第Ⅱ部門

Sequential Monte Carlo filters for streamflow forecast using a distributed hydrologic model

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1. Introduction

Data assimilation is a way to integrate information from a variety of sources to improve prediction accuracy, considering the uncertainty in both a measurement and modeling system. sequential Monte Carlo (SMC) methods, known as particle filters, are a Bayesian learning process in which the propagation of all uncertainties is carried out by a suitable selection of randomly generated particles without any assumptions about the nature of the distributions. SMC has the advantage of being applicable to non-linear and non-Gaussian state-space models. In the previous study (Noh et al., 2011), it has been found that SMC filters can be effectively implemented to update state and parameters of a conceptual hydrologic model.

In this study, we apply SMC filters for a distributed hydrologic model to enhance forecasting capability of streamflow. A lagged particle filtering approach is proposed to consider different response of hydrologic processes. A process-based distributed hydrologic model, WEP (Jia et at., 2009), is implemented for streamflow forecast through state updating. Particle filtering is parallelized and implemented in the multi-core computing environment via open message passing interface (MPI).

2. Methodology

Consider a generic dynamic state-space model which can be described as follows:

$$x_k = f(x_{k-1}, u_k) + \omega_k \qquad \omega_k \sim N(0, W_k) \tag{1}$$

$$y_k = h(x_k) + \nu_k \qquad \nu_k \sim N(0, V_k) \tag{2}$$

where $x_k \in \Re^{n_x}$ is the n_x dimensional vector denoting the system state at time k. The operator $f : \Re^{n_x} \rightarrow \Re^{n_x}$ and $h : \Re^{n_x} \rightarrow \Re^{n_y}$ express the system transition in response to the forcing data u_k. ω_k and ν_k represent the model and the measurement error, respectively. The key idea of SMC filters is based on point mass ("particle") representations of probability densities with associated weights as:

$$p(x_k \mid y_{1:k}) \approx \sum_{i=1}^{n} w_k^i \delta(x_k - x_k^i) \tag{3}$$

where x_k^i and w_k^i denote the i^{th} posterior state and its weight, respectively, and $\delta(\cdot)$ denotes the Dirac delta function. With these particles and associated weights, the estimated state vector $\hat{x}_k$ is the weighted mean of particles as:

$$\hat{x}_k = \sum_{i=1}^{n} w_k^i x_{k|k-1}^i \tag{4}$$

Resampling and regularization steps can be added to overcome the degeneracy phenomenon and sample impoverishment. For the further explanation, refer to Noh et al. (2011).

In the sequential data assimilation for a distributed hydrologic model, the delayed model response from internal processes should be considered for proper updating of internal state variables. New lagged particle filtering approach, proposed in this study, is one of alternatives not just to consider different catchment responses but only to use whole measurement information for data assimilation (Figure 1).

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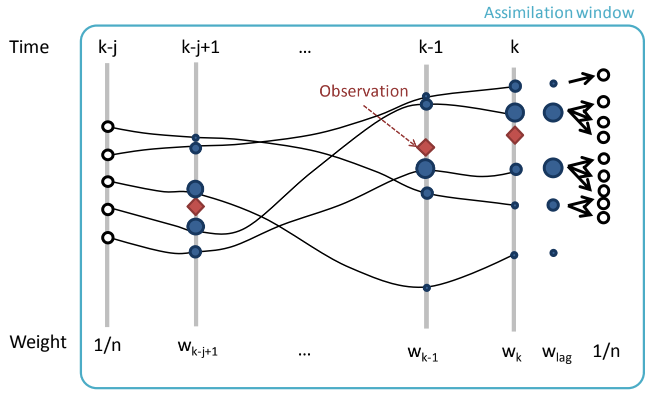

Figure 1. Concept of lagged particle filtering

3. Preliminary results and discussion

The SMC filters are applied to the Katsura River catchment to improve the streamflow forecasting. This catchment is located in Kyoto, Japan, and covers an area of 1,100 km^2 (887 km^2 at the Katsura station). The hydrologic model used is the water and energy transfer processes (WEP) model, which is developed for simulating spatially variable water and energy processes in catchments with complex land covers (Jia et al., 2009). Hourly observed precipitation and discharge data are used. We implement three different versions of SMC filters such as sequential importance resampling (SIR), lagged SIR and lagged regularized particle filter (RPF) for the streamflow forecasting.

Figure 2 illustrates the results of the lagged RPF using the WEP model from 11 to 17 July 2007. The forecasted streamflow shows good confirmity between observation and simulation, while the deterministic modeling result shows underestimation in the high flow. The particle diversity within the simulation is evaluated via ratio of the effective particle number n_{ratio} shown in Figure 3. Significant loss of sample diversity is seen in case of both lagged and simple SIR filters. However, lagged RPF does not show evidence of particle collapse, executing the regularization step when a loss of diversity happens.

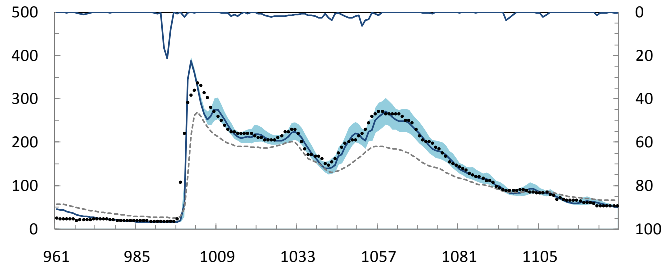

Figure 2. Hourly discharge hydrograph from 11 to 17 July 2007. Red solid and dashed lines represent estimation and 3-hr-lead forecast using SMC, respectively. Blue dashed line represents deterministic prediction without data assimilation. Blue dots denote observed values.

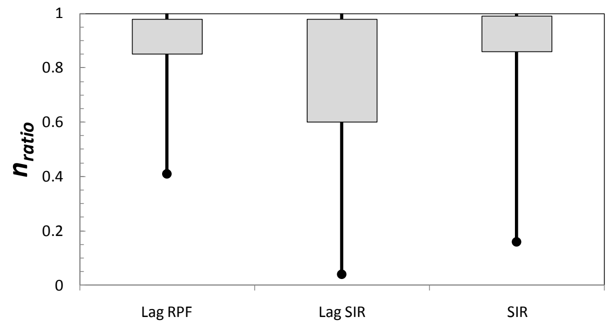

Figure 3. Distributions of ratio of the effective particle number n_{ratio} during the calibration period (1 June to July 2007). Black lines represent the maximum and minimum bounds of n_{ratio}. The grey boxes represent 90% bounds of n_{ratio}.

4. Reference:

1. Noh, S. J., Tachikawa, Y., Shiiba, M., and Kim, S. (2011) Dual state-parameter updating scheme on a conceptual hydrologic model using sequential Monte Carlo filters. Annual Journal of Hydraulic Engineering, JSCE, 55, 1-6.
2. Jia, Y., Ding, X., Qin, C., and Wang, H. (2009) Distributed modeling of landsurface water and energy budgets in the inland Heihe river basin of China. Hyrol. Earth Syst. Sci., 13, 1849-1866.