Fast monitoring and real time predication method for early warning system in Baige landslide, Tibet, China

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Abstract: Landslide early warning system (EWS) have been widely used to minimize disaster losses. In this paper, a fast monitoring and real time predication method is proposed to build the Landslide EWS for specific landslides. The fast monitoring network in this system uses ad-hoc technology to build rapid on-site monitoring network consist of Beidou terminals, which is a technology similar to GPS, and fracture monitors. The real time predication method based on the combination of kalman filtering(KF), fast fourier transform(FFT) and support vector machine(SVM),short for KF-FFT-SVM, is conducted to make a real time precursor early warning short time before the occurrence of the landslide. The KF-FFT-SVM model working here is established by analysing the precursor landslide character in deformation data got by the Beidou terminals. The deformation data can be considered as the mechanical vibration of specific landslides, and the KF-FFT-SVM model is trained to predicate the occurrence of landslide by the deformation data. The fast monitoring technique improves the robustness of on-site monitoring system, and the real time predication method provides an effective early warning method for specific landslides. It is applied in Baige landslide, Tibet, China, monitoring and results show that the KF-FFT-SVM model can predication the occurrence of landslide with high accuracy. It will make the early warning work for specific landslides more effective if numerous continuous monitored precursor landslide deformation data are used to train the model well.

1 Introduction

Landslide hazard is the most common geological hazard in natural world. It is also direct affected by human engineering activities. China is one of the countries that suffered most from landslide disasters in the world(Huang, 2007). Especially after the Ms 8.0 Wenchuan earthquake in May 12, 2008, tens of thousands of landslides over a broad area in west China were triggered, some of which buried large sections of the towns and dammed the rivers(Dai et al., 2011). So the researches on reducing property damages and casualties have always been an urgent problem, and the EWSs which have already been working in many place of the world are an effective way for landslide early warning(Bach et al., 2012; Glade and Nadim, 2014; Piciullo et al., 2017, 2018; Stähli et al., 2015).

According to the definition of the United Nations International Strategy for Disaster Reduction (UNISDR 2009), an EWS is defined as “the set of capacities needed to generate and disseminate timely and meaningful warning information to enable individuals, communities and organizations threatened by a hazard to prepare and to act appropriately and in sufficient time to reduce the possibility of harm or loss.” Refer to the above definitions, efficient landslide EWSs should comprise four main sets of actions(DiBiago and Kjekstad, 2007): (1)Monitoring activities, i.e. data acquisition, transmission and maintenance of the instruments;(2)Analysis and modelling of the phenomenon;(3)Warning, i.e. the dissemination of simple and understandable information to the exposed elements;(4)Effective response of the elements exposed to risk and risk’s knowledge. In this study we focus on the monitoring and warning model of landslide EWSs.

Landslide EWSs can be divided into regional landslide EWSs and single landslide EWSs from scale range. In the regional landslide EWSs, the warning threshold is determined by statistic method. These systems are applicable for the rainfall induced shallow landslides, and the classification early warning is given according the preset rainfall intensity–duration threshold, also considering the soil moisture(Baum and Godt, 2010; Calvello et al., 2015; Gariano et al., 2015, 2016; Hong and Adler, 2007; Rosi et al., 2015).

For single landslide EWSs, a successful EWS has the ability to measure and identify the significant indicators, called precursors, which precede a landslide catastrophic failure(Barla and Antolini, 2016). The precursor characters could be discovered from the mechanical properties of the landslide which are measured by instruments. For example, inclinometer for tilt(Dikshit et al., 2018; Lollino et al., 2002), fiber Bragg grating for fissures(Zhu et al., 2017), Ground-Based Synthetic-Aperture Radar, LiDAR, total station, GPS and photogrammetric techniques for deformations(Atzeni et al., 2015; Barla and Antolini, 2016; Jaboyedoff et al., 2012; Malet et al., 2002; Tarchi et al., 2003), geoelectrical monitor for soil moisture(Supper et al., 2014), wire extensometer for rock fracture(Intrieri et al., 2012), etc. These precursor characters are used to make early warning with respective model or integrated models(Thiebes et al., 2014; Yin et al., 2010).

It is obviously that the warning model should be built according to the mechanism of the instability of a landslide. And the predication accuracy of an early warning model relies on the high quality real-time monitoring data. In practice, the implement of on-site monitoring network always takes a long time as the design of the monitoring system is complex. Meanwhile, the on-site monitoring network is easy to broken down in the wild, which means the monitoring part of the most existing landslide EWSs are less robustness.(Intrieri et al., 2013).

In this paper, fast monitoring and deformation precursor predication method is proposed to improve the Landslide EWS. The ad-hoc network technology is used to ensure the robustness of the monitoring part the early warning system. In order to build an on-site monitoring network quickly, especially after the first failure of a landslide, only Beidou terminal and fracture monitor are used to build the monitoring stations. The early warning part is based on KM-FFT-SVM model to make a real time predication. The fast monitoring system was applied after the Baige landslide first damming event, Tibet, and, successfully, got the critical slip data of the surface moving by Beidou terminal based on China’s Beidou Navigation System. Then we use the critical slip data to train the KM-FFT-SVM model and the following damming event is predicted successfully with the trained model. Practice shows the fast monitoring and real time predication method are of general significance.

2 Fast monitoring system

2.1 Traditional monitor system

The structure of a traditional landslide monitoring network is shown in Figure 1. All kinds of monitoring sensors are connected with data acquisition terminal (DTU) through Modbus protocol or SDI-12 protocol. DTU, communication module (GPRS/3G/4G) and power supply system constitute a remote measurement unit (RTU). The measuring data are sent to the mobile communication network through the communication module and transmitted to the control center through the public network. In this way, the system robustness is poor, because if the communication module of one monitoring point breaks down, all sensor data under this monitoring point will not be collected, which means partial paralysis of the monitor system. Therefore, a more flexible and stable networking structure is needed to improve the robustness of the monitoring system.

