An Intelligent Wireless Displacement Sensor for Landslide Monitoring and Early Warning

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Abstract. Landslide poses a great threat to the safety of local communities, engineering construction and operation. Accurate monitoring and successful early-warning of rapid landslides using conventional techniques with constant and sparse sampling strategy remains a challenge in geo-disaster research and mitigation. Sampling and uploading all sensor data to cloud imposes huge burden on the power supply and radio bandwidth, which greatly reduces the long-term stability and robustness of the wireless sensor in field. With aim to achieve the best powerful sensing ability based on limited power and bandwidth of sensor, we proposed a low-cost and energy efficient wireless crack-meter sensor integrated with intelligent computing architecture for rapid deformation monitoring. A self-adaptive data sampling and uploading algorithm based on the variation of objective physical value was implemented in the embedded microcontroller of sensor node, and only the valuable information derived from sensor data to the cloud server. Experimental results demonstrated that the intelligent sensing approach can effectively collect the crucial data at a high frequency during accelerating deformation of landslide, while only update status at several hours during non-deformation phase. Several landslide monitoring applications have proved that this intelligent sensing can significantly and effectively enhance the success rate and real-time performance of early-warning for rapid landslide.

1. Introduction

The monitoring and early warning of landslide plays a vital role in natural risk management and reduction. With aim to avoid or at least reduce damage and human lives loss, accurate time-of-failure prediction of a landslide could be a key element to develop a powerful early warning system [1-3]. Temporal prediction of landslide is forecasting of the time of collapse of a landslide. Satio firstly proposed a method for forecasting the time-of-failure of landslide [4]. In this method, a creep evolution process exists during the displacement and failure of landslide. As shown in Figure 1, the whole creep process can be divided into three stages: (I) Initial phase OA; (II) constant deformation AB; (III) accelerated deformation BC. In the accelerated deformation stage (BC), the displacement rate rapidly
increases, leading to the final failure. Satio’s method suggests that the accelerated stage, called “tertiary creep”, is a process that must be experienced prior to the failure of the landslide [4-6].

With aim to accurate predict the time-of-failure of landslide, Fukuzono developed an inverse velocity method based on the interpretation of the tertiary creep stage, where the slope displacement follow an accelerating trend ultimately leading to the final collapse [7]. In this method, the relationship between velocity and the time-of-failure was presented as following equation.

\[ \frac{1}{v} = (A(\alpha - 1)(t_f - t))^{\frac{1}{\alpha - 1}} \]  

Where \( v \) represents the landslide surface velocity, and \( t_f \) is the time-of-failue of landslide. The parameter \( \alpha \) determines the trend of the inverse-velocity vs time curve. When the data close to the failure, the trend can be generally assumed as a linearity process, corresponding to \( \alpha = 2 \). And \( t_f \) can be effectively evaluated based on the surface velocity, which could be derived from the monitoring time series of displacement. However, the inverse velocity model struggles to represent brittle failures properly, since the extremely rapid deformation of a rock mass or sudden landslide failure can not be timely captured by conventional monitoring techniques with a fixed data acquisition frequency. As noted by Carlà [8, 9], significant improvements to overcome this problem can be achieved by using a high-frequency monitoring system able to accurately represent the tertiary creep phase. Meanwhile, we also don’t want to collect high-frequency data time series when the deformation of landslide has not entered the tertiary creep stage, since these too much data during the phase I and II are useless for early warning of landslide failure and it will take much more power source of wireless sensor to transmit large amounts of useless data to the early warning platform. Renewable power sources such as solar and wind can be used to sustain a landslide monitoring system, but the wireless sensors with high power consumption may become nonfunctional due to long term rainy weather.

With aim to achieve a balance between power consumption of wireless monitoring device and observation of high-frequency data samples during the tertiary creep phase, we proposed a cost-effective framework of landslide monitoring and early warning system, and developed an low-cost and energy-efficient wireless device for landslide surface displacement monitoring. An intelligent self-adaptive data acquisition algorithm was implemented in the wireless device. Practical application of the developed system in a rapidly deforming rocky landslide case shown that the proposed method is very effective and useful for successful early warning of rapidly deforming landslides.

