A Research of Four-dimension Variational Data Assimilation with ATOVS Clear Data

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Introduction

- More and more deduced atmospheric parameters from satellite data are used in numerical weather forecasting

- How to introduce radiances from satellite into numerical model

- 3D-VAR, 4D-VAR
Definition of cost function

\[ J(x) = J_b + J_s \]

\[ J_b = \frac{1}{2} (X - X_b)^T B^{-1} (X - X_b) \]

\[ J_s = \sum_i \sum_{ich} [F_i(x_{ich}) - y_{i,ich}^{obs}]^T (O + F)^{-1} [F_i(x_{ich}) - y_{i,ich}^{obs}] \]

Where \( X = (u, v, p', t, q) \) are all control variables
$F(x_{ich})$ is a fast transfer model to generate radiances.

In this test, RTTOV5 is used

$$L_{Clr}(v,\theta)=\tau(v,\theta)\varepsilon_s(v,\theta)B(v,T_s) + \int_{\tau_s}^{l} B(v,T) d\tau + (1-\varepsilon_s(v,\theta))\tau_s^2(v,\theta) \int_{\tau_s}^{l} \frac{B(v,T)}{\tau^2} d\tau$$

- Where $B(v,T)$ is Planck function
- $\tau_s(v,\theta)$ is transmittance from surface to space
- $\varepsilon_s(v,\theta)$ is the surface emissivity
the optical depth from each pressure level to space for each channel

\[ d_{i,j} = d_{i,j-1} + Y_j \sum_{k=1}^{K} a_{i,j,k} X_{k,j} \]

- \( a_{i,j,k} \) is regression coefficients
- \( Y_j \) and \( X_{k,j} \) are prediction factors
Data

- Operational TOVS data of NSMC in East Asia every day from May to August 1998

- Climatic profiles are used to represent atmospheric state from 100 hPa to 0.1 hPa for temperature and from 300 hPa to 0.1 hPa for water vapor
Confirmation of cloud-clear data

\[ T_{\text{skin}} - T_{b_{\text{ch8}}} = \begin{cases} < 10K & \text{clear} \\ > 10K & \text{cloudy} \end{cases} \]

\[ T_{\text{skin}} \] is the surface skin temperature

\[ T_{b_{\text{ch10}}} \] is brightness temperature of HIRS channel 8
Biases from computed cloud-clear radiances to satellite observations

[Bar chart showing data with units in K]
Biases from computed cloud-clear radiances to satellite observations

- **Daytime**
- **Night**
Horizontal distribution of simulated bias (K)

- simulated bias to channel 11 (left) and channel 12 (right)
Horizontal distribution of simulated bias (K)

- simulated bias to channel 6 (left) and channel 14 (right)
Horizontal distribution of simulated bias (K)

- simulated bias to channel 2 (left) and channel 17 (right)
1. smaller RMS errors of simulated brightness temperature from real observations are available after cloud clearing.

2. To channels for air temperature in upper atmosphere, the uniform simulated bias is available everywhere. To channels for water vapor and air temperature in lower atmosphere and channels for surface air temperature, similar uniform bias is obtained except in the area of Tibetan Plateau, where peak of simulated bias is demonstrated.
Conclusion(1)

3 STD at daytime and at night show a large bias in channels of 17-19 because of the impact of sun
Using 1D-VAR to get air temperature profile

- Forcing from satellite data

\[ J = \sum_{r=0}^{n} [T - T_B]^T B^{-1} [T - T_B] + [X_r(T, q) - y_r^{obs}]^T W_r [X_r(T, q) - y_r^{obs}] \]

- Variation of the forcing

\[ \delta J = 2 \sum_{r=0}^{n} F'_r(T, q) W_r [X_r(T, q) - y_r^{obs}] \cdot \delta Q \]
Weighting coefficients of assimilation variables

- Errors of HIRS data and the fast forward model are estimated

- Weighting coefficients are defined as the inverse of the square of these errors
While multi-variables are assimilated at the same time, scale of every variable must be considered.

- For instance, order of air temperature is about $1 \times 10^2$ and the order of water vapor is about $1 \times 10^{-3}$.

- Scaling factor $S_j = X_j^{\text{max}} - X_j^{\text{min}}$. 

