MONITORING THE ENVIRONMENT IN SMART CITIES: THE IMPORTANCE OF GEOSPATIAL LOCATION REFERENCING

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ABSTRACT:
The Smart City concept is taking momentum recently as big metropolises as well as mid-size cities are intensifying their efforts to improve the life of people living in dense urban environment. Local governments are eager to have up-to-date information of every aspect of city life, including environmental data, such as air and water quality parameters; mobility data, such as traffic flow, including vehicles, transit passengers; crowd control, such as public events, mobility in hospitals; life quality data, such as social status, education level, health records; etc. Monitoring all these very different data streams in space and time is a formidable challenge. While on the data acquisition side, tremendous progress has been achieved, as sensors have been deployed in increasingly large numbers on both mobile and static platforms, there is a lack of creating accurate geotags, as the quality of georeferencing varies over a large scale. It is important to note that the data acquisition is becoming largely customer-based, as smart devices are efficient sensor systems and with advancing communication technologies, crowdsourcing is quickly becoming the dominant data source on mobile platforms. In this paper, we investigate the potential to exploit the ranging capabilities of imaging and communication sensors and use the strength of the spatial network formed by the sensors to improve the georeferencing of a group of platforms operating in a close environment, such as UAS swarm or a platoon of autonomous vehicles. Transportation in cities and in general mobility are of great interest to Smart Cities, they represent one of the most significant components of the activities, so having an optimized transportation system is essential to reduce carbon footprint, decrease commute time, and just improve the quality of life. To assess the performance of collaborative navigation based accurate georeferencing, data was acquired at a simulated intersection area at The Ohio State University, where multiple vehicles, pedestrians and cyclists were moving around. In addition, drones were flying above the area. Here we report about our initial results.
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1. INTRODUCTION

Smart Cities can be defined in various ways but what makes these cities different from the others is practically the level of monitoring and data sharing capabilities (Ahvenniemi *et al*., 2017). Sensors continuously acquire data from the built-up environment as well as from all the dynamic objects, such as people and all kind of moving platforms. Digital twins may provide a virtual representation of the city environment at a variety of levels, including buildings, vehicles, man-made objects, and then human beings, vegetation, birds, etc. These systems are usually live, i.e., their content is continuously updated as new data comes in. Besides monitoring the state of the city, they provide an optimal way to control and manage every aspect of the city operations; for example, visualization, traffic control, decision making, planning, etc.

Location information, including, at minimum, coordinates and time is a very fundamental metadat of any piece of information acquired and processed in a Smart City environment. Most of the data currently come from dedicated sensor networks, but crowdsourced data is rapidly increasing and expected to become the main source of information (Toth and Jozkow, 2015). Typical smartphone has about 30 sensors and there are about 7 billion users worldwide. These numbers dwarf the industrial sensor market, which is estimated to be about $25 billion worldwide by 2023.

The intricate and multifaceted nature of urban environments poses challenges to attaining a precise, stable, and robust localization. The uncertainty and lack of GNSS in cities makes positioning especially hard, and thus, there is a necessity for new methodologies that integrate different sensors and data sources to improve the robustness of the localization processes; mainly, to assist mobility efforts (Benevolo *et al.,* 2016). Mobility is an essential element of Smart Cities, the main challenge is the georeferencing of moving objects, such as people, vehicles, UAS, UAV, etc. There are many technologies to achieve this as well as several methods. Since in most situation the mobile platforms closely share the object space, their navigation systems can collaborate by sharing location and benefit from it. Knowing the location in real-time is critical for optimizing the flow of people, vehicles, goods, etc.

In previous works, we have directed efforts towards collaborative localization techniques that incorporate Ultra-Wideband (UWB) technology (Masiero *et al*., 2022), vision and LiDAR-based positioning (Masiero *et al*., 2021b, Hosseinyalamdary *et al*., 2015) as well as crowdsourced vehicle data (Toth *et al.,* 2018) in combination with GNSS/IMU sensors to explore various scenarios and environments, including those where GNSS signals are challenged.

