

Automatic Cloud Detection and Weather Forecasting Using Gradient Based SPS

M. Mauniga¹ & S. I. Padma²

¹P.G Scholar, Department Of Communication Systems, Pet Engineering College, Vallioor.

²Assistant Professor, Pet Engineering College, Vallioor.

Abstract: Thin cloud detection is challenging in a ground-based sky-imaging systems due to low contrast and vague boundaries between cloud and sky regions. In our proposed algorithm, a series of super pixels could be obtained adaptively by SPS algorithm according to the features of clouds. In addition to that a gradient feature is drawn out from that super pixels for improving the detection of cloud types. due to its high performance in solving complex issues, simplicity of execution and low computational complexity. The nearest neighbor classifier k used. High thin clouds, high patched cumuliform clouds, stratocumulus clouds, low cumuliform clouds, thick clouds, strati form clouds and clear sky are the seven different sky condition are distinguished. Firstly local threshold for each super pixel is calculated and then determining a gradient values for the whole image. Finally comparing with the obtained threshold matrix can detect the cloud. Experiments on real natural images are conducted to show the performance of the proposed superpixel segmentation algorithm.

1. Introduction

Clouds play a crucial role in hydrological cycle. Ground based cloud observation is required the most cloud related research. Human observes at meteorological observation station estimate the cloud cover in the present situation. This method is taken high cost in terms of human resources and the result is obtaining from various observers often not suitable. In these fields automatic estimation techniques for cloud cover required. Some instruments for capturing ground based clouds such as whole sky imager, total sky imager, infrared cloud analyzer have been developed for achieving this goals. The above mentioned instruments could be obtained continuous all sky images with a set time gap. Besides a lot of algorithm is proposed to estimate the cloud cover paste and these captured images of all sky.

Presently cloud detection algorithms is treated color as a primary characteristics for differentiating cloud from sky. This is due to the scattering difference between cloud particles and

air molecules. Cloud particles are scattering similar blue and red intensity. Each pixel of all sky images is classified by cloud detection. A fixed value classifies each pixel in a cloud image moreover fixed threshold are proposed here. Although better result to be achieved. This method is a scientific. They are calculated the local threshold for each sub image. The stiff division is not flexible. Actually cloud detection treats as an application of image segmentation. Ren and Malik proposed super pixel segmentation. An image is divided by the algorithm into a series of irregular image blocks and each image block is called super pixel. The irregular divisions which is based on the texture similarity, brightness similarity and outline continuity in an image. Natural texture is reasonable to describe the cloud appearance using contour and texture cues.

2.SPS

The segmentations can treat as a graph partitioning problem for a ground based cloud image. The nodes of the graph are the entities and here they are the pixels, the edges between two nodes agree to the similarity with which these two nodes are depending to one group. Let $G=\{V,E\}$, be a weighted undirected graph, where V refers the nodes and E refers the edges. The following objective functions can formulate the segmentation

$$y = \operatorname{argmin}_N \operatorname{cut} = \operatorname{arg}$$

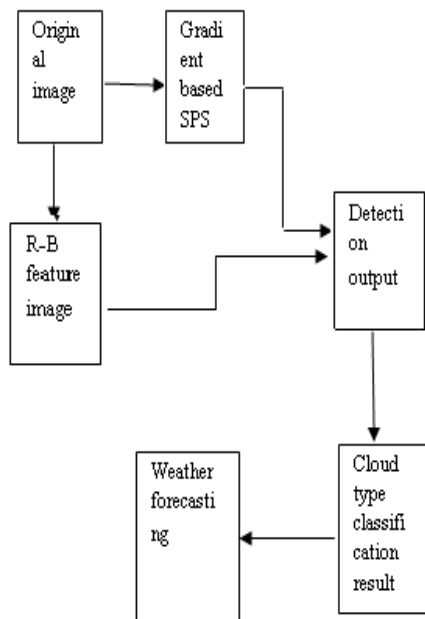


Figure 3.1. Cloud detection process

4. Gradient based super pixel segmentation method

The general form of a binary image segmentation model is firstly considered by gradient based super pixel segmentation method. When labeling the occurring segments we use an indicator function $v: \Omega \rightarrow \{0,1\}$ and it operates on the image domain. The space of these binary function

will be called $V = \{v | v: \Omega \rightarrow \{0,1\}\}$. J_v is the jump set of binary function, v represents the boundary of the interior image segments. The general form of our binary model which is given by

$$\begin{aligned}
 \inf_{v \in V} & \underbrace{\int_{\Omega \setminus J_v} \|DI(x)\|_2 dx}_{\text{intensity variation on segments}} \\
 & + \lambda_1 \underbrace{\int_{J_v} \|d(x) - \nu_b(x)\|_2^2 d\mathcal{H}^{n-1}}_{\text{directional deviation}} + \lambda_2 \underbrace{\int_{J_v} g(x) d\mathcal{H}^{n-1}}_{\text{weighted boundary length}} \\
 & + \lambda_3 \underbrace{\int_{\Omega} (1-v(x))\rho_1(x) + v(x)\rho_2(x) dx}_{\text{image data}} \quad (4.1)
 \end{aligned}$$

