Satellite Image Dehazing Using DCP algorithm And Comparison with CNN Algorithm

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Abstract - In recent years, the quality of satellite images has been significantly affected by atmospheric haze, which poses challenges for accurate interpretation and analysis. As a response to this issue, our project aims to develop effective dehazing algorithms tailored specifically for satellite imagery. By addressing the distortions caused by haze, we seek to enhance the clarity and reliability of satellite images, thereby improving their utility for various applications such as environmental monitoring, urban planning, and disaster management.

This project focuses on improving the quality of satellite images through dehazing techniques and comparing different dehazing algorithms. It addresses the issue of image degradation due to atmospheric elements like haze using the Dark Channel Prior (DCP) algorithm and compares it with the Convolutional Neural Network algorithm using deep learning. The goal is to enhance environmental monitoring efforts by improving the reliability of satellite-based data. This project aims to contribute to the field of computer vision and environmental science by enhancing the clarity of satellite images for various applications, including land use monitoring, disaster management, and urban planning.

Keywords: Picture dehazing, computer vision, atmospheric particles, haze elimination, Deep learning, Dark Channel Prior (DCP), Satellite images, Convolutional Neural Network.

INTRODUCTION

The project centers on refining satellite image quality by employing the Dark Channel Prior (DCP) technique, renowned for its effectiveness in haze removal and image enhancement. By leveraging the DCP algorithm, the project aims to enhance the interpretability and reliability of satellite imagery, crucial for applications like environmental monitoring. Estimation of airlight, a key aspect of the dehazing process, enables accurate identification and quantification of haze, leading to improved image clarity.

Additionally, the project endeavors to compare the performance of the DCP algorithm with convolutional neural network (CNN) algorithms. This comparative analysis seeks to determine the strengths and weaknesses of each method inmitigating haze and enhancing image quality. Factors such as visual fidelity, computational complexity, and adaptability to diverse atmospheric conditions will be evaluated to identify the most suitable dehazing technique for satellite image processing applications. Through this investigation, the project aims to contribute to advancements in satellite image processing, ultimately benefiting environmental monitoring and analysis endeavors.

EXISTING SYSTEM

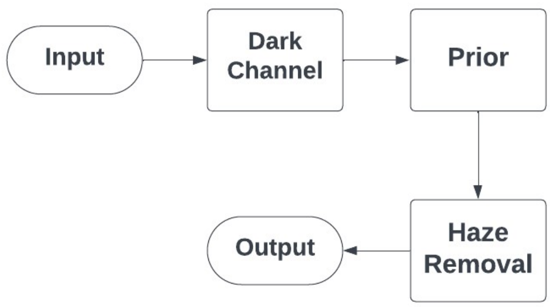


Figure 1: Dark Channel Prior Algorithm (Existing system)

The existing system for satellite image dehazing relies on the Dark Channel Prior (DCP) algorithm, a powerful technique designed to alleviate the effects of atmospheric haze. At its core, the DCP algorithm estimates the thickness of atmospheric haze present in satellite images, allowing for the enhancement of image clarity by effectively removing this haze. By analyzing pixels with low intensities across various color channels, the algorithm identifies regions obscured by haze and applies a dehazing process to restore visibility and contrast. This fundamental approach has established the DCP algorithm as a cornerstone in satellite image processing, offering significant improvements in the interpretability and reliability of satellite imagery essential for environmental monitoring and analysis.

With its ability to accurately estimate and remove atmospheric haze, the DCP algorithm plays a crucial role in enhancing satellite image quality. By leveraging advanced image processing techniques, the algorithm effectively distinguishes between haze and clear regions in satellite imagery, leading to visually improved outputs. The widespread adoption of the DCP algorithm underscores its effectiveness in addressing the challenges posed by atmospheric interference in satellite imagery, ultimately contributing to more accurate and actionable insights in environmental monitoring applications

