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Regional application of multi-layer artificial neural networks in 3-D ionosphere tomography

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Abstract

Tomography is a very cost-effective method to study physical properties of the ionosphere. In this paper, residual minimization training neural network (RMTNN) is used in voxel-based tomography to reconstruct of 3-D ionosphere electron density with high spatial resolution. For numerical experiments, observations collected at 37 GPS stations from Iranian permanent GPS network (IPGN) are used. A smoothed TEC approach was used for absolute STEC recovery. To improve the vertical resolution, empirical orthogonal functions (EOFs) obtained from international reference ionosphere 2012 (IRI-2012) used as object function in training neural network. Ionosonde observations is used for validate reliability of the proposed method. Minimum relative error for RMTNN is 1.64% and maximum relative error is 15.61%. Also root mean square error (RMSE) of 0.17×10^{11} (electrons/m^3) is computed for RMTNN which is less than RMSE of IRI2012. The results show that RMTNN has higher accuracy and compiles speed than other ionosphere reconstruction methods.

Keywords: RMTNN; Ionosphere modeling; Neural network; IRI-2012; GPS; EOFs

1. Introduction

In recent years, awareness of the ionosphere electron density distribution has been as a major challenge in field of scientific and practical interest to researchers and scientists. Ionosphere is that part of the atmosphere in which the number of free electrons is so high that, it significantly affects the propagation of radio waves. To understand the physical nature of ionosphere, it is necessary to monitor electron density variations both spatially and dynamically with high accuracy. One of the most important parameters that define the physical structure of ionosphere is total electron content (TEC). TEC is a line integral of electron density along signal path between satellites to the receiver on the ground (Hoffman-Wellenhof et al., 1992). The unit of TEC is TECU and 1 TECU equals 10^{16} electrons/m^2. Using TEC variability, temporal and spatial variations in ionosphere can be considered.

To study physical properties of the ionosphere, computerized tomography (CT) demonstrated an efficient and effective manner. 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 et al. (1988) and applied by Andreeva et al. (1990). Remarkable results reported in Andreeva et al. (1990) encouraged the further analysis and development of this method (Liu and Gao, 2003; Yin et al., 2004; Yizengaw et al., 2006; Nohutcu et al., 2010; Amerian et al., 2010; Ghaffari Razin, 2015; Ghaffari Razin and Voosoghi, 2016a). Although these studies indicate the success of the ionospheric tomography but there are two significant limitations: first, in most

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studies, observations are limited in time and space, so the electron density profiles cannot be obtained at any time and space around the world. Second, due to the sparse distribution of GPS stations and viewing angle limitations, inversion of computerized ionosphere tomography (CIT) images is an inverse ill-posed problem (Yao et al., 2014).

Over the recent 20 years, GPS networks have expanded all over the world. These networks enabled the acquisition of highly precise observation data on TEC for the CIT. Unfortunately, the GPS stations not distributed uniformly and the recorded data may have temporal gaps. To obtain and analyze spatial and temporal TEC variations over a desired locations, where a GPS stations dose not reside, an appropriate interpolation and/or extrapolation methods should be used. Simple and universal kriging, multiquadric, spherical harmonics, spline interpolation, polynomial model, neural networks, gaussian processes are some of the examples used methods to estimate TEC values for the locations where physical data are not exist (Schaer, 1999; Wielgosz et al., 2003; Moon, 2004; Orus, 2005; Ma et al., 2005; Sayin et al., 2008; Yilmaz et al., 2009; Hirooka et al., 2011; Ghaffari Razin et al., 2015).

To solve the mentioned problems, it is necessary to develop applicable local model, high spatial resolution and 3-D which uses radio signals. For this purpose, in this paper RMTNN (Liaqat et al., 2003) and data from IPGN installed by the Iran national cartographic center (NCC) is used. Recently it has become clear that the techniques derived from artificial intelligence research and modern computer science provide a number of system aids to analyze and predict the behavior of complex solar-terrestrial dynamic systems (Cander, 1998; Ghaffari Razin and Voosoghi, 2016b). Methods of artificial intelligence have provided tools which potentially make the task of ionospheric modeling possible (Habarulema et al., 2009). Artificial neural network (ANN) provides an inexplicit non-linear model to learn relations between inputs and outputs using training data. Ma et al. (2005) first presented the idea of ionospheric electron density interpolation using RMTNN in Japan. They used 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 this information. Both of these studies have low accuracy in vertical domain.

In this paper, a new approach is presented for modeling and interpolation of ionosphere electron density using RMTNN and IRI-2012 data in Iran. Because, there is only one ionosonde station in Iran and due to the lack of LEO information, in this research we suggest empirical orthogonal functions obtained from IRI-2012 data as vertical object function. The proposed method is able to estimate and predict electron density within and also near the network.

2. Computation of slant TEC

Dual frequency GPS receivers provide carrier phase Φ_i $(i=1,2)$ and code P_i $(i=1,2)$ observations on L-band (L_1, L_2) frequencies (Seeber, 2003). Using both the carrier phase and code measurements on the L_1 and L_2 frequencies, it is possible to estimate the slant TEC (STEC). Precision of the carrier phase pseudo-ranges is much higher than the code ones. Nevertheless, carrier phase derived STECs depend on the ambiguity parameters which is unknown. In contrast to STEC estimated using carrier phase, estimation of STEC using code measurements does not require any a priori information; therefore, it provides an absolute estimate for STEC. To obtain ambiguity independent and high precision STEC values, code pseudo-ranges are smoothed using “carrier to code leveling process” (Ciraolo et al., 2007). It should be noted that in carrier-phase observation, multipath and noise term has been neglected. It is much lower than the one for the pseudo range observation. If no cycle slip occurs, the ambiguity terms N_1 and N_2 are constant for every continuous arc of carrier-phase observation. Using code and carrier phase observation in both frequencies, it can be computed ionospheric observable as follow (Ciraolo et al., 2007):

$$\mathrm{STEC} = \left(\tilde{P}_4 - br - bs - \langle \varepsilon_P \rangle_{arc} + \varepsilon_L\right) \frac{f_1^2 f_2^2}{40.3\left(f_2^2 - f_1^2\right)} \tag{1}$$

In Eq. (1) STEC is the input observation for tomography method in TECU, $\tilde{P}_4$ is the pseudo range ionospheric observable smoothed with the carrier-phase ionospheric observable, $br = c\,(\tau^r_{P_1} - \tau^r_{P_2})$ and $bs = c\,(\tau^s_{P_1} - \tau^s_{P_2})$ are the differential code biases (DCB) for the receiver and satellite, respectively and f_1 and f_2 are GPS signals frequency.

3. Voxel-based ionosphere tomography

The slant TEC can be defined as the integrated value of the ionospheric and plasmaspheric electron density, including DCBs, is given by:

$$\mathrm{STEC}_r^s(t) = \int_{\vec{r}_r}^{\vec{r}_s} N(\vec{r}, t)\,ds + br + bs \tag{2}$$

In Eq. (2), $N(r,t)$ indicate the electron density at the observation time t; 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, br and bs are the receiver and the satellite DCB, respectively. In this paper, computational domain is divided into two parts: the ionospheric region from 100 km to 1000 km in altitude and the plasmaspheric region above 1000 km. It should be note that, the STEC in Eq. (2) including the plasma-sphere along the entire ray path from satellite to the receiver. Therefore, Eq. (2) is separated the ionospheric and the plasmaspheric part and discretized as:

$$\mathrm{STEC}_r^s(t) \approx \sum_{m=1}^{M} \alpha_m N(\vec{r}, t) + br + bs + P_r^s \tag{3}$$