Application of the Tikhonov regularization method to wind retrieval from scatterometer data I. Sensitivity analysis and simulation experiments*

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Scatterometer is an instrument which provides all-day and large-scale wind field information, and its application especially to wind retrieval always attracts meteorologists. Certain reasons cause large direction error, so it is important to find where the error mainly comes. Does it mainly result from the background field, the normalized radar cross-section (NRCS) or the method of wind retrieval? It is valuable to research. First, depending on SDP2.0, the simulated 'true' NRCS is calculated from the simulated 'true' wind through the geophysical model function NSCAT2. The simulated background field is configured by adding a noise to the simulated 'true' wind with the non-divergence constraint. Also, the simulated 'measured' NRCS is formed by adding a noise to the simulated 'true' NRCS. Then, the sensitivity experiments are taken, and the new method of regularization is used to improve the ambiguity removal with simulation experiments. The results show that the accuracy of wind retrieval is more sensitive to the noise in the background than in the measured NRCS; compared with the two-dimensional variational (2DVAR) ambiguity removal method, the accuracy of wind retrieval can be improved with the new method of Tikhonov regularization through choosing an appropriate regularization parameter, especially for the case of large error in the background. The work will provide important information and a new method for the wind retrieval with real data.

Keywords: scatterometer, variational optimization analysis, wind retrieval, regularization method
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1. Introduction

Sea-surface wind which is directly associated with almost all the seawater motions is an important physical parameter of oceanography. Sea-surface wind is valuable for a number of meteorological and oceanographic applications including weather and wave prediction, climate and ocean modeling research. The scatterometer which can provide all-day and large-scale wind field information has become a main instrument to obtain sea-surface wind field. Up to now, the scatterometers which are ever onboard the satellite and used including the Seasat-A scatterometer system (SASS), the scatterometer (SCAT), the National Aeronautic and Space Administration (NASA) Scatterometer, the advanced scatterometer (ASCAT), and SeaWinds.[1−3]

For wind retrieval from scatterometer data, the SeaWinds data processor (SDP) has been developed within the satellite application facility for numerical weather prediction (NWP SAF), sponsored by European Organization for the Exploitation of Meteorological Satellites (EUMETSAT). The SDP processing chain contains five steps, these being preprocessing, inversion, quality control, ambiguity removal and quality monitoring. The input of the wind retrieval is the National Oceanographic and Atmospheric Administration (NOAA) SeaWinds level 2b Binary Universal Format Representation (BUFR) wind product, and it will output a wind product with different choices of resolution including 25 km, 50 km and 100 km.[4]

For calibrating the accuracy of the retrieved wind, the triple collocation method is introduced first by Stoffelen and Anderson.[5,6] This is a useful method for performing calibration and error estimation, but it needs to use three different winds, usually with in-situ, scatterometer and forecast model wind components. As is well known, the in-situ data is sparse for large-scale special region, it is difficult for us to obtain enough in-situ data; sometimes the accuracy is calculated on the assumption that the forecast model wind is the 'true' wind which will leads to a wrong error estimation of wind retrieval. Also, Lin[7] and Li *et al.*[8] have done some valuable researches in process of inversion and ambiguity removal.

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A number of ambiguity removal methods have been proposed. The widely used methods are the median filter and Two dimensional Variational (2DVAR). Henderson *et al.*[9] and Vogelzang *et al.*[10] presented a two-dimensional variationl method with a cost function consisting of seven terms for filtering and dynamical consistency. It is comparable to the median filter ambiguity removal technique when applied to data from the National Aeronautics and Space Administration (NASA) Scatterometer (NSCAT). Vogelzang *et al.*[10] validated the 2DVAR ambiguity removal method in SDP2.0 based on SeaWinds Scatterometer Data through a general statistical comparison with model forecasts and buoy observations for fair weather condition. However, the 2DVAR still has some problems including the effective statistics of background error covariance and the observation error covariance, and the accuracy matching problem of the observation and the background data.[11] Based on the inverse problem method, the Tikhonov regularization method is proposed to improve the 2DVAR method for ambiguity removal.

First, based on the software of SDP2.0 and the NRCS information in the BUFR data which is measured during the period of 0006-0052 UTC, 1 January, 2008,[12] the simulated 'true' NRCS is calculated through the Geophysical Function NSCAT2 on the assumption that the forecast model wind is the simulated 'true' wind. Then, the sensitivity analysis experiments are performed on the NRCS and the components (u and v) of background. In the sensitivity experiment of NRCS, the noise of simulated 'measured' NRCS is assumed to be proportional to the simulated 'true' NRCS and the noise proportion changes from 1% to 20%. In the sensitivity experiment of background, the noise of the components of background has standard deviation (SD) changing from 1.5 to 2.5. Then, two simulation experiments with different representative noises in NRCS and background are taken, and the new method of Tikhonov regularization is used to improve the 2DVAR ambiguity removal method. The Tikhonov regularization of inverse problem method can guarantee not only the exclusive solution, but also the stability of the calculation. It can improve the accuracy of wind retrieval through perfectly building the relationship between the background field noise and the observation field noise.[12−14] The method presented in this paper will afford a new feasible method of improving the accuracy in wind retrieval with real scatterometer data.

