Neural Network-Based Quasi-Real-Time Single-Station Ionospheric TEC Retrieval Postprint

Authors: Lu Weijun, Ma Guanyi

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Abstract

For ionospheric total electron content (TEC) retrieval using the Global Navigation Satellite System (GNSS), the single-station approach is a flexible and straightforward method compared to multi-station observation networks. Based on artificial neural networks, this paper proposes a quasi-real-time single-station ionospheric TEC retrieval method. In this method, hardware biases from the previous epoch are used as initial values and adjusted along with observations, while ionospheric TEC is also retrieved in quasi-real time. To conduct a detailed evaluation of this method, TEC during four magnetically quiet days was retrieved using both the proposed method and the classic least squares spherical harmonic function method through a single station located in China, where reference values for hardware biases and TEC were obtained from a nearby multi-station network. In another test, TEC during an ionospheric storm event and its surrounding quiet days was also retrieved through a single station located in Europe using the aforementioned methods. During magnetically quiet days, the estimated hardware biases were overall closer to the reference values compared to the least squares spherical harmonic function method, and the retrieved TEC was also closer to the reference values. During the ionospheric storm, the TEC retrieved by both methods also showed good consistency, and the hardware biases estimated by the neural network method were closer to those of the magnetically quiet days. The results demonstrate that the proposed neural network method exhibits higher accuracy compared to the least squares spherical harmonic function method.

Full Text

Near-real-time Ionospheric TEC Derivation from Single Station with Neural Network

LU Weijun[1,2]**, MA Guanyi**[1,2]
[1] National Astronomical Observatories, Chinese Academy of Sciences, Beijing

100101, China
[2] University of Chinese Academy of Sciences, Beijing 100049, China

Abstract

In the derivation of ionospheric total electron content (TEC) using the Global Navigation Satellite System (GNSS), single-station observation offers a flexible and convenient approach compared to multi-station networks. This paper proposes a near-real-time method for single-station ionospheric TEC derivation based on artificial neural networks (ANN). In this method, instrumental biases from the previous epoch serve as initial values and are adjusted along with observations, while ionospheric TEC is derived in near-real-time. To thoroughly evaluate this approach, TEC data from four magnetically quiet days were processed using both the proposed method and the classic least squares spherical harmonic function method at a single station in China. Reference values for instrumental biases and TEC were obtained from a nearby multi-station network. In another test, TEC during an ionospheric storm event and its adjacent quiet days was derived using the same methods at a single station in Europe. During quiet days, the estimated instrumental biases were overall closer to the reference values compared to the least squares spherical harmonic method, and the derived TEC also showed better agreement with the references. During the ionospheric storm, the TEC derived by both methods demonstrated good consistency, with the neural network method producing instrumental bias estimates closer to those obtained during quiet magnetic conditions. The results indicate that the proposed neural network method achieves higher accuracy than the least squares spherical harmonic function method.

Keywords: Ionosphere; Artificial neural network; Total electron content; Instrumental bias; Ionospheric storm
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The ionosphere is an atmospheric region located approximately 60–1000 km above the Earth’ s surface, where some neutral particles are ionized into free electrons and ions [1]. Consequently, the ionosphere acts as a dispersive medium, causing group delay and phase advance of radio signals, with the magnitude of effect depending on signal frequency and ionospheric electron density. To assess the time delay impact of the ionosphere on radio signal propagation, various theoretical and empirical models describing ionospheric electron density have been proposed [2][3]. While theoretical models can reflect the physical mechanisms of ionospheric variations, their accuracy remains insufficient for ionospheric delay correction requirements. Empirical models also exhibit non-negligible deviations from the real ionosphere, correcting only partial ionospheric delays. Therefore, ionospheric modeling based on actual observations has become essential. Instruments such as ionosondes and incoherent scatter radars have been employed to probe ionospheric electron density, but these can only obtain ionospheric profiles above the stations and cannot enable large-scale ionospheric observations. With the operation of the Global Navigation Satellite System (GNSS), ionospheric observations can be conducted using GNSS multi-frequency radio signals. As GNSS operates continuously based on constellations of satellites in inclined orbits, ionospheric variations across different spatial and temporal scales can be detected through GNSS.

