A Cloud Parameters Retrieval Algorithm in the Variational Assimilation System

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Abstract—**According to the past experience of retrieving cloud parameters, the assimilation of cloud-affected infrared radiances is a difficult problem in the numerical weather prediction. Based on our own four-dimensional variational assimilation (4D-Var) system's characteristics, we have designed our own cloud-affected infrared satellite radiances variational assimilation system which includes a one-dimensional variational assimilation (1D-Var) retrieval algorithm of cloud parameters. In this system, cloud parameters are considered as the intermediary to constrain the radiative transfer calculation after they are passed to our 4D-Var system. Consequently, acquiring the accurate cloud parameters is the key step of the assimilation of cloud-affected infrared radiances. This article analyzes the 1D-Var algorithm which is used to retrieve cloud parameters in our variational data assimilation system and validates the good performance of this method.**

Keywords-cloud parameters , 1D-Var, 4D-Var

I. INTRODUCTION

It shows that the globe is covered by cloud about 70% on average [1]. Therefore, in order to fully use the advanced infrared sounders (such as AIRS, IASI) data, we are in urgent need of improving the performance of assimilation of cloudy infrared radiances.

In the case of clouds, we need to obtain accurate distribution of Atmospheric Physics state under the clouds, and use the fast radiative transfer model to simulate the channel brightness temperature, all of which require providing with the cloud parameters. Cloud parameters include cloud top pressure (cloud top height), cloud top temperature, effective cloud fraction and effective cloud emissivity, etc. Cloud parameters are the initial input variables for radiative transfer model RTTOV (Fast Radiative Transfer for (A)TOVS), and they have significant impact on simulating brightness temperature with RTTOV.

Smith proposed a method which is called simultaneous physical retrieval (SPRM) [2], which can directly retrieve the parameters related to the channel brightness temperature by solving the multi-parameters functional integral equations. Later, Dong Huachao et al. improved the SPRM, Proposing a method called ISPRM algorithm, the synchronization of non-self-consistent physical model translates into a self-consistent simultaneous retrieved model, and the retrieval accuracy has significantly improved than the SPRM, especially in the surface and the bottom of the troposphere [3]. The most common method is the CO2 slicing technique which is proposed by Wylie [4], it could retrieve the cloud top pressure and cloud fraction only through the forward radiative transfer model calculations, and the compute cost is easy and fast. The CO2 channels are used for calculating the first guess of cloud top pressure and cloud fraction in a single field of view, but it does not allow retrieving the multi-layers clouds, and ignores the scattering, cloud spectral emissivity and so on. Eyre made a minimum residual method [5], which minimizes the difference between the observed radiance and the forward model radiance, then, estimates the cloud top pressure and effective cloud fraction. The disadvantage is that all events cannot return meaningful results, and low cloud cover does not apply. Another method is developed by the University of Wisconsin MLEV (Minimum Local Emissivity Variance), which is called the minimum local emissivity algorithm. It can use the high-resolution satellite observations, the cloud top height and 10-15μm infrared wavelengths Section effective spectral emissivity of single layer clouds can be simultaneously retrieved. It is ideal for the 0.25-1cm-1 hyper-spectral instruments [6].

However, as has been demonstrated, the profiles of temperature and humidity and cloud parameters can be simultaneously retrieved by 1D-Var, therefore the cloud parameters acquired by using the 1D-Var are more accurate than the methods listed above. In the numerical weather prediction system (NWP), infrared satellite radiances need a 1D-Var initial processing stage before they are transmitted into the 4D-Var data assimilation system. Thus, the sounders which are not convergent in the 1D-Var can be filtered out before they are passed to the 4D-Var, which constitutes the framework of the variational assimilation system, we call the method as two-step method (1D +4D-Var).

This paper presents the 1D-Var algorithm of retrieving cloud parameters, and uses it in our own 4D-Var system, then the cloud parameters are passed to the 4D-Var system, to constrain the radiative transfer calculations. Section 2 describes the radiative transfer model for cloudy radiance simulation with RTTOV93, presents the principle and the application of cloud parameters in it, Section 3 describes the 1D-Var and 4D-Var algorithms, and the application of cloud parameters in them. Section 4 shows some experimental results of the cloud parameter retrieval, and summarizes the advantages and disadvantages.

