Cloud and Shadow Identification from Aerial Images

AnupaVijai, S Padmavathi, D Venkataraman

Abstract: Clouds and shadows pose severe problems in discernment of the scene and identification of objects in aerial photography. The changes in illumination,ensued by the presence of cloud and the shadow,aresome of the reasons that lead to ambiguity, while carrying out image segmentation leading to detection of targeted objects. Conventional methods are efficient in detecting thick clouds in contrastive background, but perform poorly in the perception of thin clouds, multiple clouds and their shadows. Reference images for the input are needed in most cases, and separate algorithms are pursued, to identify clouds and shadows in an image, which might not be feasible in all scenarios. Techniques used in this paperto detect cloud and shadows,obviating the need for reference images, are image enhancement, analysis of color histogram of input images, adoption of automatic thresholding and mathematical morphology on the input image. The proposed algorithm,was found to be fast,and experimented on various images that contained multiple white cloud clusters of different shapes, thickness and their shadows. The algorithmwas validated with an accuracy of 94.6% and 87.2% for identification of clouds and shadows, respectively.

Index Terms: aerial image, automatic threshold, cloud detection, color histogram, morphological operations, shadow detection

I. INTRODUCTION

Aerial surveillanceof objects, and assessment of their pertinent features, help in the detection and automated annotation of observed images. Quick recognition and assessment ofsituational changesare other areas of keen interest. Resourceful applications of aerial photographyinclude monitoring the usage of land, estimation of natural resources, identification of land encroachments, prediction of disasters and disaster management. In all these engagements, notable features of the objects present in their captured images, could be exploited for follow-up actions and appropriate decisions.

During analysis of aerial images,fewinescapable challenges crop up, when images of targeted objects are impinged with clouds and murky shadows. Scrutiny of aerial images are impeded by the daunting presence of overcast sky, with multiple clusters of clouds of various sizes, shapes, colors, thickness, impinging shadows of other objects,and poor illumination.

These environmental backgrounds render thetasks of image segmentation and recognition of objectseven more intricate exercises. Acquisition of cloud-free and shadow-free transparent images is crucial in the domain of aerial surveillance or aerial photography, when interrupted by weather factors, climate, time of day, and distance,from the object(s) of interest.

Numerous techniques were developed for eliminating effects of clouds and the cast shadows [1]. Generally, clouds appear as white clusters, of varying opacity, at different altitudes,while shadows would be exposed regions, darker than normal. Besides the targeted object, there could be more than one object of the same shape, size, and color in the image. Presence of multiple objects,with contrasting values ofpixel intensity in an image,pose inevitable impairments in the distinct identification of the clouds andthe shadows. It is imperative to find out a suitable threshold value to detect the object of interest. Towards this end, this paper presents an appraisal of remedial techniques such as image preprocessing, color histogram, thresholding and morphological operations.

This paper is organized as follows: similar works in the same areaare discussed in section II, followed by the methodology adopted in this paper, in section III. Section IV reviews results, followed by concluding remarks, in section V.

II. RELATED WORKS

Cloud detection methods are categorized based on the technique applied to find the presence of objects. Majority of these detective methods are based on the thresholding, statistical, radiances and reflectance, and neural network (NN) approaches. The most widely used method, is based on the threshold technique due to the ease and speed of implementation, long-standing familiarity and, accumulated experience of the technique.

Guo et al. [2] suggest detection of clouds based on Convolutional Neural Network (CNN) model. With the help of training samples, they extracted the model's feature followed by application of a clustering method, to create super pixels from images. Their method is incapable of detecting thin clouds, that are transparent, at the edge of a thick cloud. Reguiegueet al. [3] worked with the artificialintelligence approach to find cloudy areas in an image. They attempted both the fuzzy

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logic and neural network approaches, but preferred the lattermethod. Their algorithm is tedious and inefficient in the recognition of different types of clouds, and in particular, detection of clouds during night. Chen et al. [4] performed a CNN-based study forclassifications of clouds asthick cloud, thin cloud and, shadows. But, this is also aprolonged process. Sun et al. [5] broached the detection of clouds based on the reflectance property. They used a multi-spectral pixel dataset, as the ground truth, and then found the spectral differences between clear and cloudy images. They experimented with wavelengths in the range of the visible spectrum to short wave infra-red (SWIR).They were able to achieve 85% precision for various datasets. Nevertheless, this method is applicable only if sensor data is available, along with a reference image. Chao-Hung Lin et al. [6] pursueda method based on invariant pixel determination and radiometric normalization, by leaning on the weighted Principal Component Analysis(PCA) algorithm. All these techniques are constrained by the requirement of comparison with a reference image.

