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Unmanned Aerial Vehicle Positioning using 5G New Radio Technology in Urban Environment

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***Abstract*—Unmanned aerial vehicles (UAVs) are becoming increasingly popular for various applications, including surveillance, monitoring, mapping, delivery, and inspection. However, their positioning capabilities in urban environments can be limited due to challenges such as Non-Line-of-Sight (NLOS) propagation, multi-path interference, and signal blockage caused by tall buildings, trees, and other obstacles, which can affect their positioning capabilities. The purpose of this paper is to provide a novel approach for UAV's positioning based on Observed Time Difference of Arrival (OTDOA), combining 5G (NR) technology and an inertial measurement unit (IMU) to improve UAV positioning in urban environments. Integrating these technologies can improve UAV positioning and control systems by offering rapid, low-latency communication, a thorough and precise comprehension of the UAV's surroundings and its own condition, and more accurate assessments of the UAV's location, speed, and orientation. Simulation model shows the data from these sensors is then fused using an Extended Kalman Filter (EKF) to estimate the UAV's position and orientation. The study shows that the proposed system delivers accurate and reliable UAV positioning in these environments, outperforming traditional methods.**

***Index Terms*—5G networks, positioning, 5G networks, UAV, IMU, barometric pressure sensors, and Extended Kalman Filter (EKF).**

I. Introduction

Unmanned aerial vehicles (UAVs), or drones, have become increasingly popular in various logistics, agriculture, and surveillance industries. One commonly used UAV navigation technology is the Global Navigation Satellite System (GNSS), which includes Global Positioning System (GPS), Glonass, Galileo, and BeiDou systems. GNSS provides accurate and global positioning information for UAVs navigation system [1] [2] [3]. However, their positioning capabilities in urban environments can be limited due to challenges such as Non-Line-of-Sight (NLOS) propagation, multi-path interference, and signal blockage caused by tall buildings, trees, and other obstacles, which can affect their positioning capabilities [4] [5]. As the demand for more precise and reliable UAV positioning increases, the emergence of 5G Fifth generation technology offers promising solutions. UAVs are becoming available and connected to cellular networks [6]. The fifth generation of mobile communication. (5G) new radio (NR) is the next generation in wireless communications technology that offers significant improvements over previous generations. 5G NR provides quicker data transfer rates, reduced latency, and enhanced dependability, which makes it well-suited for various applications across diverse fields. This technology provides the necessary infrastructure for advancements in fields such as the Internet of Things (IoT), UAV (UAVs) and autonomous vehicles [7]. This development will pave the way for novel UAV applications, including self-governing flight, enhanced safety measures, and instantaneous data transmission. With the implementation of 5G NR, the UAV industry is poised for significant growth and innovation. The 5G NR technology will provide the necessary infrastructure for UAVs to take advantage of the increased speed, reliability, and low latency offered by 5G networks [5].

Overall, the use of 5G New Radio technology and the OTDOA technique for UAV positioning in urban environments has the potential to improve the accuracy and reliability of UAVs, enabling a wide range of applications and services. The results of the study have important implications for UAV positioning in urban environments using 5G New Radio technology. One of the main advantages of using 5G for UAV positioning is that it can provide more accurate and reliable position information than traditional GPS systems, which can be obstructed by buildings and other structures in urban environments. Comparing and contrasting the results with the existing literature on UAV positioning and communication in urban environments, it can be seen that there have been several studies that have explored the use of different technologies for UAV positioning and communication, including GPS, cellular networks, and Wi-Fi. However, the use of 5G New Radio technology and the OTDOA technique is a relatively new approach that has not been extensively studied in the literature. One study that is relevant to this approach is "A 5G-Enabled UAV for Communication and Positioning in Urban Environments" which proposed a 5G-enabled UAV system that uses the OTDOA technique for positioning [8].

However, this study focused on the communication aspect of the system, rather than the positioning accuracy, in comparison, the current study specifically addresses the issue of UAV positioning in urban environments using 5G New Radio technology and the OTDOA technique. The results suggest that this approach can provide accurate and reliable positioning information for UAVs in urban environments, which has important implications for a wide range of applications. One our promising approach is to incorporate an IMU (Inertial Measurement Unit) and EKF (Extended Kalman Filter) into the system, as mentioned in UAV system platform architecture development. Additionally, and incorporate barometric pressure measurements to enhance the estimation of the UAV's altitude in 3D. Barometric pressure measurements can provide an independent estimate of the UAV's altitude, which can be used to correct any errors or biases in the altitude estimates obtained from the TDOA and IMU sensors. By fusing the barometric pressure measurements with the TDOA and IMU data using an EKF, we can further refine the UAV's position and altitude estimation, leading to more accurate and reliable position estimates. This approach has the potential to improve the performance of the 5G PRS positioning system, particularly in scenarios where altitude estimation is critical, such as UAV navigation or vertical positioning in multi-story buildings. However, it is important to note that the incorporation of barometric pressure measurements also introduces additional complexity and potential sources of error, such as changes in weather conditions or altitude-dependent variations in barometric pressure.

