Aerosol Retrieval from Remote Sensing Image Using Artificial Neural Network

Houmao Wang
Yantai Institute of Coastal Zone Research
Chinese Academy of Sciences
Yantai, China
maomao318_2006@126.com

Jiakui Tang
Yantai Institute of Coastal Zone Research
Chinese Academy of Sciences
Yantai, China
jktang@yic.ac.cn

***Abstract*--The usual method of aerosol retrieval using remote sensing is interpolation of look-up-table (LUT), but it is too time-consuming. However, artificial neural network for nonlinear problem has been not applied widely for aerosol retrieval before. In this paper, aerosol optical depth (AOD) is retrieved using two methods: interpolation and neural network. Then, the retrieval capabilities of the two methods were compared. By comparison, not only is the retrieval error of the neural network within acceptable range, but also it can reduce much processing time.**

Keywords- Aerosol optical depth; remote sensing; look-up-tables;artificial neural network; interpolation

I. INTRODUCTION

Aerosol is a suspension of fine solid particles or liquid droplets in air, such as smoke, oceanic haze and air pollution etc. As one of atmospheric constituents, aerosol changes climate of the earth and has non-negligible effects on human activities.

Aerosol particles play important roles in climate system of the earth [1,2] and the hydrological cycle[3]. They significantly influence the Earth's radiation balance by scattering and absorbing solar radiation. Beside, aerosol fine particles are also harmful to human health [4]. Toxic heavy metals, acid oxide, and organic pollutants borne in PM_{10} (Particulate Matter with diameter smaller than 10μm) and $PM_{2.5}$ of aerosol total suspended particles can infect human lungs easily [5]. Finally, aerosol particles make air cloudy and blur remote sensing images. A great number of studies reveal that PM_{10} and $PM_{2.5}$ can reduce the visibility of air [6] and change apparent reflectance of satellite as a part of path radiance. Therefore, effective information of aerosol retrieval is also essential to satellite imagery atmospheric correction [7].

AOD is an exponent which represents the attenuation rate of solar radiant energy passing through aerosphere. It is an important physical quantity of atmospheric turbidity and a key factor of aerosol climatic effects. Currently, two approaches are adopted to derive AOD: ground-based detection and remote sensing retrieval. The former can derive detailed AOD and properties by sun spectrophotometer, but only acquires point data in space. The latter can provide the spatial and temporal resolution to measure the inhomogeneous aerosol fields. To date, remote sensing of aerosol over homogeneous surface, like ocean, using satellite data has been used in large quantity. However, over heterogeneous surface, like desert, it has been not mature enough yet.

Now, a method of the most popular AOD retrieval over land is Dark Dense Vegetation (DDV) [7]. It is used by National Aeronautics and Space Administration (NASA) for MODIS data with the linear correlation of surface reflectance between optical and infrared channels. In retrieval method, AOD is retrieved by interpolation of LUT founded by atmospheric radiative transfer model (6s) which is a nonlinear model. However, interpolation of LUT is too time-consuming.

Artificial neural network is a mathematical model that tries to simulate the structure or functional aspects of biological neural networks. It can simulate non-linear model and learn data automatically. It is composed of many artificial neurons connected with other ones and processes information using a connectionist approach. Neurons are the basic processing unit of neural network. They generally are nonlinear devices of multi-input and single-output. Each neuron takes input data from prior one, and then output data determined by the response function of the weighted input data.

To date, based on neuron model, dozens of neural networks have been contrived, such as perceptron [8], Back Propagation network (BP) [9], Radical Basis Function network (RBF) and Hopfield network [10] etc. These networks have been used for many fields such as pattern identification, signal processing, intelligent control and function approximation etc [11].

Artificial neural networks have an ability of approximation of any function with at least three layers (input, hidden and output layers). Among them, RBF network has the best approximation point, so its capability of approximation is higher than others, and it can make approximation completely [12]. However, when the sample data increases greatly, number of RBF hidden layer neuron is much higher than the former, and the structure of RBF network will become much more complex. Therefore, the memory of general computer machine may not meet the needs. In this paper, the training sample is very large, so AOD is retrieved using BP network which also has a strong capability of approximation function.

