Study On the Design of Risk Management Web-Monitoring System Using AANN

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***Abstract* - Recently natural disasters like flooding and slope collapse have shown the need for development of natural risk management system, as they endanger directly public health and cause severe damages on the national economy. In order to improve the efficiency of risk management systems, a certain system based on AANN (Auto-Associative Neural Network) is proposed in this paper. AANN can be effectively used for identification of abnormal data and data compression. The proposed AANN-based risk management system collects and stores measurement data from sensors and transmits them to remote server for web-monitoring. Generally, it is desirable to transmit the compressed data instead of raw data in normal state. However, if dangerous situation happens, rapid transmission of measurement data should be required. These requirements are easily satisfied by using AANN. In order to verify the feasibility of the proposed system, the AANN-based risk management system is applied to slope collapse monitoring system.**

I. Introduction

Through the much developed technology, humans live more comfortable than ever before, but they are suffering from natural disasters such as typhoons, drought, land-slide and so on every year. The development of an efficient prevention system which can predict and reduce damages of these natural disasters is required urgently. Generally, the disaster prevention system is installed on the measurement site where people can't easily visit. Thereby, it is impossible that a person collects data directly in the measurement site. Therefore, most disaster prevention systems utilize wire/wireless communication technology for receiving data from measurement site. To make disaster prevention system reliable, many sensors should be installed and also, for an efficient disaster's estimation, real-time monitoring of measured data is required.

Generally, for efficient data monitoring, it is required that measurement data stored in data logger be transmitted by using wire/wireless communication to a remote server system at the cycle of predetermined time period.

Thus, periodic transmissions of data from measurement site to remote server system are not desirable for its excessive communication cost. This comes to a problem in the performance of the whole system. Generally, a disaster is the final result that occurs in a continuous process during a certain period of time. Therefore, development of efficient remote disaster prevention system that can transmit the compressed data in normal state and raw data from that time on the incipient stage of disaster is required.

AANN was proposed by Kramer for the effective analysis of multi-variable data[1]. It has the characteristic that can compress a multi-variable data to data with lower dimension without loss of any information contained in raw data. Also, it has the characteristic that can handle efficiently the linear and nonlinear correlation that may exist in data. In this work, we wish to propose a new remote monitoring system for improving the efficiency of disaster prevention system and to prove the usefulness of the proposed system. The proposed system is based on AANN that enables data compression and its efficient data recovery[2].

II. The structure and features of AANN

Generally, PCA (Principle Component Analysis) can not be effectively applied to nonlinear data analysis. Therefore, many

researchers developed techniques that can be applied in the analysis of nonlinear data. For the analysis of nonlinear multi-variable data, AANN was proposed by Kramer to make it easy to analyze the nonlinear data. AANN shown in the Fig. 1, consists of 5 layers Input Layer, Mapping Layer, Bottleneck Layer, Demapping Layer, Output Layer. It can be thought of as a nonlinear PCA[2-3].

The input layer in Fig. 1 has M-dimensional data ($X_1 \ldots X_M$) as input. The input data, may be various sensor values measured on the measurement station. Mapping layer comprises L-dimensional neurons that compress the M-dimensional input data into smaller F-dimensional data. The neuron in this layer has the following input/output characteristics as in the equation (1)

$$F = G(X) \tag{1}$$

In the equation (1), G is a vector whose components are activation functions ($G_1, G_2, \cdots, G_L$) on L-dimension of the mapping layer, and X means measurement variables on 1×M dimension. This characteristic allows compression from M-dimension input data to F-dimension data, and ensures that compressed data are obtained from output on bottleneck layer.

Demapping layer comprises L neurons which decompress compressed 1×F dimension data to their original dimension (1×M). The characteristic of the demapping layer is as shown in the equation (2).

$$Y = H(F) \tag{2}$$

In the equation (2), H is a vector whose components are activation functions ($H_1, H_2, \cdots, H_L$) on L-dimension of the demapping layer, and Y is the output data on 1×M dimension that are the same as the ones used as input of auto-associative neural network. The neuron activation functions G and H in the equations (1) and (2) include weights that must be adjusted in training, and they are learned so that the following residue (error) may be minimized by general (ordinary) supervised learning.