A. 5G Enhanced UAV Positioning

1) Ultra-Reliable Low Latency Communications: One of the key advantages of 5G technology is its ultra-reliable and low-latency communication capabilities. This feature enables UAVs to maintain a robust and uninterrupted connection with ground stations and control centres. With minimal latency, real-time positioning updates can be transmitted swiftly, allowing for more accurate and responsive control of UAVs [2].

2) Increased Bandwidth and Data Transfer: 5G networks offer significantly higher bandwidth compared to previous generations. This enhanced data transfer capability enables UAVs to transmit large volumes of positioning-related data, such as GPS. coordinates, altitude, and orientation, in real-time. As a result, operators can obtain more precise and detailed information about the UAV's position and status [9].

3) Multi-Connectivity and Network Slicing: To ensure reliable and seamless UAV positioning, 5G networks support multi-connectivity and network slicing features, as depicted in Fig1. Multi-connectivity allows UAVs to simultaneously connect to multiple base stations, enhancing signal strength and reducing the risk of signal loss in areas with limited coverage. Network slicing enables the creation of dedicated virtual networks, ensuring prioritized and uninterrupted communication for UAV positioning requirements [10].

4) Edge Computing and Distributed Processing: 5G networks facilitate edge computing, which enables UAVs to offload certain processing tasks to edge servers located closer to the deployment area. By leveraging edge computing capabilities, UAVs can achieve faster processing of positioning data, reducing latency and improving overall positioning accuracy. This distributed processing approach also helps alleviate the computational burden on the UAV's onboard systems.

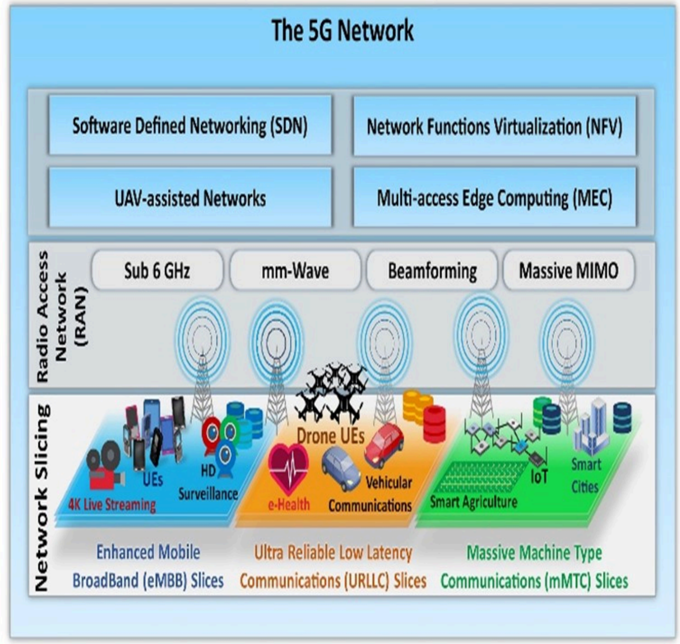

Fig. 1. 5G network enablers with network slicing and UAVs [11]

5) Integration with other Technologies: 5G technology can be seamlessly integrated with other emerging technologies to further enhance UAV positioning capabilities. For instance, combining 5G with artificial intelligence and machine learning enables advanced analytics of positioning data, leading to predictive positioning models and intelligent flight path planning. Additionally, the integration of 5G with satellite-based navigation systems, such as GNSS (Global Navigation Satellite Systems), ensures reliable and precise positioning in environments with limited GPS coverage [12] [13].

B. Position Estimation Techniques in Wireless Networks

There are two main types of signal processing techniques for position estimation in wireless networks: range-based and range-free methods [8] [14]. Range-based methods rely on the measurement of specific parameters, such as the time of arrival (ToA), it is a technique used to measure the time taken for a signal to travel between an anchor node and a target node [1]. There are several techniques that can be used for position estimation in 5G wireless networks. Here are some of them:

- Time of Arrival (ToA): This technique measures the time a signal travels from the transmitter to the receiver. Utilizing the speed of signal, the distance between the transmitter and receiver can be determined, which can subsequently be employed to approximate the location of the receiver.
- Angle of Arrival (AoA): This technique uses the angle of arrival of the signal at the receiver to estimate the position of the transmitter. Multiple antennas can be used at the receiver to determine the signal's arrival angle.

- Received Signal Strength (RSS): This technique uses the signal strength of the signal at the receiver to estimate the distance between the transmitter and receiver. By using multiple receivers, the position of the transmitter can be estimated.
- Time Difference of Arrival (TDoA): This technique uses the difference in arrival time of a signal at multiple receivers to estimate the position of the transmitter.
- Hybrid Techniques: These techniques combine two or more of the above techniques to improve position estimation accuracy. For example, a hybrid technique may combine ToA and RSS techniques to improve position estimation accuracy.

It is important to mention that various methods might be better suited for specific environments and situations, and factors like signal disruption, multi-path propagation, and environmental circumstances can influence the precision of position estimation.

These techniques can provide accurate positioning information but often require specialized hardware and may be affected by environmental factors. On the other hand, range-free methods do not rely on distance or angle measurements but instead use connectivity information and network topology to estimate the position of nodes. These methods tend to be more robust to environmental influences, easier to execute, and potentially more cost-efficient. However, they may not provide the same level of accuracy as range-based methods [15]. In this study, we proposed a novel approach for UAVs positioning based on the combination of 5G New Radio (NR), and sensor fusion. The data from these sensors is then fused using an Extended Kalman Filter (EKF) to estimate the UAV's position and orientation.