Chang et al. [7] focused on incremental learning basedscheme for the identification of cloud in images. They extracted spectral information from bright regions of images,which were used to train a neural network, to detect the presence of clouds. Shen et al. [8] succeeded in the identification of thin clouds, followed by their removal,to achieve cloud-free images, with high color fidelity. This was accomplished by extraction of spectral information from the non-clouded regions in the image. Cheng et al. [9] tried out pixel replacement technique, which was inefficient in handling changes in multi-temporal images. Mill et al. [10] developed an approachthat utilized a base image and an auxiliary image. With the help of the latter, the algorithm would map the cloudy pixels into spectrally similar pixels. They used this approach in the Tsunami early warning system. Hughes et al. [11] proposed a NN-based approach for pinpointing clouds and shadows. They achieved an accuracy of 98.8%, which outperformed all other methods. However, the parameter selection, training and testing are tedious processes thatwarrantextensive training time.

Abraham et al. [12] presented a method to eliminate cloud and cloud shadows, using the threshold scheme. The selection of threshold value was based on the local luminance, in an

image.Additional processing was required to detect and remove denser clouds. Lin et al. [13] came upwith atechnique based on information cloning, to remove clouds from multi-temporal images. They used the thresholding approach to locate clouds and cloudy shadows. But the method is inefficient in handling thin clouds. Shahtahmassebiet al. [14] carried out a thorough review of detection and then the removal of shadowswith histogram matching, multi-source data fusion, and multi-temporal imagery.They probed shadow detection, prior to the application of sensor-specific methods for the de-shadowing process. Al-Najwadiet al. [15] done a survey of overcast shadow identification methods. Their analysis was based on the object/environment dependencies and the pixel/transform domains of the algorithms. For accurate detection,they classified shadowsinto grey or color images, as chromaticity information maybe helpful in shadow detection.Factors such as illumination, geometric and texture information of objects were considered in the detection of the overcast shadows. Makarauet al. [16] worked on the automatic detection of shadows in images from urban scenes. Their concept was based on the black body description model. They probed the properties of sources of illumination, the properties of illumination in shadowed areas, and the automated setting of parametric values. Sirmaceket al. [17] offered an approach to detect shadows from an image. They used the concepts ofthe color invariant feature and the grayscale histogram, to deduce shadows in the image. Simpson et al. [18] discussed a general solution to detect cloud shadows, under arbitrary conditions, based on parameters such as cloud height and the angle subtended between the satellite and sun. But,their scheme is error prone;as the output is significantly impaired byconditions of poor illumination, if the calculation of parameters mentioned above is inaccurate. Wang et al. [19] propounded a scheme in which images were first segmented into homogeneous regions. Then,a region of interestwas chosen based on the pixel intensity of the regions. Bright regions were selected as clouds and dark regions were selected as shadows.This method is unworkable, if the mage contains other objects of high or low intensity values.

III. METHODOLOGY

The steps involved in identifying cloud and shadow are given in Fig.1. The process starts with the pre-processing of an input RGB image. Pre-processing involves enhancement techniques that are different for the identification of shadows and cloud.

Image enhancement techniques are meant to distinguish the boundary of cloud and shadow. To identify acloud, the RGB image is converted to HSV, followed by capturing a histogram of the image. This is followed byapplication of contrast adjustment procedures on the input image. The intent ofcontrast adjustment is toimprove the overall lightness or darkness in an image, which map the pixels of the image, with high intensity value, to 255, and pixels with lowest intensity values to 0. Contrast adjustments are performed on the image, because it would enhance outlines of the cloud. Image sharpening was done as a preprocessing method to identify cloud shadows. Here unsharp masking [20] was used to sharpen the image that involves an image subtraction technique.

$$Mask(s,q) = Im(s,q) - Im'(s,q) \tag{1}$$

where $Mask(s,q)$ is the sharpened image, $Im(s,q)$ is the original image and $Im'(s,q)$ is the blurred image. In order to get the blurred image, perform any smoothing technique. Here Gaussian blurring [21] was performed on the image. This is nothing the convolution of image with Gaussian kernel that takes the form,

$$GK(a,c) = \frac{1}{2\pi\sigma^2} e^{-\frac{a^2+c^2}{2\sigma^2}} \tag{2}$$

where $GK(a,c)$ *is* the Gaussian kernel for the pixel (a,c). The symbol for standard deviation is represented asσ. Next, the unsharp maskingis done to the original image. This process enhances the edges of shadows. This would also help to improve the image by increasing contrast.

