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Recurrent Neural Network with Multiple Hidden Layers for Water Level Forecasting near UNESCO World Heritage Site "Hahoe Village"

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ABSTRACT

Among many UNESCO world heritage sites in Korea, "Historic Village: Hahoe" is adjacent to Nakdong River and it is imperative to monitor the water level near the village in a bid to forecast floods and prevent disasters resulting from floods.. In this paper, we propose a recurrent neural network with multiple hidden layers to predict the water level near the village. For training purposes on the proposed model, we adopt the sixth-order error function to improve learning for rare events as well as to prevent overspecialization to abundant events. Multiple hidden layers with recurrent and crosstalk links are helpful in acquiring the time dynamics of the relationship between rainfalls and water levels. In addition, we chose hidden nodes with linear rectifier activation functions for training on multiple hidden layers. Through simulations, we verified that the proposed model precisely predicts the water level with high peaks during the rainy season and attains better performance than the conventional multi-layer perceptron.

Key words*: Flooding, Water Level Prediction, Hahoe Village, Recurrent Neural Networks, Error-Back Propagation.*

1. INTRODUCTION

Hornik et al. proved that multilayer feed-forward neural networks are universal approximators of any functions [1]-[3]. Based on the results, there have been many applications of feed-forward neural networks in various fields such as pattern recognition, speech recognition, time series prediction, fraud detection, telecommunications, and so forth [4]-[7]. Furthermore, deep learning enlarges the application area to image understanding and language processing [8]. Also, there have been reports to forecast disasters such as tide, storm surge, and landslide using feed-forward neural networks [9]-[13]. Furthermore, it is estimated that 40% of the total economic loss caused by all kinds of disasters are due to flooding [14]. Because of the drastic impact of flooding on lives and properties, many researchers have focused on the relationships between rainfalls and flood discharges or water levels of rivers [14]-[17]. We can categorize the research into deterministic, conceptual, and parametric models [18]. Among the models, the parametric model tries to find mathematical transfer functions to relate several variables to runoff. In this point of view, neural network models belong to the parametric model [18]. Since it is not necessary to elucidate the complex mechanism of phenomena to be modeled by neural networks, hydrologists attempted to forecast floods or to predict water levels using feed-forward neural networks [19]-[26].

Feed-forward neural networks are applied to forecast the peak stages of lower reaches stations at rivers [15], the flood disaster area [21] in Chian, and the flow of the River Nile in Egypt with multi-step ahead predictions [19]. There was a report to predict *T*-year flood events for 850 catchments across the UK [20]. Also, daily flows during flood events in India were modeled using neural networks [22]. It was shown that neural networks could model the rainfall-runoff relationship in a semiarid region in Morocco although there were extreme events such as floods and droughts with irregularity [23], [24]. Furthermore, neural networks were combined with a kinematic wave approach for improving event-based rainfall-runoff modeling [25].

In 1972, UNESCO concluded the "Convention Concerning the Protection of the World Cultural and Natural Heritage" for national and international protection activities of world heritage. Korea National Commission for UNESCO has taken a great role to register and to protect world heritage in Korea and, as a result, there are twelve UNESCO world heritage sites in Korea. Among them, "Historic Village: Hahoe" in Andong region is adjacent to Nakdong River and, therefore, the water level near the village should be carefully monitored for forecasting floods or preventing disasters from floods. Accordingly, there was the hydrological modeling of water level near "Hahoe Village" with feed-forward neural networks [26].

However, all these feed-forward neural networks used in [15] and [19]-[26] were trained to minimize mean-squared error (MSE) function for training data based on the error back-

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propagation (EBP) algorithm [27]. To improve the performance of flood forecasting or water level prediction, we should deal with time dynamics of the relationship between rainfalls and floods which are too complicated to be modeled in the static feed-forward neural network models [28]. Also, it is necessary to increase the number of hidden layers to resolve complex problems [8]. Besides the architecture of neural network model, we should handle the imbalance of hydrological data since low or medium level data are very much dominant over high-level data [14], [20]. During training to minimize MSE, neural networks show poor prediction performance for rare events such as high-level data or floods because of the overspecialization to low or medium level data. In this point of view, this paper proposes a recurrent neural network with multiple hidden layers for improved water level prediction near “Hahoe Village.” Also, we adopt the six-order error function between desired and real output values of the neural network to suppress the learning for abundant events and to improve the learning for rare events.

