Deep neural networks for removing clouds and nebulae from satellite images

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ABSTRACT

This research paper delves into contemporary methodologies for eradicating clouds and nebulae from space images utilizing advanced deep learning technologies such as conditional generative adversarial networks (conditional GAN), cyclic generative adversarial networks (CycleGAN), and space-attention generative adversarial networks (space-attention GAN). Cloud cover presents a significant obstacle in remote sensing, impeding accurate data analysis across various domains including environmental monitoring and natural resource management. The proposed techniques offer novel solutions by leveraging spatial attention mechanisms to identify and subsequently eliminate clouds from images, thus uncovering previously concealed information and enhancing the quality of space data. The study emphasizes the necessity for further research aimed at refining cloud removal algorithms to accommodate diverse detection conditions and enhancing the overall efficiency of deep learning in satellite image processing. By highlighting potential benefits and advocating for ongoing exploration, the paper underscores the importance of advancing cloud removal techniques to improve data quality and unlock new applications in Earth remote sensing. In conclusion, the proposed approaches hold promise in addressing the persistent challenge of cloud cover in space imagery, paving the way for more accurate data analysis and future advancements in remote sensing technologies.

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1. INTRODUCTION

In the modern era of space exploration and remote sensing [1], advanced satellite image analysis methods [2]–[4] face challenges presented by cloud coverage, which can significantly limit the availability and completeness of data [5]. This problem leads to difficulties in analyzing and interpreting information, having a significant impact on areas such as environmental monitoring [6], agricultural planning, and natural resource management [7], [8]. The ability to accurately extract information from satellite images [9] obscured by clouds and fog becomes a key factor in improving the quality of these data and, therefore, being effectively used in various applications [10]. In this work, deep learning methods such as conditional generative networks (GCN) [11]–[13], cyclic generative networks (CycleGAN) [14]–[16], and space-attention GAN (SpA GAN) [17] represent revolutionary solutions to overcome these limitations.

The purpose of this research work is to review and compare approaches based on cGAN, cyclic GAN, and SpA GAN in removing clouds and nebulae from space images. We will discuss their application, effectiveness, and prospects for recovering hidden information, which can lead to a significant improvement in data quality and expanded possibilities for scientific and practical applications in the field of earth remote sensing [18]. Technological progress in the field of deep learning [19], represented by cGAN, CycleGAN, and SpA GAN, opens new perspectives in space image processing [20]. Using artificial intelligence and generative algorithms, these methods cannot only detect cloud coverings but also actively eliminate them, restoring hidden information underneath them. The unique characteristics of each of the presented approaches create the opportunity to select the best tool depending on the task's specific requirements and the data's characteristics. However, this paper also calls for further research and improvement of cloud removal techniques using deep learning. The development of algorithms adapted to different cloud types and survey conditions [21] and improving the overall performance of networks become important directions for future research. Efficient and accurate methods for removing clouds from satellite images can significantly increase the availability and value of these data, ushering in a new era in scientific research and practical use of Earth remote sensing.

Zhang *et al.* [22] discuss the application of artificial intelligence (AI) in astronomical data processing. The authors highlight that AI is becoming central to many areas of astronomical research due to advances in data processing. The article provides a systematic review of representative examples of the application of artificial intelligence technologies in astronomical data processing. In particular, she describes the use of AI to identify pulsar candidates, detect fast radio emissions, detect gravitational waves, classify spectra, and reduce interference from radio frequency interference. In addition, the article examines possible future applications of AI in astronomical research to provide perspectives for the development of astronomical research in the era of artificial intelligence. Kulkarni and Murala [23] investigated the problem of airborne image quality degradation due to atmospheric haze, which significantly affects the accuracy of high-level applications such as military surveillance and earthquake assessment. The authors propose a novel method using deformable multi-head attention with displacement extraction with a spatially attentive approach to improve the quality of aerial images after haze removal. Experimental results on synthetic and real data, as well as an extensive ablative study, demonstrate the superiority of the proposed method over existing approaches for haze removal in aerial images.

