Joint Detection and Tracking of Unknown Beacons for Navigation with 5G Signals and Beyond

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BIOGRAPHIES

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ABSTRACT

A receiver architecture is proposed to jointly detect and track unknown beacons to extract navigation observables from fifth generation (5G) new radio (NR) signals of opportunity and beyond. Unlike conventional opportunistic receivers which require knowledge of the signal structure, particularly the reference signals (RSs), the proposed receiver requires knowledge of only the RS period and carrier frequency of the signal. The transmitted RSs for private networks are unknown for an opportunistic receiver. Moreover, to use the spectrum more efficiently, some of these RSs are only transmitted on demand in 5G NR, which limits the existing opportunistic navigation frameworks to signals which are on always-on; hence, limiting the exploitable RS bandwidth. To exploit the full available bandwidth and improve ranging accuracy, the proposed receiver is designed to estimate all the RSs contained in the transmitted signals corresponding to multiple unknown sources. Navigation observables (pseudorange and carrier phase) are subsequently derived from the estimated RSs. The proposed receiver operates in two stages: (i) detection of unknown signals and (ii) tracking. The detection of unknown signals is modeled as a sequential detection problem where the number of sources and their corresponding RSs and Doppler frequencies are unknown. The generalized likelihood ratio (GLR) test for sequentially detecting active gNBs is used to estimate the number of sources and their RSs. In order for the receiver to refine and maintain the Doppler and RS estimates provided by the acquisition stage, tracking loops are used. The output of the tracking loops, namely carrier phase and code phase, are then used to estimate the receiver’s position.

Experimental results are presented demonstrating the capabilities of the proposed receiver with real 5G signals on ground and aerial platforms, with an experiment showing the navigation results with real 5G signals on an unmanned aerial vehicle (UAV) navigating using the proposed receiver over a 416 m trajectory with a position root mean-squared error (RMSE) of 4.35 m.

I. INTRODUCTION

To address the demands of emerging applications such as internet of things (IOT) and autonomous vehicles, fifth generation (5G) has been developed, with a focus on features such as enhanced mobile broadband, ultra-reliable low-latency communications, and massive machine type communications (Parkvall et al., 2020). Based on the performance requirements set by the international telecommunication union (ITU), the third generation partnership project (3GPP) began 5G standardization in 2015 and released its first specifications on a 5G system in June 2018, which included both the new air interface, known as new radio (NR), and 5G core network (5GC) (Takeda et al., 2020). One main characteristic of 5G signals is high data rate, which necessitates a higher transmission bandwidth and more sophisticated multiplexing techniques. The scarcity of unlicensed spectrum in lower
frequencies called for using millimeter waves (mmWaves) for NR signal transmission (Baenke et al., 2020). The high path loss of propagated mmWave signals can be compensated for by beamforming techniques and massive multiple-input multiple-output (mMIMO) antenna structures (Giordani et al., 2019). Beamforming in 5G requires the knowledge of the user’s location, which means that 5G-based positioning is not only an auxiliary service, but is essential for resource allocation and beamforming for high data rate transmission (Fascista et al., 2019). Different types of positioning techniques have been evaluated by the 3GPP in Release 15 and 16.

