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Key Points:
- Cloud-base heights are operationally calculated from paired whole-sky imagers
- Cloud-base heights are geo-referenced with explicit four-dimension spatiotemporal coordinates

Supporting Information:
Supporting Information may be found in the online version of this article.

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Estimating Geo-Referenced Cloud-Base Height With Whole-Sky Imagers

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Abstract  Accurate and frequent cloud-base height calculation is beneficial to solar farming and agricultural activities and also indicative for future meteorology conditions. This study used paired whole-sky imagers to estimate cloud-base height with high quality. The study obtained quality assured cloud base feature points with a robust Shi-Tomasi-Scale Invariant Feature Transform algorithm before employing double-eye locating approach, which is fast and easy to implement operationally. The estimated cloud-base heights have high spatial coverages. Evaluated against ceilometer observations, estimated cloud-base heights have a high accuracy level, with $R^2 = 0.92$ and RMSE = 424 m. The method is generally unbiased with NME = 9.2%. The high-quality cloud-base features in this study are quantitatively geo-referenced, which would benefit a lot to meteorological studies such as fusion with satellite observations, evaluation for model simulations and upper-level wind specifications.

Plain Language Summary  The cloud-base height is an important indicator for meteorological conditions especially in the upper-level atmosphere, which is generally hard and expensive to obtain. Thanks to the development of computer vision, we could be able to obtain three-dimensional information from two-dimensional images. The whole sky cameras are often used to capture images of cloud, from which we calculated cloud-base height with high accuracy. Besides, these cloud heights data are geo-referenced. This will enable data fusion with instrument observations, modeling simulations and satellite remote sensing, greatly expanding their appliance in atmospheric studies.

1. Introduction

Clouds are suspended liquid droplets, ice crystals, or aerosol particles in the atmosphere. Clouds are critical in hydrological processes by mitigating solar radiation and energy balance in the atmosphere-terrestrial system (Harrison et al., 1990; Ramanathan et al., 1989; Shupe & Intrieri, 2004). They also influence the chemical and physical processes in the atmosphere to affect weather in short-term and climate in the long-term (Rossow et al., 2005; Stephens, 2005). These properties could be directly observed by professionals and instruments, or calculated through proper algorithms. The professional observers can record cloud types, cloud coverage, and cloud-base heights in coarse temporal and scale observations. The human observations also lack consistency among different observers with varied training background and experiences. Therefore, ground instruments and satellite sensors had been the developed to obtain constant, reliable, consistent and large-scale cloud observations (Sun et al., 2011; Tsilioudis et al., 2013). As for the cloud-base height, satellite observations have limited observation capability as the passive instrument could only observe cloud top height (Hollars et al., 2004). The most accurate method to observe cloud-base height was ceilometer and cloud radar, which has very high observation frequency (Lotteraner & Piringer, 2016; Martucci et al., 2010) and high accuracy. However, the instruments could only observe cloud-base height at the location right above it, which could cause sampling biases to reflect regional pattern. Besides, these instruments are usually quite expensive to deploy in network systems. Recently, the techniques to quantitatively observe cloud properties based on visible-light whole-sky imagers have been developed.

With fish-eye lens, the whole-sky cameras usually have a large vision angle of >170°, which enables us to observe the cloud in the whole sky. Many previous studies have worked to calculate cloud properties from whole sky images, with most of them focusing on cloud coverage estimations (Dev et al., 2017; Horváth et al., 2002; Hulley & Hook, 2008; Pfister et al., 2003) and cloud type classification (Gomez-Chova et al., 2009; Heinle et al., 2010; Li et al., 2016). As for cloud-base height estimation, both narrow vision angle high resolution dual-cameras (Janeiro et al., 2014) and whole-sky imagers (Allmen & Kegelmeyer, 1997;
Nguyen & Kleissl (2014) are used in previous studies. For example, Janeiro et al. (2014) developed a method to estimate cloud-base height with a high-resolution camera with a vision angle of 60°. The camera has an ordinary view lens which has small distortion effect. However, whole-sky images will have significant distortion effect especially on the edge of images. Kassianov et al. (2005) proposed a method to estimate cloud base height with relatively high accuracy. But this method is based on one-layer cloud assumption and need expert interference to determine cloud type and appropriate match curve, which make it complex to be operational (Kassianov et al., 2005). Nguyen and Kleissl (2014) used a window-based pixel match method to estimate cloud-base height with full-sky images. However, their method is computation intensive and estimation error could be very large even though the cloud-base height is small.

