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Pseudorange Measurement Outlier Detection for Navigation with Cellular Signals

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Background

- Autonomous ground vehicles (AGVs) will operate in deep urban canyons where global navigation satellite system (GNSS) signals are unusable or unreliable.
- In these environments, signals of opportunity, particularly cellular long-term evolution (LTE) signals are abundant and can be considered as an alternative navigation source in the absence of GNSS signals.

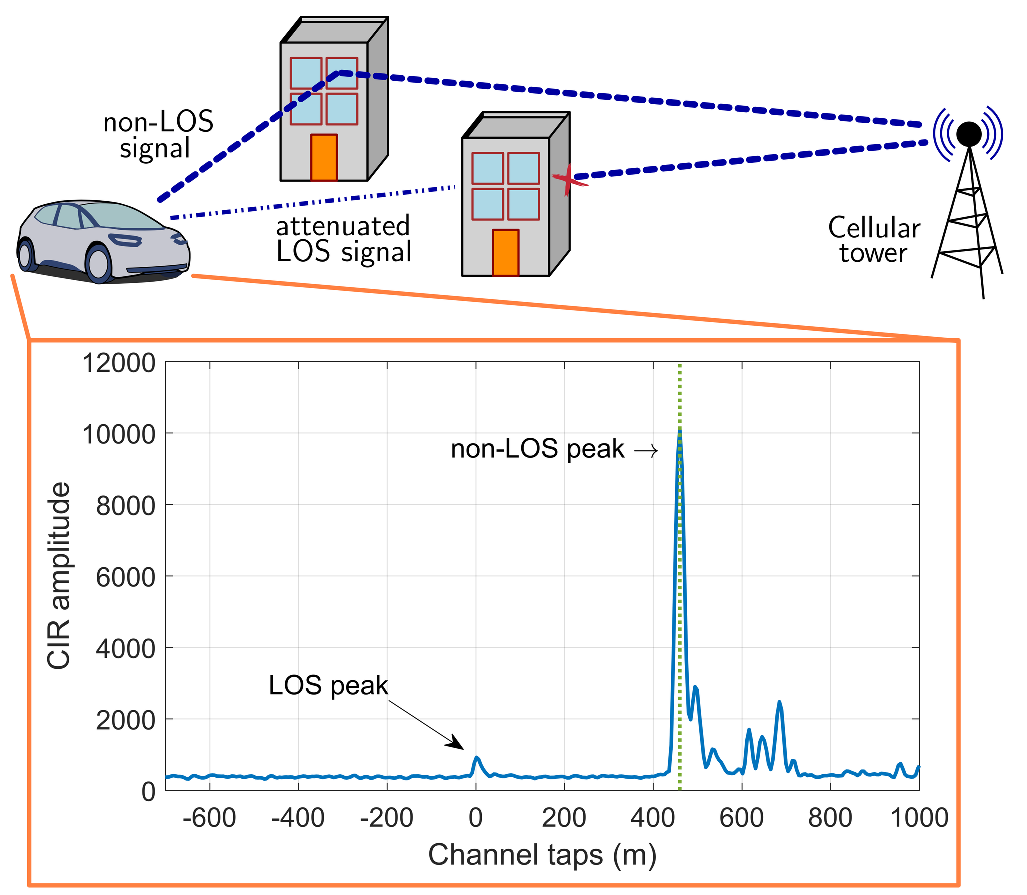
Motivation

- The ASPIN Laboratory has developed proprietary, state-of-the-art receivers and navigation frameworks for AGV navigation with LTE signals, demonstrating meter-level accuracy with standalone LTE signals.
- As the number of systems that rely on cellular signals for navigation grows, the need for monitoring the integrity of their navigation solution becomes essential.

