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Automatic extraction of rockfall source based on terrain analysis map using support vector machine

Koki Sakita, Teruyuki Kikuchi, Satoshi Nishiyama, Junsheng Song and Yuzo Ohnishi

Graduate School of Environmental and Life Science, Okayama University, 1-1-1 Tsushima-naka, Kita-ku, Okayama 700-8530, Japan

pq1i4u6h@s.okayama-u.ac.jp

Abstract. Disaster prevention inspections, without overlooking the sources of falling rock, are essential for establishing efficient slope management and countermeasures. This study presents an automatic extraction method for rockfall sources, using remote sensing and artificial intelligence technology, to reduce overlooking during the inspection cycle and improve slope management efficiency. Current inspections have some factors that lead to object overlooking, one of them being the use of maps with low expression accuracy. Furthermore, biased criteria for the interpretation of inspection points in a desk study can play a part. Therefore, improving map accuracy and using quantified interpretation methods will improve the current inspection significantly. In such cases, the use of remote sensing technology is an effective measure. The utilization of airborne laser surveying and terrain analysis methods is effective for accurately acquiring the slope surface and topography. Airborne laser surveying is a system that takes measurements with multiple sensors mounted on an airplane, and the measurement data are represented by a collection of multiple points with three-dimensional coordinates. Furthermore, the terrain analysis method, which converts the survey data to two-dimensional raster images, extracts the necessary information, such as the ridge, valley, and elevation, of the slope. In this study, two-dimensional continuous wavelet transforms, used as a terrain analysis method suitable for rockfall extraction, are adopted to create a wavelet analysis map from survey data. Furthermore, to automatically extract the inspection points, the classification technology in artificial intelligence (AI) is applied to the terrain analysis map to extract the rockfall source in a desk study. A support vector machine (SVM) is a type of AI model that classifies based on training data and works by determining the best possible separation between the closest observations belonging to different classes. By applying this classification method, the rockfall source was extracted by performing object detection on the map. First, the entire map was divided into smaller patch images. Next, each patch image is classified as a rockfall source using the trained SVM. Finally, the area corresponding to the patch image, classified as the rockfall source, was drawn on the entire map. In this study, the performance of these integrated systems was verified in an area with a falling rock hazard. In the training process, wavelet analysis maps that reflect inventory data based on past inspection results were used. The extraction performance was evaluated by comparing the verification results with the inventory data and interpretation results based on the map features. Consequently, all learned rockfall source points were extracted, obtaining high-precision readability. Furthermore, the extraction performance of the same tendency inside the inventory range was shown in the range outside the inventory, acquiring a high versatility. Accordingly, we discuss the possibilities and issues for automatic extraction of the desk survey using the proposed method.



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1. Introduction

A rockfall is a slope disaster, in which separated rock blocks are activated by a force and fall on a slope under the influence of gravity, and it can occur worldwide. Although the scale of damage caused by falling rocks is more local than that of landslides, it is extremely difficult to predict the time and place of an occurrence. However, most rockfalls are caused by the destabilization and activity of the rocky part where the slope is steep and rock surface exposed. Therefore, in terms of rockfall countermeasures, inspections are conducted while focusing on the rockfall source. A slope inspection begins by conducting a desk survey using survey materials. This desk survey extracts the inspection locations on the slope based on the inspection maps and selected survey locations. Accurate results of the desk survey are crucial because they provide preliminary information for a field survey. In current slope surveys, contour maps and aerial photographs are widely used as inspection materials because they are relatively easy to create. However, for slope surveys using these maps, it is difficult to locate the position of the rockfall source owing to poor expression accuracy. Furthermore, the results are affected by the skills and experience of the inspectors who conduct the desk survey.

