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Collaborative Navigation with Ground Vehicles and Personal Navigators

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Abstract**—An integrated positioning solution termed 'collaborative positioning' employs multiple location sensors with different accuracy on different platforms for sharing of their absolute and relative localizations. Typical application scenarios are dismounted soldiers, swarms of UAV's, team of robots, emergency crews and first responders. The stakeholders of the solution (i.e., mobile sensors, users, fixed stations and external databases) are involved in an iterative algorithm to estimate or improve the accuracy of each node's position based on statistical models. This paper studies the challenges to realize a public and low-cost solution, based on mass users of multiple-sensor platforms. For the investigation field experiments revolved around the concept of collaborative navigation, and partially indoor navigation. For this purpose different sensor**

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platforms have been fitted with similar type of sensors, such as geodetic and low-cost high-sensitivity GNSS receivers, tactical grade IMU's, MEMS-based IMU's, miscellaneous sensors, including magnetometers, barometric pressure and step sensors, as well as image sensors, such as digital cameras and Flash LiDAR, and ultra-wide band (UWB) receivers. The employed platforms in the tests include a train on a building roof, mobile mapping vans, a personal navigator and a foot tracker unit. In terms of the tests, the data from the different platforms are recorded simultaneously. Several field experiments conducted in a week at the University of Nottingham are described and investigated in the paper. The personal navigator and a foot tracker unit moved on the building roof, then trough the building down to where it logged data simultaneously with the vans, all of them moving together and relative to each other. The platforms then logged data simultaneously covering various accelerations, dynamics, etc. over longer trajectories. Promising preliminary results of the field experiments showed that a positioning accuracy on the few meter level can be achieved for the navigation of the different platforms.

Keywords-collaborative navigation, ubiquitous positioning, seamless indoor/outdoor positioning, GNSS, INS, MEMS-based sensors, UWB.

I. INTRODUCTION

Numerous military and civilian applications, including emergency response, are heavily dependent on the availability of GNSS signals. With the increasing demand for sustained navigation in GNSS-challenged environments, the concept of collaborative navigation has been developed, to further improve the navigation capability of a group of users. Collaborative navigation follows from the multi-sensory navigation approach, developed over the past several years, where GPS augmentation was provided for each user individually by sensors such as IMUs, barometer, magnetometer, odometer, digital compass, etc., for applications ranging from pedestrian navigation, to georeferencing of remote sensing sensors in land-based and airborne platforms. The objective of collaborative navigation is to develop an algorithm, which will provide an optimum navigation solution for all network users for which a navigation solution is possible (see e.g. [14]).

Field experiments revolving around the concept of collaborative positioning and navigation have been performed in an international cooperation of the joint IAG Working Group WG 4.1.1 and FIG WG 5.5 on 'Ubiquitous Positioning Systems' with participating members of the University of Melbourne, Australia, the Ohio State University, Columbus, USA, the University of Nottingham, UK, the University of New South Wales, Sydney, Australia, the National Technical University of Athens, Greece, and the Vienna University of Technology, Austria at the University of Nottingham in one week of May 2012. In this paper, a description of the field experiments and preliminary test results is given.

The next section introduces briefly the collaborative navigation concept. This is followed by a description of the field tests and some selected results in section III. Then in section IV some concluding remarks and an outlook are given.

II. COLLABORATIVE NAVIGATION CONCEPT

Collaborative (or also called cooperative) navigation can improve the individual navigation solution in terms of both accuracy and coverage, and may reduce the system's design cost, as equipping all vehicles/users with high performance multi-sensor positioning systems is not cost effective. In the most generic approach, the collaborative navigation uses range measurements (referred to as inter-nodal range measurements) between platforms or mobile users (referred to as network nodes) to assure or strengthen the navigation solution. In the collaborative navigation scenario, since more than one inter-nodal measurement vector at the target mobile user to other mobile users is generally available, all the intermodal vectors from the known (or more accurate) positions to the unknown location can be established. This is the network-based approach that can be used to obtain more accurate estimates for the unknown positions, including all other pre-estimated positions (i.e., the reference nodes). Therefore, the collaborative navigation technique based on the network approach has the advantage in that the errors at the user positions due to challenging terrain and vegetation can be compensated by other known (or more accurate) positions of other mobile users, and may result in the improvement of the navigation solution for the entire group of users [18].