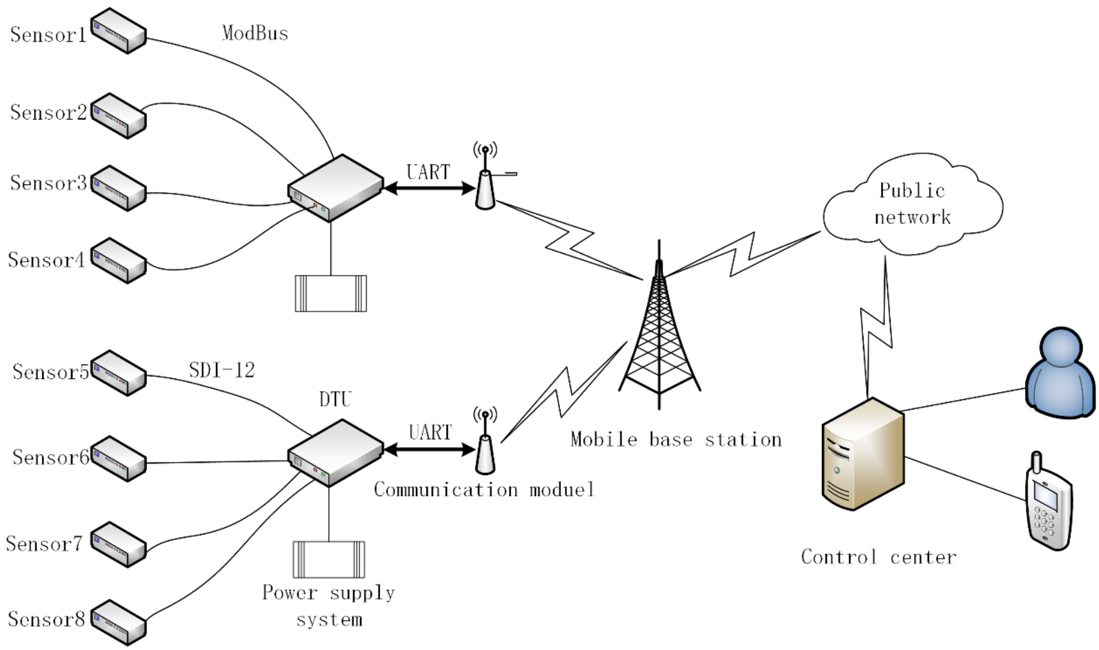

Figure 1: Traditional landslide monitoring system

2.2 Ad-hoc network monitoring system

The adaptive landslide monitoring network is based on ad-hoc network. Ad-hoc network is more secure, robust, stable and reliable comparing with traditional bus and star network by using adaptive technology. Figure 2 is the typical structure of adaptive landslide monitoring network. In here, four stations are listed and it can be expanded if more stations are needed in practical application. Each station is composed of several sensors, a data acquisition instrument and an ad-hoc router. Each ad-hoc router has the communication module of GPRS/3G/4G. At the same time, each ad-hoc router forms a local ad-hoc network through LoRa technology. The ad-hoc router acts as an AP (Access Point) node, which is responsible for the access of the external network. At the same time, the ad-hoc routers can also communicate with each other by multi-hops. When one node breaks down, the network will find other paths to bypass this node through routing algorithm, which improves the network's robustness. The adaptive landslide monitoring network has three working modes. One is Normal mode, as is shown in figure 3(a); Another is Communication fault mode, as is shown in figure 3(b). In this mode, the GPRS/3G/4G communication modules in some of the ad-hoc routers cannot work, so the system finds the new routing path to send the data out; The third is Beidou satellite communication mode, as is shown in figure 3(c). This mode means the GPRS/3G/4G communication modules in all of the ad-hoc routers cannot work, so the beidou satellite communication system will be started. With the advantage mentioned above, the ad-hoc network landslide monitoring system could be built immediately with high robustness, especially in the place where there are no mobile signals or the signals is weak.

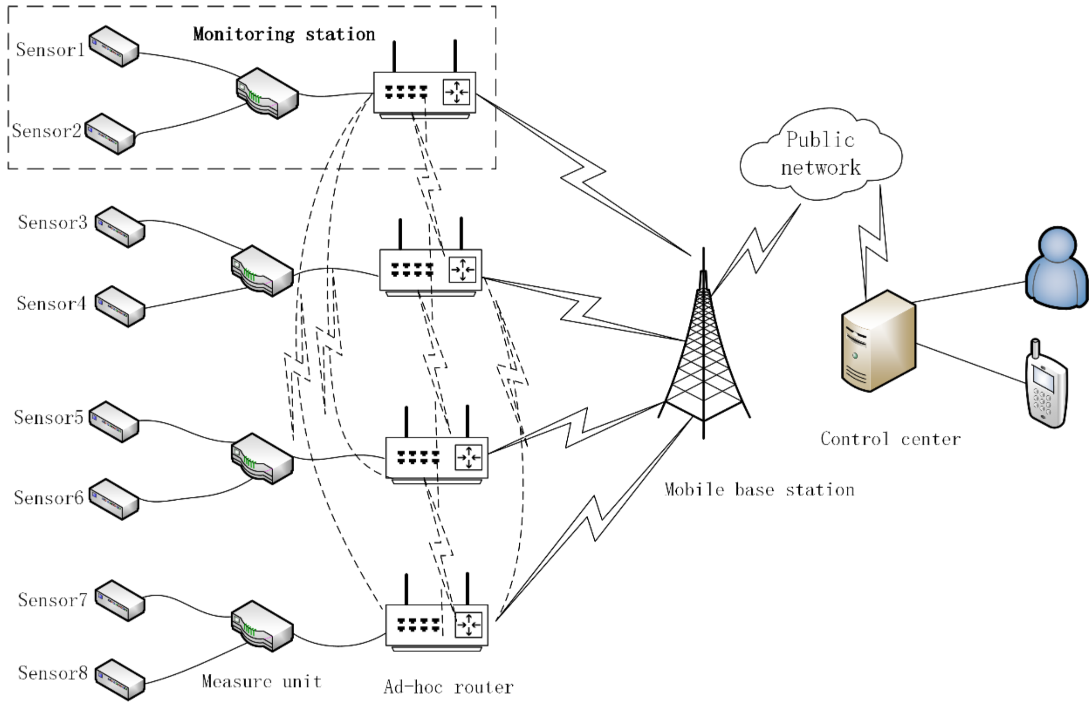

Figure 2: Ad-hoc network monitoring system

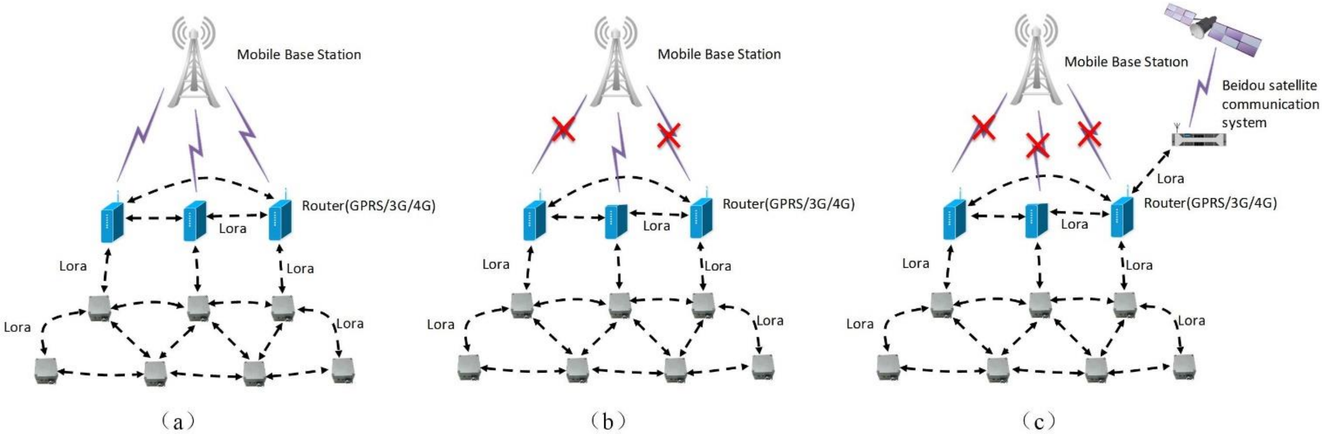

Figure 3: Adaptive landslide monitoring network working mode. Normal mode (a), Communication fault mode (b), Beidou satellite communication mode (c).