The use of airborne laser surveying and terrain analysis technology have been considered to overcome this problem. Airborne laser surveying, which is a mobile three-dimensional (3D) survey, can measure the surface of a slope as a 3D shape. Terrain analysis technology is an analysis method that calculates the slope feature, which is similar to the unevenness and slope angle included in the 3D data, and incorporates it into a two-dimensional (2D) map. Various methods exist in this technique, depending on the analysis method [1]. In this study, we used a slope map that colors shadows according to the slope angle and wavelet analysis map that expresses the unevenness of the ground surface from the correlation between the undulations of the terrain and pseudo convex function. We verified its usefulness by transparently synthesizing two maps and creating a map in a form that complements the characteristics of each map [2]. The effectiveness of the inspection, using the map, is demonstrated. However, as described above, there is a bias in the criteria when conducting a desk survey using maps. and thus, uniform results cannot be obtained. Therefore, we propose the automation of desk extraction of rockfall sources using artificial intelligence (AI) technology and examine its usefulness in slope surveys. Specifically, the above-mentioned wavelet analysis map was used as a base map. A system that applies object detection technology using a support vector machine (SVM), which is an AI method, was developed. Using this system, the rockfall source location is extracted by creating training data from the existing inspection results and feeding them to the model as the rockfall source location and other microtopographies. The consistency of the extraction result is evaluated by comparing it with the learned part and human interpretation result based on the map. Finally, the usefulness of the desk survey method using AI in the slope inspection is discussed.

2. Automatic extraction of rockfall source

2.1. Airborne laser surveying and data composition

Airborne laser surveying is a type of 3D surveying method that measures sensors mounted on rotarywing or fixed-wing aircraft. In this method, a non-prism laser rangefinder light detection and ranging (LiDAR) mounted on the aircraft performs the measurement. The laser pulse emitted from the aircraft hits the ground surface or trees, and the distance is measured by acquiring the return pulse. In addition, the aircraft is equipped with a global navigation satellite system (GNSS) sensor that measures its own position during flight and an inertial measurement unit (IMU) that measures the attitude of the aircraft. The 3D coordinates of all measurement points are calculated from the information acquired from these sensors. Accordingly, we can generate 3D data (point cloud) composed of a collection of points. For slope measurements, the laser beam may reflect off leaves and vegetation and return without reaching the ground surface. Data obtained by filtering such unnecessary parts and extracting only the ground surface are called ground data. To conduct a terrain analysis, the conversion of the data into a grid

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shape is straightforward and proceeds uniformly. This converted data is called grid data or a digital elevation model (DEM).

2.2. Two-dimensional wavelet analysis

A wavelet analysis map [3] created by applying a 2D continuous wavelet transform (CWT) to DEM data was used as the base map. This analysis method is a filtering method that emphasizes the degree of unevenness of the DEM. The analysis is defined as follows.

$$C(s,a,b) = \frac{1}{s} \iint z(x,y) \psi\left(\frac{x-a}{s}, \frac{y-b}{s}\right) dxdy \#(1)$$

C(s,a,b) denotes the wavelet coefficient. A map is created by assigning colors according to the wavelet coefficient value. In addition, (a,b) indicate the (x,y) coordinates of any point in the DEM data, and z(x,y) indicates the elevation value of the DEM corresponding to the (x,y) coordinates. The function ψ denotes the mother wavelet, expressed as

$$\psi(x,y) = (2 - x^2 - y^2)e^{-\frac{1}{2}(x^2 + y^2)}.\#(2)$$

This function is also called the Mexican hat function because it has a convex shape at the top.

$$\lambda = 4s\#(3)$$

Here, the wavelength of the Mexican hat function, λ , is changed by adjusting s, which is a parameter of wavelet analysis. This relationship is expressed by Eq. (3): when s is large, the wavelength of ψ is long, and the analysis window at one node of the DEM is wide. Figure 1 presents an example of a wavelet analysis map compared with aerial photographs at the same location. The contrast between the ridges and valleys is clearly visible. In previous studies [4], verification results indicated the map feature of transitional lines, such as rockfall sources, in the area where C(s,a,b) suddenly changed from a positive to negative value in the adjacent section. The sudden change from black to white represents this feature in the map. This feature makes it possible to represent microtopography, even in complex terrains.

2.3. Object detection by support vector machine

Object detection technology using AI is conducted by combining a search for a specific location in an image and classification, in which the searched image is identified and a cormorant pattern is determined.



