A Benchmarking Measurement Campaign in GNSS-denied/Challenged Indoor/Outdoor and Transitional Environments

Allison KEALY, Australia; Guenther RETSCHER, Austria; Jelena GABELA, Australia; Yan LI, Australia; Salil GOEL, India; Charles K. TOTH, U.S.A.; Andrea MASIERO, Italy; Wioleta BŁASZCZAK-BĄK, Poland; Vassilis GIKAS, Greece; Harris PERAKIS, Greece; Zoltan KOPPANYI, U.S.A., Dorota GREJNER-BRZEZINSKA, U.S.A.

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SUMMARY

This paper reports about a sequence of extensive experiments, conducted in GNSS-denied/challenged, indoor/outdoor and transitional environments at The Ohio State University as part of the joint FIG Working Group 5.5 and IAG Working Group 4.1.1 on Multi-sensor Systems. The overall aim of the campaign is to assess the feasibility of achieving GNSS-like performance for ubiquitous positioning in terms of autonomous, global, preferably infrastructure-free positioning of portable platforms at affordable cost efficiency. Therefore, cooperative positioning (CP) of vehicles and pedestrians is the major focus where several platforms navigate jointly together. The GPSVan of The Ohio State University was used as the main reference vehicle and for pedestrians, a specially designed helmet was developed. The employed/tested positioning techniques are based on using sensor data from GNSS, Ultra-wide Band (UWB), Wireless Fidelity (Wi-Fi), vison-based positioning with cameras and Light Detection and Ranging (LiDAR) as well as inertial sensors. The experimental schemes and initial results are introduced in this paper. The results from the experimental campaign demonstrate performance improvements due applying CP techniques.

1. INTRODUCTION

Localization in indoor and obscured GNSS (Global Navigation Satellite Systems) environments remains one of the challenging research problems. Cooperative positioning (CP) or localization (CL) has been demonstrated to be extremely useful for positioning and navigation of mobile platforms within a neighborhood. CP, however, is still based mainly on GNSS with sensor augmentation using inertial sensors. In challenging GNSS-denied or combined indoor/outdoor environments, the use of alternative positioning technologies is required (see e.g. Alam and Dempster, 2013; Kealy et al., 2015). This paper investigates the use of Ultra-wide Band (UWB), Wireless Fidelity (Wi-Fi), vison-based positioning with cameras and Light Detection and Ranging (LiDAR) technologies as alternative and complementary techniques for augmentation. A benchmarking measurement campaign was carried out at The Ohio State University in October 2017. In the experiments, vehicles and pedestrians navigated jointly together to achieve CP ubiquitous positioning (see e.g. Kealy et al., 2011; Retscher and Kealy, 2006), including seamless transitions between indoor/outdoor environments. The experimental schemes and characteristics are summarized, and initial results are presented in this paper.

2. SEAMLESS INDOOR-OUTDOOR COOPERATIVE LOCALIZATION FOR PEDESTRIANS

In the experiments, we develop a cooperative system comprising of four pedestrians using an integration of sensors such as UWB, GNSS, Raspberry Pi, Wi-Fi and camera, with the objective of achieving precise positioning in indoor environments, as well as providing a seamless position transition between indoor and outdoor environments. An overview of the sensors used in the proposed system is shown in Figure 1. These sensors are installed on a helmet that could be worn by a pedestrian. One of the helmets (with installed sensors) is shown in Figure 2. Three of the four such helmets developed in this research are shown in Figure 3.

In outdoor environments, the positioning solution is derived primarily from GNSS and relative range observations among pedestrians. In indoor and transition environments, the localization solution is estimated using relative range observations among pedestrians, camera observations, and Wi-Fi RSS (Received Signal Strength) measurements. In these experiments, four pedestrians start from outdoor environments where GNSS observations are available to all

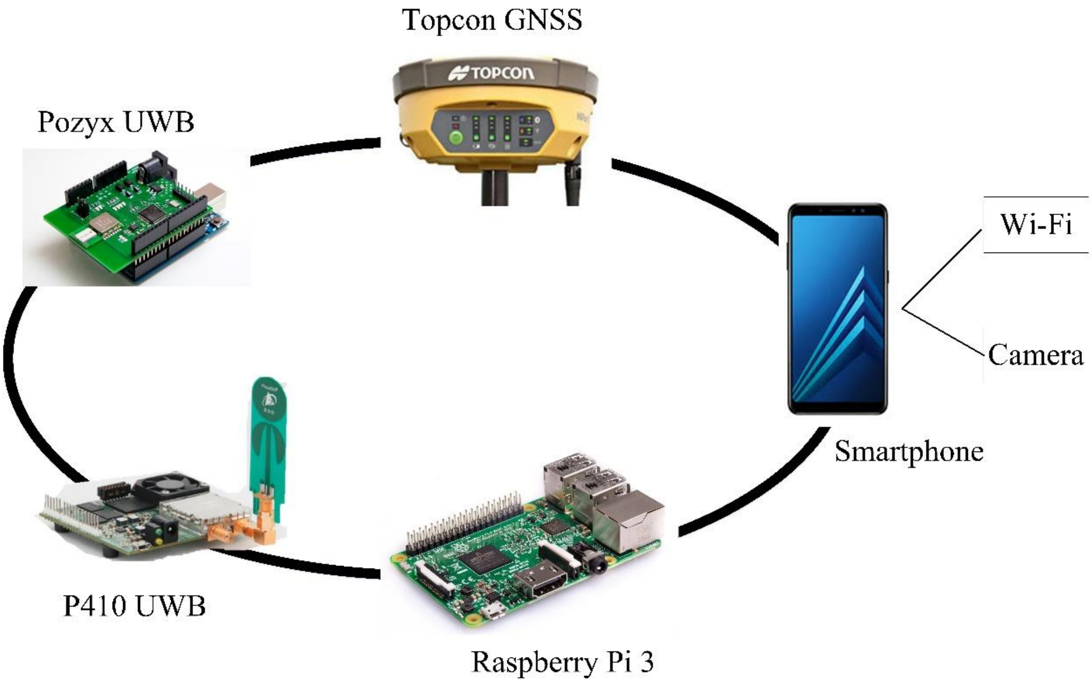

Figure 1: Overview of the sensors integrated on one of the pedestrian helmets in the developed system.

