Typhoon Damage Forecasting with Self-Organizing Maps, Multiple Regression and Decision Trees

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Abstract. Damage caused by typhoons to both people and structures has decreased in Japan due to improvements of countermeasures against natural disasters, however, such damage still occurs. A typhoon warning that represents the risk posed by a typhoon with high accuracy should be issued appropriately. Thus, we propose a new typhoon warning system which forecasts the likely extent of damage associated with a typhoon towards humans and buildings. The relation between typhoon data and damage data is investigated and typhoon damage is forecast using typhoon data. Self-organizing maps (SOM), multiple regression analysis and decision trees were used for typhoon damage forecasting. We consider two types of forecasting: two-class (*yes* or *no*) and three-class (*small*, *medium* or *large* scale) damage forecasting. Experimental results on accuracy of two-class and three-class forecasting with SOM were 93.3% and 96.8%, respectively. The accuracy with SOM was much better than that with multiple regression and decision trees. We recommend a new typhoon damage forecasting method based on these results.

1 Introduction

Intelligent techniques such as back-propagation neural networks (BPNN) [1], self-organizing maps (SOM) [2], decision trees [3] and Bayesian networks [4] have been extensively investigated, and various attempts have been made to apply them to identification, prediction and control [e.g., 1-10]. Harada et al. applied BPNN to forecasting typhoon course [8], Takada et al. applied BPNN to forecasting typhoon damage of electric power systems [9] and Udagawa et al. applied Bayesian networks to rain prediction [10]. This paper applies intelligent techniques to forecasting typhoon damage to human and buildings.

Damage caused by typhoons to both people and structures has decreased in Japan due to improvements of countermeasures against natural disasters, however, such damage still occurs [11, 12]. A typhoon warning that represents typhoon menace with high accuracy should be issued appropriately. A typical typhoon warning currently issued may be “This typhoon is large and very strong”. We propose a new typhoon warning which forecasts the risk of damage scale to both human and buildings. We investigate relation between typhoon data and damage data and forecast typhoon damage using typhoon data. The typhoon data includes the month when the typhoon

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was born, latitude and longitude where the typhoon was born, lowest atmospheric pressure, maximum wind speed and total precipitation. Damage data includes human damage data such as number of fatalities and injured persons and building damage data such as number of completely destroyed houses and number of houses under water.

We use SOM, multiple regression analysis and decision trees for typhoon damage forecasting. SOM [2] are neural networks which consist of two layers: input layer and map layer. As an interesting feature of SOM, teaching vectors are not required and input vectors are automatically classified in accordance with similarity, updating the weight of the *winning neuron* and the neighbor neurons. After trained by SOM algorithm, the weight vectors of the neurons form the cluster of input vectors. A decision tree [3] is an inductive learning algorithm. In a decision tree algorithm, an explicit decision boundary is extracted from the training data, and an example *E* is classified into class *c* if *E* falls into the decision area corresponding to *c*. *Viscovery SOMine 4.0* was used as SOM software and *See5 release 1.19* was used as decision tree software with default parameter values.

2 Forecasting Damage Data using Typhoon Data

139 data records of typhoon data and damage data from June 1981 to September 1999 were collected from the typhoon database [13, 14]. The types of typhoon and damage data are shown in Table 1. There are nine types of typhoon data and nine types of damage data, divided into three types of human damage and six types of building damage. We used 111 data records (to September 1995) for learning and 28 data records (from July 1996) for testing.

Table 1. Types of typhoon data and damage data used in this study.

Typhoon data	Month when the typhoon was born, Latitude and longitude where the typhoon was born, Lowest atmospheric pressure, Maximum wind speed, Total, one-hour and twenty-four-hour precipitation, Life span
Damage data	Number of fatalities, Number of injured persons, Number of dead and injured persons
	Number of completely destroyed houses, Number of half destroyed houses, Number of partially destroyed houses, Total number of damaged houses, Number of houses under water, Total number of destroyed non-house structures

The average and maximum of every damage type are shown in Table 2. The minimum of every damage type was zero.

Table 2. Average and maximum of every type of damage data.

Data type	Average	Maximum
Number of fatalities	5.5	100
Number of injured persons	39.2	1499
Number of dead and injured persons	44.8	1561
Number of completely destroyed houses	21.9	541
Number of half destroyed houses	1839.8	169877
Number of partially destroyed houses	1051.7	85989
Total number of damaged houses	2913.4	170418
Number of houses under water	7829.6	174124
Total number of destroyed non-house structures	163.6	15840

In this study, we consider two types of typhoon damage forecasting: two-class (*yes* or *no*) and three-class (*small*, *medium* or *large* scale) damage forecasting.

3 Two-class (Yes or No) Damage Forecasting

In two-class damage forecasting, a predictor is trained by two values (0 and 1). In this case, 0 means that the damage is zero (*no*) and 1 means that the damage is not zero (*yes*). Experiments were made with nine types of continuous typhoon data as inputs and one damage data (two values) as an output. Here, we expect that typhoon data such as lowest atmospheric pressure, maximum wind speed and precipitation can be forecast with high accuracy by a weather forecasting system such as Japanese SYNFOS [15] and hence actual typhoon data was used as inputs.

Table 3. Average accuracy of two-class (*yes* or *no*) damage forecasting.

Method	Learning data	Test data
Self-organizing maps (SOM)	100%	93.3%
Multiple regression (MR)	70.9%	70.2%
Decision trees (DT)	77.7%	63.9%

Table 4. Accuracy of two-class (*yes* or *no*) damage forecasting for test data.

