PREDICTION AND ANALYSIS OF DEBRIS FLOW (II) -APPLICATION OF NEURAL NETWORKS-

Soontak Lee* Meneo Hirano** Keiichiro Kawahara** Kiho Park***

INTRODUCTION

The debris flow causes severe damage in the downstream by depositing large amount of sand and stone. Consequently, there needs to clarify characteristics of debris flow and establish a predictin method for protecting the area from the disasters. Several practical methods have been proposed to forecast the debris flow due to heavy rainfall. But the accuracy of them is not enough for practical use mainly because of the lack of theoretical basis and inadequate procedures. In previous paper[1], the system-analysis technique is recommended to improve these points. The occurrence conditions of debris flow are analyzed to obtain the critical rainfall needed to cause a debris flow. And a mathematical model of runoff which predicts the intensity of debris flow is derived. In this study, the neural networks which learns a general rule from before events are introduced into the prediction and analysis method for the occurrence as well as the deposited volume of debris flow.

PREDICTION OF DEBRIS FLOW BY USING NEURAL NETWORKS

Neural network structure and learning algorithm

Artificial neural networks or simply "neural networks" are mathematical models that operate in manner analogous to that of biological nervous systems. Typically, neural networks consist of a set of layered processing units and weighted interconnections. Neural networks are learned by examples presented to the network, the networks adjusts itself by some learning rule. There exists a variety of neural network models and learning procedures[2]. Multi-layer neural networks most widely concerned are feed-forward networks with one or more layers of units between the input and output units. Fig. 1 illustrates a three-layer network.

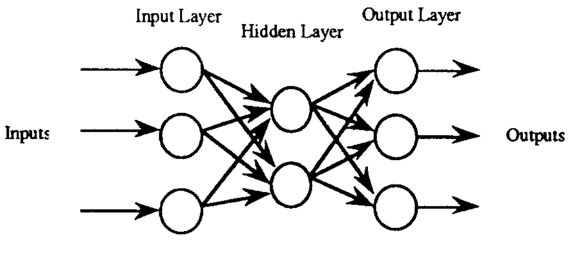


Fig. 1 Typical three-layer network

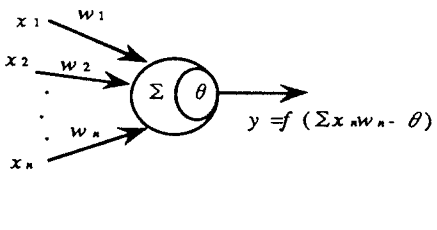


Fig. 2 Processing unit

The simplest unit forms a weighted sum of N inputs, subtracts internal threshold θ from it and passes the result through a non-linear function as shown in Fig. 2. The sigmoid function given below is commonly used as the activation function of the unit.

*Department of Civil Engineering, Yeungnam University, Korea
**Department of Civil Engineering, Kyushu University, Japan
***Department of Civil Engineering, Kyushu University, on leave from Yeungnam University

$$f(\alpha) = \frac{1}{1 - e^{-\gamma\alpha}} \qquad (1)$$

where, the gain of the sigmoid γ, determines the slant of the transition region. This function is continuous and varies monotonically from 0 to 1 as shown in Fig. 3. Typically, real values of training data are normalized from 0 to1 and are given to neural networks.

Multi-layer networks are trained by using the back propagation method[3]. Learning involves modification of connections. This learning algorithm is an iterative gradient algorithm designed to minimize the mean square error between the actual output of network and the desired output given by Eq. (2)

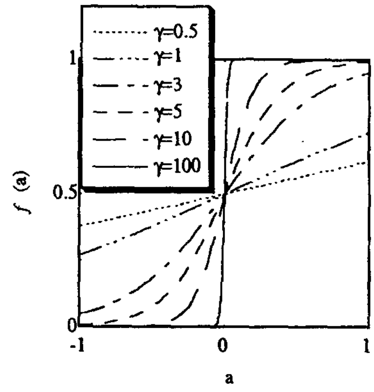


Fig. 3 Sigmoid function

$$E_p = \frac{1}{2}\sum_k (d_{pk} - o_{pk})^2 \qquad (2)$$

where, d_{pk} is the desired response of k-th unit of output pattern produced by presentation of pattern and o_{pk} is the k-th unit of the actual output pattern produced by presentation of pattern p. The criterion function to be minimized is $E = \sum E_p$. And the weights of three-layer perceptrons are determined iteratively according to

