CENX546: Digital Image Processing
First semester 1446

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A Project Report on -

Satellite Image Enhancement Using Common DSP Filters, Contrast Manipulation and Machine Learning

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Satellite Image Enhancement Using Common DSP Filters, Contrast Manipulation and Machine Learning

1. Introduction

Satellite imagery is pivotal in many applications, ranging from environmental monitoring to urban planning. However, these images often suffer from inherent quality issues, such as lack of sharpness and blurred edges, which impede their utility in precise image processing tasks. This paper delves into various enhancement techniques aimed at improving satellite images, addressing prevalent challenges such as poor image quality, indistinct object boundaries, and unsharpened edges. By employing methods using common filtering and contrast adjustment to advanced machine learning approaches using tools like MATLAB.

Our aim is to enhance the clarity and usability of satellite imagery, facilitating more accurate analysis and interpretation for various applications. Two major classes of techniques employed to enhance satellite images are Digital Signal Processing (DSP) filters and contrast manipulation methods. Through this work, the significance of effective image enhancement in harnessing the full potential of satellite data is reviewed.

2. Literature Review

In this section, we will review some common ways in literature for enhancing satellite images. Satellite image enhancement is crucial for improving the quality and usability of imagery for various applications. A range of techniques can be employed to address common issues such as poor contrast, noise, and indistinct edges.

a. Digital Signal Processing (DSP) Filters in Satellite Image Enhancement

DSP filters modify the spatial or frequency characteristics of an image to improve clarity and reduce noise. These filters can be broadly classified into linear and non-linear filters, both of which play essential roles in satellite image enhancement.

Linear Filters

Linear filters, such as low-pass and high-pass filters, are typically used to either smooth an image or emphasize edges. Low-pass filters like Gaussian and averaging filters are primarily employed for noise reduction by smoothing out high-frequency noise while maintaining the overall structure of the image [1]. While these filters are effective in noise reduction, they can blur fine details, which is a common trade-off in satellite imagery enhancement. High-pass filters, including Sobel and Laplacian filters, highlight high-frequency components of the image, particularly edges, which are critical for detecting boundaries between different land types, such as urban areas or bodies of water [2]. These filters are particularly useful for applications requiring edge detection, such as land use classification.

Non-linear Filters

Non-linear filters, on the other hand, offer a more adaptable approach to enhancement, particularly when noise suppression is required without compromising edge preservation. Median filters, for instance, are effective in removing salt-and-pepper noise from satellite images without blurring edges [3]. More sophisticated non-linear filters like anisotropic diffusion [4] and bilateral filters have been used extensively to enhance satellite images by preserving important details and edges while suppressing noise. The anisotropic diffusion filter selectively smooths areas of uniform intensity while preserving edges, making it ideal for satellite imagery where distinct features like cities or forests need to be highlighted.

Fourier and Wavelet Transforms

Fourier transforms are often applied in satellite image enhancement. These techniques work by transforming the image into the frequency domain, allowing specific frequency components to be enhanced or suppressed. Fourier transforms can be used to sharpen an image by emphasizing high-frequency components, thus improving fine details [5]. Wavelet transforms provide a more flexible approach by decomposing images into multi-resolution components, which allows selective enhancement at different scales. This technique is particularly useful when dealing with satellite images at various resolutions, allowing for the enhancement of fine details without affecting large-scale features.

b. Contrast Manipulation Techniques

Contrast manipulation methods aim to increase the visibility of features in an image by adjusting the distribution of pixel intensities. These techniques are particularly beneficial for enhancing images that have low contrast, often due to poor illumination conditions during satellite data acquisition. Common contrast enhancement techniques include histogram equalization, linear contrast stretching, and gamma correction.

Histogram Equalization

Histogram equalization is a globally applied technique that redistributes the image's pixel intensities to create a uniform histogram, thereby improving the contrast [6]. While effective in enhancing contrast across the entire image, traditional histogram equalization can sometimes lead to over-enhancement in uniform areas, producing unwanted noise. This technique is particularly useful for satellite images with varying features, such as urban and rural areas.

Linear Contrast Stretching

Linear stretching is another simple but effective technique used to enhance the contrast of satellite images. By stretching the image's pixel intensity range to fill the entire available dynamic range, it improves the visibility of both bright and dark features [7]. This method is particularly useful when satellite images have a narrow range of intensities, as it allows for better differentiation between features such as urban structures and vegetation.