2. Framework of landslide monitoring and early warning system

Figure 2 shows the framework of landslide early warning system based on the surface displacement monitoring result. The whole system consists of four main parts: (1)Wireless sensor device. It contains
wireless displacement sensor, battery and solar power source. The displacement of sliding mass of landslide is converted into a proportional voltage signal, which is collected by the wireless sensor with local adaptive acquisition algorithm. The self-adaptive acquisition algorithm is automatically triggered by the displacement rate of landslide. Consequently, only the data of interest is transmitted to the early warning system deployed on the cloud platform. (2) Remote wireless data transmission. As one standard messaging protocol for the Internet of Things (IoT), Message Queuing Telemetry Transport (MQTT) are implemented by programming within the embedded micro controller unit (MCU) of the wireless Data Logger. In addition to the commercial 3G/4G/5G/NB-IoT network, Beidu message exchange through satellite is also compatible and used for data transmission in the areas without commercial network coverage; (3) Landslide early warning system on the cloud platform. The original observed data was firstly filtered by the moving average method, and few errors would be automatically identified and removed. Four level multiple alert criterial based on displacement rate, acceleration, and improved tangential angle are established in the early warning system, more details about it can be found in our previously published paper [5]. (4) Warning notification. A real time warning message based on the multi-level alert criterial can be generated automatically and sent to the different receivers through email, APP, SMS and Wechat etc.. Emergency response is carried out when the warning message is received.

In this paper, we will focus on the development of intelligent displacement sensor with local adaptive acquisition algorithm.

Figure 2. Framework of landslide monitoring and early warning system

3. Development of intelligent wireless displacement sensor
In this study, in order to improve the efficient of landslide monitoring and early warning, we developed a low-cost intelligent wireless displacement sensor with local self-adaptive acquisition algorithm.

3.1 Hardware of wireless sensor

Figure 3 shows the structure of the developed displacement sensor. The sliding of landslide pulls the steel wire, and drives the resistance of the potentiometer proportionally changing with the displacement. Meanwhile, the potentiometer is powered by a stable reference voltage provided from the print circuit board (PCB). Therefore, the potentiometer could output an analog voltage linearly proportional to the displacement. The output voltage is converted into digital sequence by a ultra low power analog-to-digital converter (ADC) on the PCB.

![Figure 3. Hardware of wireless displacement sensor. (1) Section view of sensor; (b) Print circuit board (PCB) for data sampling; (c) Appearance of sensor.](image)

PCB is the core unit of the wireless displacement sensor. The functional block diagram of PCB is shown in Figure 4. In the diagram above, the central block is the STM32L151 microcontroller unit that performs the tasks: reading data from the analog-to-digital converter (ADC) via Serial Peripheral Interface (SPI), take real time clock from RTC chip PCF8563, identification of significant change of sampled data sequence (the interest data), send the interest data to the cloud server. The ADC capability allows data digitization at a conversion rate of 1Hz with 24-bit high resolution. In this system, ultralow power sigma-delta ADC AD7780 was applied, and its typical work current is 115uA@3.3V. A 2k bit Serial Electrically Erasable PROM (E²PROM) is used to store the calibration coefficients, wireless link parameters and other information of the sensor. The analog signal from the potentiometer is filtered before ADC by a simple RC low pass filter circuit to remove high frequency environmental noise. The cut-off frequency can be configured by choosing suitable resistor R and capacitor C due to

\[ f_{\text{cut-off}} = \frac{1}{2\pi RC} \].

The wireless module, Quectel multi-mode LTE module EC20/EC200S, is connected to the MCU through standard serial port, and the IoT standard data transmission protocol MQTT is also implemented in the MCU based on the commercial wireless network. Additionally, the wireless module can be replaced by a Beidu communication chip to solve the remote data transmission problem in mountain areas without wireless signal coverage.
However, not all sampled data sequence needs to be sent to the early warning system deployed on the cloud server, since only data in the accelerating deformation stage is important for early warning. Furthermore, wireless data transmission would consume most of the power of the sensor [10], the wireless sensors with high power consumption may become nonfunctional due to long term rainy weather. Therefore, one intelligent self-adaptive sampling algorithm proposed and implemented within the MCU to identify the significant change of displacement data sequence.

3.2 Adaptive data collection strategy

To overcome the above mentioned problem, we proposed a self-adaptive data collection strategy based on the smoothness of data variation. The core idea of the self-adaptive data collection strategy is dynamical adjusting the time interval of data collection according to the change law of the objective signal. When the objective signal changes steadily, the time interval of data collection is increased. Otherwise, the time interval of data collection can be shorten to sample more critical information of significant change.

