EXTRACTION OF DEFORMATION SIGNALS OF A SLOPE WITH KALMAN FILTERING TECHNIQUE

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Abstract: This paper discusses the methodology to extract deformation signals from the monitoring measurements of a slope with Kalman filtering technique. The first order Markoff process is used as the dynamic model to describe displacement rate of a monitoring point. The method was used to process the measurements of a steep slope at a hydropower station in south-west China. The results show that the accuracy of derived deformation parameters is significantly improved.

1. INTRODUCTION

Landslides are serious geologic disaster generating a great danger to human life, property, and environment. Much effort needs to be made, like regular slope maintenance and stabilization. Understanding of the behaviors of landslides and identification of their possible effects require a good knowledge of surface and subsurface kinematics of the sliding landmasses. Deformation monitoring of landslides can help detect early indications of rapid, catastrophic failures, and enable effective stabilization measures. In the recent years China has been constructing more and more large hydro-power projects in mountainous regions. The construction sites are usually located in deep valleys with potential landslides. Therefore landslide monitoring and analysis are of particular importance in China. Monitoring techniques include traditional survey methods with total stations, or geodetic robots; GPS; and geotechnical instrumentation. To make GPS surveys more affordable a multi-antenna system has been developed (He, et al., 2004) and widely used in a number of landslide monitoring projects. Geotechnical instrumentation can provide accurate deformation information, is easer for automatic and remote data acquisition, and has an important advantage of monitoring subsurface movements. But it can gauge only local deformations. In contrast, the geodetic methods can provide global deformations of a landslide. Each monitoring method/technique has its own merits and limitations, and an integration of different techniques and sensors is a trend. As part of landslide monitoring different approaches for analysis of monitoring data have been developed. In this study a deformation analysis procedure with a kinematic deformation model is discussed based on Kalman filtering technique. The paper first discusses kinematic deformation model used in Kalman filtering, then an example application is presented.

2. ANALYSIS OF LANDSLIDE MOVEMENTS WITH KALMAN FILTERING TECHNIQUE

Kalman filtering is known as a sequential least squares adjustment technique. It combines the information on object behavior and measurement quantities. The deformation of an object is predicted with a so-called dynamic model (also called transition function) and then the predicted deformation or deformation parameters and their variances and co-variances are used as the a priori information on unknown parameters in the least squares adjustment when new measurements of deformation become available. Therefore the Kalman filtering involves two steps: prediction and updating. Two critical issues in the application of Kalman filtering technique are building of a dynamic model for prediction, and establishing of weighting scheme of model errors with respect to measurement errors.

(1) Kinematic deformation model

There are several ways to model the kinametic deformation of a landslide. Acar et al. (2008), for instance, used a constant acceleration of movement to establish the dynamic model. This study, based on our experience in processing the monitoring data of a number of landslides, employs the first order Markov process to model the velocity of movement. Let the displacement of a point i at epoch t be $s_i(t)$ and the velocity be $v_i(t)$. Then

$$\begin{cases} \dot{s}_i(t) = v_i(t) \\ \dot{v}_i(t) = -\frac{1}{\tau} v_i(t) + w(t) \end{cases} \tag{1}$$

where τ is a selected constant time interval, and w(t) is white noise. Let the state vector X(t) be

$$X(t) = \begin{bmatrix} s_i^x(t) & s_i^y(t) & s_i^z(t) & v_i^x(t) & v_i^y(t) & v_i^z(t) \end{bmatrix}^T \tag{2}$$

where x, y, and z stand for the quantities in the respective directions (toward north, east and up), and the model errors are

$$W(t) = \begin{bmatrix} w_x & w_y & w_z \end{bmatrix}^T$$

Equation (1) can be expressed as

$$\dot{X}(t) = \begin{bmatrix} 0_{3\times3} & I_{3\times3} \\ 0_{3\times3} & -\frac{1}{\tau} I_{3\times3} \end{bmatrix} X(t) + \begin{bmatrix} 0_{3\times3} \\ I_{3\times3} \end{bmatrix} W(t) \tag{3}$$

Using equation (3) the dynamic model of the Kalman filter is expressed in a discrete form as

$$X_k = \Phi_{k,k-1} X_{k-1} + \Gamma_{k,k-1} W_{(k-1)} \tag{4}$$

where

$$\Phi_{k,k-1} = \begin{bmatrix} I_{3\times3} & \Delta t_k I_{3\times3} \\ 0_{3\times3} & (1-\frac{1}{\tau}\Delta t_k) I_{3\times3} \end{bmatrix} \quad (5)$$

$$\Gamma_{k,k-1} = \begin{bmatrix} 0_{3\times3} \\ \Delta t_k I_{3\times3} \end{bmatrix} \quad (6)$$