According to [14] the key components of a collaborative network system are: (1) inter-nodal ranging sub-system (each user can be considered as a node of a dynamic network), (2) optimization of dynamic network configuration, (3) time synchronization, (4) optimum distributed GPS aperture size for a given number of nodes, (5) communication sub-system, and (6) selection of master or anchor nodes.

In a larger network, the selection of a subnetwork of nodes is an important issue, as in case of a large number of users in the entire network, computational and communication loads may not allow for the entire network to be treated as one entity. Subnetworks of users navigating jointly can be created ad hoc where some nodes (users) may be parts of different subnetworks. Still, information exchange among the subnetworks must be assured. Conceptually, the subnetworks can consist of nodes of equal hierarchy or may contain a master (anchor) node that will normally have better set of sensors and will be collecting measurements from all client nodes to perform a collaborative navigation solution. Different sensors and techniques such as GPS, UWB, WiFi, IMU's, MEMS-based accelerometers, gyroscopes, magnetometers, barometric pressure sensors, as well as optical systems and image-based sensors (i.e., digital cameras, Flash LiDAR and laser) may be used in collaborative navigation. It should be noted that the concept of a master node is also crucial from the stand point of distributed GPS aperture, where it is mandatory to have a master node responsible for combining all available GPS signals. Network of GPS users represents a distributed antenna aperture with large inter-element spacing, which has some advantages and also drawbacks. The primary advantage is the increased spatial resolution, which allows discriminating between signals sources with small angular separations. An increased inter-element spacing, however, will lead to the loss of correlation between the signals received at various nodes. Thus, the main challenge here is to develop approaches for combined beam pointing and null steering using distributed GPS apertures. A description of major types of network configuration and sensor integration techniques may be found in e.g. [14].

III. FIELD EXPERIMENTS

The collaborative navigation concept is investigated and validated based on the field test data collected in a campaign at the University of Nottingham in one week of May 2012. A network of five kinematic platforms have been employed, i.e., a roof top train on the Nottingham Geospatial Building, two mobile mapping vans, a personal navigator from the Ohio State University and a foot tracker unit from the University of Nottingham as well as a GPS base station.

A. *Specifications of the Kinematic Platforms*

Figure 1 shows the train on the building roof in the foreground and the personal navigator in the background. The train has been equipped with a Novatel GPS, a tactical grade Novatel SPAN IMU, and two MEMS-based IMUs, i.e., the Xsens MTi-G and the Systron Donner Inertial MMQG, and an Omnisense UWB receiver in some of the tests. Figure 2 shows the setup of the IMUs and the orientation of their axes in the horizontal plane.

Figure 1. The roof top train of the Nottingham University and the personal navigator of the Ohio State University

The personal navigator from the Ohio State University consists of the sensors shown in Figure 3. Their specifications are given in Table I. In addition, an Xsens MTi IMU, either an Omnisense or Thales UWB receiver and a tracking prism have been mounted on the personal navigator. The foot tracker unit from the University of Nottingham includes the sensors given in Table II. Also a Xsens MTi-G and an UWB receiver (Omnisense or Thales) was carried with the foot tracker unit. Figure 4 shows the personal navigator and the foot tracker unit on the building roof of the Nottingham Geospatial Building.

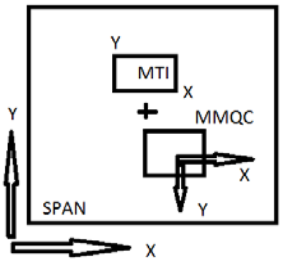

Figure 2. Setup of the IMUs on the roof top train

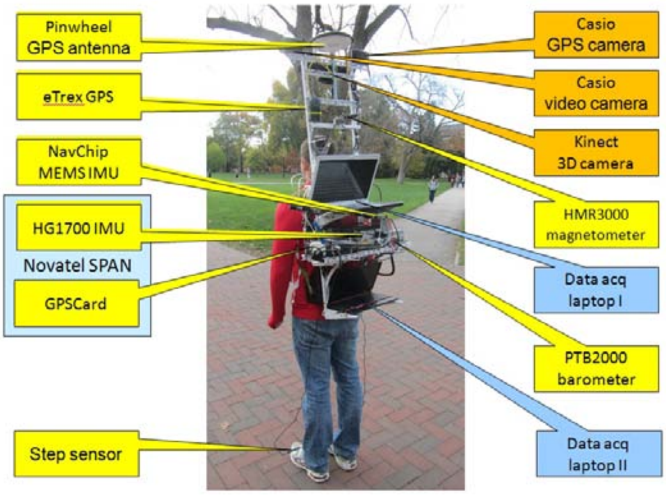

Figure 3. Sensors of the personal navigator of the Ohio State University

Figure 4. The foot tracker unit of the University of Nottingham on the left and the personal navigator of the Ohio State University on the right

