Application of image quality assessment for rockfall investigation

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ABSTRACT

This paper presents an automatic image sensing method to detect rockfall events using time-lapse photographs and digital image processing. Based on the change detection concept, an image quality assessment procedure is proposed to detect rockfall events in this study. Sets of temporal images taken from a rockfall field test are selected to assess similarity between the images. Two representative image quality assessment algorithms have been employed to find the applicability of the algorithms for rockfall event detection. In this study, the error map which highlights rockfall movements by differences between two images is visualized using OpenCV and Python scripts. The results show that time-lapse photographs obtained from a fixed photographed position can be effectively used to detect rockfall event initiated from the captured area. Also, the well-known SSIM approach gives excellent results from its efficiency of similarity detection.

Keywords: change detection; image quality assessment; SSIM; rockfall;

1 INTRODUCTION

Time-lapse photography is a technique where a target is taken over regularly spaced intervals of time. The idea of this technique is to capture the changes allowing people to view what had happened over a period of hours, days or even years. This image-based remote sensing technique can be used for various purposes according to the given intervals of time. Long time interval photograph is typically used to investigate changes in astronomical observation, geological survey, cityscape and construction. For a short-term event such as rockfalls, time-lapse photographs can be also effective for damage investigations in hazardous areas.

When using time-lapsed image data, the values of image pixels at previous time are compared with the values of the corresponding image pixels at a later time in order to determine the degree of change. In this process, it can be quite difficult to identify pixels of significant changes by controlling negligible changes due to camera motion, sensor noise and illumination variation etc. Also, because digital change detection is affected by various factors such as spatial, spectral, environmental, thematic and temporal constraints, a variety of change detection algorithms have been developed to work best for purposes. The representative aspects of change detection applications are well discussed in a scholarly journal (Lu et al., 2004).

In order to detect an object in image analysis, the selection of a suitable algorithm for a given condition is extremely important. If time-lapse images are taken at a fixed position without any changes of photographing conditions, image quality assessment (IQA) can be selected as the most applicable method for change detection. Originally, this technique was developed to monitor and adjust image quality. It has been also employed to detect differences from similar images to each other. Numerous algorithms and image quality metrics for image quality assessment have been proposed such as the mean squared error (MSE) (Chandler and Hemami, 2007) and the structural similarity index (SSIM) (Wang and Bovik, 2002). Using these algorithms, the locations and magnitudes of the errors (differences) detected in a coded image can be visualized by means of an error map.

In this study, two representative algorithms, MSE and SSIM are tested using a data set of rockfall tests. Pairs of time-lapse images at the beginning and end moment of rockfall were extracted from the test data and employed to test the algorithms. Differences between two images due to falling rocks is detected and visualized using Open CV and Python scripts to create error maps.

2 METHODOLOGY

As a feature on images, rock blocks on slopes exhibit diverse colors, shapes and textures. Considering these features, in a static state, the detection of rocks on images has been rather approached by edge-based algorithms (Thompson and Castano, 2007). However, the detection of rocks before rockfalls and after may be rather clearly approached by the change of contrast between the time-lapsed images. Based on this assumption, a pixel-based algorithm, MSE and a powerful algorithm which can measure structural comparison, SSIM are employed to study the applicability of image quality assessment (IQA) algorithms for rockfall monitoring. The overall scheme of the algorithm in this study is illustrated in Figure 1.

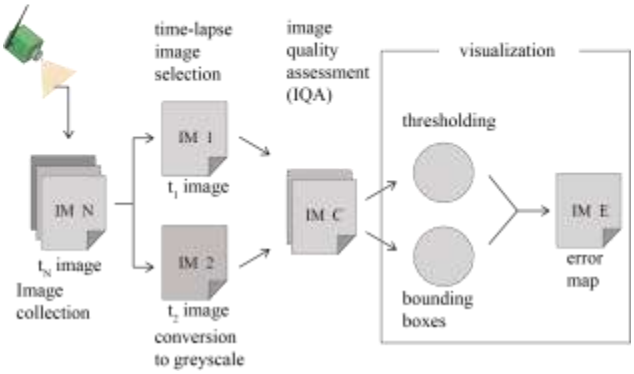

Fig. 1. Illustration of the approach in this study. The input is a grayscale image to which an image quality assessment algorithm is applied. OpenCV, is then used to obtain an error map.