2.3 Application of the fast monitoring system

In the early morning of October 11, 2018, a large-scale high-level landslide occurred on the Tibetan Bank of Jinsha River at the junction of Baige Village, Boro Township, Jiangda County, Tibet Autonomous Region, and Zeba Village, Ronggai Township, Baiyu County, Sichuan Province, which blocked the main stream of Jinsha River and formed a barrier lake. Then, on the late day of November 3, second landslide occurred and blocked the Jinsha River again. The barrier lake formed by the twice landslides is a great threaten to the people live in the lower reaches of Jinsha River. The location of the landslide is shown in figure 4.The mountain body near the Baige landslide is made of metamorphic rock. The rock in the upper part is soft, while the lower part is hard. The weak fractured rock mass affected by tectonics deforms under the action of long-term gravity and eventually loses its stability. The historical remote sensing image shows that the rocks in Baige landslide area has undergone deformation for at least 50 years, and the surface displacement in some areas is close to 50 m. There are approximate $2.2\times10^7 m^3$ rock and soil fall into the Jinsha River and form a dam river in the first landslide. The length of the dam along the valley is about 1100 m, and the width of the dam is about 500 m in the vertical direction. The maximum height of the dam over the original river surface is about 85 m, and the average thickness is 40 m. The second landslide occurred at the back edge of the first landslide. The total volume of the rock fell down is about 8.5×10^6 m^3. The unstable rock mass scrapes the broken rock mass along the way, forming debris flow, and blocking up the Jinsha River again. The weir dam is 50m higher than the one formed by the first landslide, the volume of accumulation rock is $9.3\times10^6 m^3$(Qiang et al., 2018).

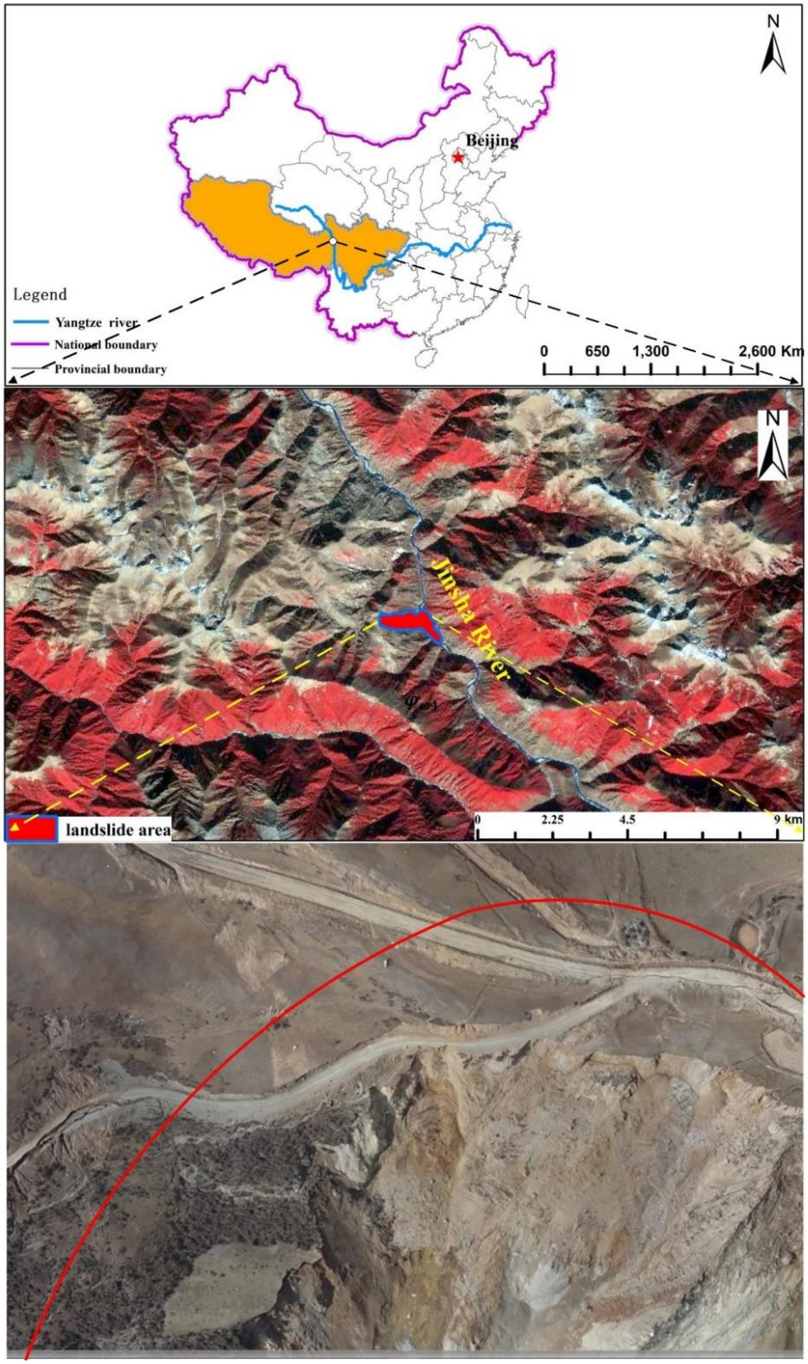

Figure 4: Location of Baige landslide.

Baige landslide occurred suddenly, and there are no monitor device working there before. While the monitoring system need to be built immediately to ensure the safety of the emergency rescue works for dredging Barrier Lake. As there are no mobile signal there, the fast monitoring system is applied there. We use surface displacement monitoring equipment and fracture monitoring equipment to build the fast monitor system, as shown in Figure 5. Figure 5(a) show the Beidou receiver which is the surface displacement monitoring equipment. Figure 5(b) show the fracture monitor which is the fracture monitoring equipment. Both of them use solar panels as an option for energy supply. The locations of these monitor equipment are showed in figure 6. BD1, BD2, BD3 and BD4 represent Beidou receiver, while FM1, FM2, FM3, and FM4 represent fracture monitor. The sensors are located nearby the back edge fault scarp to make sure to get the real deformation data of the landslide.

(a) Beidou receiver (b) Fracture monitor

Figure 5: Monitor device on the landslide.

