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Data Extraction Method for Better Failure Time Prediction of Landslides

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Abstract

Time prediction methods based on monitoring surface displacement (SD) are effective for early warning against shallow landslides. However, failure time prediction by Fukuzono's original inverse-velocity (INV) method is less accurate due to variation in the inverse-velocity ($1/v$) caused by noise in the measured SD, which amplifies the fluctuation in the resultant $1/v$. Therefore, the present study incorporates pre-analysis to acquire better prediction by reducing the effect of noise on the measured SD. The data extraction (DE) and moving average (MA) methods are used to filter the measured SD for better smoothing of $1/v$. The reproducibility of the measured SD and the scattering are assessed using the root mean square error (*RMSE*) and determining factor (f), respectively, to select the optimum SD interval (Δx) for data extraction in the DE method. The data, treated by the DE and MA methods, are utilized to predict the failure time based on the INV method and the relationship between velocity and acceleration on a logarithmic scale (VAA) method. Accordingly, Δx gives the smallest sum of the normalized *RMSE* and normalized ($1-f$), which offers a better prediction. When the SD at failure changes, Δx is changed. The best prediction is obtained by DE preprocessing with the VAA method because it minimizes the effect of the individual $1/v$ by reducing the scatter in the relationship between velocity and acceleration. However, the time prediction using data processed by the MA method shows poor prediction due to some scattering of the inverse velocity. In some cases, the prediction by the VAA method using MA data provides better prediction than the results of the INV method by MA data.

1. Introduction

The time prediction of a landslide occurrence is an important task for early warning against landslide disasters, but there is still uncertainty about its precision. However, slope scale prediction is a worldwide necessity in the framework of landslide risk reduction. In this regard, prediction based on monitoring displacement data is generally used in practice. Displacement monitoring using geotechnical methods in indoor model slopes and outdoor field experiments using a rainfall simulator have been adopted in recent studies related to the shallow landslide failure mechanisms and the forecast time of failure for early warning. For example, Fukuzono [3] monitored the surface displacement (SD) using extensometers on the large-scale indoor model slopes. Furthermore, Moriwaki et al. [5] conducted a full-scale model slope by monitoring the SD with displacement meters, and Ochiai et al. [6] reported an outdoor field experiment of monitoring displacement using extensometers on a natural slope in the city of Futtsu, Chiba Prefecture.

Many researchers have adopted time prediction methods based on monitoring the displacement of slopes [2, 3, 7, 8, 9, and 10]. As mentioned above, the prediction method of the onset of landslides is based on the monitoring of slopes, which is based on the relationship between the time and SD of a slope before the failure occurs, as shown in Fig. 1. Accordingly, the time variation in creep behaviour consists of three phases, namely, primary creep, secondary creep and tertiary creep. Among the time prediction methods adopted to date, the method proposed by Fukuzono [3] has been widely adopted in practice due to its simplicity and convenience of use.

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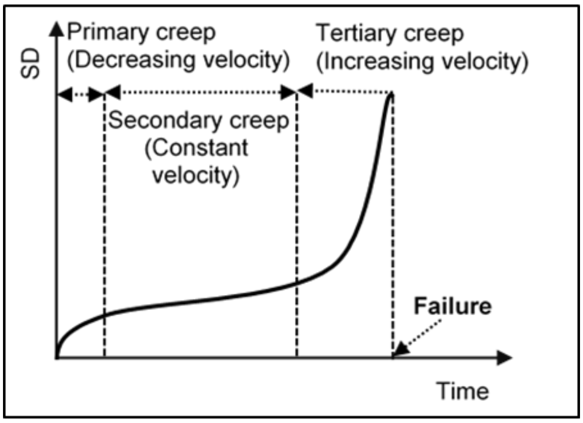

Fig. 1: The relationship between time and SD of the soil before failure under constant stress conditions (Saito, 1965)

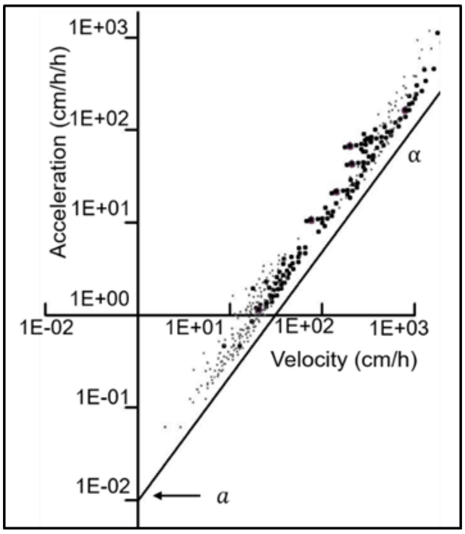

Fig. 2: The relationship between the velocity and acceleration of the SD (Fukuzono, 1985)

He proposed a relationship between the velocity and acceleration of SD just before failure (for the tertiary creep stage) in a large-scale model slope under sprinkling water, as shown in Eq. 1.

$$\left(\frac{\boldsymbol{dv}}{\boldsymbol{dt}}\right) = \boldsymbol{a} \cdot \boldsymbol{v}^{\boldsymbol{\alpha}} \quad (1)$$

where v and t are the velocities of the SD and correspondence times, respectively. In addition, $\boldsymbol{a}$ and α are the experimental constants that result from the intercept on the vertical axis and gradient of the relationship line, respectively, when the velocity and acceleration of the SD data are plotted over time (Fig. 2).

