Development and validation of neural network based ionospheric tomography

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Abstract

In order to investigate the dynamics of ionospheric phenomena, perform the 3-D ionospheric tomography is effective. However, it is the ill-posed inverse problem and reconstruction is difficult because of the small number of data. The Residual Minimization Training Neural Network (RMTNN) tomographic approach proposed by Ma et al. [3] has an advantage in reconstruction with sparse data. They have demonstrated few results in quiet conditions of ionosphere in Japan. Therefore, we validate the performance of reconstruction in the case of disturbed period and quite sparse data by the simulation and/or real data in this paper.

1. Introduction

Recently, understand the behavior of the ionospheric electron densities becoming increasingly important for not only academic purposes but also practical application. In order to investigate the dynamics of ionospheric phenomena, perform the 3-D ionospheric tomography is effective. As the ionospheric total electron content (TEC) is an integrated value of the ionospheric electron density along ray path between a GPS satellite and a ground receiver, reconstruction of the electron density distribution from a set of TEC values is a form of computerized tomography (CT). However, it is the ill-posed inverse problem, so accurate reconstruction is difficult because of the small number of data. In the past, various algorithms for ionospheric tomography have been proposed [1, 2]. These methods require an ionospheric model and/or a large amount of data for computation, although model-free reconstruction is essential in the case of disturbed ionospheric problems. Moreover, to application for the region where exists low amount of ground GPS receivers, capability of reconstruction with sparse data is necessity. In this paper, the Residual Minimization Training Neural Network (RMTNN) tomographic approach is selected [3]. TEC data with location and altitude derived by ground based GPS receivers and ionosonde are used for the method. This approach has an advantage in reconstruction with sparse data. However, validation of the performance for practical use is not enough. We validate the performance of reconstruction in the case of disturbed period and quite sparse data.

2. Ionospheric tomography using a neural network

The residual minimization training neural network (RMTNN) is a multilayer neural network that is trained by minimizing an object function composed of an appropriately prepared residual of equations [4]. In this method, we reconstruct three-dimensional ionospheric electron density distributions as a computer tomographic image by using the ability of a multilayer neural network system to approximate an arbitrary function.

A slant TEC [5] along a ray path between a GPS satellite and a ground receiver is defined as the integrated value of ionospheric and plasmaspheric electron density, including instrumental bias, as follows:

$$I_i^j = \int_{r_i}^{r^j} N(\vec{r})ds + B_i + B^j \tag{1}$$

where I_i^j is the slant TEC, $N(\vec{r})$ is the electron density, and B_i and B^j are the instrumental bias of the ith ground receiver and the jth satellite bias, respectively. In order to determine $N(\vec{r})$, which represents the electron density at a position $\vec{r}$, a neural network is constructed. The input parameter of the proposed neural network is $\vec{r}$, and the output is $N(\vec{r})$. In order to evaluate the residuals of the integral equation, the equation is discretized as

$$I_i^j \approx \sum_{q=1}^{Q} \alpha_q N(\vec{r}) + B_i + B^j + P_i^j \tag{2}$$

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where q and α denote a sampling point and the corresponding weight for the numerical integration, respectively, Q is the total number of sampling points on a ray path, and P is the contribution of the plasmaspheric electron density to the slant TEC I. We herein define altitudes of 100 to 700 km as the ionosphere and altitudes above 700 km as the plasmasphere modeled by the simple diffusive equilibrium model [6]. In order to estimate the electron density $N(\vec{r})$, we take the squares of the residuals of the above integral equations as the objective function of the neural network. The objective function $E1$ is given as

$$E1 = \sum_{q=1}^{Q} (\alpha_q N(\vec{r}) + B_i + B^j + P_i^j - I_i^j)^2 \tag{3}$$

