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Ionospheric Modeling in GNSS Positioning Using Deep Learning Models

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Introduction

Deep learning techniques are used for capturing intricate structures of large-scale data by employing computational models of multiple processing layers that can learn and represent data with multiple levels of abstraction [1]. Such methods can include Convolutional Neural Networks, stacked auto-encoders and Long-Short Term Memory (LSTM) architectures. LSTM networks are suitable for dealing with time-dependent data through mapping input sequences to output sequences as it is done, for instance, in language modeling and speech recognition. One application that has recently attracted considerable attention within the geodetic community is the possibility of applying these techniques to account for the adverse effects of the ionospheric delays on the GNSS satellite signals. LSTM architectures model long-range dependencies in time series, making them appropriate for ionospheric modeling in GNSS positioning. This paper deals with a modeling approach suitable for predicting the ionospheric delay at different locations of the IGS network stations using the LSTM networks. We also incorporate a Bayesian optimization method for selecting the best configuration parameters of the LSTM network, thus improving network's performance.

Preliminaries

The high accuracy in position estimation is of great importance for a variety of satellite navigation applications. The evaluation of Total Electron Content (TEC) and the corresponding correction of the ionospheric delay play a key role in improving GNSS performance. The combination of multi-frequency GNSS measurements allows us to remove most of the ionospheric effects. However, when using single frequency receivers this cannot be directly achieved. Augmentation systems that are used in such cases in order to improve accuracy, use grid-based models, so interpolation to a specific point is necessary, leading to a reduction of the accuracy that can be achieved [2].

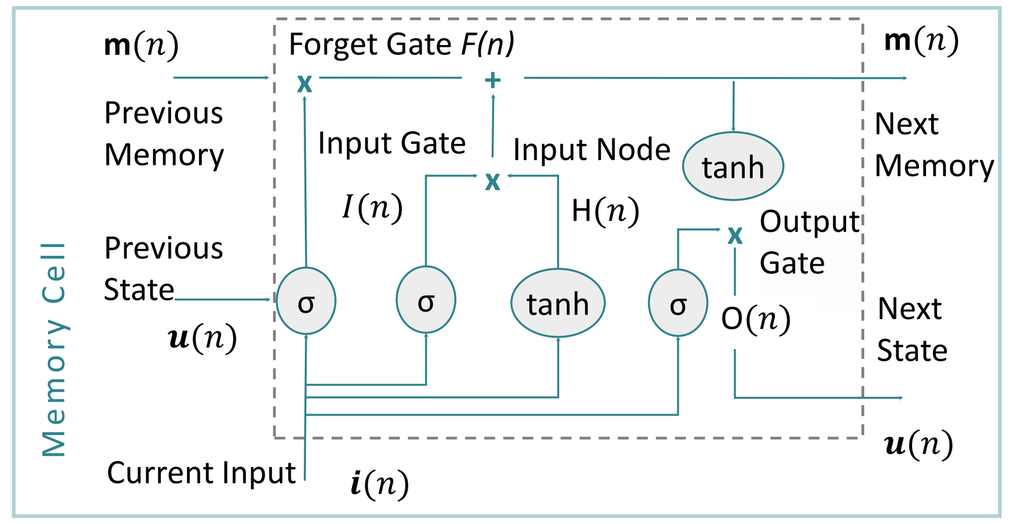

Fig.1 The memory cell of an LSTM network.

Ionospheric delay depends on three main factors: (i) the total electron content (TEC), (ii) the frequency of the GNSS signals, and (iii) the angle at which the signal enters the ionospheric layer. For this study, slant TEC data (STEC) were obtained using available GNSS measurements after processing with various techniques, such as Precise Point Positioning (PPP). STEC is mapped to its vertical counterpart VTEC at the points where the satellite-to-receiver signal paths intersect the ionospheric shell, the so-called ionospheric pierce points (IPPs) using the following mapping function [3]:

$$VTEC = \left(1 - \left(\frac{R_e}{R_e + h_s}\cos\theta\right)^2\right)^{1/2} STEC$$

where R_e is the mean radius of the Earth ; θ is the elevation angle of the satellite ; h is the height of the ionospheric layer (typically taken at 350 km).

Introducing Deep Learning for TEC prediction: DLTEC Model

It is intuitively clear that ionospheric delay forecasting is a complicated problem and as such, a complex model is required if one is to attempt to represent effectively the spatial and temporal variability of VTEC data. The objective is to predict the ionospheric delay between a station and an observed satellite at a specific time. Gaining knowledge from previous states through a training process, a large part of future ionospheric activity could be inferred. Supervised deep learning methods are necessary in order to create a model equipped with prior knowledge, able to predict ionospheric delay in future time intervals.

