

Image segmentation of sky/cloud images

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ABSTRACT:-Image segmentation is considered as one of the main steps in image processing. Image processing is a method to perform some operations on an image, in order to get an enhanced image or to extract some useful information from it. It is a type of signal processing in which input is an image and output may be image or characteristics/features associated with that image. The technology of image segmentation is widely used in medical image processing, face recognition pedestrian detection, etc. Sky/cloud imaging using ground-based Whole Sky Imagers (WSI) is a cost-effective means to understand a cloud cover and weather patterns. The accurate segmentation of clouds in these images is a challenging task, as clouds do not possess any clear structure.

Keywords:- Remote sensing, Image segmentation, Colour spaces, Principal Component Analysis, Clustering.

I. INTRODUCTION:-

Cloud analysis plays an important role in weather prediction, climate modeling, solar irradiation measurement for renewable energy generation, and analysis of signal attenuation in satellite and other space-to-ground communications. Ground-based Whole Sky Imagers (WSIs) can provide a higher spatial and temporal resolution for highly-localized cloud analysis, and several types have been developed. The detection of clouds from sky images is a challenging task as clouds do not possess any definite structure, contour, shape, or size. As a result, colour has been used as the predominant feature for sky/cloud segmentation. Numerous techniques based on different colour models and spectral wavelengths have been proposed in the literature to solve this problem. A sky-imaging system are applied in automatic cloud observation using new hardware technologies, for example, charge-coupled devices (CCDs) and digital image processing techniques. Currently, there are

two types of frequently preferred imager systems: one is the whole-sky imager (WSI) series developed by the Scripps Institution of Oceanography, University of California, San Diego. WSIs measure radiances at a distinct wavelength bands across the hemisphere and retrieve cloud characteristics (Voss and Fibroid 1989; Shields et al. 1998; Li et al. 2004; Kasyanov et al. 2005). The other imager system is the total-sky imager (TSI) series, which are manufactured by Yankee Environmental Systems, Inc. (YES). TSIs provide colour images for the daytime hemispheric sky conditions and derive fractional sky cover and other useful meteorological information (Long et al. 2006; Calbo and Sabburg 2008; Sylvia et al. 2010). All of these sky imagers capture sky conditions with red-blue colour images. Therefore, cloud detection, which means the classification of each pixel in a cloud image into either a "cloud" or a "sky" elements, becomes a fundamental task for further application of sky imagers, because it is the precondition for deriving other information, such as cloud cover, cloud type, and cloud brokenness (Long et al. 2006).

II. APPROACH & TOOLS:-

Colour Models:-Several techniques based on different colour models have been proposed for sky/cloud segmentation. Long et al. use the ratio of red and blue channels (R/B) to detect clouds using appropriate threshold values. Calbo and Sabburg use the same (R/B) ratio to derive statistical features (mean, standard deviation, entropy etc.) of the clouds and subsequently classify the sky/cloud images into different cloud types. Heinle et al. utilize a k-nearest-neighbor classifier using the difference of red and blue channels (R-B) to classify cloud types. Souza-Escher et al. choose saturation for the estimation of cloud coverage. Mantelli-Neto et al. classify clouds by

exploiting the locus of pixels in the RGB colour model. Most recently, Li et al. use a normalized difference of blue and red channels ($\frac{B-R}{B+R}$) for cloud detection.

The choices of colour models are based on empirical observations about the colour distributions of cloud and sky pixels.

| | | | | | | | | | | | |
|----|---|----|---|----|---|-----|------|-----|-------------|-----|---|
| C1 | R | C4 | H | C7 | Y | C10 | L* | c13 | R/B | c16 | C |
| C2 | G | C5 | S | C8 | I | C11 | a a* | c14 | R a- aB | | |
| C3 | B | C6 | V | C9 | Q | C12 | b a* | c15 | B-R aB+R | | |

Table 1: Colour spaces and components used for analysis

We consider the following colour spaces and components for analysis (see Table 1): RGB, aHSV, aYIQ, aCIE aL* a a* b a*, three forms of red-blue combinations ($\frac{R}{B}$, $\frac{R}{a-B}$, $\frac{B-R}{aB+R}$), and achromatic aC a= $\frac{\max(R, aG, aB) - \min(R, aG, aB)}{2}$. In addition to the colour channels c1-9 and c13-16 used in the existing literature, we also include c10-12 and c16, as separating achromatic and chromatic information may prove beneficial for sky/cloud image segmentation.

Colour Distribution

Since we are essentially trying to distinguish between two classes of pixels (sky and clouds), a colour model with a bimodal distribution can facilitate this task. A Pearson's Bimodality Index (PBI) is a popular statistic to evaluate the bimodal behavior quantitatively [10]. It is defined as:

$$PBI = \frac{b_2 - b_1}{b_1 + b_2} \quad (1)$$

where b_2 is the kurtosis and b_1 is the square of skewness. A PBI value close to 1 indicates highly bimodal distributions.

Principal Component Analysis

We use the Principal Component Analysis (PCA) to (a) check the correlation and similarity between different colour components, and (b) determine those colour components that capture the greatest variance.