$$w_{jk}(t+1) = w_{jk}(t) + \eta\, o_{pk}(1 - o_{pk})(d_{pk} - o_{pk})o_{pj} \qquad (3)$$

$$w_{ij}(t+1) = w_{ij}(t) + \eta\, o_{pi}(1 - o_{pj})\sum_k \delta_{pk} w_{jk} \quad \text{and} \quad \delta_{pk} = o_{pk}(1 - o_{pk})(d_{pk} - o_{pk}) \qquad (4)$$

where, $w_{jk}(t)$ is the weight which connects the j-th hidden unit to the k-th output unit at the t-th iteration, $w_{ij}(t)$ is the weight which connects the i-th hidden unit to the j-th output unit at the t-th iteration, and η is a positive constant called the learning rate.

The weights are typically initialized to small random values. The final weights of successfully trained neural networks represent its knowledge about a set of input/output pairs.

APPLICATION OF THE NEURAL NETWORK

Prediction of occurrence of debris flow

To check the applicability of the neural networks for prediction of occurrence of debris flow, a neural network model is introduced to the Mizunashi River, Unzen Volcano. According to the previous paper[1], Eq. (5) is derived to estimate the time of concentration and critical rainfall, T and R_c .

$$R_{max}(\tau) = max[R(t,\tau)] \quad \text{and} \quad R(t,\tau) = \int_{t-\tau}^{t} r\,dt \qquad (5)$$

where, r is the rainfall intensity, t is the time and τ is the duration .

A set of rainfall time series is characterized by various of the maximum cumulative rainfall, $R_{max}(\tau)$, expressed by Eq. (5). The various cumulative rainfalls, $R_{max}(10)$, $R_{max}(20)$,...$R_{max}(120)$, as the input data given to the input units in the prediction model. The cumulative rainfalls are calculated by ten minutes rainfall data collected at the Unzen Meteorological Observatory. Two output units are desired two binary values 0/1 when debris flow occurs and 1/0 when the debris flow doesn't occur. The neural networks for learning of occurrence and non-occurrence of debris flow is illustrated in Fig. (4).

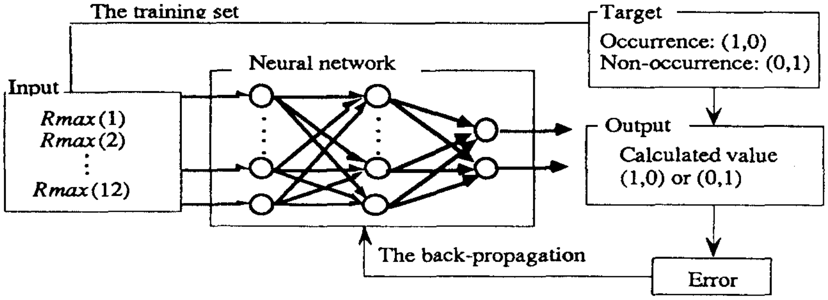


Fig.4 The learning model of the occurrence and non-occurrence of debris flow

Tab. 1 shows the contents of the training and testing data as well as their computed results. The training data of May 1991 in Fig. 5 is recognized by the model.,Fig. 6 shows the cumulative rainfall curves after May in 1991 which the model predicted to occur by learning data of May 1991. Through the 24 events, 17 were correctly and 7 were badly predicted. The probability of hit in Tab. 1 is the proportion of the number of right, wrong and occurrence predicted the network. In 1992, debris flows occurred 19 times for 29 storm evens by the occurrence predicted model. In both years, no occurrence was missed.

