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Short-term warning and integrity monitoring algorithm for coal mine shaft safety

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Abstract: A new short-term warning and integrity monitoring algorithm was proposed for coal mine shaft safety. The Kalman filter (KF) model was used to extract real global positioning system (GPS) kinematic deformation information. The short-term warning model was built by using the two-side cumulative sum (CUSUM) test, which further improves the warning system reliability. Availability (the minimum warning deformation, MWD), false alarm rate (the average run length, ARL), missed rate (the warning delay, WD) and the relationships among them were analyzed and the method choosing warning parameters is given. A test of a deformation simulation platform shows that the warning algorithm can be effectively used for steep deformation warning. A field experiment of the Malan mine shaft in Shanxi coal area illustrates that the proposed algorithm can detect small dynamic changes and the corresponding occurring time. At given warning thresholds (MWD is 15 mm and ARL is 1000)，the detected deformations of two consecutive days' deformation sequences with the algorithm occur at the 705th epoch (705 s) and the 517th epoch (517 s), respectively.

Key words: coal mine shaft; deformation; cumulative sum; short-term warning; Kalman filter; integrity monitoring

1 Introduction

With the wide use of new materials, the development of new construction techniques and design technology, more and more large-scale infrastructures are being built. However, large structures are susceptible to environmental loadings, including strong winds, earthquakes and mining [1,2]. Structural collapses will cause severe economic loss, therefore, the early warning system should be exploited to predict hazards [3].

The global positioning system(GPS) based monitoring scheme can provide real-time and high rate observations, it has been validated as an efficient tool for monitoring engineering structures such as tall buildings [4], long bridges [5] and mining deformation monitoring [6,7]. Coal mine shaft is one of the key parts in mines and the deformation of the shaft that is affected by the complex physical factors, geological factors, mechanic factors, etc., is the indication of the shaft safety [8]. It is very important to monitor the deformation of the coal mine shaft. However, systematic studies on coal mine shaft deformation monitoring and warning using GPS are seldom mentioned.

Precise and continuous displacement measurement is critical for evaluating structure's condition and generating warning in time. Significant work has been done to overcome the drawback of the inadequate accuracy of GPS. CHAN et al [9] presented an integrated GPS-accelerometer data processing technique, which can significantly enhance the measurement accuracy of the total displacement of a structure. SHAN et al [10] proposed an optimization model of the global navigation satellite system (GNSS)/PLs integration positioning system, which is helpful for improving the positioning performance in open-pit mine. A reliable independent component regression method was used to model dam deformation by DAI et al [11]. The Kalman filter model can process the deformation time series in real-time and obtain the optimal estimation [12], which is

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important for analyzing the structural dynamics.

Timely warning is of great importance for deformation monitoring, and accurate detection of deformation epochs can avoid some disasters. The multiple hypothesis filter [13] and the cumulative sum test [14] are successfully used to detect abrupt changes in time series.

A warning algorithm for coal mine shaft deformation data analysis is proposed based on Kalman filter (KF) and cumulative sum (CUSUM) test [15]. The performances of the algorithm are assessed using two sets of data that are collected from both simulated test platform and field coal mine shaft monitoring. This is followed by conclusions and potential applications of the algorithm. The algorithm can also be applied to other deformation warning fields. The results from this study support real-time GPS-based monitoring and warning.

2 Kalman filter algorithm

KF uses the measurement and dynamic state model to update the states. The discrete KF can be summarized as follows [16]:

$$\boldsymbol{x}_k = \boldsymbol{\Phi}_{k,k-1} x_{k-1} + w_{k-1} \tag{1}$$

$$\boldsymbol{y}_k = \boldsymbol{H}_k x_k + v_k \tag{2}$$

where $\boldsymbol{x}_k$ is the state vector at epoch k; $\boldsymbol{\Phi}_{k,k-1}$ is the state transition matrix from epoch (k−1)th to kth; w_{k-1} is the process noise at epoch (k−1)th with a covariance matrix $\boldsymbol{Q}_{k-1}$. Equation (2) is the measurement model with the measurement noise v_k whose covariance matrix is $\boldsymbol{R}_k$. w_{k-1} and v_k are both white noise and uncorrelated; the observation matrix is $\boldsymbol{H}_k$; the observation vector at epoch k is denoted as $\boldsymbol{y}_k$.