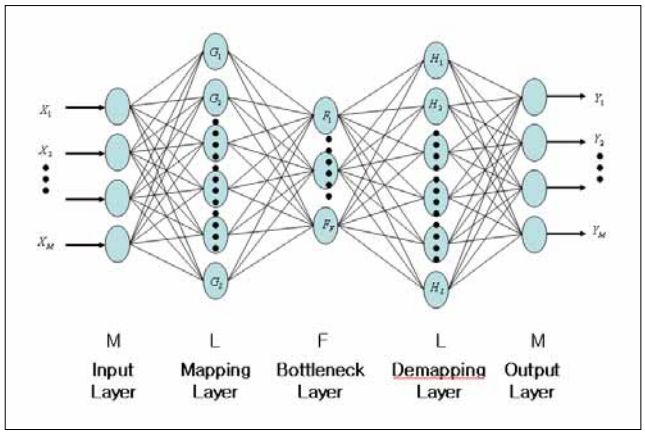

Fig. 1. The Structure of AANN

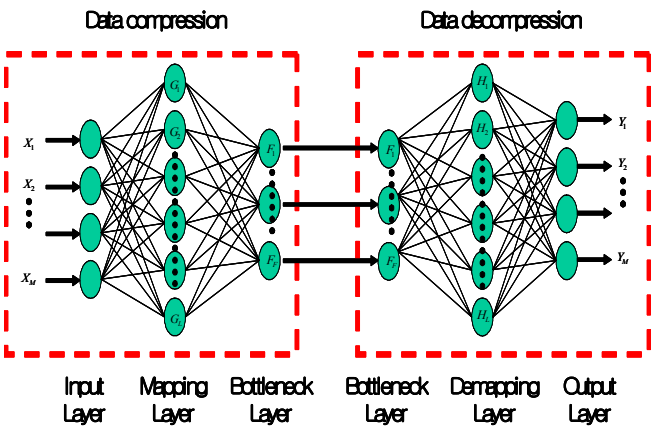

Fig. 2. AANN's characteristics of data compression and decompression

$$R = X - Y \tag{3}$$

AANN has 1:1 mapping function. If it is divided for separate use, it can be used for effective compression and decompression of multi-variable data having non-linear relation. This is as shown in Fig. 2.

Like any other artificial neural networks, AANN also ensures that correlation of information of multi-dimensional non-linear data is distributed and stored through learning, depending on neuron weights. Even if any other data but learned data are applied to AANN, original data can be recovered from the information stored in the network. Using this AANN's data recovering function allows efficient detection of abnormal data. This is as shown in Fig. 3.

Where S1, S2, S3 and S4 are actually measured data, and

s'_1, s'_2, s'_3 and s'_4 mean AANN's output for input measured data. Also, r1, r2, r3 and r4 mean residues (errors) between actually measured data and AANN output. Generally, trained AANN allows efficient recovery of data even if input data is different from the data used in learning, because the bottleneck layer comprises a number of neurons less than input layer. As shown in Fig. 3, using AANNs allows an easy detection of data having different characteristics compared with the time when training is done[4].

III. The structure of AANN-based web-monitoring system

In this chapter a new disaster prevention system that uses AANN, which has the feature of data compression/decompression and can detect abnormal data patterns from normal data patterns is presented. The proposed system is shown in Fig. 4.

