Data-Driven Fast Real-Time Flood Forecasting Model for Processing Concept Drift

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Abstract. The hydrological data of small and medium watershed develops with the passage of time. The rainfall-runoff patterns in these data often develop over time, and the models established for the analysis of such data will soon not be applicable. In view of the problem that adaptability and accuracy of the existing data-driven flood real-time forecasting model in medium and small watershed with concept drift. We update the data-driven model using incremental training based on support vector machine (SVM) and gated recurrent unit (GRU) model respectively. According to the rapid real-time flood forecasting test results of the Tunxi watershed, Anhui Province, China, the fast real-time flood forecast data-driven model with incremental update can more accurately predict the moment when the flood begins to rise and the highest point of flood stream-flow, and it is an effective tool for real-time flood forecasting in small and medium watersheds.

Keywords: Medium and small watershed · Concept drift · Data-driven model · Fast real-time flood forecasting

1 Introduction

The floods in small and medium watershed are characterized by sudden bursts, shorter concentration of flow time and shorter foresight period. Timely and effective flood warning and forecasting of small and medium watershed can help humans effectively prevent floods and reduce flood damage. It is one of the important non-engineering measures for disaster prevention and mitigation [1]. Flood prediction models are important for disaster assessment and extreme event management. Robust and accurate predictions contribute significantly to water management strategies, policy advice and analysis, and further evacuation modeling [2]. Therefore, the importance of forecasting systems for rapid real-time

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and short-term prediction of floods and other hydrological events is emphasized. At present, flood forecasting generally adopts a hydrological model based on runoff process and a data driven model considering historical data input and output. Moreover, due to the dynamic nature of climatic conditions, the prediction of flood front time and location is basically complicated. Therefore, to simulate the complex mathematical expressions of physical processes and watershed behavior, data-driven modeling basically does not consider the physical mechanism of hydrological processes and aims to establish an optimal mathematical relationship between input and output data is more popular [3].

The classic black box hydrological time series data-driven forecasting model has a long tradition in flood models, which prediction methods assimilate measured climate and hydrometeorological parameters to provide better insights, including Auto-Regressive (AR) [4], Auto-Regressive and Moving Average (ARMA) [5], Auto-Regressive Integrated Moving Average (ARIMA) [6], Linear Regression (LR) [7], and Multiple Linear Regression (MLR) [8]. Compared with the physical model considering the computational cost and the large parameters the above models have certain advantages. However, it cannot deal well with the problems of non-stationarity and nonlinearity in the hydrological process.

In the past two decades, forecasting models using data-driven technology have made great progress in predicting and simulating the application of nonlinear hydrology and capturing noise in complex data sets. Classical data-driven modeling methods mainly include Artificial Neural Networks (ANN) [9–11], Support Vector Machines (SVM) [12–14], Adaptive Neuro-Fuzzy Inference Systems (ANFIS) [15,16], Wavelet Neural Networks (WNN) [17–19], Decision Tree (DT) [20,21], and Ensemble Prediction System (EPS) [22–25].

In recent years, hydrologists have been trying to use the artificial learning method based on deep learning to deal with this hydrological time series prediction task, and [26–28] have better performance. Among these deep learning-based methods, Long and short term memory (LSTM) Neural network can be used as data-driven models for describing the rainfall-runoff relationship and the performance is better than some commonly used conventional prediction models. The Gated Recurrent Unit (GRU) structure [29] was proposed in 2014. Analysis of the work of chung2014empirical, trofimovich2016comparison shows that GRU performance is comparable to LSTM, but its advantages are more computationally efficient and fewer parameters.

In this paper, based on the SVM and GRU models, we propose an incremental update method to forecast floods in small and medium watershed with data drift.

