Flood Resilience and Mitigation

Reinforced Dynamic Neural Network for Multi-Step-Ahead Flood Forecast

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Summary


Introduction
Flood forecasting not only represents a very complex nonlinear problem, but also is extremely difficult to model.

An accurate flow prediction is crucial for flood control and water resources management. The longer the forecast steps into the future, the more beneficial it is, in terms of time for adjustment for reservoir operation and damage reduction due to flooding.
Artificial neural networks (ANNs) are a biologically motivated method in which large numbers of neurons communicate with one another through weighted connections.

- Approximating nonlinear functions
- Alternative computational approach to modeling physical-based problems
Over the last few years, dynamic recurrent neural networks (RNNs) have attracted much attention for extracting the dynamic time variation characteristics by the *capability of internal recurrence*.

The *Real-Time Recurrent Learning (RTRL)* algorithm presented by Williams and Zipser (1989) is an effective and efficient online learning algorithm for training RNNs.
Online learning and batch learning are two major different supervised machine-learning frameworks.

Advantages of online learning algorithms:
- Simple to implement
- Typically both memory and run-time efficient
- Often give strong guarantees on performance even in an intensively varying data structure of time series

Continually receive true value feedback to adjust the parameters of models.
The main defect of online learning is also a result of the requirement for continual true value feedback.

Additional information from antecedent observed values and model outputs will be beneficial to the forecast.
GOAL

Develop a reinforced multi-step-ahead RTRL algorithm for recurrent neural networks (MSA R-RTRL NN)

Demonstrate its reliability and applicability in two-step-ahead (2SA), 4SA and 6SA forecasts for a famous benchmark chaotic time series and a streamflow in Taiwan by mitigating time-lag effects and increasing the forecast accuracy
Methodology

Water resources and Hydroinformatics System Lab
Architecture of a MSA RNN

\[
\text{Input vector } \mathbf{X}(t) \\
\vdots \\
\mathbf{X}(t+N-1) \\
\text{Output} \\
\mathbf{Z}(t+n) \\
\vdots \\
\mathbf{Z}(t+n) \\
\text{Processing layer} \\
\text{Concatenated input layer} \\
\text{Output layer}
\]
Concept of MSA online learning algorithm

Implement the latest information including the latest true (observed) values and model’s output (residual) to re-adjust model parameters through on-line learning techniques.
### Water Resources and Hydroinformatics System Lab

RNN

\[ \Delta W, \Delta V \]

Weight adjustment

### Two-Step-Ahead

**Input vector at time t**

**Target output vector at time t**

**Predicted output vector at time t**

**Error**
$X(t)$ Input vector at time $t$

$D(t)$ Target output vector at time $t$

$Z(t)$ Predicted output vector at time $t$

$\hat{Z}(t)$ Repredicted output vector at time $t$

$\hat{e}(t)$ Reinforced error at time $t$

$\Delta W, \Delta V$ Weight adjustment

$\Delta \hat{W}, \Delta \hat{V}$ Reinforced weight adjustment

RNN Recurrent neural network

RNN$_{temp}$ Temporary RNN

Two-Step-Ahead

Chang et al., 2012
\[
\hat{X}(t+n) \rightarrow \hat{Z}(t+n) \\
\hat{Z}(t+n) \rightarrow \hat{X}(t+n+1) \\
\hat{X}(t+n+1) \rightarrow \hat{Z}(t+n+2) \\
\hat{Z}(t+n+2) \rightarrow \hat{X}(t+n+3) \\
\vdots
\]

\[
\Delta W, \Delta V \rightarrow X(t) \\
X(t) \rightarrow X(t+1) \\
X(t+1) \rightarrow X(t+2) \\
X(t+n-1) \rightarrow X(t+n) \\
\vdots
\]

\[
D(t+n) \rightarrow \Delta \hat{W}, \Delta \hat{V} \\
\Delta \hat{W}, \Delta \hat{V} \rightarrow \text{n-Step-Ahead}
\]
Numerical Simulation and Applications
Chaotic time series

**Mackey-Glass**

\[
\frac{dx(t)}{dt} = \frac{0.2x(t-\tau)}{1+x^{10}(t-\tau)} - 0.1x(t)
\]

\[x(0)=1.2, \ \tau = 17\]

Number of Data: 1000

\[D = 3, \ T = 7\]
Performance criteria

\[
RMSE = \sqrt{\frac{\sum_{i=1}^{N}(Q_i - \hat{Q}_i)^2}{N}}
\]

\[
G_{bench} = 1 - \frac{\sum_{i=1}^{N}(Q_i - \hat{Q}_i)^2}{\sum_{i=1}^{N}(Q_i - Q_{i,bench})^2}
\]

\[
CE = 1 - \frac{\sum_{i=1}^{N}[Q_i - \hat{Q}_i]^2}{\sum_{i=1}^{N}[Q_i - \bar{Q}]^2}
\]

\[
CC = \frac{\sum_{i=1}^{N} (\hat{Q}_i - \bar{Q})(Q_i - \bar{Q})}{\sqrt{\sum_{i=1}^{N} (\hat{Q}_i - \bar{Q})^2 (Q_i - \bar{Q})^2}}
\]

\[
MAE = \frac{\sum_{i=1}^{N}|Q_i - \hat{Q}_i|}{N}
\]

\[
G_{bench,II} = 1 - \frac{\sum_{i=1}^{N}(Q_i - \hat{Q}_i)^2}{\sum_{i=1}^{N}(Q_i - Q_{i,bench})^2}
\]

\[
\bar{Q} : \text{average of observed values} \quad \bar{\hat{Q}} : \text{average of forecasted values}
\]

\[
Q_i : \text{observed value in the } i^{th} \text{ step} \quad \hat{Q}_i : \text{forecasted value in } i^{th} \text{ step}
\]

\[
Q_{i,bench} : \text{compared time series value in the } i^{th} \text{ step} \quad N : \text{number of data points}
\]
## Mackey-Glass MSA Forecast

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Hourly inflow and precipitation data of typhoon events from 2001 to 2009

**Training data set: 2001-2006**

**Testing data set: 2007-2009**

*Thiessen polygon method*
Converts the point rainfall values

*Kendall tau rank CC & Pearson CC*
Determines the time lag of rainfall to the inflow of reservoir
Architecture

\[ Q(t+n) \]

\[ Q(t) \quad Rd(t-5) \quad Rm(t-6) \quad Ru(t-7) \]
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<th>6SA</th>
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Inflow 4SA Forecast

R-RTRL NN

Forecasted Value (---)
Observed Value (-)

RTRL NN

Forecasted Value (---)
Observed Value (-)

hr
6SA inflow forecast residuals
Inflow forecast errors (RMSE) and forecast steps

- R-RTRL NN
- RTRL NN
- LRN
- BPNN

RMSE (cns) vs. Forecasting step

- 600
- 500
- 400
- 300
- 200
- 100

Forecasting step

2 4 6
The developed \textit{MSA R-RTRL NN} can utilize antecedent information of the observed values and the corresponding model outputs adequately, and strengthens the impact that from the latest observed values by \textit{reinforced process} to moderates time-lag phenomenon in the online-learning procedure for MSA forecast.
For building a rainfall–runoff model for the Shihmen Reservoir in typhoon events, the proposed MSA R-RTRL NN has better performance on 2SA to 6SA flood forecast and significantly reduces the *time-lag effects*

The proposed R-RTRL NN repeatedly adjusts its parameters using the latest information and improves MSA forecast accuracy and mitigates time-lag effects.


THANK YOU!