Cellular positioning techniques in the literature can be classified into network-based and opportunistic approaches (del Peral-Rosado et al., 2018b; Kassas, 2021). Network-based approaches require two-way communication with the network and the transmission of a pre-specified positioning reference signal (PRS) and some system parameters such as the number of transmission antennas and the beamforming matrix. Network-based positioning capabilities in wireless communication systems have been defined since 4G systems (del Peral-Rosado et al., 2018a). In contrast to network-based approaches, in opportunistic approaches, the user equipment (UE) estimates its position from downlink signals, without communicating back with the network. As such, opportunistic approaches are more attractive than network-based approaches since: they (i) do not require additional overhead or bandwidth, (ii) preserve the UE’s privacy, (iii) do not require paying subscription to the network, and (iv) enable the UE to exploit signals from multiple cellular providers simultaneously, which improves the positioning accuracy. Opportunistic navigation frameworks usually rely on the broadcast reference signals (RSs), which are used to derive direction-of-arrival (DOA) and time-of-arrival (TOA) (Shamaei and Kassas, 2021a). These signals are known at the UE and are universal across network operators. Hence, they can be exploited for positioning without the need for the UE to be a network subscriber. In cellular long-term evolution (LTE) networks, several RSs, such as the cell-specific reference signal (CRS), are broadcast at regular and known time intervals, regardless of the number of UEs in the environments. This always-on type of transmitted RSs reduces the network’s energy efficiency and increases operational expenses and interference. One of the main features of 5G signals is ultra-lean transmission, which minimizes the transmission of always-on signals. For instance, CRS which used to be an always-on RS in LTE, is not necessarily being continuously transmitted in 5G signals. Up until now, 5G opportunistic navigation methods relied on the always-on signals, e.g., the primary and secondary synchronization signals (PSS and SSS, respectively) and the physical broadcast channel (SS/PBCH) block, none of which use the entire signal bandwidth (Shamaei and Kassas, 2021b).

This paper presents the cognitive opportunistic navigation (CON) framework originally presented in (Neinavaie et al., 2022b) as a joint detection and tracking algorithm which develops a receiver architecture to simultaneously detect the active unknown signals and track them. The rest of the paper is organized as follows. Section II surveys related research. Section III describes the received baseband signal model. Section IV presents the proposed proposed receiver architecture. Section V presents the experimental results. Section VI gives concluding remarks.

II. RELATED WORK

1. Opportunistic Navigation

Over the past decade, opportunistic navigation has been demonstrated in the literature with different types of signals, also known as signals of opportunity (SOPs). SOP examples include cellular (Gadka et al., 2019; Hong et al., 2021; Kazaz et al., 2022; Lapin et al., 2022; Maaref and Kassas, 2022; Shamaei and Kassas, 2021a; Soderini et al., 2020; Souli et al., 2021b; Strandjord et al., 2021; Wang and Morton, 2022; Xhafa et al., 2021), digital television (Hong et al., 2021; Souli et al., 2021a; Yang and Soloviev, 2020), FM radio (Aziz and Allen, 2018; Chen et al., 2020; Psiaki and Slosman, 2022), and low-earth orbit (LEO) satellite signals (Farhangian and Landry, 2020; Hartnett, 2022; Huang et al., 2022; Iannucci and Humphreys, 2022; Khalife et al., 2022; Kozhaya and Kassas, 2022; Leng et al., 2016; Wei et al., 2020). Among terrestrial SOPs, cellular signals have attracted
considerable attention due to their desirable attributes, including: (i) large transmission bandwidth, (ii) high carrier-to-noise ratio, and (iii) desirable geometric diversity. Cellular SOPs have been demonstrated to yield meter-level accuracy in urban and indoor environments experiencing severe multipath (Abdallah and Kassas, 2021; Dun et al., 2020; Jao et al., 2022; Wang and Morton, 2020; Wang and Morton, 2020; Wang et al., 2022; Whiton et al., 2022) and sub-meter-level positioning accuracy on unmanned aerial (UAVs) (Khalife and Kassas, 2022a,b).

Nevertheless, the aforementioned approaches relied on the knowledge of a subset of the RSs transmitted by the SOP. These methods would fail if (i) the receiver enters an unknown SOP environment where the number of active SOPs and their corresponding RSs are unknown, or (ii) some signal parameters change due to the dynamic nature of wireless protocols. This paper addresses these issues by estimating all available RSs within the SOP with minimal prior knowledge.