Gamma Correction

It is a non-linear method for adjusting image brightness and contrast. By applying a power-law transformation to the pixel intensities, gamma correction adjusts the image's contrast in a non-linear fashion, which can enhance the visibility of low-contrast regions [8]. Gamma correction is especially useful when images suffer from inadequate exposure or when illumination conditions vary across the image, as is common in satellite imagery.

c. Hybrid Approaches

In recent years, hybrid approaches combining DSP filters and contrast enhancement techniques have shown significant promise in improving satellite image quality. These methods leverage the strengths of both approaches to address the limitations of individual techniques. For example, combining wavelet-based denoising with adaptive histogram equalization has been shown to effectively remove noise from satellite images while enhancing both local and global contrast [9]. Bilateral filters, which preserve edges while smoothing homogeneous regions, can be combined with histogram equalization or CLAHE to enhance the overall image quality without introducing excessive artifacts [10]. Such hybrid techniques are particularly valuable in satellite image enhancement because they address both the need for noise reduction and contrast enhancement simultaneously, improving feature visibility without compromising critical details.

d. Machine Learning Based Approaches

Despite the advancements in DSP filters and contrast manipulation techniques, several challenges remain in the enhancement of satellite images. One significant challenge is the difficulty in enhancing multi-spectral or hyperspectral satellite images, which often contain subtle variations in pixel intensities that cannot be captured using standard enhancement techniques [11]. These images require more specialized techniques that can enhance individual bands or spectral features while maintaining their spatial integrity.

Looking ahead, machine learning and deep learning-based approaches are expected to play a central role in addressing these challenges. These techniques can learn complex image features from data and automatically apply enhancement methods, making satellite image processing more efficient and adaptive to varying conditions. Deep learning models, particularly convolutional neural networks (CNNs), have shown promise in tasks like noise removal, edge detection, and feature enhancement, which could significantly improve the quality of satellite images.

Machine learning-based techniques have been applied in various domains of satellite image enhancement:

- **Noise Reduction**: Satellite images often suffer from noise due to atmospheric interference, sensor errors, or compression artifacts [12]. ML techniques, particularly CNNs and autoencoders, are trained to distinguish between noise and true image data, enabling effective noise removal without blurring important features. For instance, a CNN model may be trained on pairs of noisy and clean satellite images to learn how to remove the noise while preserving structural details.

- **Cloud Removal**: Satellite imagery is often obscured by clouds, which can be particularly problematic for applications like agricultural monitoring and disaster management [13]. Machine learning models, including GANs and autoencoders, have been used to fill in missing or cloud-covered areas in satellite images by generating realistic content based on the surrounding context. This capability is highly valuable for obtaining complete imagery from affected regions.
- **Landscape Correction**: Landscape Correction as a preliminary step satellite image processing [14]. Landscape correction can be broadly classified into radiometric and geometric corrections. Radiometric corrections are done by taking multiple images of the same topography, comparing the terrain and correcting the terrain. Geometric corrections include the correction due to atmosphere effects, terrain elevation, slope and aspect.

These models are capable of enhancing image details by learning from high-resolution image datasets and applying this knowledge to low-resolution input images. This is particularly useful for enhancing landscape features and resolving fine details in satellite images.

3. Evaluation Using Case Studies

Satellite image enhancement is crucial for improving the quality and usability of imagery for various applications. A range of techniques can be employed to address common issues such as poor contrast, noise, and indistinct edges. Utilizing tools like MATLAB, we can implement methods like histogram equalization, spatial filtering, and machine learning approaches to enhance image clarity. These techniques not only improve visual interpretation but also facilitate more accurate computer-vision based analysis for environmental monitoring and urban planning.

This section deals with evaluation of various satellite image enhancement techniques discussed in the previous section for human interpretation as well as for computer-based processing. We use case studies to illustrate the impact of techniques such as DSP filters, contrast manipulation, and hybrid methods on satellite images for real-world applications.