The left part of the figure represents the data logger system installed on the measuring site. It is composed of sensor module, data compression module and detection module. The right part of the figure represents a monitoring server system that comprises decompression module and data analysis/alarm module. The functions of each part are as follows:

1. AANN's functions on the measuring system

AANN installed on the measuring site compresses sensor data and discriminates abnormal data pattern from normal data. The detailed structure is shown in Fig. 5. The detection module compares residuals to know whether the current data is normal or not. As described above, if AANN is trained with the normal operational data, it can generate the estimated normal data even if the abnormal data are input to AANN. Therefore, the residuals between X and X' from AANN is used to determine whether the emergence has occurred. When the threshold of residuals is below specified limits, compressed data from AANN's bottleneck layer are transmitted to remote server system. When the threshold of residual is above specified limits

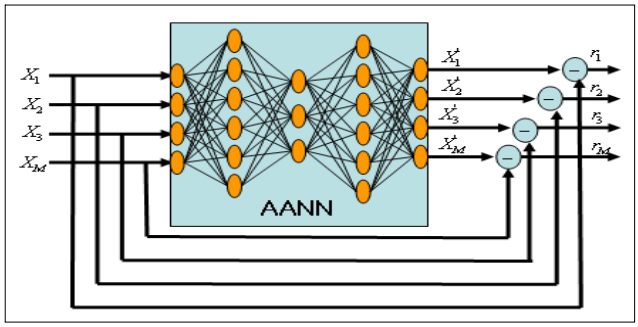

Fig.3. The detection of abnormal data using AANN's data recovering function

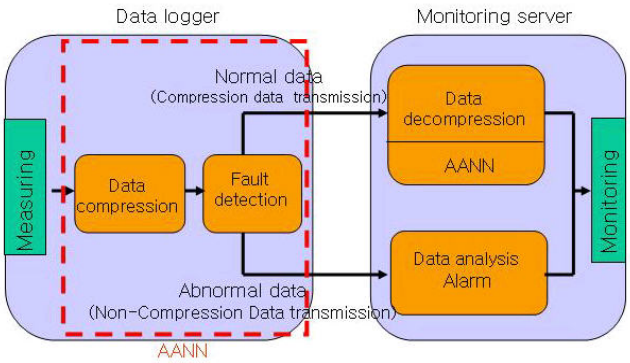

Fig.4. The structure of AANN-based remote monitoring system

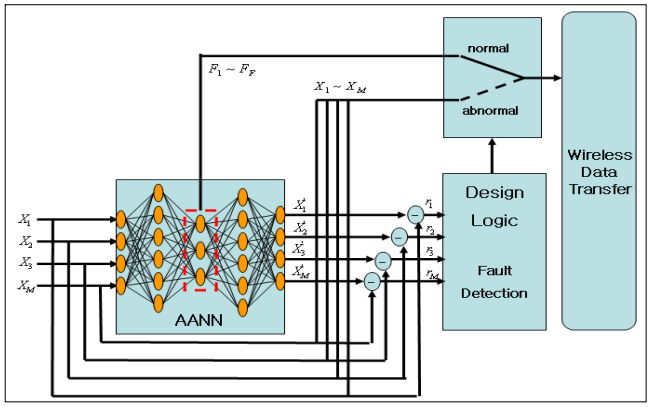

Fig. 5. AANN's functions on the measuring system (Data compression and abnormal data detection)

(if abnormal situation occurs), current data is transmitted to the remote server system at every specified interval. Both of these enable efficient data transmission.

2. AANN's functions in monitoring server system

The detailed structure of data decompression (reconstruction) module based on AANN on server system

is shown in Fig. 6.

AANN which exists in server system is same as that used on the measuring site. However, it has bottleneck layer as input layer and comprises demapping layer and output layer.

IV. Application of the proposed technique to slope collapse prevention system

In this chapter, we will apply the AANN-based disaster prevention system proposed in the previous chapter to a slope collapse prevention system. The whole system is shown in Fig. 7.

As illustrated in Fig. 7, the system comprises measurement station and monitoring server system. The measurement station is consisted of data logger and sensor system. It transmits the stored sensor data to the remote server system. The monitoring server system receives the transmitted data from the measuring system and stores them to its database. Furthermore, the data stored in database is provided with web clients.

1. Measurement system

The measurement system processes the measured data from a multitude of sensor modules and detects abnormal data and finally, sends data to the remote monitoring server system. To effectively measure many sensor data, each sensor modules are equipped with RS-485 interface. The measurement system has a structure illustrated as in Fig. 8.

