Evaluation of 5G Cell Densification for Autonomous Vehicles Positioning in Urban Settings

Sharief Saleh*, Amr S. El-Wakeel*† Sameh Sorour‡, and Aboelmagd Noureldin†‡
* Department of Electrical and Computer Engineering, Queen's University, Kingston, ON, Canada
† Department of Electrical and Computer Engineering, Royal Military Collage of Canada, Kingston, ON, Canada
‡ School of Computing, Queen's University, Kingston, ON, Canada
Email: {sharief.saleh, amr.elwakeel, sameh.sorour, nourelda}@queensu.ca

***Abstract*— A key operational requirement for Autonomous vehicles (AVs) is to have a highly reliable positioning at the sub-meter lane-level accuracy. However, it is well-known that current satellite- and perception-based positioning systems suffer in achieving this desired accuracy in urban settings and during rough weather conditions. This research explores the strong potentials of the soon-to-be-deployed 5G wireless technology that is capable of overcoming these limitations and provides an uninterrupted everywhere positioning with lane level accuracy. The high cell densities and large bandwidth ranges promised in 5G are anticipated to achieve ultra-reliable and ultra-low-latency communications, which will enable the detection of received signals at AVs with high time precision, thus improving the localization accuracy. This paper discusses the merits and limitations of using 5G small cells to provide lane level positioning services in urban environments. We consider a 5G-based positioning scheme employing time of arrival with the trilateration of ranges between 5G base stations based on least-squares and an AV in kinematic mode. We then evaluate the impact of cell densification on achieving the desired accuracy level using the considered positioning scheme. A professional 5G simulator was used to assess the positioning accuracy of a vehicle moving at an average speed of 35 km/h in a kinematic road test involving different 5G base-stations densities on a trajectory in downtown Manhattan, NY. Results show that an inter-cell spacing of 160 m can achieve sub-meter positioning accuracy for AVs in typical dense urban settings.**

***Index Terms*—5G mmWave; Autonomous vehicles; Inter-cell distance; Navigation; Small cells; Wireless positioning.**

I. Introduction

Autonomous vehicles (AVs) promise to enhance safety, and improve transportation system efficiency and reliability [1]. The present AV technology relies on on-board intelligence achieved by a suite of sensors and systems, which typically consists of a global navigation satellite system (GNSS) (including GPS), vehicle motion sensors (gyroscopes, accelerometers, and speedometers), cameras, light detection and ranging (LiDAR) and radar technologies. With the aid of their connectivity, AVs will be able to share the surrounding environment perception and the traffic participants detection that can lead to traffic flow improvement, and limiting the risk of accidents [1], [2].

Nevertheless, robust and high precision positioning and orientation information is essential for AVs at all times in all environments [1], [2]. A key AV system requirement is to have reliable positioning to the sub-meter level of accuracy to ensure their preservation of lane alignment, thus avoiding accidents and efficiently maneuvering in lane changing actions. Given the criticality and importance of these requirements, the lane-level accuracy requirement must be maintained everywhere and under all operational environments [2]. Present land vehicles rely on GNSS receivers for positioning services. However, GNSS has limitations such as strong signal blockage and severe multipath effects in urban canyons, ionospheric delays, and natural or intentional interference/jamming. Backup systems for lane-level positioning are therefore needed by AVs in these settings [3]. Vision-based positioning (VBN) relying on cameras can be utilized for pose estimation [4]. The ineptitude of features extraction in a degraded visual environment is still one key limitation of VBN [4].

Conversely, light detection and ranging (LiDAR) can operate in this degraded vision environment and can provide accurate measurements of range information with respect to the surrounding objects. Although, LiDAR is more computationally demanding to processing its 3D point cloud. In addition, LiDAR is generally more expensive, may introduce design restrictions, and has moving parts that induce more possibility of error [5]. Challenging weather conditions such as rain, snow, and fog add more limitations to the accurate positioning estimation when using both, cameras and LiDARs.

