SAR2MAP :
SAR to Map Image Transfer with Conditional Generative Adversarial Networks

Mustafa Yagmur, Kento Doi , Akira Iwasaki
*Graduate School of Engineering, the University of Tokyo, Hongo 7-3-1, Tokyo 113-8656 Japan

ABSTRACT

SAR sensors are capable of capturing Earth images without obstructed by atmospheric effects such as clouds, fogs and weather conditions. Unlike optical imaging, SAR images are obtained by utilizing microwave propagation bands that are easily penetrate the atmosphere and reach the ground surface without any intervention. However, although many preprocessing steps are applied on raw SAR images, it is quite difficult for human interpreter to understand those images visually. In this work, we propose a domain transfer approach in which to convert SAR images into corresponding maps in order to make them more interpretable for end-point users. There have been similar studies using GANs to perform domain transfer on SAR images, however, yet no study conducted on to transfer SAR images into map pairs to our knowledge.

Keywords: GANs, Aerial SAR sensor image, image-to-image transfer, aerial maps

1. INTRODUCTION

In recent years, we have been observing an edge transformation in many fields with the rise of deep learning. The deep architectures, in particular, convolutional neural networks (CNN) are being a very powerful tool to extract semantic features from images with less human interaction and high-level information retrieval performance. CNNs are mostly used in a discriminative manner in which to generate labels for a given input data. However, generating new data samples could be also useful for many for remote sensing applications.

There have been several studies recently published on SAR image generation. Those can be summarized as cloud removal from SAR images [1][2][3][4], synthetic SAR image generation [5][6][7], noise removal and despeckling [8][9], color space transformation [10][11], feature extraction and classification[12]. Among those, as an image domain transferring work, P.Wang [9] proposed to remove speckle noise from SAR images and colorize them using conditional GANs[18]. There, he also proposed to split the network into three sub-newtorks as despeckling, colourization and adversarial learning (discriminator). The author showed that the proposed algorithm (SAR-GAN) were exhibiting a good performance in both PSNR and SSIM index comparing to other traditional methods.

Similar work done by Marmanis [5] where he suggested to use SAR images to generate real-looking SAR images for augmentation purposes. Castro [3] also used SAR images to generate real-looking optical pairs. Ao [11] proposed a Dialectical GAN for SAR image transformation where he used a style-based GAN framework to transform a low resolution SAR image into a high resolution one. He used Sentinel-1 images and transform them into TerraSAR-X images by enhancing their resolution. Ley [10] also transferred SAR images into optical counterparts to improve classification performance.

In this work, we introduce the methodology to transfer SAR images into map pairs using Conditional GAN framework along with convolution operations to make SAR images easy to interpret for remote sensing applications

2. METHOD

Generative Adversarial Networks (GANs) has been influenced numerous fields since its invention in 2014 [13]. After being introduced into Machine Learning family as a generative model, research community has soon adopted and benefited advantage of adversarial training concept.

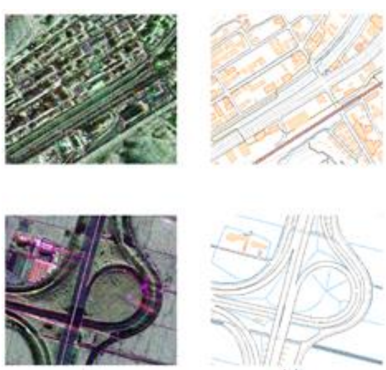
The GANs has been already started to shake most of visual fields, and applied in various ways such as image to image translation [14] , text to image synthesis [15] , image super-resolution [16], image in-painting [17] , and many more.

Image to image transfer using GANs are recently popularized application in Deep Learning community. It is first proposed as ‘Pix2Pix’ image domain transfer [14] in which proposes transferring an image A to image B. In the original work, aerial images are used as real samples given to discriminator, and corresponding Google maps were given to generator as conditioning input.

In this study, we took advantage of this image-to-image transfer concept and apply it on aerial images, in particular, SAR sensor images to convert them into map pairs in order to obtain a more human interpretable format.

3. DATASET

In this work, we collected SAR images and the same location’s map pairs using a web portal of National Institute of Information and Communications Technology (NICT). We gathered 115 image-pairs with 762 x 762 resolution, augmented them to 345 images and split into train and test dataset. We also split those image-pairs into patches, making each to six patches and hence obtained around 1800 images with 128 x 128 resolution. We conducted our experiments on both datasets to compare generation performance in quantity and visual quality.



a) b)

Figure 1. Aerial SAR images and corresponding map pairs. (Source image : http://www2.nict.go.jp/res/Pi-SAR-img)

4. EXPERIMENTS

We used ‘pix2pix’ image domain transfer approach [14] to convert aerial SAR images into corresponding maps. Loss derivation was formulated in adversarial training manner to detect generated images as real or fake. L1 loss were chosen as to generate images close to target (real) map images. As well as L1 loss, several loss formulations were applied and generation performance were compared to choose the most appropriate one for our task.

