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Real-Time Landslide Forecasting System: An Application of IoT Technology

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Abstract: Under the effects of climate change, especially the increase in rainfall intensity, the landslide has recently made a lot of consequences. Therefore, slope failure forecasting has been viewed as a key task to save human lives and economic losses. In the past, slope monitoring was often carried out manually directly on-site, therefore very difficult to get data continuously for a long time, with a too low temporal frequency that does not permit precise forecast. Recently, applying IoT (Internet of Things) technology in monitoring has begun popular. This technology allows data can be automatically gathered, updated and transmitted via the internet in real-time. This not only permits a more precise forecast but also prompt responses before the failure really happen. This paper introduces an IoT integrated model for forecasting the time of failure based on displacements. The detailed guidelines of theoretical basis, how to install devices and how to collect, process and transmit data are represented, so this would be easy and convenient to apply in practice. A small-scale physical model was made to test the function of the system. The simulation tests indicated good performance.

Keywords: Landslide failure, forecasting slope failure, IoT Technology

1. Introduction

Climate change, especially the increase in rainfall has made a lot of consequences on human life. One of the severe aftereffects is the increasing number as well as the extent of damages of landslide in many regions over the World. To minimize the effects of slope failure in terms of both human lives and economic losses, forecasting the time of failure precisely is an initial and viewed as the most important task.

To have the basis for predicting the failure time of slopes, some parameters have to be monitored for a certain period of time before the landslide really happens. In the past, monitoring works were often very difficult, expensive and dangerous also that is because gathering, updating, and processing the data were normally carried out directly at the site by manpower.

Recently, IoT (Internet of Things) technology has experienced rapid growth and become increasingly popular in many aspects of human life. In term of monitoring serving for forecasting failure time of slopes, IoT has shown its exceptional effectiveness. This is because landslide is very often happening in remote mountainous areas and spreads across widely. So, it is very difficult to carry out manually. In addition, to predict the time of failure precisely, gathering data very near

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the real failure time is very important. However, it would be very dangerous if doing this by manpower. Using IoT can overcome these difficulties of original methods.

In addition, applying IoT in monitoring landslide also help responders can access the data and be alerted anytime and anywhere. This allows making decision promptly to minimize the damages. Because of these advantages, IoT is considered as the most potential technology for landslide monitoring and failure early warning.

Regarding monitoring methods, some studies investigated the impacts of some factors such as rainfall intensity (Brunetti et al., 2010; Shieh, Chen, Tsai, & Wu, 2009), soil moisture (Ponziani et al., 2012), groundwater level (Du, Yin, & Lacasse, 2013), geo-environmental factors (Ha et al., 2021), etc. on the stability of slopes. Based on these factors, failure forecast models have been introduced. These methods rely on the fact that rainfall is a major trigger of slope instability. However, these methods are only suitably used to make temporal predictions at the regional scale (Piciullo, Calvello, & Cepeda, 2018; Stähli et al., 2015). If using these methods for forecasting failure time at slope-scale, the outcomes of these methods are often not precise enough therefore hardly to be used.

As for predicting failure time at the slope scale, prior studies argued that the most reliable and commonly used parameters could be the slope displacement and its derivative parameters such as velocity and acceleration (Intrieri, Carlà, & Gigli, 2019; Rose & Hungr, 2007). This is because these kinematic parameters are directly related to the stability conditions of the moving slope (Lacasse & Nadim, 2009). Especially, modern technology now can provide a lot of proficient instruments to monitor them in real-time effectively.

This paper introduces an IoT based model for monitoring displacements of slope and then automatically processes the data to predict the time of failure. This model also can interact with responders who can access the data, be alerted via the internet and also can send commands (e.g., evacuation warning) to the site through the system.

The layout of this paper is as follows, initially a conceptual model system is introduced which showed the components of the system and how they interact with each other. Then, the procedures of how data is collected, processed and transmitted in the system are represented. Next, an application of the conceptual model system on a popular case of unstable slope that is the sliding of cover soil on bedrock is illustrated. A simulated physical model system including sensor, processor, server, etc. was made to test the model's functions. Several simulation tests were carried out on the physical model system. The tests' results are finally showed and discussed.

2. Method

2.1 Conceptual Model System

Components of the model and the interactions between them are showed in Fig. 1. The proposed model contains five nodes: Displacement sensor; Processor; Cloud server; On-site alarm dives; and Responder

Displacement sensors are installed on the monitoring slope. Their task is to measure the displacement in certain points on the slope then send measured displacement values to the processor whenever the processor requests.