The two mobile mapping vans were equipped with the sensors described in Table III. DSRC stands for Dedicated Short Range Communication. Using DSRC, besides sharing information among vehicles, the distances between the vehicles can also be estimated by radio ranging for their positioning solutions (see e.g. [3, 11]). The specifications of the DSRC transceivers can be found in Table IV.

TABLE I. SENSOR SPECIFICATIONS OF THE PERSONAL NAVIGATOR OF THE OHIO STATE UNIVERSITY

Sensor	Interface	Data Rate	GPS Timetagging	Recording
SPAN GPSCard	COM/USB	2 Hz	n/a	Laptop II
SPAN HG1700 IMU	COM/USB	100 Hz	GPSCard	Laptop II
NavChip MEMS IMU	USB	200 Hz	Software	Laptop I
eTrex recreational GPS	n/a	1 Hz	n/a	Internal
HMR3000 magnetometer	COM/USB	100 Hz	Software	Laptop II
PTB2000 barometer	COM/USB	10 Hz	Software	Laptop II
Step sensor	USB	20 Hz	Software	Laptop II
Casio EXILIM/GPS camera I, image	n/a	0.5 Hz	Software	Internal
Casio EXILIM/GPS camera II, video	n/a	30 Hz	n/a	Internal
Microsoft Kinect 2D/3D camera	USB	5 Hz	Software	Laptop II

TABLE II. SENSOR SPECIFICATIONS OF THE FOOT TRACKER UNIT OF THE NOTTINGHAM UNIVERSITY

Sensor	Interface	Data Rate	GPS Timetagging	Recording
Microstrain 3DM-GX3-25	Serial	100Hz	No [1]	PTDL [2]
Xsens MTi-G	USB	100Hz	No [1]	Laptop
Leica GS10 with AS10 antenna	n/a	10Hz	n/a	Internal
u-blox ANTARIS 4	Serial	10Hz	n/a	PTDL [2]

[1] The MTi-G has an internal GPS receiver that can be used for time-stamping. To reduce the numbers of antennas, instead the Microstrain data is cross-correlated to this data against to derive the timestamps.

[2] PTDL refers to the Precise Time Data Logger which is a serial data logger that also timestamps data using the internal u-blox receiver’s 1PPS signal.

TABLE III. SENSORS ON THE MOBILE MAPPING VANS

Van	Sensor
1	Novatel SPAN IMU
	DSRC [3] Transceiver
	Xsens MTi-G
	MMQG
2	CIMU
	DSRC [3] Transceiver
	Xsens MTi-G
	MMQG
	Leica GS10

TABLE IV. SPECIFICATIONS OF THE DSRC [3] TRANSCEIVERS

Parameters	
Frequency	5.9 GHz
Bandwidth	75 MHz
Channels	7
Max transmit power	20 dBm
Interfaces	Serial/USB/Ethernet
Inputs	5.9 GHz and GPS antennas
Power supply	12 v DC
Data logging	Internal/External (laptop)
GPS time tagging	yes
Received signal attribute logging	RSS/CFO
Packet time tag resolution	Below 10 ns
Memory	Internal/External (Micro SD)

[3] DSRC stands for Dedicated Short Range Communication.

B. *Conducted Field Trials*

For collaborative navigation in one test the vans moved around the car park together with the persons carrying the personal navigator and the foot tracker unit. Apart from that also road tests have been performed. An overview of the performed field tests is given in Table V.