Approach

Developed an autonomous measurement outlier detection and exclusion framework for ground vehicle navigation using LTE cellular signals and an inertial measurement unit (IMU). The proposed framework accounts for:

- line-of-sight blockage
- short multipath delays



State and Measurement

State Model

$$\boldsymbol{x} \triangleq \left[\boldsymbol{x}_v^\mathsf{T}, \boldsymbol{x}_{\text{clk},r}^\mathsf{T}\right]^\mathsf{T}, \boldsymbol{x}_v \triangleq \left[{}^I_G\bar{\boldsymbol{q}}^\mathsf{T}, {}^G\boldsymbol{r}_r^\mathsf{T}, {}^G\dot{\boldsymbol{r}}_r^\mathsf{T}, \boldsymbol{b}_g^\mathsf{T}, \boldsymbol{b}_a^\mathsf{T}\right]^\mathsf{T},$$

$$\boldsymbol{x}_{\text{clk},r} \triangleq \left[c\delta t_r, c\dot{\delta t}_r\right]^\mathsf{T}, \quad {}^G\boldsymbol{r}_r \triangleq [x_r, y_r, z_r]^\mathsf{T}$$

${}^I_G\bar{\boldsymbol{q}}^\mathsf{T} \in \mathbb{R}^4$: quaternion vector
$\boldsymbol{b}_g \in \mathbb{R}^3$: gyroscope bias
$\boldsymbol{b}_a \in \mathbb{R}^3$: accelerometer bias

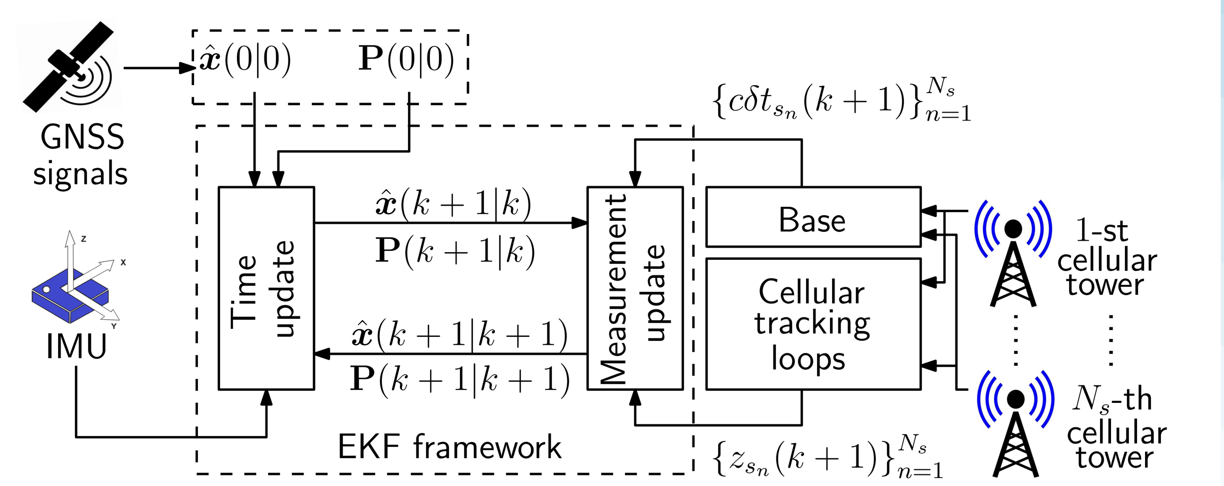
Measurement Model

$$\boldsymbol{z}_s = \left[z_{s_1}, \ldots, z_{s_{N_s}}\right]^\mathsf{T}, \quad \boldsymbol{r}_{s_n} \triangleq [x_{s_n}, y_{s_n}, z_{s_n}]^\mathsf{T},$$

$$z_{s_n}(k) = \left\|{}^G\boldsymbol{r}_r(k) - \boldsymbol{r}_{s_n}\right\|_2 + c\left[\delta t_r(k) - \delta t_{s_n}(k)\right] + v_{s_n}(k)$$

Navigation Framework

The observations $\{z_{s_n}\}_{n=1}^{N_s}$ are fused through an extended Kalman filter (EKF), which produces an estimate of the receiver's state vector $\hat{\boldsymbol{x}}$ and an associated estimation error covariance $\mathbf{P}$.



