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Cloud coverage estimation using ground based images and segmentation techniques

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ABSTRACT
Nowadays scientists and researchers started using more and more ground based sky imagers as a rich source of information about the potential of local solar production. Sky coverage rate by clouds represent a very important factor for calculating the power generation by photovoltaic panels. This paper proposes the use of image segmentation techniques to estimate the cloud coverage rate. The aim of this article is to demonstrate the effectiveness of two segmentation methods: Otsu and Multi-Objective optimization to distinguish between clouds and the sky as two different classes. We will compared the results of the Multi-Objective Optimization approach that calculates the optimal threshold with the Otsu's method.

NOMENCLATURE
MO : Multiobjective Optimization
CCR : Cloud Coverage Rate.
N_c : The number of pixels representing clouds.
N_T : the total number of image pixels.

INTRODUCTION
The cloud cover causes many changes in the received solar radiation, which decreases the power generation of PV panels. Solar radiation, temperature and other meteorological data represent vital information on factors that influence power generation. This information may be amply enriched by the use of sky imagers as a supplementary data source. Sky images can provide indications about cloud density, coverage, trajectory and velocity as statistics that can be used to estimate the solar potential of a given site or even to predict power generation fluctuations. That is why cloud segmentation is suggested as one of most important information sources for solar plant operation. Cloud coverage data can be extracted from satellite images [1].the satellite images can provide global cloud coverage data but the major disadvantage of satellite images is their large field of coverage which cannot lead to detailed local statistics [2].

In contrast with satellite images, the Ground-based sky imagers can complement the coverage of equivalent satellite instruments, and they provide more precision and higher temporal resolution. They can be used to accomplish many local studies on the potential of a local solar plant.

Recently, several approaches are developed to determine the percentage of sky area covered by clouds; the most of them proposes cloud detection methods based on color features of the clouds. To determinate the total cloud coverage S.Long et al, in [3], used a set of digital images on RGB color space. The thresholds determination is done according to the ratio of R and B intensities. For each pixel, they compared the R/B signal ratio with 0.6 value. A pixel is considered as cloudy if the value of R/B is greater than 0.6. Kreuter et al. in [4] considered the threshold 1.3 of the B/R ratio for separate between the cloudy pixels and cloud-free. Heinle et al.in [5] proposed the threshold R–B= 30 to distinct between the cloudy pixels and other ones in the sky image.

The goal of our work is to show that detection of sky based on automatic clustering-based image thresholding gives a good estimation of cloud coverage. We also compare between Otsu's method and the multi-objective optimization method proposed in [6] using a diverse set of images of typical cloud coverage situations. In addition, our study shows that the conversion of images from RGB (red-green-blue) color space to HSV (Hue-Saturation-Value) improves the obtained results.

The outline of this paper is as follows: we begin first by introducing the used data and describing the used segmentation approaches; then finally we'll have a look at the performance of each algorithm is evaluated experimentally.

MATERIAL AND METHODS

a) Material

The sky images used in this study were acquired by a standard perspective digital camera with a resolution of 16M pixels. Images of the database were taken in different cloud coverage conditions such as illumination, altitude and solar zenith angles. Acquired images were resized to a resolution of 1200 × 960 pixels. A sample of these images is shown in fig.1. The complete database is available for download from the following link [7].

Figure 1
sample Sky Images

b) Methods

Our goal is to determine the optimal threshold that allows us to obtain the correct segmentation of sky images. In this subsection; we present the two segmentation methods which were used to perform an automatic image clustering. The first algorithm is based on Otsu's method [8]. This approach assumes that the input image encloses two classes of pixels following bi-modal histogram [9], then it calculates the optimum threshold separating the two classes so that their combined intra-class variance is minimal.
Otsu's method [10] tries to search for a threshold that minimizes the intra-class variance defined as a weighted sum of variances of the two classes:

$$\sigma_\omega^2(t) \;=\; \omega_1(t)\sigma_1^2(t) + \;\omega_2(t)\sigma_2^2(t) \qquad (1)$$

ω_i : are the probabilities of the two classes separated by a threshold t.