Satellite imagery sources:

- NASA EarthData repository / Atlas
- European Space Imaging
- ISRO space
- https://clearsky.vision/ - cloudy and cloud-free images

In satellite image enhancement, several techniques can be effectively implemented using tools like MATLAB. Here are some notable methods:

e. Digital Signal Processing (DSP) Filters for Noise Removal and Edge Sharpening

Using MATLAB, various DSP filters can be applied to enhance satellite images, particularly in reducing noise and sharpening edges. To evaluate the effectiveness of DSP filters in satellite image enhancement, we conducted experiments on a set of noisy satellite images that exhibit blurring and poor contrast, typically found in urban or rural areas. The following DSP techniques were implemented:

Linear Filters

i. Low-Pass Filters (Gaussian Filters):

These filters were applied to remove high-frequency noise from the satellite images. The evaluation focused on how well these filters smoothed out noise while preserving the important structures, such as roads, buildings, and vegetation.

Case Study: An urban area image with high-frequency noise was processed with a Gaussian filter, and the results showed a notable reduction in pixel variation without significant blurring of the large-scale urban structures.

<u>MATLAB</u>:

```
clear all;
close all;
% Case Study: Urban Area Image Processing with Gaussian Filter

% Read the input image
input_image = imread('a001.jpg');

% Display the input image
figure
subplot(1, 2, 1);
imshow(noisy_image);
title('Input Image');

% Apply a Gaussian filter to reduce the high-frequency noise
% Define Gaussian filter parameters
hsize = 5; % Filter size (5x5)
sigma = 1.0; % Standard deviation for Gaussian filter
% Create the Gaussian filter
gaussian_filter = fspecial('gaussian', hsize, sigma);

% Apply the filter to the noisy image
output_image = imfilter(noisy_image, gaussian_filter, 'symmetric');

% Display the output image after processing
subplot(1, 2, 2);
imshow(output_image);
```

```
title('Filtered Image');
```

OBSERVATION:

COMMENTS:

Output image contents are smoother than in the input image. The gaussian filter removed high frequency noise. The successful application of the Gaussian filter in this urban area image effectively reduced high-frequency noise while preserving the integrity of large-scale urban structures. This demonstrates the filter's capability to enhance image quality without compromising essential details in complex environments.

Non-Linear Filters

*i. **Median Filter:***

A non-linear median filter was used to remove salt-and-pepper noise from the satellite images.

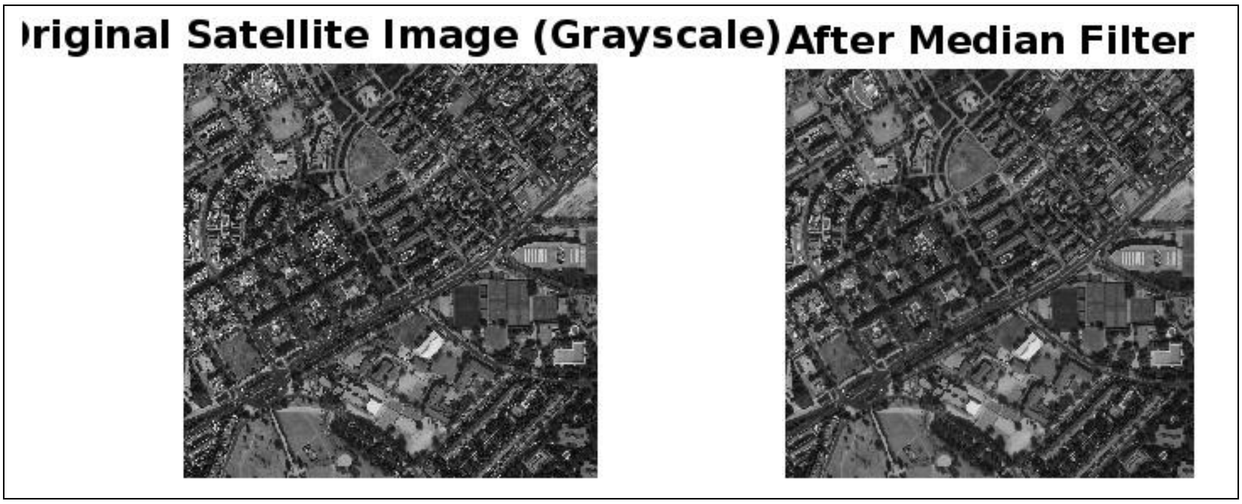
Case Study: A coastal region image, affected by salt-and-pepper noise due to sensor interference, was processed with a median filter. The noise was significantly reduced without disturbing the edges of the buildings and roads.