2.1 MSE: Mean Squared Error

In statistics, Mean squared error (MSE) is a well-known measure of the quality of an estimator. As defined in Eq. (1), this simple formulation has been applied to various fields due to its clear interpretation. For a pair of n-dimensional image vectors, MSE calculates the average squared distance between two vectors (x and y).

$$MSE = \frac{1}{n}\sum_{1}^{n}(x_i - y_i)^2, \tag{1}$$

2.2 SSIM: A Structural Similarity Measure

Automatic detection of the similarity between images has been approached by structural similarity (SSIM) index. This approach has been widely used for image quality assessment since its development by Wang and Sheikh (2004). This algorithm considers image distortion as a combination of three factors: luminance, contrast and structure errors. If *x* and *y* are two non-negative image signals, the relevant index for luminance comparison is expressed by the following equation:

$$l(x,y) = \frac{2\mu_x\mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_1}, \tag{2}$$

where the constant C_1 is a constant related to pixel values and μ_x and μ_y are the mean intensity of the two image signals. The contrast comparison function is a similar form with Eq. (2) as shown in Eq. (3). and σ_x and σ_y are the standard deviation of intensity. C_2 is again a constant related to pixel values as defined in Eq. (4) and (5).

$$c(x,y) = \frac{2\sigma_x\sigma_y + C_2}{\sigma_x^2 + \sigma_y^2 + C_2}, \tag{3}$$

$$C_1 = (K_1 L)^2 \tag{4}$$

$$C_2 = (K_2 L)^2 \tag{5}$$

where L is the range of pixel values (if 8 bit greyscale image, L is 255) and $K_1 \ll 1$ and $K_2 \ll 1$ are small constants. In the SSIM algorithm, structure comparison is followed by luminance comparison and contrast subtraction. The structure comparison function is defined as follows:

$$s(x,y) = \frac{\sigma_{xy} + C_3}{\sigma_x\sigma_y + C_3}, \tag{6}$$

Then, the final step is the combination of the above three comparisons (Eq. (2)., Eq. (3). and Eq. (6)). The SSIM index is expressed by Eq. (7) where $\alpha > 0$, $\beta > 0$ and $\gamma > 0$ are parameters to adjust the relative importance of the three components.

$$SSIM(x,y) = [l(x,y)]^{\alpha}[c(x,y)]^{\beta}[s(x,y)]^{\gamma} \tag{7}$$

2.3 Error map

In this study, the error map is visualized using OpenCV (Open Source Computer Vision Library) and Python scripts. OpenCV is a library of programming functions and an open source initiative. This library series was developed for computational efficiency and with a strong focus on real-time application. This covers computer vision and machine learning algorithms including histogram comparison, template and feature matching which is particularly interesting in the field of image comparison. MSE and SSIM indexes are implemented in the scikit-image library of OpenCV. The relevant document is well discussed by Rosebrock (2015).

3 EXPERIMENTATION

In order to assess the effectiveness of IQA algorithms, experiments are carried out on pairs of images obtained from the video records of rockfall field tests (Fig. 2). The images were recorded by a HD handy video recorder in the field test of a previous study by the authors (Kim et al., 2015). In the field test, a video clip was recorded carefully maintaining the same angle of the camera on a tripod and camera position was consistent.

Fig. 2. A captured image frame from a record of rockfall tests using a HD handy video camera (2 megapixels resolution, 30 FPS) (Kim et al., 2015).