The disadvantage of ionospheric tomography using the ground GPS receivers is the difficulty in obtaining sufficient vertical resolution due to a lack of paths. In order to solve this problem, we use information on the peak electron density (NmF2) and the corresponding height (hmF2) observed by an ionosonde station for restriction. The neural network was trained using these data through the conventional supervised back propagation algorithm [7]. The object function $E2$ for the ionosonde data is given by

$$E2 = \sum_{s=1}^{S} (N_s(\vec{r}_s) - N_s^{ion})^2 \tag{4}$$

where S is the number of ionosondes, N_s is the output of the neural network for the corresponding position that gives hmF2, and N_s^{ion} is the observed NmF2 value. Therefore, the overall objective function E is derived as

$$E = gE1 + E2 \tag{5}$$

where g is a balance parameter between the GPS and ionosonde data.
After the training is over, the neural network becomes an approximate density function $N(\vec{r})$, and the instrumental bias (B_i and B^j) are also obtained. In the training process, note the fact that the objective function $E1$ can be used only after all the density value of the sampling points on ray path are evaluated (refer to [3] for details).

3. Validation of the reconstruction capability

In order to validate the performance of RMTNN, we performed the numerical simulation with in the case of disturbed period and sparse data. In addition to the simulation, we performed the reconstruction from actual data. At first, in order to examine the effectiveness of the method for disturbed conditions, a “simple plasma bubble model” is investigated. Then, we checked the RMTNN method for the Sumatra region, Indonesia as a sparse data case.

3.1 Plasma bubble

Plasma bubble is a local ionospheric plasma depletion that occurs in the low latitude region to the middle latitude region. For the simulations, actual positions of the GPS receivers and the ionosonde station in Japan and model STEC values are used. The model STEC values are generated by the NeQuick model [8]. NeQuick model is a three-dimensional, time-dependent ionospheric electron density model developed by the Aeronomy and Radiopropagation Laboratory of the Abdus Salam International Centre for Theoretical Physics (ICTP) and the Institute for Geophysics and Meteorology of the University of Graz. In this paper, NeQuick model was used as a back ground ionospheric model, and we assumed the electron density depletion occur in the region that is extend 1.5° in longitude and south of 36° latitude. We compared the reconstructed electron density distribution with that derived from the Plasma bubble model. For the RMTNN, 40 GPS receivers from GEONET, and the observation from the ionosonde station located in Kokubunji are used. The reconstructed region is 26°N -42°N and 128°E-142°E in latitude and longitude and 100 to 700 km in altitude. The model and reconstructed distributions are shown in Figs. 1a and 1b, respectively. These figures are drawn for a vertical cross section at a fixed latitude of 35°N. The reconstructed image agrees well with plasma bubble model, and it suggests the high capability of RMTNN method for the disturbed ionosphere.

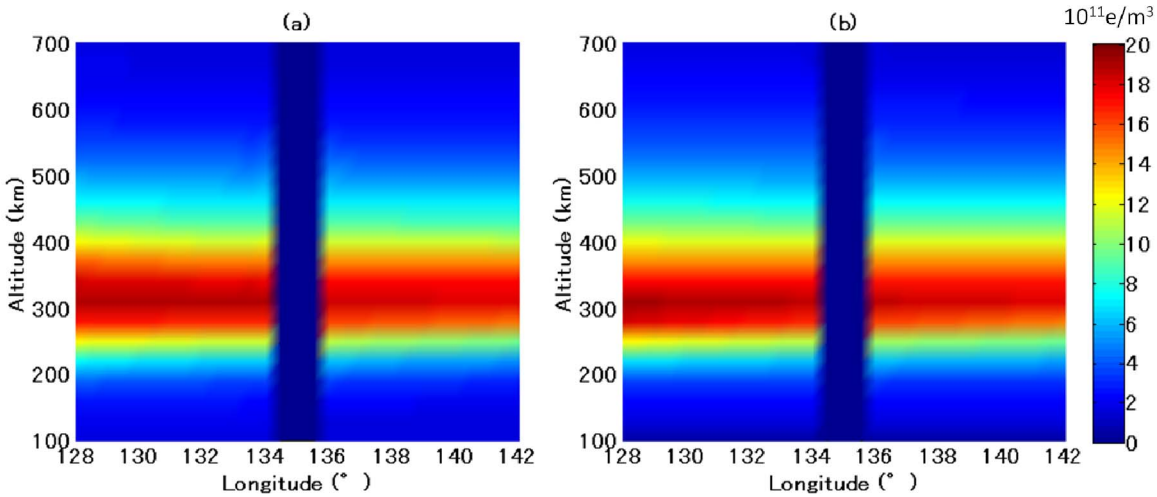

Fig. 1. Ionospheric electron density distribution at latitude 35°N.