2 The Method of Prediction Model

2.1 Concept Drifts

In machine learning, the unexpected changes in data mining and predictive analysis of basic data over time are called concept drifts [35–38]. Concept drifts of Medium and small watershed due to changing of watercourse, new reservoir, human activities or they can be attributed to a complex nature of the environment. Usually, when the research data has a conceptual drift, there are several ways to deal with it. The first is based on resampling and adaptive sliding window selection samples, [38] uses a fixed-size sliding window for sample selection, which only retains the current trusted data window to solve the concept drift in the data stream, but This led to another problem, the sample selection of model training completely abandoned the old samples outside the time window. [39] proposed a "Adwin" method, which constructs a sliding window of different sizes to select the appropriate amount of training data to learn new concepts. Second, build by updating the weights of the submodels, such as [40] learning The key idea is to automatically adjust the window size, sample selection, and example weighting separately to minimize the estimated generalization error; third, recently, the dynamic classifier set, [41] proposes a new dynamic clustering forest to handle Concept drift in the emergence of time series, this new collection method aims to classify "new and old" data by combining multiple cluster trees.

2.2 Support Vector Machine Model

Support vector machine (SVM) models based on statistical learning theory can be used for pattern classification and nonlinear regression [42–45]. Literature [14] uses SVM to predict the groundwater level, the results show that the SVM water level prediction model is more accurate than the artificial neural network model. Moreover, [12] demonstrates that the SVM model works better in terms of uncertainty and is more predictive of extreme hydrological events. [46] Under the uncertainty of climate change scenarios, the SVR model estimates regional floods more accurately than the ANN model. [47] Processing real-time flood forecasting Using support vector machine to do single output, multi-output forecasting, and multi-step iteration strategy forecasting and other experimental schemes, the results show that the single-output scheme has the highest forecasting accuracy, and the multi-step iterative forecasting accuracy is the worst.

Based on the principle of structural risk minimization, SVM maps hydrological historical sample data from nonlinear regression in low-dimensional space to high-dimensional space by solving the flood forecasting problem that belongs to nonlinear regression. Then, the linear regression of high-dimensional space is further realized to correspond to the nonlinear regression of low-dimensional space. Given a historical flood sample datasets $D = \{(\mathrm{x}_1, y_1), (\mathrm{x}_2, y_2), \cdots, (\mathrm{x}_l, y_l)\}$, where l denote sample number. The principle of flood forecasting is to find the mapping between input and output by training the sample datasets: $y = f(x)$. The basic idea of the SVM prediction is to learn a regression model so that $f(x)$ and y are as close as possible. The regression model is as follows:

$$f(x) = \omega\phi(x) + b \tag{1}$$

where $\phi(\cdot)$ denote the nonlinear mapping, ω is the wights, b is the bias. Suppose the support vector regression can allow a maximum deviation of ε between $f(x)$ and y, so the loss is calculated when the absolute value of the deviation between

$f(x)$ and y is greater than ε. As shown in Fig. 1, a strip of width 2ε is constructed on both sides of $f(x)$. When the training sample is within this space, the sample is predicted correctly.

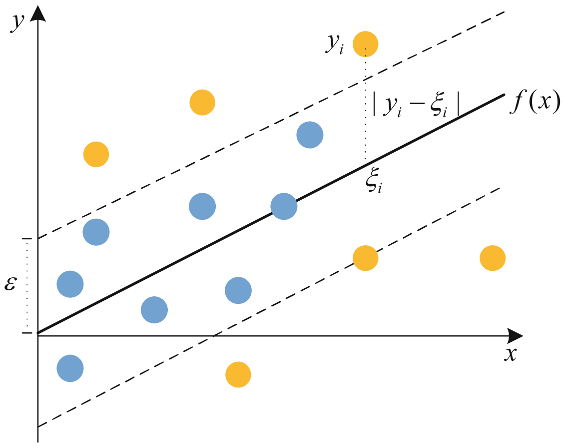


Fig. 1. Illustration of support vector machine.

2.3 Gated Recurrent Unit Model

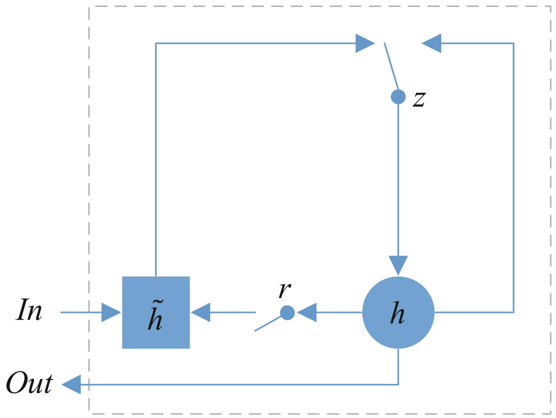


Fig. 2. Illustration of gated recurrent unit.