The processor has three main tasks: (1) Processing displacement data and then predicting the time of failure by some regression analysis whenever received new data from displacement sensors; (2) Communicating with cloud server via the internet (nowadays mainly use GPRS - a standard cellular communication network). It can also receive commands from the cloud server to do some other optional tasks (depending on certain cases), and (3) Triggering on-site alarm devices.

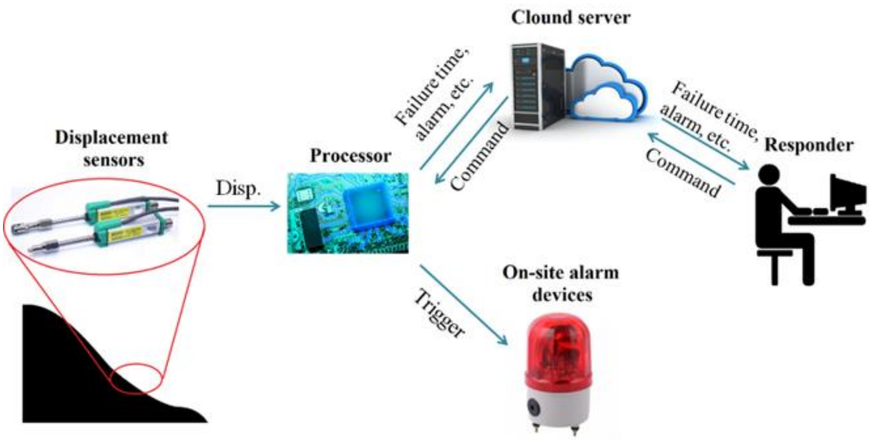

Fig. 1 - Overall model concept

Cloud server acts as an intermediate station that allows the processor and responder to communicate remotely in real-time.

Responders receive processed data and are alerted from monitoring site and respond the situation by commands via computer or Smartphone

On-site alarm devices are optional. For instance, in case there are people living under the moving mass, an on-site alarm system should be included to alert people in emergent situations. Otherwise, this component could be excluded.

2.2. Inverse Velocity Method

The inverse velocity method for forecasting the time of slope failure was first introduced by Fukuzono (Teruki, 1985). The basis of this method lies in the fact that very often, before the failure really happens, the mass displaces downward with accelerating displacement velocity until the slope collapses.

When the slope is still fairly stable velocity (V) is small, inverse velocity (V-1) is big. When the slope asymptotically towards failure, V now becomes very big; therefore, V-1 is approached zero. As the inverse velocity was plotted against time, we have trend lines through values of inverse velocity versus time that could be projected to the zero value on the abscissa (t-axis), predicting the approximate time of failure, as shown in Fig. 2.

Fukuzono (Teruki, 1985) presented three types of plots fitted to the laboratory data, including concave, convex or linear (Fig. 2). The trend lines are defined by the following equation:

$$\frac{1}{V} = [A(\propto -1)]^{\frac{1}{\alpha-1}}(t_f - t)^{\frac{1}{\alpha-1}} \tag{1}$$

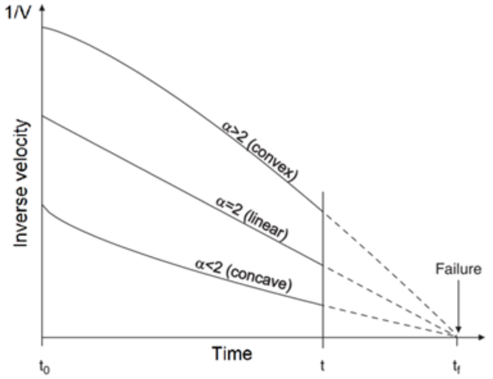

Fig. 2 - Trend lines of inverse velocity versus time Fukuzono (Teruki, 1985)

Where t is time, A and α are constants, and t_f is predicted time of failure. In the experimental measurements preceding failure, α was found to range from 1.5 to 2.2.

When α = 2, the plot is linear and the time of failure equals the predicted time from a prior method which is Saito's method (Saito, 1969). In this case, linear regression is used for the extrapolation.

When α > 2, α < 2, the curve is convex-concave respectively, Fukuzono (Teruki, 1985) suggested using a different graphical method instead of the linear regression to determine tf. This approach is rarely used because α typically does not differ much from 2 and the simplification of a linear fit is preferred, provided that it is updated on an ongoing basis to identify the onset of trend changes (Rose & Hungr, 2007).