In section 2, we briefly introduce a feed-forward neural network and its EBP training algorithm. Then, we propose a recurrent neural network which has recurrent and cross-talk connections among hidden nodes. In section 3, we simulate the water level prediction near “Hahoe Village” with real data. Finally, section 4 concludes this paper.

2. A RECURRENT NEURAL NETWORK WITH MULTIPLE HIDDEN LAYERS

2.1 Error Back-Propagation Algorithm

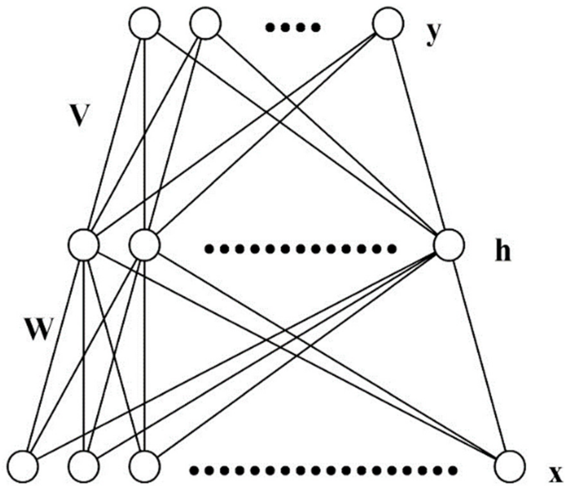


Fig. 1. The architecture of a multilayer perceptron

Consider a feed-forward neural network, so-called “MLP(multi-layer perceptron),” consisting of N inputs, H hidden nodes, and M output nodes, as shown in Fig. 1. When the p-th training data $\mathbf{x}^{(p)} = [x_1^{(p)}, x_2^{(p)}, \ldots, x_N^{(p)}]$ $(p = 1,2,\ldots,P)$ is presented to the input layer of MLP, by the forward propagation, the j-th hidden node is given by

$$h_j^{(p)} = h_j(\mathbf{x}^{(p)}) = \tanh((w_{j0} + \sum_{i=1}^{N} w_{ji} x_i^{(p)})/2), \; j = 1,2,\ldots,H. \quad (1)$$

Here, w_{ji} denotes the weight connecting x_i to h_j, w_{j0} is a bias, and tanh(.) is the sigmoidal activation function of hidden node. If we want to generate “warning-no warning signal” for flood forecasting[14], it belongs to classification problems in which we use the sigmoidal activation function for output nodes [27]. However, our goal is to predict water levels which are real numbers above zero, and we adopt a linear function as an activation function of output nodes. Consequently, the k-th output node with a linear activation function is given by

$$y_k^{(p)} = y_k(\mathbf{x}^{(p)}) = v_{k0} + \sum_{j=1}^{H} v_{kj} h_j^{(p)}, \; k = 1,2,\ldots,M. \quad (2)$$

Also, v_{k0} is a bias and v_{kj} denotes the weight connecting h_j to y_k.

Let the desired output vector corresponding to a training sample $\mathbf{x}^{(p)}$ be $\mathbf{t}^{(p)} = [t_1^{(p)}, t_2^{(p)}, \ldots, t_M^{(p)}]$. As a distance measure between the actual and desired outputs, MSE function for P training data is defined by

$$E = \frac{1}{2}\sum_{p=1}^{P}\sum_{k=1}^{M}\left(t_k^{(p)} - y_k^{(p)}\right)^2. \quad (3)$$