TABLE V. OVERVIEW OF THE PERFORMED FIELD TESTS

Day	Test	Platforms	Test area
1		Preparation and platform setup	
2	1	Train and Foot Tracker	Building roof and indoor
	2	Train, Personal Navigator and Foot Tracker	Building roof, indoor and outside building
3	3	Train, Personal Navigator, Foot Tracker and Omnisense UWB	Building roof
	4	Train, Personal Navigator, Foot Tracker and Omnisense UWB	Building roof, indoor and outside building
	5	Personal Navigator, Foot Tracker, Thales UWB and Leica Totalstation	Indoor and outdoor
4	6	Personal Navigator, Foot Tracker, Thales UWB and Leica Totalstation	Indoor and outdoor
	7	Personal Navigator, Foot Tracker, Thales UWB and 2 Vans	Outdoor in car park
	8	2 Vans	A52 Clifton Blvd.
5	9	2 Vans	A52 Clifton Blvd.

Different test scenarios with different mobile platforms in combined indoor/outdoor environments have been investigated. Several scenarios performed on the roof of the Nottingham Geospatial Building tested the use of the sensors on the train in conjunction with the personal navigator and the foot tracker unit. In these tests (i.e., tests 1 to 4 described in Table V) the train moves along a known reference track in the shape of a Figure 8. The persons with the personal navigator and the foot tracker partly followed the moving train or were walking in front of the train either in the same or different directions. In test 3 and 4 also an UWB receiver from Omnisense was carried by the person with the personal navigator and the foot tracker, another one was mounted on the train and a fourth receiver was stationary. Apart from the movement on the building roof, also in tests 1, 2 and 4 the persons with the personal navigator and the foot tracker unit moved inside the building, went downstairs to the ground floor and walked outside and away from the building. Stops on survey markers outside the building were also made in some of the tests. The path outside the building led through parts of the jubilee campus of the Nottingham University passing by several other buildings. Along the outdoor path the GPS availability varies significantly. In tests 5 and 6 especially the positioning capabilities of the personal navigator and the foot tracker inside the building was investigated. For that purpose 6 stationary UWB receivers from Thales were deployed in the building in the hallway, i.e. two each on the ground floor and on the first and second floor. Two other UWB receivers were carried by the persons with the personal navigator and foot tracker unit. In addition, a Leica total station was positioned on the ground floor near the building entrance for tracking of the personal navigator (which was equipped with a tracking prism). The two persons with the moving platforms walked around in the building, climbed the stairs up and down and also went outdoor to be able to receive GPS signals. In test 7 the two platforms and two mobile mapping vans moved around the car park in front of the Nottingham Geospatial Building. The person with the personal navigator and the foot tracker finally went also inside the building at the end of this test. Tests 8 and 9 were tests with the mobile mapping vans which were driven on road sections of the A52 Clifton Blvd. near the university campus.

C. *IMU Preliminary Test Results*

Two low-cost MEMS IMUs and a tactical grade IMU were employed in several trials, particularly during the train kinematic and mapping vans tests. A prerequisite step for multi-sensor integration is accurate time synchronization. This can be achieved by a number of ways such as utilizing GPS time and pulse-per-second (PPS) output or by cross-correlating measurements that are not time synchronized with measurements that are time synchronized. Both methods have been used throughout the experimental campaign; for example, the former method was employed for the train platform and latter for the foot tracker test.

Before the various sensors can be integrated, it is imperative to validate that the measurements from the sensors are time synchronized. One of the methods of validating time synchronization is to compare the output measurements from the various sensors. The following will present a comparison of z-axis accelerations in the ECEF frame derived from the low-cost IMU (MMQG) and GPS, using one of the train trials dataset. Here, GPS has been chosen as the benchmark of time synchronization as it is well known that GPS could provide highly accurate timing information [13]. As seen in Figure 5, the MMQG acceleration in the Z-axis has been compared to the GPS derived acceleration in the Z-axis, both of which are in the ECEF frame. Both measurements seem to cross-correlate with each other which indicates that the MMQG IMU data is time synchronized correctly to the GPS time. This is also apparent in the other two axes (not shown here), which further indicates that the MMQG measurements are correctly time synchronized.