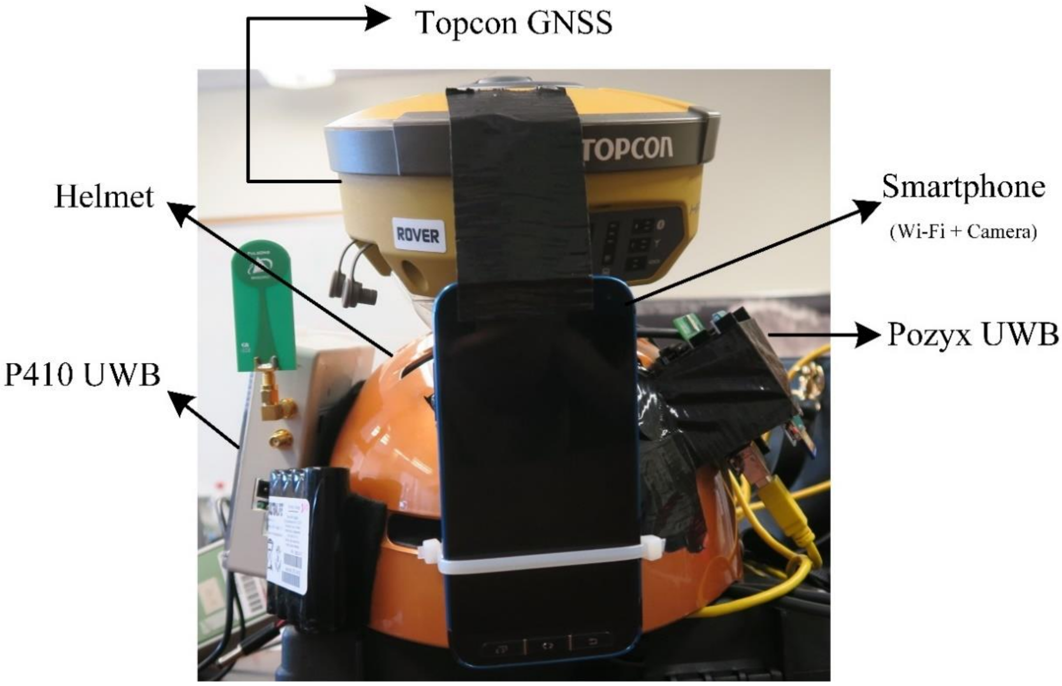

Figure 2: Sensors installed on a helmet.

Figure 3: Three of the four helmets developed in this research.

pedestrians. In addition, each pedestrian is observing relative range measurements to other pedestrians. All the pedestrians then transition from outdoor to indoor environments and thus, each pedestrian starts to lose GNSS signals successively. Once all pedestrians are indoors, GNSS observations are not available to any of the pedestrians. In such conditions, pedestrians rely on relative UWB ranges (including ranges between pedestrians, and ranges between pedestrian and anchors, i.e., a set of static devices, fixed on constant positions), Wi-Fi measurements, and camera observations, for localizing all users cooperatively. A total of 18 UWB range observations either between pedestrians or between pedestrian and static anchors are available for localization in indoor and transition environments. A plot of range measurements as observed by a pedestrian with respect to four UWBs as a function of time is shown in Figure 4. It is seen that a maximum range of at least 60 m is achievable in indoor environments. At certain instants, for example between 2500 to 2600 seconds x 100, significant outages in the UWB communication are observed. This is most likely due to non-availability of direct line of sight between the two UWBs. At time instants between 2700 and 3100 s x 100, recurring communication outages (for UWB 1) are observed. Further, it is observed that UWB ranges are corrupted by outliers that are likely because of multipath in indoor environments. Such outliers should be accounted for, within the cooperative state estimation framework.

3. COOPERATIVE OUTDOOR VEHICLE POSITIONING

As a part of this campaign, a set of outdoor data was collected. The aim of the data collection was to provide data for further research on navigation and integrity monitoring solutions for Intelligent Transport Systems (ITS) in urban environments. The outdoor tests included multiple platforms and an extended sensor configuration, as for quality and for supporting image based navigation, multiple LiDARs and a range of still and video cameras were used. The platforms included four vehicles, two cyclists and pedestrians sharing the same road section, and performing various motion patterns. These experiments were planned with challenges of urban environments (e.g. GNSS unavailability, bad satellite geometry) in mind, as well as the inadequacy of sensor fusion of Inertial Measurement Unit (IMU) and GNSS for certain applications of ITS. An ad-hoc CP network was set up to be independent of GNSS and to enable collection of redundant measurements.