Radars, which has been utilized in land vehicles for adaptive cruise control, can also be used as an alternative to LiDAR to detect objects and provide range estimation in all weathers [6]. However, most present radar-based odometry and localization techniques do not provide the sub-meter level accuracy required by AVs [6]. Another alternative for positioning information is the inertial navigation systems (INS), which depends on the measurements of accelerometers and gyroscopes to present the changes in position, velocity, and orientation of AVs, thus allowing relative positioning and navigation with

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respect to a previously known position and orientation [3]. Nevertheless, INS-acquired positions may drift rapidly over time, especially when low-cost Micro- Electro-Mechanical-Systems (MEMS) based sensors are used [3].

In summary, current positioning and navigation techniques for AVs all exhibit advantages and drawbacks, with no single technique sufficiently versatile to address the challenge of everywhere precise positioning. This papers thus aims to fill this gap by exploring the strong potentials of the soon-to-be-deployed 5G wireless technology to overcome these limitations and provide an uninterrupted everywhere positioning with lane level accuracy. The paper will first explore the source of strength, merits, and limitations of 5G as a candidate solution for this role in Section II. This section also summarizes prior trials to use 5G signaling for positioning of cellular user equipment (UE). Section III presents our experimental methodology to assess the suitability and cell densification requirements for 5G to achieve the desired lane-level accuracy for AVs. The experimental setup and discussion of and cell density recommendations from our experimental results are highlighted in Section IV. Finally, Section V concludes the paper.

II. 5G Potentials for AV Positioning

The soon-to-come 5G technology exhibit many traits that could cast it as a promising alternative technology for precise positioning everywhere. First, the high cell densities and extended bandwidth ranges promised in 5G can foster line-of-sight (LOS) coverage and precise time-based measurements from multiple surrounding 5G base-stations (BSs). These factors can collectively be employed to improve the computation of the ranges to these BSs, thus enabling high-accuracy trilateration-based localization using time of arrival (TOA), time difference of arrival (TDOA), and time of flight (TOF) based positioning approaches [1] [8]. In addition, the introduction of mmWave signaling and massive MIMO technology in 5G would enable precise angle of arrival (AOA) measurements, which can be used in performing high-accuracy triangulation-based localization [9], [10]. The accuracy of the AOA measurements will be significantly enhanced as the number of antennas increase. Furthermore, 5G cells will also be able to conduct angle of departure (AOD) measurements as they are able to utilize beamforming techniques [10].

The combination of all these aforementioned qualities in 5G can make it a saviour for AVs as it will enable the required decimeter level positioning, especially in urban environments where GNSS solutions usually fail due to their severe signal blockage and deterioration as a result of shadowing and multipath effects. Due to their potentials, several schemes were recently proposed to exploit some of these qualities separately in computing the position of typical cellular UEs, even before their emergence as collective core solutions in 5G. To achieve high precision, these schemes usually utilize hybrid trilateration and triangulation positioning solutions as well as numerous sensor fusion techniques, such as various forms of Kalman filters, particle filtering, and AI.

[1]It is worth noting that the use of TOA-based positioning in 5G settings will impose an additional synchronization requirement between BSs and UE [7]

