Tuning of 3DVAR and its application to high-resolution radar data assimilation system

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Contents

- **1. Introduction**
- 2. Radar Data and WRF Model
- 3. 3DVAR Tuning
- 4. Grid Nudging and Increment Analysis Update
- **5. Initialization Experiments**
- 6. Summary and Conclusion

Introduction

- Heavy rainfall is one of the major severe weathers over East Asia producing devastating flash flood, and consequently causing fatalities and property damage. Heavy rainfall is usually resulted from individual mesoscale storms or mesoscale convective systems (MCSs) embedded in synoptic-scale disturbances (Lee et al., 1998).
- We need high-resolution observations and radar data assimilation techniques to understand the evolution and development mechanisms of mesoscale convective storms responsible for heavy rainfall and better predict heavy rainfall events.
- Assimilation of radar data is a key scientific issue in numerical weather prediction of convective systems for very short-range forecasting (Wilson et al., 1998). In recent years considerable progress has been made in the retrieval of boundary-layer winds from Doppler radar observations, the assimilation of radar observations into convective-scale numerical models for heavy rainfall prediction, and the assimilation of radar rainfall estimates.



- The objective of this study is to investigate very short-range forecasting of the WRF model through the 3DVAR data assimilation of Dual-Doppler radar data (radial velocity and reflectivity) for a heavy rainfall case accompanying mesoscale convective systems (MCSs) over the Korean Peninsula.
- The 3DVAR system is modified by tuning the scale lengths and observation error statistics. We compare the results of the increment analysis update (IAU) and the rapid update cycle (RUC) on the modified 3DVAR system.

Radar Data



Radar Information

WSR-88D(NEXRAD)			
Radar Beam	S Band (wave length : 10cm)		
Detection range	Reflectivity : 450 km Radial velocity : 240 km		
Format	Raw data Level II		

Model Configuration



Physics processes	domain 1 (30 km)	domain 2 (10 km)	domain 3 (3.3 km)	
Horizontal Dimensions	191 X 171	160 X 178	241 X229	
Time interval (Δt)	90 sec	30 sec	10 sec	
Cumulus Parameterization	Kain-Fritsch Kain-Fritsch scheme scheme		none	
Explicit moisture	Lin et al. scheme Lin et al. scheme		Lin et al. scheme	
PBL	YSU scheme	YSU scheme	YSU scheme	
Radiation	RRTM/ Dudhia scheme	RRTM/ Dudhia scheme	RRTM/ Dudhia scheme	
Surface-Land	Noah LSM	Noah LSM	Noah LSM	
Initial and Boundary data	NCEP / FNL analysis	NCEP / FNL analysis	NCEP / FNL analysis	

Data Assimilation Experiment

Tuning of 3DVAR (Version 2.1) and

its application to high-resolution radar data assimilation system.

- The current scale-lengths of background error (about 110 km for wind and 40 km for mixing ratio) are not proper for high resolution asynoptic observations such as radar and AWS.
- The average minimization ratio of cost function, about 25 %, suggests the further minimization possible by adjusting the observation errors.
- Development of a radar data assimilation system for Increment Analysis
 Update (IAU) and Rapid Update Cycle (RUC) with 3DVAR.

Tuning of Background Scale-lengths

The O-B (observation – background value) of radar data is calculated from two MCS cases and one frontal case. The O-B correlation decreases according to short distance. It means that the radar observation detects meso- as well as micro- scale phenomena. The locality of the radar reflectivity is higher than radical velocity

O-B Statistics



Scale lengths



- The locality of the radar observation can be reflected by tuning the scale length of the background error using a recursive filter.

- 9 km and 4 km of scale lengths are proper for radial velocity and reflectivity, respectively.

3DVAR Error Tuning

- The expectation value of the minimized cost function is given by a half of the effective number of observations (Desroziers and Ivanov, 2001)
- Further minimization of cost function is possible by scaling each cost function term to satisfy the expectation values of the minimized cost function term, respectively
- The adjustment of scaling parameters are iteratively done/

3DVAR Error tuning

To adjust the real cost function to the expectation value, scaling parameters (or error factors) will be applied to each cost function term and to each observation type, and determined iteratively.

$$J = \frac{1}{s_b^2} J^b + \frac{1}{s_o^2} J^o$$

$$s_{o}^{2}\Big|^{i+1} = \left(\frac{J^{o}\Big|^{i+1}}{E(J^{o})}\right) \qquad \qquad s_{b}^{2}\Big|^{i+1} = \left(\frac{J^{b}\Big|^{i+1}}{E(J^{b})}\right)$$

where *i* means iteration number. The estimation of $E(J^{o})$ and $E(J^{b})$ (Desroziers and Ivanov, 2002).

3DVAR Error Factors

Observation	Ρ	S(0)	S(1)	S(2)	S(3)
Radial Velocity	16820	1.00	0.72	0.69	0.68
Reflectivity	26977	1.00	1.95	1.95	1.95
Jb		1.00	1.04	1.11	1.13

The numbers of effective radar radial velocity and reflectivity are 16,820 and 26,977, respectively, and the tuning parameters of the observation error converge rapidly.

Impact of tuning on minimization



J/p for ideal: 0.5 J/p for untuned: 1.38 J/p for tuned: 0.53

The decrease in the cost function of the untuned 3DVAR and the tuned 3DVAR is 25 % and 64 %, respectively.

In particular, the ratio of the minimized cost function (J) and the number of used observation (p) is 1.38 and 0.53 for the untuned 3DVAR and the tuned 3DVAR, respectively.

