Mutation Information Extraction and Fluctuation Ratio Displacement Model of Step-like Landslides Based on Subdivided Monitoring Data

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Abstract. The multi-source, massive and subdivided monitoring data provide powerful data support for revealing the causal mechanism of complex geological disasters and improving the accuracy of time prediction. Especially in the sub-monitoring period by day and hour, the relationship between displacement and factors is more complicated, and the hidden information is more abundant. In this paper, multi-point and large sample data of step-like landslides in the Three Gorges Reservoir area are used to extract landslide mutation and establish a displacement prediction model. Firstly, the standardization, the IR model and the kNN regression model were used to obtain the principal curve reflecting the common characteristics of the displacement in the region. According to the multiplicative model of displacement decomposition, the landslide displacement incremental signal was decomposed into the product of the fluctuation ratio and the trend displacement increment by FFT filtering method. Finally, by fitting the fluctuation ratio of principal curve, the displacement function model consisting of the induced factor term and the state factor term was obtained. Taking the daily monitoring data of four bank slopes in Fengdu County for nearly 3 years as an example, the result show that the model was more in conformity with the evolution of the step-like landslide by daily monitoring than other displacement prediction methods.

Keywords: Landslide mutation; Displacement prediction; Fluctuation ratio; Step-like landslides.

1. Introduction

The Three Gorges Reservoir area has abundant rainfall and surface water resources. Along with the cyclic effects of hydraulic factors[1], a large number of landslides with “step” deformation characteristics have been formed along the banks of the reservoir[2]. At present, the displacement prediction of such landslides is mainly concentrated on the monthly monitoring unit[3], and the research on the daily and hourly subdivided monitoring displacement laws is still in the exploratory stage.

In terms of data sources, the real-time and comprehensive landslide data is exploding, while the utilization rate decreases[4]; in terms of displacement indicators, scholars have decomposed displacement evolution curves, proposed superposition[5] to model displacement feature subsets and influence factors. Due to the change of the real physical meaning of displacement components, these models were over-fitting in steady-state conditions, and easy to fail when the environment changes. In terms of model application, considering the nonlinearity and complexity of landslide displacement, a large number of machine learning algorithms have been used for displacement prediction[6]. However,
the “independent-dependent variable” process could not be understood[7], which was not conducive to the analysis and decision-making of the catastrophic process. The fusion and mathematical expression based on multi-point displacement data can help reveal the deep laws of exploring landslides. This paper applied IR and kNN regression model to improve the extraction efficiency of displacement mutation features and realize the fusion analysis of landslides in the region. A multiplication model of displacement decomposition was proposed, the physical meaning of the indicator was more clear. Finally, the non-linear relationship between the factor and the fluctuation ratio was fitted to obtain the fluctuation ratio displacement model of the combination of the inducing factor item and the state factor item. The comparison and analysis of various different methods verified the effectiveness of the fluctuation ratio displacement model.

2. Landslide Dataset

2.1. Geological Environment

The study area is located along the Yangtze River and its tributaries along Fengdu County, Chongqing City, and is located in the heart of the Three Gorges Reservoir area. The region has a subtropical humid climate, with heavy rain in summer and autumn. Since 2007, the water level of the geological disasters in the reservoir area has fluctuated periodically between 145 and 175 m, with a range of 30 m. Among them, the Huangjuedang landslide, Longwangmiao landslide, Luojiapo landslide and Maoshuzi-Zhulinwan landslide are all accumulational landslides.

2.2. Displacement Data Processing

Cleaning and extracting reasonable and effective mutation information are necessary prerequisites for landslide analysis. This paper collected a total of 26,611 daily monitoring data from 4 landslides with 23 monitoring points from July 1, 2016 to August 31, 2019. Considering the elimination of the multi-point spatial structure differences, the Max-min normalization was performed on the displacement to facilitate unified quantitative comparison. Based on the PAVA (Pool Adjacent Violators Algorithm) rule of IR model, the monotonic function of the cumulative displacement \( S^{(0)} \) under least squares was obtained:

\[
\hat{S}^{(1)} = \arg \min_{s^{(0)}_i} \sum_{i=1}^{n} (S^{(0)}_i - S^{(1)}_i)^2
\]

\[
\hat{S}^{(1)}_{min} = \hat{S}^{(1)}_1 \leq \cdots \leq \hat{S}^{(1)}_i \leq \cdots \leq \hat{S}^{(1)}_n = \hat{S}^{(1)}_{max}
\]

In the formula: \( S^{(0)} \), \( S^{(1)} \) are the original displacement sequence and fitting sequence corresponding to \( t(1,2,\ldots,i) \) times. The original displacement with noise was reduced to a cumulative displacement value that satisfied the "stability-abrupt" order constraint (see Figure 1).

