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Daily water level forecasting using wavelet decomposition and artificial intelligence techniques

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SUMMARY

Reliable water level forecasting for reservoir inflow is essential for reservoir operation. The objective of this paper is to develop and apply two hybrid models for daily water level forecasting and investigate their accuracy. These two hybrid models are wavelet-based artificial neural network (WANN) and wavelet-based adaptive neuro-fuzzy inference system (WANFIS).

Wavelet decomposition is employed to decompose an input time series into approximation and detail components. The decomposed time series are used as inputs to artificial neural networks (ANN) and adaptive neuro-fuzzy inference system (ANFIS) for WANN and WANFIS models, respectively. Based on statistical performance indexes, the WANN and WANFIS models are found to produce better efficiency than the ANN and ANFIS models. WANFIS7-sym10 yields the best performance among all other models. It is found that wavelet decomposition improves the accuracy of ANN and ANFIS.

This study evaluates the accuracy of the WANN and WANFIS models for different mother wavelets, including Daubechies, Symmlet and Coiflet wavelets. It is found that the model performance is dependent on input sets and mother wavelets, and the wavelet decomposition using mother wavelet, db10, can further improve the efficiency of ANN and ANFIS models. Results obtained from this study indicate that the conjunction of wavelet decomposition and artificial intelligence models can be a useful tool for accurate forecasting daily water level and can yield better efficiency than the conventional forecasting models.

1. Introduction

The temporal and spatial variability of precipitation is very high in South Korea. About 70% of annual precipitation occurs in the summer season between June and September (Bae et al., 2007). In addition to precipitation characteristics, overpopulation, urbanization, industrialization and change of farming practices further complicate operational hydrology. The control and management of reservoir systems are essential in South Korea, since they play an important role in water supply and flood prevention. Accurate forecasting of reservoir inflow is critical for enhancing reservoir operation, water supply, flood prevention, hydropower generation, water resources management and decision support system.

Conventionally, reservoir inflow forecasting has been done using statistical models based on time series analysis, including AR (autoregressive), ARMA (autoregressive moving average), ARIMA (autoregressive integrated moving average), FGN (fractional Gaussian noise), BL (broken line), TF (transfer function), TFN (transfer function noise) and ARMAX (autoregressive moving average with exogenous terms). Since most current models can be classified as linear models, they have limited capability to forecast the inflow pattern that is highly nonlinear and non-stationary.

Over the past years, artificial intelligence (AI) techniques have been successfully developed for modeling non-linear hydrologic systems. In particular, artificial neural networks (ANNs) and adaptive neuro-fuzzy inference system (ANFIS) have been accepted as effective tools for modeling complex hydrologic systems (Bae et al., 2007; Cheng et al., 2005b; Coulibaly et al., 2000; El-Shafie et al., 2007; Figueiredo et al., 2007; Jain et al., 1999; Jeong and Kim, 2005; Jothiprakash and Magar, 2012; Karimi-Googhari and Lee, 2011; Kim et al., 2013b; Othman and Naseri, 2011; Razavi and Araghinejad, 2009; Seo et al., 2013a, 2013b, 2013c; Wu et al., 2009).

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ANNs are parallel computational models that resemble biological neural network and have better generalization capabilities. ANFIS, on the other hand, combines the advantages of both ANN and fuzzy inference system (Okkan, 2012) and is becoming more popular in hydrological applications. It is reported to perform better than ANNs for flood forecasting and long-term discharge prediction (Chau et al., 2005; Cheng et al., 2005a, 2005b). Although ANN and ANFIS have been extensively used for prediction of hydrological variables, they have also some problems when dealing with non-stationary data.

Since hydrological time series includes several frequency components and have nonlinear relationships, hybrid model approaches have been used to improve the performance of models forecasting (Okkan, 2012). These approaches include chaotic neural networks (Karunasinghe and Liong, 2006), neural networks based on set pair analysis (SPA) and principle component analysis (PCA) (Wang et al., 2006a,b; Wu et al., 2009), threshold neural networks (Wang et al., 2006b), cluster-based hybrid neural networks (Cigizoglu and Kisi, 2005), and bootstrapped artificial neural networks (Han et al., 2007; Jeong and Kim, 2005; Jia and Culver, 2006; Kim et al., 2013a; Seo et al., 2013a, 2013c; Sharma and Tiwari, 2009; Srivastav et al., 2007; Tibshirani, 1996; Tiwari and Chatterjee, 2010a, 2010b; Twomey and Smith, 1998; Zio, 2006).

