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Multiple neural networks switched prediction for landslide displacement

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ABSTRACT

An accurate prediction of landslide displacement is challenging and of great interest to governments and researchers. In order to reduce the risk of selecting the types of influencing factors and artificial neural networks (ANNs), a multiple ANNs switched prediction method is proposed for landslide displacement forecasting. In the first stage, a set of individual neural networks are developed based on different environmental factors and/or different training algorithms. In the second stage, a switched prediction method is used to select the appropriate individual neural network for prediction purpose. For verification and testing, three typical landslides in Three Gorges Reservoir, namely Baishuihe landslide, Bazimen landslide and Shiliushubao landslide, are presented to test the effectiveness of our method. Application results demonstrate that the proposed method can significantly improve model generalization and perform similarly to, or better than, the best individual ANN predictor.

1. Introduction

Landslide is one of the most important geological disasters affecting Three Gorges area of China. Many important towns are located in the Three Gorges area and a large number of people live along the Yangtze River. Once landslide hazard occurs, significant casualties and property losses will be caused. In recent years, greater awareness of disasters due to landslides has brought attention to the Chinese government. The possible time when landslides are likely to occur should be identified in advance in order to avoid or reduce the damage. The evolution process of landslide is a nonlinear dynamical system which is influenced by many complex and diverse environmental factors, such as tectonic factors, climatic factors, earthquake, and human disturbance (Lee et al., 2009; Du et al., 2013; Park et al., 2013; Wu et al., 2014). The landslide displacement monitoring data are of vital importance in analyzing the dynamics of landslide movement (Liu et al., 2013). In the last decade, with the development of global positioning system (GPS) technique, more accurate landslide displacement data can be obtained (Tagliavini et al., 2007; Wang et al., 2011a; Wang, 2012). Several different approaches on the landslide displacement prediction can be found in current literatures, such as creep theory, statistical approaches, time series approaches and artificial intelligence approaches, etc. For example, Saito (1965) used a creep rupture relationship to forecast the time of occurrence of slope failure. Hilley et al. (2004) utilized a permanent scatterer analysis to resolve detailed seasonal variations in the movement of slow moving landslides. Romeo (2000) used Newmark's model to predict earthquake-induced landslide displacements. Zhang et al. (2006) proposed a loading/unloading response ratio method for landslides prediction at the condition of rainfall. Calvello et al. (2008) proposed a numerical procedure including a groundwater model and a kinematic model to predict the behavior of rainfall-controlled slides in stiff clays. Time series analysis approaches are also widely used in the prediction of landslide displacement, such as Verhulst model (Zhou et al., 2008; Li et al., 2012), autoregressive model (Wang et al., 2011b; Xu et al., 2011) and exponential smoothing model (Liu et al., 2009).

Besides the above achievements, some artificial intelligence approaches, especially ANNs, have become powerful tools for landslide displacement prediction in recent years (Mayoraz et al., 2002; Melchiorre et al., 2008; Chen & Zeng, 2013; Du et al., 2013; Lian et al., 2013; Liu et al., 2013; Lian et al., 2014). ANNs are data-driven models. The attractive ability of ANNs is that they can learn the nonlinear relationship from historical monitoring data (Melchiorre et al., 2008). Mayoraz and Vulliet (2002) showed that ANNs can improve the prediction performance compared to purely mechanical models. Chen and Zeng (2013) improved the predictive capability of ANNs by introducing a combination of genetic algorithm and simulated annealing algorithm. Du et al. (2013) divided the accumulated displacement into a trend and a periodic component. A back-propagation neural network (BPNN) was adopted to forecast the periodic component. In order to avoid many difficulties faced by BPNN such as slow convergency and local minimum, Lian et al. (2014) used an extreme learning machine (ELM) to forecast the periodic component. Following the "decomposition-and-ensemble" principle, Lian et al. (2013) used an ensemble empirical mode decomposition (EEMD) technique to improve the prediction accuracy of landslide displacement. Liu et al.

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(2013) analyzed and compared the quality of three computational intelligence methods including the Gaussian process, support vector machines (SVM), and relevance vector machines (RVMs) for landslide displacement prediction.

However, some of the previous studies only focus on the historical landslide displacement observations but don't consider the influence of many complicated environmental factors such as rainfall and reservoir level elevation. As a contribution, this study comparatively examines the performance of different neural network predictors with different environmental factors in the case of landslide displacement prediction. Meanwhile, a shortcoming of ANN predictor is that different ANNs and different selected influencing factors can lead to different prediction performances. In most real world applications, we can hardly know which type of ANN is better or which influencing factors are more important for a specific landslide. In order to reduce the risk of selecting ANNs and influencing factors, a switched prediction method is proposed in this study.

In this paper, the one-step-ahead prediction for landslide displacement is studied. Two commonly used artificial neural networks, least squares support vector machine (LSSVM) and extreme learning machine (ELM) with kernel functions, are selected to establish the predictors. Both of these two networks have been proven to have good generalization performance and low computational cost. The influences of rainfall and reservoir level elevation to landslide displacement are considered. A set of alternative ANN predictors with different input variables are established. A switched prediction method is proposed to select the appropriate individual neural network for prediction purpose. Three typical landslides in Three Gorges Reservoir, namely Baishuihe landslide, Bazimen landslide and Shiliushubao landslide, are presented to illustrate the capability of the proposed method.