II. METHODOLOGY

The system developed for the integration of 5G, IMU, barometric pressure sensors, and Extended Kalman Filter (EKF) to enhance UAV positioning as illustrated in Fig2. The system consists of five main components: 5G receiver, Barometric Air Pressure (BAP), An Inertial Measurement Unit (IMU), and Extended Kalman Filter (EKF). The 5G receiver provides communication between the UAV and the ground station. It allows the UAV to transmit signals and receive them in real-time. The integration of a 5G receiver in a UAV offers numerous advantages that can boost its performance, such as:

- Faster data transfer speeds: 5G networks can provide much quicker than previous generations of cellular networks. This can enable UAVs to transmit large amounts of data quickly and efficiently, which can be particularly useful for real-time video streaming, remote sensing, and data collection applications.
- Improved video streaming quality: Higher bandwidth and reduced latency in 5G networks contribute to an improved video streaming experience from UAVs, facilitating real-time viewing of high-quality footage.
- Lower latency for real-time control: The minimal latency present in 5G networks heightens the responsiveness of UAVs in real-time control situations, such as remote piloting or autonomous navigation.
- Location data for positioning: 5G networks can provide location data that the UAV's positioning system can use to determine its location and orientation. This can be particularly useful in situations where GPS signals may not be available or unreliable, such as in urban canyons, indoors, or in areas with high electromagnetic interference [16].

In this work, the subsequent algorithm has undergone optimization through the employment of MATLAB software, thereby facilitating the augmentation of Unmanned Aerial Vehicle (UAV) 5G New Radio (NR) position estimation accuracy.

UAV 5G NR Position Estimation Algorithm

procedure UAV_5G_NR_POSITION_ESTIMATION($UAV\_positions, interval$)
  P_RS_Config
  P_DSCH_Config
  for $i = 1 :$ size($UAV\_positions$) $: interval$ **do**
    $UAV\_pos \leftarrow UAV\_positions(i)$
    ranges = TOA(UAV_pos) {Time of Arrival}
    $t\_start \leftarrow$ current_time
    p_hcp = HCP(UAV_pos, ranges) {Hybrid Cost-based Positioning}
    p_pso = PSO(UAV_pos, ranges, 200, 1000) {Particle Swarm Optimization}
    p_ga = GA(UAV_pos, ranges, 50, 200) {Genetic Algorithm}
    $t(i) \leftarrow$ current_time $- t\_start$
  end for
end procedure

The procedure takes in two inputs: a set of UAV positions and an interval parameter. The interval parameter determines how often the procedure is run for each UAV position. The procedure initializes two configuration variables: $P_R S_C onfig$ and $P_D SCH_C onfig$. These variables likely contain configuration settings for the physical uplink reference signal (P-RS) and downlink shared channel (PDSCH), respectively. The procedure then iterates through each UAV position in the input set, with a step size determined by the interval parameter. For each UAV position, the procedure performs the following steps:

- Calculates the ranges using Time of Arrival (TOA) measurements. TOA is a positioning technique that uses the time difference of arrival of signals from multiple base stations to determine the location of the UAV.
- Measures the time it takes to perform the positioning algorithms by recording the current time and subtracting it from the start time.
- Uses three different algorithms to estimate the UAV position: Hybrid Cost-based Positioning (HCP), Particle Swarm Optimization (PSO), and Genetic Algorithm