Tab.1 Events to the predeiction of occurrence

		Target	Right	Wrong	Probability of hit (%)
Learning (May,1991)	Occurrence	5	5	0	100
	Non-occurrence	6	6	0	
Prediction (Jun.~Dec.,1991)	Occurrence	17	17	0	54.8
	Non-occurrence	66	52	14	
Prediction (1992)	Occurrence	19	19	0	65.5
	Non-occurrence	88	78	10	

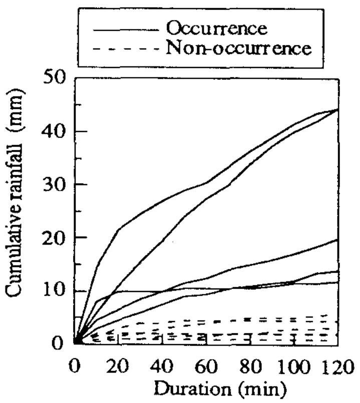


Fig. 5 Training data for learning

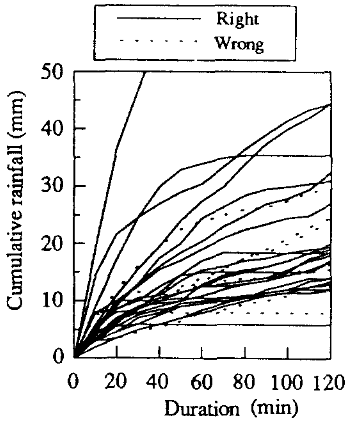


Fig. 6 Results of prediction

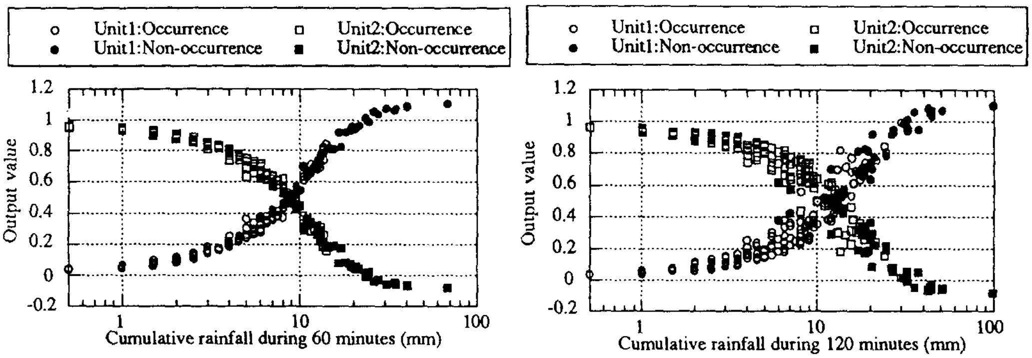
Tab. 2 shows the result that the network learned by the data of 1991 and predicted to the data of 1992 after learning. Comparing with probability of hit of 1991 and 1992 shows that the model is improved by the accumulation of the training data.

Tab.2 Events to the predeiction of occurrence

		Target	Right	Wrong	Probability of hit (%)
Learning (1991)	Occurrence	22	19	3	61.3
	Non-occurrence	72	60	12	
Prediction (1992)	Occurrence	19	16	3	66.7
	Non-occurrence	88	80	8	

Estimation of the time of concentration and critical rainfall

The time of concentration and critical rainfall are explained by using the neural networks. The networks are learned by the data from 1991 to 1992. Fig. 7 shows the output values and Input value, $R_{max}(60)$ and $R_{max}(120)$. Where, each output value is shown by continuous value. In Tab. 1 and Tab. 2, it is rounded off by the output value 1 more than or equal to 0.5 and to ignore this fraction otherwise. As is seen in Fig. 7(a), the output values and the input value $R_{max}(60)$, obtained the least fluctuations in comparison with the input value $R_{max}(120)$ are most useful to judge the occurrence or the non-occurrence. It is estimated the time of concentration is an hour and the critical rainfall is about 9mm by the cross point of two values of units .



(a) 60 minutes (b) 120 minutes

Fig .7 Estimation of the time of concentration

Volume of debris flow deposits in the Mizunashi River

The volume of debris flow deposits occurred in the Mizunashi River were measured by Nagasaki Prefecture and the Ministry of Japan Construction as shown in Fig. 8. In 1993, unusual rainfall caused large amount of deposits of debris flow. The relation between the amount of deposits and hourly rainfall data collected by the Unzen Meteorological Observatory is examined.

