LANDSLIDES DETECTION USING IMAGE TRANSFORMER OF CYCLE-GAN FOR DATA AUGUMENTATION

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ABSTRACT: In Japan, landslides often occur by extreme precipitation and earthquake. Recently, the frequency of extreme precipitation has tended to increase, which means it is possible to increase landslide disaster as well. It is necessary to detect landslides more accurately and rapidly to rescue sufferers and recover infrastructure. In our previous research, we detected seasonal change of vegetation when landslide models was generated by pix2pix and U-net by using the input combing pre- and post-disaster 4-band images. When deep learning for landslides was modeled, it is desirable to collect images taken every season to achieve high versatility. However, it is unrealistic to collect those satellite images for the extraordinary cost. In this research, we examined to perform an image transfer technique for data augmentation, which generates winter-transferred images from summer-original images and summer-transferred images from winter-original images for covering season at least summer and winter. The transferred data was mixed with original data to expand many patterns. The landslide detection model, U-net, was generated by the input data layering the transferred data and original data as pre-and post-disaster. The results of the model made by transferred data had almost the same accuracy values as a model performed only original data. As a result, our research could show the image transfer is effective for covering insufficient seasonal data.

1. INTRODUCTION

Nowadays, it is often heard from the news that record-breaking extreme precipitation events have happened in national-level and global-level. According to the Japan Meteorological Agency (2022), the frequency of daily and hourly extreme precipitation has increased in Japan. In the case of national hourly precipitation ≥ 200 mm/hr, it trends to increase 25.4 days, which is about 1.5 times more than the average number of days per year in the first decade of the statistical period from 1976 to 2021. Heavy precipitation is one of the factors triggered landslide disaster. If the frequency of extreme precipitation increases in Japan, the occurrence of landslide disasters will increase as well. Also, Japan is located on or near the boundary of four major tectonic plates where prone to occur constant seismic and volcanic activities, and landslide also happens by those natural hazards. For any reason when disaster happened, it is necessary to detect landslides more accurately and rapidly for rescuing sufferers and recovering infrastructure. Satellite data is a powerful tool to widely observe a target area. However, when satellite data is applied to detect landslide or any target, seasonal changes often induce misdetection, especially by using two different periods of images, based on our past research (Kakuta et al, 2020, Ariyasu and Kakuta, 2021). The accuracy can improve if satellite input data can cover all four seasons (spring, summer, autumn, winter), but it is unrealistic to purchase a large volume of satellite data for the extraordinary cost. Also, there are free satellite data, such as Sentinel-2 and Landsat-8/9 for now, but the resolutions are not enough to detect the long narrow landslides occurred in steep mountainous geography in Japan. Therefore, it is valuable to examine a style formation technique which transformed summer-original images to winter images and winter-original images to summer images. In a related study, Tasar et al.(2019) successfully enhanced the classification accuracy which classified building, tree, and road after transforming image by ColorMap GAN to adjust the color of satellite images. In this research, we aim to generate seasonal transferred seasonal images by image transfer method, called Cycle-Consistent Adversarial Networks (CycleGAN) at fist and perform landslide detection model, U-net, based on input data including the transferred images for enhancing versatility.

2. METHODOLOGY

2.1 Data Augmentation by CycleGAN

Data augmentation is a technique used to increase the amount of training data. Generally, the purpose of using the technique is effective for enhancing versatility in deep learning field by flipping, rotating, shifting in horizontal and vertical and/or the other transformation. Data augmentation in this study is expected to expand the seasonal variation. One of style transfer techniques, called CycleGAN, is famous for generating the output images translating a specific style of an image. This is known as image-to-image translation approach by using unpaired dataset. The characteristic is not to require paired data. CycleGAN code was downloaded by GitHub, but the code was modified for using multi-spectral images instead of the default of 3 channels.

