Minimizing GNSS Code Phase Positioning Error in Multipath Environments Using Deep Learning Model

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Abstract

Time difference of arrival (TDOA) based trilateration method is widely used in satellite-based positioning. The signal which is transmitted from satellite towards the user terminal are attenuated while traveling. The measurement is affected in multipath non-line-of-sight (NLOS) scenarios. Positioning data are time correlated so temporal relation-based modeling is helpful to make an error model. In this paper, we have proposed a deep learning model with long short-term memory (LSTM) layer with a fully connected layer to model the position error. The LSTM layers can find out the temporal correlation whether the fully connected layers correlated to the output. To avoid overfitting a drop out layer can be used.

I. Introduction

Nowadays satellite based positioning system is mostly utilized because it provides positioning in global reference frame. Global positioning system (GPS), Galileo, and GLONASS in Global navigation satellite system (GNSS) are used for providing service globally [1]. Whereas BeiDou, NavIC, and Quasi-Zenith satellite System (QZSS) are used for regional coverage. Due to the long orbital altitude of GNSS satellites from the earth surface the signal strength is very low. Moreover, the signal is also attenuated by nature and buildings. The relative geometric between user and satellite also affects the signal quality. All these are causes of degradation of satellite signals which results positioning error.

The GPS measurements are integrated with inertial measurements unit (IMU) and vision sensors for reducing the error [2]. Several research works focus on minimizing the positioning error using C/N_o, geometric dilution of precision (GDOP), elevation angle [3-5]. Bayes estimators in Kalman filter and particle filter are used to eliminate the degradation of satellite signals in the GNSS receivers. However, these solutions are constrained by assumptions. Some works follow 3-D models to filter out the loss of signal in multipath and NLOS. The accuracy of using 3-D models depends on the accurate modeling.

II. System Model

Positioning errors occur in pseudorange due to non-line-of-sight (NLOS) and multipath propagation of signal. There are mostly three ways to reduce positioning error: signal processing, antenna design and modelling in the measurement domain. Compared to all the methods, we have followed the measurement domain modelling since it does not add additional cost and can improve the accuracy using the existing hardware. The carrier-to-noise ratio (C/N_o) is an important indicator for the detection of line of sight (LOS) and non-LOS signals. Other than, C/N_o, satellite elevation angle, pseudorange residuals can also indicate the quality of pseudorange measurements. We have proposed a LSTM based deep learning model to mitigate the positioning error. Fig. 1. shows the system model.

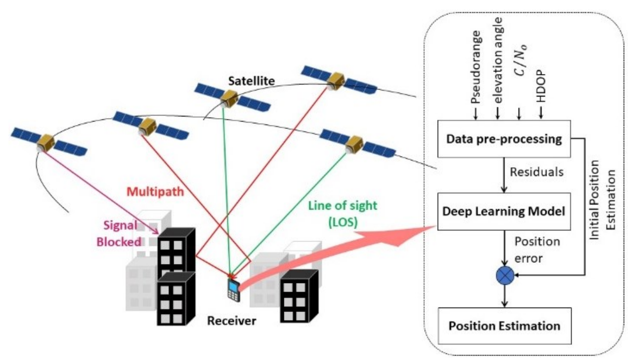

Fig. 1. Deep learning based positioning system model.

III. Proposed Method

Position error of satellite-based location systems are time correlated. The position error at time epoch t_{i+1} can also influence to the position error at epoch t_i. LSTM-based model is used because it can handle short-term and long-term sequences in pattern. The vanishing and exploding of gradients are avoided in LSTM using the forget method. A deep learning model with LSTM layer and a fully connected layer can be applied to model the position error. The LSTM layers used to extract the temporal correlation whereas the fully connected layers correlated to the output. To avoid overfitting a drop out layer can be used. Fig. 2 shows the LSTM based proposed method for positioning.

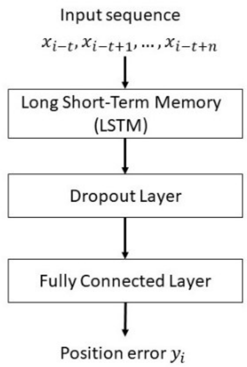

Fig. 2. LSTM based proposed method for positioning.

The cell in LSTM can be defined as

$$\tilde{f}_t = \tilde{\sigma}_f\left(\tilde{x}_t\widetilde{W}_{xf} + \tilde{h}_{t-1}\widetilde{W}_{hf} + \tilde{b}_f\right),$$
$$\tilde{o}_t = \tilde{\sigma}_c\left(\tilde{x}_t\widetilde{W}_{xo} + \tilde{h}_{t-1}\widetilde{W}_{ho} + \tilde{b}_o\right),$$
$$\tilde{c}_t = \tilde{f}_t \cdot \tilde{c}_{t-1} + \tilde{i}_t \cdot \tilde{\sigma}_c\left(\tilde{x}_t\widetilde{W}_{xc} + \tilde{h}_{t-1}\widetilde{W}_{hc} + \tilde{b}_c\right),$$
$$\tilde{h}_t = \tilde{o}_t \cdot \tilde{\sigma}_c(\tilde{c}_t) \quad (1)$$

where $\tilde{i}_t$, $\tilde{f}_t$, and $\tilde{o}_t$ are the states of the three gates, $\tilde{c}_t$ denotes the cell input state, $\tilde{h}_t$, $\tilde{x}_t$, and $\tilde{h}_{t-1}$ are the inputs, σ denotes the activation function,$\widetilde{W}_{xf}, \widetilde{W}_{xi}, \widetilde{W}_{xo}$ and $\widetilde{W}_{xc}$ denotes the respective weight vector between $\tilde{x}_t$ to all gates and cell input, $\widetilde{W}_{hi}, \widetilde{W}_{hf}, \widetilde{W}_{ho}$ and $\widetilde{W}_{hc}$ denotes the respective weight vector between $\tilde{h}_{t-1}$ to all gates and cell input, $\tilde{b}_i, \tilde{b}_f, \tilde{b}_o$ and $\tilde{b}_c$ denote the biases of the all the gates and cell input.

IV. Conclusion

GNSS code phase position uses pseudo-range for determining receiver position where pseudo-range is affected by multipath and NLOS signal propagation. Satellite elevation angle, C/N_o, pseudo-range residual can be used for mapping pseudo-range error correction. Since position error of satellite-based location are time correlated, temporal correlation-based model such as LSTM can be used to model the positioning error effectively.

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