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Dynamic Baysesian state-space model with a neural network for an online river flow prediction

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The usefulness of artificial neural networks in complex hydrological modeling has been demonstrated by successful applications. Several different types of neural network have been used for the hydrological modeling task but the multi-layer perceptron (MLP) neural network (also known as the feed-forward neural network) has enjoyed a predominant position because of its simplicity and its ability to provide good approximations. In many hydrological applications of MLP neural networks, the gradient descent-based batch learning algorithm such as back-propagation, quasi-Newton, Levenburg-Marquardt, and conjugate gradient algorithms has been used to optimize the cost function (usually by minimizing the error function in the prediction) by updating the parameters and structure in a neural network defined using a set of input-output training examples.

Hydrological systems are highly with time-varying inputs and outputs, and are characterized by data that arrive sequentially. The gradient descent-based batch learning approaches that are implemented in MLP neural networks have significant disadvantages for online dynamic hydrological modeling because they could not update the model structure and parameter when a new set of hydrological measurement data becomes available. In addition, a large amount of training data is always required off-line with a long model training time.

In this work, a dynamic nonlinear Bayesian state-space model with a multi-layer perceptron (MLP) neural network via a sequential Monte Carlo (SMC) learning algorithm is proposed for an online dynamic hydrological modeling. This proposed new method of modeling is herein known as MLP-SMC. The sequential Monte Carlo learning algorithm in the MLP-SMC is designed to evolve and adapt the weight of a MLP neural network sequentially in time on the arrival of each new item of hydrological data. The weight of a MLP neural network is treated as the unknown dynamic state variable in the dynamic Bayesian state-space model formulation. The nonlinear Monte Carlo filtering algorithm is based on recursively constructing the posterior probability density (distribution) of the state variable of neural network's weight, with respect to measured data (in our case, river flow), through a random trajectory of the state by entities called 'particles' in the dynamic state-space model formulation. A weight, which is the probability of the trajectory of the state, is assigned to each particle by a Bayesian correction term based on measurement. The algorithms differ in the way that the swarm of particles evolves and adapts to incoming online measurement data.

In order to demonstrate the efficiency and usefulness of the proposed MLP-SMC, a practical application of hydrological modeling is carried out to predict the river flow sequentially in advance on the arrival of each new item of river flow data at intervals of 10 minutes. The performance of the proposed MLP-SMC is compared with the performance of a multi-layer perceptron (MLP) model trained using the back-propagation learning algorithm (MLP-BP) in which a batch off-line learning algorithm is implemented. The results show that the proposed MLP-SMC shows superiority in terms of model accuracy and computational cost compared with MLP-BP. The sequential Monte Carlo learning algorithm implemented in MLP-SMC is shown to have less sensitivity to noisy and sparsely distributed data compared to the batch off-line learning algorithm used in MLP-BP.