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Application of Neural Network to Determine the Source Location in Acoustic Emission

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Abstract The iterative calculation by least square method was used to determine the source location of acoustic emission in rock, as so called "traditional method". The results were compared with source coordinates infered from the application of neural network system for new input data, as so called "new method". Input data of the neural network were based on the time differences of longitudinal waves arrived from acoustic emission events at each transducer, the variation of longitudinal velocities at each stress level, and the coordinates of transducer as in the traditional method. The momentum back propagation neural network system adopted to determine source location, which consists of three layers, and has twenty-seven input processing elements. Applicability of the new method were identified, since the results of source location by the application of two methods were similarly concordant.

Keywords: least square method, source location, acoustic emission, neural network

1. Introduction

Recent expansion of SOC is boosting up the development of underground space. Acoustic emission, which is a kind of nondestructive testing method in the field of rock mechanics, is widely used as a means of maintenance of structural facilities. Acoustic emission is defined as transient elastic wave generated by an abrupt release of energy when a deformation takes place within the structure and texture of materials - i. e. the transmission of sonic pulse that a part of the energy within the structure has transformed to (Lockner, 1993). Acoustic emission is widely used in various fields, for phenomenon takes place as micro-crack or deformation occurs within the material and that enables any variation in structure or texture of the material be effectively monitored.

This research, through laboratory test, has attempted to suggest a new method to efficiently analyze experimental data for determining source location - i.e., in order to resolve the problem that traditional method of iterative calculation to get approximation using least square method (M. Ohtsu 1987, R. L. Rothman et al., 1974) takes enormous time and efforts for obtaining, transmitting, recording, and analyzing data, an analyzing method by means of neural network has been studied and its result reviewed and compared with those of traditional method.

2. Experimental method and apparatus

2.1 Preparation of specimen

Considering homogeneity, and anisotropic velocity field (Chandra and Kenneth, 1988) of material, Geo-Chang granite in Korea was selected specimen to be used in this research. The physical properties of specimen used are as shown in Table 1.

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Notch was made by rock cutter for three point bending test, of which size and shape are as shown in Fig. 1. Rock specimen is 6 cm× 6 cm×40 cm in its size, which has vertical notch at the center, sized 1 mm wide and 2 cm long, which was intended to induce tensile failure.

Table 1 Physical properties of specimen

Unit weight(KN/m^3)	25.81±0.28
Longitudinal wave velocity(m/sec)	4850±1300
Porosity(%)	0.87±0.14
Uni. compressive strength(MPa)	170±58
Young's modulus($\times 10^4$ MPa)	5.18±0.44
Poisson's ratio	0.19±0.06

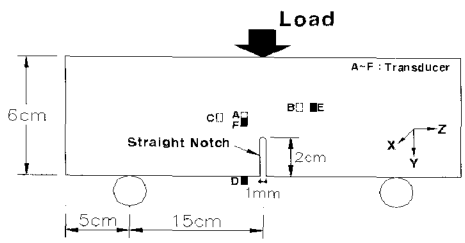


Fig. 1 Configuration of rock specimen

The reason for forming vertical notch in specimen is to apply the result of the learning terminated, after the learning of neural network of source location obtained from uniaxial compression test as shown in Fig. 2. Input data used for the learning of neural network were source location determined by the least square method.

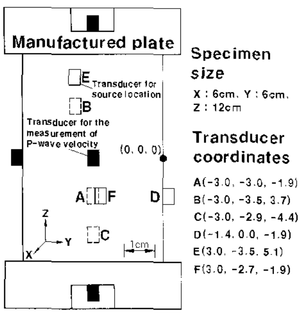


Fig. 2 Uniaxial Compression test for input data of neural network

2.2 Experimental setup and monitoring system

Test apparatus used is SFM model manufactured by UNITED Co. in USA, which is capable of both compression and tension test, up to 20tonf, with various control of displacement within the range of 0.05 to 50 mm per minute.

Instrument for acoustic emission measurement is model LOCAN-320 of PAC Co. in USA, which is capable of processing 2 to 14 signals, and rear side of acoustic emission processing unit is so designed as to be receivable of conventional acoustic emission signal.