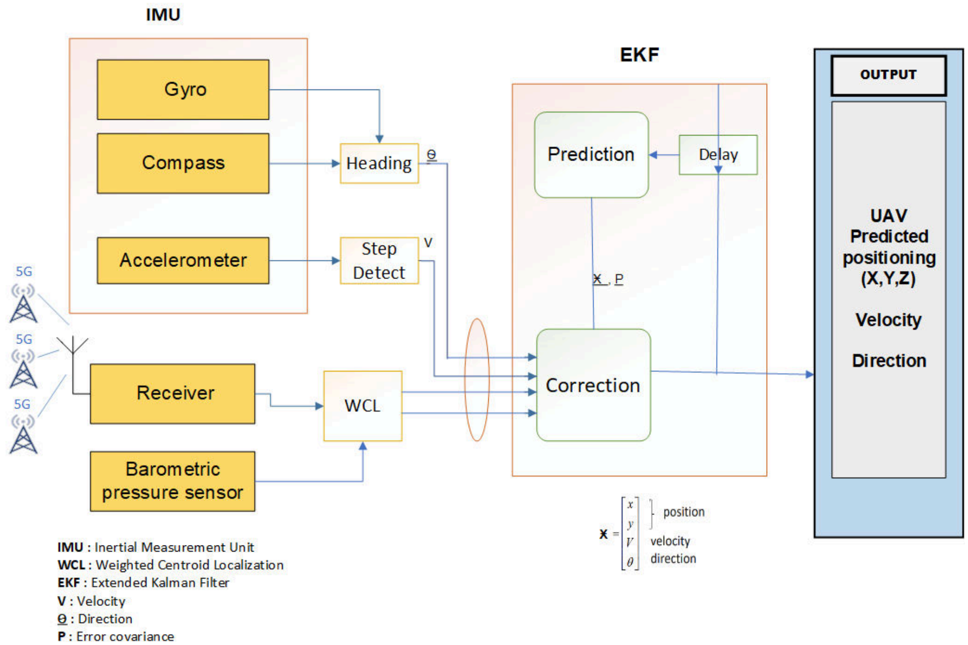

Fig. 2. UAV system platform architecture development

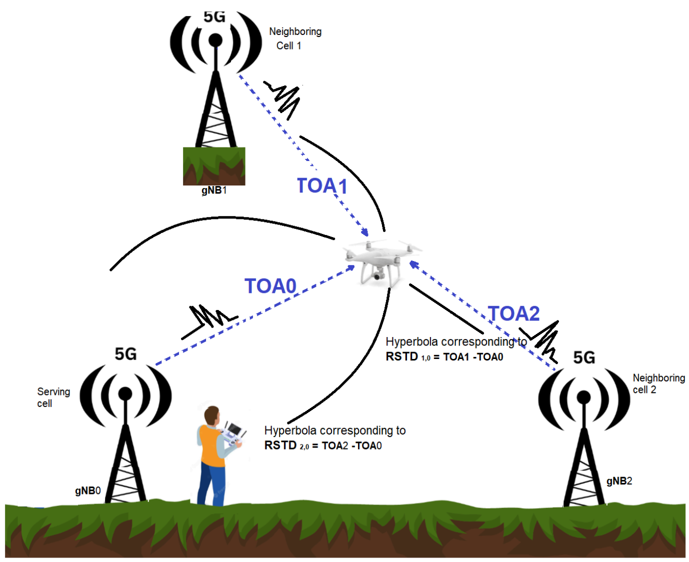

Fig. 3. positioning scenario with one reference and two neighbouring gNBs

(GA). These algorithms likely use the range measurements and other known information about the network to estimate the UAV's position.
- Records the time it took to perform the positioning algorithms.

The procedure outputs a time series of the positioning algorithm execution times. This information can be used to evaluate the performance of the positioning algorithms and to optimize their parameters. In the study, Fig3 illustrates a positioning scenario, which involves one reference gNB, serving as the primary gNB, and two neighboring gNBs. The UAV receives the PRS signals from all three gNBs at distinct timing instances (TOA0, TOA1, and TOA2) based on the geographical distance between the UAV and gNBs. The TOA values are used to obtain two RSTD values, corresponding to two hyperbolic equations, which are assumed to locate the UAV. The intersection of these hyperbolas is computed to estimate the UAV's position in 2-D.

A. *Sensor fusion Techniques*

Sensor fusion techniques are used to combine data from multiple sensors to obtain more accurate and reliable information about the environment or the object being observed. These techniques aim to overcome the limitations and uncertainties associated with individual sensors.

B. *Barometric Air Pressure*

Barometric Air Pressure (BAP): is a device that measures air pressure. This sensor is found in almost every UAV (Unmanned Aerial Vehicle) because it plays a crucial role in stabilizing the size of the UAV. The way this works is pretty simple: the altitude of a UAV can be determined from the air pressure, so the BAP sensor helps to provide that information. However, wind and changes in the UAV's movement can affect air pressure readings, so it is essential to use the onboard barometer to get more accurate data about the altitude [17]. When measuring altitude, the z-axis coordinate system is used, with the altitude of the UAV measured using an ultrasonic sensor. The altitude factor is considered the z-axis of the UAV, meaning that it can be flown up and down based on its altitude. To measure the UAV's altitude, a barometric pressure sensor is used to measure the air pressure. Using a barometric formula (1), we can calculate the altitude of the UAV. This formula considers factors like the earth's gravitational force, the molar mass of air, and the temperature in Kelvins.

$$P = P_0 \times exp(-g \times M \times \frac{h - h_0}{R \times T}) \quad (1)$$

- P is the air pressure of the AUV at altitude $'h'$
- P_0 is hte reference pressure taken when the UAV is placed on the ground
- g the gravitational force of earth, g =9.80665
- h is the altitude of the UAV,
- M is the molar mass of air, M = 0.0289644kg/mol.
- T is the temperature in Kelvins, T = 288.15k.
- R is the universal gas constant, R = 8.31432 N*m /(mol*K).

C. Inertial Measurement Unit

Inertial Measurement Unit (IMU): consists of a set of sensors that measures the acceleration, angular velocity, and sometimes the magnetic field around the UAV. These measurements are then processed to determine the UAV's orientation, velocity, and position. An IMU typically includes a combination of accelerometers, gyroscopes, and sometimes magnetometers. The accelerometers measure the UAV's linear acceleration in three dimensions, while the gyroscopes measure the UAV's rotational velocity around three axes [3]. The magnetometers measure the magnetic field, which can be used to determine the UAV's orientation concerning the Earth's magnetic field. By combining the measurements from these sensors, an IMU can estimate the UAV's position and orientation in space relative to its starting position. This is useful for applications such as autonomous flight control and navigation, where the UAV needs to know its position and orientation to perform specific tasks or missions. It's important to note that while an IMU can provide accurate positioning information over short periods, its accuracy can drift over more extended periods due to sensor noise, bias, and other factors. The basic equations of an IMU are:

Accelerometer Equations:

$$\begin{aligned} a_x &= a_{bx} + a_{nx} \\ a\_y &= a\_by + a\_ny \\ a\_z &= a\_bz + a\_nz \end{aligned} \quad (2)$$

where a_x, a_y, a_z are the measured acceleration components in x, y, and z directions, respectively. a_bx, a_by, a_bz are the bias components in x, y, and z directions, respectively, and a_nx, a_ny, a_nz are the noise components in x, y, and z directions, respectively.