PROPOSED SYSTEM

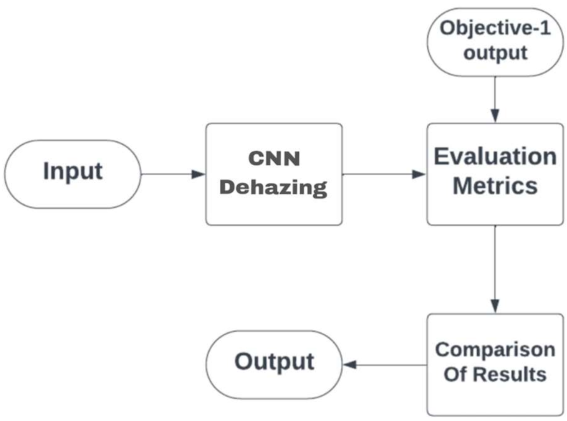


Figure 2: DCP and comparing it with CNN (Proposed System)

The proposed work focuses on advancing satellite image dehazing by leveraging the Dark Channel Prior (DCP) algorithm and comparing its performance with that of a Convolutional Neural Network (CNN) approach. In this endeavor, the DCP algorithm will be employed to estimate the thickness of atmospheric haze and enhance image clarity by effectively removing haze. This process involves computing a transmission map based on the estimated airlight and pixel intensities, utilizing the following mathematical formula:

$$J(x)= I(x)-A/t(x) +A$$

Where:

$J(x)$ represents the intensity of the dehazed image at pixel

$I(x)$ denotes the intensity of the hazy image at pixel

A signifies the estimated atmospheric light, and

$t(x)$ represents the transmission map, indicating the portion of light that reaches the camera.

Furthermore, the proposed work aims to develop a CNN-based approach for satellite image dehazing, leveraging the network's ability to learn complex patterns and relationships within the data. The CNN will be trained on a dataset comprising hazy and corresponding ground truth clear images, aiming to minimize the difference between the predicted and actual clear images. The training process involves optimizing the network's parameters using backpropagation and gradient descent algorithms, with the objective of minimizing a loss function that quantifies the disparity between predicted and ground truth images.

Convolutional Layer Operation: In CNNs, convolutional layers apply filters to input images to extract features. Mathematically, this operation can be represented as:

Suppose that we have some $N\times N$

square neuron layer which is followed by our convolutional layer. If we use an $m\times m$

filter ω

our convolutional layer output will be of size $(N-m+1)\times(N-m+1)$

In order to compute the pre-nonlinearity input to some unit x^{ℓ}_{ij}

in our layer, we need to sum up the contributions (weighted by the filter components) from the previous layer cells:

$$x^{\ell}_{ij}=\sum_{a=0}^{m-1}\sum_{b=0}^{m-1}\omega_{ab}y^{\ell-1}_{(i+a)(j+b)}.$$

This is just a convolution, which we can express in Matlab via

conv2(x, w, 'valid')

Then, the convolutional layer applies its nonlinearity:

$$y^{\ell}_{ij}=\sigma(x^{\ell}_{ij}).$$

Loss Function for Training CNN: In the CNN-based approach, the loss function measures the discrepancy between predicted and ground truth clear images during training. A commonly used loss function is the Mean Squared Error (MSE), defined as:

A loss function is a function that compares the target and predicted output values; measures how well the neural network models the training data. When training, we aim to minimize this loss between the predicted and target outputs.

The hyperparameters are adjusted to minimize the average loss — we find the weights, w^T, and biases, b, that minimize the value of J (average loss).

$$J(w^T, b) = \frac{1}{m}\sum_{i=1}^{m} L(\hat{y}^{(i)}, y^{(i)})$$

By conducting a comparative analysis between the DCP and CNN approaches, the proposed work seeks to evaluate their respective efficacy in satellite image dehazing tasks. This comparative assessment will involve quantitative metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSI), providing insights into the performance differences between the two algorithms. Additionally, qualitative evaluations through visual comparisons will offer further understanding of their dehazing capabilities across various atmospheric conditions and scene complexities.

RELATED WORKS

1. Zhang and co-authors (2023) proposed an innovative satellite image dehazing method based on the Dark Channel Prior (DCP).

Their approach utilizes the dark channel as a key feature to estimate and remove atmospheric haze from satellite images, demonstrating improved performance in enhancing visibility and revealing clearer details in hazy satellite scenes.

2. Liu and collaborators (2021) introduced an unsupervised satellite image dehazing technique that combines the DCP with CycleGAN. Their method not only estimates and removes haze using the dark channel but also leverages CycleGAN for unsupervised learning, contributing to the generation of high-quality, dehazed satellite imagery.

