Pixel Saturation Applied for Cloud Cover Estimation in Ground based All Sky Images

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Abstract

Cloud plays a vital role in many domains such as weather forecasting, power forecasting, agriculture, and so on. The fraction/ amount/ percentage of cloud cover over a region is a weather parameter to be considered for forecasting applications. Under suitable weather conditions the cloud cover plays a vital role is precipitation nowcasting. The relation between the cloud cover and precipitation can be directly related under suitable weather conditions. Here, we propose to estimate fraction/amount/percentage of cloud cover based on the ground based images. Pixel saturation is used for cloud cover estimation. Singapore High-dynamic-range Whole sky IMaging SEGmentation Database (SHWIMSEG) dataset images were used for testing the system proposed. Cloud cover in the range of no cloud cover (0%) to full cloud cover (100%) was tested. Once the test was carried out on SHWIMSEG dataset, the all sky images acquired from camera module (PYRA300C) are passed through the system for cloud cover percentage estimation. An accuracy of 92.49% was achieved on the images.

Keywords: Pixel Saturation, Cloud Cover, Ground Based Images, Forecasting.

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INTRODUCTION

Cloud cover is a key parameter for predicting and analysing rainfall, humidity, temperature, and so on. Clouds also play an important part in a variety of operations, which includes generation of solar power, air traffic control, precipitation nowcasting and so on. The domain that can utilize the cloud cover estimation is weather prediction centres, agricultural sector, geographical sectors, etc. Ground based sky images are the key to detect the cloud cover fraction/amount/percentage; Clouds presence is defined based on velocity of wind that moves the cloud in particular direction, temperature, atmospheric pressure and so on. Approaches for detecting the clouds presence in the sky and determining the percentage of sky area covered by clouds based on colour features of the clouds is being studied in [1].

The sky images can be captured using two methods: Ground based images and Satellite based images. In the present work we use the dataset which consists of ground based images. These ground based images are from “SHWIMSEG dataset” [2]. This dataset contains 52 set of high dynamic range (HDR) image captures along with the corresponding binary segmentation maps. Later we used the images from acquired by our camera and estimated the cloud cover percentage.

The unpredictable changes in position, form and density of clouds results in the difficult computational methods for cloud cover estimation. Determining the edges of cloud and distinguishing between cloudy and clear sky accurately is a challenging task. Here we use fuzzy regression and pixel saturation method to identify the cloud cover percentage. The percentage of cloud cover is important, along with some other concepts like speed of the wind, humidity, direction of the wind, temperature and many more. Our main focus is towards estimation of cloud cover percentage; which can be later used as a one of the weather for estimation nowcasting the precipitation, forecasting power generation due to solar energy. Although the use of Deep Learning (DL) methods for cloud segmentation using ground-based images is largely unexplored, Machine Learning (ML) techniques have been used for cloud pixel segmentation. In the process of cloud cover estimation the techniques used are image processing techniques along with machine learning approach.

Salah Moughyt et al. [1] aimed to demonstrate the effectiveness of two segmentation methods Otsu and multi objective optimization and calculated the optimal pressure. Seongha Park et al. [3] proposed to demonstrate that sky-facing cameras combined with ML can be utilized for prediction of solar energy output. They used Deep Neural Network (DNN) techniques and Waggle cloud data set. They faced challenges in developing methods to distinguish cloud thickness. Daniele Pepe et al. [4] presented a model for estimating direct forecasting of PV power generation using cloud cover data. Mechanism used were cloud cover index and cloud cover factor, clears sky irradiance model. Debasish Pattanaik et al. [5] described a comparative analysis of different solar PV forecasting using cloud cover estimation. Ryo Onishi et al. [6] proposed a Deep Convolution Neural Network (DCNN) for the precise prediction of cloud cover with the help of pictures. V. Kostylev et al. [7] presented a set of standards for evaluating solar power forecast performance. They used naïve models. They offered good techniques and considerable field practise, providing a solid foundation for accurate inter-agency prediction performance comparisons utilising cloud cover. Md. Nazumul Islam Sarkar [8] analyzed the relationship between fraction of sky covered by clouds and solar radiation estimation for Bangladesh. R. B. Gujanatti et al. [9] presented a survey on rainfall forecasting using machine learning approaches. In the survey for rainfall forecasting cloud cover was also considered as an important weather attribute. They used solar radiation model and deep learning model. K. Mahmud et al. [10] proposed PV Power Generation Forecasting using Machine Learning methods. G Rudrappa and Nataraj Vijapur [11 - 12] proposed use of k-means clustering and content based image retrieval for cloud classification; the result of this classification is suggested that it can be considered as another weather parameter for precipitation nowcasting.They used ANN, CNN, RNN and LSTM. Mikhal Krinitskiy et al. [13] demonstrated the models based on Convolutional Neural Networks (CNN) for cloud cover estimation. They used Total Cloud Cover (TCC) retrieval as ordinal regression. Rial A. Rajagukguk et al. [14] proposed that DL can provide estimation for the cloud cover from sky images and proposed that they will be beneficial for predicting solar irradiance with large variance.

