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CPD: A Lightweight Image Processing Framework for Cloud Presence Detection in UAV Imagery

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***Abstract*—Cloud presence in UAV imagery introduces radiometric distortions that degrade visual quality and interfere with downstream image analysis tasks. This paper presents CPD, a lightweight image processing framework for detecting cloud presence in UAV-acquired images. The proposed method leverages a combination of dark channel prior and local contrast measurement to generate a binary haze map for image-level classification. Unlike deep learning-based cloud detectors, CPD requires no training data and performs inference in a fast, scalable manner. To further improve runtime efficiency, we implement an optimized GPU-enhanced version using convolution-based approximations of morphological and statistical operators. Experimental results on three datasets, including public satellite and haze datasets as well as a UAV-based dataset, demonstrate the method's accuracy and runtime advantage. CPD achieves over 99% detection accuracy with up to 5× runtime improvement on mid-range consumer hardware, validating its applicability in real-time UAV image processing pipelines.**

***Index Terms*—cloud detection, UAV imagery, image processing, GPU acceleration, dark channel prior, local contrast**

I. Introduction

Unmanned Aerial Vehicles (UAVs) are increasingly used for real-time monitoring and high-resolution image acquisition in various fields such as agriculture, environmental surveillance, and disaster response [1]–[3]. However, the presence of clouds in UAV images often introduces radiometric distortion, obstructing ground visibility and hindering the effectiveness of downstream computer vision tasks [4], [5].

While deep learning approaches have shown promising results in pixel-wise cloud segmentation tasks [6]–[8], these methods typically require large annotated datasets and computationally expensive training processes, which limit their scalability in real-world UAV applications. Moreover, UAV-acquired imagery has different characteristics than satellite data—such as lower altitudes, higher spatial detail, and variable cloud scales—necessitating lightweight and adaptive detection methods [9], [10].

To address these challenges, this study presents a threshold-based, image-level classification algorithm for detecting cloud presence in UAV images using a combination of Dark Channel Prior (DCP) and Local Contrast Measurement (LCM). The Dark Channel Prior, initially proposed for haze removal [11], leverages the assumption that non-sky outdoor regions typically exhibit low intensity in at least one color channel. When applied to aerial images, the DCP can effectively highlight hazy or cloud-covered regions. Complementarily, local contrast serves as a spatial statistical cue to differentiate low-contrast (cloud-covered) from high-contrast (clear) regions [12].

Our proposed method first computes a binary haze mask from the dark channel and another mask from the local contrast standard deviation map. These are combined to form a final haze confidence map. Based on the ratio of haze-labeled pixels to total pixels, the image is then classified as either Clouded or Non-Clouded. The algorithm does not require training data, enabling fast and scalable classification of large UAV image sets with minimal computational resources.

This technique provides a practical alternative to learning-based methods, particularly in low-resource or real-time deployment scenarios. Compared to existing satellite-oriented methods [13]–[15], our approach demonstrates adaptability to the higher frequency noise and finer textures typically present in UAV image data.

The key contributions of the proposed framework, CPD, are summarized as follows:

- **Lightweight image processing pipeline for cloud detection**: We propose a training-free framework that combines dark channel prior analysis, local contrast measurement, and morphological operations to classify UAV images as clouded or non-clouded. This purely image processing-based approach enables fast, scalable inference suitable for real-time and resource-constrained scenarios. Furthermore, we enhance the framework through GPU acceleration by

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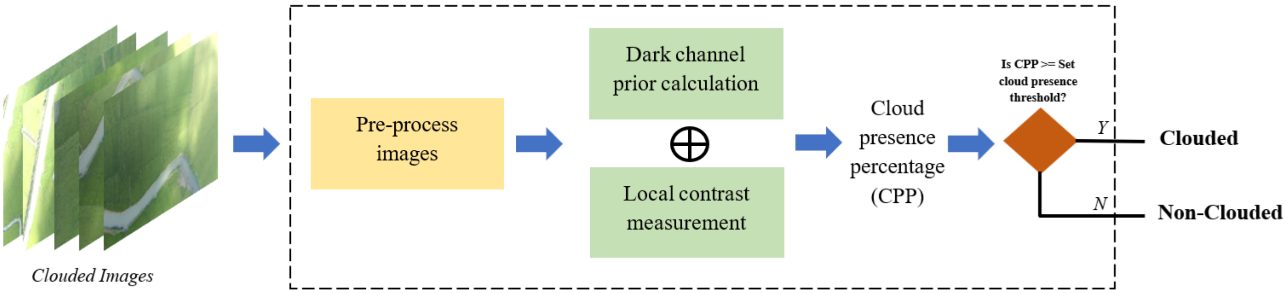

Fig. 1. Proposed cloud presence detection framework for UAV images.

replacing CPU-bound operations with parallelizable, GPU-compatible alternatives, significantly reducing processing time without sacrificing detection accuracy.