The solution of KF is a recursive procedure which contains prediction step given by

$$\begin{cases} \hat{\boldsymbol{x}}_k^- = \boldsymbol{\Phi}_{k,k-1} \hat{x}_{k-1}^+ \\ \boldsymbol{P}_k^- = \boldsymbol{\Phi}_{k,k-1} P_{k-1}^+ \boldsymbol{\Phi}_{k,k-1}^{\mathrm{T}} + Q_{k-1} \end{cases} \tag{3}$$

and update step provided as

$$\begin{cases} \boldsymbol{K}_k = P_k^- \boldsymbol{H}_k^{\mathrm{T}} \left(\boldsymbol{H}_k P_k^- \boldsymbol{H}_k^{\mathrm{T}} + \boldsymbol{R}_k \right)^{-1} \\ \hat{\boldsymbol{x}}_k^+ = \hat{\boldsymbol{x}}_k^- + \boldsymbol{K}_k \left(\boldsymbol{y}_k - \boldsymbol{H}_k \hat{\boldsymbol{x}}_k^- \right) \\ \boldsymbol{P}_k^+ = \left(\boldsymbol{I} - \boldsymbol{K}_k \boldsymbol{H}_k \right) P_k^{-1} \end{cases} \tag{4}$$

where $\hat{\boldsymbol{x}}_k^+$ and $\boldsymbol{P}_k^+$ are optimal estimates of the state vector and corresponding covariance at epoch k and $\hat{\boldsymbol{x}}_k^-$ and $\boldsymbol{P}_k^{-1}$ represent the prior estimates; $\boldsymbol{I}$ is the unity matrix; $\boldsymbol{K}_\mathrm{k}$ is the Kalman gain matrix.

3 CUSUM theory

3. 1 Basis of statistic on CUSUM

For structural monitoring applications, the displacement is usually considered one key indicator to evaluate the integrity of the structure. To ensure the safety of the buildings, the deformation sequences $\{y_k\}$(k=1, 2, 3, ⋯) are acquired and the mean μ_0 and the variance σ^2 are calculated with historical data. While the challenge is to find an optimal monitoring method to detect the disaster deformation of the buildings, and the CUSUM test is one of the algorithms for abrupt change detection and warning [17]. Consider the disaster deformation situation:

$$y_t = \begin{Bmatrix} \mu_0 + e_t & \text{if} & t \le u-1 \\ \mu_1 + e_t & \text{if} & t \ge u \end{Bmatrix}, \quad e_t \sim N(0, \sigma^2) \tag{5}$$

$$\delta\mu = \mu_1 - \mu_0$$

On line detection of the mean changes ($\delta\mu$) and disaster deformation occurring time (indicated by u) is a crucial issue that has to be confronted to realize properly warning. A two-sided CUSUM test is commonly applied in practice for no prior knowledge of changes is available, neither the magnitude of $\delta\mu$ nor its sign is known.

Considering a case where the deformation sequence y is independently distributed with probability density function given by

$$f_j(y) = \frac{1}{\sigma\sqrt{2\pi}} \exp[-(y-\mu_j)^2/(2\sigma^2)] \tag{6}$$

where the mean value is μ_j=μ_0 (no disaster deformation occurs) or μ_j=μ_1 (disaster deformation happens) and constant variance is σ^2.

At the tth observation epoch, define the logarithm of the likelihood ratio function:

$$\lambda(t) = \sum_{i=1}^{t} z_i \tag{7}$$

where random variable z_i can be transformed to

$$z_i = \ln \frac{f_1(y_i)}{f_0(y_i)} = \frac{\delta\mu}{2\sigma^2} \left(y_i - \mu_0 - \frac{\delta\mu}{2} \right) \tag{8}$$

where $\lambda(t)$ is random variable, and z_i follows a normal distribution:

$$z \sim N(\mu_z, \sigma_z^2) \tag{9}$$

where

$$\mu_z = \frac{\mu_1 - \mu_0}{\sigma^2} \left(E\{Y\} - \frac{\mu_1 + \mu_0}{2} \right), \quad \sigma_z^2 = \frac{(\mu_1 - \mu_0)^2}{\sigma^2}.$$

We can conclude that the decision function $\lambda(t)$ is cumulative and it shows a downtrend before disaster happens when a positive change in the mean, while in the case of negative shifts, it rises when the building is stable.

The decision function can be expressed as follows:

$$\lambda(t)=\lambda(t-1)+\ln\frac{f_0(y_t\mid Y_{t-1})}{f_1(y_t\mid Y_{t-1})} \tag{10}$$

The log-likelihood ratio at time t=0 is denoted by $\lambda(0)$ and it is usually assumed to be 0, $Y_{t-1}\equiv(y_1, y_2, \ldots, y_{t-1})$ indicates all prior information containing in the observations before instant t.

