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Research Article

An Improved Filtering Method and Application of Landslide Deformation Monitoring

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Real-time early warning based on deformation monitoring is an important measure to reduce the threat related to landslides. However, due to the complexity of landslide deformation, equipment accuracy, and data transmission interference, the displacement obtained by existing monitoring equipment has random errors, resulting in inaccurate landslide warning. In this paper, a tangent angle model based on the improved filtering method is proposed for the early warning of landslides. An improved filtering method is proposed based on the least-square method to smooth the measurement errors of monitoring equipment, considering both "data smoothing effect" and "accelerated deformation real-time determination". By comparing the least-squares method and the improved filtering method, the results demonstrate that the improved filtering method can more effectively smooth the fluctuation of the deformation rate. The amplitude of the error-induced tangent angle warning value fluctuation can be reduced, which provides correct early warning. The improved method provides a new approach for the real-time filtering of subsequent landslide deformation data.

1. Introductions

Landslides are a frequent natural phenomenon that can change the landform and pose a significant threat to lives, buildings, and roads. Various studies were carried out to understand the landslide mechanism, assess the landslide risk, and forecast landslide displacement [1]. The displacement evolution of landslides is an important index that can be used to forecast the deformation of landslides and the failure time of landslides [2]. More importantly, early warning based on the displacement evolution of landslides can be obtained so that a timely risk decision can be made to prevent a landslide disaster and protect society and ecosystems. Therefore, it is a precondition for early warning of landslides to obtain accurate displacement information [3].

Currently, landslide monitoring often uses surface deformation monitoring, which is widely used due to its advantages such as being the most intuitive monitoring method, high cost effectiveness, and convenient construction [4, 5]. Meanwhile, with the continuous development of monitoring sensors and internet of things technology, the way to obtain surface deformation of landslides has made great advancements. The commonly used monitoring techniques for surface deformation include global navigation satellite systems (GNSS), global positioning systems (GPS), crack gauges, and remote sensing. For example, the Heifangtai loess landslides [6] have successfully given early warning many times since 2017, and the Longjing Rockslide in Xingyi City, Guizhou Province, has successfully given early warning many times since February 17, 2019 [7]. Wang et al. [8] used eight permanent GPS stations in the Puerto Rico and Virgin Islands (PRVI) region to obtain 5 years of continuous GPS data. Mazzanti et al. [9] adopted the three-dimensional photogrammetric survey to obtain the three-dimensional digital models of the Poggio Baldi landslide in 2015, 2016, 2017, and 2018, which can be used to infer a preliminary evolutionary model capable of supporting short-term landslide scenarios. Kromer et al. [10] study the rockfall risk along a transportation corridor in Western Canada using a terrestrial laser scanner and supporting remote sensing technologies.

Using digital surface models (DSM), Roncella et al. [11] established a night photogrammetric system for rock slope monitoring and investigated the application of different camera settings and their reliability to produce accurate DSM. In fact, the accuracy of these monitoring methods is constantly improving, and even some monitoring instruments can reach the millimeter level of accuracy. However, there are many uncontrollable internal and external factors in the use of monitoring instruments, resulting in a large amount of errors in the monitoring data, among which measurement errors are more common [12], which may lead to false alarms and omissions in the early warning system.

Based on the surface deformation information obtained, the model for early warning of landslides can be established using a tangent angle model. The early warning model based on the tangent angle model has achieved good results in the process of landslide early warning [7, 13–17]. In the early warning model based on tangent angle model, a parameter α is used to determine the level of warning. Due to the measurement error in the surface deformation information obtained, the calculated α is not accurate, leading to a false early warning of landslides. In order to solve this problem, a large number of scholars have proposed various filtering methods, which can be mainly divided into two types. One type is various regression fitting methods based on analytical formulas [18, 19], least-squares method [20], moving average method, etc. However, due to the complexity of landslide deformation process, the relationship between the discriminant conditions in the analytical formula and the development trend of monitoring data cannot be well-balanced during use, resulting in poor filtering performance when using these methods alone; another type of method is mainly divided into Kalman filtering [21, 22], neural network method [23], improved wavelet denoising method [24–26], etc. Although these methods can effectively filter abnormal data, they need to be completed through third-party platforms, which may extend the warning time and make it difficult to meet the demand for real-time warning. Therefore, in order to reduce the impact of abnormal data on the recognition of early warning systems, this article takes analyzing the characteristics of monitoring data as the starting point and proposes a real-time data filtering method based on the least-squares method. This method ensures the filtering effect while also achieving real-time filtering, providing a reliable real-time data filtering model for early warning based on landslide deformation rate.

The paper is divided into four sections. Section 2 introduces the tangent angle model for the early warning of landslides and the conventional deformation data filtering method. Section 3 presents the improved filtering method for deformation rate. Section 4 introduces the results of two landslides obtained using the proposed method. The conclusions are listed in Section 5.

2. Landslide Early Warning Based on Tangent Angle Model

2.1. Tangent Angle Model. The tangent angle model for the early warning of landslides is a quantitative method. The tangent angle in this model is determined by transforming the coordinates according to the cumulative displacement–time curve and dimensionalizing the horizontal and longitudinal coordinates (Figure 1). Then, a universal multistage landslide early warning model can be constructed based on the determined tangent angles. Based on the different tangent angles, the corresponding early warning signals should be released to the residents effected by the landslides, and the corresponding emergency measures are matched according to the model to realize the real-time control and prevention of the whole process of landslide deformation. The tangent angle α is calculated as follows [27]:

$$\alpha = \arctan \frac{V_1}{V'}, \tag{1}$$

where V_1 and V are the real-time deformation rate of the landslide and the uniform deformation rate of the landslide, respectively. The tangent angle is generally between 0° and 90°. In the existing studies [28, 6, 29], it is considered that when $\alpha \approx 45°$, the warning signal is blue, and the landslide deformation is in a relatively stable state of development, and landslides basically will not occur; when the tangent angle is $45° < \alpha < 80°$, the warning signal is yellow, indicating that the when the tangent angle is $45° < \alpha < 80°$, the warning signal is yellow, indicating that the slope begins to accelerate the deformation and the deformation is obvious, but the possibility of landslides is low; when the tangent angle is $80° \leq \alpha \leq 85°$, the warning signal is orange, indicating that the deformation rate further accelerates, the slope enters into a dangerous state, and the possibility of landslides is medium; when the tangent angle is $\alpha \geq 85°$, the warning signal is red, indicating that the deformation rate of the slope is not converging, and landslides may occur at any time.

