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CLOUD REMOVAL BASED ON DARK CHANNEL PRIOR: A SYSTEMATIC LITERATURE REVIEW

Nazifa Hamidiyati[1], Laksmita Rahadianti[2]
Universitas Indonesia, Indonesia[1,2]
Email: nazifa.hamidiyati@ui.ac.id[1], laksmita@cs.ui.ac.id[2]

Abstract

Remote sensing satellite technology has revolutionized the way we gather information about our planet. Through the use of advanced imaging capabilities, satellite images have become invaluable in various aspects of daily life. These images are extensively utilized in environmental protection, agricultural engineering, and other fields. Remote sensing satellite maps are used for tasks such as geological mapping, monitoring urban heat islands, environmental surveillance, and detecting forest fires from remote sensing images. However, clouds present a significant hindrance when utilizing satellite imagery for ground observations, as they obstruct the view and can limit the accuracy of the analysis. While there are numerous advanced state-of-the-art approaches available, it is important to note that they often require a substantial amount of data for training. On the other hand, if a more general approach is desired without the need for extensive training data, pixel-based methods provide a viable option. One of the widely used pixel-based methods for cloud removal in satellite images is Dark Channel Prior (DCP). DCP is often combined with other methods to improve the image quality. This systematic literature review will demonstrate the development of the DCP method in cloud removal from satellite images.

Keywords: Cloud removal, dark channel prior (DCP), satellite imagery, remote sensing

Introduction

The Dark Channel Prior (DCP) theory, proposed by (He, Sun, & Tang, 2009), is one principle used to calculate the dark channel in an image. This principle can be applied to overcome challenges caused by clouds and atmospheric interference in remote sensing images. Based on this, the atmospheric light A and transmission factor t(x) were estimated to conduct image dehazing using an atmospheric scattering model. Additionally, to address the issue of brightness in the initial dehazed images, different methods can be employed, including both linear and non-linear approaches. Linear enhancement techniques typically involve converting the RGB image into alternative color spaces such as Hue, Saturation, Luminance (HSL) or Hue, Saturation, Value (HSV). After adjusting the components in the HSL/HSV space, the image is transformed back to the RGB space. This method provides precise control over the image hierarchy, but it may be hindered by its complexity and slower processing speed. Furthermore, significant changes in image brightness can lead to noticeable distortions. On the other hand, non-linear enhancement methods involve directly adding or subtracting values to the RGB pixel values. This approach offers simplicity and faster processing speed, but it may result in some loss of image information and a less vibrant and layered appearance in the adjusted image (Zhang, et al., 2018).

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The main principle behind Dark Channel Prior is derived from haze-free outdoor scenes. In a haze-free image, the dark channel exhibits very low intensity values that are close to zero, resulting in a dark appearance. By normalizing the image, the pixels with the highest intensity, representing the brightest 0.1% of pixels, are considered as skylight. It is assumed that the color of atmospheric light closely resembles the color of the sky and is always a positive value. The dark channel is defined as the minimum intensity across the RGB channels, with at least one color channel having very low values near zero (Anwar & Khosla, 2017).

Monitoring the atmospheric light using the dark channel prior is a reliable approach, especially when a large local mask is used to evaluate the dark channel. Therefore, if the local mask size used for dark channel evaluation is not large enough, it is recommended to utilize an additional dark channel with a larger local mask size specifically for atmospheric light monitoring. The use of local entropy is also found to be beneficial in enhancing monitoring accuracy as it helps prevent the inclusion of intense objects in atmospheric light estimation (Singh & Kumar, 2018).

In order to estimate the scattered light, determine the lowest intensity within a patch for each HSI image containing clouds. The intensity in the HSI color space reflects the level of brightness, allowing the opacity of clouds to be inferred from this intensity. Through observations, it has been noticed that cloud pixels often exhibit significantly higher intensities compared to cloud-free pixels, which can be attributed to the clouds appearing as white or grey sheets in the image (Markchom & Lipikorn, 2018).

Based on the model of atmospheric scattering in satellite imagery, the bright pixels within the satellite area are influenced by the hazy atmospheric light. To estimate the atmospheric light, a decomposition technique called Atmospheric Light Estimation (ALE) utilizes local statistics to preserve image details. Unlike filters that tend to blur out noise with higher variances, this adaptive filter effectively smooths out noise with lower variation. As a result of its adaptable nature, this filter is able to retain features in both low and high-contrast areas (Kumar, Shivakumar, & Bachu, 2022).