Using GNSS, the integrated measurement of ionospheric electron density, known as Total Electron Content (TEC), serves as the parameter indicator for ionospheric derivation. Instrumental biases generated when radio signals of different frequencies pass through satellite and receiver hardware channels must be eliminated as systematic errors. GNSS multi-station observation networks are typically designed for estimating ionospheric hardware biases and deriving ionospheric parameters. Nevertheless, single-station ionospheric derivation remains valuable as a flexible, convenient, and low-cost approach. Algorithms for single-station ionospheric derivation mainly include grid-based methods, Kalman filtering, and polynomial methods [4]. Polynomials in these methods can be quadratic polynomials, trigonometric series, or spherical harmonic functions [5]. Generally, quadratic polynomials and trigonometric series are only suitable for derivation over small areas, whereas spherical harmonic functions can better describe ionospheric variations across different spatial scales by adjusting their degree and order.

For fitting methods in ionospheric derivation, least squares and Kalman filtering are commonly employed. With the introduction of Artificial Neural Networks (ANN), they have been rapidly applied to ionospheric derivation [6]. A feed-forward neural network based on error backpropagation can approximate any continuous real function with arbitrary precision. This fitting is performed iteratively, with the weights corresponding to various parameters adjustable dynamically. Consequently, this dynamic fitting approach is well-suited for near-real-time ionospheric derivation.

Based on artificial neural networks, we propose a near-real-time single-station ionospheric derivation method. We first derive the principles of ionospheric derivation and the proposed method. Subsequently, experiments were conducted using GNSS data from a single station at 30.28°N, 109.46°E during the spring equinox, summer solstice, autumn equinox, and winter solstice of 2014, with 18 stations along the 110°E meridian serving as validation stations. In another experiment, data from an ionospheric storm event on October 13, 2016, were also used for ionospheric derivation, with results compared to those from quiet days before and after the event. The final section provides a summary of the paper.

1.1 Spherical Harmonic Function Fitting

GNSS satellites broadcast signals at two different L-band frequencies. Using dual-frequency receivers, pseudorange and carrier phase observations can be obtained. The observation equations can be expressed as:

For pseudorange and carrier phase on frequency i ($i = 1, 2$):

$$P_i = \rho + c(\delta t_r - \delta t^s) + I_i + T + b_{r,i} + b_i^s + \epsilon_{P,i} \tag{1}$$

$$\Phi_i = \rho + c(\delta t_r - \delta t^s) - I_i + T + \lambda_i N_i + b_{r,i} + b_i^s + \epsilon_{\Phi,i} \tag{2}$$

where P_i and Φ_i are pseudorange and carrier phase observations on frequency i, ρ is the true geometric distance between satellite and receiver, c is the speed of light, δt_r and δt^s are receiver and satellite clock errors (including group delay for pseudorange and phase advance for carrier phase), I_i is the ionospheric delay on frequency i, T is the tropospheric delay, λ_i is the wavelength, N_i is the integer ambiguity, and ϵ represents observation residuals.

By differencing observations from different frequencies, the Slant TEC (STEC) along the propagation path can be derived from both pseudorange and carrier phase observations:

$$STEC_P = \frac{f_1^2 f_2^2}{40.28(f_1^2 - f_2^2)}(P_2 - P_1)$$

$$STEC_\Phi = \frac{f_1^2 f_2^2}{40.28(f_1^2 - f_2^2)}(\Phi_1 - \Phi_2)$$

Considering that pseudorange contains relatively large observation noise and carrier phase includes unknown integer ambiguities, high-precision STEC can be obtained by smoothing pseudorange with carrier phase [7]:

$$STEC_k = \frac{1}{k} STEC_{\Phi,k} + \frac{k-1}{k} STEC_{k-1} + w_k \left(P_k - \Phi_k - \frac{1}{k-1} \sum_{j=1}^{k-1} (P_j - \Phi_j) \right)$$

where k represents the epoch, w_k denotes weights that can be related to satellite elevation angle. For the first epoch, the smoothed STEC equals the pseudorange-derived STEC.