Based on the above relationship, he introduced a prediction method called the inverse-velocity (INV) method, which was created by integrating the relationship between the velocity and acceleration of SD by time just prior to failure (Eq. 2).

$$\frac{\boldsymbol{1}}{\boldsymbol{v}} = \{\boldsymbol{a}(\boldsymbol{\alpha}-\boldsymbol{1})\}^{\frac{\boldsymbol{1}}{\boldsymbol{\alpha}-\boldsymbol{1}}}(\boldsymbol{t_r}-\boldsymbol{t})^{\frac{\boldsymbol{1}}{\boldsymbol{\alpha}-\boldsymbol{1}}} \quad (2)$$

where t_r is the predicted failure time. Fukuzono [3] noted that the inverse velocity reached zero just before failure. Therefore, the failure time of a slope by the INV method could be determined by extrapolating the resultant curves to cross the time axis.

The past literature reveals that many researchers have adopted the INV method to forecast the failure time of landslides and that some of them achieved precise prediction, while some of them did not succeed completely. For example, Carlà et al. [1] predicted the failure time of a natural rockfall by the ground-based interferometric synthetic aperture radar method using the INV method, and they conveyed that the INV method gives precise results. Mazzanati et al. [4] highlighted that an improved version of the INV method called 'average data Fukuzono' (ADF) is necessary to achieve the best results. ADF incorporates the moving average of the displacement data over time and effectively minimizes the prediction error due to scattering of inverse-velocity values. Furthermore, Zhou et al. [11] emphasised that the time prediction effectiveness using the INV method is limited for actual landslides and that accuracy can be improved by introducing controllable variables. He proposed the modified INV method, which improves the accuracy of the predicted failure time by avoiding earlier prediction than actual failure time. That report noted that the forecasting effectiveness of the INV methods directly depends on the quality of the measured displacement data.

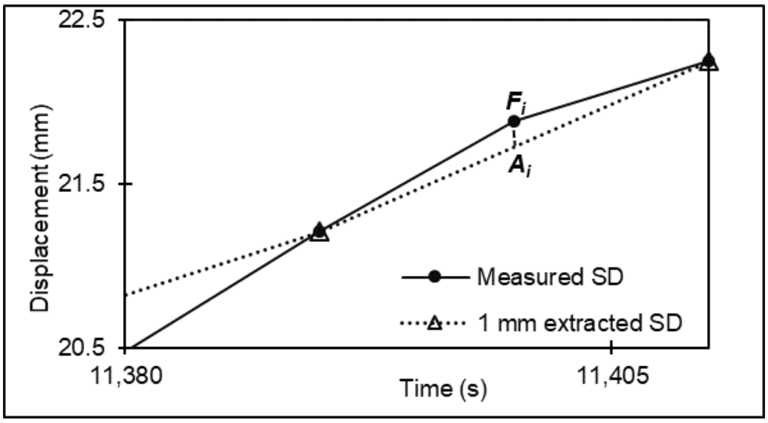

Fig. 3: The comparison of time variation of displacement for measured SD and extracted SD by 1 mm interval

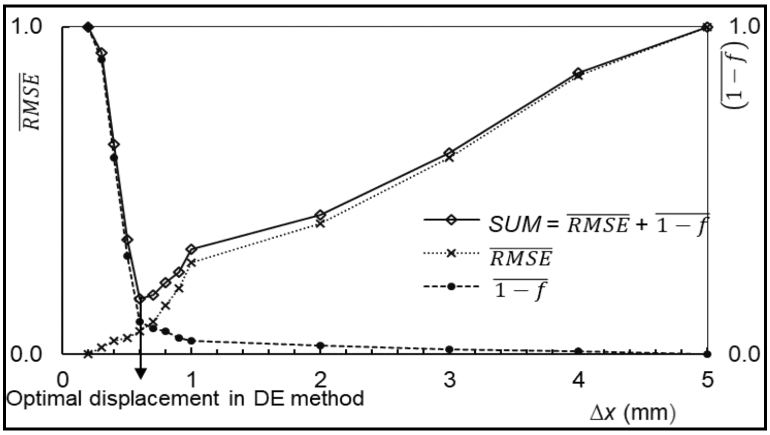

Fig. 4: $\overline{RMSE}$ and $\overline{(1-f)}$ value variation with different interval for SD data extraction

Accordingly, the time prediction by Fukuzono's original INV method may succeed in some cases but not in others because the results are widely affected by the quality of the measured data, as the displacement noise amplifies the resultant velocity. If the error in displacement data is not so considerable, the velocity variation, which is calculated using the same displacement data, becomes higher. This results in causes several peak values with up and down variations in velocities over time before failure. Hence, the present study focuses on improving the failure prediction by minimising the influences of the inverse velocity fluctuation by introducing the preprocessing of displacement data before the prediction.