Recently, LSTM and GRU Recurrent Neural Networks (RNN) have proven to achieve the most advanced results in many time series applications (e.g., machine translation, and speech recognition). Their powerful predictive performance, ability to capture long-term time-dependent and variable-length observations are also advantageous in processing predictions in hydrological time series data. We use a GRU-based rapid flood forecasting model because it has higher computational efficiency and fewer parameters than LSTM. The structure of GRU is shown in Fig. 2. For a hidden unit, GRU has a update gate z and a reset gate r, z_t determine how much the previous state of the unit is updated to the current state at time t, r_t is used to forget the state of the previous calculation. z_t and r_t are calculated as follows

$$z_t = \sigma(W_z \mathrm{x}_t + U_z h_{t-1}) \tag{2}$$

$$r_t = \sigma(W_r \mathrm{x}_t + U_r h_{t-1}) \tag{3}$$

The activation h_t and candidate activation $\widetilde{h}_t$ of the GRU at time t are computed as follow

$$\widetilde{h}_t = tanh(W_h \mathrm{x}_t + U_h(r_t \odot h_{t-1})) \tag{4}$$

$$h_t = (1 - z_t)h_{t-1} + z_t\widetilde{h}_t \tag{5}$$

where matrices W_z, W_h, W_r, U_z, U_h, and U_r are model parameters.

3 Experiment

3.1 Datasets

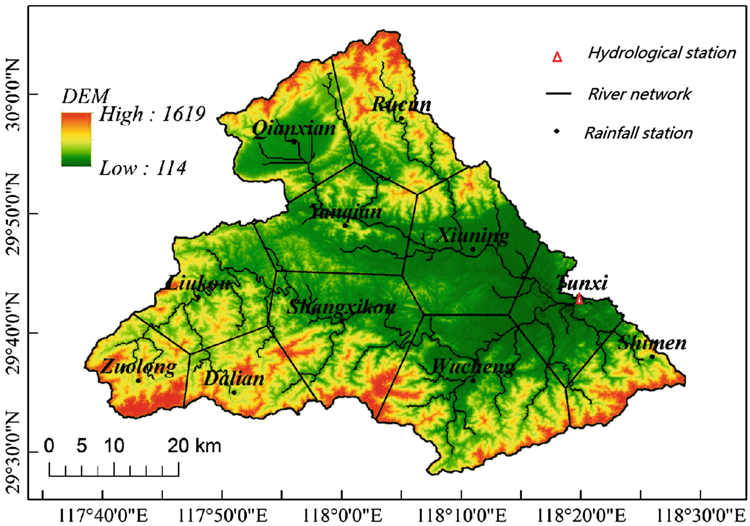


Fig. 3. Map of the study Tunxi watershed.

In this paper, our study used a datasets from 1981–2003 in Tunxi watershed, Anhui Province, China. As shown in Fig. 3, Tunxi hydrological station is located in the river outflow location of Tunxi watershed, and it monitors the flow and rainfall values. In addition, there are another 10 rainfall stations in the Tunxi watershed.

3.2 Model Forecasting Method

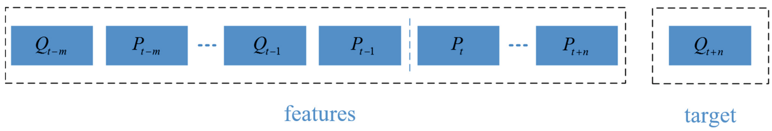


Fig. 4. Features and target of the forecasting model.

In order to improve the flood forecasting and early warning period in small and medium watershed, we use rainfall forecast information that is known in advance. As shown in Fig. 4, Our forecast target stream-flow Q_{t+n} is contributed by creatures previous rainfall $[P_{t-m} \cdots P_{t-1}]$, previous stream-flow $[Q_{t-m} \cdots Q_{t-1}]$, and forecast rainfall $[P_t \cdots P_{t+n}]$. Where Q_{t-m} denote actual measured stream-flow at time $t-m$, P_{t-m} denote actual measured area rainfall at time $t-m$, Q_{t+n} denote forecasted stream-flow at time $t+n$, P_{t+n} denote future area rainfall at time $t+n$, m denote m hours before the start of the forecast time t, n denote model forecast n hours.