2.2 Landslide detection by U-net

U-net is a convolutional neural network that was originally developed for medical image segmentation (Zhu et al., 2017). It is a type of semantic segmentation which processed by assigning a label to every pixel. As a result, many researchers have been applied it for landslide (Ronneberger et al., 2015). Also, U-net is expected to detect narrow and small landslides width several meters to several ten meters. Also, the advantage of using U-net is enhanced training effect even sample number is a little. In the past research, Kakuta et al. (2020) reported landslide model by pix2pix using 4-band satellite data that combined pre- and post-disaster was higher accuracy than only 3 channel (RGB) image and only post-disaster 4 channel images for landslide detection. Also, the other past research was shown U-net by multi-channnel has higher accuracy than Pix2Pix in the same input data (Ariyasu and Kakuta, 2021). Thereby, this research also applied multi-channeled U-net models after downloading U-net by GitHub.

2.3 Evaluation for Image translation and Landslide Detection

The image transformation results in this study are validated as objective metrics with PSNR (Peak Signal to Noise Ratio) and SSIM (Structural Similarity). PSNR is the ratio between the maximum possible power of an image and the power of corrupting noise that affects the quality of its representation. The formula of PSNR method indicates less distortion when it is the higher values.

$$\mathrm{PSNR} = 10log_{10}\left(\frac{\mathrm{R}^2}{MSE}\right) \tag{1}$$

where R indicates the maximum possible pixel value of the image, and MSE defines the mean squared error.

SSIM is a perceptional measure that predicts the image and the truth image (Wang et al., 2004). A higher SSIM means the more similarity of the luminance, contrast, and structures of the two images.

$$\mathrm{SSIM(x, y)} = \frac{(2\mu_x\mu_y+C_1)(2\sigma_{xy}+C_2)}{(\mu_x^2+\mu_y^2+C_1)(\sigma_x^2+\sigma_y^2+C_2)} \tag{2}$$

2.4. Evaluation for Landslide Detection

The model for landslide detection was evaluated by precision, recall, and F1. Precision indicates the ratio of the number of correct landslide detections to the total detected landslides. Recall indicates the ratio of the number of correct landslide detections to the total actual landslides. Those equations calculate the value of true positive, false positive and false positive. Those metrics are indicated by eq. (3), (4), and (5).

$$\mathrm{Precision}(T, P) = \|T \cap P\| / \|P\| \tag{3}$$

$$\mathrm{Recall}(T, P) = \|T \cap P\| / \|T\| \tag{4}$$

where T and P are two regions for truth and prediction for a given class, $\|T\|$ is the area of truth in pixels, $\|P\|$ is the area of prediction in pixels, and $\|T \cap P\|$ is the intersection of truth and prediction in pixels.

F1 Score is the weighted average of Precision and Recall.

$$\mathrm{F1}(T, P) = 2\,\|T \cap P\| / (\|T\| + \|P\|) \tag{5}$$

3. EXPERIMENTS

3.1 Datasets for data augmentation by CycleGAN

Datasets for data augmentation are shown in Table 1. To generate two types of transfer models by CycleGAN, datasets were arranged that a model for train A, which selected satellite data acquired at the summer period from July to August, and the other model for train B, which selected for the winter period from February to April as well. In the process, train A transforms from summer to winter and train B transforms from winter to summer in the learning phase by CycleGAN. After that, those data were combined pre- and post- disaster as a set of a data including original data and transformed data. Two test images were selected for evaluating the transfer model.

Table 1. Dataset lists for data augmentation

Dataset	Location	Satellite	Acquisition date (mm/dd/year)	Resolution
Train A (Summer)	Fukuoka	GeoEye-1	07/17/2017	0.7m
	Okayama	GeoEye-1	07/09/2018	0.7m
	Hiroshima	Pleiades	07/09/2018	0.5m
	Hiroshima	WorldView-2	06/01/2018	0.7m
	Iwate	SPOT7	08/15/2016	1.5m
Train B (Winter)	Okayama	WorldView-4	02/24/2018	0.7m
	Hiroshima	Pleiades	02/16/2017	0.5m
	Hokkaido	WorldView-3	04/12/ 2018	0.7m
	Ibaraki	WorldView-2	02/02/2015	2.8m
	Fukushima,	SPOT6	02/14/ 2021	1.5m
Test A	Hiroshima	Pleiades	07/14/2018	0.5m
Test B	Hiroshima	Pleiades	02/16/2017	0.5m

The training samples were randomly extracted 1200 scenes, considering land cover types (vegetation, soil, and water) was equally arranged. The model was executed by 600 epochs and latest with default hyper parameters. The patch size was sampled by 256 x 256 pixels.