The challenge of this study to design an LSTM network able to handle a specific sequence of steps in the prediction problem whereby both the inputs and the target prediction estimates are sequences of data (i.e. timeseries). An input sequence is a quadruplet containing longitude (λ_{IPP}) and latitude (ϕ_{IPP}) for each IPP point between the station and a specific satellite and approximate values of longitude (λ_r^0) and latitude (ϕ_r^0) for the station in the ground. Consequently, a target sequence is a timeseries of the ionospheric delay with 1 min time step and varying time duration depending on the satellite's previous visibility from the station.

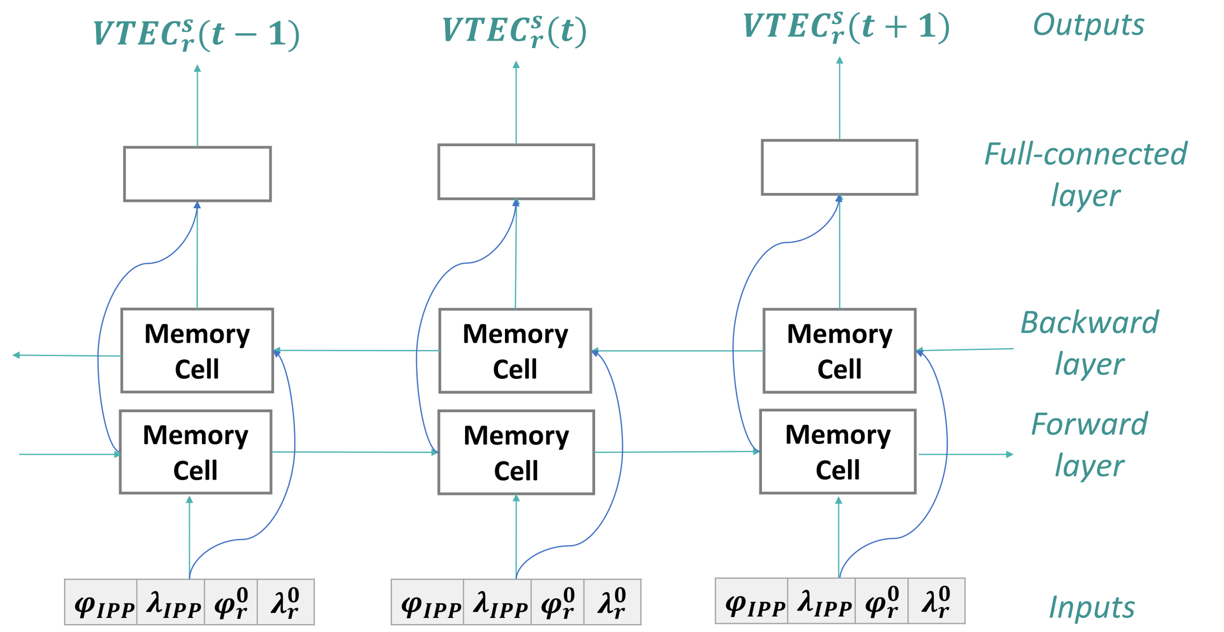

Fig.2 DLTEC model used for ionospheric delay prediction. The inputs are sequences of longitude and latitude for each IPP point between the station and a specific satellite and approximate values of longitude and latitude for the station in the ground. Outputs are timeseries data of the predicted ionospheric delay.

Short-range dependencies are not adequate for ionospheric delay estimation. For this reason, a bidirectional LSTM network is adopted in this paper, as an alternative regression model for ionospheric delay estimation, called DLTEC. LSTMs are of similar structure to the bidirectional recurrent regression model but each node in the hidden layer is replaced by a memory cell, instead of a single neuron [4]. The structure of a single memory cell is depicted in Fig. 1, while Fig. 2 indicates an unfolded LSTM network over time.

The memory cell contains three different components (see Fig. 1); (i) the forget gate, (ii) the input node and the input gate, and (iii) the output gate. Each component applies a non-linear relation on the inner product between the input vectors and respective weights (estimated through a training process). Some of the components have the sigmoid function, expressed as $\sigma(\cdot)$ in Fig. 1, while others use the hyperbolic tangent function, $\tanh(\cdot)$.

The forget gate $F(n)$ separates the worth-remembering information from the unnecessary information, by keeping the latter out of the memory cell. The input node $H(n)$ activates appropriately the respective state (true or false output from the $\tanh(\cdot)$ function activation). The input gate $I(n)$ regulates whether the respective hidden state is significant enough for the accurate estimation of the ionospheric delay. The output gate $O(n)$ regulates whether the response of the current memory cell is significant enough to contribute to the next cell.

