

Retraction Retracted: MEC-Driven Fast Deformation Monitoring Based on GNSS Signal

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

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Research Article MEC-Driven Fast Deformation Monitoring Based on GNSS Signal

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In the deformation monitoring based on satellite positioning, the extraction of the effective deformation signal which needs plenty of computing resources is very important. Mobile-edge computing can provide low latency and near-edge computing agility for the deformation monitoring process. In this paper, we propose an edge computing network architecture to reduce the satellite observation time while maintaining a certain positioning accuracy. In such architecture, the state transition equation is established for monitoring, and the Kalman filter is used to reduce the error caused by the reduction of the observation time. At the same time, the method of determining the initial filter value and the filtering process are given. Through the actual monitoring of a certain section of railway track, the feasibility of the proposed method is proved.

1. Introduction

Deformation is a common phenomenon in nature. The deformation body's shape, size, and location are changed in space and time domain by a variety of loads. The socalled deformation monitoring is the monitoring to the deformation phenomena of the deformation body by the use of special instruments and methods of measurement and deformation monitoring. Its task is to determine space state and time feature of the deformation body's shape, size, and location changes in the effects of various loads and external force [1]. As we all know, engineering buildings during construction and operation, due to the influence of a variety of subjective and objective factors, will cause deformation. If the deformation exceeds the prescribed limit, it will endanger the safety of the building and bring huge losses to the society and people. Therefore, the study of collecting accurate deformation data of objects has important engineering application value.

Currently, the primary techniques for monitoring convergence deformation are automatic tracking total-station technique, automatic close-range photogrammetry, and convergence gauge [2]. They have been widely used in engineering, such as References [3-5]. However, these monitoring technologies cannot be used on a large scale area because of their high cost. Meanwhile, due to the limitation of the precision of equipment, these technologies cannot be applied to the harsh environment for a long time. In addition to GPS, the global navigation satellite system (GNSS) includes Russia's GLONASS, China's Beidou satellite navigation system, and the European Union's Galileo system, which are under formation. Conventional GNSS positioning technology usually requires a long time of synchronous observation to ensure the accuracy and reliability of positioning results. With the establishment of global positioning system and the rapid popularization of GPS positioning technology, its application has been more and more wide, such as geodetic survey, engineering survey, and deformation monitoring.

However, the long-term positioning technique is not suitable for these new applications (because the positioning time is too long, there are other options). Therefore, in recent years, researchers have been looking for fast GNSS positioning techniques that can obtain the required accuracy only by short observation time, in order to greatly improve the operation efficiency. Thus, it can make GNSS positioning technology more competitive in these applications. With technological developments, the global positioning system has been widely used for the real-time deformation monitoring of natural hazards and structures such as landslides and bridges. It helps us better understand the tendency of deformations and prevent disasters [6]. In [7], a large-section shallow buried tunnel deformation monitoring method based on GNSS technology was proposed. The GNSS automation equipment and its technology are combined to realize the real-time acquisition of monitoring data, and the displacement trend diagram of monitoring points is displayed. By designing high-precision GNSS data processing strategy, the authors facilitate the extraction and analysis of vertical deformation of suspension bridge pylon and explain its deformation mechanism [8]. In the South-to-North Water Transfer Project in China, GNSS is used to monitor the deformation of dams [9].

Moving edge computing is an effective method to deal with massive data [10, 11]. With the increase of the number of observations and the number of monitoring stations, the number of signals (navigation messages, etc.) received by the monitoring stations from satellites will become very large. The requirement of the processor for solving in the monitoring station will increase accordingly. The data processing power of the system can be significantly improved by moving the data to the adjacent MEC server [12]. In [12], it investigates the system of unmanned aerial vehicle (UAV) daily routine inspection in a wind farm, where UAV performs detection and sensory data processing with the aid of edge server and satellite. In [13], it proposed a collaborative UAV-enabled edge computing network for the power Internet of Things (IoT) system. In [14], the computation efficiency is studied for the UAV-enabled MEC network by jointly optimizing the offloading times, the trajectory of the UAV, etc. The UAV-enabled MEC network in which the UAV servers are powered by microwave power station is introduced in [15]. However, when GNSS is used for positioning, a relatively accurate coordinate value needs to be solved through a certain observation duration. In the case of shortening observation time, some multipath errors cannot be eliminated due to the reduction of observation data, so that the positioning accuracy cannot be guaranteed.

In this paper, we propose an edge computing network architecture to reduce the satellite observation time while maintaining a certain positioning accuracy. That is, the Kalman filter model is used to establish the state space of the monitoring points, and the optimal estimated state of the observation points is obtained by combining GNSS observation values. In this way, the problem of accuracy decline caused by the decrease of observation time can be reduced to a certain extent. The feasibility of this method is proved in the real monitoring of high-speed railway tracks.