Gyroscope Equations:

$$\begin{aligned} \omega_{\mathrm{x}} &= \omega_{\mathrm{bx}} + \omega_{\mathrm{nx}} \\ \omega_{\mathrm{y}} &= \omega_{\mathrm{bx}} + \omega_{\mathrm{ny}} \\ \omega_{\mathrm{z}} &= \omega_{\mathrm{bx}} + \omega_{\mathrm{nz}} \end{aligned} \quad (3)$$

where _x, _y, _z are the measured angular velocity components in x, y, and z directions, respectively. _bx, _by, _bz are the bias components in x, y, and z directions, respectively, and _nx, _ny, _nz are the noise components in x, y, and z directions, respectively.

Quaternion Equations:

$$\mathrm{q\_\ dot} = 0.5 * [0, \omega\_\mathrm{x}, \omega\_\mathrm{y}, \omega\_\mathrm{z}] * \mathrm{q} \quad (4)$$

where q is the quaternion that describes the rotation of the IMU frame with respect to the global frame, and q_dot is the derivative of the quaternion. [0, _x, _y, _z] is the angular velocity vector expressed in quaternion notation.

$$\begin{aligned} \mathrm{p\_\ dot} &= \mathrm{R} * \mathrm{v} \\ \mathrm{v\_\ dot} &= \mathrm{a} \end{aligned} \quad (5)$$

where p_dot is the derivative of the position vector, v_dot is the derivative of the velocity vector, R is the rotation matrix derived from the quaternion, and a is the acceleration vector measured by the accelerometer. These equations can be used to estimate the position, velocity, and orientation of an IMU over time. However, due to the accumulation of errors and biases over time, it is common to use a combination of other sensors, such as GPS, to correct for these errors and improve the overall accuracy of the estimation [6].

D. Extended Kalman Filter (EKF):

The EKF is used to estimate the state of the UAV based on the sensor measurements and the system's dynamics. It provides a way to fuse the sensor data and estimate the position, velocity, and orientation of the UAV. The EKF can also handle the uncertainty and noise in the sensor measurements, which can improve the reliability of the positioning system. The integration of 5G, sensor fusion, barometric pressure sensors, and EKF can enhance the positioning accuracy of UAVs, which is critical for applications such as aerial surveying, mapping, and inspection. A benefit of 5G technology is that it provides high-speed, low-latency communications that enable real-time data transmission and reception [18]. The integration of barometric pressure data with IMU data can improve the accuracy of altitude measurements and enhance overall positioning accuracy. The use of EKF can handle the uncertainty and noise in the sensor measurements and provide a way to fuse the sensor data to estimate the position, velocity, and orientation of the UAV [19].

1) A sensor fusion algorithm steps:

- The algorithm collects data: from multiple sensors, including accelerometers, gyroscopes, magnetometers, and barometric pressure sensors.
- Data Pre-processing: The collected data is pre-processed to remove noise, outliers, and other anomalies
- Data Fusion: The pre-processed data from the sensors are combined to estimate the UAVs' positioning state. This can be done using techniques such as Kalman filtering, particle filtering, or extended Kalman filtering.
- State Estimation: The algorithm estimates the UAV's state, such as its position, velocity, and orientation, based on the fused data.

- Output: The estimated state is provided as the algorithm's output and can be used by the application to determine the Unmanned Aerial Vehicle Positioning.
- Update: The algorithm continuously repeats the data collection, data pre-processing, data fusion, and state estimation steps to update the positioning in real-time [20].

Kalman filter (KF)is a popular technique for sensor fusion that can be used to combine data from multiple sensors to provide more accurate and reliable estimates of position, velocity, and other states of a system [21]. Systems by linearizing the system dynamics and measurement functions. Here is an overview of how the EKF can be used for sensor fusion [22].