METHODOLOGY FOR CLOUD COVER ESTIMATION

Fig. 1 shows the implementation methodology for estimation of cloud cover percentage. The blocks are explained in brief below.

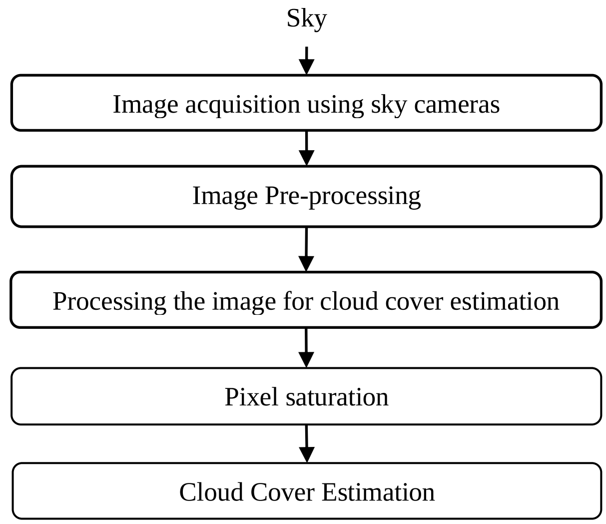


Fig. 1. Methodology for cloud cover percentage estimation

A. Image acquisition

The process of capturing the image from the source using hardware components like cameras, sensors etc. The component which will be used in cloud cover estimation is the high-resolution camera.

B. Image Pre-processing

Whenever the image is captured, it can be corrupted due to noise or the image needs to be enhanced for further image processing steps, hence we need to pre-process the image to eliminate the noise content or enhance the image. If the image is corrupted by salt and pepper noise (It presents itself as black and white pixels) whose Probability Density Function (PDF) is given in equation (1). For reducing either salt or pepper noise, median or morphological filter can be used. Both salt noise and pepper noise cannot be eliminated simultaneously. In order to reduce both, a Contra-harmonic filter can be used.

$$p(z) = \begin{cases} P_s & ,z = 2^k - 1 \\ P_p & ,z = 0 \\ 1 - (P_s + P_p), & z = V \end{cases} \quad (1)$$

C. Image Enhancement

Image Enhancement is process of operating an image, such that the image becomes more suitable for the specific application. Here, the term "specific" refers to the application-based manipulations, which can be reducing or nullifying noise, making images clearer etc.

D. Image Processing

The method that we are proposing for image processing is pixel saturation. Pixel saturation, which occurs when incident light causes one of the camera lenses' colour channels to respond to its maximum values, can result in unwanted artefacts in digital colour photographs.

E. Image Conversion

In the beginning, the sky images will be captured using all sky cameras. CCD cameras are one of such type. In this case, we will be capturing the images from the ground will be in RGB format. Later those captured images will be sent for the conversion from RGB (Red Green Blue) to HSI. The conversion from RGB to HSI will be done using equations (2) – (4) [15].

$$\theta = \cos^{-1}\left\{\frac{\frac{1}{2}[(Red - Green) + (Red - Blue)]}{[(Red - Green)^2 + (Red - Blue)(Green - Blue)]^{\frac{1}{2}}}\right\} \quad (2)$$

$$Hue = \begin{cases} \theta & if\ Blue \le Green \\ 360 - \theta & if\ Blue > Green \end{cases} \quad (3)$$

$$Saturation = 1 - \frac{3}{(Red + Green + Blue)}[min(Red, Green, Blue)] \quad (4)$$

F. Pixel Saturation

Saturation refers to the colour's strength in an image. If the value of saturation is low, the image reaches towards the grey scale images. If the saturation is low, the image is said to be 'muted' or calming impact takes place. If the saturation value increases, the image turns out to be a brighter one.