To minimize E, according to the negative gradient of MSE, output weights v_{kj}'s are iteratively updated by

$$\Delta v_{kj} = -\eta \frac{\partial E}{\partial v_{kj}} = \eta \delta_k^{(p)} h_j^{(p)}, \quad (4)$$

where

$$\delta_k^{(p)} = -\frac{\partial E}{\partial y_k^{(p)}} = \left(t_k^{(p)} - y_k^{(p)}\right) \quad (5)$$

is the error signal of output node and η is the learning rate. Also, by the backward propagation of the error signal, hidden weights w_{ji}'s are updated by

$$\Delta w_{ji} = -\eta \frac{\partial E}{\partial w_{ji}} = \eta x_i^{(p)} \frac{(1 - h_j^{(p)})(1 + h_j^{(p)})}{2} \sum_{k=1}^{M} v_{kj} \delta_k^{(p)} \quad (6)$$

In Eq. (6), the error signal of output node is back-propagated through output weight v_{kj}. The above weight-updating procedure for the training of MLP is the EBP algorithm [27].

2.2 *n*-th Order Error Function

Given the nature of hydrological data, there is an imbalance of data in which low or medium level data are very much dominant over high-level or peak data [14], [20]. When training neural networks to minimize MSE, neural networks are highly tuned to the abundant events with low or medium level data [29]. Consequently, we attain poor prediction performance for the high-level or peak data although it is essential to predict peaks in hydrological modeling [14]. To resolve the imbalanced data problem, we need to generate a strong error signal for output nodes far from desired values and a weak error signal for output nodes near desired values [29], [30]. This strategy has the effects that weak updating of weights for abundant events and robust updating of weights for rare events.

In this sense, the error function

$$E_n = \frac{1}{n}\sum_{p=1}^{P}\sum_{k=1}^{M}\left(t_k^{(p)} - y_k^{(p)}\right)^n \tag{7}$$

was proposed, where n is an even number [31]. If n=2, Eq. (7) is the same with MSE. Using the above error function, the error signal of output node is

$$\delta_k^{(p)} = -\frac{\partial E_n}{\partial y_k^{(p)}} = \left(t_k^{(p)} - y_k^{(p)}\right)^{n-1}. \tag{8}$$

The other equations in the EBP algorithm are the same.

2.3 A Recurrent Neural Network with Multiple Hidden Layers

Since there are complex time dynamics in the relationships between rainfalls and runoffs or water levels, the static feed-forward neural network models have some limitations to predict the water level or to forecast floods [28]. Also, neural networks with multiple hidden layers have better capability to learn a complicated system than those with a single hidden layer [8]. As shown in Figure 2, we propose a recurrent neural network with L hidden layers to predict the water level of Nakdong River near "Historic Village: Hahoe." Since hidden nodes have recurrent and cross-talk connections with time delays, the weighted sum to the j-th hidden node in the l-th layer is given by

$$\hat{h}_j^{(l)}(t) = w_{j0}^{(l)} + \sum_{i=1}^{H^{(l-1)}} w_{ji}^{(l)} h_i^{(l-1)}(t)$$
$$+\sum_{k=1}^{H^{(l)}}\sum_{\tau=1}^{T} r_{jk\tau}^{(l)} h_k^{(l)}(t-\tau),\ \ j = 1,2,\ldots,H^{(l)}, \tag{9}$$

where t is the time index, $H^{(l)}$ is the number of hidden nodes in the l-th hidden layer, $w_{ji}^{(l)}$ is the weight connecting $h_i^{(l-1)}$ to $h_j^{(l)}$, $r_{jk\tau}^{(l)}$ is the recurrent or cross-talk connection between $h_j^{(l)}$ and $h_k^{(l)}$ with τ delays, and T is the maximum value of τ. Also, we adopt the linear rectifier unit (ReLU) as an activation function of hidden nodes for learning of deep architecture [32]. Then, the the j-th hidden node in the l-th layer is given by

$$h_j^{(l)} = \begin{cases} \hat{h}_j^{(l)}, & \hat{h}_j^{(l)} > 0 \\ 0, & \hat{h}_j^{(l)} \le 0. \end{cases} \tag{10}$$

In the EBP training of the proposed recurrent network to predict the water level near "Hahoe Village," we use the error function given by Eq. (7) with n=6 " for better prediction of peaks as well as preventing overspecialization to low or medium level data.