Cheng *et al.* [24] present a new system for image denoising called noise basis network (NBNet). Unlike previous works, they propose an approach to solve this complex problem from a new perspective: noise reduction through image-adaptive projection. The basic idea is to train a network capable of separating signal and noise by learning a set of reconstruction bases in the feature space. Next, removing noise from the image is achieved by selecting the appropriate basis of the signal subspace and projecting the input data into this subspace. An important aspect is the proposed spatially self-attention (SSA) module, which explicitly learns to generate bases and project into a subspace. SSA integrates with NBNet, structured as UNet, designed for end-to-end image denoising. Evaluation results on standard datasets including standard image denoising dataset (SIDD) and Darmstadt noise dataset (DND) show that NBNet achieves state-of-the-art peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM) performance at a significantly lower computational cost. Waldner and Diakogiannis [25] proposes a method to automatically extract field boundaries from satellite images for digital agriculture. The deep convolutional neural network residual UNet-a is used to solve the problem of image segmentation, highlighting field areas, boundaries, and the distance to the nearest boundary. The problem is formulated as multi-task semantic segmentation. The model is trained on a single sentinel-2 composite image, providing accurate mapping of field boundaries and recognition of individual fields. Experiments show that the model successfully generalizes to different resolutions, sensors, and periods without overfitting, and averaging predictions across multiple images helps reduce temporal variations in accuracy. The approach of this work is expected to simplify the extraction of field boundaries on a scale.

This study explores advanced methods for cloud and haze removal from space images using deep learning technologies such as CGN, CycleGAN, and SpA GAN, which apply spatial attention mechanisms to identify and remove clouds. Experiments on the RICE1 and RICE2 datasets show that SpA GAN performs better in PSNR and SSIM metrics, especially in dense cloud conditions. The study highlights the need to further improve cloud removal algorithms to enhance the quality of space data. In conclusion, the results confirm that using GAN for cloud removal significantly improves the quality of ground object reconstruction. The RICE1 and RICE2 datasets are valuable resources for studying atmospheric phenomena, confirming the high performance of SpA GAN in various atmospheric conditions and providing directions for future research in the field of cloud removal using deep learning.

2. METHOD

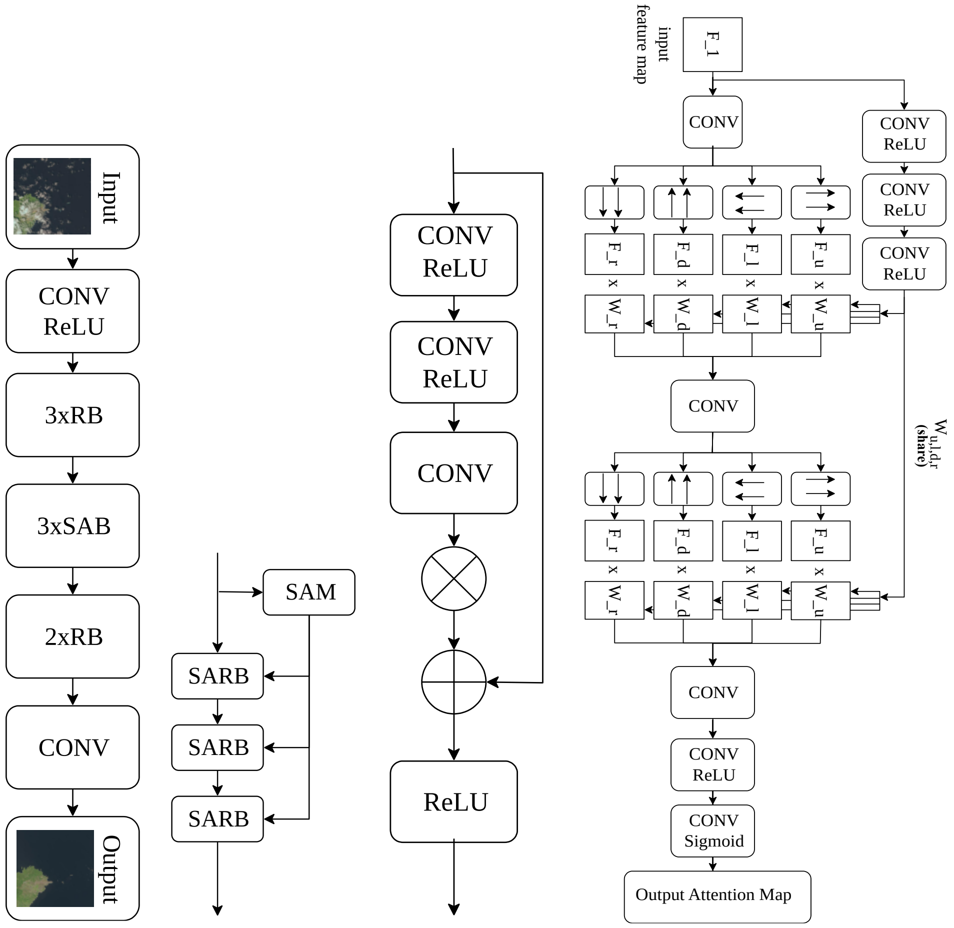
SpA GAN is used to generate and transform spatial data, such as high-resolution images from low-resolution images, translate images between different domains (for example, satellite imagery into maps), as well as improving the quality and diversity of spatial data, create detailed maps from coarse data, modeling urban growth and predicting environmental patterns. SpA GAN is also used in medical imaging to improve the quality of magnetic resonance imaging (MRI) or computerized tomography (CT) images, as well as generate realistic medical images for training machine learning models, as well as in other areas where spatial data generation and transformation are required. Also, SpA GAN is an innovative approach in the field of remote sensing image processing with a special focus on the task of cloud removal. This technology differs from traditional methods due to its ability to analyze and process information in detail at the pixel level, using sophisticated attention mechanisms to identify and eliminate cloud cover without losing valuable information about the underlying surface. The architecture of SpA GAN is based on a structure called spatially attentive network (SPANet), which efficiently analyzes images for cloud cover and removes them while preserving important details and characteristics of the earth's surface. SpA GAN also includes several key components:

a. Convolutional layers used to initially extract feature maps from input images.
b. Residual blocks used for deep processing of features without loss of information throughout the network.
c. Spatial attention blocks (SABs) are the heart of SpA GANs, consisting of spatial attentional residual blocks (SARBs) and spatial attention modules (SAMs) that operate in parallel. These units can dynamically focus on areas with clouds, determine their boundaries and characteristics, and then guide the image restoration process in such a way as to ensure the most accurate cloud removal. The spatial attention engine in SpA GAN aims to emulate human visual attention, which is capable of recognizing and focusing on key elements of visual perception. In cloud removal research, this means that the network can identify cloudy areas in an image and give them more emphasis during processing. This approach allows not only to accurate removal of clouds but also the restoration of information underneath them with a high degree of detail, which is extremely important for the accuracy and usefulness of the resulting data. The application of SpA GAN in the field of remote sensing opens up new possibilities for the analysis of the Earth's surface and atmosphere. Improved cloud-free image quality helps better monitor environmental change, manage natural resources, urban and agricultural planning, and enhance research capabilities in climate, ecology, and meteorology.

Fundamental differences and innovations of SpA GAN are:

a. Unlike standard generative adversarial networks, SpA GAN introduces a sophisticated spatial attention system (SPANet) that allows the model to focus on key regions of the image for more accurate cloud removal. This represents a significant improvement in machine visual perception by emulating the human attention mechanism.
b. Deep processing using spatial-attentional blocks. Each spatial attention block in SPANet contains a unique configuration of spatial attentional residual blocks (SARBs) and spatial attention modules (SAMs) that provide fine-grained processing of each aspect of the input data. This allows SpA GAN to adapt to complex cloud patterns and effectively reconstruct information about the earth's surface at a level of detail never seen before.
c. One of the key advantages of SpA GAN is the ability of the model to dynamically adapt to different types and densities of cloud coverage, which is achieved through the use of attention maps. These maps allow the model to determine the amount of attention that should be given to each pixel, thereby providing flexibility and accuracy when processing images with varied cloud coverage.
d. SpA GAN uses a multidimensional approach to image processing, which includes not only the removal of clouds but also a deep analysis of the underlying surfaces to restore detailed information, which is made possible thanks to the complex structure of the network, including many layers and blocks with a high degree of specialization.

Figure 1(a) shows the structure of the spatial attentional network (SPANet) as a whole. In particular, Figure 1(b) clearly demonstrates the spatial attention block (SAB), which consists of three spatial attentional residual blocks (SARB) blocks and one spatial attentional module (SAM) module. Figure 1(c) details one of the SARB blocks, which is actively applied to effectively remove clouds using negative residuals guided by an attention map. This block is an important component in the process of data processing and information recovery under the cloud. Also, Figure 1(d) presents the spatial attention module (SAM), which is described as a two-circuit, four-way recurrent neural network. This module plays a key role in providing accurate spatial attention when removing clouds, which significantly improves the efficiency of the algorithm. This set of images and blocks, including SAB, SARB, and SAM, represents an innovative approach in the field of spatial attention and cloud removal from satellite images. Decoding of shortened words such as SAB, SARB, and SAM indicate the use of spatial attentional units, spatial attentional residual units, and spatial attention units, respectively. These components are an integral part of the developed system aimed at improving the quality of space data processing using deep learning methods.