In general, the warning rules of the two-sided CUSUM test are given by [14]

1) When $\delta\mu>0$, the warning rule is

$$\lambda^+(t)-\min_{0\le i\le t}\{\lambda^+(i)\}\ge h^+ \tag{11}$$

2) When $\delta\mu<0$, the warning rule is

$$\lambda^-(t)-\min_{0\le i\le t}\{\lambda^-(i)\}\ge h^- \tag{12}$$

and

$$\lambda^+(t)=\lambda^+(t-1)+\frac{\delta\mu_{\min}}{2\sigma^2}(y_j-\mu_0-\frac{\delta\mu_{\min}}{2})$$

$$\lambda^-(t)=\lambda^-(t-1)+\frac{\delta\mu_{\min}}{2\sigma^2}(-y_j+\mu_0-\frac{\delta\mu_{\min}}{2})$$

where h^+ and h^- are the decision thresholds under two conditions.

3.2 Selection of warning parameters

When the CUSUM warning algorithm is used to carry out the short-term disaster deformation warning, optimal determination of CUSUM parameters is a prerequisite to achieve a better performance. The average warning delay length becomes a key parameter once (h, $\delta\mu$) are determined in advance. The average run length (ARL) denotes the probability that the model does not warn while the disaster deformation occurs, where the Type-I error probability occurs.

Under the condition that the missed rate L, is given, the warn threshold is calculated immediately. The minimum warning deformation (MWD) $\delta\mu$ is decided according to the demands of deformation structures. In some cases, MWD can be decided as two or three standard deviations of the stable time history. Then, the warn delay is obtained on condition that the average warning delay is the shortest, where Type-II error probability occurs. The relationship between L and h can be approximately expressed as [14]

$$\begin{cases} L=\{\exp[-2(\frac{\mu_z h}{\sigma_z^2}+1.166\frac{\mu_z}{\sigma_z})]-1+ \\ \quad 2(\frac{\mu_z h}{\sigma_z^2}+1.166\frac{\mu_z}{\sigma_z})\}/(2\mu_z^2\sigma_z^{-2}),\ \mu_z\ne 0 \\ L=(\frac{h}{\sigma_z}+1.166)^2,\ \mu_z=0 \end{cases} \tag{13}$$

where μ_z and σ_z are easily obtained in Eq. (9), the warning threshold (WT) is given by Eq. (13), which is used for system warning.

To show the relationship among the minimum warning deformation (MWD), the average run length (ARL) and the warning delay (WD) with respect to the warning threshold, we simulate deformation signal with μ_0=0, σ=2, $\delta\mu$=5 and solve the warning threshold (WT) with nonlinear formula (13). The detail is given by Table 1 [18].

Table 1 shows the equivalence between false alarm rate (FAR) and ARL. The warning delay in the simulated deformation signal is different with the magnitude variation of the stochastic noise. For 1.5 and 2 mm steep deformation, FAR would occur once the stochastic noise distribution is not good, because the simulated disaster deformation is less than the MWD. The algorithm can provide effective alarm information when the steep deformation is larger than 5 mm and the warning delay is longer for slowly glowing deformation.

4 Scheme for CUSUM-based warning algorithm

To implement real-time integrity monitoring algorithm of deformation warning, one needs to deal with the noises associated with deformation time history to avoid false alarm, and the warning method should be able to distinguish the errors and real deformation. So, the preprocessing to the original deformation sequence is essential, and KF is employed in this paper, which can also make precise dynamic predictions. The magnitude of the errors in the filtered data is decreased, thus, the error which is lower than MWD will not lead to sustained increase in CUSUM test [19], and then the FAR is decreased.

Table 1 Prediction model parameters and warning delay [18]

Warning parameter			Warning delay (WD)/epoch				
MWD, $\delta\mu$/mm	False alarm rate (ARL)	WT, h	Steep deformation				Slowly growing deformation
			1.5 mm	2 mm	5 mm	>5 mm	Slope 0.1/(mm·s^{-1})
5	0.01(ARL=100)	2.8510	21	2	0	0	16
	0.001(ARL=1000)	5.1351	21	2	0	0	16
	0.0001(ARL=10000)	7.4351	21	2	0	0	16

For an optimal CUSUM test, the minimum WD should be achieved at a specific FAR. It is necessary to realize fast warning after the failure occurs. The FAR is equivalence to ARL and the threshold h can be decided by formula (13) to warn.

On the condition that the minimum monitoring deformation $\delta\mu$ is given, the mean alarm delay $L(\delta\mu)$ can be calculated with the missed rate value. If $L(\delta\mu)$ reaches the users' demands, the algorithm is available. Otherwise, it turns to other warning algorithm. Figure 1 shows the integrity monitoring scheme of CUSUM-based warning algorithm.