Transducer used for analyzing source location of micro-crack at loading is model WD-A having resonance frequency of 550 kHz of PAC Co. This transducer has such distinction that sensitivity drop down at lower frequency than 100 kHz and reasonably reacts at frequency range between 100 kHz and 1 MHz. Signal reached to the transducer is, via preamplifier and through BNC cable, carried to an input channel at rear side of acoustic emission processing unit.

Meanwhile, acoustic emission waveform emitted out of 6 channels, after recording by waveform recorder(model CS225), were saved in the form of digital data in a personal computer for source analysis. Fig. 3 briefly depicts the monitoring system of acoustic emission.

Displacement control method was used for this test, and displacement rate was maintained to be 0.05 mm/min.

3. Construction of neural network system

Traditional iterative calculation by means of the least square method was used to determine source location in acoustic emission when uniaxial compression test was performed in laboratory, and the result of source location thereof was used for the learning of neural network. And the neural network completed with learning in return was used for determining new source location of rock specimen in three point bending test.

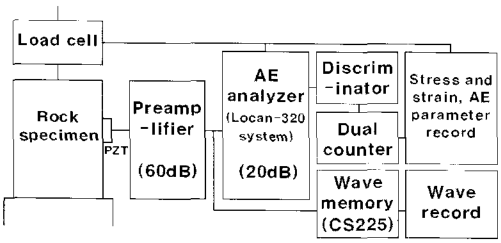


Fig. 3 Block diagram of experimental setup for monitoring

The least square method which is an iterative calculation method is used to obtain output from equations of non-linear interrelation. Therefore multi-layer neural network, which is adaptable to non-linear and capable of large data input, has been employed as calculating system for determination of source location, and in addition application of feed forward neural network system was deemed to be desirable feed back possible error output through its own network layer. This is called as error back propagation neural network (Rumelhart and McClelland, 1986, Rumelhart, et al., 1986), which effectively performs its function of learning the network that error signal from output layer of the network is used to adjust weights between hidden layer and output layer, and error signal transmitted back to hidden layer adjusts weights between input layer and hidden layer of the network.

Mathematical model of non-linear formula using a batch system to determine source location is put forward as following equation (1).

$$
\begin{aligned}
y(k) = f\ (&y(k-1), \cdots, y(k-n) \\
&u(k-1), \cdots, u(k-n)) + e(k) \\
&y(k) = [y_1(k), \cdots, y_m(k-n)]^T \qquad (1) \\
&u(k) = [u_1(k), \cdots, u_r(k)]^T \\
&e(k) = [e_1(k), \cdots, e_m(k)]^T
\end{aligned}
$$

where, $u(k)$ is input data to the system, which denote coordinates of transducer, time difference of the first motion of longitudinal wave arrived to transducer, and anisotropic velocity of rock. $y(k)$ is output data from the system, which denotes source location. e(k) denotes error signal, and f() denotes vector of non-linear formula.

Fig. 4 is neural network model used to deduce source location, and no bias factor in this case was applied. Back propagation neural network is used to adjust weights and bias of the network so as to minimize squared error sum of the network, which performs its function by iteratively altering weights and bias of the network in case that the output error is greater than initial set error value. Therefore, alteration of weights and bias is effecting squared error sum of the network to be proportional to its source factors.

Those variable which are used for least square method when used as input data to neural network take long time for learning because they range too widely in their values, and also learning process tends to disperse rather than converge.