In the last years, the conjunction of wavelet transform and AI techniques has been successfully implemented in hydrological applications (Abiyev, 2011; Adamowski and Chan, 2011; Adamowski and Prasher, 2012; Adamowski and Sun, 2010; Anctil and Tape, 2004; Belayneh and Adamowski, 2012; Cannas et al., 2006; Khanghah et al., 2012; Kisi, 2008, 2011; Kisi et al., 2011; Nejad and Nourani, 2012; Nourani et al., 2012; Okkan, 2012; Okkan and Serbes, 2013; Rajaee, 2010; Rajaee et al., 2011; Tiwari and Chatterjee, 2010b; Wang and Ding, 2003; Wang et al., 2009; Wei et al., 2012). The wavelet transform is another data-preprocessing technique which can analyze a signal in both time and frequency so that it can overcome the drawbacks of conventional Fourier transform. The wavelet transform provides an effective decomposition of time series so that the decomposed data can increase the performance of hydrological forecasting models by capturing the useful information on different resolution levels (Nourani et al., 2009, 2011).

Adamowski and Sun (2010) proposed a method based on coupling discrete wavelet transforms and ANN for streamflow forecasting for non-perennial rivers in semi-arid watersheds. The performance of the coupled wavelet-neural network models (WA-ANN) was compared with the ANN models for streamflow forecasting. They found that the WA-ANN models provided more accurate streamflow forecasting than the ANN models.

Tiwari and Chatterjee (2010b) developed a hybrid wavelet-bootstrap-ANN (WBANN) model to investigate the potential of wavelet and bootstrapping techniques for developing an accurate and reliable ANN model for hourly flood forecasting. They compared the performance of WBANN model with three different ANN models including traditional ANN, wavelet-based ANN (WANN) and bootstrap-based ANN (BANN). They found that the overall WBANN model was more accurate and reliable as compared to the other three models. They also found that the WBANN model improved the reliability for flood forecasting with greater confidence.

Adamowski and Chan (2011) proposed a method coupling the discrete wavelet transform and ANN for monthly groundwater level forecasting. Comparing the proposed coupled wavelet-neural network models (WA-ANN) with ANN and ARIMA models for groundwater level forecasting, they found that the WA-ANN models provided more accurate average groundwater level forecasts than the ANN and ARIMA models.

Kisi (2011) proposed a simple wavelet regression (WR) approach for modeling daily reference evapotranspiration. The accuracy of the WR models was compared with that of the single linear regression (LR) and the empirical models including CIMIS Penman, Hargreaves, Ritchie and Turc. Comparison of these models showed that the WR models performed better than the LR and empirical models for modeling daily reference evapotranspiration.

Kisi et al. (2011) proposed a new method combining wavelet and gene expression programming (WGEP) methods for forecasting long-term air temperature. This method combines the discrete wavelet and genetic programming methods. Comparing the accuracy of single GEP and WGEP models, they found that the WGEP model performed much better than the single GEP model. They also found that the WGEP model significantly increased the accuracy of single GEP model especially for forecasting long-term air temperatures.

Adamowski and Prasher (2012) compared support vector regression (SVR) and wavelet networks (WN) for daily runoff forecasting in a mountainous watershed. They found that the best WN model performed slightly better than the best SVR model.

Nejad and Nourani (2012) applied wavelet-based global soft thresholding method to denoise daily time series of streamflow. The denoised time series was imposed on an ANN model to forecast streamflow. They found that the results of the ANN model for streamflow forecasting could be improved by 11% when the wavelet-based denosing approach, as a pre-processing method, was applied to the data.

Okkan (2012) developed a hybrid model using discrete wavelet transform (DWT) and feed forward neural networks (FFNNs) for

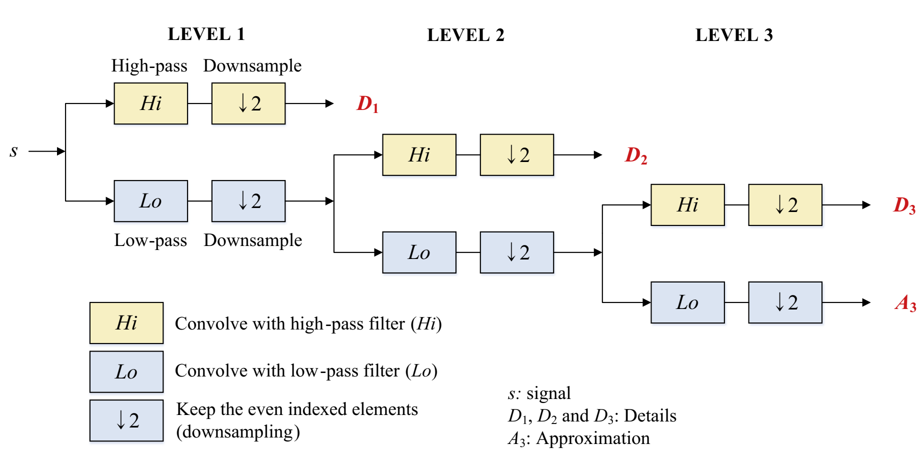

Fig. 1. Mallat's algorithm for three-level decomposition of a signal.