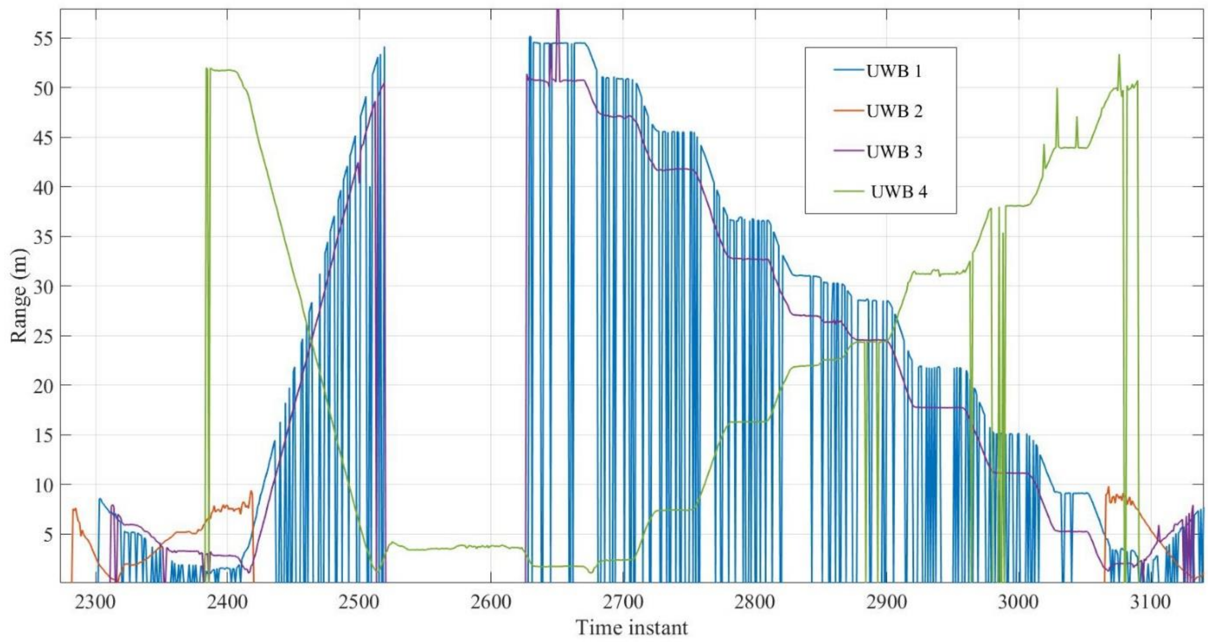

Figure 4: Plot of range observations from 4 UWBs with time.

A total of 16 points were set up as static infrastructure nodes. Infrastructure nodes were equipped with Time Domain P440 and P410 UWB radios for relative ranging. This allowed vehicles to communicate with infrastructure and position themselves based on the known position of infrastructure nodes and measured relative ranges between them. That defines the Vehicle-to-Infrastructure (V2I) CP. To allow for communication between the four cars, every car was equipped with P410 UWB radios. With every car sharing its position and relative range to the other cars, Vehicle-to-Vehicle (V2V) CP was enabled. This set-up is shown in Figure 5. Every car was equipped with survey-grade GNSS receiver and one UWB radio for V2V CP. Given the limited number of available sensors, only one vehicle was equipped with additional UWB radio for V2I CP and IMUs (H764G1 and H764G2 Honeywell, 3DM-GX3-35 MicroStrain).

The datasets were collected in an open sky environment, which enabled simultaneous collection of ground truth. Further, this experiment consists of two different tasks. The first part of the experiment aimed to collect the data when the cars are driving in different formations along the lane (Figure 6). The second part of the experiment was focused on intersection level positioning were the cars were performing different operations at intersections (Figure 7). These two sets of data provide an opportunity of further research on optimal CP network geometries given a specific ITS application requirements (integrity, accuracy, continuity, availability).

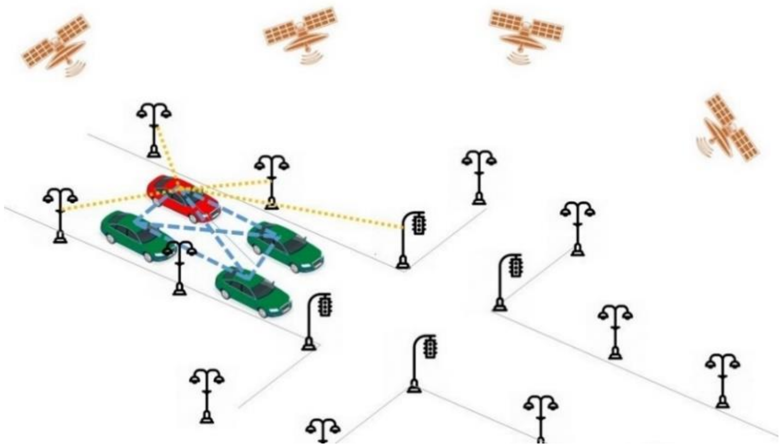

Figure 5: Experimental set-up of V2V and V2I CP.

Figure 6: Lane level experiment. On the left: map of the trajectory for 1 car. On the right: a photograph of the data collection process and the experimental set-up on field.

Figure 7: Intersection level experiment. On the left: map of the trajectory for 1 car. On the right: a photograph of the data collection process and the experimental set-up.

3.1 The Reference Vehicle (GPSVan)

A GMC Suburban customized measurement vehicle, called GPSVan (Grejner-Brzezinska 1996), customized for autonomous vehicle research (Toth et al., 2018; Koppanyi and Toth, 2018) was used for the data acquisition, see Figure 8. The navigation sensors, GPS/GNSS receivers and IMUs are located inside the van. A light frame structure installed on the top and front of the vehicle provides a rigid platform for the antennas and UWB units, and imaging sensors, such as LiDAR and different types of cameras. The sensor configuration used during the data acquisition consists of two GPS/GNSS receivers, three IMUs, four UWB transmitters, three high-resolution DSLR cameras for acquiring still images, 13 P&S (Point and Shoot) cameras for capturing videos, and seven mobile LiDAR sensors, see Table 1. The four primary purposes of the various sensors are categorized as:

1. Georeferencing and time synchronization: GPS/GNSS, UWB and IMU sensors provide accurate time as well as position and attitude data of the platform, allowing for sensor time synchronization and sensor georeferencing (Kim et al., 2004).
2. Optical image acquisition: these sensors are carefully calibrated and synchronized in order to provide accurate geometric data for mapping; for instance, by using stereo, multiple-image photogrammetric and computer vision methods (Geiger et al., 2011).
3. Video logging: these sensors provide a continuous coverage of the environment during the tests. The quality of these sensors does not allow for accurate time synchronization and calibration, applied to high quality still image sensors. Nevertheless, the moderate geometric accuracy combined with the high image acquisition rate allows for efficient object extraction and tracking of traffic signs, road signs, and obstacles, etc. (Maldonado-Bascon et al., 2007; Greenhalgh and Mirmehdi, 2012). In addition, dynamic objects, such as vehicles, cyclists, pedestrians, etc., can be tracked.
4. 3D data acquisition: Velodyne LiDAR sensors allow for direct 3D data acquisition that can be used for object space reconstruction, and object tracking (Azim and Aycard, 2012; Jozkow et al., 2016).