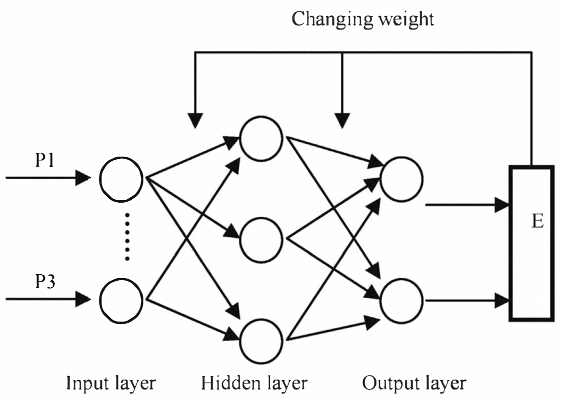


Fig.1 BP network structure. P1 and P3 are input parameters. E is error of root mean square.

Back Propagation network is a multilayer forward neural network based on error anti-propagation. It includes at least three layers. As the same layer nodes without coupling, outputs of each layer only influence outputs of the next layer nodes. So BP network can be considered as nonlinear mapping from input to output. The general structure is shown in Fig. 1.

BP network based on gradient descent method can learn nonlinear problem with training input and output data. If output layer of BP network can not get an expected export, it will switch to back propagation to return information of error and alter the weight of each hidden layer automatically. Then, it switches to propagate forward again to get new information of error. The two processes are operating repetitively until the output values of the network reach certain accuracy in comparison with training data.

In this paper, based on LUT which is founded by atmospheric radiative transfer model (6S), AOD is retrieved using interpolation and BP network respectively (section Ⅱ). Section Ⅲ provides the comparison of retrieval AOD with the true AOD which is derived from atmospheric radiative transfer model. Section Ⅳ gives the results of comparison and further studies.

II. RETRIEVAL OF AOD

A. *The second simulation of the satellite signal in the solar spectrum model(6S model) and look-up-table*

6S model simulates the path of sunlight photons from extra-atmosphere passing through the atmosphere, reaching the ground surface and reflected back to remote sensors. The input parameters of 6S are divided into six parts as follows:

a) Date and geometric conditions.

b) Atmospheric mode.

c) Aerosol model and AOD at 0.55μm.

d) Spectral and remote sensor.

e) Height of remote sensor and target.

f) Surface reflectance.

If the parameters above are known, apparent reflectance can be calculated automatically and LUT will be founded. LUT is composed of solar zenith angle (Asol), relative azimuth angle(Phi0), azimuth angle(Avis), surface reflectance(Ro) and apparent reflectance(Refet). Based on the LUT, AOD can be retrieved using interpolation and BP network.

B. *Retrieval of AOD*

1) Interpolated retrieval.

Based on LUT, we can derive AOD using procedure of Lagrange interpolation written using Fortran. In this paper, it is called inter-AOD.

2) BP network retrieval

a) BP network including two hidden layers using matlab is founded. The statement is as follows:

net_1=newcf (minmax(P1), [10,10,1], {'tansig', 'tansig', 'purelin'}, 'trainlm')

where tansig is transfer function of hidden layer, purelin is transfer function of output layer, trainlm is learning algorithm and 10 is the number of hidden layer nodes.

b) The normalization of training sample is carried out.

c) The BP network is trained using matlab. The statements are as follows:

```
net_1.trainParam.show = 50;
net_1.trainParam.lr = 0.05;
net_1.trainParam.mc = 0.9;
net_1.trainParam.epochs = 1000;
net_1.trainParam.goal = 1e-4;
```

Then, the trained network is simulated and MSE=0.00233.

d) Next, the weight and threshold of BP network are saved.

e) Finally, AOD is retrieved using trained BP network. In this paper, it is called ANN-AOD.

Fig.2 shows the steps of retrieval process.