2. Configurations of simulated 'true' wind, 'true' NRCS and background wind

2.1. Configurations of simulated 'true' wind and 'true' NRCS

The Simulated scatterometer data in this paper is based on the BUFR SeaWinds scatterometer data in the period of 0006- 0052 UTC, 1 January, 2008 which include 29190 useful wind vector cells (WVCs). The useful WVCs consist of 4184 low speed (speed lower than 5 m/s) WVCs, 20589 middle speed (speed lower than 12 m/s, but higher than 5m/s) WVCs, and 4420 high speed (speed higher then 12 m/s) WVCs. The model forecast wind field in the data is regarded as the simulated 'true' wind, and the simulated 'true' NRCS field is calculated through applying the Geophysical model Function NSCAT2 to the simulated 'true' wind. Then, with the information about polarization, azimuth, incidence angle in every WVC and the rain flag formation in the measured BUFR data, different simulated BUFR data will be configured.

2.2. Configuration of simulated background wind

In the simulation experiment, the simulated background wind is configured by adding a noise to the simulated 'true' wind with the non-divergence constraint.[12] The noised simulated 'true' wind does not conform to the principle of non-divergence and the wind field retrieved from the scatterometer is the 10 m wind of the ocean surface which should conform to the principle of quasi-horizontal zero non-divergence for the fair weather condition, so the high quality background wind field must be formed with the non-divergence constraint. The non-divergence constraint is given by[12]

$$\frac{\partial u}{\partial x} + \frac{\partial v}{\partial y} = 0. \tag{1}$$

Supposing that the background field before the non-divergence constraint adjustment is $(\tilde{u}, \tilde{v})$ and the analysis field (the background field after the adjustment) is (u, v), with the variational optimization analysis method, the following equation can be obtained

as

$$\begin{cases} J[u,v] = \dfrac{1}{2}\displaystyle\int_{\Omega} \left[(u-\tilde{u})^2 + (v-\tilde{v})^2\right] \mathrm{d}x\mathrm{d}y = \min!, \\ \dfrac{\partial u}{\partial x} + \dfrac{\partial v}{\partial y} = 0. \end{cases} \tag{2}$$

This is a conditional variational problem. By introducing the Lagrange operator, the target functional of Eq. (2) can be re-written as

$$\begin{aligned} J^*[u,v] = & \int_{\Omega} \left[\frac{1}{2}(u-\tilde{u})^2 + \frac{1}{2}(v-\tilde{v})^2 \right. \\ & \left. - \lambda(x,y)\left(\frac{\partial u}{\partial x} + \frac{\partial v}{\partial y}\right)\right] \mathrm{d}x\mathrm{d}y \\ = & \min! \end{aligned} \tag{3}$$

$\delta J = 0$ yields

$$\begin{cases} u = \tilde{u} - \dfrac{\partial \lambda}{\partial x}, \\ v = \tilde{v} - \dfrac{\partial \lambda}{\partial y}, \end{cases} \quad \text{or} \quad (u,v) = (\tilde{u},\tilde{v}) - \nabla\lambda. \tag{4}$$

In Eq. (4), λ is calculated from the Passion equation

$$\begin{cases} \Delta\lambda = \dfrac{\partial \tilde{u}}{\partial x} + \dfrac{\partial \tilde{v}}{\partial y}, \\ \lambda|_{\Gamma} = 0, \end{cases} \tag{5}$$

with $\lambda(x,y)$, the analysis field (u,v) can be obtained from Eq. (4) by using the relaxation iterative method. Furthermore, the generalized variational analysis method can also be used to remove the noise influence on configuring the background field.[15]

3. Sensitivity analysis experiments

The error of retrieved wind is caused not only by the wind retrieval method, but also by the observed NRCS and the background wind field. For finding the effects of 'measured' NRCS and background field on the accuracy of retrieved wind, the following sensitivity analysis experiments will be conducted: first, the no-noise experiment is performed on the assumption that the simulated background field and the simulated 'measured' NRCS both have no noise, and the result of the experiment indicates that the SDP2.0 has a high accuracy for wind retrieval with scatterometer data; then, the sensitivity analysis experiments to the NRCS and components of background are carried on to reveal the effects of different factors on the wind retrieval.

3.1. No-noise experiment

The no-noise experiment is based on the assumption that the simulated background field equals the simulated 'true' wind field and the simulated 'measured' NRCS equals the simulated 'true' NRCS.

The simulated BUFR data of this experiment is put into wind retrieval, then the wind speed, the wind direction and the components (u and v) of retrieved wind are obtained. The mean values (MSs) and the root mean squares (RMSs) of the differences in speed and direction between the retrieved wind and the simulated 'true' wind are shown in Table 1.