2.2. Conventional Deformation Data Filtering Method

2.2.1. Moving Average Method. The moving average method calculates the average value of the time series one by one according to a certain number of terms, so as to reflect the future development trend of the time series. This method can be divided into a simple moving average and a weighted moving average according to the weight distribution of elements in the number of items. The moving average method is defined as follows:

$$M_t = \frac{y_t + y_{t-2} + \cdots + y_{t-n}}{n}, \tag{2}$$

where M_t is the moving average value, $y_1, y_{t-2}, \ldots, y_{t-n}$ is the observation value, $n > t$, and n is the moving average number of items. The equation for calculating the weighted moving average is given by:

$$M_{tw} = \frac{w_1 y_1 + w_2 y_2 + \cdots + w_n y_{t-n-1}}{w_1 + w_2 + \cdots + w_n}, t > n, \tag{3}$$

where M_{tw} is the weighted moving average at time t, and w_i is the weight of y_{t-i-1}. In the application of landslide displacement

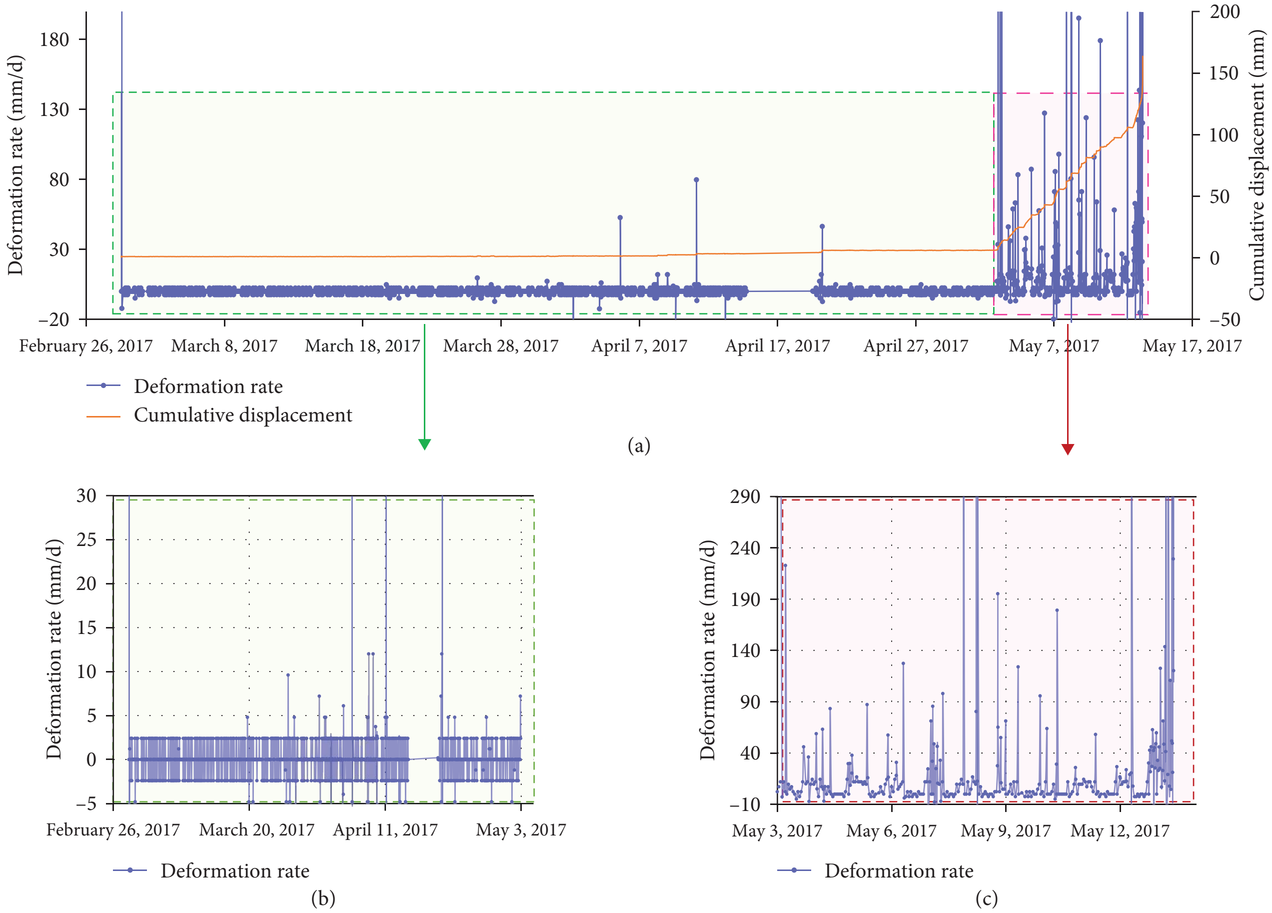

Figure 1: Deformation data characteristics of landslide (a–c).

prediction, based on the moving average method, the landslide displacement is divided into trend terms and periodic terms, and the sum of the two terms is the final cumulative displacement prediction value.

2.2.2. Least-Squares Method. The least-square method is a standard method in regression analysis. By minimizing the sum of squares of errors and finding the best function matching of data, the sum of squares between unknown data and actual data can be minimized. It is a common method to solve the problem of curve fitting. $(\boldsymbol{x}, y)$ is a set of observations, $\boldsymbol{x} = [x_1, x_2, \cdots, x_n]^T \in \mathscr{R}^n$ and $y \in \mathscr{R}$:

$$y = f(x, \omega), \tag{4}$$

where ω is a parameter, and $\omega = [\omega_1, \omega_2, \cdots, \omega_n]^T$. For a given m group of observation data (x_i, y_i) $(i = 1, 2, \ldots, m)$, the objective function is solved in order to find the optimal estimated value of ω:

$$\min f(x) = \sum_{i=1}^{m} L_i^2(x) = \sum_{i=1}^{m} [y_i - f(x_i, \omega_i)]^2, \tag{5}$$

where $L_i(x)$ $(i = 1, 2 \cdots, m)$ is the residual function. In the process of filtering landslide monitoring data, the specific steps are as follows: first, the number of monitoring values n needs to be determined, and the coordinates of the monitoring values are (x', y'); second, assume that the fitting line is $y = ax + b$, where y is the cumulative displacement, x is time, a is the deformation rate, and b is the intercept. Finally, the final fitted line is determined based on the minimum square of the vertical distance from all monitoring values to the fitted line.