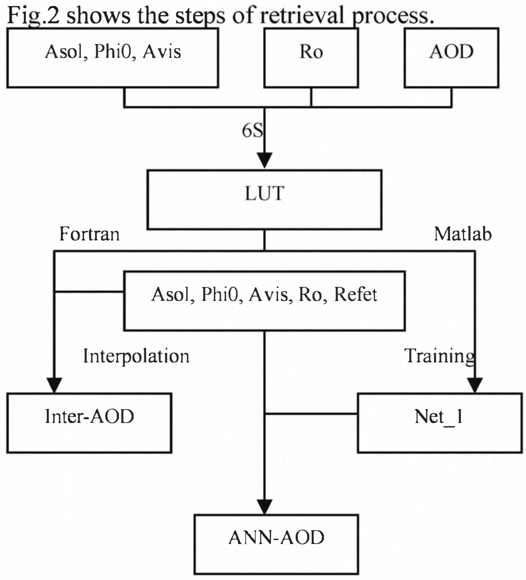


Fig.2 the flowchart of AOD retrieval

3) *Acquisition of true AOD*

In the case of other parameters known and fixed in 6S model, one AOD is corresponding to one apparent reflectance. If inter-AOD is acquired, it will be centered in an interval of 0.2 with a step 0.001. Therefore, two hundred AODs can be obtained and apparent reflectance can be calculated by 6S with the 200 AODs. Among calculated apparent reflectance, there must be one that is almost equal to the apparent reflectance as an input parameter for interpolation. The AOD which is corresponding to the one (apparent reflectance) is called as true AOD.

III. ANALYSIS OF AOD ERROR

As five variables determining AOD: Asol, Phi0, Avis, Ro and Refet, the accuracy of retrieval AOD is described by changing one variable and fixing the remaining four variables (Table I).

Fig.3 and Fig4 are scatter-plots showing the comparisons of AOD and errors of AOD retrieved by two methods with the true AOD. Shown in the two figures, the conclusions are as follows:

1) The approximations of the two methods are both precise enough, though interpolation is a little better than BP network overall. Maximum absolute error of inter-AOD is 0.02, while ANN-AOD is 0.04. Provided that true AOD is 1, the relative error just is 2% and 4% respectively, while the current retrieval accuracy of AOD is 20% generally. Therefore, the retrieval errors of both are within the allowable range.

2) Interpolation method approximates the true value by linear relationship in each interval, so the precision depends on the interval number in LUT. As Lagrange theory is adopted in interpolation, retrieval accuracies of the two endpoints of interval determine the accuracies of other points of the interval directly. When true AOD is not linear with variables, parts of approximation will be poor and errors are volatile (Fig.4). If higher precision is needed, the time of founding LUT must be prolonged because more intervals in LUT are needed. When the true AOD is an almost linear relationship with variable, the error of approximation of two methods will be less fluctuant (Fig.3).

3) Interpolation method is time-consuming, while using neural network is timesaving. For example, to a 400 × 400 remote sensing image, interpolation requires 12 ~ 14 hours, while training neural network only needs 1 ~ 2 hours. Besides, once the model is trained successfully, it can be used many times.

Therefore, neural network has great potential for aerosol remote sensing. Not only is its retrieval precision allowable, but also it can save much time. However, the method has some limitations as follows:

1) It is not very easy to train an appropriate network. For one thing, with large sample data, some algorithms of neural network such as RBF can not be used for training. Besides, apparent reflectance calculated by 6S varies irregularly in LUT, which increases the difficulty of training network and lowers the retrieval precision.

2) Even with the same sample data, the training results of neural network may be not the same as different training times or goals. Therefore, neural network training by matlab is unstable.

IV. CONCLUSION AND FUTURE WORK

The precision of ANN-AOD with the maximum relative error of 4% is much less than the current aerosol retrieval accuracy (20%). The error is within allowable range. Besides, neural network is much more timesaving with interpolation requiring 12 ~ 14 hours, while training neural network just 1 ~ 2 hours.

