Flood Water Level Forecast Using Machine Learning

Tasuku Kubo[1], Takeo Okazaki[2]

[1]*Graduate School of Engineering and Science, University of the Ryukyus*

1 Senbaru Nishihara, Okinawa 903-0123, Japan, e175764@ie.u-ryukyu.ac.jp

[2]*Department of Computer Science and Intelligent System, University of the Ryukyus*

1 Senbaru Nishihara, Okinawa 903-0123, Japan, okazaki@ie.u-ryukyu.ac.jp

Abstract

In predicting flood water level, underestimation may lead to delay on decision making. In order to decrease the underestimation, we proposed the method using weighted loss function in Deep Neural Network. Mean squared error (MSE), mean absolute error (MAE) and Huber loss are used to evaluate the performance of the proposed model. The models are effectively used by weighting the loss for underestimation, and the results of verification showed that we succeeded in reducing underestimation in actual flood cases.

Keywords: Flood forecast, water level, machine learning, weighted loss function, underestimation.

1. Introduction

Recently, flood disaster has threatened Japan with extensive damage. These floods are mainly caused by increased rainfall due to typhoons, stationary fronts, as well as reduced river drainage due to land development. In order to minimize such damages, it is important to grasp the water level changes in rivers in advance and to take countermeasures and evacuate from the rivers in the early stage. For this purpose, the effective method with advanced technology to predict the water level fluctuations of rivers with high accuracy is necessary. It is considered that many factors affect the fluctuation of water level in rivers, such as the amount of rainfall in the basin, changes in the drainage function due to land development, and the thickness of the geology and soil.

However, some recent studies have achieved high accuracy by using Machine Learning [1][2][3]. These studies collect a large amount of past flood data for a particular river, and by learning the characteristics of the rainfall-runoff relationship, they were able to accurately predict the fluctuation of water levels in a particular river during a flood. On the other hand, since the prediction accuracy depends largely on the data used for training, there is a concern that the system may underestimate the water level or fail to reproduce the peak water level for flood cases that have not been experienced in the past.

In the prediction of water levels during floods, a low estimation of water levels causes a long delay in making evacuation decisions and bring more issues in evacuation advisories, in which more damages will be aggravated. Hence, the purpose of this study is to predict the water level more suitable for disaster prevention by using machine learning.

2. Application of Neural Networks to Water Level Prediction

Water level problem is a kind of time series data problem that there is a strong correlation between the value at a certain point in time and the values of several time points before that. In forecasting, it is necessary to select features while considering this time-series nature. In addition, if we try to predict the water level directly, we may end up using the water level of the previous time point as the predicted value due to this autocorrelation.

Hitokoto et al. [1] applied an artificial neural network (ANN) to the prediction of water level in a river. Data obtained from several hours of various water level stations and rainfall stations in the river basin to predict water level changes up to several hours after at the target point (Fig. 1).

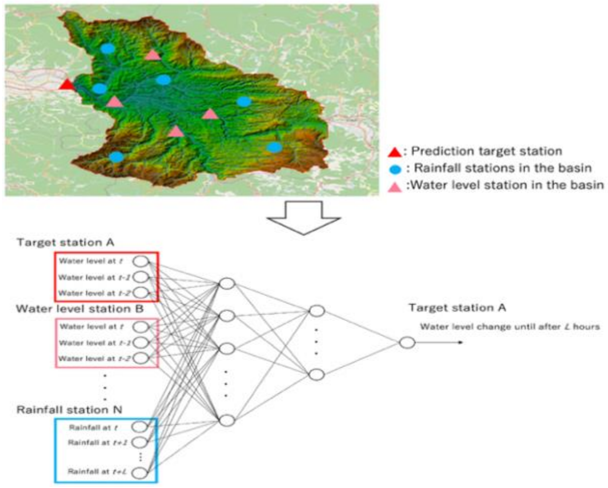


Fig. 1: Procedure of water level prediction by ANN

To evaluate the prediction performance of machine learning models for numerical time series data, mean squared error (MSE) or mean absolute error (MAE) is popularly used. Most of previous studies have used MSE as loss function to evaluate prediction models of water level problem. MSE is a loss function in which the larger the error, the larger the loss (Eq. 1). Therefore, it has a drawback that it is sensitive to outliers.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 , \tag{1}$$

General loss functions, such as MSE and MAE, focus only on the magnitude of the error, and the losses resulting from positive errors (underestimation errors) and negative errors (overestimation errors) are treated as equivalent.