Recently, automatic monitoring equipment for geological disasters has become increasingly popular. However, the monitoring equipment during the monitoring process will be affected by accuracy errors, external environment, and other factors, resulting in the landslide deformation data will show certain fluctuations, which are mainly composed of accuracy errors and accidental errors (Figure 2). At the same time, due to accuracy errors in monitoring equipment, when the landslide does not occur deformation, the accumulated displacement obtained by monitoring always oscillates within a certain range, showing obvious regular fluctuations. An example is the GNSS deformation monitoring station widely used for landslide deformation monitoring; its equipment monitoring accuracy is about ±5 mm. If the time scale is unified to the time unit calculated by taking 1 day as the deformation rate, the deformation rate will show a large fluctuation of ±120 mm/d. This leads to the ineffectiveness of traditional methods to smooth the fluctuation of time series curve caused by measurement error and accidental error (Figure 3).

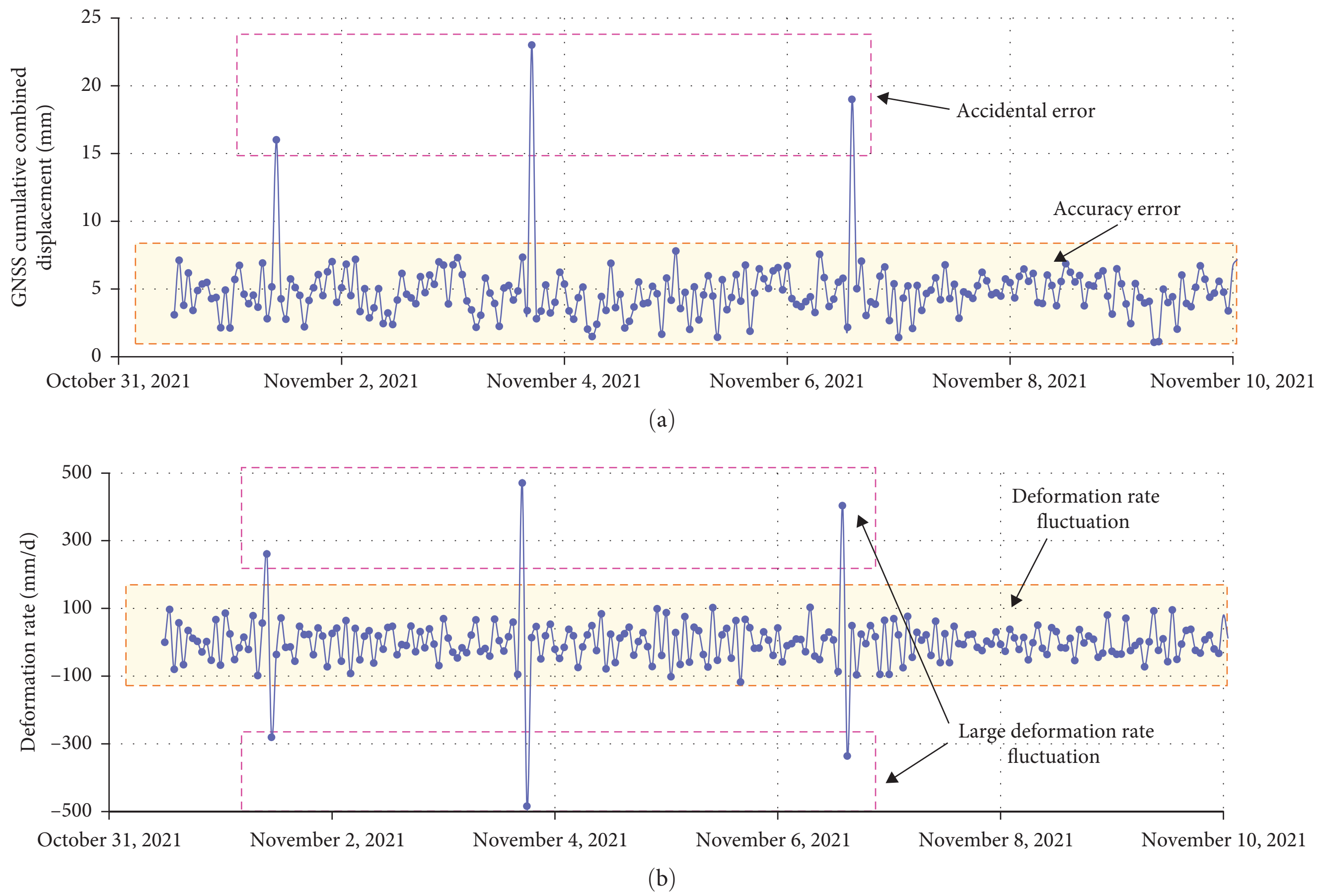

Figure 2: Schematic diagram of error fluctuation characteristics of landslide deformation monitoring (a and b).

3. Tangent Angle Model Based on Improved Filtering Method

3.1. Improved Filtering Method. In the real-time filtering process of landslide deformation monitoring data, the balance between"data smoothing effect" and "real-time determination of accelerated deformation" should be considered, and the pursuit of data smoothing should not blindly lead to delayed landslide warning. For the"data smoothing effect," the common least-square method is better for smoothing and filtering the deformation rate. Therefore, this paper takes the least-square method as the basic principle, further considers the influence of the development trend of the early deformation data on the subsequent data fitting.

Considering that the conventional monitoring equipment obtains one monitoring data every hour, the deformation data (x_i, y_i) $(i = 1, 2, \ldots, 24)$ obtained in 24 hr is first analyzed using the least-squares method. The regression eaquation can be written as follows:

$$Y_1 = a_1 X + b_1, \tag{6}$$

where X is the time, Y_1 is the regression value of the deformation corresponding to the time of X, and a_1 is the slope of the straight line and represents the mean deformation rate of the smoothing and filtering displacement between x_1 and x_{24}. Based on Equation (7), the smoothing and filtering displacement ${Y_m}^1$ can be determined at ${x_m}^1$ where ${x_m}^1 = (x_1 + x_{24})/2$.

When a new data (x_{25}, y_{25}) have acquired using the landslide deformation monitoring equipment, a new regression eaquation for (x_i, y_i) $(i = 2, 3, \ldots, 25)$ can be established as follows:

$$Y_2 = a_2 X + b_2, \tag{7}$$

where Y_2 is the regression value of the deformation corresponding to the time of X, and a_2 is the slope of the straight line and represents the mean deformation rate of the smoothing and filtering displacement between x_2 and x_{25}. Based on Equation (7), the smoothing and filtering displacement Y_{25} can be determined at x_{25}.