(2) Observation equations

The observed quantities are 3D displacements of point i at epoch t. They are functions of the state vector as

$$\begin{bmatrix} s_i^x(t) \\ s_i^y(t) \\ s_i^z(t) \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} s_i^x(t) \\ s_i^y(t) \\ s_i^z(t) \\ v_i^x(t) \\ v_i^y(t) \\ v_i^z(t) \end{bmatrix} + \begin{bmatrix} V_x \\ V_y \\ V_z \end{bmatrix} \quad (7)$$

where $V_{x,y,z}$ are residuals (or observation errors). Let

$$Z(t) = \begin{bmatrix} s_i^x(t) & s_i^y(t) & s_i^z(t) \end{bmatrix}^T$$

Then observation equations read

$$Z(k) = HX(k) + V(k) \quad (8)$$

with

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix}$$

(3) Solution

Equation (4) is used to predict the state vector at epoch k based on the state vector at epoch (k-1), i.e.,

$$X_{k,k-1} = \Phi_{k,k-1}\hat{X}_{k-1} \quad (9)$$

The variance-covariance (V-C) matrix of the predicted state vector is

$$C_{X_{k,k-1}} = \Phi_{k,k-1} C_{\hat{X}_{k-1}} \Phi_{k,k-1}^T + \Gamma_{k,k-1} C_W \Gamma_{k,k-1}^T \quad (10)$$

where $C_{\hat{X}_{k-1}}$ is the V-C matrix of the state vector at epoch (k-1) and C_W is the system noise or model error. It is most difficult to estimate. Inaccurate estimation will result in unreliable estimation of the state vector at epoch k. One way to evaluate the appropriateness of C_W is to compute the residuals using the predicted state vector:

$$V(k,k-1) = Z(k) - HX_{k,k-1} \tag{11}$$

If V(k, k-1) is significantly larger compared with the system noise, it suggests the C_W is too small and must be adjusted. The other way is to modify C_W by multiplying a scalar α, i.e., system noise is αC_W and use the variance-covariance component estimation technique (Chen et al., 1990) to estimate α in the updating adjustment.

Updating procedure is to combine observation equations (8) with the predicted state vector (equation (9)). The estimated state vector at epoch k reads

$$\begin{aligned} \hat{X}_k &= X_{k,k-1} - G_k V(k,k-1) \\ G_k &= C_{X_{k,k-1}} H^T (H C_{X_{k,k-1}} H^T + C_k)^{-1} \\ C_{\hat{X}_k} &= C_{X_{k,k-1}} - G_k H C_{X_{k,k-1}} \end{aligned} \tag{12}$$

where C_k is the V-C matrix of observations, and G_k called gain matrix.

3. AN EXAMPLE APPLICATION

3.1. Test Area

Xiaowan hydropower station on the Lanchnag River in Yunnan province, China, consists of a double-curvature arch dam, 292 meter high. Construction began in January 2002 and is expected to complete by the end of 2010. Steep slopes in the river valley, typically with slope 40^0, post serious problems for the construction engineers. Heavy rain or further rock excavation could cause slopes near arch dam to slide. To reduce landslide risk, engineers have employed several conventional techniques, traditional surveying equipment, and specialized geotechnical instruments to monitor the stability of the high-risk slopes. They also used multi-antenna GPS system as a monitoring tool for high-risk slopes. Usually several monitoring points must be distributed on a slope to fully understand the stability and ongoing deformation that could cause slope failure. Typically it required 16 points to be monitored for a high-risk slope of 300 by 500 meters.

The GPS monitoring data of a slope there are used in this study. The slope has the sliding landmasses of about 35m in depth, 700m long and 190m wide. It may slide due to the construction activities nearby. Therefore monitoring of its stability is crucial to the dam construction. The multi-antenna GPS system has been operated for over 3 years, and lots of data were collected.

3.2. Data Analysis

The demonstrated example includes 120 set of data observed from 25 July to 22 September 2005 for two points 1II-TP11 and LS-TP-04. The results are presented in Figures 1 to 4. Figure 1 shows the 3D displacements for Point 1II-TP11 and Figure 2 is its velocity of movement; Figure 3 and 4 are for point LS-TP-04. It can be seen from the figures that the displacements of a point tend to a stable value after some variation in the initial period and the rate tends zero. This suggests the points are stable.

To assess the efficiency of the methodology we selected 30-day observations of 14 monitoring points. The statistics for sample points is given in Table 1. The results indicate that the accuracy is better compared with the original observations. The observed displaycements have standard deviation of 2.0-3.0 mm in horizontal directions, and 4.0-7.0mm in vertical direction. After filtering the horizontal errors reduced to about 1.3mm and vertical error to 3.5mm.

