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Landslide displacement prediction based on wavelet transform and long short-term memory neural network

Prédiction des déplacements utilisant transformation en ondelettes et réseau neuronal longue mémoire à court terme

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ABSTRACT: The prediction of landslide displacement is a key component of an early warning system to mitigate landslide risk. Most of the models for landslide displacement prediction are static models. Yet, landslides move dynamically. This paper proposes a novel dynamic model combining the wavelet transform and the multivariate long short-term memory neural network to predict landslide displacement. In the Three Gorges Reservoir Area (TGRA) in China, step-wise landslides have been observed. One such step-wise landslide, the Baijiabao landslide, was used as case study for this paper. The cumulated displacement was decomposed into a trend displacement, a periodic displacement and noise using the wavelet transform. The periodic displacement was predicted by the multivariate long short-term memory (LTSM) neural network considering various causal factors. For comparison, the static multivariate support vector machine (SVM) model and univariate LSTM model were also implemented. The results demonstrate that the multivariate LSTM model achieved higher prediction accuracy than the multivariate SVM and univariate LSTM models, and that the method is preferable for predicting the displacement of step-wise landslides in general, and for the TGRA in particular.

RÉSUMÉ: La prédiction de l'étendue des glissements de terrain constitue un élément important pour la reduction du risque. La majorité des modèles existants pour glissements sont de nature statique. Un glissement se déplace cependant de manière dynamique. Cet article propose un nouveau modèle dynamique qui allie une transformation en ondelettes des signaux avec une analyse par réseau neuronal 'longue mémoire à court terme' (LSTM) avec multivariables. Autour du barrage "Three Gorges" en Chine, on a observé nombres de glissements "par étapes", dont le glissement de Baijiabao. Les déplacements cumulatifs sont composés d'une partie "trend" et une partie périodique. Le déplacement périodique a été modelé avec le réseau neuronal LSTM, considérant la précipitation et la variation du niveau du réservoir. Des comparaisons sont aussi faites avec un modèle statique, le modèle SVM (machine à vecteurs de support avec multi.variables) et un modèle univariable LSTM. Les résultats démontrent que le modèle LSTM avec multivariables fait un bien meilleur modelage que les deux autres modèles, et que cette méthode est préférable pour la prédiction des déplacements des glissements en général, et en particulier pour les glissements "par étapes" dans la région du barrage Three Gorges.

Keywords: Step-wise landslide; Wavelet transform; Long short-term memory neural network; Displacement Prediction; Three Gorges Reservoir: Landslide; dam

1 INTRODUCTION

Landslides are a common geological hazard in China, especially in the Three Gorges Reservoir Area (TGRA) (Lian et al 2015). They can cause massive casualties and significant losses and damage to property. An accurate prediction of landslide displacement would help mitigate losses and contribute importantly to early warning systems (Huang et al 2017).

Physical models and data-based models have been proposed to predict landslide displacement (e.g., Jiang et al 2011; Li et al 2018). Data-based models are often preferred because they are simpler, can give accurate predictions and involve lower costs (Corominas et al 2005; Zhou et al. 2018). Du et al (2013) predicted the displacement of colluvial landslides in the TGRA with a back propagation neural network (BPNN). Miao et al (2018) applied a support vector machine (SVM) model with multi-algorithm optimization to predict landslide displacement.

The above prediction models implement different algorithms, but all use static models, treating landslide displacement as a static regression problem (Yao et al 2015). Landslides, however, evolve as dynamic processes (Qin et al 2002). Dynamic predictors, establishing relations between landslide displacement at different times, should prove more suitable than static models.

Recurrent neural networks (RNN) have been used earlier to construct dynamic predictors (e.g. Han et al 2004; Yao et al 2015). The long short-term memory neural network (LSTM) is an improved version of the RNN, and has been used earlier to predict the displacement of landslides in the TGRA (Xu and Niu 2018).

In the TGRA, the velocity of the landslide displacements increased during heavy rainfall and reservoir water level fluctuation and decreased during periods with less external loading (Miao et al 2014). The accelerating and decelerating movements resulted in step-wise accumulated displacement versus time (Fig. 1).