The real-time deformation time series obtained using GPS technique is firstly filtered with KF model to acquire the de-noised real deformation signal. Secondly, the CUSUM statistic is computed based on the deformation magnitude at the epoch and the availability of the warning algorithm is decided by threshold h and the warning time delay is computed based on $\delta\mu$, false alarm rate and missed alarm rate. Then, the warning criteria should be judged when the warning algorithm is available. If threshold h is exceeded, the system will warn to remind that something is wrong, otherwise, the system is good and the next deformation observation will be put into the algorithm. Once the warning algorithm is unavailable, some other warning programs must be activated.

5 Experiments and results

5.1 Platform for coal mine shaft deformation simulation

A test platform for coal mine shaft deformation simulation is built. The simulated system is composed of three moving axes (x, y, z). It can move along any axis, and also can simulate plane curve vibration at any angle, or simulate arbitrary deformation of the spatial geometry under the control of computers. The vibration frequency can be both fixed and mixed or random changed. The coal mine shaft deformation can be simulated with a certain program and the real displacements are obtained with the displacement sensor (Fig. 2).

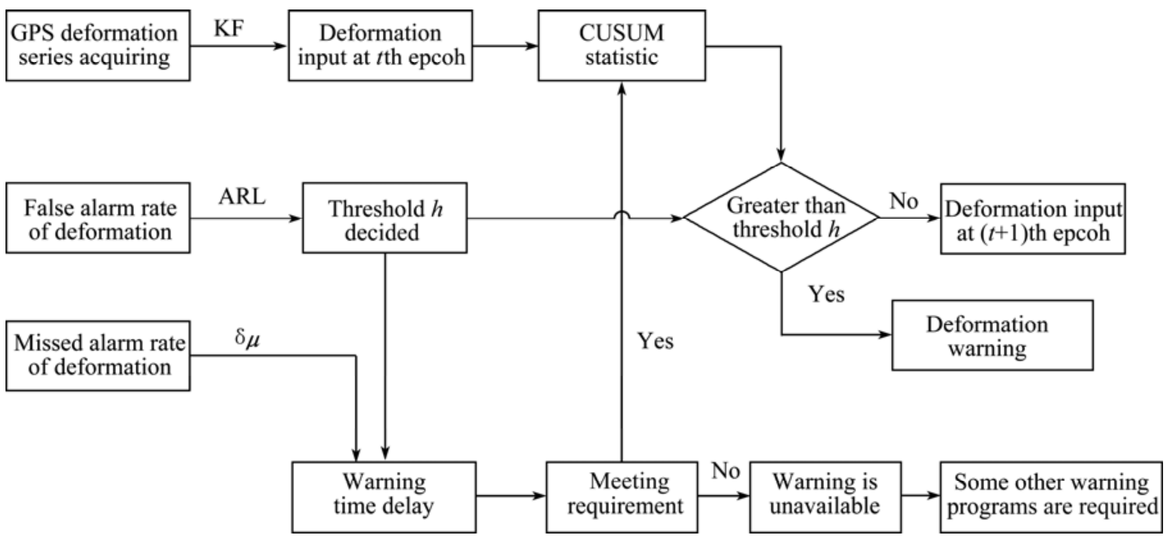

Fig. 1 Scheme for CUSUM-based warning algorithm

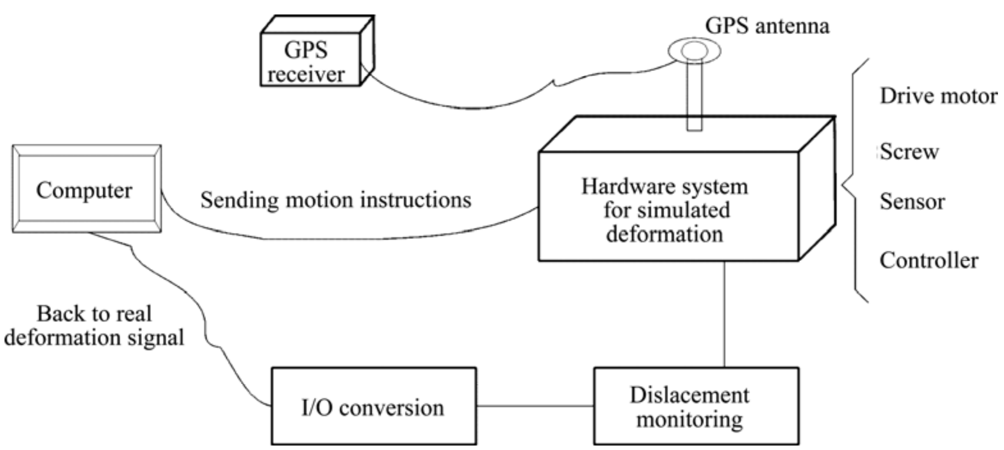

Fig. 2 Scheme of test platform for coal mine shaft deformation simulation

