



Real-time high-precision landslide displacement monitoring based on a GNSS CORS network

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ABSTRACT

GNSS technology is an effective all-weather, continuous and real-time method of detecting three-dimensional landslide displacement. However, current positioning methods such as the network real-time kinematic (RTK) technique based on virtual reference station (VRS) technology have some limitations, particularly a sensitivity to atmospheric modeling error. In this study, taking advantage of existing GNSS continuously operating reference stations (CORS), we propose a network RTK algorithm (virtual atmosphere constraint (VAC)) for high-precision landslide monitoring. Network modeling atmosphere delays were used as virtual observations for the terminal position solution, by which their accuracy information can be considered. Additionally, a noise reduction method that combines complementary ensemble empirical mode decomposition and median filtering was proposed to reduce GNSS signal residual errors in the original RTK coordinate time series. To validate the effectiveness of the algorithm, we processed one week of data from two monitoring receivers on the Heifangtai landslide and four surrounding CORS using the VAC and VRS methods. Results show that the original displacement time series processed with VRS was prone to jitter, whereas the VAC method exhibited better accuracy, stability, and ambiguity fixing rates. Horizontal and vertical RMS errors at a stable monitoring point were 1.7 cm and 3.9 cm for VRS-RTK and 0.9 cm and 2.3 cm for VAC-RTK; thus, VAC reduced the error by 40.1% and 20.5%, respectively. After noise reduction, the RMS values of the VAC method at the stable and the other collapsed monitoring point were both reduced to an mm-level accuracy.

1. Introduction

A landslide is a gravity-driven mass-consumption process that generally occurs on steep or mechanically weak slopes [1]. Various external factors could induce the occurrence of landslide disasters, including heavy rainfall, earthquake, and human activities. Landslides have affected many countries around the world, resulting in human deaths and economic losses in many mountainous regions [2]. In recent years, landslides have caused almost 4500 casualties per year, and the economic losses from these landslides amount to \$20 billion per year [3]. Therefore, it is important to monitor the deformation movements of landslides to help us understand how their motion evolves in time and to provide early warning of possible future slope failure events [4–5].

Because of its global, all-weather, continuous and real-time characteristics, GNSS technology has been widely used for monitoring

landslide deformation and other geological disasters [6–9]. In recent years, the Ministry of Natural Resources of China has vigorously promoted a model of geological disaster monitoring and early warning based on “civil + technical defense,” and accordingly built 48,000 GNSS automatic monitoring points. Currently, the application of GNSS technology to geological disaster monitoring mainly adopts the monitoring mode of “one reference station for one landslide” [10–13]. The advantage of this mode is the small distance between the monitoring station, which can better eliminate the influence of atmospheric errors such as ionosphere and troposphere delays on the monitoring results [14]. However, this mode has the following problems: (1) the monitoring cost is high, and the number of reference stations accounts for approximately 30% of the number of monitoring stations; (2) the signal quality of the reference station cannot be guaranteed in complex geological disaster areas; (3) reference stations are prone to drifting along with unstable

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geological bodies [15].

Since the completion of BDS-2 and BDS-3 satellites, a network of continuously operating reference stations (CORS) has flourished in China [16]. The Ministry of Natural Resources is currently upgrading BDS-3 for more than 3,000 reference stations across the country. According to incomplete statistics, more than 6,000 reference stations have been built by national and provincial institutions [17]. The CORS network benefits from high construction specifications, good data quality, and stable benchmarks. At present, ground-based reference stations are mainly used for high-precision location services such as coordinate frame maintenance, basic surveying and mapping, and engineering construction [18].

Based on the CORS network, the most widely used technology in GNSS high-precision positioning is virtual reference station (VRS) technology [19,20]. Compared with conventional short-baseline real-time kinematic (RTK) technology, GNSS network RTK technology has the advantages of wide coverage and no need for users to set up a base station. In the VRS process, the rover sends the approximate coordinates to the data processing center, and VRS observations are generated based on the interpolated double-differenced atmosphere delay and the master reference station observations [21]. The advantages of this method are as follows: 1) the user only needs to receive the VRS observations, and the pressure of data communication is small; 2) the server does not need to broadcast the coordinates of the physical reference station, and the confidentiality is good; 3) VRS is compatible with conventional RTK algorithms, which have a wide range of market applications. Recently, scholars have applied VRS technology in the field of geological disaster monitoring [13,22,23]. However, this method is sensitive to network atmospheric modeling errors, that is, when the reference station distance is too long or the atmosphere conditions are active, the resulting large modeling ionosphere and troposphere error will directly hinder terminal ambiguity fixing [24,25]. Even if the ambiguity is successfully fixed, the positioning accuracy will drop significantly [26,27]. As a result, the accuracy and stability of the VRS network RTK are inferior to short-range RTK (the tropospheric and slant ionospheric delays can be assumed negligible [28]) in most cases.

In view of the shortcomings of the traditional “one reference station for one landslide” monitoring mode and network RTK algorithm, in this study, we propose a high-precision landslide displacement monitoring method based on existing CORS network resources. Firstly, we propose a network RTK service method that considers atmosphere modeling errors, then we introduce a coordinate time series noise reduction method that considers the characteristics of signal residual errors. Finally, based on GNSS data of the monitoring station in Heifangtai landslide, China, and the CORS network in Gansu Province, China, we compare the deformation monitoring effect of the proposed method and the traditional VRS algorithm. The results of this research can provide technical support for promoting the application of CORS networks in the field of geological disaster monitoring.

2. Methodology

2.1. Concept of landslide monitoring based on the CORS network

Fig. 1 shows the data processing flow of the high-precision deformation monitoring system based on the GNSS CORS network. The system involves three key parts: 1) GNSS data of CORS network and landslide monitoring stations; 2) a network RTK processing module for dynamic coordinate solutions of monitoring stations; 3) a coordinate time series processing module for high-precision landslide monitoring.

As an alternative to VRS technology, we developed a network RTK algorithm called the virtual atmosphere constraint (VAC) method for landslide deformation monitoring. Implementation of the VAC software platform comprises three steps: 1) a double-differenced model is constructed to quickly solve the reference station baseline ambiguity; 2) slant-path ionosphere and zenith troposphere delays are both extracted

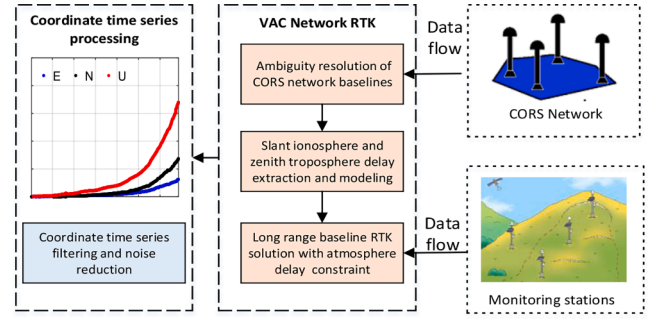


Fig. 1. Data processing flow of the GNSS landslide monitoring platform based on the CORS network.

and modeled with the approximate coordinates of the monitoring station; 3) the long-range RTK (the ionospheric and tropospheric delays are necessary to model or estimate [28]) algorithm is performed with data from the monitoring station and the closest CORS station; the modeling atmosphere delays obtained in step (2) are regarded as virtual observations, which is similar to the principle of the ionospheric weighted model [29,30]. In contrast to the VRS technique, the accuracy information can be considered by using the modeled atmosphere delays. In the process of generating the VRS observations, the atmosphere modeling error directly enters the VRS observations [20], and the user terminal positioning performance will degrade when the atmospheric conditions are complex.