Experimental Setup

The evaluation of the proposed model for forecasting ionospheric delay values was carried out using GNSS measurements for various stations of MGEX campaign [5], analyzing different ionospheric activity situations with varying spatio-temporal features. Fig. 3 illustrates the spatial distribution of various stations used in the present study, which were suitably selected with the following scenaria in mind:

- **Scenario A: 4 adjacent stations within the greater area of Central Europe.** These stations are: WTZZ (Germany), GRAZ (Austria), GOPE (Czech Republic) and PEN2 (Hungary).
- **Scenario B: 3 stations situated on the same meridian.** These stations are: SOD3 (Finland), ISTA (Turkey), MBAR (Uganda). SOD3 station is further north (with $\phi > 60^0$), MBAR is near the equator and ISTA is situated in mid-latitude between these two stations.

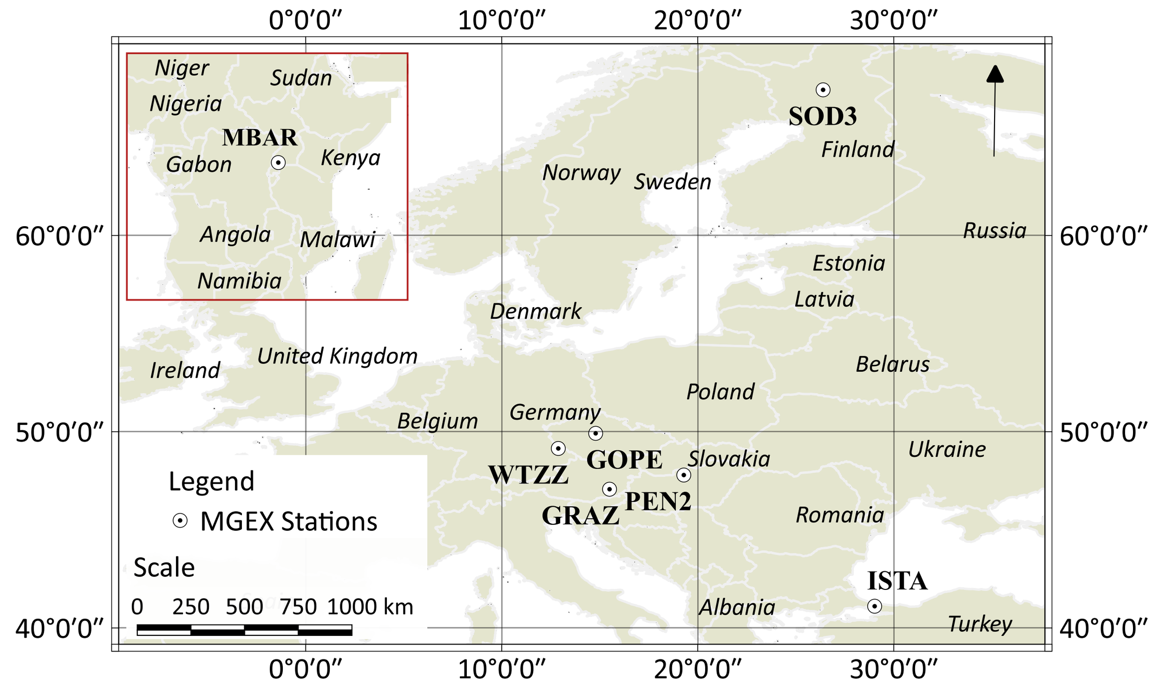

Fig.3 Geographic locations of the MGEX stations used in the study.