σ_i^2 : are variances of these classes.
Otsu demonstrates that minimizing the intra-class variance is equivalent to maximizing inter-class variance

$$\boldsymbol{\sigma_b^2(t) \;=\; \sigma^2 - \sigma_\omega^2(t) \;=\; \omega_1(t)\omega_2(t)[\mu_1(t) + \;\mu_2(t)]} \qquad \mathbf{(2)}$$

Which is expressed in terms of class probabilities ω_i and class means μ_i .
The class probability $\omega_t(t)$ is calculated from the histogram as t:

$$\omega_1(t) \;=\; \sum_0^t p(i) \qquad (3)$$

While the class mean $\mu_1(t)$ is:

$$\mu_1(t) \;= \left[\sum_0^t p(i)\; x(i)\right] / \omega_1 \qquad (4)$$

Where $x(i)$ is the value at the center of the ith histogram bin. $\omega_2(t)$ and μ_2 computed on the right-hand side of the histogram for bins greater than t. The class probabilities and class means can be computed iteratively.

The Otsu's method algorithm operates as follows:

- Calculate histogram and probabilities of each intensity level.
- Compute the initial $\omega_i(0)$ and $\mu_i(0)$.
- Sweep all possible thresholds t= 1……… maximum intensity
- Update ω_i and μ_i
- Calculate $\sigma_b^2(t)$
- Optimal threshold corresponds to the maximum $\sigma_b^2(t)$

Two maxima can be computed (and their two corresponding thresholds). $\sigma_{b1}^2(t)$ is the greater max and $\sigma_{b2}^2(t)$ is the greater or equal maximum
Optimal

$$\text{threshold} = \frac{\boldsymbol{threshold1 \;+\; threshold2}}{\mathbf{2}} \qquad (5)$$

The second method is the Multiobjective optimization (MO) [11] which extends the optimization theory by permitting several design objectives to be optimized simultaneously. A MO problem is solved in a way similar to the conventional single-objective (SO) problem. The goal is to find a set of values for the design variables that simultaneously optimizes several objective (or cost) functions. In general, the solution obtained through a separate optimization of each objective (i.e. SO optimization) does not represent a feasible solution of the Multiobjective problem.

Thresholding [12] based on within-class variance tends to classify an image as the object and the background of similar sizes. In order to overcome this drawback, an objective function is derived from the classical within-class variance criterion; some a priori knowledge about the characteristics of the resulting segmentation such as uniformity, or homogeneity, of the regions and simplicity of the interiors of the regions are introduced. The proposed modification consists in the integration in the criteria of the ideal segmentation properties. The criterion expressing the uniformity and the homogeneity of the regions is the within class variance criterion, defined as follows [13].

$$MVar(I) = \alpha \sum_{j=1}^{NR} \left(\frac{Var(j)^2}{\beta_j} + \gamma_j\right) \qquad (6)$$

Where

$$\alpha = \left({}^{1}\!/_{1000}\,\mathrm{xM}\right)\sqrt{\mathrm{NR}} \qquad (7)$$

NR is the size of image.

$$\beta_j = \frac{1}{1+\log(N_j)}, \qquad (8)$$

Nj denotes the number of pixel in the region j.

γ_j is given by :

$$\left(\frac{\mathrm{R}(N_j)}{N_j}\right)^2 \qquad (9)$$

$R(N_j)$ is the number of the regions of which cardinal is equal to N_j .

$$Var(R) = \frac{1}{N}\sum_{i\in R}\big(R(i) - m(R)\big)^2 \qquad (10)$$

Where

$$m(R) = \frac{1}{N}\sum_{i\in R} R(i) \qquad (11)$$

N is the number of pixels in region R, in our case N=2.

R(i) is the value of pixel i.

m(R) the average in region R.