4.1. Intensity variation on segments

It is essentially penalized any large deviation of intensity values on each segments, ignoring intensity changes and it occurs at a segments boundary. Which will be described by the

jump set J_v . For example a similar time can be founded in the Mumford-shah functional, J_v is a null set with respect to the n dimensional Hausdroff measure on Ω is to be understood as the distributed derivative of the intensity I .

4.2. Directional deviation

V_{j_v} which is the inner unit normal to the boundary of the set $\{x: v(x)=1\}$. The boundary which coincides with the jump set J_v . The normal vector is closely related to the distributional derivative of the indicator function. $d(x)$ represents a suggestion for the units normal vector of the boundary passing through x .

4.3. Length of the weighted boundary

The length of the weighted boundary penalizes the large boundary measures and additionally weights penalization at each point x by $g(x) > 0$, an idea is also occurring in the edge based segmentation approach.

4.4. Image data

Image data is served as a regularize which involves the data terms $\rho_i(x)$. $\rho_i(x)$ gets an image data related the cost of arranging label I at point x . Without the image data term $v = \text{const.}$ on Ω . the jump set J_v is empty and no segmentation is taken place. It tends to be the optimal solution of the problem. It has to elude problem which designed with the purpose of obtaining solutions while the computational effort is minimized. This will be coincided with the ability to transform a relaxed version of the problem is to a convex saddle point problem. Extending the solution space and one additional dimension only can obtained the saddle point problem. With the help of image gradient our approach is working directly by transferring problem (1) we are able to preserve dimensionality of the solution space. Afterward's obtaining a convex saddle point representation for this problem. The only term which needs to be modified is the intensity variation term

$$\int_{\Omega \setminus J_v} \|DI(x)\|_2 dx \quad . \text{ According to the Appendix we are assuming the following decomposition of the distributional derivative } DI: DI = \nabla I + CI + (I^+ - I^-) \nu_I d\mathcal{H}^{n-1} \quad (4.2)$$

From this representation it presents the following:

$$\begin{aligned}
 \int_{\Omega \setminus J_v} \|DI(x)\|_2 dx & = \int_{\Omega} \|DI(x)\|_2 dx - \int_{J_v} \|DI(x)\|_2 dx \\
 & = \int_{\Omega} \|DI(x)\|_2 dx - \int_{J_v} (I^+(x) - I^-(x)) d\mathcal{H}^{n-1} \quad (4.3)
 \end{aligned}$$

In a discrete setting, i.e. with ∇I as the numerical derivative and calculation taking place on an equidistant grid, we get

$$\int_{\Omega} \|DI(x)\|_2 dx - \int_{J_0} (I^+(x) - I^-(x)) d\mathcal{H}^{n-1} \approx \int_{\Omega} \|\tilde{\nabla} I(x)\|_2 dx - \int_{J_0} \|\tilde{\nabla} I(x)\|_2 d\mathcal{H}^{n-1} \quad (4.4)$$

Replacing the term (4.3) into (4.1) and making the use of the fact that the term $DI(x)-2dx$ is not influencing the optimal argument of the entire optimization problem We are arriving at the final version of our binary segmentation model .Several advantages of our proposed SPS algorithm could be concluded.

1)Our SPS can suite with the different shape ,size and locations of clouds and can be divided the images into a series of irregular region.

2)We are using R-B as a feature image which can be increase the difference of clouds and clear sky elements.

3)For each super pixel we are calculate in its local threshold which suitable for all kinds of cloud images. When cloud and clear sky pixels are existing in the same super pixel done at the same time.

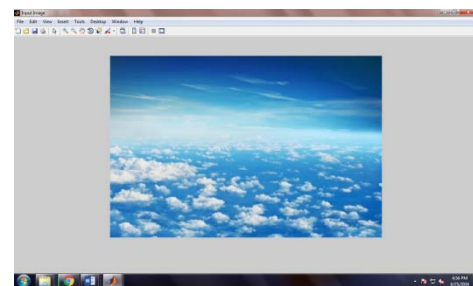
4)Bilinear interpolation calculates the gradient feature. It can give guarantee of the smoothness of the gradient values between different super pixels and avoid the boundary effect in cloud detection, but better detection results could be achieved.