A straight line eaquation can be determined by $({x_m}^1, {Y_m}^1)$ and (x_{25}, Y_{25}) and for simplicity, it can be written as follows:

$$Y_1^* = a_1^* X + b_1^*, \tag{8}$$

where ${a_1}^*$ is the slope of the straight line, which is used to represent the uniform deformation rate V^{25} at x_{25}. By analogy, the uniform deformation rate V can be continuously

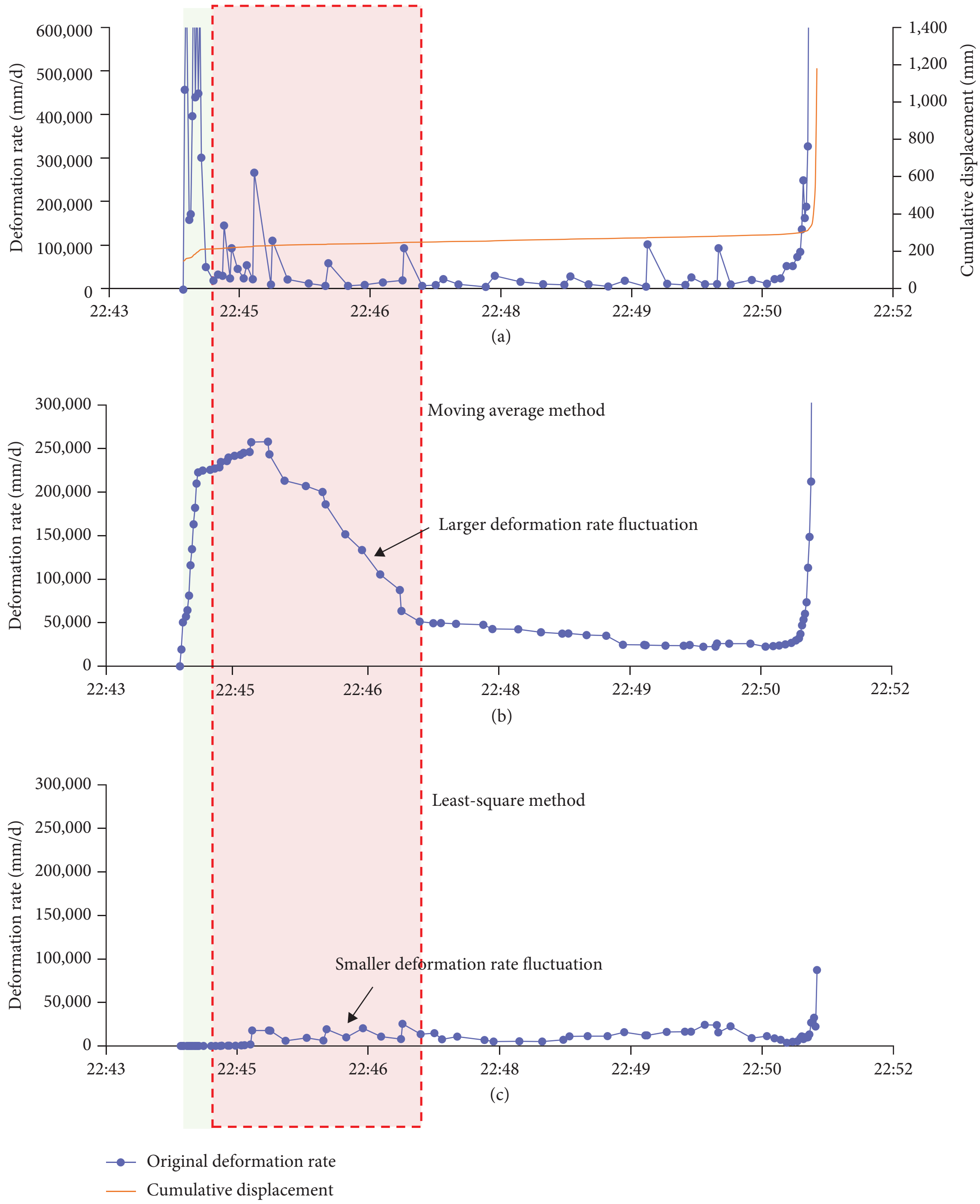

Figure 3: Comparison of deformation rate filtering effect of landslide in the accelerated deformation stage (a–c).

calculated, and the deformation rate curve is finally used for landslide deformation warning. The schematic diagram of improved filtering method is shown in the Figure 4.

The best aspect of this technique is that it fully exploits the benefits of the least-square method and takes into account how the previous deformation rate affected the most recent deformation rate. In comparison to the real-time slope state, the deformation rate determined by the proposed approach will still have some lag time. However, with the extensive application of various high-frequency landslide deformation monitoring equipment, especially the use of some adaptive frequency conversion monitoring equipment, the deformation monitoring frequency of the landslide in the accelerated deformation stage can be automatically increased to a maximum of 1 s. For filtering and determining the deformation rate after the landslide starts to

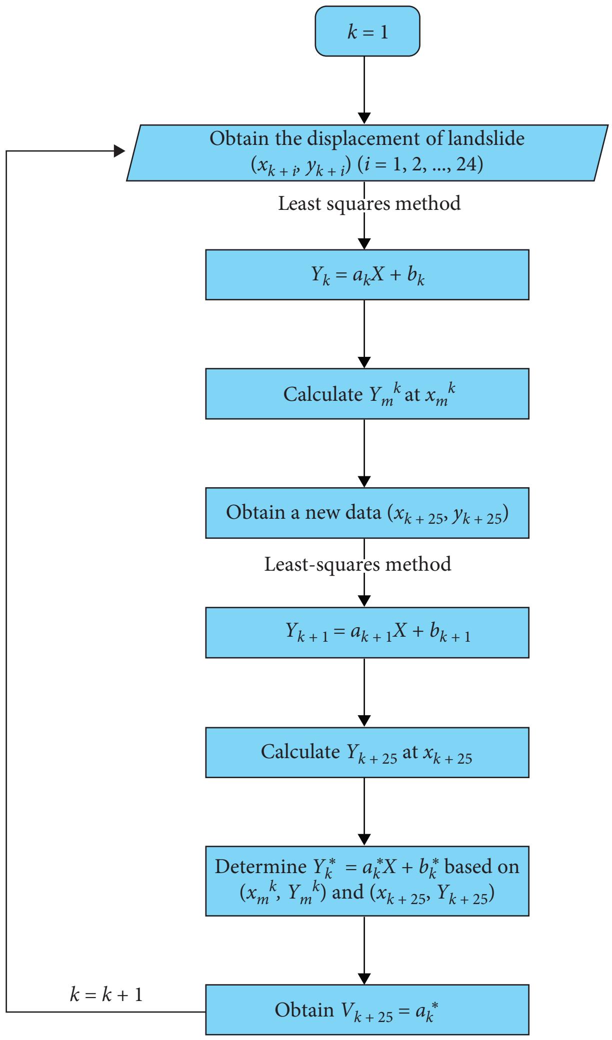

Figure 4: Schematic diagram of improved filtering method.

