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DEVELOPING DEEP LEARNING MODELS TO PREDICT LONG-TERM SATELLITE CLOCK BIAS CORRECTIONS

Abstract

Clock error corrections for Global Positioning System (GPS) satellites are currently evaluated with a quadratic polynomial (QP) model and transmitted every two hours. These corrections often still contain potential bias from drift of over 12 ns, corresponding to at least 4 m pseudo-range errors, which limits the accuracy of GPS navigation solutions. Time-series statistical models, such as the autoregressive integrated moving average (ARIMA) model, have been suggested as a more accurate solution to the QP model, but are only capable of predicting clock biases accurately for very short time horizons. This paper expands on the state of the art by using machine learning to predict satellite clock error corrections for longer time horizons.

Machine learning models can be trained with existing clock drift data to predict high-rate satellite clock corrections. These models increase estimation accuracies by learning non-linear patterns in the data. Long short-term memory (LSTM) models have demonstrated prediction accuracies of at least 5 ns, at the trade-off of only forecasting for periods of less than an hour. Transformer models have achieved accuracies below 2 ns for a two-hour time horizon in single-frequency receivers.

This paper expands on the development of transformer models for clock bias corrections by demonstrating a deep learning model that yields time horizon predictions of over two hours while maintaining a correction accuracy below 2 ns. The model is trained, validated, and tested with broadcast and posterior clock bias products published by the International GNSS Service (IGS). This study compares QP, ARIMA, and transformer models based on (1) time horizon, (2) accuracy, and (3) time scale of data required for training. Each model's performance is assessed with the root mean square error (RMSE) taken from the residual between the predicted clock corrections and the test set values. Results showed that the deep learning model produced the lowest RMSE values.

Another application of machine learning-based clock corrections is for increased autonomy in deep space spacecraft. Given the Deep Space Network's high workload, a long-term deep learning clock correction model can reduce the required number of contacts for deep space missions. Transfer learning can bring the wealth of clock correction data from mature Global Navigation Satellite System (GNSS) to aid in timing for deep space missions.