Positioning Performance of LTE Signals in Rician Fading Environments Exploiting Antenna Motion

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BIOGRAPHIES
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ABSTRACT
A navigation framework based on a multi-state constraint Kalman filter (MSCKF) is proposed to reduce the effect of time-correlated pseudorange measurement noise of cellular long-term evolution (LTE) signals. The proposed MSCKF navigation framework uses a tightly-coupled inertial navigation system (INS) aided by pseudoranges to multiple eNodeBs to estimate the position of the receiver along with the difference of the clock bias of the receiver and each of the eNodeBs. Simulation results with a Rician fading channel multipath environment are presented showing a reduction of 44.31% in the two-dimensional (2D) position root mean squared-error (RMSE) using the proposed approach compared to an extended Kalman filter (EKF) approach. Experimental results on a ground vehicle navigating in an urban environment are presented showing a 2D RMSE of 6.05 m over a trajectory of 1380 m using the proposed approach. The results show a reduction of 48% in the 2D position RMSE and 50% in the 3D position RMSE using the proposed framework compared to an EKF.

I. INTRODUCTION
Traditional approaches to overcome global positioning satellite system (GNSS) limitations focused on fusing GNSS receivers with sensors (e.g., gyroscope, accelerometer, compass, barometer, lidar, camera, etc.). Recent approaches aimed at exploiting ambient signals of opportunity (SOPs). SOPs are radio frequency (RF) signals which are not designed for navigation purposes, but are freely available and may be exploited for navigation and timing when GNSS signals become unusable [1–4]. Examples of SOPs are: (1) AM/FM radio [5,6], (2) digital television (DTV) [7,8], (3) wireless local area network (WLAN or Wi-Fi) [9,10], and (4) cellular signals [11–16]. Cellular long-term evolution (LTE) signals are particularly attractive for navigation in deep urban canyons due to their desirable characteristics: abundance, large transmission bandwidth, high received power, frequency diversity, and geometric favorability of transmitter locations [17].

The literature on exploiting LTE signals for navigation have analyzed the achievable navigation accuracy with different types of LTE reference signals [18–20]. The navigation solution obtained from LTE signals was also evaluated
Several signal processing-based methods have been proposed to remove the effect of multipath in GNSS signals including a multipath-estimating delay-locked loop (MEDLL) [27], a batch filter to estimate the multipath using a known antenna motion [28], and a technique to correct multipath errors using signal-to-noise ratio [29]. These approaches have either high computational cost or they require prior knowledge of the multipath condition. Another approach to reduce the effect of multipath is based on beamforming. Beamforming can be performed using an antenna array, which has a bulky structure. Alternatively, one can synthesize an antenna array by moving the antenna. In synthetic aperture navigation (SAN), the antenna movement can be uniform or arbitrary. In a uniform movement, computationally low-cost approaches (e.g., multiple signal classification (MUSIC) or estimation of signal parameters via rotational invariance techniques (ESPRIT)) can be used to estimate the direction-of-arrival (DOA) [30,31], whereas computationally expensive algorithms (e.g., space-alternating generalized expectation-maximization (SAGE)) must be used to estimate the DOA in an arbitrary movement [32]. Uniform structures require a bulky hardware platform, and the performance of arbitrary structures depends on the accuracy of the antenna location, which depends on the accuracy of the inertial measurement unit (IMU). It has been shown that the antenna motion can also be used to decorrelate the error induced by multipath. Antenna motion was used in [33] to improve the detection performance and in [34] to reduce the carrier-phase error in carrier-phase differential GNSS (CDGNSS) positioning, where a first-order Gauss-Markov process was used to model the relative antenna position with respect to the reference antenna.