3.2 Datasets for Detection of Landslides

Datasets for landslide detection are shows in Table 2. The sites of dataset was selected by three large-scaled landslides in Japan. Training data and validation selected for Fukuoka and Hiroshima sites. The site is Fukuoka which was damaged many landslides by heavy rainfall on 5th and 6th July, 2017, and the next site in Hiroshima also happened landslide by heavy rainfall at the beginning of July 2008. The ratio separating with training and validation was 80% of the train data and 20% of the test data without overlapping. The test site was selected in Hokkaido, where occurred a historical destructive landslide induced by 6.6 Mw earthquake in Iburi, Hokkaido on 6th September, 2018. The satellite images both pre- and post-disaster ranges from 19 km x 9 km in Fukuoka, 33 km x 13 km in Hiroshima, and 21 km x 26 km in Hokkaido. The test dataset utilized 3 patterns by 3 different pre disaster images.

Table 2. Satellite image datasets for landslide detection

Dataset	Disaster name, year	Acq. date for Pre-disaster	Acq. date for post-disaster
Training and Validation	Heavy Flood in Fukuoka, 2017	2016/03/21 (Pleiades) 2017/05/29 (Pleiades)	2017/09/10 (Pleiades) 2017/09/30 (Pleiades)
	Heavy Flood in Hiroshima, 2018	2017/02/16 (Pleiades)	2018/7/9 (Pleiades) 2018/7/14 (Pleiades)
Test	Hokkaido Eastern Iburi Earthquake in Hokkaido, 2018	2015/09/23 (WorldView-2) 2017/10/14 (WorldView-2) 2018/4/12 (WorldView-3)	2018/10/20 (GeoEye-1)

In annotation, landslides are categorized into three types in Japan: debris flows, steep slope failures, and deep-seated landslides. Annotation was targeted the all types of landslides, and the landslide was labeled by visual interpolation with checking both pre- and post-disaster satellite data. The patch size is sampled by 256 x 256 pixels. The training data were for 4944 tiles and the validation data were for 1237 tiles.

4. RESULT AND DISCUSSION

4.1 Test Result for CycleGAN

Two models were evaluated with every epoch by PSNR and SSIM (Figure 1). On the whole, both PSNR and SSIM indicated winter-transferred result was lower values than summer-transferred result in all epoch numbers. In PSNR, summer-transferred data declined the value by 19.40 at epoch 150, and became stable after leaching the maximum value, 20.59 at epoch 450. Alternatively, winter-transferred data reached the maximum value, 19.4, at epoch100, and generally deteriorated. In SSIM, the values of SSIM remained around 0.6 for winter-transferred data and around 0.35 for summer-transferred data in every epoch.