However, in water level prediction of rivers, especially in flood prediction, it is acceptable to predict a little larger than the actual value, but to predict a little smaller value may be a risk of increasing damage. In this study, we propose to construct a model that minimizes underestimation as much as possible by weighting the losses caused by underestimation and overestimation, referring to the studies on learning with asymmetric loss functions [4]. In defining the weighted loss function, we used the Huber loss [5] as the base loss function. Huber loss is a function that is a combination of MSE and MAE, where the square of the error is given if the absolute value of the error is less than or equal to the reference value. The same value is given if the absolute value is greater than the reference value (Eq. 2).

$$E = \begin{cases} \frac{1}{2}(y-\hat{y})^2 & for\ |y-\hat{y}| \le \delta, \\ \delta\left(|y-\hat{y}| - \frac{1}{2}\delta\right) & otherwise. \end{cases} \tag{2}$$

Furthermore, the weighted loss function (WHL) is expressed by the following equation.

$$L(y,\hat{y},\alpha) = \begin{cases} \alpha \cdot L_{Huber}(y,\hat{y}) & y-\hat{y} \ge 0, \\ (1-\alpha)\cdot L_{Huber}(y,\hat{y}) & y-\hat{y} \le 0, \end{cases} \tag{3}$$

where, L_{Huber} is Huber loss function and α is a coefficient that determines the ratio of weights for underestimation and overestimation errors. As in Fig. 2, when $\alpha = 0.5$, the loss is symmetric with respect to the axis of 0 and gives the same loss as the usual Huber loss. However, when α get larger ($\alpha \ge 0.6$), the loss for underestimation error becomes larger.

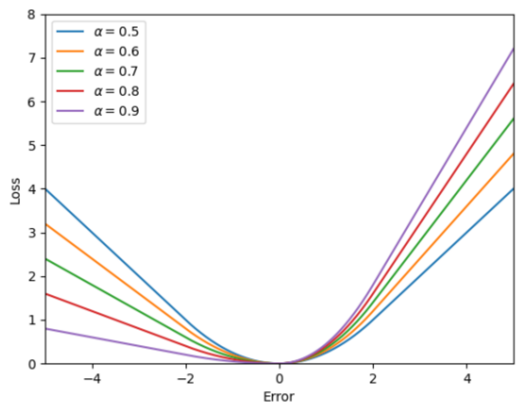


Fig. 2: Error and loss for each α

In Fig. 2, $\delta = 2$, the horizontal axis represents the error between the predicted and measured values, and the vertical axis represents the loss given to it.

3. Verification experiment using past flood cases

We conducted a validation experiment on Tsuwano River, which flows in Shimane and Yamaguchi prefectures. The target flood was occurred on July 26, 2013, and one week's data was used as the test data. We used data from Machida station and two rainfall stations in the basin, and the geographical relationship between them is shown in Fig. 3.

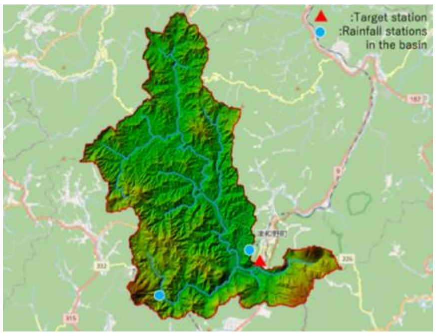


Fig. 3: Machida water level station and rainfall stations in the basin

Features and target variable are summarized as shown in Table 1.