To predict the displacement of step-wise landslides, the displacement was decomposed into components (e.g. Huang et al 2017). To do this decomposition, several time series methods are available, such as the moving average (MA) (Miao et al 2018), the empirical mode decomposition (EMD) (Xu and Niu 2018) and the wavelet transform (WT) methods (Zhou et al 2018). The latter WT method can decompose time series measurements into components of different frequencies, and also remove system noise effectively.

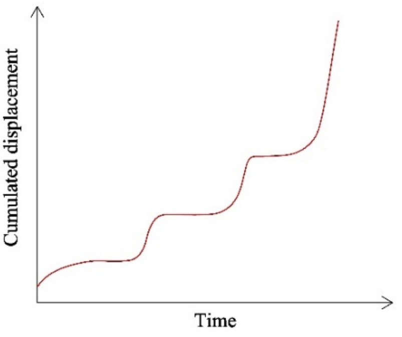

Figure 1. Evolution of step-wise landslide

The approach in this paper combines the WT method and the LSTM neural network to predict the displacement of the Baijiabao landslide:

1) WT was used to remove the system noise from the measured displacement sequence and was then used to decompose the displacement into a trend and a periodic component.
2) The LSTM models were applied to predict the trend and periodic components.

To verify the performance of the new model, the latter part of the displacements of the Baijiabao landslide were predicted and compared with the measurements. The multivariate LSTM results were also compared with displacement predicted with a static multivariate support vector machine (SVM) model and a univariate LSTM model. The goodness of each prediction was compared quantitatively, using the root mean square error (RMSE), mean absolute percentage error (MAPE) and relation coefficient (R). Details of those statistical indices can be found elsewhere (Zhou et al 2018).

2 PROPOSED MODEL

2.1 Time series decomposition

The displacement was decomposed into three components: a trend, a periodic and system noise component. The long term displacement, controlled by 'internal' geological conditions such as lithology, geological structure and progressive weathering, was the trend component. In the TGRA, the displacement on the short-term was influenced by two 'external' factors: rainfall and reservoir water level. This short term displacement was the periodic component (Zhou et al 2018). Additionally, the system error always exists during deformation monitoring process. The cumulated displacement time series (D) was then:

$$D = T + P + N \tag{1}$$

where T is the trend displacement, P is the periodic displacement, and N is the noise from system error of monitoring.

2.2 Wavelet transform

Wavelet transform (WT) is an analysis method for signal processing, which provides efficient localization in both time and frequency domains (Daubechies 1990). The approach includes two classes of transformation: continuous wavelet transformation (CWT) and discrete wavelet transformation (DWT). The DWT was selected to decompose the landslide displacement time series because of less time-consuming and easier to implement. The DWT was defined as follows:

$$DWT_y(m,n) = 2^{-\frac{m}{2}} \int_{-\infty}^{+\infty} s(t)\sigma^*(2^{-m}t - n)\,dt \tag{2}$$

where m is the scaling constant; n is the translating constant (an integer); $s(t)$ is the landslide displacement time series; and $\sigma^*(x)$ is the complex conjugate function.

The DWT algorithm had a set of high-pass and low-pass filter to extract an "approximation" sequence and a "detail" sequence. The approximation sequence represented low-frequency displacement and reflected the trend component. The detail sequence contained high-frequency displacement and reflected the periodic component.

2.3 Long short-term memory neural network

Long short-term memory neural network is an improved verion of recurrent neural network (RNN) proposed by Hochreiter and Schmidhuber (1997). Traditional RNN cannot handle long-range relationships because of problems with vanishing gradient and exploding gradient. The LSTM can overcome these drawbacks.

The LSTM neural network is composed of an input layer, a (or several) hidden layer(s) and an output layer. The units in the hidden layer are related to the others from one time step to the other. The basic unit of the hidden layer is its memory block consisting of an input gate, a forget gate, an output gate and a memory cell (Fig. 2). The 'Input gate' controls the flow of input activations into the memory cell. The 'Forget gate' controls whether the information from the previous time step is remembered or forgotten. When the 'Forget gate' is open, information from the previous time step is passed along to the next time step; when the 'Forget gate' is closed, all the information from the previous time step is forgotten before the next time step. The 'Output gate' controls the flow of output activations into other blocks or to the final results (Xu and Niu, 2018).