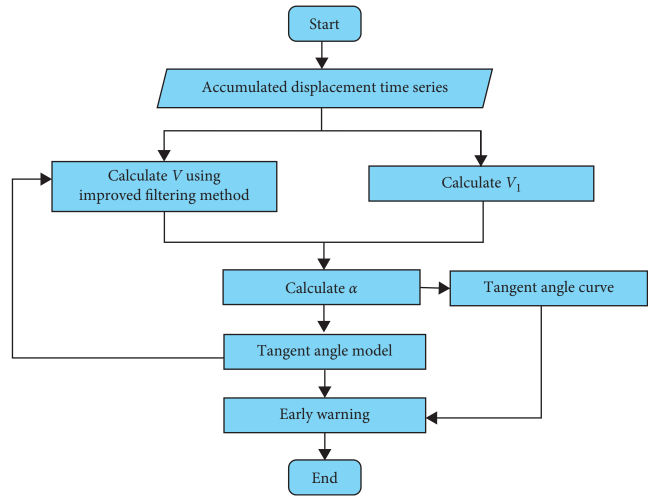

Figure 5: Flowchart of the tangent angle model based on the improved filtering method for the early warning of landslides.

accelerate, the time delay after filtering 24 groups of data is only 24 s, which fully meets the real-time landslide warning needs.

3.2. Tangent Angle Model Based on Improved Filtering Method for Landslide Early Warning. Based on the improved filtering method, the flowchart of the tangent angle model for landslide early warning is exhibited in the Figure 5. The detailed implementation steps of this model are as follows:

Step 1: Obtain the displacement of landslides using the monitoring equipment.

Step 2: Calculate the real-time deformation rate V_1. According to the division of the deformation stage of the landslide, the deformation rate V_1 of the uniform deformation stage can be quickly calculated.

Step 3: Calculate the real-time deformation rate of the landslide V using the improved real-time filtering method.

Step 4: Calculate the tangent angle α according to Equation (1).

Step 5: The early warning of landslides based on the calculated tangent angle α.

4. Application to the Heifangtai Landslides

4.1. Landslide Site. Heifangtai, located in Yanguoxia Town, Yongjing County, Gansu Province, is a loess plateau composed of Heitai and Fangtai, with an area of less than 15 km^2 (Figure 6). Because the groundwater level rise and long-term irrigation, many loess landslides have occurred. The Dangchuan 4 # and 7 # landslides are more typical. Due to the active geological tectonic movement in the Dangchuan landslide area, multilevel terraces have been formed under erosion. The terraces are mainly composed of four layers of loess, clay, gravel, and bedrock (Figure 7), with the upper layer being Malan loss (Q_3^{eol}), with a thickness of about 30–50 m; the second layer is a clay layer (Upper Pleistocene), with a thickness of approximately 3–20 m; below the clay layer is a gravel layer composed of gravel, quartz, and granite, with a thickness of approximately 1–10 m; The bottom layer is bedrock, mainly composed of sandstone and mudstone (Lower Cretaceous), with a thickness greater than 70 m [30]. In order to obtain landslide deformation data, automatic deformation monitoring equipment was installed at the rear edge of two landslide areas (Figure 8). This device adopts adaptive frequency conversion technology for data collection, which can automatically adjust the collection frequency based on the deformation rate of the landslide. The low-frequency collection frequency is 2 times/hr, and the maximum collection frequency can reach 3,600 times/hr. It also uses a solar power supply system to integrate monitoring and power supply equipment, allowing the monitoring equipment to balance long-term and high-frequency monitoring functions. The adaptive variable frequency crack meter mainly adopts a rope type crack meter. When the measured slope undergoes displacement, the steel rope connected to it is pulled, and the steel rope drives the sensor