Outlier Detection

In order to distinguish between outlier-free measurements and those subject to outliers, a measurable scalar parameter is defined that provides information about pseudorange measurement errors. This parameter, called a test statistic, is a random variable with a known distribution (i.e., chi-square) and is defined as

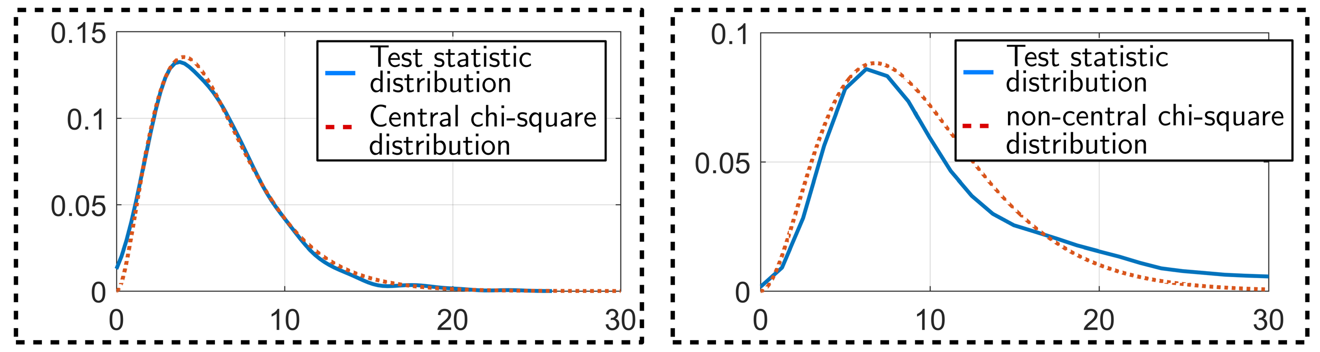
