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Investigating the performance of wavelet neural networks in ionospheric tomography using IGS data over Europe

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Abstract

Ionospheric tomography is a very cost-effective method which is used frequently to modeling of electron density distributions. In this paper, residual minimization training neural network (RMTNN) is used in voxel based ionospheric tomography. Due to the use of wavelet neural network (WNN) with back-propagation (BP) algorithm in RMTNN method, the new method is named modified RMTNN (MRMTNN). To train the WNN with BP algorithm, two cost functions is defined: total and vertical cost functions. Using minimization of cost functions, temporal and spatial ionospheric variations is studied. The GPS measurements of the international GNSS service (IGS) in the central Europe have been used for constructing a 3-D image of the electron density. Three days (2009.04.15, 2011.07.20 and 2013.06.01) with different solar activity index is used for the processing. To validate and better assess reliability of the proposed method, 4 ionosonde and 3 testing stations have been used. Also the results of MRMTNN has been compared to that of the RMTNN method, international reference ionosphere model 2012 (IRI-2012) and spherical cap harmonic (SCH) method as a local ionospheric model. The comparison of MRMTNN results with RMTNN, IRI-2012 and SCH models shows that the root mean square error (RMSE) and standard deviation of the proposed approach are superior to those of the traditional method.

Keywords: Ionospheric tomography; RMTNN; MRMTNN; IRI-2012; SCH; GPS

1. Introduction

Ionosphere is an atmospheric region that covers from 50 to 1500 km above the Earth's surface. It is characterized by the presence of a significant number of free electrons, positively charged atoms and molecules. It is very important to know ionospheric electron density distribution for scientific studies and practical applications. Ionosphere is mainly affected by solar zenith angle and solar activity (Habarulema et al., 2010). In the day-time, ionization in ionosphere is at the highest level and the ionospheric effects are stronger. In the night-time, ionization decreases and the effects of ionosphere gets weaker (Erturk et al., 2009). Using dual-frequency GPS receivers, slant total electron content (STEC) is computed. STEC contains valuable information about the ionosphere. It is a very important quantity used for ionospheric processes.

In the past two decades the idea of using tomography method to determine physical properties of the ionosphere is studied. In fact, ionospheric tomography is a reconstruction method which uses TEC measurements as an input parameter. This technology was first successfully used in medical science and then extended to other applications. The application of the tomographic reconstruction to 3-D modeling of the electron density using radio waves was proposed for the first time by Austen (Austen et al., 1988) and applied by Andreeva et al. (1990). So far, many algorithms and methods provided for ionospheric tomography (Nesterov and Kunitsyn, 2011; Wen et al., 2012;

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Yao et al., 2014; Ghaffari Razin, 2015a; Ghaffari Razin and Voosoghi, 2016a; Yang et al., 2016). Although the results of all studies indicates high efficiency of ionospheric tomography, but two major limitations can be considered to this method: first, due to the poor spatial distribution of GPS stations and limitations of signal viewing angle, computerized ionospheric tomography (CIT) is an inverse ill-posed problem. Second, in most cases, observations are discontinuous in time and space domain, so it is not possible determining the density profiles at any time and space around the world. In order to solve the mentioned problems, it is necessary to develop reliable local model and high temporal-spatial resolution which uses radio signals. For this purpose, in this paper modified residual minimization training neural network (MRMTNN) and data from international GNSS service (IGS) in the Europe at 3 days (2009.04.15, 2011.07.20 and 2013.06.01) with different solar activity index is used.

In recent years the idea of using artificial intelligence and modern computer science provide a number of system aids to analyze and predict the behavior of complex solar-terrestrial dynamic systems. An artificial neural network (ANN) is an information processing paradigm that is inspired by the way biological nervous (Ghaffari Razin et al., 2015b). The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. An ANN is configured for specific applications, such as pattern recognition or data classification, through a training process. For training of the network and modifications of the weights, there are so many ways. One of the most famous and simplest methods is back-propagation (BP) algorithm which trains network in two stages: feed-forward and feed-backward (Mars et al., 1996). In feed-forward process, input parameters move to output layer. In this stage, output parameters are compared with known parameters and the errors is identified. The next stage is done feed-backward. In this stage, the errors move from output layer to input layer. Again, the input weights are calculated. These two stages are repeated until the errors reaches a threshold expected for output parameters. Usually to active the neurons, activation functions is used. It can be used wavelet neural network (WNN) instead of using the conventional sigmoid activation functions. The WNN employing non-linear wavelet basis functions (named wavelets), which are localized in both the time and frequency space, has been extended as an alternative approach to non-linear fitting problem (Ghaffari Razin and Voosoghi, 2016b, 2016c, 2016d). The concept of a WNN is to adapt the wavelet basis to the training data. Therefore, the wavelet estimator is expected to be more impressive than a sigmoid NN (Zhang and Benveniste, 1992).

Ma et al. (2005) first presented the idea of ionospheric electron density reconstruction using residual minimization training neural network (RMTNN) in Japan. They used the ionosonde observations for improve the vertical resolution. Following this work, Hirooka et al. (2011) used low earth orbit (LEO) observations as vertical constraints and updated neural weights using these information's. Both of these studies have low accuracy in time and vertical domain. The goal of this paper is modeling and prediction of ionospheric electron density using MRMTNN in time and space domain. To achieve this goal, WNN with BP training algorithm and SCH are evaluated.

2. Definition of total cost function

On issues related to ANN, definition of the cost functions to parameter estimation is very important. These functions are usually defined by observations and desired outputs. In ionospheric tomography, the squares of the residuals of the integral equations are considered as the cost function of the MRMTNN system. To estimate the $N(\vec{r},t)$ can be written:

$$STEC_r^s(t) = \int_{\vec{r}_r}^{\vec{r}_s} N(\vec{r},t)ds \tag{1}$$

$$E_{total} = \left(\sum_{m=1}^{M} \alpha_m N(\vec{r},t) + P_r^s - STEC_r^s\right)^2 \tag{2}$$

In Eq. (1), $STEC_r^s$ is the slant total electron content, $N(\vec{r},t)$ indicate the electron density at the observation time; r and s shows total number of receivers and satellites, r_r and r_s are the position of the rth ground receiver and the sth satellite, respectively. In Eq. (2) m show mesh points and α corresponding weight for the numerical integration, M is the total number of the mesh points on a path and P_r^s is the contribution of the plasmaspheric electron density to the slant TEC. In order to estimate the electron density, the cost function should be minimized. This minimization is done during the training process.

2.1. Definition of vertical cost function

The vertical resolution in ionospheric tomography is generally not very good. Therefore, a priori information is necessary to form the vertical basis functions that span the entire space in the vertical direction. This is accomplished using empirical orthogonal functions (EOFs) (Ghaffari Razin and Voosoghi, 2016a). EOFs are derived from empirical data of the ionospheric electron density, such as the international reference ionosphere (IRI) model. Fig. 1 show the first 3 EOFs extracted from electron density profiles obtained from IRI-2012 for 3-days (2009.04.15, 2011.07.20 and 2013.01.05).

The neural network is trained with back-propagation algorithm and the vertical cost function is given as:

$$E_{vertical} = \sum_{e=1}^{E} \left(N_e(\vec{r}) - N_e^{EOF}\right)^2 \tag{3}$$