GPS/GNSS, UWB and IMU sensors provide accurate georeferencing of the platform, and accurate time base for the time synchronization. Antennas located on the top of the GPSVan deliver the GPS/GNSS signals to multi-frequency receivers located inside the vehicle. The Septentrio PolaRx5 receiver with PolaNt-x MC antenna (SEPT) is a state-of-the-art multi-constellation system that supports data logging of multi-frequency signals at high temporal resolution (Septentrio, 2018). The GPS, a Novatel DL-4 with Novatel 600 antenna an older model is primarily used for time synchronization and backup positioning sensor. The GNSS data is post-processed with DGNSS (using phase measurements) technique. The positioning accuracy of the post-processed GNSS data is at centimeter-level for open-sky areas. However, at several areas at the OSU campus, the positioning accuracy is lower due to the limited clear line of sight to the satellites; urban-canyon effect. An UWB network was installed in the test area, providing UWB positioning for the testing.

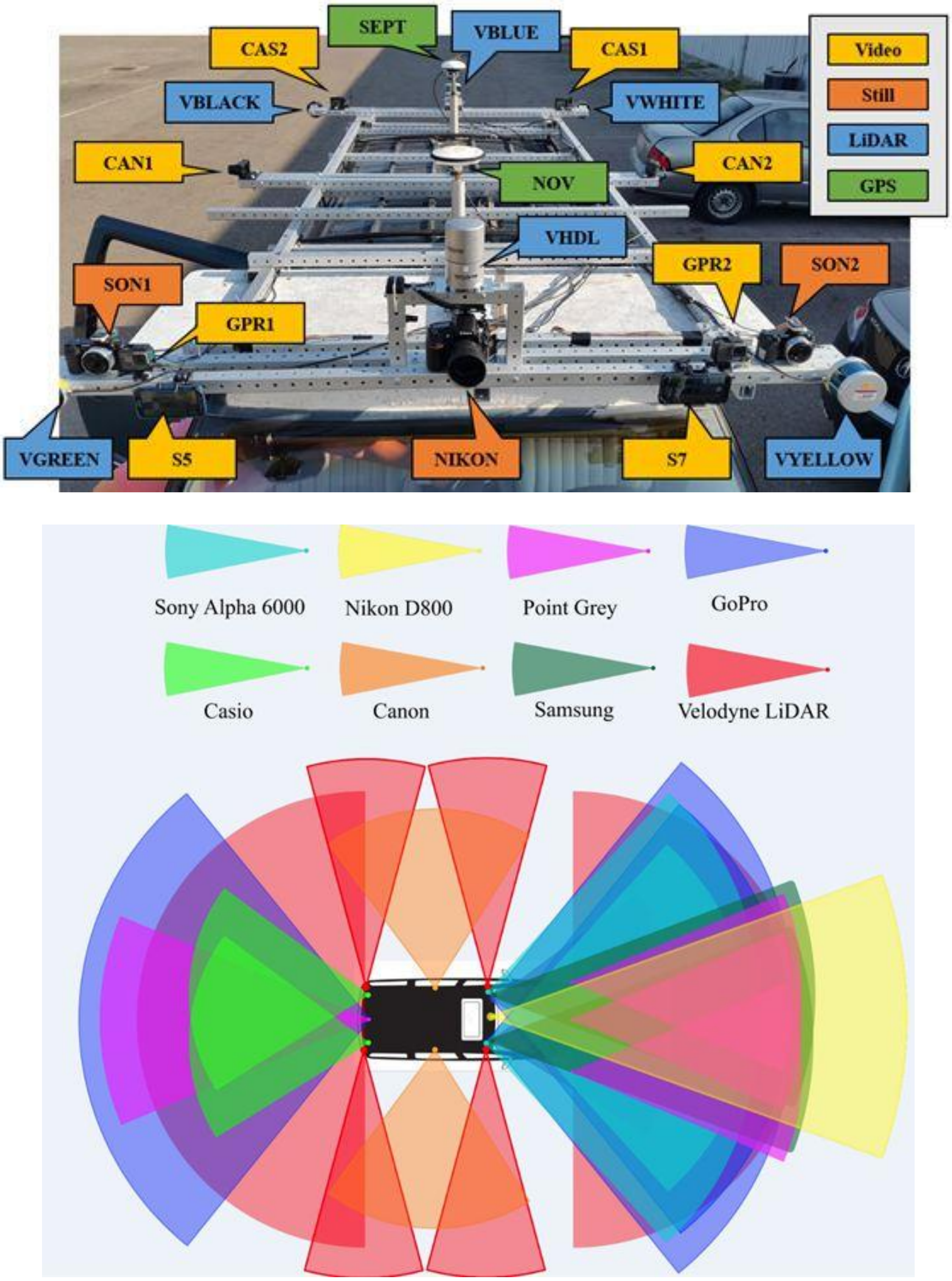

Figure 8: The top view of the GPSVan and field of views of the imaging sensors.

Table 1. Overview of the sensors; see explanation in the text.

Purpose	Type	Sensor Model	Num. of Sensors	Location
(1)	GNSS	Septentrio PolaRx5 GPS	1	Top
	GPS	Novatel DL-4 GPS	1	Top
	IMU	MicroStrain 3DM-GX3	1	Inside
	IMU	H764G IMU	2	Inside
	UWB	TimeDomain 410/440	2	Top
	UWB	Pozyx	2	Top
(2)	Image	Sony Alpha 6000 (ILCE)	2	Front, L/R
	Image	Nikon D800	1	Front-center
(3)	Video	Canon PowerShot SX710	1	Right Side
	Video	Canon PowerShot G7X	1	Left Side
	Video	Casio EX-H20G	2	Back, L/R
	Video	GoPro HERO5 Black	2	Front, L/R
	Video	GoPro HERO3+ Black	1	Back-center
	Video	Point Grey Flea3 8.8	1	Front-bottom
	Video	Point Grey Flea3 1.3	1	Back-center
	Video	Point Grey Flea3 1.3	2	Front, L/R
	Video	Samsung S5/S7	2	Front, L/R
(4)	LiDAR	Velodyne HDL-32E	1	Front, Top
	LiDAR	Velodyne VLP-16	6	F/B, L/R (1+1)

The IMU sensors provide attitude data for the georeferencing, and are also used for obtaining navigation solution during GPS/GNSS-outages. Two types of IMUs were used during the data acquisition. H764G is a high accuracy navigation-grade IMU. Two of these sensors are located inside the platform, however only the H764G-1 is used during the post-processing, and fused with the SEPT GPS in a Kalman filter to derive the navigation solution. The MicroStrain 3DM-GX3 sensor is a lower-grade IMU which is used for sensor performance comparison.