- Define the State Vector: defining the state vector is the first step in monitoring a system, which represents the system's current state. For example, the state vector might include the vehicle's position, velocity, and acceleration in a navigation system.
- Define the System Dynamics: The next step is to define the system dynamics, which describe how the state vector evolves over time. This can include equations that model the motion of the vehicle based on its current state.
- Define the Observation Model: The next step is to define the observation model, which describes how the measurements from each sensor relate to the state vector. This can include equations that relate the position and velocity measurements from a GPS sensor to the position and velocity components of the state vector.
- Predict the State: Using the system dynamics and the current state vector, the EKF can predict the state vector at the next time step.
- Update the State: When new measurements become available from the sensors, the EKF can update the state vector based on these measurements. The EKF uses the observation model to predict what the measurements should be, and then compares this prediction to the actual measurements to determine the difference, or residual.
- Compute the Kalman Gain: The Kalman Gain is a weighting factor that determines how much to trust the predicted state versus the measurements. The Kalman Gain is computed based on the uncertainty in the predicted state and the uncertainty in the measurements.
- Correct the State: Finally, the EKF corrects the predicted state by applying the Kalman Gain to the residual. This results in an updated state vector that considers the measurements from all the sensors.
- By combining measurements from multiple sensors, the EKF provides more accurate and reliable estimates of a system's state. Thus, autonomous vehicles, robotics, and navigation can all benefit from this technology.
- The Extended Kalman Filter (EKF) is a mathematical model used in estimation and control problems, particularly in the field of navigation and guidance systems. It's an extension of the Kalman filter to nonlinear systems, which is a common problem in many real-world applications [23].
- The EKF algorithm consists of the following steps: Initialization: Set an initial estimate of the state vector x and its covariance matrix P.
- Prediction: Use the nonlinear system model to predict the state vector x at the next step based on the current estimate. This step involves linearizing the system model around the current estimate, which is used to compute the predicted state and the prediction error covariance matrix.
- Update: Use the measurement data to correct the predicted state estimate. This step involves computing the innovation (or measurement residual) and the innovation covariance, which is used to determine the Kalman gain matrix. The Kalman gain matrix is then used to update the predicted state estimate and its covariance matrix.
- Repeat steps 2 and 3 for each new measurement.

2) The mathematical equations for the EKF algorithm can be expressed as follows: [15].

Initialization:

$$\begin{aligned} & x\_\text{hat}\ (0) = x\_0 \\ & P(0) = P\_0 \end{aligned} \tag{6}$$

Prediction:

$$\begin{aligned} \mathrm{x_{hat\ _{pred}}} &= \mathrm{f}\left(\mathrm{x_{hat(k)}}, \mathrm{u(k)}\right) \\ \mathrm{P_{pred}} &= \mathrm{J_f} * \mathrm{P(k)} * \ \mathrm{J_f^T} + \mathrm{Q} \end{aligned} \tag{7}$$

Where f(x, u) is the nonlinear system model, J_f is the Jacobian matrix off with respect to x, u is the control input, Q is the process noise covariance matrix, and k is the current time step.

Update:

$$\begin{aligned} & \mathrm{y} = \mathrm{z(k)} - \mathrm{h}\left(\mathrm{x_{hat\ _{pred}}}, \mathrm{u(k)}\right) \\ & \mathrm{S} = \mathrm{J\_h} * \mathrm{P\_pred}\ *\ \mathrm{J\_h\verb|^|T} + \mathrm{R} \\ & \mathrm{K} = \mathrm{P\_pred}\ *\ \mathrm{J\_h\verb|^|T} *\ \mathrm{S\verb|^|} - 1 \\ & \mathrm{x_{hat\ (k)}} = \mathrm{x_{hat\ _{pred}}} + \mathrm{K} * \mathrm{y} \\ & \mathrm{P(k)} = (\mathrm{I} - \mathrm{K} *\ \mathrm{J_h}) * \mathrm{P_{pred}} \end{aligned} \tag{8}$$

Where z(k) is the measurement, h(x, u) is the measurement model, J_h is the Jacobian matrix of h with respect to x, R is the measurement noise covariance matrix, I is the identity matrix, and S is the innovation covariance matrix [24]. These equations form the core of the EKF algorithm and can be used to estimate the state of nonlinear systems in real-time [22]. In this study, we aimed to develop a system for unmanned aerial vehicle (UAV) positioning in urban environments using 5G New Radio technology. To achieve this, we used a combination of hardware and software tools, including an IMU sensor, a pressure sensor, a 5G receiver, and Simulink and MATLAB simulation tools.

3) Data Collection: We conducted experiments to collect data on the UAV's position and altitude using the above-mentioned sensors. The IMU sensor provides information on the UAV's acceleration, orientation, and angular velocity in three dimensions (x, y, and z). The pressure sensor provided data on the UAV's altitude. The 5G receiver was used to collect positioning data from the 5G network. We collected data for different UAV trajectories and flight scenarios to ensure that the system was robust and could work in different conditions. To analyse the data collected, we used the Extended Kalman Filter (EKF) algorithm to fuse the information from the sensors and estimate the UAV's position and altitude in real-time. The EKF algorithm is a widely used method for sensor fusion in UAV positioning systems and has been shown to be effective in various studies.

4) Simulation Modelling: Using MATLAB 5G Toolbox, we configured and generated PRS signals according to the 5G NR specifications. We carefully selected PRS parameters such as time-frequency pattern and sequence length for optimal performance. The PRS sequence for each gNB was generated using the 'nrPRS' function, and the transmitted signal was obtained after applying appropriate windowing and precoding operations to the PRS sequence. The received signal at the UAV was simulated by passing the transmitted PRS signal through the channel model. Next, we detected the PRS signals at the UAV and estimated the TDOA values. Suitable synchronization and channel estimation techniques were applied to the received signal, and matched filtering and thresholding were employed to detect the PRS signals from the gNBs. Cross-correlation techniques were then used to estimate the TDOA for each detected PRS signal, and the TDOA values were determined with sub-sample accuracy using interpolation methods such as polynomial fitting or sinc interpolation. We then estimated the position of the UAV using the TDOA values. Hyperbolic equations that relate the UAV position to the positions of the gNBs were computed, and nonlinear least squares or other optimization techniques were employed to solve the hyperbolic equations and obtain the UAV position estimate. We evaluated the performance of the 5G PRS positioning system by comparing the estimated position with the true position, using metrics such as root-mean-square error (RMSE) and circular error probable (CEP).