The system is composed of PC communication software and lower position machine system. The system design diagram is shown in Fig. 3. The lower computer is cascade with two single-chips, the smallest single-chip system 1 completes serial communication with the upper computer, the received data are analyzed and transformed to the control signal of the stepper motor, and the pulse and direction signals caused by the timer are input into the stepper motor controller by the driving circuit. Moreover, P0 is connected with the extended memory as bus. P2 supports as bidirectional communication with the smallest single-chip system 2. The smallest system 2 is mainly used to detect the movement whether it exceeds the range of transmission shaft. The two single chips communicate with each other and are triggered by an eternal the external interrupt. Figure 4 shows the developed physical system.

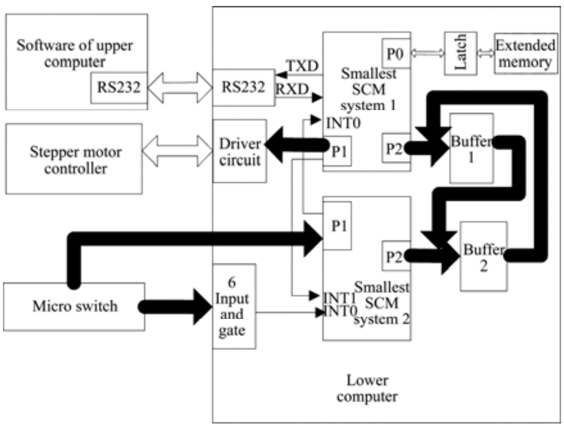

Fig. 3 System design diagram

5.2 Simulated deformation and warning analysis

The experiment was carried out on 19 March 2010, at Wenchang area, China University of Mining and Technology (CUMT). A triaxial simulated equipment of dynamic deformation was used to control the moving trajectory of a Leica GPS receiver (see Fig. 4), then the GPS deformation series was collected and only the height component results were used to analyze for the lower precision in vertical direction. The GPS measurement mean square error in vertical direction was set to 10 mm based on times of test, the minimum alarm deformation was given as 20 mm and the false alarm rate was 0.001 (ARL=1000), and the threshold was h=5.2732. The position results were recorded at a 20 Hz sample rate over a period of 60 s (1200 epochs). The corresponding GPS time series and the KF results over the period are plotted in Fig. 5. Figure 6 shows the filtered deformation signal and the corresponding test statistic variations. Note that the CUSUM test is valid and deformation occurs at the 481st epoch.