The utilized cameras can be divided into two groups according to their capabilities and operating modes. The first group includes the DSLR cameras. These cameras captured still images with high resolution but with low sampling frequency (0.5-1 Hz). Due to the low temporal resolution, the main usage for these cameras is to provide high-resolution images for deriving accurate geometric data; these cameras are well-calibrated and precisely synchronized to the UTC reference time system. In the other group, the cameras captured images in video mode, and thus, the environment is recorded with high temporal resolution, but at lower image-resolution. These cameras are not rigorously calibrated and synchronized. These data streams can be used for real-time scene understanding, image interpretation, obstacle detection or tracking. The various types of sensors allow for performance comparison of the imaging capabilities of the different sensors.

3.2 Ultra-Wide Band Ranging

An UWB-based positioning system is usually formed by a set of static devices, fixed on constant positions (anchors), and a set of moving ones (rovers). When anchor positions are known a priori, the system typically ensures positioning with errors at decimeter-level. Despite this level of accuracy is sufficient for several applications, the potential of the system shall be higher. Indeed, UWB range measurements are usually characterized by a random error at centimeter-level and by a (typically larger) systematic error, which depends on the environment (e.g. multipath) and on the configuration of the UWB devices.

The experiment aims at investigating the possibility of calibrating the UWB system in order to compensate for the effects of the static parts of the environment on UWB measurements, hence obtaining an improvement of the overall positioning accuracy. To this aim, 14 Pozyx and 14 TimeDomain UWB anchors were fixed on the walls along a corridor in one single floor as well as in the staircase in the Bolz Hall building of the Ohio State University, and calibration and validation range measurement datasets were collected by a rover on 35 checkpoints along the corridor, see Figure 9.

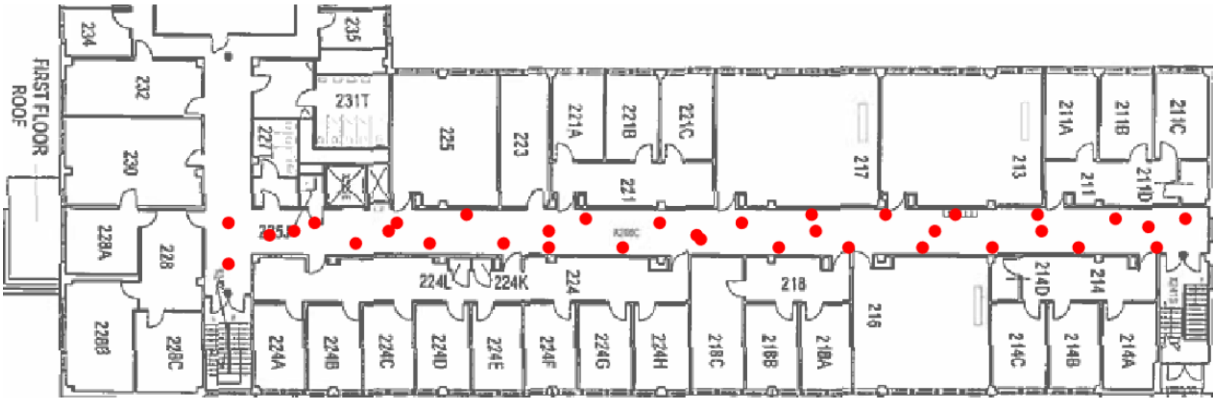

Figure 9: Positions of the checkpoints along the considered corridor.

Preliminary results were obtained by considering a very simple calibration model, where for each checkpoint the range error measured during calibration was considered as the bias to be removed during validation on the same checkpoint. Figure 10 shows the UWB range error distribution for the Pozyx rover on the validation dataset, and the corresponding distribution after removing the bias estimated during the calibration. The results show that the considered approach can potentially be useful to reduce the effect of the systematic error on the UWB measurements. However, this kind of approach can be used only to reduce the effect of the static part of the environment, whereas the effect of moving objects/persons is not removed. Since the simple calibration model can be applied only on the same positions used for its derivation, generalizations, based on bi-dimensional spline interpolation and on machine learning, are under investigation.

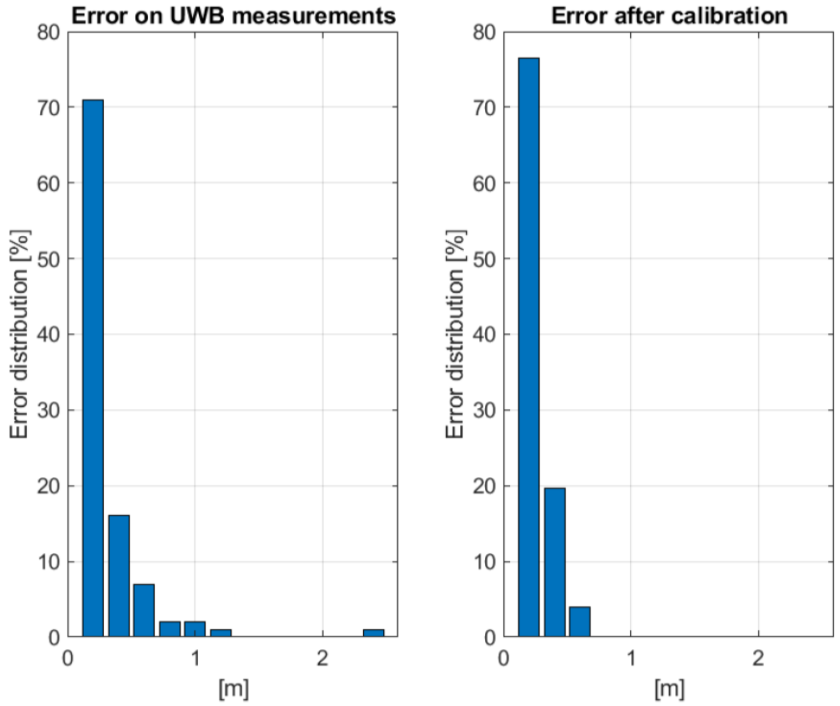

Figure 10: Distribution of the range error for the Pozyx rover in the validation dataset (left), and distribution of the error taking into account of the estimated environment effect (right).