Because of the influence of residual errors such as the multipath error and troposphere delay estimation error [31], the results of the long-range RTK solution may be noisy and unable to reflect the real displacement of the landslide. As a result, we developed the coordinate time series processing module to reduce the influence of signal residual errors.

2.2. Atmospheric delay extraction and modeling based on the CORS network

The basic DD pseudo-range and carrier phase equations of the long-range reference station baseline can be presented as follows [32]:

$$\begin{cases} \Delta \nabla P_{AB,k}^j = \Delta \nabla \rho_{AB}^j + \mu_k \Delta \nabla I_{AB}^j + \alpha_A^j T_A - \alpha_B^j T_B + \Delta \nabla \varepsilon_{P,k} \\ \Delta \nabla L_{AB,k}^j = \Delta \nabla \rho_{AB}^j - \mu_k \Delta \nabla I_{AB}^j + \alpha_A^j T_A - \alpha_B^j T_B + \lambda_k \Delta \nabla N_{AB,k}^j + \Delta \nabla \varepsilon_{L,k} \end{cases} \quad (1)$$

where $\Delta \nabla$ represents the DD operator, k is the GNSS signal frequency number; and superscripts i and j denote the observed and reference satellites, respectively. Subscripts A and B identify the reference stations. The DD geometric range ρ can be calculated with the known station and satellite coordinates. P and L represent the pseudo-range and carrier phase observations; μ is the coefficient that can convert the ionosphere delay I on frequency 1 into frequency k ; T denotes the zenith troposphere delay (ZTD) that can be converted into the slant delay with the mapping coefficient α , where the ZTD estimated here is actually the zenith wet delay (ZWD), and the zenith hydrostatic delay (ZHD) can be corrected accurately using a prior troposphere model. λ is the carrier wavelength; N is the ambiguity; and $\varepsilon_{P,k}$ and $\varepsilon_{L,k}$ represent the measurement noise and other errors of pseudo-range and carrier phase observations.

Ambiguity resolution (AR) is a prerequisite for extracting high-precision atmospheric errors. To improve the AR fixed rate, the partial AR strategy was used in this study [27,33]. When the float ambiguity solution is obtained by Kalman filter or sequential least squares, the first step is to form wide-lane (WL) and narrow-lane (NL) ambiguities, as well as its variance-covariance matrix, from the original L1/L2 ambiguity [33]. Then, WL and NL ambiguities are fixed with the LAMBDA method

[34]. After WL ambiguities are fixed, the precision of the NL (L1) ambiguity can be improved by the following equation:

$$\begin{cases} \tilde{d}_2 = \hat{d}_2 - Q_{\hat{d}_2\hat{d}_1} Q_{\hat{d}_1\hat{d}_1}^{-1} (\hat{d}_1 - \tilde{d}_1) \\ Q_{\hat{d}_2\hat{d}_2} = Q_{\hat{d}_2\hat{d}_2} - Q_{\hat{d}_2\hat{d}_1} Q_{\hat{d}_1\hat{d}_1}^{-1} Q_{\hat{d}_1\hat{d}_2} \end{cases} \quad (2)$$

where $\hat{d}_1$ and $\tilde{d}_1$ represent the float and fixed WL ambiguities; Q is the variance-covariance matrix. $\hat{d}_2$ and $\tilde{d}_2$ are the float and updated NL ambiguities. Compared to the original float ambiguity, the updated ambiguities are more accurate and are more easily fixed. After NL ambiguities are fixed using the LAMBDA method, the double-differenced ionosphere and troposphere delay can be extracted by the following equation:

$$\begin{cases} T_{AB}^{ij} = L_{AB,IF}^{ij} - \rho_{AB}^{ij} - \lambda_{IF} N_{AB,IF}^{ij} + \varepsilon_{IF}^{ij} \\ I_{AB,1}^{ij} = L_{AB,1}^{ij} - \rho_{AB}^{ij} - \lambda_1 N_{AB,1}^{ij} - T_{AB}^{ij} + \varepsilon_1^{pq} \end{cases} \quad (3)$$

Meanwhile, the zenith troposphere delay can be updated using the fixed ambiguities:

$$\tilde{T} = \hat{T} - Q_{\hat{T}\hat{d}} Q_{\hat{d}\hat{d}}^{-1} (\hat{d} - \tilde{d}) \quad (4)$$

After extracting the atmospheric delays of all baselines in the coverage area, regional atmospheric modeling can be performed for the ionosphere and troposphere delays. The linear interpolation method [35] was used in this study. The equation for ionosphere delay modeling is as follows:

$$I_{AB}^{pq} = a_I^{pq} x_{AB} + b_I^{pq} y_{AB} \quad (5)$$

where $x_{AB} = x_B - x_A$, $y_{AB} = y_B - y_A$, (x_A, y_A) and (x_B, y_B) are the plane coordinates under the Gaussian projection of stations A and B; and a_I and b_I denote the ionospheric model coefficient. Unlike the ionosphere delay, the troposphere has a strong correlation with the height of the station [36], and the interpolation accuracy of the troposphere will be significantly reduced even if the height is regarded as a modeling parameter. Therefore, the tropospheric delay of all reference station baselines were normalized to the same elevation datum using an existing GPT2w tropospheric model [37], by which the height-correlated systematic error can be compensated and the troposphere modeling accuracy can be improved [38,39]. After normalization, similar to ionospheric delay modeling, only the plane coordinate difference needs to be considered.

$$T_{AB,H_0} = a_T x_{AB} + b_T y_{AB} \quad (6)$$

Here, T_{AB,H_0} represents the normalized relative zenith tropospheric delay (RZTD), and $T_{AB,H_0} = T_{B,H_0} - T_{A,H_0}$; the normalized elevation datum is H_0 ; and a_T and b_T are the RZTD model coefficients. According to equations (5) and (6), the modeled coefficients can be solved by least squares estimation:

$$\begin{bmatrix} I_1^{pq} \\ \vdots \\ I_n^{pq} \\ T_{1,H_0} \\ \vdots \\ T_{n,H_0} \end{bmatrix} = \begin{bmatrix} x_1 & y_1 & 0 & 0 \\ \vdots & \vdots & 0 & 0 \\ x_n & y_n & 0 & 0 \\ 0 & 0 & x_1 & y_1 \\ 0 & 0 & \vdots & \vdots \\ 0 & 0 & x_n & y_n \end{bmatrix} \begin{bmatrix} a_I^{pq} \\ b_I^{pq} \\ a_T \\ b_T \end{bmatrix} \quad (7)$$

where n represents the number of baselines involved in the modeling coverage region. Based on the above equation, the DD ionosphere for each satellite and the RZTD modeling coefficients can be obtained by least squares estimation. Furthermore, the DD ionosphere and RZTD modeling accuracy can be obtained by:

$$\sigma = \sqrt{\frac{\sum_{i=1}^n v_i^2}{n-1}} \quad (8)$$

where v represents the observation residuals, which refers to the difference between the extracting atmospheric information and the estimated atmospheric information; and i represents the baseline number.