2. Methodology

Methods for Raw Data preprocessing:

Data preprocessing is introduced to obtain a better prediction of landslide failure, which reduces the sudden fluctuation of $1/v$ values by decreasing the effect of noise on the measured SD. Two approaches called the data extraction (DE) and moving average (MA) methods are utilized in the present study.

Data extraction (DE) method

The DE method is carried out to determine the optimal displacement interval (Δx) for extracting the data to predict the failure time, which minimizes the scattering of $1/v$ values by avoiding the noise of the measured SD. The root mean square error (*RMSE*) and determining factor (f) values are used as supportive parameters to evaluate the reproducibility of the measured data and scattering in the relationship between velocity and acceleration in order to select Δx for the DE method. The *RMSE* values are calculated by Eq. 3.

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$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(F_i - A_i)^2} \tag{3}$$

Where N is the total number of the data, F_i is the measured SD at time t_i, A_i is the extracted SD at time t_i, and $(F_i - A_i)$ indicates an error between the measured and extracted SD. Suppose there are no data at the time t_i for the extracted data. In that case, data corresponding to t_i are projected by considering the proportional distribution of the extracted data before and after time t_i, as shown in Fig. 3. Generally, when the data extraction interval is increased, the reproducibility of the measured data is decreased, and the calculated *RMSE* values become larger.

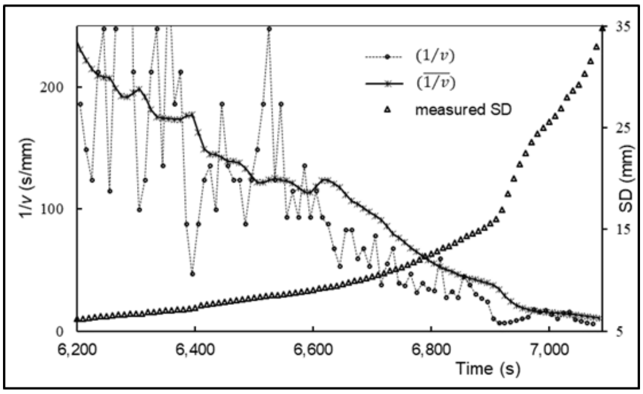

Fig. 5: Time variation of the inverse velocity derived from both the measured 1/*v* and smoothed inverse velocity ($\overline{1/v}$) and the SD

The *f* values measure how well the regression line fits with the velocity and acceleration on a logarithmic scale (Fig. 2). The linear regression line was obtained using Microsoft Excel for the relationship between the velocity and acceleration on a logarithmic scale utilized to get the *f* values. It expresses how much of the total variation in acceleration (vertical axis) is described by the velocity variation (horizontal axis) in the relationship between velocity and acceleration on a logarithmic scale which is always between 0.0 to 1.0. A value of 1.0 indicates a higher relationship strength. It means the lowest value of (1-*f*) gives the lowest scattering. However, calculated *RMSE* and (1-*f*) are not in the same range, which causes the weight ratio between *RMSE* and (1-*f*), is changed depending on the displacement interval used for the data extraction. So, in the case of *RMSE*, though the minimum value is zero, the maximum value is changed by more than 1.0. In that case, the maximum and minimum value difference is equal to the one and calculate all values within the range of 0.0 to 1.0 as normalized *RMSE* ($\overline{RMSE}$). So, both values are normalized into the same range, 0.0 to 1.0, assigning the weight ratio 1:1 between *RMSE* and (1-*f*), as shown in Fig. 4. The Δx increases, the discrepancy between measured and extracted data increases, and scattering in the relationship between the velocity and acceleration decreases. Considering the optimum Δx, it gives at the lowest summation of ($\overline{RMSE}$) and normalized (1-*f*), ($\overline{1-f}$).

Moving average (MA) method

The moving average inverse velocity ($\overline{1/v}$) values (calculated by considering consecutive 1/*v* values) are used to smooth the time variation of 1/*v* in the MA method. In this regard, we calculate ($\overline{1/v}$) by considering different consecutive values and select the best consecutive value, which gives the best smoothing time variation of 1/*v*. The ($\overline{1/v}$) at time step *t* is calculated using Eq. 4.

$$\left(\overline{1/v}\right)_t = \frac{(1/v)_t + (1/v)_{t-1} + \cdots (1/v)_{t-(n-1)}}{n} \tag{4}$$

Where *n* is the number of considered 1/*v* values and *t* is the present time step. As shown in Fig. 5, if the disturbance of SD is not significant, the 1/*v* variation calculated using the same SD becomes higher. However, the individual fluctuation is lower when considering ($\overline{1/v}$), which gives a smoother curve.

Prediction of the Failure Time

Calculation of velocity and acceleration values

The calculation of the velocity and acceleration from the measured SD and time data is explained below. First, the velocity is defined as the SD difference between the previous and present time steps divided by the corresponding time step difference. Second, the acceleration is defined as the velocity difference between the previous and present time steps divided by the corresponding time step difference.