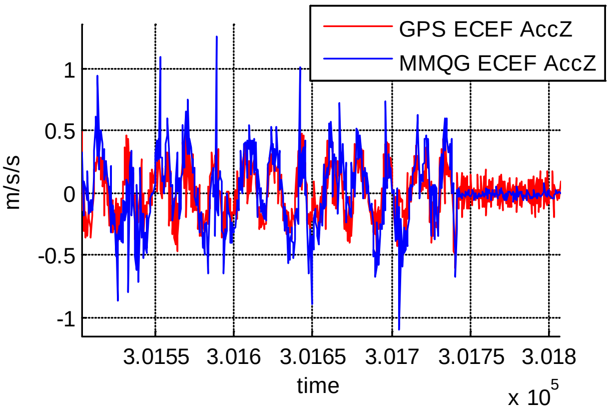

Figure 5. Comparison of Acceleration Z between MMQG and GPS

Now that the IMU measurements are properly time synchronized, they can be used to integrate with GPS. One of the most common integration algorithms used in the area of IMU and GPS integration is through the use of an extended Kalman Filter (EKF). IMU/GPS integration is well documented such as in [15] therefore is not elaborated further. The next section will evaluate the performance of integrated MMQG/GPS system using a segment of the day 3, test 3, train dataset.

Figure 6 illustrates the resulting trajectories of three systems; GPS single point positioning (SPP), integrated MMQG/GPS and integrated SPAN HG1700 IMU/relative-GPS, here referred to as SPAN/GPS. The SPAN/GPS is treated as the reference data as it consists of tactical grade inertial sensors and uses dual frequency GPS as its aiding system, thus able to output high accuracy and precision navigation solution. On the other hand, the MMQG is tightly integrated with GPS pseudo-ranges, therefore, its expected accuracy is only as good as that of GPS-SPP. However, it is advantageous over GPS only system as it is able to bridge the gap during GPS outages using its inertial measurements.

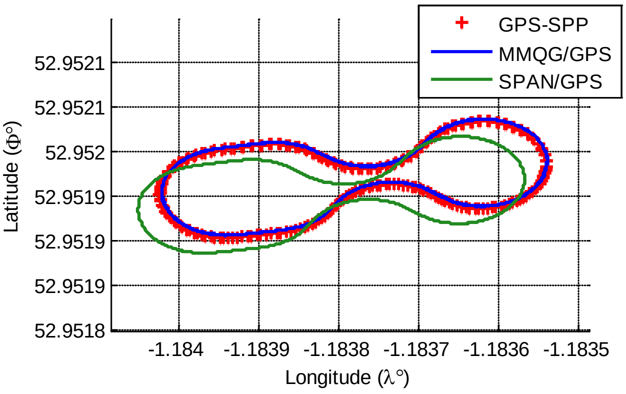

Figure 6. Comparison of the resulting trajectories from GPS-SPP, Integrated MMQG/GPS and Integrated SPAN/GPS

Table VI lists the error root-mean-squared (RMS) of both GPS-SPP and MMQG/GPS when compared against the truth data, SPAN/GPS in both 2 and 3 dimensions. As expected, the error RMS of MMQG/GPS is close to GPS-SPP where the 2D error RMS for example is about 3 m. This is seen in Figure 6, where both GPS-SPP and MMQG/GPS trajectories are similar. In addition, it can be observed from Figure 6 that both GPS-SPP and MMQG/GPS show signs of systematic error where the solutions shift slightly towards the north-east direction, away from the true trajectory. This might be caused by unfavorable satellite geometry as seen in Figure 7, where the geometric dilution of precision (GDOP) value is on average, 9.3. A more ideal GDOP value would be 1~4.

TABLE VI. INTEGRATED MMQG/GPS ERROR RMS

Error RMS (m)	**2D**	**3D**
GPS-SPP	3.412	10.126
MMQG/GPS	3.356	9.805

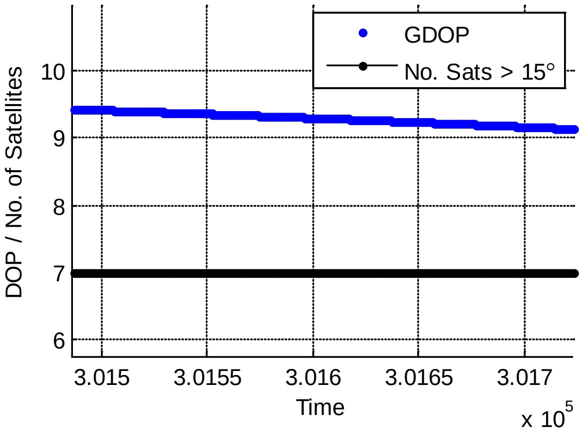

Figure 7. DOP and number of satellites

Another advantage of IMU/GPS integrated system over GPS only is it could provide attitude (pitch and roll) and heading solutions. Apart from their use in the inertial navigation system (INS) mechanization, they are also useful for applications that require attitude information such as aerial-photogrammetry and LiDAR scanning. Figures 8, 9 and 10 show the attitude and heading solution from MMQG/GPS and SPAN/GPS integrated systems.