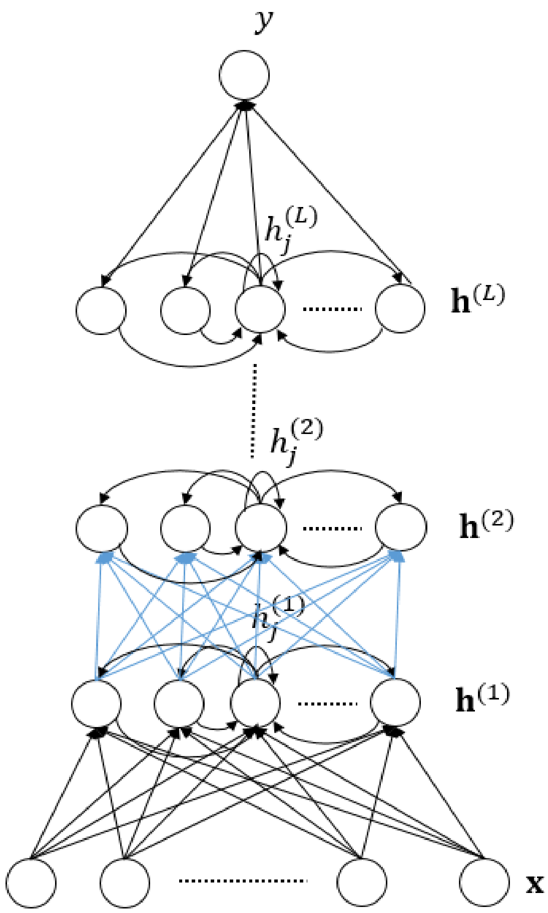


Fig. 2. The architecture of the proposed recurrent neural network with L hidden layers

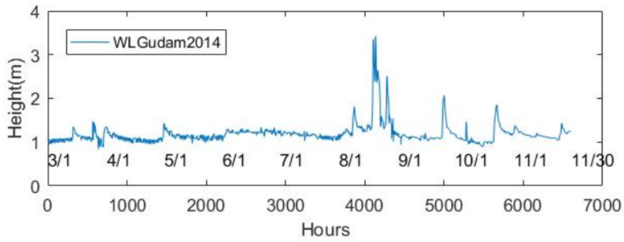
3. SIMULATIONS

3.1 Hahoe Village

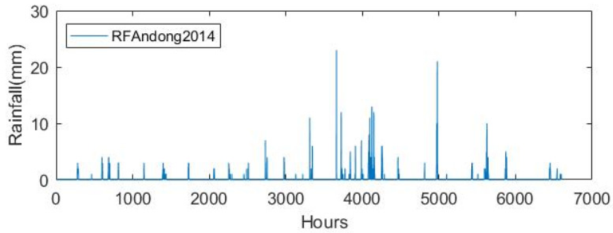
"Historic Village:Hahoe" located in Andong-city, Korea, is home to descendants of the Ryu clan and is well known for its traditional houses with history. Fig. 3 is a map of Andong region, in which Nakdong River flows around the perimeter of "Hahoe Village." If there are floods during rainy season, the historic village must be destroyed. So, we should carefully monitor the water level of Nakdong River near the village for forecasting or preventing floods. After careful investigation of water level and rainfall data provided by "Nakdong River Flood Control Office" and "Korea Water Resource Corporation," we selected the three monitoring locations of rainfalls, "Pungsan," "Iljik," and "Andong," which are denoted as red circles in Fig. 3. The rainfall gauge at "Andong" is the upper reaches of "Hahoe Village." The rainfalls at "Pungsan" and "Iljik" should be considered for the prediction since there are tributary rivers from the two locations to Nakdong River. We select the gauge at "Gudam" to monitor the water level near "Hahoe Village," since there is not a water level gauge at "Hahoe Village" and the nearest one is the gauge at "Gudam" [26].