This study presents a brief overview of the test scenarios and experimental sensor configurations employed during a data collection campaign executed at OSU West Campus, including preliminary findings. In contrast to an earlier effort, which considered a 2D road environment (Retscher *et al*., 2020), the navigation space was extended to 3D by including four UAS during the experiments. Thus, the focus here is on jointly positioning a group of vehicles, swarms of robots, such as UAS and UGV, etc., in urban environment.

2. COLLABORATIVE NAVIGATION

The basic concept of collaborative navigation is that platforms navigating in close proximity can share their sensor data and thus a joint navigation solution for all the platforms should be better than the individual platform solutions. A key condition is that platforms should have inter-platform range/distance measurements, which allow to geometrically constrain the platform locations. In simple terms, for example, good GPS/GNSS position information can be propagated to other platforms which may have compromised GPS/GNSS. Fig. 1 shows a simple four-car arrangement, where assuming 2D positioning, knowing all the six inter-vehicle ranges, positioning of all platforms is feasible if at least two platforms have good GPS/GNSS positions. Obviously, the spatial relationship conditions the collaborative solutions. For example, if the four cars are in a line, then there is no observation in the lateral direction, so only compromised solutions can be obtained. Similarly, if only one platform has GPS/GNSS data, then relative positioning is possible, but the heading is undefined for all the vehicles; unless, aiding from other sources is available.

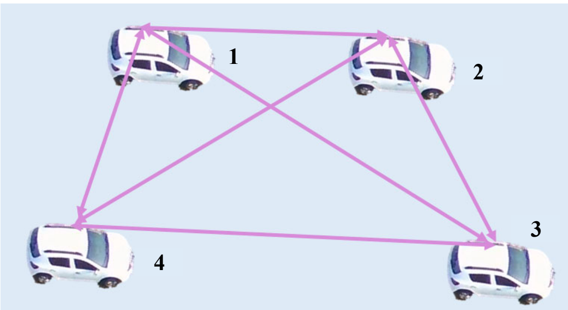


Figure 1. Collaborative navigation concept

The concept of collaborative navigation is not really new, but lack of affordable technologies prevented implementations until recently. Early works focused on integrating the inter-nodal range/bearing measurements or locally generated maps (Roumeliotis and Beke, 2002; Bryson and Sukkarieh, 2009; Grejner-Brzezinska et al., 2009). Also, a similar concept, community relative navigation, was studied before GPS was introduced, and can be traced back at least to the 1970s (e.g., Rome and Stambaugh, 1977; Widnall and Gobbini, 1982; Schneider, 1985).

Recent developments in communication and sensors have made the implementation of collaborative navigation solutions affordable as well as attractive. In the RF domain, for example, inter-platform range measurements can be obtained in a wireless sensor network through RSS (Received Signal Strength), TOA (Time of Arrival), TDOA (Time Difference of Arrival), and AOA (Angle of Arrival) techniques. Dedicated technologies, such as Ultra-Wideband (UWB) ranging, using a broad bandwidth and thus providing for time transfer, communication and centimeter level ranging capability, is of particular interest to positioning and navigation applications (MacGougan et al., 2009). In addition, the UWB transceivers can self-localize and form an ad-hoc network of beacons (Sluis and toth, 2021; Ladai and Toth, 2022). Furthermore, optical sensors, such as cameras and LiDAR can also provide range and AOA information that can be used alone or combined with RF sensor-based observations (Masiero *et al*., 2021a). Finally, vehicle motion modeling and IMU data can further improve the efficiency of collaborative navigation implementations.

When clear LOS (Line of Sight) is available, obtaining range and angular data (AOA) is generally feasible. But when obstacles exist in the space where the platforms are deployed, there may be not enough information to estimate the network. Therefore, we selected a generally open area with a few buildings where reference points could be easily established and surveyed at high accuracy.