**scaling factor**
Gradients test (TL)

The check to tangent linear model

\[ \Phi(\alpha) \equiv \frac{\|Q_r(z + \alpha h) - Q_r(z)\|}{\|\alpha P_r h\|} = 1 + O(\alpha) \]

\[ \alpha \cdot \left( \frac{\delta x}{\alpha} \right) \frac{(Forward (x + \delta x) - Forward (x))}{TL(\delta x)} = 1 \]
Gradients test(TL)

TL= -0.2828500366E+02

BRUTE FORCE: -0.2928326416E+02  0.1035292983E+01  1
BRUTE FORCE: -0.2839401245E+02  0.1003853917E+01  2
BRUTE FORCE: -0.2830657959E+02  0.1000762820E+01  3
BRUTE FORCE: -0.2836608887E+02  0.1002866745E+01  4
BRUTE FORCE: -0.2777099609E+02  0.9818275571E+00  5
BRUTE FORCE: -0.1525878906E+02  0.5394656658E+00  6
BRUTE FORCE: -0.3051757813E+02  0.1078931332E+01  7
Gradients test (AD)

The check to the adjoint model

\[ SumR = SumP \]

\[ SumR = \sum DBT \cdot \delta y_{random} \]
\[ SumP = \sum D Proof \cdot \delta x_{random} \]

\[ \delta x_{random} \xrightarrow{TL} DBT \]
\[ \delta y_{random} \xrightarrow{AD} D Proof \]

- SUMRAD = -0.1463224602E+02
- SUMPROF = -0.1463224697E+02
Convergence of cost function

(c) 白天、陆地

(d) 夜间、陆地
Assimilated air temperature
Biases from profiles of 1D-VAR to radio sounding data

(a) 00UTC

(b) 12UTC
4D-VAR

- Numerical model: MM5
- Central of the test domain: 25° N, 120° E
- Grid spacing: 45 km
- Total grids: 61*61
- Prediction period:
  - 12 UTC, July, 21, 2002 – 12 UTC, July, 22, 2002

- Fast transfer model: RTTOV5
4D-VAR

- Assimilation window: 2 hours
- Background data: T106 analysis fields
- Satellite data: HIRS cloud-clearing radiances
The flow of the 4D-VAR

First guess

Integration MM5:

Cost function: $J$

Adjoint of MM5 and RTTOV5

Gradients of cost function

semi-Newton algorithm

The final field: $(y_0)_p$

observations

new initial field

Whether the precision is satisfied
Channel selection

- Errors of these channels are independent for the pressure layers of the channels do not overlap

- Selected HIRS channels should be more than the number of vertical levels in MM5

- Errors of these channels should be less than a given value
Channel selection

- O$_3$ channel and short wave window channels (channel 17-19) are ignored

- Data from 9 HIRS channels are used to be involved in the data assimilation

- Channel: 2, 4, 6, 7, 8, 10, 11, 12, 13, 14, 15
How to select the independent satellite data

- In general, errors of sounding data should be independent to each other.

- The density of cloud-clear HIRS data are much more than the radio soundings.

- Every two or three HIRS observations are introduced into the data assimilation.
Gradients test

- Similar to the check to tangent linear model in HIRS 1D-VAR:

\[
\frac{\frac{TL}{AD} \left( x + \alpha \cdot \delta x \right)}{\left( \alpha \cdot \delta x \right)} = 1
\]
Gradients test

\[ \alpha_0 = 0.0000000E+00 \]
\[ \alpha_0 = 9.9999990E-05 \]

\[ I=1 \quad \alpha = 0.10000E-04 \quad F(A) = 0.1002861300E+01 \]
\[ I=2 \quad \alpha = 0.10000E-05 \quad F(A) = 0.9989470500E+00 \]
\[ I=3 \quad \alpha = 0.10000E-06 \quad F(A) = 0.1019896300E+01 \]
\[ I=4 \quad \alpha = 0.10000E-07 \quad F(A) = 0.9372019800E+00 \]
\[ I=5 \quad \alpha = 0.10000E-08 \quad F(A) = 0.5512952800E+00 \]
Geopotential height and streamline field on 500 hPa at 24th-hour (the control test: left; the assimilation test: right)
Air temperature and streamline field on 500 hPa at 24th-hour (the control test: left; the assimilation test: right)
Geopotential height and streamline field on 500 hPa at 24th-hour (the control test: left; the assimilation test: right)
Air temperature and streamline field on 500 hPa at 24th-hour (the control test: left; the assimilation test: right)
total 24-hours’ precipitation in control test (right) and assimilation test with satellite data (left)
Conclusion

Assimilation HIRS data from satellite could get certain improvement to numerical model prediction.

- The forecasted quantity of precipitation and the location of precipitation center are quite different from the results in control experiment.
- Due to the impact of cloud, meso-scale forecasting in cloud area could not get any change.
Work in the future

1. Introducing AMSU data into the 4D-VAR
2. Prolonging the length of assimilation window
3. Adding other satellite products, such as estimated precipitation, into the 4D-VAR
4. Testing other examples
Thank you!