The next step is filtering on the image components, separately, to remove noise from the image, while preserving its edges. Next, median filtering [22] is performed, where the value of the pixel is substituted with the medianof the neighboring pixel intensity values. The detection could be improved further, if the color histograms of the input images were analyzed separately. If the valuesof pixel intensity at the same pixel position planes are very high, then it could be considered as cloud pixel, and if the value is very small that could be the shadow pixels. Then a linear mapping is performed so that the pixel values would be in the range (0 to 1).

The mentioned threshold value can be cross-verified with the threshold value obtained from Otsu’s method. Simplicity of the proposed technique should be conspicuous by the minimal needs for human intervention, processing time, and resource requirements. Another noteworthy point is the proposed technique’scapability to identify multiple clouds of different sizes, shapes as well as thin clouds. Review of the test results reveal that the threshold value for detection vary from 0.32 to 0.009, and above 0.54 to 0.8 for clouds. On performing thepreprocessing steps, the points above the specified threshold range were selected,from the image. A mask was created from the image,based on the threshold value. Next, an area opening, within a range of 50-150,was performed, assuming the size of the image as 300 x 300.

The unique approach,outlined in Fig.1, was assessed with 30 images. Diverse types of the captured aerial images are presented in Fig. 2(a)through Fig. 6(a). The Fig. 2(a) contains a single cluster of cloud and shadow, Fig. 3(a) contains four clusters of clouds and many shadows, Fig. 4(a) contains two

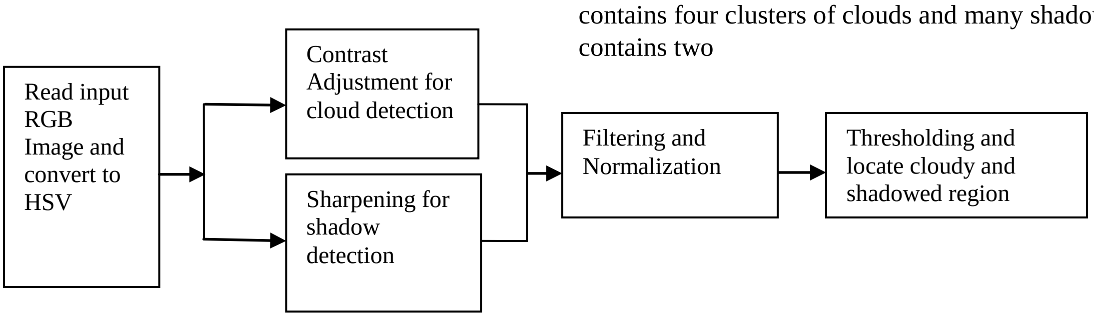

Fig. 1. Approach to identify clouds and shadows

Following this, Otsu’s automatic thresholding [23] was carried out, to segment the cloud and its shadow. The **thresholded** image would act as a mask. Since the threshold value is different, the mask would be different for different images. Subsequent to this step, a sequence of morphological techniques [24] were applied on the image. Area opening is a compound operation where erosion is performed on the image followed by **dilation**. This would help in smoothing the target shape and the brightened area. The limit that was selected for area opening was based on the estimated size of the connected component regions. Area opening was performed first, followed by dilation operation. The resultant image had to undergo dilation operation. Dilation would help fill in the small gaps, within the region, and derive a fair rounded boundary. The structural element that was chosen for this step would be either disk or circle, the shape that is closer to the target object’s shape.The region of interest was irregularly shaped cloud and its shadow; hence, disk or circle would be the ideal choice. Finally,image subtraction was performed to level the uneven image and detect the shadow or cloud

IV. RESULT AND DISCUSSION

The uniqueness of the proffered approach is its simplicity and the fact that the combination of histogram analysis and morphological operations were used to obtain the intended result. The HSV histogram affords an estimate of the threshold value and the number of white and dark pixels.

clusters of clouds of almost similar size and shape and its shadows, Fig. 5(a) has multiple cloud clusters of various shapes
and sizes and its shadows, Fig. 6(a) has a single cluster with thin clouds towards its edges.

Execution of the suggested method produced clear outputs for identification of clouds and shadows. Few discrepancies were observedin terms of misclassification of darker objects as shadows (refer Fig. 4(c) and Fig. 5(c)). The accuracy of identification was found to determine the efficiency of the method, by considering the true positives and true negatives.The accuracy for cloud detection, including thick and thin cloud,was 94.6 %, and 87.2 %for detection of shadow, including thick and thin shadow.