2.3. Long-range baseline RTK solution with the virtual atmosphere delay constraint

To obtain RTK solutions of the monitoring station, a base station must be selected in the surrounding area. Generally, the CORS nearest to the monitoring station is selected as the base station. The ionospheric delay of each satellite and relative zenith troposphere delay is then interpolated according to the atmospheric modeling coefficient of (7):

$$\begin{cases} \bar{T}_{MR}^{pq} = a_I^{pq} x_{MR} + b_I^{pq} y_{MR} \\ \bar{T}_{MR,H_0} = a_T x_{MR} + b_T y_{MR} \end{cases} \quad (9)$$

where x_{MR} and y_{MR} represent the coordinate difference between the monitoring station M and reference station R . The monitoring station coordinate can be calculated by standard point positioning. It should be noted that the RZTD T_{MR,H_0} calculated here is at the normalized H_0 elevation datum. Therefore, the interpolated tropospheric delay needs to adjust to the actual elevation of the monitoring and base stations.

$$\bar{T}_{MR} = \bar{T}_{MR,H_0} + w_{M,H_0} - w_{M,H_M} + w_{R,H_0} - w_{R,H_R} \quad (10)$$

The adjusted value w is also calculated by the GPT2w troposphere model. Then, the atmospheric delay information is considered as the virtual observations and input into the double-difference observation equations, we obtain:

$$\begin{cases} P_{RM,k}^{ij} = \rho_{RM}^{ij} + \mu_k I_{RM}^{ij} + \alpha_k^{ij} T_R - \alpha_M^{ij} T_M + \varepsilon_{P,k} \\ L_{RM,k}^{ij} = \rho_{AB}^{ij} - \mu_k I_{RM}^{ij} + \alpha_k^{ij} T_R - \alpha_M^{ij} T_M + \lambda_k N_{RM,k}^{ij} + \varepsilon_{L,k} \\ \bar{T}_{RM}^{ij} = I_{RM}^{ij} + \varepsilon_I, \quad \sigma_I^2 \\ \bar{T}_{RM} = T_M - T_R + \varepsilon_T, \quad \sigma_{\bar{T}_{RM}}^2 \end{cases} \quad (11)$$

The variance model σ_I^2 and $\sigma_{\bar{T}_{RM}}^2$ are constructed according to atmosphere modeling residual error in Equation (8). The RTK observation equations, in which the baseline components, ambiguities, and slant ionosphere and zenith troposphere delays are unknown parameters, are given as follows:

$$E \begin{bmatrix} P \\ L \\ \bar{T} \\ \bar{T} \end{bmatrix} = \begin{bmatrix} A & \Lambda & B & 0 \\ A & -\Lambda & B & C \\ 0 & 1 & 0 & 0 \\ 0 & 0 & D & 0 \end{bmatrix} \begin{bmatrix} a \\ b \\ c \\ d \end{bmatrix} \quad (12)$$

where $E[\cdot]$ denotes the expectation operator; P and L denote the DD pseudo-range and the carrier phase vector; $\bar{T}$ and $\bar{T}$ denote the external network atmosphere modeling information; a, b, c and d denote the baseline coordinate, DD ionosphere delay, zenith troposphere delay, and DD ambiguity vectors, respectively; and A, Λ, B and C are their corresponding coefficient matrix. The VAC model estimates the atmospheric delay as a parameter and sets the corresponding variance information for the modeling atmosphere. According to this method, the residuals of parameter estimation are smaller than the modeling errors in VRS mode, and atmospheric errors have less impact on the terminal positioning results.

2.4. Noise reduction of the GNSS coordinate time series

In GNSS relative positioning, various errors such as satellite clock,

receiver clock, and orbit errors can be eliminated or greatly reduced by double-difference operating; however, the observation environment of the landslide monitoring station is complex, and the baseline length is long for a CORS network; therefore, the positioning results may be contaminated by the multipath error, wrong ambiguity fixing error, troposphere mapping function error, etc.. Therefore, the GNSS landslide monitoring sequence will include landslide displacement as well as various noise items.

Considering that the movement of a landslide is usually consecutive and with a specific directionality, and the signal residual error has periodic characteristics, coordinate time series noise reduction can be conducted to extract clean displacement items of the landslide. Fig. 2 shows the data processing flow of a coordinate time series based on complementary ensemble empirical mode decomposition (CEEMD) and median filtering [40,41]. Firstly, gross errors in the coordinate time series were removed by the three-sigma criterion. Then, the CEEMD method was used to extract and eliminate low-frequency periodic errors. Finally, the median filtering method was used to remove high-frequency/impulse/abnormal noise.

CEEMD eliminates the residual auxiliary noise in the reconstructed signal by adding a complementary processing method of positive and negative white noise to the signal, which can effectively solve the modal mixing in the EMD method. This approach has great advantages for analyzing nonlinear and non-stationary time series. The specific steps of this method are as follows:

- (1) Add Gaussian white noise to the original time series, and perform EMD:

$$IMF_{k+1} = \frac{1}{W} \sum_{i=1}^W E_1(r_k + \varepsilon_i E_k(\omega_i)) \quad (13)$$

In the formula, E_1 is the first eigenmode of the original signal after EMD; ω_i is the white noise of the normal distribution; ε_i is the noise coefficient; $k = 1, 2, \dots, N$.

- (2) Calculate IMF_{k+1} cyclically; the decomposition ends when the number of residual extreme points is less than 2.
- (3) Determine the boundary point K between the noise component and the useful signal. As residual errors such as the multipath error in the GNSS landslide monitoring time series are mainly low frequency [42], we used fast Fourier transform spectrum analysis for each IMF component, then removed the IMF component with low-frequency characteristics to obtain the dividing point K [43].
- (4) Reconstruct the remaining IMF components and residual terms to obtain the final noise reduction result, which is expressed as:

$$C = \sum_k^n IMF_k + R \quad (14)$$

where C is the final signal after noise reduction; and R is the remaining trend term components of CEEMD decomposition. After CEEMD pro-

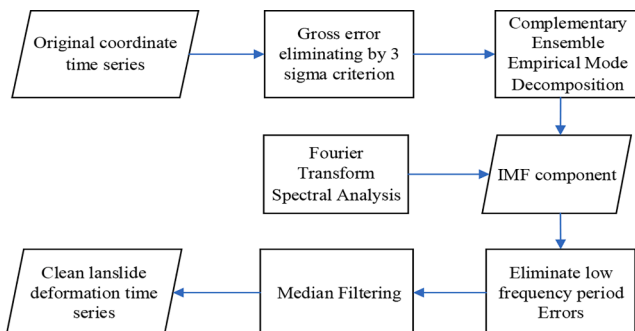


Fig. 2. Data flow of GNSS coordinate time series processing.

