Creating synthetic night-time visible-light meteorological satellite images using the GAN method

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ABSTRACT
Meteorology satellite visible-light images are critical for meteorologists. However, there are no satellite visible-light channels data at night, so we propose a method based on deep learning to create synthetic satellite visible-light images during night. Specifically, to produce realistic-looking products, we trained a generative adversarial network (GAN) model. The model can generate satellite visible-light images from corresponding satellite infrared (IR) channels data and numerical weather prediction (NWP) products. Considering to explicitly evaluating the contributions of different satellite IR channels and NWP products elements, we suggest using a channel-wise attention mechanic, e.g. a ‘Squeeze and Extraction Block’ (SEBlock) to quantitatively weigh the importance of different input data channels. The experiments based on the NWP products and the meteorology satellite data show that the proposed method is effective to create realistic synthetic satellite visible-light images during night.

1. Introduction
Meteorology satellite images characterize the distribution of clouds, which can be used to track the evolutions of large-scale weather systems. The data can be mapped to images in visible and infrared (IR) channels. There are multiple visible-light sensing channels for most modern meteorology satellites, which can be merged to Red-Green-Blue (RGB) images. The merged visible-light RGB images are intuitive for users, which are rich in details and easy to understand. Since the satellite visible-light channels are not available during night, it is impossible to observe the clouds continuously by satellite visible-light channels for 24 hours a day. Users need to switch the sensing channels and change the analysis mode when the day and the night shift, that is, using the visible-light channels at daytime and the IR channels at night-time. For the above reasons, we investigate the problem of creating synthetic meteorology satellite visible-light images during night. Recently, there are several researches try to generate satellite visible-light images during night from IR channels data (Kim et al. 2019; Harder et al. 2020). We further combine the IR channels data with numerical weather prediction (NWP) products in the proposed method to create more realistic-looking satellite visible-light images.
Deep learning methods (LeCun, Bengio, and Hinton 2015) have been widely used in computer vision and other fields, which greatly improve the model capability of adapting data with complex spatial structures. But in the current researches, the deep generative methods based on convolutional neural networks (CNN) usually lead to generating blurred synthetic images by using the Euclidean distance (Pathak et al. 2016; Zhang, Isola, and Efros 2016; Mathieu, Couprie, and Lecun 2016). Recent advances in the domain of image generation have been driven particularly by the invention of generative adversarial networks (GAN) (Goodfellow et al. 2014). GAN-based methods have achieved state-of-the-art results in producing very realistic images in an unsupervised setting (Radford, Metz, and Chintala 2016; Lin et al. 2020; Zhang et al. 2017; Zhao, Mathieu, and LeCun 2017). Conditional GAN (CGAN) (Isola et al. 2017) is a relatively straightforward variant of the basic GAN framework, which can learn the data distribution conditional to a given input.

The goal of this work is to create synthetic meteorology satellite visible-light channels images during night in a realistic way. We propose to learn the non-linear mapping from meteorology satellite IR channels data and NWP products to meteorology satellite visible-light channels images by introducing a CGAN model. We also use a channel-wise attention mechanic, e.g. Squeeze-and-Excitation Block (SEBlock) (Hu, Shen, and Sun 2018), at the front of the model to quantitatively weigh and evaluate the importance of the input data channels. The proposed method is evaluated on the European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis v5 data (ERA5) and FengYun-4A (FY-4A) geostationary meteorology satellite Advanced Geosynchronous Radiation Imager (AGRI) multi-channel data. Experimental results demonstrate that our method can effectively create realistic synthetic satellite visible-light images during night.

2. Data

This work is conducted on the FY-4A meteorology satellite data and the ERA5 NWP reanalysis data. The training and testing data region cover the latitude from 100N to 500N and longitude from 900E to 1300E. The FY-4A satellite data can be downloaded from the website of the China National Satellite Meteorological Centre (NSMC) starting from April 2018. So, we select the data ranging from 1 April 2018, to 20 July 2018, which are about 2500 hourly data samples to compose the training dataset. And the hourly data samples ranging from July 21 to 22 July 2018, are chosen to compose the test dataset.

FY-4A meteorology satellite, which is a second-generation geostationary meteorology satellite of China, was launched on 11 December 2016 (Zhang et al. 2018, 2019). It was fixed at the position of 99.50E above the equator. The AGRI instrument are on board with the FY-4A satellite. The number of channels of the AGRI hits 14 (from 0.45 μm to 13.8 μm) with high spatial and temporal resolutions. The true colour images (with RGB channels) can be merged by the AGRI channels ‘CH01’, ‘CH02’, and ‘CH03’, which are used as the target products, the IR channels ‘CH07’-‘CH14’ are used as parts of the model input data.