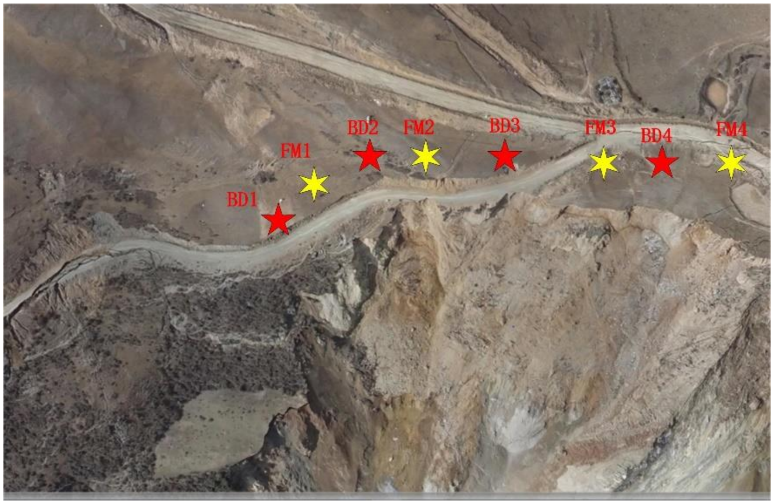

Figure 6: Locations of the equipment on the landslide

3 KF-FFT-SVM model

3.1 Kalman filtering

Kalman filtering (KF) is a linear recursive filtering method based on probability theory and mathematical statistics. It is based on limited data and according to the principle of linear unbiased minimum variance estimation. This method does not need to store the past observation data. When the new data is generated, the best estimation of the current data can be calculated by using the state transition equation of the signal itself and the recursive formula based on the estimated value of the previous moment and the observed value of the present moment. Kalman filter was put forward by R.E. Kalman in 1960. He introduced the concept of state space into the filtering theory. With the help of the state transition equation of the system, a recursive method was adopted to estimate the new states and observations according to the estimated values at the previous moment and the observed values at the present moment.

Given a discrete time system, and we have $X_1, X_2, X_3, \cdots, \ X_k$ as the system state vectors at kT_s , where $X_k \in R^n$, T_s is the measuring interval. Define the system control input U_k, the incentive noise W_k . Then, the stochastic difference equation of system state is describe in equation 1.

$$X_k = AX_{k-1} + BU_k + W_k. \tag{1}$$

Define the observation variable $Z_k \in R^n$, observation noise V_k, we get the observation formula:

$$Z_k = HX_k + V_k. \tag{2}$$

A, *B*, *H* is state transition matrix, W_k, V_k are independent normal distribution white noise:

$$W_k \sim N(0, Q) \tag{3}$$

$$V_k \sim N(0, R) \tag{4}$$

In the discrete system state estimating, the formula (1) is used to give the value of $\hat{X}_{j|k}$, which is the best estimating value of X_j in time jT_s . So there are three situation in the use of formula (1):

a. When *j*=*k*, $\hat{X}_{j|k}$ is the optimum filtering of X_k;

b. When *j*>*k*, $\hat{X}_{j|k}$ is the optimum predicting of X_k;

c. When *j*<*k*, $\hat{X}_{j|k}$ is the optimum smoothing of X_k;

The solution of kalman filtering can describe as time update process and state update process. Time update process:

$$\hat{X}_{k|k-1} = A\hat{X}_{k-1|k-1} + BU_{k-1} \tag{5}$$

$$P_{k|k-1} = AP_{k-1|k-1}A^T + Q \tag{6}$$

Where *P* is error estimating matrix:

$$E_k = X_k - \hat{X}_k \tag{7}$$

$$P_k = E(E_k E_k^T) \tag{8}$$

State update process:

$$K_k = P_{k|k-1}H^T(HP_{k|k-1}H^T + R)^{-1} \tag{9}$$

$$\hat{X}_{k|k} = \hat{X}_{k|k-1} + K_k(Z_k - H\hat{X}_{k|k-1}) \tag{10}$$

$$P_{k|k} = (I - K_k H)P_{k|k-1} \tag{11}$$

3.2 Fast fourier transform

Fast Fourier transform (FFT) is a highly efficient algorithm of Discrete Fourier Transform (DFT).Given finite length sequence x(n), length N and its DFT is described as:

$$\mathrm{X(k)} = \sum_{\mathrm{x=0}}^{\mathrm{N-1}} \mathrm{x(n)W_N^{nk}} \tag{12}$$

FFT uses the symmetry, periodicity and reducibility of W_N^{nk} in formula (12), i.e. (13) ~ (15), to decompose a large point DFT into a combination of several small point DFTs.

$$\mathrm{(W_N^{nk})^* = W_N^{-nk} = W_N^{(N-n)k} = W_N^{n(N-k)}} \tag{13}$$

$$\mathrm{W_N^{nk} = W_N^{(N+n)k} = W_N^{n(N-k)}} \tag{14}$$

$$\mathrm{W_N^{nk} = W_{mN}^{mnk} = W_{N/m}^{nk/m}} \tag{15}$$

Following is a time-based 2-FFT algorithm. Given the $N=2^M$, then divide x (n) into 2 groups. When n is even numbers, let n=2r. When n is odd numbers, let n=2r+1. Let $x(2r)=x_1(r)$, $X_1(k)=DFT[x_1(r)]$, $x(2r+1)=x_2(r)$, $X_2(k)=DFT[x_2(r)]$, where r=0,1,…,N-1. Then formula (12) can be describe as:

$$\mathrm{X(k) = X_1(k) + W_N^k X_2(k)} \tag{16}$$

$$\mathrm{X(k + N/2) = X_1(k) + W_N^k X_2(k)} \tag{17}$$

It can be calculated that an N-point FFT operation needs NlogN complex multiplication and NlogN complex addition, which greatly improves the operation efficiency of DFT.

3.3 Support Vector Machine

Support Vector Machine (SVM) is a statistical Learning Method for Constructing the Optimal Hyperplane based on the principle of structural risk minimization. It maps input vectors into high-dimensional feature space by non-linear transformation. Then find the optimal classification hyperplane in high-dimensional feature space, which separates the two types of data points as many as possible, and maximize classification interval at the same time. Suppose a training sequence$\{x_i, y_i\}$; i=1,2,…,l; $x_i \in R^{\boldsymbol{n}}$, $y_{\boldsymbol{i}} \in \{-1, +1\}$; l is the number of samples, n is the dimension of x_i. In the case of linear reparable, a classification hyperplane $\boldsymbol{w}x + \mathrm{b} = 0$ can be found to separate 2 samples completely. For nonlinearity situation, it should be mapping from the low dimension feature space to a high dimension feature space by a nonlinear mapping function $\boldsymbol{\Phi}(x)$. Then the classification hyperplane can be expressed as $\boldsymbol{w\Phi}(x) + \mathrm{b} = 0$. Where $\boldsymbol{w}$, b is the variable to be determined. Find the classification hyperplane equivalence maximize $2/\|\boldsymbol{w}\|$. This problem can be solve by Lagrange multiplier method：

$$\begin{cases} \min \dfrac{\|\boldsymbol{w}\|^2}{2} + C\sum_{i=1}^{l} \xi_i , \\ s.t. \;\; y_i(\boldsymbol{w} \cdot x_i + b) \geq 1 - \xi_i, \\ \xi_i \geq 0, i = 1,2 \ldots, l. \end{cases} \tag{18}$$

Where ξ_i is relaxation factor, C is penalty factor. Its duel problem is given by KKT (Karush-Kuhn-Tucher):

$$\begin{cases} \max \sum_{i=1}^{l} \alpha_i - \dfrac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l} \alpha_i \alpha_j \, y_i y_j \boldsymbol{\varphi}(x_i) \cdot \boldsymbol{\varphi}(x_j) \\ s.t. \qquad 0 \leq \alpha_i \leq C, \sum_{i=1}^{l} \alpha_i \, y_i = 0. \end{cases} \tag{19}$$

Solve the problem by SMO algorithm, we can get the classification function:

$$f(x) = \mathrm{sign}\left\{\sum_{i=1}^{l} \alpha_i y_i [\boldsymbol{\Phi}(x_i) \cdot \boldsymbol{\Phi}(x_i)] + b\right\} \tag{20}$$

Kernel function $K(x_i, x_i) = \boldsymbol{\Phi}(x_i) \cdot \boldsymbol{\Phi}(x_i)$ can be found, which simplified the function operation to inner product of vectors. The commonly used kernels are linear kernel function, polynomials kernel function, radial basis (Gauss) function and sigmoid kernel function.