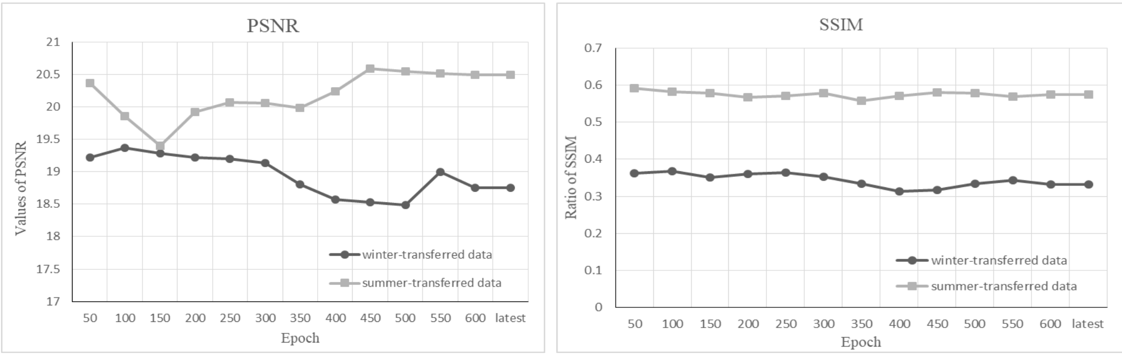

Figure 1. Evaluation by PSNR (left) and SSIM (right) of style transfer results at every epoch

After generating transferred images from the two seasonal models, tiled transferred results were mosaicked and visually compared with the original images. The transferred image selected epoch 200, considering the evaluation of two indices and visibility. Figure 2 indicates the results of image transfer performed at epoch 200 in a part of the test site; (a) was transferred from summer-original image to winter-transferred image and (b) was transferred from original winter-original image to summer-transferred image. Generally, characteristic of summer in Japan is greenness of vegetation is the highest values and winter is greenness of vegetation is phonologically declined. Compared with the transferred results, winter-transferred image in Figure 2 (a) was altered the color of vegetation like winter, which shows a dark red color on vegetation in a false color image. Also, urban areas were not significantly changed, but color patches with processing units appeared in lake and urban areas. Summer-transferred image in Figure 2 (b) was color of vegetation was similar to summer color. The urban areas and lake mostly remained the color feature of the original image. As a result, the transferred images could generate similar color tones of the seasonal pattern. However, those models were not classified as vegetation type. Moreover, there were no characteristics of topographic effects caused by the aspect and the low solar zenith angle.

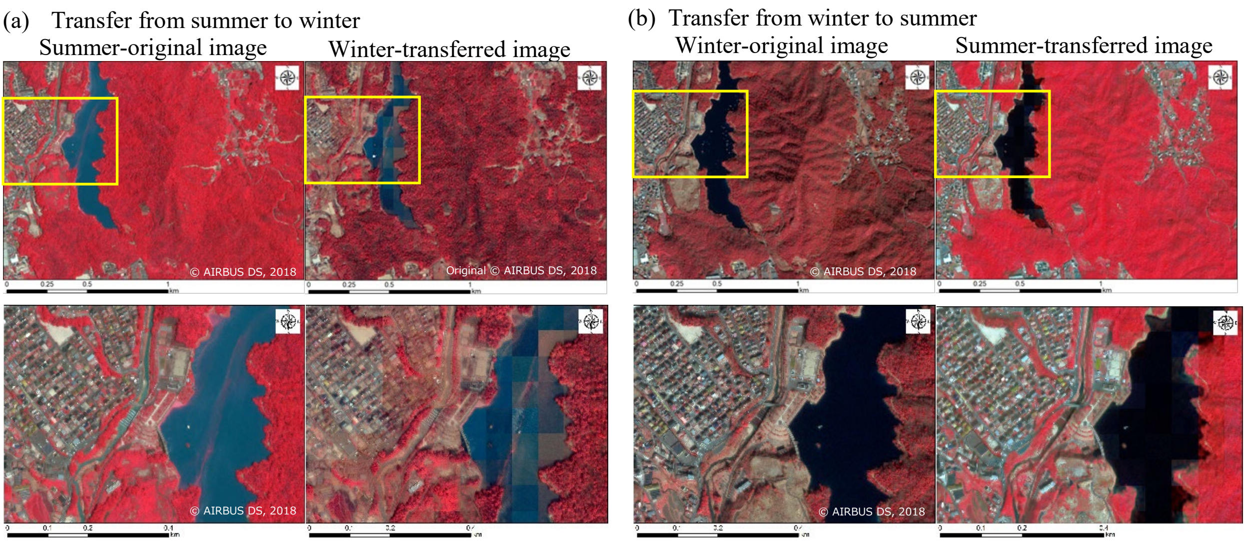

Figure 2. Transferred false color images by CycleGAN at epoch 200 in a part of the test site