In [11], the authors have proposed an algorithm that computes the position of the UE using one BS through utilizing TOA, AOA, and AOD of multipath signals. This is done by first solving a data association problem, then performing positioning and mapping via a belief propagation algorithm. In [12], a scheme that jointly processes the AOA observations obtained at BSs was proposed. This scheme is based on a compressive sensing framework that exploits channel properties to distinguish between LOS and non-LOS (NLOS) signals. The work in [13] estimates the UE position and orientation along with the unknown scatterers' position through an iterative Gibbs sampler using a compressive sensing approach with iterative refinement steps. This approach helps to compute an accurate estimation of the channel parameters, including AOA, AOD, and TOA for each observed propagation path. [14] presents a two-stage algorithm for position and orientation estimation. The algorithm's coarse estimation stage is based on multiple measurement vectors matching pursuit, while the fine estimation stage is based on the space-alternating generalized expectation maximization algorithm. A recursive Bayesian filtering named Channel-SLAM is described in [15]. This approach assumes that multipath components are emitted from virtual transmitters, which will technically increase the number of transmitters and hence will increase the accuracy. The proposed algorithm then estimates the receiver and the virtual transmitters' positions simultaneously. Authors in [16] propose a gradient-assisted particle filter (GAPF) estimator to estimate the UE position, in addition to the locations of nearby scatterers, through TOA, AOA, and AOD measurements. Although many of the proposed methods have a merit, yet, their performances are usually computed under manually controlled scenarios, where scatterers/reflectors are manually placed, while neglecting important details that highly affects the 5G performance such as obstructions and diffractions from in-path vegetation and/or dynamically moving objects.

The ultimate target of this paper is to evaluate the 5G cell density to achieve the AVs lane-level required positioning accuracy.This will enable 5G-based wireless positioning services to mitigate the existing challenges and limitations in present positioning and navigation technologies. The scientific objectives of this paper include:

- Building a realistic 5G wireless scenarios in challenging downtown environments utilizing a professional 5G simulation tool able to mimic real deployment of both the 5G BSs and mobile vehicle(s).
- Developing a wireless trilateration-based position estimation algorithm that employs TOA to estimate the ranges between 5G BSs and the moving vehicle.
- Examining the performance of the developed method for a simulated land vehicle in kinematic mode traveling in challenging urban environment.

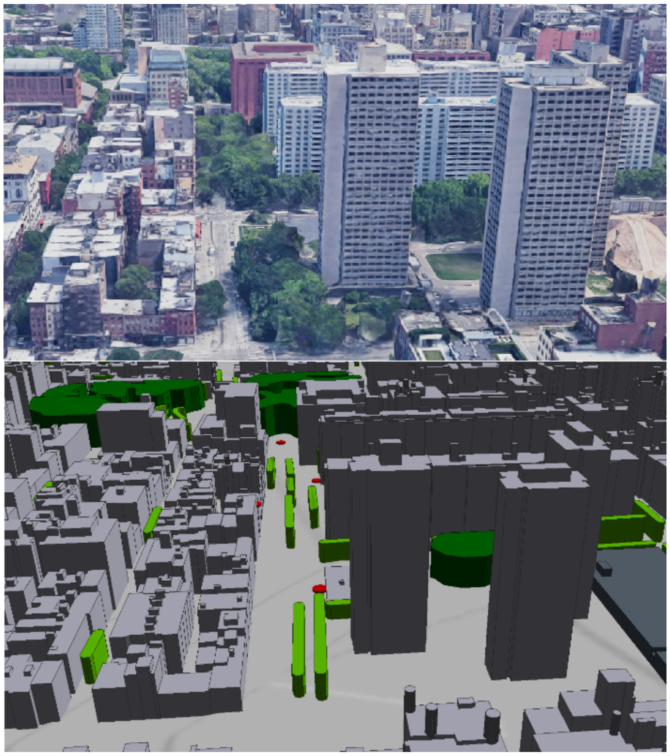

Fig. 1. Downtown Manhattan, New York, NY, Google earth (up), *S_5G_Channel* simulator environment (down)

- Discussing the merits and limitations of the proposed 5G wireless positioning method.
- Assessing the achievable positioning accuracy as a function of the deployment density of 5G BSs.
- Evaluating the impact of 5G cell deployment density on achieving lane-level positioning accuracy for AVs.

In the next section, we will highlighted the employed methodology to achieve the above targets.