In a Kalman filter, the measurement noise is assumed to be time-uncorrelated. A time-correlated measurement noise will induce an error in the navigation solution estimate. Since the dynamics of the errors due to multipath is unknown, whitening approaches cannot be used to decorrelate the measurement noise. This paper addresses this challenge by making two contributions. First, a navigation framework based on a multi-state constraint Kalman filter (MSCKF) is proposed. The MSCKF was first introduced in robotics literature [35]. In this framework, an IMU is used to capture the position of the antenna over a window of measurements. Unlike a traditional extended Kalman filter (EKF), which uses a single measurement epoch to update the state estimate, this paper employs an MSCKF to use a sliding window of measurement epochs along with the antenna motion to decorrelate the measurement noise and provide constraints on the position estimate. Moreover, the difference of the clock bias of the receiver and each of the LTE base stations (also known as evolved node Bs or eNodeBs) are estimated along with the position of the antenna since the eNodeBs’ clock biases are unknown to the receiver. Second, the results are evaluated with simulations and experiments. There are several factors that characterize the behavior of a wireless channel e.g., terrain features, relative speed of the transmitter and receiver, etc. Propagation mode including line-of-sight (LOS), reflections, diffractions, and scattering is among these factors to characterize a wireless channel. Two channel models were introduced to capture these factors namely Rician and Rayleigh fading channels [36]. A channel with LOS can be modeled with a Rician fading, while a channel with no LOS can be modeled with a Raleigh fading. The simulation environment assumes the receiver to have access to the LOS signal and the channel is modeled as a Rician fading channel. The pseudorange errors are simulated assuming a time-correlated Rician channel. The trade-off between the integration time and the achievable positioning accuracy is analyzed in the simulations. The experimental results show a reduction of 48% in the 2-dimensional (2D) position root mean squared-error (RMSE) and a reduction of 50% in the 3D position RMSE using the proposed approach compared to using a traditional EKF.

The remainder of this paper is organized as follows. Section II presents the proposed navigation framework, which specifies the state, propagation, and update models. Section III shows simulation results comparing the proposed
method with an EKF approach. Section IV presents experimental results. Section V concludes the paper.

II. NAVIGATION FRAMEWORK

This section presents the MSCKF-based navigation framework.

A. State Propagation and Augmentation

The MSCKF state vector comprises (1) IMU states, (2) clock error states, and (3) a history of the receiver’s past position and the difference of clock biases between the receiver and each of the eNodeBs. The IMU measurements are fed to an inertial navigation system (INS) as they become available, which propagates the receiver’s position state. The clock error states are propagated at the same rate as the IMU states according to the standard model describing the time evolution of the clock bias and drift (double integrator driven by noise) [37,38], which is composed of the clock bias and drift. Once LTE pseudorange measurements become available, the current receiver’s position and the difference of clock biases between the receiver and each of the eNodeBs are appended to the state vector and the pseudorange measurements are appended to the measurement vector. After N measurements have been obtained, the EKF undergoes a measurement update using all N measurements to impose constraints between all N appended receiver positions from which the pseudorange measurements were obtained.

The vehicle’s state vector \( \mathbf{x}_r \) is defined as

\[
\mathbf{x}_r = [\mathbf{x}_{\text{MU}}^T, \mathbf{x}_{\text{clk}}^T, \mathbf{\pi}_1^T, \mathbf{\pi}_2^T, \cdots, \mathbf{\pi}_N^T]^T,
\]

where \( \mathbf{x}_{\text{MU}} \) represents the IMU state vector, \( \mathbf{x}_{\text{clk}} \) is the clock state vector, and \( \mathbf{\pi}_i \) is composed of the receiver’s position and the difference between the clock bias of the receiver and each of the eNodeBs at the \( i \)-th pseudorange measurement.

The IMU state vector is given by

\[
\mathbf{x}_{\text{MU}} = \left[ \mathbf{I}_{\text{q}}^T, \mathbf{G}_{r_{\text{MU}}}^T, \mathbf{G}_{v_{\text{MU}}}^T, \mathbf{b}_g^T, \mathbf{b}_a^T \right]^T,
\]

where \( \mathbf{I}_{\text{q}}^T \) is the unit quaternion representing the rotation from a global frame \( G \), such as an Earth-centered inertial (ECI) frame, to the IMU frame \( I \); \( \mathbf{G}_{r_{\text{MU}}} = [x_{\text{MU}}, y_{\text{MU}}, z_{\text{MU}}]^T \) and \( \mathbf{G}_{v_{\text{MU}}} = \mathbf{G}_{r_{\text{MU}}}^\prime \) are the 3D position and velocity of the IMU in the global frame, respectively; and \( \mathbf{b}_g^T \) and \( \mathbf{b}_a^T \) are the gyroscope and accelerometer biases, respectively. Standard IMU state propagation model can be used to propagate the states of the IMU [38–41].