- **Dataset-level evaluation using ground truth labels**: To evaluate our method, we apply the CPD framework to our UAV images, as well as to ground-based and satellite-based images from publicly available datasets, all of which exhibit haze or cloud-related effects. Each image is classified individually, and predictions are compared to ground truth folder labels indicating cloud presence. Accuracy is computed based on the number of correctly identified clouded images relative to the total in each labeled set, providing an interpretable, folder-level evaluation without relying on pixel-wise annotation. The evaluation metric is defined as:

$$\text{Accuracy} = \frac{N_{\text{correct}}}{N_{\text{total}}} \times 100\% \tag{1}$$

where N_{correct} is the number of correctly classified clouded images, and N_{total} is the total number of clouded images according to the ground truth.

The remainder of this paper is organized as follows: Section 2 presents the materials and methods used in this study, including details on geometric correction technique and cloud removal algorithm. Section 3 discusses the experimental results and comparative performance against existing approaches. Finally, Section 4 concludes the study with a summary of findings and potential directions for future research.

II. Materials and Methods

This study addresses the challenge of detecting cloud presence in UAV-acquired images using a lightweight and scalable image processing framework. The proposed method integrates complementary visual cues—dark channel prior and local contrast statistics—to identify hazy or cloud-covered regions in single-frame aerial imagery. Preprocessing includes image resizing and grayscale conversion, followed by the computation of haze indicators through minimum channel intensity and local standard deviation analysis. Morphological operators are then applied to refine the binary masks and suppress noise artifacts. This combined strategy enables efficient image-level classification of cloud presence without reliance on training data or deep models, as illustrated in Figure 1.

A. Dataset

To evaluate the effectiveness of the proposed CPD framework, we used three datasets representing cloud and haze conditions. The dataset introduced by Ancuti et al. (2019) [16] includes densely hazy scenes that resemble cloud presence and atmospheric scattering in natural environments. The second dataset, from Lin et al. (2019) [17], consists of satellite images with varying degrees of cloud coverage. Additionally, a UAV-based dataset containing aerial image sequences was used to represent real-world cloud presence conditions. These datasets were used to test the CPD framework across different environmental conditions and image types.

B. Cloud Detection Algorithm

The proposed CPD framework detects cloud presence in UAV imagery using a combination of dark channel prior and local contrast analysis. The method involves preprocessing, haze detection via thresholding, mask combination, and final image classification based on estimated cloud coverage. The complete steps are summarized as follows:

1) Image Preprocessing: All UAV images are resized to 512×512 resolution for uniform processing. Each image is converted to grayscale and smoothed using a Gaussian filter to reduce noise and enhance spatial homogeneity [18].

2) Dark Channel Prior Computation: The dark channel prior (DCP) is calculated by taking the minimum intensity across the RGB channels for each pixel:

$$D(x, y) = \min_{c \in \{R,G,B\}} I_c(x, y) \tag{2}$$

To enhance dense haze or cloud-like areas, morphological erosion is applied using a disk-shaped structuring element. After erosion, a global threshold is applied to the resulting dark channel image. In this work, we set the dark channel threshold to $T_{DCP} = 30$. Pixels with intensities below this value are marked as potential cloud regions, forming a binary haze mask [19].

3) Local Contrast Measurement: Local contrast is estimated by calculating the standard deviation of pixel intensities within a fixed-size neighborhood window. This measure highlights texture variation in the image. A predefined contrast threshold of $T_{LCM} = 10$ is used in this study. Regions with contrast values below this threshold are classified as low-contrast areas, which are commonly associated with cloud presence. A binary mask is generated to mark these regions accordingly.

4) Mask Combination: Inspired by the multi-feature enhancement strategy proposed in Salazar-Colores et al. [20], we combine the binary masks generated from the dark channel prior and local contrast measurement. The two binary masks M_{DCP} and M_{LCM} are combined using logical AND to produce a final haze/cloud mask:

$$M_{\text{cloud}}(x, y) = M_{DCP}(x, y) \cdot M_{LCM}(x, y) \tag{3}$$

5) Cloud Coverage Estimation and Classification: The percentage of clouded pixels is computed as:

$$\text{Cloud Coverage (\%)} = \frac{\sum_{x,y} M_{\text{cloud}}(x, y)(PixelCounts)}{H \cdot W(HazeMaps)} \times 100 \tag{4}$$

where H and W are the height and width of the image. A cloud presence threshold of 97% is applied. If the estimated cloud coverage exceeds this value, the image is classified as *Clouded*; otherwise, it is labeled as *Non-Clouded*.