On the other hand, Fukuzono (Teruki, 1985) also found that a linear trend fit through inverse-velocity data usually provided a reasonable estimate of failure time shortly before failure (the most useful period of time). Many later studies applied Fukuzono method used linear trend (α = 2) and got very good results as predicted time of failure precisely (D. Petley, Dunning, Rosser, & Hungr, 2005; D. N. Petley, Bulmer, & Murphy, 2002; Rose & Hungr, 2007).

2.3. Sampling and Data Processing

According to Rose and Hungr (Rose & Hungr, 2007), the inverse velocity method is not suitable for forecasting over a very long period, which should be constantly updated to assess the significance of apparent trend changes. Some studies applied the inverse velocity method and discovered that the most recent displacement monitoring data increase the confidence when estimating the time of failure. Older data, especially data collected before the initiation of tertiary creep, should be excluded (Intrieri et al., 2019; Rose & Hungr, 2007).

Regarding frequency of data gathering, in their study, Rose and Hungr (Rose & Hungr, 2007) introduced 4 case studies. The four slopes collapsed already; before the failures, monitoring activities were carried out. The time intervals of displacement sampling vary from 15 minutes to 2 hours and velocities were calculated on from 2 hours to 2-day basis. This aimed to reduce noises generated by instruments and/or sudden geological changes. The predicted t_f of the four cases showed good accuracy and human activities were successfully stopped with advanced warning of impending slope failure.

To use the inverse velocity method, we have to have data of time series $d_1 \ldots d_i$, $t_1 \ldots t_i$, where di and t_i are the most recent displacement and time, respectively. The applied filtering method in this study used n last observation to calculate velocity. The most recent velocity (V_i) is calculated as the slope of a linear regression line (Eq. 2), plotted through the last n observation points.

$$V_i = \frac{\sum_{j=i-n-1}^{i} t_j d_j - n\overline{t_n}\overline{d_n}}{\sum_{j=i-n-1}^{i} t_j^2 - n\bar{t}_n^2} \tag{2}$$

Where $\overline{t_n}$ and $\overline{d_n}$ are the average of *n* last values of t and d time series, respectively.

Finally, the predicted time of failure (t_f) is estimated by determining a linear regression line ($V^{-1} = a t + b$) and t_f is estimated by determining the intersection between the regression line and the abscissa (t-axis) (**Fig. 2**). Whenever a new data of velocity (V_i) comes, we have a different regression line and therefore we have a new corresponding value of forecasted time of failure (t_{fi}). Even if sometimes more predictions are made together with new data, usually only one (the most recent) is used since it is considered as the most reliable prediction.

3. Simulation and Discussion

3.1. Landslide Case Study

The simulated model in this study deals with a very popular case of unstable slope that is the sliding of cover soil on bedrock derived by man-made cut slope (Fig. 3.). Because of the popularity of this case study in practice, there is a large number of prior empirical researches which also investigated this (Saito, 1969; Teruki, 1985).

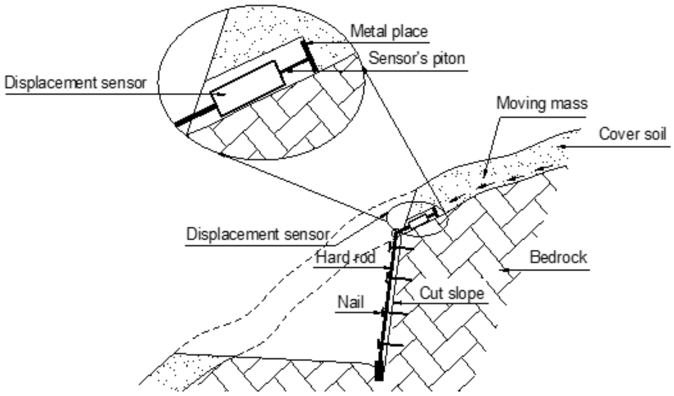

Fig. 3 - Typical cut slope and displacement sensor setup

An installation design of displacement sensors is recommended in this study, as shown in Fig. 3. The head of the sensor is connected to a hard metal rod which is nailed to the bedrock layer. In this case, the hard rod is assumed not to be moved when the mass was moving. This assumption is reasonable if the bedrock is hard and stable when the topsoil mass was moving downward. The piton of the sensor is fixed with a metal place that is well contacted with the mass. That allows the piston to displace exactly the same as the displacement of the mass. Depending on particular cases, we can install more than one displacement sensor as long as the head of the sensor can be fixed well on the hard rod (Fig. 3 shows the case of installing one displacement sensor).