$$\varphi(k+1) \triangleq \boldsymbol{\nu}^\mathsf{T}(k+1)\mathbf{S}^{-1}(k+1)\boldsymbol{\nu}(k+1),$$

where $\boldsymbol{\nu}$ and $\mathbf{S}$ represent the innovation vector and its associated covariance, respectively. Outlier detection is achieved by comparing $\varphi(k+1)$ against a detection threshold T_h, namely

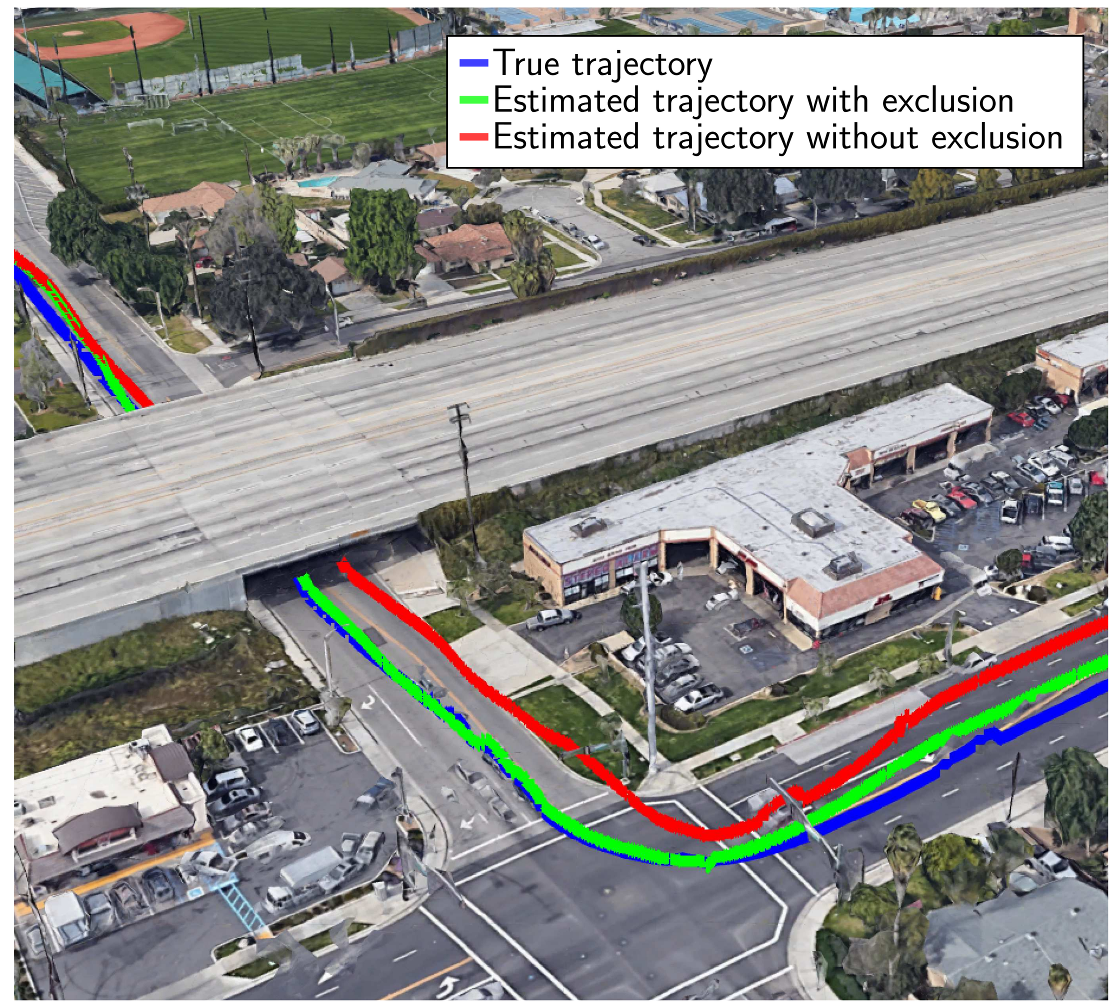
$$\varphi(k+1) \leq T_h : \text{no outliers present},$$
$$\varphi(k+1) > T_h : \text{outlier present}.$$

