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DisMon-GAN: 24X7 All-Weather Optical Domain Surveillance Using Progressively Growing Adversarial Networks With Patch Discriminator

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Abstract

- Disasters such as floods, cyclones, etc. are difficult to monitor due to the occlusions of clouds in the area under the monitor.

- SAR can capture images at night and see right through clouds and smoke. It is a 24-hour, all-weather technology. The only drawback is owing to the difficulty of perceiving for a novice user.
- We exploit the valuable imaging properties of SAR images to propose a Generative Adversarial Network to synthesize realistic and semantic optical images by conditioning them over the microwave images.

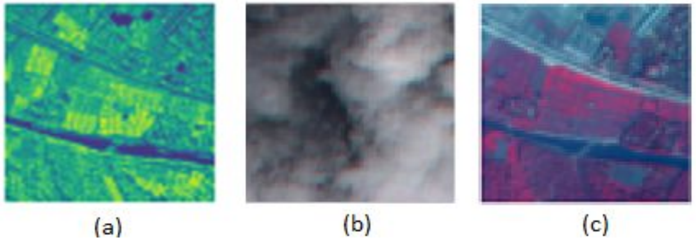
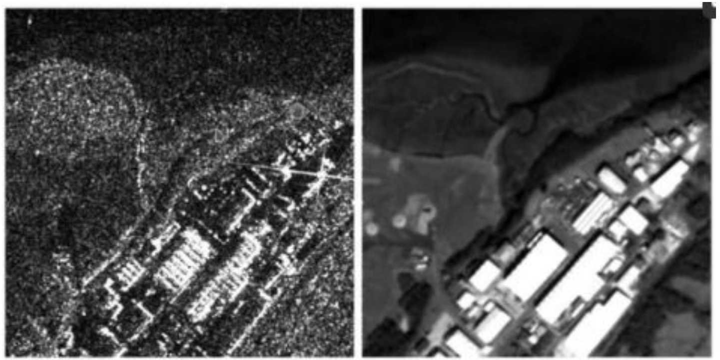


Fig. 1. The synthesized optical image by DisMon-GAN using Risat-2, SAR sensor image as evidence. (a) The originally imaged Risat-2 data passed as input. (b) Original Cartosat-2S image with cloud over the same region that was imaged in temporal proximity. (c) The generated optical image with only the SAR image as evidence. The network generates an optical image with semantic features and radiometry.

Previous Work

(Lei Wang et. al. 2019)
Using CNN and autoencoder

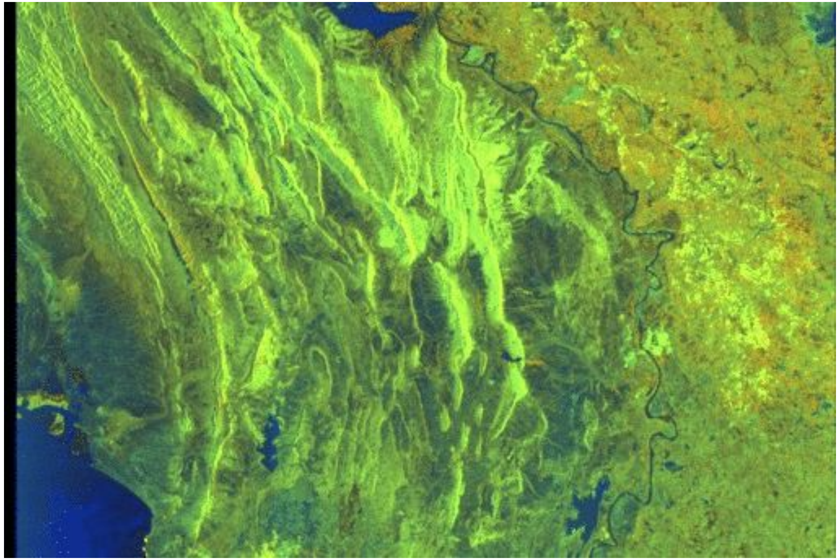


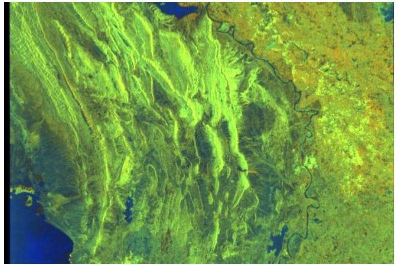
(Mario et. al. 2019)
Using conditional GAN

Preliminary simulations

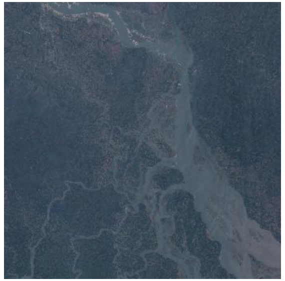
- Convolution layers from pre-trained VGG-19 network to extract deep features.