As seen in Figure 9, the roll angles of the integrated systems do not match but do show similar profiles. This is due to the small physical misalignments of the MMQG relative to SPAN. As shown in Figures 8 and 10 however, the pitch and heading angles are almost identical indicating that the pitch and heading directions of these two systems are well aligned. Overall, the attitude and heading solutions of the low-cost MMQG/GPS is comparable to SPAN/GPS.

This section has shown the capability of the low-cost MEMS inertial sensor compared to the tactical grade inertial sensor. The MMQG/GPS positional performance is similar to that of GPS-SPP whilst its attitude and heading solution are comparable to the SPAN/GPS solutions. This makes the low-cost inertial sensor an attractive alternative to the higher grade (tactical or navigational) inertial sensors which are more expensive and bulky, to be used as one of the components in collaborative positioning.

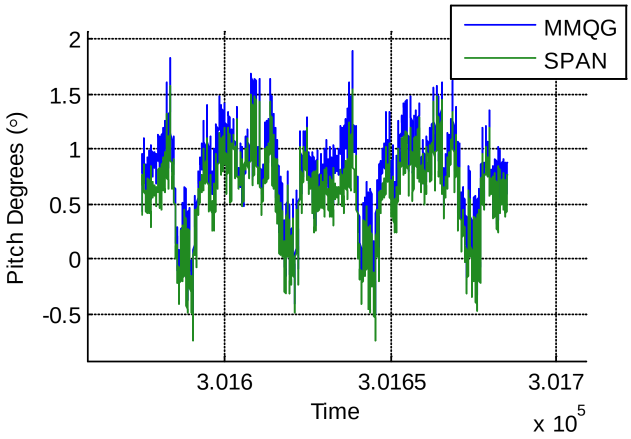

Figure 8. Comparison of Pitch between Integrated MMQG/GPS and Integrated SPAN/GPS

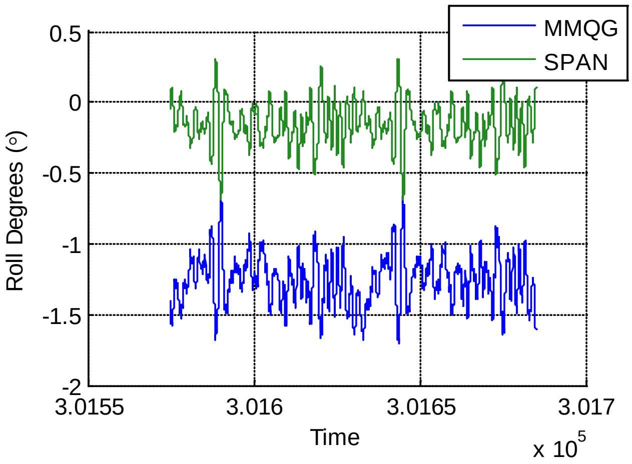

Figure 9. Comparison of Roll between Integrated MMQG/GPS and Integrated SPAN/GPS

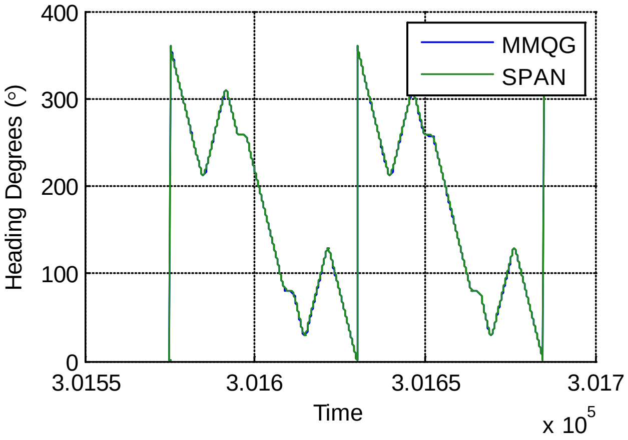

Figure 10. Comparison of Heading between Integrated MMQG/GPS and Integrated SPAN/GPS

D. DSRC Performance

A pair of DSRC transceivers was employed for the different trials of the mobile mapping vans during the conducted experimental campaign. The important parameters for evaluating the functionality and performance of these equipment include the Received Signal Strength (RSS) observation noise, precision of the received packets time tags, Carrier Frequency Offset (CFO) observation noise, and the packet delivery rate.