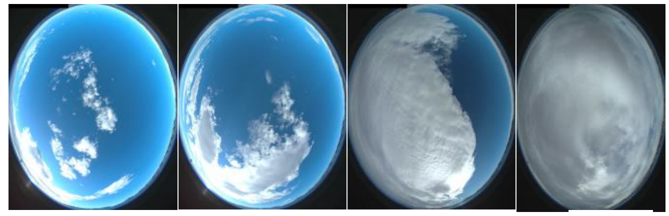
When the camera captures the image, the pixel values will be in BRG. The BRG values are not suitable for direct display of images. Hence, image processing is done using Pixel saturation method. Whenever pixels are saturated, some information is lost. Hence, the Pixel Saturated images should be handled carefully.

G. Cloud Cover Estimation

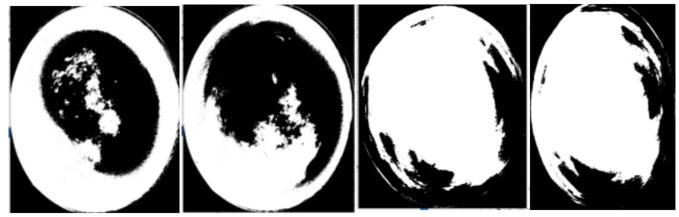
Once the images are converted to HSI and then pixel saturation is estimated. The pixels are saturated into black and white images and then the white pixels are considered as cloud pixels and then the cloud cover is estimated from the total pixels present in the images.

RESULTS AND DISCUSSION

The images are saturated to low values, that is, it was turned to a Gray scaled image. The white portion covered in the saturated image is calculated using the values of pixels. Below images show the conversion of the images. The pixels are saturated into black and white images and then the white pixels are considered as cloud pixels and then the cloud cover is estimated from the total pixels present in the images. Fig. 2(a) to Fig. 2(d) shows the images captured of the sky by ground based camera. Fig. 2(f) to Fig. 2(i) shows the results of pixel saturation applied to the captured images represented in Fig. 2(a) to Fig. 2(e) respectively.



a b c d



e f g h

Fig. 2(a) - 2(d). Shows RGB image of the sky captured from the camera

Fig. 2(e) - 2(h). Shows results of pixel saturation for the images shown in Fig. 2(a) – 2(e) respectively

A. Authors and Affiliations

Fig. 3(a) shows the camera module (PYRA300C) used for capturing the sky images. The camera module contains option for automatic capturing of the sky images or manual capturing of the sky images, which is shown in Fig. 3(b) and Fig. 3(c).

Fig. 3(a) Camera Module used to capture sky images

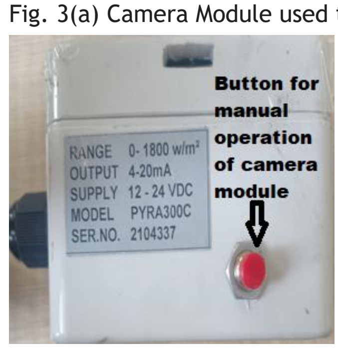


Fig. 3(b). Specifications of the camera module

Fig. 3(c). On/Off and Power supply points of camera module

From Fig. 2(f) to Fig. 2(j) the cloud cover percentage is being estimated based on the black and white pixels present in the image. White pixels correspond to the cloud pixels. The results of cloud cover percentage are given in Table 1 below. The deviation in the cloud cover percentage in few of the images is because of the intensity variations observed in different images while capturing the images. Fig. 3 provides the image if camera module used for acquiring the sky image.

Table I. Results Of Cloud Cover Percentage Estimated For Images In Fig. 2(a) To Fig. 2(d)

Sl. No.	Sample Image	Cloud Cover	Cloud Cover (%)
1.	Fig. 2(a)	0.2574158	25.74158
2.	Fig. 2(b)	0.3744151	37.44151
3.	Fig. 2(c)	0.5078083	50.78083
4.	Fig. 2(d)	0.9999292	99.99292

Conclusion And Future Scope

Using the pixel saturation we were able to estimate the cloud cover percentage. The cloud cover percentage was estimated from no cloud cover (0%) to complete cloud cover (100%). The method was tested on the SHWIMSEG dataset images and an accuracy of 92.49% was achieved with the method proposed. Variations in the percentage cloud cover were observed due to the challenges imposed because of light intensity while acquiring the images. Future scope of the proposed work is to enhance the accuracy of cloud cover percentage estimation and use the cloud cover percentage/amount/fraction as one of the weather attributes for nowcasting precipitation.