2. Deformation Monitoring Based on GNSS System

2.1. Preliminary. The GNSS monitoring system can be used to measure the monitoring area in all-weather, continuous, and full coverage. And the three-dimensional space position of the monitoring point can be obtained by it in real time. It is mainly composed of three parts: data acquisition subsystem, data transmission subsystem, and data processing and analysis subsystem. In order to improve the accuracy and reliability of the monitoring data, we use reference stations and monitoring stations as the reference basis for the data acquisition subsystem. The reference station is the frame of reference for the whole subsystem to collect displacement data. This monitoring system was installed with a stable monitoring reference station, and it can meet the observation conditions of GNSS satellites. The monitoring station is the main basis for the subsystem to collect surface displacement. Representative points are selected for monitoring stations which can reflect the deformation state of the rail in real time and also can meet the conditions of GNSS satellite observation. With long-term continuous tracking and observation of satellite signals, each monitoring point combined with the observation data and the original coordinates of base station to obtain the real-time three-dimensional coordinates of the monitoring point in the center of the control system. The GNSS displacement data collected by the monitoring point relies on the data transmission subsystem to transmit it to the disk through the Internet communication technology and computer system integration technology. Finally, the server of data processing and analysis subsystem control center processes, analyzes, stores, and manages monitoring data which come from monitoring point.

2.2. GNSS Monitoring System for Guangshan Railway. Aiming at the wide distribution, large number, and huge satellite observation data of Guangshan Railway track monitoring points, this paper combines mobile-edge computing with traditional GNSS automated online monitoring systems to provide low latency and near-edge computing agility for the deformation monitoring process. Its overall structure is similar to the traditional monitoring system, as shown in Figure 1.

But at the reference stations, the processor is replaced with edge devices with more powerful computing capabilities. It is different from the traditional positioning monitoring station solution, and the solution task of the system is carried out on the edge device, as shown in Figure 2.

By installing a GNSS antenna and a GNSS receiver on the edge device, it not only serves as a computing node but also has the function of a reference station. Therefore, the monitoring station only needs to perform simple data forwarding work. It sends satellite signals such as navigation messages received from satellites to edge devices. On the edge device, the satellite signal from the monitoring station and the satellite signal from the reference station are differentially calculated to eliminate the error caused by the signal propagation in space, and finally, the three-dimensional coordinates of the monitoring station are obtained. Therefore, it reduces the hardware performance requirements of



FIGURE 1: Traditional system architecture.



FIGURE 2: System architecture based on edge computation.

the monitoring station. The traditional positioning method forwards the satellite signal received by the reference station to the monitoring station and performs differential calculations in the monitoring station. From the perspective of the overall structure of the system, the flow of data has changed from the base station to the monitoring station to from the monitoring station to the base station, but the process of data transmission has not become complicated, and it is still a one-way single transmission. Therefore, the data processing capabilities of edge computing can provide low latency and near-edge computing agility for the deformation monitoring process. The general positioning process is shown in Figure 3.

This system realizes the centralization of computing tasks, enabling monitoring stations to be manufactured with lower-performance and inexpensive processors. However, the demand for computing power of edge devices will increase, but it can provide solution services for multiple monitoring stations at the same time, and the overall cost will be lower than that of traditional monitoring systems. At the same time, the power environment of the edge device is better than the power environment of the monitoring



FIGURE 3: Positioning process.

station, which can give full play to the system hardware performance, and can greatly improve the endurance of the monitoring station. To a certain extent, the expansion cost of the traditional positioning network is reduced, which is conducive to its further popularization in the field of deformation monitoring.

2.3. Monitoring and Reference Point Placement. The selection of deformation monitoring reference station and monitoring station position is very important to the monitoring results, and the accuracy and reliability of monitoring are directly affected by it. Therefore, when we select monitoring stations and reference stations, it is necessary to avoid radar stations, substations, tall buildings, and large water areas around the observation point to ensure that the observation point is empty and free of obstructions and eliminate all interference from external factors. At the same time, the position of the reference point should be set to meet the convenience of observation and not be affected by factors such as construction. And the reference station should be closely integrated with the bedrock to ensure that the base point does not produce displacement. With consideration of the convenience of measurement and the safety of monitoring personnel, the monitoring point is set in a representative, deformation-sensitive, and relatively stable place to reflect the true deformation of the rail. After analyzing the actual geographical conditions of the Guangshan Railway and the deformation requirements of the rails, the monitoring point has mainly been placed in a location which is prone to deformation of the Guangshan Railway. The monitoring point is mainly set at the tortuous part of the Guangshan Railway, because it is under greater pressure and has a higher probability of deformation. In this paper, the GNSS real-time online monitoring system has successively established a reference point and 6 monitoring points and the measuring stations are mainly distributed on two monitoring baselines. The distribution of monitoring points is shown in Figure 4.

