P 1.20 MULTILEVEL CLOUD RETRIEVAL FROM THE GOES PLATFORM

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1. INTRODUCTION

Since GOES NEXT (series 8 through 11) became operational, there has been significant efforts to maximize information in the GOES platform, including both measured radiances as well as derived products from the measurements. For example, cloud-top pressure derived from GOES sounder data has been used in operational 20km Rapid Update Cycle (RUC) at National Center for Environmental Prediction (NCEP) since April 2002 (Kim and Benjamin, 2001). Also, cloud track winds derived from GOES imager data has significantly contributed to forecast improvement (Velden et al. 1997).

Data from each instrument have relative merit. Imager data have better coverage and higher spatial resolution (4 km) than sounder data (10km). Sounder data have better measurement accuracy and 19 channels data make it possible to retrieve vertical temperature and humidity profiles. Figure 1 is cloud product obtained from NESDIS, showing cloud-top temperatures, effective cloud amount (between 0 for clear and 100 for overcast), and cloud-top pressure at each field-of-view (FOV) collected around a location at latitude of 36.61°N and longitude of 97.49°W (ARM/CART site, marked with *). Figure 2 shows brightness temperatures of both GOES imager window channels at the same location and almost the same time (21 minutes apart) collected from the local GVAR station at NOAA Forecast Systems Laboratory. Comparing the two figures, notice that imager data provide better cloud boundaries. Therefore, vertical distribution of clouds (not the effective cloud amount) within the sample domain is better defined. Also, Kim (1998) has shown that sample means of imager data and sounder data are statistically equivalent when there are clouds.

We describe the adaptive clustering approach (Kim, 1996) applied to GOES imager data to extract cloud-top distributions in section 2. Minimization formula to combine sounder and imager radiances is given in section 3 with preliminary results.

2. PREPROCESSING OF IMAGER DATA

Let $f_n(x)$ be the fractional probability density function of random variable x defined on non

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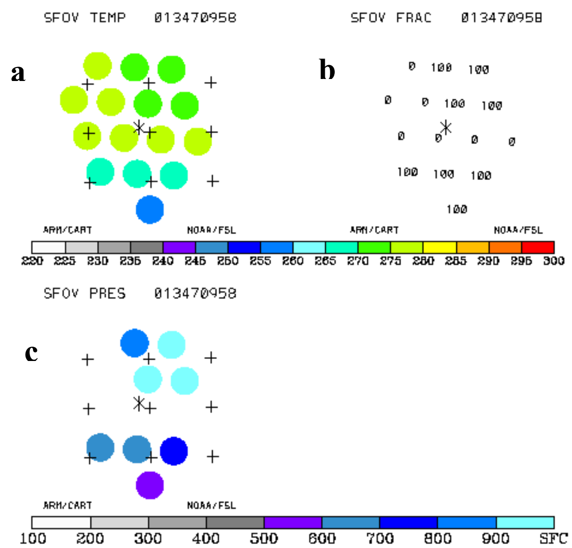

Fig.1 Three variables in the NESDIS cloud product derived from GOES sounder data. a) Cloud-top temperature or skin temperature if clear, b) Effective cloud amount, 0 mean clear, c) Cloud-top pressure in hPa, where clear FOV s are not plotted. The samples valid for 1000UTC December 19, 2001 are collected near ARM/CART site (marked with "") and nearby RUC20 grid points (marked with "+").*

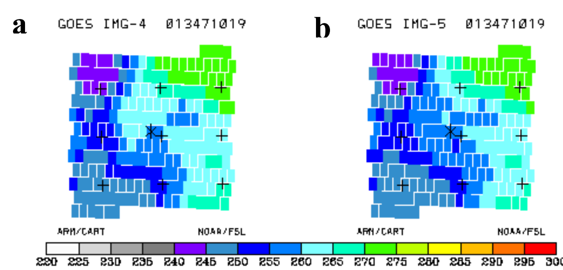

Fig.2 The brightness temperatures of GOES imager channel 4 (11 μm) and channel 5 (12 μm) at the ARM/CART site. The valid time is the same as Fig. 1 but measurement time is differ by 21 min, which we account as sampling error.

