Comparison of inpainting methods for generating true ortho images from satellite images

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1. Introduction

Satellite images are subject to occlusions due to cloud cover or relief displacement of above-ground structures. These occlusions are judged to be errors and need to be removed. To generate true ortho images, inpainting of such occluded areas must be applied. Gap filling is typically performed using multi-images collected from different camera location that possess texture information over the occluded areas. However, there are challenges with data compatibility and data collection, in particular, for satellite imagery. Moreover, when blank areas occur in urban areas, more images are required for natural gap filling. Inpainting techniques for natural restoration of urban areas are required.

In the past, inpainting methods primarily relied on the relationships between the pixel values of nearby areas in the images. They used pixel values within the image and does not require any additional data. However, traditional inpainting methods were mainly performed on images for non-satellite images. To interpolate complex blank areas or pixel values of high-resolution satellites, a more precise inpainting technique is required. Recently, research on inpainting using a machine learning model based on training data has been actively conducted. A machine learning models have the disadvantage of requiring a lot of learning data to generate new values. The need to construct learning materials has similar limitations to existing satellite image inpainting.

Therefore, this study will perform satellite image inpainting to fill the gaps based on an urban area and compared the inpainting results (Roy et al., 2020). Additionally, the inpainting process generates results by dividing them into two methods: traditional computer vision-based approaches and generative models. We compare and analyze results from the two methods. Through this, we aim to confirm the possibility of generating satellite true ortho images from natural satellite imagery.

2. Materials and methods

2.1 Traditional computer vision-based algorithms

In this study, we test inpainting techniques based on traditional computer vision-based algorithms and machine learning-based algorithms. Traditional computer vision-based algorithms mainly use the relationship between neighboring pixels to estimate the value of the target pixel (Late & Dharashive, 2013).

We selected as traditional computer vision-based algorithms the NS and Telea inpainting algorithms provided by OpenCV. The NS algorithm (Bertalmio et al., 2001) is based on heuristics and distinguishes areas where pixel values change according to Navier stroke fluid dynamics. Internal pixel values are calculated to maintain the boundary. The Telea algorithm (Telea, 2004) is based on fast marching method, the inner values are gradually generated from the boundary. Both methods ensure that boundaries near blank areas are maintained. As a statistical technique, the pixel value of the target pixel was calculated by averaging the pixel values of surrounding pixels.

2.2 Machine learning-based algorithms

In contrast to the traditional methods, machine learning-based algorithms use training data to build a model that generates new values for the blank areas. Convolutional networks are employed primarily for the extraction and learning features of images. To obtain new values for the blank area, we used an generative adversarial network (GAN) model as a generative model. Figure 1 shows the GAN model architecture we used. The generative model is based on the pix2pix architecture (Isola et al., 2018) and focuses on conversion between two image domains. Satellite images without blank spaces and aerial orthoimages of the same location were used as training materials. This enhances the reliability of the generated pixel values and improves their continuity with the surrounding areas.

The generator uses satellite and aerial pairs to create fake satellite image values based on input aerial image. We used a U-Net-based generator to maintain the structure of the input data. The Patch GAN-based discriminator compares the authenticity of the generated satellite images. To verify the learned model, aerial ortho images of the blank area in the satellite image is used as input data. Inpainting is performed by inputting the pixel values of the satellite image generated through prediction. We use a mask to maintain the pixel values of the original image and add newly created values only in blank areas.