3. DATA ACQUISITION

A massive field test, including multiple ground and UAS platforms was organized and executed on OSU West Campus, May 8-16, 2022. The main objective was to simultaneously acquire a rich dataset from multiple transportation modalities that can support research on collaborative navigation. The ground platforms included four vehicles, two cyclists and two pedestrians, and four simultaneously flying UAS in the air. There was a ground control network established and UWB sensors were deployed. The overall effort included more than 22 people and the data collection lasted over eight days. Fig. 2 shows a session when all platforms were utilized; note that the bird's eye view image was taken from the UAS platform flying at the lowest altitude.

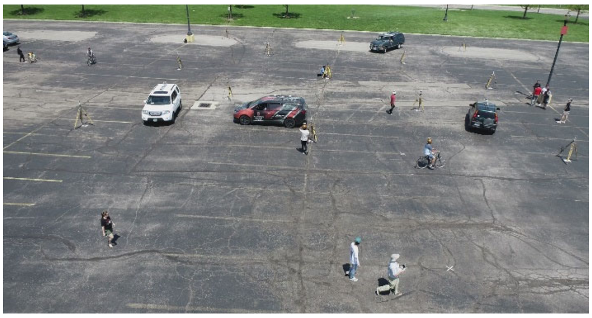


Figure 2. Test are with ground platforms

The data acquisition campaign included ground control deployment and surveying, ground vehicle data collection sessions, UAS rehearsals, and combined ground/air data acquisitions as well as a few repeat tests in each category. A key aspect of the campaign was to obtain highly accurate platform trajectory data, which can be used as reference for performance evaluation as well as for various simulation scenarios. The ground platforms and drones primarily moved/flew predefined trajectories and rich sensor data was collected. There was no intention to run collaborative navigation software in real-time due to lack of communication capabilities, and thus, everything was logged for postprocessing.

A remote parking lot of OSU West Campus was selected for all the experiments as it was practically unused during the tests and allowed to fly UAS without significant restrictions. Another consideration was that the selected location was in an open-sky and RF friendly area to assure that as accurate GPS/GNSS as possible was acquired to obtain high-quality refence solutions. A simulated intersection was defined by ground control, as this represents one of the most important traffic situations in Smart Cities.

From the 50 m by 50 m area used for the main tests, the central area of 30 m by 30 m was populated by 13 signalized ground targets. During the data acquisition sessions, tripods were installed over the target locations and used to mount the UWB transmitters. A total of 12 UWB units formed the ground network that was used to provide local positioning capabilities; note that it was totally independent from GNSS. Fig. 3 shows the ground control layout in the area; note that the inter-node ranges are marked by green. Fig. 4 shows a ground control point and an UWB transceiver mounted on a tripod.

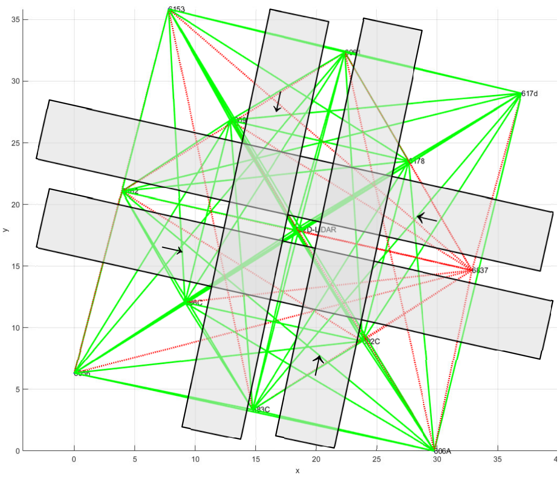


Figure 3. Ground control network deployed at the simulated intersection area

Figure 4. Ground target to support image-based georeferencing and UWB transceiver installed on tripod area