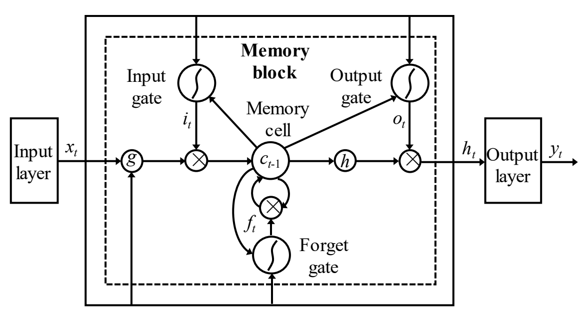

Figure 2. Architecture of LSTM neural network

For an input sequence $x=(x_1, x_2,\ldots, x_T)$, the output sequence $y=(y_1, y_2,\ldots, y_T)$ is obtained from time t=1 to time T through iteration of the following equations (Fan et al, 2014):

$$i_t = \sigma(W_{xi}x_t + W_{hi}h_{t-1} + W_{ci}c_{t-1} + b_i) \quad (3)$$

$$f_t = \sigma(W_{xf}x_t + W_{hf}h_{t-1} + W_{cf}c_{t-1} + b_f) \quad (4)$$

$$c_t = f_t c_{t-1} + i_t \tan h\,(W_{xc}x_t + W_{hc}h_{t-1} + b_c) \quad (5)$$

$$O_t = \sigma(W_{xo}x_t + W_{ho}h_{t-1} + W_{co}c_{t-1} + b_o) \quad (6)$$

$$h_t = o_t \tan h\,(c_t) \quad (7)$$

$$y_t = W_{hy}h_t + b_y \quad (8)$$

where i_t, f_t, o_t and c_t are the values of the input gate, forget gate, output gates and memory cell in the memory block at time t; b_i, b_f, b_o and b_c are their corresponding bias values; W_x are the weights between input nodes and hidden nodes; W_h are the weights between hidden nodes and cell memory; W_c are the weights connecting memory cell to output nodes; σ is the sigmoid activation function; $\tan h$ is the hyperbolic tangent function mapping data to [-1, 1]; and h_t is the hidden state, containing information about the history of earlier elements in the series.

3 BAIJIABAO CASE STUDY

3.1 Overview of the Baijiabao landslide

The Baijiabao landslide occurred in the Zigui town on the west side of the Xiangxi River, a major tributary of the Yangtze River. The front part of the landslide was submerged in the reservoir water. Four GPS monitoring stations were installed on the ground surface of the landslide in late 2006. The displacement has been measured at one month intervals since then.

Cao et al (2015) analyzed the time and spatial evolution of the Baijiabao landslide deformation. The analysis indicated that the Baijiabao landslide deformed as an entity. The monitoring data obtained from station ZG324 at the center of the landslide was used to establish the forecast model for the Baijiabao landslide.

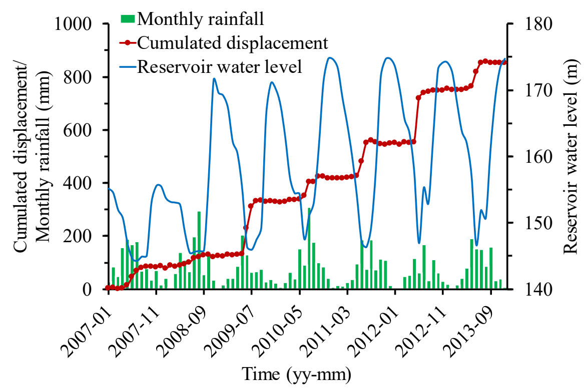

Figure 3. Rainfall, reservoir water level and cumulated displacement at ZG324, Baijiabao landslide (2007-2013)

Figure 3 shows the monitored displacements at station ZG324 versus time, as well as the measured rainfall and reservoir water level. Each year, the cumulated displacement increased from May to September under reservoir water drawdown and heavy precipitation. The reservoir level started to rise in October and was held constant (175 m) until April. During that period, the precipitation was gentle and the landslide experienced only small displacements. The step-wise increase in displacement was caused by seasonal rainfall and reservoir drawdown.