Ionospheric derivation involves using STEC to obtain vertical TEC within the derivation region. It is commonly assumed that all ionospheric electrons are concentrated in an infinitely thin single layer, leading to the introduction of the ionospheric single-layer model shown in Figure 1 [Figure 1: see original paper] [8]. In this model, points S, R, and O represent the satellite, receiver, and Earth' s center, respectively. The intersection point between the satellite-receiver line-of-sight and the ionospheric single layer is defined as the Ionospheric Piercing Point (IPP), whose latitude and longitude equal those of the corresponding Sub-Ionospheric Point (SIP). Therefore, TEC can be calculated based on the geometric relationships illustrated in Figure 1:

$$TEC = STEC \cdot \cos(z') = STEC \cdot \sqrt{1 - \left(\frac{R_e \cos(\epsilon)}{R_e + h_i} \right)^2}$$

where b^s and b_r are satellite and receiver instrumental biases, z and ϵ are zenith angle and elevation angle, R_e is Earth' s mean radius, and h_i is the ionospheric single-layer height.

On the other hand, TEC in the established model can be expressed as a spherical harmonic function with parameters of colatitude and longitude in the solar-terrestrial coordinate system corresponding to the IPP [5]:

$$TEC(\theta, \lambda) = \sum_{n=0}^{n_{max}} \sum_{m=0}^{n} \tilde{P}_{nm}(\cos\theta)(a_{nm}\cos(m\lambda) + b_{nm}\sin(m\lambda))$$

where θ and λ are colatitude and longitude in the solar-terrestrial coordinate system, respectively. For single-station applications, the degree and order are typically set to 5 ($n_{max} = m_{max} = 5$). $\tilde{P}_{nm}$ denotes the normalized Legendre function; a_{nm} and b_{nm} are spherical harmonic coefficients that can be obtained through least squares or other fitting methods.

1.2 Artificial Neural Network

Artificial neural networks consist of numerous neurons that form an input layer, an output layer, and several hidden layers. Typically, one hidden layer is sufficient. A multi-layer feedforward neural network based on error backpropagation can approximate any continuous real function with arbitrary precision [6]. Figure 2 [Figure 2: see original paper] shows a schematic diagram of the neural network used for near-real-time ionospheric derivation.

In ionospheric derivation, satellite and receiver instrumental biases must be simultaneously estimated and removed. An additional network is designed for bias estimation. The input parameters include the colatitude corresponding to STEC, longitude in the solar-terrestrial coordinate system, and elevation angle. The output parameters are the spherical harmonic coefficients shown in Equation (8) and the instrumental biases, from which TEC above the observation station can be obtained through the spherical harmonic coefficients.

The input layer neurons include, in addition to initial values of instrumental biases, the IPP colatitude θ and longitude λ in the solar-terrestrial coordinate system, as well as the zenith angle z. The output layer includes instrumental biases and spherical harmonic coefficients. The number of nodes in the hidden layer is a random value less than 200. The output values are adjusted through dynamically tuned weights, which are determined via the gradient descent algorithm based on residuals between observations and model estimates [9]:

$$w_{ij}(t+1) = w_{ij}(t) - \eta \frac{\partial E}{\partial w_{ij}}$$

According to Equation (9), using STEC from all satellites within each 15-minute interval as the training dataset, the weights and output layer nodes are continuously adjusted during neural network training until Equation (9) converges.

Due to the continuous nature of ionospheric variations, the weights and output layer nodes trained in the current epoch can serve as initial values for the next epoch, enabling training with new datasets to achieve rapid convergence.

For the first epoch, instrumental biases from the previous day are used as initial values, and each subsequent epoch uses the biases from the preceding epoch as initial values. Input values undergo nonlinear transformation into the input layer, then are processed layer by layer through hidden units to the output layer. The output layer evaluates residuals between estimated and observed values; if residuals exceed a threshold, backpropagation is initiated to modify neuron weights via the gradient descent algorithm until conditions are satisfied. Since observations corresponding to different satellites contain non-uniform observation errors [10][11], and ionospheric disturbances also vary dynamically over time, neural networks represent an excellent algorithm for near-real-time estimation.