Review Methods

To demonstrate the advancements in dark channel detection methods for cloud removal in satellite imagery, we conducted a systematic review of the existing literature. This was done to showcase the success rate of previous methods and propose potential methods that could be utilized in the future. The procedure consists of 6 steps, represented in the diagram below.

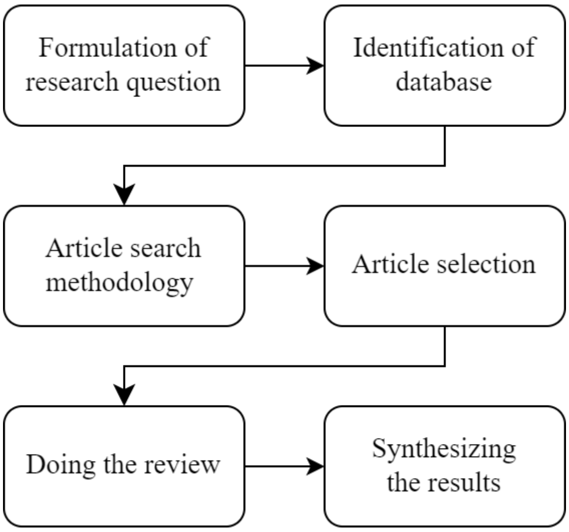

Figure 1. The Review Procedure

A. Formulation of Research Questions

The research questions were formulated to establish the scope of discussion during the systematic literature review (SLR). The research questions can be seen in the following Table 1.

Table 1. Research Questions

ID	Research Questions
RQ1	How is the DCP method approach utilized for cloud removal?
RQ2	What are the proposed modifications to enhance the performance of the DCP method for cloud removal?

B. Identification of Database

The articles gathered and analyzed in this study are sourced from a comprehensive scientific database, comprising six reputable platforms: IEEE Xplore, Scopus, Science Direct, SpringerLink, and ACM Digital Library.

C. Article Search Methodology

The keywords used for the search were: (‘cloud removal’ or 'cloud') and (‘dark channel prior’ or 'dark channel' or 'dark pixel'). The following criteria, as presented in Table 2, were utilized to identify the candidate articles.

Table 2. Articles Criteria

Population	Remote sensing image
Intervention	The approach of the DCP method
Comparison	Modification of the DCP method
Outcome	Improvement of DCP performance
Context	Cloud removal

Using the specified keywords and criteria, we choose the articles that were published in 2017-2022. The initial phase of the article search yielded from the selected database can be seen in the following Table 3.

Table 3. Article Search Result from Each Database

Database	Number of Articles
IEEE Xplore	34
Scopus	105
Science Direct	8632
SpringerLink	15639
ACM Digital Library	2209

D. Article Selection

The initial phase of the article selection involves applying inclusion and exclusion criteria, which are detailed in Table 4.

Table 4. Article Inclusion and Exclusion Criteria

Inclusion	The article is written in English
	The article is published between 2017-2022
	The full text of the article can be accessed
	The article is related to the search keyword query
	The article can answer the research questions
	The article discusses the DCP method modification
Exclusion	The article is not written in English
	The article is not published between 2017-2022
	The full text of the article can not be accessed
	The article is not related to the search keyword query
	The article does not answer the research questions
	The article does not discuss the DCP method modification

E. Doing the Review

Table 5 will provide the articles obtained from each database after applying the inclusion and exclusion criteria. The systematic literature review (SLR) will be conducted based on the selected articles.

Table 5. Article Selection Result

Database	Number of Articles
IEEE Xplore	13
Scopus	22
Science Direct	30
SpringerLink	25
ACM Digital Library	17

F. Synthesizing the Results

The purpose of this section is to address our research questions and gather relevant information from the selected articles. The results will be presented in the next section.

Results and Discussion

Based on the conducted literature review of selected articles, it can be concluded that in traditional DCP methods, modifications are made by combining DCP with specific techniques. On the other hand, in learning-based methods, modifications are made to the model used to determine the atmospheric light, as the atmospheric light utilizes the dark channel prior as an approach for atmospheric light estimation. The summary of the results can be seen in the following Table 6.