II. SIMULATION OF CLOUDY RADIANCES WITH RTTOV93

In order to implement the 1D-Var analysis, RTTOV93 should be able to represent the effect of cloud-affected infrared radiances in a simple way. Clouds are assumed to be

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single-layer, gray bodies, and the cloud thickness is ignored, too. So, cloud-affected radiance Lcld can be computed as follows:

$$L_{cld} = (1 - \mathrm{N_e}) L_{clr} + \mathrm{N_e} L_{cc}(\mathrm{p_c}) \tag{1}$$

Where Lclr is clear-sky radiance, Lcc is the radiance which is contributed by the opaque cloud layers, pc is cloud top pressure (cloud top height) ,Ne is the effective cloud fraction.

For calculating the simulated brightness temperature with the forward model, we should provide the surface temperature, surface pressure and cloud parameters to the RTTOV93 model. The tangent linear and adjoint model which are used for calculating the perturbation of cloud variables and gradient make up the lack of the simplified observation operator in the 4D-Var analysis.

Cloud parameters are set in two ways in RTTOV93: the first is a simple way, only cloud top pressure and cloud fraction should be provided; the second is more complex, because it involves the calculation of multiple scattering, needs to provide the data on each level.

III. VARIATIONAL ASSIMILATION ALGORITHM

A. 1D-Var algorithm

1D-Var is set up on the theory of Bayesian optimal estimation algorithm. Gives a background variable x0 (that is, a priori information), the background error covariance matrix B, observations y, the observation error covariance matrix R, analysis variable xa is the statistical optimal value, which is acquired by minimizing the difference between background and observation radiance：

y(x) represents the radiance which is simulated by the forward model with RTTOV93, where x is the input parameters of RTTOV93, which includes the cloud parameters.

Minimization of the cost function is created by an iterative process. The gradient value of the cost function is:

Superscript T is on behalf of matrix transpose, superscript -1 represents the inverse of the matrix. When▽J(x) =0, the cost function achieves minimization.

The minimization of J(x) uses the Marquardt-Levenberg (M-L) algorithm：

$$J(\mathbf{x}_a) = (\mathbf{x} - \mathbf{x}_0)^T \mathbf{B}^{-1} (\mathbf{x} - \mathbf{x}_0) + (\mathbf{y} - \mathbf{y}(\mathbf{x}))^T \mathbf{R}^{-1} (\mathbf{y} - \mathbf{y}(\mathbf{x})) \tag{2}$$

xn is the Nth-step estimation of atmospheric profiles (background profile is the first step estimation, i.e. x0), and Hn=▽y(xn),J' is the first differential of the additional cost function which is related to x, and evaluated at xn; J″ is the second differential. In this minimization method, γ changes as the degree of nonlinearity and the close degree to the expected solution.

1D-Var algorithm is as follows:

$$\nabla_{\mathbf{x}} J(\mathbf{x}) = \mathbf{B}^{-1}(\mathbf{x} - \mathbf{x}_0) + \mathbf{H}^T \mathbf{R}^{-1} (\mathbf{y} - \mathbf{y}(\mathbf{x})) \tag{3}$$

Step 1: Prepare the observation and background data and their error covariances; Note that the cloud top pressure and cloud fraction don't need background error covariance, and their error covariance is set to be very large acquiescently. This setting can ensure the cloud parameters can be effectively ignored in the background vectors once the cloud parameters are going to retrieve.

Step 2: Initialization. Read in control files, select M-L minimization algorithm, the maximum number of iterations is 10, and cloud parameters (cloud top pressure and the cloud fraction) should pay special attention to set to be retrieved. Initialize observation and background data; initialize RTTOV93 model and its coefficients files. Judge the initialized data is correct or not.

If (error), then stops running and gives the error message; Else, enter the step 3.

Step 3: Process the input data files. Read in the observations; convert the background profiles; generate simulated brightness temperature from the background profiles; use CO2 slicing technology to get better first guess of cloud properties;

If (normal), then go to step 4; Else, stop running！ Export the error message;

Step 4: Minimize the cost function.

a) Call RTTOV93, calculate the simulated brightness temperature and Jacobians;

b) Use the results from a), the interface of cost function is called, consequently acquires the cost function value; Call the minimization subroutine; select the M-L algorithm to calculate the minimum;

If (not convergence), go to step a), continue to calculate until convergence;

Else, directly gives the results (including the retrieved state vectors, retrieved brightness temperature et al.)

For the Numerical weather forecast system, the 1D-Var initial processing stage is made before the satellite radiance is passed to the 4D-Var system. If the sounders cannot be convergent in the 1D-Var stage, then they will be removed from the assimilation system.