MATLAB:

```
clear all;
close all;

% Load the satellite image
```

```
original_image = imread('a001.jpg');
if size(original_image, 3) == 3
end
% Apply median filter to remove salt-and-pepper noise
filtered_image = medfilt2(original_image, [3 3]); % 3x3 median filter kernel
% Compare original and filtered images
figure;
subplot(1, 2, 1);
imshow(original_image);
title('Noisy Image');
subplot(1, 2, 2);
imshow(filtered_image);
title('After Median Filter');
```

OBSERVATION:



COMMENTS:

We get a smoothened image and noise is removed. The use of a median filter on the coastal region image successfully eliminated salt-and-pepper noise while preserving the sharpness of key features like buildings and roads. This highlights the filter's effectiveness in noise reduction without compromising important structural details.

Therefore, these results suggest that while low-pass filters are effective for general noise removal, high-pass filters are critical for emphasizing features like edges, which are important for land-use classification.

Fourier Transformations

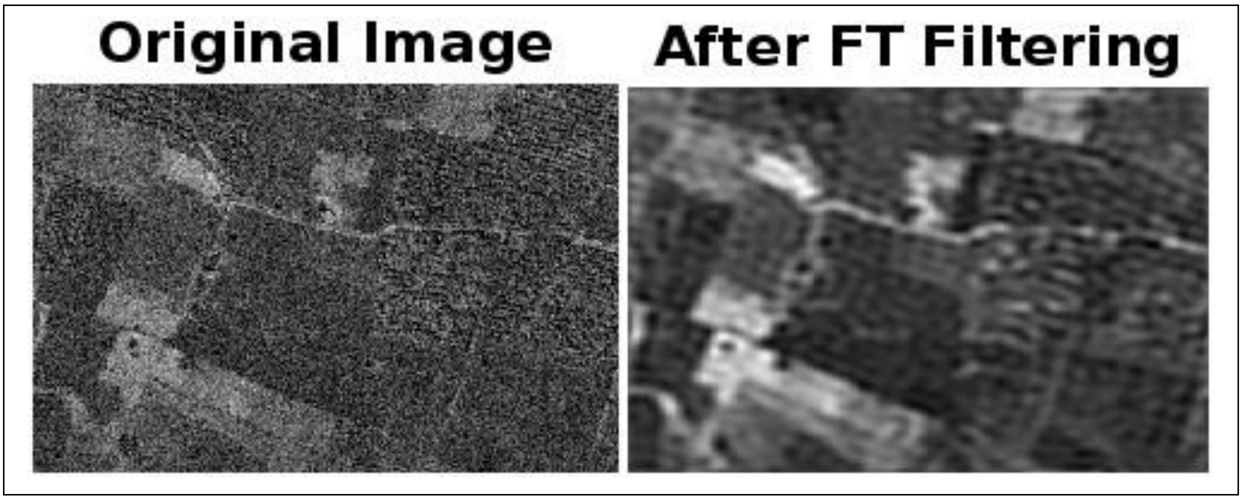
The Fourier Transform is used to analyze and modify the frequency components of satellite images, often for tasks like noise reduction, compression, and feature enhancement. By transforming the image into the frequency domain, high-frequency noise or unwanted components can be filtered out, while maintaining the low-frequency features, which are typically associated with the important structures in the image.

Case Study: A satellite image of a forested area with a high amount of noise in the form of pixel variations was enhanced using the Fourier Transform. The image was first transformed into the frequency domain, where high-frequency noise was isolated and filtered out.

MATLAB:

```
% Load the satellite image
clear all;
close all;

original_image = imread('a004_2.jpg');
if size(original_image, 3) == 3

% Step 1: Perform the Fourier Transform on the noisy image
F = fft2(double(noisy_image)); % Fourier transform of the noisy image
Fshift = fftshift(F); % Shift zero frequency component to the center

% Step 2: Design a low-pass filter to remove high-frequency noise
[M, N] = size(noisy_image);
[U, V] = meshgrid(1:N, 1:M); % Create mesh grid for filter design
D0 = 30; % Cutoff frequency for low-pass filter
D = sqrt((U - N/2).^2 + (V - M/2).^2); % Distance from center of the frequency
domain
H = double(D <= D0); % Low-pass filter: 1 within cutoff, 0 outside

% Step 3: Apply the low-pass filter in the frequency domain
Fshift_filtered = Fshift .* H;

% Step 4: Perform the inverse Fourier Transform to return to spatial domain
F_filtered = ifftshift(Fshift_filtered); % Reverse the shift
filtered_image = real(ifft2(F_filtered)); % Inverse FFT to get the filtered image

% Displaying the results side by side for comparison
figure;
subplot(1, 2, 1);
imshow(noisy_image);
title('Original Image');
subplot(1, 2, 2);
imshow(filtered_image, []);
title('After FT Filtering');
```