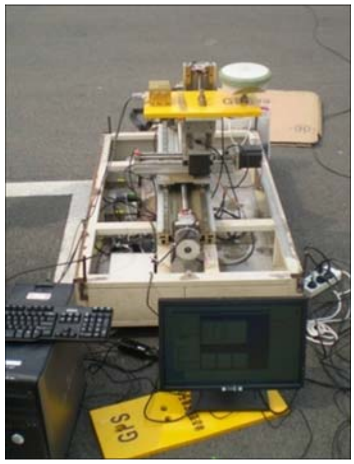

Fig. 4 Physical system for coal mine shaft deformation simulation

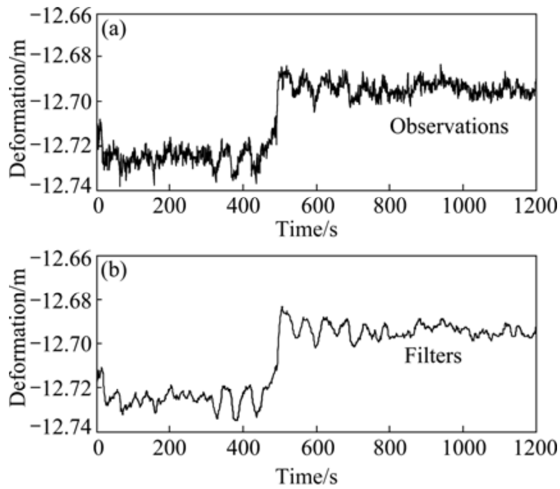

Fig. 5 GPS time series and KF results

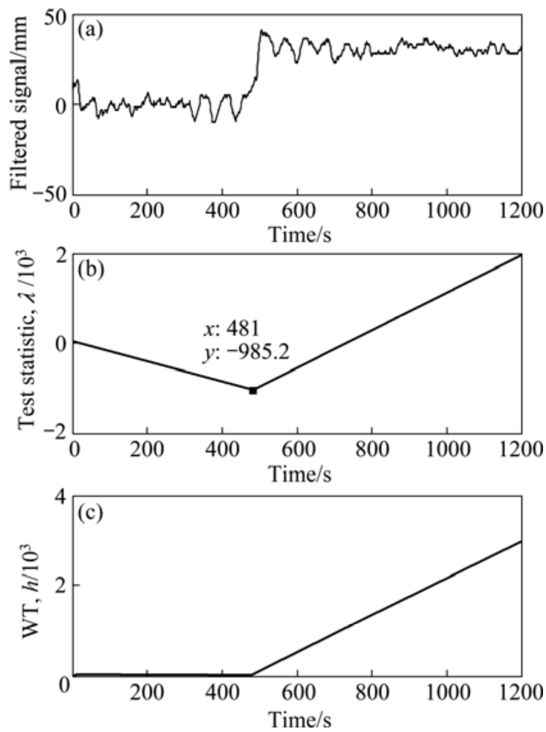

Fig. 6 Test statistic variations with field GPS data

Fig. 7 Setup of experiment

5.3 Field deformation warning analysis

The experiment was carried out on 13, 14 March 2010, at Malan Mine in Shanxi, China. Figure 7 shows the setup of the experiment. Two Leica GPS receivers were used to collect deformation data at 1 s sampling interval. The GPS skyplot in the first day during the measurement is plotted in Fig. 8, and the two consecutive days' deformation sequences are shown in Fig. 9 (1000 samples were used). In this paper, only the height time series was used as a demonstration for the detection of abrupt changes. The corresponding KF model was built to process the height component, and the filtered deformation signal is shown in Fig. 10. We can see an abrupt change occurs at some epoch of the first days' data and slowly growing deformation is contained in the second day's data. After the KF strategy, CUSUM test should be conducted for warning, the CUSUM parameters are chosen as σ=5 mm, the minimum alarm deformation 15 mm and the false alarm rate 0.001 (ARL=1000), and we can get the threshold h=4.9159. The corresponding test statistic results of the two days' time series are shown in Fig. 11. Note that the CUSUM test is valid and deformation occurs at the 705th epoch for the first day and at the 517th epoch for the second day. We should also know that if the minimum alarm deformation is set too large, the warning algorithm may not work (Fig. 12).

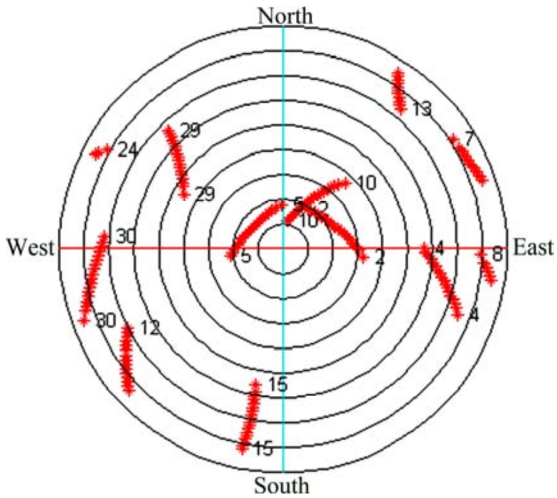

Fig. 8 GPS satellite skyplot during measurement (on 13 March 2010)