We developed a near-real-time single-station ionospheric derivation program using MATLAB based on the neural network architecture shown in Figure 2. The program performs ionospheric derivation every 15 minutes using real-time GNSS data, obtaining a set of spherical harmonic coefficients and updating instrumental biases. Tests on a workstation with a 3.4 GHz CPU and 15 GB of RAM confirmed that each ionospheric derivation can be completed in approximately one minute, thereby enabling near-real-time single-station ionospheric derivation.

2.1 Test Observation Network and Data Processing Method

Figure 3 [Figure 3: see original paper] illustrates the distribution of GNSS observation stations, where the station at 30.28°N, 109.46°E serves as the test station, and the remaining 18 stations near the 110°E meridian are validation stations. To thoroughly evaluate the proposed near-real-time neural network method (RTANN), we used dual-frequency GPS observation data from the test station to derive ionospheric TEC using both RTANN and the Least Squares Method with spherical harmonics (LSM). Simultaneously, dual-frequency GPS data from the 18 validation stations were used to estimate instrumental biases via a 1° × 1° adaptive grid method [12], followed by ionospheric TEC derivation every 15 minutes using a 2° × 2° grid method [13]. These results served as reference values for comparison with those obtained from RTANN and LSM. The adaptive grid method has been applied for instrumental bias estimation during ionospheric storms in [12], making it appropriate for obtaining reference bias values in this study. Additionally, although multi-station network derivation results also contain errors, they offer higher accuracy and better stability than single-station results when station distribution is reasonable, thus serving as suitable reference values. In the experiments, we selected observation data from the spring equinox, summer solstice, autumn equinox, and winter solstice of 2014, all of which were magnetically quiet days. The epoch interval was 30 seconds, the elevation cutoff angle was set to 20°, and the ionospheric single-layer height was set to 400 km.

2.2 Estimated Instrumental Biases

In ionospheric derivation, satellite and receiver instrumental biases are coupled together as a whole. We employ zero-mean processing to separate satellite and receiver biases by subtracting their mean from each satellite bias and incorporating the mean into the receiver bias. Figure 4 [Figure 4: see original paper] shows the differences between satellite instrumental biases estimated by RTANN and LSM and the reference values, with (a)-(d) representing results for the spring equinox, summer solstice, autumn equinox, and winter solstice, respectively. Across the four days, the differences between satellite biases obtained through RTANN and the reference values were overall smaller than those from LSM. This improvement stems from the dynamic adjustment capability of instrumental biases enabled by the neural network, which reduces the impact of observation noise and ionospheric disturbances on derivation results. Additionally, a very small number of satellites exhibited relatively large deviations from reference values due to the zero-mean processing. Some satellites were unavailable during testing, and thus their results are not shown in the figure. Calculations revealed that the root mean square errors (RMSE) of biases estimated by RTANN were 0.38, 0.25, 0.37, and 0.31 ns for the four days, respectively, whereas LSM yielded 0.84, 0.61, 0.67, and 0.68 ns. The most significant improvement occurred during the spring equinox, which is related to larger TEC values during this period causing greater noise interference in bias estimation, as will be further analyzed below.

2.3 Derived TEC

Figure 5 [Figure 5: see original paper] presents the ionospheric TEC at the single station location (30.28°N, 109.46°E) derived by RTANN and LSM, with (a)-(d) showing results for the spring equinox, summer solstice, autumn equinox, and winter solstice, respectively. Reference values were obtained from the 18 stations using the grid method with independent derivations every 15 minutes. Notably, TEC during the spring equinox in Figure 5(a) is significantly larger than on the other three days, consequently the hardware biases estimated simultaneously with TEC through Equation (6) are more affected by noise. Comparison of single-station derived TEC with reference values reveals that TEC derived by RTANN is closer to the references than that from LSM, particularly at noon and midnight. The improvement at noon is more pronounced because TEC values are larger, and the neural network reduces noise impact on derivation. At midnight, TEC values are smaller, making LSM results more susceptible to hardware bias effects, whereas RTANN provides more accurate bias estimates. Additionally, TEC derived by RTANN is not smooth, which we speculate may be related to ionospheric disturbances, as most fluctuation trends correspond to those in the reference values. Calculations show that RMSE values for RTANN were 2.76, 1.00, 0.99, and 1.73 TECU, respectively, while LSM yielded 3.46, 2.32, 0.94, and 1.46 TECU. Therefore, TEC derived by the real-time neural network method is more accurate than that from LSM.