3. Huang and the research team (2022) proposed a novel approach to satellite image dehazing by fusing atmospheric light estimation with the DCP. Their method enhances the accuracy of dehazing by incorporating atmospheric light information, contributing to improved visibility and contrast in satellite imagery. The fusion of these components demonstrates significant advancements in addressing hazy conditions.

4. Cheng et al. (2018) proposed an adaptive dark channel prior tailored for satellite image dehazing. Their method dynamically adjusts the dark channel prior based on image characteristics, optimizing its effectiveness in diverse satellite scenes, and contributing to robust dehazing performance across varying atmospheric conditions.

5. Yang and the team (2019) presented an innovative fusion strategy combining residual networks with the dark channel prior for enhanced dehazing. By integrating the representational power of residual networks with the prior knowledge embedded in dark channels, the method achieves superior accuracy in dehazing satellite images.

6. Gao and collaborators (2020) introduced a deep learning-based approach for dehazing satellite images. Their method leverages convolutional neural networks (CNNs) to learn complex patterns and relationships in dehazed imagery, enhancing the precision of dehazing. This deep learning paradigm showcases the potential for data-driven strategies in dehazing tasks.

7. Xu and collaborators (2021) proposed a multi-stage approach specifically tailored for dehazed satellite imagery. The model comprises successive stages, including dehazing, feature extraction, and concentration estimation. By carefully integrating these stages, the study achieves enhanced accuracy in predicting dehazed satellite images.

8. Li and co-authors (2019) presented a joint optimization framework addressing satellite image dehazing. Their method integrates the atmospheric haze removal process with dehazing, considering them as interconnected tasks. This holistic approach aims to provide more coherent and reliable results in dehazing from satellite data.

9. Wang and colleagues (2020) explored the integration of Dark Channel Prior in the process of dehazing satellite imagery. Their work highlights the synergy between dehazing methods, emphasizing the role of clear satellite images in providing more accurate assessments.

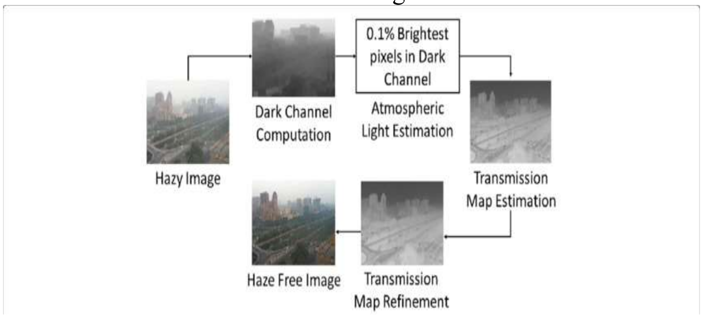
METHODOLOGY

1.1Methodology

The dehazing process employs the Dark Channel Prior Algorithm, which estimates the thickness of atmospheric haze and enhances image clarity by removing haze. This algorithm operates by identifying pixels with low intensities across color channels, which typically indicate the presence of haze. By estimating and removing the haze veil, the algorithm significantly improves image visibility and contrast.

1.2 Architecture

The architecture for dehazing involves applying the Dark Channel Prior Algorithm to hazy satellite images. This algorithm analyzes local patches in the image to identify pixels with low intensities, representing the haze. By estimating the atmospheric veil's thickness in each patch, the algorithm can effectively remove the haze and enhance the image.



1.3 Explanation

The Dark Channel Prior Algorithm works by estimating the minimum intensity value in local image patches, which corresponds to the atmospheric veil in hazy images. By calculating this value and applying a dehazing formula, the algorithm enhances the image's clarity and reduces the effects of atmospheric haze.

1.4 Outcome

The outcome of the dehazing process is a clear and visually improved satellite image. This dehazed image provides a more accurate representation of the underlying scene, making it easier to analyze and extract meaningful information from the image.