4.2 Validation and Test Result for Landslide Detection

Validation and test results are indicated in Table 3. The validation result performed U-net with original data were 0.875 in precision, 0.872 in recall and 0.874 in F1, and U-net with transferred images indicated 0.868 in precision, 0.870 in recall, and 0.869 in F1. As a result, U-net with original and transferred data are almost of the same quality in all the evaluation results. The test result showed U-net with original data were 0.697 in precision, 0.818 in recall, and 0.753 in F1, and U-net with transferred images presented 0.752 in precision, 0.721 in recall, 0.736. Even though the data were mixed transferred data, which means fake images, the qualitative evaluation shows similar values with dataset made from original images.

Table 3. Evaluation results of validation and Test sites

Dataset	Method	Precision	Recall	F1
Validation	Original data + U-net	0.875	0.872	0.874
	CycleGAN + U-net	0.868	0.870	0.869
Test	Original data + U-net	0.697	0.818	0.753
	CycleGAN + U-net	0.752	0.721	0.736

Figure 3 indicates the results of landslide detection with two models at a part of the test data, Hokkaido. Figure 3 (a) shows pre-disaster input data acquired on 23rd September, 2015 and (b) shows post-disaster input data acquired on 20th October, 2018. Figure 3(c) shows the U-net with original data and (d) for the U-net with transferred data. The results was colored yellow, and the truth shows in red line. Both models could detect every large-scaled landslide in the test site. However, both models falsely detected areas happened seasonal change, such as agricultural fields. Moreover, U-net with the original data were detected the shadow on the forests which might be caused by the fallen leaves of deciduous trees and low sun-zenith angle, while U-net with transferred data was improved not to affect the shadow of the forests. As a result, U-net, which generated from various seasonal data even not-real data, is helpful to reduce misdetection caused by seasonal change.

