AN APPROACH TO SUPER-RESOLUTION OF SENTINEL-2 IMAGES BASED ON GENERATIVE ADVERSARIAL NETWORKS

Kexin Zhang 1, Gencer Sumbul 2, Begüm Demir 2

1 Shanghai Jiao Tong University, 2 Technische Universität Berlin

ABSTRACT

This paper presents a Generative Adversarial Network based super-resolution (SR) approach (which is called S2GAN) to enhance the spatial resolution of Sentinel-2 spectral bands. The proposed approach consists of two main steps. The first step aims to increase the spatial resolution of 20m and 60m bands by the scaling factor of 2 and 6, respectively. To this end, we introduce a generator network that performs SR on the lower resolution bands with the guidance of 10m bands by utilizing the convolutional layers with residual connections and a long skip-connection between inputs and outputs. The second step aims to distinguish SR bands from their ground truth bands. This is achieved by the proposed discriminator network, which alternately characterizes the high level features of the two sets of bands and applying binary classification on the extracted features. Then, we formulate the adversarial learning of the generator and discriminator networks as a minimax game. In this learning procedure, the generator aims to produce realistic SR bands as much as possible so that the discriminator will incorrectly classify SR bands. Experimental results obtained on different Sentinel-2 images show the effectiveness of the proposed approach compared to both conventional and deep learning based SR approaches.

Index Terms— Sentinel-2, super-resolution, generative adversarial network, remote sensing

1. INTRODUCTION

The new generation of satellite multispectral sensors (e.g., WorldView-3 and Sentinel-2) can acquire images with multiple spectral bands with different spatial resolutions. This is mainly due to the storage and transmission bandwidth restrictions [1]. Accordingly, one of the most important research topics in remote sensing (RS) is to develop methods for super-resolving the lower-resolution bands and having all bands available at the highest spatial resolution. To this end, several super-resolution (SR) methods have been introduced in RS. During the last years deep neural networks, in particular convolutional neural networks (CNNs), have been found very effective for SR problems and thus have attracted great attention. As an example, in [2], SR of multispectral RS images with convolutional layers is introduced by utilizing the single image SR using CNN [3] approach, which mainly aims at recovering a higher resolution image from a single low resolution computer vision image. In [4], residual connections are integrated into the single image SR based architecture to enhance SR performance. In [1], deep residual networks [5] based SR approach is introduced to additionally utilize higher resolution bands present in RS images in contrast the single image SR task. Recently, Generative Adversarial Networks (GANs) have been significantly increasing the performance of image enhancement methods in computer vision [6, 7]. However, there are a few SR studies based on GANs in RS. In [8], a particular GAN framework (PSGAN) is utilized to address SR image pan-sharpening problem. The PSGAN significantly improves the performance of conventional pan-sharpening methods. However, it is not directly applicable to SR problems. In [9], SRGAN architecture without the batch normalization layers (TGAN) are trained on computer vision images and fine-tuned with RS images to apply the SR. This approach utilizes only RGB image bands and thus limits to apply SR on the other spectral bands.

To address these limitations, we propose a GAN based SR approach (S2GAN) on multi-spectral multi-resolution RS images. In this paper, we mainly focus on the super-resolution of Sentinel-2 images. The proposed approach aims to increase the spatial resolution of Sentinel-2 20m and 60m bands and to accurately recover the fine texture details. To this end, the S2GAN exploits the Sentinel-2 bands associated to 10m spatial resolution as a guidance for learning the SR task on lower resolution bands. Experimental results confirm that the S2GAN effectively and accurately recovers high resolution bands with plentiful details from low resolution bands by the adversarial training of generator and discriminator networks. To the best of our knowledge, we present the first study on the application of GANs to Sentinel-2 image SR problem.