Table 1. MSs and RMSs of the no-noise experiment.

	speed V/(m/s)	direction θ/(°)	u/(m/s)	v/(m/s)
MS	0.04867	2.08189	0.14154	0.15273
RMS	0.08823	4.56706	0.22591	0.21425

Table 1 shows that the MSs and the RMSs of speed and components (u and v) are all small, but those of direction are relatively large. The main reason for the larger direction error is caused mainly by the numerical calculation method of inversion. In the inversion of wind retrieval, the maximum likelihood estimator method will result in 144 ambiguous solutions with the multiple solution scheme (MSS). Directions of the 144 ambiguous solutions lie in a range from 0° to 360° evenly, and ambiguity removal process will select only one of the solutions as the 'true' wind, so the accuracy of direction will not be very small. For example, if the direction of the true wind is 181°, the best retrieved direction which is closest to the true solution can only be 180°, thus a one-degree difference in direction still exists. In summary, the MS and the RMS of the retrieved wind are small enough which powerfully indicate that the SDP2.0 is suitable for wind retrieval with scatterometer data.

3.2. Sensitivity analysis experiment of NRCS

The sensitivity analysis experiment of NRCS is on the assumption that the simulated background field is the simulated 'true' wind field and the simulated 'measured' NRCS is configured by adding a proportional noise (δ) to the simulated 'true' NRCS. The noise lies in a normal distribution, and δ changes from 0.01 to 0.2.

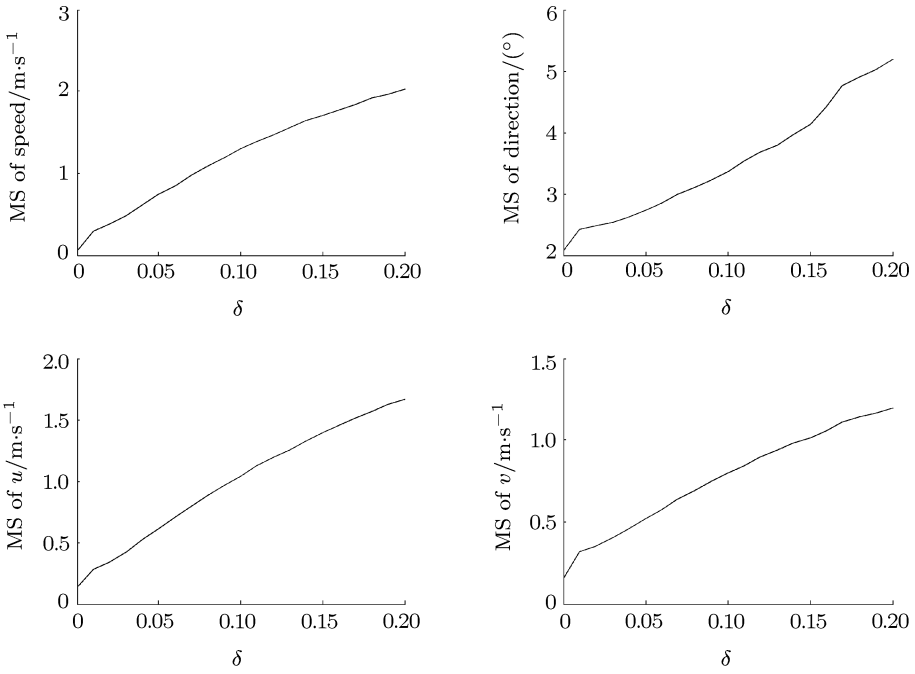


Fig. 1. Curves for MS versus the value of proportional noise δ in the sensitivity analysis experiment of NRCS.