3 Ionospheric Storm Data Test

We derived TEC during the ionospheric storm on October 13, 2016, using both RTANN and LSM through single-station processing. Figure 6 [Figure 6: see original paper] shows the distribution of GNSS observation stations, where the station at 40.52°N, 3.09°W serves as the test station, and the remaining seven stations near the 0° meridian and 40°N parallel are validation stations. According to [14], the storm onset occurred at 2100 UT on the 12th, with the initial phase lasting from 2300 UT to 0600 UT on the 13th, followed by a main phase lasting 18 hours. The seven validation stations in Figure 6 observed positive storm effects during daytime and negative storm effects at night on the 13th. Combined with ionospheric uplift observed by ionosondes, this confirmed that the primary physical mechanism causing this ionospheric storm was disturbance dynamo effects.

Figure 7 [Figure 7: see original paper] shows the root mean square error of satellite instrumental biases estimated by different methods relative to the 10-day daily averages from October 8 to 17, 2016. Due to the ionospheric storm on October 13, the estimated instrumental biases varied significantly compared to quiet days. However, instrumental biases actually depend on the instruments themselves and their external environment; they are only affected by ionospheric variations because they are coupled with TEC during the derivation process. The RMSE of RTANN was smaller than that of LSM throughout these 10 days, particularly during the storm on the 13th. This demonstrates that instrumental biases estimated by RTANN are less affected by ionospheric variations, making it superior to LSM.

Figure 8 [Figure 8: see original paper] shows TEC derived by different methods from October 8 to 17, 2016. Compared to TEC on quiet days (8-11), TEC on the 13th exhibited a pronounced positive storm effect during daytime, with an increase rate exceeding 100%, while a clear negative storm effect began at night on the 13th and persisted until the 15th. Additionally, the derived TEC aligns with results from [14] and is consistent with the physical mechanism of equatorward disturbance neutral winds. During storms, equatorward neutral winds can lift the ionosphere while also causing compositional changes. Positive storms occur during daytime due to photoionization replenishment at lower ionospheric heights, whereas negative storms occur at night when photoionization ceases and ion recombination rates increase. Furthermore, comparison of derivation results between RTANN and LSM reveals good consistency in TEC derived by both methods. RTANN better reflects ionospheric variations, particularly at noon and midnight, with lower nighttime TEC from the neural network method also consistent with results shown in Figure 5.

Conclusion

We have proposed a near-real-time single-station ionospheric derivation method based on artificial neural networks. In the designed neural network, the input layer includes the previous day' s instrumental biases as initial values, along with IPP colatitude, longitude in the solar-terrestrial coordinate system, and elevation angle. The output layer comprises spherical harmonic coefficients and instrumental biases. Through continuously adjusted weights, the output layer can iterate via the gradient descent algorithm based on residuals. Consequently, instrumental biases can be dynamically adjusted with observations, and TEC can be derived in near-real-time. In one experiment, GNSS data from quiet days during the 2014 spring equinox, summer solstice, autumn equinox, and winter solstice at a single station (30.28°N, 109.46°E) were used for ionospheric derivation with both the proposed method and the classic least squares spherical harmonic function method. Eighteen stations along the 110°E meridian served as reference stations to obtain reference values for instrumental biases and TEC via the grid method. Results demonstrate that instrumental biases estimated using the proposed method were overall closer to reference values, and derived TEC showed better agreement with references compared to LSM. In another experiment, TEC during the October 13, 2016 ionospheric storm event was derived using both methods at a single station (40.52°N, 3.09°W). TEC derived by both methods showed good consistency, with neural network-based instrumental bias estimates closer to those from quiet days. These results indicate that the proposed neural network method achieves higher accuracy than the least squares spherical harmonic function method. Neural networks are also applicable to near-real-time multi-station ionospheric derivation and warrant further development.

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Note: Figure translations are in progress. See original paper for figures.