The pairs of time-lapsed images are the start-to-mid point and the start-to-end point of each test. 21 images were captured and extracted from the record for seven rockfall tests so that 14 pairs of time-lapsed images were used in the analysis as listed in Table 1. In order to detect an object from images, the size of pixels composing the object of interest can be an issue in image analysis. The size of object in pixels depends primarily on field of view (FOV). It was estimated from the analyzed pictures that a pixel represents a size of 7×7 mm object on the slope. In practice, sizes of 20 and 30 mm rock fragments enclosed by red boxes are visible to the naked eyes as shown in Figure 3.

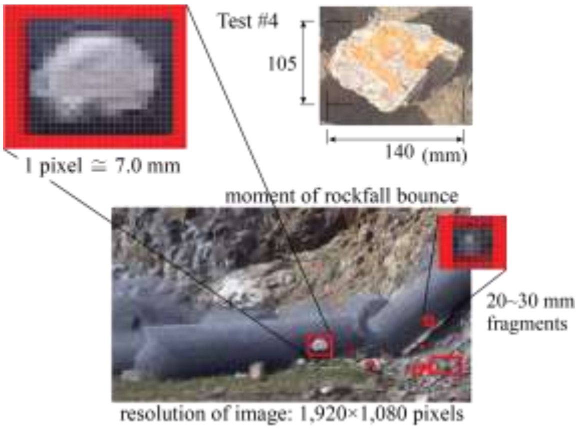

Fig. 3. A changed image with bounding boxes enclosing the changed objects from the original image.

3.1 MSE and SSIM indices

The MSE and SSIM indices obtained from IQA is presented in Table 1. If an image is at 8 bit color depth, the values of MSE are ranged from 0 (no difference) to 65,025 (maximum difference). In the case of SSIM, the acceptable values are from 0 (maximum difference) to 1 (no difference). The rockfall trials created similar falling, rolling and bouncing patterns with 2 to 4 times of collision. Further, as the changed objects, the rock blocks and fragments features are relatively small in the whole region of each picture. Consequently, it is quite acceptable that the values of both MSE and SSIM indices in Table 1. are within a minor change region.

As discussed by Dosselmann and Yang (2008), the SSIM index has been shown to outperform MSE to the problem of image quality assessment. Also, in this experiment, SSIM gives better performance in terms of consistency. The range from 0.912 to 0.939 represents the consistent rockfall patterns well. Generally, it is known that MSE has shown inconsistent performance for distorted images with different visual quality (Wang and Bovik, 2009). However, in this study, the quality of the images extracted from the video record is nearly equivalent so that the range of MSE values is not appreciably different from that of SSIM.

Table 1. Image quality assessment values

Test no.	Size of Rock block (W×L, mm)	1st comparison start-to-mid point		2nd comparison Start-to-end point	
		MSE	SSIM	MSE	SSIM
1	150×200	83.59	0.929	92.55	0.925
2	130×150	63.37	0.926	67.01	0.926
3	130×130	101.87	0.925	126.43	0.920
4	140×105	110.87	0.925	121.29	0.921
5	95×180	75.21	0.935	72.25	0.939
6	100×100	107.77	0.916	118.35	0.912
7	107×135	106.08	0.923	112.60	0.921

3.2 Visualization by error map

In the rockfall test, the motions created collisions and consequential rock fragments along trajectories on the slope surface. Using error maps, the locations and magnitudes of changes are visualized as shown in Figure 4. In thresholded images, black colored sections of the map represent areas in which there are few discernible errors. Bright white portions of the thresholded image indicates more noticeable changes. As shown in Figure 4. a) and c), the falling rock and rolling rock fragments are clearly detected in the thresholded images at the moments when the rock reached to a midpoint and the bottom.