The clock bias state vector is defined as

\[
\mathbf{x}_{\text{clk}} = \left[ \mathbf{x}_{\text{clk}}^{(1)}^T, \cdots, \mathbf{x}_{\text{clk}}^{(U)}^T \right]^T,
\]

where \( U \) is the total number of eNodeBs; \( \mathbf{x}_{\text{clk}}^{(u)} = [c\Delta \hat{t}_{s}^{(u)}, c\Delta \hat{t}_{s}^{(u)}] \); \( \Delta \hat{t}_{s}^{(u)} = \hat{t}_{s}^{(u)} - \hat{t}_{s}^{(u)} \) with \( \hat{t}_{s}^{(u)} \) and \( \hat{t}_{s}^{(u)} \) representing the clock biases of the receiver and the \( u \)-th eNodeB, respectively; \( \Delta \hat{t}_{s}^{(u)} = \hat{t}_{s}^{(u)} - \hat{t}_{s}^{(u)} \) with \( \hat{t}_{s}^{(u)} \) and \( \hat{t}_{s}^{(u)} \) representing the clock drifts of the receiver and the \( u \)-th eNodeB, respectively.

The vector \( \mathbf{\pi}_i \) is defined as

\[
\mathbf{\pi}_i = \left[ \mathbf{G}_{r_{A_i}}^T, \mathbf{x}_{ci}^T \right]^T,
\]

where \( \mathbf{G}_{r_{A_i}} = [x_{A_i}, y_{A_i}, z_{A_i}]^T \) and \( \mathbf{x}_{ci} = [c\Delta \hat{t}_{i}^{(1)}, \cdots, c\Delta \hat{t}_{i}^{(U)}]^T \) are antenna’s position in the global frame and the difference between the clock bias of the receiver and each of the eNodeBs, respectively, at the \( i \)-th pseudorange measurement.
B. Measurement Update

Once $N$ pseudorange measurement epochs are appended the measurement vector, an EKF measurement update is performed. After each update, the states corresponding to the antenna’s position and the difference between the clock bias of the receiver and each of the eNodeBs corresponding to $N_{\text{rem}}$ epochs are removed from the state vector. The pseudorange measurements corresponding to these states are also removed from the measurement vector and the filter returns to the state propagation stage.

III. SIMULATION RESULTS

To evaluate the proposed framework, a simulation environment was developed comprising a receiver navigating in an urban area (downtown Riverside, California) over a 6 km trajectory that includes straight segments and turns. The locations of the eNodeBs were simulated using real eNodeBs’ locations in that environment. The simulation environment showing the receiver’s trajectory and the eNodeBs’ positions is shown in Fig. 1. The receiver’s and eNodeBs’ clocks were simulated with a temperature-compensated crystal oscillator (TCXO) and an oven-controlled crystal oscillator (OCXO), respectively.

The IMU’s rotational velocity and linear acceleration measurements were generated at $T = 0.01$ s. The IMU’s measurement noise and time evolution of the IMU’s biases are determined by the grade of the IMU. In this work, data for a consumer-grade IMU was generated.

It is assumed that the LTE pseudoranges were estimated every LTE frame duration, which is $T_{\text{sub}} = 10$ ms. A Rayleigh and a Rician fading model can be used to model the propagation mode of the wireless channel. In a Rayleigh fading, it is assumed that the signal does not have LOS. While in the Rician fading channel, it is assumed that the signal has LOS. In this section, the receiver is assumed to have access to LOS. Therefore, a Rician fading channel was used to model the channel impulse response (CIR). Moreover, to characterize the LOS and multipath signal power and delay profile, the CIR was simulated based on an extended vehicular A (EVA) channel model [42] and the multipath error affecting the pseudorange was simulated based on the model presented in [43, 44]. The simulated CIRs were assumed to be correlated with two different correlation coefficients $\rho = \{0.8, 0.98\}$. For comparison purposes, Fig. 2 shows the simulated multipath for one of the eNodeBs over 10 s. The standard deviation of the generated multipath was 1.1 m. The measurement noise was assumed to be additive white Gaussian with a standard deviation obtained based on the carrier-to-noise ratio of the received signal for each eNodeB [45].