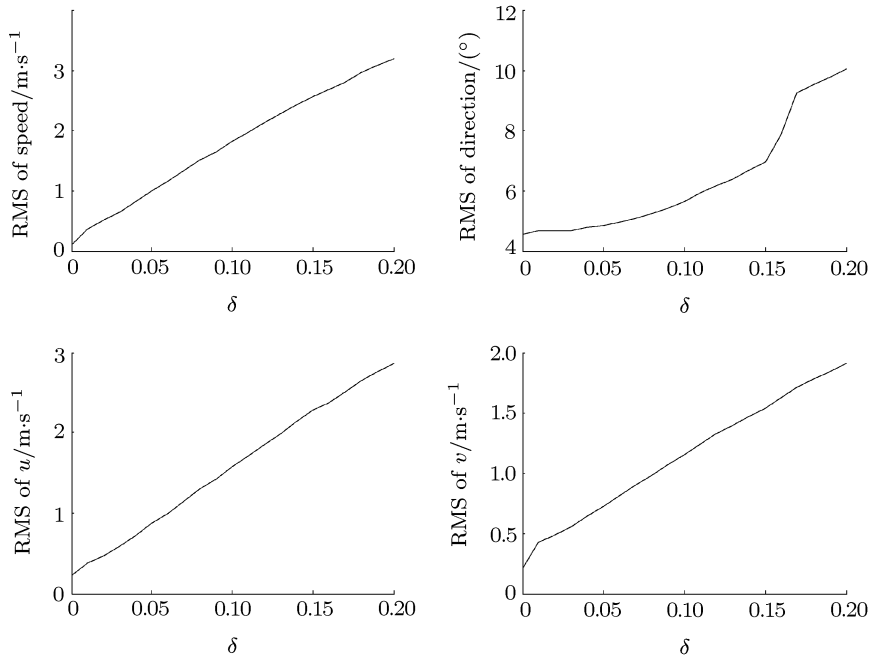


Fig. 2. Curves for RMS versus the value of proportional noise δ in the sensitivity analysis experiment of NRCS.

This is to say, the simulated 'measured' NRCS has a proportional noise of 1%–20% compared with the simulated 'true' NRCS. Supposing that the noise distributions of the four simulated 'measured' NRCSs in a WVC are all the same, the noise of the j NRCS in i WVC can be written as

$$\text{disturb}(i,j) = \text{Sigma0}(i,j) * \delta * \text{randn}(i), \quad (6)$$

where the disturb(i,j) represents the noise of the j simulated 'measured' NRCS in the i WVC, the Sigma0(i,j) denotes the j simulated 'true' NRCS in the i WVC, and randn(i) is the i noise function value which lies in a normal distribution.

The simulated BUFR data of this experiment is put into wind retrieval, then the wind speed, the wind direction and the components (u and v) of retrieved wind are obtained. The relations of MS and RMSs of the differences in speed and direction between the retrieved wind and the simulated 'true' wind to the value of proportional noise (δ) are shown in Figs. 1 and 2.

Figures 1 and 2 show that the MS and the RMS increase linearly as the value of proportional noise increases while the number of WVCs with effective retrieved wind decreases when the value of proportional noise increases. When noise proportional value increases to 0.2, the number of WVCs reduces almost 13.4%. The reason is that the large noised NRCS has been removed by the quality control. In other words, the noise of the simulated 'measured' NRCS not only influences the accuracy of wind retrieval, but also determines the number of the WVCs which can be retrieved.

3.3. Sensitivity analysis experiment of background components

The sensitivity analysis experiment of background components is on the assumption that the simulated 'measured' NRCS equals the simulated 'true' NRCS and the u, v components of the simulated background field are configured by adding a noise with non-divergence constraint. The noise lies in a normal distribution and has a standard deviation (SD) σ changing from 1.0 to 2.5.

The simulated BUFR data of this experiment is put into wind retrieval, then the wind speed, wind direction and the components (u and v) of retrieved wind are obtained. The relations of MSs and RMSs of the differences in speed and direction between the retrieved wind and the simulated 'true' wind to the noise standard deviation σ are shown in Figs. 3 and 4.

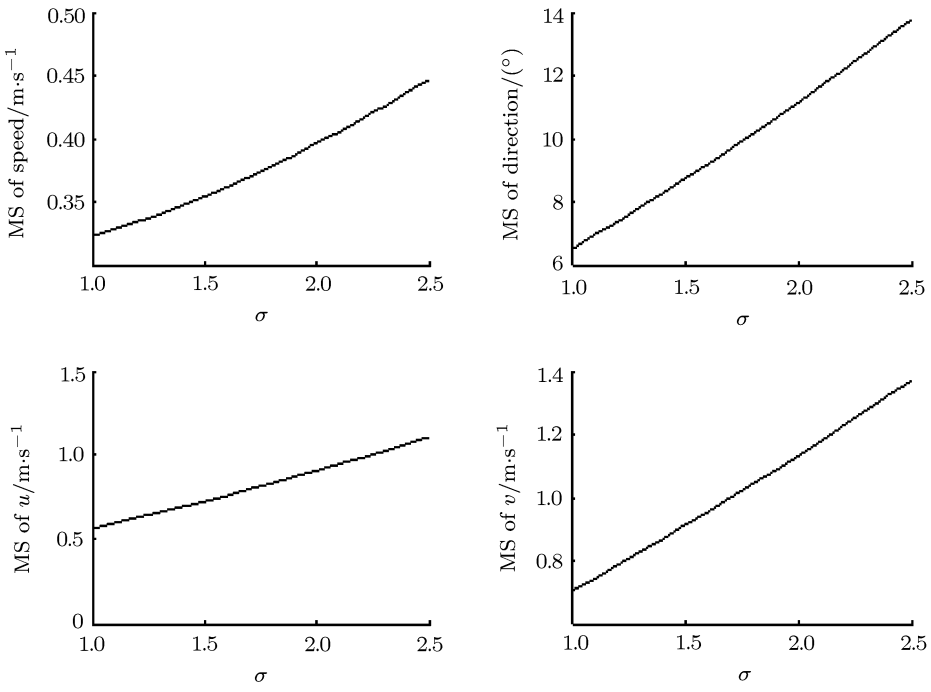


Fig. 3. Curves for MS versus SD for the sensitivity analysis experiment of background components.