2. Methodologies

2.1. LSSVM for regression

LSSVM (Suykens et al., 1999) is the modification of the traditional SVM. LSSVM uses equality optimization constraints instead of inequalities, which can provide fast implementations of the traditional SVM.

Table 1
Prediction schemes.

LSSVM1	LSSVM only based on landslide displacement
LSSVM2	LSSVM considering rainfall
LSSVM3	LSSVM considering reservoir level elevation
LSSVM4	LSSVM considering rainfall and reservoir level elevation
ELM1	ELM only based on landslide displacement
ELM2	ELM considering rainfall
ELM3	ELM considering reservoir level elevation
ELM4	ELM considering rainfall and reservoir level elevation
COM1	Simple averaging of all neural network models
COM2	Using only the single “best” neural network model
COM3	Switched prediction

Given a set of training data $(\mathbf{x}_i, t_i)$, $i = 1, \ldots, N$, where $\mathbf{x}_i \in \mathbf{R}^n$ is the input data, $t_i \in \mathbf{R}$ is the corresponding output data. LSSVM model can be expressed as:

$$f(\mathbf{x}) = \mathbf{w}^{\mathrm{T}}\phi(\mathbf{x}) + b \tag{1}$$

where $\phi : \mathbf{x}_i \rightarrow \phi(\mathbf{x}_i)$ is the nonlinear mapping that transforms the original input data into a higher dimensional feature space, $\mathbf{w}$ is the unknown regression parameters and b is the bias term. The optimization problem is given as follows:

$$\begin{aligned}&\text{Minimize} : J(\mathbf{w}, \mathbf{e}) = \frac{1}{2}\mathbf{w}^{\mathrm{T}}\mathbf{w} + \frac{1}{2}C\sum_{i=1}^{N} e_i^2 \\ &\text{Subject to} : t_i = \mathbf{w}^{\mathrm{T}}\phi(\mathbf{x}_i) + b + e_i, i = 1, \ldots, N\end{aligned} \tag{2}$$

where e_i is the error between the actual output and the predictive output of the ith sample, C is the regularization parameter that controls the trade-off between model complexity and approximation accuracy. Based on the KKT theorem, the above optimization problem can be transformed to the dual problem as follows:

$$L(\mathbf{w}, b, \mathbf{e}, \alpha) = J(\mathbf{w}, \mathbf{e}) - \sum_{i=1}^{N}\alpha_i\left(\mathbf{w}^{\mathrm{T}}\phi(\mathbf{x}_i) + b + e_i - t_i\right) \tag{3}$$

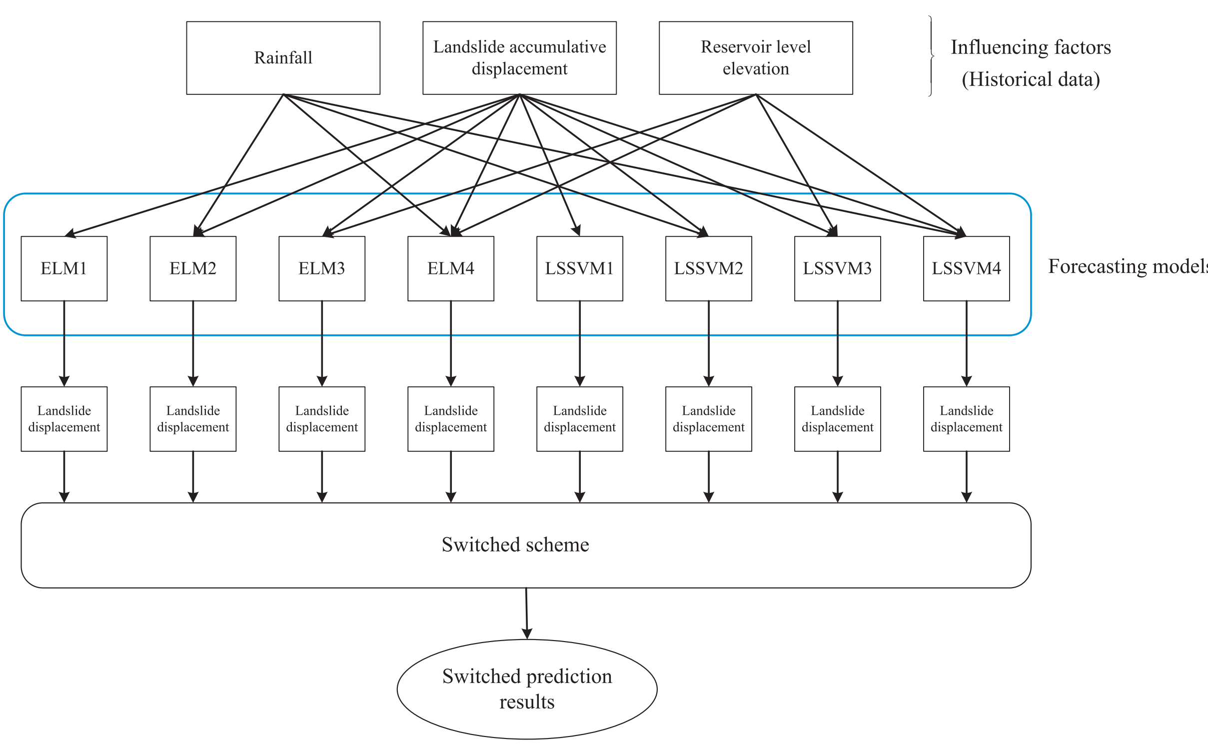

Fig. 1. The scheme of ANNs-switched prediction method.