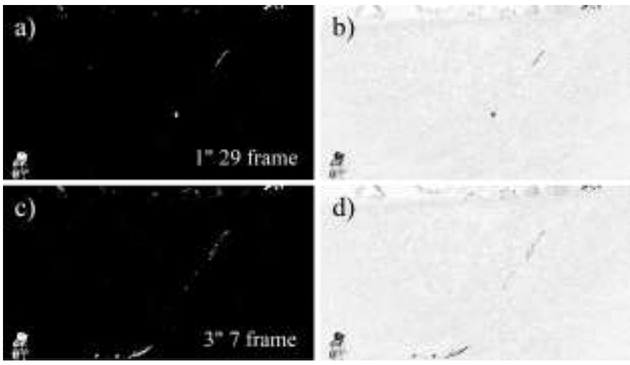

Fig. 4. Thresholded and highlighted images illustrating rock fragments movements along the rockfall trajectory of test #2; a), b) a moment (1" 29th frame) reached to midpoint, c), d) a moment (3" 7th frame) arrived at the bottom.

Python script is also written to place rectangles around the regions identified as “different”. Figure 5 shows the rock detection results with red boxes around differences and the thresholded image. The SSIM maps of Fig. 5 indicate that SSIM successfully detect most of changes from the complicated geological features, even though they are small rock fragments. Interestingly, the SSIM algorithm inevitably detected slight movements of the cloud in the sky, plants and the movements of the person in orange safety vest as well.

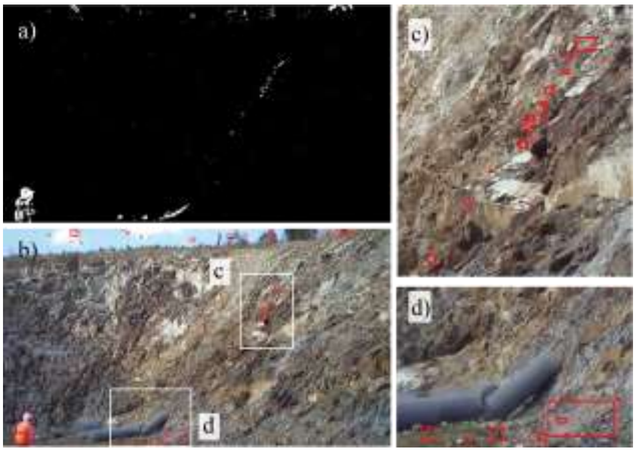

Fig. 5. Contextual images – examples of detection results from the SSIM algorithm; a) threshold image, b) detected rock fragments inside red boxes along the rockfall trajectory, c), d) indicate zoom regions.

4 RESULTS AND DISCUSSION

In this study, the potential application of MSE and SSIM to rockfall monitoring has been discussed. SSIM index has been developed for measuring the similarity between original images and their distorted images in order to overcome the major drawback of the simple measures of MSE. However, image quality assessment for rockfall monitoring by comparing between time-lapsed images can be rather simple. Consequently, the results of this study has revealed that the SSIM index is directly linked with the MSE index. This can be explained by the fact that time-lapsed images taken at the same positions can significantly reduce the influencing factors to the differences of image quality caused by distortion or blurring.

In slope monitoring area, the paradigm of structural image quality assessment is still at a preliminary stage. Also, this study insufficiently covers relevant issues on the applicability of the other existing similarity indices and on resolving the shortcomings of SSIM for slope monitoring. For future work, we strongly hope to study further advanced image quality assessment techniques for slope monitoring. As a related research, a prototype of camera systems for slope monitoring based on a single-board computer is developing by the corresponding author.

5 CONCLUSION

In this study, an image-based rockfall monitoring has been approached by image quality assessment algorithms. MSE and SSIM measures achieve consistent and favorable results for the diverse morphologies and textures of rock slopes based on the images obtained from field rockfall tests. Time-lapsed images can be an excellent information source for emergency response to rockfall events. Although further studies are required, SSIM has shown great potential to be used in real time rockfall monitoring in the future development because of its good image quality prediction accuracy.

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