3.4 Proposed KF-FFT-SVM model

Landslide can be treat as a multi-dimensional nonlinear dynamic system influenced by various factors(Eid, 2014). Many researches predicate the deformation of landslide based on these factors. In this paper, we don't have too many prior knowledge about the Baige landslide. The only quantitative data we got is are deformations measured in finite time. So in the KF-FFT-SVM landslide early warning model, firstly, we used the finite deformation data sequence S_k got by Beidou receivers to build the input of kalman filtering predication model $X_k = (S_k, V_k, A_k)$, where V_k and A_k are the velocity and acceleration of S_k , respectively. After the first step we got the predication and filtering result ofA_n. Formula (21) is the precision evaluation of kalman filtering predication model. Secondly, we use FFT to analysis the spectrum characteristics of the deformation acceleration sequence A_n nearby the occurring time of landslide, and find the precursor character of the Baige landslide 'Step k ' which represents the precursor frequency character of A_n. Finally, we use A_n form the training data and testing data according to the precursor character 'Step k 'and label them. Then the SVM model is trained with the training data and the trained SVM model will be used to make predication by a newA_k to find out if the warning is made at that time. The predication result B_n is a vector with the same dimension of A_k and its value is either '0'or '1'. '0' represents that there is no warning while '1' represent that there is a warning. The precision of classification result is given as formula (22). The whole process of KF-FFT-SVM landslide early warning model is showed in figure 7.

$$\mathrm{RMS} = \frac{1}{M}\sqrt{\sum_{\mathrm{i}=1}^{\mathrm{N}}(X_i - Z_i)^2} \tag{21}$$

$$Accuracy = \frac{Right\ classification\ numbers}{whole\ samples} \tag{22}$$

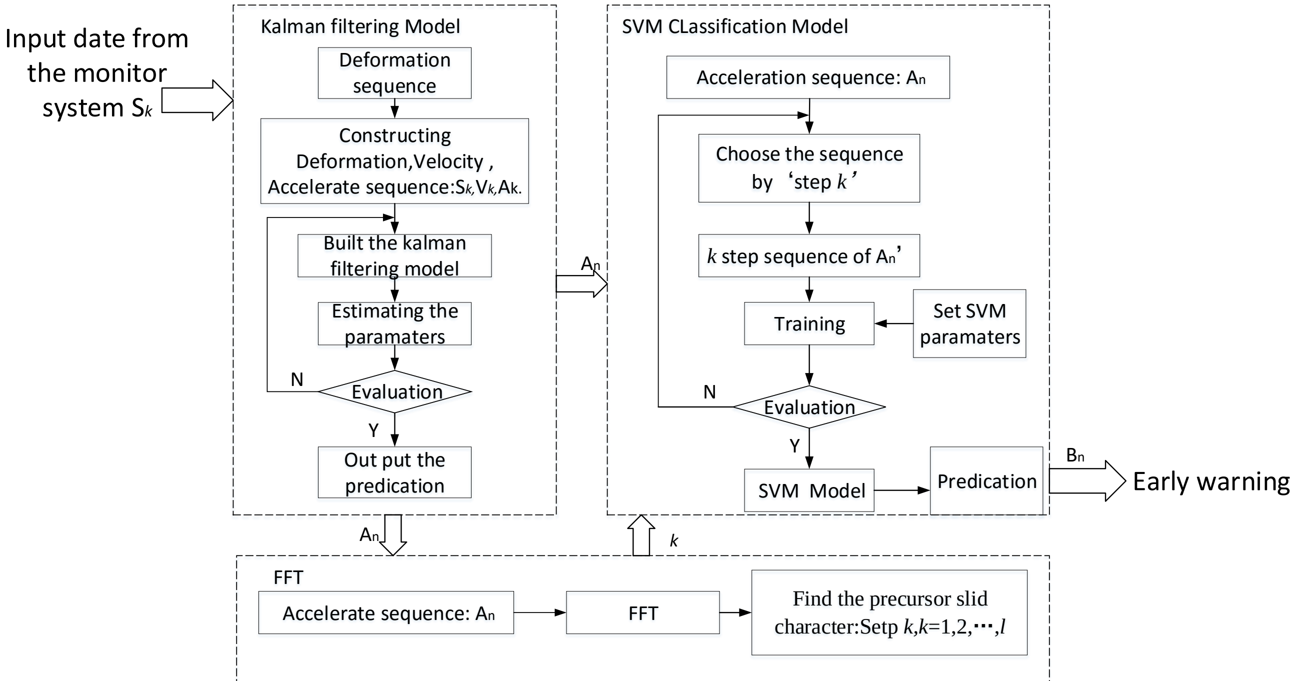

Figure 7: Process of KF-FFT-SVM model

4 Application of real time predication method

4.1 Data pre-processing

The deformation data of Baige landslide after its first slide were gotten by Beidou receivers. The second landslide occurred on late November 3, so we choose the date from October 31 to November 6 to train the KF-FFT-SVM early warning model. Figure 8 shows the raw data of BD1, BD2, BD3 and BD4 and the horizontal deformation data are used here. The raw deformation data are gotten at the interval of 10 minutes. It is know from fig.8 that there are noise in the data and the deformation data gotten on much points at 10 minutes interval are unchanged. So we make a 30 minutes statistics, which means a 30 minutes interval sampling. The 30 minutes statistics result is shown in figure 9. The statistical data are used to build the kalman filttering model.

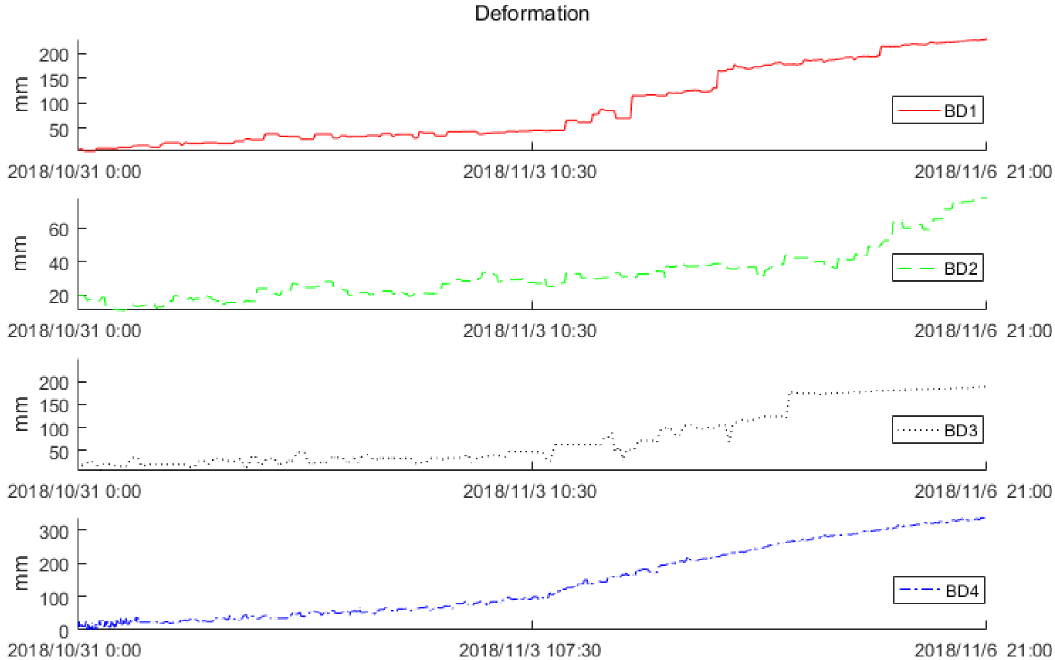

Figure 8: Raw data of deformation.