3.2 Simulated Model System

A simulated monitoring and warning system was made in the laboratory. This model system simulates the displacement of the cover soil layer on bedrock. The system includes full of nodes, as shown in Fig. 1. The functions of this system are to generate time series of t_f (each time getting new data of displacement, we have a new value of t_f). Whenever tf is smaller than an assumed safe remaining time, speaker and a flashlight will be triggered to generate warning signals, and warning notifications also will be sent to the responder via Smartphone. The physical system is illustrated in Fig. 4.

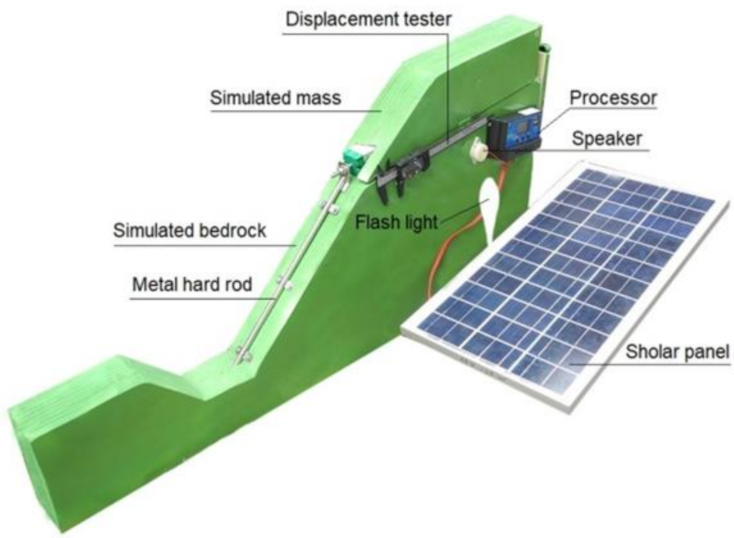

Fig. 4 - Physical simulated model system

The displacement sensor was used in this study is a potentiometer linear position sensor. As the piston move, the resistance of the sensor changes that makes the output voltage also changes. The processor measures the output voltage to determine the current position of the piston compared to the reference point. From this, we have the current displacement value. The displacement tester is an independent device from the monitoring system, which was calibrated before installing; this was used to test the accuracy level of the displacement sensor.

The solar panel and built-in battery can help the system function independently from external electric sources. The speaker and the flashlight are used as simulated on-site warning devices. Whenever received warning command, the speaker and flashlight will be triggered to alert people nearby the site. The functions of the other components such as the processor, the hard metal rod, and processor are similar to that described herein Section 2.1.

3.3. Data Processing and Streaming

Fig. 5 below shows how data is processed and streamed in the system.

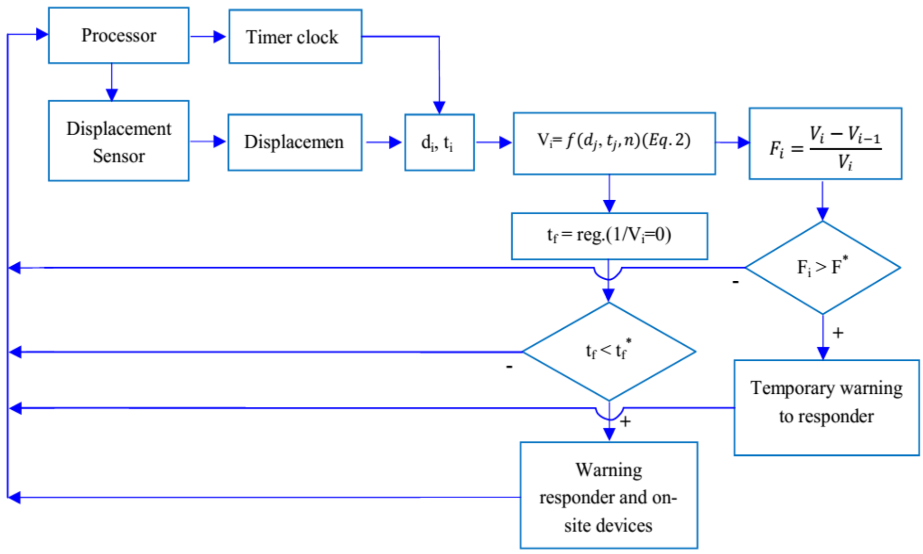

Fig. 5 - Data processing and streaming in the model system

In this study, the time interval of displacement sampling was 15-minute and velocities were calculated on 1-day basis (n = 96). The processor controls the timer clock and displacement sensor to get new data of displacement every 15-minute; we have time-series $d_1 \ldots d_i$, $t_1 \ldots t_i$. The most recent velocity (V_i) is calculated based on the *96* most recent values of displacement using **Eq. 2** (n = *96*, corresponding with 1-days basis).