III. Methodology

In this work, we utilize a very high-resolution 5G signal tracing simulator, namely the *S_5G_Channel* simulator developed by Siradel, to generate comprehensive scenarios for 5G signals in a realistic urban area (e.g., Manhattan, New York City, NY) with variable vehicle speeds and densities. The *S_5G_Channel* simulator is capable of

1) Importing very high precision 3D maps mimicking real urban environments as shown in Fig. 1.
2) Deploying 5G BSs with different specifications (e.g., transmit power, frequency bands, carrier and antenna configurations) at any location within this environment.
3) Collecting wireless parameters such as timing information (e,g., TOD, TOA) and received signal strength (RSS) from each of the individual signal paths (including all reflections, diffractions, and attenuation across all encountered surfaces) at both the fixed BSs and the mobile UE/vehicle in this environment.

In this work, we use the *S_5G_Channel* simulator to set our experimental 5G simulation environment. Within this environment, we conduct different 5G propagation scenarios that pertain to the 28 GHz mmWave frequency band, which will be used in 5G (Release 15) for small-cell deployments and LOS communications. The BSs and UE/vehicle are using time division duplex (TDD) technology and the transmitting and receiving antennas are chosen to be isotropic antennas. The transmit power was set to 43 dbm to align with the requirements of 5G small cells [17]. For the 5G wireless propagation channel modeling and analysis, we utilize the Volcano3D ray-based models that predict the signal RSS, path loss, and signal to noise ratio (SNR) on each of the signal paths between the BS antennas and the UE/vehicle(s). We are also considering parameters such as the LOS and NLOS free space path loss, LOS/NLOS vegetation effects, and those of moving surrounding objects on the signal power levels and delays at our target vehicle. The analysis relies on the predicted excess path-loss (EPL), which is defined as follows:

$$EPL = PL_{Iso} - PL_{FS} = PL_{Iso} - 20\frac{\lambda}{4\pi d} \qquad (1)$$

where the EPL is expressed in dB; PL_{Iso} is the path-loss measured with isotropic antennas (dB); PL_{FS} is the path-loss in free space (from FRIIS equation); λ is the wavelength (m); and d is the path distance (m).

In our scenario generation procedures, we deploy 5G BSs with variable densities at different locations of the shown 3D map of a segment in Manhattan, New York City, NY. In addition, we also create a vehicle trajectory with specifications that accurately mimics real driving scenarios with varying traffic densities and dynamics in the streets of Manhattan. A blend of the 5G signal extracted parameters, such as RSS and TOA, is employed inside our 5G positioning algorithms along the simulated trajectories. TOA is a measurable that is based on the measurement of the propagation delay of the radio signal between the vehicle and one or more BSs. The vehicle position can be estimated by converting the propagation time to distance by multiplying the propagation time by the speed of the signal. Estimating the location of the vehicle in a 2D plane requires at least three BSs. The position of the vehicle can also be calculated by using the least-squares algorithm. The algorithm works on minimizing the sum of squares of a nonlinear cost function. With the assumption that the vehicle location is X_i,Y_i and the time taken from the signal to travel with the speed of light C from the BS_k to the vehicle is t_k, the cost function can be derived by:

$$F(X_i, Y_i) = \sum_{k=1}^{M} \gamma_k^2 f_k^2(X_i, Y_i) \qquad (2)$$

such that

$$f_k(X_i, Y_i) = t_k C - \sqrt{(X_k - X_i)^2 + Y_k - Y_i^2} \qquad (3)$$

where (X_k,Y_k) is the 2D location of BS_k, M is the number of BSs, and γ_k^2 is the measurement uncertainties weighing factor. In this work, the TOA measurements of BSs and the vehicle are used to estimate the dynamic position of the vehicle in different scenarios using the leas-square algorithm.

In the following section, multiple experiments are conducted to evaluate the positioning accuracy and assess the 5G small cell densification requirements (expressed in terms of inter-cell distance) to enable continuous and accurate sub-meter positioning that aligns with the AVs driving demands.