2. Positioning with 5G Signals

The characteristics of mmWave signals were evaluated for positioning in (Wymeersch et al., 2017). Cramér-Rao lower bounds (CRLBs) of the direction-of-departure (DOD), DOA, and TOA for both uplink and downlink mmWave signals were derived in (Abu-Shaban et al., 2018; Abu-Shaban et al., 2018), showing sub-meter positioning error, and sub-degree orientation error. To exploit the sparsity of mmWave channels, tools relying on compressed sensing were proposed in (Lee et al., 2014),(Yacong, 2018) to estimate DOD, DOA, and TOA of the UE, showing sub-meter level position error via simulation results. The DOD and UE’s position were estimated in a two stage Kalman filter using the signal strength from multiple base stations in (Rastorguev-Foi et al., 2018), which yielded sub-meter-level three-dimensional (3-D) position accuracy. The joint estimation of the position and orientation of the UE, as well as the location of reflectors or scatterers in the absence of the line-of-sight (LOS) path were considered in (Mendrzik et al., 2018), showing less than 15 m position RMSE and less than 7 degree orientation RMSE. A two-way distributed localization protocol was proposed in (Abu-Shaban et al., 2018) to remove the effect of the clock bias in TOA estimates. In (Fascista et al., 2019), a positioning method for multiple-output single-input systems was proposed, where the DOD and TOA of the received signal were used to localize a UE. In (Ma et al., 2020), estimation of signal parameters via rotational invariant techniques (ESPRIT) was used to estimate the DOA and DOD of the signal. Experimental results in (Abdallah and Kassas, 2022) showed meter-level navigation using TOA estimates from 5G signals. The results presented therein rely only on the PSS and SSS for TOA estimation. It is shown that the proposed receiver yields a narrower RS autocorrelation function, which translates to more accurate TOA estimates. Moreover, the proposed receiver architecture can be readily adapted to any type of signal containing periodic RSs.

3. Detection of Unknown Signals in the Presence of Noise and Interference

The acquisition stage of the proposed receiver is modeled as a sequential matched subspace detection problem, which comprises estimating the number of gNBs, an initial estimate of normalized Doppler, and an initial estimate of the RSs. The detection problem of an unknown source in the presence of other interfering signals falls into the paradigm of matched subspace detectors which has been widely studied in the classic detection literature (Gini and Farina, 2002; Kraut et al., 2001; Scharf and Friedlander, 1994). Matched subspace detectors are used frequently in the signal processing literature, e.g., in source localization in multiple-input multiple-output (MIMO) radars (Korso et al., 2012) , passive bistatic radar (Zaimbashi et al., 2013), and navigation with unknown signals (Neinavaie et al., 2022a,b). In the navigation literature, detection of unknown signals has been studied to design frameworks which are capable of navigating with unknown or partially known signals. The problem of detecting Galileo and Compass satellites signals was studied in (Gao, 2008), which revealed the spread spectrum codes for these satellites. Preliminary experiments on navigation with partially known signals from low and medium Earth orbit satellites were conducted in (Khalife et al., 2021, 2022; Merwe et al., 2020; Neinavaie et al., 2021, 2022a). While these approaches yielded useful insights, they exploited signals that have a simpler structure compared to 5G. In (Neinavaie et al., 2022b), using the concept of matched subspace detection, a full receiver architecture is derived, analyzed and tested with real 5G signals. It was shown that the proposed receiver was capable of detecting the number of active gNBs, along with their corresponding RSs and Doppler frequencies with only the prior knowledge of the frame duration and the carrier frequency.

III. RECEIVED BASEBAND SIGNAL MODEL

As it was mentioned previously, the SS/PBCH block is not transmitted on the whole signal’s bandwidth. Therefore, methods which only rely on SS/PBCH block, cannot exploit the full ranging accuracy that can be achieved by 5G signals. Other periodic RSs are not necessarily always-on and the cognitive receiver should be able to exploit them to be able to achieve the available ranging accuracy. In this paper, with a focus on exploiting navigation observables using the RSs in the entire 5G bandwidth, the 5G NR signal is modeled as an unknown periodic signal in the presence of interference and noise. If an RS is being periodically transmitted, it will be detected by the receiver, estimated, and used to derive navigation observables. The estimated RS will involve an estimation of always-on signals such as the SSs and any other active reference signal that is being periodically transmitted. It will be shown experimentally in section V that the exploited bandwidth by the proposed cognitive method is
larger than that of the method which only relies on always-on signals. The received base-band signal model can be expressed as