The sensor modules gather the important information related with the status of the slope. The measured data are transmitted to data logger via RS-485 interface in accordance with the command from data logger.

Data logger is an embedded XP system. It has RS-485 interface for effective interface with multiple sensor modules installed on the extensive area of measurement site. Also, it has an industrial modem for transmission of data to a remote server system. Application GUI for data logger system is programmed by Micro Soft Visual

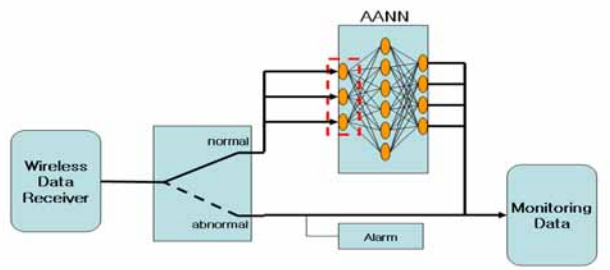

Fig. 6. AANN's functions in server system (Data recovery in server system)

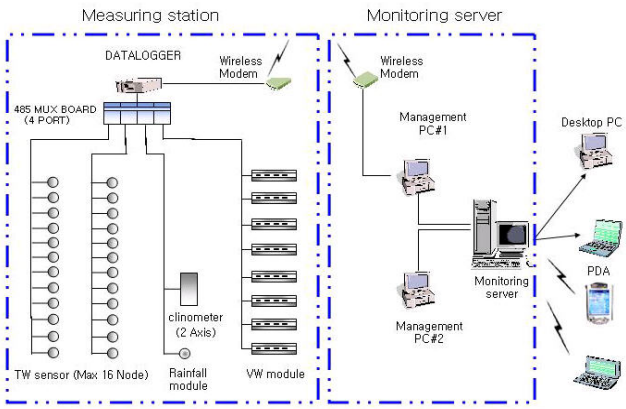

Fig. 7. The structure of AANN-based disaster prevention system

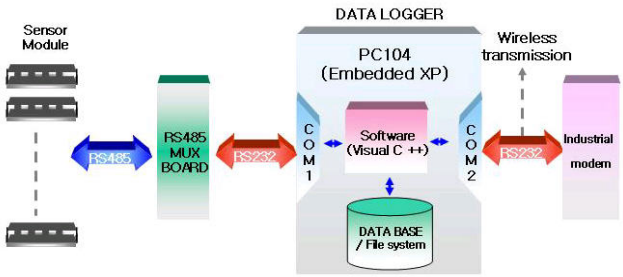

Fig. 8. The structure of measurement system

C++. The application performs following tasks: remote setup for sensor modules, data measurement and storage, module test, data compression, detection of any changes in obtained data, and transmission of data to remote server system.

The measurement system uses AANN algorithm to detect abnormal data. If the current measured data is greater than predetermined threshold, the station recognizes that the abnormal situation has occurred. From that time on, measurement station transmits the raw data to the remote server system at a predetermined cycle.

2. *Remote monitoring server system*

The remote monitoring server system receives compressed data and reconstructs the estimated sensor values when the status of slope is normal. However, emergent status has occurred in measurement site, it receives the raw data from measurement system. The application program is programmed with MS Visual Basic. To build the server system, Windows NT and MS-SQL Server for database management are installed. The whole system is shown in Fig. 9.

3. *Application of the proposed method to slope collapse prevention system*

In this application, 13 sensors such as TW (Tension Wire) and rain-gauge are installed in Hongchun of Kangwon Province. The measured values are transmitted to remote monitoring server system via industrial modem.

The data transmitted from measurement system are as shown in Fig. 10. These data represent the normal status of the slope.

Normal measurement data shown in fig. 10 are utilized for training AANN. As mentioned above, the number of neurons in the bottleneck layer is smaller than the number of neurons in the input/output layer. This feature is the same as non-linear PCA, which makes it possible to compress large size of data into smaller one. In this case, the number of each layer is as follows: 13 neurons in input layer, 20 neurons in mapping/demapping layer and 5 neurons in bottleneck layer. The residuals between estimated data and raw input data for each sensor are shown in fig. 11.