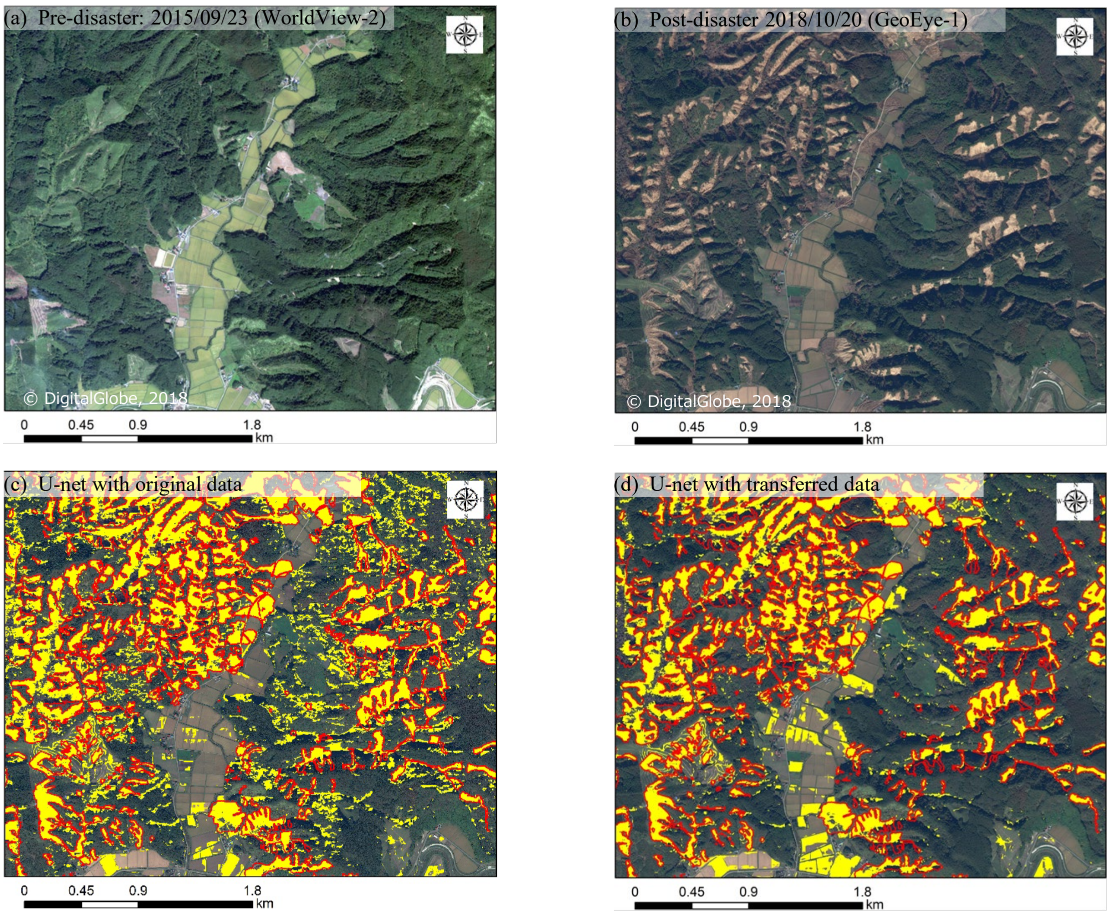

Figure 3. Landslide detection results at a part of test site (yellow area-results, red line-truth)

4. DISCUSSION

The image transfer technique was able to successfully increase seasonal different images with CycleGAN. The two model was performed to transform from summer-original data to winter-transferred data and from winter-original data to summer-transferred data. The result was not certainly natural because color patches appeared, especially at the lake, on the winter-transferred image. However, the overall transferred images showed similar color adjustments with the truth image. In fact, those color patches spots are not affected the result by inducing incorrect detection. Totally, it was difficult to evaluate which is the best transferred image, based on the results of PSNR and SSIM. In the next study, it is necessary to consider the other objective evaluation metrics, such as the inception score.

Landslide detection was shown mostly higher accuracy of qualitative evaluations in validation and test results. The result by the model using the transferred image was not drastically changed with model using the original data. In the case of the test site, the given data was autumn to winter in pre-disaster area and autumn in post-disaster and different biome. The results clearly recognized that the U-net model detected the shadows everywhere, whereas the proposed model detected shadow at a little. Unfortunately, the proposed model detected seasonal-changed agricultural fields. It is necessary to improve the problem.

5. CONCLUSION

Japan is often occurred landslides causing from heavy rainfall in the rainy season and typhoon every year. Also, it is still a fresh memory that Iburi Earthquake triggered historical large-scaled landslides in Japan on 2018. In any cases of landslide, it is important to rapidly detect damaged area with higher accuracy for the next rescue action. However, the factor of seasonal change always made a problem for misdetection. In our research, we examined to detect landslide by using satellite data added with artificially transferring summer and winter data by one of image transfer techniques, CycleGAN. We performed two models generating summer-transferred data from winter-original data and winter-transferred data from summer-original data. Transferred data were evaluated with PSNR and SSIM, and winter-transferred data showed higher values than summer-transferred data at both indices, which means the winter-transferred data can transfer more similar to the original data. Overall, both transferred images expressed almost same color tone of the season, especially at urban areas and vegetation, while both transferred data existed color patches, especially at the lake on the winter-transferred data. The landslide model executed by using the input data combined pre- and post-disaster from randomly selecting original data and transferred data. The landslide model by U-net including transferred data compared with the model by U-net using original data. In the evaluation, U-net model with transferred data was almost equal to U-net with original data at recall, prediction and F1. Visually, when U-net model with the original data was detected shadows caused by fallen leaves of deciduous trees, the model with transferred data correctly did not detect the shadow caused from deciduous trees at the test site, Hokkaido. Therefore, transferred data was not perfect at all, but it was effective for use in augmenting seasonal variety. The next research will try to perform an image transfer for reducing misdetection by adding agricultural fields.

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