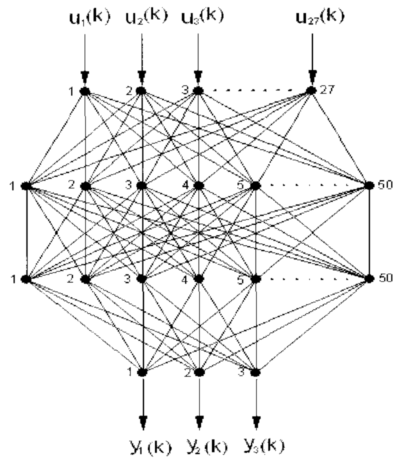


Fig. 4 Neural network model to apply source location

Therefore, in order to eliminate such deleterious factor to the stability of the network, input value settings for coordinates of the transducer and transmitting velocity of elastic wave were so intended that they should range between -1 to +1, by dividing each original value of them by the extreme value of the variables, and values statistically processed as shown in equation (2) were taken as input value for transmitting time to arrive each transducer, as the transmitting time varies to its medium and acoustic emission source, and object values used the coordinates of acoustic emission source obtained from uniaxial compression test without any adjustment.

"Tan-sigmoid" of non-linear function was employed to activate weights input layer and hidden layer, while "pure-linear" of linear function was employed for that between hidden layer and output layer as shown in Fig. 5 (Rumelhart, et al., 1986, Grossberg, 1986). It is because least square method result in non-linear function that the tan-sigmoid was employed. For the coordinates of acoustic emission source, which were used as object values for neural network, pure-linear function was applied so that output values of it can make out various distribution.

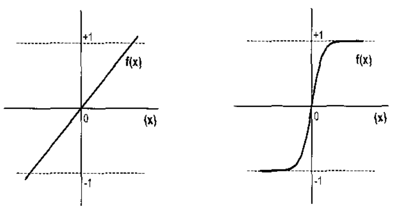
$$(x(k) - \sigma_{std})/\sigma_{mean} \qquad (2)$$

where, x : input value

k : number

σ_{std} : standard deviation of input values

σ_{mean} : average of input values



(a) Pure-linear (b) Tan-sigmoid

Fig. 5 Activation function without bias

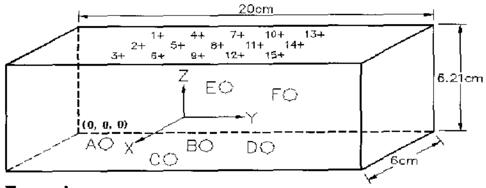
4. Results

4.1 Preliminary test result

The variation of longitudinal wave velocity and time difference arrived to transducer with the location of transducer fixed were employed to learn neural network. For the ability and security of neural network, its learning was attempted using variables obtained from the preliminary test as shown in Fig. 6, where the input pairs of neural network applied were those 30 input pairs which were obtained from the pulse input.

Table 2 shows root mean squared error when learning with various number of neuron between input layer, hidden layer, and output layer. Average root mean squared error in this case was obtained by averaging the result of 5 tests at each number of neuron(or processing element), and random value between -1 and +1 was taken as initial weights.

As shown in Table 2, root mean squared error increases as the number of neuron exceeds 60. Therefore, 50 number of neurons were chosen for each neural network layer.



Transducer

A(6.0, 7.0, 2.0) B(6.0, 12.2, 1.9)
C(4.5, 9.6, 0.0) D(2.0, 14.8, 0.0)
E(0.0, 9.4, 1.8) F(0.0, 14.4, 1.6)

Input point by pulse

1.(1.5, 6.0, 6.21) 2.(3.0, 6.0, 6.21) 3.(4.5, 6.0, 6.21)
4.(1.5, 8.5, 6.21) 5.(3.0, 8.5, 6.21) 6.(4.5, 8.5, 6.21)
7.(1.5, 11.0, 6.21) 8.(3.0, 11.0, 6.21) 9.(4.5, 11.0, 6.21)
10.(1.5, 13.5, 6.21) 11.(3.0, 13.5, 6.21) 12.(4.5, 13.5, 6.21)
13.(1.5, 16.0, 6.21) 14.(3.0, 16.0, 6.21) 15.(4.5, 16.0, 6.21)

Fig. 6 Transducers array and input points for preliminary test

Table 2 Average RMS error vs. number of processing elements

(iteration : 500)

No. of PE's	10	20	30	40	50	60	70	100
Ave. RMS err(cm)	7.4	4.5	2.0	2.1	1.0	0.8	1.2	1.8

Table 3 shows comparison of learning rates by the back propagation learning algorithm and by the momentum back propagation learning algorithm (Rumelhart, et al., 1986, Sejnowski and Rosenberg, 1987). This tell us that learning rate by the momentum back propagation learning algorithm is 2.5 times faster than that by the back propagation learning algorithm. Whereas neural network of the back propagation learning algorithm which uses learning rate between 0 to 1 generally takes long time to reach to the objective values as the variation of weights in each learning stage relatively reduces, but neural network of the momentum back propagation learning algorithm is deemed to be able to considerably shorten its learning time by making supplementary use of weights variation ($\Delta w_i(j\text{-}1)$) in previous learning stage.