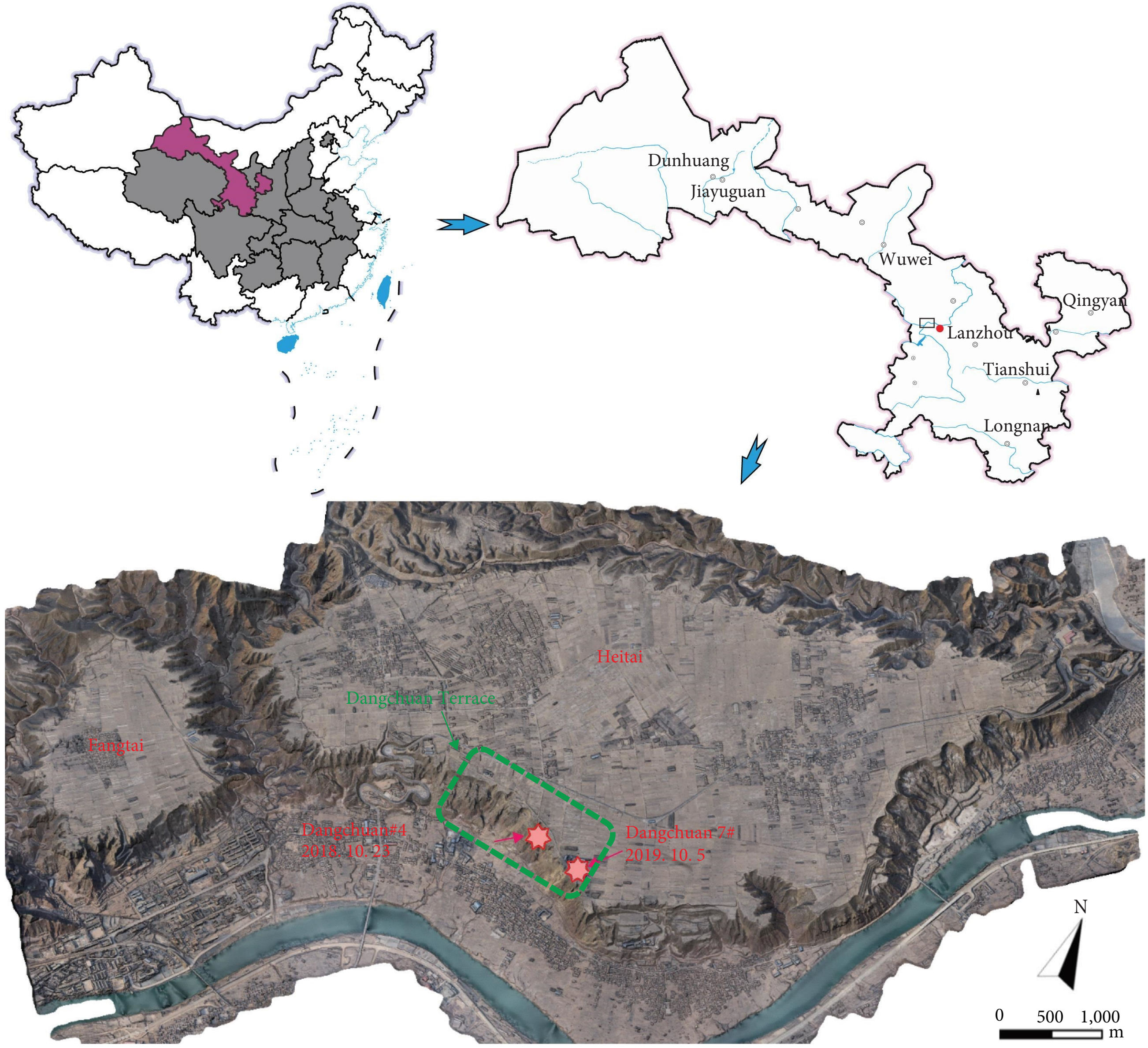

Figure 6: Location map for the loess landslides.

transmission mechanism to rotate synchronously with the sensing element; when the slope moves in the opposite direction, the rotation device inside the sensor will automatically retract the rope and maintain its tension during the rope extension and retraction process, thereby outputting an electrical signal proportional to the amount of rope movement. Electrical signals can be transmitted to the monitoring platform for early warning through wireless sensors in a timely manner.

4.2. Performance of Different Filtering Methods. Figures 9(a) and 10(a) show the cumulative displacement time curves of Dangchuan Landslides 4 and 7 obtained using an adaptive variable frequency crack meter. The deformation data of Dangchuan 4 # landslide is from April 4 to October 23, 2018. The deformation data of Dangchuan 7 # landslide is from June 1 to October 5, 2019. Due to the errors in the monitoring equipment, resulting in fluctuations in the cumulative displacement–time curve, which seriously affects the judgment of the early warning system, it is necessary to use the filtering method based on the improvement of the least-squares method to filter the data and improve the accuracy of the monitoring data. To demonstrate the applicability of the improved filtering method and compare the effectiveness of traditional and improved filtering methods in dealing with real-time deformation rate curve fluctuations, data from the overall landslide in the continuous deformation stage were selected, which has the characteristics of large cumulative displacement and deformation rate, and can reflect the robustness of the improved filtering method to a certain extent, as shown in Figures 9(b), 9(c), 10(b), and 10(c). It can be seen from the figure that

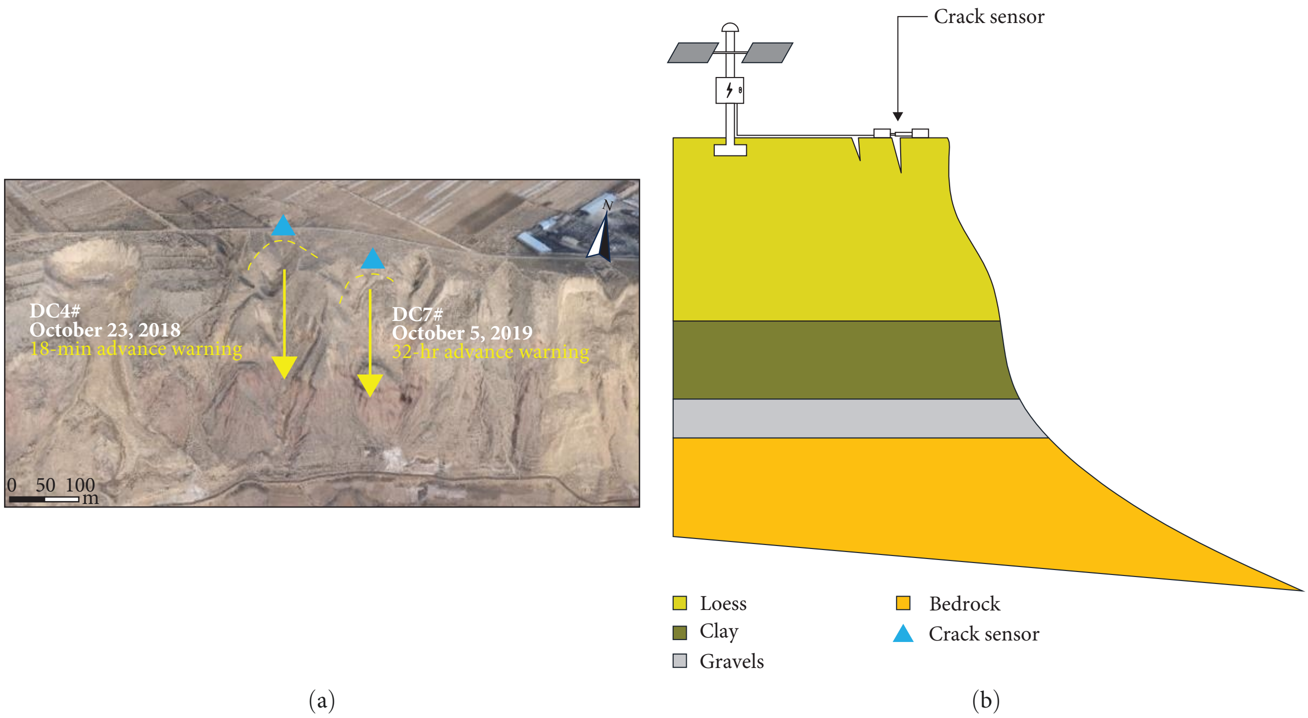

Figure 7: Distribution map of landslide in Dangchuan region (a and b).