In recent years, the full-sky camera has developed its strength for its low price, wireless transmission and high resolution. Besides, new techniques of image computations developed rapidly for feature extract and match. Based on these newly developments, this study developed a method to calculate cloud-base height from paired whole-sky cameras with relatively high accuracy. The method does not need calibration and is fully automated and continuously reports the cloud-base height. The method was implemented in an in situ measurement system to evaluate the performance.

2. Methods

2.1. Full-Sky Imager

We used a full-sky imager with a fish-eye lens. The lens has a field of view angle of 180°. We extracted a rectangle area with across corner-to-corner angle of 170°. The captured image has a resolution of 1,074×1,074 pixels. In the field deployment, the imager observes the sky with a zenith angle of 0°. Meanwhile, the azimuth angle of the image bottom was 180° with the north being defined as 0°.

2.2. Image Pre-Processor

To calculate the cloud properties with high accuracy, we resized and transformed the image from equal-angel projection to equal-length projection. The raw image used an equal-angel projection scheme shown in Figure 2. In this scheme, each pixel in the photo corresponds to a pre-defined fixed view angle. Consequently, an objected will be distorted in this projection a pixel would cover a larger area when it is in the edge area than in the center area of an image. To obtain an image that can reflect the real size and locations of objects, a preprocessing transformation procedure had to be implemented.

Considering that side-to-side $N = 1,072$ pixels corresponding to the vision angle of $\alpha = 120°$, one single pixel represents a small vision angle of $\alpha = V/N = 120/1,072 = 0.112°$. Suppose we have a point in the image which was the $i$th pixel in the horizontal direction, and $j$th pixel in the vertical direction, the actual locations for the pixel was $(x, y)$. It should be noted that their coordinate origins are located in the center of the image. We will have a transformation equation as the following.

$$
\begin{align*}
  x &= \tan(\alpha \times \sqrt{i^2 + j^2}) \times \frac{i}{\sqrt{i^2 + j^2}} \\
  y &= \tan(\alpha \times \sqrt{i^2 + j^2}) \times \frac{j}{\sqrt{i^2 + j^2}}
\end{align*}
$$

(1)

With the Equation 1, we can transform pixel array in an original into a new array where pixels are in their real-locations. However, as exhibited in Figure S1, these new pixels would not be uniformly distributed, with the pixels in the edge area sparser than in those in the central area. Therefore, the spatial resampling procedure was employed to generate quadrate images with equal-distance pixel arrays. Pixels within a coordinate range of $\pm 1.67$ were used for analysis as shown in Figure S2a. In this study, we used nearest neighbor resampling method. The pixel size after resampling was determined according to the median value of the distances between the two nearest neighbor pixel points.

The pre-processing procedure was critical to improve the accuracy of all cloud height observations. One pixel represents a larger area when it is further away from the center of an image. Therefore, the distributions
transformed pixels locations are denser in the center and sparser in the edge areas (Figure S2a). In other words, distances between two closest neighboring pixels are larger in the edge. Assuming the cloud height as 1, histograms of the distances was generally in the form of negative binominal distributions (Figure S2b). Transformation method performed well to correct the distorted straight line of the objects in image (Figures 1a and 1b). The distorted object shapes in the raw image will influence the performance of cloud type recognizer, which considers shape features a lot in the classification model. The distorted object size will cause large uncertainties as the pixel sizes are not linearly correlated with the real areas that they represent. As exhibited in Figures 1c and 1d, the cloud coverage will be quite different in two images, of which the latter one will better reflect the real cloud shape and sizes.