Table 3 Comparison between learning rates by 2 algorithm

(network error : 0.3)

Algorithm	Back propagation	Momentum back propagation
Iteration (N)	4,209	1,749

It was reviewed if deduction of source location by means of iterative calculation method in consideration of anisotropic velocity structure is possible when a new input value is given after learning neural network is completed. Results of the above review is shown in Table 4.

The fact that the variation of error summation fell under the range within 1cm in both cases without distinct variation of error summation except the first and last trial proved that deduction of source location by means of neural network is good enough. In this review, learning rate of 0.012, momentum constant of 0.3 and error rate of 1.04 were provided. These were the optimum values obtained out of repeated modification for learning neural network.

Iterative calculation by means of the least square method takes long time in repeated modification to minimize the error. However, using neural network completed with learning is considered to be an effective enough way applicable to acoustic emission signal that requires quick processing as it obviates repeated calculation.

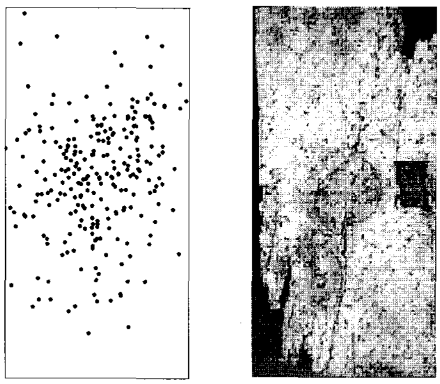
4.2 Result from application of neural network in three point bending test

In order to find source location in application of neural network at time of three point bending test learning of neural network was performed using 250 source locations derived from uniaxial compression test as shown in Fig. 7. That means 250 input pairs were used for learning neural

Table 4. Accuracy of source location (x, y, z coordinate)

Coordinates of input point by pulse (cm)	Calculated coordinates by the least square method (cm) (A)	Predicted coordinates by neural network application (cm) (B)	Error summation (cm)	
			(A)	(B)
1.5, 8.0, 6.21	1.17, 7.86, 7.07	1.08, 7.86, 7.27	0.93	1.15
3.0, 8.0, 6.21	3.14, 7.90, 6.36	3.16, 8.10, 6.60	0.23	0.44
4.5, 8.0, 6.21	4.68, 8.03, 6.33	4.33, 8.16, 6.05	0.22	0.28
1.5, 10.0, 6.21	1.05, 9.99, 6.93	1.07, 10.37, 6.51	0.85	0.64
3.0, 10.0, 6.21	3.22, 9.73, 6.47	3.29, 9.68, 6.38	0.43	0.46
4.5, 10.0, 6.21	4.70, 9.31, 6.58	4.59, 10.19, 6.78	0.81	0.60
1.5, 12.0, 6.21	0.87, 11.99, 6.25	1.15, 11.82, 6.31	0.63	0.40
3.0, 12.0, 6.21	2.73, 11.93, 6.49	2.93, 12.55, 6.51	0.39	0.63
4.5, 12.0, 6.21	4.78, 11.42, 6.23	4.68, 12.49, 5.85	0.64	0.63
1.5, 14.0, 6.21	1.01, 13.60, 5.75	1.61, 13.69, 5.75	0.78	0.56
3.0, 14.0, 6.21	2.54, 13.81, 6.69	2.99, 13.30, 6.19	0.69	0.69
4.5, 14.0, 6.21	5.10, 13.72, 7.23	4.20, 13.97, 5.73	1.21	0.56

network. Conditions for the neural network in this test were so given as learning rate to be 0.0025, momentum constant 0.3, error rate 1.04, and total error of 250 neural network patterns to be 15, thus network error of each pattern to be 0.06. Fig. 8 shows sum squared error resulted from epoch(or number of iteration), and sum squared error of input pairs and target pairs of neural network. This reveals that sum squared error for most input/target pairs were less than 0.4. This means sum squared error are within the range of 4 mm.