2. PROPOSED SUPER-RESOLUTION APPROACH

Sentinel-2 sensor acquires images with 13 spectral bands (bands 1 to 8, 8A and 9 to 12) with 10m, 20m and 60m spatial resolutions (for a detailed explanation, see [10]). Bands 2 to 4 and 8 are associated to 10m resolution, whereas bands 5 to 7, 8A, 11 and 12 have 20m resolution. Remaining bands (1, 9 and 10) are associated to 60m resolution. Let I be a Sentinel-2 image and I_{LR, I_{HR}, I_{SR}} be the sets of lower resolution, higher resolution and SR bands, respectively. I_{HR}...
composes of the spectral bands 2 to 4 and 8, each of which is a section of $W \times H$ pixels. We assume that the set of lower resolution bands can include either bands 5 to 7, 8A, 11, 12 or 1, 5 to 7, 8A, 9 to 12. This can be defined with respect to the scaling factor of the approach, which is either 2 or 6. We aim to learn a function $f$, which applies super-resolution on $I_{LR}$ by exploiting $I_{HR}$ as follows:

$$
\begin{align*}
  f &: I_{HR}, I_{LR} \rightarrow I_{SR} \\
  \forall I_{HR} &\in \mathbb{R}^{W \times H \times 4} \\
  \forall (I_{LR} &\in \mathbb{R}^{W \times H \times 6}) \oplus (I_{LR} \in \mathbb{R}^{W \times H \times 6} \times \mathbb{R}^{W \times H \times 3}) \\
  \exists I_{SR} &\in \mathbb{R}^{W \times H \times 6}
\end{align*}
$$

(1)

where $I_{SR}$ denotes the SR bands of $I_{LR}$ and $\oplus$ denotes the XOR gate, which results true if one, and only one, of the inputs to the gate is true. To this end, we propose a GAN based SR approach, which consists of two main steps: 1) characterization of SR bands by the generator neural network; and 2) classification of SR and ground truth bands by the discriminator neural network. Let $G$ and $D$ be the generator and discriminator networks, respectively. $G$ maps the sets of $I_{LR}$ and $I_{HR}$ to the set $I_{SR}$. $D$ aims to accurately distinguish generated image bands $I_{SR}$ from their ground truth bands. To this end, we define the adversarial loss over $N$ training images as follows:

$$
\mathcal{L}_{Adversarial} = \sum_{n=1}^{N} \log(1 - D(G(I_{LR}, I_{HR}))).
$$

(2)

$D$ aims to maximize this loss for better discrimination ability, whereas $G$ aims to minimize this loss to fool discriminator such that discriminator will incorrectly label SR image bands as true bands. Thus, this min-max game of $G$ and $D$ is formulated as follows:

$$
\begin{align*}
  \min_{\theta} \max_{\beta} &\mathbb{E}_{I_{GS} \sim p_{data}(I_{GS})} \log D(I_{GS}; \beta) + \\
  \mathbb{E}_{(I_{LR}, I_{HR}) \sim p_{G}(I_{LR}, I_{HR})} &\log(1 - D(G(I_{LR}, I_{HR}; \theta); \beta))
\end{align*}
$$

(3)

where $\theta$ and $\beta$ are the parameters of generator and discriminator, respectively, and $I_{GS}$ is the set of higher resolution ground truth bands associated to $I_{SR}$. Each step of the proposed approach is explained in the following sections.

2.1. Characterization of Super-Resolution Bands

This step aims at producing realistic SR image bands, which have similar data distribution as ground truth bands. To obtain the SR image bands, we propose a generator neural network, which is inspired by [1]. Different from conventional single image SR approaches, the higher resolution image bands are also utilized in this step together with the lower resolution bands to guide SR learning problem. Thus, the generator learns to transfer information present in higher resolution bands to lower resolution bands. To this end, low resolution image bands are first upsampled with the bilinear interpolation to the size of higher resolution bands and then concatenated with them. The following convolution layer, activation layer and 18 Residual blocks are adopted to extract essential features from combined set of image bands. Additionally, there exits a long skip-connection between upsampled lower resolution bands and final output. This enables the generator network to map the upsampled image bands to the desired higher resolution output with the high quality, detailed information and preserved radiometry of the input image [1]. In residual blocks, we remove the batch normalization layers. This has been proved to reduce computational complexity and gain better performance in SR [7]. The proposed generator neural network is illustrated in Fig. 1. It is worth noting that, in addition to the adversarial loss, the pixel-wise mean absolute error (MAE) between the SR and the ground truth bands ($I_{GS}$) is also utilized as the content loss of the generator.

2.2. Classification of Super-Resolution Bands

This step aims to correctly distinguish SR image bands from their ground truth bands by extracting the high level features for better classification. To this end, this step includes three consecutive blocks, each of which includes single layer of convolution, activation and batch normalization. The kernel size of all convolutional layers in the discriminator is $3 \times 3$. Numbers of filters in convolutional layers are 64, 128 and 128. Strides of 2, 2 and 1 are utilized in those layers to reduce the dimensionality of the input. To increase the stability of the adversarial training, Leaky ReLU is used as the activation function of the blocks with batch normalization. Finally, a Fully Connected layer is included to produce final binary classification probabilities. The proposed discriminator neural network

![Fig. 1: The proposed generator neural network for the characterization of super-resolution bands.](image-url)
Fig. 2: The proposed discriminator neural network for the classification of super-resolution and ground truth bands.