6) Classification Output: Each image is saved to its respective folder (`Clouded` or `Non-Clouded`) based on the decision rule:

$$\text{Class} = \begin{cases} \text{Clouded}, & \text{if Cloud Coverage} \geq 97\% \\ \text{Non-Clouded}, & \text{otherwise} \end{cases}$$

III. Experimental Results

To assess the performance of the proposed CPD framework, we conducted experiments on three datasets containing images with cloud or haze-related effects: the Dense Haze dataset introduced by Ancuti et al. [16], the RICE-1 satellite dataset from Lin et al. [17], and our own UAV-based dataset. Each dataset includes images labeled as having cloud presence, allowing for dataset-level evaluation.

Figure 2 presents a comparative analysis between the actual number of clouded images and the number detected by our method. The CPD framework achieved 100% detection accuracy on both the Dense Haze and UAV-based datasets, and 99.8% accuracy on the RICE-1 dataset, successfully identifying 499 out of 500 clouded satellite images. These findings indicate that the CPD framework may generalize well to diverse imaging conditions and datasets.

To further evaluate the runtime efficiency of the proposed method, we compared the performance of CPU-based and GPU-based implementations across all datasets. Table I presents the total processing time measured for each dataset using a single-threaded CPU instance versus a single GPU instance. The GPU-accelerated version consistently outperformed the CPU implementation, particularly for larger datasets, achieving over 2× speedup in the case of the RICE-1 dataset. These results demonstrate the scalability and runtime advantage of the CPD framework when deployed on GPU-capable hardware.

Table II provides a technical breakdown of the functional differences between the original CPU-based and the optimized GPU-enhanced implementations of the CPD framework. The CPU implementation utilizes sequential operations such as `imerode` for dark channel estimation and `colfilt` for local contrast computation, both of which are not optimized for parallel execution.

In contrast, the GPU-enhanced implementation replaces these operations with parallelizable alternatives that are compatible with `gpuArray`, including convolution-based approximations for both minimum filtering and local standard deviation via `imfilter`. Logical operations and cloud coverage calculations are also performed on the GPU, with only minimal data transfer to the CPU for final output saving.

All experiments were conducted on a laptop equipped with an Intel(R) Core(TM) i7-8750H CPU @ 2.20 GHz, 16 GB of RAM, and an NVIDIA GeForce GTX 1050 Ti GPU (4 GB VRAM), running a 64-bit Windows operating system. This setup reflects a mid-range, consumer-grade hardware configuration, demonstrating that the proposed GPU optimization achieves significant runtime improvements without relying on high-end server-class hardware.

The implementation strategy effectively reduces CPU-GPU memory transfer overhead, leverages the GPU's parallel processing capabilities, and achieves performance gains of up to 5× while maintaining the original classification logic and accuracy.

IV. Conclusion and Future Work

This paper introduced CPD, a lightweight and training-free framework for detecting cloud presence in UAV imagery using dark channel prior and local contrast analysis. The method operates entirely on image-level statistics and binary masks, enabling fast classification without requiring ground truth segmentation maps. We further demonstrated the effectiveness of a GPU-enhanced implementation that replaces CPU-bound operations with convolution-based approximations for improved computational efficiency.

Experimental evaluation on three diverse datasets confirmed that CPD achieves near-perfect accuracy in identifying clouded images while significantly reducing processing time, particularly in GPU-supported environments. The use of publicly available haze and satellite datasets, in addition to a custom UAV dataset, also validated the method's generalizability across platforms.

In future work, the framework may be extended to perform pixel-level cloud segmentation using rule-based heuristics or lightweight learning models. CPD can also be integrated as a preprocessing module in UAV image stitching or object detection pipelines to improve the performance of subsequent visual tasks.