Next t_f is estimated by following two steps:

(1) Determining regression line ($V^{-1} = a t + b$) based on time series $V^{-1}_1 \ldots V^{-1}_i$, $t_1 \ldots t_i$. Using the Ordinary Least Square method, a and b are estimated by following equations

$$a = \frac{\sum_{j=1}^{i} t_j V_j^{-1} - i\bar{t}\overline{V^{-1}}}{\sum_{j=1}^{i} t_j^2 - i\,\bar{t}} \quad (3)$$

$$b = \overline{V^{-1}} - a\bar{t} \quad (4)$$

Where $\bar{t}$ and $\overline{V^{-1}}$ are the average values of t and d time series, respectively.

(2) Estimating the current t_f value: According to Fukuzono (Teruki, 1985) method, t_f is the intersection between the regression line ($V^{-1} = a t + b$) and t-axis, so V^{-1} is assumed to equal to zero and we have t_f is simply equal to -b/a.

Next, t_f is compared to a safe remaining time threshold from the current time (t_f^*). If t_f is smaller than t_f^*, the responder will be alert via Smartphone and computer. On-site alert devices (speaker and flashlight) will also be triggered.

Apart from the above traditional warning procedure, this paper proposes a new form of warning that is "Temporary warning". This aims to catch the situation that landslide could occur caused by sudden impacts such as an earthquake or human activities on the mass. The reason for using this kind of warning is that the traditional method of using t_f might not be sensitive enough to generate warning signals when sudden impacts occur. This is because t_f is calculated based on a linear regression model which is estimated based on historically recorded data. The bigger historical data is the smaller effect of a single temporary data on the regression model is. In short, using the proposed temporary warning concept, warning even will be much more sensitive with sudden impacts on slope compared to the traditional method (using t_f).

The parameter used as the basis for generating temporary warnings is $F = (V_{i-1} - V_i)/Vi$ (%). The nature of F is the difference in displacement velocity between the two nearest observations (V_{i-1} and V_i). If F is big, that means there is a sudden increase in displacement velocity. So, this is more likely that a landslide could occur soon. In certain cases, based on slop conditions (geological characteristic, slope geometric, etc.) and design reliability level, the safe threshold of F should be recommended (F^* in **Fig. 5**). When F is bigger than F^*, a temporary warning should be triggered.

3.4. Simulation Tests

Simulation tests were carried out aiming to test functions of the system, including displacement sensor's accuracy, system delay, warning responder and warning devices. The description and results of the tests are showed in Table 1.

As can be seen from Table 1, the error of the potentiometer linear displacement sensor was relatively small, at 1.2% on average, SD = 0.05%. So, this kind of sensor is potentially used in practice. On average, the delay time of the system was 405.0 milliseconds (SD = 20.1 milliseconds). With the purpose of monitoring slope displacement and landslide warning, the delay time of the system is as small as around 400 millisecond that is a very good result and suitable to use in practice. The tests of warning responder and warning devices also showed good functions.

Table 1 - Simulation tests

Test	Description	Result
Displacement sensor's accuracy[(a)]	Comparing displacements measured by displacement sensor and the calibrated displacement tester	The difference: Mean = 1.2%, SD = 0.05%
System delay[(b)]	Time duration from when processor sends a message until the time the message successfully sent to Smartphone or Computer	Mean = 405.0ms, SD = 20.1ms
Warning responder	Testing to see whether responder can get warning notification or not	Yes
Warning devices	Testing whether speaker and flashlight could be triggered in the right way or not	Yes

Note
[(a)] 50 independent trial measurements were carried out (sample size: n = 50)
[(b)] System delay was tested in Hanoi city, using 3G service provided by Viettel Telecom - a mobile data cellular service provider in Vietnam. Sample size n = 50.

4. Conclusion

This paper has proposed a model that applies IoT technology on monitoring slope displacements, then automatically predicts the time of failure, and alerts both responders and people at the monitoring site when a landslide could occur soon. The representation in this paper can be viewed as a detailed guideline of how to build and implement the system, so this would be easy and convenient to apply in reality. The current study also introduces a method using time series of displacement velocity to forecast landslide that could suddenly occur under the effects of temporary impacts such as an earthquake or human activities on the mass.

In the past, slope monitoring was hard to be carried out because the old technology required a lot of manpower for collecting, updating, and processing data. This is dangerous for responders and expensive also. Applying the proposed model could save a lot of manpower and also could offer more reasonable prices compared to original technologies. Therefore, this is very potentially to apply the model in practice in a large scale to save both human lives, and economic losses with affordable expenses.

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