The Guangshan Railway focuses on stability control to achieve the purpose of early warning. It is necessary to ensure a certain monitoring density to be able to continuously observe the dynamic displacement of the railway. The monitoring period is 12 months, and the monitoring frequency is once a day. However, in order to further grasp the dynamic displacement of this section of the Guangzhou-Shantou Railway, it needs to reduce the duration of satellite observation, that is, to increase the frequency of monitoring-from once a day to once every 30 minutes. Due to the reduction of observation time, some short-term multipath errors cannot be eliminated, thus resulting in lower positioning accuracy. In order to solve this problem, this paper proposes a strategy of using the Kalman algorithm to solve the decrease of the positioning accuracy caused by the decrease of the observation time to ensure the positioning accuracy.

3. Fast Deformation Monitoring of Guangshan Railway with Kalman Filtering

3.1. Kalman Filtering Model. For the railway deformation monitoring system in this article, for the monitoring points, its deformation process is gradual, it takes time, and it is also irreversible (except for extreme conditions such as earth-quakes). Therefore, the recursive Kalman filter technology is used to establish its state transition equation for the monitoring point and combined with the GNSS observations to



FIGURE 4: Distribution of monitoring stations.

obtain the optimal estimation value of the current state of the monitoring point. At the same time, it occupies a small amount of memory (except for the previous state, there is no need to keep other historical data), and the calculation speed is fast. Therefore, it is more suitable to be applied to this system. So Kalman filtering can solve the problem of reduced positioning accuracy due to the reduction of GNSS observation time to a certain extent.

The mathematical model of the Kalman filtering algorithm includes two parts: state equation (also known as dynamic equation) and observation equation, and its discretization form is as follows:

$$\begin{aligned} X_t &= F X_{t-1} + Q, \\ Z_t &= H X_t + R. \end{aligned} \tag{1}$$

 X_t is the state vector of the system at time t; Z_t is the observation vector of the system at time t; F is the system state transition matrix from t - 1 to t; H is the observation matrix; Q and R are dynamic noise and observation noise, respectively.

Assuming that both the dynamic noise and the observed noise meet the Gaussian distribution, the recursive formula of Kalman filtering can be obtained as follows:

State prediction equation:

$$X_t^- = F X_{t-1}.$$
 (2)

State covariance matrix prediction:

$$P_t^- = F P_{t-1} F^T. aga{3}$$

State estimation:

$$X_t = X_t^- + K_t (Z_t - HX_t^-).$$
(4)

State covariance matrix estimation:

$$P_t = (I - K_t H) P_t^{-1}.$$
 (5)

In this, *K* is the filtering gain matrix, whose specific form is as follows:

$$K_{t} = P_{t}^{-} H^{T} \left(H P_{t}^{-} H^{T} + R \right)^{-1}.$$
 (6)

It can be seen from the above formula that when the system is observed Z_t at time t, the observed value can be used to modify the forecast value and obtain the optimal state estimate X_t of the system at time t. In this way, the recursive prediction and filtering are repeated to solve the problem that the positioning accuracy of GNSS is reduced due to the reduction of observation time. The specific process is shown in Figure 5.

3.2. Determination of State Equation and Observation Equation. In this paper, GNSS is used as the tool of the automatic system of three-dimensional track deformation monitoring. When GNSS is used to monitor the track deformation, the position of the monitoring point is the coordinate (x, y, z) in the independent coordinate system of the project itself. The position of the monitoring point X = (x, y, z), the deformation rate \dot{X} $= (\dot{x}, \dot{y}, \dot{z})^T$, and the acceleration $\ddot{X} = (\ddot{x}, \ddot{y}, \ddot{z})^T$ of the monitoring point are selected as the state vectors. The change rate of the acceleration of the monitoring point is regarded as random interference, and the state equation can be established as

$$\begin{bmatrix} X\\ \dot{X}\\ \ddot{X}\\ \ddot{X} \end{bmatrix}_{k} = \begin{bmatrix} I & \Delta tI & \frac{1}{2}\Delta t^{2}I\\ 0 & I & \Delta tI\\ 0 & 0 & I \end{bmatrix} \begin{bmatrix} X\\ \dot{X}\\ \ddot{X} \end{bmatrix}_{k-1} + Q.$$
(7)

In this formula, 0 and I are third-order zero matrices and



FIGURE 6: x axis coordinate raw data and Kalman filter data.

third-order identity matrices, respectively. $\Delta t = t_k - t_{k-1}$ is the difference between adjacent observation moments.