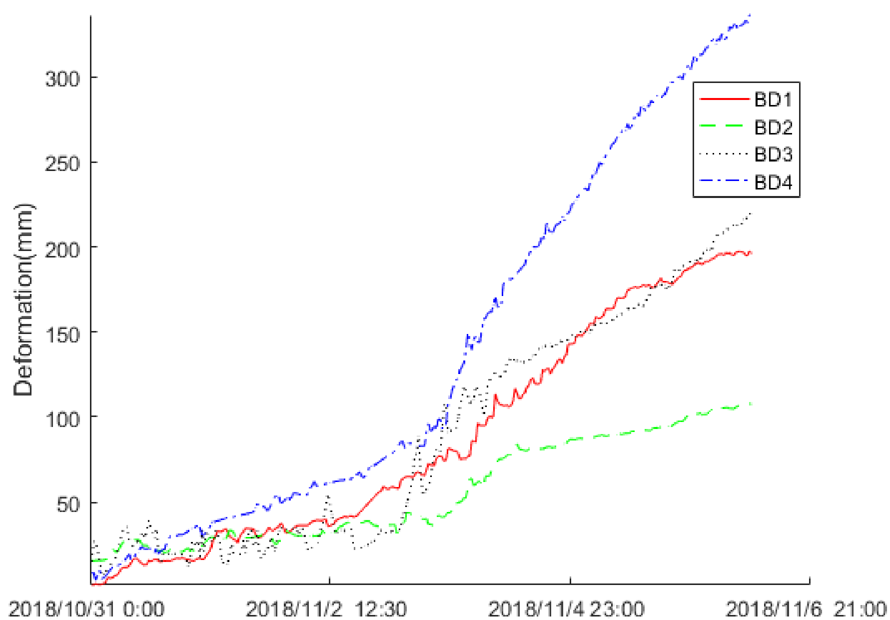

Figure 9: 30 minutes statistics of the raw deformation data

4.2 KF-FFT-SVM model analysis

4.2.1 KF model build

In built landslide deformation KF model, we choose deformation, deformation velocity and deformation acceleration as the state vectors, which are S_k, V_k and A_k respectively .The relations between them are:

$$\begin{cases} X_k = [S_k, V_k, A_k]^T, \\ S_k = S_{k-1} + V_{k-1} \cdot T_s + w_{k-1}^1, \\ V_k = V_{k-1} + A_{k-1} \cdot T_s + w_{k-1}^2, \\ A_k = A_{k-1} + w_{k-1}^3. \end{cases} \tag{23}$$

Where T_s is the data acquisition interval; w_k^1, w_k^2, w_k^3 are random errors. Let $T_s = 1$， then the stochastic difference equation of system state is:

$$X_k = \begin{bmatrix} 1 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} X_{k-1} + [w_{k-1}^1, w_{k-1}^2, w_{k-1}^3]^T \tag{24}$$

The observation formula is described as formula (25):

$$Z_k = [1\ 1\ 0] X_{k-1} + v_{k-1} \tag{25}$$

Where v_k is random error, and we got A = $\begin{bmatrix} 1 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$, H= [1,1, 0]. The random error w_k and v_k are unknown, and our purpose is to use formula (5) ~ (11) to determine the solution of them. At the beginning, we can set a random value of Q and R, then use the date in section 4.1 to find a couple value of Q and R that makes the KF model converge to optimal solution. Figure 10 is the fitting result of BD1, BD2, BD3 and BD4, seeing the red curve. In this KF model W_k=[5,3,3]^T, V_k=3. The max fitting error is 5.73mm which means the built KF model has a good prediction and filtering result.