Fig. 3. The map of Andong region, in which red circles are the locations of water level gauge at "Gudam" and rainfall gauges at "Pungsan," "Iljik," and "Andong."

Because of icing and snowing in the winter season, we collect the data at each gauge from March 1st to November 30th in the year of 2012, 2013, and 2014 with the interval of one hour. So, there are 6,600 data records in each year, provided by "Nakdong River Flood Control Office" and "Korea Water Resource Corp." We use the data in 2012 and 2013 to train neural networks and the other to test the performance of water level prediction. Fig. 4 shows the water level and rainfalls in the year of 2014, in which we can find many irregularities between the water level and the rainfalls. For easy readability of the horizontal axis, we include the index "month/day" just above the data index on the horizontal axis in Fig. 4(a). We can find that there are very high peaks of the water level during the rainy season and a long period of low or medium water levels.



(a)



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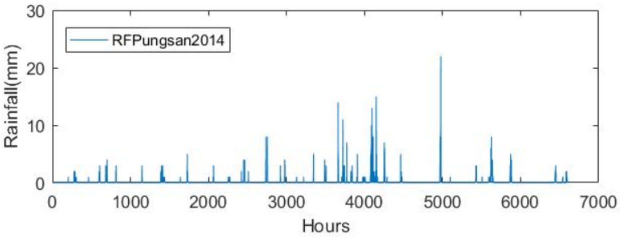
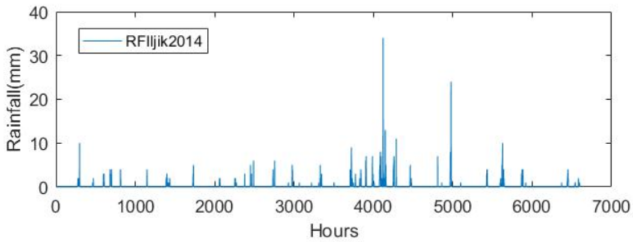


(c)



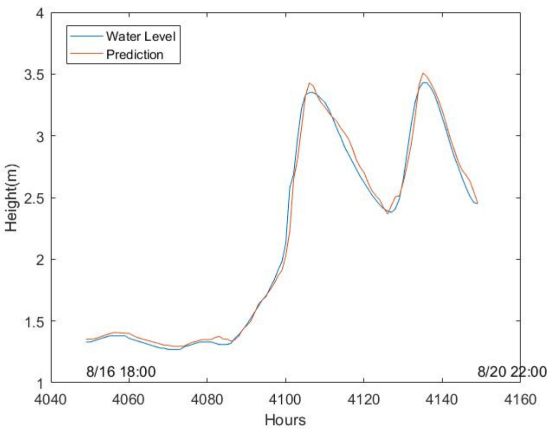
(d)

Fig. 4. Collected data in 2014. (a) Water level at "Gudam," (b) Rainfalls at "Andong," (c) Rainfalls at "Pungsan," and (d) Rainfalls at "Iljik."

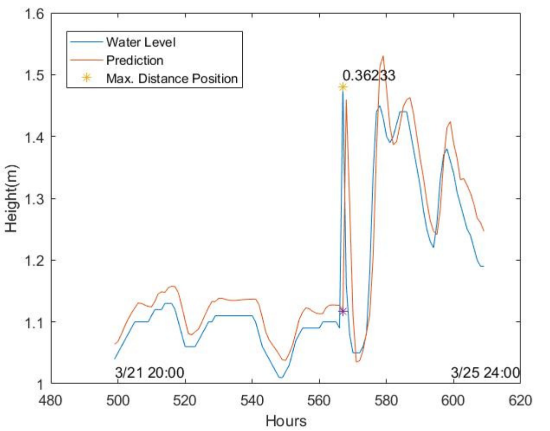
3.2 Predicting the Water Level with the Proposed Recurrent Neural Network with Multiple Hidden Layers