- Multi-objective optimization function layer for the final injection of style into SAR data.

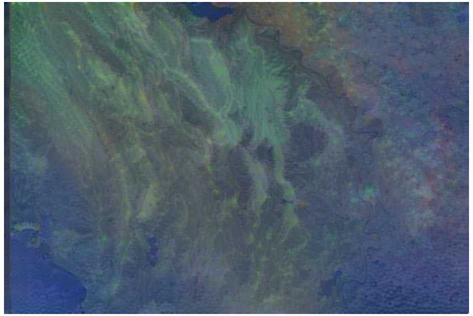




(Content)



(Style)



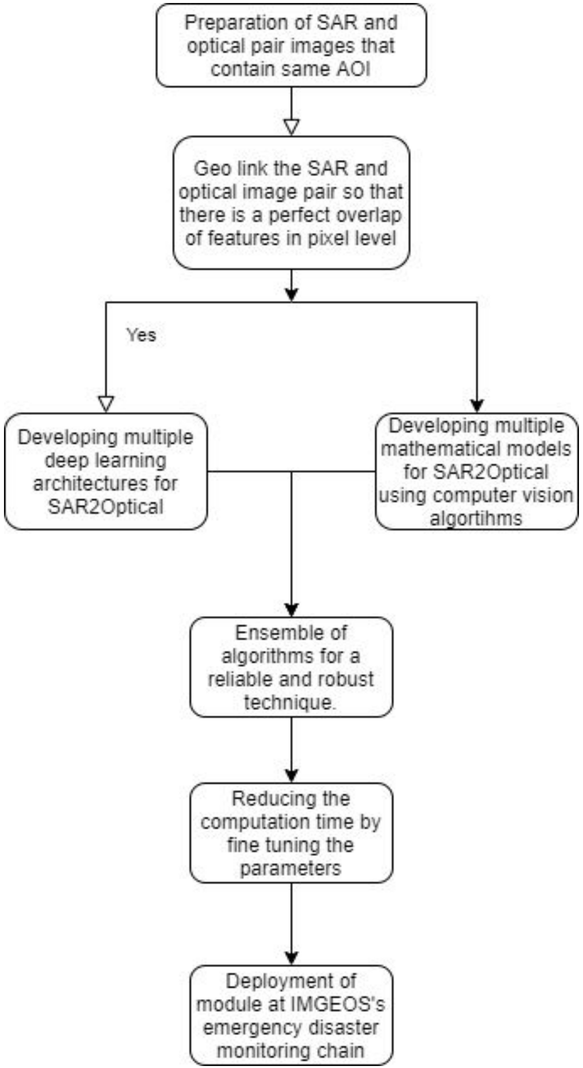
(SAR data in optical space)

Overall Proposed Approach

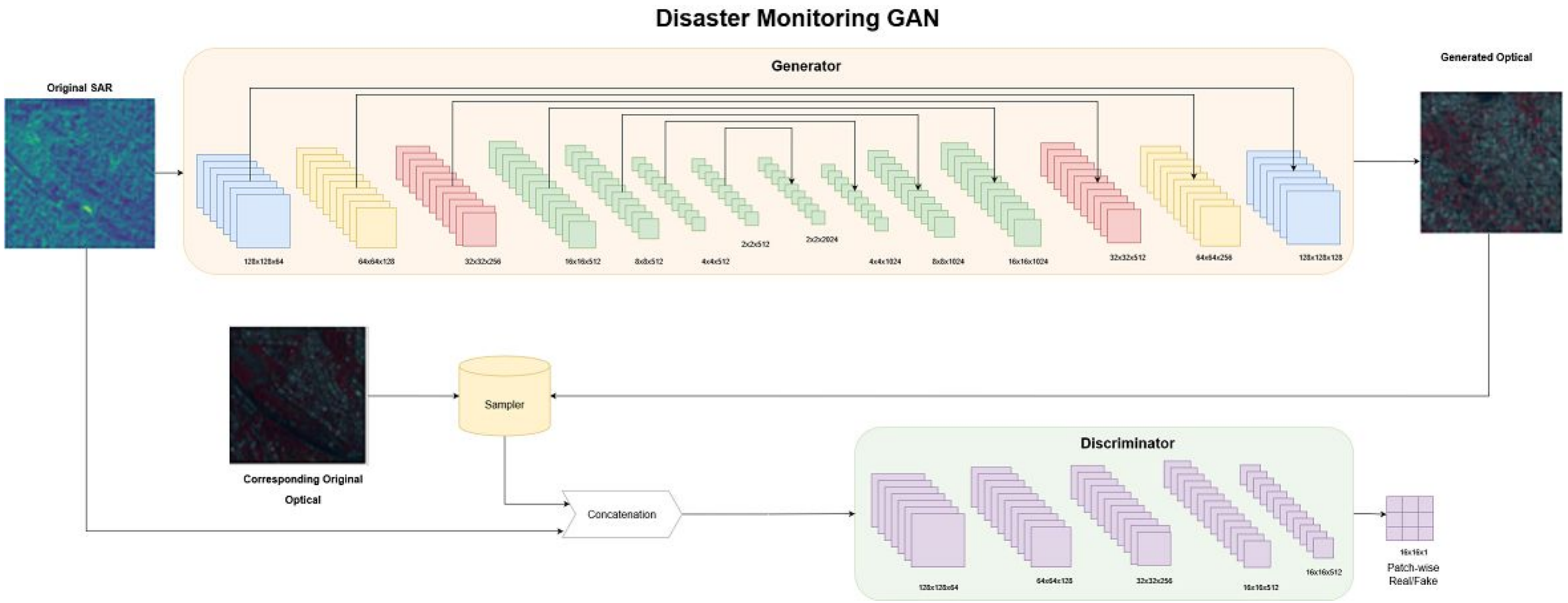
The algorithms was developed and studied over 2 regions:

1. Urban (Built-up area)

2. Vegetation (Forests, agriculture fields)



Network Architecture



Experiment

1. **L1 + Adversarial Loss:** 2 weeks for training 1.7 million epochs on a training dataset of 5000 samples. Validation average global PSNR of 20.17 dB and Structural Similarity Index Measure (SSIM) of 0.57

2. **L1 + Adversarial Loss + Rad Loss:** 3 days transfer learning , Validation SSIM of 0.85.

$$D_{Loss} = log\mathbf{D}(Opt, SAR) + log(1 - \mathbf{D}(Gen, SAR)) \quad (1)$$

$$Where\ \mathbf{D}\ is\ Discriminator$$

$$L1_{Loss} = \sum_{i=1}^{cH}\sum_{j=1}^{cW}\sum_{k=1}^{3} |Gen_{i,j,k} - Opt_{i,j,k}| \qquad (2)$$

$$F_{Loss} = \sum_{i=1}^{cH}\sum_{j=1}^{cW}\sum_{k=1}^{3} |((F_{net}(Gen_{i,j,k}) - F_{net}(Opt_{i,j,k}))| \qquad (4)$$

- *The feature extracting network **Fnet** of a pre-trained RTC-GAN (a convnet) is used to compare deep features by transfer learning*

Analysis

Table 1. Ablation Study of loss functions used to train DisMonGAN. The metrics considered are PSNR, SSIM (0-1) and Mean Opinion Score (1-10). * represents final model loss.

Loss	PSNR (dB)	SSIM	M.O.S
L1+Entropy	20.17	0.57	3.4
L2+Entropy	18.03	0.42	2.7
L1+Entropy+Radiometry*	**37.25**	**0.85**	**8.3**
S-Cycle-GAN [1]	11.2	0.37	-
FG-GAN [3]	21.51	0.61	-

Table 3. Comparison of DisMonGAN performance on various other microwave sensors without exclusive training.

Source	PSNR (dB)	SSIM
NovaSAR	27.38	0.56
Risat-1	30.46	0.65
Risat-2	37.25	0.85

[1] Wang, L., Xu, X., Yu, Y., Yang, R., Gui, R., Xu, Z., Pu, F. (2019). SAR-to-optical image translation using supervised cycle-consistent adversarial networks. IEEE Access, 7, 129136-129149.

[3] Zhang, J., Zhou, J., Lu, X. (2020). Feature-guided SAR-to-optical image translation. IEEE Access, 8, 70925-70937.

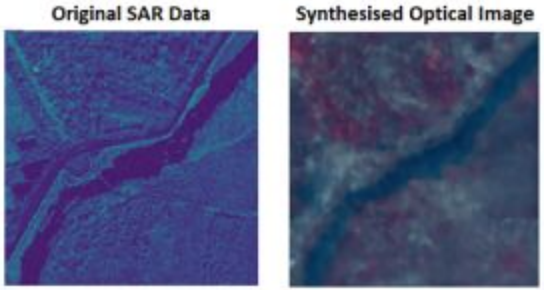


Fig. 4. Optical image synthesis by the model when using a standard patch GAN without the radiometry and L1 losses. The output has restored the low frequency features, but lacked the higher frequency crispness like sharp edges. The addition of deep feature loss resulted in generation of realistic images.

Thank You

Any questions ?

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References

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