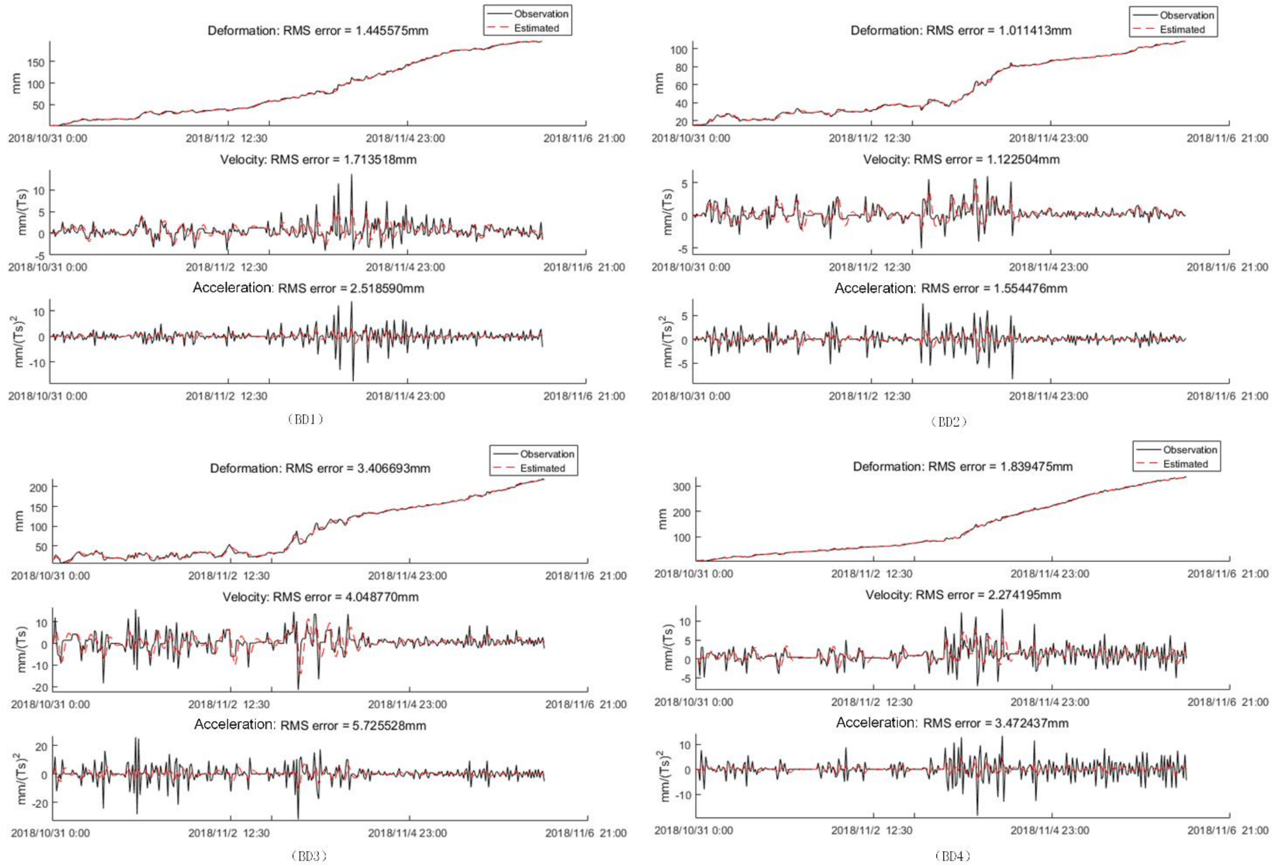

Figure 10: Kalman filtering fitting result

4.2.2 FFT analysis

In the FFT analysis, we choose 64 deformation acceleration data gotten by section 4.2.1 between November 3 and November 4, which is the time close to the moment the secondary landslide happening, to conduct FFT analysis. Figure 11 show the FFT result of deformation acceleration date during the precursor stage. The FFT length N is 64 and the acquisition interval is T_s. Let $T_s = 1$, the acquisition frequency can be simplified to 1 Hz. In figure 11, there are two major amplitude peak value nearby 0.2 Hz and 0.9 Hz, which means, in time domain, the precursor landslide character period is nearby $5T_s$. So we choose the step sequence $k = 2,3,4,5,6,7,8$ to construct deformation acceleration sequence.

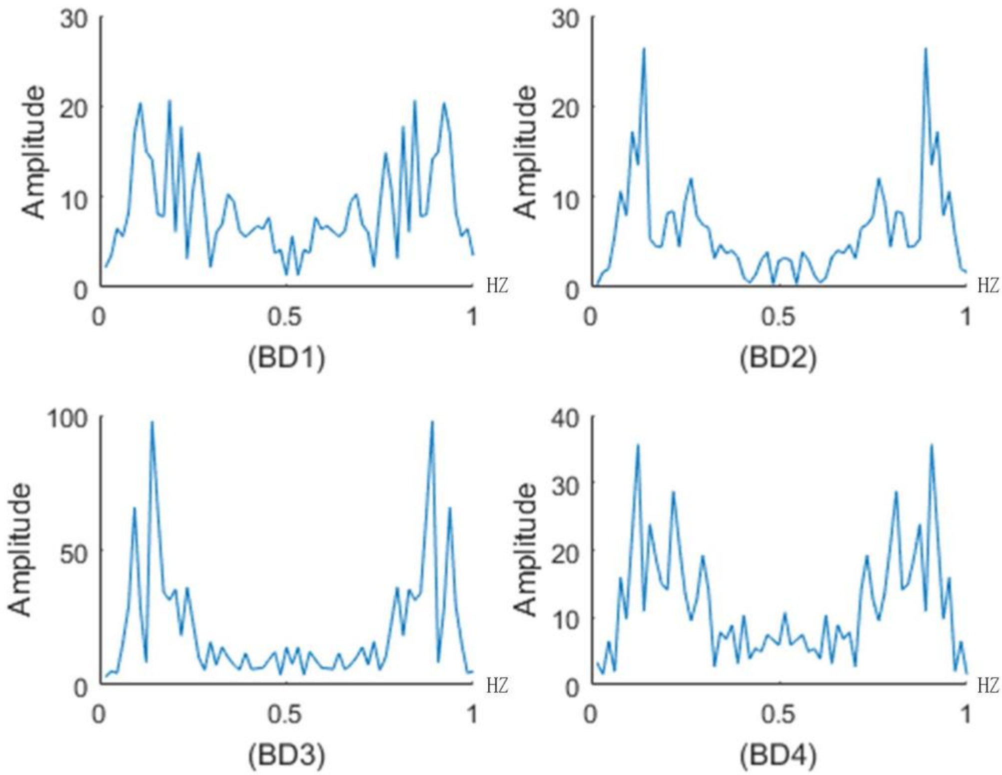

Figure 11: FFT of precursor landslide character

4.2.3 SVM model training

Before SVM model is trained, we mark the deformation acceleration data of BD1, BD2, BD3 and BD4 manually. The data between November 3 and November 4 are marked with label "+1" which represents the precursor landslide character, others are marked with label "-1" which represents the non-precursor landslide character. Then, we use the marketed BD1, BD2, BD3 and BD4 data respectively to construct acceleration sequence A'_n,

$$\mathrm{A}'_n = [\mathrm{A}_n, \mathrm{A}_{n+1}, \ldots, \mathrm{A}_{n+k-1}, label] \tag{26}$$

where $k = 2, 3,4,5,6,7,8$, which is given in part 4.2.2; $n = 1,2, \ldots ,336 - k$; label is marked value of A_n.

Then we get the marked set $\mathrm{A}'_{n(BD1)}$, $\mathrm{A}'_{n(BD2)}$, $\mathrm{A}'_{n(BD3)}$, and $\mathrm{A}'_{n(BD4)}$. Choose $\mathrm{A}'_{n(BD1)}$, $\mathrm{A}'_{n(BD2)}$ and $\mathrm{A}'_{n(BD3)}$ as training data, while $\mathrm{A}'_{n(BD4)}$ as testing data. For example, when $= 2$, the training data and testing data is showed in formula (27):

$$\begin{cases} & \mathrm{A}'_{n(BD1)} = [\mathrm{A}_n, \mathrm{A}_{n+1}, label]_{(BD1)} \\ training\ data: & \mathrm{A}'_{n(BD2)} = [\mathrm{A}_n, \mathrm{A}_{n+1}, label]_{(BD2)} \\ & \mathrm{A}'_{n(BD3)} = [\mathrm{A}_n, \mathrm{A}_{n+1}, label]_{(BD3)} \\ testing\quad data: & \mathrm{A}'_{n(BD4)} = [\mathrm{A}_n, \mathrm{A}_{n+1}, label]_{(BD4)} \end{cases} \tag{27}$$

4.3 Predicting result

Use RBF function and SMO algorithm to search the best C and γ.The predicting results at different step sequence are showed in figure 12. Figure 12 also show the 3 steps sequence training data scatters in 3D coordinate and it is obvious to know that they cannot be well separated in 3D space. So we should separate them in high dimension, which means k>3. From figure 12, we can know that when k=6, the optimal result is gotten and the highest accuracy =0.915, the best C=4, and $\gamma = 1$. The result is proved by the FFT analysis that the best precursor landslide character is nearby 0.2Hz, which equal to 6 steps sequence in SVM model.

5 Discussion

The fast monitoring and real time predication method in this paper focus on the monitoring, warning model of the landslide EWSs. Effective response manners is beyond the discussion of this paper. The use of ad-hoc technology help to build a redundancy on-site monitoring network, which improves the robustness of the landslide EWSs. The monitoring system built here only includes Beidou terminals and fracture monitors. So it can be built in a short time, and it will be useful for the landslide monitoring immediately after the first-time failure of a landslide, because the secondary landslide may occur at any time, which is a great threat to rescuers.