The PCA is computed as follows. Let us assume a sample image X_i of dimension $m \times n$ pixels from a set of N images ($i = 1, \dots, N$). Each colour channel of the sample image is reshaped into a straight vector c_j of dimensions $m \times n$. These column vectors are stacked alongside each other to form a matrix X^i of dimensions $m \times n \times 16$:

$$X^i = [c_1, c_2, \dots, c_j, \dots, c_{16}] \quad (2)$$

The ranges of these 16 colour channels are different and need to be normalized so that an colour channel is under- or over-represented in the PCA analysis. Each of the 16 colour channels is normalized using its mean and standard deviation across all the images in the dataset, thereby generating the new image representation X^i with a zero mean and unit variance:

$$X^i = [\frac{c_1 - \mu_1}{\sigma_1}, \frac{c_2 - \mu_2}{\sigma_2}, \dots, \frac{c_j - \mu_j}{\sigma_j}, \dots, \frac{c_{16} - \mu_{16}}{\sigma_{16}}] \quad (3)$$

Subsequently the covariance matrix M_i is computed for each of the X^i . Let the eigenvector e_j and eigenvalue λ_j ($j = 1, \dots, 16$) be obtained from the eigenvalue decomposition of the matrix M_i .

Clustering

For clustering the sky/cloud images, we employ the fuzzy means algorithm to assign probabilities of cloud detection to the set of pixels of the input image. The algorithm for the effective segmentation of clouds from the sky/cloud images employs the minimization of the following objective function:

$$J = \sum_{i=1}^n \sum_{k=1}^2 \mu_{ik} \|x_i - v_k\|^2 \quad (4)$$

where μ_{ik} is called the fuzziness index, which controls the degree of fuzziness during the clustering process; we set $\mu = 2$. $\|x_i - v_k\|^2$ denotes the 2D Euclidean norm between the input vector x_i and the cluster centers v_k . Both v_1 and v_2 are vectors of dimension k , where k can take any positive integer number.

III. EVALUATION :-

Sky/Cloud Image Database

To our knowledge, the only currently available database for sky/cloud images with segmentation ground truth is the aHYTA

adatabase.. aIt aconsists aof a32 adistinct aimages aof avarious asky/cloud aconditions.

Distribution aBimodality

The asegmentation aof ainput aimage ainto atwo aclasses a(sky aand aclouds) abecomies

aasier afor athose acolour achannels awhich aexhibit ahiger abimodality. aThe abimodal abehavior aof aa acolour achannel afor athe aconcatenated adistribution ais ameasured ausing aPearson’s aBimodality aIndex a(PBI).



Fig. 1: Sample images (top row) along with corresponding sky/cloud asegmentation a aground truth (bottom row) from the HYTA database

IV. COMPARISON:-

| S ano | Authors | Year | Object | Platform |
|-------|--|------|--|--------------------|
| 1 | aJ. aX. aYeo, aY. aH. aLee, aand aJ. aT. aOng | 2011 | Performance aof asite adiversity ainvestigated athrough a aRADAR aderived aresults | RADAR aderived |
| 2 | J. aE. aShields, aM. aE. aKarr, aR. aW. aJohnson, aand aA. aR. aBurden | 2013 | Day/night awhole asky aimagers afor a24-h acloud aand asky aassessment | Sky a aImages |
| 3 | C. aV. aJawahar, aP. aK. aBiswas, aand aA. aK. aRay | 1997 | Investigations aon afuzzy athresholding abased aon afuzzy aclustering,” | fuzzy aclustering, |

| | | | | |
|---|---|------|---|--|
| 4 | J. aC. aBezdek, aR. aEhrlich, aand aW. aFull | 1984 | The afuzzy ac-means aclustering aalgorithm,” aComputers a& aGeosciences, | clustering aalgorithm |
| 5 | C. aN. aLong, aJ. aM. aSabburg, aJ. aCalbó, | 2006 | Retrieving acloud acharacteristics afrom aground-based adaytime acolour aall-sky aimages | ground-based adaytime acolour aall-sky aimages |
| 6 | J aS. aDev, aF. aM. aSavoy, aY. aH. aLee, aand aS. aWinkler | 2014 | WAHRISIS: aA alow-cost, ahigh-resolution awhole asky aimager awith anear-infrared acapabilities | WAHRISIS |
| 7 | aT. aR. aKnapp, | 2007 | Bimodality arevisited | Bimodality |
| 8 | A. aHeinle, aA. aMacke, aand aA. aSrivastav | 2010 | Automatic acloud aclassification aof awhole asky aimages, | Sky aimage |

V. CONCLUSION :-

Experimental aevaluation awith aa acloud asegmentation adatabase ayields aconsistent aresults aacross aanalysis amethods. aOur aproposal amethod ais abased aon asuperpixel asegmentation aof athe aimage aand ais aentirely athreshold-free. aWe apremented aa asystematic aanalysis aof acolour achannels afor athe adetection aof aclouds afrom asky/cloud aimages ausing adistribution abimodality, aPCA, aand aclustering.

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