We construct a recurrent neural network to predict the water level at "Gudam" after D hours. The input layer consists of the rainfalls at "Pungsan", "Iljik", and "Andong" as well as the water level at "Gudam" from the current (denoted by "c") to the previous c-I hours [22], [26]. Since there is not a detailed theoretical guide to determine parameter values of neural networks, we usually use the method of trial and error. Accordingly, through many trials and errors, we determine that I is eleven, the number of hidden layers L is two, the number of hidden nodes in each hidden layer $H^{(l)}$ is forty, and the maximum delay for recurrent and cross-talk connections T is two. Therefore, we have forty-eight inputs and one linear output node. After initializing the recurrent neural network with random weights uniformly distributed on $\left[-1\times10^{-3},\ 1\times10^{-3}\right]$, the EBP algorithm updates the weights to minimize the error function given by Eq. (7) with n=6. Here, we derive the learning rate so that $\int_0^1 \eta\delta_k^{(p)}dy = 0.0025$ under the assumption that output node y is uniform on [0,1]. That is, $\eta = 0.015$.

Firstly, we train the proposed recurrent neural network with D=1 for 50,000 iterations. For verifying the prediction performance for the test data, we plot the real and predicted values of the water level at "Gudam" in 2014. Fig. 5(a) shows the detail curves from August 16th to 20th – the period with the highest peak in 2014. We can find that the prediction for the high-level values is very close to the real values. We also investigate the maximum distance between the real and predicted values in 2014, which is 36.23cm as shown in Fig. 5(b). However the gap of 36.23cm is at a specific time of test period belongs to medium-level data, and we successfully predict the water level with high peaks, as shown in Fig. 5 (a).



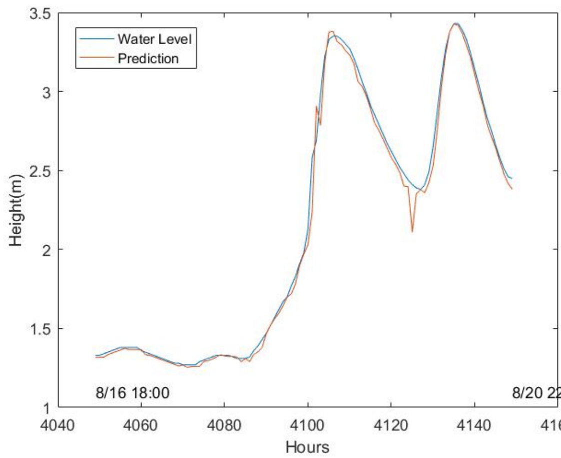
(a)



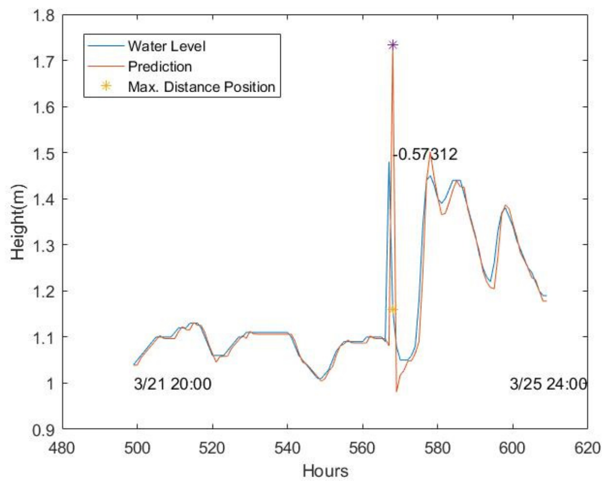
(b)

Fig. 5. The water level at "Gudam" and its predicted value by the proposed recurrent neural network with D=1 after 50,000 iterations of learning. (a) Period with the highest peak: August 16th 18:00 ~ 20th 22:00, 2014, (b) Period with maximum prediction distance: March 21st 20:00~25th 24:00, 2014