Since the measurement result of GNSS is the threedimensional coordinate of the monitoring point, the threedimensional coordinate result is taken as the observation measurement, and the observation equation is established as follows:

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix}_{k} = \begin{bmatrix} I \ 0 \ 0 \end{bmatrix} \begin{bmatrix} X \\ \dot{X} \\ \ddot{X} \end{bmatrix}_{k-1} + R.$$
(8)

3.3. Determination of Initial Filtering Value. It can be seen from the Kalman filter equation that to determine the state of the system at the time of *t*, the initial state of the system must be known first. That is, the initial value of the system should be understood. In general, the initial state of the system before filtering is difficult to be determined accurately. However, if the selection of the initial value does not meet certain requirements, it may cause a large error in the filtering result, and the deformation of the GNSS point according to the filtering result will be distorted. Therebefore, when the observation time is reduced, a correct and appropriate initial

value is one of the prerequisites for obtaining correct results. The initial value of system filtering includes initial state vector X_0 , process covariance matrix P_0 , the dynamic noise covariance matrix Q, and the observation noise covariance matrix R.

When the position, speed, and acceleration of the monitoring point are used as the state vectors, it can be obtained according to the previous two periods of monitoring data. Their initial values are selected as follows:

$$X_{0} = \frac{X_{I} + X_{II}}{2},$$

$$\dot{X}_{0} = \frac{X_{I} + X_{II}}{\Delta t},$$
(9)

$$\ddot{X}_{0} = \frac{X_{I} + X_{II}}{\Delta t^{2}}.$$

In this, the variance R of the observed noise can be directly determined by the observation data processing method. That is, the positioning accuracy after reducing the observation time is directly used as the variance of the observation noise. At the same time, it is also used as the initial position variance in the initial variance matrix P of the position state vector parameter. The initial velocity variance and the initial







FIGURE 8: z axis coordinate raw data and Kalman filter data.

acceleration variance can be obtained by the law of covariance propagation. In the dynamic noise covariance matrix, the position variance is R, the corresponding instantaneous rate variance is $4\Delta t^{-4}R$, and the instantaneous acceleration rate variance can be a smaller number.

After determining the state equation, observation equation, and filtering, the entire Kalman filtering process is as follows:

- (1) Determining the system state transition matrix *F*, the dynamic noise matrix *Q*, and the observation matrix *H* from the mathematical model relations of the deformed system
- (2) Using the first set of data in the *m* sets of observation data to determine the initial value of the filter
- (3) Reading *m* groups of observation data and implement Kalman filtering
- (4) Storing the state vector estimate X and the corresponding covariance matrix P of the last group in the filtering result
- (5) Waiting for the data of the current observation period
- (6) Remove the first set of observation data from the above m sets of observation data, put the current

new set of observation data at its rearmost position, reconstitute the m sets of observation data, go back to the first step, and perform Kalman filtering again

4. Evaluation Results

The data in this paper is taken from the monitoring data of Guangshan Railway Monitoring Station M005. The observation time is May 30, 2018 (it can be considered that the point is still and there is no deformation on that day). After reducing the observation time from 6 hours per solution to 15 minutes per solution, there are 92 sets of valid data. The data result contains the three-dimensional position information of the monitoring point: radial direction (x), tangential direction (y), and vertical direction (z). The recursive Kalman filtering method is used to process it, and the optimal estimation value of the state vector X = (x, y, z) of the data sequence can be obtained. We show the comparison between the observation data and the Kalman filtering result of the monitoring points on the x, y, and h directions in Figures 6, 7, and 8, respectively.

It can be seen from the above figure that the Kalman filter model established is reasonable and reliable. According to the calculation, the variance of the original observation sequence in x, y, z three directions is 1.782 mm, 1.708 mm, and 3.486 mm. The values are reduced to 0.625 mm, 0.829 mm, and 1.320 mm after Kalman filtering. Meanwhile, the fluctuation range of the filtered curve is obviously smaller than that of the original observation series curve. It is shown that the Kalman filter can effectively reduce the multipath error and better reflect the real state of the track. Therefore, it can be clearly seen from the above three pictures that the accuracy of the filtering value is higher than the original observation value. Therefore, Kalman filtering technology can effectively solve the problem of positioning accuracy decline due to the shortening of observation time.

5. Conclusion

This paper proposed a deformation monitoring scheme driven by mobile-edge computing. It applied mobile-edge computing technology to the traditional GNSS automated online monitoring system, providing low latency and nearedge computing agility for the deformation monitoring process. And it is suitable for general dam deformation monitoring, roadbed settlement, bridge deformation, and other open-air and open-view occasions. At the same time, Kalman filter technology was applied on this basis. It solved the problem of positioning accuracy caused by the reduction of observation time. With the combination of the state transition equation of the monitoring point and the GNSS observation value, it gave the optimal estimation of the state of the monitoring point and eliminates the influence of part of the periodic error to improve the positioning accuracy. The feasibility of this method was verified by analyzing the measured data of Guangshan Railway.

Data Availability

Data sharing is not applicable to this article as no datasets were generated or analyzed during the current study.

Conflicts of Interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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