ERA5 is the 5th-generation NWP reanalysis dataset from the ECMWF, which is one of the most widely used NWP reanalysis datasets (Hersbach et al. 2020). In this work, we use the hourly ERA5 NWP reanalysis products with the spatial resolution of 0.250×0.250 as parts of the model input data. The ERA5 meteorological elements and the vertical pressure levels selected in this work include multi-levels elements (12 levels: 100, 200,
300, 400, 500, 600, 700, 800, 850, 900, 950, 1000 (hPa)): Fraction of cloud cover, U-component of wind, V-component of wind, Vorticity, Temperature, Relative humidity, and single-level elements: Skin temperature, total column cloud liquid water, total column cloud ice water. There are a total of 75 channels of the data considering NWP elements and levels.

3. Method

We train a GAN model to generate the satellite visible-light images given the corresponding satellite IR channels data and NWP products. GANs work by training two different networks: a generator network G and a discriminator network D. G generates the target samples as realistic as possible from the input data. D has trained to estimate the probability of the input drawn from the real data, that is, D tries to classify an input sample as ‘real’ or ‘fake’ (synthetic one). Following the GANs principle, both networks are trained simultaneously with D trying to correctly discriminate between real and synthetic samples, while G is trying to produce realistic samples that will confuse D.

For the generator network G, we use a U-Net (Ronneberger, Fischer, and Brox 2015) neural network as the backbone structure, combined with a SEBlock as the front module. There are 83 channels of the input data (8 for the FY-4A satellite IR channels and 75 for the ERA5 NWP products). Since the sizes of the ERA5 NWP products are lower than the FY-4A satellite data, and an upsampling module is added to increase the ERA5 NWP products sizes to the satellite IR channels data. A SEBlock is introduced behind the input layers, to improve the representation capability by explicitly getting the channel-wise attention of the input data. In the SEBlock, the 83 input elements are transferred to 83 weighted elements by multiplying weights. The weights corresponding to the original elements were obtained by a small network consisting of an average pooling layer and a full connected neural layer (FCNLayer). D is a standard classification convolution network. D can discern whether the module input data is a real satellite visible-light image or a synthetic one. During the GAN training process, D tries to correctly classify the real and the synthetic satellite visible-light data, while G tries to generate the synthetic satellite visible-light data as realistic as possible so that D cannot distinguish between them. To extract the mapping relationship between the input data x and the satellite visible-light data y, the CGAN model is used as the basic structure of D, that is x and y are used together as the input of D (the discriminator of the basic GAN only uses y as the input).

G and D networks are described in detail in Figure 1. To train the GAN model, we alternatively train the generator network G with one batch of the input data and the discriminator D with two batches, in which one batch contains real samples and the other contains generated samples.

4. Experiment results and analysis

To value the effect of the proposed method, we use mean absolute error (MAE) and root mean squared error (RMSE) as the quantitative metrics. In addition, the peak signal-to-noise ratio (PSNR) and structural similarity index measure (SSIM), which are commonly used in the domain of image reconstruction are evaluated.
The training data were collected from April 1 to 20 July 2018. The number of the training samples was 1057 (only using the daytime hourly data from 08:00 to 17:00 (All the following items are local time, Universal Time Coordinated (UTC)+8). The sizes of the ERA5 NWP products are 160 × 160 pixels, and the sizes of the satellite IR channels products are 1000 × 1000 pixels. The sizes of the targeting satellite visible-light images are 1000 × 1000 pixels. We implemented the model with Pytorch 1.0.1. Adam (Kingma and Ba 2015) optimizer was used with a learning rate of 0.001. The parameters $\beta_1$ and $\beta_2$ of Adam optimizer were set to 0.5 and 0.999. The mini-batch size is set to 8. We trained the model for 300 epochs, and the training time was approximately 25 hours. Figure 2 displays selected examples of the synthetic satellite visible-light images and corresponding real satellite images at different times.

Figure 2 shows that the proposed method can create realistic-looking satellite visible-light images. The textures of the synthetic satellite visible-light images are similar to the real samples at daytime. There is a tropical cyclone in the middle right part, which is the 2018 No.10 typhoon ‘AMPIL’. We cannot conduct the continuous observation of the tropical cyclone only using the visible-light channels and need to switch to IR channels during night. Taking the advantage of the proposed method, the continuous observation can be maintained in the satellite visible-light channels, and the users need not change the analysis mode to IR channels during night.

