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Ionospheric modeling in GNSS positioning using deep learning models

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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. 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 to output sequences as, 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.

Ionospheric delay depend 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. The combination of multi-frequency GNSS measurements allows us to remove most of the ionospheric effects. However, ionospheric prediction models have to be applied for single-frequency ionospheric estimation in order to remove this effect. This can be done using Global Ionospheric Maps (GIMs) available from the International GNSS Service (IGS) and evaluating the TEC effect via a mapping function involving the azimuth and elevation angles of the GNSS signals.

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. LSTM architecture models long-range dependencies in time series, making it appropriate for ionospheric modeling in GNSS positioning.

As experimental data we used actual GNSS observations from the global IGS network stations participating in the MGEX project that provides various satellite signals from the currently available multiple navigation satellite systems. Slant TEC data (STEC) were obtained using the available GPS/GLONASS/Galileo signals after processing with various techniques, such as Precise Point Positioning (PPP). The combination of multi-GNSS signals in PPP, allows us to investigate additional biases such as Differential Code Biases (DCBs) that are closely related to the ionospheric delays. Consequently, a basic LSTM network structure is created, having as minimum inputs the following: time epoch, GNSS signal azimuth and elevation angle, ionospheric delays for the previous and present observation epochs. The sequential GNSS observations are fed one by one in a chain-like structure, in a way that a single state is stored in a unique node with a single activation function in the network at one timestep and then is propagated to the next timestep. In this way, the LSTM algorithm is able to predict future ionospheric delay values. Topics to be discussed in the paper include the design of the LSTM network structure, the Bayesian optimization strategy, the training methods exploiting steepest descent algorithms, data analysis, as well as preliminary testing results of the ionospheric delay predictions as compared, for instance, with the IGS ionosphere products and the widely used Klobuchar model.