To verify the error-detect ability of AANN, some lamp-type bias is added to 4th sensor. If they are input to AANN, the residuals between output of AANN and raw data are simply calculated as in fig. 12. This figure shows that detection of abnormal status using AANN can be efficiently carried out.

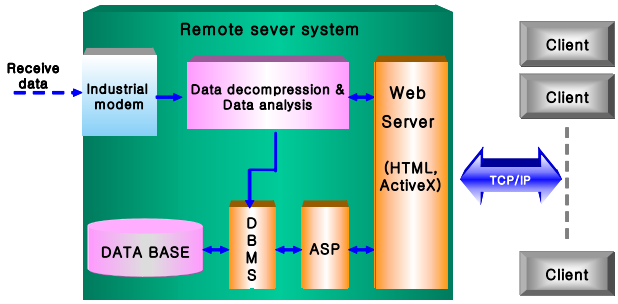

Fig. 9. The structure of remote monitoring system

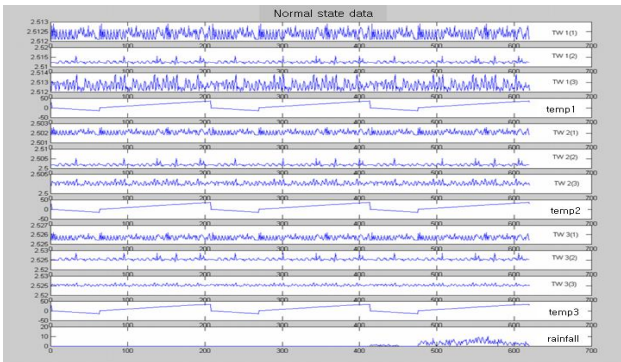

Fig. 10. Data from each measurement station (normal state)

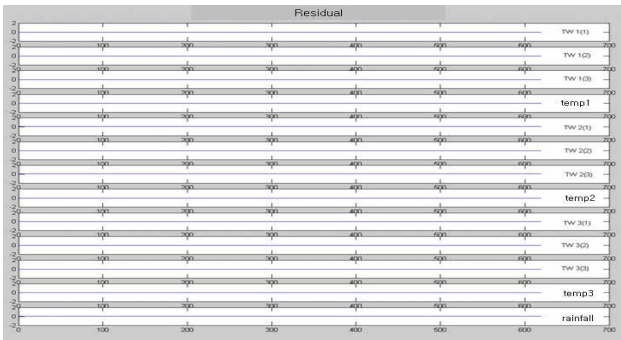

Fig. 11. Residual between raw input data and estimated data

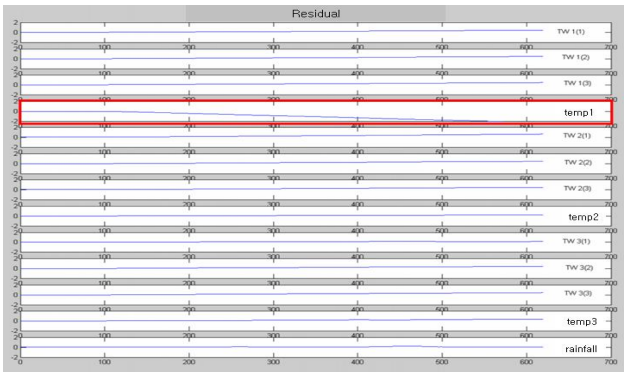

Fig. 12. Detection of abnormal data

V. Conclusion

In this work, AANN-based risk management system which can effectively collects and transmits sensor data to remote server system is proposed. It can transmit the compressed data instead of raw data in normal state. Furthermore, if dangerous situation occurs, rapid transmission of measurement data is carried out. To verify the feasibility of the proposed system, the AANN-based risk management web-monitoring system is applied to slope collapse. The simulation result shows that the proposed system can be effectively used in slope collapse monitoring system.

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