In this study, the smoothness of data variation is used to identify the significant change of displacement. The smoothness of data variation can be presented as follows:

\[
sdv(m,n) = \frac{\Delta S_m}{S_n} \quad (n \geq m > 0) \quad (2)
\]

Where \( \Delta S_m \) is the average variation of displacement in the past time with \( m \) displacement observations, \( S_n \) is the average value in the past time with \( n \) displacement observations.

\[
\Delta S_m = \frac{\sum_{j=1}^{m-1} |S_{j+1} - S_j|}{m} \quad (3)
\]

\[
S_n = \frac{\sum_{j=1}^{n-1} S_j}{n} \quad (4)
\]

It can be found that smoothness of data variation \( sdv \) is a dimensionless indicator, which is greater than 0 and less than 1. The larger indicator value indicates that the displacement have a significant change, while a smaller indicator value indicates a steady displacement. Therefore, we only need to set an appropriate threshold for this indicator to identify the accelerating deformation phase of landslide. When the indicator value is greater than the threshold, the sampled displacement during the accelerating phase can be sent to the early warning system through wireless data transmission. When the indicator value is smaller than the threshold, the sampled displacement data can be sent to the server at very long interval.
to minimize the power consumption. According to equation (1), high-density displacement data in the accelerating phase prior to the landslide collapse is very beneficial for successful early warning in real time. It was noting that the threshold can be set according to the significance of the data change by considering the quality of data time series in the real environment.

4. Results

4.1 Calibration

Each developed wireless sensor need to be calibrated firstly to build an accurate linear relationship between the voltage output from the potentiometer and the digital data converted by ADC. Figure 4 shows the calibration result of one of our developed sensor. The calibration parameters can be written to the E2PROM of sensor for reading at startup. The result demonstrated that the linearity of the sensor is perfect. The resolution of sensor can reach to 0.05mm, and the monitoring range depends on the diameter of the coil spring. We have designed two specifications: 1000mm and 2000mm.

![Figure 5. Calibration of the developed sensor; (a) Scale tool; (b) Calibration result.](image-url)

4.2 Testing result

With aim to verify the performance of the self-adaptive collection algorithm, we did a simulation of the multi-stage deformation phases of landslide. In this test, the time window size $m$ was set to 60s, while $n$ was set to 10s. The threshold of $sdv$ was set as 0.01. Figure 5 shows the testing result of the proposed method. It was found that the significant change of displacement can be identified effectively. Therefore, the MCU can select different data transmission time interval according to the judgement result. When the $sdv$ value does exceed the threshold, it means that the landslide is in an accelerating
phases, the sampled data can be sent to the remote cloud server at the fastest frequency of one second. Otherwise, the sampled data can only be transmitted to the server at a frequency of several hours.

![Figure 6. Identification result of accelerating displacement using the proposed method](image)

4.3 Application

![Figure 7. Application in successful early warning of “2・17” Xingyi landslide](image)
Figure 6 shows our first application in monitoring and early warning of a rapid rocky landslide occurred on 17, Feb. 2019, Guizhou Province, China. The rocky landslide only taken a few hours from accelerating deformation to failure. We deployed eight displacement sensors along the back crack of landslide (Figure 6(b)). If the traditional monitoring technology such as GPS with at least 30min data collection frequency, very few data points during the accelerating deformation stage could be obtained, which was very unfavorable for timely and accurately early warning. In this case, the warning information was issued 53 minutes before the final failure due to our proposed technology.

5. Conclusions

Accurate monitoring and successful early-warning of rapid landslides using conventional techniques with constant and sparse sampling strategy remains a challenge in monitoring and early warning of rapid landslide and/or rockfall. With aim to achieve the best powerful sensing ability based on limited power and bandwidth of sensor, we developed a low-cost and energy efficient wireless crack-meter sensor based on self-adaptive data collection strategy. A self-sensing, adaptive data sampling and uploading algorithm based on the variation of objective physical value was implemented in the embedded microcontroller of sensor node, and only the valuable information derived from sensor data to the cloud. When the significant change of displacement occur, the self-adaptive data collection strategy triggers the wireless data transmitter in real time. If no significant change of displacement occur, sensor consumes very low power and will be awakened by RTC and then transmit periodically to refresh the status of long term.

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