FLOOD DETECTION AND FORECAST BY IOT TECHNOLOGY

J.H. Jang
Hydraulic and Ocean Engineering, National Cheng Kung University, Taiwan
(e-mail: jamesjang@mail.ncku.edu.tw)

T.W. Li*
Hydraulic and Ocean Engineering, National Cheng Kung University, Taiwan
(e-mail: tonyfiveli123@gmail.com)

ABSTRACT

Under the influence of climate change, the scale and impact of flood disasters have become more and more severe in Taiwan due to the increase in rainfall intensity and urbanization. To strengthen the technology of flood detection and forecast in urban areas, an IoT (Internet of Things) based flood sensor (named flood box) and a flood prediction model based on machine learning (ML) technology were developed in this study. For flood detection, the flood boxes are installed at several low-lying locations in Tainan, Taiwan, for inundation depth measurement. Pressure tests show that the flood boxes functioned normally under outdoor rainy weather conditions. For flood forecast, the observed data by flood sensors are processed by a SVR (Support Vector Regression) ML model to predict the inundation depth at the locations where flood sensors are absent or malfunctioned in a flood event on 13 August in 2019. Satisfactory agreements between prediction and observation are found with the overall RMSE (Root-Mean-Square Error) equivalent to 5.73 cm.

1. INTRODUCTION

Integrating observation information from instruments, images, and telemetry is an important issue for establishing reliable flood warning systems. In Taiwan, since 2016, the Water Resources Agency (WRA) started a project to install pressure-type wireless flood sensors on the major roads in Tainan City. However, because these sensors are customized under closed systems, it is very costly and not possible to widely installed. Recently, IoT flood sensors based on LPWAN (Low-Power Wide-Area Network) technologies have become more and more popular due to their low cost in development and maintenance (Loftis et al., 2018). Meanwhile, ML methods has been widely used to properly interpret the data gathered by IoT sensors. In San Carlos, Brazil, Furquim et al. (2018) developed the SENDI (System for detecting and forecasting Natural Disasters based on IoT) system, based on IoT, ML, and WSN (wireless sensor networks) for the detection, forecast, alert issuing of natural disasters. Widiasari and Nugroho (2017) used MLP (Multilayer Perceptron) to analyze the time series of ultrasonic rainfall sensors to increase the accuracy of flood event prediction. Khan et al. (2018) applied artificial intelligence networks to analyze sensor data such as laser rangefinders, pressure gauges, and thermometers to reduce errors in early warning systems. Cruz et al. (2018) used

ANN to integrate rainfall, water level, and soil sensors for early warning of flood risks. Although the application of IoT technology has showed advantages in early warning due to its efficiency, limitations still exist regarding the quantity and quality of measured data. Bias corrections of the measured and forecasted results using ML or physical models has become an important issue (Jabbari and Bae, 2018; Sun and Scanlon, 2019). In this study, a new type of low-cost flood sensor and ML model are developed to increase the quantity of flood data and reduce the uncertainty in flood early warning, respectively.

2. STUDY SUBJECTS

The Tainan City in Taiwan is selected as the study area. In this area, 13 flood sensors out of the sensors installed by WRA are selected for analysis as shown in Figure 1. The historical flood event occurred on Aug. 13 in 2019 is selected for case study, which has brought 188 mm of rainfall in 3 hours.