\[
r[n] = \sum_{i=1}^{N} \alpha_i c_i [\tau_n - t_{s_i}[n]] \exp(j\theta_i[\tau_n]) + d_i[\tau_n - t_{s_i}[n]] \exp(j\theta_i[\tau_n]) + w_i[n],
\]

(1)

where \(r[n]\) is the received signal at the \(n\)th time instant; \(\alpha_i\) is the complex channel gain between the UE and the \(i\)th gNB; \(\tau_n\) is the sample time expressed in the receiver time; \(N\) is the number of gNBs; \(c_i[n]\) is the periodic RS with a period of \(L\) samples; \(t_{s_i}[n]\) is the code-delay corresponding to the UE and the \(i\)th gNB at the \(n\)th time instant; \(\theta_i[\tau_n] = 2\pi f_{D_i}[n]T_n\) is the carrier phase in radians, where \(f_{D_i}[n]\) is the Doppler frequency at the \(n\)th time instant and \(T_n\) is the sampling time; \(d_i[\tau_n]\) represents the samples of some data transmitted from the \(i\)th gNB; and \(w_i[n]\) is zero-mean independent and identically distributed noise with \(E\{w_i[m]w_i[n]\} = \sigma_w^2 \delta[m-n]\), where \(\delta[n]\) is the the Kronecker delta function. The desired RS from the \(i\)th gNB is defined as

\[
s_i[n] \triangleq \alpha_i c_i [\tau_n - t_{s_i}[n]] \exp(j\theta_i[\tau_n]),
\]

(2)

and the equivalent noise is

\[
w_{eq_i}[n] = d_i[\tau_n - t_{s_i}[n]] \exp(j\theta_i[\tau_n]) + w_i[n].
\]

(3)

Hence, the system model can be rewritten as

\[
r[n] = \sum_{i=1}^{N} s_i[n] + w_{eq_i}[n].
\]

(4)

It should be noted that due to the periodicity of the RS, assuming a constant Doppler in the processing time, i.e., \(f_{D_i}[n] = f_{D_i}\), the desired RS has the following property

\[
s_i[n + mL] = s_i[n] \exp(j\omega_i mL) \quad 0 \leq m \leq L - 1,
\]

(5)

where \(\omega_i = 2\pi f_{D_i}T_s\) is the normalized Doppler, and \(-\frac{1}{2} \leq \omega_i \leq \frac{1}{2}\). The acquisition stage will estimate \(s_i[n]\) and the estimation of \(s_i[n]\) will be used at the receiver to obtain the navigation observables.

**Definition:** The coherent processing interval (CPI) is defined as the time interval during which the Doppler, delay, and channel gains are considered to be constant.

One can form a vector of \(L\) observation samples corresponding to the \(k\)th period of the signal as

\[
y_k \triangleq [r[(k-1)L + 1], r[(k-1)L + 2], \ldots, r[kL]]^T.
\]

(6)

Considering a CPI of length \(K \times L\) samples, the observation vector is constructed as \(y = [y_1^T, y_2^T, \ldots, y_K^T]^T\). Therefore,

\[
y = \sum_{i=1}^{N} H_i s_i + w_{eq_i},
\]

(7)

where \(s_i = [s_i[1], s_i[2], \ldots, s_i[L]]\), \(w_{eq_i}\) is the equivalent noise vector corresponding to the \(i\)th source, and the \(KL \times L\) Doppler matrix corresponding to the \(i\)th source is defined as

\[
H_i \triangleq [I_L, \exp(j\omega_i L) I_L, \ldots, \exp(j\omega_i (K-1)L) I_L]^T,
\]

(8)

where \(I_L\) is an \(L \times L\) identity matrix.