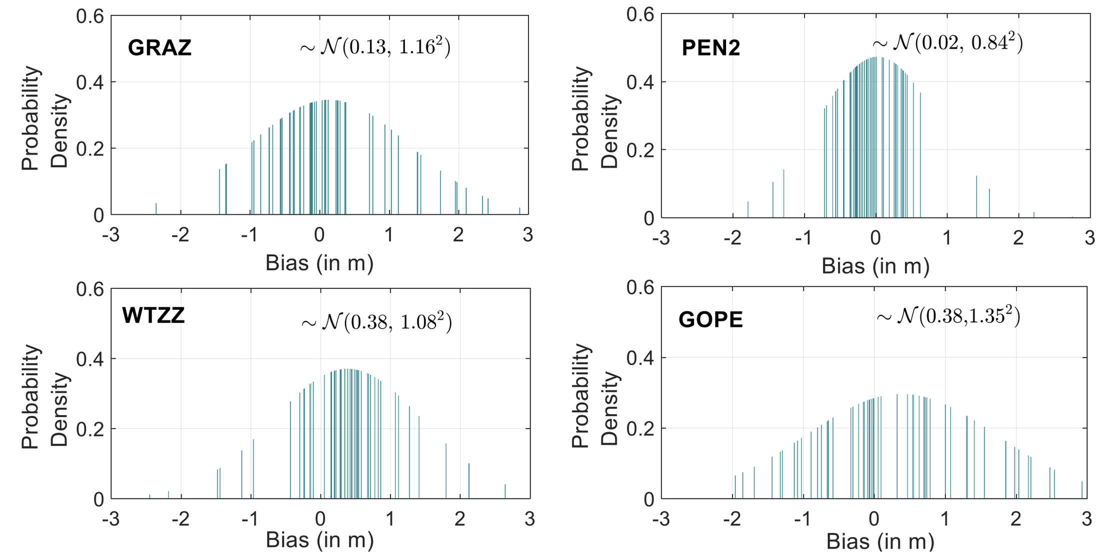

Fig. 4 **Scenario A**: Probability distribution of the differences between predicted and observed TEC value (in m) for 4 MGEX stations.

In order to evaluate the validity of the ionospheric delay predictions resulting from the DLTEC model, we have computed the $Bias_r^s(t)$ of the predicted values per station as follows:

$$Bias_r^s(t) = VTEC_{r,DLTEC}^s(t) - VTEC_{r,RTKLIB}^s(t)$$

where $VTEC_{r,DLTEC}^s(t)$ is the predicted value provided as the outcome of the DLTEC model; $VTEC_{r,RTKLIB}^s(t)$ is the corresponding estimated value that is independently computed using the RTKLIB PPP processing results. The proposed method is implemented using MATLAB software. The LSTM network is fine-tuned using the Bayesian optimization [6].

Performance

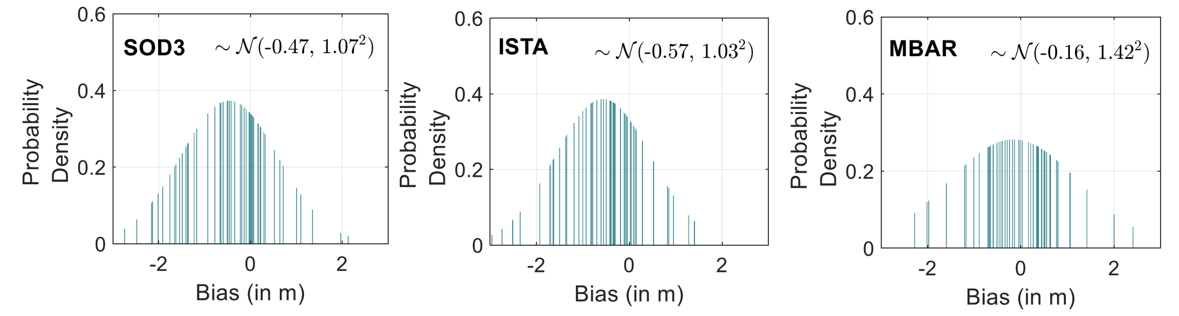

Fig. 5 **Scenario B**: Probability distribution of the differences between observed and predicted TEC values, i.e. of the *Bias* $(\cdot)$ values previously described, given in meters for the 3 north-south situated MGEX stations.

The models are trained using varying time periods of prior GNSS measurements. Specifically, the training period for the **Scenario A** is selected as the window of observations between 10/12/2018 to 12/12/2018, while for **Scenario B** the observational window was between 4/09/2017 to 6/09/2017. The time interval for Scenario B was purposely selected since at that time period high ionospheric activity had been observed. Thus, we have the opportunity to examine our models' response under both 'normal' as well as 'special' ionospheric conditions. Fig. 4 and 5 show that the $Bias_r^s(t)$ values follow normal distribution with a mean value and standard deviation $\mathcal{N}(\mu, \sigma^2)$. For instance, for the GRAZ station (Fig. 4), the probability of predicting ionospheric delay with a bias approximately to $0.13m$, from the estimated value, is equal to 36%. Similarly, adjacent stations showed comparable estimation errors, which can be explained due to largely similar atmospheric conditions. Fig. 5 shows that the BIAS of the ionospheric delay predictions at stations in high-latitude areas (e.g. SOD3) or close to the equator (e.g. MBAR) exhibit higher variance as compared to the predictions for mid-latitude stations like ISTA.

Conclusions

First results, using two different scenarios for various MGEX stations, indicate that the proposed DLTEC model is able to yield predictions of TEC values on a daily basis and with high accuracy suitable for many geodetic GNSS applications. Further research is required to examine the possibility to create an integrated LSTM network architecture that will contain various stations simultaneously, as well as including in the process additional parameters (e.g. inputs of geomagnetic indices) in order to allow better training of the DLTEC models under high ionospheric conditions.

Acknowledgements

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