Figure 1. Comparison of aerial photograph and wavelet analysis map

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In this research, we attempted to extract the rockfall source from the wavelet analysis map using object detection technology [5], which applies a SVM[6]. The SVM is not only a powerful pattern classification method, but also has advantages, such as low calculation cost, compared to recent deep learning models. The purpose of this method is to determine the optimum separation hyperplane that separates the two classes of data from the learning pattern and to classify the unknown pattern accordingly. The vertical distance from the separated hyperplane to the nearest learning pattern (support vector) is called the margin, and the separated classes. In general classification problems, it is often difficult to clearly separate the learning patterns. In such a case, by introducing the slack variable ξ_i into the classification condition, it is possible to allow a certain degree of misclassification and enable the condition of a soft margin to advance learning. These concepts are illustrated in Fig 2. In learning, it is necessary to determine parameter C, which is associated with a slack variable. By reducing C, we can create a model that accepts many misclassifications.

In the case of a classification problem for an image, as one pixel of the image corresponds to one variable, the classification problem for a multidimensional pattern is performed. Object detection is performed using the two processes shown in Fig. 3. In the training process, data for training are prepared based on past inventory data. In this verification, the inventory is divided into two classes: rockfall source and other topography. Therefore, the range corresponding to each of the two classes is cut out and organized as training data. This is fed to the support vector machine to proceed with the training. In the extraction process, the rockfall source is extracted from the image using the sliding window method. This method shifts an arbitrary window size by the same width from the upper left of the image and generates the image contained in the window as one tile. This tile image is classified by a support vector machine, and the location classified as the rockfall source is presented on the map to enable automatic extraction.

These processes are built on Python programming, and SVM classification is performed by the scikitlearn module [7].







Figure 3. Explanation of the object detection method using a support vector machine and terrain analysis map

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3. Experimental condition

3.1. Study area

The study area is Mitsu, Kuso, Kita-ku, Okayama City, on Route 53, Okayama Prefecture, Japan. An aerial photograph of this area is shown in Fig 4. The slopes in this area are steep, with an average slope exceeding 40°, and are affected by river erosion. In addition, the Paleogene mudstone and sandstone areas are distributed, and the ground surface exposed by the influence of erosion; therefore, it is designated as an area with a high risk of rockfall. On the road adjacent to the slope, in the case of heavy rainfall exceeding 200 mm, traffic regulation is subject to consideration with a risk of disaster, and rockfall measures are taken on a daily basis.

3.2. Mapping and analysis condition

In the experiment, object detection was performed on the wavelet analysis map using a SVM to extract the rockfall source location. The airborne laser survey was conducted with a point density of 10 $point/m^2$ at the time of planning. From the result of data analysis, the mode density of this ground data was about 5 point/ m^2 . A DEM was created based on this data, and terrain analysis was applied. A wavelet analysis map was created using Eq. (1) with the parameter s = 1. The inventory data used for training were obtained from the results of previous research [4]. In the study, the target area was divided into three areas, field surveys were conducted, and 48 microtopographies including the rockfall source were confirmed, as shown in Fig. 5. In this study, 92 sites, including 44 flat slopes, were used as training data. The breakdown of the data at 92 locations is presented in Table 1. At the time of training, it was necessary to verify whether the classification by the SVM was performed accurately. These 92 training datasets were divided into two datasets: training and verification. Fig. 6 shows a summary of this dataset. In the image example of the microtopography shown in Fig. 6, abrupt changes in the value in the adjacent section, which is a characteristic of the wavelet analysis map, are observed at the rockfall source. In the histogram, the rockfall source tends to have a wider skirt than other microtopographies, and the results are consistent with the aforementioned characteristics. In addition, 10 sub-datasets with different combinations were created from the training/validation datasets, so that the results would not vary depending on the data to be trained, and K-fold cross-validation was performed for each of them. In each of the 10 learning cycles, an attempt to improve the accuracy was conducted by tuning the parameter C. Moreover, the radial basis function was adapted as kernel function in SVM [6], and the kernel parameters were set to the default settings on the scikit-learn function [7].

The conditions for the object detection were obtained. For object detection, the search window size and slide width must be specified. In the microtopography example shown in the Fig. 6, the minimum width and height were 10 pixels and maximum width and height were 30 pixels. Therefore, we randomly determined the window size 10 times in this range, performed 10 searches for each window size with a pixel slide width of 5, and integrated the results to create the final extraction result.