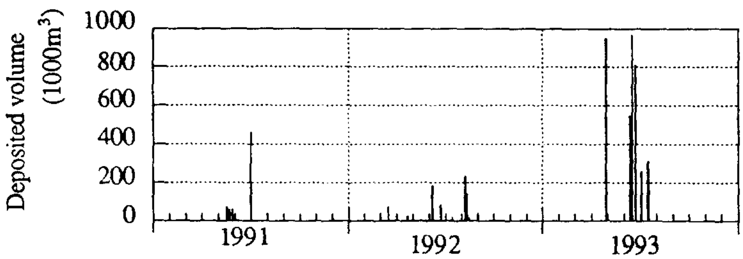


Fig.8 Volume of debris flow in the Mizunashi River

Fig.9 represents the maximum hourly rainfalls plotted against the deposited volumes of debris flows in the Mizunashi River. There is close relation between the deposited volume and the maximum hourly rainfalls observed in 1991-1992, while in 1993, quite different trend is observed. Fig. 10 shows the relation between the cumulative rainfall R_a , and the volumes of sediment deposits. There is close relation between the deposited volumes and the cumulative rainfalls throughout three years. Therefore, the volume of debris flow deposits is closely related with the cumulative rainfall of long duration.

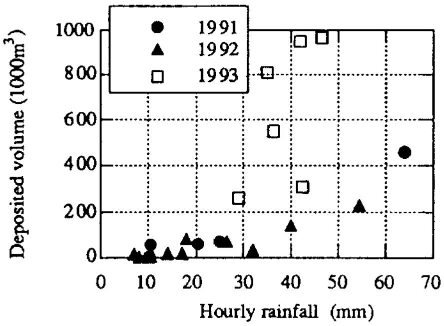


Fig.9 Relation between the maximum hourly rainfall and the volume of debris flow

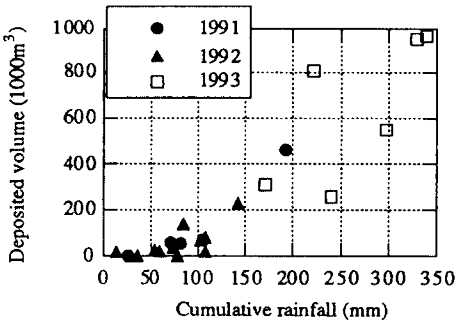


Fig.10 Relation between the cumulative rainfall and the volume of debris flow

Prediction of deposited volume of debris flow

The deposited volume of debris flow is closely related to the cumulative rainfall for long duration, as previously has been pointed out. But duration of rainfall data should be chosen as the input remains unclear. The solution of the problem is given by observing the RMS error after the learning. Here, we use the cumulated rainfall of whole duration R_a , and maximum cumulative rainfall for various time of duration $R_{max}(\tau)$, as the input data. The volume of deposits is used as the target data. Where, both of them is normalized from 0 to 1 before given to their units. The RMS error in the case-4 is minimum as presented in Tab. 3. The relation between the measured volume and the computed volume of case 4 is shown in Fig. 8. The coefficient of correlation between the measured volume and the computed volume is 0.99. This indicates the training sets learned with a high accuracy.

Tab. 3 Input data end error after learning

Case	Input data	RMS Error
1	Ra,R_{max}(1),..,R_{max}(3)	0.109
2	Ra,R_{max}(1),..,R_{max}(6)	0.0944
3	Ra,R_{max}(1),..,R_{max}(9)	0.0895
4	Ra,R_{max}(1),..,R_{max}(12)	0.0373
5	Ra,R_{max}(1),..,R_{max}(15)	0.0385
6	Ra,R_{max}(1),..,R_{max}(18)	0.0396
7	Ra,R_{max}(1),..,R_{max}(24)	0.0465