Figures 3 and 4 show that the MSs and the RMSs of speed, direction, u andv components all increase linearly as the SD increases, but the MS and the RMS of v component are larger than those of u component. This is to say, the v component of the retrieved wind is more sensitive to the noise of the simulated background

field. The noises of u and v components all influence the accuracy of retrieved winds strongly, so the background field is very important in wind retrieval.

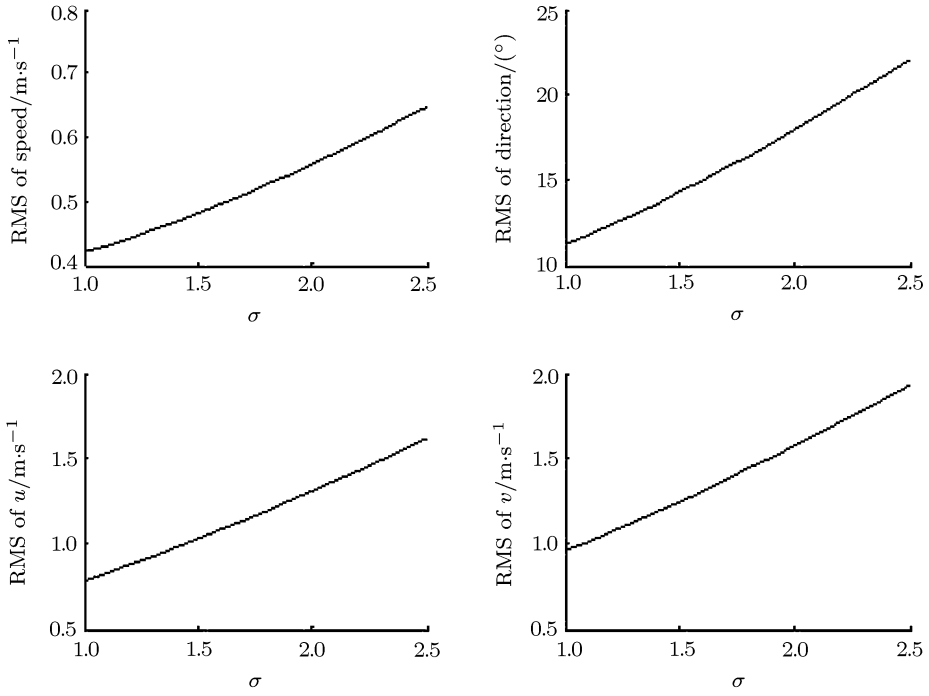


Fig. 4. Curves for RMS versus SD for the sensitivity analysis experiment of background components.

From the sensitivity analysis experiments of NRCS and background components, it is clearly that the experiment on u and v components with an SD of 2.5 m/s (the noise smaller than 10%) results in larger MS and RMS than the experiment of NRCS with a value of proportional noise of 10%. In other words, the accuracy of retrieved wind is more sensitive to the noise of background field, but the noise of the NRCS determines the number of the WVCs from which useful wind can be retrieved.

4. Simulation experiments and regularization method improvement

Stoffelen pointed out[16] that the statistical properties of error in the components of wind were much simpler than in wind speed and direction. There are two reasons. Firstly, although the difference in SD of speed depends weakly on actual wind speed, the difference in SD of wind direction shows a strong variation with wind speed. Secondly, the simple error distribution of the components of background will cause complicated distributions of speed and direction errors. For example, assuming that the errors of the components are $\Delta u = \Delta v = 2.25$ m/s, since $V = (u^2+v^2)^{1/2}$ and $\phi = \arctan(u/v)$, the distributions of wind speed and direction errors are quite complicated. So, the noise is added to the components of wind field but not the speed and direction in order to configure the simulated background in the following simulation experiments. The pre-launch specification for the NRCS error is a proportional error of 10%.

In the first simulation studies of Stoffelen,[16] noise with a normal distribution was added to the components of simulated 'true' wind with a SD of 2.25m/s in order to configure the simulated background, and to the NRCS with a SD of 10%, which is proportional to the signal, in order to configure the simulated 'measured' NRCS. As a matter of fact, they found that both the NRCS noise and the background noise were both overestimated, the noise in the wind components should be ∼1.5m/s and the noise in NRCS should be close to 5%.

Simulation studies with the above two different noise assumptions in configuring the simulated background field and the simulated 'measured' NRCS are

conducted, and the new method of Tikhonov regularization is used in ambiguity removal and compared with 2DVAR.

