

Improving the Water Level Prediction in Andong Region

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1. Introduction

Andong is a very important region because of UNESCO world heritage site, "Hahoe Village." For protecting the site from severe disasters, we must consider DPD(Disaster Prevention Design) in "Hahoe Village." Among various disasters, flooding has been focused because of its drastic impact on lives and properties in wide area. It is estimated that of the total economic loss caused by all kinds of disasters, 40% are due to flooding. However, the relationship between rainfall and flood discharge is very complex [1]. Therefore, modelling the relationships between rainfall and flooding or runoff are still unsolved problems [2-7].

When modelling a phenomena using artificial neural networks (ANNs), it is not necessary to elucidate complex mechanisms involving the phenomena [6]. In this point of view, ANN has been widely applied in hydrology and multi-layer perceptron was used for predicting the water level of Nakdong River in Andong region [9]. In this paper, we improve the water level prediction of Nakdong River using a modified error function.

2. Multi-Layer Perceptron (MLP)

Based on the proof that multi-layer perceptron (MLP) can approximate any function with enough hidden nodes, MLP has been applied to many fields such as pattern recognition, time series prediction, fraud detection, hydrology etc. Fig. 1 shows the architecture of MLP consisted of input vector x , hidden node vector h , output node vector y , and their connection weights. When an input vector $x = [x_1, x_2, \dots, x_N]^T$ is presented to the MLP, a weighted sum to h_j is given by $a_j = \sum_{i=1}^N w_{ji}x_i + w_{j0}$ and then the hidden node value is given by $h_j = \tanh(a_j)$. Here, w_{j0} is a bias and w_{ji} is a weight between h_j and x_i . The k -th output node y_k is calculated through the same procedure of weighted sum and nonlinear transform $\tanh(\cdot)$ using the weight v_{kj} and the hidden node value h_j . When $t_k^{(p)}$ is given for a specific

training exemplar $x^{(p)}$, we usually updates weights w_{ji} and v_{kj} to minimize the mean-squared error (MSE) function $E^{out} = \frac{1}{2} \sum_{p=1}^P \sum_{k=1}^M (t_k^{(p)} - y_k^{(p)})^2$. Here, P is the number of training exemplars and M is the number of output nodes. The error back-propagation (EBP) algorithm provides updating procedure of w_{ji} and v_{kj} as follows[8]:

$$\Delta v_{kj} = -\eta \frac{\partial E^{out}}{\partial v_{kj}} = \eta \delta_k^{(p)} h_j^{(p)} \text{ where } \delta_k^{(p)} = -\frac{\partial E^{out}}{\partial y_k^{(p)}} = (t_k^{(p)} - y_k^{(p)}) f'(\hat{y}_k^{(p)})$$

$$\Delta w_{ji} = -\eta \frac{\partial E^{out}}{\partial w_{ji}} = \eta f'(\hat{h}_j^{(p)}) x_i^{(p)} \sum_{k=1}^M v_{kj} \delta_k^{(p)}$$

Since we adopt a linear output MLP for predicting the water level, $y_k = \sum_{j=1}^H v_{kj} h_j + v_{k0}$ and $f'(y_k) = 1$.

3. Hydrological Modelling of Andong Region and Improving the Water Level Prediction

Previously, we proposed the hydrological modelling of Andong region, that is, the relationship among the water level of Gudam and the rainfalls of Pungsan, Iljik, and Andong (their locations are indicated by "red circles" in Fig. 2) [9]. During 2012, 2013, and 2014 years, the rainfalls of Pungsan, Iljik, and Andong had been recorded in the period from March 1st to November 30th with the interval of one hour. Also, the water level of Gudam had been recorded in the same period. Therefore, each data file has 6600 records in each year.

In order to predict the water level at Gudam after D hours, we construct an MLP whose input layer consists of the water level at Gudam and rainfalls at Pungsan, Iljik, and Andong from current (denoted by "n") to previous $n-L$ hours. When determining the number of parameters in MLPs, we usually adopt the method of trial and error since there is not a concrete theoretical guidance. Accordingly, we determine that L is two and the number of hidden node is forty through many trials and errors. Therefore, the three rainfall data and the water level of Gudam at n , $n-1$, $n-2$ are presented to the input layer of MLP and the water level of Gudam after D hours is presented as a target value of MLP output. EBP algorithm updates the weights of MLP to

predict the water level after one hour. Here, we use $D=1$.

MLP with 12 inputs, 40 hidden nodes, and one output node is initialized with the weights uniformly distributed on $[-1 \times 10^{-4}, 1 \times 10^{-4}]$. We adopt a learning rate of 0.01. The MLP is trained with the data in 2012 and 2013 and tested with the data in 2014 for performance evaluation of MLP. We estimate the correlation coefficient between the water level of Gudam and its predicted value as a performance measure. After training of 10000 iterations, the correlation coefficient is 0.99692. However, the maximum distance between real and predicted water levels is 55.51cm.

In order to reduce the maximum distance, we propose a new error function $E^{out} = \frac{1}{4} \sum_{p=1}^P \sum_{k=1}^M (y_k^{(p)} - \hat{y}_k^{(p)})^4$ for the EBP algorithm and the predicted result with the modified method is in Fig. 4. Now, the correlation coefficient is 0.99714 and the maximum distance is reduced to 40.85cm.

4. Discussion and Conclusion

In this presentation, we briefly introduced the hydrological model of Andong region using MLP. The MLP was trained with the water level and rainfalls during 2012 and 2013, and then tested with them in 2014. Predicting the water level of Gudam after one hour with the rainfalls of Andong, Pungsan, and Iljik with the modified method was better than the conventional EBP algorithm.

5. Acknowledgement

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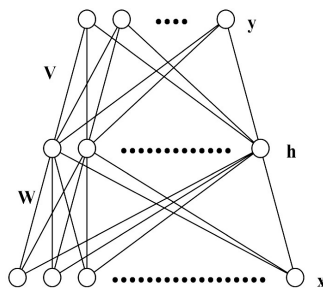


Figure 1. The architecture of MLP.

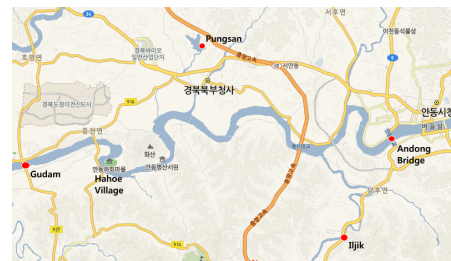


Figure 2. The location of Gudam, Pungsan, Iljik. And Andong (indicated by "red circles").

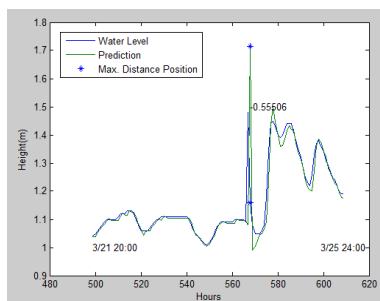


Figure 3. Prediction results with MSE.

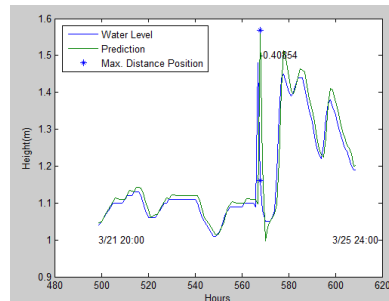


Figure 4. Prediction results with modified method.