Failure prediction from Fukuzono's original inverse-velocity (INV) method

The INV method is based on the relationship between 1/*v* and time, which reaches zero just before failure. Therefore, the failure time prediction can be predicted by extrapolating resultant curves to cross the time axis, which is given by the time differentiation 1/*v* in Eq. 2 and some arrangement to produce the ratio of 1/*v* to the increment of the inverse velocity, as shown in Eq. 5.

$$\left(\frac{1}{v}\right) \Big/ \left(\frac{d(1/v)}{dt}\right) = -(\alpha - 1)\,(t_r - t) \tag{5}$$

The failure time can be calculated using the ratio of the 1/*v* to its increment ratio at two different times, as shown in Eq. 6, which is the process of the INV method initially proposed by Fukuzono (1985).

$$\boldsymbol{t_r = \frac{t_2 (1/v)_1/(d(1/v)/dt)_1 - t_1 (1/v)_2/(d(1/v)/dt)_2}{(1/v)_1/(d(1/v)/dt)_1 - (1/v)_2/(d(1/v)/dt)_2}} \tag{6}$$

Failure prediction from the relationship between velocity and acceleration (VAA) method

The failure time prediction by the VAA method can be derived from the rearrangement of Eq. 2 to Eq. 7.

$$t_r = t + \frac{1}{a(\alpha - 1)}\left(\frac{1}{v}\right)^{\alpha - 1} \tag{7}$$

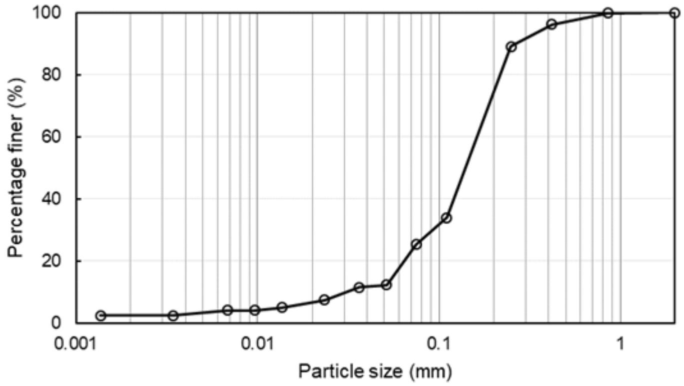

Fig. 6: Grain size distribution of the surface soil at the experimental site

Table 1: Physical properties of the surface soil layer

Soil particle density (g/cm^3)	2.574
Minimum density (g/cm^3)	1.082
Maximum density (g/cm^3)	1.361
Coefficient of uniformity	5.57

The failure time can be derived by substituting the present time (t) and corresponding inverse-velocity values ($1/v$) with $\boldsymbol{a}$ and α values into Eq. 7. The $\boldsymbol{a}$ and α values are derived from the relationship between velocity and acceleration on a logarithmic scale from linear regression analysis as shown in Fig. 2.

Landslide field experiment on a natural slope in Futtsu, Chiba Prefecture

Experimental Conditions

A landslide field experiment on a natural slope in the city of Futtsu in Chiba Prefecture was conducted on 12 December 2018 using a rainfall simulator as requested by NHK, Nippon Hoso Kyokai (Japan Broadcast Corporation). The experimental site was sparsely forested with hardwoods with a slope of approximately 40 degrees and with a smooth slope surface. The grain size distribution of the surface soil layer and the physical properties of the soil are shown in Fig. 6 and Table 1, respectively. The thickness of the surface soil layer was approximately 1 m based on the results of a portable penetration test (Japanese Geotechnical Society, 2017) using a number of blows (10 cm penetration) with a 5 kg weight dropped from a height of 50 cm. During the experiment, artificial rainfall was supplied to an area 10 m long and 10 m wide. A landslide occurred after four hours and 25 minutes of rainfall with an intensity of 140-300 mm/h, and the depth of the landslide was approximately 1 m according to Ochiai et al. [6]. A total of six extensometers at three locations along two survey lines were installed (Fig. 7(a)). Extensometers 1, 2, and 3 were placed on line 1(Fig. 7(b)), and the others were placed on line 2. Furthermore, Fig. 7 shows the cross-section before failure (straight line) and after failure (dotted line), and it reveals that the failure was a sliding-type landslide. A detailed explanation of the experiment can be found in Ochiai et al. [6].

Experimental Results

Although six extensometers were installed on the experimental slope, only Nos. 1 and 5 were within the landslide mass, and the others were out of the landslide area. Therefore, the SD measured at their corresponding times by extensometers Nos. 1 and 5 was used for the present study. Extensometers No. 1 (line 1) and No. 5 (line 2) show movement along the surface approximately 275 mm to 204 mm just before the failure.