overlapping domain Ω_n such that $\int_{\Omega n} f_n(x)dx$ is the n^{th} fraction of N clusters of cloud. The sum of fractional probability density function is 1, and the expected value of the n^{th} fraction is $\int_{\Omega n} x f_n(x)dx$, which we consider as the representative value of the n^{th} fractional cloud coverage. In this application, the random variable is the brightness temperature, the density function is the histogram of relative frequency and the domain Ω spans within feasible limits, namely, between minimum and maximum brightness temperatures. The steps of adaptive clustering are;

1) Conversion of spatial data into relative frequency (density) histogram,
2) Applying kernel function until subsets are available,
3) Obtain number of subsets, their fractional value, and their corresponding representative radiance value,
4) Derive cloud-top height from the representative radiance values by using forward model.

Figure 3 shows an example of adaptive clustering applied to imager channel 4 data in Fig.2a. Imager pixel data are converted to relative frequency (density) within feasible domain bounded by 240 deg K to 280 deg K. The density function is smoothed enough to clearly identify distinctive sub-domains. Currently, we apply smoother until maximum five subsets are identified. If no clear subsets are identified, then we consider total sample mean as representative value. All the steps are done automatically.

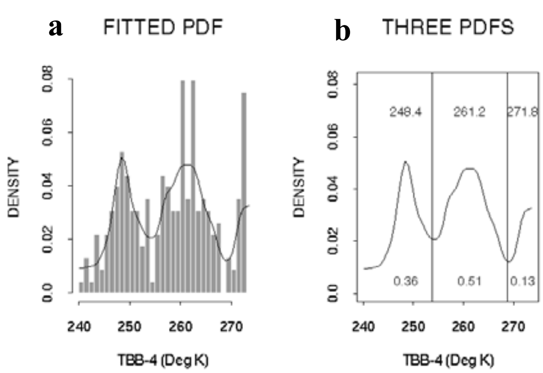

Fig.3 Example of adaptive clustering applied to imager Band 4 data in Fig.2a. a) The density histogram overlain with smoothed PDF. (b) Three PDFs determined by clustering. In this example, three groups are defined with representative brightness temperatures of 248.4, 261.2 and 271.8 deg K and with corresponding cloud fractional coverage of 0.36, 0.51 and 0.13.

Figure 4 is an example of adaptive clustering results using GOES channel 4 brightness temperatures for five days from 10 to 15 April 2002. The horizontal tic mark indicates representative cloud-top temperature, and the vertical bar stands for range of cloud-top temperature. Thus, more than one horizontal tic marks connected by vertical bar stand for multilevel cloud structure. Of course, fractional coverage for each horizontal tic marks are not plotted. This hourly time-series show clear cases (warm and single level, day 100 of the year), overcast case (cold and single level, 1200 UTC to 2000 UTC in day 103 of the year), and many multilevel structures in other times as indicated by vertical bar. Such multilevel structure, which is derived from fractional cloud information is added value to refine cloud assimilation (Kim and Benjamin, 2001) which picks a median value to represent a grid point value.