3.2 Decomposition of time series

In monitoring of surface displacement by GPS, noise cannot be avoided (Zhou et al 2018). The WT can remove system noises from the measured displacement time series. The noise was removed by the automatic one-dimensional denoising method in the wavelet toolbox of MATLAB.

The decomposition of the displacement sequence was also done with the wavelet toolbox of MATLAB. The type of wavelet function used is significant for the decomposition of the landslide displacement series. The function of Daubechies 4 (where 4 is the vanishing moments) was selected for this study. Figure 4 shows the displacement decomposition results.

A total of 84 monitoring data from station ZG324 were available from January 2007 to December 2013. The first 72 data points, spanning from January 2007 to December 2012, are used to train the LSTM model, and the remaining data from January to December 2013 are used to test the model (Fig. 4).

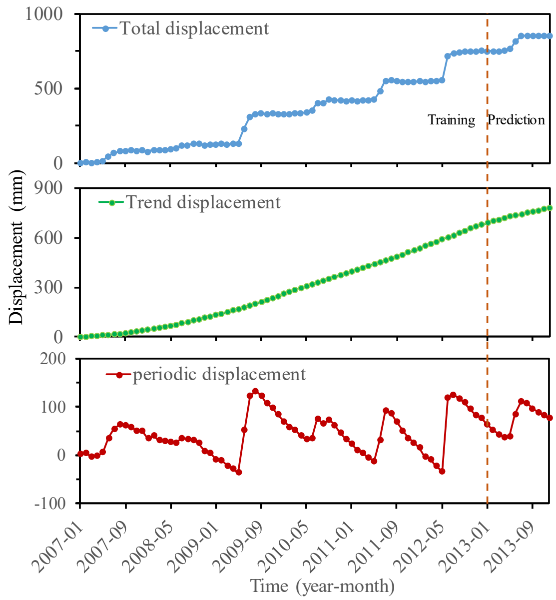

Figure 4. Displacement decomposition at ZG324

3.3 Prediction of trend displacement

The trend displacement due to the 'internal' conditions (lithology, structure, weathering, etc.), increased monotonically (Du et al 2013).

Some researchers have developed a prediction model of the trend displacement from the shape of the curve of displacement (Zhou et al 2016; Miao et al 2018). However, a single function may not be enough to fit the curve well (Yang et al 2018). In this study, a univariate LSTM model describing the relationship between time and the trend displacement was used to predict the trend displacement. The model yielded a good prediction, as shown in Figure 5. The resulting values of RMSE, MAPE, and R were 1.7, 0.2%, and 1, respectively.

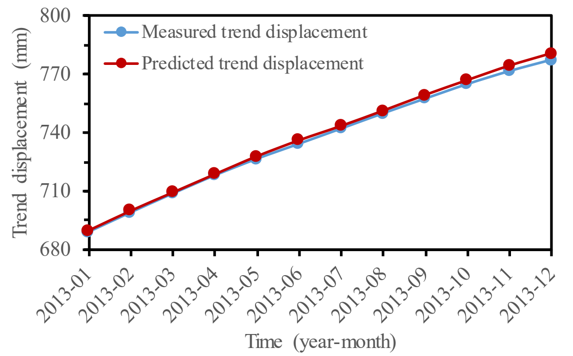

Figure 5. Predicted and measured trend displacement

3.4 Prediction of periodic displacement

3.4.1 Factors influencing periodic displacement

The periodic displacement at the Baijiabao landslide site was controlled by rainfall and reservoir water level. Consideration of the most important trigering factors is the key to a good prediction of the periodic displacement component for a step-wise landslide.