Results: Data Preprocessing

This section presents only the results corresponding to extensometer No. 5 (line 2). The recorded SD and time at failure were 204.4 mm and 22,680 s, respectively. Fig. 9 shows the result of the DE method, which reveals that the 3.0 mm SD interval is the best Δx for data extraction to failure time prediction. The analysis is carried out by selecting an SD interval from 0.1 mm to 1.0 mm by a 0.1 mm difference and then a 1.0 mm interval difference until 10.0 mm. $\overline{RMSE}$ gradually increases when the extracting displacement interval is increased except at the 0.1 mm interval and 3.0 mm interval. The calculated $\overline{RMSE}$ at the 3.0 mm interval is a similar value, 0.30, with the 2.0 mm interval. The parameter $(\overline{1-f})$ gradually decreases as the extracting displacement interval increases, but a small increase of less than 0.03 can be observed until 0.8 mm. Subsequently, the $(\overline{1-f})$ values suddenly drop until reaching 2.0 mm and then decrease smoothly. However, the sum of $\overline{RMSE}$ and $(\overline{1-f})$ shows the lowest value at 3.0 mm as 0.37. The 2.0 mm interval also shows a closer value, 0.38 to 3 mm, as the sum of $\overline{RMSE}$ and $(\overline{1-f})$.

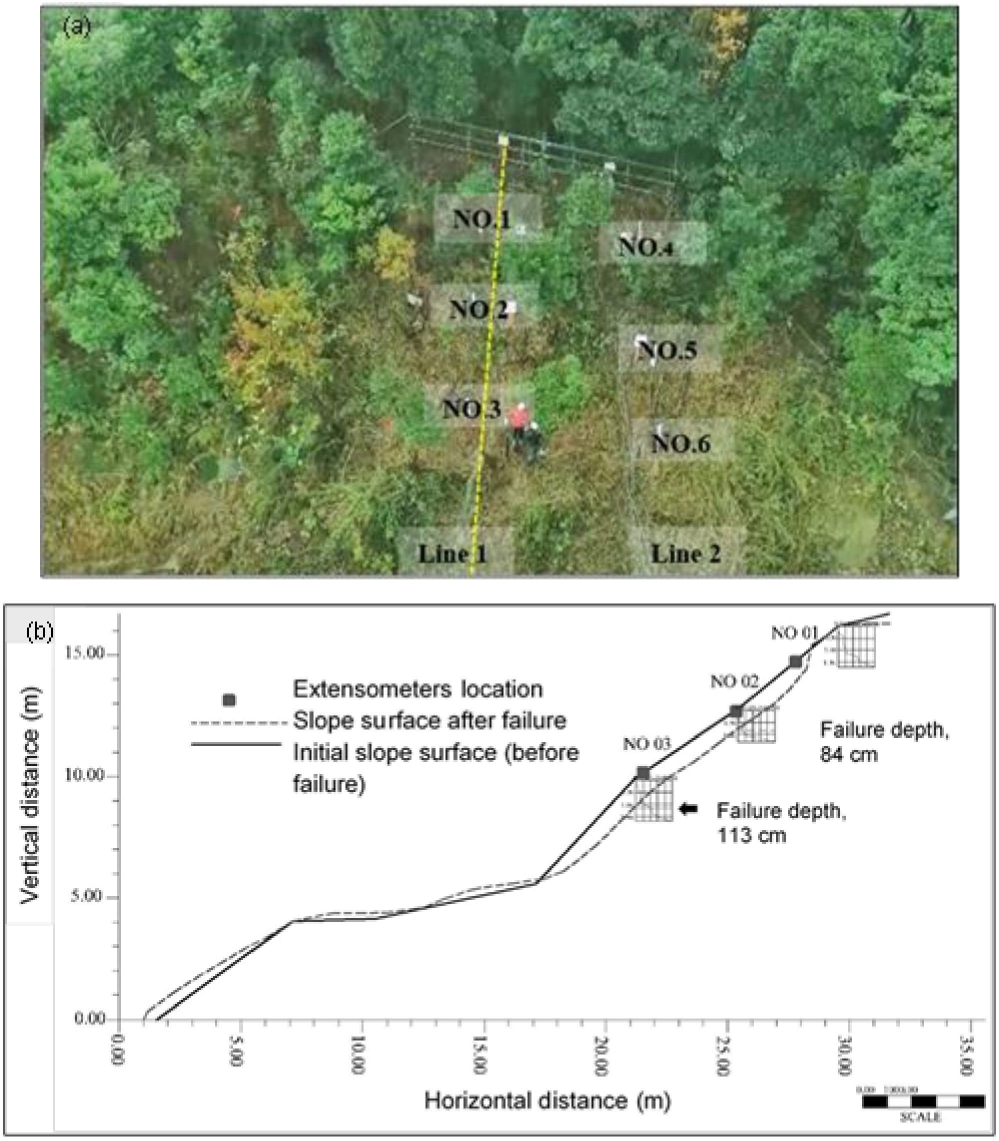

Fig. 7: (a) Front view of the natural slope in Futtsu and arrangement of extensometers, and (b) longitudinal section along experimental slope at Futtsu (with the locations of displacement gauges Nos. 1, 2, and 3 along survey line 1)

Fig. 10 shows the time variation of $1/v$ and $(\overline{1/v})$, which is calculated by considering the different number of consecutives $1/v$ to select the best smooth time variation of $(\overline{1/v})$ in the MA method for extensometer No. 5. Accordingly, moving average velocities are calculated using 2, 5, 10 and 20 consecutives (2MA, 5MA, 10MA and 20MA). The results reveal that when the considered number of consecutive increases, the smoothness of the resultant time variation $(\overline{1/v})$ curves is improved.