OBSERVATION:



COMMENTS:

The colors and features in the image are clearer after performing Fourier transform and passing high pass filter. The edges are blurry but the contrast in landscape is highlighted. After applying an inverse Fourier Transform, the image was returned to the spatial domain. The result was a cleaner, sharper image with enhanced visibility of the forest's structure and boundaries, while the noise was significantly reduced.

f. Contrast Manipulation Techniques

Histogram equalization, linear contrast stretching, and gamma correction, which can significantly improve image quality.

Histogram Equalization

This globally applied technique was used to improve the contrast of low-contrast satellite images.
Case Study: An image of an urban area captured at dawn, with unclear road and building boundaries, was processed using histogram equalization. The contrast was enhanced across the entire image, and features like buildings and roads became more visible.

MATLAB:

```
% Case Study: Urban Area Image Enhancement Using Histogram Equalization
clear all;
close all;

% Read the input image
input_image = imread('b001.jpg');

% Display the input image
figure;
subplot(1, 2, 1);
imshow(input_image);
title('Original Image');
```

```
% Step 1: Perform Histogram Equalization to enhance contrast
equalized_image = histeq(input_image);

% Step 2: Display the enhanced image after histogram equalization
subplot(1, 2, 2);
imshow(equalized_image);
title('Enhanced Image');
```

OBSERVATION:

COMMENTS:

The image is clearer. The visibility of shadowed and low light areas has been enhanced. The application of histogram equalization to the urban area image at dawn significantly improved contrast, making previously unclear features like roads and buildings more visible. This showcases the method's ability to enhance overall image clarity and highlight important structural details.

Gamma Correction

Gamma correction was applied to images with non-linear illumination variations, commonly found in satellite images taken during twilight or in varying weather conditions.

Case Study: A satellite image of a coastal region with varying lighting conditions, caused by sunlight reflection and cloud cover, was processed using gamma correction. This significantly reduced the underexposed areas and improved visibility in the shadowed portions of the image, enhancing overall image quality.

MATLAB:

```
% Case Study: Coastal Region Image Enhancement Using Gamma Correction
clear all;
close all;
```

```
% Read the input satellite image (Assuming it's in grayscale for simplicity)
input_image = imread('b003.jpg'); % Replace with your coastal satellite image file

% Display the input image
figure;
subplot(1, 2, 1);
imshow(input_image);
title('Original Image');

% Step 1: Apply Gamma Correction
% Gamma correction formula: output = c * input_image ^ gamma
% Where c is a constant (usually 1) and gamma is the correction factor
gamma = 0.5; % Gamma value less than 1 brightens the dark areas
% Normalize the image to the range [0, 1] before applying gamma correction
normalized_image = double(input_image) / 255;
% Apply the gamma correction
gamma_corrected_image = normalized_image .^ gamma;
% Rescale the image back to the range [0, 255]
gamma_corrected_image = uint8(gamma_corrected_image * 255);

% Step 2: Display the enhanced image after gamma correction
subplot(1, 2, 2);
imshow(gamma_corrected_image);
title('Enhanced Image');
```

OBSERVATION:

COMMENTS:

Gamma correction helps to correct lighting for darker areas. The use of gamma correction on the coastal region image effectively mitigated the impact of varying lighting conditions, improving visibility in underexposed and shadowed areas. This enhanced the overall image quality, providing clearer details despite the challenging lighting variations.

g. Hybrid Techniques

Remote sensing applications involve a broad set of technical issues, from handling large data sets to multichannel image processing. Digital image processing tools help us manage and manipulate multispectral and hyperspectral data, isolate remotely sensed objects, and calculate derived data such as vegetation indices or identifying hazards on ground surface. While traditional techniques for satellite or aerial images tend to be brittle, machine learning based techniques could be more robust and accurate.