IV. Experimental Setup, Results, and Discussion

In this section, several simulated road experiments were conducted to evaluate and assess the effect of 5G inter-cell distance and cell density on the vehicle's positioning accuracy within the simulation environment detailed in Section III. As explained above, the simulated experiments were built to accurately mimic a driving scenario in downtown Manhattan, New York City, NY. The simulated trajectory have started at the intersection of Washington Square South and LaGuardia Place and have ended at the intersection of West Broadway and Spring Street. The trajectory length is approximately 800 m. Also, the simulated area includes two-way roads, high rising buildings, and varying vegetation density which is a challenging environment for the mmWave 5G signal propagation. To ensure the practicality of the simulated scenario, the subject vehicle was traveling in the trajectories while being surrounded by 25 vehicles. The surrounding vehicles were created of different types and sizes, as shown in Fig. 2. All vehicles are set to travel at an average speed of 35 km/h, which aligns with typical driving speeds in moderate-traffic downtown settings. This experiment is repeated for three different cell density scenarios, namely 3 BSs, 5 BSs and 8 BSs as shown in Fig. 3, Fig. 4, and Fig. 5 respectively.

In the first experiment setup, shown in Fig. 3, 3 BSs were deployed alternatively on the two sides of the road along the trajectory to ensure a decent coverage and good geometry as required for position estimation. The BSs are deployed on street lamp posts at a height of 10 m above the street level. In this scenario, the inter-cell distance between the BSs was approximately $400m$. The S_{5G} simulator was utilized to extract signal parameters for the 3 BSs at the vehicle end at every time epoch. Every signal parameters extraction includes measurements of the RSS and TOA.

To calculate the position, the least-squares algorithm used the TOA measurements of the 3BSs at each time epoch. Compared to the reference trajectory, the 2D root-mean-square (RMS) position error was 3.68 m and maximum position error of 5.36 m. The calculated position errors are relatively low when compared to the deteriorated GNSS positioning accuracy in downtown cores. However, the estimated positioning accuracy is not suitable for AVs, which require sub-meter lane-level positioning accuracy. Fig. 6 shows a portion of the positioning solution of the reference trajectory versus the estimated position using the TOA measurements of the 3BSs

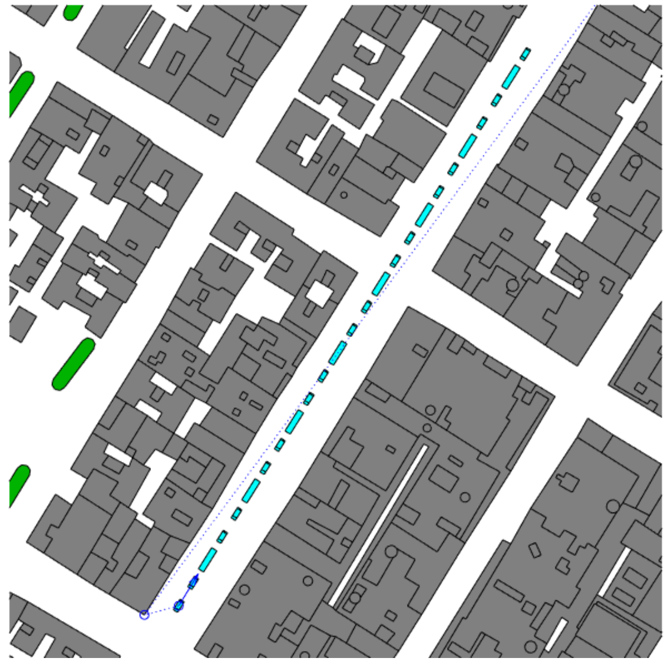

Fig. 2. The simulated trajectory, including the traffic density

setup. Considering the environment of the simulated trajectory, it can be inferred from Fig. 3 that the dense vegetation and high rising buildings in the first 400 m of the trajectory limited the LOS signal components from the first and second BSs (located at the beginning and end of this segment of the trajectory) and resulted in severe multipath fading, which affected the predicted TOA measurements of the BSs and in-turn the estimated vehicle position.