cessing, median filtering was conducted with specific sliding windows:

$$G_{t_i} = \text{med} \quad (g_{t_j}), \quad j \in (i - k, i) \quad (15)$$

where G_{t_i} is the coordinate value at time t_i after filtering; g_{t_j} denotes the original coordinate value at time t_j ; and k represents the time span of the filtering window. In practical landslide monitoring, the deformation rate may be changed under different monitoring periods. Therefore, an adaptive window median filtering was proposed to consider the different deformation rates. The adaptive window median filtering in this study is defined as follows: Before the start of the adaptive median filtering, the initial values of the filtering window size and the deformation threshold (d_{thr}) are first given; Then, the deformation and speed (v_{def}) values are calculated after each segment window. If such landslide deformation value exceeds the prior threshold (d_{thr}), the new window size t_{win} will be calculated and adopted adaptively based on the following equation:

$$t_{win} = d_{thr} / v_{def} \quad (16)$$

3. Results

3.1. Datasets and processing strategies

Heifangtai landslide is located in Yongjing County, Gansu Province, China, which is a typical loess landslide. As a result of precipitation and irrigation, the landslide has formed some collapsed soil pits with a large number of developed fissures. The elevation of the landslide is about 1670 m and there is no obvious vegetation coverage on the landslide surface. Two GNSS monitoring stations (HF06, HF11) and a base station (HF01) have been deployed on the landslide by Chang'an University, as shown in Fig. 3 (right). The distance between the base and monitoring stations is less than 1 km. At about 20:24 on 4 October 2019 (UTC), the deformation at the HF06 monitoring station accelerated and eventually collapsed. The monitoring station HF11 and base station HF01 were stable during the study period. One week of data (28 September to 5 October 2019) from two monitoring stations and the base station was collected. During the study period, the weather is sunny, and no rainfall or extreme weather event that may cause significant changes in the atmospheric disturbance. The GNSS receivers used in this study are manufactured by the Unicore Communications Ltd. of China, which can track multi-GNSS multi-frequency signals, including BDS: B1, B2, and B3; GPS: L1, L2, and L5. The GNSS antennas are from the HighGain Company Ltd. of China. The total cost of one set of GNSS devices (one receiver and one antenna) is less than ¥2500.

To evaluate the effect of the proposed real-time high-precision landslide monitoring algorithm based on the GNSS CORS network, we also collected data of four CORS in Gansu province from the same period. As shown in Fig. 3, the landslide is located in the middle of a CORS network. A total of five baselines (black line) were formed according to the Delaunay triangle network criterion, with an average station spacing of 105.4 km. Table 1 shows the length and height difference of the five baselines, where the longest baseline is 128.7 km and the maximum height difference is 609.0 m. All CORS were equipped with Trimble NetR9 receivers and TRM 59900.00 antennas. Using the IGS final precise products, one week data from HF01 and the other four CORS stations were processed by GAMIT software. The reference coordinates of base station HF01 were computed as a mean value from daily network solutions. While for the monitoring stations HF06 and HF11, the reference coordinates were both calculated based on the short-range baseline RTK solutions with a noise reduction, i.e., HF06-HF01 and HF11-HF01. The stable monitoring point (HF11) noise reduction was processed by CEEMD and 24 h-window median filtering, while the sliding point (HF06) was processed by CEEMD and the adaptive window median filtering.

GPS/BDS dual-frequency data from HF11 and HF06 were processed

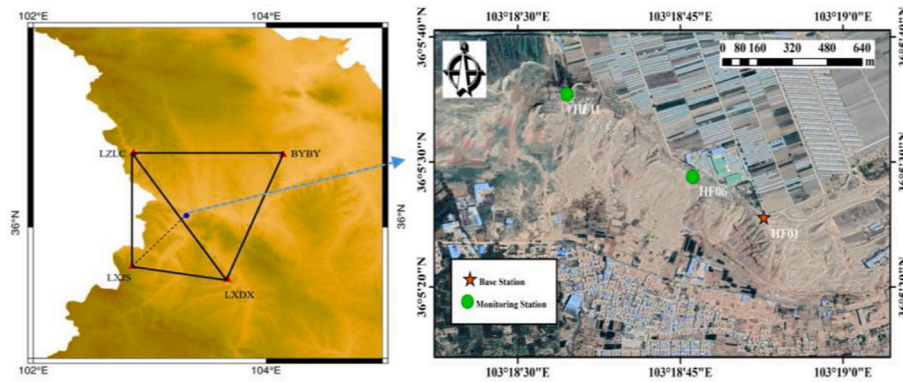


Fig. 3. Distribution of the four continuously operating reference stations (CORS) (left) and landslide monitoring stations (right).

Table 1

Baseline information.

Baseline	Length (km)	Elevation difference (m)
LZLC-LXJS	95.2	−439.3
LXJS-LXDX	74.5	−3.4
LXDX-LZLC	128.7	442.6
LXDX-BYBY	113.6	609.0
BYBY-LZLC	115.1	−166.4

using both the VAC-RTK and VRS-RTK models. In the VRS-RTK mode, the modeling atmospheric delays and the closest CORS were used to generate VRS observations; the VRS was used as a base station and the atmospheric delays were ignored when performing short-range RTK at the user terminal. For the VAC-RTK model, the closest CORS was directly used as the base station and the modeling atmospheric delays were used as virtual observations. The closest CORS to the landslide monitoring stations was LXJS and the distance was approximately 60 km. The processing strategies of VRS-RTK and VAC-RTK are detailed in Table 2. It should be noted that the modeling atmospheric delay used in VAC-RTK was different from that of VRS-RTK, that is, the DD ionosphere delay and RZTD were used as virtual observations in VAC-RTK, whereas the DD ionosphere and DD troposphere delays were used to generate the VRS. Similar to the baseline solution in the CORS network, partial ambiguity resolution strategies were adopted to obtain reliable fixed RTK solutions for the monitoring station.

Table 2

Data processing strategy of VRS-RTK and VAC-RTK methods for landslide monitoring stations.

	VRS-RTK	VAC-RTK
Baseline	VRS (base) + monitoring station (rover)	LXJS (base) + monitoring station (rover)
Observations (variance)	Uncombined DD pseudo-range (σ_p^2) and phase (σ_L^2)	Uncombined DD pseudo-range and (σ_p^2) and phase (σ_L^2)
Virtual observations (variance)	/	DD ionosphere delay (σ_I^2) and RZTD (σ_T^2) derived by the CORS network
Coordinate	Dynamic estimation	Dynamic estimation
Troposphere delay	/	Random walk estimation: zenith wet delay + GMF mapping function [37]
Ionosphere delay	/	Random walk estimation: DD ionosphere delay on slant path
Ambiguities	Static estimation + PAR	Static estimation + PAR

3.2. Precision analysis of modeling atmosphere delays

The modeling atmospheric delay can increase the AR speed of terminal positioning; thus, it is important to evaluate its accuracy prior to use. Considering the spatial correlation of atmospheric errors, the atmospheric delay of user baselines is usually interpolated based on the atmospheric information of nearby baselines. As shown in Fig. 3, the landslide is in the middle of the CORS network; therefore, all five baselines participated in atmospheric modeling.