Figure 8: Monitoring equipment for landslide deformation.

fluctuation amplitude of the curve decreases obviously. By comparison, the fluctuation range of the the real-time deformation rate curve of the improved filtering method is smaller than that of the traditional method. The amplitude of Dangchuan 4# landslide was reduced by more than 50%, and that of Dangchuan 7# landslide by more than 35%. Especially when the deformation amount increases in a short period of time, the monitoring frequency will also increase, and the filtering effect of the least-squares method is significantly poor, which cannot better reflect the true deformation rate.

4.3. Influences of Different Filtering Methods on Landslide Early Warning. Based on the deformation rates of landslides obtained by different filtering methods, the maximum tangent angle of Dangchuan Landslides 4 and 7 during a certain period of time was calculated using a tangent model, as shown in the Figures 9(c), 9(d), 10(c), and 10(d). As can be seen from the figure, for dangchuan 4# loess landslide, the maximum tangent angle of the least-square method is 56.73° and the maximum tangent angle of the improved method is 25.68°. For dangchuan 7# loess landslide, the maximum tangent angle of the least-square method is 56.68° and the maximum tangent angle of the improved method is 36.58°. It shows that the maximum tangent angle based on the deformation rate obtained by the improved method is lower than that of based on the deformation rate obtained by the least-square method. The maximum tangent angle reduced by 54.73% and 35.46%, respectively, for Dangchuan 4# and 7# landslides. In addition for Dangchuan 4# landslide, it is found that the tangent angle fluctuates 83 times in the range of 45°–80° when using the least-square method, and the fluctuation is less than 45°after using the improved method. For Dangchuan 7# landslide, it is found that the tangent angle fluctuates 70 times in the range of 45°–80° when using the least-square method, and the fluctuation is less than 45°after using the improved method. Therefore, the improved method can effectively smooth the monitoring data. As the deformation rate is significantly smoother than the least-square method, especially in the early initial accelerated deformation stage, the tangent angle calculated according to the deformation rate will also significantly reduce the fluctuation, which can significantly reduce the early warning and false alarm (Figures 9(c), 9(d), 10(c), and 10(d)). Under the same deformation curve, the

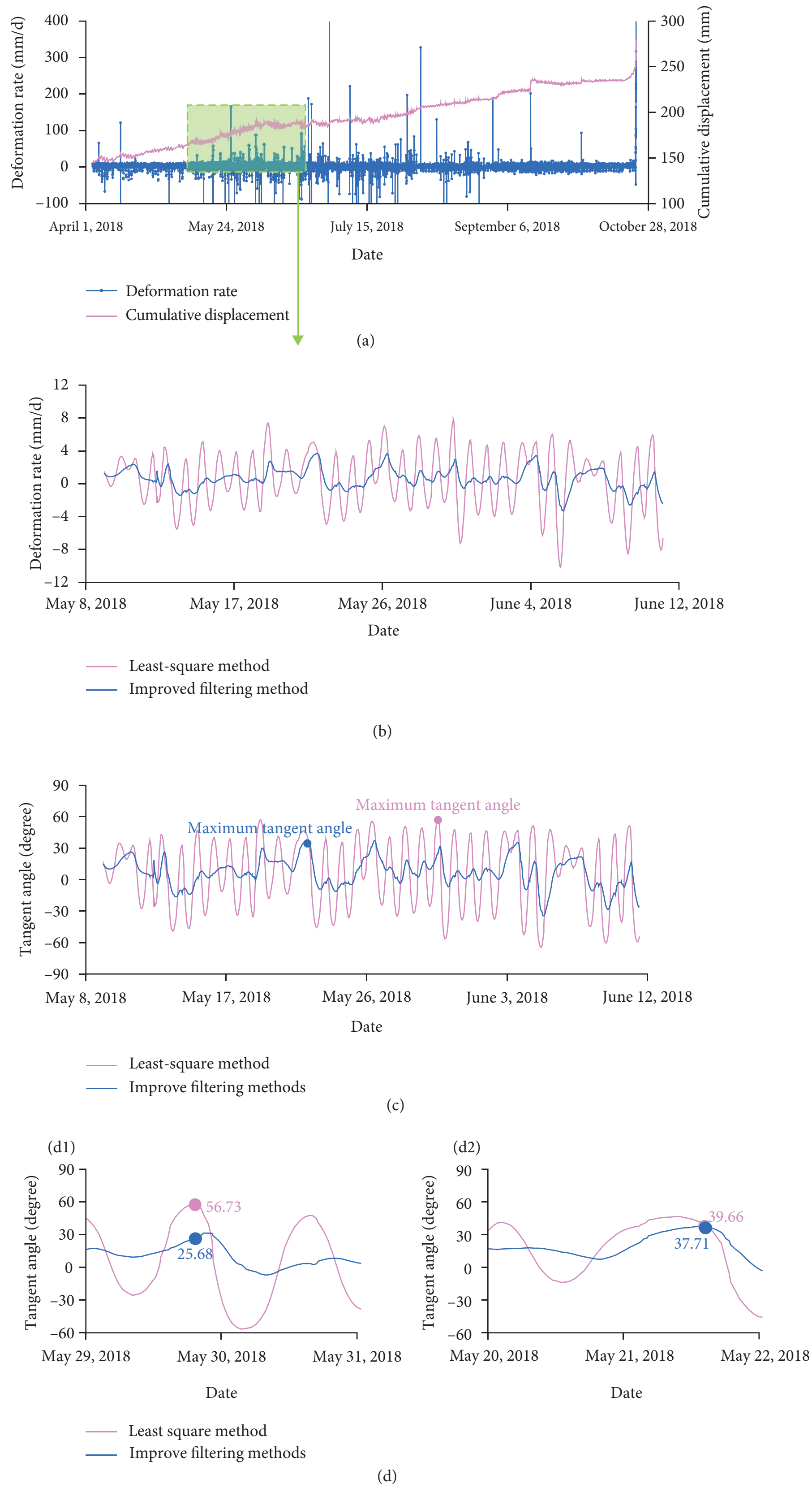

Figure 9: Dangchuan 4# loess landslide: (a) the cumulative displacement–time curves and the deformation rate curve, (b) deformation rate curve obtained by the least-squares method and the improved filtering method, (c) tangent angle curves, and (d) maximum tangent angle; (d1) least-square tangent angle and (d2) improved tangent angle.