In the second experiment, two more BSs were added, as shown in Fig. 4, resulting in 5 alternatively deployed BSs that provide more coverage at the dense vegetation area. The inter-cell density in this trajectory is approximately 160 m. In this trajectory, the subject vehicle traveled the same distance at the same average speed and surrounded by the 25 vehicles as in the first experiment. Similarly, the signal parameters are measured in each time epoch at the BSs and the vehicle along its entire trajectory. The corresponding positioning results have exhibited an improved estimated positioning accuracy, with 2D RMS error of $1m$ and maximum positioning error of $1.95m$, a reduction of 73% and 64%, respectively, compared to the first experiment. These gains were obtained due to the better signal measurements and that resulted from reduction of inter-cell distance (i.e., higher cell density). These positioning accuracies are promising as they start to meet the needs of AV positioning. Fig. 7 presents part of the estimated positioning solution in the case of 5 BSs versus the reference trajectory.

To further investigate the merits of higher cell densification on the positioning accuracy, a third experiment was conducted with 8 BSs deployed alternatively on the two sides of the road, as shown in Fig. 5. The cell densification reduced the inter-cell distance to 100 m, approximately. Again, the

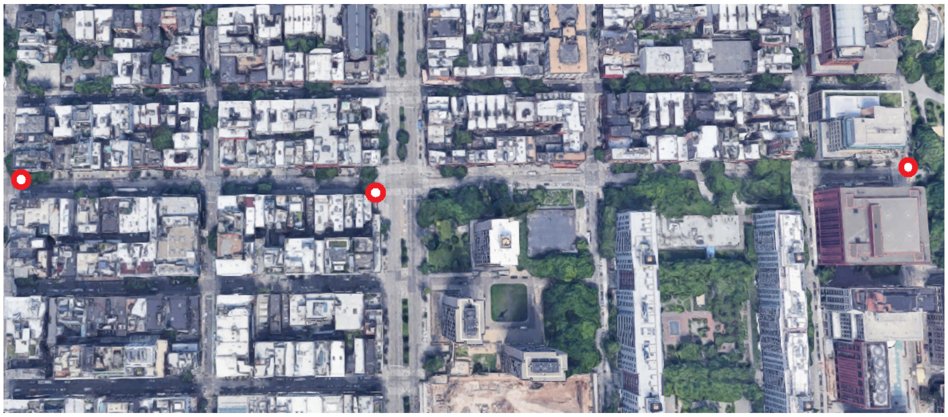

Fig. 3. First simulation scenario, 3 base stations

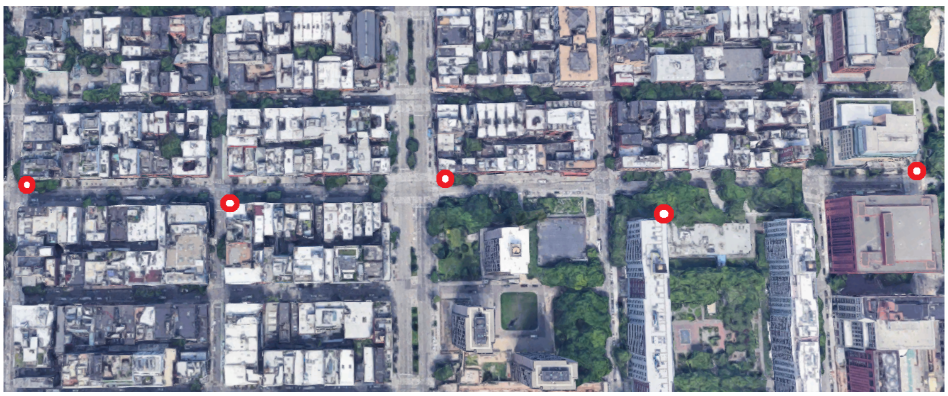

Fig. 4. Second simulation scenario, 5 base stations

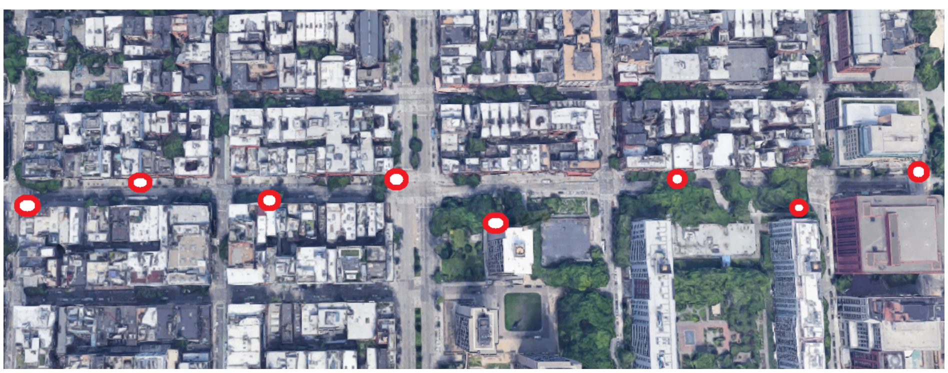

Fig. 5. Third simulation scenario, 8 base stations

subject vehicle traveled the same trajectory of the first and second experiment in the exact same road conditions. Similar to the other scenarios, the least-squares algorithm was used to predict the vehicle position from the measure TOAs measurements at the 8 BSs and the vehicle at each time epoch. However, the estimated positioning accuracy did not significantly change, achieving 2D RMS 0.95 m and a maximum error of 2 m. Thus, excessive cell densification does not necessarily enhance the positioning accuracy in all cases and environments, and are thus not needed