Outlier Exclusion

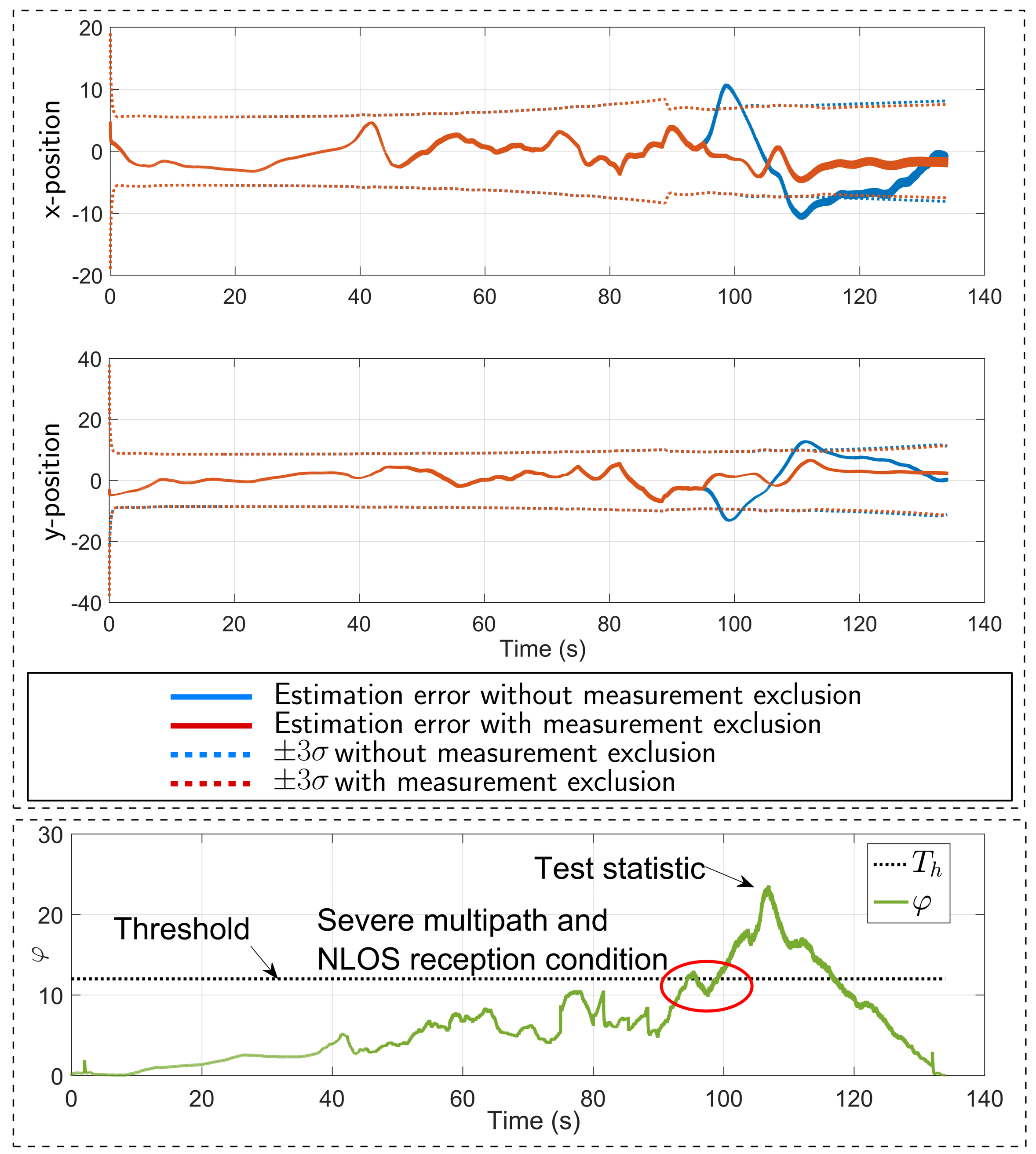
Step 1: Construct N_s subsets of $N_s - 1$ pseudorange measurements each of which excludes one pseudorange measurement.
Step 2: Assuming that only one of the cellular measurements is outlier, apply outlier detection procedure to each subset.
Step 3: This results in a test statistic failure in all subsets except one.
Step 4: Feed the navigation solution block with the measurement subset with successful test statistic.