RSS is widely considered for radio ranging purposes in the literature for Collaborative Positioning (CP) due to its simplicity. Some examples of RSS-based vehicular CP systems are presented in [7, 8, 11, 19, 22]. However, as explained in [3], the RSS ranging is effectively useless for vehicular CP applications due to the dynamicity of environment. Apart from this, the noise of RSS observations also affects the performance of RSS-based ranging for static, indoor, and less-dynamic applications. Here, the level RSS observation noise of our DSRC equipment will be explained.

Time of Arrival (TOA) and Time Difference of Arrival (TDOA) are the time-based ranging techniques considered for indoor and outdoor CP purposes. Some examples are presented in [7, 20]. These methods require time synchronization among the nodes. This requirement is technically very complex, especially for vehicular environments. The DSRC equipment employed in the experiments can synchronize their internal clocks with the GPS time. However, other uncontrolled parameters including the channel access time and the workload of the processor prevents a guaranteed transmit time.

CFO can be used for range-rating and positioning enhancement in vehicular networks. Some examples of CFO-based CP are presented in [4, 5, 6]. The accuracy of range-rating depends on the CFO observation noise. The experimental results achieved using our DSRC equipment are explained in this section.

Packet delivery rate depends on the number of competing nodes which use a common channel of DSRC for a specific application, for example CP [23]. Only two transceivers were available for this experimental campaign and, therefore, the evaluation of packet delivery rate constraints was not possible technically.

Here, we summarize the different parameters evaluated for the DSRC transceivers employed in this experimental campaign. For RSS and CFO observation noise, transmit power was set at two different levels, 10 dBm and 20 dBm. Table VII shows the Standard Deviation (STD) of the observations for different conditions. As can be seen, the RSS observation noise is the same for both transmit powers but the performance of CFO estimation improves when the transmit power is higher. This is consistent with the results for CFO estimation performance presented in [9, 10] and similar articles.

For evaluating the precision of the received packets time tags, two different packet transmit rates were considered. For each case, the STD of the receive time tags with regard to the set rate was calculated. Table VIII shows the results. As can be seen, the time tags of the received packets have some uncertainty which is less for higher transmit rate. Here, we do not have enough insight and motive to investigate this behaviour of timing in terms of transmission rate but considering the very accurate and high resolution of receive time tagging, in the order of ns, it can be concluded that such uncertainty is due to the transmit schedule at Physical Layer (PHY) of the DSRC transmitter. A more important issue is the order of the timing uncertainty. Although DSRC clocks were synchronised with GPS time, the millisecond order is achieved which is absolutely useless for ranging purposes. However, this accuracy can be used for coarse synchronization required for the CP techniques presented in [4, 6].

The position results show that the proposed statistical network-based collaborative navigation algorithms significantly improved the results of the individual navigation solutions and the group of solutions.

IV. CONCLUDING REMARKS

This paper has presented the challenges to realize the concept of collaborative positioning which is based on multiple sensor platforms. It has described a series of field experiments undertaken at the University of Nottingham where various sensors ranging from low-cost to tactical grade IMUs, GNSS receivers, UWB, DSRC and several other sensors were deployed and tested in different scenarios and platforms. The paper has also described the performance of the low-cost MMQG IMU where its positional error is similar to GPS-SPP but with the benefit of being able to provide continuous navigation solutions in a GPS difficult environment. Furthermore, the paper has presented the performance of DSRC.

TABLE VII. STANDARD DEVIATION (STD) OF THE DSRC OBSERVATIONS

Parameter	**Transmit Power: 10 dBm**	**Transmit Power: 20 dBm**
STD of RSS observation noise	1.4 dBm	1.4 dBm
STD of CFO observation noise	135 Hz	115 Hz

TABLE VIII. STANDARD DEVIATION (STD) OF TWO DIFFERENT PACKET TRANSMIT RATES

Parameter	**Transmit Rate: 10 packet/sec**	**Transmit Rate: 10 packet/sec**
STD of time tags around the anticipated receive times	2.3 ms	1.6 ms

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