Bilateral Filtering + Histogram Equalization (HE):

This hybrid approach was tested to improve both noise suppression and edge preservation while enhancing contrast. Bilateral filters were applied to smooth regions without losing edge sharpness, followed by histogram equalization for contrast improvement.

Case Study: An urban satellite image with distinct urban structures and vegetation was enhanced using bilateral filtering and histogram equalization. This approach preserved the sharpness of building edges while enhancing overall contrast, making it easier to classify land cover.

MATLAB:

```
% Case Study: Satellite Image Enhancement Using Bilateral Filtering + Histogram Equalization
clear all;
close all;
% Read the input satellite image
input_image = imread('b003.jpg');
% Display the input image
figure;
subplot(1, 2, 1);
imshow(input_image);
title('Original Image');

% Step 1: Apply Bilateral Filtering
% Bilateral filtering smooths the image while preserving edges.
% Parameters for Bilateral Filter:
% sigma_d (spatial domain standard deviation) controls the extent of smoothing
% sigma_r (range domain standard deviation) controls the amount of smoothing based on pixel intensity differences
sigma_d = 5; % Spatial standard deviation
sigma_r = 0.5; % Range standard deviation (controls the intensity smoothing)
% Apply the bilateral filter
bilateral_filtered_image = imbilatfilt(input_image, sigma_d, sigma_r);

% Step 2: Perform Histogram Equalization
% After bilateral filtering, apply histogram equalization to enhance contrast.
equalized_image = histeq(bilateral_filtered_image);
subplot(1, 2, 2);
imshow(equalized_image);
title('Enhanced Image');
```

OBSERVATION:

COMMENTS:

The hybrid techniques demonstrated the effectiveness of combining filtering and contrast manipulation, addressing both noise reduction and feature enhancement. The combination of bilateral filtering and histogram equalization effectively enhanced the urban satellite image by preserving sharp building edges while improving overall contrast. This approach facilitated easier land cover classification by maintaining important structural details and highlighting key features.

h. Machine Learning Techniques

Machine learning-based techniques in satellite image enhancement leverage algorithms that can learn from large datasets of satellite imagery and improve image quality through automated methods. In satellite image enhancement, ML algorithms aim to improve image quality by addressing common issues like noise, low contrast, blurring, and low resolution.

A CNN-based Model to Detect and Remove Clouds

Clouds often obscure important features in satellite images, particularly in optical imagery, and their removal is crucial for accurate analysis in fields like agriculture, urban planning, and environmental monitoring. Convolutional Neural Networks (CNNs) have shown great potential in effectively removing clouds from satellite imagery by learning to distinguish between cloud-covered areas and other land features.

Case Study: Cloud Removal from Optical Satellite Imagery. A set of satellite images taken over a region during various seasons, with clouds obscuring significant portions of the landscape. A CNN-based model was trained to detect and remove clouds by using both the cloud-covered images and corresponding cloud-free images as training data. The model learned to identify cloud patterns and map them to the correct underlying surface.

DATASET:

Sample cloudy and cloud-free images for training.