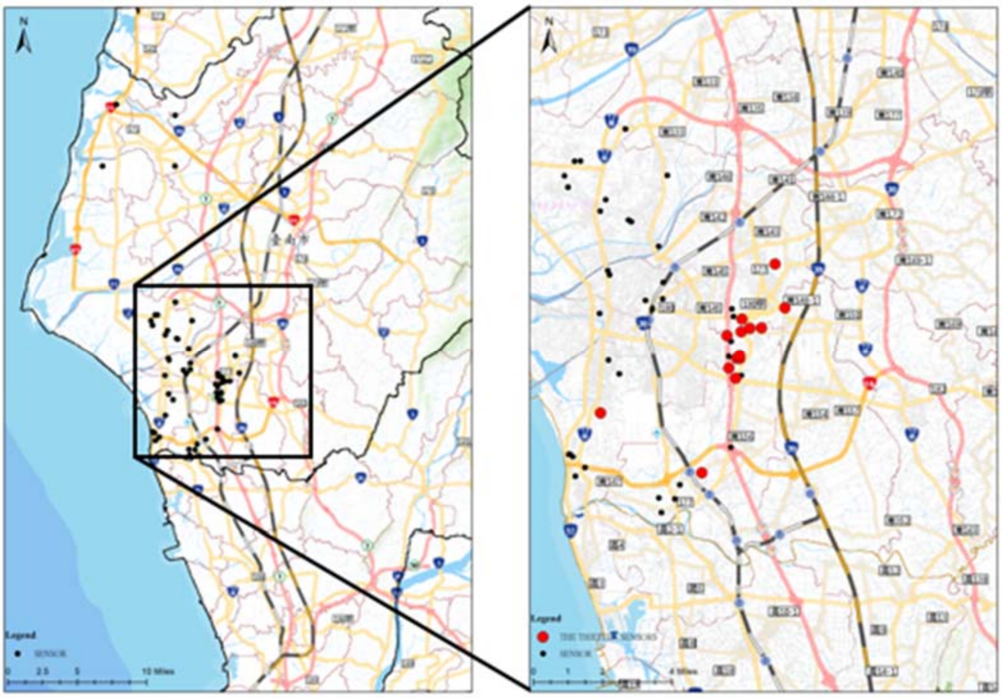

Figure 1. The locations of flood sensors in this study

3. METHODOLOGIES

3-1 FLOOD BOX

Each flood box (Figure 2) contains five components, including an ultrasonic sensor, an arduino circuit board (with LoRa module function), an analog signal display, a power supply battery, and a circuit board connected to an antenna. The flood box is set up at a high place with the ultrasonic sensor installed below to measure the distance between water surface and ground with a precision of 2 mm. The measured water levels are wirelessly transmitted to a Raspyberry Pi via LoRa and upload to a cloud server in a period of 10 mins. The device is small in size, low in power consumption, and using open source language to reduce cost.

Figure 2. Flood sensor

3-2 ML MODEL

Support Vector Regression (SVR) is a ML method which succeeds the characteristics of support vector machine (SVM) by adding a ε-insensitivity loss function to the original SVM. In this study, the inundation depths measured by the 13 flood sensors during the study event are served as the database for the SVR model. For each sensor, there are a total of 59 inundation depths recorded every 10 minutes from 3:00 a.m. to 12:40 p.m. in 13 Aug., 2019, which are divided into two groups with a ratio of 6: 4 for training and test, respectively. By assuming there is a sensor failed once a time, the data of the rest 12 sensors are used to predict the inundation depths for the failed sensor. The regression function can be express as (1)

$$f_i(x) = \dot{\omega} \cdot \dot{x} + b \tag{1}$$

in which $f(x)$ is the inundation depth of sensor i, $\dot{x}$ is the inundation depths of the remaining 12 sensors, $\dot{\omega}$ is the vector of weights; b is the bias.

4. CONCLUSION

The errors between observation and forecast are estimated by RMSE (Root Mean Square Error), EPP (Error Percentage of flood Peak) and ETP (Error of Time to peak), respectively. Overall, the predictions given by the SVR are satisfactory with RMSE = 5.73 cm, EPP = 4%, and ETP = 11.82 mins. However, under-/over- estimations of flood depth can be found at individual stations which might lead to miss/false alarms in flood warning, respectively. Shown in Figure 3 are the comparisons between the observed and predicted inundation depths when Station #13 and Station #5 are assumed to be failed. It is seen that the predictions are slightly underestimated and overestimated for Sensor #13 and Sensor #5, respectively. This may be attributed to the fact that ML models require big data for training, but in this study, only 36 data are used due to the lack of historical events. This problems can be overcome because more data will be collected by the IoT sensors in the future. In addition, the comparison of the ML results with those by a physical model will be valuable for clarifying the reliability of the system.