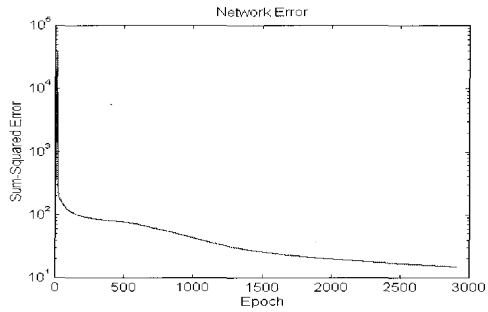
(a) Source location (b) Failure shape

Fig. 7 Source location and failure shape in uniaxial compression test

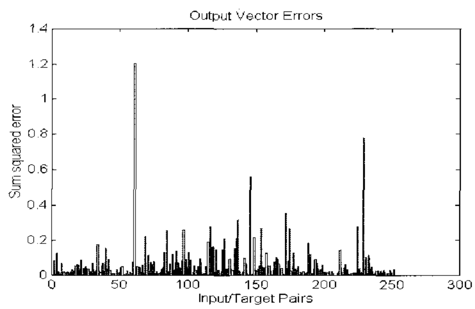
Therefore, determination source location by means of neural network will be possible using such variables as coordinates of transducer, time difference arrived to transducer, and anisotropic velocity at each stress level, those which were obtained from three point bending test and define source location, as new input data to the neural network which is completed with learning.

Results obtained by applying neural network were compared with the result from iterating calculation by the least square method. Fig. 9 shows source location by the application of neural network, and this delineates source location over the area of 5 cm to the left and 5cm to the right from the notch. Source location based on the application of neural network includes anisotropic velocity field, where longitudinal wave velocity of granite is 4,360 m/sec to X-direction, 3,370 m/sec to Y-direction and 4,590 m/sec to Z-direction thus to show anisotropy to Z-direction is among the most. Total 129 events have happened during the test until failure take place. Those signals, of which arrival time of longitudinal wave cannot be identified due to the complication with noise from amplified signals, and which failed to arrive to one channel of six transducers were excluded from the analysis. As a result the above, 92 events were used for source analysis.

It is noted when source location is analyzed in consideration of anisotropy velocity the source location is well in coincidences with the crack face, and the result from the analysis in application of neural network also shows no big difference from the Fig. 9(a) and reveals to be almost identical to the former case having the range of 0.1~1.1cm in root sum squared the difference of coordinates obtained in two cases.