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References

S. Moughyt, Z. El Jaouhari, O. El Kadmiri, L. Masmoudi, Z. El Kadmiri, and Y. Zaz, "Cloud coverage estimation using ground based images and segmentation techniques The reddening patterns of Al-ghord Lahmarmegabarchans (Khnifiss National Park, South-West of Morocco) View project stereo matching View project Cloud coverage estimation using ground based images and segmentation techniques," 2015, doi: 10.13140/RG.2.1.4040.9767.

S. Dev, F. M. Savoy, Y. H. Lee, S. Winkler, "High-dynamic-range imaging for cloud segmentation," Atmospheric Measurement Techniques, vol. 11, no. 4, pp. 2041-2049, April 2018.

S. Park, Y. Kim, N. J. Ferrier, S. M. Collis, R. Sankaran, and P. H. Beckman, "Article prediction of solar irradiance and photovoltaic solar energy product based on cloud coverage estimation using machine learning methods," Atmosphere (Basel)., vol. 12, no. 3, pp. 1–2, 2021, doi: 10.3390/atmos12030395.

D. Pepe, G. Bianchini, and A. Vicino, "Model estimation for solar generation forecasting using cloud cover data," Sol. Energy, vol. 157, pp. 1032–1046, 2017, doi: 10.1016/j.solener.2017.08.086.

D. Pattanaik, S. Mishra, G. P. Khuntia, R. Dash, and S. C. Swain, "An innovative learning approach for solar power forecasting using genetic algorithm and artificial neural network," Open Eng., vol. 10, no. 1, pp. 630–641, 2020, doi: 10.1515/eng-2020-0073.

Onishi, R., & Sugiyama, D. (2017). Deep convolutional neural network for cloud coverage estimation from snapshot camera images. Scientific Online Letters on the Atmosphere, 13, 235–239. https://doi.org/10.2151/SOLA.2017-043

V. Kostylev and A. Pavlovski, "Solar power forecasting performance - towards industry standards," 1st Int. Work. Integr. Sol. Power into Power Syst. Aarhus, Denmark, pp. 1–8, 2011.

M. N. I. Sarkar, "Estimation of solar radiation from cloud cover data of Bangladesh," Renewables Wind. Water, Sol., vol. 3, no. 1, 2016, doi: 10.1186/s40807-016-0031-7.

R. B. Gujanatti, N. Vijapur, S. S. Jadhav, P. Manage and A. Konnur, "Machine Learning Approaches Used for Weather Attributes Forecasting," 2021 2nd International Conference for Emerging Technology (INCET), 2021, pp. 1-5,
doi: 10.1109/INCET51464.2021.9456291.

K. Mahmud, S. Azam, A. Karim, S. Zobaed, B. Shanmugam, and D. Mathur, "Machine Learning Based PV Power Generation Forecasting in Alice Springs," IEEE Access, vol. 9, pp. 46117–46128, 2021, doi: 10.1109/ACCESS.2021.3066494.

G. Rudrappa and N. Vijapur, "Cloud Classification using K-Means Clustering and Content based Image Retrieval Technique," 2020 International Conference on Communication and Signal Processing (ICCSP), 2020, pp. 0700-0704.
doi: 10.1109/ICCSP48568.2020.9182211.

Gujanatti Rudrappa, Nataraj Vijapur, Sushant Jadhav, Prabhakar Manage,"Cloud Classification Using Ground Based Images Using CBIR and K-Means Clustering", Biosci. Biotechnol. Res. Commun. Vol. 13, Issue 13,Dec 2020,pp. 95–99.

Krinitskiy M, Aleksandrova M, Verezemskaya P, Gulev S, Sinitsyn A, Kovaleva N, Gavrikov A. On the Generalization Ability of Data-Driven Models in the Problem of Total Cloud Cover Retrieval. Remote Sensing. 2021; 13(2): 326.
https://doi.org/10.3390/rs13020326

R. A. Rajagukguk, R. Kamil, and H. J. Lee, "A deep learning model to forecast solar irradiance using a sky camera," Appl. Sci., vol. 11, no. 11, 2021, doi: 10.3390/app11115049.

R. C. Gonzalez and R. E. Woods, Digital Image Processing, Global Edition, vol. 19, no. 3. 2017.