Prediction of the Failure Time

Prediction results by the INV method

In the present study, the time remaining to failure (t_r-t) approaching zero is considered an indicator for failure prediction, which is almost similar to considering the predicted failure time (t_r) as an indicator of the failure. But in the practical scenario, prediction accuracy cannot be assured based on the t_r due to the poor relationship of time variation t_r. In contrast, the time variation (t_r-t) leads to a more precise prediction. Fig. 11 (a) and (b) show the failure time prediction by the INV method using the data processed by the DE method and MA method in an orderly manner. Fig. 11 (a) contains the time variation of (t_r-t) by the INV method from the data processed by the DE method by only 0.1 mm, 0.6 mm, 3 mm, and 10 mm. The predicted (t_r-t) by the INV method using DE data tends to lie along the time axis with some up and down fluctuation in the 0.1 mm extracted data. However, upon comparing the results of higher data extracting SD interval, the prediction shows the values away from the time axis, suggesting that when the data extraction interval is higher, the method gives an earlier prediction. However, the prediction using the INV method and DE data shows negative values throughout the prediction in all SD intervals, which means that during the experiment, the prediction results indicate that slope failure has already occurred.

Fig. 11 (b) contains the time variation of (t_r-t) by the INV method from the data processed by the MA method only for 2MA, 5MA, and 20MA.

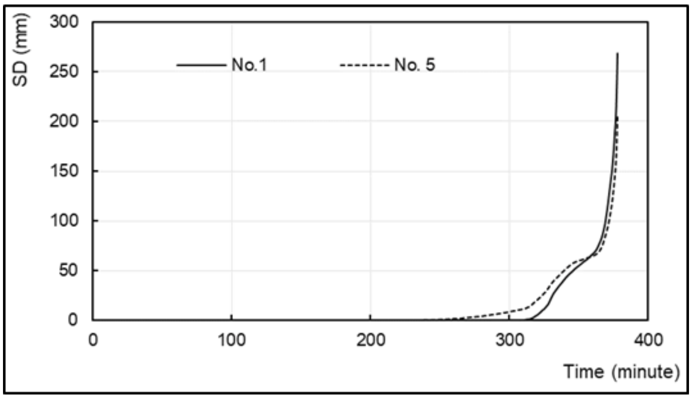

Fig. 8: The time variation of the SD, measured by extensometer Nos. 1 and 5

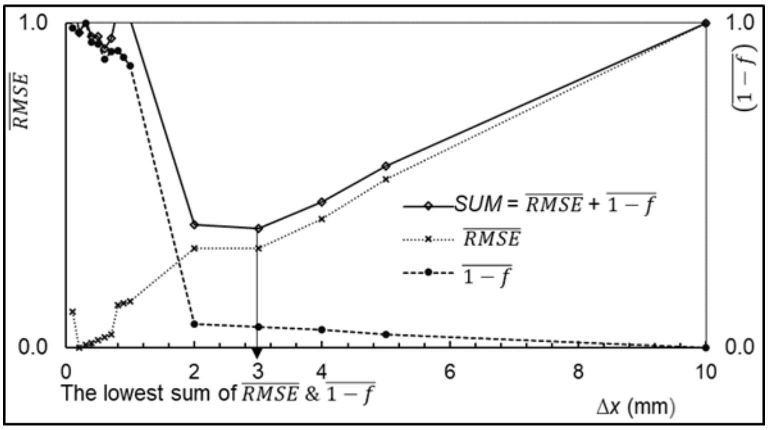

Fig. 9: $\overline{RMSE}$ and ($\overline{1-f}$) value variation with the different SD intervals in the DE method for extensometer No. 5

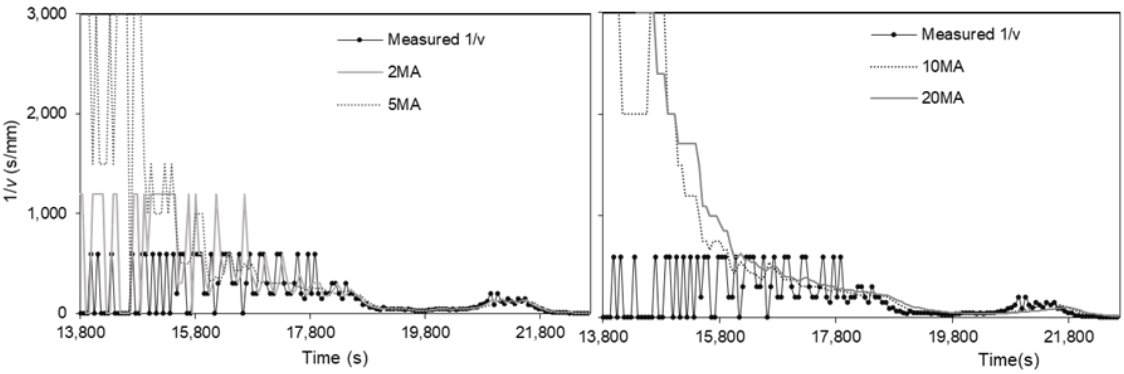

Fig. 10: Time variation of 1/v and ($\overline{1/v}$), (a) for 2MA and 5MA, and (b) for 10MA and 20MA

The results of the predicted (t_r-t) by the INV method using MA data also show the same result as the DE method (Fig. 11 (a)). The results are almost identical to the results of the DE data; it shows when the number of consecutive used for calculating the moving average is higher, an earlier prediction is obtained. Therefore, the prediction using the INV method, with both DE and MA data, shows poor prediction because the results still show scattering and negative values just before failure.