(a) (b) (c) (d)

Figure 1. The architecture of the SpA GAN method: (a) SPANet, (b) spatial attentive block, (c) SARB, and (d) SAM cGAN (conditional GAN)

Conditional generative adversarial networks (cGAN) represent a significant development in the field of generative modeling. These networks, proposed by Mirza and Osindero in 2014 [26], extend the capabilities of traditional GANs by introducing an element of conditionality, allowing data to be generated based on specific information. Integrating conditionality into cGANs improves their applicability in various tasks such as image-to-image translation, style transfer, and data synthesis. A standard GAN consists of a generator (G) and a discriminator (D) participating in a minimax game, where the generator strives to generate realistic data to fool the discriminator, while the discriminator strives to correctly distinguish between real and generated samples. The object of the discriminator is to maximize the probability of correctly classifying the data, while the goal of the generator is to minimize this probability. Mathematically, this adversarial training is expressed by the following minimax game (1):

$$min_G \, max_D \, V(D,G) = E_{x\sim p_{data}(x)}[logD(x)] + E_{z\sim P_z(z)}[log(1 - D(G(z)))] \quad (1)$$

where $E_{x\sim p_{data}(x)}[logD(x)]$ is the expected value of the logarithm of the probability that the discriminator classifies the real data and $x\sim p_{data}(x)$ represents the distribution of the real data. $E_{z\sim P_z(z)}[log(1-D(G(z)))]$ is the expected value of the logarithm of the probability that the discriminator classifies fake data generated by the generator G. $P_z(z)$ represents the distribution of random noise z, $G(z)$ is the generated sample. Here $p_{data}(x)$ represents the distribution of real data, z is a random noise vector selected from $P_z(z)$, and $G(z)$. In this cGAN work, the traditional GAN architecture is extended to include conditional information. The generator now takes as input both random noise z and conditional information y, generating samples $G(z, y)$. Similarly, the discriminator considers both data x and conditional information y when making classification. The loss function object for cGAN is modified accordingly (2).

$$min_G\, max_D\, V(D,G) = E_{x\sim p_{data}(x)}[logD(x|y)] + E_{z\sim P_z(z)}[log(1-D(G(z|y)))] \tag{2}$$

In this formulation, $D(x|y)$ and $G(z|y)$ indicate that the discriminator and generator are conditional on y, allowing the generation of data with certain characteristics. Introducing conditional information gives cGAN the ability to control and manipulate the generated results. For example, in image synthesis tasks, the conditional information y may represent a class label or certain attributes, influencing the generated image accordingly. cGANs have found wide application in various fields. In image-to-image translation tasks, such as converting satellite images into maps or converting black-and-white photographs to color, cGANs excel in producing realistic and contextually relevant results. The conditional nature of these networks makes them versatile tools in the fields of generative modeling and artificial intelligence.

The CycleGAN architecture consists of two $(G_{A\to B})$ and $(G_{B\to A})$ and two discriminators $(D_A \text{ и } D_B)$. The first generator converts images from domain A to domain B, and the second generator performs the reverse conversion. Discriminators evaluate how real the generated images, the original images, and their looped versions look. CycleGAN loss functions include losses for discriminators and generators. The main components of loss functions include (3)-(5).

$$L_{adv}(G_{A\to B}, D_B, A, B) = E_{b\sim p_{data}(B)}[\log D_B(b)] + E_{a\sim p_{data}(A)}[\log(1-D_B(G_{A\to B}(a)))] \tag{3}$$

where $p_{data}(A)$ and $p_{data}(B)$ are the distributions of images in domains A and B, respectively.

$$L_{cyc}(G_{A\to B}, G_{B\to A}, A, B) = E_{a\sim p_{data}(A)}\left[\left|\left|G_{B\to A}\left(G_{A\to B}(a)\right) - a\right|\right|_1\right] + E_{b\sim p_{data}(B)}[||\mathrm{G}_{A\to B}\left(\mathrm{G}_{B\to A}(\mathrm{b})\right) - \mathrm{b}||_1] \tag{4}$$

where $||\cdot||_1$ – normal L1.

$$L_{id}(G_{A\to B}, G_{B\to A}) = E_{a\sim p_{data}(A)}\left[\left|\left|G_{B\to A} - a\right|\right|_1\right] + E_{b\sim p_{data}(B)}[||\mathrm{G}_{A\to B}(\mathrm{b}) - \mathrm{b}||_1] \tag{5}$$

CycleGAN's iterative approach facilitates efficient learning without the need for explicit pairwise data between different domains. This model is extensively applied in tasks such as style transfer and image transformation, demonstrating its versatility. The study emphasizes the necessity for continued optimization of models and experiments to enhance overall performance, particularly in challenging conditions like high cloud cover. cGAN, SpA GAN, and CycleGAN differ in their approaches to frame-spanning cloud removal. cGAN uses conditional data to generate images that match given conditions, such as current weather conditions. SpA GAN employs external attention mechanisms to better identify and exploit cloud regions, achieving high PSNR and SSIM. CycleGAN does not require paired images and uses two generators and two discriminators to transform images from a cloudy state to a non-cloud state and vice versa, which is useful when there are no clear correspondences between cloudy and non-cloudy images.