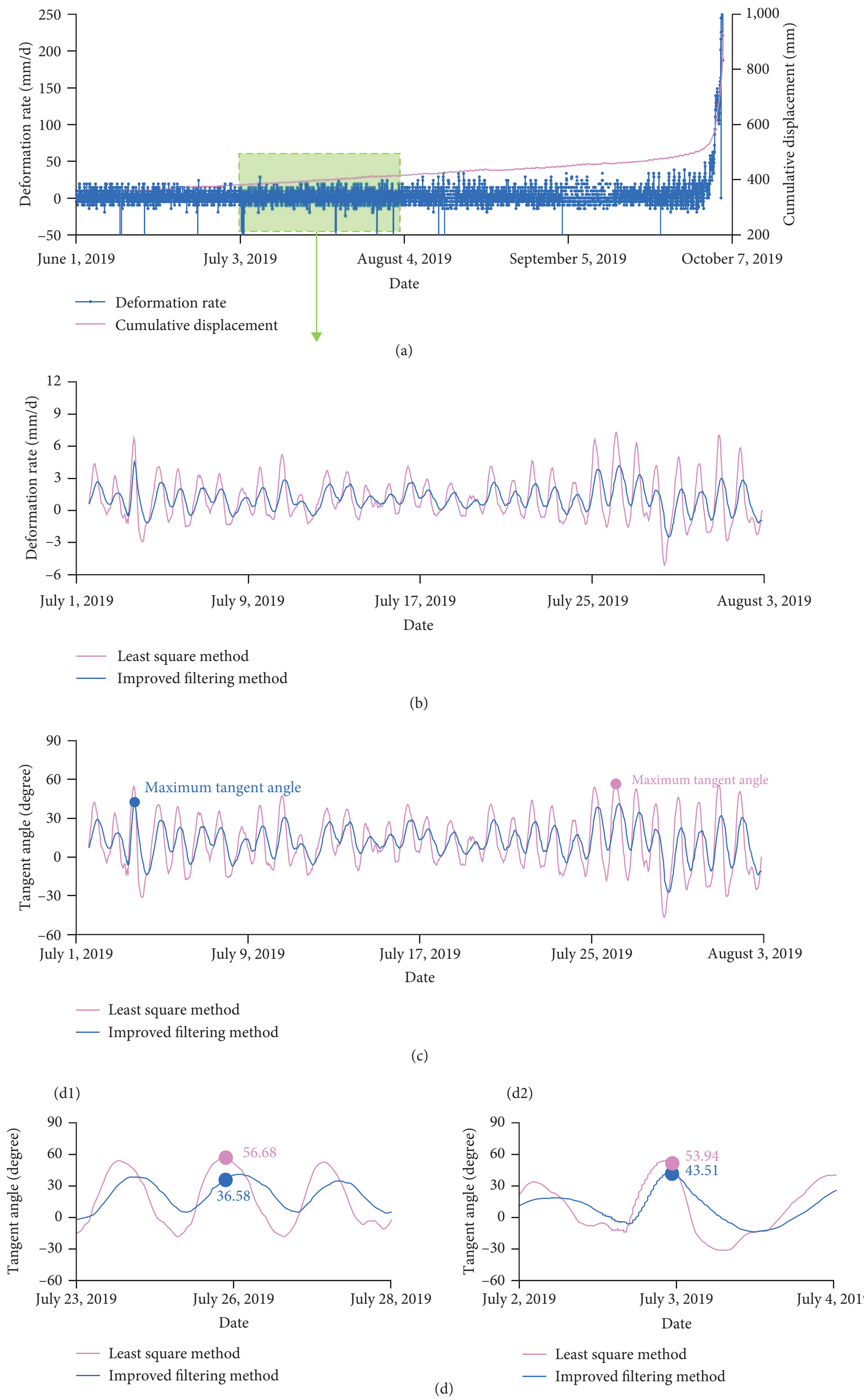

FIGURE 10: Dangchuan 7# loess landslide: (a) the cumulative displacement–time curves and the deformation rate curve, (b) deformation rate curve obtained by the least-squares method and the improved filtering method, (c) tangent angle curves, and (d) maximum tangent angle; (d1) least-square tangent angle and (d2) improved tangent angle.

fluctuation amplitude of the tangent angle calculated after filtering by the conventional least-square method is also significantly greater than that of this method, which will still produce many false positives.

However, this method also has some limitations that can be improved. First, although this filtering method has a good smooth effect, it does not consider the possible accidental large errors of monitoring data. When the deformation data occasionally produces large errors, the real-time change trend of the deformation data cannot be well-restored without eliminating the accidental jumping errors. Second, the filtered deformation rate curve cannot achieve the effect of smoothing the deformation rate curve generated by post fitting. This problem can be solved by improving the monitoring accuracy of the monitoring equipment and smoothing the data after removing accidental errors to the maximum extent. Third, the warning results may be delayed after using filtering methods. To effectively avoid the delay of warning results, monitoring equipment with adaptive frequency conversion technology can be used in the future to obtain a large amount of monitoring data in a short period of time when the landslide enters accelerated deformation, significantly reducing the delay caused by data smoothing.

5. Conclusions

During the landslide warning process, the monitoring equipment is susceptible to the natural environment, resulting in some anomalies in monitoring data. The filtering effect is uneven and there is a certain delay, which will seriously affect the timeliness of the warning system's identification. The filtering method proposed in this paper can effectively eliminate abnormal data, timely and effectively identify and warn landslides, which is of great significance for disaster prevention and reduction of landslides. The following conclusions are drawn:

(1) This filtering approach considers the trend of changes in monitoring data collected from the crack meter before and after, making the data correspond to each other as much as feasible and recovering the genuine change in crack width.

(2) Applying the improved filtering method to practical cases, it was found that the improved filtering method can effectively smooth the deformation curve, but there may be a certain delay in obtaining key data. Therefore, this filtering method needs to be combined with adaptive monitoring equipment to improve the timeliness of early warning.

(3) The crucial step in landslide warning is correctly recognizing the tangent angle. Compared with the traditional least-squares method, the improved filtering method efficiently reduces the fluctuation amplitude of tangent angle in deformation curves, providing more realistic filtering results.

(4) The improved method has been well used for instability loess landslides. Due to the long-term and complex deformation process of landslides, the improved method will continue to be applied to other types of landslides in the future to improve its universality.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflict of interest.

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