4.1. Regularization method

The regularization method was proposed first by Tikhonov to solve the ill-posed problem in mathematic inverse problem research, and now is widely used in many areas including retrieval from satellite data.[12,17] The regularization method is closely related to the variational problem.

Now , we consider a problem of

$$Kx = y. \tag{7}$$

Given the observations of y^δ such that it satisfies

$$\left\|y^\delta - y\right\| < \delta, \tag{8}$$

where δ represents the error of observations, and the $\|\|$ is a predefined norm. By using the least squares method, the solution of x can be obtained through

$$\min\ J(x) = \left\|Kx - y^\delta\right\|. \tag{9}$$

The solution of Eq. (9) is not unique for some cases. To select one solution from the possible solutions, a penalized part which is called the Tikhonov functional is always added to the minimization function, and the cost function is[12]

$$\min\ J(x) = \left\|Kx - y^\delta\right\|^2 + \gamma \left\|x - x_b\right\|^2, \tag{10}$$

where γ is the Tikhonov regularization parameter, and x_b is the first guess of x.

The biggest difference between the regularization method and the 2DVAR is that the regularization method needs to add a regularization parameter to the stable function part of the cost function in order to make the solution more reliable. The cost function of regularization method for scatterometer wind retrieval can be expressed as

$$J(x) = J_0\left(v_0^i, \delta x\right) + \gamma J_b(\delta x), \tag{11}$$

where $J_0 = \left\|Kx - y^\delta\right\|^2$ is the observation cost function, $J_b = \left\|x - x_b\right\|^2$ is the background field term, and v_0^i is the vector of scatterometer retrieved wind vector solutions

$$\delta x = (x - x_b) = \begin{pmatrix} u \\ v \end{pmatrix}, \tag{12}$$

with u being the west-to-east component of the wind, and v the south-to-north component.

From the knowledge of regularization inverse method,[17] the accuracy of retrieved wind will first increase as γ increases, and when the value of γ exceeds a particular value, the accuracy will decrease; but there still exists a case where the accuracy will go to a certain value as γ increases to infinity. In other words, this is a problem about how to choose the best regularization parameter.

4.2. Simulation experiment I

In the simulation experiment I, noise with a normal distribution is added both to the components of simulated 'true' wind with a SD of 2.25 m/s and to the simulated 'true' NRCS with a SD of 10% in order to configure the simulated background and the simulated 'measured' NRCS. After the variational adjustment with non-divergence constraint, the simulated background wind field is used together with other information in origin BUFR data to configure the simulation experiment I BUFR data. Then, the simulated BUFR data are put into wind retrieval by using the new method of Tikhonov regularization, and then the wind speed, the wind direction and the components (u and v) of retrieved wind are obtained. The MSs and the RMSs of the differences in speed and direction between the retrieved wind and the simulated 'true' wind changing with the Tikhonov regularization parameter γ are shown in Figs. 5 and 6.

Figures 5 and 6 show that the MSs and the RMSs of direction and components all decrease first and then increase as the Tikhonov regularization parameter increases, and that the best regularization parameter is obvious but not for the MS and RMS of speed. The RMS of speed seems go to a certain value as the regularization increases, and there still exists the lowest point at $\gamma = 60$, which is because the speed changes very little. Although the lowest points of speed, direction and components are different, it is still easy to choose $\gamma = 4.5$ as the best regularization parameter and the accuracy of the retrieved wind is improved compared with that obtained from the 2DVAR method ($\gamma = 1.0$).

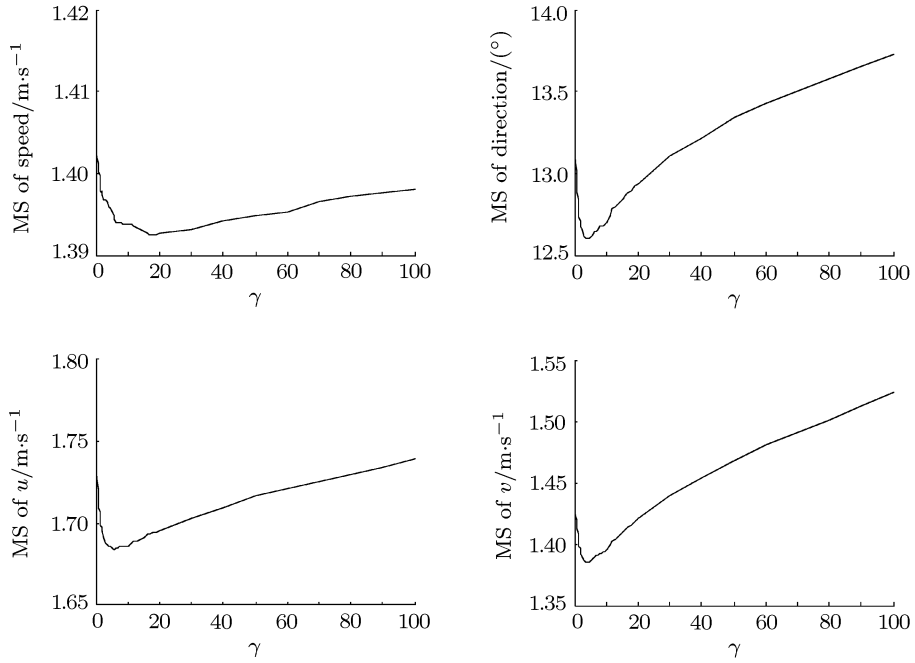


Fig. 5. Curves for MS versus Tikhonov regularization parameter in the simulation experiment I.