B. 4D-Var algorithm and the application of cloud parameters in which

Maintaining the dynamic coordination in the whole time series analysis process is the basic idea of 4D-Var, it can use the observations which are distributed as the time, and it is to do the assimilation in a period of time. The cost function is defined as：

$$\mathbf{x}_{n+1} = \mathbf{x}_0 + [\mathbf{B}^{-1} + \mathbf{H}^T \mathbf{R}^{-1} \mathbf{H} + \mathbf{J}'' + \gamma \mathbf{I}]^{-1} \{\mathbf{H}^T \mathbf{R}^{-1} [(\mathbf{y} - \mathbf{y}(\mathbf{x}_n)) + \mathbf{H}(\mathbf{x}_n - \mathbf{x}_0)] - \mathbf{J}' + \mathbf{J}''(\mathbf{x}_n - \mathbf{x}_0) + \gamma(\mathbf{x}_n - \mathbf{x}_0)\} \tag{4}$$

Where subscript i represents the given observation time, which is distributed in time section [0,TN];Ri is the observation error covariance matrix at the ith time, B is the background error covariance matrix which is specified by the initial time; yi[xi] is the observation operator at the ith time; yi、xi is respectively observation and prediction amount of state vectors at the ith time and xi follows the equation xi=M0-i(x), （i=0,1, … n）,M0-i is the model forecast operator from start to the ith time.

The core strategy of assimilation of cloudy infrared satellite radiances in 4D-Var system is that, the analysis control vector is extended to include the cloud parameters, and estimate the cloud variables simultaneously with the temperature and humidity variables which are in the analysis field, consequently improves the accuracy of simulation of cloudy radiances with RTTOV93, and also improves the accuracy of cloud parameters and atmospheric parameters because of adding the infrared satellite data.

We can see from Fig.1, 1D-Var retrieved results which are considered as the intermediary in the 1D+4D-Var system framework, which is equivalent to provide a new observation type to the 4D-Var. Therefore, 1D-Var retrieval has directly impact on the quality of the final 4D-Var assimilation. 4D-Var is a more complex and extensive assimilation system, this paper focuses on the problem of 1D-Var retrieval cloud parameters algorithms, and the effectiveness of cloud parameters which are retrieved by 1D-Var. As for the 4D-Var system effectiveness, we discuss in detail later.

IV. THE RETRIEVAL RESULTS

We use a model profiles database which is obtained from 40 years reanalysis data at ECMWF(European Centre for Medium-Range Weather Forecasts) to make a AIRS cloudy brightness temperature simulation study. As follows are the results of cloud parameters retrieval and experimental study by 1D-Var. The cloud parameters first guess are acquired by the CO2 slicing technique. For each atmospheric profile, 324 brightness temperature channels is selected (a total of 2378 of the AIRS channels).

$$J(\mathbf{x}) = (\mathbf{x}-\mathbf{x}_0)^T \mathbf{B}^{-1}(\mathbf{x}-\mathbf{x}_0) + \frac{1}{2}\sum_{i=1}^{n}(\mathbf{y}_i-\mathbf{y}_i[\mathbf{x}_i])^T \mathbf{R}_i^{-1}(\mathbf{y}_i-\mathbf{y}_i[\mathbf{x}_i]) \quad (7)$$

In order to verify the retrieved effect of cloud parameters, we define Ne' is the maximum value of effective cloud fraction, dividing into different sections (0-0.2, 0.2-0.4, 0.4-0.6, 0.6-0.8, 0.8-1). Effective cloud top pressure pc', that is, defines as the lowest pressure where the profile of effective cloud fraction overruns 10% of its max, and dividing into four sections (0-400hPa, 400-600hPa, 600-800hPa, and 800-1050hPa).

TABLE I. THE CORRELATION BETWEEN PC' AND PC AT DIFFERENT NE' RANGES

Ne'	**0-0.2**	**0.2-0.4**	**0.4-0.6**	**0.6-0.8**	**0.8-1**
r(pc& pc')	0.59	0.62	0.69	0.71	0.78

Tab.1 shows that the case of thick cloud is better, such as 0.8-1, the correlation coefficient is larger, but retrieval skill becomes poorer as the effective cloud fraction decreases. This may result from that the multi-layer cloud structure is included in the context of thin cloud. Tab.2 reflects the correlation between Ne and Ne'. It shows that high cloud is better than the low cloud.