4. VALIDATION OF GPS/GNSS PNT SOLUTIONS

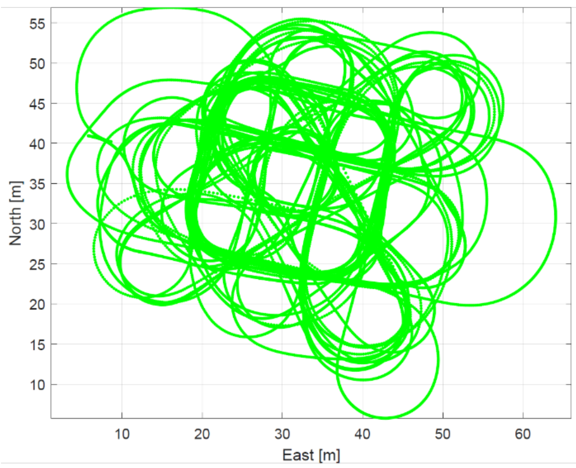
Creating a reference navigation solution is essential for any subsequent investigation, such as validating other sensor data-based solutions, introducing GPS/GNSS gaps to assess the impact on integrated navigation solutions, simulating spoofing (Wang *et al*., 2022), introducing hardware malfunctioning, etc. In our tests, most platforms carried geodetic-grade GNSS receivers, which provided excellent data in the open-sky environment. The Inertial Explorer was primarily used for reference solution creation, though RtkLib as well as in-house tools were also utilized for validation. The Inertial Explorer provides an internal estimate of the precision, which is generally viewed as somewhat optimistic, yet it is a good relative measure of performance. Table 1 lists the results for all the platforms where GNSS data was available. As expected, the component values are in 1-2 cm range.

Table 1. Precision of post-processed GNSS/INS and GNSS solutions

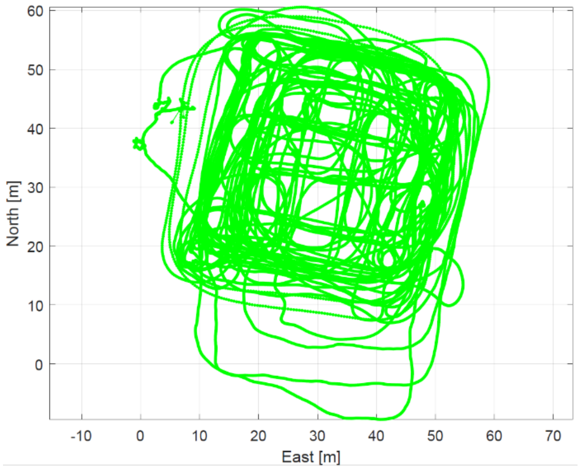
Platform	Solution Type	Position [m]		
		East	North	Height
GPSVan	GNSS/INS	0.001	0.001	0.003
Pilot	GNSS/INS	0.001	0.001	0.003
CRV	GNSS	0.007	0.006	0.013
CyberCar	GNSS	0.007	0.006	0.013
Cyclist 1	GNSS	0.007	0.006	0.012
Cyclist 2	GNSS	0.007	0.006	0.013
Pedestrian 1	GNSS	-	-	-
Pedestrian 2	GNSS	-	-	-
UAS1	GNSS	0.007	0.006	0.013
UAS2	GNSS	0.007	0.007	0.014
UAS3	GNSS	0.007	0.007	0.014
UAS4	-	-	-	-

For two vehicles, there were high-end IMU data streams available, so attitude data was also obtained, 5-10 arcsec and 20-30 arcsec range for pitch/roll and heading, respectively. While it is not independently validated, they provide a realistic reference for performance validation; consider the UWB ranging accuracy to be in the 10-30 cm range in open areas (clear LOS).