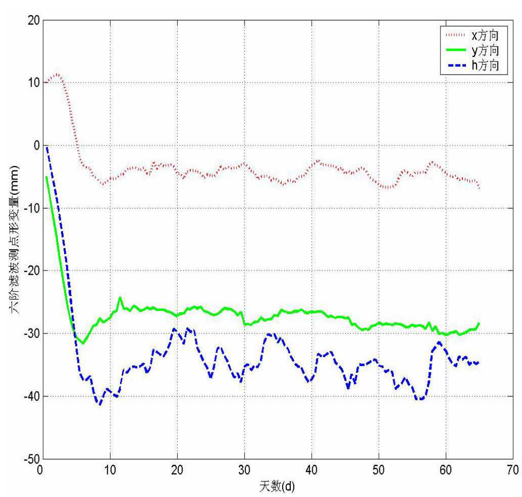

Figure 1 the displacement of point 1II-TP-11

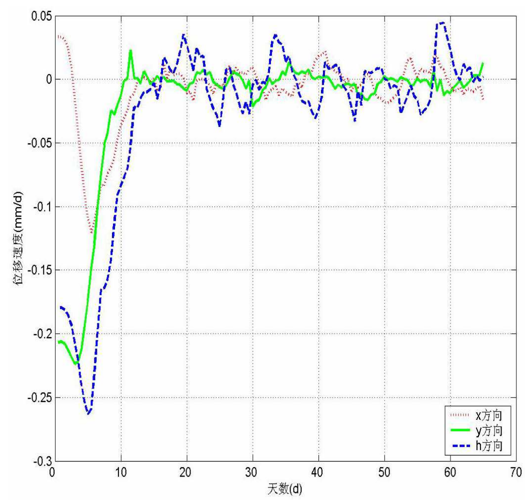

Figure 2 displacement rate of point 1II-TP-11

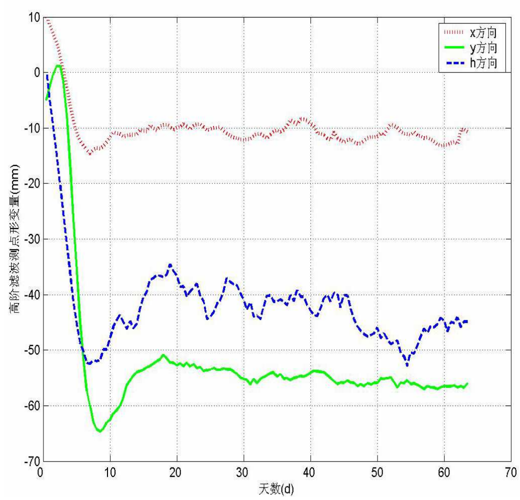

Figure 3 the displacement of point LS-TP-04

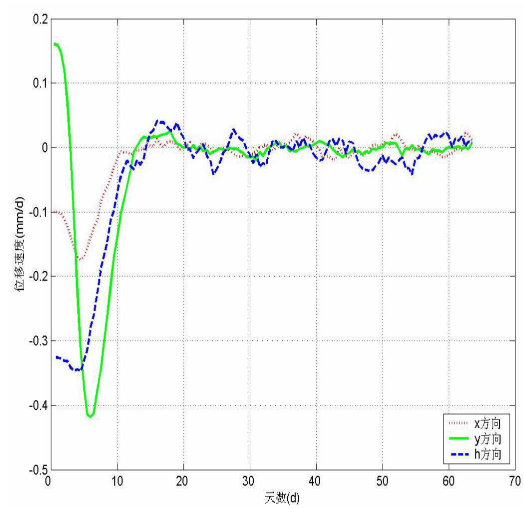

Figure 4 displacement rate of point LS-TP-04

Sample pts	direction	Obs error	Predicted error	Error after filtering
1II-TP-11	x	1.93	1.27	1.14
	y	1.78	1.27	0.64
	z	5.98	2.94	2.67
1II-TP-17	x	2.51	1.11	1.08
	y	1.72	1.19	1.02
	z	6.51	2.85	2.81
LS-TP-04	x	2.28	1.20	1.07
	y	1.57	0.63	0.58
	z	5.46	2.39	2.26
LS-TP-09	x	1.32	0.93	0.86
	y	1.68	0.96	0.97
	z	4.47	1.74	1.53

Table 1 - Error statistics (in mm)

4. CONCLUDING REMARKS

In this paper the Kalman filter is employed to study the movements of landslides. The state vector includes the 3D displacements and velocities of a monitoring point; and the velocities at any epoch are assumed to follow the first order markoff process, based on which the dynamic model is established. The approach was tested with the monitoring data in a slope near Xiaowan hydropower station on the Lanchnag River in Yunnan province, China. The results indicated the approach works well for the analysis of landslide deformations.

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