**IV. PROPOSED RECEIVER STRUCTURE**

This section presents the structure of the proposed receiver. The proposed receiver consists of two main stages: (i) acquisition and (ii) tracking. Each of these stages are discussed in details next.
1. Acquisition

In this paper, the acquisition stage is modeled as a sequential matched subspace detection problem. The acquisition stage comprises estimating the number of gNBs, an initial estimate of normalized Doppler, and the RSs, i.e., \( \hat{N}, \omega_i, \) and \( s_i \), respectively. At each step of the acquisition, a test is performed to detect the most powerful gNB when the subspace of the previously detected gNBs are nulled. In the following subsection, matched subspace detection is overviewed and the hypothesis test for detection of multiple gNBs is formulated.

a) Matched Subspace Detector

As it was mentioned previously, in the first step of the proposed sequential algorithm, the presence of a single gNB is tested and if the null hypothesis is accepted, then \( \hat{N} = 0 \), which means that no gNB is detected to be present in the environment under the test. If the test rejects the null hypothesis, the algorithm verifies the presence of at least one source and performs the test to detect the presence of other gNBs in the presence of the previously detected gNBs. The unknown Doppler and the RS of each gNB are estimated at each step. In general, if the null hypothesis at the \( i \)th level of the sequential algorithm is accepted, the algorithm is terminated and the estimated number of gNBs will be \( \hat{N} = i - 1 \).

In order to test the presence of \( s_i \), at the \( i \)th stage of the acquisition algorithm, the observation vector can be written as

\[
y = H_i s_i + B_{i-1} \theta_{i-1} + w_{\text{eq}}. \tag{9}
\]

\[
B_{i-1} \triangleq [H_1, H_2, \ldots, H_{i-1}], \quad \theta_{i-1} \triangleq [s_1^T, s_2^T, \ldots, s_{i-1}^T]^T. \tag{10}
\]

The following binary hypothesis test is used to detect the \( i \)th gNB:

\[
\{ \mathcal{H}_0^i : y = B_{i-1} \theta_{i-1} + w_{\text{eq}} \}
\]

\[
\{ \mathcal{H}_1^i : y = H_i s_i + B_{i-1} \theta_{i-1} + w_{\text{eq}} \}. \tag{11}
\]

For a given set of Doppler frequencies, \( \mathcal{W}_i = \{ \omega_1, \omega_2, \ldots, \omega_i \} \), the GLR at the \( i \)th stage is derived as (Neinavaie et al., 2022b)

\[
L_i(y|\mathcal{W}_i) = \frac{y^H P_{\mathcal{X}} y}{y^H P_{\mathcal{X}}^\perp P_{\mathcal{X}}^\perp y}. \tag{12}
\]

where \( y^H \) is the Hermitian transpose of \( y \), \( P_{\mathcal{X}} \triangleq X(X^H X)^{-1}X^H \), denotes the projection matrix to the column space of \( X \), and

\[
P_{\mathcal{X}}^\perp \triangleq I - X^H X^H, \tag{13}
\]

denotes the projection matrix onto the space orthogonal to the column space of \( X \), and \( s_i = P_{B_{i-1}}^\perp H_i \).

The reader is referred to (Scharf and Friedlander, 1994) for further interpretations of matched subspace detectors. The ML estimate of \( \omega_i \) is obtained by maximizing the likelihood function under \( \mathcal{H}_1^i \) which yields

\[
\hat{\omega}_i = \arg\max_{\omega_i} \| H_i^H P_{\mathcal{X}}^\perp y \|^2, \tag{14}
\]

and is used to construct \( \hat{P}_{B_{i-1}}, \hat{H}_i, \) and \( \hat{\lambda}_i \). For a known \( \omega_i \), the least squares (LS) estimate of the \( i \)th source, i.e., \( s_i \), is given by

\[
\hat{s}_i = \frac{1}{\lambda_i} H_i^H P_{\mathcal{X}}^\perp y, \tag{15}
\]