The simulation was repeated for 20 different multipath and noise conditions. Fig. 3 shows the average of the 2D and 3D position RMSE over the entire simulated trajectory for each run using the proposed method. The values of the 2D and 3D position RMSEs were obtained for different update time (i.e., $N_{\text{rem}}T_{\text{sub}}$). The results were compared with an EKF, where the state update is done whenever a pseudorange measurement is available and no state augmentation is performed. For the sake of comparison, in the EKF approach, it is assumed that the pseudorange measurement is available every $N_{\text{rem}}T_{\text{sub}}$. The value of $N$ was set to 100.

The following conclusions can be drawn from the simulation results.

Fig. 1. Simulated traversed trajectory and the positions of the LTE eNodeBs. Map data: Google Earth
Remark 1 For both the MSCKF and EKF approaches, the 3D position RMSE is worse than the 2D RMSE, since the eNodeBs have approximately similar height and the geometric diversity in the vertical direction is poor.

Remark 2 The proposed MSCKF approach outperforms the EKF approach. The reduction in the RMSE for $\varrho = 0.98$ is higher compared to $\varrho = 0.8$, which means that when the measurement noise is highly time-correlated, the proposed approach can significantly reduce the position estimation error.

Remark 3 From several sets of simulations, it was concluded that a good rule of thumb for choosing $N_{\text{rem}}$ is such that $N_{\text{rem}} \approx \lfloor N/2 \rfloor$. Such rule of thumb reduces the RMSE while maintaining a reasonable computational complexity (update time).

Next, the 2D position RMSE was evaluated for different values of $N$. For this purpose, the value of $N$ was selected from the set $\{0, 25, 50, 100\}$ and $N_{\text{rem}}$ was set to $\lfloor N/2 \rfloor$. Note that when $N$ is zero, the MSCKF approach is equivalent to an EKF since no augmentation is performed. Fig. 4 shows the results for this simulation, which was obtained by averaging the obtained 2D position RMSE over 20 different simulated multipath and noise realizations. The results show that increasing $N$ decreases the RMSE, especially for higher time-correlation in the measurement noise (i.e., $\varrho = 0.98$). However, increasing $N$ increases the update time, which increases the computational burden.

IV. EXPERIMENTAL RESULTS

To evaluate the performance of the proposed approach, an experiment was performed in an urban area (downtown Riverside, California). This section describes the experimental hardware setup and presents the experimental results.
A. Experimental Hardware Setup

A ground vehicle was equipped with two consumer-grade 800/1900 MHz cellular omnidirectional Laird antennas to receive the LTE signals at 739 MHz and 1955 MHz carrier frequencies, which were used by AT&T operator. A dual-channel National Instruments (NI) universal software radio peripheral (USRP)-2954R, driven by a GPS-disciplined oscillator (GPSDO) was used to simultaneously down-mix and synchronously sample LTE signals with 10 Msps. A laptop was used to store LTE samples for post-processing. A Septentrio AstreX-i V, which is equipped with dual antenna multi-frequency GNSS receiver with real-time kinematic (RTK) and a VectorNav VN-100 micro electromechanical systems (MEMS) IMU, was used to estimate the position and orientation of the ground vehicle, which was used as the ground truth. The stored LTE samples were processed by the Multichannel Adaptive Transceiver Information eXtractor (MATRIX) SDR developed by the Autonomous Systems Perception, Intelligence, and Navigation (ASPIN) Laboratory, producing pseudoranges to LTE eNodeBs in the environment. The proposed framework was used to estimate the receiver’s position using the derived pseudoranges. The receiver was assumed to have access to GPS signals at its initial position. Therefore, the receiver was able to estimate the initial values of the its position and the difference of its clock bias with each of the eNodeBs, which makes the estimation problem observable [46]. Fig. 5 shows the experimental hardware setup.