Fig. 4 shows the ionospheric modeling values and their errors of the HF11-LXJS baseline on DOY 273 and 277 for all ambiguity-fixed satellites (different colors represent different satellites). The reference ionospheric delay was calculated using this baseline by regarding the monitoring station as the reference station. As shown in Fig. 4, the DD ionosphere delay is typically less than 20 cm, and the ionosphere modeling error for partial periods may reach 5 cm or even 10 cm; the corresponding modeling error will be directly introduced to the RTK results when the VRS method is used. Moreover, the ionosphere delay varies greatly between different days. The average DD ionosphere delays on DOY 273 and 277 are 3.9 cm and 2.7 cm, whereas the corresponding modeling errors on these two days are 2.5 cm and 1.5 cm, indicating a substantially higher modeling error on DOY 273 than on DOY 277. In addition to the ionospheric delay, the DD tropospheric delays used to generate the VRS are also presented. Fig. 5 shows the DD tropospheric modeling values and their errors of the HF11-LXJS baseline on DOY 273 and 277. The reference tropospheric delay was also extracted by the ambiguity-fixed solution of the LXJS-HF11 baseline. Similar to RZTD modeling, the prior GPT2w model must be used for elevation normalization before and after tropospheric modeling. According to Fig. 5, the DD tropospheric model delay for partial satellites can reach a maximum of 50 cm, which is substantially larger than the ionosphere delay, predominantly because of the large height difference; however, the troposphere modeling error with the elevation compensation modeling method is smaller than the ionosphere delay, with RMS values on DOY 273 and 277 of 1.1 cm and 1.0 cm, respectively. Table 3 summarizes the RMS results of ionosphere/troposphere modeled values and errors on DOY 271–277 for the HF11-LXJS baseline. It is noted that the “ref value” and “model value” in Table 3 denote the RMS values of reference and model-derived atmospheric delays over the study period, respectively. While the “model error” values represent RMS values of the differences between reference and model-derived atmospheric delays. Accordingly, the ionosphere modeling errors of the first four days are generally higher than those of the last three days. Moreover, the larger the double-difference ionosphere value, the larger the modeling error.

For the VAC-RTK mode, we used the DD ionospheric delay and RZTD information. The RZTD modeled here was the zenith wet component. Table 4 shows the RMS statistics of the RZTD modeling values and errors from DOY 271 to 277 for LXJS-HF11, in which the definition of each column is similar to that of Table 3. It can be found that the RZTD

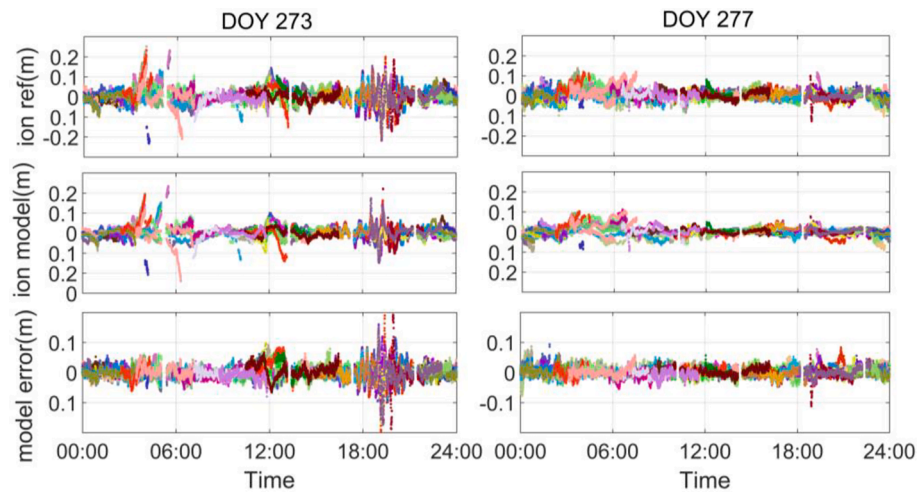


Fig. 4. Results of ionospheric model values and errors on DOY 273 and 277 for LXJS-HF11.

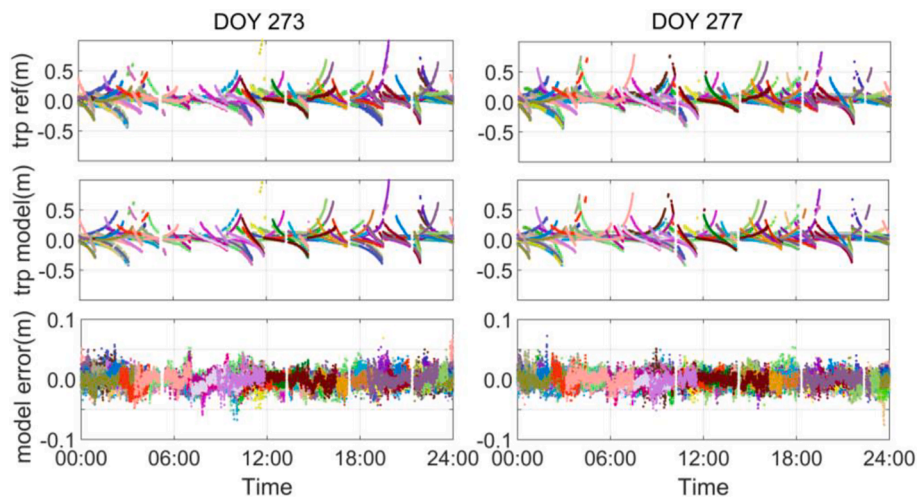


Fig. 5. Results of troposphere model values and errors on DOY 273 and 277 for LXJS-HF11.

Table 3

RMS statistics (cm) of DD atmosphere modeling value and error on DOY 271–277 for LXJS-HF11.

LXJS-HF11	ref value (RMS)		model value (RMS)		model error (RMS)	
	ion	trp	ion	trp	ion	trp
271	3.8	12.6	3.6	13.5	2.3	1.6
272	3.9	12.5	3.6	13.1	2.0	1.6
273	3.9	13.3	3.2	13.3	2.5	1.1
274	4.0	11.1	3.5	11.7	2.5	1.5
275	2.9	13.1	2.6	13.1	1.6	1.1
276	2.4	13.6	2.2	14.0	1.5	1.2
277	2.7	13.9	2.7	13.8	1.5	1.0

modeling errors are relatively large and unstable, varying from 6 mm to 22 mm on different days. According to Table 1, the height difference among the CORS stations can reach a few hundred meters, indicating that the zenith wet troposphere delay is difficult to model accurately in complex mountainous environments.