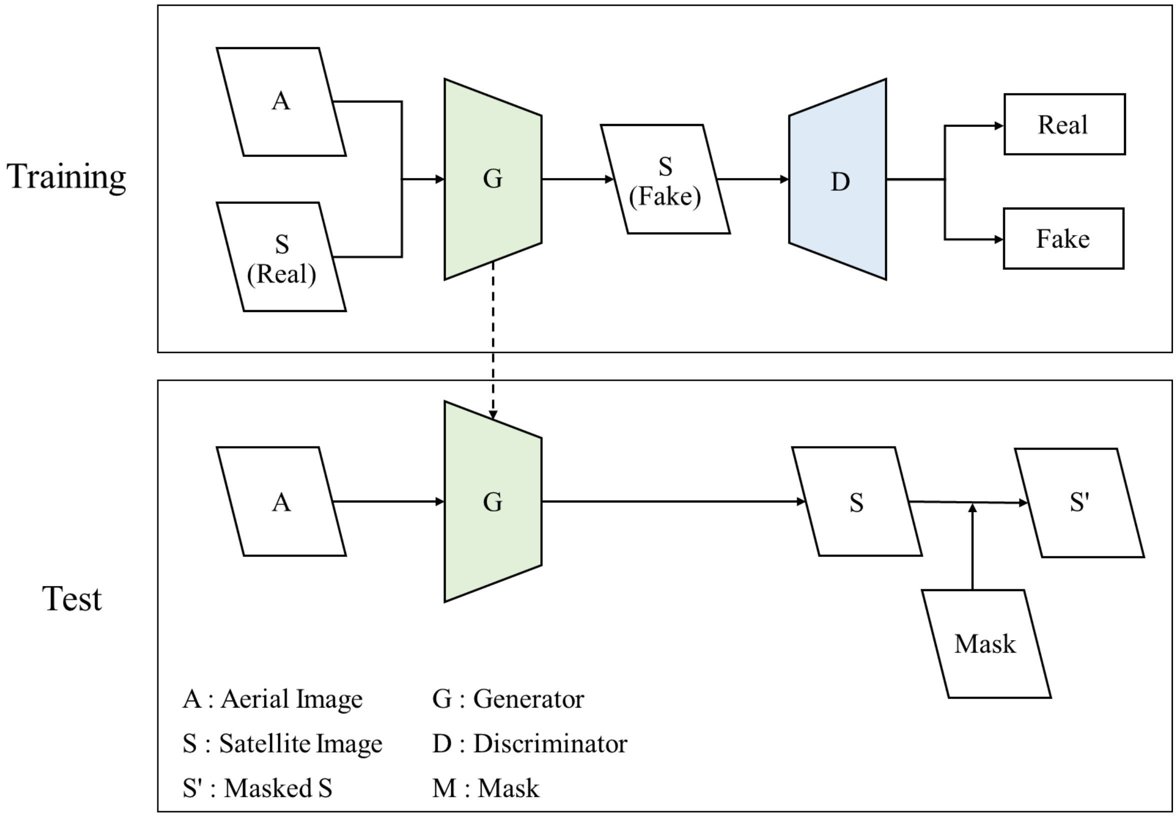

Figure 1: GAN Model Architecture

2.3 Dataset

We used pre-processed satellite images which had been undergone geometric correction and orthorectification. In this study, the orientation of the building in the true ortho image was removed to check whether the polygon-shaped blank area was properly inpainted. To confirm a linearity was maintained as a result of inpainting, we selected the urban area including roads and buildings as the target

The satellite image used has a spatial resolution of 0.5m, and the aerial ortho images have a resolution of 0.25m. The training material was resized to 0.25m and extracted into patches of size 64*64 from the target area. The blank area subject to inpainting was model verification data and was excluded from the training data.

3. Results and Discussion

Figure 2 shows the target image and inpainting results. Compared to the traditional computer vision methods, the images generated using the GAN model exhibited more natural appearance. As a result of the Telea and NS, the boundaries of nearby pixel values were maintained and blank areas are filled. However, the difference in pixel values filled inside the area was stark and the object appears unclear and blurry. Likewise, the average method preserved pixel values in nearby area. We found that the input was similar to the inpainting direction, which accumulated error.

The GAN results produced values similar to the neighboring pixels. The result was an object that not only had similar pixel values, but also had a similar texture to the surface object. Nevertheless, a value of linear objects that were not included did not generated. There were also boundaries in the form of patches that were created within the resulting image.