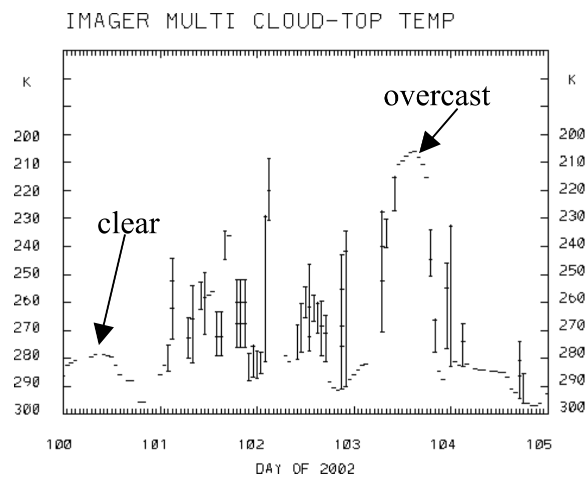

Fig.4 Five day time-series of hourly imager channel 4 brightness temperature data adaptively clustered to depict sub set. The vertical bar explains the range of cloud-tops and small horizontal tic marks stand for each representative cloud-top temperature. The small horizontal tic marks in warm temperature is clear case (day 100) and single bar in cold temperature is overcast case (day 103)

3. FORMULATION TO MERGE IMAGER AND SOUNDER DATA

We formulate a minimization procedure in which sounder radiance data are treated as observation, while cloud fraction and brightness temperatures from imager are used as a weak constraint. The formulation follows Kim (1996) except application is to GOES sounder and imager data. The linear regression formulation is,

$$y = X\beta + \varepsilon,$$

where ε is error, y is a vector whose elements are difference of computed clear radiances from measured radiance for selected sounder channels (currently we use sounder channels 7, 8 sensitive to the cloud). The design matrix, X has two column vectors whose elements correspond to difference of computed clear radiances from computed overcast radiances, and β is a column vector of vertically distributed cloud fraction whose error covariance is modeled as inverse of the multilevel cloud fraction matrix obtained from imager data. The imposition of constraint to the minimization of differences of computed and measured will give rise to constrained minimization, whose functional is defined by

$$J = \left\| y - X\beta \right\|^2 + \lambda \quad \beta^t \beta \, .$$

The solution to the functional is the constrained least squares estimator, which is vertically distributed cloud fraction, not the vertical distribution of effective cloud amount. The parameter λ can be obtained by generalized cross validation method (Wahba 1990), but for the reason of efficiency we use pre-determined value.

4. RESULTS OF AN EXPERIMENT

The experiment is carried with samples of GOES sounder and imager data collected from FSL's GVAR station. The verification of the result is made by comparing measured radiances with computed radiances with multilevel cloud assumption during the month of April 2002. We select the cases of multilevel clouds and compared the measured brightness temperatures (sample mean of sounder data from GVAR station) and computed brightness temperatures using estimated cloud fraction as described in previous section. Figure 5 is the scatter plots for channel 7 and 8, whose correlation coefficients are 0.81. There appeared to have some outliers which are under investigation.

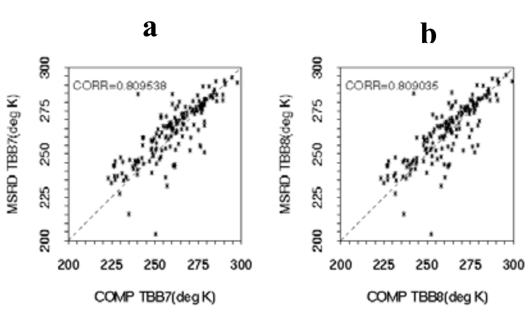

Fig.5 Scatter plots of measured brightness temperatures (sample mean of sounder data) and computed brightness temperatures using fractional clouds for a) Band 7, b) Band 8.

5. SUMMARY

Our experiment is designed to incorporate fractional cloud coverage obtained from the high spatial resolution imager data with sounder data. It is an extension of earlier experiment with simulated data to real data, which are prone to many errors. The mismatch of temporal sampling, i.e., 21 min difference can contribute outlier in Fig.5 due to high variability of clouds. Therefore, we plan to establish re-sampling of imager data to reduce representative errors.

ACKNOWLEDGMENTS

This research is supported by NASA/NOAA Joint Center for Satellite Data Assimilation. Authors acknowledge Dr. Devenyi for careful editorial review.

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