III. Results And Discussion

The results presented in this paper illustrate Four different scenarios, which are studied to enhance the UAV positioning estimation. The results of this study have important implications for UAV positioning in urban environments using 5G New Radio technology. Our experiment has demonstrated the 5G PRS positioning system's effectiveness in accurately estimating a UAV's position. The simulation model used in the study shows that the proposed system can provide accurate UAV positioning in urban environments, outperforming traditional methods. In the first scenario, the estimated UAV position was denoted by the coordinates (500, 20), while the simulated estimation yielded the coordinates (501, 24.2). This resulted in a positional error of 4.4 meters. This outcome can be visually observed in Fig4.

In the second scenario, the actual position was represented by the coordinates (550, 30), and the estimated position de-

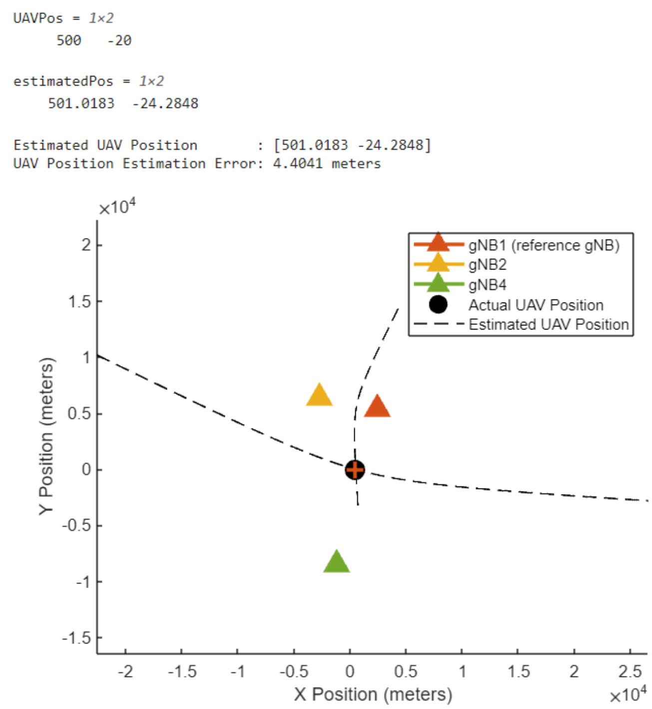

Fig. 4. Eistimated UAV positioning

rived from the simulation was (547.9, 23.5). The discrepancy amounted to an error of 6.77 meters, as depicted in Fig5.

In the third scenario, the actual position was characterized by the coordinates (600, 80), whereas the simulation produced an estimated position of (593.6, 81.8). This led to a positional error of 6.6 meters, which can be examined in Fig6. Lastly, in the fourth scenario, the true position was given by the coordinates (800, 280), and the simulation-generated estimated position was (793.3, 278.8). The resulting error was 3 meters, as illustrated in Fig7.

The presented outcomes, which displays the results from four differences UAV scenarios, demonstrate that the proposed methodology is both robust and versatile for different UAV positions. Estimation errors range from 2.8 to 7 meters, indicating the effectiveness of the technique. These findings imply that the 5G PRS positioning system holds significant potential for a variety of applications, especially those demanding high accuracy, like autonomous vehicles and emergency services.

However, we also noted that there are factors can impact the performance of the system, such as noise, multipath effects, channel conditions, and estimation inaccuracies in the TDOA values. To further improve the performance of the system, we suggest exploring different avenues such as refining the PRS signal design, enhancing TDOA estimation techniques, incorporating more advanced channel models, and investigating the impact of different system parameters and network configurations. By pursuing these directions, we can optimize the accuracy of the 5G PRS positioning system and improve its performance for a wide range of applications and