Overall probability of error criterion

To determine the optimal threshold, the overall probability of error is minimized. For two successive Gaussian probability density functions (PDF), it is given by

$$e(T_i) = P_i \int_{-\infty}^{Ti} P_i(x)dx + P_{i+1}\int_{Ti}^{+\infty} P_{i+1}(x)dx \qquad (12)$$

Where I=1;2;…………;d-1 with the respect to the threshold Ti.

the overall probability to minimize is

$$E(T) = \sum_{i=1}^{d-1} e(Ti) \qquad (13)$$

Where

T is the vector of thresholds: 0<T1<T2<….<T_{d-1}<255.

The weighting parameters are given by

$$W_1 = 1 - W_2 \qquad (14)$$

Where

$$W_2 = \frac{\sum_{i=1}^{d}\sigma_i^2}{\sigma_{Histogram}^2} \qquad (15)$$

d is the number of the Gaussians (in our case =2).

σ_i is the standard deviation of the ith Gaussian PDF; and $\sigma_{Histogram}$ is the standard deviation of the original histogram.

EXPERIMENTAL RESULTS

In this section, we present experimental results obtained by using the Multiobjectives optimization method and the Otsu's method to segment the sky from the original images in order to estimate the cloud coverage.

We have conducted a preliminary experimental study in order to determine the color space which provides the best performance regarding color features discrimination in different image acquisition conditions. Several color spaces were compared including YCbCr, RGB, HSV and L*a*b color space. This study has convinced us to choose the HSV as an optimal representation space for sky images.

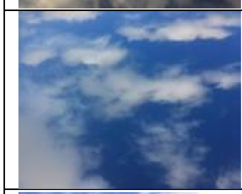
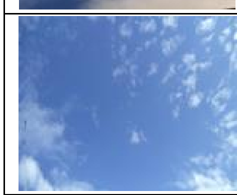
First of all each original image which in usually acquired and represented in the RGB color space, is converted to the HSV color space. Where H is the hue, S is the saturation and V is the value or the illumination intensity of each pixel. The second step consists of extracting the S component from the HSV image. The studied segmentation methods will be applied directly to this color channel. In this subsection we provide sample segmentation results given by each approach.

The final step is to calculate the cloud coverage using the thresholded binary images. The cloud coverage rate is calculated as follows:

$$\mathrm{CCR} = \frac{\mathrm{N_c}}{N_T} \qquad (16)$$

The source code for the two compared algorithms are available for download at [14].

Table 1
Representation of the segmentation results given by Otsu’s method and MO, and the calculated cloud coverage rate (CCR).

Original image	S	Seg_MO	CCR_MO (%)	Seg_Otsu	CCR_Otsu (%)
			40.17		48.70
			79.86		83.90
			28.37		48.71
			12.57		20.89
			88.89		88.15
			23.06		28.41

DISCUSSION

From the obtained results, it can be seen clearly that Otsu’s method is able to threshold effectively sky images providing the best performance. From Table 1 we can see that Otsu’s method has separated the image into two classes without missing small could areas which were considered by the Multiobjectives optimization method as free-cloud zones. In contrast to segmentation methods based on a fixed threshold value, automatic clustering-based image thresholding offers the advantage of adaptability to changes caused by different factors that affects the acquired images such as illumination variations. Thus, such results can be used more effectively to perform a long-term study on cloud coverage rates, which is a very valuable information about the solar potential of a given production site.

CONCLUSION

In this paper, we described two segmentation approaches to find the optimal thresholds discriminating the sky and the clouds in ground based digital images. Studied methods were applied to sky images in order to determinate the cloud coverage rate. It is clearly seen from the experimental results that the Otsu's method provided more accurate results than the Multi-objective in the case of sky images. We used segmentation results to calculate the cloud coverage which we plan to exploit as a supplementary information on the solar potential in future works.

KEYWORDS

Cloud coverage, Multiobject, Otsu, unsupervised, segment, ground base image , segmentation of sky, cloud detection, cloud segmentation.

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