Table 6. Results Summary

Ref	Methods	Description
(Shi, Zhang, Zhou, & Cheng, Cloud Removal for Single Visible Image Based on Modified Dark Channel Prior with Multiple Scale, 2021)	Modified Dark Channel Prior with Multiple Scale (MDCPMS)	• For thin-cloud removal • Multiple scales and DCP are integrated together. • Multi-scale decomposition. • Decomposition of the input image into high-frequency and low-frequency components. • The low-frequency component is processed using DCP. • The resulting image exhibits minimal color distortion. • The evaluation metrics indicate superior results compared to DCP and non-local methods.
(Zhang, et al., 2020)	Dark channel subnet (NGAD)	• Based on the Gabor transform and Attention modules • Encoder–decoder structure and incorporated with Dark channel subnet • The feature map is reconstructed by dark channel subnet with the Spatial attention module
(Li, Hu, & Ai, 2019)	Sphere Model Improved Dark Channel Prior	• The sphere model is utilized to enhance DCP based on the radius (R) of the sphere used to determine the minimum pixel intensity in cloud-contaminated areas. • The radius (R) approximates the standard deviation of pixels in the local patch. • The DCP algorithm is subsequently employed after obtaining the transmission map based on the Sphere model. • The process is relatively slow.
(Fazlali, Shirani, McDonald,	Deep convolutional autoencoder	• Thin-cloud removal

Brown, & Kirubarajan, 2020)		• Utilizing the simple linear iterative clustering (SLIC) superpixel segmentation method • Using a deep convolutional autoencoder for dehazing aerial images • Generating a dehazed version of the image without the need for additional information like transmission map or atmospheric light value • Treating dehazing as a one-step problem rather than a two-step process to prevent error amplification between stages • Utilizing the Adam optimization approach to minimize the loss function.
(Cheng, Zhang, Zhou, & Shi, 2021)	Low-Rank and Sparse Constrained Dark Channel Prior	• Involving Lagrange multipliers and DCP. • Decomposing the scatter matrix and low-rank matrix using Lagrange multipliers to remove thick clouds. • Utilizing Dark Channel Prior (DCP) to remove thin clouds. • The DCP method works well in removing thin clouds but cannot eliminate thick clouds. • The proposed method can remove both thin and thick clouds while reconstructing information from cloud-covered areas.
(Shi, Zhang, Zhou, & Cheng, A Novel Thin Cloud Removal Method Based on Multiscale Dark Channel Prior (MDCP), 2022)	Multiscale Dark Channel Prior (MDCP)	• The problem of cloud removal is transformed into image fusion. • The combination of multiscale transformation and sparse representation (SR) is used for traditional image fusion. • DCP is integrated into this fusion framework. • The fusion framework applies the low-frequency component after the multiscale transformation (MST) process. • Modified traditional Laplacian sharpening operations are employed to enhance the sharpness of the results.
(Tang, Yao, Chen, Li, & Zhang, 2022)	Multimodel Fusion	• U-Net and SegNet are utilized as the base network models. • The AdaBoost algorithm is employed to enhance the cloud feature extraction results. • Test-time augmentation (TTA) and the DCP model are used in the post-processing layer to improve accuracy and edge extraction effects. • The DCP model can enhance the similarity level of LFIs in high-resolution satellite images to detect and remove thin clouds.

