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Wavelet support vector machine-based prediction model of dam deformation

Huaizhi Su [a,b,*], Xing Li [b], Beibei Yang [c], Zhiping Wen [d]

[a] State Key Laboratory of Hydrology-Water Resources and Hydraulic Engineering, Hohai University, Nanjing 210098, China
[b] College of Water Conservancy and Hydropower Engineering, Hohai University, Nanjing 210098, China
[c] National Engineering Research Center of Water Resources Efficient Utilization and Engineering Safety, Nanjing 210098, China
[d] Department of Computer Engineering, Nanjing Institute of Technology, Nanjing 211167, China

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ABSTRACT

Considering the strong nonlinear dynamic characteristics of dam deformation, the prediction model of dam deformation is investigated. Support vector machine (SVM) is combined with other methods, such as phase space reconstruction, wavelet analysis and particle swarm optimization (PSO), to build the prediction model of dam deformation. Firstly, the chaotic characteristics and the predictable time scale of dam deformation are identified by implementing the phase space reconstruction of observation data series on dam deformation. Secondly, a SVM-based prediction model of dam deformation is proposed. The reconstructed phase space of observed deformation and the Morlet wavelet basis function are selected as the input vector and the kernel function of SVM. Thirdly, the PSO algorithm is improved to implement the parameter optimization of SVM-based prediction model of dam deformation. Finally, the displacement of one actual dam is taken as an example. The results demonstrate the modeling efficiency and forecasting accuracy can be improved.

1. Introduction

Dam engineering in safe status can bring significant economic and social benefits. Once the dam breaks, the disaster will be caused by the sudden uncontrolled water [1,2]. Since the 1920s, severe accidents of dam failure have occurred in many countries such as USA (St. Francis Dam, 1928; Teton Earth Dam, 1976), France (Malpasset Arch Dam, 1959), Italy (Vajont Arch Dam, 1963), China (Banqiao Earth Dam and Shimantan Earth Dam, 1975; Gouhou Dam, 1993). In fact, most of dam failures did not arise suddenly, but experienced a process from the quantitative to qualitative changes [3]. If the prototypical observations on dam structural responds are analyzed in time and some appropriate prediction models are built, most of hidden dangers can be found and the catastrophic accidents can be voided by identifying accurately the structural behavior and its development trend.

As the most intuitive and comprehensive respond of structural behavior, the deformation is observed by almost all of dam engineering. According to the prototypical observations on dam deformation, many prediction models of dam deformation have been proposed [4–7]. Especially in recent years, the artificial intelligence methods, such as neural network, genetic algorithm, ant colony algorithm, have been introduced to build the prediction models of dam deformation [8–10]. However, the influence mechanism of many factors on dam deformation behavior needs to be investigated. New models and methods

* Corresponding author at: State Key Laboratory of Hydrology-Water Resources and Hydraulic Engineering, Hohai University, Nanjing 210098, China.
E-mail address: su_huaizhi@hhu.edu.cn (H. Su).

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need to be presented to improve the prediction accuracy. The observation data-based prediction model of dam deformation, which is built by analyzing the space-time features of dam deformation and their influence factors, is still an important research problem in dam engineering field.

In the 1990s, the support vector machine (SVM) for learning was proposed [11]. Based on the principle of structural risk minimization, SVM has obvious advantages in solving the nonlinear problems with fewer samples and high dimensions. With the in-depth research, some improved algorithms on SVM have been developed by adding function items and variables [12]. Other forms of SVMs, such as the least squares SVM, the Bayesian SVM, and the fuzzy SVM, have been presented. The quadratic programming problem in the standard SVM is transformed into the linear programming problem in the least squares SVM [13]. In the Bayesian SVM, Bayesian theory is used to improve the SVM criterion and estimate the SVM parameters, which can make the prediction accuracy be improved [14]. In the fuzzy SVM, the anti-noise capability of SVM can be advanced by assigning a fuzzy membership value to each sample [15]. SVM has also been applied to the approximation and prediction of nonlinear structural behavior in dam engineering. Some kernel functions, such as Gaussian (radial basis function) kernel and polynomial kernel, were selected for building the SVM-based identification models of dam structural behavior [16]. The sensitivity analysis for SVM input on output was implemented to optimize the input vector of SVM [17].

It has been known that the performance of SVM is closely related to kernel function, kernel parameter and penalty factor. However, a set of complete basis in L_2 space cannot be obtained after the translation of conventional kernel functions. So it is difficult to approximate any nonlinear function with SVM. When SVM is used to solve a convex optimization problem, the optimization selection of kernel parameter and penalty factor cannot be fulfilled by the training algorithm. Furthermore, the forecast capacity of built model is also highly dependent on the following operations, namely the identification of nonlinear characteristics and predictable time scale on dam deformation from observation data series, and the reasonable optimization of SVM input vector.

According to the observation data on dam deformation, this paper focuses on building the prediction model of dam deformation by combining SVM with other methods. This paper is organized as follows. In Section 2, a wavelet support vector machine (WSVM), namely SVM with the Morlet wavelet basis function as the kernel function, is introduced. The WSVM-based prediction model of dam deformation, which can make good use of regression analysis ability of SVM, is presented. In Section 3, the phase space reconstruction method and the particle swarm optimization (PSO) algorithm are adopted to build the WSVM-based prediction model of dam deformation. The phase space reconstruction of observation data series on dam deformation is implemented to identify the chaotic characteristics of dam deformation, estimate the predictable time scale of dam deformation, and then determine the input vector of WSVM. The improved PSO algorithm is used to implement the parameter optimization of WSVM. Section 4 presents the construction process of WSVM-based model predicting dam deformation. In Section 5, one actual dam is taken as an example. Its prediction models of deformation behavior are built using the proposed method and other traditional methods. The modeling efficiency and forecasting accuracy are compared. Section 6 summarizes the main conclusions reached in this work.

2. Construction principle of WSVM-based model predicting dam deformation

A training sample set of dam deformation, $\{(\mathbf{x}_i, y_i)\}$ $(i = 1, 2, \ldots, l)$, is selected for a SVM as shown in Fig. 1. $\mathbf{x}_i \in \mathrm{R}^n$ represents the input column vector of the ith group of training sample and $y_i \in \mathrm{R}$ is the corresponding output value. l is the number of training sample points. The component of $\mathbf{x}_i$ is called the input feature factor. $\mathbf{x}_i = [x_i^1, x_i^2, \ldots, x_i^n]^T$. The training sample set is mapped to a high-dimensional feature space by the nonlinear mapping function $\varphi(\cdot)$. The following linear regression function is obtained in the feature space.

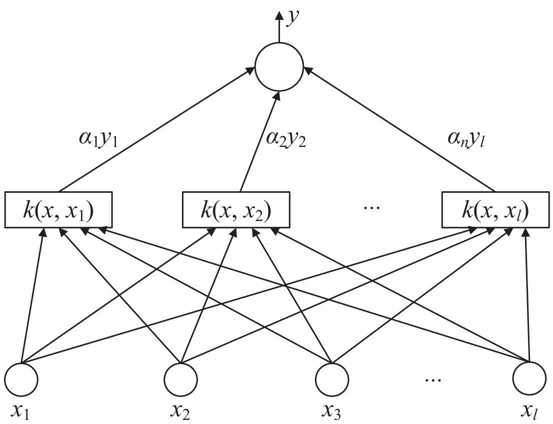

Fig. 1. Structure diagram of SVM.