Over the course of the experiment, the receiver was listening to 5 eNodeBs with the characteristics shown in Table I. The receiver traversed a trajectory of 1380 m over 190 s.
TABLE I

<table>
<thead>
<tr>
<th>eNodeB</th>
<th>Carrier frequency (MHz)</th>
<th>$N_{\text{Cell}}^{1D}$</th>
<th>Bandwidth (MHz)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1955</td>
<td>216</td>
<td>20</td>
</tr>
<tr>
<td>2</td>
<td>739</td>
<td>319</td>
<td>10</td>
</tr>
<tr>
<td>3</td>
<td>739</td>
<td>288</td>
<td>10</td>
</tr>
<tr>
<td>4</td>
<td>739</td>
<td>151</td>
<td>10</td>
</tr>
<tr>
<td>5</td>
<td>739</td>
<td>232</td>
<td>10</td>
</tr>
</tbody>
</table>

The receiver’s orientation, position, and velocity, and their covariances were initialized using the output of the AsteRx-i V’s GNSS-INS. The gyroscope’s and accelerometer’s biases were initialized by taking the mean of 5 seconds of IMU data, when the receiver was stationary. The initial clock bias and drift uncertainties were set to 3 m$^2$ and 0.3 (m/s)$^2$, respectively. The measurement noise variance was determined empirically.

B. Experimental Results

Fig. 6(a) shows the estimated pseudoranges and their corresponding ranges for all eNodeBs. For comparison purposes, the initial value of the pseudoranges and ranges were subtracted from the pseudorange and range values over the entire trajectory. Therefore, the presented pseudoranges and ranges in Fig. 6(a) start from zero. Fig. 6(b) shows the empirical cumulative function (CDF) of the difference between the estimated pseudoranges and their corresponding actual ranges after removing the initial clock biases. These differences are due to the unmodeled effects, such as clock drifts, multipath, and measurement noise.

Fig. 7 shows the 2D and 3D position RMSE for different values of $N$. In these results, it is assumed that $\varphi = 0.98$ and $N_{\text{rem}} = \lfloor N/2 \rfloor$. It can be seen that both the 2D and 3D position RMSE decreased by increasing $N$ from 1 to 50. However, the payoff due to increasing $N$ from 50 to 100 diminishes. Fig. 7 shows that the proposed MSCKF approach could reduce the 2D and 3D position RMSE by 5.55 m and 10.32 m, respectively, compared to the EKF approach, where $N$ is set to one.

Fig. 8 compares the navigation solutions obtained by the proposed MSCKF approach and the EKF approach versus the ground truth. Table II summarizes the resulting 2D and 3D position RMSE.
Fig. 7. Experimental 2D and 3D RMSE for different values of $N$

Fig. 8. Experimental results showing the ground vehicle’s ground truth trajectory (from a GNSS-IMU RTK system), the estimated trajectory with the proposed MSCKF and an EKF. The total traversed trajectory was 1380 m. Image: Google Earth.

<table>
<thead>
<tr>
<th>Method</th>
<th>2D RMSE [m]</th>
<th>3D RMSE [m]</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSCKF</td>
<td>6.05</td>
<td>10.45</td>
</tr>
<tr>
<td>EKF</td>
<td>11.60</td>
<td>20.77</td>
</tr>
</tbody>
</table>

V. CONCLUSION

In this work, the effect of the time-correlated pseudorange error caused by multipath and the receiver’s loop filter on the position estimation error was addressed. A navigation framework based on an MSCKF was proposed to reduce the positioning error in the presence of time-correlated error. Simulation results were presented to evaluate the
effect of the correlation on the position estimation error. The simulation results assumed a LOS channel with Rician fading. The simulation results showed a reduction of 44.31% in the 2D position RMSE using the proposed approach compared to the EKF. The experimental results showed a 48% reduction in the 2D position RMSE compared to the EKF approach. The total 2D position RMSE was 6.05 m for a ground vehicle navigating in an urban environment over a 1380 m trajectory.

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