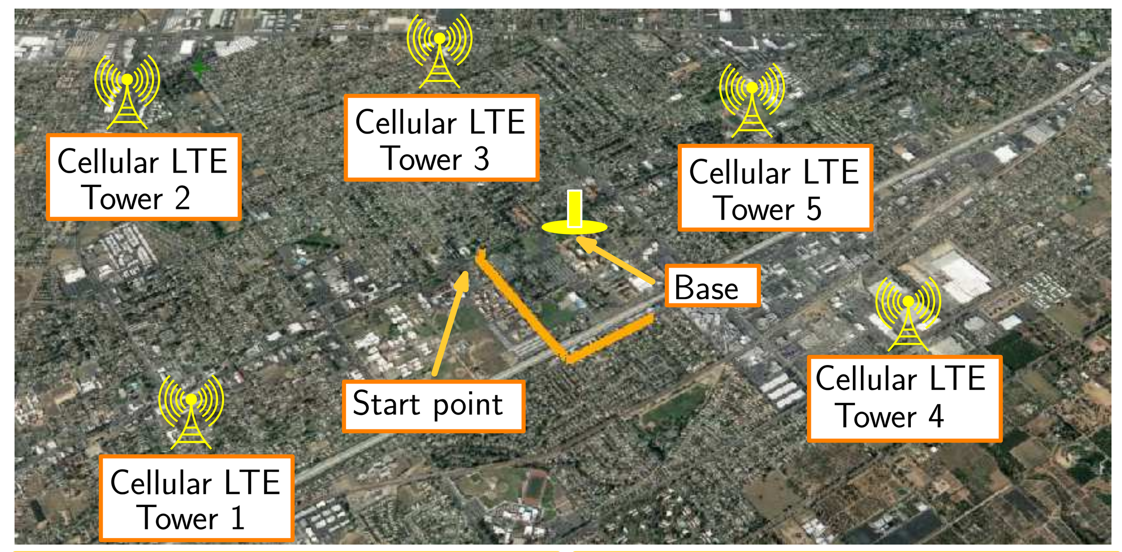


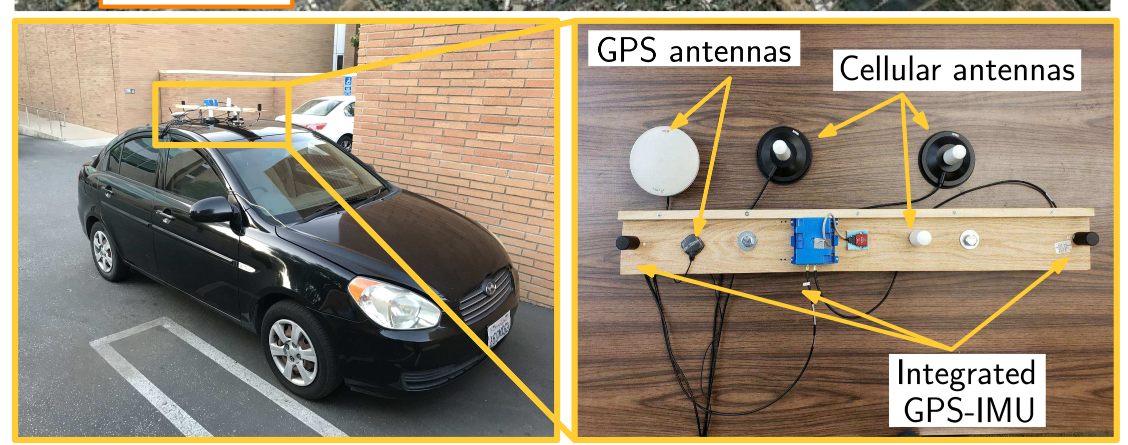
Test statistic PDF in the subset without outlier measurement
Test statistic PDF in $N_s - 1$ subsets with outlier measurement



Experimental Demo







Navigation solutions with and without outlier exclusion

Error	With exclusion	Without exclusion	Improvement
RMSE 2-D	4.8 m	8.2 m	42 %
Max. 2-D	11.6 m	20.4 m	43.3 %

Acknowledgment and References

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WiP Abstract: Pseudorange Measurement Outlier Detection for Navigation with Cellular Signals

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ABSTRACT

We present an autonomous measurement outlier detection and exclusion framework for ground vehicle navigation using cellular signals of opportunity (SOPs) and an inertial measurement unit (IMU). The experimental results demonstrate the proposed framework successfully detecting and excluding outlier measurements, improving the position root mean-squared error (RMSE) by 42%. The demo session will showcase work in progress, namely (1) demo (in the form of a video of our experiment driving in downtown Riverside, California) and (2) a poster that includes the navigation framework, the proposed outlier detection method, and the experimental results.

ACM Reference Format:

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1 INTRODUCTION

Global navigation satellite system (GNSS) signals are insufficient for reliable and accurate ground vehicle navigation in deep urban environments due to the inherent weakness of their space-based signals. Among alternative sensing modalities to compensate for GNSS limitations and vulnerabilities, signals of opportunity (SOPs) represent a particularly fruitful class of sensing modalities LaTeX [2]. SOPs are radio frequency signals that are not intended for navigation but can be exploited for navigation purposes, such as AM/FM radio signals, digital television, cellular, and low Earth orbit (LEO) satellites.

Despite the promise of SOPs as a reliable and accurate sensing modality, their integrity has not been fully studied. An initial work on integrity monitoring for SOP-based navigation was conducted in LaTeX [3]. This paper extends the work in LaTeX [3] by developing an autonomous measurement outlier detection and exclusion method for cellular long-term evolution (LTE) SOPs due to two main sources of errors: line-of-sight (LOS) blockage and short multipath delays. Experimental results are presented validating the efficacy of the proposed method for a ground vehicle navigating in an urban environment (downtown Riverside, California) over a trajectory of 1.4 km. The position root mean-squared error (RMSE) is reduced by 42% when the measurement outliers are detected and excluded via the proposed method.