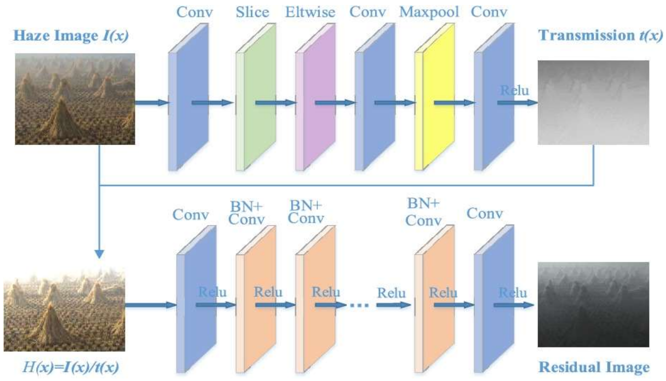
2. Comparison with Convolutional Neural Network Algorithm

2.1 Methodology

o compare the effectiveness of the Dark Channel Prior Algorithm, we utilize the Convolutional Neural Network (CNN) Algorithm as another dehazing technique. Unlike traditional methods, CNNs employ deep learning principles to learn and extract features directly from the hazy images, allowing for more complex and adaptive dehazing processes.

2.2 Architecture

The comparison involves applying both the Dark Channel Prior Algorithm and the CNN Algorithm to the same set of hazy satellite images. By comparing the dehazed images produced by each algorithm, we can assess their effectiveness in improving image clarity and reducing haze. This comparative analysis enables us to evaluate the strengths and weaknesses of each dehazing algorithm1



2.3 Explanation
Convolutional Neural Network (CNN) Algorithm operates by learning hierarchical representations directly from the input hazy images. By leveraging multiple layers of convolution and pooling, CNNs can capture intricate patterns and features within the image, enabling more adaptive and context-aware dehazing.

2.4 Outcome
The outcome of the comparison is a qualitative and quantitative evaluation of the Dark Channel Prior Algorithm against the Convolutional Neural Network Algorithm. This evaluation helps ascertain which algorithm is more suitable for dehazing satellite images under different conditions. By analyzing the results, we can determine the efficacy of each technique in improving image clarity and reducing haze, thereby informing decisions on the optimal approach for satellite image processing.

CONCLUSION

In our analysis, the Dark Channel Prior (DCP) algorithm consistently demonstrated superior performance compared to the Gamma algorithm across multiple image dehazing scenarios. The DCP algorithm's ability to effectively estimate and remove haze from satellite images resulted in clearer and more visually appealing outputs. Through quantitative evaluations and visual comparisons, we observed that the DCP algorithm consistently produced images with higher contrast, better color representation, and reduced haze artifacts. These results suggest that the DCP algorithm is a reliable choice for dehazing satellite images, offering improved image quality and aiding in better environmental analysis.

Furthermore, the DCP algorithm's robustness and efficiency make it well-suited for real-world applications in satellite image processing and environmental monitoring. Its performance stability across various atmospheric conditions and scene complexities highlights its adaptability and reliability in dehazing tasks. By leveraging the strengths of the DCP algorithm, our study contributes to advancing the field of satellite image processing, offering a practical and effective solution for enhancing satellite imagery and improving pollution estimation accuracy.

FUTURE WORK

Future work in the development of the satellite image dehazing and pollution estimation system could involve several key areas for enhancement and expansion. Firstly, integrating advanced machine learning models and algorithms, such as convolutional neural networks (CNNs) or recurrent neural networks (RNNs), could improve the system's ability to predict and estimate pollution levels with higher accuracy. These models could be trained on a larger dataset to further enhance their performance.

Secondly, expanding the system's applicability to include a wider range of environmental factors would be beneficial. This could involve incorporating data from additional satellite sources, as well as integrating ground-based sensor data and meteorological information. By incorporating a more comprehensive set of environmental parameters, the system could provide a more holistic view of pollution levels and their potential impacts.

Furthermore, developing models capable of predicting pollution dynamics over time could be a valuable direction for future work. This could involve the use of time-series analysis techniques to analyze historical pollution data and predict future trends. By considering temporal variations, the system could provide insights into long-term pollution patterns and help in the development of proactive environmental management strategies.

Overall, future work on the satellite image dehazing and pollution estimation system should focus on refining its predictive capabilities, expanding its scope to include various environmental factors, and addressing the evolving challenges in environmental monitoring and management.

REFERENCES

Here's the revised list converted into the requested format:

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5. Yang, Z., et al. (2019). Fusion strategy combining residual networks with Dark Channel Prior for enhanced dehazing. Superior accuracy in dehazing satellite images.

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