REDUCING STRIPE NOISE IN EO-1 HYPERION SATELLITE IMAGERY USING CYCLEGAN-BASED DENOISING

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1. INTRODUCTION

Satellite images provide cost-effective and invaluable information about Earth's features for a variety of purposes, including agriculture, forestry, geology, land use/cover changes, disaster monitoring, water resource management, water quality assessment, and atmosphere. However, it is essential to select and process the images in accordance with the study requirements, taking into consideration factors such as resolution, and image quality.

Despite the advancement of satellite technologies, image distortions may occur due to factors such as sensor errors, atmospheric effects, sun illumination, and viewing geometries (Sunar et al., 2017). The accuracy of the studies is directly affected by the quality of the images. Therefore, it is very important to apply appropriate techniques during the pre-processing step to correct distortions in order to increase the reliability of the study.

One of the commonly observed image distortions is “stripe noise”. Stripe noise is caused by a variety of reasons, including drop lines, differences in scanning directions (i.e., differences forward and backward), and variation in calibration changes in multi-spectral sensors (Tsai and Chen, 2008). Depending on the scanning direction of the sensor system, horizontal or vertical stripe patterns are formed in the image (Torres and Infante, 2001).

Denoising is a critical challenge in digital image processing techniques, and various methods have been developed in the spatial and frequency domains depending on the properties of the noise. In the previous study of Oguzhanoglu et al., 2022, it was observed that conventional denoising methods (i.e., Median Filter with different kernels) do not give an effective performance for stripe noise removal without loss of information. However, in the current literature, deep learning applications have shown remarkable success in denoising, outperforming conventional methods. One of these approaches is CycleGAN, a cycle-consistent generative adversarial network. By training on unmatched pairs of reference and noisy images, CycleGAN learns the mapping between the two domains (Song et al., 2020). Therefore, CycleGAN has great potential to advance noise removal techniques and improve the quality of satellite images for various applications.

For this purpose, the efficiency of the CycleGAN denoising method was investigated using hyperspectral (EO-1 Hyperion) and optical (Landsat 8) remote sensing data. The image quality analysis of denoised images was evaluated as qualitative (statistical methods; SSIM (Structural Similarity Index Measure), PSNR (Peak Signal to Noise Ratio)), and quantitative (visual analysis)). Afterwards, the Random Forest algorithm, a supervised image classification technique, was used to classify the denoised and original images, and the results were compared. For the accuracy assessment of the classified images, comparison was done visually and statistically (Overall accuracy and Kappa coefficient statistics).

2. STUDY AREA AND DATA

2.1 Study Area

Located in the southeast of Turkey, Şanlıurfa is an important province known for its large agricultural areas. This region, which has great importance in the agricultural sector, shows the diversity of agricultural activities. For this study, a study area covering mainly agricultural regions in Şanlıurfa was selected (Figure 1).

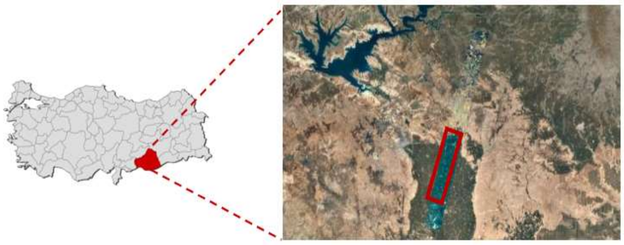


Figure 1. Satellite image of test areas in Şanlıurfa – (©2020, Google Earth).

2.2 Data Used

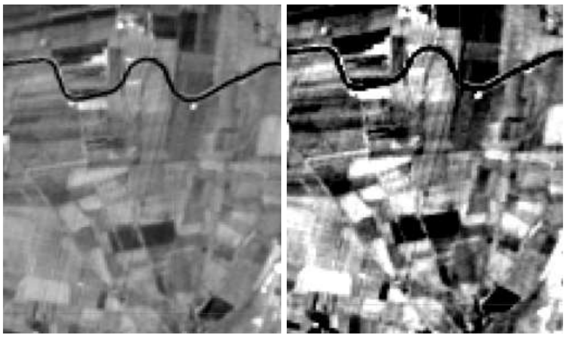
In the analysis, CycleGAN was applied on EO-1 Hyperion dated August 24, 2016 and Landsat 8 dated August 22, 2016 was used as the reference satellite image. The characteristics of these two datasets are given in Table 1. The proximity of the acquisition dates for the Hyperion and Landsat 8 images is expected to make a significant contribution in evaluating the denoising performance during pre-processing and in achieving accurate classification results during post-processing.

Satellite	Landsat 8 Multispectral	EO-1 Hyperion Hyperspectral
Spectral Range	0.4 - 2.3 µm (excluding TIR)	0.4 - 2.5 µm
Spatial Resolution	30 m	30 m
Swath Width	185 km	7.5 km
Spectral Coverage	Discrete	Continuous
Total Bands	7	220

Table 1. Landsat 8 and EO-1 Hyperion band properties.

3. METHODOLOGY

As a first step, CycleGAN based on the principle of cycle-consistent adversarial networks was trained on reference Landsat images and noisy EO-1 Hyperion images to establish the relationship between the two domains (Figure 2). The proposed method achieves effective results by using the competitor loss, which makes that the generated denoised images are nearly identical to the real (reference) images (Zhu et al., 2017). By implementing this method, noise can be effectively removed from the input images while retaining important image properties and structures.



(a) (b)

Figure 2. Example of stripe noise in test areas shown in different bands of EO-1 Hyperion images (a) Band 84. (b) Band 90.

As a second step, the effectiveness of the denoising algorithm will be evaluated both quantitatively and qualitatively. Qualitative evaluation will involve visual analysis, comparing denoised images with reference images to assess the reduction of stripe noise and the preservation of important image details and structures. In the quantitative evaluation, quantitative metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) will be used to statistically assess the quality of the denoised images. The quality metrics to be used are described in Table 2, providing an objective basis for evaluating the algorithm's performance. Furthermore, the denoised images' ability to preserve the spectral characteristics of the reference images will be examined. This analysis will involve examining their spectral reflectance signatures (and/or spectral profiles), which are essential for remote sensing image analysis.

Quality Metric	Definition	Ideal Value
PSNR	The ratio of the peak signal to the noise between the reference image and the denoised image.	High (Higher values indicate higher quality.)
SSIM	Measures the structural similarity between the reference image and the denoised image in terms of correlation loss, brightness, and contrast.	High (Values range between 0 and 1, approaching 1 indicates higher quality.)

Table 2. Quality metrics used (Bhutada et al., 2011).

As a final step, the denoised EO-1 Hyperion images will be subjected to a Random Forest classification process. By using the robust capabilities of this machine learning algorithm, which involves the complex construction of multiple decision trees, our analysis aims at a comprehensive evaluation of the effect of denoising on classification performance compared to the original noisy images. Therefore, this analysis will also demonstrate the potential of CycleGAN-based denoising in various remote sensing applications for post-processing steps such as land use/land cover (LULC) classification.

In conclusion, the proposed denoising approach using CycleGAN will be shown to provide a solution to denoise stripe noise in EO-1 Hyperion images, and the effective usability of denoised images and CycleGAN in various remote sensing applications will be highlighted through spectral analysis and classification processes.

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