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2 NAVIGATION FRAMEWORK

The environment is assumed to comprise N_s terrestrial cellular transmitters, denoted $\{S_n\}_{n=1}^{N_s}$ and the vehicle is assumed to be equipped with an inertial measurement unit (IMU) and a receiver capable of producing pseudorange measurements to cellular transmitters. It is assumed that the vehicle knows the location of the cellular transmitters (e.g., from a local or a cloud-hosted database). It is also assumed that the vehicle has an initial period of access to GNSS signals. During this period, the vehicle estimates its state. After this period, it is assumed that GNSS signals become unusable, and the vehicle begins to navigate exclusively with cellular signals and the IMU. In addition, the proposed framework assumes the presence of an stationary agent in the vehicle's environment, referred to as the base, which has knowledge of its own state at all time. The base's purpose is to estimate the dynamic stochastic clock bias states of cellular transmitters and to share these estimates with the navigating vehicle. The cellular receiver draws pseudorange observations from each cellular transmitters, given by

$$z_{s_n}(k) = \left\|\boldsymbol{r}_r(k) - \boldsymbol{r}_{s_n}\right\|_2 + c\left[\delta t_r(k) - \delta t_{s_n}(k)\right] + v_{s_n}(k), \quad (1)$$

where $\boldsymbol{r}_r$ and $\boldsymbol{r}_{s_n}$ are the location of the receiver and n-th cellular transmitter, respectively; δt_r and δt_{s_n} represent the clock bias of the receiver and n-th cellular transmitter; and v_{s_n} is the measurement noise, which is modeled as a discrete-time zero-mean white Gaussian sequence. The clock biases of the cellular transmitters $\left\{\delta t_{s_n}\right\}_{n=1}^{N_s}$ are known to the navigating vehicle through a base receiver. The observations $\left\{z_{s_n}\right\}_{n=1}^{N_s}$ are fused through an extended Kalman filter (EKF), which produces an estimate of the receiver's state vector $\hat{\boldsymbol{x}}$ and an associated estimation error covariance $\mathbf{P}$. The EKF-based estimation framework is illustrated in Figure 1.

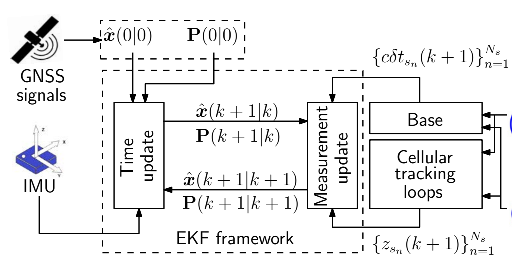

Figure 1: EKF-based estimation framework to fuse IMU data with cellular.

3 OUTLIER DETECTION

In the presence of a measurement bias due to LOS signal blockage or due to short multipath delays, a bias with magnitude b_n is injected in the pseudorange measurement drawn from the n-th cellular transmitter, rendering that particular measurement an outlier. In order to distinguish between outlier-free measurements and those subject to outliers, a measurable scalar parameter is defined that provides information about pseudorange measurement errors. This parameter, called a test statistic, is a random variable with a known distribution. Under outlier-free, normal operation, the innovation vector $\boldsymbol{\nu}_0(k+1)$ and its associated innovation error covariance $\mathrm{S}(k+1)$ are given by

$$\boldsymbol{\nu}_0(k+1) \triangleq \boldsymbol{z}(k+1) - \hat{\boldsymbol{z}}(k+1|k) \approx \mathbf{H}(k+1)\hat{\boldsymbol{x}}(k+1|k) + \boldsymbol{v}_s(k+1),$$
$$\mathrm{S}(k+1) \triangleq \mathbf{H}(k+1)\mathrm{P}(k+1|k)\mathbf{H}^{\mathsf{T}}(k+1) + \mathbf{R},$$

where $\boldsymbol{v}_s \triangleq [v_{s_1}, \ldots, v_{s_{N_s}}]^{\mathsf{T}}$, $\mathbf{H}$ is the measurement Jacobian, $\boldsymbol{z}$ is the vector of pseudorange measurements, and $\mathbf{R}$ is the measurement noise covariance matrix. Whenever the n-th measurement experiences an outlier bias, the biased innovation vector $\bar{\boldsymbol{\nu}}(k+1)$ may be expressed as

$$\bar{\boldsymbol{\nu}}(k+1) = \boldsymbol{\nu}_0(k+1) + \boldsymbol{u}_n(k+1),$$

where the vector $\boldsymbol{u}_n(k+1) \triangleq [0, \ldots, 0, b_n(k+1), 0, \ldots, 0]^{\mathsf{T}}$ is the bias vector resulting when a bias of magnitude b_n is present in the pseudorange measurement drawn from the outlier cellular tower. Note that $\bar{\boldsymbol{\nu}}(k+1)$ has the same covariance as $\boldsymbol{\nu}_0(k+1)$. Denote $\boldsymbol{\nu}(k+1)$ the innovation vector evaluated by the filter. The hypothesis test relies on the normalized innovation squared (NIS)-based test statistic, which is defined as

$$\varphi(k+1) \triangleq \boldsymbol{\nu}^{\mathsf{T}}(k+1)\mathrm{S}^{-1}(k+1)\boldsymbol{\nu}(k+1).$$