(a) Original electron density distribution (plasma bubble model).

(b) Reconstructed electron density distribution.

3.2 Sparse condition

Ma et al. [3] demonstrated the effectiveness of reconstructing the electron density using the RMTNN algorithm for the GEONET in Japan. Then, we checked the RMTNN method for the Sumatra region, Indonesia as a sparse data case. For the RMTNN, 22 GPS receivers from SuGAr, two GPS receivers from IGS, and the observation from the ionosonde station located in Kototabang are used. We compared the reconstructed electron density distribution with that derived from the NeQuick model. The reconstructed region is 10°S-10°N and 90°E-110°E in latitude and longitude and 100 to 700 km in altitude. It is found that the reconstruction indicates a good agreement with the model data except below 250 km altitudes. In order to improve these difficulties, information on electron density at the lower ionosphere (100 km altitude) by NeQuick model for restriction is used. As a result, the proposed method shows a great improvement in estimation of densities at lower altitudes below 250 km.

4. Conclusion

In this study, we validate the performance of RMTNN tomography in the case of disturbed period and sparse data. We found the high capability of RMTNN tomography for disturbed ionosphere (e.g Plasma bubble) and quite sparse data. However, in case of sparse condition, in the lower altitude is underestimated compared to other altitudes and appears to be latitude dependent. This seems to be due to a lack of restrictions on electron density at lower altitudes. Therefore, In order to improve these difficulties, information on electron density at the lower ionosphere (100 km altitude) by NeQuick model for restriction is used. As a result, the proposed method shows a great improvement in estimation of densities at lower altitudes below 250 km. These results of the present study indicate the applicability of the RMTNN method to the investigation of ionospheric electron density in several conditions.

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6. References

1. M. Garcia-Fernandez, M. Hernandez-Pajares, M. Juan, J. Sanz, R. Orus, P. Coisson, B. Nava, and M. Radicella, "Combining ionosonde with ground GPS data for electron density estimation," *J. Atmos. Sol. Terr. Phys*, 65, 2003, 683-691.

2. A. Saito, S. Teraishi, G. Ueno, N. Fujita, and T. Tsugawa, "GPS Ionospheric Tomography over Japan with Constrained Least-squares Method," American Geophysical Union, Fall Meeting, abstract #SA13A-1061, 2007.

3. X. F. Ma, T. Maruyama, G. Ma, and T. Takeda, "Three-dimensional ionospheric tomography using observation data of GPS ground receivers and ionosonde by neural network," *J. Geophys. Res*, Vol. 110, A05308, 2005.

4. X. F. Ma, M. Fukuhara, and T. Takeda, "Neural network CT image reconstruction method for small amount of projection data," *Nucl. Instrum. Method Phys. Res*, A, 449, 2000, 366-377.

5. A. J. Mannucci, B. D. Wilson, D. N. Yuan, C. H. Ho, U. J. Lindqwister, and T. F. Runge, "A global mapping technique for GPS derived ionospheric electron content measurements," *Radio Sci*, 33, 1998, 562-582.

6. J. J. Angerami, and J. O. Thomas, "Studies of planetary atmospheres : The distribution of electrons and ions in the Earth's exosphere," *J. Geophys. Res*, 69, 1964, 4537-4560.

7. D. E. Rumelhart, G. E. Hinton, and R. J. Williams, "Learning internal representations by error propagation, In Parallel Distributed Processing," Vol.1, MIT Press, 1986, 318-362.

8. S. M. Radicella, and R. Leitinger, "The evolution of the DGR approach to model electron density profiles," *Adv. Space Res*, **27**, 2001, 35–40,.