given the extra network complexity and the implementation cost associated with such excessive densification. Table I summarizes the 2D RMS and maximum estimated positioning errors in the three scenarios. According to the results and findings, an inter-cell distance of approximately 160 m can be sufficient to achieve the AVs lane-level positioning accuracy requirements in typical dense urban settings with high-rise buildings, in-street vegetation, and dynamically moving surrounding objects.

Fig. 6. Window of the estimated positioning solution (3BSs scenario) versus the reference trajectory

Fig. 7. Window of the estimated positioning solution (5BSs scenario) versus the reference trajectory

TABLE I
2D RMS AND MAXIMUM POSITIONING ERROR RESULTS SUMMARY

No. of BSs	RMS error (x)	RMS error (y)	RMS error	Max error (x)	Max error (y)	Max error
3 BSs	3.0432	2.0750	3.6833	4.2561	3.2560	5.3587
5 BSs	0.7715	0.6470	1.0069	1.3364	1.4200	1.9500
8 BSs	0.7787	0.5437	0.9497	1.5803	1.2350	2.0056

V. CONCLUSION

The trustworthiness in the safe operation of AVs is highly correlated with several technical considerations, one most important of which is reliable and accurate lane-level positioning accuracy everywhere. Present positioning technologies face limitations that are either self-contained or environmentally dependent, especially in dense urban settings. 5G, the promising emerging technology, is not only a savior from the communication capacity crunch but also opens avenues for accurate and reliable positioning in such urban settings where other alternative technologies may fail. In this paper, the benefits of 5G small cell deployments for accurate positioning was highlighted and discussed. Three dynamic road experiments were conducted in a well-validated commercial 5G simulation environment to evaluate the impact of 5G cell densification on achieving lane-level accuracy for AVs using TOA based positioning. The experiments' results have shown that the reduction of inter-cell distance to a certain extent can significantly enhance the positioning accuracy. It was concluded that an inter-cell spacing of 160m can achieve the desired lane-level positioning accuracy for safe AV operation.

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