3. RESULTS AND DISCUSSION

The RICE dataset used in our experiments is publicly available and can be found at the following link *https://pan.baidu.com/s/1h6SFWSnzH7GQJoM2UxO_ng*. For the input data used in our models, preprocessing included image normalization to ensure consistency of pixel intensity values across datasets. Specifically, each image was normalized by subtracting the mean and dividing by the standard deviation of the pixel values calculated across the entire dataset. This step was critical to standardizing input data and improving the performance of our deep-learning models by bringing data to a common scale. The models were trained on a system equipped with an NVIDIA Tesla V100 GPU, which significantly accelerated the training process. Training each model took about 48 hours on average. This setup allowed us to efficiently handle the extensive computation required for deep generative models and manage the large volumes of data involved in our cloud and nebula removal tasks.

The dataset is divided into two subsets: RICE1, which includes thin cloud images, and RICE2, which focuses on dense cloud images. Each subset was designed to address different cloud detection and removal challenges, providing a comprehensive resource for evaluating our models under different atmospheric conditions. The RICE dataset, which consists of two subsets: RICE1 and RICE2, plays an important role in the research of cloud removal from satellite images. Both subsets represent unique datasets collected using different technologies, designed to study atmospheric phenomena such as clouds under a variety of lighting and density conditions. RICE1 is an innovative dataset containing 500 high-resolution image pairs acquired using the Google Earth platform. Each pair includes an image of the same area with and without clouds. The focus is on images of subtle clouds such as nebulae, making RICE1 a valuable resource for research related to subtle atmospheric phenomena and their impact on the visibility of the earth's surface. RICE2, in turn, is compiled from data from Landsat 8 OLI/TIRS sensors, known for their ability to provide high-quality images of the Earth. A specialized focus is on dense cloud imagery, making RICE2 an important tool for research into clouds and their impact on climate and weather.

Experiments conducted with various deep learning models on both subsets revealed the results that on the RICE1 data set with thin clouds, conditional GAN achieved a PSNR of 27.427 dB and SSIM of 0.905, CycleGAN showed a PSNR of 26.930 dB and SSIM of 0.887, and SpA GAN showed the best results with a PSNR of 33.232 dB and SSIM 0.963, highlighting its outstanding performance in thin cloud conditions. These results highlight the importance of choosing an appropriate model for a particular cloud type and support the application of SpA GAN in thin cloud conditions, where this model exhibits the best performance as shown in Table 1.

In the evaluation of the RICE2 dataset under dense cloud conditions, conditional GAN demonstrated a PSNR of 26.354 dB and SSIM of 0.824. Conversely, CycleGAN exhibited slightly lower performance with a PSNR of 24.79 dB and SSIM of 0.783. Remarkably, SpA GAN outperformed both models, achieving the highest results with a PSNR of 29.432 dB and SSIM of 0.912, highlighting the efficacy of its attention mechanism, especially in challenging scenarios with dense cloud cover as shown in Table 2.

Table 1. Model accuracy results with thin clouds

Model	Quantitative metrics	
	PNSR	SSIM
cGAN	27.427	0.905
CycleGAN	26.930	0.887
SpA GAN	33.232	0.963

Table 2. Accuracy results for dense cloud models

Model	Quantitative metrics	
	PNSR	SSIM
cGAN	26.354	0.824
CycleGAN	24.79	0.783
SpA GAN	29.432	0.912

These results highlight the importance of careful model selection when processing images with varying degrees of cloud cover and difficulty in cloud removal. SpA GAN, relying on spatial attention mechanisms, has demonstrated superior skill in recovering ground truth objects from both thin and dense cloud images. The SpA GAN model performs best in most conditions, however, we emphasize the importance of careful model selection when processing images with varying degrees of cloudiness for the following reasons: images can vary greatly in cloudiness and other weather conditions, and in some specific conditions other models may perform better; unique project requirements may require specialized models optimized for specific conditions; the use of a variety of models improves the reliability and stability of data analysis; multitasking and the flexibility of some tasks require choosing the most suitable model for each specific situation. In addition, other models are also applicable in the task of removing clouds and nebulae from images, so we compared them with the commonly used SpA GAN method. Thus, while SpA GAN did show excellent results, it is important to consider that different models may be more effective in certain conditions, ensuring comprehensive and reliable data analysis and successful completion of the complex tasks facing our information system.