The real time predication method based on the KF-FFT-SVM model makes the predication according to the acceleration characters of landslide deformation. It is on the principle that the mechanical vibration of landslide failure can be recorded by the deformation data. Then the precursor deformation acceleration characters is considered as the vibration of landslide failure. In this study, the Beidou terminals have the ability to record the deformation of landslide in a short time (10 minutes) with an accuracy of a few millimetres which is given by the manufacture. The raw deformation data are showed in figure 8, it is obviously that there are random errors gotten by the Beidou terminals as the deformation data are not continuous rise in several periods. That’s why the raw data are pre-processed and the 30 minutes statistics of the raw deformation data are, then, given in figure 9. Suppose 30 minutes as one unit time scale, then KF method is used to filter the random error, and FFT is used to find the precursor deformation acceleration characters which represent the mechanical vibration frequency of landslide failure. Finally, the characteristic frequencies gotten by the FFT method are different between BD1, BD2 and BD3, then several frequencies are used to generate different length time sequences. SVM model is trained by these sequences respectively and the accuracy is tested by BD4 to find the best character frequency which can be used to make the early warning for this specific landslide.

There are limitations and uncertainties in the application of real time predication method. The most important features of the method is that it can quickly build monitoring network and uses the deformation data to carry out precursor landslide early warning. The problem is that, in KF-FFT-SVM model, we consider the deformation data measured by Beidou terminals as the mechanical vibration of landslide. While, there must be distortion for the transformation from vibration signal to deformation signal. Meanwhile, the monitoring position is also a key factor for the authentic record of the precursor landslide characters.

In practice it is difficult to put the measuring instrument directly on the top of deformation place. We can only locate the Beidou terminals near the surface fracture to make sure that the precursor landslide characters are recorded as authentic as possible. In this study, we only use finite data to train the model, and the method will be more effective if there are more data sets used to train the warning model.

In the future study, we will do researches on the relationship between the surface deformations and inner vibration of the landslide. By doing so, rock and soil press sensor will be used to measure the authentic vibration of the landslide. We will also build a data base of the landslide precursor monitoring data and use landslide monitoring data by other type of sensors to train the KF-FFT-SVM model.

6 Conclusion

In this study, the fast monitoring and real time predication method for landslide is proposed. This method uses ad-hoc technology to facilitate the repaid building of the on-site monitoring network, which improves the robustness of traditional landslide EWSs. Furthermore KF-FFT-SVM model is built to make real time early warning for single landslide through the analysis of the precursor landslide characters from the deformation data. The KF-FFT-SVM model trained by the precursor deformation data of landslide makes the single landslide early warning more effective and it also can be combined with the monitoring of the acoustic emissions from a specific landslide(Hu et al., 2018).

The most important features of the method is that it can quickly build a monitoring network and uses the deformation data to make precursor landslide early warning. This is very useful for the early warning of the specific landslide after its first-time failure. It provides a new idea for monitoring and early warning of single landslide, which not only improves the robustness of the landslide early warning system but also makes landside early warning does not depend too much on the study of landslide mechanism characteristics and the monitoring of many landslide elements. Another innovation of the study is that we extracte precursor characters, which are considered as the mechanical vibrations of the landslide failure, from the deformation data, then make the real time early warning according to the precursor deformation data of landslide.

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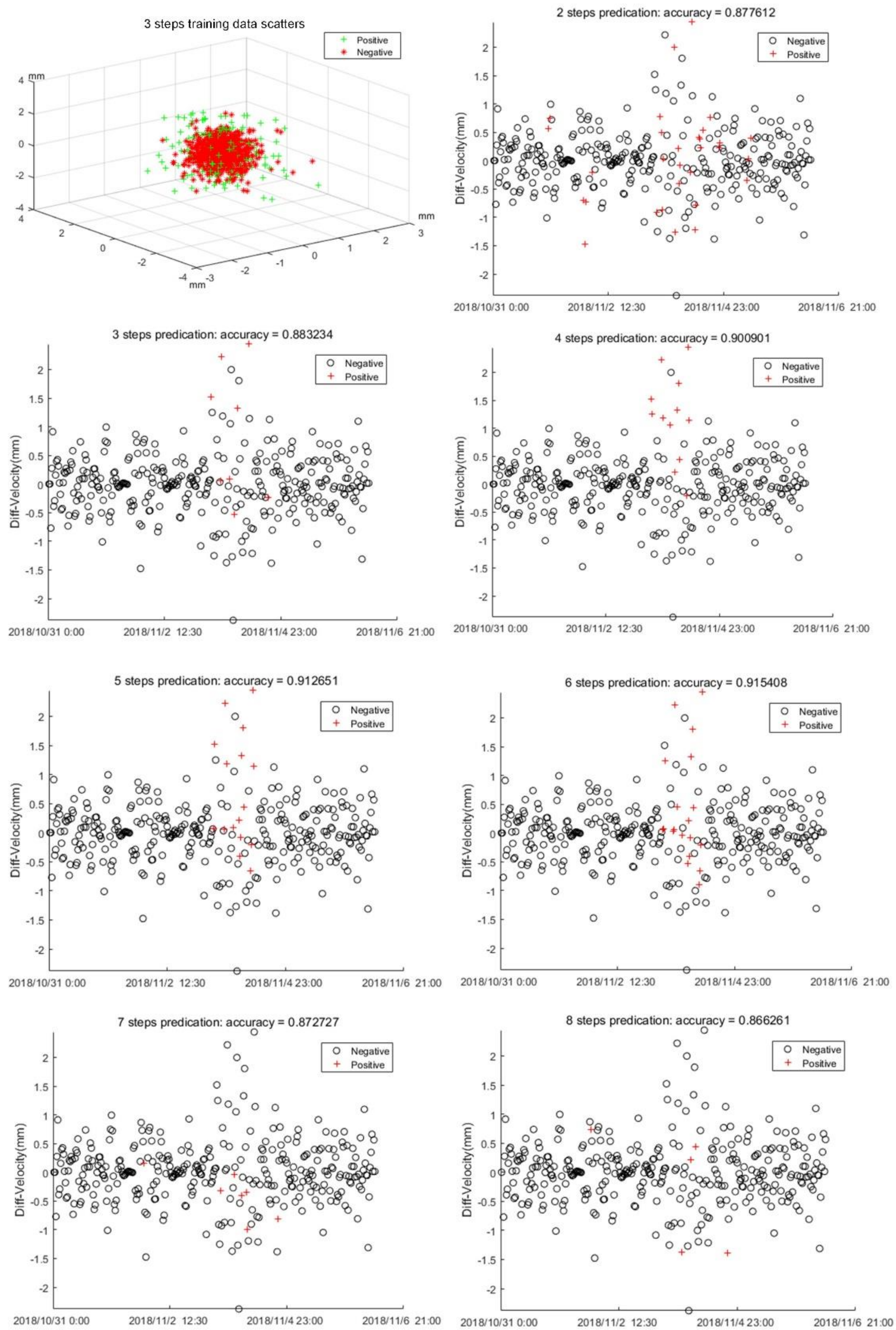

Figure 12: Prediction result at different steps sequence

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