2.3. Cloud Feature Match

To calculate the cloud-base height, we need to match the cloud features of the images in the paired whole-sky images. In this study, the Shi-Tomasi-Scale Invariant Feature Transform (SIFT) corner detection and matching algorithm was implemented to obtain and match cloud features (Azad et al., 2009). The algorithm uses the Shi-Tomasi algorithm to detect candidate good features (Shi & Tomasi, 2002), before using SIFT algorithm to describe and match these features in two images of paired cameras (Ng & Henikoff, 2003). The original image was normalized to 0–255 to minimize the effect of brightness variances. The Shi-Tomasi algorithm was developed from Harris corner detection technique, with improved performance to find more robust features. The algorithm is not sensitive to vision angle, brightness and rotation and so on, and computation effective. The SIFT algorithm was effective to describe features’ direction and scale, which is also very robust to brightness, scale and rotation. The combination of algorithms Shi-Tomasi and SIFT was accurate, widely feasible and fast in operational applications.
After we have paired features, a quality control algorithm was performed to ensure correct match. Considering that whole-sky cameras have the same install azimuth, the connecting lines between matched features in two pre-processed images should be parallel (Figure 2). First, the average direction of connecting lines between matched feature points was obtained by calculating the mean vector of all the matched vectors. For each individual matched point pair, its included angle with the mean vector should be less than 10° to ensure its relatively high quality. The quality-assured paired features will be used to estimate cloud base heights.

2.4. Multi-Angle Cloud Height Estimator

The cloud height was calculated based on a “double-eye” distance estimator. To calculate the cloud height, two cloud imagers are required. Meanwhile, the two instruments should keep a relative distance with each other. The distance should neither be too large to ensure that the same cloud will be observed by both two imagers simultaneously, nor too small to ensure the accuracy and resolution in the calculation. The diagram of Figure 3 exhibited the theory for cloud height observation. In the surface triangle made up of imager 1 \((x_1, y_1)\), imager 2 \((x_2, y_2)\) and sub-cloud point, there will be a relation in terms of the Cosine theorem assuming the cloud height as \(h_c\),

\[
\begin{align*}
    d_i^2 &= \left(\frac{h_i}{\alpha_1}\right)^2 + \left(\frac{h_i}{\alpha_2}\right)^2 - 2 \times \frac{h_i}{\alpha_1} \times \frac{h_i}{\alpha_2} \times \cos(\beta) \\
    (2)
\end{align*}
\]

According to this equation, the cloud height could be then calculated,
where the $d_i$ refers to the distance between two imagers. The cloud elevation angles from imager 1 and imager 2 are respectively designated as $\alpha_1$ and $\alpha_2$. The horizontal angle of two imagers from the sub-cloud point is designated as $\beta$, which could be calculated through imager azimuth angles. Except from estimating cloud-base heights, we cloud also have geo-locations of feature points given cloud height as exhibited in Figure 3.

2.5. In Situ Observation System

We build up a prototype in situ observation system to collect real-world images and further evaluate the accuracy and effectivity of the comprehensive algorithms, as shown in Figure 4. The system contains to coupled imagers, which are respectively located in the roof tops of Changping Meteorological Agency (CPMA) (40.224715°N, 116.217675°S, 75.86 m) and Huayun Sounding Corporation (HYSD) (40.204167°N, 116.224174°S, 63.83 m). The distance between the two imagers is 2.63 km. The imagers were deployed strictly following the angle requirements as described in Section 2.1.1. The two images will simultaneously take cloud image shots every five minutes. The two imagers both used 4G transmitter modules to transfer images to an online server and conduct automatic time correction to ensure their synchronization.

To evaluate the cloud-base height estimation results, a ceilometer (Vaisala CL51) was deployed to conduct simultaneous observations. It is located on the roof top of Huayun Sounding Corporation, around 10 m away from the all-sky camera HYSD. Therefore, the instrument was able to observe cloud-base height at every second for the cloud at the center of HYSD images. To evaluate the algorithm, mean values for those estimated cloud heights located within 100 pixels to image center are used to pair with observations at the same observational time. Observations at daytime from 9:00 a.m. to 17:00 p.m. at Beijing local time were...
used for analysis. The observational period was from September 11 to September 29, 2018. There is a total of 181 paired data points.