Figure 4. Aerial view of Mitsu Kuso, Okayama Prefecture, Japan

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Figure 5. Inventory data based on existing survey results shown on the wavelet analysis map and examples of inspection results

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Table I	Number	of images	used for	training and	Verification	of support	vector machines
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	Training	Validation	Total
Source of rockfall	30 or 31	2 or 1	32
Other topography	52 or 51	8 or 9	60



Figure 6. Example images and histogram of two classes of tiled data used for learning/verification

4. Result

Figure 7 shows the results of extracting the rockfall source location by object detection using SMV. In the figure, the microtopography used for training and verification is marked in red for the rockfall source and blue for the other microtopographies. In addition, the part extracted as the source of the rockfall is surrounded by a yellow frame. The location extracted as the rockfall source location is over a wide range. As shown above in the wavelet analysis map, the topography of the step, such as the rockfall source, is located where the value changes rapidly in the adjacent range. When the extracted range based on this characteristic was confirmed, most of the extracted parts were identified by this feature. Conversely, this feature does not appear in the area of the southern slope adjacent to Area 2, implying that the plane surface is beyond the extraction. The linear microtopography that developed

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along Areas 1, 2, and 2, 3 is a valley formed by erosion, and the result was extracted along them. To verify the accuracy of the extracted results, the extraction rates of the range used for training and verification are listed in Table 2. As a result, it was confirmed that all 32 rockfall sources were extracted. As for the other microtopographies, 45 out of 60 locations were not extracted as rockfall sources.

5. Discussion

As shown in Section 4, rockfall sources were extracted by an object detection system using a support vector machine. We succeeded in extracting all 32 rockfall sources used for learning and verification. However, other microtopographies were misinterpreted in 15 places, and there was a tendency for over-extraction as a whole. In the actual slope inspection, a field survey was conducted after the desk survey. Therefore, the extraction must be performed without overlooking the duration of the desk survey. However, when considering the actual use of the system, it is inefficient to inspect all extracted sections; therefore, it is necessary to further narrow down and determine the inspection priority. For example, Fig. 8 shows colored extraction results, according to the inclination angle of the slope. Locations with a large inclination angle exceeding 50°, that is, where the bedrock is likely to become unstable and has a high risk, are colored red to black. These are locations where field surveys are highly necessary. In this way, by narrowing down the survey points based on the results extracted by object detection and other information, an inspection is expected to be more effective.

6. Conclusion

In this study, we proposed a extraction method of the rockfall source that uses AI technology to interpret maps. We established an inspection method and verified its usefulness as a method for extracting rockfall sources. Using the detection results, we succeeded in extracting all rockfall source points used for learning and verification, and demonstrated the usefulness of the inspection method. In addition, based on the extraction result, unstable locations were visualized using color, according to the inclination angle, and the results proved useful in improving the inspection. in an actual desk survey, the inspection priority is low from the viewpoint of risk management for rockfall sources along the valley, where it is easy to predict rockfalls, and locations that do not face the road. In addition, in an actual desk survey, the inspection priority is low from the valley, where it is easy to predict rockfalls, and locations that do not face the road. In addition, in an actual desk survey, the inspection priority is low from the valley, where it is easy to predict rockfalls, and locations that do not face the road. It is necessary to improve the system so that the inspection points can be determined in a way that is closer to human judgment by adding more inspection factors. Furthermore, advanced consideration is necessary on the use of aerial laser surveying. Previous studies have shown that point density of the survey data also

affects the map expression and extraction performance [4]. Therefore, the utilization of low-density data



Figure 7. Extraction results of rockfall source location by the object detection using the wavelet analysis map

Table 2. Confusion matrix of extraction results

 based on existing inventory data

	Extracted	Unextracted
Source of rockfall	32	0
(32 places)	(100%)	(0%)

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Other topography	15	45
(60 places)	(25%)	(75%)

is likely to overlook the rockfall source even with AI technology. Conversely, surveying with a drone equipped with LiDAR enables high-density measurement and can be expected to be used for the slope inspection. In order to further improve the efficiency of inspection, the utilization of such sensing technology is also an issue to be considered in the future.

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Figure 8. Color stage diagram of the slope angles at the extraction locations