Based on the monitoring data (Fig. 3), rainfall and reservoir water level are the dominant factors inducing the step-wise displacement. Crozier (1986) suggested that the state of evolution of the landslide is also an important factor affecting the dependence of the movement on the external factors. Following earlier researchers (Cao et al 2016; Zhou et al 2018), the triggering factors listed in Table 1 were selected for the periodic displacement prediction: rainfall, reservoir water and evolution state of the landslide.

The Grey relational analysis was applied to measure the degree of correlation between the periodic displacement and each influence factor. The periodic displacement was selected as the primary sequence and the influencing factors were selected as sub-sequences. The sequences were normalized as:

$$X_k(i)' = X_k(i)/\frac{1}{n}\sum_{i=0}^{n} X_k(i) \tag{9}$$

where $i = 0,1,\cdots,n$; $k = 0,1,\cdots,m$; n and m are the number of data points and influencing factors, respectively. The correlation coefficients were calculated from:

$$\delta\left((x_0(i)', x_k(i)'\right) = \frac{p+\rho q}{\left|x_k(i)' - x_0(i)'\right| + \rho q} \quad (10)$$

$$p = \min_k \min_i \left(x_k(i)' - x_0(i)'\right) \quad (11)$$

$$q = \max_k \max_i \left(x_k(i)' - x_0(i)'\right) \quad (12)$$

where ρ is the resolution coefficient and is normally set to 0.5.

The grey relational grade (GRG) was used to evaluate the correlation between each variable. The GRG was obtained from:

$$r(x_0, x_i) = \frac{1}{n}\sum_{k=1}^{n} \delta\left((x_0(i)', x_k(i)'\right) \quad (13)$$

The values of the GRG ranges from 0 to 1. A GRG-value ≥ 0.6 designates a strong correlation. Table 1 lists the GRG-values for the correlation between periodic displacement and each influence factor. All the GRG-values are larger than 0.6, suggesting that the input influence factors were properly selected for the forecast model.

3.4.2 Prediction of periodic displacement

A multivariate LSTM model was used to predict the periodic displacement of the Baijiabao landslide. With the seven causal factors as input (Table 1), the periodic displacement was the output. The inputs and output were normalized between [-1, 1]. Samples of the data used in the periodic displacement model are shown in Table 2. The grid search method was used to search for the optimization parameters of the LSTM model.

Table 1. Input to the LSTM model and GRG between each influencing factor and periodic displacement

Inputs 1-7	Grey relational grade (GRG)
Input 1: the 1-month antecedent rainfall	0.69
Input 2: the 2-month antecedent rainfall	0.66
Input 3: average reservoir elevation in the current month	0.62
Input 4: change of reservoir level over the last 1 month	0.73
Input 5: the displacement over the past 1 month	0.86
Input 6: the displacement over the past 2 months	0.77
Input 7: the displacement over the past 3 months	0.71

The LSTM model was implemented in Python by the Keras package and used TensorFlow as a backend. Furthermore, a static multivariate SVM model using particle swarm optimization (PSO) to optimize its parameters, and a univariate LSTM model were also applied to predict the periodic displacement for comparison.

Figure 6 and Table 3 present the results of the three analysis. The multivariate LSTM analysis gave better agreement with the measured values than the multivariate SVM model and the univariate LSTM model. The values of the RMSE, MAPE and R indices are 9.1, 9.7% and 0.96, respectively.

Table 2. Data samples used in the modelling of periodic displacement

Time	Input 1	Input 2	Input 3	Input 4	Input 5	Input 6	Input 7	Output
2013-01	-0.97	-0.94	0.86	-0.33	-0.92	-0.87	-0.89	0.18
2013-02	-0.89	-0.95	0.56	-0.55	-0.94	-0.91	-0.92	0.06
2013-03	-0.74	-0.80	0.28	-0.52	-0.92	-0.91	-0.94	-0.06
2013-04	-0.48	-0.54	0.17	-0.34	-0.87	-0.84	-0.90	-0.13
2013-05	0.23	0.08	-0.15	-0.57	-0.87	-0.80	-0.83	-0.10