3.3 Velodyne LiDAR Data Reduction

As seen above measurements with various sensors were performed, among others Velodyne LiDAR. Velodyne HDL-32 LiDAR generates up to ~1.39 million points per second, Velodyne VLP-16 LiDAR generates up to ~600 thousands points per second. Thus, using these sensors a huge volume of data is acquired in a very short time. In many cases, it is reasonable to reduce the size of the dataset with eliminating points in such a way that the datasets, after reduction, meet specific optimization criteria. A lot of frames from Velodyne LiDAR were obtained during the experiments with millions of points. After pre-processing and georeferencing we can prepare the 3D point cloud. Standard georeferencing of MLS data was based on the transformation from the scanner local coordinates to global coordinates using boresight parameters and navigation information from the on-board GPS and IMU. The reduction can take place either on the stopped frame, obtained directly from the Velodyne LiDAR measurement, or can be performed on the entire 3D point cloud. For reducing the numbers of points we can use the OptD (Optimum Dataset) method.

The OptD method for processing data from Airborne Laser Scanning and Terrestrial Laser Scanning was presented in Błaszczak-Bąk (2016) and Błaszczak-Bąk et al. (2017). The OptD method can be performed in two variants: (1) with one criterion optimization called the OptD-single, and (2) with multi criteria optimization called the OptD-multi. The OptD method uses linear object generalization methods, but the calculations are performed in a vertical plane which allows for accurate control of the elevation component. Błaszczak-Bąk et al. (2018) outlined the modification of the OptD method, with one criterion for Mobile Laser Scanning data captured by Velodyne sensors (called OptD-single-MLS). The OptD-single-MLS method is implemented in nine consecutive steps described in Błaszczak-Bąk et al. (2018).

From the tests, the option 1 (with one frame) is presented in Figure 11. The original dataset for Frame 1 and the derived datasets after OptD-single-MLS reduction are characterized in Table 2. The OptD method allowed keeping Z_{min} and Z_{max} values, the average value of the height in the set will change and the SD parameter means the range of the height of the measurement points in relation to the mean. SD will increase as the number of points in the point cloud decreases. The OptD-single-MLS method removes those points which do not have relevant effect on the terrain characteristics from a practical point of view. The OptD-single-MLS method provides total control over the number of points in the dataset.

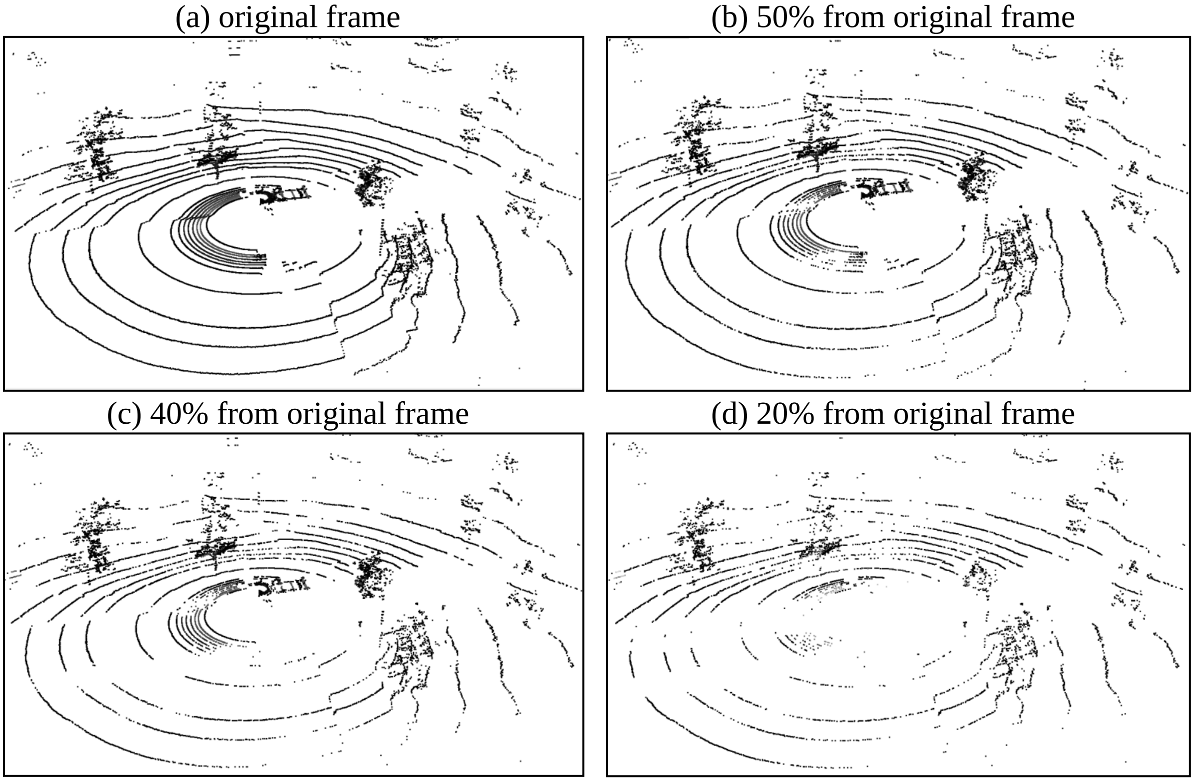

Figure 11: MLS data (a) original frame, (b) 50% of points after reduction, (c) 40% of points after reduction, (d) 20% of points after reduction.