![Figure 1. Displacement characteristic curves of FD0104 point of Huangjuedang landslide.](image)

2.3. Delay Factor Analysis

The daily prediction of landslide displacement needs to consider the lag effects of main factors such as rainfall and reservoir water. The study used the gray correlation degree of non-linear evaluation[5] to quantify the correlation values between the cumulative displacement of the data set \( S^{(0)}, S^{(1)} \).
It was inferred that the precipitation infiltrated the landslide from the upper part and experienced a slower infiltration process; the continuous impact of the daily reservoir water change was more intense in the past week; the dominant factors were selected to be $p_{27}$ and $r_4$ for subsequent modeling analysis; the overall results also reflected the effectiveness of the aforementioned pretreatment method.

3. Displacement Principal Curve and Fluctuation Ratio Indicator

3.1. Factor Weighted KNN Optimization Regression Model

In order to make full use of the rich sample data to obtain the displacement principal curve that reflects the overall evolution of the same type of landslide in the region, based on the basic idea of the $k$NN model, this paper proposed a multi-factor weighted regression prediction method for displacement samples. The study selected cumulative rainfall $p_{27}$, reservoir water change $r_4$ and monitoring period $t$ as the $S$ data characteristic elements. Calculate the average of $p_{27}$, $r_4$ at the corresponding time $t$, and use it as the input characteristic parameter of the main curve of the displacement to be predicted. Considering the different importance of the factors, the Pearson, Spearman and Kendall correlation coefficients were used as factor weights. Ten-fold cross-validation and test comparison were performed on the data set. Based on the RMSE and $R^2$ indicators, the Kendall correlation coefficient was selected as the feature weight combination. The IR model eliminated the problem of "upside down" of the data, and the displacement principal curve (see Figure 2) was obtained finally which represented the overall response level of the landslide displacement.

3.2. Fluctuation Ratio Decomposition

In the monitoring unit period, the superposition decomposition mode of the cumulative displacement is:

$$\Delta S(t) = \Delta \phi(t) + \Delta \eta(t)$$  \hspace{1cm} (2)

Where $\Delta \phi(t)$, $\Delta \eta(t)$ are the increment of the trend term and the fluctuation term respectively. At this time, a new index of the displacement component of the wave term is defined:

$$\Delta S(t) = \eta^{(S)}(t) \cdot \Delta \phi(t)$$ \hspace{1cm} (3)

Where $\eta^{(S)}(t)$ is the fluctuation ratio, and the corresponding cumulative displacement increment is expressed as the product of the fluctuation ratio and the increment of the trend term. It can be known from equations (2) and (3):

$$\eta^{(S)}(t) = 1 + \frac{\Delta \eta(t)}{\Delta \phi(t)}$$ \hspace{1cm} (4)

When the landslide is in the stable creep stage, $\eta^{(S)}(t) \leq 1$; it enters the accelerated creep stage, $\eta^{(S)}(t) > 1$, and a larger value indicates that the landslide is accelerated more severely.

The low-pass parabolic FFT filter trend method was used to extract the trend displacement of the landslide displacement master curve, and two different feature subsets of trend term and volatility ratio were obtained according to formula (3) (see Figure 3).

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**Figure 2.** The principal curve of landslide displacement and corresponding factors.

**Figure 3.** Decomposition result of displacement.
4. Fluctuation Ratio Prediction Model

Due to the sufficient basic sample size, the data was divided into three different phases: The 973 periods of data from 2016.7.1 to 2019.2.28 was used as the training set to construct displacement prediction models; The 92 periods of data from 2019.3.1 to 2019.5.31 was used as the prediction set I to test the prediction effect of the model; The 92 periods of data from 2019.6.1 to 2019.8.31 was used as the prediction set II, which is used to further evaluate the applicable performance of the model.