Although the results showed that the neural network retrieval has a good precision, further studies should be done in future: Neural network will be used for AOD retrieval in specific areas and the results will be compared with the measured AOD or satellite data. Meanwhile, the method of training network will be proposed to get better precision.

ACKNOWLEDGMENT

The work described in this paper is supported by the projects “Aerosol Retrieval Using Remote Sensing Data Over Costal Zone Based Grid Technology” supported by NSFC, China (40801124), "Subject database of remote sensing information in coastal environment (INFO-115-C01-SDB4-17)", “Research on key remote sensing technologies of coastal environment” and “Research on Novel Data Oriented SVM for Remote Sensing Information Extraction” supported by CAS, CHINA.

REFERENCES

[1] Tegen I., Lacis A.A., Fung, I., 1996. The influence on climate forcing of mineral aerosols from disturbed soils. Nature 380, 419–422.

[2] Duce, R.A., 1995. Sources, distributions, and fluxes of mineral aerosols and their relationship to climate. In: Charlson, R.J., Heitzenberg J. (Eds.), Aerosol Forcing of Climate. Wiley, New York, pp. 43–72.

[3] Houghton, J. T., Y. Ding, D. J. Griggs, M. Noguer, P. J. van derLinden, X. Dai, K. Maskell, and C. A. Johnson, Eds., 2001: Climate Change 2001: The Scientific Basis. Cambridge University Press, 944 pp.

[4] Samet, J. M., F. Dominici, F. C. Curriero, I. Coursac, and S. L.Zeger, 2000: Fine particulate air pollution and mortality in 20 US Cities, 1987–1994. New Engl. J. Med., 343, 1742–1749。

[5] Waldman J M, Lioy P J, Zelenka M, et al. Winter-time measurements of aerosol acidity and trace lelments in Wuhan city in central China[J]. Atmosphere Environmental, 1991, 25B(1),113-120

[6] B. R. Appel, Y. Tokiwa. Visibility as related to atmospheric aerosol constituents. Atmos. Environ. , 1985 , 19 (9) : 1525 – 1534

[7] Kaufman, Y. J., & Tanre′, D. (1996). Direct and indirect methods for correcting the aerosol effect on remote sensing. Remote Sensing of Environment, 55, 65– 79.

[8] Rosenblatt F., 1962, Principles of Neuro-dynamics: Perceptrons and the Theory of Brain Mechanisms, Washington, DC: Sprtan.

[9] Rumelhart, D. E., and J. L. McClelland, (1986). *Parallel Distributed Processing*, MIT Press, Ch. 8, pp. 318-362.

[10] J. Hopfield, "Neural networks and physical systems with emergent collective computational abilities", *Proceedings of the National Academy of Sciences of the USA*, vol. 79 no. 8 pp. 2554-2558, April 1982.