We experimented our approach in multiple setting to achieve an acceptable visual and similarity metric performance. Since GAN training process suffers much from convergence, early collapse of training and mode collapse, hyperparameter changes and network setting for feature extraction are quite important in order to generate real-looking samples. There, as a starting point, we adopted Conditional GAN [18] with DCGAN framework [19] for generation process. Aerial map pairs of a given SAR images were input to the generator. We used these map images as to condition and guide the generation process to generate real-looking map pairs. The generator network is constructed in the form of a U-Net network which is very similar to an encoder-decoder network, or namely autoencoder, except with skip connections at each layer of it. These skip connections are critical to re-use feature information of preceding layers to generate sharper images.

Selection of loss function was critical as well as optimizer selection. We found that L1 loss on reconstruction and L2 loss for adversarial training of discriminator was the best option to achieve sharper and semantically more consistent map pairs. Similarly, ‘RMSprop’ optimizer was relatively strong to keep training stable and helps for convergence.

Remaining process includes changing learning rate, number of epochs and data augmentation. We also compared these parameters by simply comparing whether they had a major effect on the training or not. Table 1 shows a summary of these selections.

We also observed that generator was weak to produce plausible images when it is given smaller size images, but was doing its job pretty good when given bigger ones.

We can summarize general setting as in following:

- All experiments were performed on a Nvidia Ti 1080 GPU computer, using batches from 1 to 32. Increasing batch size were found not useful, but 16 was the best choice in our case.

- Images were normalized between [-1,1] before feeding into generator
- Removing noise by applying blurring filters were found not much effective
- Training epochs were set to 200 and 500. More epochs helping to generate more visually acceptable images.
- Learning rate were chosen as 0.0002 after several trials.

	LR	Augmentation	# of epoch
762 x 762	Yes	Yes	Yes
128 x 128	Yes	No	No

Table 1. Different settings and their effect in the experiments

As for qualitative analysis, we used our test dataset to compare generated images visually. Figure 2 show evaluation results of test dataset. One can see that generated images are very similar looking to target images.

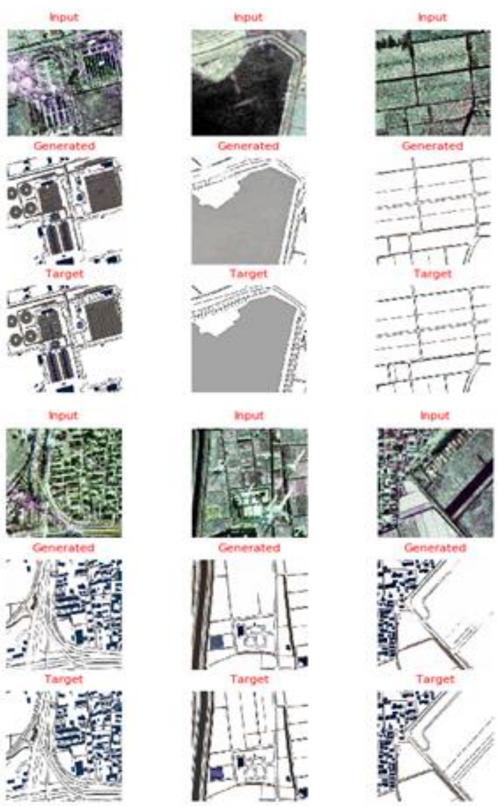


Figure 2. Test results for SAR-to-map image transformation (top: input condition SAR image, middle: generated map, bottom: real map of same location)

For quantitively evaluating generated samples, we performed image similarity check process. We chose results of epoch #270, #320 and #450 to compare generated and target images. We used SSIM metric to compare images in terms of their color, texture and neighborhood consistency.

In the Figure 3, we display a sample SAR image and generated map pair with its SSIM score . As it is seen that SSIM scores are quite high and this shows generated images are being very close to target ones

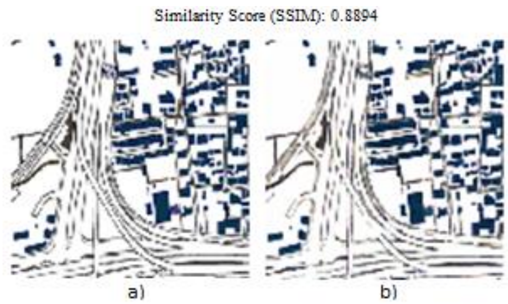


Figure 3. Comparison of target and generated maps with their SSIM score: (a) target, (b) generated

We also used generated maps to blend with corresponding aerial SAR images in order to get a sharpened image. Figure 4 shows the original SAR image and blending result. This implies that proposed method can be useful for basic image enhancement purposes for SAR images as well.

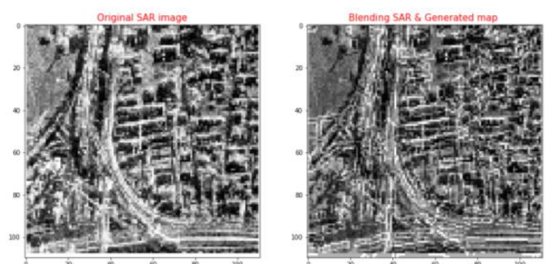


Figure 4. Blending the original SAR image and its generated map

5. CONCLUSION

In this study, we proposed an image-to-image transfer method for SAR images to convert them into ground maps. Due to its difficulty to interpret SAR sensor images, our proposed method could be useful for many applications in remote sensing. Both in quantitative and qualitative, results were found promising as to apply our image to map concept. We found that proposed method could be also used for sharpening SAR images in grey-scale by simply blending a SAR image with its generated map.