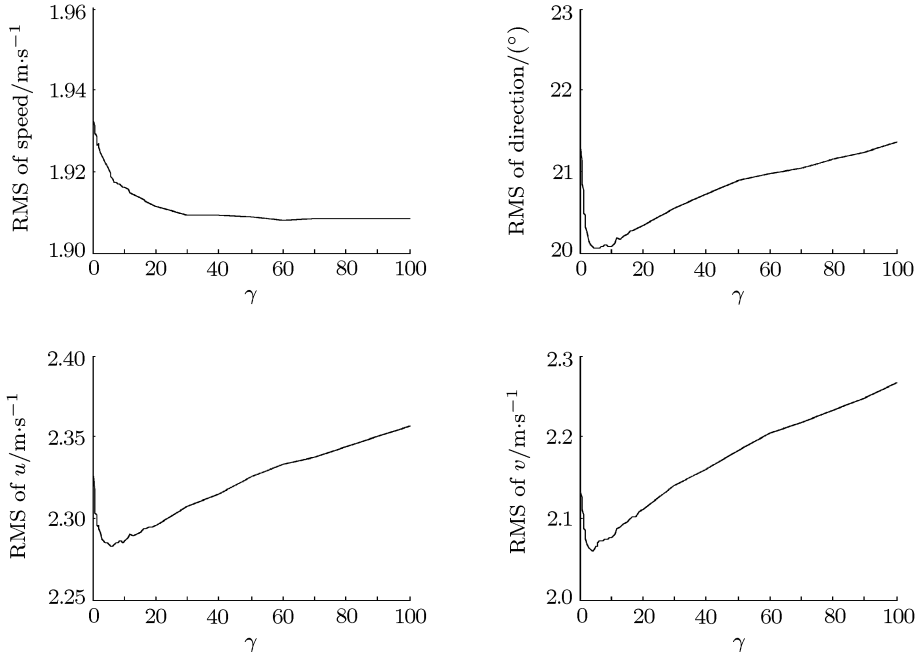


Fig. 6. Curves for RMS versus Tikhonov regularization parameter in the simulation experiment I.

4.3. Simulation experiment II

In the simulation experiment II, the simulated BUFR data configured are similar to those in simulation experiment I, but the SDs of the noise in simulated backgournd and simulated 'measured' NRCS are 1.5 m/s and 5%, respectively. Then, the simulated BUFR data are put into wind retrieval by using the new method of Tikhonov regularization, and then the wind speed, the wind direction and the components (u and v) of the retrieved wind are obtained. The MSs and RMSs of the differences in speed and direction between the retrieved wind and the simulated 'true' wind changing with the Tikhonov regularization parameter γ are shown in Figs. 7 and 8.

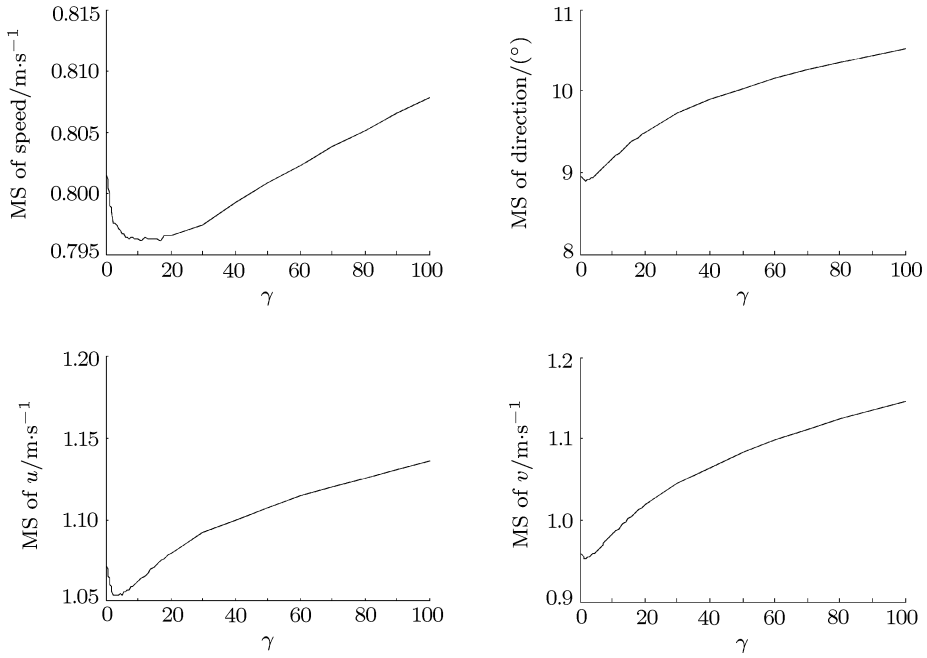


Fig. 7. Curves for MS versus Tikhonov regularization parameter in the simulation experiment II.