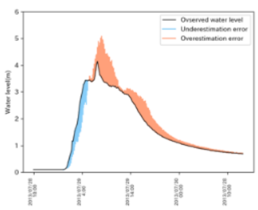
Table 1: Features and target

Features			Target
Type	Point	Time	Water level change at Machida station from 0 to t hours later
Water level change	Machida	-3~0	
Water level	Machida	0	
Rain	Tsuwano, Nayoshi	t-5~t	

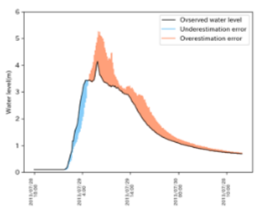
The details and various settings for training, such as the division of test data and training data, are shown in Table 2.

Table 2: Settings for training

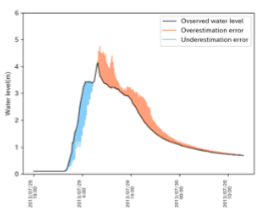
Type	
Training data period	2009/3/1～2013/7/23
Test data period	2013/7/24～7/31
Number of training data	About 270,000
Batch size	32
The number of elements in each layer	79-40-20-1



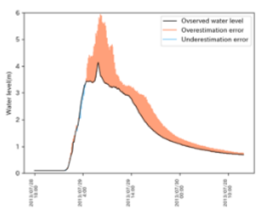
(a) Prediction using MSE



(b) Prediction using MAE



(c) Prediction using Huber



(d) Prediction using WHL

Fig. 4: Result of 3hours ahead prediction in Tsuwano river

Table 3: Evaluation of each result

Evaluation index	MSE	MAE	Huber	WHL
Difference in peak water level (m)	0.93	1.11	0.61	1.79
Difference in peak time (min)	50	10	30	30
RMSE	0.45	0.49	0.48	0.65
Total underestimation	17.06	14.88	26.32	2.16
Maximum underestimation	2.12	2.19	2.05	0.43

Fig. 4a～4d show the 3hours ahead prediction results for MSE, MAE, Huber loss, and weighted Huber loss as loss functions, respectively. The black line in the figure shows the actual observed water level, and the red and blue lines show the over-prediction error and under-prediction error of the predicted water level and the actual observed water level, respectively. All are calculated by adding the predicted water level change after 3 hours predicted at that time to the water level 3 hours ago. Table 3 summarizes the values of each evaluation index calculated from the predicted and observed values.

The overall results show that the peak water level is overestimated in all cases. In particular, the overestimation of weighted Huber loss is the largest, indicating that the loss is given small for the overestimation error. RMSE scores also show that weighted Huber loss has a larger error between the prediction and actual values than MSE and MAE. On the other hand, weighted Huber is the best in terms of total underestimation and maximum underestimation error. Furthermore, comparing the results in Fig. 4, it can be seen that, on the whole, there are many overestimations when the water level falls and many underestimations when the water level rises, but the prediction using weighted Huber has few underestimations when the water level rises.