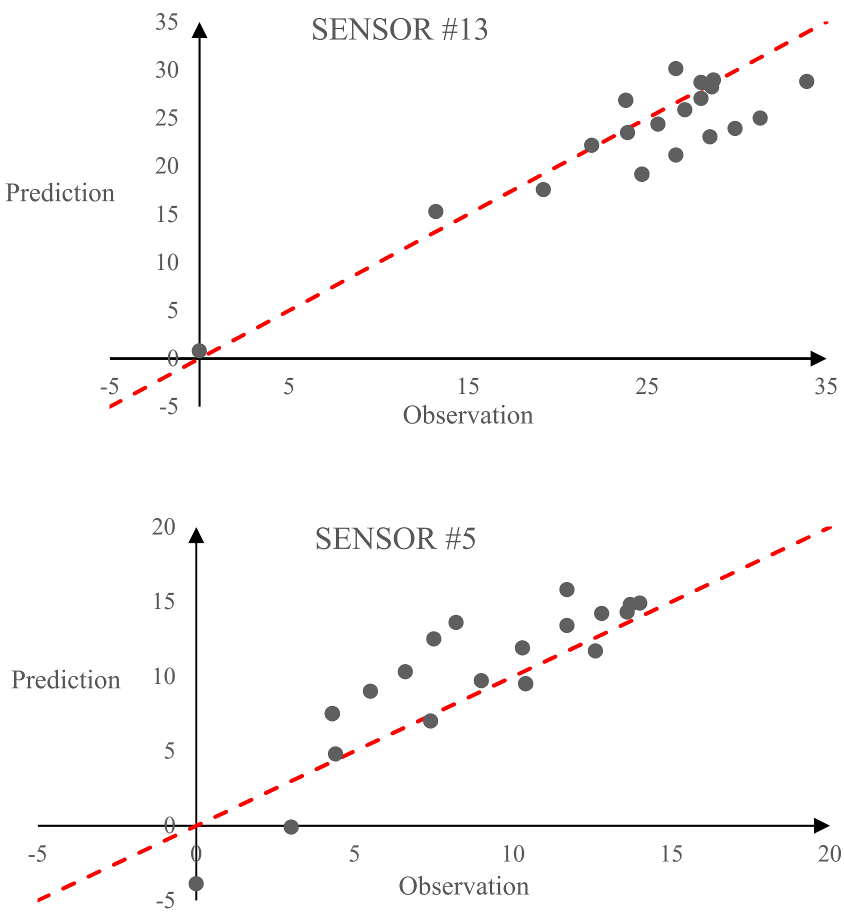

Figure 3. Comparison between observed and predicted inundation depths for Sensor #13 and Sensor #5.

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REFERENCES

Cruz F.R.G., Binag M.G., Ga M.R.G., and Uy F.A.A. (2018). Flood prediction using multi-layer artificial neural network in monitoring system with rain gauge, water level, soil moisture sensors. *Proceedings of the TENCON 2018-2018 IEEE Region 10 Conference*, Jeju, Korea.

Furquim G., Filho G.P.R., Jalali R., Pessin G., Pazzi R.W., and Ueyama J. (2018). How to improve fault tolerance in disaster predictions: a case study about flash floods using IoT, ml and real data. *Sensors*, 18, 907.

Jabbari, A. and Bae, D.H. (2018) Application of artificial neural networks for accuracy enhancements of real-time flood forecasting in the Imjin Basin. *Water*, 10, 1626.

Khan T.A., Alam M., Kadir K., Shahid Z., Mazliham S.M. (2018). A novel approach for the investigation of flash floods using soil flux and CO2: An implementation of MLP with less false alarm rate. *Proceedings of the 2018 2nd International Conference on Smart Sensors and Application (ICSSA)*, Kuching, Malaysia.

Loftis D., Forrest D., Katragadda S., Spencer K., Organski T., Nguyen C., and Rhee S. (2018). StormSense: A new integrated network of IoT water level sensors in the smart cities of Hampton Roads, VA. *Marine Technology Society Journal*, 52(2), pp. 56-67.

Sun, A.Y. and Scanlon, B.R. (2019). How can big data and machine learning benefit environment and water management: A survey of methods, applications, and future directions. *Environ. Res. Lett.*, 14(7), 28.

Widiasari I.R., and Nugroho L.E. (2017). Deep learning multilayer perceptron (MLP) for flood prediction model using wireless sensor network based hydrology time series data mining. *Proceedings of the 2017 International Conference on Innovative and Creative Information Technology (ICITech)*, Salatiga, Indonesia.