2. Tracking

After obtaining coarse estimates of the Doppler frequencies and estimates of the RSs in the acquisition step, the receiver refines and maintains these estimates. Specifically, phase-locked loops (PLLs) are employed to track the carrier phases of the detected RSs and carrier-aided delay-locked loops (DLLs) are used to track the RSs’ code phases. The details of the tracking loops are presented in (Neinavaie et al., 2022b).
V. EXPERIMENTAL RESULTS

This section validates the proposed receiver experimentally. To this end, three experiments are conducted: (i) an experiment on a ground vehicle with real 5G NR signals, (ii) and an experiment on UAV with real 5G NR signals. The objective of these experiments are to: (i) evaluate the acquisition and tracking performance of the proposed receiver, (ii) demonstrate the capability of detecting multiple sources transmitting on the same carrier frequency, (iii) and showcase the navigation solution obtained via the proposed receiver.

1. Real 5G Signals: Comparison with a Conventional 5G Receiver on a Ground Vehicle

The first experiment aims to compare the acquisition and tracking performance of the proposed receiver with the conventional 5G receiver (Shamaei and Kassas, 2021b) which only relies on the always-on RSs. The experimental setup and results for the experiment with real 5G NR signals are discussed next.

a) Experimental Setup and Environmental Layout

In this experiment, a ground vehicle was equipped with a quad-channel National Instrument (NI) universal software radio peripheral (USRP)-2955 and four consumer grade 800/1900 MHz cellular antennas to sample 5G signals near Fairview Road in Costa Mesa, California, USA. Only one channel from the USRP was used and was tuned to a 872 MHz carrier frequency, which is a 5G NR frequency allocated to the U.S. cellular provider AT&T. The sampling rate was set to 10 Mega-samples per second (MSps) and the sampled 5G signals were stored on a laptop for post-processing. In order to obtain ground-truth, the vehicle was equipped with a Septentrio AsteRx-i V GNSS-aided inertial navigation system (INS), which is a dual antenna, multi-frequency GNSS receiver with real-time kinematics (RTK) capabilities. The GNSS receiver is coupled with a Vectornav VN-100 micro electromechanical systems (MEMS) inertial measurement unit (IMU) to estimate the position and orientation of the ground vehicle at a rated horizontal accuracy of 0.6 cm in clear sky conditions (RTK performance). The vehicle traversed a trajectory of 4.1 km in 315 seconds. The acquisition results are presented next.

b) Acquisition Results

The recorded 5G signals were processed in two ways for comparison: (i) using the proposed receiver and (ii) using the conventional 5G receiver proposed in (Shamaei and Kassas, 2021b). The conventional 5G receiver detected 1 gNB with an initial Doppler frequency of -7.2 Hz. Note that the limited number of gNBs was expected as 5G gNBs are sparsely deployed at the present time. The location of the gNB was mapped prior to the experiment. Next, the signal acquisition stage was applied to detect the ambient 5G gNB. The detection threshold was set such that $P_{fa} = 10^{-4}$, which yielded $\eta = 1.008$, $K$ was set to 40, and $T_{sub}$ was set to 20 ms. Doppler estimation was performed by searching for the maximizer of the likelihood function according to (14) with a step size of 1 Hz. The acquisition stages in the proposed receiver is shown in Fig. 1.

![Figure 1: Acquisition stages in the proposed receiver for 5G NR signals on a ground vehicle showing the likelihood function at each stage and the detected and nulled sources. The DC component, i.e., at zero Doppler frequency, was nulled as it was saturating the detector.](image)

(c) Tracking Results

After acquiring the Doppler and the RSs, the tracking loops are initialized and the signal is tracked. Fig. 2 show the resulting Doppler frequency and delay, expressed in meters, obtained using the proposed and conventional receivers. As it can be seen in Fig. 2(b) the estimated delays for the proposed and the conventional receivers are slightly drifting away from the ground-truth which is due to the clock drifts. The effect of clock drift is considered in the carrier phase model (see equation (16)). Note that the initial value of the delays were subtracted out to facilitate comparison. The Doppler and delay RMSE values were calculated from ground-truth for both receivers and are summarized in Table 1, which shows that the proposed receiver outperforms the conventional one.