4.1. Displacement Prediction Reconstruction

4.1.1. Prediction of trend term displacement. The extracted landslide trend term was slightly "S" shaped, and was fitted using a cubic polynomial with time parameters as variables:

$$\phi(t) = 2.206 \times 10^{-7} + 7.200 \times 10^{-4} \cdot t - 3.787 \times 10^{-3} \cdot t^2 + 2.191 \times 10^{-10} \cdot t^3$$

(5)

4.1.2. Fluctuation ratio prediction model. The regression function of the prediction model was based on the idea of the relationship between the response rate of external factors at different deformation stages of the landslide proposed by Xu Q et al[2], and combined with the correlation trend curve of the factors to construct. The expression of the model was simplified to:

$$\eta^{(5)}(t) = [\eta_2(t) + \eta_3(t)] \cdot \eta_4(t)$$

(6)

The training set data was taken for fitting, and the parameter estimates were obtained by the universal global optimization method. Simple correction was made based on the fluctuation ratio of training set and the relationship between the fitted and extracted values of the cumulative displacement. The regression function of the fluctuation ratio displacement model was:

$$\eta^{(6)}_{\text{cor}}(t) = \{3.649 + 1.074 \times 10^{-1} \cdot p_2(t) - 3.008 \times 10^{-4} \cdot [p_2(t)]^2 - 1.563 \times 10^{-1} \cdot r_3(t) - 8.383 \times 10^{-2} \cdot [r_3(t)]^2\} \times [1.289 \times 10^{-1} + 9.038 \times 10^{-2} \cdot c(t) - 2.023 \times 10^{-3} \cdot [c(t)]^2] - 8.750 \times 10^{-1}$$

(7)

Among them, $p_2(t) \in [1.85, 351.61]$, $r_3(t) \in [-6.83, 7.85]$, $c(t) \in [0, 25.61]$.

4.2. Plausibility Test

Based on the actual monitoring curve and the normalized landslide displacement main curve and the predicted value of the modified model, the study randomly selected the monitoring point FD0202 located in the middle of the main section of Luojiapo landslide (see Figure 4).

It can be seen from Figure 4 that the abrupt change phase of the displacement main curve and the model prediction value is in good agreement with the measured displacement, and the changes in external factors corresponding to the abrupt change are concentrated in the period of continuous decline of water level and rainfall increase[8].

4.3. Comparison of Different Prediction Models

Compared with various different prediction models of ARIMA, SVR, RF and MLP in the mode of superposition, results in Figures 5 and Table 1 showed that prediction models were time-effective, the
model proposed in this paper had reached a higher level of prediction on subdivided monitoring data.

![Figure 5. Comparison of predicted curves of fluctuation ratio model and different superimposed models](image_url)

**Table 1.** Prediction effects of different methods.

| Models        | I   | II  |
|---------------|-----|-----|
|               | RMSE | R²  | RMSE | R²  |
| Suggested      | 3.78×10⁻³ | 0.940 | 3.00×10⁻² | 0.916 |
| Superimposed-ARIMA | 5.35×10⁻² | 0.892 | 1.92×10⁻¹ | 0.881 |
| Superimposed-SVR  | 8.35×10⁻² | 0.397 | 1.36×10⁻¹ | 0.331 |
| Superimposed-RF   | 7.44×10⁻² | 0.700 | 1.32×10⁻¹ | 0.851 |
| Superimposed-MLP  | 6.07×10⁻² | 0.911 | 1.26×10⁻¹ | 0.560 |

5. Conclusion
In this paper, four typical “step” landslides in the bank section of Fengdu County in the Three Gorges Reservoir area were used as examples. Multi-point and large-sample measured data were used to analyze the abrupt evolution of this type of landslides. The fluctuation ratio displacement index was proposed as the fluctuation term component of the external cause response. The displacement regression function of the combination of the inducing factor term and the state factor term was used as the fluctuation ratio displacement model, which could well achieve the sudden change and stable prediction of daily displacement in the effective period.

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