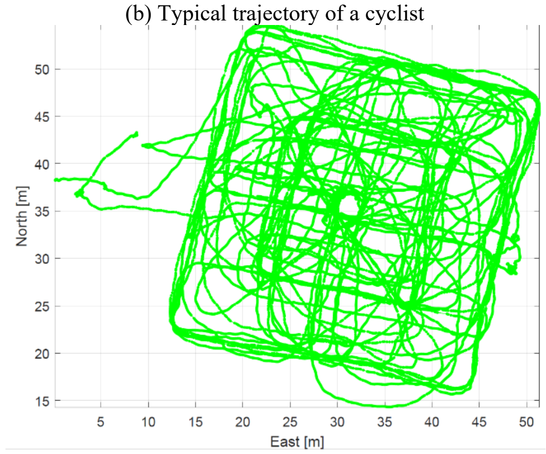
Reference trajectories computed for ground vehicles are shown in Fig. 5. Note the different patterns, such as a car, cyclist and then a pedestrian all make turns at different curvature, and obviously, the speed varies too; though not shown in the figures.



(a) Typical vehicle trajectory of the GPSVan



(b) Typical trajectory of a cyclist



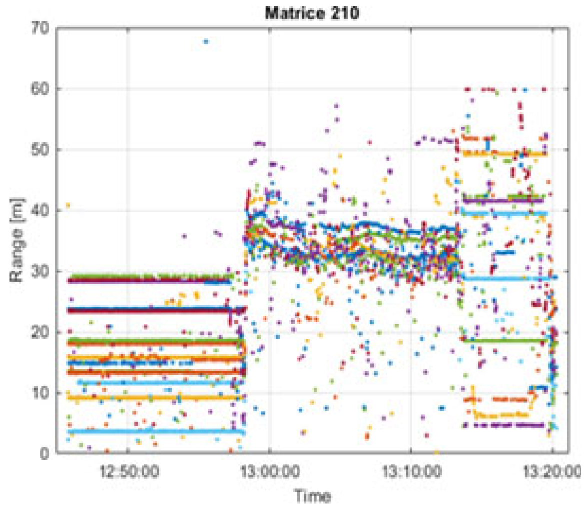
(c) Typical trajectory of a pedestrian

Figure 5. Typical platform trajectories from a test run

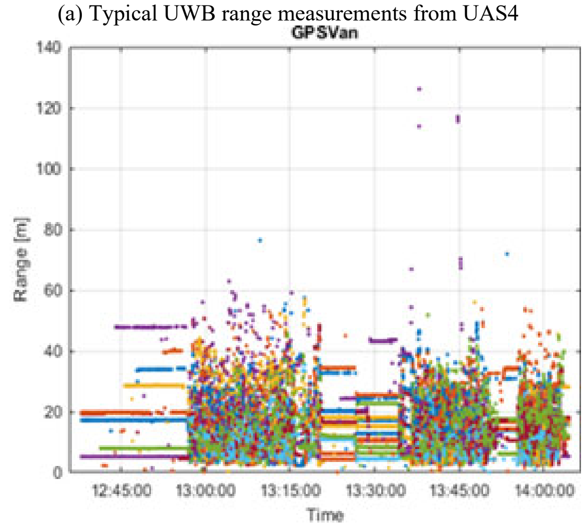
5. UWB PERFORMANCE EVALUATION

The UWB transceivers played an important role in our experiments as they provided the range measurements between the various platforms in the first phase. 12 units, as anchors formed the ground network, see Fig. 3, and then 8 units were deployed on four vehicles and four UAS platforms. Cyclists and pedestrians had only GNSS receivers installed on helmets, and thus, range data could be estimated from GNSS solutions.

Since UWB transceivers are restricted to operate at a very low power level, comparable to GNSS signals, the measurements are repeated several times to obtain acceptable results. Obviously, the distance between two transceivers as well obstacles, such as other vehicles or pedestrians blocking LOS, further decrease the performance. Therefore, the UWB acquired range data was analyzed first, and then cleaned before it was used for positioning. Fig. 6 shows two examples for range data acquired from mobile platforms: the GPSVan and UAS4. The horizontal lines show periods when the platforms were not moving. Note that the number of outliers, ranges that are likely incorrect is larger when the platforms are moving. Knowing the dynamics of the motion those outliers can be filtered, and then the data can be used for collaborative network formation. Also note that the time duration is different for the measurements, as the drone has a limited flight time, while the GPSVan continued running for a while.