These findings highlight the effectiveness of SpA GAN in a variety of atmospheric conditions, supporting its role as a powerful satellite image processing tool in the fields of meteorology, climatology, and remote sensing. The differences in model performance on the RICE1 and RICE2 test datasets can be explained as follows. On the RICE1 dataset, conditional GAN generates images while preserving spatial continuity, but the results may have fuzzy areas and ground detail may not be fully recovered, which explains the relatively low PSNR and SSIM scores. While, CycleGAN showed the worst results among the models, which may be due to the lack of pairwise discriminative information, which is especially important for high-resolution remote sensing and cloud removal. This results in a loss of spatial continuity and an inability to reconstruct details of ground objects. Also, SpA GAN shows the best results because it effectively uses attention mechanisms to detect cloudy areas and improve the cloud removal process, preserving more detail and consistency of the image, and making it visually closer to the true cloudy image as shown Figure 2.

On the RICE2 conditional dataset, GAN faces the problem of losing information about ground objects under dense clouds, which makes reconstruction difficult and results in lower quality scores. CycleGAN removes the white region of dense clouds, but due to the complete loss of information about ground objects under dense clouds, it requires training on a large amount of similar data to reconstruct them. SpA GAN also performs better in this case, thanks to its ability to learn from large amounts of data and the effective use of the attention mechanism for detecting cloud areas, which can significantly improve cloud removal performance, even when information about ground objects is completely lost as shown Figure 3.

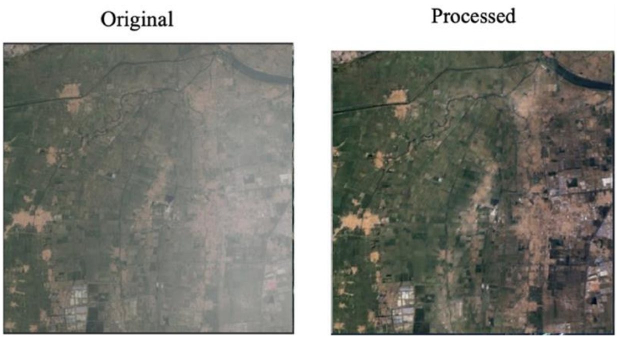


Figure 2. SpA GAN result for nebula removal on RICE1 dataset

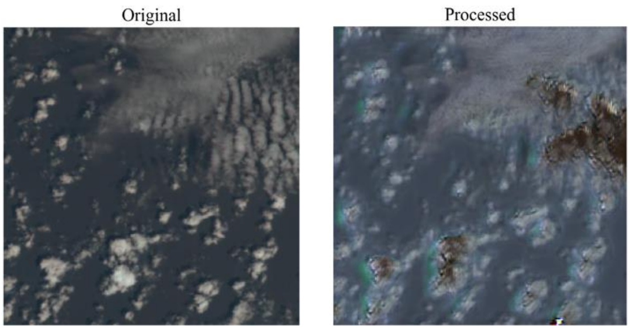


Figure 3. SpA GAN results for dense cloud removal on the RICE2 dataset

SpA GAN excelled in both evaluations due to its groundbreaking incorporation of spatial attention mechanisms, mirroring the human visual system's ability to recognize and concentrate on cloudy areas. This innovative approach enables the precise identification of cloudy regions and enhances the restoration of information related to ground objects. Consequently, SpA GAN proves effective in handling various cloud scenarios, including both thin clouds and dense cloud situations, leading to the generation of high-quality reconstructed images.

In our research, we used both our developments and standard libraries: GAN-based algorithms, including cGAN and CycleGAN, were implemented using the popular PyTorch library, which made it possible to take advantage of its convenience for operations with tensors and automatic differentiation, especially regarding implementation mechanisms of conditional generation and cyclic transformations. The development of SpA GAN included the creation of a unique spatial attention architecture and the development of custom attention modules built from scratch by our research team, including detailed modeling and tuning of spatial attention units for efficient cloud cover identification and removal. This combined approach optimized the learning process and increased the accuracy of the results, and we hope that the information provided will assist researchers and practitioners in reproducing or developing the proposed methods.

Our experiments sometimes encountered problems such as overfitting, especially when training on highly homogeneous cloud structures in RICE2. Additionally, while our models were successful at removing clouds, they sometimes altered cloud-free areas, subtly affecting the natural appearance of the landscape. Recognizing these limitations is essential for future improvements and realistic satellite image reconstruction. Future research will focus on applying our cloud removal techniques to other fields, such as urban planning and agricultural monitoring, where accurate Earth observation data is critical. Moreover, extending our methodologies to other types of atmospheric occlusions such as smoke and haze could further demonstrate the generality and impact of our work beyond the RICE dataset.