For comparison, we simulate the MLP with I=2, forty hidden nodes, and one linear output node [26]. After initializing the MLP with uniform random weights on $\left[-1\times10^{-4},\ 1\times10^{-4}\right]$, we train the MLP for 50,000 iterations with $\eta = 0.005$ which is derived from $\int_0^1 \eta\delta_k^{(p)}dy = 0.0025$. The test result for the highest peak is in Fig, 6(a), which is more coarse than the predicted water level with the proposed recurrent neural network. As shown in Fig. 6(b), the maximum prediction distance of MLP is 57.31cm which is much higher than the one with the proposed recurrent neural network. When we increase I value to eleven, which is the same condition with the recurrent network, the maximum distance becomes 84.06cm. This result argues that time dynamics of the relationship between water levels and rainfalls are too complicated to be modeled by the static feed-forward neural networks and recurrent neural networks are better to model the complicated time dynamics.



(a)

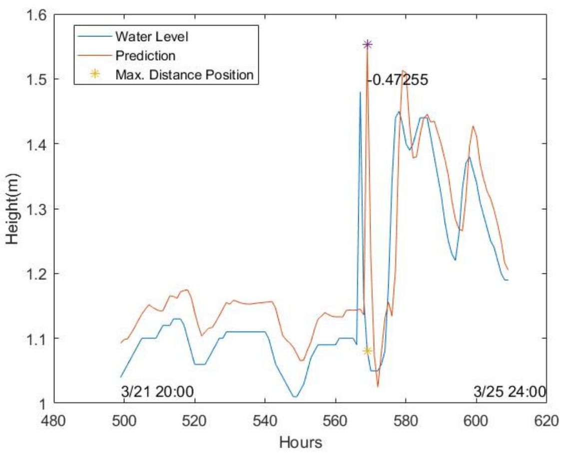


(b)

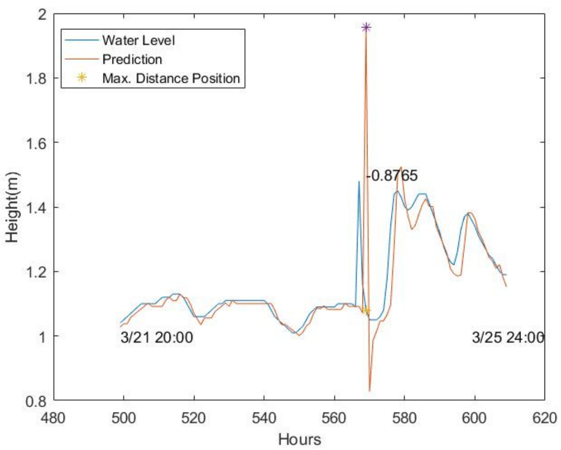
Fig. 6. Test results after training of MLP with D=1. (a) Period with the highest peak: August 16th 18:00 ~ 20th 22:00, 2014, (b) Period with maximum prediction distance: March 21st 20:00~25th 24:00, 2014

Secondly, we simulate the training of the proposed recurrent network and MLP with D=2. The other parameters are the same with the simulations of Fig. 5 and 6. Fig. 7 shows the test results for the period with the maximum distance between real and predicted values. The proposed recurrent network shows much better performance than the conventional MLP trained to minimize MSE.

For further comparison, we train the proposed recurrent network and the conventional MLP nine times with different initializations of weights. Also, we train MLPs based on the error function given by Eq. (7) with n=4 [31]. After training of neural networks for 50,000 iterations, we investigate the maximum distance between real and predicted water levels for the test data. We average the maximum distance of nine-time simulations and plot the averaged data in Fig. 8. Here, "MLP," "MLP(n=4)," and "Recurrent" denotes MLP trained with MSE, MLP trained with the n-th order error function (n=4), and the proposed recurrent neural network, respectively. The proposed recurrent neural network attains the best performance. The performances of MLP and MLP(n=4) rapidly degrade when D increases. When D increases, the time dynamics of the relationship between rainfalls and water levels become more complicated. Since the proposed recurrent neural network has a better capability to learn the time dynamics, its maximum distance is much lower than those of MLP and MLP(n=4).