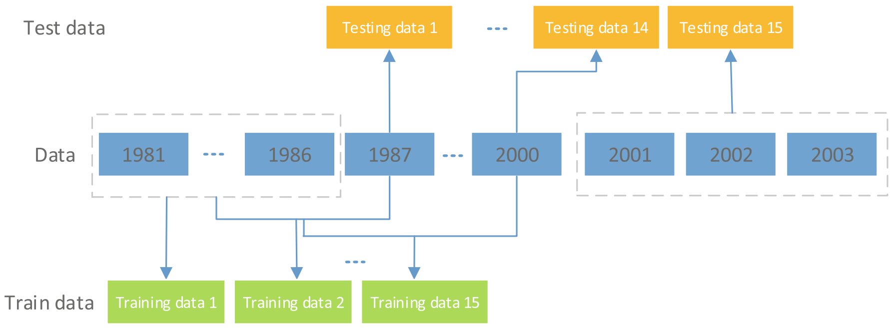


Fig. 5. Distribution of data training sets and test sets in Tunxi watershed. Data from the Tunxi watershed from 1981 to 2003, where the data from 1981 to 1986 was used as the first batch training data, and each subsequent year's data is added to the training set in batches. The data from 2001 to 2003 was used as the final batch testing data.

The training data and test data distribution method of adding our model is shown in Fig. 5. We first use the data from 1981–1986 as the training data for the initial model, We first use the data from 1981–1986 as the training data of the initial model, and then the data of each year was added to the training data. Testing data was also added in a similar way. The training model was updated as shown in Fig. 6. We feed the assigned training data to the corresponding training model, and then the training model is updated by the test error of the testing data. The training models 2–15 are updated in the same way. Finally, the prediction model performance is evaluated by the testing data 15.

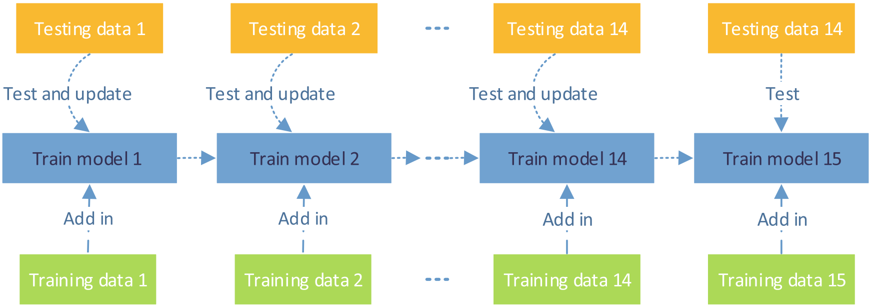


Fig. 6. The incremental update method of training model. First, the training data 1 was added to the training model 1, and then the training model 1 was tested by the testing data 1, and finally the training model 1 was updated to the training model 2 based on the error between the test result and the real value.

In this paper, we trained two types of data-driven models with incremental update capabilities using experimental data with conceptual drift. As a comparative experiment, we also trained two types of without using incremental update data driven models. The model is classified as follows

- **SVM:** The support vector machine model that does not use incremental updates.
- **SVM-IU:** The support vector machine model that use incremental updates.
- **GRU:** The gated recurrent unit model that does not use incremental updates..
- **GRU-IU:** The gated recurrent unit model that use incremental updates.

3.3 Model Performance Criteria

The average deviation between the flood forecast value and the actual value in the experiment is to be measured by the following four evaluation criteria. forecast error of the maximum flow value of a flood is calculated as

$$E_{Q,max} = \left| \frac{Q'_{max} - Q_{max}}{Q_{max}} \right| \times 100\% \tag{6}$$

where Q'_{max} denote the peak value of a flood forecasting stream-flow, Q_{max} denote the recording peak value of a flood stream-flow.