(a) Typical UWB range measurements from UAS4



(b) Typical UWB range measurements from the GPSVan

Figure 6. Typical UWB range data acquired by two platforms

First, the self-localization of the ground UWB network was analyzed, using 13 transceivers. The data was acquired in a static mode, and then ranges were used to estimate the relative position of UWB units; i.e., a 2D geodetic network in a local coordinate system. Note that not all possible measurements, $\binom{n}{2}$ were acquired due to environmental limitations. Only about 85% of the ranges were available, which still represented a highly overdetermined system. Using standard least squares adjustment, a 2D solution was computed, as the area is reasonably flat. The internally estimated precision was about 5 cm (1σ). The relative positions of the local network were then compared to the surveyed ground control points. The RMSE obtained was about 10 cm (2D), which is larger than expected but can be explained by two things. First, the network formed by UWB ranges assumed a planar distribution of the locations, while the ground control points were surveyed in 3D with a few-cm accuracy. Second, the tripod setup over the surveyed points and the mounting of the UWB transceivers introduced some mounting bias too.

In the next step, a vehicle platform trajectory was computed based on using the static UWB network. The data rate of acquiring UWB ranges varies due to the environmental conditions. On an average for a single vehicle data collection, we typically obtained an about 20 Hz, which represents about 0.25-0.5 m spatial sampling at the typical moving platform speed of 5-10 m/s. Fig. 7 shows the estimated positioning precision of an about 1-minute run; the horizontal axis is in epochs and the vertical is in m. This decimeter-level positioning performance is clearly adequate for transportation applications; even for lane-following it is suitable.

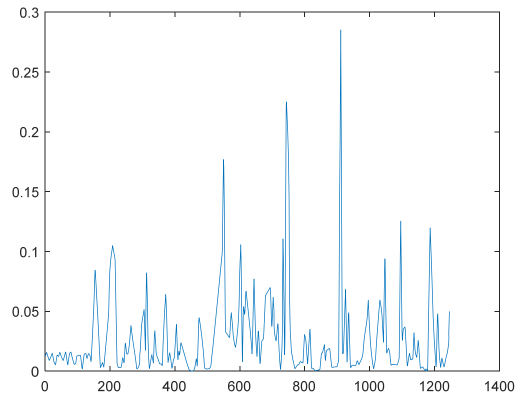


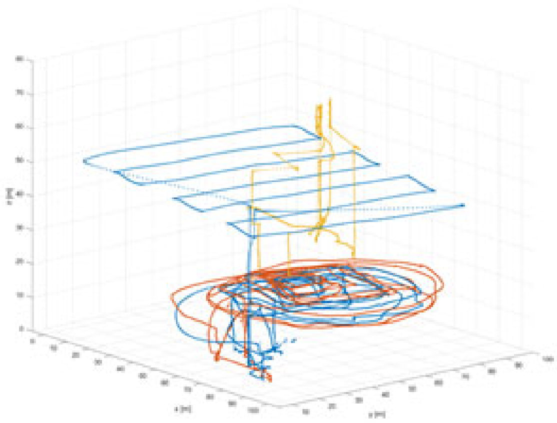
Figure 7. Internally estimated positioning precision in 2D