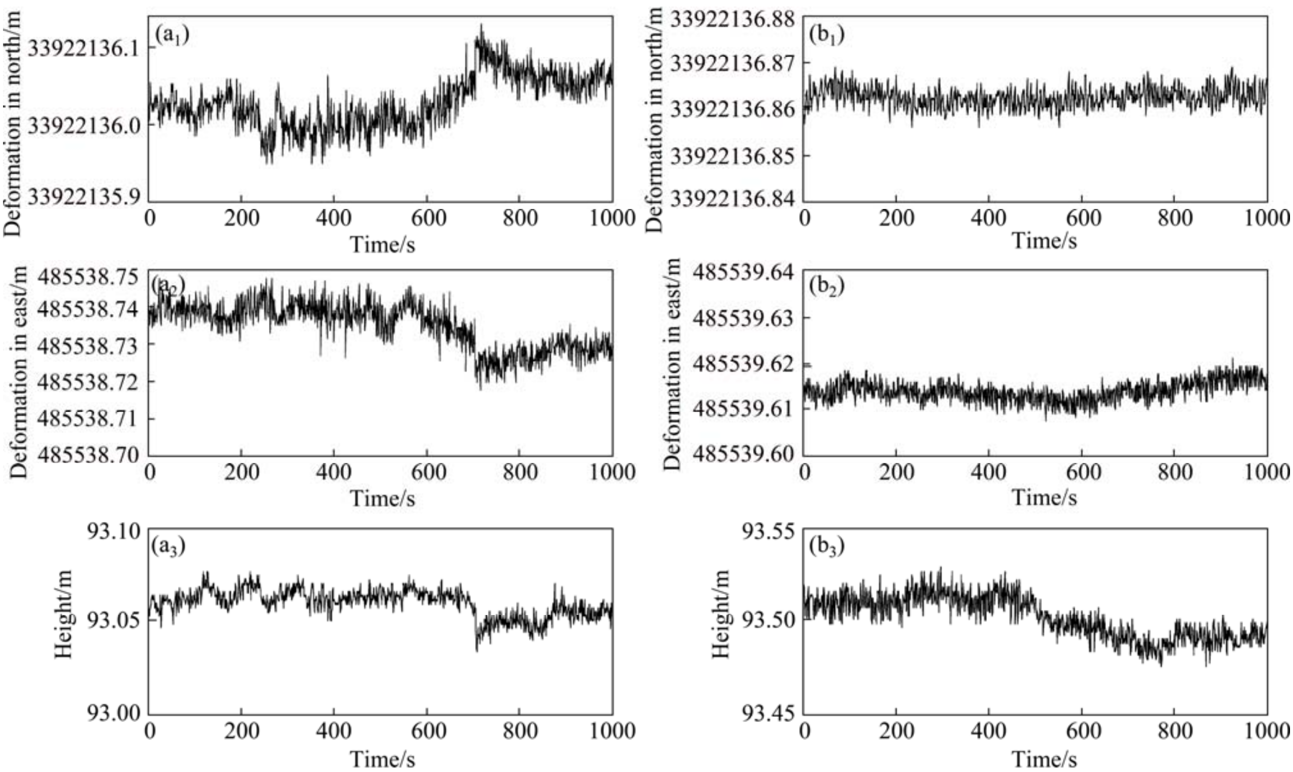

Fig. 9 RTK deformation time series on two consecutive days: (a_1, a_2, a_3) 13 March 2010; (b_1, b_2, b_3) 14 March 2010

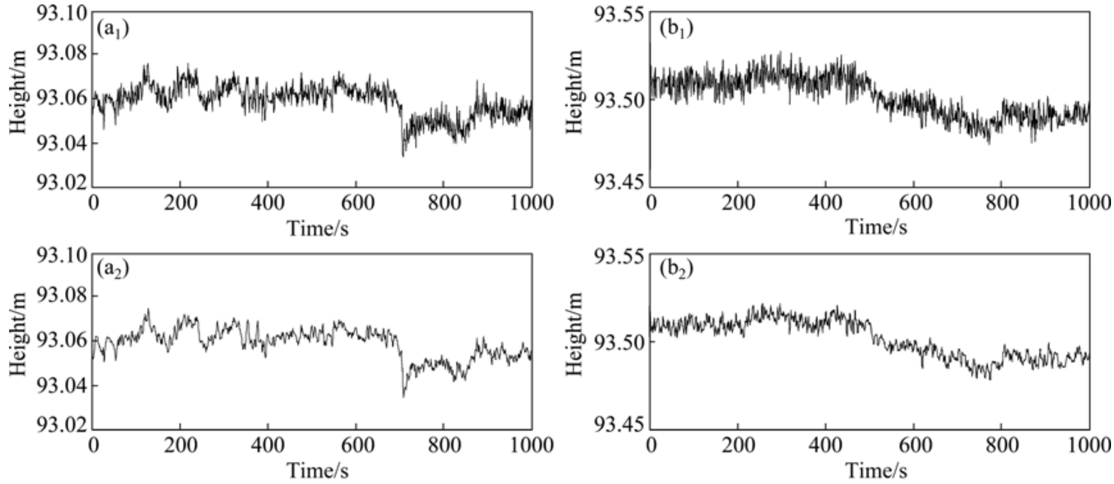

Fig. 10 KF results on two consecutive days: (a_1, a_2) 13 March 2010; (b_1, b_2) 14 March 2010