6. REFERENCES

1. K. Enomoto, K. Sakurada, W. Wang, H. Fukui, M. Matsuoka, R. Nakamura, and N. Kawaguchi, “Filmy cloud removal on satellite imagery with multispectral conditional generative adversarial nets,” in 2017 IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), July 2017, pp. 1533–1541.
2. P.Singh , N.Komodakis, “Cloud-Gan: Cloud Removal for Sentinel-2 Imagery Using a Cyclic Consistent Generative Adversarial Networks” in 2018 IEEE International Geoscience and Remote Sensing Symposium
3. C Grohnfeldt, M Schmitt, XX Zhu, “A conditional generative adversarial network to fuse SAR and multispectral optical data for cloud removal from Sentinel-2 images” in 2018 IEEE International Geoscience and Remote Sensing Symposium
4. Castro, Jose & N. Happ, P & Oliveira, Dário & Feitosa, Raul. (2018). SAR TO OPTICAL IMAGE SYNTHESIS FOR CLOUD REMOVAL WITH GENERATIVE ADVERSARIAL NETWORKS. ISPRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences. IV-1. 5-11. 10.5194/isprs-annals-IV-1-5-2018.
5. Marmanis, D.; Yao, W.; Adam, F.; Datcu, M.; Reinartz, P.; Schindler, K.; Wegner, J.D.; Stilla, U. Artificial generation of big data for improving image classification: A generative adversarial network approach on SAR data. arXiv 2017, arXiv:1711.02010.
6. J.Guo, B. Lei, C. Ding, Y. Zhang , “Synthetic Aperture Radar Image Synthesis by Using Generative Adversarial Nets”, IEEE Geoscience and Remote Sensing Letters, 2017.
7. Wenlong Liu, Yuejin Zhao, Ming Liu, Liquan Dong, Xiaohua Liu, Mei Hui, “Generating simulated SAR images using Generative Adversarial Network”, SPIE Optical Engineering and Applications, Proceedings Volume 10752, Applications of Digital Image Processing XLI, 2018
8. Wang P., Zhang H., Patel V.M. SAR image despeckling using a convolutional neural network. IEEE Signal Process. Lett. 2018;24:1763–1767.
9. Wang, Puyang & M. Patel, Vishal. (2018). Generating high quality visible images from SAR images using CNNs. 0570-0575. 10.1109/RADAR.2018.8378622.
10. Ley, A.; d’Hondt, O.; Valade, S.; Hänsch, R.; Hellwich, O. Exploiting GAN-based SAR to optical image transcoding for improved classification via deep learning. In Proceedings of the 12th European Conference on Synthetic Aperture Radar, Aachen, Germany, 4–7 June 2018; pp. 396–401.
11. Ao, D.; Dumitru, C.O.; Schwarz, G.; Datcu, M. Dialectical GAN for SAR Image Translation: From Sentinel-1 to TerraSAR-X. arXiv 2018, arXiv:1807.07778.
12. Y. Tao, M. Xu 1,2, Y. Zhong, Y. Cheng, ”GAN-Assisted Two-Stream Neural Network for High-Resolution Remote Sensing Image Classification”, Remote Sensing 2017, 9(12), 1328;
13. Goodfellow, I.; Pouget-Abadie, J.; Mirza, M.; Xu, B.; Warde-Farley, D.; Ozair, S.; Courville, A.; Bengio, Y. Generative adversarial nets. In Proceedings of the Advances in Neural Information Processing Systems, Montreal, QC, Canada, 8–13 December 2014; pp. 2672–2680
14. P. Isola, J.-Y. Zhu, T. Zhou, and A. A. Efros, "Image-to-image translation with conditional adversarial networks," arXiv:1611.07004, 2017
15. S. Reed, Z. Akata, X. Yan, L. Logeswaran, B. Schiele, and H. Lee, “Generative adversarial text to image synthesis,” arXiv preprint arXiv:1605.05396, 2016.
16. C. Ledig, L. Theis, F. Huszar, J. Caballero, A. P. Aitken, A. Tejani, J. Totz, Z. Wang, and W. Shi, “Photo-realistic single image super-resolution using a generative adversarial network,” CoRR, vol. abs/1609.04802, 2016
17. R. A. Yeh, C. Chen, T. Lim, M. Hasegawa-Johnson, and M. N. Do, “Semantic image inpainting with perceptual and contextual losses,” CoRR, vol. abs/1607.07539, 2016
18. Mirza, M.; Osindero, S. Conditional generative adversarial nets. arXiv 2014.
19. A. Radford, L. Metz, and S. Chintala, “Unsupervised representation learning with deep convolutional generative adversarial networks,” arXiv preprint arXiv:1511.06434, 2015.