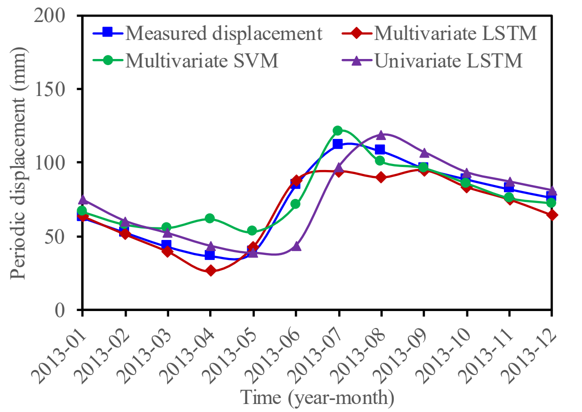

Figure 6. Predicted and measured periodic displacement

Table 3. Prediction accuracy of periodic displacement

Model	RMSE	MAPE(%)	R
Multivariate LSTM	9.1	9.7	0.96
Univariate LSTM	14.5	14.5	0.84
Multivariate SVM	10.8	16.2	0.92

3.5 Prediction of total displacement

The total displacement was obtained by adding the trend and periodic displacements. Figure 7 and Table 4 show that the multivariate LSTM achieved the best prediction of the three models.

4 DISCUSSION

Compared with the univariate LSTM, the multivariate LSTM predicted better the step-wise displacement. For example, the displacement increase of 53 mm of June 2013 occurred under combined reservoir drawdown and heavy rainfall. The absolute mean percentage error (APE) of the predicted results obtained by the multivariate and univariate LSTM models were 0.6% and 4.8%, respectively. The univariate LSTM method cannot simulate as well the relationship between deformation and triggers.

For the same input, the dynamic model LSTM showed higher prediction accuracy than the static model SVM. The LSTM model resulted in RMSE, MAPE and R-values of 8.2, 0.8% and 0.99, while the static SVM model had values of 10.8, 1.1% and 0.98. The LSTM model could establish connections between the data in different time steps. The LSTM model learns rules from historical information and then applies these rules to the current step.

Furthermore, the LSTM model can judge, filter and remember the information from previous time steps. The useful information is remembered; the useless information is forgotten. For the SVM model, connections between different time steps are not possible. The SVM model learn rules from a time step and cannot use historical data, and therefore cannot model the response of landslide deformation as well.

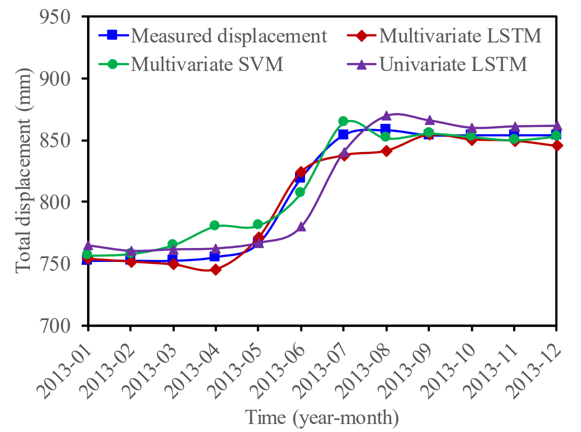

Figure 7. Predicted and measured total displacement

Table 4. Prediction accuracy of total displacement

Model	RMSE	MAPE(%)	R
Multivariate LSTM	8.2	0.8	0.99
Univariate LSTM	14.6	1.4	0.95
Multivariate SVM	10.8	1.1	0.98

5 CONCLUSION

Seasonal rainfall and reservoir water level fluctuations are the dominant factors inducing the step-wise deformation of landslides in the TGRA. It is thus necessary to consider these triggering factors in the forecast models to improve the prediction models.

The dynamic LSTM model is one such model because it builds relationships between different time steps, and makes full use of historical information. This information can be filtered by the "memory block" and the accuracy of the prediction will not be disturbed by past information from a long time ago. These characteristics of the model contribute to improving the predictions, compared with other models.

The proposed dynamic model combined with WA and LSTM achieved accurate prediction in the case of slow step-wise landslides. Based on this study, the approach can be recommended to predict landslide displacement in the TGRA and other landslide-prone regions.

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