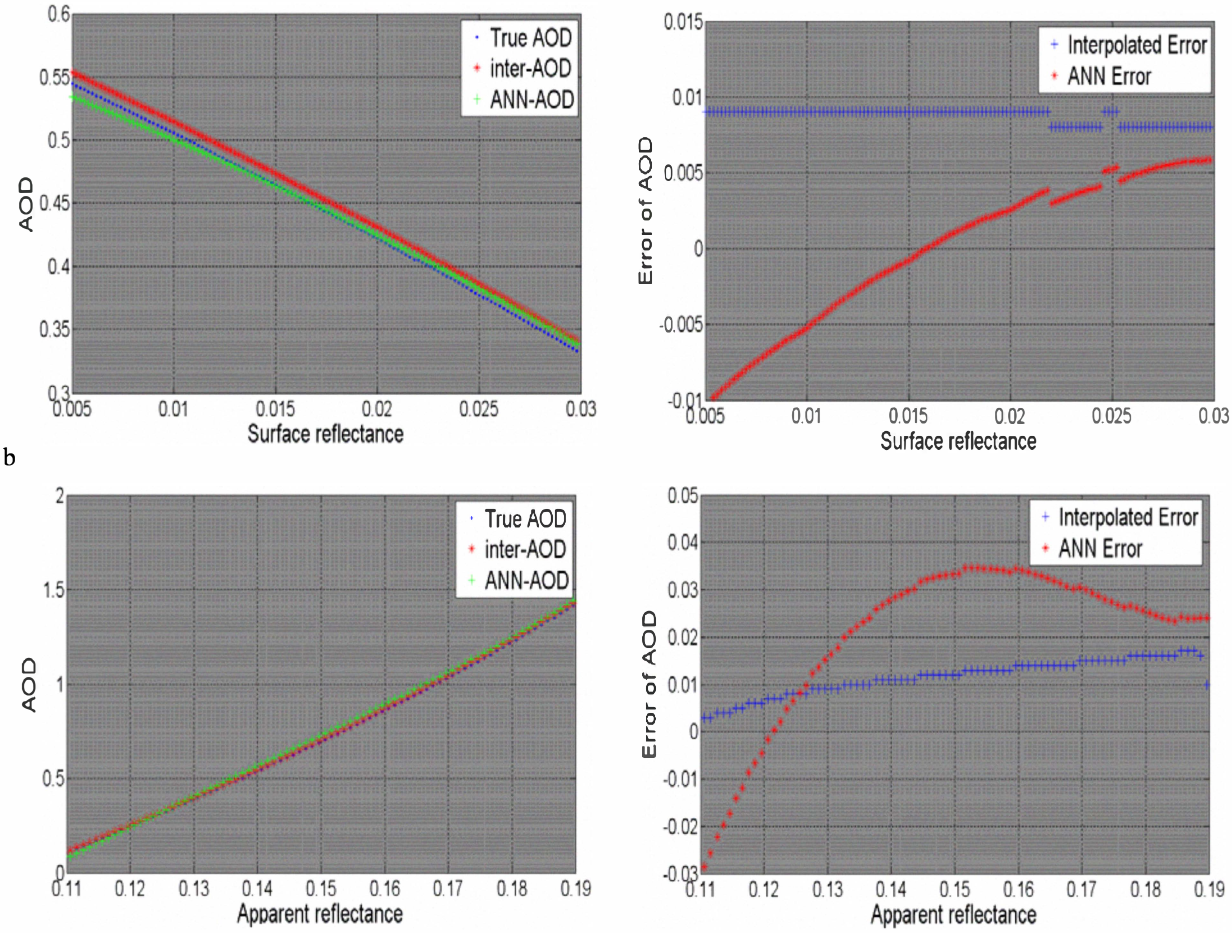
[11] Widrow, B., Rumelhart, D., and Lehr, M. A., 1994, Neural networks: Applications in industry, business, and science, Commun. ACM, 37(3):93-105

[12] Jooyoung Park, Irwin W. Sandberg. Approximation and Radial-Basis-Function Networks. Neural Computation March,1993, Vol. 5, No. 2, Pages: 305-316

TABLE Ⅰ. INPUT PARAMETERS OF RETRIEVAL AOD

variables	Ro	Asol/degree	Phi0/degree	Avis/degree	Refet	Error of AOD
Ro	0.005~0.03	28	18	28	0.1246	Analysis 1
Asol	0.032	1.0～84.0	18	28	0.1246	Analysis 2
Phi0	0.032	28	0.0～178.0	28	0.1246	Analysis 3
Avis	0.032	28	18	1.0～84.0	0.1246	Analysis 4
Refet	0.032	28	18	28	0.11～0.1896	Analysis 5

a



(1) (2)

Fig.3 horizontal ordinate for surface reflectance(a), apparent reflectance(b) and vertical coordinate for AOD.
(1): blue lines represent true AOD, and red lines inter-AOD, green lines ANN_AOD.
(2): blue lines represent interpolated retrieval error and red lines ANN retrieval error.