The results obtained in our study are realistic and correct. If part of the image is not covered by clouds or nebula, it should be left unchanged. Changing only those parts of the image that require correction preserves the original information and image quality. This is especially important to ensure the accuracy and reliability of the results since changes in areas that do not require correction can lead to distortion and loss of important details. We also compared various models commonly used for cloud and nebula removal tasks, such as SpA GAN, with other approaches to confirm our hypothesis that careful model selection is necessary depending on the conditions. Thus, our results highlight the importance of proper model selection for processing images under different cloud conditions to ensure high accuracy and reliability of data analysis.

4. CONCLUSION

The study demonstrates that using GAN to remove clouds from satellite images can significantly improve the quality of ground object reconstruction. SpA GAN, thanks to its spatial attention mechanisms, stands out among other models, providing high accuracy and detail. The RICE dataset, which includes subsets RICE1 and RICE2, is a valuable resource for studies on cloud removal from satellite images. Both subsets, collected using different technologies, provide unique data for studying atmospheric phenomena under a variety of lighting conditions and cloud densities. RICE1, with its innovative approach focusing on thin clouds such as nebulae, provides a valuable research tool for analyzing subtle atmospheric phenomena and their impact on the visibility of the earth's surface. RICE2, based on Landsat 8 OLI/TIRS data, with a focus on dense clouds, provides important inputs for studies of clouds and their influence on climate and weather.

Experiments with different deep learning models on both subsets demonstrated that under thin cloud conditions, SpA GAN shows the best performance with high PSNR and SSIM values. Even in more challenging environments with dense clouds, SpA GAN proves its effectiveness, delivering outstanding results. Thus, the research results on the RICE dataset highlight the importance of model selection depending on cloud characteristics, supporting the application of SpA GAN in different cloud scenarios and confirming its high efficiency in satellite image processing under a variety of atmospheric conditions. The results pave the way for future research in cloud removal using deep learning, suggesting the exploration of new architectures and techniques to further improve accuracy and efficiency.

REFERENCES

[1] Y. Zhang, J. Jiang, and G. Zhang, “Compression of remotely sensed astronomical image using wavelet-based compressed sensing in deep space exploration,” *Remote Sensing*, vol. 13, no. 2, pp. 1–16, Jan. 2021, doi: 10.3390/rs13020288.

[2] G. A. Fotso Kamga, L. Bitjoka, T. Akram, A. Mengue Mbom, S. Rameez Naqvi, and Y. Bouroubi, “Advancements in satellite image classification : methodologies, techniques, approaches and applications,” *International Journal of Remote Sensing*, vol. 42, no. 20, pp. 7662–7722, Sep. 2021, doi: 10.1080/01431161.2021.1954261.

[3] A. Asokan, J. Anitha, M. Ciobanu, A. Gabor, A. Naaji, and D. J. Hemanth, “Image processing techniques for analysis of satellite images for historical maps classification—an overview,” *Applied Sciences*, vol. 10, no. 12, Jun. 2020, doi: 10.3390/app10124207.

[4] G. Rajmohan, C. V. Chinnappan, A. D. John William, S. Chandrakrishan Balakrishnan, B. Anand Muthu, and G. Manogaran, “Revamping land coverage analysis using aerial satellite image mapping,” *Transactions on Emerging Telecommunications Technologies*, vol. 32, no. 7, Mar. 2021, doi: 10.1002/ett.3927.

[5] K. Daurenbekov *et al.*, “Noisy image enhancements using deep learning techniques,” *International Journal of Electrical and Computer Engineering*, vol. 14, no. 1, pp. 811–818, Feb. 2024, doi: 10.11591/ijece.v14i1.pp811-818.

[6] M. Yessenova *et al.*, “Application of informative textural Law’s masks methods for processing space images,” *International Journal of Electrical and Computer Engineering*, vol. 13, no. 4, pp. 4557–4566, Aug. 2023, doi: 10.11591/ijece.v13i4.pp4557-4566.

[7] M. Yessenova *et al.*, “Features of growth of agricultural crops and factors negatively affecting their growth,” *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 30, no. 1, pp. 625–632, Apr. 2023, doi: 10.11591/ijeecs.v30.i1.pp625-632.

[8] A. K. Rangarajan, R. Purushothaman, M. Prabhakar, and C. Szczepański, “Crop identification and disease classification using traditional machine learning and deep learning approaches,” *Journal of Engineering Research (Kuwait)*, vol. 11, no. 1, pp. 228–252, Nov. 2023, doi: 10.36909/jer.11941.

[9] J. Tussupov *et al.*, “An introduction to machine and deep learning methods for cloud masking applications,” *IEEE Access*, vol. 12, pp. 19902–19910, 2024, doi: 10.1109/ACCESS.2024.3361046.