Table 2. Characteristics of obtained datasets after the OptD-single-MLS method for one frame

Dataset	Z_{min} (m)	Z_{max} (m)	Z_{mean} (m)	Number of Points	SD (m)
frame	−2.401	7.667	−1.018	34 650	1.283
50% of frame	−2.401	7.667	−0.846	17 283	1.450
40% of frame	−2.401	7.667	−0.787	13 867	1.504
20% of frame	−2.401	7.667	−0.637	6 863	1.673

4. WI-FI INDOOR POSITIONING USING LOCATION FINGERPRINTING

The vast majority of current indoor localization systems are designed for sub-meter accuracy in position estimation, which is unnecessary for most indoor navigation applications (see e.g. Pritt, 2013). Room-level or region-level granularity of location is sufficient for most location aware services (Castro et al., 2001; Chen et al., 2012; Jiang et al., 2012; Jiang et al., 2013). RSS-based Wi-Fi fingerprinting is a typical method frequently used for location estimation, since it does not need any prior knowledge of Access Points (APs) deployment. The idea of the fingerprint technology is to use online RSS measurements to match the fingerprint database previously generated at every location in the offline training phase. In the probabilistic fingerprint approach, a model for the statistical distribution of the RSS for each different location is built, based on the sample data collected during the training phase. In the online phase, Bayesian inference is used to calculate the probability that a user is at a certain location given a specified observation, and estimate the most likely location of the mobile device. The accuracy of the statistical distribution model directly affects the final performance of the probabilistic fingerprint positioning (Xia et al., 2017). Li et al. (2018) proposed a statistical approach to localize the mobile user to room level accuracy based on the Multivariate Gaussian Mixture Model (MVGMM). The proposed system is designed to handle practical problems such as device heterogeneity, signal reliability and environment complexity, thereby the users have no basic knowledge about the base stations deployed within the environment in advance. A Hidden Markov Model (HMM) is applied to track the mobile user, where the hidden states comprise the possible room locations and the RSS measurements are taken as observations.

The aim of the test is to build up the training database for a probabilistic indoor localization system which can localize mobile user with room level accuracy based on an University wireless network. The test scenario consisted of three stages which are (1) calibration of the smartphones, (2) training data measurements and (3) test data collection. The calibration has to be performed to mitigate the RSS variance problems due to the device heterogeneity. For that purpose, static (stop-and-go mode of the smartphone CPS App[1]) observations are carried out where all devices collect 200 scans at different locations simultaneously. This is followed by the training data collection to be able to construct the fingerprint database for each room in the indoor environment. Here the collection mode is static while each user chooses different reference points in the rooms. Their locations must to be randomly chosen and need not to be known, but they need to be manually labeled with the room ID. In the final stage, the test data is collected to track the user's trajectory to verify the proposed system. In this case the collection

[1] Combined Positioning System App developed by Hannes Hofer at TU Wien (see e.g. Hofer and Retscher, 2017).

mode is kinematic (dynamic walking mode of the CPS App). In total, 11 kinematic walking trajectories are carried out with the different smartphones.

Figure 12 shows two examples of obtained trajectories of one smartphone user. As shown in Li et al. (2018) the walking trajectories along the reference points could be obtained with matching success rates of up to 97%. The MVGMM is efficient at approximating the RSS distribution for each room that takes the signal correlations into computation. The system obtained a reliable 93.0 % matching accu racy for half of the trials. The performance was further improved to 97.3 % by introducing the conditional likelihood observation function, which takes advantages of the unseen signatures of APs. Thus, the proposed system demonstrated a practical prototype model of a reliable room location awareness system in a real public environment. It can handle the data uploaded by diverse devices and the noisy environment (Li et al., 2018).

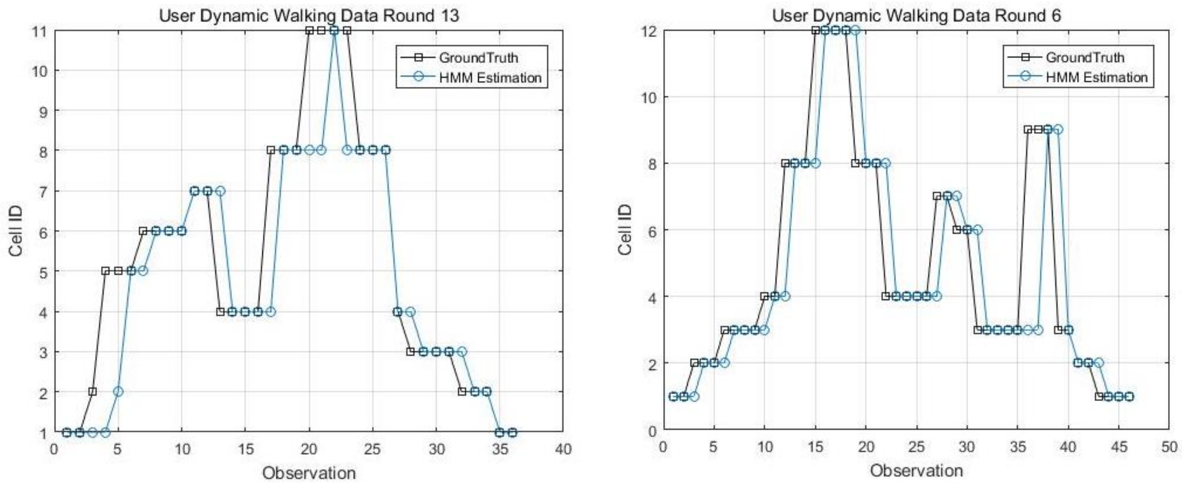

Figure 12: Examples of two kinematic walking trajectories.

5. CONCLUSIONS AND OUTLOOK

In the one-week benchmarking measurement campaign presented in this paper, the main focus was led on CP of different platforms, i.e., vehicles, bicyclists and pedestrians, in GNSS-denied/challenged in-/outdoor and transitional environments. An overview of the field experimental schemes, set-ups, characteristics and sensor specifications along with preliminary results including measurement data reduction, UWB sensor calibration and Wi-Fi indoor positioning with room-level granularity as well as user trajectory determination is given. It could be proven that the test set-ups and employed sensors for the CP localization of all involved sensor platforms – either if they are vehicles or pedestrians – in the different test scenarios are suitable and practicable. In the indoor environment, for instance, trajectories of pedestrians walking around could be obtained with around 97% matching success rate on average using Wi-Fi fingerprinting. In the case of UWB, positioning is possible even better than on the decimeter-level. Further data processing and analyses is currently in progress and the results indicate significant performance improvements of users navigating within a neighborhood. The extensive dataset is available from the joint FIG/IAG Working Group.