3.3. Analysis of stable monitoring points on the landslide

To evaluate the accuracy of the proposed landslide deformation monitoring algorithm based on the CORS network, one week of

Table 4

RMS statistics (cm) of RZTD modeling values and errors on DOY 271–277 for LXJS-HF11.

LXJS-HF11	ref value (RMS)	model value (RMS)	model error (RMS)
271	1.4	2.2	2.0
272	1.6	2.2	2.2
273	1.8	1.8	1.0
274	1.5	1.7	1.4
275	1.1	1.5	0.7
276	1.7	2.0	1.3
277	1.7	1.8	0.6

observation data from two landslide monitoring sites (HF11 and HF06) were processed using the VAC and VRS methods according to the data processing strategy introduced in subsection 3.1. The monitoring results of the stable landslide point HF11 are presented first.

Fig. 6 shows the coordinate time series of the RTK fixed solution in the east, north, and up direction, where the gray and purple colors represent the VRS-RTK and VAC-RTK, respectively. According to Fig. 6, the stability of the positioning results for the VAC algorithm is much better than that of the VRS method. The VRS positioning results have large oscillations, and the positioning error in the up direction is up to

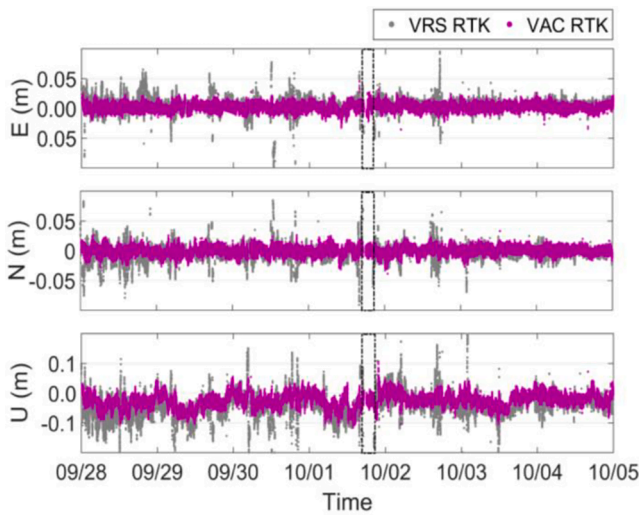


Fig. 6. HF11 displacement time series of the fixed solution obtained by VRS-RTK and VAC-RTK methods.

10 cm during some time periods. Compared with VRS, the positioning accuracy of the VAC algorithm is improved in both the horizontal and up directions. The RMS errors of the VRS-RTK fixed solutions in the horizontal and vertical directions are 1.7 cm and 3.9 cm, respectively, whereas those of the VAC-RTK fixed solutions are 0.9 cm and 2.3 cm, respectively; thus, VAC reduced the error by 47.1% and 20.5%, respectively. In addition, the terminal fixed rate of the VAC method is higher than that of VRS; the average fixed rates of VAC-RTK and VRS-RTK are 97.7% and 93.1%, respectively. Furthermore, the fixed solution is not obtained in VRS-RTK mode for a longer period of time on October 1 (dashed box in the figure). This is because the positioning error in VRS mode includes the influence of the atmospheric delay modeling error; hence, the VRS-RTK positioning ambiguity will be difficult to fix and the positioning error will be large during atmospherically active periods. For VAC-RTK mode, the atmospheric delay was estimated and the atmospheric modeling value was used as a virtual observation value. Typically, the parameter estimation residual is smaller than the modeling error, and the positioning accuracy is less

affected by the modeling error.

Fig. 7 shows the denoising result of the VAC-RTK and VRS-RTK coordinate time series for the HF11 monitoring station. The legend “MD” indicates that the original RTK coordinate time series is processed by the CEEMD method, respectively, and “MD + MF-xx” indicates that the original series is processed by both CEEMD and median filtering with a specific time span window. Three sliding windows of 2/4/8h and the adaptive window were set for the median filter method. The initial window of MF-ADP is set as 24 h and the deformation threshold is set as 2 cm. Table 5 shows the RMS statistics of the positioning error after noise reduction, where the reference value was derived by the short-range baseline (HF11–HF01) RTK solution with a noise reduction. From Fig. 7 and Table 5, it can be seen that the positioning accuracy of the two methods is significantly improved when low-frequency noise is removed by the CEEMD method. Compared with the original RTK time series, the positioning error in the horizontal and up directions for VRS-RTK are reduced by 24.6% and 48.1%, respectively, and the corresponding values for VAC-RTK are reduced by 18.2% and 40.8%. In addition, the time series of the VAC method becomes relatively stable after removing the low-frequency noise, whereas the VRS method still shows some impulsive and abnormal noise caused by the randomness of the atmospheric modeling error.

Moreover, the accuracy of the monitoring sequence is improved when the CEEMD processing sequence is further processed by median filtering, and the high-frequency/impulse/abnormal noise is significantly suppressed. After median filtering with a 2-h smoothing window, both VRS and VAC achieve millimeter-level positioning accuracy in horizontal and up directions. The positioning accuracy of the VAC

Table 5

RMS statistics of the HF11 monitoring error after noise reduction for VRS and VAC methods.

Mode	VRS			VAC		
	E(mm)	N(mm)	U(mm)	E(mm)	N(mm)	U(mm)
Original RTK	11.6	11.9	39.7	6.2	6.8	23.8
CEEMD (MD)	8.6	9.1	20.6	4.8	5.8	14.1
MD + MF-2 h	3.4	3.3	9.6	1.3	1.9	3.2
MD + MF-4 h	2.4	3.0	8.6	1.2	1.6	2.7
MD + MF-8 h	2.2	3.0	8.3	1.1	1.5	2.7
MD + MF-ADP	2.2	2.9	8.1	1.1	1.4	2.5

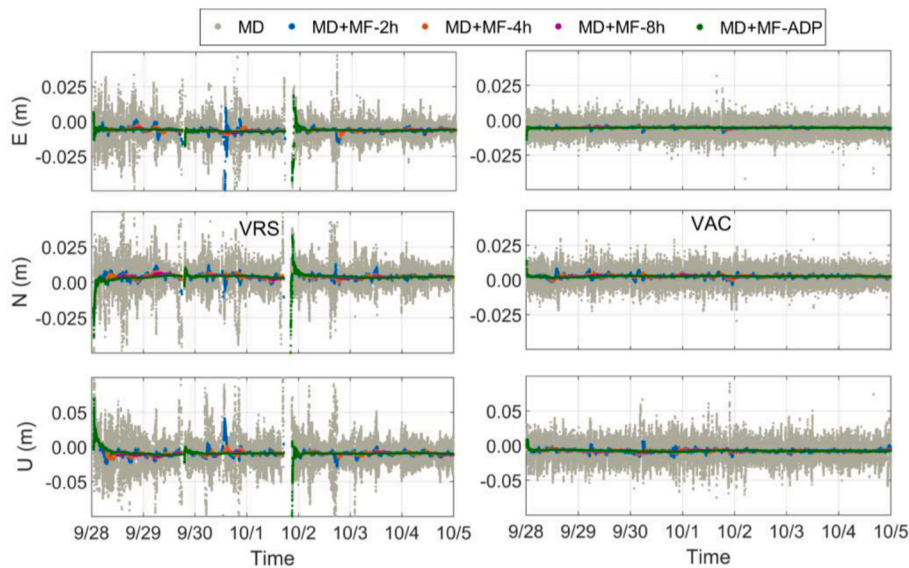


Fig. 7. Denoising result of VRS-RTK (left) and VAC-RTK (right) displacement time series for the HF11 monitoring station (the MD, MD + MF-2 h, MD + MF-4 h, MD + MF-8 h, MD + MF-ADP results are denoted in grey, blue, orange, pink, and green color, respectively). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