Grid nudging and IAU for WRF

$$\frac{\partial \mu \chi}{\partial t} = F_{\chi}(\mathbf{x}, t) + \left\{ G_{\chi} W(\mathbf{x}, t) \mu \left(\chi - \chi_{anal} \right), \quad G_{\chi} \mu \chi'_{anal} \right\}$$

$$W(x,t) = (w_{\eta} \cdot w_{t}), G_{\chi}$$
: nudging coefficient

- For the grid nudging, we have implemented time-variant nudging (=1) and target nudging (=3)
- Surface (in planetary boundary layer) nudging (or IAU) is not yet implemented.
- The nudging of U, V, and T is currently tested.







6h accumulated rainfall amount (mm)





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Initialization Experiments

3-hr assimilation period with 1-hr update frequency and 6-hr forecast

Three initialization experiments are performed.

- UNTUNE : IAU with untuned 3DVAR increments
- RUC : RUC with tuned 3DVAR
- IAU : IAU with tuned 3DVAR increments

Initialization Experiments



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Heavy Rainfall Case (25 July, 2003)

6-h accumulated rainfall and time series



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Soundings at Kwangju



CAPE rapidly increased for 6 hours from 18 UTC 24 to 00 UTC 25 July. Mesoscale convective systems with 3 cells developed in the unstable environment.

Enhanced IR and Radar images





The initialization experiments are applied to an intense rainfall event accompanying MCSs that has three convective cells.



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Initial radar data (reflectivity and radial velocity)



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Increment Fields

UNTUNE



IAU



Water Vapor mixing ratio (g/kg) Wind vector (m/sec)

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Time-height section of area-mean u- and w- wind

UNTUNE



RUC



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504540353025201510 5 0 5 101520253035404550

Time series of hydrometeors





130 E

130 E

dBZ

a Ħ

dB7

эс

6h accumulated rainfall amount (mm)



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Time series of rainfall amount at maximum point



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Profile of u, v, RH and T at 00 UTC 25 July



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RMSEs of radial velocity



Conclusions

- In this study, radar data has much shorter scale-lengths in 3DVAR compared to the typical synoptic observations. The scale length is 9 km for redial velocity, and 4 km for reflectivity.
- The error factors show that the error for radial velocity (2 m/s) is overestimated (70 % of the currently used error), and that for reflectivity (5 dBZ) is underestimated (190 % of the currently used error). Therefore, the error factors rapidly converge within one iteration.
- In the radar data assimilation, the tuned 3DVAR improves the maximum rainfall amount that is in better agreement with observation than that of the UNTUNE. The RMSEs of the tuned 3DVAR (RUC and IAU) are also smaller than that of the untuned 3DVAR. It is necessary to tune the scale lengths for the 3 DVAR assimilation of radar data.
- Effectiveness of model forecast by the assimilation of radar data appear to be within 3~4 hours.







Grid nudging and IAU for WRF

Nudging

$$\frac{\partial \mu \chi}{\partial t} = F_{\chi}(\mathbf{x}, t) + \left\{ G_{\chi} W(\mathbf{x}, t) \mu \left(\chi - \chi_{anal} \right), \ G_{\chi} \mu \chi'_{anal} \right\}$$

 $W(x,t) = (w_{\eta} \cdot w_{t}), G_{\chi} : \text{nudging coefficient}$ ***** For grid nudging, we have implemented time-variant nudging (=1) and target nudging (=3)

- Surface (in planetary boundary layer) nudging (or IAU) is not yet implemented
- ***** The nudging of U, V, and T is currently tested



June 20, 2006



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3DVAR Error Tuning

 "a posteriori diagnosis on the minimized cost function to determine a priori parameters" (Desroziers and Ivanov, 2001).

Methodology of 3DVAR Error tuning

The expectation values of the observation and background components of a cost function are given by

$$E(J^{O}) = \frac{1}{2} (p - \text{Tr}(\mathbf{HK})) , \quad E(J^{b}) = \frac{1}{2} \text{Tr}(\mathbf{KH})$$

where *p* is the number of observations, H is the linearized observation operator, and K is the Kalman-gain matrix

$$\mathbf{K} = \mathbf{B}\mathbf{H}^T (\mathbf{H}\mathbf{B}\mathbf{H}^T + \mathbf{R})^{-1} = \mathbf{P}^a \mathbf{H}^T \mathbf{R}^{-1}$$
)

Methodology of 3DVAR Error tuning

The expectation value for the total cost function is given by a half of the number of effective observations (Desroziers and Ivanov, 2001).

$$E(J) = E(Jb) + E(Jo) = p/2$$

To adjust the real cost function to the expectation value, error factors will be applied to each cost function terms and to each observation types.

$$J = \frac{1}{s_b^2} J^b + \frac{1}{s_o^2} J^o$$

Methodology of 3DVAR Error tuning

Error factors are determined iteratively,

$$s_{o}^{2}\Big|^{i+1} = \left(\frac{J^{o}\Big|^{i+1}}{E(J^{o})}\right) \qquad \qquad s_{b}^{2}\Big|^{i+1} = \left(\frac{J^{b}\Big|^{i+1}}{E(J^{b})}\right)$$

where *i* means iteration number. The expectation values are computed using a randomized estimation of the trace of matrix, HK and KH (Desroziers and Ivanov, 2001).

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Radial velocity RMSE (m/s) 1

RMSE of radial velocity at 3.0 km

FCST Hour

RMSE of radial velocity at 3.5 km







RMSE of radial velocity at 4.5 km





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June 20, 2006