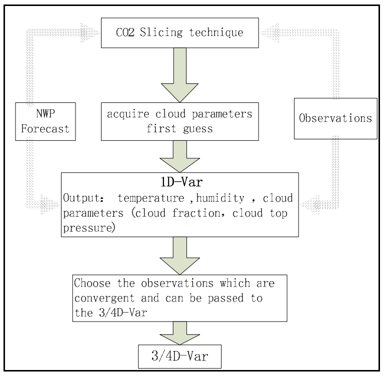

Figure 1. 1D+4D-Var assimilation frame-saw

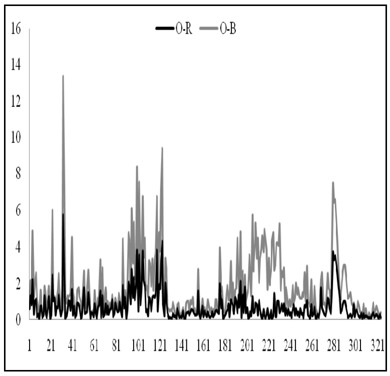

Figure 2. ｜O-B｜and｜O-R｜at different channels

In addition, we also analyze the 1D-Var retrieved brightness temperature to test the quality of the algorithm. Figure 2 shows the absolute difference values between observed brightness temperature (O) and the background brightness temperature (B) of a selected typically assimilation observation, and absolute differences values between observed brightness temperature (O) and the 1D-Var retrieved brightness temperature(R). Figure 2 illustrates that, absolute difference values of O-R are generally smaller than the absolute difference values of O-B during the selected 324 channels. This fully demonstrates that the 1D-Var algorithms is suited to retrieval of the cloudy brightness temperature, and it can be used for the assimilation of infrared satellite radiances.

TABLE II. THE CORRELATION BETWEEN NE AND NE' AT DIFFERENT PC' RANGES

pc'(hPa)	**0-400**	**400-600**	**600-800**	**800-1050**
r(Ne&Ne')	0.76	0.68	0.52	0.45

TABLE III. CORRELATION COEFFICIENT BETWEEN O AND R

	N	**Correlation coefficient**	**Sig.**
R&O	324	.999	.000

The 1D-Var retrieved brightness temperature and observed brightness temperature is one to one, in order to test the differences between them, we use a paired T test to analyze the quality of retrieved data. The correlation coefficient between observed and retrieved brightness temperature is 0.999 in Table 3, very close to 1, consequently, it is significantly correlated, indicating that the retrieved brightness temperature is very accurate. The results of paired T test are in Table 4, significant levels of sig is far greater than 0.05, indicating that difference between observed values and the retrieved values is very small, the 1D-Var retrieval performance is very well.

TABLE IV. PAIRED T TEST BETWEEN O AND R

R&O	**Mean**	**Standard deviation**	**Standard error of the mean**	**95% confidence interval difference**		**Sig. (bilateral)**
				Lower limit		
	0.0048	1.0637	0.0591	-0.1114	0.935	

V. SUMMARIES

Based on the 1D+4D-Var system framework, we designs our own variational assimilation system which is used for directly assimilating the cloudy infrared radiances, the observations are subject to a pretreatment by 1D-Var before they are passed to the 4D-Var system. The key of the assimilation system is the retrieval of cloud parameters, this paper mainly studies the problem of cloud parameters retrieval by 1D-Var. The retrieved effect is ideal when the cloud is high and thick. On the contrary, when the cloud is low or thin, the effect is not very well. But adding the 1D-Var cloud parameters retrieval algorithm into our own 4D-Var system is still very valuable.

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REFERENCES

[1] Wylie DP et al. Eight years of high cloud statistics using HIRS. J.Climate, 1999, PP:170–184.

[2] Smith W L et al.; Advances in Remote Sensing Retreval Methods. Ed.by A Deepak et al. , 1985, PP:221-232.

[3] Dong Huachao et al.; Test of the simultaneous physical retrieval method for cloud parameters and total precipitation amount. J.InfraredMillim.Waves, 1992, PP395-400.

[4] Wylie DP; Menzel WP; Woolf HM; Strabala KI; Four years of global cirrus cloud statistics using HIRS. J.Climate, 1994, PP1972–1986.

[5] Eyre JR.; Inversion of cloudy satellite sounding radiances by nonlinear optimal estimation. I: Theory and simulation for TOVS. Q.J.R.Meteorol.Soc, 1989, PP1001–1026.

[6] Guan Li et al.; Retrieval of cloud parameters using Infrared Hyperspectral observations. Chinese Journal of Atmospheric Sciences, 2007, PP1123-1128.