Prediction results by the VAA method

Fig. 12 shows the time variation of (t_r-t) by the VAA method from the data processed by the DE method. In order, Fig. 12 (a) and (b) refer to the whole experiment duration and the time just before failure (from 21,000 s to failure), respectively. The prediction begins after 10,560 s because values higher than 0.1 mm, the lowest displacement interval, are used for data extraction. The prediction from data extracted using 0.1 mm and 0.6 mm intervals between 15,330 s to 18,705 s shows negative values. However, the prediction, using 3 mm and 10 mm shows only positive values, and the general trend of decreasing (t_r-t) with time and reaches closer to zero just before failure (Fig. 12 (b)). The fluctuation of time remaining to failure (t_r-t) from the extracted data using 3 mm and 10 mm intervals is minimal compared with the other predictions. When comparing the results of time variation produced from the data extracted using 3 mm and 10 mm intervals, the 3 mm interval gives a better linear decreasing trend than the 10 mm interval. Therefore 3 mm is the optimum displacement interval for DE, as it offers the best results for failure prediction by the VAA method.

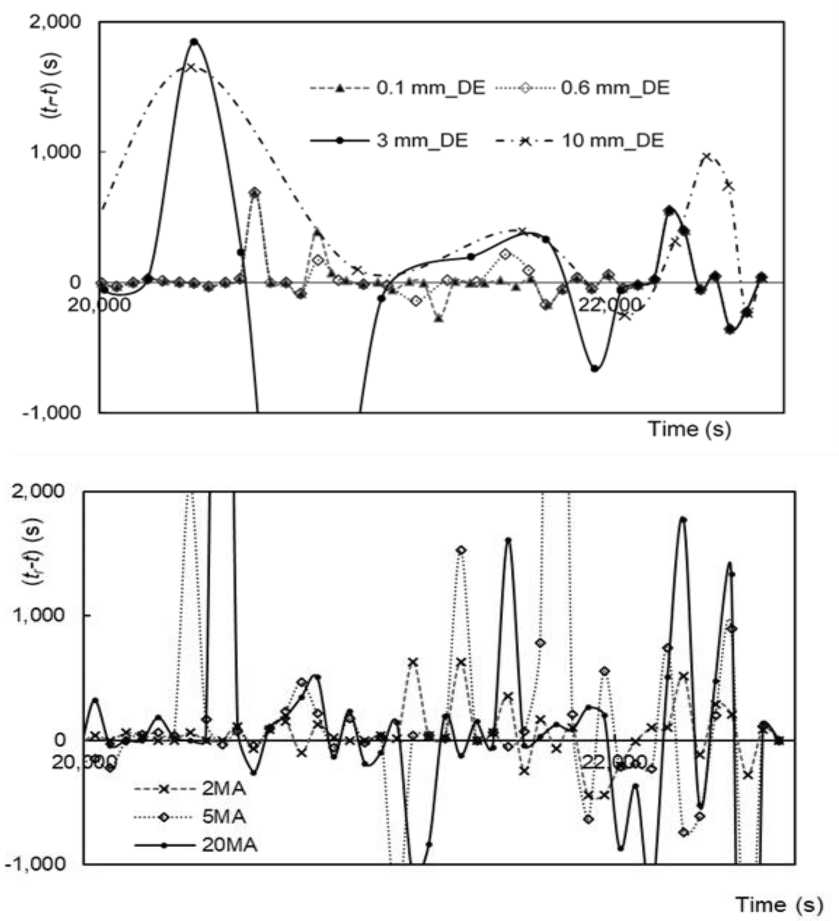

Fig. 11: Time variation of the time remaining to failure (t_r-t) by the INV method (a) using the data processed by the DE method (0.1 mm_DE, 0.6 mm_DE, 3 mm_DE, and 10 mm_DE represent the results from the DE by SD intervals of 0.1 mm, 0.6 mm, 3 mm, and 10 mm), and (b) using the data processed by the MA method

Fig. 13 shows the time variation of (t_r-t) by the VAA method for the data processed by the MA method. Fig. 13 (a) and (b) refer to the whole experiment duration and just before failure (from 20,000 s to failure), respectively. Fig. 13 (a) highlights that the VAA method's prediction using the MA method's processed data gives both negative and positive predictions, regardless of the number (n) used for calculating the moving average. Further prediction with 5MA also gives a negative value just before failure. However, the prediction with 2MA and 20MA shows a general trend of decreasing (t_r-t) just before the failure.