One main reason behind proposed performing better than a conventional 5G receiver is the fact that the latter exploits the RSs in
the entire bandwidth, making the bandwidth of the estimated RS higher than the RSs used in the conventional receiver, mainly
the PSS and SSS. Fig. 3 illustrates this showing a narrower normalized autocorrelation function of the RS estimated with the
proposed receiver compared to that of a 5G PSS.

Table 1: Delay and Doppler RMSE for the proposed and conventional receivers.

<table>
<thead>
<tr>
<th></th>
<th>Delay RMSE (m)</th>
<th>Doppler RMSE (Hz)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conventional</td>
<td>24.3</td>
<td>3.66</td>
</tr>
<tr>
<td>proposed</td>
<td>21.88</td>
<td>2.28</td>
</tr>
</tbody>
</table>

Figure 3: Normalized autocorrelation function of the RS estimated with the proposed receiver compared to that of a 5G PSS.

2. Real 5G signals: The First Navigation Results on a UAV

The second experiment aims to find a navigation solution on a UAV using the proposed receiver. To the best of author’s
knowledge this is the first navigation results with real 5G signals on a UAV.

a) Experimental Setup and Environment Layout

In this experiment, the navigator was an Autel Robotics X-Star Premium UAV equipped with a single-channel Ettus 312 USRP
connected to a consumer-grade 800/1900 MHz cellular antenna and a small consumer-grade GPS antenna to discipline the
on-board oscillator. The cellular receivers were tuned to the cellular carrier frequency 632.55 MHz, which is a 5G NR frequency
allocated to the U.S. cellular provider T-Mobile. Samples of the received signals were stored for off-line post-processing. The
ground-truth reference trajectory was taken from the on-board Ettus 312 USRP GPS solution. The UAV traversed a trajectory
of 416 m. Fig. 4 shows the environment layout and the vehicle trajectory. The acquisition results are presented next.

b) Acquisition Results

Next, the signal acquisition stage was applied to detect the ambient 5G gNBs. The proposed receiver detected 2 gNBs with initial
Doppler frequencies of 3.5 Hz and 11.5 Hz. The location of the gNBs was mapped prior to the experiment. The acquisition
stages in the proposed receiver are shown in Fig. 5.
c) Tracking Results

After acquiring the Doppler and the RSs, the tracking loops are initialized and the signal is tracked. Fig. 6 shows the resulting Doppler frequencies and delays, expressed in meters, obtained using the proposed receiver.

d) Navigation Solution

In the following, it is assumed that (i) the UAV’s altitude is known at all time and (ii) the UAV has an estimate of its position at time-step $k_0$, prior to navigating with 5G signals. The carrier phase to the $i$-th gNB $z_i(k)$ at time-step $k$ expressed in meters can be modeled as

$$z_i(k) = ||r_r(k) - r_{s_i}|| + c\delta t_r(k) - c\delta t_{s_i} + v_i(k),$$  \hspace{1cm} (16)

where $r_r$ and $r_{s_i}$ are the three-dimensional (3–D) position vectors of the UAV-mounted receiver and the $i$-th gNB, respectively; $c$ is the speed of light; $\delta t_r$ is the UAV-mounted receiver’s clock bias; $\delta t_{s_i}$ models the $i$-th gNB’s clock bias and carrier phase ambiguity; and $v_i(k)$ is the measurement noise, which is modeled as a zero-mean Gaussian random variable with variance $\sigma^2_i$ (Shamaei and Kassas, 2019). Note that since the UAV’s altitude is known, e.g., using an altimeter, only its two-dimensional (2–D) position is estimated. The time reference for the transmitter and receiver clocks is chosen such that $\delta t_r(k_0) = 0$. Using the position estimate at $k_0$ and the fact that $\delta t_r(k_0) = 0$, the gNBs clock biases can be estimated from $z_i(k_0)$ resulting in the estimate $\hat{\delta t}_{s_i}$. Next, define the corrected carrier phase measurement $\bar{z}_i(k) \triangleq z_i(k) + \hat{\delta t}_{s_i}$ which can be approximated as

