	0.475	0.0030	1.22	68.65	3012.6	175	174.68	0.18
WB-46-01	0.528	0.1208	1.07	71.84	4003.7	483	482.21	0.16
WB-46-02	0.371	0.0504	1.07	69.52	1690.5	297	293.30	1.25
WB-46-03	0.402	0.0146	1.19	65.46	666.6	299	276.57	7.50
WB-46-04	0.402	0.0406	1.28	67.73	485.9	64	67.13	4.88
WB-46-05	0.544	0.0474	1.25	69.91	2240.5	491	490.93	0.01
WB-46-06	0.367	0.0390	1.28	70.58	426.5	56.5	50.52	10.58
WB-47-01	0.370	0.0075	1.29	64.77	870.9	244	276.78	13.43
WB-47-02	0.318	0.0152	1.26	64.17	5822.9	333	332.79	0.06
WB-47-03	0.582	0.0337	1.02	71.15	630.4	223	247.32	10.91

DISCUSSION AND CONCLUSIONS

This study has suggested a method to assess the runout distance of debris flow on natural terrain using the artificial neural network. The analysis of artificial neural network was performed using twenty four debris flows. The input data for each debris flow were changing rate of slope angles, permeability coefficient, dry density, porosity, volume of debris and sand proportion.

The analyses results of the artificial neural network were determined using a small number of data. However, there was a limitation to acquire enough data to satisfy the reliability of analysis because this study had a premise to select debris flows without interference of other debris flows. Considered with the limitation of data acquisition, most of the error rates of inferences were lower than 10%. The results can be considered as good learning reliabilities. However, further studies based on a larger number of debris flows and test models are needed to draw more accurate inference models.

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