[10] N. Uzakkyzy *et al.*, “Image noise reduction by deep learning methods,” *International Journal of Electrical and Computer Engineering*, vol. 13, no. 6, pp. 6855–6861, 2023, doi: 10.11591/ijece.v13i6.pp6855-6861.

[11] X. Ding, Y. Wang, Z. Xu, W. J. Welch, and Z. J. Wang, “CcGAN: continuous conditional generative adversarial networks for image generation,” *International Conference on Learning Representations*, 2021.

[12] H. Yan, Q. Zheng, and L. Zeng, “Conditional generative adversarial networks for groundwater contamination characterization and

source identification," *Journal of Hydrology*, vol. 632, Mar. 2024, doi: 10.1016/j.jhydrol.2024.130900.
[13] Z. Zuo *et al.*, "Statistics enhancement generative adversarial networks for diverse conditional image synthesis," *IEEE Transactions on Circuits and Systems for Video Technology*, pp. 1–1, 2023, doi: 10.1109/TCSVT.2023.3348471.
[14] J. Yang, K. Wang, F. Luan, Y. Yin, and H. Zhang, "PreCaCycleGAN: perceptual capsule cyclic generative adversarial network for industrial defective sample augmentation," *Electronics (Switzerland)*, vol. 12, no. 16, Aug. 2023, doi: 10.3390/electronics12163475.
[15] F. Luleci, F. Necati Catbas, and O. Avci, "CycleGAN for undamaged-to-damaged domain translation for structural health monitoring and damage detection," *Mechanical Systems and Signal Processing*, vol. 197, Aug. 2023, doi: 10.1016/j.ymssp.2023.110370.
[16] X. Liu, T. Zhang, and M. Liu, "UDF-GAN: unsupervised dense optical-flow estimation using cycle generative adversarial networks," *Knowledge-Based Systems*, vol. 271, Jul. 2023, doi: 10.1016/j.knosys.2023.110568.
[17] Y. Chen, T. Hummel, A. S. Koepke, and Z. Akata, "Where and when: space-time attention for audio-visual explanations," *arXiv:2105.01517*, May 2021.
[18] A. Anzalone, A. Pagliaro, and A. Tutone, "An introduction to machine and deep learning methods for cloud masking applications," *Applied Sciences*, vol. 14, no. 7, Mar. 2024, doi: 10.3390/app14072887.
[19] A. Naizagarayeva *et al.*, "Detection of heart pathology using deep learning methods," *International Journal of Electrical and Computer Engineering*, vol. 13, no. 6, pp. 6673–6680, Dec. 2023, doi: 10.11591/ijece.v13i6.pp6673-6680.
[20] X. Wang, W. Wang, Y. Cao, C. Shen, and T. Huang, "Images speak in images: a generalist painter for in-context visual learning," in *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, Jun. 2023, vol. 2023-June, pp. 6830–6839, doi: 10.1109/CVPR52729.2023.00660.
[21] J. Liu, W. Yin, H. Wang, Y. CHen, J.-J. Sonke, and E. Gavves, "Dynamic prototype adaptation with distillation for few-shot point cloud segmentation," *2024 International Conference on 3D Vision (3DV)*, Mar. 2024, doi: 10.1109/3dv62453.2024.00045.
[22] H. Zhang, J. Wang, Y. Zhang, X. Du, H. Wu, and T. Zhang, "Review of artificial intelligence applications in astronomical data processing," *Astronomical Techniques and Instrument*, vol. 1, no. 1, pp. 1–15, 2024, doi: 10.61977/ati2024001.
[23] A. Kulkarni and S. Murala, "Aerial image dehazing with attentive deformable transformers," in *Proceedings - 2023 IEEE Winter Conference on Applications of Computer Vision, WACV 2023*, Jan. 2023, pp. 6294–6303, doi: 10.1109/WACV56688.2023.00624.
[24] S. Cheng, Y. Wang, H. Huang, D. Liu, H. Fan, and S. Liu, "NBNet: noise basis learning for image denoising with subspace projection," in *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, Jun. 2021, pp. 4894–4904, doi: 10.1109/CVPR46437.2021.00486.
[25] F. Waldner and F. I. Diakogiannis, "Deep learning on edge: extracting field boundaries from satellite images with a convolutional neural network," *Remote Sensing of Environment*, vol. 245, Aug. 2020, doi: 10.1016/j.rse.2020.111741.
[26] M. Mirza and S. Osindero, "Conditional generative adversarial Nets," *arXiv:1411.1784*, Nov. 2014.

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