6. COLLABORATIVE NAVIGATION RESULTS

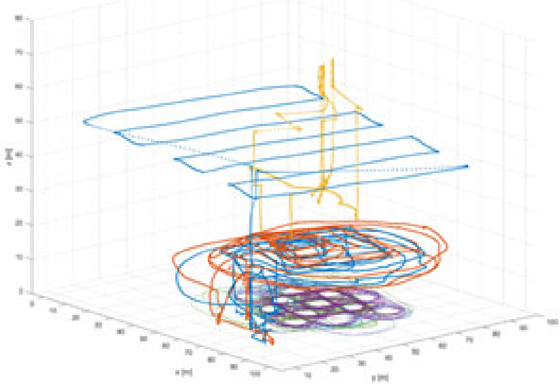
In earlier research efforts, we tested our collaborative network-based approach only on 2D data, such as four vehicles moving on road or in an intersection area. Now for the first time, we have real 3D data, as the drones were simultaneously flying over the ground vehicles. The approximate size of the envelop, the bounding box that includes all the various platform trajectories was about 100 m x 100 m x 80 m. Initial trajectory solutions are shown in Figure 8. The top image (a) presents the 4-drone only solution while the one below (b) provides the joint 4-drone and 4-vehcile solution. Note that the 12-unit ground UWB network was also used in obtaining collaborative navigation solutions.

The quantitative evaluation is still in the works, as obtaining the optimal solution and comparing it to the reference solution is a formidable task; say, in contrast to the static network-based positioning of a single mobile platform. A major challenge is the timing, time synchronization, i.e., using the correct time tags for all sensor data streams, which is, obviously, essential to achieve the highest feasible accuracy for the given specification of the sensors.

All sensors were GPS time-synchronized locally, either built-in GPS or via an Android interface, at an about 5-10 msec or better accuracy. Therefore, given the platform dynamic, the error introduced by timing is negligible. Having eight mobile UWB transceivers constantly polling each others as well as the 12-unit ground network, however, increases the chances for interference; despite the fact that UWB works with very short pulses and high repetition rate. Our data shows a varying rate of range data acquisition of about 2 – 5 Hz. Considering the vehicle motion of 5-10 m/s, a platform may move a few meters at that rate. Therefore, motion compensation should be considered, such as for straight line trajectories, projecting the ranges to a virtual location (epoch) to compute a consistent network solution. Turning and 3D motion, such as the case for UAS, may need better modeling. The local motion modeling of platforms is generally available from an EKF-based navigation filter; though, the quality may fluctuate over a large range. The UWB range-based network solutions can be considered as GNSS fixes in the standard GNSS/INS integration scheme, i.e., they provided fixes when new measurements become available.



(a) Solutions for four drones



(b) Solutions for four drones and four vehicles

Figure 8. Collaborative network-based positioning

Another aspect of having platform solution is that UWB measurements are not always reliable, as there could be outliers and no measurements at all. An outlier detection algorithm for collaborative navigation introduced in (Xiong *et al*., 2021) models the GNSS measurements and inter-platform range measurements into common and specific parts and tries to exclude the faulty measurements with a greedy search strategy. Test results show the algorithm has a better detection of GNSS faults than tradition Receiver Autonomous Integrity Monitoring (RAIM) and good sensitivity to the faulty UWB range measurements.

7. CONCLUSION

With the proliferation of sensors, inter-platform range measurements are becoming available, which, combined with increasing communication capabilities, provide a good bases for implementing collaborative navigation. The key idea is to exploit the strength of the geometry, defined by a geodetic network, formed by the platforms, to provide independent constraints for a group of platforms, and thus, achieving better overall navigation solution for all the platforms.

In this study, an UWB sensor network, installed on both static and mobile platforms provided the range measurements, but, of course, any other sensor measurement can be used. The initial evaluations show that fairly good ranging accuracy could be obtained in an intersection size area, resulting in performance that meets the requirements of most transportation activities in Smart City environment.

In summary, the results obtained so far in a 3D scenario clearly demonstrate the potential of collaborative navigation. It is important to emphasize that using this approach requires not more than utilizing already available sensor measurements on smart devices. Then, while inter-platform communication is available, such as DSRC (Dedicated Short-Range Communications), which is being phased out, cloud-based peer-to-peer communication is becoming widely available.

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