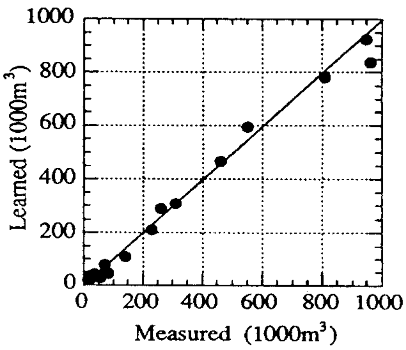


Fig.11 Result of the learning in Case-4

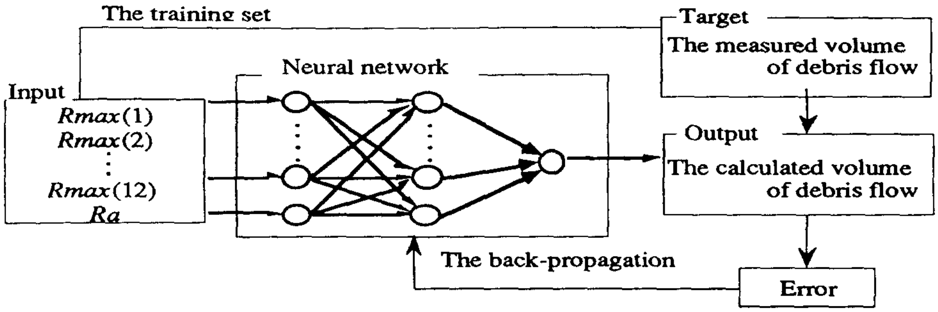


Fig.12 The learning model of the deposited volume of debris flow

In order to predict the volume of deposits, $R_{max}(1)$, $R_{max}(2)$,...,$R_{max}(12)$ and R_a are used as the input units. At first, the neural networks learn using the data of 1991. Then the volume of deposits of the first event in 1992 is predicted using rainfall data of the event. After that, the networks learn again with the data including the data of this event and predict volume of the next event. Repeating this procedure, the predicted amount of deposits are obtained. The history of the leaning and predicting is shown in Fig. 13. In Fig. 14, the predicted volume is compared with the observed one and fairly good agreement is obtainable.

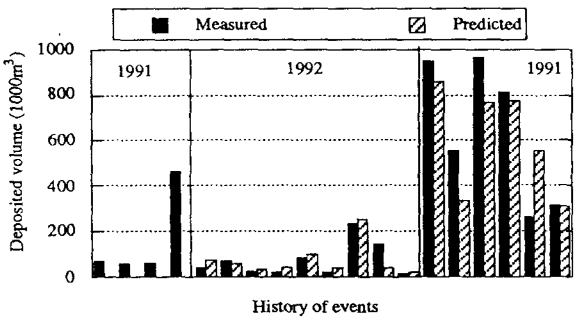


Fig.13 History of events and Prediction results

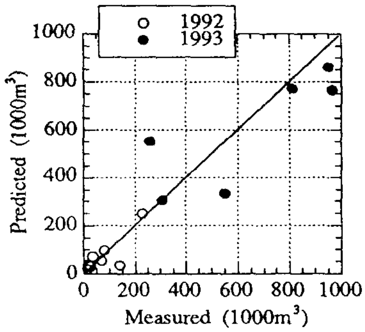


Fig.14 Relation between the measured and the predicted volume

CONCLUSIONS

The neural networks was introduced to predict the debris flow. The prediction models using the neural networks were proposed to predict the occurrence as well as the deposited amount of debris flow. The models were verified by applying to the Mizunashi River acrossed Unzen volcanic area. The predicting results shows the neural networks is applicable to forecast the occurrence and deposited volume of debris flow. The time of concentration is obtainable by applying the neural networks and examining the output from the model. Input factors to represent the volume of debris flow deposits is clear by the learning of acutual data.

PREFERENCES

1)Soontak Lee, M. Hirano and K. Park(1994): Prediction and analysis of debris flow. vol. 27, no. 2, pp.147-154, Journal of KAHS.

2)R.P.Lippmann(1987): An Introduction to Computing with Neural Nets, IEEE ASSP magazine, pp.4-22, April.

3)J,L. MacCelland and D.E. Rumelhart(1986): Parallel Distributed Processing. vol. 1, pp. 318-362, MIT Press.