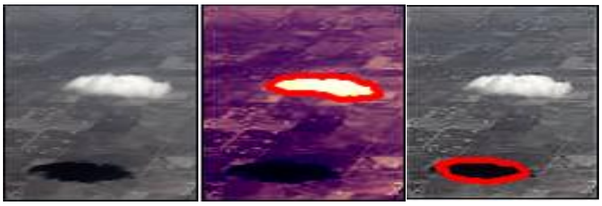

Fig 2(a). Source ImageFig 2(b). Cloud region Fig 2(c). Shadow region

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Fig 3(a). Source ImageFig 3(b). Cloud region Fig 3(c). Shadow region

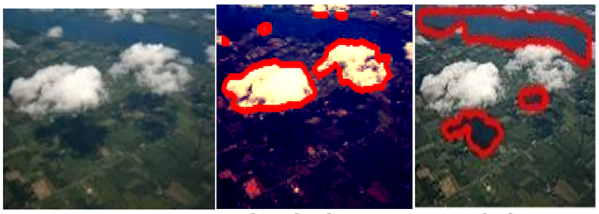
Fig 4(a). Source ImageFig 4(b). Cloud regionFig 4(c). Shadow region

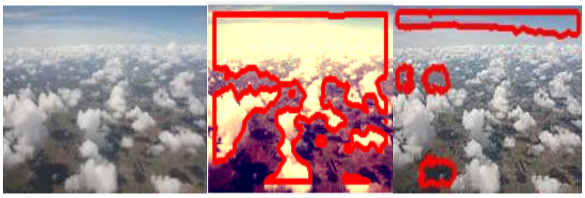
Fig 5(a). Source ImageFig 5(b). Cloud region Fig 5(c). Shadow region

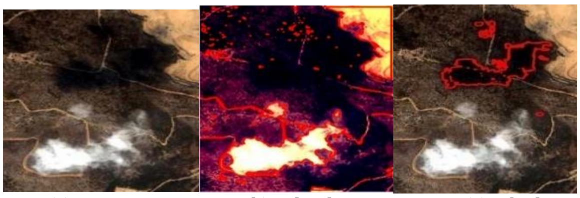
Fig 6(a). Source ImageFig 6(b). Cloud region Fig 6(c). Shadow region

The performance of the method is analyzed for various cases and is summarized below.

Table I

Categories	**Accuracy**
Thick Cloud	98.2%
Thin Cloud	91.6%
Thick Shadow	95.1%
Thin Shadow	83.7%

V. CONCLUSION

A simple method for identifying shadow and cloud was discussed in the paper where the color histogram techniques together with automatic thresholding is used to detect the threshold value to find the presence of cloud and shadow in the image. After finding the threshold value, various morphological operations had applied on the image map to identify the location of cloud and shadow in the image.The assessment of the proposed approach, hasvalidated detection of thick and thin clouds, multiple and scattered clouds as well as darker cloud shadows present in aerial images. However, darker objects being misidentified as shadows, and identification of the lighter shadows, in an image, are areas thatwarrant refinements to the proposed method. These deficiencies could very well be improved by incorporation ofmachine learning approaches, which is conceived as topics for additional research.