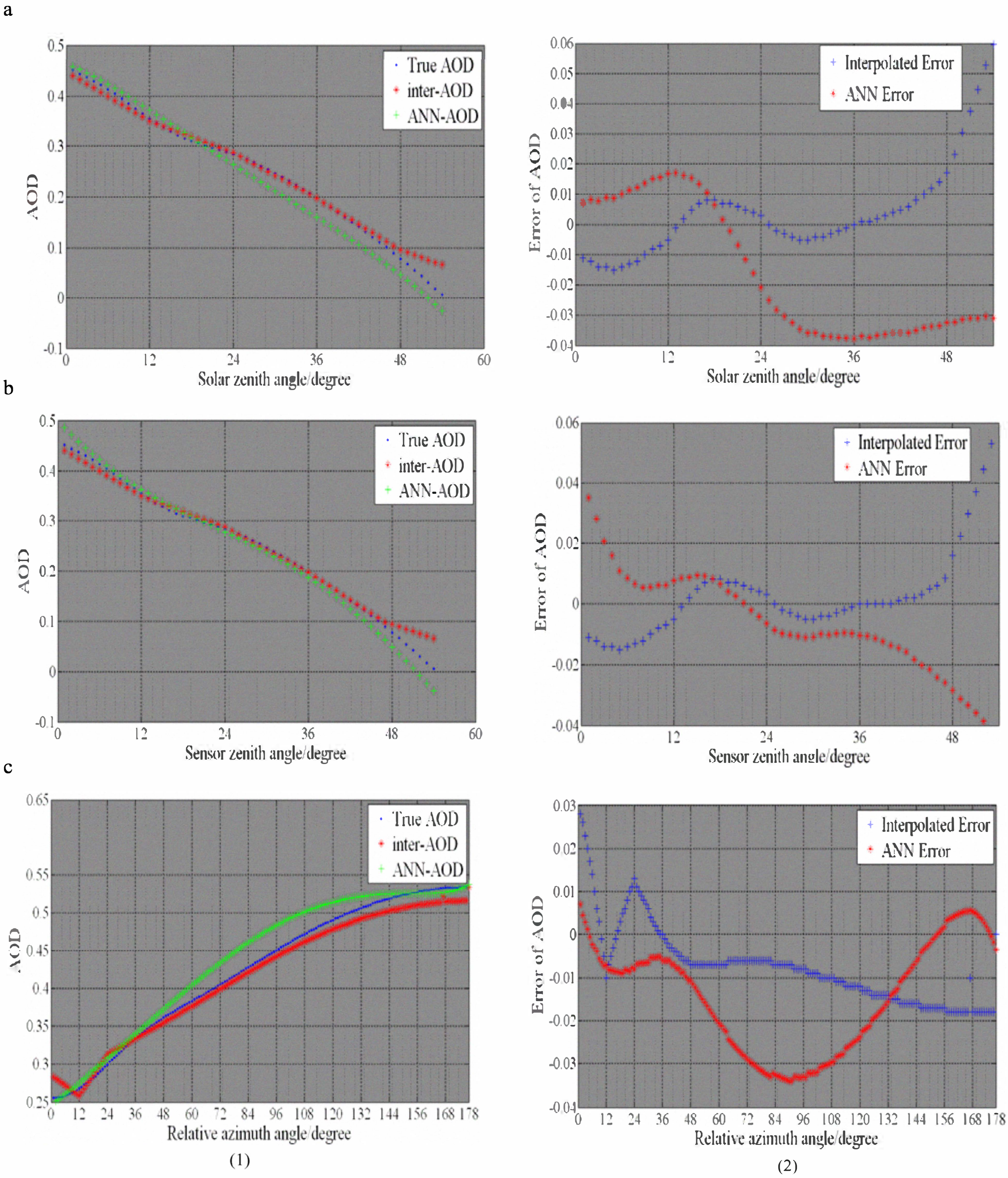


Fig.4 Horizontal ordinate for the solar zenith angle(a), sensor zenith angle(b), relative angle(c) and vertical coordinate for AOD.
(1): blue lines represent true AOD, and red lines inter-AOD, green lines ANN_AOD.
(2): blue lines represent interpolated retrieval error and red lines ANN retrieval error.