(Ju, Ding, Guo, & Zhang, 2018)	Robust gamma-correction-based dehazing model (RGDM)	• For thin-cloud removal • The Scene Albedo Restoration Formulae (SARF) is employed to streamline the subsequent refinement process and effectively handle the issue of non-uniform illumination • In the proposed SARF, the patch size of DCP, patch size of BCP, and mean filter size need to be manually initialized • The traditional gamma correction technique is used to approximate the atmospheric scattering model, which can be represented by an exponential form.
(Lin, He, Zhang, & Wu, 2022)	Three-step post-processing strategy	• Based on radiation transmittance differences between cloud-covered and non-cloud-covered landscapes • The radiation transmittance is estimated based on the dark channel prior (DCP) • The overestimated radiation transmittance is corrected using spectral features • The modified radiation transmittance map for cloud detection is focused on reducing the impact of buildings with high reflectance on cloud detection
(Ma, Wang, Tong, & Atkinson, A deep learning model for incorporating temporal information in haze removal, 2022)	Temporal information injection network (TIIN)	• Parallel CNN-based architecture • a cirrus band from a cloudy region was employed as a reference to simulate a nonuniform haze cover • The group convolution block consisting of three layers is used for feature extension by extracting multiscale semantic and contextual information. • only one channel is considered consistently for the convolutional layers to achieve spatial attention
(Wu, Luo, Hu, Yang, & Yang, 2018)	Sparse dark pixel region detection	• Using the thin-cloud mask • A nonparametric measure is used to evaluate the density of local dark pixels • The region with the sparse dark pixel is selected as the thin-cloud candidate • The multispectral images obtained by the Wide Field View (WFV)
(Zi, et al., 2021)	Combination of the traditional method and deep learning method	• U-Net is utilized to estimate the reference thin cloud thickness map from the original cloudy image. • The thin cloud thickness map for each spectral band is obtained by searching for dark pixels within a local window in the cloudy image.

		• A novel CNN architecture called Slope-Net is developed to obtain the thin cloud thickness map for each spectral band. • A new method for simulating wavelength-dependent thin clouds is proposed to generate suitable multispectral cloudy images for training U-Net and Slope-Net.
(Wen, Pan, Hu, & Liu, 2021)	Wasserstein generative adversarial network (WGAN) in YUV color space (YUV-GAN)	• End-to-end thin cloud removal by learning luminance and chroma components • the generator adopts a residual encoding–decoding network • adequate simulated pairs were used to train the YUV-GAN • cloud-free images in RGB color space can be obtained by the post-processing Inverse Transformation operation.
(Bi, Si, Zhao, Qi, & Lv, 2022)	The principal component pursuit and alternating direction multiplier method (PCP-ADMM)	• Incorporating the low-rank and sparse prior (LSP) concept • The dark channel of a hazy image is decomposed into two components: the dark channel of direct attenuation with sparsity and the atmospheric veil with low rank • The PCP-ADMM algorithm is employed for low-rank and sparse decomposition to obtain an initial estimation of the atmospheric veil • The refined atmospheric veil is then utilized to estimate the atmospheric light
(Ma, Wang, & Tong, A spectral grouping-based deep learning model for haze removal of hyperspectral images, 2022)	Spectral grouping network (SG-Net)	• For thin-cloud removal • Groups each HSI into several spectral subsets based on the intra-spectral correlations • The spectral correlation in HSI is considered in the SG-Net-based data-driven method for thin-cloud removal • Using different attention modules to transfer useful information among the spectral bands

Based on the literature review results, various methods have been developed to address the issue of thin cloud removal in satellite and aerial imagery. Traditional methods such as Dark Channel Prior (DCP) have been modified with multi-scale approaches and mathematical model integration, such as sphere models and frequency decomposition methods, to enhance accuracy in thin cloud removal. On the other hand, machine learning and deep learning-based methods, such as convolutional autoencoders and neural networks, provide more efficient and accurate solutions by utilizing superpixel segmentation and parallel convolution models. These methods overcome the limitations of traditional DCP by reducing color distortion and improving the accuracy of atmospheric light estimation, resulting in higher-quality images without the need for separate steps in the dehazing process.

Furthermore, the integration of new techniques such as Generative Adversarial Networks (GANs), U-Net convolutional networks, and fusion models demonstrates significant potential in enhancing thin cloud removal outcomes. These techniques enable more realistic cloud image simulations and leverage spectral transformations to correct uncertainties in transmittance estimation. Multimodel and fusion approaches, such as combining U-Net and SegNet, offer more precise results by sharpening edges and improving accuracy in cloud removal. With these advancements, the dehazing process becomes more efficient, providing a one-step solution that minimizes cumulative errors between stages, supporting enhanced image quality for further applications in remote sensing and mapping.

Conclusion

Based on the conducted review, several conclusions can be drawn: (1) Modified DCP methods have shown improved results in both cloud removal tasks and enhancing the color quality of images. (2) There is an increasing trend in utilizing learning-based approaches for modifying DCP methods. (3) The majority of modifications to DCP methods have been focused on thin-cloud removal, while modifications specifically targeting thick-cloud removal are still limited.

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