5. Classification Using KNN classifier

KNN method is often referred to as a nearest neighbor classifier .The lower side of the simple approach is a lack of robustness that characterizes the resulting classifier .The high degree of local sensibility is making nearest neighbor classifier highly susceptible to noise in the raining data .Locating k can achieve more robust models. $k > 1$ neighbors majority votes decide the outcome of the class labeling .A higher value of k results in a smoother less locally sensitive functions. The nearest neighbor classifier is regarded as a special case of the more general k nearest neighbor's classifier. This approach can be eluded by limiting the influence of the distant instance one way of doing. So it is to assign a weight to each vote .The weight is a function of the distance between the unknown instance and known instance. Each weight can be defined by the inversed squared the distance between the known and unknown instance votes cast. Dense clouds developed vertically in the form of rising mounds,

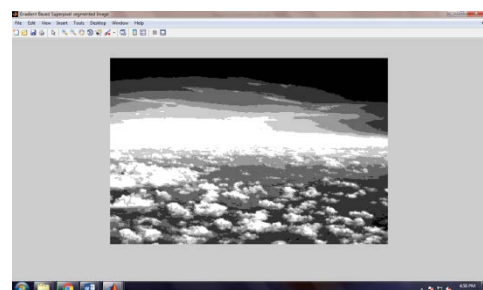
domes or towers with bulging upper parts frequently appearing a cauliflower .The sun light part of these clouds are mostly brilliant white but these bases are relatively dark and horizontal .When the sun is visible to this clouds, its outline will clearly discernible .Gray or white patch ,sheet or layer clouds always have done mosaic rounded mass or rolls. Regularly the arrange small element with an apparent width of more than five degrees. The edge of altocumulus process in front of the sun or moon a corona appears. The outside ring has red color and inside ring has blue color and occurs within a few degree of the sun or moon .Many times altocumulus will be appeared with other cloud type.

6. Result and discussion



Fig(a) original image

RGB cloud image is taken as an original image.



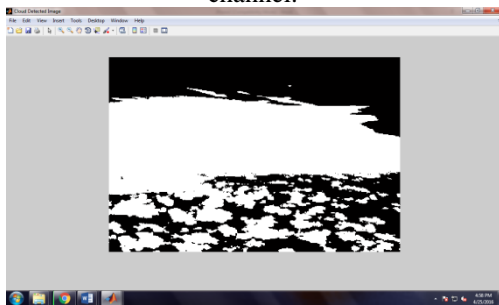
Fig(b) Gradient based SPS

Divide the cloud images by using SuperPixel Segmentation. To implement the cloud detection algorithm, we need to calculate the local threshold for each superpixel and the threshold matrix. With the help of the four steps such as Intensity variation on each segment, directional deviation, weighted boundary length, image data obtain local threshold.



Fig(c) R-B feature image

Transfer RGB image to R-B feature image, which simply difference of the Red channel and Blue channel.



Fig(d) Final cloud detected output

Calculate the difference between the gradient based superpixel segmentation and feature image pixel by pixel. If the result is greater than 0, the corresponding pixel is classified as a cloud element, otherwise as a clear sky one.

Table 1. Comparison for SPS vs Gradient based SPS algorithm

Parameter	SPS	Gradient based SPS
Precision	0.84	1
Recall	0.82	0.99
F-Value	0.81	0.995

Three criteria are selected to measure how well each algorithm matches the ground truth precision, recall and final score. Precision and recall are explained as follows

$$\text{Precision} = \frac{TP}{(TP+FN)}$$

$$\text{Recall} = \frac{TP}{(TP+FP)}$$

$$\text{Fscore} = \frac{2 \cdot \text{recall} \cdot \text{precision}}{(\text{recall} + \text{precision})}$$

False cloud pixels and false sky pixels in a detected images are TP,FP,FN.F-score which measures the detection accuracy by considering both recall and precision. We can see that the GBSPS achieve

highest detection accuracy for all of the three criteria.

7. Conclusion

In this project an automatic cloud detection algorithm is based on SPS .Threshold matrix is used by the existing system .This matrix is based cloud detection scheme but it is taken more implementing time to calculate the cloud type. In this proposed scheme gradient based super pixel segmentation method is proposed .It is compared with the fixed threshold ,global threshold and local threshold interpolation algorithm. The experimental results shows that our algorithm which achieves the highest performance for cloud detection. High thin clouds ,high patched cumuliform clouds, stratocumulus clouds, low cumuliform clouds, thick clouds, strati form clouds and clear sky are seven different sky conditions distinguished. This proposed method provides better results when compared with the existing scheme.