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BIOGRAPHICAL NOTES

Allison Kealy is a Professor in the School of Science, Geospatial Science at RMIT University, Australia. She holds a degree in Land Surveying from The University of the West Indies, Trinidad, and a PhD in GPS and Geodesy from the University of Newcastle upon Tyne, UK. Allison's research interests include sensor fusion, Kalman filtering, high precision satellite positioning, GNSS QC, wireless sensor networks and LBS. She is the co-chair of the joint FIG WG5.5/IAG WG4.1.1 on Multi-sensor Systems, vice president of the IAG, Com. 4 on Positioning and Applications and technical representative to the US Institute of Navigation.

Guenther Retscher is an Associate Professor at the Department of Geodesy and Geoinformation of the TU Wien – Vienna University of Technology, Austria. He received his Venia Docendi in the field of Applied Geodesy from the same university in 2009 and his Ph.D. in 1995. His main research and teaching interests are in the fields of engineering geodesy, satellite positioning and navigation, indoor and pedestrian positioning as well as application of multi-sensor systems in geodesy and navigation. Guenther is currently the co-chair of the joint FIG WG 5.5 and IAG WG 4.1.1 on Multi-sensor Systems.

Jelena Gabela is currently working towards the PhD degree at The University of Melbourne, Australia. Her research interests include sensor fusion, integrity monitoring of multi-GNSS and cooperative positioning. She received her BE and MS degrees in geodesy and geoinformatics, from the University of Split, Croatia in 2014, and the University of Zagreb, Croatia in 2016.

Yan Li is currently working towards the PhD degree in the department of electrical and electronic engineering, The University of Melbourne, Australia. She received her BE degree in the school of astronautics from Northwestern Polytechnical University, China in 2011, the MS in the center of autonomous systems in University of Technology, Sydney in 2014. Her research interests include wireless sensor networks and inertial navigation.

Salil Goel earned his Ph.D. jointly from the University of Melbourne, Australia and IIT Kanpur, India as a Melbourne India Postgraduate Academy (MIPA) scholar in 2017. After working as a Research Fellow at RMIT University, Australia, Salil joined IIT Kanpur, India as Assistant Professor in June 2018. His research interests are sensor fusion for mapping and navigation, LiDAR, Filtering and estimation and Unmanned Aerial Vehicles.

Charles Toth is a Research Professor in the Department of Civil, Environmental and Geodetic Engineering, The Ohio State University, USA. He received a MSc in Electrical Engineering and a PhD in Electrical Engineering and Geo-Information Sciences from the Technical University of Budapest, Hungary. His research expertise include spatial information systems, LiDAR, high-resolution imaging, surface extraction, data acquisition, modeling, integrating and calibrating of multi-sensor systems, 2D/3D signal processing, and mobile mapping technologies. He has published over 400 peer-reviewed journal and proceedings papers, and is the co-editor of the widely popular book on LiDAR: Topographic Laser Ranging and Scanning: Principles and Processing. He is ISPRS 2nd President (2016-2020) and ASPRS Past President.

Andrea Masiero has a Post-doc position at the Interdepartmental Research Center of Geomatics of the University of Padua, Italy. His research interests range from geomatics to computer vision, smart camera networks, modeling & control of adaptive optics systems. He is currently working on low cost positioning and mobile mapping systems.

Wioleta Błaszczak-Bąk is an Assistant Professor at the Institute of Geodesy of the University of Warmia and Mazury in Olsztyn, Poland. She received her PhD in 2006. She is conducting research on LiDAR point cloud processing. She is an author of papers on big data optimization.

Vassilis Gikas received the Dipl. lng. in Surveying Engineering from the National Technical University of Athens, Greece and the PhD degree in Geodesy from the University of Newcastle upon Tyne, UK. Currently he is a Professor with the School of Rural and Surveying Engineering, NTUA. His areas of research are in sensor fusion and Kalman filtering for navigation, engineering surveying and structural deformation monitoring and. He is the chair of IAG Sub-Com. 4.1.

Harris Perakis is a PhD candidate at School of Rural and Surveying Engineering of the National Technical University of Athens. He holds a Dipl. lng. in Surveying Engineering from the same School (2013). His scientific interests include positioning within indoor and hybrid environments, trajectory assessment and geodetic sensor data fusion.

Zoltan Koppanyi is post-doctoral researcher at The Ohio State University, USA. He received degrees in computer science, civil engineering, and a MSc in Land Surveying and GIS Engineering. He received his PhD in Earth Sciences at the Budapest University of Technology and Economics. His research interests cover several fields of navigation and mapping, such as navigation in GNSS-denied or corrupted environments, LiDAR & image-based tracking, UWB positioning, sensor fusion, bundle adjustment and dense reconstruction from images.

Dorota Grejner-Rzezinska is a Professor and Associate Dean for Research at the College of Engineering, The Ohio State University (OSU). She served as s Chair of the Dept. of Civil, Environmental and Geodetic Engineering, and Director of the SPIN Laboratory, OSU. Her research interests cover GPS/GNSS algorithms, GPS/inertial and other sensor integration for navigation in GNSS-challenged environments, sensors and algorithms for indoor and personal navigation. She published over 300 peer reviewed journal and proceedings papers and led over 55 sponsored research projects.

CONTACTS

Dr. Guenther Retscher
Department of Geodesy and Geoinformation
TU Vienna – Vienna University of Technology
Gusshausstrasse 27-29 E120/5
1040 Vienna, AUSTRIA
Tel. +43 1 58801 12847
Fax +43 1 58801 12894
Email: guenther.retscher@tuwien.ac.at
Web site: http://www.geo.tuwien.ac.at/