(a) Sum-squared error vs. epoch



(b) Sum-squared err. vs. input/targer pairs

Fig. 8 Network sum squared error after learning neural network

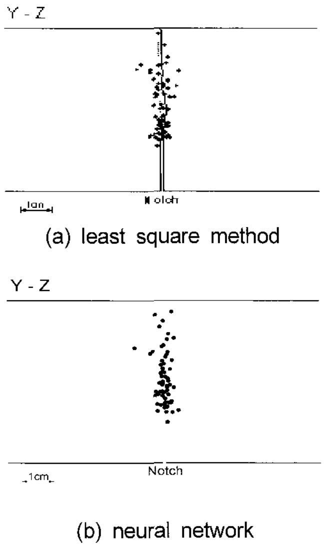


Fig. 9 Source location in three point bending test

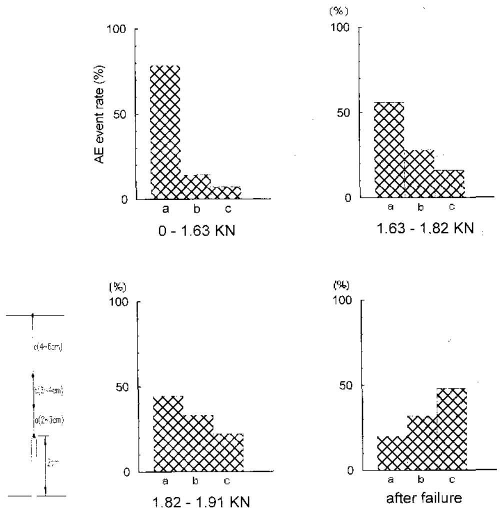


Fig. 10 Histogram of events as a function of the height (a: 2-3 cm, b: 3-4 cm, c: 4-6 cm)

Meanwhile, in order to find out the progress of crack in bending test following analysis were conducted based on the results from source analysis by means of neural network. Spacing of 1 cm, 1 cm and 2 cm from edge of straight notch i. e. spacing of 2~3 cm, 3~4 cm, and 4~6 cm on the bottom were denoted as section a, b, and c respectively and distribution of source location obtained under the four step loading condition were shown in the form of histograms. Histograms showing the above result are as shown in Table 5 and Fig. 10.

Fig. 10 explains that frequency ratio of acoustic emission events is so characterized that when load level is 0 to 1.63KN almost all the source locations are distributed near the edge of straight notch, and as the load level increases the edge of notch move gradually upward. This tells us that it is possible to find reliable source location in application of neural network.

Table 5 Frequency ratio of events and load interval

Load interval (KN)	Frequency of events as a function of height (No.)			Frequency ratio (%)		
	a	b	c	a	b	c
0.00~1.63	11	2	1	78.57	14.29	7.14
1.63~1.82	14	7	4	56.00	28.00	16.00
1.82~1.91	8	6	4	44.44	33.33	22.22
after failure	5	8	12	20.00	32.00	48.00

5. Discussion

Time difference of longitudinal wave arrived to transducer, longitudinal wave velocity, and coordinates of transducer as those in iterative calculation method by means of least square method were applied. That means total 27 data including 18 coordinates for 6 transducers, 3-directional longitudinal wave velocity, and time difference arrived to 6 transducers, were input to neural network, 3 coordinates of 3-dimensional source location were used for output of neural network.

It is a disadvantage of iterative calculation method that it requires at least 5 transducers and therefore transmission, acquisition, recording and analysis of data should be made in large scale. Particularly because data recording involves iterative calculation taking long time if other event take place during calculation process the process in most instance fails to proceed. For this reason analyzing systems using existing acoustic emission software is designed to perform single dimensional analysis only, which does not take long time for calculation. Moreover, the system involves such problem that, because approximate calculation process for single dimensional analysis does not use any algorithm to reduce the errors from longitudinal wave velocity per load level and source location, determination of source location is likely to deviate from actual point of crack.

Now, as an alternative means to resolve the above mentioned problem, application of neural network for analyzing source location is proposed. If source locations analyzed through laboratory test and various field data are used as input data to neural network this thesis defines and they are combined with existing acoustic emission analyzing system, fairly precise source location could be sought as the transmitting, acquiring, recording and analyzing the data will be made in real time via simple calculation process. And it is also assured that if the accumulated source locations are fed back to reactivate the neural network, source location could easily be sought without recourse to any complicate algorithm. Therefore, this study lead to a conclusion that application of neural network can be a new enhancing method for source locating in a sense that it could be more time-saving, economical and simple to do yet maintaining the preciseness.

6. Conclusion

Laboratory test on acoustic emission was performed with rock specimen of Geo-chang granite. Firstly, measurement of arrival time of first motion of longitudinal wave was made at loading, then iterative calculation method by means of least square method was used to determine source location by applying the measured value. Then momentum back propagation neural network, which is a new analyzing method for determining 3 dimensional source location, was taken into practice in order to compare its output with that from the iterative calculation method to see the applicability of output value from the momentum back propagation neural network. Result of taking the neural network into practice was similar enough to that from the iterative calculation method, and because the neural network can possibly process successive calculation in a way of multiple and parallel processing, it made fairly simple and speedy data processing be possible.

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