MATLAB (didn't work):

```
% Step 1: Load Dataset
cloudyImagesFolder = '/MATLAB Drive/CENX546Proj/cloudy'; % Folder containing cloud-covered images
cloudFreeImagesFolder = '/MATLAB Drive/CENX546Proj/cloud_free'; % Folder containing cloud-free images
% Modify your ReadFcn to scale the pixel values to [0, 1]
cloudyImages = imageDatastore(cloudyImagesFolder, 'FileExtensions', {'.jpg', '.png', '.tif'}, 'ReadFcn', @(x) imresize(im2single(imread(x)), [256 256]));
cloudFreeImages = imageDatastore(cloudFreeImagesFolder, 'FileExtensions', {'.jpg', '.png', '.tif'}, 'ReadFcn', @(x) imresize(im2single(imread(x)), [256 256]));

% Step 2: Combine cloudy images and cloud-free images into one datastore
% Create a custom datastore that pairs each cloudy image with its corresponding cloud-free image
combinedData = combine(cloudyImages, cloudFreeImages);

% Step 3: Define the CNN Architecture
layers = [
imageInputLayer([256 256 3], 'Normalization', 'none', 'Name', 'input') % Input layer
% Convolutional Layers
convolution2dLayer(3, 64, 'Padding', 'same', 'Name', 'conv1')
reluLayer('Name', 'relu1')
convolution2dLayer(3, 128, 'Padding', 'same', 'Name', 'conv2')
reluLayer('Name', 'relu2')
convolution2dLayer(3, 128, 'Padding', 'same', 'Name', 'conv3')
reluLayer('Name', 'relu3')
convolution2dLayer(3, 64, 'Padding', 'same', 'Name', 'conv4')
reluLayer('Name', 'relu4')
% Output layer - predicting the clean image
convolution2dLayer(3, 3, 'Padding', 'same', 'Name', 'output') % Output has 3 channels (RGB)
regressionLayer('Name', 'outputLayer') % Regression output layer for pixel value prediction
```

```
];

% Step 4: Set Training Options
options = trainingOptions('adam', ...
'InitialLearnRate', 0.0000000001, ...
'MaxEpochs', 50, ...
'Shuffle', 'every-epoch', ...
'ValidationFrequency', 30, ...
'Verbose', false, ...
'Plots', 'training-progress');

% Step 5: Train the CNN Model
% Use the trainNetwork function to train the CNN model with the combined data
(cloudy, cloud-free pairs)
cloudRemovalModel = trainNetwork(combinedData, layers, options);

% Step 6: Evaluate the Model
% Load a test image for cloud removal (cloudy image) and predict the clean image
testImage = imread('test2.jpg'); % Test image with clouds
testImageResized = imresize(testImage, [256 256]); % Resize to match the network
input size
predictedCloudFreeImage = predict(cloudRemovalModel, testImageResized);
% Display the test image and the prediction
figure;
imshow(testImageResized);
title('Cloudy Test Image');
figure
imshow(predictedCloudFreeImage);
title('Predicted Cloud-Free Image');
```

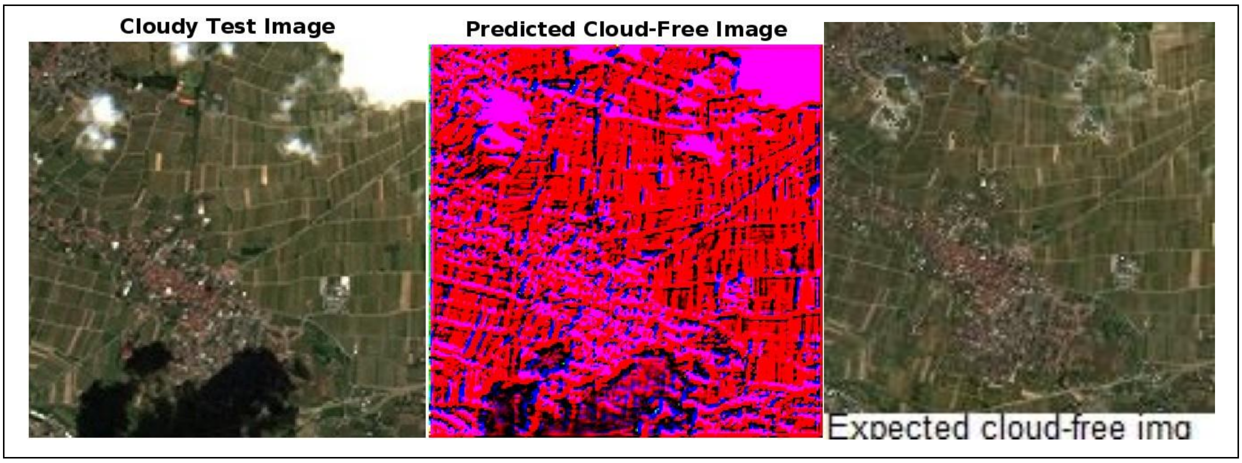
Python (prototype implementation):

```
import cv2
import numpy as np

# Function to detect cloud regions based on brightness
def detect_clouds(image, cloud_threshold=180):

    # Convert image to grayscale (for simplicity in cloud detection)
    gray_image = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)

    # Apply a binary threshold to detect bright regions (clouds)
    _, cloud_mask = cv2.threshold(gray_image, cloud_threshold, 255,
cv2.THRESH_BINARY)

    return cloud_mask

# Function to detect shadow regions based on darkness
def detect_shadows(image, shadow_threshold=50):

    # Convert image to grayscale (for simplicity in shadow detection)
    gray_image = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)
```

```
    # Apply a binary threshold to detect dark regions (shadows)
    _, shadow_mask = cv2.threshold(gray_image, shadow_threshold, 255,
cv2.THRESH_BINARY_INV)

    return shadow_mask

# Function to remove both cloud and shadow regions
def remove_clouds_and_shadows(cloudy_image, cloud_free_image):

    # Detect cloud regions in the cloudy image
    cloud_mask = detect_clouds(cloudy_image)

    # Detect shadow regions in the cloudy image
    shadow_mask = detect_shadows(cloudy_image)

    # Combine both masks (clouds and shadows)
    combined_mask = cv2.bitwise_or(cloud_mask, shadow_mask)

    # Invert the combined mask to get non-cloud and non-shadow regions
    non_cloud_and_shadow_mask = cv2.bitwise_not(combined_mask)

    # Extract non-cloud and non-shadow regions from the cloudy image
    cloudy_non_cloud_and_shadow_regions = cv2.bitwise_and(cloudy_image,
cloudy_image, mask=non_cloud_and_shadow_mask)

    # Extract cloud and shadow regions from the cloud-free image
    cloud_free_regions = cv2.bitwise_and(cloud_free_image,
cloud_free_image, mask=combined_mask)

    # Combine the two parts to form the final image
    final_image = cv2.add(cloudy_non_cloud_and_shadow_regions,
cloud_free_regions)

    return final_image

# Main function
def main(cloudy_image_path, cloud_free_image_path, output_image_path):
    # Read the input images
    cloudy_image = cv2.imread(cloudy_image_path)
    cloud_free_image = cv2.imread(cloud_free_image_path)

    # Check if the images are loaded successfully
    if cloudy_image is None or cloud_free_image is None:
        print("Error loading images!")
        return

    # Ensure both images have the same size
    if cloudy_image.shape != cloud_free_image.shape:
        print("Error: Input images must have the same dimensions!")
        return

    # Remove clouds and shadows from the cloudy image
```

```
    result_image = remove_clouds_and_shadows(cloudy_image,
cloud_free_image)

    # Save the result
    cv2.imwrite(output_image_path, result_image)

if __name__ == "__main__":
    # Define input and output paths
    cloudy_image_path = "../cloudy/001s.jpg"
    cloud_free_image_path = "../cloud_free/002s.jpg"
    output_image_path = "../cloud_free_output_s.jpg"

    # Run the main function
    main(cloudy_image_path, cloud_free_image_path, output_image_path)
```