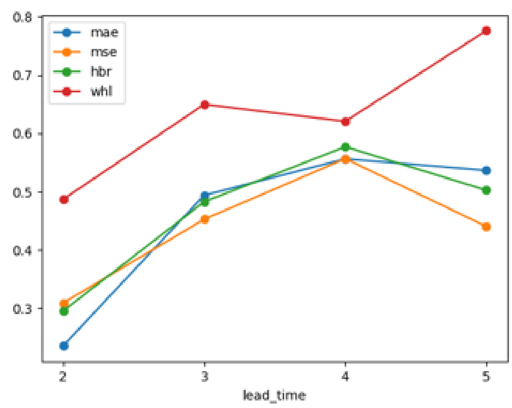


Fig. 5: RMSE for each lead time

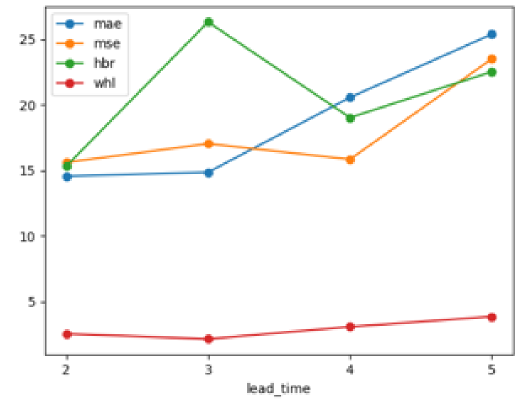
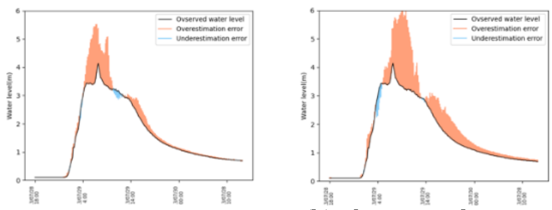


Fig. 6: Total underestimation error for each lead time



(a) 2hours prediction (b) 5hours prediction

Fig. 7: Results for different lead time (WHL)

In addition, we validated the performance of each model by varying lead time (LT). Fig. 5, 6 show RMSE and total underestimation for each lead time. Fig.7a, 7b show results for different lead time prediction using WHL.

According to Fig.5, for all three methods except for WHL, when LT is more than 3 hours, RMSE does not change significantly with LT. This is probably due to Hitokoto's method using future rainfall up to time t for prediction. When LT is more than 3 hours, the relationship between target and features except for rainfall is less than when LT is 2 hours. Therefore, the prediction depends mainly on rainfall when LT is more than 3 hours, and there were few differences in accuracy. It can also be seen that RMSE of the proposed method is larger than other methods. It is probably due to the proposed method allowing larger errors because the loss for overestimation is smaller as mentioned above.

According to Fig.6, total underestimation error tends to increase as LT is expanded. However, for Huber loss, total underestimation error is largest when LT is 3 hours. It indicates that there is a possibility that the threshold δ was little bit small for target value, and the model learned to focus on the small water level change. On the other hand, WHL is stable at a low level, which indicates that the method is superior in terms of disaster prevention.

4. Conclusion

We focused on the difference in risk between underestimation and overestimation in water level prediction during floods and proposed a prediction method that minimizes underestimation by weighting the loss function of machine learning. In addition, we demonstrated the effectiveness of the proposed method by comparing it with the conventional method. The result showed that we succeeded in reducing underestimation in actual flood cases.

References

[1] Masayuki Hitokoto, Masaaki Sakuraba, and Yuichi Sei. "Development of the real-time river stage prediction method using deep learning." *Journal of Japan Society of Civil Engineers. Ser. B1, Hydraulic engineering*, Vol. 72, No. 4, pp. 187–192, 2016.

[2] Ryota Okazaki, Makoto Nakatsugawa, and Yosuke Kobayashi. "A proposed method for flood water level prediction using the random forest method." *Journal of Japan Society of Civil Engineers. Ser. B1, Hydraulic engineering*, Vol. 74, No. 4, pp. 1459–1464, 2018.

[3] Masayuki Hitokoto and Masaaki Sakuraba. "Hybrid deep neural network and distributed rainfall-runoff model for the real-time river stage prediction." *Journal of Japan Society of Civil Engineers. Ser. B1, Hydraulic engineering*, Vol. 73, No. 1, pp. 22–33, 2017.

[4] Matthias Petri, Alistair Moffat, Joel Mackenzie, J. Shane Culpepper, and Daniel Beck. "Accelerated Query Processing Via Similarity Score Prediction." *SIGIR '19. Association for Computing Machinery*, New York, NY, USA, 2019.

[5] Peter J. Huber. "Robust estimation of a location parameter." *Ann. Math. Statist.*, Vol. 35, No. 1, pp. 73–101, 03 1964.