Fig. 3: Example of Sentinel-2 images, on which the experiments were conducted.

is illustrated in Fig. 2. The input to the network is either SR bands from the generator network or the corresponding ground truth bands and the output is the label, which denotes whether the input is ground truth or SR bands ($I_{SR}$). Accordingly, to define the discriminator loss, we incorporate the adversarial loss with the following loss:

$$L_{Discriminator} = \sum_{n=1}^{N} \log(1 - D(I_{GS})).$$  \hspace{1cm} (4)

When the input data is the ground truth bands of the $I_{SR}$, the output should be near to 1, indicating that the input has a large probability to be realistic.

3. EXPERIMENTAL RESULTS

Experiments were conducted on different Sentinel-2 images. We used the same training, validation and test images provided in [1]. Fig. 3 shows an example of the images. We trained and tested our approach on downsampled bands since a 10m resolution ground truth band is not available for all Sentinel-2 bands. To optimize the loss functions, we used the mini-batches of size 128 throughout 56 epochs. At each iteration, the generator and the discriminator networks were trained sequentially on NVIDIA Tesla P100 GPU. We compared our approach with: 1) the bicubic interpolation; 2) the area-to-point regression kriging (ATPRK) [11] that is a pansharpening based approach; 3) the Super-Resolution for Multispectral Multiresolution Estimation (SuperReME) [12] approach; 4) the Superres [13] that is a geometrical model based approach; and 5) the DSen2 [1] that is a CNN based approach. Results of each approach are provided in terms of four performance evaluation metrics: 1) Root Mean Squared Error (RMSE), 2) Signal to Reconstruction Error Ratio (SRE), 3) Universal Image Quality Index (UIQ) and 4) Spectral Angle Mapper (SAM). SRE measures the angular deviation between the spectral signatures of the ground truth and SR bands, and thus provides the values in degrees. In Sentinel-2 images, 10m spatial resolution is not available for 20m and 60m resolution bands. Thus, SR performance of the S2GAN on these bands can be evaluated with the performance metrics and the visual results obtained for the super-resolution of downsampled lower resolution bands. To this end, 20m resolution bands are downsampled to 40m, and then we applied SR with all approaches. The average results over all test images associated to the scaling factor of 2 are given in Table 1. As we can see from the table, our approach (S2GAN) performs better than the other approaches under all metrics. These results show that our approach effectively applies SR on the lower resolution Sentinel-2 bands to accurately enhance their spatial resolutions similar to the ground truth bands. To visually evaluate the performance of the S2GAN, we selected one test image, which includes relatively high subtle details, and compared our approach with the DSen2. Fig. 4 shows the color composite of 20m resolution bands, corresponding RGB bands and absolute differences between SR bands and ground truth bands for one portion of this image. Additionally, Table 2 presents the RMSE values for each SR bands of this image obtained by the bicubic interpolation, the DSen2 and the S2GAN. In such a relatively difficult scenario, the performance of the S2GAN for super-resolution task is more apparent compared to the bicubic interpolation and the DSen2 that also serves the superiority of our approach on all bands over the state-of-the-art approaches.

4. CONCLUSION

This paper proposes a GAN based approach (S2GAN) to enhance the spatial resolution of multi-spectral multi-resolution
work, we plan to improve the network structures of generator and discriminator steps, which can be achieved by integrating the realistic discriminator or Wasserstein GAN into our approach. The proposed approach can be also applied to any other RS image. As a future work, we plan to improve the network structures of generator and discriminator steps, which can be achieved by integrating the realistic discriminator or Wasserstein GAN into our approach.