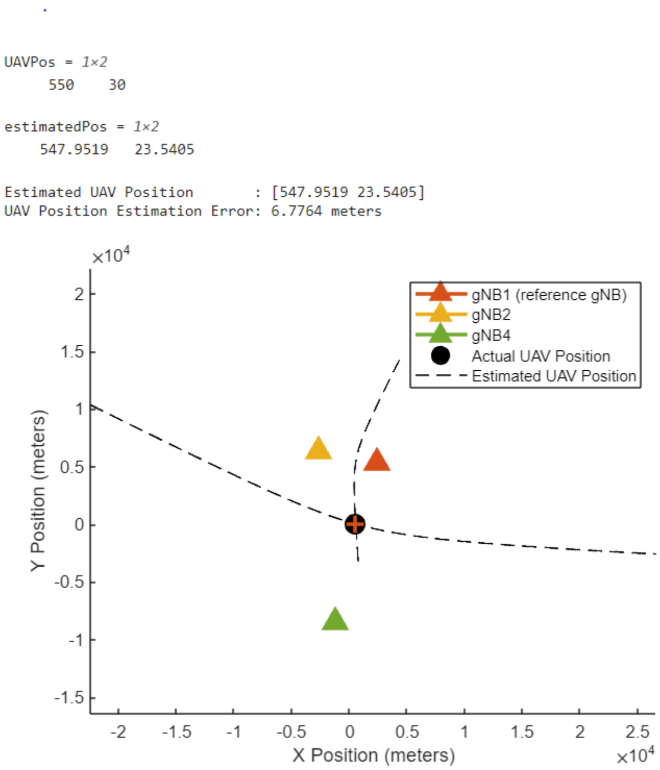

Fig. 5. Eistimated UAV positioning

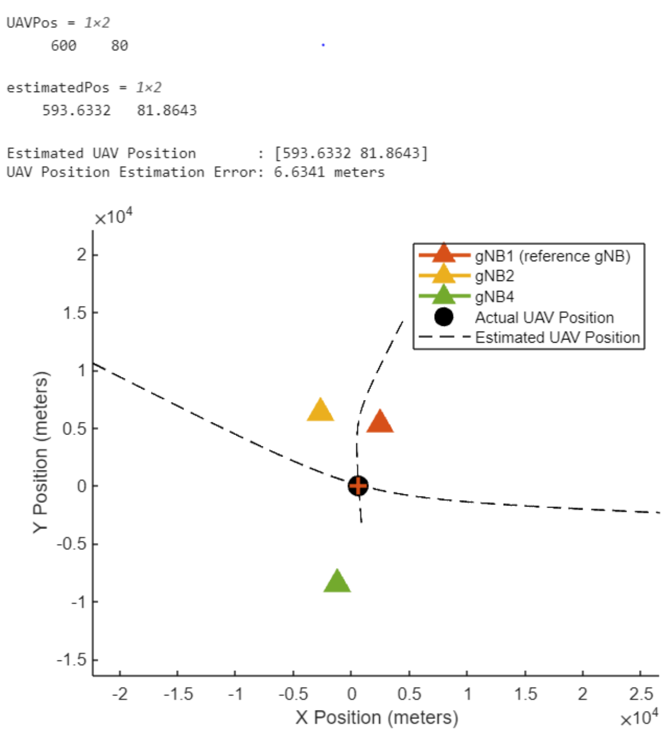

Fig. 6. Eistimated UAV positioning

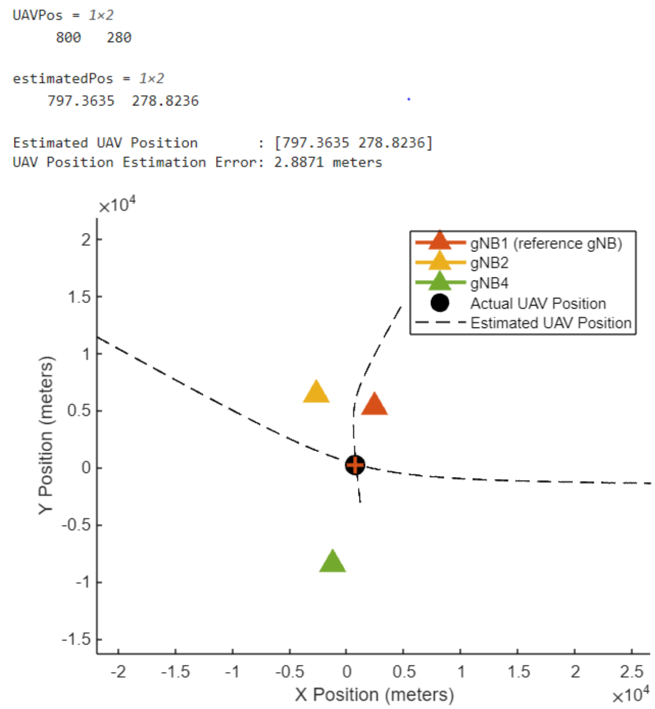

Fig. 7. Eistimated UAV positioning

conditions. Overall, the results and discussion presented in this paper suggest that the 5G PRS positioning system is a promising technology for providing accurate location information, and the proposed methodology can be used as a basis for future research and development in this area. The use of the OTDOA technique allows the estimation of the UAV position based on the time differences or signal strength differences between different gNBs This can be especially useful in urban environments where there are many gNBs available, allowing for more accurate positioning and reducing the risk of signal interference. Accurate UAV positioning is important for a wide range of applications, including surveillance, search and rescue, and delivery services. For example, in surveillance applications, accurate positioning can help identify the location of potential threats or monitor traffic flow in real-time. In search and rescue scenarios, UAVs can be used to quickly locate missing persons or identify hazards in disaster zones. In delivery services, accurate positioning can help ensure that packages are delivered to the correct location and improve delivery times. By pursuing this approach, we can further optimize the accuracy of the 5G PRS positioning system and improve its performance for a wide range of applications and conditions. The incorporation of an IMU, EKF, and barometric pressure measurements represents a promising direction for future research and development of the 5G positioning system.

IV. Conclusions

The contributions of the study to the field of UAV positioning and communication in urban environments using 5G New Radio technology are significant. The study demonstrates the potential of this technology for accurate and reliable positioning of UAVs in urban environments, which has important implications for a wide range of applications. The study also highlights the importance of the OTDOA technique for UAV positioning, which has not been extensively studied in the literature.

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