(a)



(b)

Fig. 7. Test results for the period with maximum distance between real and predicted water levels. (a) The proposed recurrent neural network with D=2. (b) MLP with D=2

Since the error functions for training of the three methods are different, we investigate MSE of each method for comparison. Fig. 9 shows MSE of each method for the test data after the finish of training. Because of the overspecialization to the training data, "MLP" shows the worst MSE for the test data. On the contrary, MSE for the test data in the proposed method is better than MLP, since we adopt the sixth order error function to prevent the overspecialization. MLP(n=4) is slightly better than the proposed recurrent network in a viewpoint of MSE for the test data. However, in the prediction of water level to forecast floods, it is crucial to predict water levels with high peaks and to decrease the maximum distance between real and predicted water levels. In this sense, the proposed method is better than MLP(n=4).

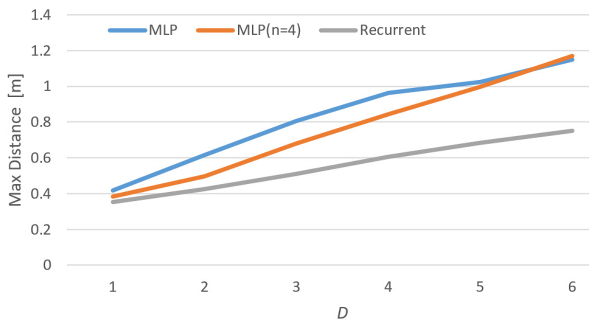


Fig. 8. The maximum distance between real and predicted water level at "Gudam" in 2014. The horizontal axis is the time steps D of predictions. "MLP", "MLP(n=4)", and "Recurrent" denotes MLP trained with MSE, MLP trained with the n-th order error function (n=4), and the proposed recurrent neural network, respectively

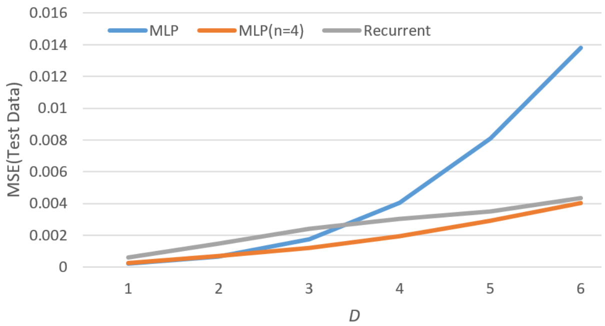


Fig. 9. Mean-Squared Error for the test data

4. CONCLUSIONS

In this paper, we proposed a recurrent neural network with multiple hidden layers to improve the prediction of water level near "Historic Village: Hahoe." The recurrent and cross-talk connections among hidden nodes are helpful to learn complicated time dynamics between rainfalls and water levels, which are difficult to be learned by static neural networks. Multiple hidden layers will supply neural networks with the better learning capability. In hydrology, it is essential to predict the peak of hydrograph or water level, although low or medium level data are very much dominant to high-level data. When we train neural networks to minimize MSE, neural networks are highly tuned to the abundant events with low or medium level data and, consequently, we attain poor performance for rare events with high peaks. To resolve the imbalanced data problem in hydrology, we adopted the sixth order error function between real and desired output values.

Through simulations, we verified that the proposed recurrent neural network with multiple hidden layers precisely predict the water level with high peaks during the rainy season. In the same period with high peaks, MLP showed a coarse prediction. By investing the maximum distance between real and predicted values with various time steps for prediction, the proposed recurrent network attained lower distance than MLP trained with MSE and MLP trained with the fourth order error function. This result argues that the proposed recurrent network have the better capability to learn the complicated time dynamics of the relations between rainfalls and water levels. From the plot of MSE of test data, we found that MLP trained with the fourth order error function and the proposed recurrent network showed lower MSE than the conventional MLP trained with MSE by preventing overspecialization to training data.

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