sequence in horizontal and vertical directions reaches 2.3 mm and 3.2 mm, respectively. Furthermore, the stability and accuracy of the positioning sequence are further improved by extending the size of the smoothing window from 2 h to 4 h; however, the positioning accuracy shows almost no change when the smoothing window size is greater than 4 h. This confirms that the low-frequency noise is effectively suppressed by CEEMD processing. The window size of MF-ADP is not changed throughout the whole period due to that the monitoring point is stable, which equals the result of 24 h static window. In general, the positioning result of VAC-RTK is better than that of VRS-RTK after noise reduction filtering, the horizontal and vertical positioning accuracy of VAC-RTK can reach 1.8 mm and 2.5 mm, whereas VRS-RTK achieves maximum accuracy of 3.6 mm and 8.1 mm, respectively.

3.4. Analysis of a collapsed monitoring point on the landslide

Fig. 8 shows one week of coordinate time series data calculated by the two methods of VRS and VAC for the collapsed monitoring station HF06; only the positioning results of the fixed ambiguity solution are shown. During this period, the monitoring point experienced a transition from uniform deformation to accelerated deformation and then collapse. This point collapsed at 20:24 on October 4, GPS time. According to Fig. 8, both methods can capture the trend of landslide deformation. Similar to the results of the stable point HF11, the monitoring results of VAC-RTK are more stable than those of VRS, and the positioning accuracy is higher. Referenced to the coordinates of the short-range baseline HF06-HF01 RTK with a noise reduction, the RMS of the VRS-RTK positioning errors in the horizontal and up directions are 17.7 mm and 47.2 mm, and the corresponding values for VAC-RTK are 10.4 mm and 27.2 mm, indicating a reduction of 41.0% and 42.4%, respectively. The average fixed rates of VAC-RTK and VRS-RTK this week are 97.9% and 84.8%, respectively.

Fig. 9 shows the coordinate time series of the HF06 monitoring station after noise reduction for the VRS and VAC methods. Table 6 shows the RMS statistics of the positioning error after noise reduction. Same as HF11, the initial window is set as 24-h and the deformation threshold is set as 2 cm. The positioning accuracy of the two methods is significantly improved after low-frequency noise is removed by CEEMD; however, significant impulse noise and interruption still exist in the VRS time series. After further processing by median filtering, the time series of VRS and VAC become much smoother, but significant differences exist in the response of deformation with different sliding windows in different landslide stages. Specifically, when the window length is set to

2–8 h, the monitoring sequence can respond to the deformation information well before October 2, but the deformation speed is fast in the imminent slip stage and the response speed has different degrees of lag. The longer the window setting, the greater the lag time and the worse the monitoring accuracy. For a 2-h window, the RMS errors of VAC in the horizontal and up directions are 3.5 mm and 8.7 mm, whereas the corresponding values for an 8-h window are 7.8 mm and 16.9 mm. The median filtering with adaptive window (MF-ADP) can respond well to landslide deformation in the near-slip stage, and the RMS value is slightly better than that of the 2-h sliding window. Similar to the results before noise reduction, the monitoring results of the VAC method are generally better than those of the VAC method after noise reduction.

4. Discussion

From the above analysis, it can be seen that the VAC method exhibits obvious advantages over the VRS method. The performance of the VAC method mainly depends on the accuracy of atmospheric variance modeling [27]. The atmosphere constraint will result in a bias for the coordinate parameters when the corresponding variance is too small. For the VRS method, without estimating the atmosphere parameter, the ionosphere and troposphere delay is directly corrected in phase and pseudo-range observations, which equals to that the variance of atmospheric constraint is set infinitely close to zero. In contrast, if the variance is excessively large, then the contribution of constraints will fade. Possible introduced bias and the positive effect of external atmosphere corrections should be balanced. For landslide monitoring and warning, large deviations in the GNSS coordinate series may cause a false alarm. As a result, a larger variance is usually proposed to ensure monitoring reliability under tough conditions such as long baselines or active atmosphere.

Meanwhile, it should be mentioned that the performance of VRS-RTK is also preferable for landslide deformation monitoring when the CORS station spacing is short or the atmosphere activity is calm. Using a CORS network with an average station spacing of 60 km [23], the RMS value of VRS-RTK in E/N/U direction can reach to 5.5/5.8/11 mm, respectively. Table 7 shows the daily RMS statistics of the HF11 monitoring station for VRS-RTK and VAC-RTK modes. Owing to smaller ionosphere and troposphere modeling error on DOY 277, the RMS value of the VRS-RTK solutions in E/N/U directions were only 6.1/6.9/23.2 mm, respectively, which is comparable to that of VAC-RTK solutions. Compared to the results in [23], the accuracy of VRS-RTK solution in this study is worse due to large height difference and long baseline length in the CORS network. Also, it should be noted that the research area in this study is located in the northwest China, the ionosphere activity is relatively weak and the vegetation coverage is less, more GNSS data of the landslides in different latitudes and observation circumstance will be processed and analyzed in our further work.

GNSS timer series is generally contaminated by noise, e.g., multipath error, and sidereal filtering is a common technology for multipath error reduction [43,44]. Different from GPS, the orbit repeat period of the BDS, GLONASS, and Galileo MEO satellites is about 7, 8, and 10 days, respectively. Therefore, more than one week of data is needed to mitigate multipath error when the observation domain sidereal filtering is used. In this study, the CEEMD is adopted to suppress the low-frequency error in the coordinate domain, which is a blind signal separation method and thus more convenient and efficient for the multi-GNSS data denoising process compared to the other observation domain noise reduction methods. This is significantly important for practical landslide monitoring applications, especially when the landslide monitoring site is in a harsh environment, e.g., a GNSS-denied environment. The observation satellite geometry structure becomes weak, and the data quality decrease, which may lead to unreliable monitoring results and bring new challenges to coordinate noise reduction.