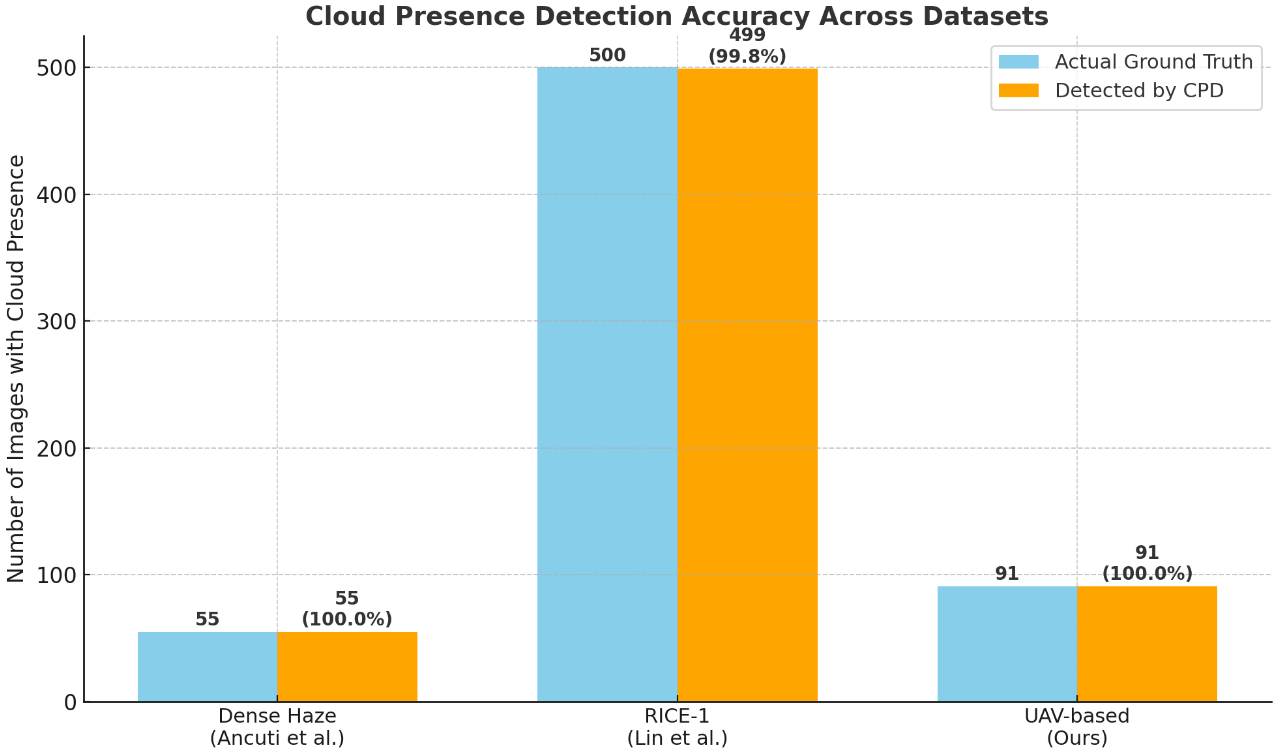

Fig. 2. Comparison of actual and CPD-detected clouded image counts across three datasets. The proposed method achieves near-perfect classification accuracy results.

TABLE I
RUNTIME COMPARISON BETWEEN CPU AND GPU IMPLEMENTATIONS

Dataset	CPU-Based (Single Instance)	GPU-Based (Single Instance)
Ancuti et al. (2019), original image size before downscaling: 1600×1200, 55 images	28.90 seconds	18.77 seconds
Lin et al. (2019), original image size before downscaling: 512×512, 500 images	183.22 seconds	83.61 seconds
Ours (UAV-based Dataset), original image size before downscaling: 512×512, 91 images	20.52 seconds	4.08 seconds

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REFERENCES

[1] E. Salami, C. Barrado, and E. Pastor, “Uav flight experiments applied to the remote sensing of vegetated areas,” *Remote Sensing*, vol. 6, no. 11, pp. 11 051–11 081, 2014.

[2] S. Mohajerani, T. A. Krammer, and P. Saeedi, “Cloud detection algorithm for remote sensing images using fully convolutional neural networks,” *arXiv preprint arXiv:1810.05782*, 2018.

[3] L. Zhang, J. Sun, X. Yang, R. Jiang, and Q. Ye, “Improving deep learning-based cloud detection for satellite images with attention mechanism,” *IEEE Geoscience and Remote Sensing Letters*, vol. 19, pp. 1–5, 2021.

[4] L. Sun, X. Zhou, J. Wei, Q. Wang, X. Liu, M. Shu, T. Chen, Y. Chi, and W. Zhang, “A new cloud detection method supported by globeland30 data set,” *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 11, no. 10, pp. 3628–3645, 2018.

[5] D. Singh and V. Kumar, “Single image haze removal using integrated dark and bright channel prior,” *Modern Physics Letters B*, vol. 32, no. 04, p. 1850051, 2018.

[6] A. Kumthekar and G. R. Reddy, “Redesigning u-net with dense connection and attention module for satellite based cloud detection,” *IAES International Journal of Artificial Intelligence*, vol. 11, no. 2, p. 699, 2022.