Forecast error of the time when the peak of the flood occurs is calculated as

$$t_{max} = |t'_{max} - t_{max}| \tag{7}$$

where t'_{max} denote the moment of the predicted flow maximum, t_{max} denote the moment of the recording flow maximum.

Root mean square error is calculated as

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(P_i - Q_i)^2}{N}} \tag{8}$$

Determination coefficient is calculated as

$$D_y = 1 - \frac{\sum_{i=1}^{N}(P_i - Q_i)^2}{\sum_{i=1}^{N}(P_i - \overline{Q})^2} \tag{9}$$

where P_i denote stream-flow recording value at time i, Q_i denote stream-flow prediction value at time i, $\overline{Q}$ denote average stream-flow recording value, and N is the number of test samples.

3.4 Results and Analysis

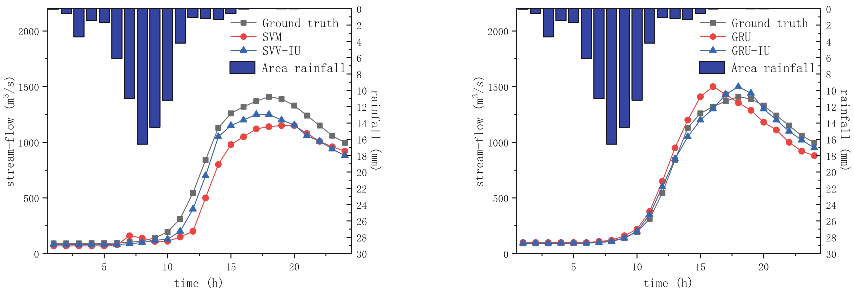
Table 1. Average performance criteria of the models.

Model	$E_{Q,max}(\%)$	$t_{max}(s)$	$RMSE$	$D_y(\%)$
SVM	25.21	2.88	421	71.32
SVM-IU	**15.38**	**1.58**	**255**	**81.65**
GRU	16.51	1.61	262	82.35
GRU-IU	**10.81**	**0.63**	**114**	**87.98**

In this section, we compare data-driven models under different training methods. To be fair, we present the best performance for each type of method under different parameter settings in Table 1. Moreover, the same kinds of model uses the same parameters for different update methods.

In terms of fast real-time flood stream-flow prediction, we propose four indicators to evaluate model performance. The predicted flood peak error $E_{Q,max}$ and the error at the moment of occurrence t_{max} are the most important indicators for hydrologists. SVM-IU shows 9.83% and 1.3 s improvements beyond SVM on $E_{Q,max}$ and t_{max}. GRU-IU shows 5.7% and 0.98 s improvements beyond GRU on $E_{Q,max}$ and t_{max}. In addition, $RMSE$ and D_y are the fitting performance of the evaluation prediction model. SVM-IU shows 166 and 10.33% improvements beyond SVM on $RMSE$ and D_y. GRU-IU shows 148 and 5.63% improvements beyond GRU on $RMSE$ and D_y. We conclude that the SVM improvement is higher than the GRU improvement after using incremental update training method.

A more clear illustrate of the real-time prediction performance of the models is shown in Fig. 7. The model using incremental training can more accurately predict the moment when the flood begins to rise and the highest point of flood stream-flow occurs.



(a) Comparison with SVM and SVM-IU (b) Comparison with GRU and GRU-IU

Fig. 7. Comparison with the ground truth stream-flow and predicted stream-flow computed by SVM and GRU model, where (a) shows a comparison of SVM models using incremental update and no using incremental update, (b) shows a comparison of GRU models using incremental update and no using incremental update.

4 Conclusion

In this paper, we propose a incremental update method based on SVM and GRU flood predict model in the Tunxi watershed with drift concept. In the proposed data-driven forecasting model with incremental updates, we construct training data and testing data in batches through the hydrological characteristics of small and medium watersheds. During training, we update the model based on the error of the small batch of test data on the initial model. Experiment results on the Tunxi dataset show the proposed method outperforms initially comparative methods and the effectiveness of the proposed incremental update model. In the future, our work includes the exploration on other hydrology purposes with the proposed method, such as flood submergence area warning and urban storm flooding.

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