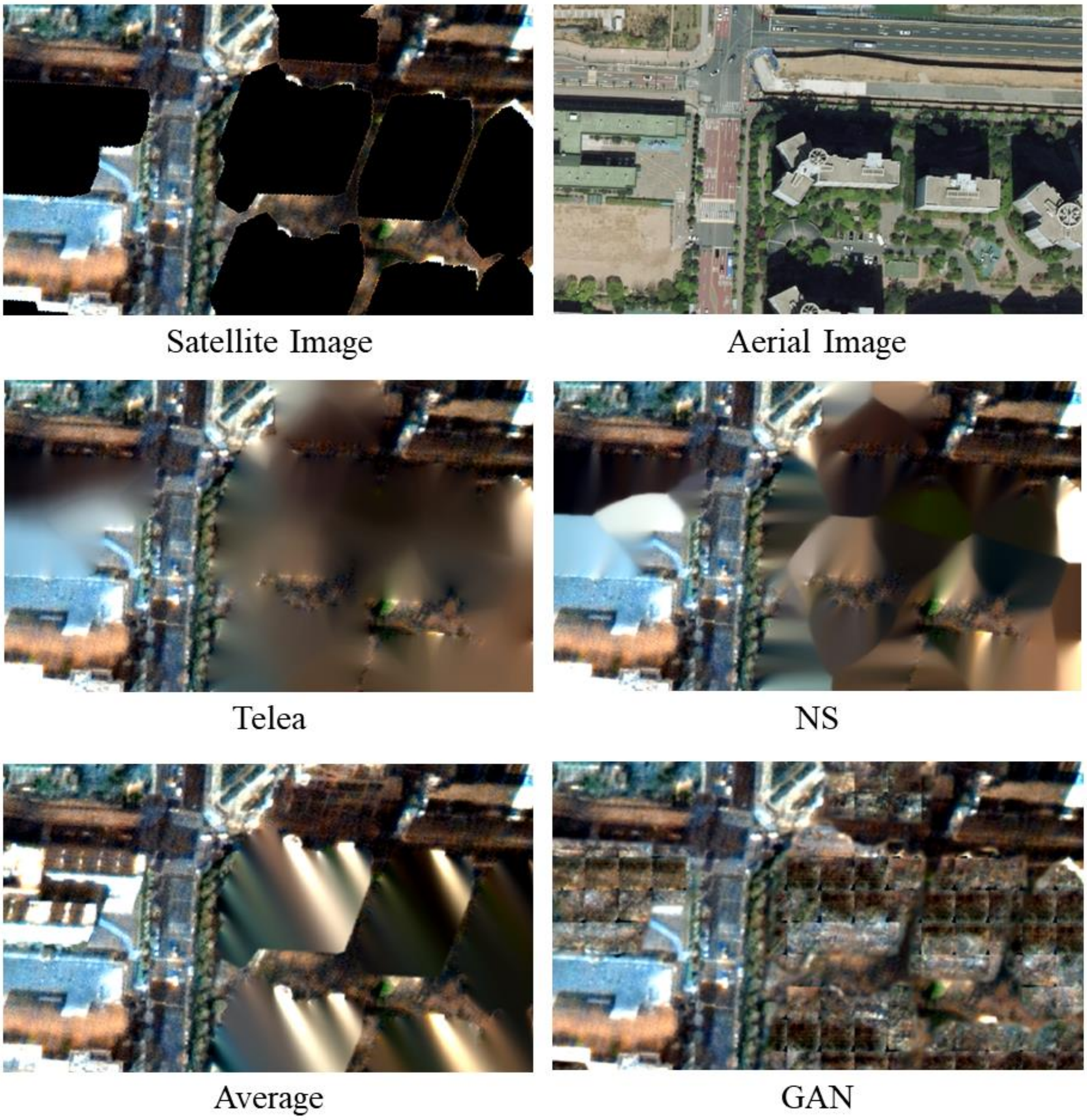

Figure 2: Target area and inpainting results by algorithm

4. Conclusion and Recommendation

In this study, we performed an inpainting algorithm targeting urban areas to generate satellite true ortho images. We compared the results of traditional computer vision algorithms and machine learning models. As a result, the results through machine learning model were more natural than traditional CV methods. The inpainting results of GAN model was successfully performed using a satellite image as input, including training data generation. Through this, the possibility of natural inpainting of blank area in urban was confirmed.

However, the GAN model created objects on a per-patch basis. This resulted in entire patches that were blank areas that were not connected to the newly created patches around them. There was also the issue of recreating errors in the learning materials, such as shadows. Further analysis is needed using selected high-quality training data and models with advanced architectural structures.

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