According to the historical track data of tropical cyclones, ‘AMPIL’ had the strongest period from 09:00 July 21 to 03:00 July 22, and the maximum wind speed gradually reached 28 ms$^{-1}$. Correspondingly in the synthetic satellite visible-light images, we can find that the cyclone cloud system gradually shrank and became dense in columns (a) to (c). At 06:00 to 09:00 July 22, the maximum wind speed weakened to 25 ms$^{-1}$ and 23 ms$^{-1}$. Correspondingly in the synthetic images, we can find the dense cloud system began to be loosened in column (d), and it became further loosened and more asymmetry in column (e). The cloud system shown in the synthetic visible-light images reflects the evolution of
Figure 2. Samples of the synthetic satellite visible-light images. (latitude: 10ºN – 50ºN, longitude: 90ºE – 130ºE. **Rows:** (i) Real satellite visible-light images. (ii) Synthetic satellite visible-light images generated by NWP + IR data. (iii) Synthetic satellite visible-light images generated only by IR data. (iv) Synthetic satellite visible-light images generated only by NWP products. (v) Satellite IR channel images (CH12). (vi) NWP total cloud amount element products. (vii) Difference between visible-light images and synthetic satellite visible-light images. **Columns:** (a) Day 0 (21 July 2018), 17:00. (b) Day 0, 19:00. (c) Day 1 (22 July 2018), 0:00. (d) Day 1, 05:00. (e) Day 1, 08:00.)
the typhoon exactly. The synthetic satellite visible-light images provide more details about ‘AMPIL’, which are helpful to analyse the characteristics of the tropical cyclone. Haven the synthetic visible-light images, we can analyse the complex meteorological events such as typhoons in detail during night.

By comparing the weights of SEBlock corresponding to each input channel, we can roughly understand the contribution of each input channel to the final target product. The channel-wise attention weights in SEBlock at 00:00 22 July 2018, are shown in Table 1. It can be found from the Table 1 that the IR channels data have the greatest individual contribution to generating the synthetic visible-light image during the night. The reason may be that the IR channels data have the same resolutions as the visible-light data, which is higher than the NWP products. So, the IR channels data can provide more detailed information. As for the NWP products, the contribution of the temperature (combined contribution of the 12 levels) element is highest among the NWP products according to the weights. We assume the reason is the brightness temperature data sensed by satellite IR channels change rapidly from day to night, and the NWP temperature elements can be used as an important feature to adjust the effect of the generated target visible-light images.

To quantitatively evaluate the proposed method, the optical flow method is introduced to extrapolate a forecast image at 18:00 from the visible-light images at 16:00 and 17:00 on 21 July 2018. At 18:00 there are no real visible-light channels data in the bottom right 1/4 part (corresponding to the area of latitude 40°N-50°N, longitude 20°-30°E). So, the bottom right 1/4 part of the forecast image extrapolated by the optical flow method at 18:00 is used as the test benchmark. The real, forecast, and synthetic visible-light images are shown in Figure 3.

Table 2 shows MAE (smaller values are better), RMSE (smaller values are better), PSNR (larger values are better), and SSIM (larger values are better) as the model input of IR channels data, NWP products, and IR channels data combined with NWP products. MAE and RMSE are evaluated using the albedo values of the visible-light channels data, which

Table 1. Channel-wise attention weights in SEBlock at 00:00 22 July 2018.

| Category                              | Element                          | Weight |
|---------------------------------------|----------------------------------|--------|
| NWP products (multi-level elements)   | Fraction of cloud cover          | 0.11   |
|                                       | U-component of wind              | 0.18   |
|                                       | V-component of wind              | 0.19   |
|                                       | Vorticity                        | 0.33   |
|                                       | Temperature                      | 0.61   |
|                                       | Relative humidity                | 0.15   |
|                                       | Skin temperature                 | 0.16   |
|                                       | Total column cloud liquid water  | 0.12   |
|                                       | Total column cloud ice water     | 0.05   |
| NWP products (single levels products) | CH07(wave band: 3.5~4.0(High) μm)| 0.81   |
|                                       | CH08(wave band: 3.5~4.0(Low) μm) | 0.6    |
|                                       | CH09(wave band: 5.8~6.7μm)       | 0.25   |
|                                       | CH10(wave band: 6.9~7.3μm)       | 0.76   |
|                                       | CH11(wave band: 8.0~9.0μm)       | 1      |
|                                       | CH12(wave band: 10.3~11.3μm)     | 1      |
|                                       | CH13(wave band: 11.5~12.5μm)     | 0.97   |
|                                       | CH14(wave band: 13.2~13.8μm)     | 0.49   |
range from 0 to 1.65. PSNR and SSIM are evaluated using the raw images directly. It can be found that the synthetic images generated by combined data quantitatively outperform the others.

5. Conclusion

In this work, we have presented a method using GAN architecture to create synthetic satellite visible-light images during night. We leverage the idea from taking the combination of satellite IR channels data and the NWP products as the model input. The experiment results suggest that the combined satellite IR channels and NWP product inputs generate more realistic synthetic night-time visible-light images compared to the individual IR channel data or NWP products as input. For future work, we will investigate merging the geographic information and other data to improve the effect of the synthetic satellite visible-light images, both in perceptional and quantitative similarities.

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