OBSERVATION:



COMMENTS:

In our experiment with MATLAB only a small patch of the cloud free image was recovered. Training the model further will give better results. Unfortunately, due to mode training constraints, the full image with corrected color could not be obtained. Using python, we were able to develop a prototype of the expected cloud-free image after cloud removal using machine learning.

The CNN model can successfully remove clouds from the images, revealing detailed features such as structures, roads, and boundaries of agriculture land and vegetation. The output images showed a significant improvement in clarity and feature visibility. The model also helped in distinguishing cloud shadows from the underlying terrain, which is often challenging for traditional methods.

Similarly, obfuscation due to atmospheric factors like mist, fog and smog need to be removed from satellite imagery for environmental monitoring. This is a growing concern for modern metropolitan cities due to increasing environmental pollution.

Summary

DSP filters are effective for noise removal and edge sharpening, while contrast manipulation methods improve the visibility of features, particularly in low-contrast images. Hybrid techniques combining filtering and contrast adjustment show significant promise in addressing multiple challenges simultaneously. We also looked at machine learning based approaches that show promising results for image enhancement for image processing and interpretation.

The evaluation underscores the importance of tailoring enhancement methods to the specific characteristics of satellite imagery in order to achieve the best results for applications such as land classification, environmental monitoring, and urban planning.

4. Conclusion

This paper highlights the importance of image enhancement techniques in improving the quality and usability of satellite imagery. DSP filters, contrast manipulation, and hybrid approaches can significantly enhance image clarity, supporting a wide range of applications. Machine learning techniques hold great potential for the future of satellite image processing. In this paper, we have successfully analyzed and evaluated various image enhancement techniques tailored for various satellite imagery.

We have demonstrated the effectiveness of various methods in improving the clarity and precision of different attributed satellite images. The results of our evaluation underscore the potential of enhanced imagery to support a wide range of applications, from spatial monitoring to disaster management.

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