$$\bar{z}_i(k) \approx ||r_r(k) - r_{s_i}|| + c\delta t_r(k) + v_i(k), \hspace{1cm} \forall k > k_0.$$  \hspace{1cm} (17)

Subsequently, the corrected carrier phase measurements were fed to an extended Kalman filter (EKF) to solve the state vector $\bar{x}(k) \triangleq \left[r_r^T(k), \bar{v}_r^T(k), c\delta t_r(k), c\dot{\delta t}_r(k)\right]^T$, where $\bar{r}_r(k)$ is the UAV’s 2–D velocity vector and $\dot{\delta t}_r(k)$ is the receiver’s clock
drift. A nearly constant velocity model was used for the UAV’s position and velocity dynamics, and a standard double integrator driven by process noise was used to model the clock bias and drift dynamics (Kassas, 2021). As such, the discrete-time dynamics model of $x$ are given by $x(k + 1) = Fx(k) + w(k)$, where $F$ is the state transition matrix obtained according to (Kassas, 2021) and $w(k)$ is the process noise vector, which is modeled as a zero-mean Gaussian random vector with covariance matrix $Q$ obtained according to (Kassas, 2021). The UAV’s $x, y$ acceleration process noise spectra in the nearly constant velocity model were set to $q_x = q_y = 10 \text{ m}^2/\text{s}^3$, and the receiver’s clock process noise was chosen to be that of a typical temperature-compensated crystal oscillator (TCXO) (Kassas, 2021). Note that $r_p(k)$ is expressed in an East-North-Up (ENU) frame centered at the UAV’s true initial position. The EKF state estimate was initialized at $\hat{x} = 0_{6 \times 1}$ with an initial covariance of $\Sigma = 4 \cdot I_{6 \times 6}$. The measurement noise covariance was set to $R = 2 \cdot I_{2 \times 2}$. The position RMSE of the UAV was calculated to be 4.35 m with the aforementioned parameters. The true and estimated UAV trajectories are shown in Fig. 7.

Figure 6: (a) Doppler tracking and (b) delay tracking results for the UAV 5G experiment. The ground-truth is calculated according to the true position of the vehicle and the gNBs.

Figure 7: Ground-truth and estimated trajectories using proposed receiver for 5G NR signals on a UAV. The proposed receiver yielded a UAV position RMSE of 4.35 m. Map data: Google Earth.

VI. CONCLUSION
A joint detection and tracking method was proposed to extract navigation observables from 5G signals, without requiring knowledge of the 5G RSs. To exploit the full ranging accuracy that can be achieved with 5G signals, the proposed receiver was designed to estimate the RSs from multiple 5G gNBs and exploit them for navigation purposes. The acquisition stage of the receiver was modeled as a sequential detection problem. The GLR test was used to sequentially estimate the number of active gNBs, their RSs, and Doppler frequencies. Tracking loops were also designed in order to refine and maintain the estimates provided by the acquisition stage. Extensive experimental results were presented demonstrating the capabilities of the proposed receiver with real 5G signals on ground and aerial platforms. On a ground vehicle, it was demonstrated that the proposed receiver yields a reduction of 10% and 37.7% in the estimated delay and Doppler RMSE, respectively, over that achieved with a conventional opportunistic navigation 5G receiver. On a UAV, it was demonstrated that the proposed receiver enables the UAV to navigate over 416 m trajectory with 5G NR gNBs, achieving a position RMSE of 4.35 m.
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