8. Future Enhancement

Improving the hardware and the image processing are the two directions for future research stemming from the current work. One possibility for device improvement is mounting a fish-eye camera on a solar path and shading lens with a shading range, instead of a shadow strip or shadow band. The area of indistinct sky could be reduced. However, it is also obtained that the smaller the “dome” or mirror surface used, Obstruction such as drops of rain adversely affect the greater portion of the sky image. Regarding the image processing will investigate further parameters such as CB, and how the parameters is relating with classical cloud types.

9. Reference

- [1]Feister.U,Shields.J,“Cloud and radiance measurement with the VIS/NIR Daylight Whole Sky Imager at lindenberG (Germany),” Meterol.Zeitschrift, vol.14,no.4 ,pp. 627-639,2005.
- [2]Genkova.I,Long C.N,“Assesing cloud spatial and vertical distribution with infrared cloud analyzer”in Proc. 14Th ARM Sci.Team Meet.,2004,pp.22-26.
- [3]Heinle.A,Macke.A,“Automatic cloud classification of whole sky images,”Atmos.Meas. Technol.,vol.3, no.1, pp.557-567.
- [4]Kreuter.A,Zangerl.M,“All-sky imaging: A simple, versatile system for atmospheric research,” Appl.opt.Vol. 48,no. 6,pp. 1091-1097,Feb 2009.

[5]Kalisch J,Macke.A.,,"Estimation of the total cloud cover with high temporal resolution and parameterization of short-term fluctuations of sea surface insolation,"*Meteorol.Zeitschrift*,Vol.17,no.5,pp.603-611,oct ,2008 ,

[6]Long.C.N.,Deluisi J.J,"Development of an automated hemisphere sky imager for cloud fraction retrievals,"in *Proc.10th Symp.Meteorol.Cbserv.Instrum.*,1998,pp.171-174.

[7]Long.C .N., sabburg. J. M," Retrieving cloud characteristics from ground- based daytime color all-sky image,"*J.Atmos.Ocean.Technol.*,vol.23,no.5,pp.633-652,May 2006.

[8]Malik.J,Belongie.S,"Contour and texture analysis for image segmentation,"*Int.J.Comput. Vis.*,vol.43,no.1,pp.7-23,june 2001.

[9]Mori.G.,," Guiding model search using segmentation,"in *Proc.10th IEEE Int.Conf.Comput.Vis.*,2005,pp.1417-1423.

[10]Neto,S.L.M, Pereira E.B,"The use of Euclidean geometric distance on RGB color space for the classification of sky and cloud pattern,"*J. Atmos.ocean. Techol.*, vol.27,n0.7,pp.1504-1517,sep.2010.

[11]Otsu.N,"A threshold selection method from gray level histograms, "IEEE *Trans. Syst. Man Cybern.*,vol.9,no.1,pp.62-66,jan.1979.

[12]Peng.B,Zhang.L,"Automatic image segmentation by dynamic region merging, "IEEE *Trans. Image Process.*,Vol.20,no.12,pp.3592-3605,Dec.2011.

[13]Ren.X.F,Malik.J," Learning a classification model for segmentation, "in *proc.9th IEEE Int.Conf. Comput. Vis.*,2005,pp.1417-1423.

[14]Shields.J.E.,Karr.M.E,"Automated day/night whole sky imagers for field assessment of cloud cover distribution and radiance distributions,"in *Proc.10th Symp.Meteorol.Observ.Instrum.Amer.Meteorol.Soc.*,1998 ,pp.11-16.

[15]Souza-Echer.M.P,Pereira.E.B,"A simple method for the assessment of the cloud cover state in high latitude regions by ground-based digital cameras,"*J.Atmos. Meas.Technol.*,vol.3,no.1,pp.557-567,May 2010.

[16]Yang.J,Yao.W.,,"An automatic ground based cloud detection method based on adaptive threshold,"*J.Appl. Meteorol.Sci.*, Vol.20,no.6,pp.713-721,2009.

[17]Yang.J,Wang.J,"Thin cloud detection of all sky images using Markov Random Fields,"*IEEE Geoscience. Remote Sens.Lett.*,vol.9,no.3,pp.417-421,may 2012.

[18]Yang.J,Yao.W,"An automatic ground-based cloud detection method based on local threshold interpolation,"*Acta Meteorol.Sinica*.vol.68,no.6,pp.1007-1017.20.