The VAA method's prediction using the MA shows a decreasing trend in the latter time before the failure compared with the results of the VAA method using DE data. On the other hand, the results obtained from the VAA method using the MA show a higher scatter just before the failure, while the VAA method using DE gives relatively less scatter. Furthermore, the prediction given by the VAA method using MA data has uncertainty and depends on the conditions, which could not be ensured in every case. For example, if the prediction by the VAA method using 2MA and 20MA gives a decreasing trend, then 5MA gives a poor prediction. Based on the present analysis, the prediction given by the VAA method using 2MA gives a linearly decreasing trend compared to 20MA with the above-explained complications. Therefore, the best prediction is obtained from the VAA method using data processed by the DE method.

3. Conclusions

The present study predicted the failure time using two methods with different preprocessing data methods to evaluate the effectiveness of the preprocessing data methodologies to improve the failure prediction using field experiment data on a natural slope in Futtsu, Chiba Prefecture. During the study, the following conclusions could be drawn.

1. The failure prediction by the VAA method using DE preprocessing gives the best prediction because it minimizes the individual velocity variation. In the process of DE, not only reproducibility but also equal priority is given to reducing the scatter in the relationship between velocity and acceleration.

2. The optimal displacement interval (Δx) by the DE method corresponds to the smallest sum of $\overline{RMSE}$ and ($\overline{1-f}$), which gives the best prediction using the data extracted by the VAA method. The Δx changes depending on the distance moved by the landslide. Therefore, more studies on a different scale of landslides are needed to obtain the relationship between Δx and the moved displacement.

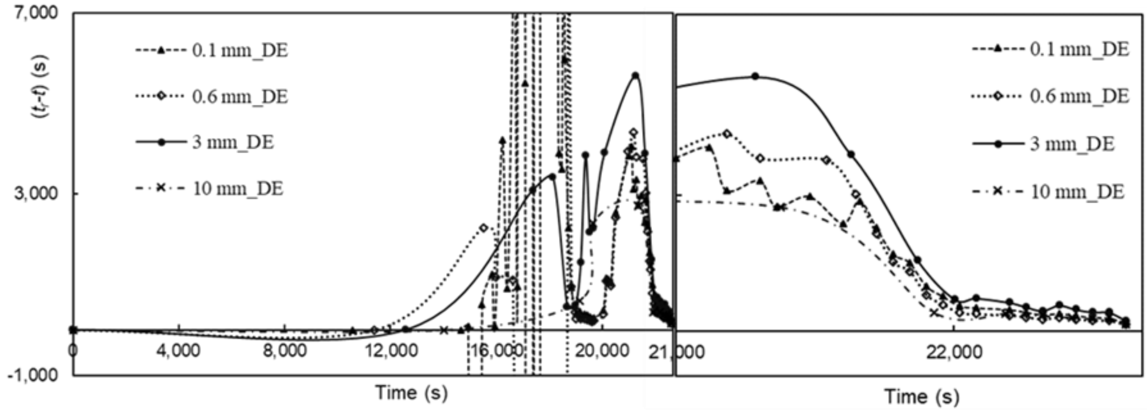

Fig. 12: Time variation of the time remaining to failure (t_r-t) by the VAA method using the data processed by the DE method (a) for the whole experiment duration, and (b) just before failure (from 21,000 s to failure)

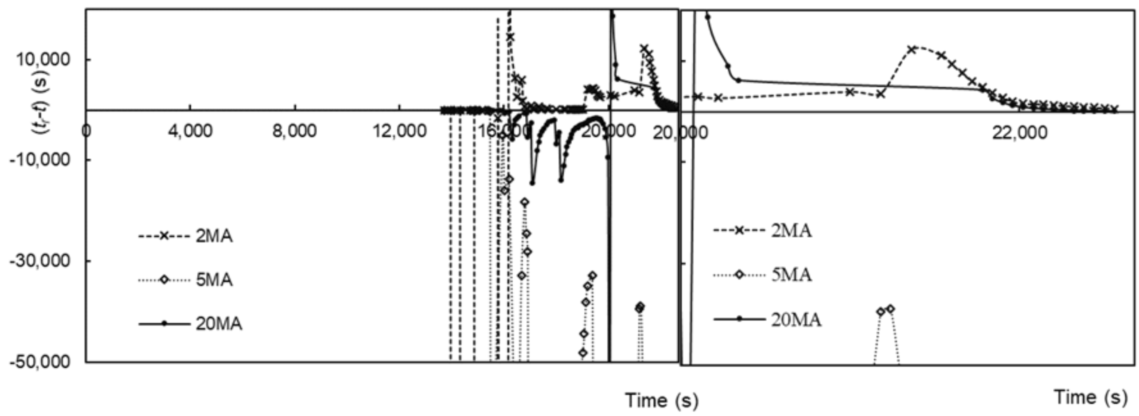

Fig. 13: Time variation of the time remaining to failure (t_r-t) by the VAA method using the data processed by the MA method (a). For the whole experiment duration, and (b). Just before the failure (from 20,000 s to failure)

3. Best smoothing of the time variation of the inverse velocity curve is obtained from the moving average velocities calculated by a larger number of consecutive velocities than a small number of consecutive velocities. However, the time prediction using data processed by the MA method shows poor prediction due to some scattering of the inverse velocity. In some cases, the prediction by the VAA method using MA data gives better prediction compared with the results of the INV method by MA data.

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