Note that the test statistics follows a chi-square distribution under outlier-free operation and a non-central chi-square distribution in the presence of outliers LaTeX [1]. The degrees of freedom of the distributions under both conditions is $d = N_s$. Outlier detection is achieved by comparing $\varphi(k+1)$ against a detection threshold T_h, namely

$$\varphi(k+1) \leq T_h : \text{no outliers present},$$
$$\varphi(k+1) > T_h : \text{outlier present}.$$

4 EXPERIMENTAL RESULTS

A vehicle was equipped with an IMU and a cellular receiver (Figure 2). Over the course of the experiment, the vehicle-mounted receiver was listening to 5 LTE base stations. The outlier detection test was performed throughout the experiment. The results are shown in Figure 3 and Figure 4. Figure 3 shows the outlier detection test which compares the test statistic φ against the detection threshold T_h. It can be seen that at $t = 95$ s, the threshold is exceeded; therefore, the test is not declared successful (see the red circle in Figure 3). This implies that at least one of the measurements was detected as an outlier and its contribution to the test statistic was significant enough for the test to fail. Figure 4 shows the resulting position estimation error and corresponding $\pm 3\sigma$ bounds with and without using the proposed outlier exclusion. As can be seen, outlier exclusion results in a significant reduction in the x- and y-direction estimation error. The position RMSE without measurement exclusion was 8.2 m, whereas the position RMSE with the proposed autonomous measurement outlier exclusion method was 4.8 m. Hence, incorporating the proposed algorithm reduced the position RMSE by 42%.

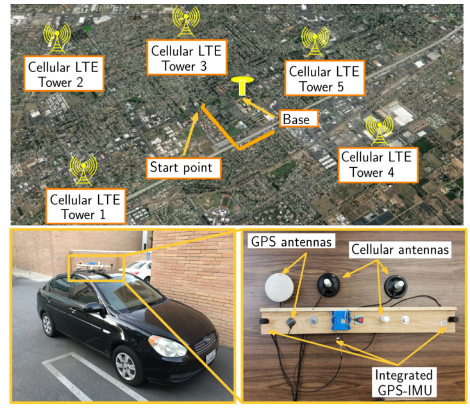

Figure 2: Experimental hardware setup and the traversed trajectory along with the position of cellular towers.

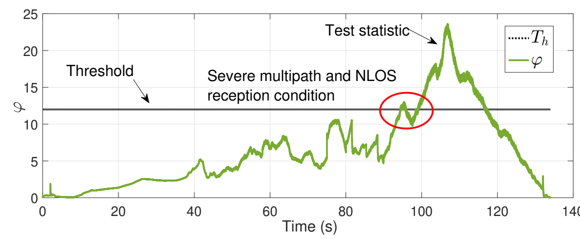

Figure 3: The resulting fault detection test.

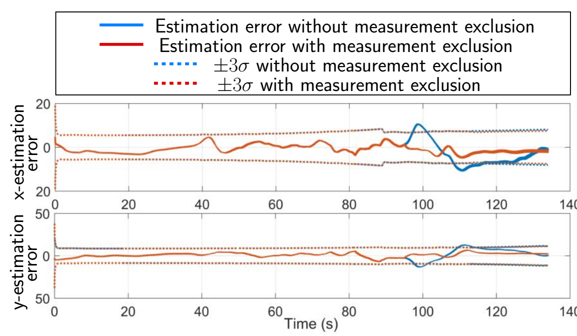

Figure 4: Vehicle's position estimation errors in the x- and y-directions with and without the proposed autonomous measurement outlier exclusion method.

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