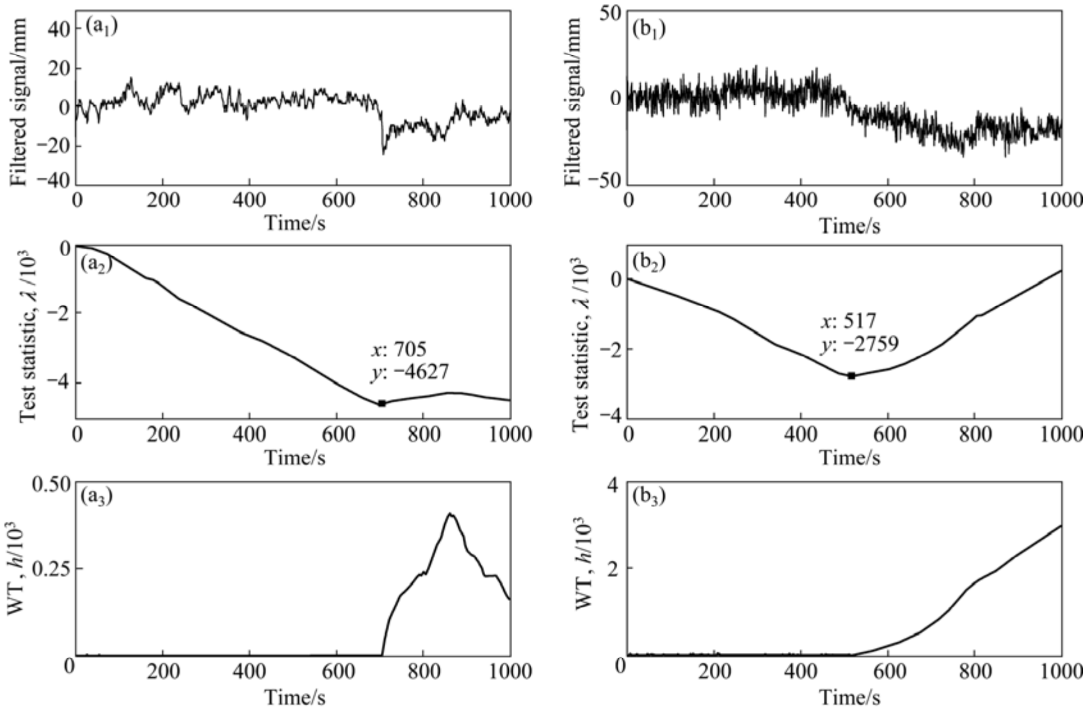

Fig. 11 Test statistic variations on two consecutive days (ARL=1000, $\delta\mu$=15 mm): (a_1, a_2, a_3) 13 March 2010; (b_1, b_2, b_3) 14 March 2010

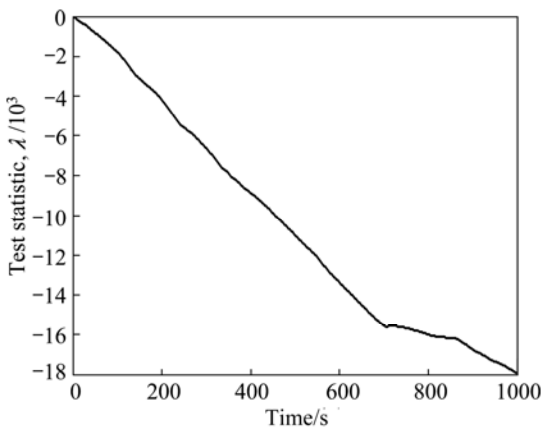

Fig. 12 Test statistic variations based on larger minimum alarm deformation ($\delta\mu$=30 mm)

6 Conclusions

1) The deformation analysis based on Kalman filter model was applied to different deformation time series. Appropriate modeling of Kalman filter can provide precise position time series in real time. The Kalman filter model can improve the reliability of warning and reduce the time delay.

2) The CUSUM-based warning and integrity monitoring algorithm is proposed and the performance of the proposed algorithm is satisfactory. The proposed algorithm can effectively detect the dynamic changes and the deformation epoch for coal mine shaft deformation monitoring with the preset warning threshold.

3) The proposed strategy provides an overall quality control for the establishment of short-term warning theory and will be further tested and researched. The results from this study support the extension of the warning model to other similar deformation fields.

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矿井安全的短期预警及完备性监测算法

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摘　要：提出一种新的矿井安全短期预警及完备性监测模型。通过 Kalman 滤波提取真实 GPS 动态变形信息，并构建双边累积和检验统计量，建立短期预警模型，进而提高预警系统的可靠性。通过分析预警模型的可得性(最小预警变形)、误警率(平均运行长度)及漏警率(预警延迟)与预警参数之间的关系，给出预警参数的选取方法。变形试验平台模拟实验表明，预警模型能够有效用于陡坡变形预警。山西马兰矿矿井实测变形数据研究表明：本预警算法能够有效地探测微小变形及变形发生的时刻，在给定预警参数(最小预警灾害变形为 15 mm，平均运行长度为 1000)的条件下，本算法探测出相邻两天的变形发生时刻分别为第 705 历元(705 s)和 517 历元(517 s)。

关键词：矿井；变形；累积和；短期预警；Kalam 滤波；完备性监测

(Edited by Wei-ping CHEN)