3. Results

The algorithm was able to identify cloud height at a relatively large scale. Considering that the effective observational vision angle was about 120°, the minimum cloud height we could observe was around 800 m. When cloud-base heights become larger, we will have larger observation range of clouds in the image. Therefore, this instrument setting and algorithm enable us to estimate cloud-base height simultaneously at many points, rather than at one single point like ceilometer. The examples exhibited in Figure 5 revealed the spatial consistency of cloud-base height estimations. There are effective 289 estimation points in panel Figure 5a, which has a mean cloud height of 4,568 m and a standard deviation of 308 m. There are 106 estimated cloud heights in panel Figure 5b, with mean value of 4,339 m and a standard deviation of 332 m. It is evident that the dark cloud in the lower left part of image has lower cloud-base heights, which are around 4,000 m. The cloud-base height increases gradually to the top-left direction, finally to around 5,000 m (Figure 5b). In the third panel Figure 5c of isolated cumulus cloud, there are 17 recognized data points, with a mean cloud-base height of 2,499 m and a standard deviation of 70 m. The three examples exhibited the relatively high spatial consistency of the cloud estimation algorithm.

The estimated cloud-base height was compared against cloud-base height observed by ceilometer as exhibited in Figure 6. The estimation generally had good performance with a high R² value of 0.92, a low RMSE value of 424 m, which indicated a high accuracy. The low NME value of 9.2% also indicated the algorithm has a very low systematic bias, while the estimation errors mainly result from random errors. As the observed cloud-base height increases, the estimation error also gradually increases. When the cloud-base height becomes larger than 4,000 m, the error could be around 1,000 m.

4. Discussions and Conclusions

Accurate and frequent cloud-base height calculation is beneficial to solar farming and agricultural activities and also indicative for future meteorology conditions. This study used paired whole-sky imagers to estimate cloud-base height with high quality. The study obtained quality assured cloud base feature points with a robust Shi-Tomasi-SIFT algorithm before employed double-eye locating approach. The estimated cloud base
heights have high spatial coverages. Evaluated against ceilometer observations, estimated cloud-base heights have a high accuracy level, with $R^2 = 0.92$ and RMSE 424 m. The method is generally unbiased with NME = 9.2%. Our method is fast and easy to implement operationally.

The feature points in the stratus and cirrus cloud type were generally harder to extract as do not exhibit sufficient and relatively unique textures. Comparatively, it is easier to find effective features points in the cumulus and fractured stratus clouds. Note that the algorithm does not define values over the whole image, as some parts do not look similar in the two images due to the different view angle. Therefore, the clouds with relatively flat base will be easier to track and match feature points in two paired whole-sky images, as there would be weaker shelter effects.

The cloud base heights in this study was not continuous compare to the study by Nguyen and Kleissl (2014), as they used the window-based matching method. Their method needs to extract cloud area first before implementing recursive trial tests, which is time-consuming and employing new uncertainties of wrong cloud segmentations. Our method used a quality control method to allow low quality feature match to ensure abundant cloud-base height estimation points.

The method has limitations for ranges of estimated cloud base heights. First, it could not detect very low cloud heights due to relatively long distances between two imagers and small vision angle. As exhibited in Figure 3, two elevation angles of $\alpha_1$ and $\alpha_2$ should be larger than 30° considering that the imagers have upright vision angles of 120°. Given the distance between two imagers being 2.63 km, the system could only observe cloud base heights approximately >1,400 m, as shown in Figure 6. In other words, cloud base heights of low clouds such as cumulus clouds, stratus clouds and cumulonimbus clouds could not be observed in some occasions. Furthermore, the system also has limited ability to detect very high clouds. This was because estimated cloud base heights would be very sensitive to the coordinates of matched feature points, as revealed by illustrative diagram Figure 3 and calculation Equations 1 and 2. Such increased sensitivities would lead to higher uncertainties of estimated cloud heights, since coordinates of detected and paired feature points have errors due to installation inaccuracies and feature location error due to image sampling approximation. Therefore, estimation errors could be as large as >1,000 m when observed cloud heights are higher than 5,000 m as exhibited in Figure 3.

It should be noted that the estimated cloud-base heights in this study are geo-referenced with four dimensions of latitude, longitude and altitude, along with observational time. These geo-referenced cloud-base points have many useful quantitative applications, such as fusion with satellite observations and comparison with model simulations. What’s more, given cloud pixel specifications, we could have quantitative estimations of shadow area on the ground, which would be valuable to industries such as solar farming. In the temporal dimension, matching these geo-referenced features in two consecutive images will allow us to estimate cloud moving speed and direction, which will be very helpful for meteorological forecasts.

**Data Availability Statement**

The data repository is underway on FAIRSharing.org platform.

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