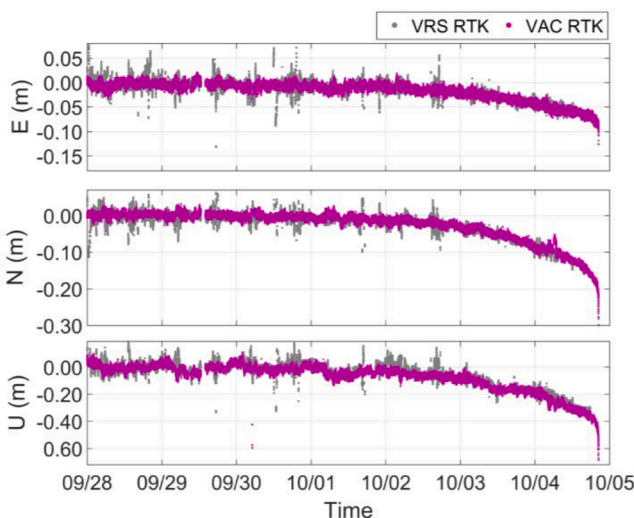


Fig. 8. HF06 monitoring station displacement time series obtained by VRS-RTK and VAC-RTK fixed solutions.

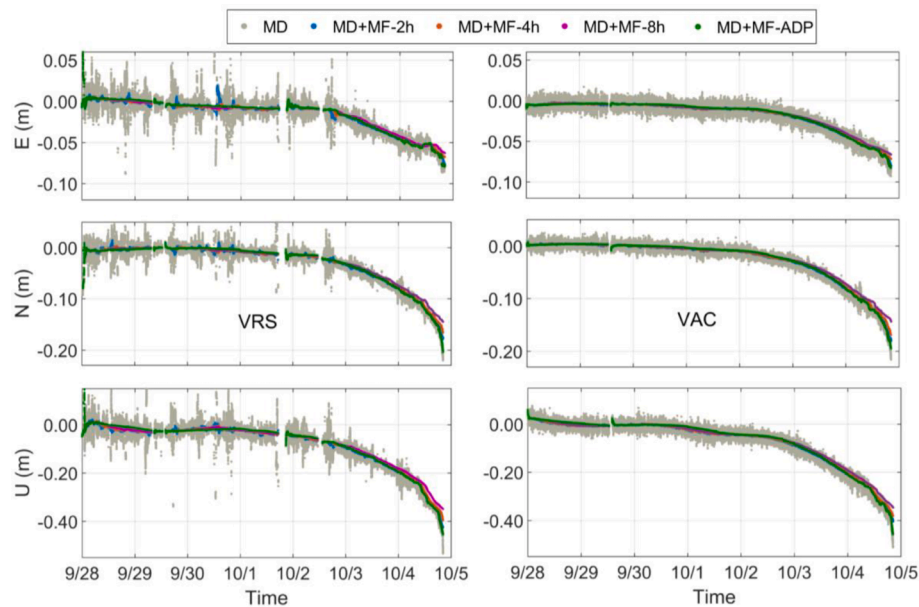


Fig. 9. VRS (left) and VAC (right) displacement time series of the HF06 monitoring station after noise reduction filtering (The MD, MD + MF-2 h, MD + MF-4 h, MD + MF-8 h, MD + MF-ADP results are denoted in grey, blue, orange, pink, and green color, respectively). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 6

RMS statistics of the HF06 monitoring station after noise reduction for VRS and VAC methods.

Mode	VRS			VAC		
	E(mm)	N(mm)	U(mm)	E(mm)	N(mm)	U(mm)
Original RTK	11.8	13.2	47.2	6.6	8.1	27.2
CEEMD (MD)	10.7	11.7	31.5	5.5	6.8	16.7
MD + MF-2 h	4.2	4.6	15.2	2.4	3.5	8.7
MD + MF-4 h	3.7	5.2	16.8	2.1	4.5	11.1
MD + MF-8 h	3.8	7.5	21.7	2.1	7.5	16.9
MD + MF-ADP	3.8	4.6	13.8	2.3	3.5	8.1

Table 7

Daily RMS statistics of the HF11 monitoring station before noise reduction for VRS and VAC methods.

Doy	VRS-RTK			VAC-RTK		
	E(mm)	N(mm)	U(mm)	E(mm)	N(mm)	U(mm)
271	14.9	17.4	48.6	6.0	7.5	23.7
272	10.7	11.2	40.7	6.5	7.3	28.9
273	18.4	13.8	47.9	5.7	6.5	21.3
274	11.4	12.0	44.7	7.7	7.8	30.1
275	9.1	11.7	37.6	6.2	7.2	19.4
276	7.0	8.3	31.5	5.5	5.9	21.5
277	6.1	6.9	23.2	5.5	5.4	20.1

5. Conclusions

In this study, we proposed a millimeter-level GNSS landslide monitoring algorithm based on multiple reference stations. Atmospheric delay data and its accuracy information interpolated with the CORS network were used as virtual observations to rapidly obtain the fixed coordinate solutions of the monitoring terminal. Additionally, the noise of the RTK coordinate time series was reduced by considering the characteristics of the GNSS signal error. To validate the algorithm, we processed one week of data from two monitoring stations located on the Heifangtai landslide as well as four surrounding reference stations in Gansu Province using both the proposed (VAC-RTK) and VRS-RTK

algorithms. The following conclusions were drawn.

- (1). Because of the atmospheric modeling error of the long-range GNSS CORS network, the original coordinate time series processed with the VRS algorithm is prone to jitter, with the monitoring errors in the horizontal and up directions of many epochs reaching 5 cm and 10 cm. Conversely, the original monitoring results of the VAC algorithm tend to be stable and convergent. For the stable monitoring point HF11, the RMS statistics of VRS in horizontal and up directions are 1.7 cm and 3.9 cm, whereas the corresponding values for VAC-RTK are 0.9 cm and 2.3 cm, respectively, indicating an error reduction of 39.2% and 43.8%. For the collapsed point HF06, the RMS errors of the VAC-RTK in horizontal and up directions are 1.0 cm and 2.7 cm, which are 41.0% and 42.4% lower than those of the VRS positioning results in the same respective directions.
- (2). The influence of the GNSS signal residual error in the GNSS monitoring sequence can be reduced by combing CEEMD and the median filtering method, thereby improving the accuracy of GNSS landslide monitoring results. After removing low-frequency noise with CEEMD and processing with 2-h sliding window median filtering, the coordinate time series of the VRS and VAC methods can achieve millimeter-level monitoring accuracy for the stable monitoring point. The RMS errors of the VRS results in horizontal and vertical directions are 4.7 mm and 9.6 mm, and the corresponding values for the VAC method are 2.3 mm and 3.2 mm. Overall, the accuracy and stability of the VAC monitoring time series after noise reduction are better than those of VRS because the noise reduction process may lose effectiveness when the ambiguity is not fixed for a long time or there is obvious abnormal noise in the coordinate time series. Although the noise reduction process can achieve a stable and smooth monitoring sequence, the real deformation information of the landslide may be hidden when the smoothing window size is set too large; therefore, it is necessary to adjust the size of the sliding window according to the landslide deformation rate.

Data

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CRedit authorship contribution statement

Bao Shu: Conceptualization, Software, Formal analysis, Writing – original draft. **Yuanhao He:** Software, Formal analysis. **Li Wang:** Conceptualization, Formal analysis, Writing – original draft. **Qin Zhang:** Writing – review & editing. **Xinrui Li:** Software. **Xuanyu Qu:** Writing – original draft. **Guanwen Huang:** Data curation, Writing – review & editing. **Wei Qu:** Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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