[7] Z. Wang, L. Zhao, J. Meng, Y. Han, X. Li, R. Jiang, J. Chen, and H. Li, “Deep learning-based cloud detection for optical remote sensing images: A survey,” *Remote Sensing*, vol. 16, no. 23, p. 4583, 2024.

[8] N. Wright, J. M. Duncan, J. N. Callow, S. E. Thompson, and R. J. George, “Clouds2mask: a novel deep learning approach for improved cloud and cloud shadow masking in sentinel-2 imagery,” *Remote Sensing of Environment*, vol. 306, p. 114122, 2024.

[9] L. P. Osco, J. M. Junior, A. P. M. Ramos, L. A. de Castro Jorge, S. N. Fatholahi, J. de Andrade Silva, E. T. Matsubara, H. Pistori, W. N. Gonçalves, and J. Li, “A review on deep learning in uav remote sensing,” *International Journal of Applied Earth Observation and Geoinformation*, vol. 102, p. 102456, 2021.

[10] Y. Li, W. Chen, Y. Zhang, C. Tao, R. Xiao, and Y. Tan, “Accurate cloud detection in high-resolution remote sensing imagery by weakly supervised deep learning,” *Remote Sensing of Environment*, vol. 250, p. 112045, 2020.

[11] Y. Iwamoto, N. Hashimoto, and Y.-W. Chen, “Fast dark channel prior based haze removal from a single image,” in *2018 14th international conference on natural computation, fuzzy systems and knowledge discovery (ICNC-FSKD)*. IEEE, 2018, pp. 458–461.

[12] A. Levin, Y. Weiss, F. Durand, and W. T. Freeman, “Understanding and evaluating blind deconvolution algorithms,” in *2009 IEEE conference on computer vision and pattern recognition*. IEEE,

TABLE II
COMPARISON OF CPU-BASED AND GPU-ENHANCED CPD ALGORITHMS

Feature	**CPU-Based Implementation**	**GPU-Enhanced Implementation**
Preprocessing	Per-image grayscale and Gaussian blur on CPU	Per-image grayscale and GPU-based Gaussian blur
Dark Channel Estimation	Erosion via `imerode` (CPU-bound)	Min-filter via `imfilter` (GPU-compatible)
Local Contrast Analysis	Local std. dev. using `colfilt` (CPU)	Local std. dev. via mean + variance using `imfilter` on GPU
Mask Combination	Logical AND on CPU	Logical AND on GPU
Cloud Coverage Calculation	Entirely CPU	Final sum via `gather` after GPU processing
I/O Operations	Read and write using `imread/imwrite` (CPU)	Read/write still on CPU, minimal transfer from GPU
Performance Gain	Baseline for all comparisons	Up to 5× faster (dataset-dependent)

2009, pp. 1964–1971.
[13] M. Shi, F. Xie, Y. Zi, and J. Yin, "Cloud detection of remote sensing images by deep learning," in *2016 IEEE International Geoscience and Remote Sensing Symposium (IGARSS)*. IEEE, 2016, pp. 701–704.
[14] J. Zhang, Q. Zhou, X. Shen, and Y. Li, "Cloud detection in high-resolution remote sensing images using multi-features of ground objects," *Journal of Geovisualization and Spatial Analysis*, vol. 3, no. 2, p. 14, 2019.
[15] R. Richter and D. Schläpfer, "Atmospheric/topographic correction for satellite imagery (atcor-2/3 user guide, version 8.3. 1, february 2014)," *ReSe Applications Schläpfer, Langeggweg*, vol. 3, 2013.
[16] C. O. Ancuti, C. Ancuti, M. Sbert, and R. Timofte, "Dense-haze: A benchmark for image dehazing with dense-haze and haze-free images," in *2019 IEEE international conference on image processing (ICIP)*. IEEE, 2019, pp. 1014–1018.
[17] D. Lin, G. Xu, X. Wang, Y. Wang, X. Sun, and K. Fu, "A remote sensing image dataset for cloud removal," *arXiv preprint arXiv:1901.00600*, 2019.
[18] R. C. Gonzalez and R. E. Woods, *Digital Image Processing*, 4th ed. Pearson, 2018.
[19] K. He, J. Sun, and X. Tang, "Single image haze removal using dark channel prior," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 33, no. 12, pp. 2341–2353, 2011.
[20] S. Salazar-Colores, J.-M. Ramos-Arreguín, J.-C. Pedraza-Ortega, and J. Rodríguez-Reséndiz, "Efficient single image dehazing by modifying the dark channel prior," *EURASIP Journal on Image and Video Processing*, vol. 2019, no. 1, pp. 1–14, 2019.