REFERENCES

1. Krishnan, Aiswarya, Poojitha Jayadevan, and J. VinithaPanicker. "Shadow removal from single image using color invariant method." In *Communication and Signal Processing (ICCSP), 2017 International Conference on*, pp. 0583-0587. IEEE, 2017.
2. Guo, Zhengsheng, Canhai Li, Zhimin Wang, Expo Kwok, and Xu Wei. "A cloud boundary detection scheme combined with aslic and CNN using ZY-3, GF-1/2 satellite imagery." *International Archives of the Photogrammetry, Remote Sensing & Spatial Information Sciences* 42, no. 3 (2018).
3. Reguiegue, Mourad, and Fatima Chouireb. "Automatic day time cloud detection over land and sea from MSG SEVIRI images using three features and two artificial intelligence approaches." *Signal, Image and Video Processing* 12, no. 1 (2018): 189-196.
4. Chen, Yang, Rongshuang Fan, Muhammad Bilal, Xiucheng Yang, Jingxue Wang, and Wei Li. "Multilevel Cloud Detection for High-Resolution Remote Sensing Imagery Using Multiple Convolutional Neural Networks." *ISPRS International Journal of Geo-Information* 7, no. 5 (2018).
5. Sun, Lin, Xueting Mi, Jing Wei, Jian Wang, Xinpeng Tian, Huiyong Yu, and Ping Gan. "A cloud detection algorithm-generating method for remote sensing data at visible to short-wave infrared wavelengths." *ISPRS Journal of Photogrammetry and Remote Sensing* 124 (2017): 70-88.
6. Lin, Chao-Hung, Bo-Yi Lin, Kuan-Yi Lee, and Yi-Chen Chen. "Radiometric normalization and cloud detection of optical satellite images using invariant pixels." *ISPRS Journal of Photogrammetry and Remote Sensing* 106 (2015): 107-117.
7. Chang, Carolina, and Fernando Vaca. "Automatic Detection of Clouds from Aerial Photographs of Snowy Volcanoes." In *Mexican Conference on Pattern Recognition*, pp. 145-155. Springer, Cham, 2015.
8. Shen, Huanfeng, Huifang Li, Yan Qian, Liangpei Zhang, and Qiangqiang Yuan. "An effective thin cloud removal procedure for visible remote sensing images." *ISPRS Journal of Photogrammetry and Remote Sensing* 96 (2014): 224-235.
9. Cheng, Qing, Huanfeng Shen, Liangpei Zhang, Qiangqiang Yuan, and Chao Zeng. "Cloud removal for remotely sensed images by similar pixel replacement guided with a spatio-temporal MRF model." *ISPRS Journal of Photogrammetry and Remote Sensing* 92 (2014): 54-68.
10. Mill, Salamahn, DafeUkaivbe, and Weiwei Zhu. "Clouds and Cloud Shadows Removal from Infrared Satellite Images in Remote Sensing System." In *ASEE 2014 Zone Conference, University of Bridgeport, Bridgeport, CT, USA*. 2014.
11. Hughes, M. Joseph, and Daniel J. Hayes. "Automated detection of cloud and cloud shadow in single-date Landsat imagery using neural networks and spatial post-processing." *Remote Sensing* 6, no. 6 (2014): 4907- 4926.
12. Abraham, Lizy, and M. Sasikumar. "Cloud extraction and removal in aerial and satellite images." In *Intelligent Informatics*, pp. 341-347. Springer, Berlin, Heidelberg, 2013.
13. Lin, Chao-Hung, Po-Hung Tsai, Kang-Hua Lai, and Jyun-Yuan Chen. "Cloud removal from multi-temporal satellite images using information cloning." *IEEE transactions on geoscience and remote sensing* 51, no. 1 (2013): 232-241.
14. Shahtahmassebi, AmirReza, Ning Yang, Ke Wang, Nathan Moore, and Zhangquan Shen. "Review of shadow detection and de-shadowing methods in remote sensing." *Chinese Geographical Science* 23, no. 4 (2013): 403-420.
15. Al-Najdawi, Nijad, Helmut E. Bez, Jyoti Singhai, and Eran A. Edirisinghe. "A survey of cast shadow detection algorithms." *Pattern Recognition Letters* 33, no. 6 (2012): 752-764.
16. Makarau, Aliaksei, Rudolf Richter, Rupert Muller, and Peter Reinartz. "Adaptive shadow detection using a blackbody radiator model." *IEEE Transactions on Geoscience and Remote Sensing* 49, no. 6 (2011): 2049-2059.
17. Sirmacek, Beril, and CemUnsalan. "Damaged building detection in aerial images using shadow information." In *Recent Advances in Space Technologies, 2009. RAST'09. 4th International Conference on*, pp. 249-252. IEEE, 2009.
18. Simpson, James J., ZhonghaiJin, and James R. Stitt. "Cloud shadow detection under arbitrary viewing and illumination conditions." *IEEE*

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Transactions on Geoscience and Remote Sensing 38, no. 2 (2000): 972-976.
19. Wang, Chengye, Liuqing Huang, and Azriel Rosenfeld. "Detecting clouds and cloud shadows on aerial photographs." *Pattern Recognition Letters* 12, no. 1 (1991): 55-64.
20. Polesel, Andrea, Giovanni Ramponi, and V. John Mathews. "Image enhancement via adaptive unsharp masking." *IEEE transactions on image processing* 9, no. 3 (2000): 505-510.
21. Deng, Guang, and L. W. Cahill. "An adaptive Gaussian filter for noise reduction and edge detection." In *Nuclear Science Symposium and Medical Imaging Conference, 1993, 1993 IEEE Conference Record,* pp. 1615-1619. IEEE, 1993.
22. Huang, T., G. J. T. G. Y. Yang, and G. Tang. "A fast two-dimensional median filtering algorithm." *IEEE Transactions on Acoustics, Speech, and Signal Processing* 27, no. 1 (1979): 13-18.
23. Otsu, Nobuyuki. "A threshold selection method from gray-level histograms." *IEEE transactions on systems, man, and cybernetics* 9, no. 1 (1979): 62-66.
24. Gupta, Deepa, and Leema Nair. "Improving OCR by effective pre-processing and segmentation for Devanagari script: A quantified study." *Journal of Theoretical & Applied Information Technology* 52, no. 2 (2013).

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