Damage type	SOM	MR	DT
No. fatalities	92.9%	57.1%	50.0%
No. injured persons	89.3%	75.0%	75.0%
No. dead and injured persons	96.4%	89.3%	85.7%
No. completely destroyed houses	92.9%	57.1%	57.1%
No. half destroyed houses	89.3%	71.4%	71.4%
No. partially destroyed houses	92.9%	67.9%	60.7%
Total no. of damaged houses	96.4%	75.0%	64.3%
No. houses under water	96.4%	85.7%	78.6%
Total no. destroyed non-house structures	92.9%	53.6%	32.1%
Average	93.3%	70.2%	63.9%

SOM: self-organizing maps, MR: multiple regression, DT: decision trees

The average accuracy of two-class (*yes* or *no*) damage forecasting for the three intelligent methods is shown in Table 3. Here, average accuracy means the average of the accuracy of nine damage data. The average accuracy of the learning and test data using SOM was 100% and 93.3%, respectively. This experiment confirmed that damage data are well related with typhoon data and that SOM learned the nonlinear relation very well. The accuracy for each damage test data is shown in Table 4. Each damage data was forecast very well by SOM. The accuracy with SOM was much better than that with multiple regression and decision trees.

4 Three-class (Small, Medium or Large Scale) Damage Forecasting

In three-class damage forecasting, two experiments were made with nine types of continuous typhoon data as inputs and one damage data as an output. In the first experiment, a predictor is trained by continuous damage data. As this is a regression problem, decision trees were not used. The average of each damage data was calculated as shown in Table 2. *Small scale* corresponds to under half of the average, *medium scale* corresponds to between half of the average and the average, and *large scale* corresponds to over the average, respectively. The prediction was considered accurate when both the predicted value and the actual value correspond to the same size. The average accuracy of three-class damage forecasting when trained by continuous damage data is shown in Table 5. The average accuracy of the learning and test data with SOM was 100% and 78.6%, respectively. The accuracy for each damage type is shown in Table 6. The accuracy with SOM was much better than that with multiple regression, however, each damage data was not always forecast very well by SOM. For example, accuracy for number of fatalities and number of partially destroyed houses was 67.9% and 92.9%, respectively.

Table 5. Average accuracy of three-class (*small*, *medium* or *large* scale) damage forecasting when trained by continuous damage data.

Method	Learning data	Test data
Self-organizing maps (SOM)	100%	78.6%
Multiple regression (MR)	52.8%	43.7%

Table 6. Accuracy of three-class (*small*, *medium* or *large* scale) damage forecasting for test data when trained by continuous damage data.

Damage type	SOM	MR
No. fatalities	67.9%	35.7%
No. injured persons	75.0%	46.4%
No. dead and injured persons	75.0%	42.9%
No. completely destroyed houses	60.7%	46.4%
No. half destroyed houses	89.3%	42.9%
No. partially destroyed houses	92.9%	42.9%
Total no. of damaged houses	89.3%	39.3%
No. houses under water	82.1%	39.3%
Total no. destroyed non-house structures	75.0%	57.1%
Average	78.6%	43.7%

In the second experiment, a predictor is trained by three values (0, 1 and 2). As this is a classification problem, decision trees were used. In the learning data, 0 means that the damage is *small scale*, 1 means the damage is *medium scale* and 2 means the damage is *large scale*. The prediction was considered accurate when the predicted size was equal to the actual size. The average accuracy of three-class damage forecasting when trained by three values is shown in Table 7. The average accuracy of the learning and test data with SOM was 100% and 96.8%, respectively. This also confirmed that damage data are also well related with typhoon data. The accuracy for each damage type is shown in Table 8. Each damage type was also forecast very well by SOM. For example, accuracy for number of fatalities and number of partially destroyed houses was 85.7% and 100%, respectively. The accuracy with SOM was also much better than that with multiple regression and decision trees.

Table 7. Average accuracy of three-class (*small*, *medium* or *large* scale) damage forecasting when trained by three values.

Method	Learning data	Test data
Self-organizing maps (SOM)	100%	96.8%
Multiple regression (MR)	77.5%	65.1%
Decision trees (DT)	90.1%	78.6%

Table 8. Accuracy of three-class (*small*, *medium* or *large* scale) damage forecasting for test data when trained by three values.

Damage type	SOM	MR	DT
No. fatalities	85.7%	42.9%	78.6%
No. injured persons	100%	53.6%	71.4%
No. dead and injured persons	100%	53.6%	71.4%
No. completely destroyed houses	92.9%	39.3%	53.6%
No. half destroyed houses	100%	85.7%	96.4%
No. partially destroyed houses	100%	85.7%	85.7%
Total no. of damaged houses	100%	85.7%	92.9%
No. houses under water	92.9%	50.0%	60.7%
Total no. destroyed non-house structures	100%	89.3%	96.4%
Average	96.8%	65.1%	78.6%

5 Conclusions

We investigated typhoon damage forecasting with intelligent techniques. Using nine types of typhoon data as inputs to SOM, experimental results on the average accuracy of two-class (*yes* or *no*) and three-class (*small*, *medium* or *large* scale) damage forecasting were 93.3% and 96.8%, respectively. The accuracy with SOM was much better than that with multiple regression and decision trees. As a result, a typhoon forecasting method is proposed as follows: 1) Evaluate two-class damage forecasting, 2) When two-class forecasting result is *yes*, evaluate three-class damage forecasting, 3) Issue a typhoon warning based on above three-class damage forecasting. For example, such a warning may be issued, “According to the Japanese typhoon database, we forecast that the coming typhoon has a risk of causing both large scale human and building damage. Please take care.” In further research, we will consider more detailed damage forecasting and use other predictors such as support vector machines.

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