Table 2: SR results associated to the scaling factor of 2 obtained by the proposed S2GAN and the DSen2 on each downsampled 20m resolution bands of a Sentinel-2 test image.

| Method | B5   | B6   | B7   | B8A  | B11  | B12  | Avg. |
|--------|------|------|------|------|------|------|------|
| DSen2  | 25.2 | 51.2 | 61.8 | 63.0 | 33.4 | 30.6 | 44.2 |
| S2GAN  | 23.2 | 43.4 | 52.0 | 53.2 | 30.8 | 28.0 | 38.4 |

Sentinel-2 images. The proposed approach consists of two main steps: 1) accurately increasing the spatial resolution of 20m or 60m bands with the guidance of 10m bands by the generator neural network; and 2) effectively distinguishing the SR image bands from their ground truth bands by the discriminator neural network. We also applied the adverserial learning of generator and discriminator networks. Experimental results obtained on the Sentinel-2 images indicate that our approach achieves promising performance for the super-resolution of Sentinel-2 lower resolution bands with respect to the state-of-the-art SR approaches. We would like to that S2GAN approach can be also applied to any other RS image. As a future work, we plan to improve the network structures of generator and discriminator steps, which can be achieved by integrating the realistic discriminator or Wasserstein GAN into our approach.

5. ACKNOWLEDGMENTS

This work was supported by the European Research Council under the ERC Starting Grant BigEarth-759764. The authors would like to thank Yakun Li, DFKI GmbH, Germany and Dr. Hua Yang, Shanghai Jiao Tong University, China for the helpful suggestions.

6. REFERENCES

[1] C. Lanaras, J. Bioucas-Dias, S. Galliani, E. Baltsavias, and K. Schindler, “Super-resolution of sentinel-2 images: Learning a globally applicable deep neural network,” ISPRS J. Photogram. Remote Sens., vol. 146, pp. 305–319, 2018.
[2] L. Liebel and K. Marco, “Single-image super resolution for multispectral remote sensing data using convolutional neural networks,” Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci., vol. 41, pp. 883–890, 2016.
[3] C. Dong, C. C. Loy, K. He, and X. Tang, “Image super-resolution using deep convolutional networks,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 38, no. 2, pp. 295–307, 2016.
[4] S. Lei, Z. Shi, and Z. Zou, “Super-resolution for remote sensing images via local–global combined network,” IEEE Geosci. Remote Sens. Lett., vol. 14, no. 8, pp. 1243–1247, 2017.
[5] B. Lim, S. Son, H. Kim, S. Nah, and K. M. Lee, “Enhanced deep residual networks for single image super-resolution,” in IEEE Proc. Comput. Vis. Pattern Recog. Workshop, 2017.
[6] C. Ledig, L. Theis, F. Huszár, J. Caballero, A. Cunningham, A. Acosta, A. Aitken, A. Tejani, J. Totz, Z. Wang, and W. Shi, “Photo-realistic single image super-resolution using a generative adversarial network,” in IEEE Conf. Comput. Vis. Pattern Recog., 2017, pp. 4681–4690.
[7] X. Wang, K. Yu, S. Wu, J. Gu, Y. Liu, C. Dong, Y. Qiao, and C. C. Loy, “ESRGAN: Enhanced super-resolution generative adversarial networks,” in European Conf. Comput. Vis., 2018.
[8] X. Liu, Y. Wang, and Q. Liu, “Psgan: A generative adversarial network for remote sensing image pan-sharpening,” in IEEE Intl. Conf. Image Process., 2018, pp. 873–877.
[9] W. Ma, Z. Pan, J. Guo, and B. Lei, “Super-resolution of remote sensing images based on transferred generative adversarial network,” in IEEE Intl. Geosci. Remote Sens. Symp., 2018, pp. 1148–1151.
[10] “MSI Instrument – Sentinel-2 MSI Technical Guide – Sentinel Online,” https://earth.esa.int/web/sentinel/technical-guides/sentinel-2-msi/msi-instrument, accessed 08 Oct. 2019.
[11] Q. Wang, W. Shi, P. M. Atkinson, and E. Pardo-Igúzquiza, “A new geostatistical solution to remote sensing image downscaling,” IEEE Trans. Geosci. Remote Sens., vol. 54, no. 1, pp. 386–396, 2015.
[12] C. Lanaras, J. Bioucas-Dias, E. Baltsavias, and K. Schindler, “Super-resolution of multispectral multiresolution images from a single sensor,” in IEEE Proc. Comput. Vis. Pattern Recog. Workshop, 2017, pp. 20–28.
[13] N. Brodu, “Super-resolving multiresolution images with band-independent geometry of multispectral pixels,” IEEE Trans. Geosci. Remote Sens., vol. 55, no. 8, pp. 4610–4617, 2017.