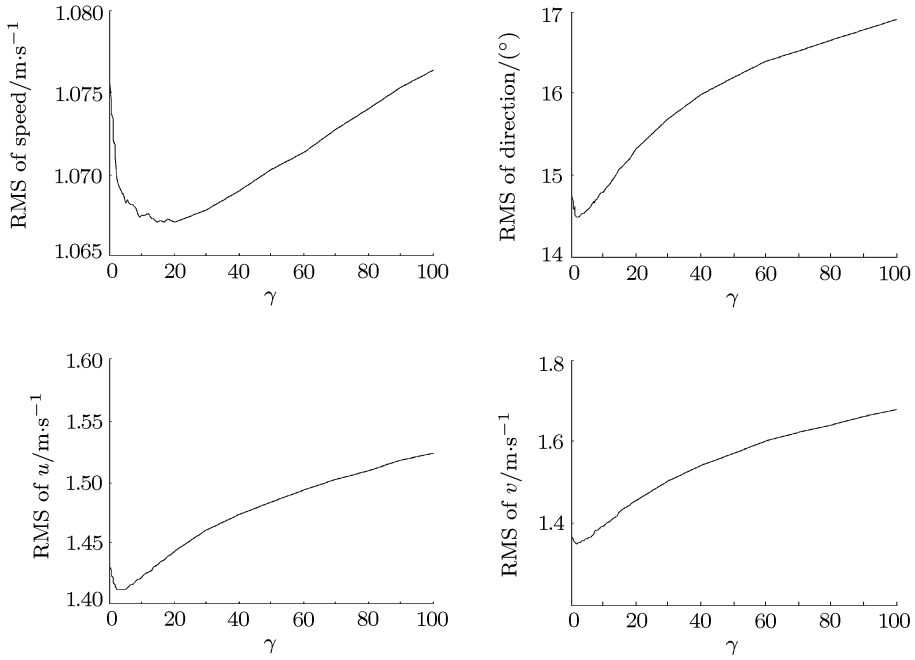


Fig. 8. Curves for RMS versus Tikhonov regularization parameter in the simulation experiment II.

Figures 7 and 8 show that the MSs and the RMSs of speed, direction and components all decrease first and then increase as the Tikhonov regularization parameter increases, and that the best regularization parameter is obvious. When the MS and the RMS reach the lowest points, the responding regularization parameter is the best regularization parameter. Although the lowest points of speed, direction and components are different, it is still easy to choose $\gamma = 2.5$ as the best regularization parameter.

From the simulation experiments I and II, the results show that when the accuracy of wind retrieval reaches the highest value, the Tikhonov parameters of the two experiments are both not equal

to 1(the 2DVAR method). So, compared with the 2DVAR, the Tikhonov regularization ambiguity removal method can improve the accuracy of wind retrieval through setting an appropriate regularization parameter (which is 4.5 in experiment I, and 2.5 in experiment II). The best regularization parameter of experiment II is lower than that of experiment I, this is to say, as the noise of background field and measured NRCS decrease, the Tikhonov regularization parameter has a tendency to decrease. And the larger the background error (experiment I), the more prominent will the improvement of the regularization method be, with the regularization parameter chosen appropriately.

Note: in simulation experiments I and II, the error of background components and measured NRCS are assumed to have the same normal distributions. The experiments with different normal error distributions are also taken, of which the results make no big difference.

5. Conclusion

Based on the software of SDP2.0, the simulated 'true' NRCS is calculated through the Geophysical model Function NSCAT2, and on the assumption that a forecast model wind is the simulated 'true' wind. Then, the sensitivity analysis experiments are performed on NRCS and the components (u and v) of background wind field. The results show that the accuracy of wind retrieval is more sensitive to the noise of background than that of the NRCS. After this, two simulation experiments are conducted with different representative errors in simulated 'measured' NRCS and the simulated background, and the new method of Tikhonov regularization method is used to improve the accuracy of ambiguity removal, which is 2DVAR in SDP2.0. The results of the simulation experiments show that when the regularization parameter is chosen appropriately, the accuracy of wind retrieval will be effectively improved compared with that obtained from the 2DVAR method, and the improvement is more obvious when the error of background is large. In order to choose an optimal regularization parameter in the real data wind retrieval, we still need to do more studies. The work in this paper will afford valuable information about how to improve the accuracy of wind retrieval with real scatterometer data.

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